

Article

Optimization Method of Multi-Mode Model Predictive Control for Wind Farm Reactive Power

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Abstract: This paper presents a novel approach for optimizing wind farm control through the utilization of a combined model predictive control method. In contrast to conventional methods of controlling active and reactive power in wind farms, the suggested approach integrates a wind power prediction model driven by a neural network and a state-space model for wind turbines. This combination facilitates a more precise forecast of active power, thereby enabling the dynamic prediction of the range of reactive power output from the wind turbines. When combined with the equation of state in wind farm space, it is possible to accurately optimize the reactive power of a wind farm. Furthermore, the impact of active power on voltage fluctuations in the wind farm collector system was examined. The utilization of model predictive control enhances voltage regulation, optimizes system redundancy, and increases the reactive capacity. Sensitivity coefficients were calculated using analytical methods to enhance computational efficiency and to resolve issues related to convergence. In order to validate the proposed methodology and control scheme, a wind farm simulation model comprising 20 turbines was developed to assess the feasibility of the scheme.

Keywords: model predictive control; reactive power control; wind power forecasting; wind farm; convolutional neural network



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1. Introduction

The rapid development of new energy is attributed to the ongoing optimization and adjustment of the energy structure. The proliferation of offshore wind farms, the development of extensive onshore wind power facilities, the growing integration of wind power generation, and the expanding scale of wind farms have introduced new challenges to the modern grid system [1]. The new energy field stations play a more integral role in servicing the power system [2]. The regulation of active power and the provision of reactive power in wind farms have emerged as crucial factors in ensuring the stable operation of the power grid. In the future, wind farms will serve as crucial active output nodes and voltage regulation nodes, necessitating a departure from traditional methods of active and reactive power control. In order to meet the new grid's requirements for system stability, support for power generation operators is necessary [3].

The power output of wind farms is influenced by the variability of wind patterns. Reactive power can be produced by wind turbine generators (WTGs) and other converter regulation equipment, such as static transformer compensators and static transformer generators [4]. In traditional wind farm control systems, active and reactive power controllers are independent of each other [5–7]. The active power is constrained by the wind farm's active power output through the grid-side AGC (Automatic Generation Control) system. The active power output of the wind farm is typically constrained by the average limitation of the WTGs. Not only does this approach not succeed in reducing the fatigue load of the WTGs, but it also does not effectively mitigate the voltage fluctuation within the wind farm.

Furthermore, it does not fully leverage the reactive power output characteristics of the WTGs to optimize the distribution of reactive power in the collector system or to support the reactive power demand of the grid system [8].

The capacity for regulating reactive power in a wind turbine is constrained by the operational limits of the converter. The range of values for the dynamic system is contingent upon the terminal voltage and the generation of active power [9]. When WTGs are operating near full load, there are notable decreases in both the reactive power capacity and voltage support capability. Thus, by appropriately adjusting the active power reference of the WTGs, the variable capacity of the entire wind farm can be optimized to manage potential voltage disturbances.

When modeling and analyzing wind farms, the issue of “dimensional catastrophe” arises when attempting to evaluate the stability of the system [3]. The high density of wind turbines within each wind farm is the cause of this issue. The analysis of power system stability, particularly in terms of transient stability and computational efficiency, presents a significant challenge. The utilization of data-driven methods to train neural networks for the development of operational conditions and identification models for wind farms is progressively addressing the issue of convergence challenges or unsolvability that arise in traditional physical modeling approaches. The combination of physical and data models is becoming more widely acknowledged as an innovative method for analyzing power system stability and addressing optimization challenges.

Power control in wind farms has been the focus of industry research, traditionally emphasizing the optimization of the reactive power regulation capabilities of SVC/SVG devices [10–12]. Several studies have been conducted to reduce the fatigue load on wind turbines and extend their service life by implementing rational active power allocation [13]. Considering the reactive power output capability of the wind turbine itself, many studies have utilized wind turbines in conjunction with SVC/SVG devices to coordinate Static Var Compensators (SVCs) and Static Var Generators (SVGs), along with other regulation devices, to manage the voltage at the point of connection (POC) to improve voltage stability in wind farms [14–18]. Meanwhile, some studies have categorized wind farms into normal and emergency operation states and utilized the redundancy capability of the wind farm reactive output to enhance grid stability [19]. Some studies suggested that the lengths of the collector lines and the active power of the WTGs in wind farms have a significant impact on voltage variations. Therefore, integrating coordinated active and reactive power control in WTGs can enhance subactive and reactive power control in wind power stations. All these studies were primarily focused on physical models and current cross sections for reactive power optimization, which do not facilitate excessive reactive power control. With the development of artificial intelligence, the wind power prediction technique can further enhance the wind farm model to predict the active and reactive power for the next moment, enabling advanced control at that time.

The primary contribution of this paper is the proposal of a hybrid model-based predictive control for the joint regulation of active and reactive power in wind farms. This control method aims to enhance voltage control and optimize the allocation of reactive power in wind farms. In comparison to conventional methods, the suggested approach offers the following benefits, as outlined below:

1. The multi-modal model predictive control approach for reactive power in wind farms combines physical modeling and data modeling for the development of predictive control models. Model predictive control enables the coordinated management of active and reactive power in wind turbines. Voltage sensitivity coefficients and reactive power sensitivity coefficients were calculated using analytical methods to determine the optimization parameters. Hybrid model predictive control was utilized to achieve the optimal control of reactive power in wind farms.
2. The effects of collector system impedance and wind turbine active power variations on the wind farm voltage were considered in the conventional operation mode of the

wind farm. The reactive power output of the wind turbine was optimized to minimize the voltage deviation in the wind farm collector lines and busbars.

3. The method dynamically evaluates the upper and lower range of the reactive power output of wind turbines by predicting the active power of the wind turbines. It calculates the reactive power at the next moment at each node of the collector line in order to minimize voltage fluctuations, and it reduces the frequency of the SVG startup.

The rest of the paper is structured in the following manner. Section 2 delineates the primary framework of the wind farm and hybrid model predictive control, while Section 3 expounds on the modeling of wind energy prediction. Additionally, Section 4 provides detailed insights into the modeling of each controlled device. Section 5 delineates the procedure for computing the voltage sensitivity factor. Section 6 focuses on predictive control models. Section 7 comprises the presentation and discussion of real-life cases. Section 8 marks the conclusion of the paper.

2. Wind Farm Control Structures

In this study, a wind farm consisting of 20 wind turbines of 1.5 MW, located in Qixia City, Shandong Province, China, was used as a control object. The standard layout of the wind farm is depicted in Figure 1. The wind farm comprised a POC 220 kV bus, a main transformer, a 35 kV low voltage bus, a dynamic reactive power compensation device SVC/SVG, and wind turbines. The busbars at the wind farm station encompassed those at the POC, the convergence point (LV side of the main transformer), and the collector lines of the wind turbine within the wind farm.

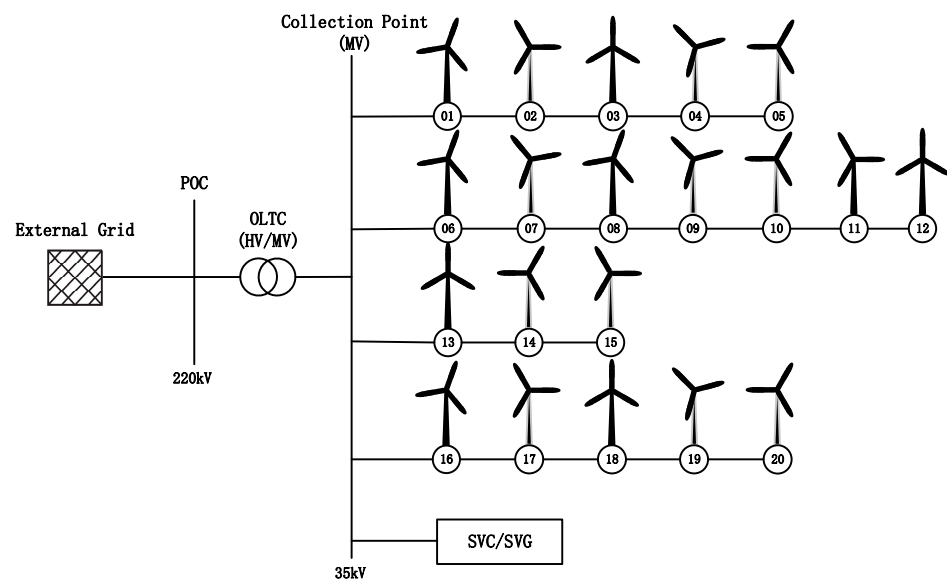


Figure 1. Configuration of a wind farm. Note: The numbers in the diagram represent turbine numbers.

The general layout of the WFC is depicted in Figure 2. The wind farm POC's active power and voltage references P_{wf}^{ref} and V_{poc}^{ref} were determined based on the IEEE 14 grid system and then transmitted to the WFC. A DC_LCNN wind power prediction model was constructed using historical data from the wind farm SCADA, and the subsequent active power prediction was carried out by gathering measurement data from the wind farm. Data from individual WTGs and Static Var Compensator/Static Var Generators (SVC/SVGs) were gathered and sent to the wind farm controller (WFC). Model predictive control (MPC) involves the computation of voltage sensitivities ($\frac{\partial V}{\partial P}$, $\frac{\partial V}{\partial Q}$) and the utilization of active power prediction models for WTGs and prediction models for static varistor generators (SVGs). The general framework of the MPC model was then established. Upon resolving the model predictive control (MPC) issue, all WTGs (P_{wt}^{ref} , Q_{wt}^{ref}) and SVC/SVGs (V_s^{ref}) were

regarded as control entities, and the ensuing regulatory directives were ascertained and conveyed to the local controller.

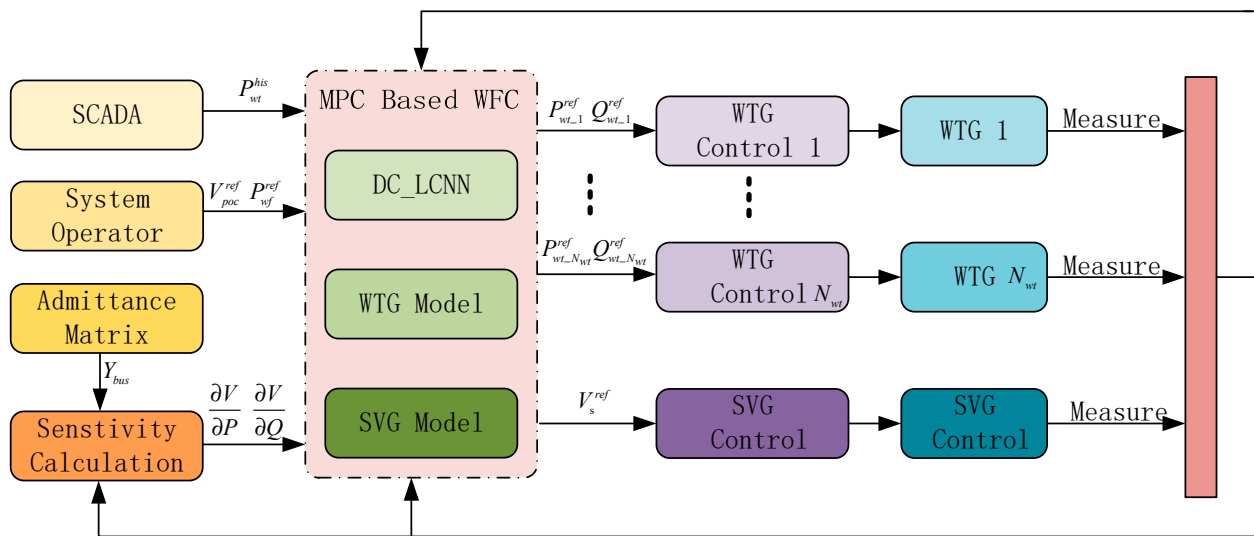


Figure 2. Wind farm control structure.

3. Wind Power Prediction Model

A wind power prediction modeling method with enhanced temporal resolution, known as DC_LCNN, utilizes an improved light convolutional architecture for the prediction of wind power. The method commences with the source data and introduces a novel dual-channel data input mode to offer diverse combinations of feature data for the model. This approach enhances the upper limit of the overall model's learning capability. Additionally, the dual-channel convolutional neural network (CNN) architecture extracts various spatio-temporal constraints of the input features. Furthermore, the lightweight global max-pooling approach replaces the flattening operation combined with the fully connected (FC) prediction method in traditional CNNs. It extracts the most important global features while directly reducing the data, which significantly enhances the prediction accuracy and efficiency of the model [20,21].

A schematic representation of the research methodology proposed in this paper is illustrated in Figure 3. The model was designed with a dual-channel data input mode to provide different combinations of feature data for the model, which improves the upper limit of the learning capability of the whole model; the dual-channel convolutional neural network (CNN) structure extracts different spatio-temporal constraints of the input features; a lightweight global max-pooling method is used to replace the flattening operation combined with the fully connected (FC) prediction method in the traditional CNN and the extraction of the most significant features in the global while directly performing data downscaling. The flow is briefly outlined below.

3.1. Proposed Light Convolutional Neural Network Architecture

Aiming to meet the demand for real-time wind power prediction results from wind farms to facilitate efficient scheduling and operational control decisions, this study introduced a DC_LCNN model that focuses on data sources, model calculation mechanisms, and architecture. The model architecture is shown in Figure 4.

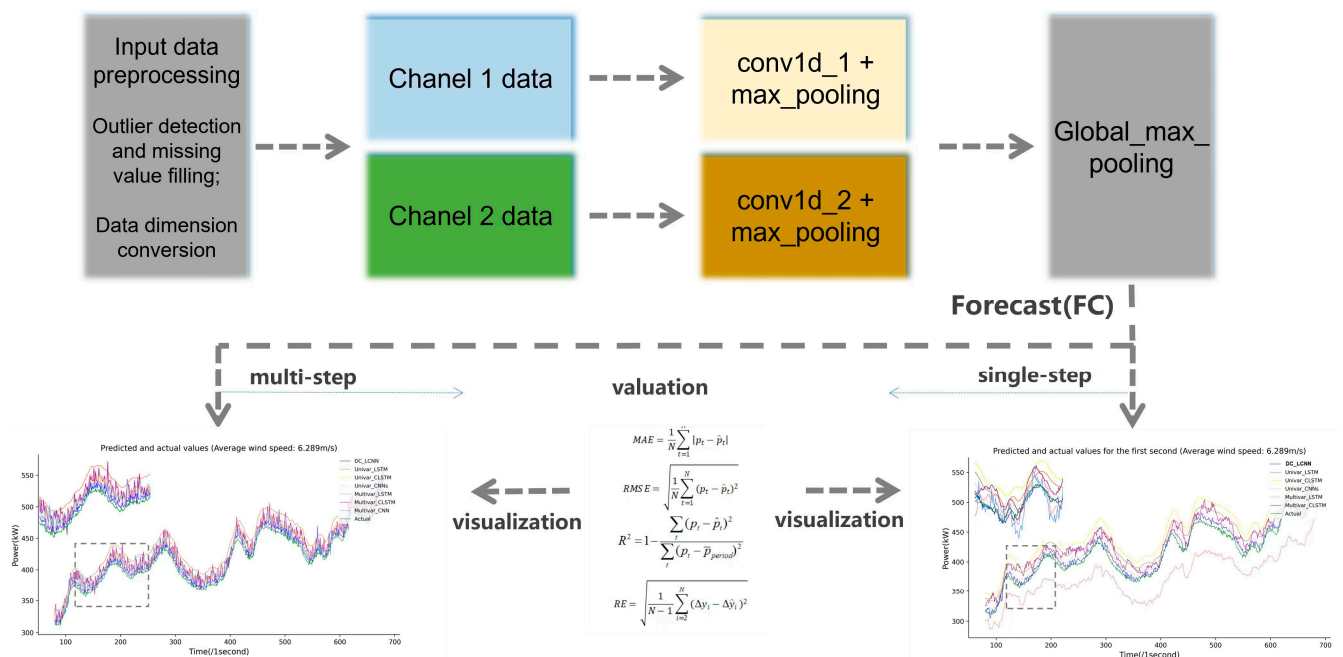


Figure 3. The overall research flow of the methodology proposed.

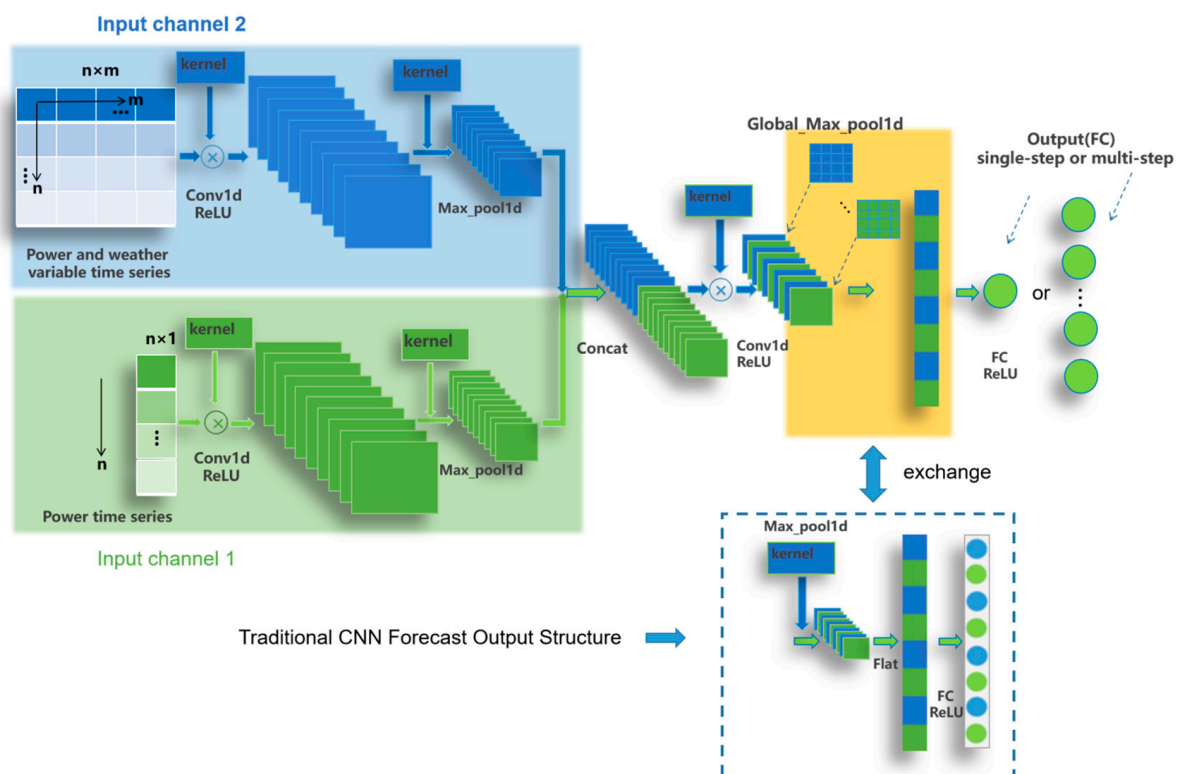


Figure 4. The architecture of the proposed model.

3.2. The Parameters of the Proposed Model

The parameters of all models were obtained through trial and error; Table 1 shows the parameter settings of the proposed model for single- and multi-step forecasting. “Conv1D_1(Input 1)” and “MaxPooling1D_1” represent the convolutional and maximum pooling layers in input channel 1 (green background regions of Figure 4), respectively; “Conv1D_2(Input 2)” and “MaxPooling1D_2” represent the convolutional and maximum

pooling layers in input channel 2 (blue background regions of Figure 4), respectively; “Conv1D_3” and “Global_MaxPooling1D_1” represent the convolutional and global maximum pooling layers in the high hidden layer (yellow background regions of Figure 4), respectively. Table 1 shows the parameter settings of all baseline models for single- and multi-step forecasting. The prefix “Univar_” represents the univariate input pattern, and the prefix “Multivar_” represents the multivariate input pattern. The parameters of the power prediction model in this paper are shown in Table 1 below.

Table 1. The parameters of the proposed model.

The Layers for the DC_LCNN	The Parameters of Each Layer
Conv1D_1(Input 1)	Filters = 32, kernel size = 2, stride = 1, activation = ‘relu’, padding = ‘same’
MaxPooling1D_1	kernel size = 2, stride = 1
Conv1D_2(Input 2)	Filters = 32, kernel size = 2, stride = 1, activation = ‘relu’, padding = ‘same’
MaxPooling1D_2	kernel size = 2, stride = 1
Dropout_2	Rate = 0.1
Conv1D_3	Filters = 32 (single-step forecasting), filters = 10 (multi-step forecasting), kernel size = 2, stride = 1, activation = ‘relu’, padding = ‘same’
Global_MaxPooling1D_1	-
Dense	neurons = 1 (single-step forecasting); neurons = 10 (multi-step forecasting)
Others	Epochs = 150; EarlyStopping:monitor = ‘mse’; batch size = 24, patience = 5; min_delta = 0.0001

This study utilized measured data obtained from wind farms, specifically data collected from 20 wind turbines. They were the sum of the data of 20 wind turbines. The DC_LCNN model was employed for training on and predicting the active power of wind turbines at a temporal resolution of 1 s. Figure 5 illustrates the real output power of a solitary wind turbine at low-power output in comparison to the anticipated power. The model predictive control module will receive the output. The results of the wind power prediction are utilized in the predictive control of the Wind Turbine Generator (WTG) active power model to forecast the active power of the WTGs in the subsequent moment based on historical data and real-time, collected WTG data. The MPC model is also supplied with data for predicting the reactive power of the WTGs and for rolling optimization.

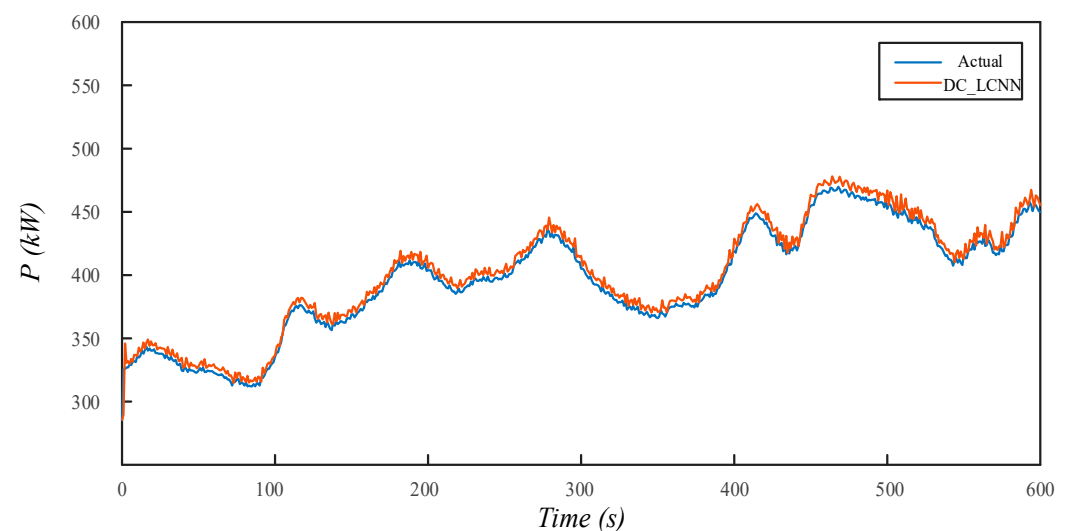


Figure 5. Predicted effects of the low-power production of a solitary wind turbine.

Figure 6 illustrates the real output power of a single WTG at high-power output in comparison to the anticipated power. The error of the WTGs increases in absolute value in comparison to the low-power output. There are two main reasons why the error increases. First, wind speed and wind power exhibit a cubic relationship, meaning that a doubling of wind speed theoretically results in an eightfold increase in wind turbine output power. Therefore, small fluctuations in wind speed can lead to significant variations in output power during high-wind conditions, making prediction more challenging. Secondly, under strong wind conditions, the meteorological conditions tend to be more complicated. This includes increased turbulence intensity, frequent changes in wind direction, and an amplified wind shear effect. These factors make wind speed prediction more challenging, resulting in an increase in the margin of error in wind power prediction.

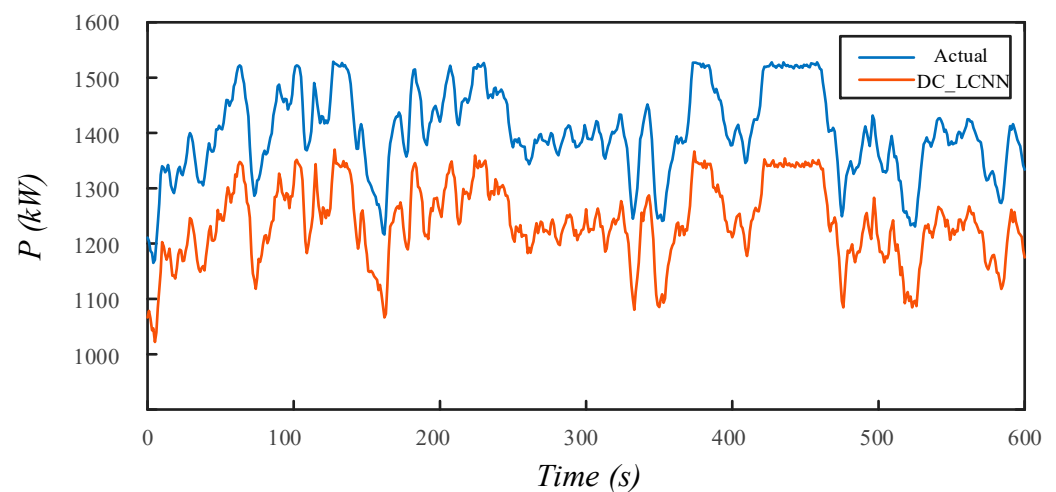


Figure 6. Predicted effects of high-power production.

The wind power prediction model DC_LCNN was developed to integrate a dual-channel input mode, with the aim of augmenting the diversity and richness of feature information for the neural network. This model utilizes the local cross-feature extraction capability of convolutional neural networks, along with the computational mechanism of weight sharing and pooling, to attain an accurate and efficient prediction performance. Moreover, it employs the global maximum pooling technique to extract globally salient features and reduce data dimensionality, thereby replacing the conventional CNNs' FC weight allocation and dimension conversion function. The integration of a dimension conversion function into conventional CNNs is intended to improve the predictive accuracy and efficiency of the model. This study successfully accomplished single-step wind power prediction with a 1 s lead time and multi-step wind power prediction, addressing the requirement for reactive power control in wind farms and the application of high-resolution wind power prediction results across different time scales. There is a 10 s time advance.

4. Modeling the WTG and SVG

This section outlines the modeling approach for the WTG and SVC/SVGs. A discrete system combination model was employed as a predictive model for the model predictive control (MPC) system and as an objective for wind farm control.

4.1. Modeling of WTG

In wind farm control (WFC), the control loops for active power and reactive power are decoupled. The WTG is considered an actuator that generates output in accordance with specified power commands P_{wt}^{ref} and Q_{wt}^{ref} .

- (1) Closed-loop control of active power: the wind turbine power control model was developed using the National Renewable Energy Laboratory (NREL) for the representation

of variable speed pitch control wind turbines [20]. It is composed of aerodynamics, pitch, a drive train, a generator system, a tower, and a local WTG controller. The wind turbine torque control as well as the WTG pitch control system are large inertia systems with respect to the control system and their fast dynamic changes can be ignored. The sampling time of the WFC is usually measured in seconds. The fluctuations in active power are significantly smaller in comparison to the fluctuations in wind speed. Thus, the active power output P_{wt} is approximately equivalent to the power reference value P_{wt}^{ref} .

This study exploited the property that the nonlinear model can be linearized in the vicinity of the operating point in order to expedite the system solution [12]. The simplified state-space model of the wind turbine is described by the following equation:

$$\dot{x}_{wt}^p = A_{wt}^p x_{wt}^p + B_{wt}^p P_{wt}^{ref} + E_{wt}^p \quad (1)$$

In the equation, x_{wt}^p refers to the state vector defined by $x_{wt}^p \triangleq [\theta, \omega_r, \omega_f]'$, θ is the pitch angle, ω_r and ω_f are the rotor speed and the filtered generator speed, respectively [11]. The state-space matrices are provided in Appendix A for the exact matrix representation.

- (2) Closed-loop reactive power control: the dynamic characteristics of the constant reactive power control for wind turbines can be elucidated through a first-order function [22]. The response time varies between 1 and 10 s [23]. The state-space model is as follows:

$$\dot{x}_{wt}^q = A_{wt}^q x_{wt}^q + B_{wt}^q Q_{wt}^{ref} \quad (2)$$

The state-space equation x_{wt}^q is a state variable as follows: $x_{wt}^q \triangleq Q_{wt}$,

$$A_{wt}^q = -\frac{1}{\tau_q}, \quad B_{wt}^q = \frac{1}{\tau_q} \quad (3)$$

where A_{wt}^q and B_{wt}^q are time constants for the closed loop control of the reactive power.

4.2. Modeling of SVC/SVG

The dynamic equations governing the constant reactive power control loop of the SVC/SVG can be represented by a first-order function [11].

$$Q_s = \frac{1}{1 + s\tau_s} Q_s^{ref} \quad (4)$$

The case study employed an SVG as the simulation object. s represents the time constant for reactive device regulation in milliseconds (20–100 milliseconds for SVG) [24]. In this illustrative model, a control input of 100 ms V_s^{ref} was employed to adjust the reactive power output through the SVG simulation model's PI controller. The equivalent reference value for the reactive capacity Q_s^{ref} can be determined using the following equation:

$$Q_s^{ref} = Q_s^0 + K_{p-s}(V_s^{ref} - V_s) + K_{i-s} \frac{1}{s}(V_s^{ref} - V_s) \quad (5)$$

where Q_s^0 is the reactive power at the operating point, and K_{p-s} and K_{i-s} are the proportional and integral gains of the PI controller, respectively [11].

The voltage at the point of connection bus POC V_s is dependent on the variations in P_{wt} , Q_{wt} , and Q_s , as well as on the internal installations of the wind farm and the parameters of the collector lines, indicating a change in a variable. ΔP_{wt} , ΔQ_{wt} , and ΔQ_s indicate

the variable change, i.e., $\Delta P_{wt} \triangleq P_{wt} - P_{wt}^0$, $\Delta Q_{wt} \triangleq Q_{wt} - Q_{wt}^0$, and $\Delta Q_s \triangleq Q_s - Q_s^0$. The formula for V_s is as follows:

$$V_s = V_s^0 + \frac{\partial |V_s|}{\partial Q_s} \Delta Q_s + \frac{\partial |V_s|}{\partial P_{wt}} \Delta P_{wt} + \frac{\partial |V_s|}{\partial Q_{wt}} \Delta Q_{wt} \quad (6)$$

In defining V_{int} as the integral of the deviation between V refs and V_s ,

$$V_{int} \triangleq \frac{V_s^{ref} - V_s}{s} \quad (7)$$

$$\dot{x}_s = A_s x_s + B_s V_s^{ref} + E_s P_{wt} + F_s Q_{wt} + G_s \quad (8)$$

Unlike in traditional methods, the active power value is obtained from the equivalent of the predicted active power value [11], as shown in Equation (8). In this study, the DC_LCNN model provides active power prediction values. Here, P_{wt} is regarded as a constant. $E_s P_{wt}$ and G_s are merged into E_s in this paper's formulation. Equations (4)–(7) can be rewritten in the following state-space forms:

$$\dot{x}_s = A_s x_s + B_s V_s^{ref} + F_s Q_{wt} + E_s \quad (9)$$

$$A_s = \begin{bmatrix} -\frac{1}{\tau_s} (1 + K_{p-s} \frac{\partial |V_s|}{\partial Q_s}) & \frac{K_{js}}{T_s} \\ -\frac{\partial |V_s|}{\partial Q_{wt}} & 0 \end{bmatrix}, B_s = \begin{bmatrix} \frac{K_{ps}}{T_s} \\ 1 \end{bmatrix}, F_s = \begin{bmatrix} -\frac{K_{p-s}}{\tau_s} \frac{\partial |V_s|}{\partial Q_{wt}} \\ -\frac{\partial |V_s|}{\partial Q_{wt}} \end{bmatrix} \quad (10)$$

$$E_s = \begin{bmatrix} -\frac{K_{p-s}}{\tau_s} \frac{\partial |V_s|}{\partial P_{wt}} P_{wt}^0 - \frac{K_{p-s} \Delta V_s^0}{\tau_s} + \frac{Q_s^0}{\tau_s} \\ -\frac{\partial |V_s|}{\partial P_{wt}} P_{wt}^0 - \Delta V_s^0 \end{bmatrix} \quad (11)$$

Further information regarding the derivation of Equation (9) is available in [11]'s Appendix A.

4.3. Combined System

The control loops for active and reactive power in the aforementioned WTG and SVG models can be integrated. The combined system model, comprising N_{wt} WTGs and 1 SVG, can be represented in the state-space form as follows:

$$\dot{x} = Ax + Bu + E \quad (12)$$

where x and u denote the state vector and control input vector, respectively, defined by the following equations:

$$x \triangleq [x_{wt_1}^q, \dots, x_{wt_N_{wt}}^q, x_s]^T \quad (13)$$

$$u \triangleq [u_{wt_1}^q, \dots, u_{wt_N_{wt}}^q, u_s]^T \quad (14)$$

The state matrix is as follows:

$$A = \begin{bmatrix} A_{wt}^{q-set} & 0 \\ F_s & A_s \end{bmatrix}, B = \begin{bmatrix} B_{wt}^{q-set} & 0 \\ 0 & B_s \end{bmatrix}, E = \begin{bmatrix} 0 \\ E_s \end{bmatrix} \quad (15)$$

The matrices A_{wt}^{q-set} and B_{wt}^{q-set} represent the diagonal matrices with diagonal entries as the state-space matrices of the corresponding WTG models in Equation (2). Similarly, A_s , B_s , E_s , and F_s are the state-space matrices of the SVC/ SVG models in Equation (10).

The continuous model in Equation (12) can be transformed into a discrete form by introducing the step index k . The state-space matrices (A_d , B_d , E_d) can be determined using the approach outlined in the literature [25].

$$x(k+1) = A_d x(k) + B_d u(k) + E_d \quad (16)$$

4.4. Local Constraints

(1) WTG: According to [25], the limitations for WTGs encompass

$$P_{wt}^{ref}(k) \in [0, P_{wt}^{avi}(k)] \quad (17)$$

$$\omega_r(k) \in [\omega_{\min}, \omega_{\max}] \quad (18)$$

$$\theta(k) \in [\theta_{\min}, \theta_{\max}] \quad (19)$$

$$\Delta\theta(k) \in [-\Delta\theta_{lim}, \Delta\theta_{iim}] \quad (20)$$

where P_{wt}^{avi} is the upper limit of the available wind energy, $\omega_{\min}$ and $\omega_{\max}$ are the minimum and maximum values of the angular velocity of the wind turbine, respectively, $\theta_{\min}$ and $\theta_{\max}$ are the minimum and maximum values of the blade pitch angle, respectively, and $\Delta\theta$ is the slope limit of the amount of pitch angle variation.

In this case, a type three variable speed constant frequency wind turbine is used, and the reactive power capacity is limited by the operating limits of the converter [26]. The rated power wind turbine's reactive power output capacity decreases with the increase in active power output. And when the terminal voltage changes, the reactive power output capacity changes accordingly. Therefore, this paper provides a typical PQ capacity curve for a typical 1.5 MW Fixed Pitch Control (FPC) wind turbine, as shown in Figure 7. The constraint of its reactive power is

$$Q_{wt}^{ref}(k) \in [Q_{wt}^{\min}(k), Q_{wt}^{\max}(k)] \quad (21)$$

where Q_{wt}^{ref} is the reference open value of dynamic reactive power, and $Q_{wt}^{\min}$ and $Q_{wt}^{\max}$ are the minimum and maximum values of the reactive capacity. It depends on the terminal voltage and active power of the WTG [26,27].

$$Q_{wt}^{\min} = f_Q^{\min}(P_{wt}, V_{wt}), \quad Q_{wt}^{\max} = f_Q^{\max}(P_{wt}, V_{wt}) \quad (22)$$

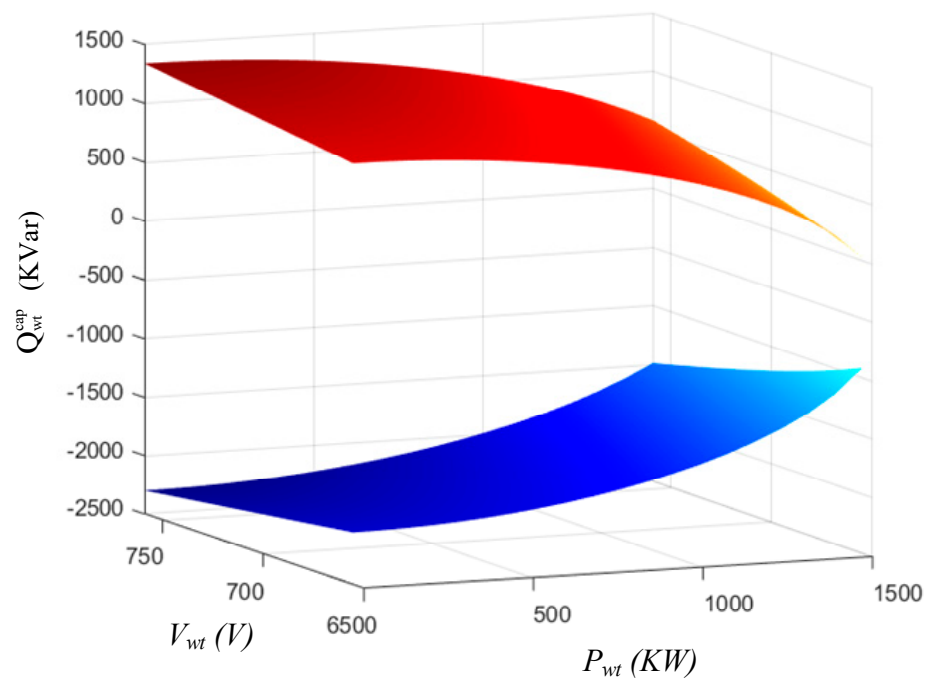


Figure 7. Capacity curves for FPC wind turbines in active and reactive modes. Note: Red represents the upper limit of wind turbine reactive power output, blue represents the lower line of reactive power output.

The function f_Q is nonlinear, and it is related to the active capacity and terminal voltage of the wind turbine. For different models, it can be expressed using the look-up table method or piece-wise affine function. It is possible to calculate $Q_{wt}^{\min}$ and $Q_{wt}^{\max}$ explicitly from the function, the latter being used in this case.

$Q_{wt}^{\min 0}$ and $Q_{wt}^{\max 0}$ are defined as the minimum and maximum reactive power capacity within the rated operating range of the wind turbine. $Q_{wt}^{\min}$ and $Q_{wt}^{\max}$ can be predicted from the Taylor series approximation as an approximation in step k . The approximation is based on the Taylor series approximation as follows:

$$Q_{wt}^{\min}(k) \approx Q_{wt}^{\min 0} + \frac{\partial f_Q^{\min}}{\partial P_{wt}} \Delta P_{wt}(k) + \frac{\partial f_Q^{\min}}{\partial V_{wt}} \Delta V_{wt}(k) \quad (23)$$

$$Q_{wt}^{\max}(k) \approx Q_{wt}^{\max 0} + \frac{\partial f_Q^{\max}}{\partial P_{wt}} \Delta P_{wt}(k) + \frac{\partial f_Q^{\max}}{\partial V_{wt}} \Delta V_{wt}(k) \quad (24)$$

(2) SVCs/SVGs: For an SVC/SVG, the constraints are mainly as follows:

$$Q_s^{\min} \leq \Delta Q_s + Q_s^0 \leq Q_s^{\max} \quad (25)$$

$$V_s^{\min} \leq V_s^{ref} \leq V_s^{\max} \quad (26)$$

where $Q_s^{\min}$ and $Q_s^{\max}$ are the minimum and maximum reactive capacity of the SVC/SVG, respectively, and $V_s^{\min}$ and $V_s^{\max}$ are the minimum and maximum terminal voltages allowed for the SVC/SVG.

5. Sensitivity Calculation

To solve the problems of reactive capacity allocation and node voltage optimization in a wind farm collector system. In this study, the research results from [1] are used. The calculations of voltage sensitivity and Var capacity sensitivity are described in this section.

5.1. Voltage Sensitivity

In order to solve the problem of the Newton Raphson method failing to converge due to the relatively low X/R in wind farms [28], this study adopted the analytical calculation method of the sensitivity calculation coefficients of [29] when calculating the voltage sensitivity. Since the collector system of a wind farm is similar to a radial distribution system, this method was used in this study [30].

Consider a wind farm with N_b buses, where N is defined as the bus set $N \cong \{1, 2, \dots, N_b\}$. The apparent power injection $\bar{S}_i$ is given by

$$\bar{S}_i = \bar{V}_i \sum_{j \in N} (Y_{bus}(i, j) V_j) \quad (27)$$

where i and j represent bus and collector indexes, Y_{bus} denotes the conductance matrices, and $\bar{S}$ and $\bar{V}$ are the conjugates of S and V , respectively. Additionally, the partial derivatives $\bar{S}_i$ at bus $i \in N$ of active P_l and reactive power Q_l with respect to bus $l \in N$ are represented by Equations (25) and (26), respectively.

$$\frac{\partial \bar{S}_i}{\partial P_i} = \frac{\partial \{P_i - jQ_i\}}{\partial P_i} = \frac{\partial \bar{V}_i}{\partial P_i} \sum_{j \in N} Y_{bus}(i, j) V_j + \bar{V}_i \sum_{j \in N} Y_{bus}(i, j) \frac{\partial V_j}{\partial P_i} = \begin{cases} 1, & \text{if } i = l. \\ 0, & \text{else.} \end{cases} \quad (28)$$

$$\frac{\partial \bar{S}_i}{\partial Q_l} = \frac{\partial \{P_i - jQ_i\}}{\partial Q_l} = \frac{\partial \bar{V}_i}{\partial Q_l} \sum_{j \in N} Y_{bus}(i, j) V_j + \bar{V}_i \sum_{j \in N} Y_{bus}(i, j) \frac{\partial V_j}{\partial Q_l} = \begin{cases} 1, & \text{if } i = l. \\ 0, & \text{else.} \end{cases} \quad (29)$$

According to a literature theorem [30], Equations (28) and (29) possess a singular solution for radial grids. After obtaining $\frac{\partial V_i}{\partial P_i}$ and $\frac{\partial \bar{V}_i}{\partial Q_i}$, the partial derivatives of the voltage magnitude $\frac{\partial |V_i|}{\partial Q_i}$ can be calculated using the following method:

$$\frac{\partial |V_i|}{\partial P_i} = \frac{1}{|V_i|} \text{Re}(\bar{V}_i \frac{\partial V_i}{\partial P_i}), \quad \frac{\partial |V_i|}{\partial Q_i} = \frac{1}{|V_i|} \text{Re}(\bar{V}_i \frac{\partial V_i}{\partial Q_i}) \quad (30)$$

5.2. Reactive Power Capacity Sensitivity

Khatod et al. [29] suggests that the analytical equations for sensitivity can be derived when the analytical expressions for $f_Q^{\min}$ and $f_Q^{\max}$ are known. If a P-Q curve look-up table is accessible, the sensitivity can be estimated through interpolation as outlined below:

$$\frac{\partial f_Q^{\min}}{\partial P_{wt}} = \frac{f_{\min}(P_{wt}^0 + \Delta P_{wt}, V_{wt}^0) - f_{\min}(P_{wt}^0, V_{wt}^0)}{\Delta P_{wt}} \quad (31)$$

Additional sensitivity coefficients are computed in a similar manner.

6. MPC Problem Formulation

As discussed in this section, three objective functions were developed for the hybrid model predictive control approach to optimize wind farm control. These objectives include the POC voltage stability control, wind farm collector voltage control, and the reactive power redundancy capability [3]. The constraints were identified in the case where all the voltages at the wind farm fall within the permissible range, i.e., $\left| V_{poc}^0 - V_{poc}^{ref} \right| \leq V_{poc}^{th}$ and $\left| V_{wt}^0 - V_{wt}^{ref} \right| \leq V_{wt}^{th}$; the wind farm control will be operational in this mode. V_{poc}^0 is the measured voltages at the point of common coupling (POC). V_{wt}^0 is the vector of the WTG bus voltages, denoted as $V_{wt}^0 \triangleq [V_{wt-1}^0, V_{wt-2}^0, \dots]^T$. The reference value from the system operator (typically 1.0 p.u.) and V_{wt}^{ref} are the nominal voltage of each WTG (typically 1.0 p.u.). V_{poc}^{th} and V_{wt}^{th} refer to the thresholds of V_{poc} and V_{wt} , respectively. V_{poc}^{th} differs according to different grid code requirements [11–13].

The Optimization of Objectives 1, 2, and 3 Was Conducted in the Regular Mode

- (1) The main objective of optimization is to minimize the deviation in the wind farm's measured voltage from the reference voltage (ΔV_{poc}):

$$Obj1 = \sum_{k=1}^{n_p} \left| \Delta V_{poc}(k) \right|_{W_{poc}}^2 \quad (32)$$

$$\Delta V_{poc}(k) = V_{poc}^0 + \frac{\partial |V_{poc}|}{\partial P_{wt}} \Delta P_{wt}(k) + \frac{\partial |V_{poc}|}{\partial Q_{wt}} \Delta Q_{wt}(k) + \frac{\partial |V_{poc}|}{\partial Q_s} \Delta Q_s(k) - V_{poc}^{ref} \quad (33)$$

where W_{poc} refers to its weighting factor.

- (2) The second optimization objective is to minimize the deviation between the measured voltage and the reference voltage (ΔV_{wt}) of the wind farm collector line:

$$Obj2 = \sum_{k=1}^{n_p} \left| \Delta V_{wt}(k) \right|_{W_{wt}}^2 \quad (34)$$

$$\Delta V_{wt}^{pre}(k) = V_{wt}^0 + \frac{\partial |V_{wt}|}{\partial P_{wt}} \Delta P_{wt}(k) + \frac{\partial |V_{wt}|}{\partial Q_{wt}} \Delta Q_{wt}(k) + \frac{\partial |V_{wt}|}{\partial Q_s} \Delta Q_s(k) - V_{wt}^{ref} \quad (35)$$

where W_{wt} refers to its weighting factor.

- (3) Thirdly, the rapid dynamic support capabilities of Var will be optimized to address potential disturbances. The implementation involves minimizing the Q_s to the middle

level of the operating range, denoted as $Q_s^{mid} = 0.5(Q_s^{max} + Q_s^{min})$. The shortage of Var will be offset by the slower Var devices (WTGs) to maintain the voltage of buses within the wind farm, i.e.,

$$Obj3 = \sum_{k=1}^{n_p} \left| Q_s^{pre}(k) - Q_s^{mid} \right|_{W_s}^2, \quad (36)$$

where W_s refers to its weighting factor. According to Equations (32), (34) and (36), the cost function is expressed by

$$\min_u (Obj1 + Obj2 + Obj3) \quad (37)$$

The primary objective of this study was to introduce a hybrid model predictive control of wind farms into the field of wind farm control and to assess the optimal control impact of the hybrid model on reactive power allocation in wind farms. The optimization objective does not take into account the wind farm voltage emergency control method or the fatigue load of the unit. In this context, it is important to highlight that there is no need to compromise the active power control performance in order to maintain the voltages of the nodes within the wind farm, as all the measured voltages of the wind farm fall within the specified threshold range. The weighting coefficients may be established through sensitivity analysis, with the caveat that the wind farm's active power control performance is not constrained. The reactive power is primarily utilized to mitigate voltage deviations (ΔV_{poc} ; ΔV_{wt}), and ultimately, the wind farm's reactive power redundancy is taken into account for system support. This study established the priority order as $Obj1 > Obj2 > Obj3$. Consequently, the weighting factors can be chosen using

$$\left(\frac{\partial V_{poc}}{\partial u} \right)^2 W_{poc} > \left(\frac{\partial V_{wt}}{\partial u} \right)^2 W_{wt} > \left(\frac{\partial Q_s}{\partial u} \right)^2 W_s \quad (38)$$

(4) The constraints are as follows:

$$u(i \cdot n_s + k) = u(i \cdot n_s) \quad (39)$$

$$i \in [0, n_p - 1], k \in [0, n_s - 1]. \quad (40)$$

7. Case Study

The case study utilizes a wind farm comprising 20 wind turbines of 1.5 MW and 10 MVar SVGs. The configuration is shown in Figure 1. As depicted in Figure 8, this control pertains to the internal control of the wind farm and is regarded as an infinite system for the systems connected to the grid system with a capacity exceeding ten times that of this wind farm. For different power systems, it has wide applicability as long as it satisfies the system requirements for an infinite system. Therefore, we chose the IEEE 14-node model. The wind farm is integrally connected to the IEEE 14 bus system, and the connection point is located at the grid terminal bus location 03, as depicted in Figure 8. The modeling of the wind farm considers turbulence and wake effects. The wind farm was modeled using SimWindFarm [31], a toolbox for dynamic wind farm modeling, simulations, and controls.

Two scenarios were identified to test the actual effect of the hybrid wind farm model predictive control. Low-power and high-power production operations were used in each scenario, respectively. In both scenarios, the reactive power compensation device was tested without any input, with only the SVG compensation device, and with the coordinated reactive power compensation device of the wind turbine. The results of the three scenarios were then compared. The voltage control of the point of common coupling (POC) node and the redundant capacity of reactive power were tested for comparison. The optimization of the reactive power output was also conducted.

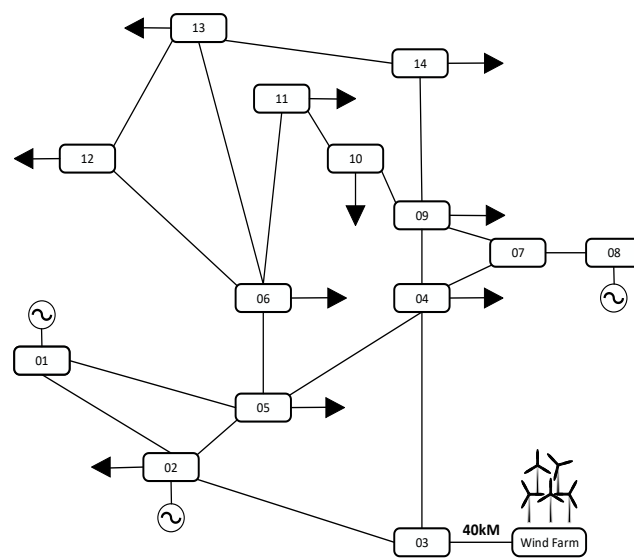


Figure 8. IEEE 14 bus system with wind farm.

In this study, simulation experiments were conducted using the second power curves of actual wind farms to test the actual effect of the hybrid model predictive control. The full-field curve of the wind farm under high-power operation and the full-field curve under low-power operation are shown in Figure 9; both curves are the sum of the active power of 20 WTGs of 1.5 MW each.

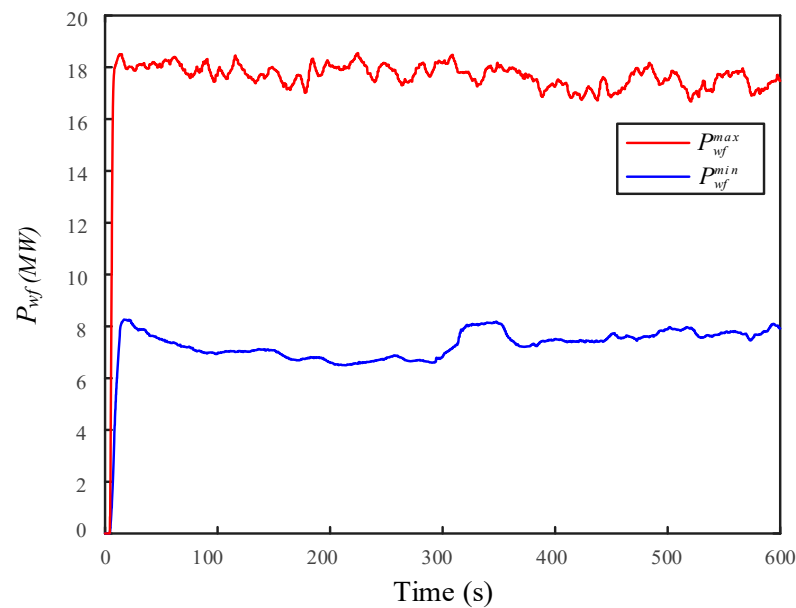


Figure 9. The wind farm of low- and high-power production.

7.1. Case Scenario 1: Low-Power Production

Case 1 occurs under conditions of low-power production. The active power case involves the use of individual turbine power curves, as depicted in Figure 5, and the total power curve of the wind farm, as illustrated in Figure 9. Case 1 simulates and compares the output characteristics of POC node voltage deviation (V_{poc}), WTG collector line deviation (V_{wt}), and reactive power for three scenarios of wind farm reactive power and voltage control: without control, SVG individual control (SIC), and the combined control of WTGs and SVGs (COM).

Figure 10 displays the simulation results for the POC node voltage and WTG 12 node voltage under three different control scenarios: no voltage control (VFC), independent control of SVGs (SIC), and the combined control of WTGs and SVGs (COM). In Figure 10a, the control deviation in the POC node voltage is minimized through joint control. Furthermore, WTG 12 represents the voltage node located at the termination of the collector line, and efforts were made to minimize its voltage deviation. The aforementioned conclusion indicates that joint control has the most favorable impact on voltage control deviation. When objective 3 was selected as the optimization objective, the system operator retained the SVG reactive power redundancy for voltage support.

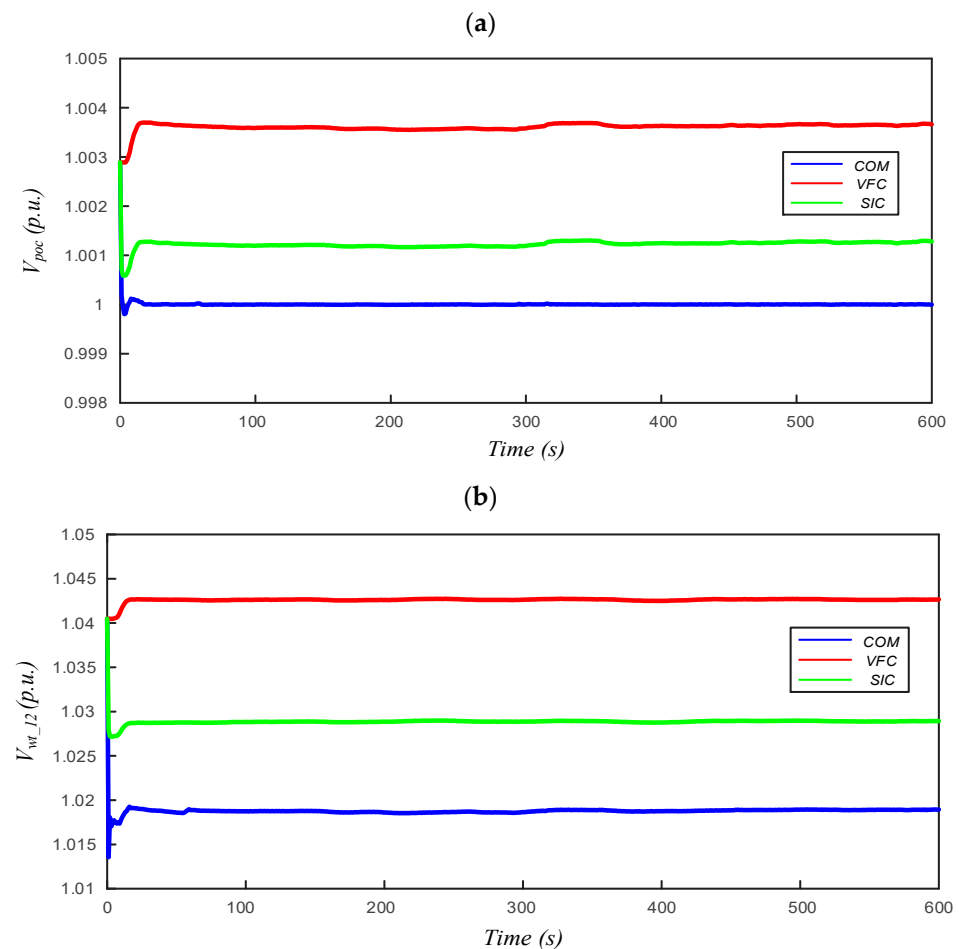


Figure 10. Voltages at (a) POC and (b) WT12 for Case 1.

Figure 11 illustrates the reactive power output characteristics of the Static Var Generator (SVG) under combined control with the WTG and Static Var Compensators/Static Var Generators (SVCs/SVGs), as well as when the SVG operates independently to issue reactive power. The conclusion is evident that a higher reactive capacity is required to support voltage stabilization when the Static Var Generator (SVG) is operated independently. The reactive power redundancy of the SVCs/SVGs is adequate when operating in combined control mode (COM).

Figure 12 shows the reactive power output and the upper and lower reactive power limit ranges for all WTGs in the combined control mode.

Table 2 illustrates that in both cases, the volatility of the POC node voltage and the collector line voltage is minimized in the COM control mode compared to the other two modes. The residual reactive capacity is highest during Static Var Generator (SVG) operation, except in VFC mode.

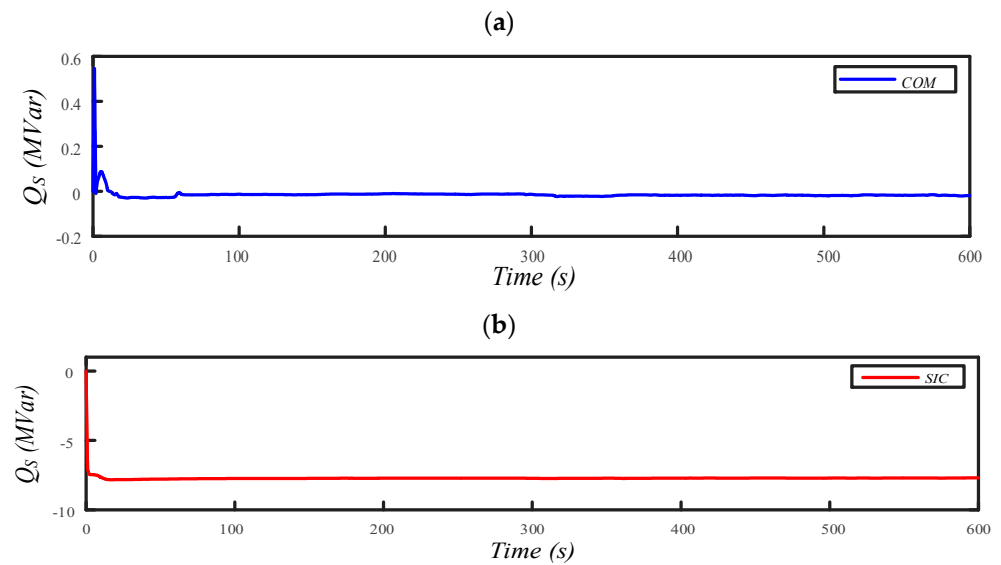


Figure 11. SVG reactive power output in Case 1 under COM (a) and SIC (b) control.

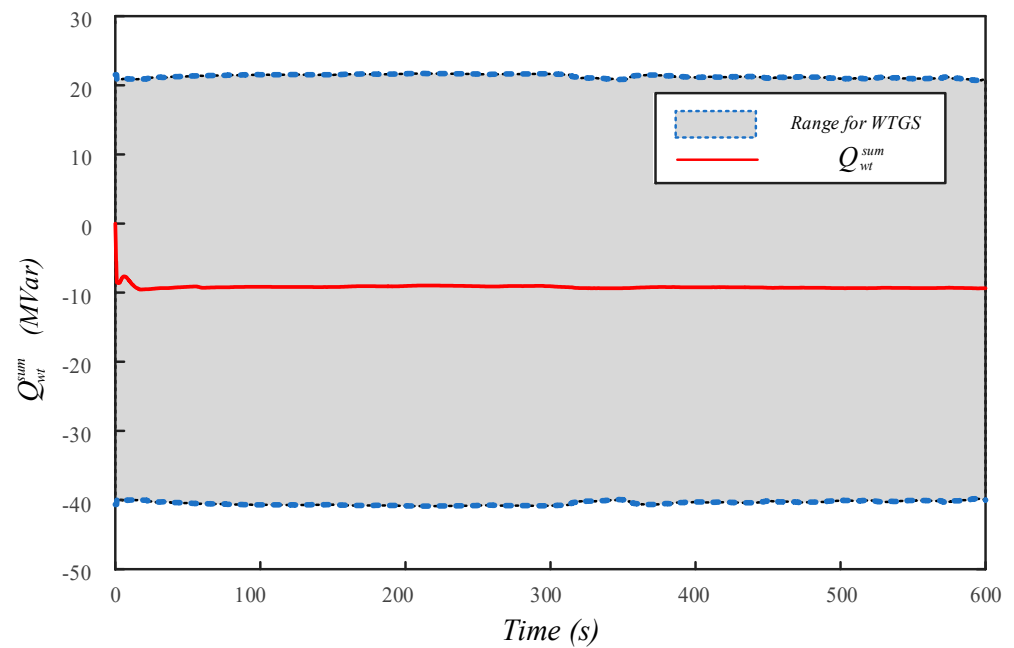


Figure 12. Reactive power capability of WTGs for Case 1.

Table 2. The optimal results of three methodologies for Cases 1 and 2.

Indexes	Control Methods	Max. Voltage Deviation		Percentage of Residual Capacity in SVG Reactive Power %
		V_{POC}	V_{WT_12}	
Case Scenario 1	Com	0.0002	0.018	99%
	SIC	0.0013	0.0425	25%
	VFC	0.0037	0.028	100%
Case Scenario 2	COM	0.0001	0.018	95%
	SIC	0.0020	0.031	25%
	VFC	0.0044	0.044	100%

7.2. Case Scenario 2: High-Power Production

Case 2 is under high-power production conditions. The active power case uses individual turbine power curves, as shown in Figure 5, and the total power curve of the wind farm, as shown in Figure 9. Case 1 simulates and compares the output characteristics of the POC node voltage deviation (V_{poc}), WTG collector line deviation (V_{wt}), and reactive power for three cases of wind farm reactive power and voltage control without control, SVC/SVG individual control (SIC), and the combined control of WTGs and SVGs (COM).

Figure 13 shows the simulation results for POC node voltage and WTG 12 node voltage for no voltage control (VFC), SVG independent control (SIC), and the combined control of WTGs and SVGs (COM). In Figure 13a, the control deviation in the POC node voltage is minimized for joint control. Also, WTG 12 is the voltage node at the end of the collector line, and its voltage deviation is minimized. From the above conclusion, it can be seen that the joint control has the optimal effect on voltage control deviation. And with objective 3 as the optimization objective, the SVG reactive power redundancy for voltage support is retained for the system operator.

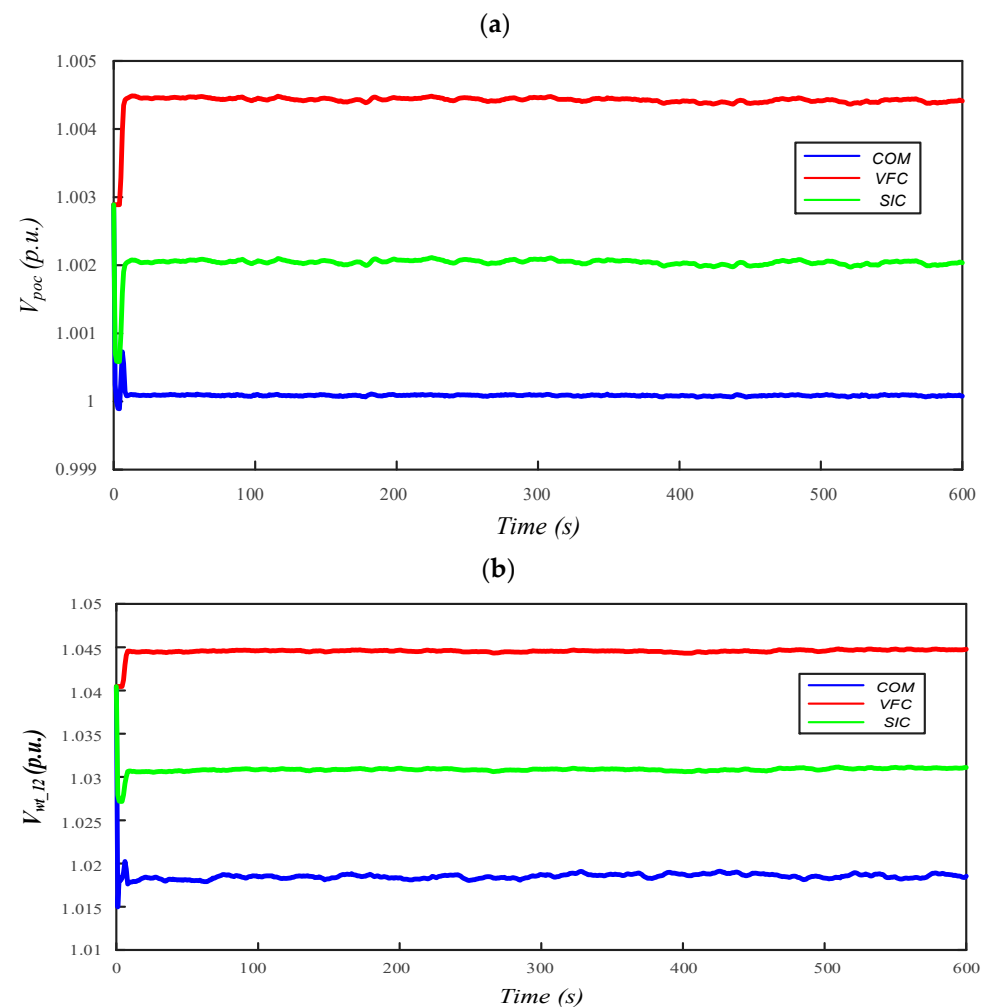


Figure 13. Voltages at POC (a) and WTG 12 (b) for Case 2.

Figure 14 shows the reactive power output characteristics of the SVG when it is controlled by a combination of WTGs and SVGs under high-power production conditions, as well as the reactive power output characteristics when the SVG alone generates reactive power. It is clear that a more reactive capacity is needed to support voltage stabilization when the SVG is controlled alone. In the combined control mode (COM), the reactive power redundancy of an SVG is sufficient.

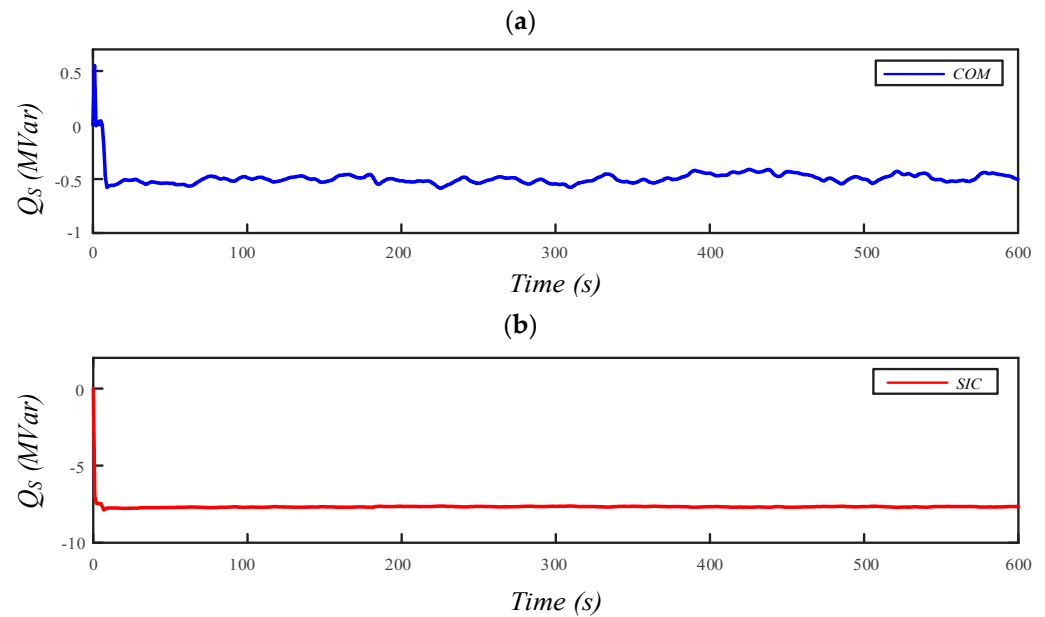


Figure 14. SVG reactive power output in Case 2 under COM (a) and SIC (b) control.

Figure 15 shows the reactive power output and the upper and lower reactive power limit ranges for all WTGs in the combined control mode.

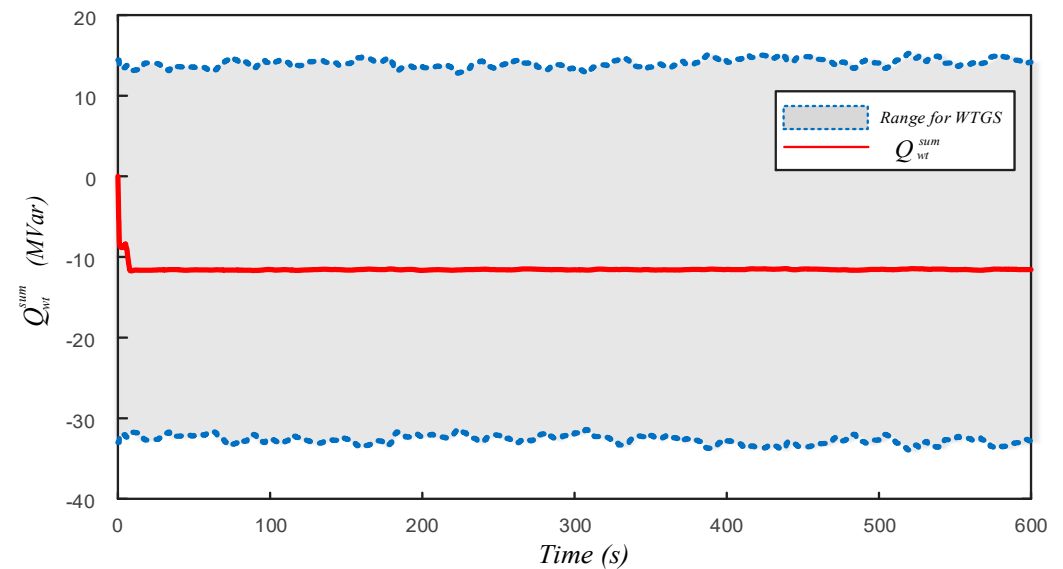


Figure 15. Reactive power capability of WTGs for Case 2.

8. Conclusions

This study developed a deep learning model to establish a digital model for the active power prediction of wind turbines and a multi-mode MPC model composed by combining a physical model of wind turbines. A combined WFC based on hybrid model MPC used to optimize the coordination of reactive power regulation device equipment has different wind energy conditions for better voltage control. The hybrid model predictive control achieves the optimal coordination of the WTGs and SVGs to minimize bus voltage deviations, especially at the POC, and wind farm collector line voltage deviations under low-power production conditions and maximizes the fast-variation capability to cope with potential disturbances. Moreover, through the maximum reactive power redundancy optimization, the SCG retains a more reactive power capacity under the joint control mode.

of the WTG and SVG. A more reactive power support capacity is provided for the next emergency control. Due to space constraints, this paper does not analyze the impact of wind power prediction errors on the model predictive control, communication delays, or related issues such as the application of online modeling systems. These issues will be investigated in future work.

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Data Availability Statement: Wind farm operators require the data to be kept confidential.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

The state-space matrices are as follows:

$$A_{wt}^{p-set} = \begin{bmatrix} 0 & -\frac{K_{p-\theta}\eta_g}{\tau_g} & \frac{K_{p-\theta}}{T_g} - K_{i-\theta} \\ \frac{K_{\theta T_r}}{J_t} & \frac{K_w T_r}{J_t} + \frac{1}{J_t} \frac{P_{wt}^0 \eta_g}{\mu \omega_g^2} & 0 \\ 0 & \frac{\eta_B}{T_{8s}} & -\frac{1}{T_g} \end{bmatrix}, B_{wt}^p = \begin{bmatrix} 0 \\ -\frac{\eta_g}{J_t \mu \omega_g^0} \\ G_s \end{bmatrix}, E_{wt}^p = \begin{bmatrix} 0 \\ \frac{K_w T_r v_w^0}{J_t} \\ 0 \end{bmatrix}$$

The variables in the equation are defined as follows: η_g represents the gearbox ratio, $J_t \triangleq J_r + \eta_g^2 J_g$ stands for the equivalent inertia, τ_g is the time constant of the generator speed filter, and T_r is the rotor torque. P_{wt}^0 , θ^0 , ω_g^0 and v_w^0 denote the measured power output, pitch angle, generator speed, and wind speed at the operating point, respectively. $K_{p-\theta}$ and $K_{i-\theta}$ denote the proportional and integral gains of the pitch controller. $K_{\theta T_r}$, $K_{\omega_r T_r}$, and $K_{v_w T_r}$ are the coefficients derived from the Taylor approximation of T_r at the operating point [11].

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