DISTRIBUTED MODEL PREDICTIVE CONTROL OF A WIND FARM WITH CLUSTERING

*Mallika. S., M. Dharani Kumar, P. Manimegalai

Karpagam Academy of Higher Education, Coimbatore, India
1*mallikanagu14@gmail.com

ABSTRACT

This work gives a concise overview of the role that distributed model predictive control has el the development of the advanced wind turbine control algorithms. The benefits of the model predictive control compared to conventional controllers convoluted in wind turbine control are defined. Wind turbine model predictive active power controller based on identified piecewise affine discrete-time state space wind turbine model is designed. The designed D-MPC controller showed better performance. A wind farm with ten wind turbines was used as the test system. Research were attend and evaluated, which include the operation of the wind farm with the D-MPC under low and high wind conditions, and the dynamic achieved with a wind turbine out of service. With the fast gradient method, the convergence rate of the D-MPC has been significantly improved, which decrease the iteration numbers. Appropriately, the communication burden is reduced.

Keyword: Distributed model predictive control (D-MPC), dual decomposition, fast gradient method, wind farm control.

1. INTRODUCTION

Wind energy has become fastest growing renewable source considering the installed capacity per year [1]. Unlike the other alternative sources, wind power industry has reached mature commercial phase. Never-the less, wind turbines are continuously increasing size and nominal power capacity to achieve more compete-tive cost of energy compared to conventional sources. Among the large wind turbines, variable-speed and pitch controlled turbines are predominant.

The efficiency that they achieve depends mostly on the control algorithm used for turbine operation. Besides, to make the turbine profitable, controller must take care for structural loads mitigation. Only considering both fore mentioned control objectives can lead to optimal lifetime and production combination that will lead to maximal profit. It is high intermittence of wind power and high nonlinearity of multiple input-multiple output (MIMO) wind turbine dynamics that make this task a challenge. Most of the research on the development of wind turbine controllers is mainly based on linear controllers (e.g. [2, 3]). The main drawback they have in the wind turbine control is impossibility to consider system constraints. Besides advanced control algorithms which have already been developed, interesting role in the future of large wind turbines control will for sure be reserved for model predictive control (MPC) [4]. Good mathematical wind turbine model together with measuring instruments of upcoming wind or short-term meteorological service data can be used to reduce the loads of a wind turbine along with maintaining high electricity production demands. MPC inherently handles multiple objective MIMO systems what makes it particularly interesting for the wind tur-bine control.

2.D-MPC wind Farm Control Strategy

The hierarchical structure of the D-MPC centralized power control of a wind farm is illustrated in Fig. 1. Like the hierarchical structure proposed in, the high-level control operates at a slow time scale. Specifically, the wind farm power reference P_{ref}^{wfc} is generated based on the requirements from the system operator and the available wind farm power. With the wind field model and measurement data, the mean wind speed of a certain period (several minutes) can be estimated. Several approaches have been developed to distribute the mean power references to individual wind turbines ($\overline{P_{ref}^{WT1}}$, $\overline{P_{ref}^{WT2}}$,.... $\overline{P_{ref}^{WTi}}$,) with $\sum \overline{P_{ref}^{WT1}} = P_{ref}^{wfc}$ which is reviewed. The proportional distribution algorithm proposed is adopted to distribute the mean power references to individual wind turbines, which are according to the available power of each turbine. Conventionally, these mean power reference signals are directly assigned to the individual wind turbines without considering the effect of turbulence. In this paper, these references are modified by the D-MPC controller locally equipped at each wind turbine, which can be considered as the low-level wind farm control for short time-scale dynamics. It can reduce the wind turbine load by adjusting the power reference to each turbine.

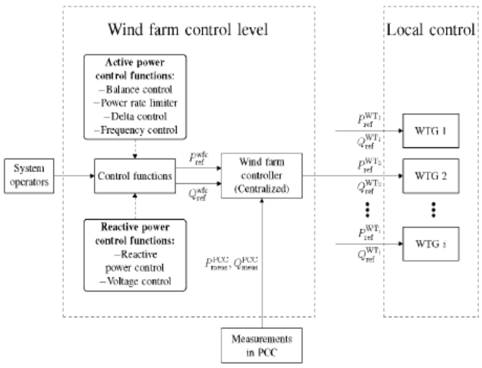

Fig 2.1 Centralized Wind Form Power Control

A centralized approach to the optimization of large wind farm operation is an extremely complex control problem. Namely, the system in scope is best described as a coupled, constrained multiple-input multiple-output model whose order grows very fast with the number of wind turbines in the wind farm. The wind turbine and especially the wind field are highly nonlinear systems. Furthermore, the system is subjected to large number of disturbances due to random nature of wind, and/or possible wind turbine malfunctions that may prevent or restrict its operation. Finally, wind farm model inherently comprises processes acting on very different time scales: the mechanical part of a typical megawatt scale wind turbine with local speed and power controller has dominant dynamics in the time scale of 1 second, while the typical propagation time of wind between two rows of wind turbines can be significantly longer than 10 seconds.

Using the clustering-based piece-wise affine (PWA) wind turbine model developed and the measurement feedback the D-MPC can determine in which operation region the wind turbine. The corresponding prediction model and the matrix for local optimization can be formulated. With the communication with the central unit (see Fig. 2), the iterations are executed to meet the global constraints. Different from the central unit does not have much computation. It is used to update the dual variables by collecting the matrices from wind turbines which are computed offline. Then, the modified power references ($\overline{P_{ref}^{WT1}}$, $\overline{P_{ref}^{WT2}}$,…. $\overline{P_{ref}^{WTi}}$,) with $\sum \overline{P_{ref}^{WT1}} = P_{ref}^{wfc}$ are assigned to the individual wind turbine controller. The reference signals for the converters and blade pitch controller of each wind turbine are generated according to $\overline{P_{ref}^{WTi}}$.

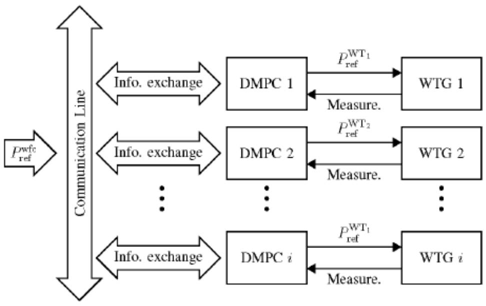

Fig 2 Block diagram wind farm active power control

2.1 Mathematical Modeling of Wind Turbine

Aerodinamical properties of wind turbine blades allow converting airflow energy into the rotational energy of the rotor which is then converted to the electrical energy. Power stored in air cylinder with the radius R, the density ρ and the wind velocity V_w is given with

$$Pw = 1/2\ R\ 2\pi\rho V_w^3 \qquad (1)$$

The amount of wind power that is extracted by a wind turbine depends on the power coefficient Cp

$$Pwt = 1/2\ R\ 2\pi\rho V_w^3 Cp(\lambda, \beta) \qquad (2)$$

where β refers to the blade pitch angle and λ is a dimensionless quantity known as the tip speed ratio

$$\lambda = \frac{|\omega R|}{V_w} \qquad (3)$$

where ω denotes the rotational speed of the rotor and R is the rotor radius.

To obtain a dynamical model of the wind turbine, aerodynamic forces acting on wind turbine blades have to be modeled. Precise mathematical model which describes forming of the lift and drag forces along the blades due to the airflow through the swept area of the rotor is based on implicit equations [5]. For that reason, it is impractical for the controller design. The model used in this work is a simplified nonlinear model of the wind turbine dynamics. It describes all significant physical phenomenas experienced by the wind turbine with rated power 1 [MW]. Therefore, it is a good starting point for the design of a controller with objectives to optimize power production and reduce fatigue of the wind turbine's tower. The assumptions of the model are: (i) rigid blades, (ii) the wind tower has fore-aft deflections that can be well modeled using first mode, (iii) the wind is uniform over the wind field. The dynamics of the rotor is given with

$$J_t\boldsymbol{\omega} = Ma(\beta,\omega, V_w) - M_g \qquad (5)$$

where Ma holds for the aerodynamic torque and M_g is the generator torque. Fore-aft deflections xt of the tower top are modeled with the second order diferential equation

$$M_t\ddot{x}_t + D_t\ddot{x}_t + C_t x_t = F_t\ (\beta, \omega, \vartheta_m\ ) \qquad (6)$$

where Mt denotes the modal mass, D_t is the damping coefficient and Ct the spring constant of the wind turbine tower. F_t is the effective thrust force experienced by the rotor? Blade pitching servo system can be well modeled with

$$T_\beta\ddot{\beta}\ \ +\beta\ = \beta_{ref} \qquad (7)$$

where T_β is the time constant of the system and βref the pitch angle reference?

2.2 D-MPC through Dual Decomposition with Fast Dual Gradient Method

Wind Turbine Linearization for D-MPC

The discrete model of a single wind turbine developed in Part I is used as the prediction model. It is a PWA model whose operation regions are determined according to the current state and input variables. Accordingly, the computation task of the prediction model has been done offline and stored based on these regions. Since these states can be directly measured and wind speed can be well estimated, the prediction model can be updated by searching the current operation region for each time step. It should be noticed that wind speed in this paper refers to "effective wind speed" which is used to describe the wind speed affecting the entire rotor. The estimation methods have been nicely reviewed and compared. For the D-MPC design in this paper, it is necessary to obtain a discrete linear time-invariant (LTI) wind turbine model. Therefore, it is assumed that the obtained prediction model is kept invariant during the prediction horizon, expressed by

$$x\ (k+1) = A_d x(k) + B_d\ u(k) + E_d\ d(k) + F_d$$

$$Y(k) = C_d x(k) + D_d u(k) + G_d d(k) + H_d$$

where x, u, d, and y indicate state, input, disturbance, and output vectors, respectively, x = [ωr, ωf, θ], u = $\overline{P_{ref}^{WT1}}$, d = V_w , y = [Ts, Ft], θ is the pitch angle, ωr and ωf are the rotor speed and the filtered generator speed, respectively, Ft is the thrust force, Ts is the shaft torque, PWT ref is reference power derived from the wind farm, and represents the wind speed, which V_w is regarded as a disturbance. The formulation of A_d, B_d, C_d, E_d, F_d, G_d and H_d depending on the sampling time is explained in Part I.

2.3 MPC Problem Formulation

The cost function of the D-MPC design takes into account both the tracking performance of the wind farm power reference and the minimization of the wind turbine load. During the wind farm operation, it is assumed that the mean wind speed V_w of a certain period (10 min) can be estimated and an initial distribution of individual wind turbine power references for this period is known. Therefore, the mean power Reference for the ith wind turbine P_{ref}^{WT1} can be calculated by a proportional algorithm according to the available power

$$P_{ref}^{WT1} = \alpha_i \, P_{ref}^{wfc} \ , \text{ with } \sum_{i=1}^{n_t} \alpha_i = 1$$

where n_t is the number of wind turbine in the wind farm, P_{ref}^{wfc} is the power reference for the wind farm, and α_i indicates the distribution factor for the ith wind turbine. Accordingly, other steady-state variables, e.g., the shaft torque T_s^{WTi}, can be determined.

The prediction horizon is chosen as np and k indicates the prediction index. The MPC problem at time *t* can be formulated as follows

$$u^{min} \sum_{i=1}^{n_t} \left(\sum_{k=0}^{n_p} \left\| u_i(k) - P_{ref}^{WTi} \right\| Q_p + \sum_{k=0}^{n_p} \left\| S_1 . y(k) - T_s^{WTi} \right\| Q_T + \sum_{k=0}^{n_p-1} \left\| \Delta \left(S_2 . y(k) - T_s^{WTi}\right) \right\| Q_F\right.$$

Subjected to

$$x_i(k+1) = A_d x_i(k) + B_d u_i(k) + E_d d_i(k) + F_d$$

$$I \in [1, \ldots, n_t], \; k \in [0, \ldots, n_p - 1]$$

$$y_i(k) = C_d x_i(k) + D_d u_i(k) + G_d d_i(k) + H_d$$

$$I \in [1, \ldots, n_t], \; k \in [0, \ldots, n_p - 1]$$

$$\sum_{i=1}^{n_t} u_i(0) = P_{ref}^{wfc}$$

$$x_i \in X_i \, , \; u_i \in u_i$$

where Q_p, Q_t, and Q_F are the weighting factors. The second and third terms in the cost function are used to penalize the deviation of the shaft torque from the steady state and the derivative of the thrust force to reduce the wind turbine load; X_i and U_i are the local state and control input constraint sets, respectively. As the optimization variable u, the first values (ui(0), i ∈ [1, . . . , Nt]) are taken as the control inputs for each turbine. The control inputs are coupled whose sum equals the power reference of the wind farm P_{ref}^{wfc}.

2.4Parallel Generalized Fast Dual Gradient Method

The MPC problem can be reformulated as a standard quadratic programming (QP) problem, which is rewritten in the following format with Hessian matrix $H_i \in$ Rnp × np (positive definite) and coefficient vector $g_i \in$ Rnp×1. H_i and g_i can be calculated according to the equality constraints and prediction horizon n_p.

$$\text{Min } \Phi = \sum_{i=1}^{n_t} \Phi_i(u_i) = \sum_{i=1}^{n_t} \left(\frac{1}{2} u_i' H_i u_i + g_i' u_i\right.$$

Subjected to

$$\vartheta \in u$$

Gu =b

In this case, the coupling of the control inputs can be equivalently rewritten as the equality constraint. Since only the

First U_i control input is coupled with all the others, $\sum_{i=1}^{n_t} u_i(0) = P_{ref}^{wfc}$ G, and b can be obtained.

$$G = [G_1, \ldots\ldots, G_{n_t}], \; G_i = [1, 0, \ldots.., 0], \; G_1 \in R^{1 * n_p}$$

$$b = P_{ref}^{wfc}$$

3.Properties of Dual Problem

In this part, the key properties required to apply fast dual gradient methods are described. Obviously, the functions Φ and Φi are strongly convex with matrix H and H_i. H is defined as H = blkdiag ($H_1, \ldots, H_{nt}$). By introducing the dual variables λ, the primal problem is transformed into the following Lagrange dual problem

$$sup_\lambda inf_u\{\Phi(u) + \lambda(G_u - b)\} = sup_\lambda \sum_{i=1}^{n_t} [inf_{u_i}\{ \Phi_i(u_i) + (\lambda(G_i) u_i - \lambda \frac{b}{n_t}$$

With the definition of conjugate functions for Φ and Φi

$$\Phi^* (-G' \lambda) = sub_u (-\lambda G_u - \Phi(u))$$

$$\Phi^* (-G' \lambda) = sub_u (-\lambda G_u u_i - \Phi(u_i))$$

The dual problem above can be rewritten as

$$sub_\lambda \{ -\Phi^* (-G' \lambda) - \lambda b \}$$

$$= sub_u \sum_{i=1}^{n_t} \{ \Phi_i(u_i) + (\lambda(G_i) u_i - \lambda \frac{b}{n_t}$$

For simplicity, the following dual problem equations are defined

$$d_i(\lambda) = -\Phi^* (-G' \lambda) - \lambda \frac{b}{n_t}$$

$$d(\lambda) = -\Phi^* (-G' \lambda) - \lambda b \quad d = \sum_{i=1}^{n_t} d_i$$

The following property for the dual problem can be derived according, which is the theoretical foundation for the distribution optimization algorithm.

Property 1: If the primal function Φ and its local function Φi are strongly convex with matrices H and Hi, we have the conclusion that the dual function d and its local function Φi are concave, differentiable, and satisfy

$$d(\lambda_1) \geq d(\lambda_2) + \nabla d(\lambda_2)(\lambda_1 - \lambda_2) - \frac{1}{2}\|\lambda_1 - \lambda_2\|^2$$

$$d(\lambda_1) \geq d(\lambda_2) + \nabla d(\lambda_2)(\lambda_1 - \lambda_2) - \frac{1}{2}\|\lambda_1 - \lambda_2\|^2 L_i$$

Compared with what has been presented in the literature, this property provides a tighter quadratic lower bound to the dual function. It can be further proved that the obtained bound is the best obtained bound. Therefore, more accurate approximation of the dual function can be derived, which improves the convergence rate. In the next part, a generalized parallel optimization algorithm for D-MPC is described.

3.1 Distributed optimization Algorithm

The parallel fast dual gradient method is implemented below for the wind farm control. Dual variables λ, η, and ϕ are introduced. Normally, the iteration stops if the stopping criterion is met. In this paper, a fixed number of iteration kmax is selected as the stopping criterion to limit the online computation time.

Algorithm for Parallel fast dual gradient method for wind farm control

Require: Initial guesses λ[1] = η[0], ϕ[1] = 1.

For k = 1, . . . , k_{max}, do

Step 1: Send λ[k] to all wind turbines j ∈ {1, ..., n_t } through communication (Central Unit ⇒D-MPC).

Step 2: Update and solve the local optimization with augmented cost function in individual D-MPC:

$u_i^{[k]}$=arg min_u { Φi + $u_i' G_i' \lambda^{[k]}$}

Step 3: Update L_i^{-1} in individual D-MPC, if the operating region changes.

Step 4: Receive $U_i^{[k]}$from each turbine and form $U^{[k]} = [U_1^{[k]},\ldots U_{nt}^{[k]}]$ (D-MPC ⇒ Central Unit).

Step 5: Receive the updated L_i^{-1}(D-MPC ⇒Central Unit).

Step 6: Update L^{-1} according to L_i^{-1} and the dual variables in Central Unit:

$\eta^{[k]} = \lambda^{[k]} + L^{-1}$ (G$u^{[k]}$- b

$$\varphi^{[k+1]} = \frac{1+\sqrt{1+4(\varphi^{[k]})2}}{2}$$

$$\lambda^{[k+1]} = \eta^{[k]} + \left(\frac{\varphi^{[k]}-1}{\varphi^{[k+1]}}\right)(\eta^{[k]} - \eta^{[k-1]})$$

End For

According to the property the algorithm is proved to converge with the rate

$$d(\lambda^*) - d(\lambda^k) \leq \frac{2\|\lambda^* - \lambda_2\|^2 L}{(k+1)^2} \quad \forall k \geq 1$$

where k represents the iteration number. The details of the proof are described. As illustrated, the convergence rate is improved from O(1/k) to O(1/k^2) with negligible increase in iteration complexity, compared with the standard gradient method. As L = G$H^{-1}G'$ has the tightest lower bounds to d(λ) and is adopted in this paper. Since all the turbines are correlated, the L^{-1} can be calculated as follows:

$$L^{-1} = \sum_{i=1}^{n_p} L_i^{-1} = \sum_{i=1}^{n_p} (GH^{-1}G')^{-1}$$

To be noticed, the linearized model of the individual turbine varies with the change of the operating region. As described H_i. is dependent on model parameter. Accordingly, the Hessian matrix H_i. is time-variant, which further leads to the variation of L_i^{-1}. Obviously, the variables involved in the computation, including H_i and L_i^{-1}, can be pre-computed offline and stored according to the operation regions.

The computation burden of the central unit only consists of the calculation of L^{-1}, which is the simple addition of the individual L^{-1} and the dual variable updates during iterations. Most computation tasks are distributed to the local D-MPCs. Besides, due to the reduced iteration number, the communication burden between D-MPC and the central unit is largely reduced. In summary, this control structure is independent from the scale of the wind farm and suitable for modern wind farm control application.

The optimality of the D-MPC is dependent on the accuracy of the wind turbine model. The adopted model is a simplified model where some fast dynamics are ignored. In the practical operation, there exist errors and uncertainties in the system parameters, which include the inertias of the mechanical part, control parameters of pitch control, and identified parameters. In this paper, in order to investigate the robustness of the D-MPC under parameter errors, the errors of the inertias and measurements are considered and the control parameters are assumed to be perfectly known. The errors existing in the inertias are assumed to be bounded and follow a normal distribution. The identified parameters rely on the measurements of state and input variables (effective wind speed estimation). Similarly, the measurement errors are also assumed to be bounded and follow a normal distribution.

4.Simulation Result and Discussion

4.1 Operation under High and Low Wind Conditions

The operation of the wind farm was simulated under both high and low wind conditions. Accordingly, the power references of the wind farm P_{ref}^{wfc} are defined as 40 and 30 MW and assumed to be constant during the simulation. For the wind input to individual wind turbines, the turbulence is assumed to be fixed. A constant difference (4 m/s) is added in the mean part. As an example, the wind speed of WT 05 for both wind conditions were studied and covers the range between 11 and 20 m/s.

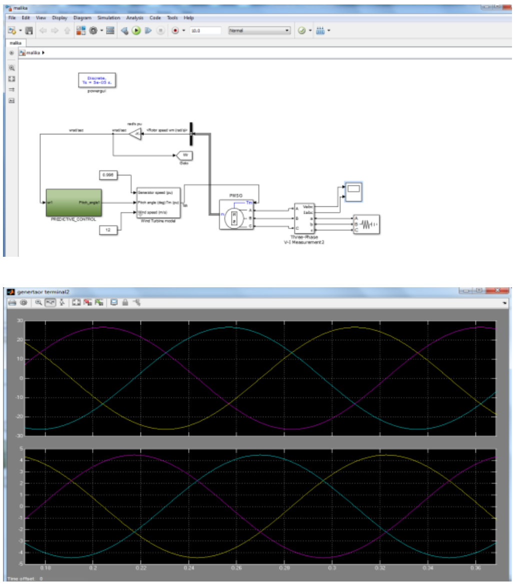

Fig 4.1 Simulation Output for Operation under High and Low Wind Conditions

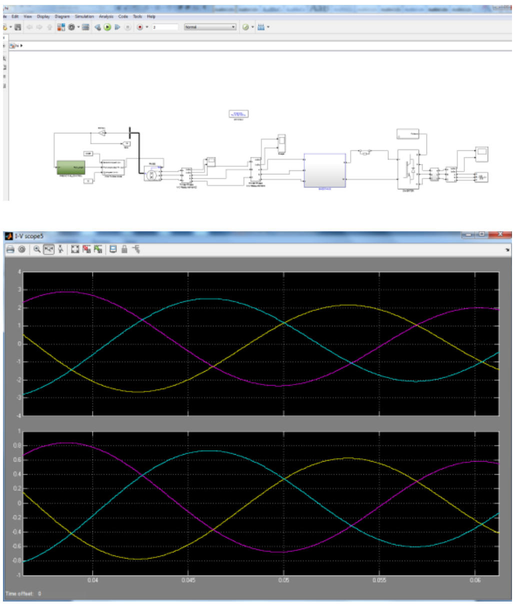

Fig 4.2 Simulation Output for Operation under High and Low Wind Conditions

5.CONCLUSION

In this project, the D-MPC algorithm based on the fast-dual gradient method is developed for the active power control of a wind farm. Compared with the conventional wind farm control, the D-MPC strikes a balance between the power reference tracking and the minimization of the wind turbine loads. Different from C-MPC, in the developed D-MPC, most of computation tasks are distributed to the local D-MPCs equipped at each wind turbine. The computation burden of the central unit is significantly reduced, which is only responsible for the update of dual variables. This control structure is independent from the scale of the wind farm. Besides, with properly calculated Lipschitz constant L, the adopted fast dual gradient method can significantly improve the convergence rate from O(1/k) to O(1/k2), which reduces the iteration number. Consequently, the communication burden between local D-MPC and central unit is largely reduced. By means of the developed PWA model in Part I, the calculation work of L dependent on the model parameter of the operation region can be done offline and stored. Through different case studies, the power tracking control performances of the developed D-MPC are verified to be identical to these of C-MPC. The mechanical loads experienced by individual wind turbines have been largely alleviated without affecting tracking the power reference of the wind farm. The robustness of D-MPC to errors and uncertainties of system parameters is also investigated and verified by including errors of the mechanical inertias and measurements. The D-MPC can be used for real-time control of modern wind farms.

Future Scope: In future for reducing the computational complexity of the existing project, it has been planned to implement frequency propagation method.

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