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Sun Tracking using a Weightless Q-Learning Neural Network

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Abstract. Photovoltaic(PV) systems are one of the leading technologies to address climate change. Tracking systems improve energy generation by moving the surface to follow the sun's position however, these methods do not ensure optimal results in cloudy environments. This article proposes a closed-loop control algorithm for tracking based on reinforcement learning and weightless neural networks, compared to an astrological model. The method was applied in a single PV array on a single-axis tracking system, simulated with PVLib. Results showed that the architecture could improve results in cloudy environments but not in a clear-sky situation, as expected for a first approach.

1 Introduction

Addressing climate change is one of the most important and urgent goals for humanity according to United Nations [1], and renewable sources have a key role in the context, supplying the increasing energy demand with a low carbon footprint. In the projections of the International Energy Agency, renewables will become the largest source of electricity by 2025 global. Solar PV has been the fastest-growing technology and installed power capacity will be the largest in the world by 2027 [2].

Searches in PV Solar systems aims to improve the overall production with limited efficiency of the array cells[3], one of the approaches to solve the problem is the use of sun track systems. By following the sun, this system improves the amount of irradiance in the plane of the array, generating more electricity. The main challenges of sun tracking systems are to optimize the tracker position in cloudy environments. Studies showed that the direct sun tracking usually leads to an increase on the overall energy in a large period, but can lead to losses in cloudy days [4, 5].

This article proposes a control algorithm for sun tracking based on reinforcement learning and Weightless Neural Networks on a Single Axis Sun Tracking System. Weightless Neural Networks are supervised machine learning models based on kernel methods that have the advantage of being flexible and with low computational cost compared to traditional/weighted Artificial Neural Networks [6, 7].

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2 Background

Irradiance modeling. The irradiance on a surface depends on its position in relation to different sources. In the case of photovoltaic systems, the total plane of array irradiance is the sum of the direct beam irradiance, the diffuse irradiance in the sky, and the irradiance from the ground [8]. The PVlib package [9] is an open-source tool to simulate the performance of photovoltaic systems implementing multiple irradiance models.

Sun Tracking Systems. Solar Trackers are devices that position the surface towards the direct beam [3]. There are divided into three methods:(i) astronomical methods, calculated using latitude, longitude, and timestamp, (ii) image processing, using images from the sky to determine the sun's position, and (iii) LDR base, using luminosity sensor. Also, they may move the surface in one direction (single axis) or in two (double axis).

Q-Learn. Reinforcement learning is the set of methods to find optimal control of Markov decision. *Q-Learning* are off-policy temporal difference methods, which means that the Q function is learning during the process without considering the policy. It learns the optimal control by learning the optimal action-state value function, Q [7].

N-tuple Regressor. The Wisard is a lightweight online learning supervised learning model based on the N-Tuple classifier [10]. There is an alternative version adapted to perform regression task, called Regression Wisard [11]. It is composed of a set of N RAM nodes. It receives discrete inputs and learns by counting the occurrence of n-tuple patterns and summing the respective output. The prediction process is the average of the outputs of repeating patterns in the input. Katopodis et al [12] proposed the inclusion of a forgetting mechanism using a discounting rate, which improves the performance of the model in sequential decision contexts, such as reinforcement learning.

3 Weightless Q-Learning Neural Network Architecture

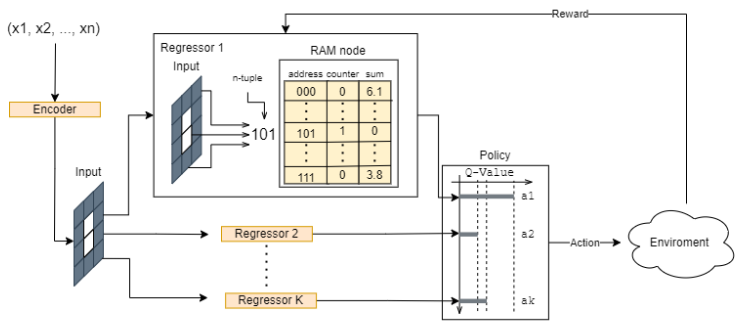

Fig. 1: Weightless Q-Learning Neural Network (WQNN) architecture representation.

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The proposed model aims to produce a control algorithm, whose inputs and feedback come from the environment, represented by Figure 1.

State and Encoder The first step of the model is to encode the continuous variables from the state, applying thermometers [13]. There are many types of thermometers and their choice should describe the input samples distribution, in order to maintain the relation between the Hamming distance of the encoded input and the actual difference of the samples.

N-tuple Regressor The principle of Q-Learn algorithms is to predict the Q values, given action, and state . N-tuple Regressors have the advantage of combining low usage of computational resources in training and prediction, with the high capability of generalization with a low number of hyperparameters. In this context, is important to include a forgetting mechanism in order to deal with the changes in the Q distribution [12].

Policy The policy uses the Q values predicted for each action to choose how to act. However, it is important to calibrate exploration and exploitation. Because of this, the policy to be applied must be chosen carefully.

Rewards The design of the reward is critical in reinforcement learning. The choice of the reward sets the goal of the algorithm and has a major influence on the convergence and stability of reinforcement learning methods [7].

In this article, inputs are the horizontal irradiance (ghi), solar zenith, solar azimuth, and array position/angle and the encoding method for each of them was the distributive thermometer, except by the array position that was a linear thermometer, resulting in 1320 bins in total. The regressor model to predict Q is the Regression Wisard, applying one predictor per action that receives the environmental variables as input. There are 5 available actions, moving 5 and 10 degrees up and down, or do not move, with the limitation that the position may stay between -60 and 60 degrees.

4 Evaluation Methodology

Dataset description Two datasets were applied in this article: (i) generated simulating a clear- sky meteorological year by PVlib and (ii) dataset from the weather station [A608] MACAE - RJ, published by INMET (National Institute of Meteorology) . The present work uses the PVLib to produce and decompose irradiance [14, 8] data supposing an array of PV modules in Macaé in 2022. The PVlib package [9] is an open-source tool to simulate the performance of photovoltaic systems. Some measurement errors from the weather station were adjusted and the final datasets are avaiable in `https://github.com/GlermS/esann-WQNN-2023`.

Learning process The learning process is based in daily episodes, sampled randomly. The algorithm applies the model in 2500 episodes and picks the last 25% the evaluate the results.

Parameters evaluation The present article explores 3 types of hyperparameters: (i) Tuple size z and discount rate α, related to the prediction model; (ii) Decay rate γ and learning rate β, related to *Q-Learn*; (iii) The ϵ, that controls

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the ϵ-*Greedy* policy. For each parameter, five values are tested (0.25, 0.50, 0.7, 0.9, 0.98), except by the tuple size has the following values tested: 10, 20, 40, 80, 160, 320, 640. The learning algorithm was applied in daily episodes randomly sampled.

5 Results

The results were divided in 2 subsections. The first presents the algorithm performance in the ideal scenario compared to the astronomical method, that is the exact solution in clear-sky conditions, referred as *astro model* [15]. The second subsection shows the application of the model in real conditions.

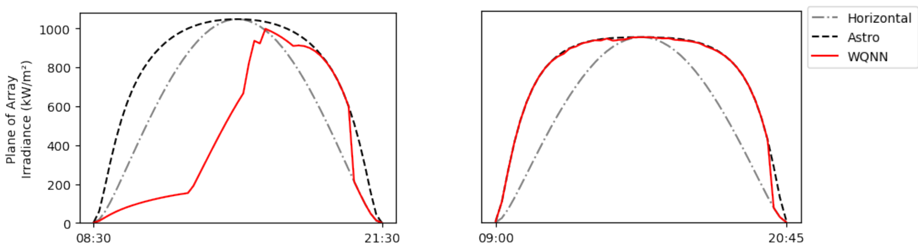
5.1 Clear sky conditions

The table 1 presents the 5 best parameters combinations in clear-sky conditions, measured by PR. The former is the Performance Ratio - the ratio of the accumulated plane of array irradiance using WQNN by the astro model. The transposition gain TG is the ratio of the accumulated plane of array irradiance compared to an horizontal static array.

ϵ	β	γ	α	z	$TG - Astro$	$TG - WQNN$	$ratio$
0.98	0.90	0.25	0.25	320	1.3468	1.3321	0.9891
0.98	0.70	0.25	0.70	160	1.3424	1.3241	0.9863
0.98	0.70	0.25	0.50	80	1.3213	1.3025	0.9858
0.98	0.90	0.25	0.50	160	1.3431	1.3240	0.9858
0.98	0.70	0.25	0.25	160	1.3318	1.3129	0.9858

Table 1: Best parameters combinations in clear-sky conditions.

It is noticeable that the algorithm was able to learn, even though the $WQNN$ was 1% below the *astro model*, there was a 30% gain compared to a static horizontal array. Figure 2 confirms the observation and shows the performance of both algorithms before and after the learning process.



(a) Before - 25^{th} eposide (b) After - 2500^{th} eposide

Fig. 2: Evolution of the proposed model in clear-sky.

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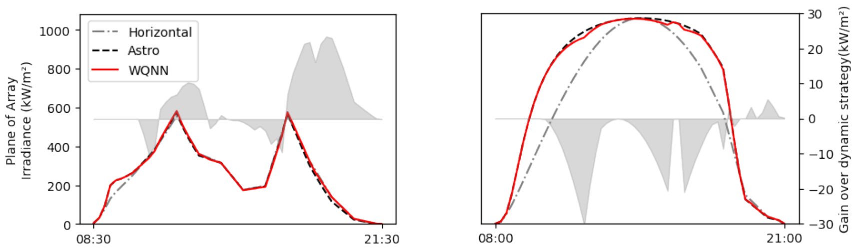
5.2 Real conditions

In cloudy conditions, the *astro model* does not ensure the optimality of the solution. Then, table 2 shows the best parameters combination applying data in 25 randomly sampled days from the real scenario, comparing the TG of both Base and $WQNN$ algorithms e their ratio.

ϵ	β	γ	α	z	$TG - Astro$	$TG - WQNN$	$ratio$
0.98	0.5	0.25	0.5	80.0	1.1181	1.1084	0.9913
0.98	0.5	0.25	0.7	320.0	1.1228	1.1127	0.9910
0.98	0.5	0.25	0.7	40.0	1.1458	1.1336	0.9893
0.9	0.98	0.25	0.25	80.0	1.1130	1.1008	0.9890
0.9	0.98	0.25	0.7	160.0	1.1333	1.1201	0.9884

Table 2: Best parameters combinations in real conditions.

The results in the table confirm that $WQNN$ can learn how to track also in a real scenario. The best parameters combination achieves 99.13% of the energy of the *astro model* and 111% compared to the static array. On the other hand, figure 3 demonstrates the advantage of $WQNN$ over *astro model* in cloudy moments, while tracking correctly in sunny moments.



(a) Cloudy day ($PR = 101.68\%$). (b) Sunny day ($PR = 99.83\%$).

Fig. 3: Real scenario application in different day. The grey area describes the difference between the $WQNN$ and the astronomical model.

6 Conclusion

This article proposed a closed-loop control algorithm based on reinforcement learning for sun tracking systems. The architecture was applied in a single array PV system simulated with the assistance of PVlib, compared with an astronomical model, and using a real and a clear-sky generated dataset. The methodology was based on random daily episodes with results evaluated in the last 25 episodes, reaching 99.11% of the astronomical model with 11% of transposition gain.

As expected, the $WQNN$ produced better results on cloudy days while tracking reasonably in clear-sky periods. These results give a good perspective as a

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first approach considering its flexibility, and simplicity. It is an plug-n-play algorithm to reach near-optimal results.

There is space for improvement in each of the steps of the architecture, opening opportunities for future works. The next works will compare the N-tuple regressor with other regression models, such as weighted Artificial Neural Networks. Further investigations will explore different decision policies to mitigate losses due to exploration. The algorithm has also the potential to maximize generation in more complex PV systems.

References

[1] Department of Economic United Nations and Social Affairs Sustainable Development. Transforming our world: the 2030 agenda for sustainable development, 2015.

[2] Global energy review 2021. Technical report, IEA, 2021.

[3] Gaafar E. G. Mustafa, Baraah A. M. Sidahmed, and Mustafa O. Nawari. The improvement of ldr based solar tracker's action using machine learning. In *2019 IEEE Conference on Energy Conversion (CENCON)*, pages 230–235, 2019.

[4] A Mohamad, H Mhamdi, NAM Amin, M Izham, NA Aziz, and SY Chionh. A review of automatic solar tracking systems. *Journal of Physics: Conference Series*, 2051(1):012010, oct 2021.

[5] R.G. Vieira, F.K.O.M.V. Guerra, M.R.B.G. Vale, and M.M. Araújo. Comparative performance analysis between static solar panels and single-axis tracking system on a hot climate region near to the equator. *Renewable and Sustainable Energy Reviews*, 64:672–681, 2016.

[6] L. A. Q. Villon, Z. Susskind, A. T. L. Bacellar, I. D. S. Miranda, L. Santiago de Araújo, Priscila M. V. Lima, M. Breternitz Jr., L. John, and D. L. Cadette Dutra Felipe M. G. França. A wisard-based conditional branch predictor. In *ESANN*, 2022.

[7] Richard S. Sutton and Andrew G. Barto. *Reinforcement Learning: An Introduction.* A Bradford Book, Cambridge, MA, USA, 2018.

[8] P.G. Loutzenhiser, H. Manz, C. Felsmann, P.A. Strachan, T. Frank, and G.M. Maxwell. Empirical validation of models to compute solar irradiance on inclined surfaces for building energy simulation. *Solar Energy*, 81(2):254–267, 2007.

[9] William F. Holmgren, Clifford W. Hansen, and Mark A. Mikofski. pvlib python: a python package for modeling solar energy systems. *Journal of Open Source Software*, 3(29):884, 2018.

[10] Pedro M. Xavier, Massimo De Gregorio, Felipe M. G França, and Priscila M. V. Lima. Detection of elementary particles with the wisard n-tuple classifier. In *ESANN*, 2020.

[11] Leopoldo A.D. Lusquino Filho, Luiz F.R. Oliveira, Aluizio Lima Filho, Gabriel P. Guarisa, Lucca M. Felix, Priscila M.V. Lima, and Felipe M.G. França. Extending the weightless wisard classifier for regression. *Neurocomputing*, 416:280–291, 2020.

[12] Rafael F. Katopodis, Priscila M.V. Lima, and Felipe M.G. França. Functional gradient descent for n-tuple regression. *Neurocomputing*, 500:1016–1028, 2022.

[13] Hugo C.C. Carneiro, Felipe M.G. França, and Priscila M.V. Lima. Multilingual part-of-speech tagging with weightless neural networks. *Neural Networks*, 66:11–21, 2015.

[14] H Hottel and B Woertz. Performance of flat-plate solar-heat collectors. *Trans. ASME (Am. Soc. Mech. Eng.); (United States)*, 64, 1 1942.

[15] Arslan A. Rizvi, Khaled Addoweesh, Abdelrehman El-Leathy, and Hany Al-Ansary. Sun position algorithm for sun tracking applications. In *IECON 2014 - 40th Annual Conference of the IEEE Industrial Electronics Society*, pages 5595–5598, 2014.