Wind turbine participation in micro-grid frequency control through self-tuning, adaptive fuzzy droop in de-loaded area

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Abstract: The purpose of this research is to present an innovative load frequency control in the presence of wind turbines in islanded micro-grid (MG). As islanded MG suffers from low inertia and insufficient primary frequency response (PFR), utilising the variable wind turbines in de-loaded area can be considered as an alternative solution to deal with frequency control problems. In this context, the de-load area is referred to a region where wind turbines release their stored kinetic energy in rotational masses following frequency disturbances. For effective utilisation of wind turbines, a self-tuning, adaptive fuzzy droop is proposed, whose membership function parameters are optimised through artificial bee colony algorithm based on a multi-objective decision making process. A comparison is made between the obtained results of the self-tuning, adaptive fuzzy droop with conventional proportional integral derivative droop control in order to assess the proposed method performance in different disturbances.

1 Introduction

In recent decades, harmful impacts of fossil fuels on climatic patterns, especially the global warming issue and the carbon emissions, have resulted in a widespread use of renewable energy sources (RESs) [1, 2]. As a result, the amount of renewable generation like wind energy is expected to grow strongly over the upcoming years [3, 4]. A hybrid power generation/energy storage system can combine all different kinds of available RESs along with available energy storage units. It is widely accepted that a feasible way to operate power system with combination of technologies, such as RESs, controllable loads, and storage is micro-grid (MG) [5, 6]. However, high integration of RESs and less amount of synchronous generation can threaten system security, in particular frequency stability [5].

It is well understood that wind turbine output power is intermittent due to wind speed variable nature [7]. Nowadays, MGs comprise of large number of wind turbines, thereby leading to intermittent system generation profile. Consequently, MG is likely to face generation/load mismatch leading to difficulties in its operational stability. Therefore, it is necessary to design an effective load frequency control (LFC) strategy to stabilise frequency deviations caused by renewable energy sources, especially wind power.

Adequate load frequency control in MG is essential to mitigate these problems. As the inertia of MG is low compared to conventional power systems, it is very important to determine a well-tuned droop control to deal with frequency deviations [8]. To design a suitable droop control, the droop coefficient must be tuned to the system condition. This tuning must be done in a way that it can provide the primary frequency response (PFR) and also maintain the steady-state error less than acceptable values. As frequency deviation is a function of the active power injected into the micro-grid, the objective is to stabilise the output power of wind turbines to minimise the frequency deviation.

The technique of adjusting the speed droop by utilizing the adaptive fuzzy droop control (AFDC) provides an efficient solution to automatically adjust the droop coefficient according to system conditions. The AFDC is an adaptive control method based on fuzzy logic. It studies the effect of the wind speed on the power produced by the wind turbine generator (WTG) and adjusts the speed droop to ensure the proper power output of the wind turbine in reference to the wind speed [9].

In the study, the adaptive fuzzy droop control of wind turbine generators is compared with the classical droop control and the results are presented as a case study problem. The performance of both methods is compared with the real-time simulation results from Powerfactory. The results show that the adaptive fuzzy droop control can guarantee the frequency stability in the islanded micro-grid.

The rest of this paper is arranged as follows. In Section 2, the micro-grid architecture and problem formulation are given. In Section 3, the AFDC is introduced and the optimization model for finding the optimal membership function parameters is presented. In Section 4, the results of the simulation are given and discussed. Finally, in Section 5, conclusion is stated.

Nomenclature

**Abbreviation**

ABC: artificial bee colony
LFC: load frequency control
MPPT: maximum power point tracking
PID: proportional-integral-derivative
DER: distributed energy resources
RES: renewable energy resource
PFR: primary frequency response
MG: micro-grid
WTG: wind turbine generator
FESS: flywheel energy storage system
BESS: battery energy storage system
PV: photovoltaic panel
FC: fuel cell

**Parameters**

- $\rho$: air density in kg/m³
- $A$: the swept area of wind turbine in m²
- $V_w$: wind speed in m/s
- $X$: de-loading factor
- $C_p$: turbine performance coefficient
- $\beta$: blade pitch angle
- $P_{max}$: maximum power peak tracking in wind turbine
- $P_{res}$: reserve power in wind turbine
- $P_{del}$: de-loaded input power of wind turbine
- $\omega_{rot}$: rotor speed in MPPT
- $\omega_{del}$: rotor speed in de-loaded area
- $\Delta P_{el}$: electrical power of wind turbine
- $k_p$: speed regulator proportional constant.
- $k_i$: speed regulator integral constant
- $\Delta P_{mech}$: mechanical power of wind turbine
- $\Delta P_{LFC}$: active power injection by fuzzy droop
- $\Delta P_{WTG}$: total power injection of wind turbine
- $\Delta P_{L}$: power variations of load
- $f$: frequency deviation
- $R$: speed droop regulation constant
- $D$: damping constant of micro-grid
- $H$: inertia constant of micro-grid
- $T_g$: governor time constant
- $T_t$: turbine time constant
- $T_{con}$: time constant of converter
- $T_{C.-De}$: time constant of command device
- $a'$: derivative constant for fuzzy droop
- $b'$: integral constant for fuzzy droop
- $K_k, K_v$: scaling factor for fuzzy droop
- $T_{FC}$: time constant of fuel cell
- $T_{in}$: time constant of inverter
- $T_{IC}$: time constant of interconnection device
- $K_s$: supplementary control gain
- $X_{ij}$: early (primary) food source position
- $\Phi_{ij}$: random number between [-1, 1]
- $V_{ij}$: new food source position in search space
- $P_{i}$: probability value related to food source
- $f_i$: fitness function value for ith bee
- $SN$: number of bees

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frequency control. Most wind turbines are connected to the system through a power electronic interface, therefore being separated from the main system. Therefore, wind turbine does not respond to frequency changes inherently. While wind turbines predominate power system and number of synchronous generators decreases, system inertia plunges down to a precarious level. The resulted low-inertia condition affects the overall frequency regulation and reduces system security. Therefore, it is important to find an alternative solution to compensate lack of synchronous generators in MG using available technologies [8, 9]. Regarding wind turbine technology, two prevalent kinds of variable-speed wind turbine exist: permanent magnet synchronous generator and doubly fed induction generator [10–12]. Variable-speed wind turbines are able to provide inertia response for the system as well as primary frequency control (PFR) by taking advantage of back-to-back converters in their structure and high level of controllability. This work is aimed to utilise wind turbines as a way to provide inertia response and PFR for MG while it is subjected to frequency disturbances. As previously stated, in forthcoming of wind turbine structures and their control mechanisms, it is possible to provide an opportunity to support system frequency during severe contingencies [13–15].

In low-inertia condition, there is higher risk of drastic frequency variation following generation/load mismatch, hereby causing inability for traditional controllers used in the structure of wind turbines to meet their standards in maintaining the wind turbine stability, let alone its participation into frequency control scheme. Another reason for inability of wind turbine conventional stability, let alone its participation into frequency support. There is opportunity to support system frequency during severe contingencies which mostly restricts the wind turbines to their design strategy. Technically, traditional controllers are designed based on pre-determined operating points which mostly are different from actual operating points; therefore, the need for a reliable strategy arises in order to manage a wide range of system operational set points [16, 17]. A wide range of controller mechanisms like proportional-integral-derivative (PID) controller [18], intelligent controller [19] and robust fuzzy controller [20] have been presented to provide frequency response for MG. One of the intelligent initiatives is to operate wind turbine in de-loaded area to capture its spinning reserve; then, deliver it to the system while it is needed. Through three sets of methods previously provided in literature, wind turbines can increase its rotor speed and support MG frequency [21].

In [22], wind turbines operate in de-loaded area so that they are restricted to operate in a limited range; however, the full capacity of wind turbines is not exploited. In [23], authors have suggested an algorithm to tune blade pitch angle to participate wind turbine into frequency control scheme. Another set of investigations has used droop control in order to participate wind farm into frequency support. Vidyanandan and Senroy [24] demonstrate an approach to permanently tune wind turbine droop during different wind speeds. This variable droop in de-loaded area improves PFR as well as injected output power smoothness. Reference [25] considers an intelligent approach to handle wind turbine active power output in order to control frequency. To optimally utilise the kinetic energy stored in wind turbine, a hierarchical coordinated control strategy has been studied. The authors in this paper have shown that fuzzy-based approach can adjust controller coefficients adaptively to damp frequency oscillations. In [26], a coordinated strategy in the presence of wind turbine is presented. This strategy potentially avoids excessive effort to control pitch angle, preventing wind turbine life-span degradation. The third set of investigations have coordinated wind turbines with conventional power plants, allowed wind turbines to be aware of frequency deviations [27, 28].

In this paper, the main purpose is to introduce a new droop control strategy for wind turbines operating in de-loaded area in order to provide PFR subsequent to inertia response for MGs. In this method, wind turbine conventional controllers are replaced by proposed fuzzy droop control strategy. What is more, the artificial bee colony (ABC) algorithm specifies the parameters of membership functions based on a multi-objective function which includes de-loading factor, settling time, integral square error, and maximum frequency slope. To evaluate the performance of proposed adaptive fuzzy droop, several simulations are discussed in various operating conditions such as MG load change and wind power fluctuations in MATLAB/Simulink environment. The simulated results show the proposed self-tuning, adaptive fuzzy droop is able to arrest the frequency following a contingency and bring it back to normal operating band faster than conventional PID controller.

2 System modelling

2.1 Wind turbine model

The maximum output power which is extracted from the wind turbine is basically calculated based on the following formulation [29]:

$$P_{\text{max}} = \frac{1}{2} \rho AV_w^2 C_p(\lambda, \beta)$$  \hspace{1cm} (1)

where wind turbine output power mainly depends on wind speed ($V_w$), air density ($\rho$), swept area by turbine blades ($A$), and turbine performance coefficient ($C_p$). Essentially, wind turbine output power is defined by non-dimensional curves of performance coefficient $C_p$, which is a function of the tip speed ratio $\lambda$ and the blade pitch angle $\beta$ [30]:

$$C_p(\lambda, \beta) = (0.44 - 0.0167\beta) \sin\left(\frac{\pi(\lambda - 2)}{13 - 0.3\beta}\right) - 0.00184(\lambda - 2)^2$$ \hspace{1cm} (2)

$$\lambda = \frac{\omega R}{V_w}$$ \hspace{1cm} (3)

where $R$ is blade radius and $\omega$ is mechanical speed of turbine. For effective cooperation of wind turbines in contingency frequency control, the WT should have adequate generation margin which can be available for any instant, so-called as headroom. If wind turbine operates in maximum power point tracking (MPPT) mode, it cannot create sufficient headroom to ameliorate frequency deviation in different operating situations; consequently, wind turbines need to be de-loaded if frequency support is a concern.

According to Fig. 1, the wind turbine can be de-loaded by moving its operating set point towards the right side of maximum power point (MPP). In general, wind turbine works on MPP in perpetual positions but there is capability for it to have $P_{\text{d}}$ value as spinning reserve active power to inject during load perturbations. Within frequency deviation, the output power of wind turbine can be changed between $P_{\text{max}}$ and $P_{\text{d}}$ by changing its rotor velocity between $\omega_{\text{max}}$ and $\omega_{\text{d}}$. The maximum de-loaded margin for turbine is considered 15% to provide sufficient spinning reserve. More details on de-load strategy can be found in [8, 22, 27]. The de-loaded factor determines the amount of active power headroom as follows:

$$0 \leq X \leq 1$$ \hspace{1cm} (4)

$$P_{\text{d}} = P_{\text{max}}(1 - X)$$ \hspace{1cm} (5)
where $P_{ref}$ is the new equilibrium point of wind turbine while it is working in de-loaded area. Under this de-loading, wind turbine has $(P_{max} - P_{ref} = P_{res})$ headroom for emergency conditions. It is noteworthy that the amount of de-loading percentage is determined with respect to maximum limitation of turbine rotor speed. The de-loaded wind turbine model for participation into frequency control includes the wind turbine aerodynamics, pitch angle controller mechanism, MPPT and de-loaded mechanism and the secondary frequency loop which is shown in Fig. 2. The pitch angle controller generally is used to regulate the blade angle in de-loading area for miscellaneous wind speed. The stabilisation of angle deviation is guaranteed by PID controller in order that the rotor speed signal and the reference signal is entered into PID controller and finally actuating signal represents the desired pitch angle [31].

According to the proposed load frequency control depicted in Fig. 2, a self-tuning, adaptive fuzzy droop is proposed instead of fixed droop ($R$). This controller helps to inject a burst of power into the grid in case of frequency deviation. In this paper, the output power variation of fuzzy-based droop is considered as follows:

$$
\Delta P_{FLC} = \Delta \omega \frac{dP}{d\omega} + \Delta \beta \frac{dP}{d\beta} + \Delta V_w \frac{dP}{dV_w}
$$

(7)

The implicit derivative $\frac{dP}{d\omega}$ can be calculated by the simultaneous use of (1) and (2):

$$
\frac{dP}{d\omega} = \frac{1}{2} \frac{\rho \rho V_w^2}{(13 - 0.3 \beta)} \times \cos \left( \frac{\pi (\hat{\lambda} - 2)}{13 - 0.3 \beta} \right)
$$

(8)

According to (2), $C_p$ is a non-linear combination of tip speed ratio ($\hat{\lambda}$) and the blade pitch angle ($\beta$); consequently, $\frac{dC_p}{d\beta}$ is obtained:

$$
\frac{dC_p}{d\beta} = \frac{(0.44 - 0.0167 \beta)}{(13 - 0.3 \beta)} \times \cos \left( \frac{\pi (\hat{\lambda} - 2)}{13 - 0.3 \beta} \right) - 0.00184 \beta
$$

(9)

The new statement $\frac{dP}{d\beta}$ is acquired as similar approach:

$$
\frac{dP}{d\beta} = \frac{3}{2} \frac{\rho \rho V_w^2}{AC_p V_w^2}
$$

(10)

Also final term for wind power variation due to changes in the wind speed called $\frac{dP}{dV_w}$ is presented as

$$
\frac{dP}{dV_w} = \frac{3}{2} \frac{\rho \rho V_w^2}{AC_p V_w^2}
$$

(11)

In adaptive fuzzy droop, the frequency deviation ($\Delta f$) and the rate of the changes of frequency deviation ($\Delta f/\Delta t$) are considered as input signals. In this paper, the output power variation of fuzzy-based droop is considered as follows:

$$
\Delta P_{FLC} = \alpha' \beta' \int b dt
$$

(12)

In (12), $b$ stands for interface parameter which is combination of frequency deviation and the rate of the changes of frequency deviation:

$$
\beta = A + K_c \frac{\Delta f}{\Delta t} + K_i \frac{\Delta f}{\Delta t}
$$

(13)

Finally, the output active power of fuzzy droop ($\Delta P_{FLC}$) can be used as a set point for variations in quick power injection by wind turbine generator (WTG) in the load frequency control.
It can be concluded from last (14) that this fuzzy droop controller operates as time-variable PID controller due to three various components. \((\alpha' K_1 + \beta' K_2)\) is a symbol for proportional coefficient, \((\beta' K_1)\) is a sign for integral coefficient and \((\alpha' K_2)\) is derivative coefficient of PID controller [32]. Table 1 shows the parameters which are used for wind turbine in this study.

2.2 Conceptual model of isolated micro-grid

The schematic in Fig. 3 generally illustrates the sources of power generation units in the universal MG. As can be seen in the mentioned diagram, the AC-MG structure comprises distributed energy resources (DERs) such as WTG, photovoltaic (PV) panels, diesel engine generator, fuel cell (FC) and energy storage devices including flywheel energy storage system (FESS) and battery energy storage system (BESS) and various loads [33–35]. Some distributed sources may have high-order dynamical frequency models, but low-order models can generally propose in order to study the load frequency control (LFC) scheme efficiently.

![Diagram](image)

**Fig. 3** Micro-grid diagram including wind turbine modelling in de-loaded area

This work states the battery energy storage system (BESS) and flywheel energy storage system (FESS) dynamic models based on two control blocks. According to [36, 37], using a battery management system along with the BESS, it is reasonable to suppose that the battery is still working in a normal zone. The main feature of the normal zone of BESS is a constant output voltage while the load is drawing variable. Consequently, a significant issue is to consider the command delay and the converter delay in the presented model. In addition, a different model of FESS is presented in this paper. In reference [36], authors claim that flywheel energy storage systems (FESS) play an important role in storing and releasing energy at any time. As a result, a second-order model including command delay block and AC–AC converter block can be considered in order to investigate the dynamic behaviour of this energy resource in load frequency control (LFC) scheme.

In addition, FC can be presented through three various blocks including DC–AC convertor, an electrical interconnect devices. In references [38] for FC in frequency studies is suggested a three order model. Besides, an appropriate PV model is presented according to reference [29]. Tables 2–4 illustrate the parameters of MG which have been employed in this paper.

### Table 1 Parameters values of wind turbine generator

| Symbol   | Description              | Value |
|----------|--------------------------|-------|
| \(H_{WT}\) | wind turbine inertia constant | 6     |
| \(T_{WT}\) | wind turbine time constant | 1.5   |
| \(K_p\) | speed regulator proportional constant | 10    |
| \(K_i\) | speed regulator integral constant | 0.1   |
| \(K_p\) | pitch angle controller proportional constant | 8     |
| \(K_i\) | pitch angle controller integral constant | 18    |
| \(K_d\) | pitch angle controller derivative constant | 2     |
| \(\alpha'\) | derivative constant for fuzzy controller | 5.21  |
| \(\beta'\) | integral constant for fuzzy controller | 3.14  |
| \(K_1\) | scaling factor | 5.23   |
| \(K_2\) | scaling factor | 2.54   |
| \(T\) | servo motor time constant | 0.1   |
3 Control mechanism

3.1 Self-tuning and adaptive fuzzy droop

To provide an adaptive, self-tuning fuzzy logic model, the numerical values of membership functions for fuzzy-based controller must be determined by utilising of a well-defined tuning approach. According to Fig. 4a, the adaptive fuzzy droop is presented based on a procedure which is named 'adaptation mechanism'. This adaption process includes two miscellaneous loops that perceive the signals from the control system and adjust the parameters of mentioned controller in order to present the satisfactory performance even if there are changes in the plant. In general, internal loop adjusts the optimal numerical values of the membership function according to the multi-objective function and external control loop operates as a fundamental feedback loop. In this research, ABC algorithm is used to accommodate the mentioned tuning mechanism.

Generally, one controller which is designed according to fuzzy logic includes different four steps: fuzzification, interface mechanism, fuzzy rule based, and final step is named de-fuzzification. In the first level, input/output control variables and their changing are interpreted and the dynamical behaviour of system is specified accurately. In the second stage, membership functions are produced for mentioned input/output variables. Afterwards, the suggested approach defines a convenient inference mechanism and builds the fuzzy rules. The fact is that IF-THEN strategy that determines the system behaviour is evaluated. Finally, the rules combine and de-fuzzify the outputs. The frequency deviation and the changes of frequency deviation are considered as input signals and the output control signal is utilised as the set point for variations in quick power injection by wind turbines in the MG scheme. The Mamdani-type inference system is applied. Furthermore, membership functions which are considered for the proposed fuzzy-based controller includes seven levels. The membership functions are defined large negative (LN), medium negative (MN), small negative (SN), Zero (ZO), small positive (SP), medium positive (MP), and large positive (LP). Besides, the membership functions are symmetric 7-segments triangular to acquire quick responses from the control system [39]. A rule base set, entailing 49 fuzzy rules traces the input space to the output space and this fuzzy rule base is demonstrated in Table 5.

It can be clearly observed that the pattern of input signals are introduced through a, b, and c parameters such that this restriction \((\text{min} < a < b < c < \text{max})\) is assumed within the frequency control scheme. This layout for input signal is demonstrated in Fig. 4b. Also for the output signal of fuzzy logic controller, as shown in Fig. 4c, only one parameter is necessary to be considered defined \(d\) parameter.

To achieve the optimal combination of the parameters of frequency response, a multi-objective function is formulated as follows:

\[
X = \text{de} - \text{loading factor} < \text{Max}
\]

\[
\text{MSFC: Maximum slope of the frequency characteristic}
\]

3.2 ABC algorithm

The presented approach utilises an ABC algorithm in order to find the best parameters for membership function. The ABC algorithm first generates finite number of populations as initialisation step. In fact, ABC method is to construct search space. In the second step, ABC algorithm cycles through a specific iterative process in order to update bees (i.e. populations). During the second step, the employed are looking for food sources. In this work, employed bees are unknown parameters of membership functions. Then, the on-looker bees are placed on the food sources. This replacement depends on the feedback signal which is provided by employed bees. Similar to employed bees, on-looker bees also include design parameters of membership functions. Simultaneously, the scouts are sent to the search space to discover new food sources. While the best food sources are found, they are saved into memory and then the next iteration will come up using the best value of previous one.

Two fundamental numerical values including the number of employed bees (i.e. number of food resources) and on-looker bees are used to identify the row of search space matrix in the ABC algorithm. In addition, the column of this matrix is defined by the

| Symbol | Description | Value |
|--------|-------------|-------|
| \(D_{pu/Hz}\) | frequency sensitive load coefficient | 0.012 |
| \(R\) | droop constant | 2 |
| \(2H\) | inertia constant | 0.1667 |
| \(T_{FC}\) | FC time constant | 0.26 |
| \(T_g\) | governor time constant | 0.08 |
| \(T_t\) | turbine time constant | 0.4 |
| \(T_{IN}\) | inverter time constant | 0.04 |
| \(T_{IC}\) | interconnection device time constant | 0.004 |
| \(T_{WT}\) | wind turbine time constant | 1.5 |
| \(T_{PV}\) | photovoltaic time constant | 1.8 |
| \(K_s\) | supplementary control gain | 2 |

| Symbol | Description | Value |
|--------|-------------|-------|
| \(T_{C_{-DC}}\) | DC–AC converter time constant | 0.1 |
| \(T_{C_{-De}}\) | command time constant | 0.01 |

| Symbol | Description | Value |
|--------|-------------|-------|
| \(T_{C_{-AC}}\) | AC–AC converter time constant | 0.1 |
| \(T_{C_{-De}}\) | command time constant | 0.01 |

**Table 3** Parameter values of battery energy storage system

**Table 4** Parameter values of flywheel energy storage system

**Fig. 4** The pattern of membership functions for

(a) Input signals, (b) Output signal, (c) Proposed layout for self-tuning/adaptive fuzzy droop
number of unknown parameters. As a result, this search space matrix with the dimension of $n \times m$ can be shown as:

$$X_{\text{Search-space}} = [x_{ij}]_{n \times m}$$  \hspace{1cm} (16)

The parameters of membership functions are initialised through some random values and the cost function is calculated in each reiteration based on given multi-objective function. This algorithm completes the optimisation process based two strongly linked stages. At the first stage, the employed bees start to move towards the different food sources and cost function value is obtained for each employed bees based on presenting the best frequency response during different operational conditions. In the following, the mentioned bees finished the process of search and afterwards they inform on-looker bees of their position and try to share the nectar information of food resources with them. At the second stage, on-looker bees assess this nectar and they will select a food source with a probability corresponded to its nectar value. The fact is that they choose a food resource according to the probability which is associated with that of food source. This probability function is presented by the following statement:

$$P_i = \frac{fit_i}{\sum_{n=0}^{SN} fit_n}$$  \hspace{1cm} (17)

At the final stage, these on-looker bees decided to move to the best position intelligently according to the given multi-objective function in (15) [40, 41].

### 4 Simulation results and discussions

Simulations are carried out based on two various scenarios as follows:

(a) Scenario I: The comparison between the performance of proposed fuzzy droop and traditional PID droop controller:

In this section, wind turbine works in the de-loaded area. As a result, wind turbine has adequate headroom to inject active power into MG and this injection prevents the frequency to deviate dramatically. To clarify how the self-tuning, adaptive fuzzy droop works in de-loaded area, it is needed to look at wind turbine active power change following load increment. Furthermore, the rotor speed of wind turbine during frequency support is worth being investigated.

As previously discussed, 0.1 pu load increment is applied to the MG. According to Fig. 5a, MG frequency oscillates considerably when the traditional PID droop is used. The traditional PID droop increases the settling time dramatically and has no capability to control the system effectively. However, the proposed fuzzy-based droop controller rapidly mitigates the system frequency deviation when a load disturbance occurs. It is worth noticing that frequency reaches its stead-state point faster, thus improving generating cost and economic issues [42].

![Fig. 5 The Comparison between simulation results of various scenarios](image)

| Fuzzy rule base for the proposed fuzzy logic controller | The changes of frequency deviation |
|--------------------------------------------------------|----------------------------------|
| LN MN SN ZO SP MP LP                                   | LN MN SN ZO SP MP LP             |
| frequency deviation                                    | frequency deviation              |
| LN LP LP MN SN ZO SP MP LP                             | LN LP LP LP LP MN SN ZO SP MP LP |
| MN LP MP MN SN ZO SP MN LP                             | MN LP MP MP MP MN SN ZO SN MN MN |
| SN LP MP MP MP SP MN MN                                 | SN LP MN MN MN MN MN MN MN MN |
| ZO MP MP SP SP ZO MN MN                                 | ZO SP SN SN MN MN MN MN MN MN |
| SP MP SP ZO SN MN MN MN                                 | SP MP ZO ZO MN MN MN LN LN LN |
| MP ZO SN MN MN MN MN MN                                 | MP ZO SN MN MN MN MN MN MN MN |

**Table 5**

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In the following section, the rotor speed behaviour under load increment is illustrated in Fig. 6a. For two miscellaneous strategies, wind turbine rotor speed decreases because both methods increase the injected active power. The fact is that active power injection through wind turbine causes rotor speed to change within permissible range in load frequency control scheme. This sharp variation of rotor speed is seen due to acceptable performance of fuzzy-based PID droop controller to manage the injected active power in de-loaded area.

Finally, the PID controller is considered in this approach in order to change the value of blade angle. The fact is that the pitch angle controller alters the $\beta$ angle in order to increase the mechanical power extracted from the wind turbine. In accordance with Fig. 6b, fuzzy-based PID droop controller highly changes $\beta$ angle more than conventional PID controller. The blade angle pitch variation for fuzzy controller equals to 2° while it is around 1° for conventional one. This considerable difference in variation of $\beta$ comes from more satisfactory performance of fuzzy-based controller during wind turbine collaboration in frequency control scheme.

Fig. 5b depicts output active power change of wind turbine for two different strategies such that more suitable performance of the fuzzy-based PID controller is clearly concluded. The fuzzy droop controller causes more active power injection due to de-loaded area operation, while the conventional PID controller does not work in de-loaded area effectively, thus leading to less active power injection. The response time for fuzzy-based droop controller is around 0.09 s, while this value is 0.058 s for the conventional PID control. In addition, the proposed frequency control strategy employs diesel engine generator and FC, hereby resulting in full reserve which is considered for two strategies.

Fig. 7a shows how fuzzy droop controller not only harnessed the intensive effects of wind power excursions, but also outperforms the conventional PID droop in utilising spinning reserve which is considered for two strategies.

### 5 Conclusion

Authors in this paper introduce a novel strategy for wind turbine in order to use the kinetic energy stored in rotational masses in the frequency control scheme of MG. For effective contribution in load frequency control scheme, wind turbine is exploited in de-loaded area. In addition, the self-tuning/adaptive fuzzy droop is proposed in the structure of wind turbine and the ABC algorithm is used to find the optimal numerical values for designed controller’s parameters. The performance of the fuzzy droop is compared to the conventional PID droop in terms of frequency deviation, the amount of injected active power and variations in rotor speed of wind turbine during different operating conditions.
Fig. 7 The presented patterns for (a) Wind turbine power fluctuations, (b) Frequency deviation for different scenarios

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