
# Implementation of neural network Multivariable Predictive Control of command a Variable Speed wind turbine

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## ABSTRACT

**Implementation of a neural network model-based predictive control a wind energy conversion system constrained by the linear matrix inequality LMI is proposed is described in this paper. For that, the multi-variable predictive control strategy is used with an artificial neuro-fuzzy model and applied to a non-linear wind energy conversion system. Among the advantages of this approach is to calculate future order entries from past input measurements, based on the solution of a convex optimization problem. Optimal control of multi-variable systems is achieved using linear matrix inequality formalism and by taking into account that whole wind energy conversion system can be structured as several interconnected subsystems. A neural network is designed to estimate the optimum value of the power-efficiency ratio of wind turbines.**

**Keywords:** *Wind turbines; Multi-Model predictive control; LMI design; artificial neural network control.*

## 1. INTRODUCTION

Predictive control is a method that uses a model to predict the response of the system to be controlled under a certain number of constraints. This method did not really develop until the early 1980s, thanks to the work of D. W. Clarke [1][2][3]. MPC is a control technique for systems with relatively slow dynamics or, at least, compatible with the fact that at each sampling time the control signal results from solving an optimization problem. Predictive control is a wide and varied field and integrates disciplines such as optimal control, multi-variable control and constrained control. However, there is currently a lot of work and applications for predictive controllers that are successfully operating in the process industry. Advances technology and the use of computers have made it possible to implement more complicated and sophisticated techniques, which in turn has made it possible to develop the MPC approach. The practical interest of MPC is mainly due to the fact that today's processes need to be operated under tight performance specifications and more constraints need to be satisfied. MPC is the possible solution for that due to its constraints handling capability. A linear Matrix Inequalities (LMIs) formulation for the MPC problem permits to obtain a controller optimizing [3][4][5].

In this poster, we present the multi-variable predictive control strategy (MMPC) and uses neural network approach for Estimation Power Coefficient of wind energy conversion systems and determinate model. The MPC constrained optimization problem is formulated by LMI constraints. The conversion systems for the entire wind energy can be structured as several interconnected subsystems.

## 2. Constraints for Predictive Control

The predictive approach closest to the standard theory (Díaz et al., 2018; Nanayakkara et al., 1997) for linear systems is certainly the one that considers a model by state representation:

$$x(k+1) = Ax(k) + Bu(t) \qquad (1)$$

$$y(k) = C_y x(k) \qquad (2)$$

$$z(k) = C_z x(k) \qquad (3)$$

Where $k \in \mathbb{Z}^+$, $x(k) \in \mathbb{R}^n$ $n$-dimensional state vector in time k, $u(k) \in \mathbb{R}^l$ le command vector $y(k) \in \mathbb{R}^{m_y}$ $m_y$-dimensional outputs vector of the measured, $z(k) \in \mathbb{R}^{m_z}$ $m_z$-dimensional output vector to be controlled, *A, B,* $C_y$ et $C_z$ matrices of appropriate dimensions. Controlled outputs *z(k)* may in principle depend on *u(k)* .

## 3.Minimizing a Performance Criterion

The cost function $J$ to be minimized at each sampling time, its penalizes the deviations of the predicted outputs $\tilde{z}(k+i|k)$ from a reference trajectory $r(k+i|k)$ in the variations of the control vector $\Delta u(k) = u(k) - u(k-1)$, it is often given by the quadratic form [6] [7]:

$$J(k) = \sum_{i=H_{\min}}^{H_p} \left(r(k+i) - \hat{z}(k+i)\right)^T Q \left(r(k+i) - \hat{z}(k+i)\right) + \sum_{i=H_{\min}}^{H_p} \sum_{i=0}^{H_u-1} \left(u(k+i)^T R\, u(k+i) + \Delta u(k+i)^T S\, \Delta u(k+i)\right) \quad (4)$$

$H_p$ , $H_u$ prediction horizon and the control horizon, $H_u \leq H_p$ et $\Delta\hat{u}(k+i|k) = 0$ for $i \geq H_u, Q(i) \geq 0, R(i) > 0$ its weighting matrix.

## 4.Constraints for Predictive Control

$$\begin{bmatrix} \Delta\hat{u}(k|k) \\ \vdots \\ \Delta\hat{u}(k+H_u-1|k) \end{bmatrix} \qquad (5)$$

for Eq. (3) the prediction value of $z$ is

$$\begin{bmatrix} \hat{z}(k+1|k) \\ \vdots \\ \hat{z}(k+H_p|k) \end{bmatrix} = \begin{bmatrix} C_z & 0 & \cdots & 0 \\ 0 & C_z & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & C_z \end{bmatrix} \begin{bmatrix} \hat{x}(k+1|k) \\ \vdots \\ \hat{x}(k+H_p|k) \end{bmatrix} \qquad (6)$$

From Eq. (4) we have :

$$J(k) = \|Z(k) - T(k)\|_{\bar{Q}}^2 + \|\Delta U(k)\|_{\bar{R}}^2 \qquad (7)$$

where

$$Z(k) = \begin{bmatrix} \hat{z}(k+H_w|k) \\ \vdots \\ \hat{z}(k+H_p|k) \end{bmatrix} \quad T(k) = \begin{bmatrix} \hat{r}(k+H_w|k) \\ \vdots \\ \hat{r}(k+H_p|k) \end{bmatrix} \quad \Delta U(k) = \begin{bmatrix} \Delta\hat{u}(k|k) \\ \vdots \\ \Delta\hat{u}(k+H_u-1|k) \end{bmatrix}$$

The weighting matrices $\bar{Q}$ and $\bar{R}$ are obtained by:

$$\bar{Q} = \begin{bmatrix} Q(H_w) & 0 & \cdots & 0 \\ 0 & Q(H_w+1) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & Q(H_p) \end{bmatrix} \quad \bar{R} = \begin{bmatrix} R(0) & 0 & \cdots & 0 \\ 0 & R(1) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & R(H_u-1) \end{bmatrix}$$

For Eq. (8) and Eq. (9), *Z*(*k*) we obtain

$$J(k) = const - \Delta U(k)^T G + \Delta U(k)^T H \Delta U(k) \qquad (8)$$

where

$$G = 2\Theta^T \bar{Q} \varepsilon(k) \qquad (9)$$

$$H = \Theta^T \bar{Q} \Theta + \quad (10)$$

$$\nabla_{\Delta U(k)} J(k) = -G + 2H\Delta U(k) \qquad (11)$$

The optimal sequence of future control variation is:

$$\Delta U(k)_{opt} = \frac{1}{2} \qquad (12)$$

$H^{-1}$existe car $H > 0$.

$$u(k)_{opt} = \Delta U(k)_{opt} + u(k-1) \qquad (13)$$

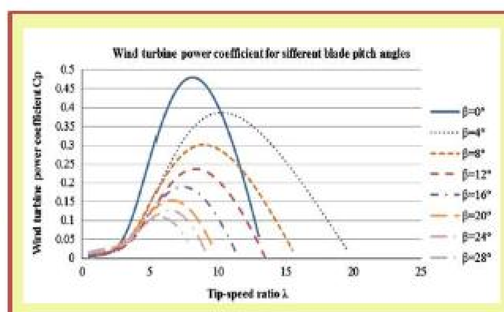
Constants formed are :

$$E\begin{bmatrix} \Delta U(k) \\ 1 \end{bmatrix} \leq 0, \quad F\begin{bmatrix} U(k) \\ 1 \end{bmatrix} \leq 0 \quad , \quad G\begin{bmatrix} Z(k) \\ 1 \end{bmatrix} \leq 0$$

The neuron model is used to estimate power coefficient the process and determinate the model of wind turbine, and predict output speed control under the constraints :

$$\begin{bmatrix} I \\ -I \\ L \\ L \\ \Lambda \\ -\Lambda \end{bmatrix} \Delta U_n \leq \begin{bmatrix} \tilde{U}_{\max} \\ -\tilde{U}_{\min} \\ U_{\max} \\ -U_{\min} \\ Y_{\max} - \Gamma \\ -Y_{\max} + \Gamma \end{bmatrix}$$

## 5.Constraints for Predictive Control



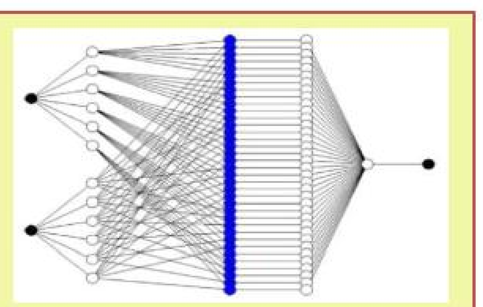
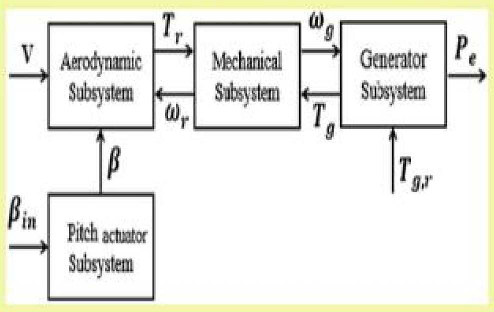



**Figure 1** Wind turbine power coefficient *Cp* as function of tip-speed ratio *λ* and blade pitch angle *β*. And neural network of Cp.

The variables in the wind turbine are assumed to vary with in the operating range $V_1 \leq V \leq V_2$. $\beta_1 \leq \beta \leq \beta_2$.
Therefore, the non-linear system can be estimated parameters the equivalent model of wind turbine with estimate power coefficient by neural network[7-11].




## 6 . Simulation Results

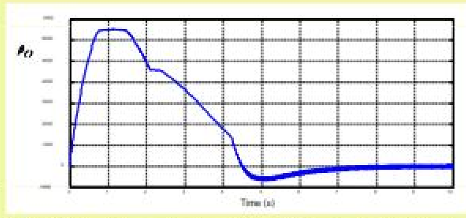



**Figure 2** Desired control angle with the MMPC controller using Adaptive neural network Approach for Estimation Power Coefficient..

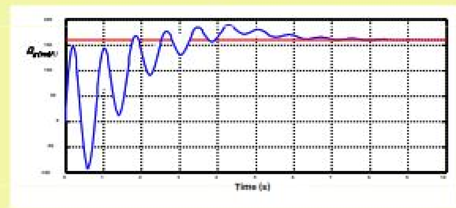



**Figure 3** Variation of the speed rotation

**The purpose of the control is to achieve the optimal performance of the nominal power while regulating the rotor speed. The system converges to the reference value, and then stabilizes. With a little overtaking. This response is obtained for a horizon $H_p$=90 and $H_u$=1 and the torsion angle $\theta_s$ reduces because the values of the speeds $\Omega_g$ and $\Omega$ are nearly equal. Figure 2, the constants on the control are $u \in [-3, 3.2]$. The optimization problem at each step is solved using Matlab software.**

## 6. CONCLUSIONS

In this work, we presented the design and simulation of the multivariable predictive control (MPC) based on artificial neural network Approach in order to estimate the wind turbine parameters. An Adaptive neural network Approach is designed to estimate the optimum value of the power-efficiency ratio of wind turbines.

The experiments and the tests show the importance of the choice of the control prediction horizon. A low prediction horizon may not take into account the future performance of the process properly, while a high prediction horizon requires a high computation time. The obtained results show the efficiency of the proposed approach.

In future work, it would be interesting to implement the control algorithm proposed in this work to control the wind energy conversion system and other nonlinear systems in real time.

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