Article

Improving the Performance of Controllers for Wind Turbines on Semi-Submersible Offshore Platforms: Fuzzy Supervisor Control

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Abstract: The use of sea wind energy is restricted by the limited availability of suitable sites in shallow waters. To overcome this challenge, wind turbines located on offshore semi-submersible platforms appear as a valuable option, as they also allow the exploitation of other resources like wave energy or aquaculture. Nevertheless, the literature addressing this kind of design is scarce, and the interactions of the wind turbine and the platform movements increase the complexity of the control system with respect to the wind turbines with fixed foundations. Within this context, fuzzy control is a promising alternative to deal with these issues. However, while fuzzy controllers can be an alternative to substitute conventional PI control, the latter is a well-known, robust choice for operators. In this sense, fuzzy controllers can be designed to work in collaboration with PI controllers to ease their adoption. To this end, this paper addresses those gaps in the literature by presenting a methodology, its application to enhance controllers for large-scale wind turbines in semi-submersible offshore platforms and the results attained. The methodology is based on the implementation of an integrated simulation tool, together with the definition of three indexes that describe the performance of the control system in the overall platform behaviour regarding key aspects of its exploitation. Using it, an Anti-Wind-Up algorithm was designed to improve the behaviour of the conventional controller and is presented and evaluated along a fuzzy supervisor controller. In this kind of configuration, the fuzzy controller modifies the values of the PI controller. Finally, a comparison of the performance using the reference PI and the improved PI, in both cases together with a fuzzy supervisor controller modifying their values, is presented and discussed, contributing to extend the state of the art of controllers for large-scale wind turbines on offshore semi-submersible platforms.

Keywords: floating offshore wind turbines (FOW); modelling and control of FOW; renewable energy systems; PID control; fuzzy control

1. Introduction

On the one hand, renewable energy sources are already well established as safe, clean, and profitable energy sources [1]. Among them, wind energy stands out as one of the most well-established technologies [2], with the greatest capability of economic exploitation and large-scale implementation in electrical systems [3,4]. In fact, the installed wind power worldwide rose by 372.95 GW from 2007 to 2016, and specifically, the offshore power increased by 12.99 GW in the same period [5]. In addition, there is an undoubtedly environmental benefit in installing and starting up wind farms [6]. Furthermore, when comparing land parks (onshore wind) with marine wind farms (offshore wind) some disadvantages arise, in terms of less environmental impact and more harvested power in the case of offshore wind. Nevertheless, suitable locations on the continental shelf, i.e.,
shallow waters, are limited, so placing wind turbines in deep water appears as a promising alternative [7]. A feasible approach is its installation on semi-submersible platforms [8], which can also be used for other purposes such as tidal energy or shellfish aquaculture [9].

On the other hand, the increase in the quantity of electricity fed to the electrical systems by renewable sources brought the requirement to have controllers regulating the instantaneous electrical power that is produced in this kind of facilities [10], so as not to degrade the power quality of the grid they supply, particularly in wind energy for its significant contribution to the energy mix in countries like Spain [11,12], but also to increase the profitability of the investment as well [13]. When the level of wind power penetration is small, the harmful issue can be neglected, but for instance, a rate as low as 7% and excessive produced power in wind farms caused destabilizations in European grids in 2006 [14].

Precisely, the most common method presently used to carry out such control is the simultaneous regulation of torque using MPPT (Maximum Power Point Tracking) algorithms and the pitch (or angle of attack of the blades) control [15–19]. While the former is mature, in the latter, the research community has not reached an agreement, thus there exists a broad range of approaches. As an example, in [20,21], the pitch control techniques are classified into four categories: ascending search control, closed-loop power control, optimal TSR (Tip to Speed Ratio) search and intelligent control. As previously stated, offshore platforms are under the influence of currents and waves, which produce motions in the platform that modify the aerodynamic conditions for the wind turbine [22,23]. These interactions are difficult to model and control using conventional techniques, making intelligent control a suitable approach. Fuzzy logic is an alternative with good results in wind technology due to the flexibility it provides [24–32] as well as in Wave Energy Converters (WECs) [33–35]. In particular, it has already proven to be useful to control large wind turbines [36]. As an example, [37] develops and tests a controller for a 3.5 kW wind turbine using three fuzzy logic controllers, which raises the difficulty and the effort required to implement the control system. In addition, the wind turbine is considerably smaller than the industrial ones, and the studied system is onshore. A fuzzy logic controller coupled with a PI on an offshore 5 MW wind turbine system is presented in [32], with the NREL (National Renewable Energy Laboratory) simulation model, though the foundation and specific details of the NREL model used are not told. In addition, it requires following a complex method prior to the design of the fuzzy controller, which is then compared to the NREL reference controller. A similar control problem is addressed in [38], although the semi-submersible platform is different and the controller is based on traditional techniques. To conclude, Ref. [39] presents an exhaustive revision of fuzzy logic control applied to wind turbines. Finally, the main alternative to fuzzy logic control is the use of machine learning, either to anticipate or predict the wind behavior [30,40–44], to assist in higher-level control [45] or to implement a controller [46]. In particular, both Reinforcement Learning [47–50] and Adaptive Neuro Fuzzy Inference Systems [51,52] seem to be promising techniques also.

Then, as it can be seen, control problems of large-scale wind turbines located on semi-submersible platforms [53,54] have attracted little attention in the literature. Although control problems concerning energy generation by wind turbines have been explored, the simulations are limited to onshore or offshore multi-MW models, all with fixed foundations, and systems tested consist of multi-kW wind turbines [55,56]. To conclude, there exist gaps in the literature that demand more research to address the implementation of controllers for industrial large-scale wind turbines located on semi-submersible platforms. Thereby, this article aims to contribute with developments and a discussion to fill these gaps. To fulfil its purpose, first, it describes a methodology and its application to enhance controllers for wind turbines in semi-submersible offshore platforms. The methodology is centred around the implementation of an integrated simulation tool and the definition of a set of performance indexes that enables the comparison of control strategies for this type of system. In this manner, the methodology helps to fine-tune the controllers, which have the potential to increase the performance of the wind turbine due to the improvement of the control system. The proposed methodology is proven to be effective in the design.
of an Anti-Wind-Up feature for the reference PI controller. Then, these enhancements are exploited by a fuzzy supervisor controller. A stand-alone fuzzy controller was also designed using this methodology, and successfully substituted the PI controller. Both control systems are compared with the help of the performance indexes.

Then, in this paper, the problem and current solutions are described in Section 1. Section 2 presents the system and the model on which it works. Section 3 details the methodology to develop, implement and test new control strategies. The main contribution of this work is the use of the proposed methodology to develop, improve and test PI and fuzzy controllers for the large-scale wind turbine on a semi-submersible platform. Results obtained with a controller developed using this presented methodology are presented, compared, and discussed against the reference controller in Section 4. Finally, Section 5 presents the conclusions extracted from the comprehensive work carried out.

2. System Description

The research goal of our team is to control a real system that consists of two large-scale wind turbines on a semi-submersible platform: the W2Power platform developed by EnerOcean. It enables 12 MW on one single floating foundation, using two commercially offshore available wind turbines. W2Power is, since spring 2019, the first multiturbine floating solution to reach testing in open seas in the world [57].

2.1. Reference System

Instead of facing the simulation of the complete system, a single wind turbine in the centre of the semi-submersible platform is selected as a valid first approach to the problem. The NREL of 5 MW [58] is identified as the closest model of wind turbine to be controlled. This wind turbine, due to its features, is a representative model of the wind turbines in development for offshore wind energy at this time [59]. As for the platform, the OC4 [60] is selected as the most similar model. This way, using this combination of NREL 5 MW and OC4, a broad range of studies can be carried out in the early stages of the development of new offshore designs. Additionally, it may be used as a model to research control techniques [36].

2.2. Parameters

The majority of the parameters of the NREL 5 MW are inherited from the REpower 5 M [61]. A list of the most relevant parameters is shown in Table 1.

Table 1. NREL 5 MW most relevant specifications [58].

| Parameter                                | Value                                |
|------------------------------------------|--------------------------------------|
| Rated power                              | 5 MW                                 |
| Cut-in, Nominal, Cut-out wind speed      | 3, 11.4 and 25 m/s                   |
| Number of blades, rotor topology         | 3, upwind                            |
| Rotor, hub diameters                      | 126, 3 m                             |
| Hub height                               | 90 m                                 |
| Regulation                               | Collective pitch, variable speed     |
| Drivetrain, ratio                        | High speed, multi-stage gearbox, 1:97|
| Rotor, generator rated speed             | 12.1, 1173.7 rpm                     |
| Efficiency                               | 94.4%                                |

2.3. Equations

The key equations [62] that describe the behaviour of a standard wind turbine [17,63] are presented in this subsection. The size of the wind turbine defines the total power that may be harvested from the wind. The power of the wind that enters the sweeping area of the wind turbine multiplied by a coefficient \( C_p \) is equal to the amount of harvested power.
This coefficient is described by a non-linear function of TSR (usually noted as $\lambda$), pitch ($\beta$) and nine wind turbine parameters that, in general, only the manufacturer knows:

$$C_P(\lambda, \beta) = \frac{P_{\text{harvested}}}{P_{\text{wind}}} = C_1 \left( \frac{C_2}{\lambda_1} - C_3 \beta - C_4 \beta^2 - C_5 \right) e^{-\frac{C_6}{\lambda_1} + C_7 \lambda} \quad (1)$$

$$\frac{1}{\lambda_1} = \left( \frac{1}{\lambda - C_8 \beta} - \frac{C_9}{\beta^3 - 1} \right) \quad (2)$$

where the pitch is a variable controlled by the operator and the TSR is stated as the ratio between the linear velocity at the tip of the blades and that of the wind:

$$\lambda = \frac{V_{\text{tip}}}{V_{\text{wind}}} = \frac{\Omega_{\text{rotor}} R}{V_{\text{wind}}} \quad (3)$$

The power of the wind equals the product of the swept area of the rotor, the wind speed cubed, the air density and a constant of value $\frac{1}{2}$:

$$P_{\text{wind}} = \frac{1}{2} \rho_{\text{air}} A_{\text{rotor}} V_{\text{wind}}^3 \quad (4)$$

That is, the harvested power of the wind depends on the square of the radius of the rotor, which makes it desirable to look for larger wind turbines. It is possible to find the torque of the rotor and the low speed shaft ($\omega_{\text{LSS}}$) produced by the wind, usually noted as $T_{\text{Aero}}$, starting from the harvested power and the speed of rotation of the low speed axis (often calculated as the high speed axis, $\omega_{\text{HSS}}$, measured with an encoder or similar, between the gearbox multiplication ratio, $N_{\text{gear}}$),

$$T_{\text{Aero}} = \frac{P_{\text{harvested}}}{\omega_{\text{LSS}}} = \frac{P_{\text{wind}} \times C_P}{\omega_{\text{HSS}} N_{\text{gear}}} \quad (5)$$

In contrast, there is a control torque, or torque of the generator. This is a variable that the wind turbine operator controls. In the rated operation of the wind turbine, it is usually assumed a constant value equal to the rated torque.

$$T_{\text{HSS Generator}} = \frac{P_{\text{harvested}}}{\omega_{\text{HSS}}} = \frac{P_{\text{wind}} \times C_P}{\omega_{\text{HSS}} N_{\text{gear}}} \quad (6)$$

Hence, if the balance on the low-speed axis is considered, in the rated state it rotates at a constant speed (ideally). It must be considered that the torque of the generator is defined with respect to the inertia of the high shaft and that the wind torque is in relation to the low one.

$$T_{\text{Aero}} - T_{\text{Generator}} = I_{\text{Drivetrain}} \times \alpha \quad (7)$$

$$T_{\text{LSS Generator}} = \frac{T_{\text{HSS Generator}}}{N_{\text{gear}}} \quad (8)$$

where $I_{\text{Drivetrain}}$ is the inertia cast to the axis of low speed, since the two torques are also calculated with respect to that reference. Finally, $\alpha$ represents the angular acceleration of the axis.

Therefore, acting on the control variables $T_{\text{HSS Generator}}$ and $\beta$ (pitch), the behaviour of the wind turbine can be controlled in terms of captured power, speed, etc.

2.4. Baseline Control

The baseline controller considers a control system that consists of two subsystems: generator torque control and synchronized control of the pitch of the blades, as usual in this kind of system [58]. These two control subsystems are designed to work almost independently, as the former works when the wind speed is below the rated value and
the latter when it is above. Then, the goal of the former is to harvest the maximum available power of the wind through an MPPT algorithm, while the latter is responsible for controlling the generator speed when working above the rated wind speed. It is in the latter regulation scheme (pitch control subsystem) where exists chances of improving the behaviour of the system by modifying the reference PI provided by NREL [58], for which it is mandatory to beforehand integrate a simulation and comparison tool with a design methodology. The control system acts in a closed-loop manner, as shown in Figure 1.

![Closed-loop scheme of the controller.](image1)

**Figure 1.** Closed-loop scheme of the controller.

### 3. Methodology

The proposed methodology consists of the creation of an integrated simulation tool, the definition of meaningful performance indexes and the controller configuration based on expert knowledge from wind turbine operators and designers.

#### 3.1. Integration of Stand-Alone Simulation Tools

The first element of the presented methodology is the creation of an integrated simulation tool. To get wind profile data in a compatible format with FAST [64–70], measured wind data are used as input to TurbSim [71,72]. These wind profiles in a well-matched format are the input to a FAST model, which is integrated into Matlab/Simulink, producing the simulated outputs of the system (see Figure 2). FAST is a computer-aided engineering tool developed by NREL to simulate the response of horizontal axis wind turbines. Development and simulation of controllers for different wind turbines are enabled due to the use of the integration of stand-alone tools, which was used to implement and evaluate a baseline controller and an upgraded version of the same controller, as well as fuzzy controllers as described below.

![Stand-alone software tools integration process.](image2)

**Figure 2.** Stand-alone software tools integration process.

#### 3.2. Performance Indexes

Wind turbines on onshore sites present some differences when compared to wind turbines located on offshore platforms. On one side, an offshore platform may be multiuse, equipped for instance with wave converters or aquaculture, enhancing the profitability of the platforms. On the other side, these additions, as well as the movements of the platform, yield interactions with the wind turbine, producing oscillations that modify the aerodynamic conditions for energy production. Additionally, these oscillations may also...
modify the structural loads at the base of the turbine, changing the conditions for fatigue to appear [73].

In order to evaluate the controllers developed using this methodology, three performance indexes have been proposed [74]. These indexes comprise measurements of key performances of the platform: the influence in the structural loads, the efficiency in the generation of electric energy and the behaviour of the wind turbine compared with the rated operation. In this sense, the proposed indexes are as follows:

- Structural index, StI. It provides an estimation of the influence of the controller on the lifespan of the platform through the loads it produces on the structure. It is computed as the average of the absolute values of the reaction moment at the base of the wind turbine, for every time step, considering a rigid joint.

\[
\text{StI} = \frac{1}{N} \sum_{i=1}^{N} M_{\text{Base},i}
\]  

- Generation index, GI. It measures the difference in MW between the generated electric power and its rated value. It is calculated as the average of the absolute value of this difference, for every time step.

\[
\text{GI} = \frac{1}{N} \sum_{i=1}^{N} |P_i - P_{\text{rated}}|
\]  

- Speed index, SpI. It shows the difference between the speed of the electric generator and its rated value. It is calculated as the average of the absolute value of this difference, for every time step.

\[
\text{SpI} = \frac{1}{N} \sum_{i=1}^{N} |\omega_i - \omega_{\text{rated}}|
\]  

### 3.3. Controller Configuration

First of all, the reference pitch controller was described in detail in [74], but it is also summarized here. It is a proportional–integral (PI) controller proposed by NREL, working on the speed error of the generator. It contains a gain-schedule, namely \(GK(\theta)\), to change the PI gains as a function of the measured pitch of the wind turbine, where \(GK(\theta)\) is computed according to the following equation [58]:

\[
GK(\theta) = \frac{1}{1 + \frac{\theta}{\theta_k}}
\]  

In this expression, \(\theta\) represents the measured pitch, and \(\theta_k\) has a value of 6.3 degrees [58]. This gain factor represents how the harvested power of the wind is reduced as the pitch angle increases. Thus, this controller is considered as a baseline in terms of the performance indexes defined above. A simplified block diagram is presented in Figure 3.

![Figure 3. Diagram of the reference PI controller.](image-url)
In addition, a Simulink implementation of this controller is shown in Figure 4. It should be observed that it does not consider the dynamic response, and thus it is a controller that offers a limited performance.

Secondly, as shown in the introductory section, fuzzy control is a promising option for improving the performance of wind turbines, particularly in the case of the ones placed on semi-submersible platforms. However, there can be different options to define the fuzzy controller configuration. One possibility, discussed in [74], is to design a fuzzy controller to substitute the conventional PI controller. In this case, the fuzzy controller receives the generator speed as an input and produces a pitch reference for the wind turbine (see Figure 5). This fuzzy controller is known as Independent Fuzzy Logic Controller. Specifically, this fuzzy controller is of Mamdani-type. Membership functions are triangular and trapezoidal for the input, and triangular for the output. A set of ten rules was defined and tuned according to the expert knowledge of EnerOcean. Based on the performance indexes, results showed a better performance compared with the reference controller. The performance indexes of this controller, re-calculated under the new simulation scenarios, are shown in Tables 2–4 in the column labelled as Independent Fuzzy Logic Controller, along with the values for the controllers proposed in this work.

Thirdly, another possibility is to keep the conventional controller (PI) and to integrate a fuzzy controller acting as a supervisor, modifying the PI gains. This configuration is described in detail in [75]. The fuzzy controller is also of Mamdani-type. Membership functions are triangular and trapezoidal for both input and output. Seven rules were tuned based on the expert knowledge of EnerOcean. A simplified block diagram is shown in Figure 6. This configuration is well-suited for actual implementation, since keeping the PI controller limits the changes with respect to current practice in wind turbine control.

Furthermore, this controller improves the performance of the wind turbine compared with the stand-alone fuzzy controller, as shown in the next section, regardless of the PI to supervise. However, it can be seen in the results section that enhancing the PI by adding an Anti-Wind-Up algorithm significantly impacts the results, being the performance far better with respect to both the independent fuzzy controller and the supervisor fuzzy controller with the reference PI. Particularly, since the supervisor fuzzy retains the reference controller, it inherits its limitations, in particular, as mentioned above, the consideration of the dynamic response. To address this problem, the authors have developed and implemented an Anti-Wind-Up block following the proposed methodology, which was added to the reference PI. This block performs a reset in the integral speed error, amending the lack of dynamic considerations that causes the system to be prone to oscillations.
This conventional controller is then the base for an improved supervisor fuzzy controller, following the approach in Figure 7.

![Simplified block diagram of the supervisor fuzzy controller.](image-url)

**Figure 6.** Simplified block diagram of the supervisor fuzzy controller.

![Implementation of the Anti-Wind-Up block in SIMULINK.](image-url)

**Figure 7.** Implementation of the Anti-Wind-Up block in SIMULINK.

4. Results

Firstly, using the proposed methodology, an integrated software tool for the evaluation of the behaviour of the system under different controllers was developed. Secondly, three performance indexes were proposed to resume the system behaviour in the form of three values. Together, the simulation tool and the indexes allow comparing different controllers in terms of performance in this section. Results as curves for different magnitudes are shown in Figures 8–10. for the reference PI controller with the supervisor fuzzy controller, and in Figures 11–13 for the improved PI controller with the supervisor fuzzy controller. The simulations have considered a wind profile with an average speed of 13, 15 and 18 m/s, respectively, and turbulence A [76]. They cover a range of average wind speeds: 13 m/s, 15 m/s and 18 m/s. These values were chosen to characterize the behaviour of the system under a certain controller when the wind speed is around three key values. The first, 13 m/s, is a value around the rated value of the wind turbine, i.e., the wind speed value required by the wind turbine to produce the rated power with a 0° (null) pitch. The second, 15 m/s, represents a scenario in which the wind speed values are between the nominal wind speed and the maximum wind speed. Finally, the third value (18 m/s) it is observable over the rated value, often reaching and exceeding the maximum wind speed. It is at higher wind speeds when a pitch controller must produce a good behaviour of the system, since operators frequently rely only on torque control for wind speeds below the rated value.
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Figure 8. Simulation for reference PI with the Fuzzy Supervisor Control, under a wind profile of average speed of 13 m/s and turbulence A.

Figure 9. Simulation for reference PI with the Fuzzy Supervisor Control, under a wind profile of average speed of 15 m/s and turbulence A.

Figure 10. Simulation for reference PI with the Fuzzy Supervisor Control, under a wind profile of average speed of 18 m/s and turbulence A.
Figure 9. Simulation for reference PI with the Fuzzy Supervisor Control, under a wind profile of average speed of 15 m/s and turbulence A.

Figure 10. Simulation for reference PI with the Fuzzy Supervisor Control, under a wind profile of average speed of 18 m/s and turbulence A.

Figure 11. Simulation for improved PI with the Fuzzy Supervisor Control, under a wind profile of average speed of 13 m/s and turbulence A.

Figure 12. Simulation for improved PI with the Fuzzy Supervisor Control, under a wind profile of average speed of 15 m/s and turbulence A.
Figure 11. Simulation for improved PI with the Fuzzy Supervisor Control, under a wind profile of average speed of 13 m/s and turbulence A.

Figure 12. Simulation for improved PI with the Fuzzy Supervisor Control, under a wind profile of average speed of 15 m/s and turbulence A.

Figure 13. Simulation for improved PI with the Fuzzy Supervisor Control, under a wind profile of average speed of 18 m/s and turbulence A.

4.1. Comparison between the Controllers

While the graphics show the responses of the system under different controllers, they also do not ease the understanding of the benefits of the developed controllers. Using the proposed indexes, Tables 2–4 present the values of the indexes achieved in the different simulations with the three different wind profiles, for all controllers. In accordance with the definition of the proposed indexes, a lower value at the indexes means better performance. When the wind speed rises a little (13 m/s wind profile) above the rated value of 11.4 m/s, the behaviour of the improved PI plus the supervisor fuzzy controller is better than that of the reference PI plus the same fuzzy supervisor controller. The difference is even bigger for higher wind speeds. These results show that the improved PI controller outperforms the baseline one, opening the path to developing more blocks that improve the performance further. Another line of work opened by the proposed methodology is the development of intelligent controllers, which outperform the baseline PI and possess a great escalation potential.

Table 2. StI: Structural Index (MN·m).

| Wind Mean Speed (m/s) | Baseline PI + Supervisor Fuzzy | Improved PI + Supervisor Fuzzy | Independent Fuzzy Controller |
|-----------------------|--------------------------------|--------------------------------|-----------------------------|
| 13                    | 69.1708                        | 69.7611                        | 70.2202                     |
| 15                    | 62.0628                        | 61.9917                        | 63.2591                     |
| 18                    | 51.7847                        | 51.8146                        | 53.1199                     |

Regarding the impact on the life cycle of the platform, as shown in the second row of Table 2 (13 m/s), the values are almost the same due to the lack of necessity of pitch control during a large proportion of the simulation, and the torque control being the same for all the controllers. However, as wind speeds rise, the difference in the performance rating
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Table 3. GI: Generation Index (MW).

| Wind Mean Speed (m/s) | Baseline PI + Supervisor Fuzzy | Improved PI + Supervisor Fuzzy | Independent Fuzzy Controller |
|-----------------------|--------------------------------|--------------------------------|-----------------------------|
| 13                    | 0.3349                         | 0.3349                         | 0.4193                      |
| 15                    | 0.3310                         | 0.2105                         | 0.3809                      |
| 18                    | 0.4786                         | 0.2318                         | 0.6129                      |

Table 4. SpI: Speed Index (rpm).

| Wind Mean Speed (m/s) | Baseline PI + Supervisor Fuzzy | Improved PI + Supervisor Fuzzy | Independent Fuzzy Controller |
|-----------------------|--------------------------------|--------------------------------|-----------------------------|
| 13                    | 51.0791                        | 34.5912                        | 57.5163                     |
| 15                    | 70.2047                        | 39.9463                        | 83.0064                     |
| 18                    | 110.4390                       | 52.4833                        | 141.9723                    |

Regarding the impact on the life cycle of the platform, as shown in the second row of Table 2 (13 m/s), the values are almost the same due to the lack of necessity of pitch control during a large proportion of the simulation, and the torque control being the same for all the controllers. However, as wind speeds rise, the difference in the performance rating grows too, yet the difference is not significant enough to state that one controller is clearly better than its counterpart based only on this index. However, as it was mentioned before, a small difference in this value may have a relevant impact on fatigue, so even marginal gains are relevant. Thus, the PI schemes offer better behaviours regarding this index.

Again, at 13 m/s there is little pitch control but the differences in the controllers start to impact the performance of the system, stating that the Independent Fuzzy Controller is not capable of reaching the quality of control attained by the supervisor fuzzy controller. As wind speeds rise, the difference in the performance rating that describes energy generation grows too, even faster than in the previous index (StI), showing that the improved PI makes the system achieve a better electrical energy generation with respect to the reference PI. This index reflects a key feature: the capability of the system to adhere to the power setpoint, presenting the demanded flexibility and resiliency to feed the electrical system.
In contrast with previous simulations, at 13 m/s there is no difference in the performance of the controllers related to the speed index among the reference PI with supervisor fuzzy and the independent fuzzy, but there is between them and the improved PI with the supervisor. As wind speeds rise, the difference in the performance rating grows too, even faster than in both previous indexes. The improved PI impact positively the system, which under its control follows accurately the speed reference. The importance of this index lies in that it summarizes the stability that the evaluated controller achieves, something closely related to the life cycle and the requirements of the grid operators.

4.2. Discussion of the Results

Finally, the results previously shown are discussed. First, as it can be seen in reference [75], improving the PI control by incorporating an Anti-Wind-Up allows improving the response of the system by better adjustment of the rotor speed, mainly thanks to the enhancement of pitch control, thus avoiding power generation above the rated power of the wind turbine continuously over time. Secondly, according to our results, it is shown that an equivalent response has not been achieved with the fuzzy supervisor control without the integration of the Anti-Wind-Up algorithm. Looking at Figures 8–10, this same effect occurs in almost all simulated time, except when the wind speed falls below the rated speed (11.4 m/s).

To sum up, a combination of both the fuzzy supervisor and the Anti-Wind-Up algorithm has presented the best results obtained so far, reaching a reduction of 22.5–27% for 15 m/s and 36–39% for 18 m/s, both for the Generation Index and for the Speed Index, with respect to the reference PI with Anti-Wind-Up described in the cited reference. Thereby, it is evident that the fuzzy supervisor controller positively improves the Gain-Scheduling presented in the reference PI, although in the results without Anti-Wind-Up its contribution is blocked by the inadequate response of the reference PI’s integral term.

5. Conclusions

To begin with, wind turbines are systems of great complexity, even greater when they are located on a semi-submersible platform due to the interaction between the oscillations of the platform and the turbine. This complex and non-linear behaviour may affect the performance of the energy production and the lifespan of the overall system. The design and evaluation of controllers play a key role in maximizing the performance of large-scale wind turbines, particularly on offshore sites. In this sense, this article addresses the gaps in the literature by offering a methodology that describes a process of design and evaluation for the case of the NREL 5 MW placed on a semi-submersible platform. To study different wind scenarios and to simulate the behaviour of the platform in terms of energy production and structural loads, an integrated simulation tool was implemented. Additionally, a set of performance indexes was defined to quantify the performance of wind turbine controllers. The proposed methodology may help the early stages of development and improvement of controllers, for example by adding features like Anti-Wind-Up methods, which appear as a promising process to improve the performance of wind turbines in semi-submersible offshore platforms and at the same time keeping the trustworthy conventional PI controllers.

In addition, intelligent control is a suitable alternative for controlling large-scale wind turbines on semi-submersible platforms due to the nonlinear interactions between platform and turbine. In particular, fuzzy logic controllers are specially fit this problem, since they allow for gradual improvement by adding new rules to cope with new requirements, like adding new uses to the platform that may change the overall behavior. However, to implement these new controllers in actual systems, the first step is to prove their feasibility and performance. Using the proposed methodology, the reference PI controller and the improved PI were compared under the supervision of a fuzzy controller, and their performance was evaluated with the help of the proposed indexes, sharing the strengths and drawbacks of the different configurations. Results show that a supervisor fuzzy
controller modifying the values of an improved PI offers better results. Additionally, the behaviour of the system, summarized by the performance indexes, suggests that keeping a PI in the control system can help adoption in actual systems while achieving better performance. Future lines of work include the implementation and evaluation of additional features, like the inclusion of a derivative term in the PI or the application of Reinforcement Learning techniques, but also the implementation and evaluation of the proposed supervisor fuzzy controller in the actual W2Power platform.

To conclude, the conclusions and contributions of this work are highlighted:

- Wind energy needs new locations to keep up with the growing trend, but these must be out of the continental platform. Semi-submersible platforms are an appealing option.
- The complex physical interactions between the wind turbine and the platform increase the difficulty to control the system. Intelligent controllers show interesting results and may suit this need.
- A methodology needs to be used to compare different controllers, and to design and enhance them. This must be based on an open-source simulation model and laid on solid performance metrics.
- Wind turbine operators are reluctant to abandon PI controllers in order to adopt new types of controllers. A technology like Fuzzy Logic that can be integrated with PIs is promising.
- The proposed methodology was used to design fuzzy controllers and to improve the reference PI by the development of an Anti-Wind-Up algorithm that helps the controller deal with the dynamics of the system.
- The supervisor fuzzy controller integrated with the reference PI and the Anti-Wind-Up (i.e., the improved PI) offers the best performance, while keeping the well-known PI in the control scheme. Precisely, these improvements are presented for scenarios with different wind profiles. In particular, an enhancement of 100% in some metrics was achieved.

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