Increasing the Penetration of Distributed Wind in an Isolated Microgrid Through Data-driven Frequency Regulation using Reinforcement Learning

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***Abstract*—Wind availability in Alaska is the highest in the United States. Small and dispersed communities can easily satisfy their demand based on wind power. However, this renewable resource is challenging to handle: wind speed can ramp up or down a 50% in just a few seconds, which translates to abrupt power generation swings. The intermittency and variability of distributed energy resources in isolated power grids with high-renewable energy penetration can lead to significant frequency deviations. For this reason, wind generation is typically curtailed below its actual capabilities. In this paper, we propose a data-driven Reinforcement Learning controller for Wind Turbine Generators (WTGs) that maximizes the wind penetration in St Mary's, a small Alaskan town, while providing frequency regulation through pitch angle adjustments. Results show that the proposed method increases the WTG output by more than 18% compared to the no-control case and more than 4% compared to a traditional frequency-droop control case while keeping frequency close to nominal. The reduction in fuel consumption is estimated to be more than 21% and 5%, respectively.**

***Index Terms*—distributed wind, wind turbine generator, frequency regulation, reinforcement learning**

I. Introduction

The increasing integration of renewable energy resources is creating interest in using such devices to support grid activities. Good power quality depends on several factors, such as keeping voltages and frequency inside an acceptable range. IEEE Standard 1547-2018 encourages the participation of Distributed Energy Resources (DERs) in both voltage and frequency regulation [1]. This paper is focused on the participation of Wind Turbine Generators (WTGs) in frequency regulation activities for wind-diesel hybrid microgrids.

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II. Background

A WTG's electrical output power, P, has a very non-linear relationship with wind-speed w (indeed, $P \propto w^3$) [2], which is an extremely intermittent and variable resource that can cause frequency and voltage fluctuations [3], [4], [5]. Isolated systems that incorporate wind power can be subjected to noticeable power swings and frequency deviations. In low wind generation scenarios, other resources such as Diesel Generators (DGs) can provide primary frequency regulation. However, under significant wind penetration, these DGs are disconnected or working at low power and WTGs become principal actors in frequency regulation. Therefore, the research on WTG's frequency regulation capabilities at all grid levels (transmission, distribution, and microgrids) is very relevant. Traditionally, WTGs provide frequency regulation in two different ways: Either using a droop control, which monitors the system frequency, or using an inertial control that is related to the frequency variation [6], summarized below.

- Droop control: The WTG operates in a deloaded mode (sub-optimal power output) which provides an active power headroom. In the case of an under-frequency event, this reserve can be used to inject additional power to mitigate the disturbance. On the contrary, further curtailment can be commanded in an over-frequency event.
- Inertial control: Additional active power can be momentarily extracted from the kinetic energy stored in the rotating masses during under-frequency events. Inertial control does not need curtailment. This additional power injection can be achieved using power electronics.

In general, each method has potential advantages and disadvantages. For the droop control, the WTG deloading is commonly achieved by adjusting the blades' pitch angle. This approach is mainly employed once the wind speed is enough to drive the generator at its rated power, and the goal is to regulate the generator speed to ensure the turbine's safety. The blade pitch control system typically uses a Proportional Integral (PI) control to regulate the generator speed closer to rated [2]. In the above-rated wind-speed region, this control reduces the WTG's blades' aerodynamic efficiency to decrease the generator speed and avoid excessive vibrations [6]. On the other hand, this technique can be used in the entire wind-speed range for active power curtailing. One of the main

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disadvantages of frequency regulation by using blade pitch control is the excessive wearing of the servo motors that adjust the blades' angle.

Multiple references state that inertial control in inverter-based WTGs is faster than droop control [6], [7]. The reason is that pitch control is based on mechanical elements, while inertial control is driven by power electronics. However, wind power output must be decreased afterward to get rotational speed back to normal [7], which may aggravate the situation later on. In practice, the pitch angle control is easier to operate than the speed control [6]. The frequency-droop control as mentioned above is the main actor of WTG's primary frequency regulation. It is important to note that the droop control does not guarantee no-error adjustment [8]. The goal is just to stabilize frequency at a value close to nominal. Afterward, secondary frequency regulation achieves zero error by tweaking generators' operational set points [9].

Looking at frequency regulation in hybrid wind-diesel islanded microgrids, proposed controls in the literature are quite flexible regarding the resource to be used in frequency regulation (wind turbines, solar panels, batteries, or diesel generators). The work in [10] proposes a genetic algorithm to address frequency deviations due to solar irradiance and wind speed in a microgrid. Frequency regulation is provided with a small spinning reserve using diesel generators. In [7], a frequency-droop control for wind turbines is proposed. The curtailment during normal operation is 3% to provide enough active power headroom. In the worst-case scenario, the frequency decreased by half an Hertz (Hz), while the blade pitch angle increased by about a degree. In [11], a pitch angle controller using a conventional PI controller is used to provide a constant wind output. In scenarios of medium wind penetration, the diesel generator takes care of the voltage and frequency regulation. At higher wind generation scenarios, the diesel generators can be disconnected and the pitch angle controller and some capacitor banks take care of the system regulation. For the particular WTG used, just as a reference, a pitch angle between 0 and 45 degrees and a rotational speed of about 10 degrees per second are acceptable values. In [12], a Model Predictive Control (MPC) is employed for WTG pitch angle control and electric vehicle power exchange control. The goal is to reduce frequency fluctuations. The control weights are tuned using particle swarm optimization. The frequency regulation using pitch angle control is only available for the region in which the WTG is providing the rated power.

Other works propose the use of Reinforcement Learning (RL) to provide an optimal frequency regulation control. The paper in [13] introduces an inertial control based on a multi-agent Deep Deterministic Policy Gradient (DDPG) model [14], [15]. The proposed RL control uses both WTG-related information (rotor torque and speed, wind speed, pitch angle, etc.) and structural information (tower and blade deflection and displacement). With their control, they can maximize the WTGs' frequency-regulation capabilities while minimizing the structural efforts. Similarly, the paper in [16] proposes a pitch angle control for frequency regulation for Type III WTGs in the IEEE 39-bus system. The RL control can mitigate the frequency deviation for specific sudden loss of generation and load increase.

To summarize, the frequency-droop control output is proportional to the frequency deviation, although this frequency regulation method is designed to work only at rated power and does not guarantee zero error. In addition, a permanent fixed headroom is required to provide both upward and downward regulation capacity. Compared to existing techniques, our RL model combines both primary and secondary frequency regulations (mitigates sudden frequency deviations and achieves zero error) during the entire WTG operational range, minimizes continuous curtailment to provide headroom, and increases renewable energy penetration while decreasing fuel consumption in wind-diesel hybrid islanded microgrids.

III. Simulation Model

The village of St. Mary's, located on the western edge of Alaska, is an islanded power system with a peak load of 600 kW and a minimum load of 150 kW. Historically, power has been provided by three diesel engines, each rated at 499 kW, 611 kW, and 908 kW [17]. To reduce diesel generation, a 900 kW Type-IV, pitch-controlled WTG was installed in 2018. A diagram of the St. Mary's power system is shown in Fig. 1 [18]. Note that the WTG typically operates in a conservative curtailed state of 50% rated power to minimize power swings due to sudden wind speed variations [19].

A simulation model consisting of a WTG [20], three DGs, and variable loads is developed in MATLAB/Simulink. The simulation model is executed in real-time in an OPAL-RT target. System-wide measurements (voltage, frequency, and active and reactive power flows) for each of the loads, the DGs, and the WTG are gathered every 0.2 seconds using a Modbus Input/Output interface. For the purpose of frequency regulation, it is possible to select the WTG operating mode: a fixed active power, a Frequency-Watt Curve (FWC) control, or a custom control. The real-time control setup for the controller and the simulation model is shown in Fig. 2.

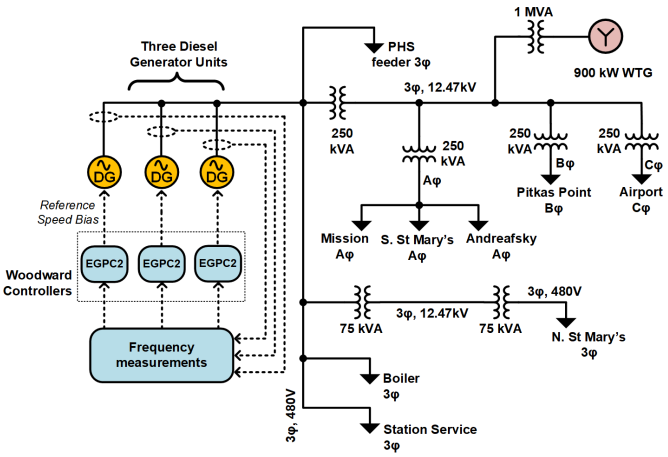

Fig. 1. Diagram of the St. Mary's power system [18].

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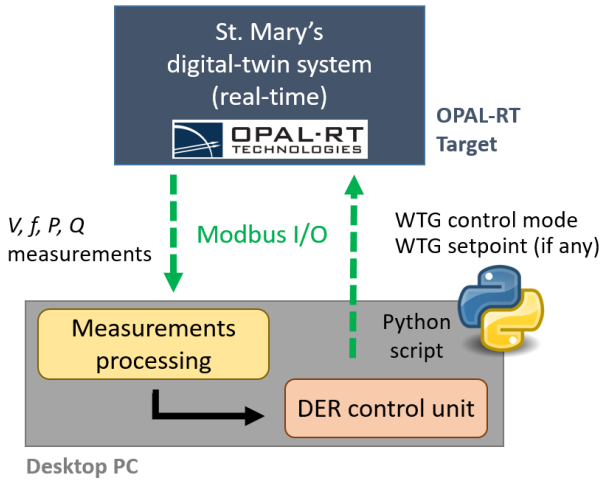

Fig. 2. Diragram of the real-time control setup.

IV. Methodology

The frequency-regulation control in this paper is based on the RL DDPG algorithm, which is a model-free, off-policy, actor-critic algorithm that can learn optimum policies in continuous action spaces. The actor network maps states S to actions A and the critic network evaluates the actor's policy $\pi(S)$ based on the value function $Q(S, A)$. The actor network optimal policy $\pi(S)$ aims to maximize the expected return R though selecting the optimal action A:

$$\pi(S) = \arg\max_{A} Q(S, A). \tag{1}$$

The critic networks estimates the value function $Q(S, A)$, which can be expressed as follows:

$$Q(S, A) = \mathbb{E}[R|S, A]. \tag{2}$$

In each control time step i, the critic network is trained by minimizing the loss L,

$$L = \frac{1}{N}\sum_{i}(y_i - Q(S_i, A_i))^2. \tag{3}$$

Here, y_i is calculated using the Bellman equation:

$$y_i = R_i + \gamma Q'(S_{i+1}, \pi'(S_{i+1})), \tag{4}$$

where γ is the discount factor and Q' and π' are the target networks that are periodically updated to increase training stability. These networks are updated using the smoothing factor τ. Furthermore, the actor policy is updated using the sampled policy gradient:

$$\nabla_{\theta^\pi} J \approx \frac{1}{N}\sum_{i} \nabla_A Q(S, A)|_{S=S_i, A=\pi(S_i)} \nabla_{\theta^\pi} \pi(S)|_{S_i}, \tag{5}$$

where θ is the actor network weights.

In this application, the state S is comprised of 6 observations: voltage at the point of interconnection V, frequency f, injected active power P, injected reactive power Q, global active power P_{Glob}, and normalized resource (wind speed) U.

The first four are observations that all DERs must provide according to [1]. The P_{Glob} measurement is provided by a centralized software that acts as the DER Management System (DERMS) in which system-wide monitoring is carried out. It is calculated for each control time step i as:

$$P_{Glob.,i} = \sum_{g=1}^{3} \frac{P_{g,i}}{P_{g,Nom.}} + \frac{P_{WTG,i}}{P_{WTG,Nom.}}, \tag{6}$$

where g is the index of the diesel generator, P_g is the instantaneous active power for each generator, P_{WTG} is the WTG's instantaneous active power, $P_{g,Nom.}$ is the nominal active power of each generator, and $P_{WTG,Nom.}$ is the WTG's nominal active power. Finally, the normalized resource is calculated by the following expression:

$$U_i = \frac{ws_i}{WS_{WTG,Nom.}}, \tag{7}$$

where ws_i is the instantaneous wind speed (measured using an anemometer with a 1-second resolution) and $WS_{WTG,Nom.}$ is the maximum rated wind speed, which for the St. Mary's WTG is 26 m/s (the WTG shuts down for higher wind speeds).

The action provided by the actor network every control time step i is the WTG's active power setpoint $P_{WTG,Set.}$. The actor network is composed of three fully-connected layers of 64 neurons each. The two first layers use "ReLU" for the activation function, while the last one uses "sigmoid" to provide an output between 0 and 1 to automatically match $P_{WTG,Set.}$ range. The pitch-angle controller then tries to follow the power reference by tilting the WTG blades with a servomotor. The block diagram is shown in Fig. 3.

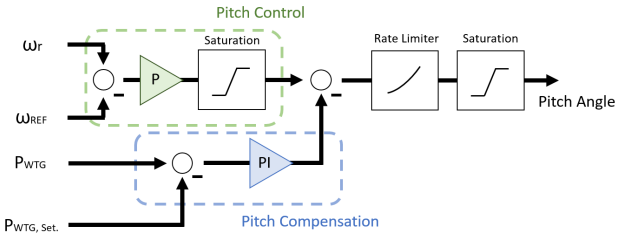

Fig. 3. Diagram of the pitch-angle controller block.

The reward function R is composed of several terms aiming at maximizing the wind energy penetration in the system while minimizing frequency excursions. At each control time step i, R can be defined as in the following sum of terms:

$$R_i = \alpha_1 \cdot R_{1,i} + \alpha_2 \cdot R_{2,i} + \alpha_3 \cdot R_{3,i} + \alpha_4 \cdot R_{4,i}, \tag{8}$$

$$R_{1,i} = \frac{|max(P_{LOAD,i} - P_{WTG,Opt.,i}, 0) - P_{DG,i}|}{P_{WTG,Nom.}}, \tag{9}$$

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$$R_{2,i} = a \cdot Freq_i^2 - b \cdot Freq_i, \tag{10}$$

$$R_{3,i} = |P_{WTG,Set.,i-1} - P_{WTG,Set.,i-2}|, \tag{11}$$

$$R_{4,i} = |P_{WTG,i} - min(P_{LOAD,i}, P_{WTG,Opt.,i})|. \tag{12}$$

where $a = 6.35$, $b = -0.28$, $\alpha_1 = -1.5$, $\alpha_2 = -1$, $\alpha_3 = -1$, and $\alpha_4 = -1.5$. Regarding the meaning of these terms, R_1 tracks the amount of power injected into the system by the diesel generators P_{DG}. The diesel generation should be minimized whenever possible if there is enough wind power available $P_{WTG,Opt.}$ to satisfy the load P_{LOAD}. On the other hand, R_2 penalizes the deviation from the nominal frequency in a quadratic fashion. Furthermore, R_3 penalizes the sudden changes in the WTG's active power setpoint $P_{WTG,Set.}$ to minimize abrupt pitch angle modifications. The requirement for comparing the last two setpoints is related to the training workflow shown in Fig. 4. Note that the observations at control step i show the results of the control action $P_{WTG,Set.}$ of the previous control step, $i-1$. The reward in i actually evaluates the action in the $i-1$ time step. Therefore, the change of setpoint calculation requires access to the setpoints in the control time steps $i-1$ and $i-2$. Finally, R_4 tracks the deviation between the observed active power P_{WTG} and the feasible available wind penetration, i.e. either the available amount of wind power or the total demand, whichever is less.

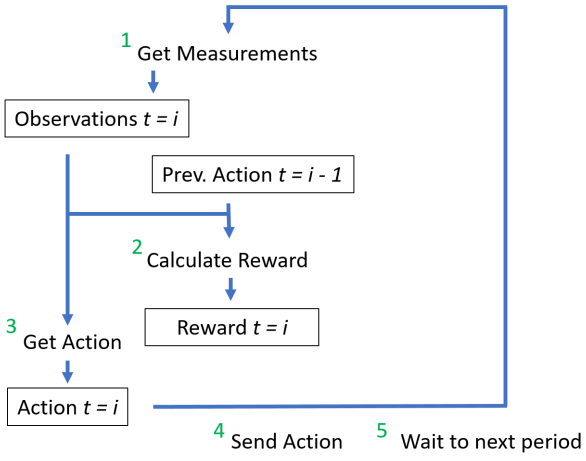

Fig. 4. Diagram of the training workflow.

V. Simulation Results

The reward maximization for the proposed DDPG model during 250 training episodes of 100 seconds each can be appreciated in Fig. 5. These episodes have diverse and variable load and wind speed profiles. The testing in 100 previously unseen episodes compares the performance of 3 control approaches: A) the Base case - no active power control, but curtailment at 75% of the rated power, B) a grid-support FWC, and C) the DDPG model. The employed FWC control is shown in Fig. 6. In the first place, the overall performance of these methods is presented. Secondly, a scenario in which the Base case leads to an unsustainable frequency deviation is analyzed to show the DDPG control behavior in detail.

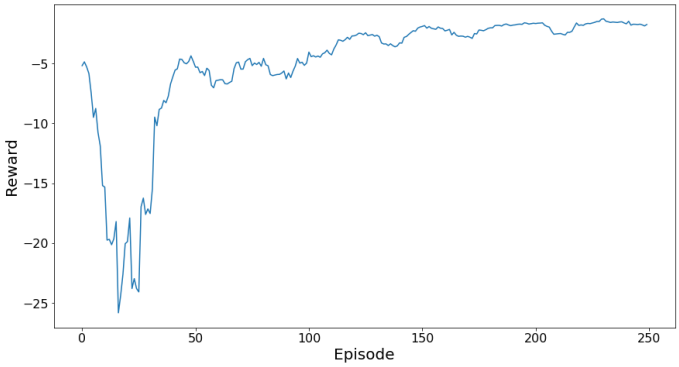

Fig. 5. Averaged episodic reward during training.

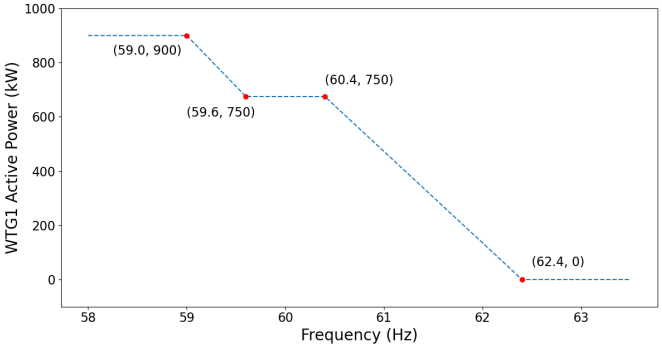

Fig. 6. Diagram of the Frequency-Watt Curve.

A. Overall Performance

As it can be seen in Table I, the average frequency is very close to 60 Hz and the standard deviation (STD) is low in all cases. However, large frequency deviations can still occur under certain circumstances. The largest recorded frequency excursion is almost 3 Hz above nominal in the Base case. The usage of the FWC control can substantially mitigate these excursions, although the proposed DDPG controller keeps frequency the closest to nominal.

TABLE I
Frequency (f) Performance per Case

Case	Avg. f	STD f	Max f	Min f
DDPG	**60.06 Hz**	**0.08 Hz**	**60.88 Hz**	59.48 Hz
FWC	60.08 Hz	0.11 Hz	61.52 Hz	**59.54 Hz**
Base	60.08 Hz	0.18 Hz	62.95 Hz	59.49 Hz

The key contribution of the DDPG model is to enable additional wind energy penetration without sacrificing system

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TABLE II
GENERATION PERFORMANCE PER CASE

Case	Avg. Diesel Active Power	Avg. WTG Active Power
DDPG	**334.21 kW**	**504.06 kW**
FWC	353.74 kW	483.95 kW
Base	426.35 kW	425.73 kW

stability. Fig. 7 shows the measured level of wind penetration against the available (or optimal) wind power. The three models provide all the WTG power when the available wind power is less than 600 kW. However, both Base and FWC cases have their output flattened above 700 kW, while the DDPG is the only control that can reliably extract up to 800 kW from the WTG. Similarly, the average DG usage is about 100 kW lower for the DDPG case compared to the Base and FWC cases after the wind speed exceeds 11 m/s, which is when the WTG starts to work at rated power. As can be seen in Table II, the DDPG control increases wind generation by more than 18% compared to the Base case and more than 4% compared to the FWC case. The reduction in fuel consumption in the DDPG case is estimated to be more than 21% and 5% compared to the other cases, respectively. Fig. 8 shows the average diesel generation against available wind speed.

B. Episode analysis

This subsection analyses the behavior of the three control schemes during a sudden wind speed change that leads to a significant power swing in the microgrid. The frequency excursion can be seen in Fig. 9. At $t = 48$ seconds, a sudden burst in wind speed leads to a large increase in the available wind power. For the Base case, this generates a surplus of almost 100 kW in less than 10 seconds, as can be seen in Fig. 10. This creates an upward frequency deviation of 2.5 Hz in the Base case and 1 Hz in the FWC case. Using the proposed DDPG model, the active power setpoint is reduced in 100 kW immediately to avoid a sudden WTG power increase and, thereby, a significant deviation.

This response is achieved by a slightly faster and larger variation of the pitch angle compared to the Base and FWC cases, as can be seen in Fig. 11. Note the variability in the DDPG setpoint in Fig. 10. In the Base and FWC cases, the WTG pitch angle mechanical control will try to keep (with a certain delay) the power at 75% rated power, or 675 kW. At $t = 63$ seconds, a more abrupt wind increase creates a larger frequency deviation in the Base case which drives the simulation out of bounds, while the DDPG control is able to dodge any impact on the system stability thanks to its fast response which mitigates the frequency excursion.

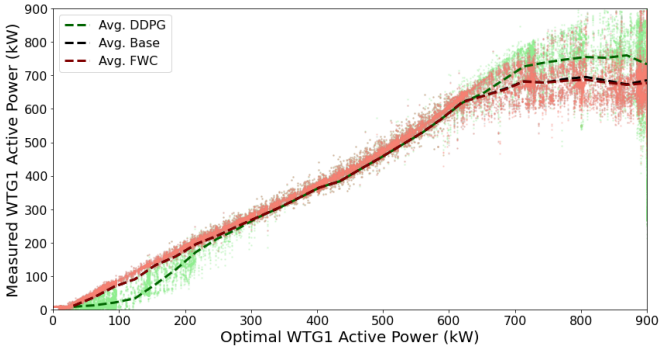

Fig. 7. Wind turbine active power vs. optimal active power for the Base, Frequency-Watt Curve, and Deep Deterministic Policy Gradient cases.

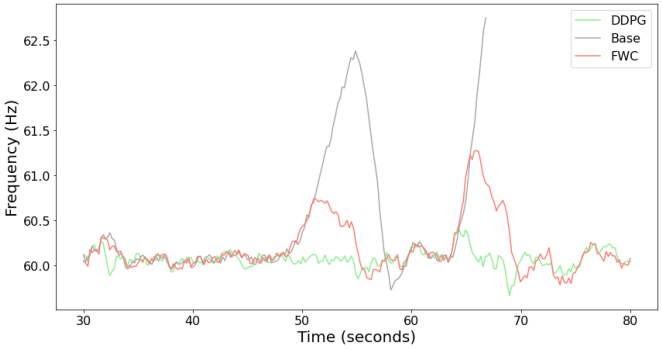

Fig. 9. Deviations present in the system frequency for the Base, Frequency-Watt Curve, and Deep Deterministic Policy Gradient cases.

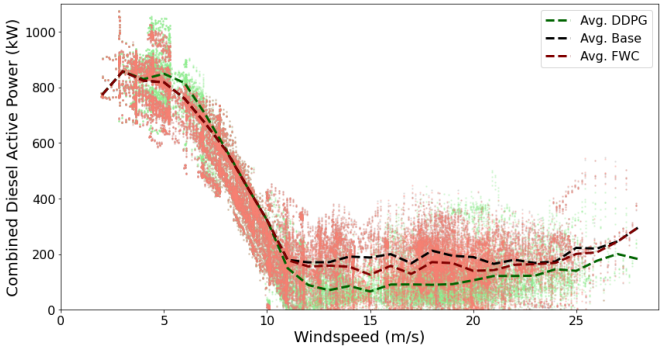

Fig. 8. Average diesel generation output against wind speed or the Base, Frequency-Watt Curve, and Deep Deterministic Policy Gradient cases.

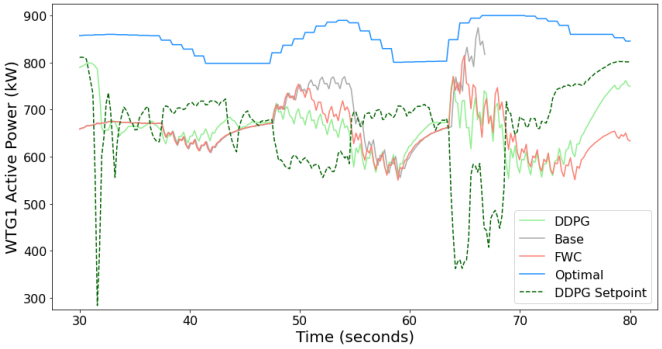

Fig. 10. Observed wind turbine active power and optimal active power for the Base, Frequency-Watt Curve, and Deep Deterministic Policy Gradient cases.

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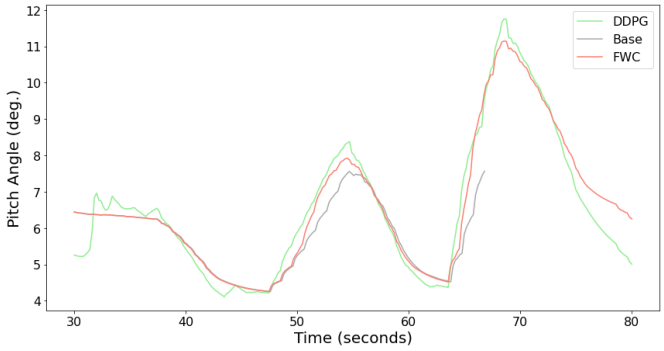

Fig. 11. Wind turbine pitch angle for the Base, Frequency-Watt Curve, and Deep Deterministic Policy Gradient cases.

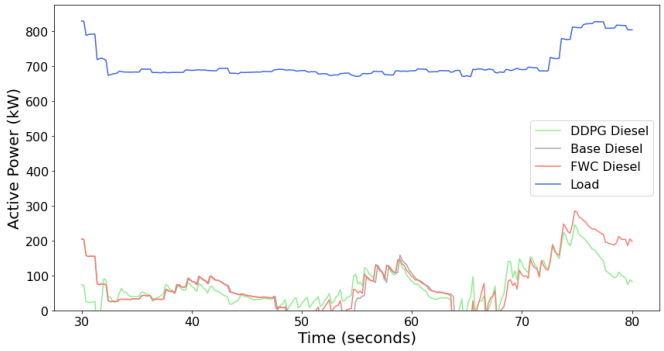

Fig. 12. System-wide load and diesel output for the Base, Frequency-Watt Curve, and Deep Deterministic Policy Gradient cases.

Note that the DG output is related to the WTG action to provide an acceptable generation-demand balance, as shown in Fig. 12. The effect of the diesel generators on the system frequency response is embedded into the DDPG control policy. In this episode, the load is relatively small compared to the available wind power generation. During certain parts of the episode, the system is entirely running on wind power.

VI. Conclusion

In this paper, a Reinforcement Learning (RL)-based frequency regulation controller has been proposed for diesel-wind hybrid isolated microgrids. The controller is based on the Deep Deterministic Policy Gradient (DDPG) model. Its performance is tested against a Base, no-control, case where the wind power is curtailed at 75%, and a frequency-droop case that employs a Frequency-Watt Curve (FWC) type of control. The comparison takes place on a digital-twin model of the Alaskan town of St Mary's, which is executed in real-time in an OPAL-RT target.

Results show that the FWC control has some benefits compared to the Base case. However, the DDPG control performance is higher both in frequency regulation capabilities and reliably increasing renewable energy penetration. Compared to others, the DDPG model can improve power quality by keeping frequency closer to nominal and significantly minimizing frequency excursions. In addition, the DDPG model can increase wind penetration and reduce fuel consumption.

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