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Original Article

Automatic Load Frequency Control for Wind-Thermal Micro Grid Based on Deep Reinforcement Learning

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Abstract - *Renewable energy demand keeps increasing each day due its significances over the conventional sources of energy, particularly in this era where the world is faced with many challenges related to clean energy. Among Renewable Energy Resources (RERs), wind energy has proven to be cheaper and readily available. However, it is intermittent in nature and therefore affecting the voltage and frequency stability of microgrid systems, especially in occurrence of wind power ramping events. In this work, a simple Deep Reinforcement based Automatic Load Frequency Controller (DRL-ALFC) is designed so as to improve the frequency stability of an ALFC during wind power ramping events in a wind-thermal micro grid. A DRL-ALFC for wind-thermal microgrid is verified in MATLAB/Simulink environment where it shows the ability to adapt to the variations wind power fluctuation and load.*

Keywords - *Automatic load frequency controller, Deep Reinforcement based Automatic Load Frequency Controller (DRL-ALFC), Renewable energy resources (RERs), Wind-Thermal microgrid.*

I. INTRODUCTION

In recent time, increased environmental impact due to use of fossil fuel as a conventional source of electric power generation has made researchers to put more attention on renewable energy resources as alternative energy resources. Thus, there is high penetration of renewable energy resources in today's micro and main power grid system. This is because the wind energy and other renewable energy resources are greener sources of energy and do not depreciate with time [1]. Although, renewable energy resources like wind energy are intermittent in nature and cause power system imbalance especially on the occurrence of wind power ramping events [2][3].

The occurrences of wind power ramping events may cause serious frequency stability problem to the microgrid [4]. This necessitates the need to develop an intelligent automatic load frequency controller that is capable to capture the predicted wind pattern and establishes control effort that will minimize the effect of wind power ramping events [5].

Availability and reliability of conventional energy resources like thermal is quite high and predictable [6]. Hence, the wind power plant can be integrated with thermal power plant so as to enhance the stability and reliability of the system [7]. Wind-thermal MG systems behave in a non-linear fashion; however, traditional control architectures for maintaining power system frequency are designed assuming that plant can be modelled using ordinary linear differential equations. This assumption is reasonable for minor frequency deviations given the present level of non-linearity in power systems. Owing to an increase in the proportion of wind power generation, along with an increase in the use of battery energy storage systems, power system dynamics are becoming increasingly non-linear [8]. The conventional controls are PI/PID based with fixed gains. The gains are optimally tuned by several means to reduce frequency deviation and maintain system frequency under steady state conditions.

Several researchers have considered/included RERs in their proposed automatic load frequency control (ALFC) studies using various controllers during the last decade. Ref [9] authors proposed traditional proportional integral controller for distributed V2G frequency control, in [10] an adaptive PID controller was discussed, in [11], [12] authors presented a robust proportional integral controller, in [13] an ALFC based on the method of model predictive controller is discussed, Fuzzy based multi area load frequency controller is discussed in [9], [14].

The methods that have been discussed above considered the power system model as a linear system, thermal power plant nonlinearities like dynamics of the boiler, governor dead-band (GDB), turbine reheat mechanism, and generator rate constraint (GRC) were not put into considerations. Moreover, volatile nature associated with RERs and use of fast acting power conversion devices which reduces inertia of the power system, the power system operation is highly affected [15]. In order to manage aforementioned challenges of non-linear feature of a microgrid, the MG operation requires a robust and intelligent load frequency controller [16].

Since evolution of deep learning, DRL based control strategy has been showing promising results in solving the load frequency control problem [17], [18], [19], [20], [21]. These control strategies use frequency signal to optimize the control action in order to improve the system response [21]. In this context, ref. [17], [18], [19] designed multi-agent generation control based on reinforcement learning to improve generation scheduling, where optimal control actions are obtained. Ref. [22] studied a data driven model based on DRL to continuously optimize the actions in order to improve the performance of the load frequency controller in a single-area power system. However, the existing works again neglect the effect of generation dead bands (GDB), generation rate constraints (GRC) and power ramping events for RERs which results to respond in the nonlinear fashion. However, in practice such nonlinear behaviors should not be neglected [14], [23].

The aim of this paper is to study the performance of an ADRL-ALFC for a wind-thermal micro grid with the DRL-Agent trained using DDPG algorithm. Depending on operating condition, the agent is trained to give optimal gain values, which good enough maximize the long-term reward and the results reveal its strength in frequency control with nonlinear behavior of the system. In addition to that, the controller is robust and gives good results during the event of wind power ramping.

The technique suggested in this study consists of offline learning to achieve intended objective and online utilization. The control problem is designed as deep reinforcement problem, which uses the deep neural network to corelate the observation and optimal actions by adjusting network parameters, all this is done in the course of offline training. Then the trained network is deployed online, the controller gives out the control command which is a result of required proportional and integral gain values based on the observed system states. The RL agent with DDPG algorithm is used to solve the problem.

II. SYSTEM CONFIGURATION AND MATHEMATICAL MODEL

A. Mathematical modelling of Thermal Power plant

The mechanical power is provided by prime mover, in thermal power plant mover a steam turbine and the mechanical power is controlled by opening and closing the steam valve. Let ΔP_{valve} be denoting the change in steam valve position to control amount of steam to the turbine, and $\Delta P_{mech-therm}$ be denoting the change in mechanical power of the turbine caused by ΔP_{valve}. If τ_T is a steam turbine time constant then, the relation between ΔP_{mech} and ΔP_{valve} can be expressed as;

$$\Delta P_{mech-therm} = \frac{1}{1+\tau_T s} \Delta P_{valve} \qquad (1)$$

If the signal ΔP_c is input to the governor and τ_g be the governor time constant therefore, equation (2) states the relation between the ΔP_c and ΔP_{valve}

$$\Delta P_{valve} = \frac{1}{1+\tau_g s} \Delta P_c \qquad (2)$$

In the case where there is large power imbalance between the source and load, the linearized MG model may not give required response. The nonlinear response of the wind-thermal micro grid is contributed by the GDB and GRC, therefore to it is important to include these constraints in the model. These non-linearities can be modelled as per equation (3) and (4) and summarized in figure 1.

$$\Delta P_{valve} = \max(0, \Delta P_c(t) - GDB) + \min(0, \Delta P_c(t) + GDB) \qquad (3)$$

$$\Delta P_m = \int [min\left(\sigma, \max\left(0, \frac{dP_m}{dt}\right)\right) + max\left(-\sigma, \min\left(0, \frac{dP_m}{dt}\right)\right)] \, dt \qquad (4)$$

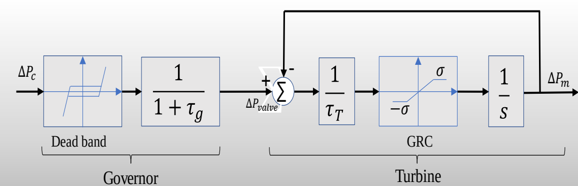

Fig. 1 The governor and turbine non-linear model

B. Mathematical modelling of Wind Power plant

Here the wind power plant is assumed to follow Maximum power point tracking. That is to say the wind speed change will always direct affect the wind power output hence the electrical power generated by wind turbine generator. Figure 1, conceptualize the MPPT for wind turbine model.

Since we are interested with only electrical output variation then, the above model can be considered as a black box which gives variable electrical output.

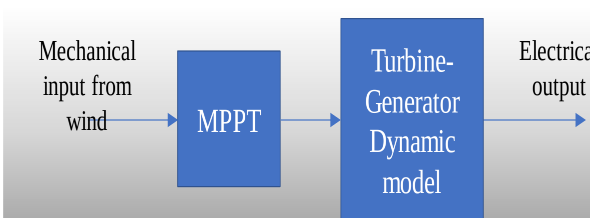

Fig. 2 wind power plant

B. Mathematical of the generator-load dynamics

If the MG is supplying power to some motor loads, there is a need to include the load dynamic model in load frequency control. This is because the motor loads are sensitive to frequency variations. If D is a p.u change in load due to p.u change in frequency and ΔP_e is a net change in electrical power then the change in electric power out of the system will be balanced by;

- Any change in electrical power demand (ΔP_L) in the network and
- Change in load due to frequency deviation.

Therefore, it can be stated as;

$$\Delta P_e = \Delta P_L + D\Delta\omega \qquad (5)$$

In the occurrence of any imbalance, there will be power swing, represented by swing equation (4)

$$M\frac{d(\Delta\omega(t))}{dt} = \Delta P_m - \Delta P_e \qquad (6)$$

Substituting equation (3) into the swing equation (4) can be represented in Laplace and make $\Delta\omega$ as the dependent variable then,

$$\Delta\omega(s) = (\Delta P_m - \Delta P_e)\frac{1}{Ms + D} \qquad (7)$$

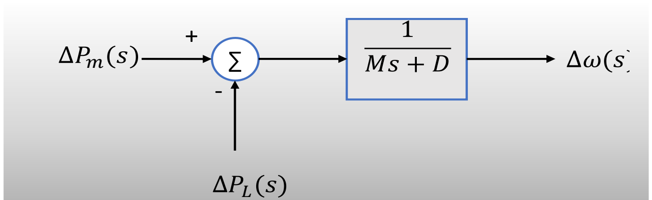

Fig. 3 Generator-load model

III. THE PROPOSED METHOD

A. Methodology

In this work, the wind-thermal MG load frequency control problem is designed in RL environment. The objective is to improve the system performance by designing a intelligent and robust to minimize the frequency deviation when the MG is operated under several different conditions.

In Deep reinforcement learning environment, a deep neural network is used to learn to give proper actions based on system's inputs. The DNN use the reinforcement learning technique to adjust its weights.

The core of reinforcement learning constitutes of the RL Agent and environment, the environment is defined to represent the dynamics of the wind-thermal microgrid model defined as equations (1)-(7). The environment always changes its state based on the action given by the agent to it. The RL agent is trained to take proper actions i.e the optimal gain values to which makes up the control signal used to control the amount of steam by opening and closing the steam valve. The good control actions are ones which minimize the frequency deviation by balancing the demand and the source. In this problem, the environment states observed by the agent are the frequency deviation, rate of change of frequency and integral of the frequency deviation signals of the MG.

The suggested solution is conceptualized as illustrated in figure 4. The technique involves two important phases, the offline phase where the training process will adjust neural network's weights and biases and the online deployment of the trained agent model. In the course of learning, the agent tries to explore the environment by giving different actions that will maximize the agent's rewards. Here the rewards are defined as the function of frequency deviation, with the objective of minimizing the deviation. After explorations, proper weights and biases of the agent are updated. This will define the RL agent that can be applied to control the thermal power plant generation to compensate the wind power deviation in order to meet the load demand. Considering environment constraints (1)-(7), the actor gradients are calculated and used to adjust neural networks' weights and biases that will represent the agent.

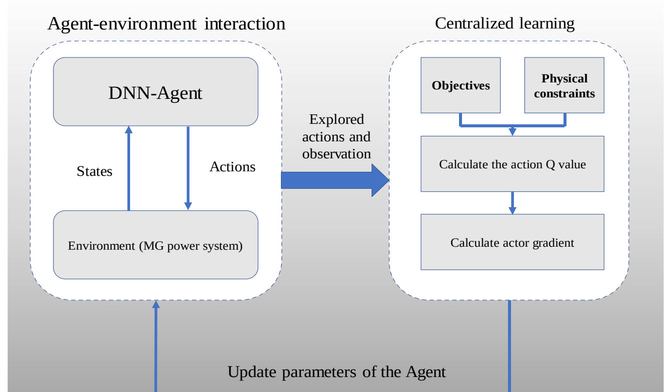

Fig. 4 Framework of proposed work

B. Deep Reinforcement Learning

The training process aims to adjust the agent's parameters, a Deep Neural Network (DNN) is utilized to adjust the generation command (ΔP_c) by giving the proper gain values towards global objective of load frequency control. The agent's parameters are the DNN's weights and biases denoted by $\theta^\mu = [W^T, b]$.

In order to improve model's frequency response, the reward function is defined as sum of the reciprocal of the absolute of frequency deviation with denominator added by one in order to avoid denominator to be infinite when frequency deviation equals to zero. This can also be used to define the action-value function modeled as;

$$Q(s,a) = \sum_{t=0}^{T} \Delta t \sum_{i=1}^{n} \left(\frac{1}{1+\Delta f_i} \right) \tag{8}$$

Where $Q(s,a)$ is a function of actions a and states s, defined as per equations (9) and (10) below;

$$a_t = \{K_p(t), K_i(t)\} \tag{9}$$

$$s_t = \left\{ \Delta f_t, \frac{d(\Delta f_t)}{dt}, \int \Delta f_t \right\} \tag{10}$$

Each step of exploring the environment, one scenario called episode step is created. At the end of each episode, the system frequency deviation will be calculated.it is always expected that the Q function has to be maximized in such a way that the agent's parameters are optimal. It can be written that parameter θ^{μ} as;

$$\underset{\theta^{\mu}}{maximize} E_D[Q(s,a)] \tag{11}$$

where, D stands for memory replay buffer (containing information of all episode steps), records controller's experience. D contains the states s, control actions a and rewards.

C. Deep Deterministic Policy Gradient based solution

Training the DRL Agent, the problem is formulated using equation (1)-(7) together with (9). Using the deep deterministic policy gradient, the actor's gradient is computed and iteratively adjust the agent's parameters.
The initialization of the exploration stage is achieved by means of picking random actions from a noise sample. The moving average noise is employed as the exploration noise [15].

$$\mu'(s_t) = \xi_t \mu(s_t, \theta_t^{\mu}) \tag{12}$$

The randomly selected factor ξ_t for every iteration has to be computed from a sequence of random numbers by the use of the moving average. On completion of the exploration step, the expected Q-value made maximum by changing the agent's actions $\boldsymbol{a}$ depending on the environment's reward, here the agent's action $\boldsymbol{a}$ is optimally changed by optimizing parameters of the agent. Using the chain rule, the agent's weights and biases are updated depending on the gradient of Q value function differentiated with respect to each control actions $\boldsymbol{a}$ [15].

$$\theta^{(k+1)} = \theta^{(k)} + n\nabla_{\theta^{(k)}} J \tag{13}$$

$$\nabla_{\theta^{(k)}} J \approx \frac{1}{m} \sum_i \nabla_a Q(s,a|\theta^{Q})|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^{\mu}} \mu(s|\theta^{\mu})|_{s=s_i} \tag{14}$$

With m representing a mini-batch size and n represents learning rate.

D. DDPG Architecture framework

The DDPG architectural framework is presented in the figure 5. The working flow is explained in the section E below

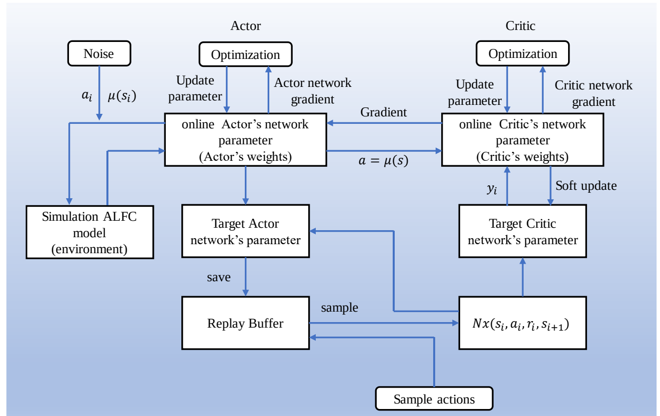

Fig. 5 DDPG architecture framework

E. The Algorithm

The proposed control method uses DDPG algorithm to train the agent's parameters that will enable the controller to give out optimal action values depending on the system's states. This is only achieved after successful training of the agent. Based on the designed ADRL ALFC environment the parameter can be updated by means of DDPG algorithm as illustrated in table 1 below;

Table 1. The DDPG algorithm

Algorithm 4: DDPG Algorithm	
1	Randomly initialize critic $Q(s,a|\theta^{Q})$ and actor $\pi(s|\theta^{\pi})$ with weights θ^{Q} and θ^{π} respectively
2	Initialize target network Q' and μ' with weights $\theta^{Q'} \leftarrow \theta^{Q}$ and $\theta^{\mu'} \leftarrow \theta^{\mu}$
3	Initialize replay buffer D
4	**for** *episode* $\leftarrow 1{:}M$ **do**
5	Initialize random process N for action exploration
6	Receive initial observation state s_1
7	**for** $t \leftarrow 0{:}(T-1)$ **do**
8	Select action $a_t = \mu(s_t|\theta^{\mu}) + \xi_t$ with exploration noise
9	Execute action a_t and observe reward r_t and observe new state s_{t+1}
10	Store transition (s_t, a_t, r_t, s_{t+1}) in D
11	Sample a random minibatch of N transitions (s_i, a_i, r_i, s_{i+1}) from D
12	Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{Q'})$
13	Update critic by minimizing the loss: $L = \frac{1}{m}\sum_i (y_i - Q(s_i, a_i|\theta^{Q}))^2$

Update the actor policy using the sampled policy gradient:

$$\nabla_{\theta^\mu} J \approx \frac{1}{m} \sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s|\theta^\mu)|_{s=s_i}$$

Update the target networks:

$$\theta^{Q'} = \tau\theta^Q + (1-\tau)\theta^{Q'}$$
$$\theta^{\mu'} = \tau\theta^\mu + (1-\tau)\theta^{\mu'}$$

end for

end for

IV. SIMULATION RESULTS AND DISCUSSION

A. Simulation model

The MG ALFC mathematical model was developed in Simulink environment, the model dynamics reflect equations (1)-(7). The model constituted of an RL Agent block, Reward calculation subsystem and observation subsystem as shown in figure 6, the model parameters are shown in table

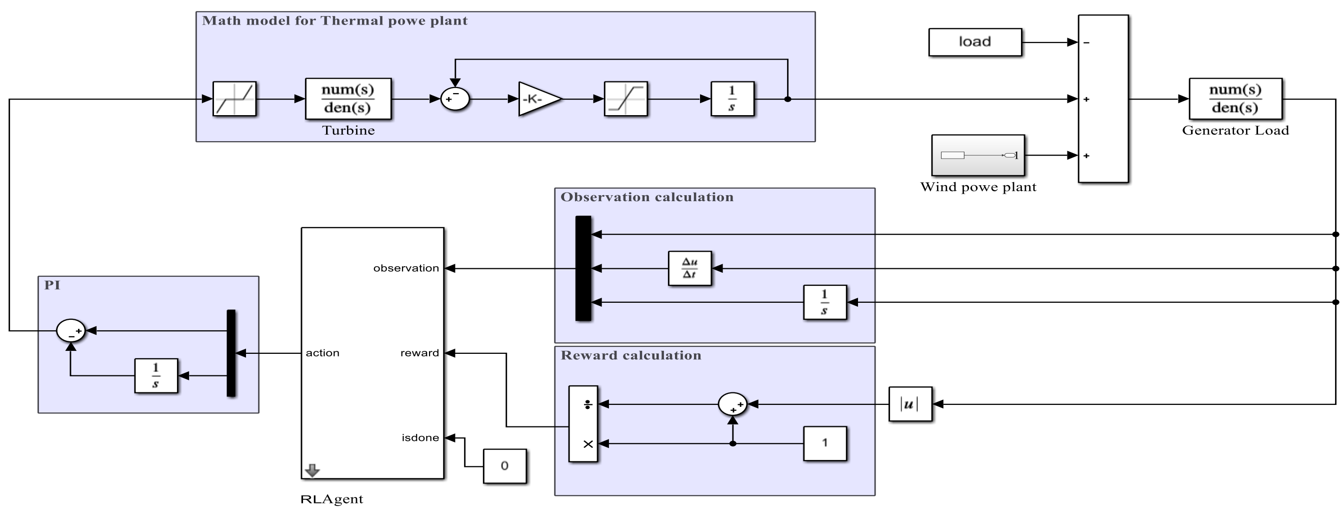

Fig. 6 Wind-thermal Micro Grid ADRL-ALFC Simulation model

2. In this model the reward, action and observations are defined as per equation (8)-(10)

Table 2. Parameter values of the thermo power plant

Parameter	Value
τ_T	0.5s
τ_g	0.2s
D	0.8
GDB	0.06%
GRC	0.00017p.u/s
M	10
M	10

The implementation was done by the help of deep designer app of MATLAB r2020b version. The DDPG training hyperparameter settings are summarized in table 3 below.

Table 3. Algorithm hyperparameters

Parameter	Value
Target smooth factor	0.001
Experience buffer length	1000000
Discount factor	0.99
Minibatch size	256
Actor learning rate	0.0001
Critic learning rate	0.001

The wind thermal microgrid with non-reheated thermal as in the figure 6 was simulated in the MATLAB/Simulink environment. The wind and the wind power variation of the whole day is shown in the figure 7, it can be seen in the interval of time from 8th to 20th hour there was a wind power ramping event.

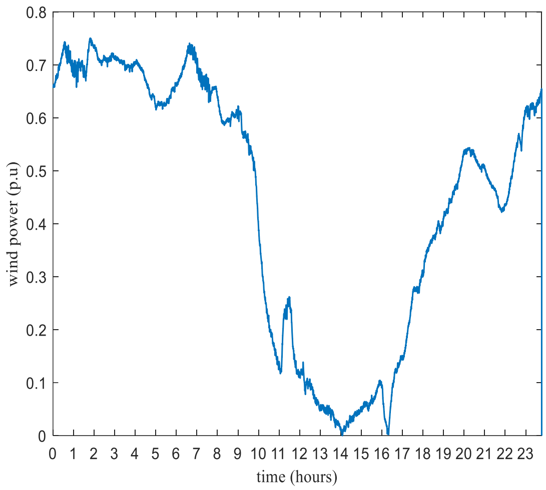

Fig. 7 24 hours wind power pattern in an area

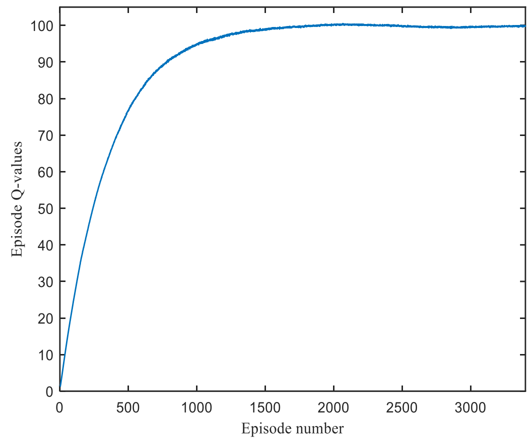

Fig. 9 Episode Q-Value plot for each episode step of the training phase

A. Agent training results

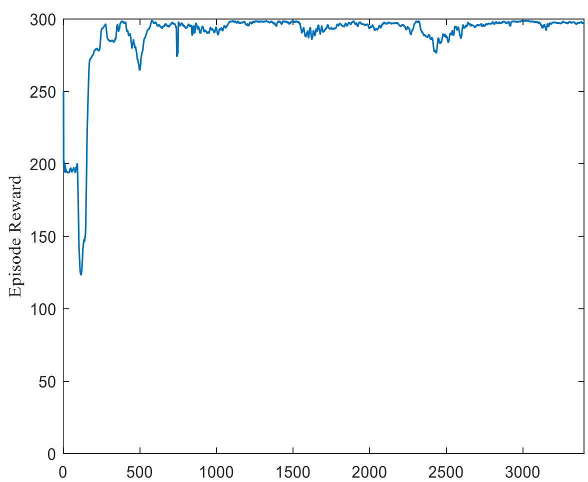

Fig. 8 Episode rewards for each episode number of the training phase

The model was trained for 150 episodes and each episode had 300 steps. Each step returned a reward value which was summed to obtain an overall episode reward. Figure 8 shows a plot of episode reward against the episode number. Figure 9, is a plot of episode *Q* values against the episode number. The training was targeted to achieve at least average reward of at least 298 for better results.

B. Simulation Testing Results Under Different Scenarios

Scenario I*: Comparison of the proposed method based on DDPG algorithm Vs DQN algorithm.*

Here a step change of 0.2 p.u of wind power occurred at instant t = 1 second is considered while assuming the load remain constant. The figure 10 below shows that in the proposed method, frequency deviation is negligibly small as compared to the DQN based algorithm.

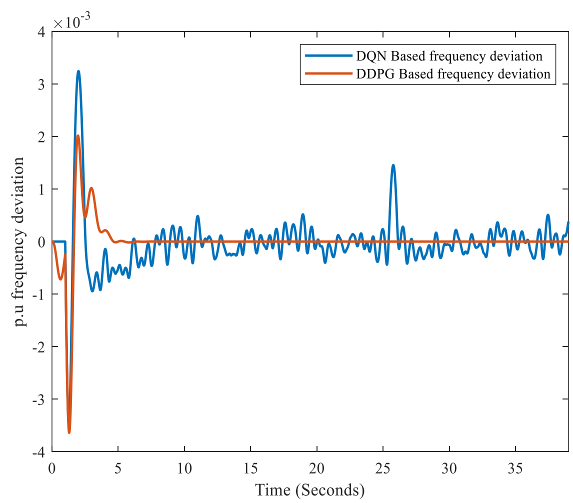

Fig. 10 Effect of 0.2 p.u change of wind power

Scenario II*: Effect of wind power ramping event.*

Both ramp up and ramp down events are considered and the frequency deviation for two algorithms are compared. The results controller is able to effectively adjust the generation command in order to maintain the frequency and meet the load requirement as required. Figure 11 below shows the occurrence of power ramping and the frequency deviation.

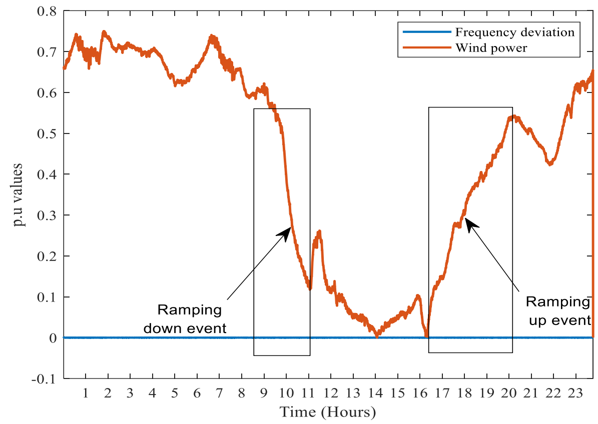

Fig. 11 Effect of wind power ramping on frequency deviation

***Scenario III**. Test of robustness of the controller*

The generator time constants were allowed to vary by +25% and -25% and the frequency response were studied. It shows that there is negligible effect in the frequency deviation due to variation of the time constants. This prove that the controller is efficient and robust.

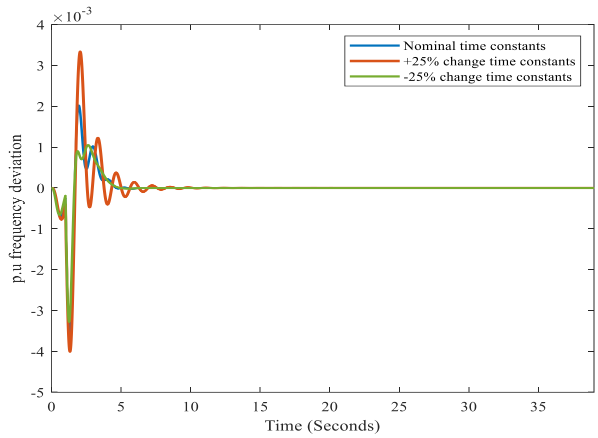

Fig. 12 Robustness of the proposed controller

***Scenario IV**: Comparison of the control action signal.*

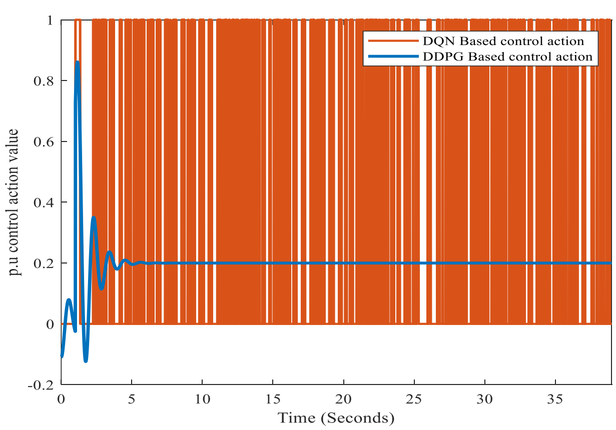

Fig. 13 Comparison of the control action signal

Following a step change of 0.2 p.u of wind power, the control signal smoothness is evaluated, the DDPG based stress/tear and wear to the actuator or the steam valve of the thermal power plant. While that of DQN based controller is having higher on-off frequency hence high degree of tear and wear of the steam valve. This is because that the DQN action space is discrete while that in DDPG is continuous

V. CONCLUSION

This paper has tried to analyze the performance of adaptive load frequency controller based on deep reinforcement learning. The wind power ramping events, robustness of the controller and effect of control action to steam valve were taken into consideration and the proposed method seems to have promising results. DDPG based ALFC outperform the DQN based controller.

The operation of Wind-thermal microgrid can be used to reduce the ozone layer depletion and hence global warming effect, this is because the proposed controller considers the maximum wind power point tracking and the thermal was used just to compensate the deviations so as to meet the load demand.

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