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Enhancing Solar Panel Efficiency through Deep Deterministic Policy Gradients (DDPG) Reinforcement Learning Control

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***Abstract*— This study introduces a novel two-degree-of-freedom orientation mechanism for photovoltaic panels, utilizing 3D-printed gears and controlled by the DDPG reinforcement learning algorithm. The research highlights the potential for enhanced solar energy capture. The integration of mechanical design with machine learning showcases a promising interdisciplinary approach to renewable energy systems.**

Keywords—Reinforcement learning, DDPG, photovoltaic panel, orientation control.

I. Introduction (*Heading 1*)

One of the sources of renewable energy that has had a positive development has been solar energy, which is defined as the generation of electrical energy from the reception of solar rays by means of photovoltaic panels [1]. A photovoltaic module (PV) is a device that allows solar energy to be converted into electrical energy without the production of harmful waste for the environment, in addition, they are cheaper and easier to install than wind or biofuel systems [2]. However, the main shortcoming of a PV system is its low efficiency.in the conversion [3]. Therefore, there are 3 ways to improve the efficiency of the conversion of solar energy to electricity: increasing the incidence of solar rays on the panel, improving the conversion efficiency of the electrical diodes, or improving the monitoring of the maximum power point of the panel array.

One way to improve the conversion of solar energy systems is to implement a control system that ensures a greater collection of solar energy with a repositioning of the cell based on the rotation movement of the earth, increasing the daylight hours it receives. This can be achieved with the use of control systems that integrate effective solar tracking algorithms. Recently, reinforcement learning (RL) has been applied to solar tracking systems, providing an adaptive and intelligent control mechanism. RL algorithms learn optimal control policies through trial-and-error, enhancing the system's ability to respond to varying environmental conditions. Models like Q-learning have shown promising results in maximizing solar energy capture [10].

Combining 2-DOF control strategies with reinforcement learning offers a powerful approach to solar tracking. In this paper, we present an innovative mechanical design for the 2-degree-of-freedom orientation of a photovoltaic panel, aimed at maximizing solar energy capture. Our approach leverages the Deep Deterministic Policy Gradients (DDPG) reinforcement learning algorithm, utilizing the intensities of solar rays as system states and controlling angular movements of individual motors as actions [11].

II. Methodology

A. Design of the Orientation Mechanism of the PV

Here we present the design of a two-degree-of-freedom orientation mechanism tailored which offers the flexibility of rotation in two distinct planes, allowing the panel to follow the sun's path both horizontally and vertically. Fig 1 shows the general design of the orientation mechanism.

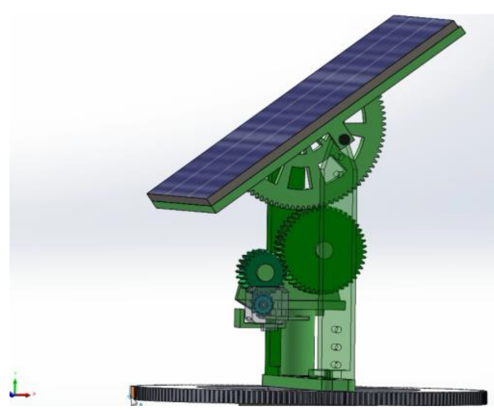

Fig. 1. General arrangement of the design of the orientation mechanism.

B. *Angular position control using the DDPG algorithm*

With the intention of controlling the angular position of the DC motor in radians, we use the deep reinforcement learning algorithm called DDPG, where a neural network called actor is used to approximate the policy of actions and another neural network called critic la which approximates the state-action functions (Q-values).

The algorithm parameters are shown in Table 1. The reward function used is:

$$\rho = -\left|\theta - \theta_{ref}\right|$$

Where θ is the angular position given in radians. The θ_{ref} value is given by the angle where the greatest amount of intensity of solar rays is received at a given moment by the sensors, at each start of the episode we propose as training start and set-point:

$$\theta_0 = \frac{\pi}{2} * u\left[0,1\right] \quad \theta_{ref} = \frac{\pi}{2} * u\left[0,1\right]$$

Where $u\left[0,1\right]$ is a uniform distribution function in the interval 0,1. So it guarantees us to explore each state and each action within this range of angles.

III. RESULTS OF SIMULATIONS

Fig 2 shows the graph of the reward obtained per episode, the value of the reward converges to a stationary value which results in a policy of deterministic actions.

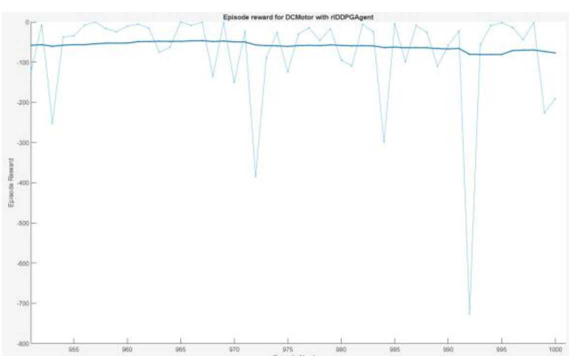

Fig. 2. . Rewards per episode

TABLE I. NEURAL NETWORK TRAINING PARAMETERS FOR CRITIC AND ACTOR

Learning Parameter	***Value***
Layers in the critic's NN	3 layers with 24 neurons
Layers in the actor's NN	5 layers with 24 neurons
Actor and critic learning rate	0.001
Sampling time	0.02 seg
buffer length	1000000
discount factor	0.99
lot size	64
Maximum number of episodes	1000
Average number of episodes	50

The results of the training are observed in Table 2

TABLE 2. SIMULATION RESULT

Description	***Value***
episodes	1000
average reward	-77.09
stop criteria	maximum number of episodes

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Fig 3 shows a tracking from 1.31 rad to 1.03 rad=.

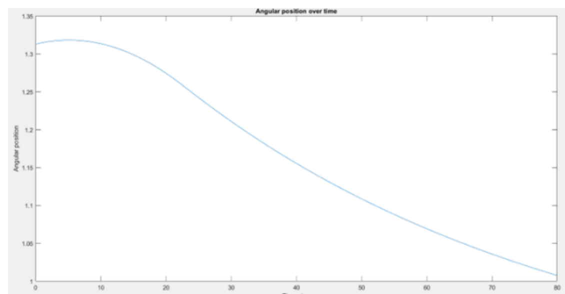

Fig. 3. Trajectory Tracking, Angular Position of the panel

IV. CONCLUSIONS

The integration of the DDPG algorithm for control demonstrates a promising approach to maximizing solar energy capture. Future work may explore further optimization and real-world applications of this mechanism.

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