Fuzzy model based multivariable predictive control design for rapid and efficient speed-sensorless maximum power extraction of renewable wind generators

Introduction. A wind energy conversion system needs a maximum power point tracking algorithm. In the literature, several works have interested in the search for a maximum power point wind energy conversion system. Generally, their goals are to optimize the mechanical rotation or the generator torque and the direct current or the duty cycle switchers. The power output of a wind energy conversion system depends on the accuracy of the maximum power point tracking controller, as wind speed changes constantly throughout the day. Maximum power point tracking systems that do not require mechanical sensors to determine the wind speed offer several advantages over systems using mechanical sensors. The novelty. The proposed work introduces an intelligent maximum power point tracking technique based on a fuzzy model and multivariable predictive controller to extract the maximum energy for a small-scale wind energy conversion system coupled to the electrical network. The suggested algorithm does not need the measurement of the wind velocity or the knowledge of turbine parameters. Purpose. Building an intelligent maximum power point tracking algorithm that does not use mechanical sensors to measure the wind speed and extracts the maximum possible power from the wind generator, and is simple and easy to implement. Methods. In this control approach, a fuzzy system is mainly utilized to generate the reference DC-current corresponding to the maximum power point based on the changes in the DC-power and the rectified DC-voltage. In contrast, the fuzzy model-based multivariable predictive regulator follows the resultant reference current with minimum steady-state error. The significant issues of the suggested maximum power point tracking method, such as the detailed design process and implementation of the two controllers, have been thoroughly investigated and presented. The considered maximum power point tracking approach has been applied to a wind system driving a 5 kW permanent magnet synchronous generator in variable speed mode through the simulation tests. Practical value. A practical implementation has been executed on a 5 kW test bench consisting of a dSPACEEds1104 controller board, permanent magnet synchronous generator, and DC-motor drives to confirm the simulation results. Comparative experimental results under varying wind speed have confirmed the achievable significant performance enhancements on the maximum wind energy generation and overall system response by using the suggested control method compared with a traditional proportional integral maximum power point tracking controller. References 24, tables 3, figures 15.

Key words: small-scale wind generator, maximum power point tracking, fuzzy system, fuzzy model based multivariable predictive control, linear matrix inequalities approach.

Вступ. Система перетворення енергії вітру потребує алгоритму відстеження точки максимальної потужності. У літературі є кілька робіт, присвячених пошуку системи термінового трохи із точки максимальної потужності. Як правило, їх метою є оптимізація механічного обертання або відстані, що крутить, генератора і перемикачі постійного струму або робочого циклу. Вихідна потужність системи перетворення енергії вітру залежить від точності контролера відстеження за максимальною потужністю, оськиї відкісність вітру постійно змінюється протягом дня. Системи відстеження за точками з максимальною потужністю, яким не потребляють механічні датчики для вимірювання швидкості вітру, мають ряд переваг у порівнянні з системами, що використовують механічні датчики. Нова система. Пропонована робота представлена інтелектуальним методом відстеження точки максимальної потужності, заснований на нечіткій моделі та багатопараметричному прогнозуючому контролері, для отримання максимальної енергії для маломасштабної системи перетворення енергії вітру, підключеної до електричної мережі. Пропонований алгоритм не вимагає вимірювання швидкості вітру або значного параметра турбіни. Мета. Побудова інтелектуального алгоритму відстеження точки максимальної потужності, який не використовує механічні датчики для вимірювання швидкості вітру та визначає максимально можливе потужність з вітробензогенератора, а також простий та зручний у реалізації. Методи. У цьому підході до управління нечітка система на основному використовується для генерування еталонного постійного струму, що відповідає точці максимальної потужності, на основі змін потужності постійного струму та постійної вимірюваної напруги. Навпаки, багатопараметричний прогнозуючий регулятор на основі нечіткої моделі слідує за результуючим еталонним струмом з мінімальною помилкою, що встановлюється. Існуючі проблеми запропонованого методу відстеження точки максимальної потужності, які викликають процес детального проектування та реалізація даних контролерів, були ретельно досліджені та представлені. Розглянутий підхід до відстеження точки максимальної потужності був застосований до вітробензогенератора, що працює у дію синхронний генератор з постійними магнітами потужністю 5 кВт у режимі змінної швидкості за допомогою моделювання. Пріоритети цінність. Для підтвердження результатів моделювання було виконано практичну реалізацію на випробувальному стенде виготовленого 5 кВт, що складається з плази контролера dSPACEEds1104, синхронного генератора з постійними магнітами та електропроводів з дисплейної постійного струму. Проведені експериментальні результати при різних швидкостях вітру підтвердили значні поліпшення продуктивності з максимального вироблення енергії вітру і загального відхилку системи при використанні запропонованого методу управління в порівнянні з нерядковим пропорційно-інтегральним контролером спостереження за точкою максимальної потужності. Бібл. 24, табл. 3, рис. 15.

Ключові слої: малогабаритний вітробензогенератор, відстеження точки максимальної потужності, нечітка система, багатопараметричне прогнозичне управління на основі нечіткої моделі, метод лінійних матричних нерівностей.
scale wind turbines to achieve low cost and complexity, high reliability, and good performance by controlling the electromechanical energy conversion with minimal influence on the electrical network [3, 4], notably if the converter control is exploited with the appropriate maximum power point tracking (MPPT) algorithm. As for the MPPT algorithms, there are many MPPT approaches have been mentioned in the literature.

In most cases, these approaches rely on wind velocity measurement or wind speed-sensorless method, such as duty cycle control method, look-up table for optimum rotor speed control method, and optimum tip-speed ratio (TSR) control method. However, these schemes require precise knowledge of the wind power system parameters either before or during execution.

Moreover, the wind turbine components tend to modify their characteristics over time. Therefore, a control strategy independent of the wind generator parameters does not necessitate any prior information of the wind speed, such as the perturbation and observation (P&O) method, which is very flexible and accurate [5-7]. Moreover, this strategy is straightforward, simple, and suitable for wind generators with low inertia. Recently, there have been many articles on the MPPT methodology, especially the simplified and advanced P&O methods [8], adaptive MPPT method [9], two-stage MPPT algorithm [10], hill-climb searching algorithm [11], and modifiable step size-based P&O algorithm [12]. Despite being simple and adaptable, these MPPT techniques suffer from the problems of high steady-state errors and huge frequency variations. Other MPPT algorithms, such as fuzzy reasoning-based MPPT technique [13], neural network technique [14], and advanced vector technique [15], have also been proposed in the literature. Moreover, these control strategies necessitate extensive calculations and are not always effective. Moreover, these control techniques need extra control efforts as well as costly sensors [16].

The goal of the paper is to introduce a new intelligent maximum power point tracking method for a small-scale wind generator connected to the electrical network.

The suggested MPPT technique is mainly based on a fuzzy system for deriving the reference DC-current. An innovative fuzzy model-based multivariable predictive algorithm is used to follow the reference DC-current accurately and then implement the intelligent MPPT algorithm. The suggested MPPT method can capture the maximum amount of energy from a wind generator while retaining excellent performance and quality.

Subject of investigations. This article explains how to properly manage important challenges in the design and implementation of the two regulators. Experimental results demonstrate the significant performance enhancements that can be achieved in the maximum power generation and overall system response using the suggested intelligent MPPT method. The two regulators are simple and easy to operate in modern wind power generators equipped with a six diode rectifier and boost circuit.

System description. The synoptic schematic of the considered wind power system is illustrated in Fig. 1. The conversion circuit comprises of a wind turbine with three blades, a multi-pole three-phase PMSG, a six-diode bridge rectifier, a DC-DC boost chopper, and a source voltage inverter (VSI), which is coupled to the grid. The harvested wind energy is sent immediately to the PMSG, which is transformed into electrical power by this generator.

![Fig. 1. Synoptic schematic of the considered wind system](image)

The resulting electrical power can then be converted using a conventional rectifier. The boost chopper boosts the rectified DC-voltage ($V_{dc}$), then supplied into the electrical network through the VSI. Because the traditional rectifier is uncontrollable, a boost chopper is employed to guarantee the maximum power capture of electrical energy from the wind generator. Only one electronic switch is required, which minimizes the system's cost and simplifies its control, consequently maintaining high system reliability and stability [17].

The VSI adjusts the power flow between the DC-bus voltage ($V_0$) and the electrical grid as a result independent grid-side. The mechanical power produced by the wind generator can be expressed as in [18]:

$$P_m = C_p \frac{1}{2} \rho \pi D^2 \frac{V^3}{R}$$
where \( \rho \) represents the air mass density; \( C_p \) indicates the performance coefficient of the wind generator; \( A \) denotes the swept surface of the three blades, \( \nu_w \) denotes the wind velocity; \( \lambda \) is the tip speed ratio (TSR); \( \beta \) is the inclination angle of the blade (in this study set to zero).

A general form is utilized for modeling \( C_p \). The equation is derived from the characteristics of the wind turbines [19]:

\[
C_p = 0.5176 \left( \frac{116}{\lambda} - 0.4 \beta - 5 \right) - \frac{21}{\lambda^2} + 0.0068 \lambda ;
\]

(2)

where \( \lambda \) is the ratio of the linear turbine rotation to the wind velocity, which is stated as:

\[
\lambda = \frac{\omega_m R}{\nu_w},
\]

(4)

where \( \omega_m \) and \( R \) are the turbine rotational speed and radius, respectively.

Figure 2 displays the \( C_p \) against \( \lambda \) graph obtained by (2). It’s worth noting, that there is a unique optimum value of the \( \lambda_{opt} \) at which the \( C_p \) is at its highest value \( C_{p_{max}} \) [20].

![Fig. 2. \( C_p = f(\lambda) \) of the considered wind generator](image)

Thus, the mechanical energy collected from the wind generator is likewise at its peak if the wind generator works at the MPP (\( \lambda_{opt}, C_{p_{max}} \) = (8.08, 0.47)). The optimum mechanical power (\( P_{max} \)) can be established by replacing (4) into (1), as shown in:

\[
P_{max} = k_p \omega_m^3 \omega_{m_{opt}}^3,
\]

(5)

where \( \omega_{m_{opt}} \) represents the optimum mechanical angular speed of the wind generator for a given wind velocity; \( k_p \) is the power control coefficient calculated as follows:

\[
k_p = \frac{\rho \omega^2 R^5 C_{p_{max}}}{2 \lambda_{opt}^3}.
\]

(6)

From (1), (5) the approximate relationship is obtained:

\[
P_{max} \propto \nu_w^3 \propto \omega_{m_{opt}}^3 \omega_{m_{opt}}^3.
\]

(7)

where symbol \( \propto \) indicates that the relationship is an approximation between the two variables.

The back-EMF of the PMSG is proportional to rotational velocity, and can be calculated as:

\[
E = k_e \nu_w = k_e \omega_{m_{opt}}^3,
\]

(8)

where \( k_e \) is the back-EMF coefficient of the wind generator.

The phase terminal AC voltage \( V_{ac} \) in the root-mean square (RMS) for a three-phase PMSG is defined as:

\[
V_{ac} = E - I_{ac}(R_s + j \omega_s L_s),
\]

(9)

with:

\[
\omega_s = p \omega_n,
\]

(10)

where \( I_{ac}, R_s, L_s \) are the line-current in RMS, the line-resistor, and the line inductance, respectively; \( \omega_s \) is the electrical angular speed of the PMSG; \( p \) is the number of pole pairs.

Using a six-diode bridge rectifier, the rectified DC-voltage \( (V_{dc}) \) is related to the phase-voltage of the PMSG, therefore can be calculated as:

\[
V_{dc} = \frac{3 \sqrt{6}}{\pi} V_{ac}.
\]

(11)

Assuming no power losses, the electrical DC-power \( (P_{dc}) \) can be expressed as:

\[
P_{dc} = 3 V_{ac} I_{ac} = V_{dc} I_{dc},
\]

(12)

where \( I_{dc} \) represents the rectified DC-current, which can be determined by replacing (11) in (12):

\[
I_{dc} = \frac{\pi}{6} I_{ac}.
\]

(13)

Equations (8)–(10) can then be used to get the following equation:

\[
\begin{align*}
V_{dc} &= 3 \sqrt{6} \left( k_e - \frac{\sqrt{6}}{6} \right) L_{ac} \omega_{m_{opt}}^3; \\
V_{dc} &= 3 \sqrt{6} \left( k_e - \frac{\sqrt{6}}{6} L_{ac} \omega_{m_{opt}}^3 \right) I_{dc}.
\end{align*}
\]

(14)

where \( V_{dc} \) is the optimum rectified DC-voltage at the MPP. Substituting (5) into (14) gives:

\[
V_{dc} \propto \omega_m \text{ and } V_{dc} \propto \omega_{m_{opt}}.
\]

(15)

From (5), (14) at the MPP, the following relationship is valid:

\[
V_{dc} \propto \omega_m \text{ and } P_{max} \propto \left( \frac{V_{dc}}{\omega_m} \right)^3.
\]

(16)

Meanwhile, the optimum DC-power can be described as:

\[
P_{dc} \propto \omega_m \text{ and } \omega_m \propto \omega_{m_{opt}}.
\]

(17)

As indicated in (18), (19), \( I_{dc} \) is proportional to the square of \( V_{dc} \), and is directly related to \( P_{dc} \). As a result, when \( I_{dc} \) is kept close to its optimal (reference \( I_{dc}^{opt} \)) value \( I_{dc}^{opt} \), the wind generator may produce the maximum amount of electrical power \( P_{dc}^{max} \).

**Fuzzy-based MPPT controller for wind power generator.** The main objective of this section is to
To create the fuzzy sets of inputs and output variables, the input/output parameters, i.e. \( \Delta P_{dc}[k] \) and \( \Delta V_{dc}[k] \), are represented by linguistic terms, such as Positive-Big (PB), Positive-Medium (PM), Positive-Small (PS), Zero (ZE), Negative-Big (NB), Negative-Medium (NM), and Negative-Small (NS).

The following IF–THEN rules define the desired relationships between inputs and outputs:

\[
R_i: \text{IF } \Delta P_{dc}[k] \text{ is } A_i \text{ and } \Delta V_{dc}[k] \text{ is } B_j \text{ THEN } \Delta I_{dc}^{opt}[k] \text{ is } C_k,
\]

where \( i, j = 1, 2, \ldots, 7; k = 1, 2, 3, \ldots, 49 \), and \( A_i, B_j \), and \( C_k \) indicate the antecedents and consequent parts, respectively.

The IF–THEN rules are summarized in Table 1. This article uses a fuzzy system with Mamdani method for the inference process [21].

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<th>( \Delta P_{dc} )</th>
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The output level \( \Delta I_{dc}^{opt}[k] \) of each fuzzy rule is normalized by a factor related to the firing strength \( w_i \), which is calculated from the minimum operation such as:

\[
w_i = \min\mu_{\Delta P_{dc}}(\Delta P_{dc}[k]), \mu_{\Delta V_{dc}}(\Delta V_{dc}[k]),
\]

The defuzzification is realized using the centroid method (COA) of a last combined fuzzy set. The last combined fuzzy set is determined by the sum of all rule output fuzzy sets using the maximum aggregation approach [22]. Therefore, the variation in the optimum DC-current \( \Delta I_{dc}^{opt}[k] \) is calculated according to the following relationship:

\[
\Delta I_{dc}^{opt}[k] = \frac{\sum_{j=1}^{n} \mu\left(\Delta I_{dc}^{opt}(j)\right) \mu\left(\Delta V_{dc}[k]\right)}{\sum_{j=1}^{n} \mu\left(\Delta V_{dc}[k]\right)}.
\]

The output of the fuzzy MPPT system is \( \Delta I_{dc}^{opt}[k] \), which is converted to the optimum DC-current, \( I_{dc}^{opt}[k] \) by:

\[
I_{dc}^{opt}[k] = I_{dc}^{pot}[k-1] + \Delta I_{dc}^{opt}[k].
\]
Fuzzy model based multivariable predictive (FMMP) regulator. In this part, a FMMP regulator is developed for a DC-DC boost chopper in order to follow the optimum DC-current ($I_{dc}$). The FMMP regulator is effective for DC-DC boost chopper because this control strategy is a sort of control technique that was primarily introduced to regulate constrained linear and nonlinear systems. In addition, the FMMP regulator has a quick dynamic behavior, excellent stability, and robustness against parameter variation in a variety of working conditions.

Control system design. Since the PMSG can provide the rectified DC-current ($I_{dc}$), it can be used as a current source. Therefore, only the dynamic of the boost chopper is studied and described in this paper. In the next part, the T-S fuzzy model of the boost chopper is utilized to represent the nonlinear behavior for the control design goal using the sector nonlinearity method.

T-S fuzzy model of the DC-DC boost chopper. As can be seen from Fig. 1, the global nonlinear dynamical behavior of the DC-DC boost chopper in regular state can be seen from Fig. 1, the global nonlinear dynamical behavior of the DC-DC boost chopper in regular state can be expressed as follows:

$$\begin{bmatrix}
\frac{dl_d}{dt} \\
\frac{dV_o}{dt}
\end{bmatrix} =
\begin{bmatrix}
0 & -\frac{(1-u)}{L} \\
\frac{(1-u)}{C} & -\frac{1}{R_iC}
\end{bmatrix}
\begin{bmatrix}
l_d \\
V_o
\end{bmatrix} + \begin{bmatrix}
1 \\
0
\end{bmatrix} V_{dc}, \quad (26)
$$

where $I_d$ is the input inductor current or DC-current; $u$ is the equivalent control signal that takes values in the domain $[0, 1]$; $R_i$ is the total equivalent resistance; $V_o$ is the output DC-voltage; $I_d$ is the output DC-current; $C$ and $L$ are the capacitance and inductance values respectively.

Finally, a DC-DC boost chopper's discrete-time state space representation is used to derive (26), considering the sampling period $T_s$ and replacing the control signal $u$ by its respective duty ratio $D(k)$. The result of this discretization can be expressed as:

$$\begin{bmatrix}
I_d(k+1) \\
V_o(k+1)
\end{bmatrix} =
\begin{bmatrix}
1 & -\frac{T_s}{L} \\
T_s & -\frac{T_s}{R_iC}
\end{bmatrix}
\begin{bmatrix}
I_d(k) \\
V_o(k)
\end{bmatrix} + \begin{bmatrix}
\frac{T_s}{C} \\
I_d(k)T_s
\end{bmatrix} D(k). \quad (27)
$$

According to the expressions (26), (27) and the T-S fuzzy model [23], the boost chopper can be described by a second-order $r$-rule fuzzy system. The $r$th rule of the discrete T-S fuzzy model is written as follows:

Fuzzy rules $r_i$:

IF $w_i(l)$ is $F_i$, and ... and $w_g(l)$ is $F_g$, THEN $x(k+1) = A_ix(k) + B_iu(k)$; where $i = 1, 2, ..., k$; $A_i \in \mathbb{R}^{n_{x}},$ $B_i \in \mathbb{R}^{n_{x} \times k}$ values denote the number of fuzzy rules; $w_i$, $w_2$, ..., $w_g$ are the premise variables; $F_i$ ($i = 1, 2, ..., g$) are the fuzzy sets; $x(k) \in \mathbb{R}^n$ are the system variables; $u(k)$ is the control input signal; $A_i$, $B_i$ are the state vectors of the local sub-system inadequate sizes.

Using the singleton fuzzification, product inference rule, and weighted average defuzzification, the above fuzzy rules base is deduced as follows:

$$x(k+1) = \sum_{i=1}^{k} \mu_i(w(k)) \big( A_ix(k) + B_iu(k) \big), \quad (28)$$

where:

$$\mu_i(w(k)) = \frac{\prod_{j=1}^{g} F_{ij}(w_j(k))}{\sum_{i=1}^{k} \prod_{j=1}^{g} F_{ij}(w_j(k))}. \quad (29)$$

The term $F_{ij}(w_j(k))$ is the grade of membership of $w_j(l)$ in $F_i$. Note that, where for $i = 1, 2, ..., k$. For deriving the T-S model of the DC-DC boost chopper, let the fuzzy premises variable vector $w(k)$ be selected as:

$$w_1(k) = I_{dc}(k), \quad w_2(k) = V_o(k).$$

Since, the system states of the boost chopper are bounded; the premise variables will also be bounded. In this paper, the fuzzy premise variables vary in the range defined as:

$$\max (I_{dc}(k)) = D_1, \quad \min (I_{dc}(k)) = d_1; \quad \max (V_o(k)) = D_2, \quad \min (V_o(k)) = d_2.$$  

From the above, the corresponding MFs of the T-S system can be written as:

$$F_{11} = I_{dc}(k) - d_1, \quad F_{12} = 1 - F_{11};$$

$$F_{21} = V_o(k) - d_2, \quad F_{22} = 1 - F_{21}.$$ 

These membership functions are considered triangular shape as demonstrated in Fig. 4.

Based on the sector nonlinearity notion, we have the following relationships:

$$I_{dc}(k) = F_{11}D_1 + F_{21}d_1, \quad V_o(k) = F_{21}D_2 + F_{22}d_2.$$  

As a result, the complete fuzzy boost chopper model is equivalent to:

$$x(k+1) = A_0x(k) + \left( \sum_{i=1}^{4} \mu_i(I_{dc}(k), V_o(k))B_i \right) d(k), \quad (30)$$

where $A_0$ and $B_i$ are the local sub-models matrices given by (for $i = 1, 2, ..., 4$):

$$A_0 = A_1 = A_2 = A_3 = A_4 = \begin{bmatrix}
1 & -\frac{T_s}{L} \\
\frac{T_s}{C} & 1 -\frac{T_s}{R_iC}
\end{bmatrix}.$$
and:

\[ B_1 = \begin{bmatrix} (V_{dc} - d_2)T_s \frac{L}{d_1 T_s} \\ - \frac{L}{d_1 T_s} \end{bmatrix}, \quad B_2 = \begin{bmatrix} (V_{dc} - d_2)T_s \frac{L}{D T_s} \\ - \frac{L}{D T_s} \end{bmatrix} \]

It can be seen that (30) corresponds with the system (27) inside the polytope area \([d_1, D_1] \times [d_2, D_2]\). This operating space is shown in Fig. 5.

**Fig. 5. T-S Fuzzy representation of the boost chopper**

**Multivariable predictive current control.** A multivariable predictive current control method based on the T-S fuzzy model is introduced to obtain an accurate tracking control of the optimum DC-current \(I_{dc, opt}\) for the DC-DC boost chopper. In this work, the boost chopper’s state variables are restricted by physical limits required by the wind generator users due to the technical specifications of the power converters. Therefore, constraints must be set while designing the boost chopper regulator. The primary function of the multivariable predictive control (MPC) is to compute a series of future operating signals in such a way that it reduces a specified objective function calculated over a prediction horizon [24]. The quadratic objective function to be minimized by the MPC controller is given by:

\[
\text{min} J = \sum_{j=H_p}^{H_p} \left( r(k+j) - \hat{y}(k+j) \right)^T Q \left( r(k+j) - \hat{y}(k+j) \right) + \sum_{j=1}^{H_p} \left( r(k+j) - \hat{y}(k+j) \right)^T \Delta u(k+j-1) \tag{31} \]

Subject to the following constraints:

\[
x_{\text{min}} \leq \hat{x}(k+j) \leq x_{\text{max}}; \quad y_{\text{min}} \leq \hat{y}(k+j) \leq y_{\text{max}}; \quad u_{\text{min}} \leq \hat{u}(k+j) \leq u_{\text{max}}; \quad \Delta u_{\text{min}} \leq \Delta u(k+j) \leq \Delta u_{\text{max}},
\]

where \(k\) is the current sampling instant; \(H_p\) indicates the control cost horizon; \(H_n\) denotes the start point of the prediction horizon; \(H_p\) signifies the end point of the prediction horizon; \(H_p < H_n\) and \(\Delta u(k+j-1)\) represents the control increments vector, \(r(k+j)\) is the future reference trajectory, \(y(k+j)\) is the \(j\) step-ahead prediction of the system; \(Q\) is the weighting matrix of the tracking error; \(R\) and \(S\) are the weighting matrices.

Thus, two parts determine the objective function (32): the first part is concerned with reducing the difference between predicted output and reference trajectory. The second part is a penalty for exerting control effort. Further, the above-mentioned objective function can be defined in a more comprehensive matrix form [25]:

\[
J(U_n) = J_{\text{min}} + 2 \left( [\Gamma + \Theta U_{k-1} - Y_{\text{ref}}] \Lambda U_n + \Delta U_n^T \left[ \Gamma \Lambda + R + S \right] \Lambda U_n \right), \tag{32}
\]

where

\[
J_{\text{min}} = Y_{\text{ref}}^T \Theta Y_{\text{ref}} + \Gamma^T \Theta \Gamma - 2 Y_{\text{ref}}^T \Theta \Gamma + U_{k-1}^T \Theta U_{k-1} + \Delta U_n^T \left[ \Gamma \Lambda + R + S \right] \Lambda U_n.
\]

The fuzzy model (30) is utilized to predict the output of the system, subject to amplitude and rate saturation on the system states and control inputs:

\[
I_{\text{opt}} = \left[ \begin{array}{c} \hat{U}_{\text{min}} \\ \hat{U}_{\text{max}} \\ \hat{U}_{\text{min}} \\ \hat{U}_{\text{max}} \end{array} \right] \in R^{H_n \times 10} \tag{34}
\]

and

\[
Y = \Gamma + \Delta U_n \tag{35}
\]

where the predicted output may be written as:

\[
\hat{y}(k) = Y \hat{x}(k) \tag{36}
\]

The Hessian matrix \(H\) is positive-definite if it satisfies the following condition:

\[
\text{rank}(H) = H_n. \tag{37}
\]

Thus, the restrictions (34) can be expressed in one form that can be simply exploited later by the proposed optimization method:

\[
\Delta U_n(k) \leq B. \tag{38}
\]

The Schur complement theorem is utilized to make the non-linear criterion (36) in Linear Matrix Inequalities (LMI)
format. Moreover, this theorem can minimize the linear objective function with LMI restrictions [27]. Therefore, the LMI-based problem of central importance to this paper is that of minimizing a linear subject to LMI constraints:

\[ \text{minimize } c^T x, \]
\[ \text{subject to : } F(x) > 0, \]
where \( F(x) \) is the symmetric matrix that depends affinely on the variable \( x \), and \( c \) is the real vector. The solution then minimizes the linear term \( c^T x \) [28].

**LMI problem.** An optimization LMI problem necessitates restructuring the main problem to include a linear objective function with LMI restrictions [27]. Therefore, the equivalent minimization algorithm:

Minimize \( \gamma \) and finding an acceptable \( \Delta U_n \) that satisfies the following condition:

\[ J(\Delta U_n) < \gamma. \] (39)

The relationship (32) can be converted to LMI form using Schur complement [27].

**Simulation and experimental verifications.** At first, the performance of the suggested control method incorporating fuzzy based MPPT algorithm is thoroughly examined in simulation using MATLAB/Simulink software. Then experimental tests are performed in laboratory to validate the proposed control strategy.

**Simulation investigation of wind energy conversion system (WECS) control system based FMMP current controller.** This part shows the advantages of implementing the derived predictive algorithm and the fuzzy MPPT control scheme. First, the off-line calculations which are necessary for the calculation of the control signal are stated. Second, the system is simulated based on the small-sized wind turbine model, the key parameters utilized in numerical simulations are listed in Table 2. Finally, simulation results that demonstrate the prevalence of the suggested control algorithm are presented. The control problem is to keep the wind generator at the maximum output power while controlling the DC-current of the boost chopper without oscillations, since these oscillations can cause a variety of issues for consumers for example, and the power outage. The discrete time T-S fuzzy system (30) of the boost chopper can be created using a sampling interval of 0.001 ms, the FMMP scheme is developed with the following conditions: the control horizon is \( H_u = 2 \), and the prediction horizon is \( H_p = 20 \). The limitations are selected as:

\[ 0 \leq I_{dc} \leq 10 \, \text{A} \quad \text{and} \quad 0 \leq V_o \leq 600 \, \text{V}. \]

An additional restriction on the boost duty cycle is imposed as follow:

\[ 0 \leq d(k) \leq 0.98. \]

The values of the weighting matrices in (31) are:

\[ Q = \text{eye}(H_p), \]
\[ S = 0.5 \cdot \text{eye}((H_u + 1)n_i), \]
\[ R = 0.1 \cdot \text{eye}((H_u + 1)n_i), \]
where eye returns an \((n \times m)\) matrix with ones on the main diagonal and zeros elsewhere.

**Table 2**

<table>
<thead>
<tr>
<th>System parameters</th>
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<tbody>
<tr>
<td>Parameters of the PMSG utilized in simulation</td>
</tr>
<tr>
<td>Nominal power</td>
</tr>
<tr>
<td>Nominal voltage</td>
</tr>
<tr>
<td>Pole pairs</td>
</tr>
<tr>
<td>Nominal torque</td>
</tr>
<tr>
<td>Nominal speed</td>
</tr>
<tr>
<td>Nominal current</td>
</tr>
<tr>
<td>Back-EMF coefficient</td>
</tr>
<tr>
<td>Stator resistor</td>
</tr>
<tr>
<td>d-axis inductor</td>
</tr>
<tr>
<td>q-axis inductor</td>
</tr>
<tr>
<td>Inertia</td>
</tr>
</tbody>
</table>

**Simulation results.** The simulation plots of each state variable are shown in Fig. 6. The outcomes were obtained based on a 50 s variable wind profile. Figure 6.α shows the wind input used in the computer simulations. The variation in the wind velocity comprises high wind velocity ranges from 11 to 13 m/s.
Figure 6.b exhibits the simulated waveform of the $C_p$, which is maintained at the optimum value of 0.478, and it is not influenced by the variations in the wind speed, which shows the good performances of the developed fuzzy based MPPT scheme. The resulting TSR is shown in Fig. 6.e. It shows that the TSR of the blade remains approximately constant and changes only at limited values around the best TSR of 8.08. It can be observed from Fig. 6.d, that the DC-current tracks the optimum current accurately by using the suggested control method, which adjusts the torque generator to obtain the maximum electrical power from the wind turbine with a fast response time. As depicted in Fig. 6.e, the rotational speed of the generator is constantly adapted to the wind velocity, so that the maximum energy is captured from the wind generator.

The mechanical torque waveform is illustrated in Fig. 6.f, as can be observed from Fig. 6.f the torque generator changes according to the variation in wind velocity to accommodate the variations in the DC-current of the boost chopper. Figure 6.g displays the generator output power, which is well correlated to changes in wind speed. It can also be noted that using the recommended control technique, the generator output power quickly recovers to its maximum value according to changes in wind velocity. The DC-DC boost chopper can also be used to increase the rectified DC-voltage.

As shown in Fig. 6.h, the optimal DC-current is proportional to the rectified DC-voltage, their relationship is in line with (14). Therefore, it can be better controlled to obtain the optimal rectified DC-voltage by using the suggested control approach. The simulation results demonstrate that the designed control method can generate the maximum wind power under different wind speeds by adjusting the DC-current of the boost chopper.

Experimental verification of WECS control system based on FMMP current controller. The 5 kW semi-controlled WECS scheme is built in laboratory to prove the effectiveness of the suggested MPPT algorithm. In the experimental WECS, the PMSG is attached to the shaft of a 5 kW DC-motor to emulate the dynamic and static behaviors of the real wind generator. A conventional boost chopper is utilized to drive the DC-motor. The design parameters of the developed WECS prototype are summarized in Table 3.

The boost chopper is built with SEMIKRON IGBT modules, and the driver circuit for the IGBTs modules is SEMIKRON SKH61. The rectified DC-voltage and DC-current are measured using a voltage sensor and a Hall-effect current sensor, respectively. The proposed intelligent MPPT regulator is implemented using a dSPACE DS1104 controller board installed in a host PC computer, the sampling time is set as 20 kHz, and the
The switching frequency of the IGBTs is also kept at 20 kHz. A portable power meter and a digital oscilloscope are utilized to record the experimental results.

The schematic circuit of the complete hardware-setup is depicted in Fig. 7, and the experimental elements of the developed WECS prototype are shown in Fig. 8.

### Table 3

<table>
<thead>
<tr>
<th>Parameters of the WECS for experiments</th>
<th>Values</th>
<th>Parameters of the WECS for experiments</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated power</td>
<td>5 kW</td>
<td>Torque constant</td>
<td>2.39 N·m/A</td>
</tr>
<tr>
<td>Rated voltage</td>
<td>380 V</td>
<td>Mechanical time constant</td>
<td>2.3 ms</td>
</tr>
<tr>
<td>Pole pairs</td>
<td>4</td>
<td>DC-motor parameters</td>
<td></td>
</tr>
<tr>
<td>Rated torque</td>
<td>22.5 N·m</td>
<td>Rated current</td>
<td>15 A</td>
</tr>
<tr>
<td>Rated speed</td>
<td>2000 rpm</td>
<td>Rated voltage</td>
<td>220 V</td>
</tr>
<tr>
<td>Rated current</td>
<td>12 A</td>
<td>Grid-connected converter parameters</td>
<td></td>
</tr>
<tr>
<td>Permanent magnet flux</td>
<td>0.39 Wb</td>
<td>DC-bus capacitance</td>
<td>2200 μF</td>
</tr>
<tr>
<td>Stator resistor</td>
<td>0.65 Ω</td>
<td>Filter inductor</td>
<td>10 mH</td>
</tr>
<tr>
<td>d-axis inductor</td>
<td>8 mH</td>
<td>Filter resistor</td>
<td>0.2 Ω</td>
</tr>
<tr>
<td>q-axis inductor</td>
<td>8 mH</td>
<td>Grid voltage</td>
<td>220 V</td>
</tr>
<tr>
<td>d-space DS1104 controller board</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Experimental results

In this part, the performance of the suggested intelligent MPPT algorithm is verified for different wind velocities and compared with that of a traditional PID regulator. In the first test, the wind velocity is step-function or ramp-function changed arbitrarily from 6-8 m/s as illustrated in Fig. 9,

The $C_p$ of the emulated wind turbine and the rectified DC-voltage, the output power of the PMSG (DC-power), and the duty ratio of the boost chopper are illustrated in Fig. 9,

Despite the change in wind velocity, the real value of $C_p$ closely matches its optimal value (0.478). Besides the rapid change in the wind velocity, the rectified DC-voltage and the DC-power are smoothed because of the system inertia.

Experiments have also been carried out with time-varying wind speeds. All the waveforms are given in Fig. 10,

Fig. 7. Arrangement of laboratory system

Fig. 8. Laboratory test rig

Fig. 9. Experimental results with step-variations in wind velocity

Fig. 10. Experimental results with time-varying wind speeds.
The functionality of the proposed FMMP current controller was also experimentally verified and compared with the typical PI regulator. The comparison has been done by observing the $C_p$, the rectified DC-voltage, the DC-power, and the boost duty cycle waveforms. The test results in Fig. 11 display the programmed switching between the proposed FMMP and PI current control methods. During the last testing scenario, the $C_p$ and the optimal output power followed their peak values well by utilizing the suggested fuzzy MPPT control method.

The maximum divergence of the $C_p$ from its peak value is 0.02 with the suggested MPPT method. We can also note that there is no deviation between the real and optimal output powers. On the other hand, when utilizing the traditional PI regulator, the $C_p$ values oscillate in a larger range, and deviations of electrical power from its peak values are also observed from moment to moment.

We can see in Fig. 12, that the electrical energy produced by the wind generator using the suggested intelligent MPPT controller ($E_{FMMP}$) is greater than that produced by the traditional PI control method ($E_{PI}$). Therefore, it proves the effectiveness of the suggested intelligent MPPT controller.

Figure 13 depicts the experimental results of the output three-phase voltage (a) and current (b) of the PMSG for a wind speed of 10 m/s.
Finally, Fig. 15a displays that the total harmonic distortion (THD) of the injected grid current and voltage is 2.5%, which is below the threshold limit of 5%. In addition, it meets the requirement of a power factor with a value of 0.996, as depicted in Fig. 15b.

Conclusions.

In this article, an extension of fuzzy model based multivariable predictive current control strategy has been applied to the DC-DC boost chopper of wind energy conversion system to enhance the capability of capturing the maximum output energy based on an intelligent fuzzy maximum power point tracking controller. The considered control algorithm synthesis of the fuzzy model based multivariable predictive controller is based on the fuzzy system, optimization technique, and linear matrix inequalities formulation. In this approach, at every sampling period, a quadratic cost function with a specific prediction horizon and control horizon is minimized such that constraints on the control input are satisfied.

Furthermore, the designed intelligent maximum power point tracking regulator has also been employed to derive the optimum DC-current corresponding to the maximum power point of the wind generator based on the changes in the DC-power and rectified DC-voltage. While the fuzzy model based multivariable predictive current regulator has been designed to follow the derived optimum DC-current with minimum steady-state tracking error, this allows the wind generator to produce the maximum electrical energy.

Simulation and experimental results have affirmed the significant improvements in maximum electrical energy harvesting and mechanical stresses minimization. In addition, compared to the traditional proportional integral controller, the suggested control approach has greater overall control efficiency and can be utilized to harvest maximum wind power more efficiently.

Conflict of interest. The authors express their no conflicts of interest.

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