IRRADIANCE PREDICTION OVER TIME SERIES FOR THE USE OF PHOTOVOLTAIC ENERGY

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Motivation

- The use of fossil fuel-based energy worldwide is around 80%. [1]
- Approximately 52% of the Colombian territory is not *electrically interconnected*. [2].
- Call 933 Minciencias.
- Increase the accuracy of prediction.

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Problem Statement

Given $m \in N$, $I_k \in R^N$ where N is the amount of samples in the time serie, the relationship between I_k and its past values $I_{k-1}, I_{k-2}..., I_{k-m}$ can be described by

$$I_k = \phi_1 f(I_k - 1) + \phi_2 g(I_k - 2) + ... + \phi_m f(I_k - m) \quad (1)$$

There are several ways to calculate the coefficients ϕ and the functions involving irradiance values [3], [4].

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Problem Statement

Based on the previous description, the following problems can be identified:

1 **Non-stationarity due to climate variability prevents models from capturing the complex relation among the data** [3], [4].

2 Most methods are focused on specific locations and cannot be generalized to other locations [5].

3 The non-linearity of time series makes it difficult to represent complex dependencies over time, including long-term progressions and seasonal patterns [6].

4 Data augmentation due to missing data can lead to problems related to the failure to extract intrinsic properties and task dependence[7],[4].

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Classification according to the prediction method

Figure: State of the art in irradiance prediction

DATASETS

The following datasets are used to make experiments

Dataset	Variable	Max Value	Min Value
Solcast	Global Solar irradiance (w/m^2)	1134	0
Ideam	Global solar irradiance (w/m^2)	1103	0
Fronius	Global solar irradiance (w/m^2)	1773.5	0
Jenna	Temperature (℃)	37.3	-22.6

Table: Datasets Information

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Solcast

Solcast operates a global cloud tracking and prediction system that uses near real-time satellite imagery from 11 weather satellites and weather data from 7 numerical weather prediction (NWP) models [8].

Geographic Coverage	**Temporal Coverage**
Global (except for the ocean and polar region)	Since January 2007
Udenar is used in the research	January 2014-April 2024 is used in the research
Time Recording	**Variables**
5 minutes	Global Solar Irradiance (w/m^2)
	Precipitation (mm/h)
60 minutes is used in the research	Temperature (℃), etc

Table: Solcast Information

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Ideam

IDEAM (Instituto de Hidrología, Meteorología y Estudios Ambientales) plays a crucial role in monitoring and prediction weather patterns in order to manage water resources, and conducting environmental assessments in Colombia [9].

Udenar 52045080		
Temporal Coverage	**Time recording**	**Variables**
Since 01/01/16 until 31/07/21	One hour	Irradiation (whr/m^2)
Since 01/11/16 until 18/04/24		Precipitation (mm) Temperature (°C) Min temperature (°C) Max temperature (°C) Humididty (%)

Table: Ideam Information

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Fronius

Fronius is an Austrian company that specializes in solar energy, welding, and battery charging technology. This technology is currently being used at Udenar to measure data on the energy produced in the area [10].

Geographic Coverage	**Temporal Coverage**
Udenar	January 2023-June 2023
Time Recording	**Variables**
5 minutes	Voltage (V)
60 minutes is used in the research	PV production (Kw.hr/day), etc

Table: Fronius Information

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Jenna

Jena Climate is weather time series dataset recorded at the Weather Station of the Max Planck Institute for Biogeochemistry in Jena, Germany [11].

Geographic Coverage	**Temporal Coverage**
Jenna, Germany	January 2009-December 2016
Time Recording	**Variables**
10 minutes 60 minutes is used in the research	14 (temperature, *pressure*, humidity, etc)

Table: Jenna Information

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predictorS

As a preliminar analysis the following predictors are used:

- Long Short Term Memory (LSTM)
- Gated Recurrent Unit (GRU)
- Extreme Gradient Boosting (XGB)

The previous methods are used in a time-based cross-validation scheme to evaluate them across all samples.

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LSTM

LSTM is a improved version of recurrent neural network (RNN) since the network can remember both short term and long term values [12].An LSTM unit is composed of cells, each with an input gate, output gate, and forget gate.
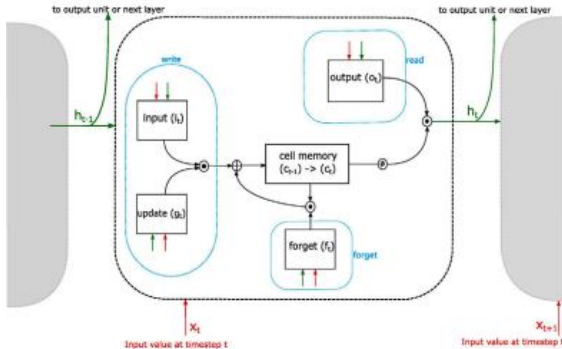

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Figure: LSTM General architecture. Taken from [13])

GRU

GRU is another type of RNN designed to address problems related to vanishing and exploding gradients. Unlike LSTM, GRU is simpler to apply and compute [4].
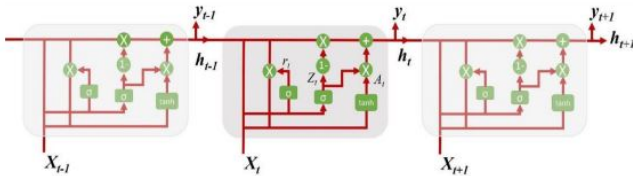

Figure: GRU General architecture. Taken from [4]

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XGB

An XGBoost method is an ensemble of several models that work together to fit the residuals of each preceding model. Therefore, XG-Boost can easily learn interactions among features [14].
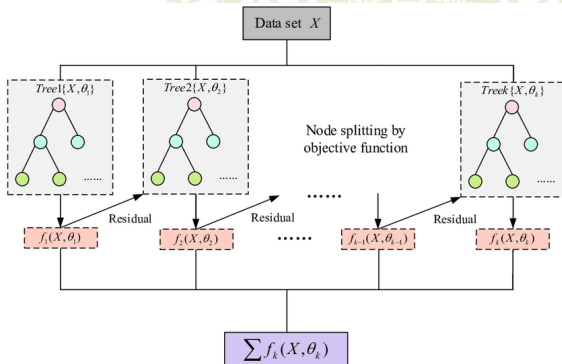

Figure: XGB General architecture. Taken from [15]

Architectures

Based on the research carried out by [16], the next architectures are evaluated over the datasets.

LSTM and GRU	
Inputs	None (ghi or temperature)
Outputs	1(ghi or temperature)
Number of layers	3 (input, hidden with 20 neurons, output)
Epochs	30
Learning algorithm	Adam (learning rate=0.07)
XGB	
Inputs	None (ghi or temperature)
Outputs	1(ghi or temperature)
Booster	gbtree
n estimators	100
max depth	4

Table: Architectures used

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MEASUREMENTS: Auto Correlation

Auto correlation measures the similarity between observations of a time series at different time lags. This measurement is used to determine whether the series are independent and to establish the number of samples required for certain tests in the experimental section.

$$k(t, t - k) = \frac{Cov(X_t, X_{t-k})}{\sqrt{Var(X_t)Var(X_{t-k})}} \tag{2}$$

where $Cov(.)$ represents the covariance and $var(.)$ the variance.

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MEASUREMENTS: Accuracy measurements

The next measurements are used to evaluate the accuracy of the predictors.

Measurement	Abrev	Fórmula	Rango
Mean Bias Error [5]	MBE	$\frac{1}{N}\sum_{i=1}^{N}(p_m - p_p)$	$[\infty, \infty]$
Root Mean Square Error [17]	RMSE	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_m - p_p)^2}$	$[0, \infty]$
Determination coefficient [7]	R^2	$1 - \frac{\sum_{i=1}^{N}(p_m - p_p)^2}{\sum_{i=1}^{N}(p_m - \bar{p}_m)^2}$	$[0, 1]$

Table: Measurements used

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EXPERIMENTS

To apply the previously described prediction methods, first a preprocessing step is carried out, followed by four sets of tests.
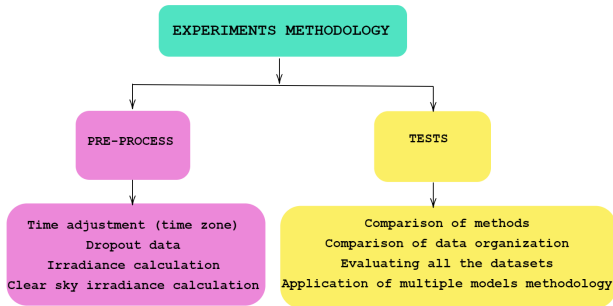

Figure: Methodology of experiments

Pre process

1. **Time adjustment** is applied to Solcast data to align it with the Colombian time zone.

2. **Dropout night data** is done since there is no irradiance at this time.

3. Since Fronius and Ideam record PV production and irradiation respectively, there is a need to **calculate irradiance** first.

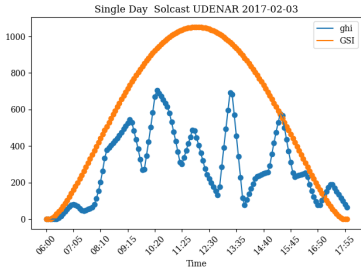4. **Clear sky irradiance** is also calculated to make future experiments.

Pre process

Figure: Measured and theoretical GHI from Solcast

Figure: Measured temperature from Jenna
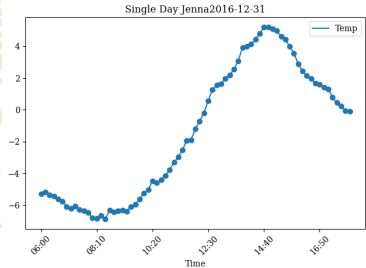
Figure: Parameters after the pre process

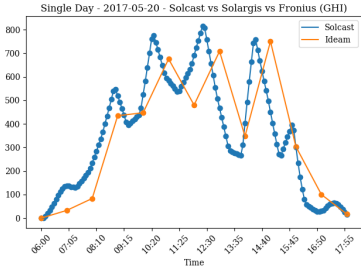UNIVERSIDAD
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Pre process

Figure: Measured GHI from Solcast and Ideam
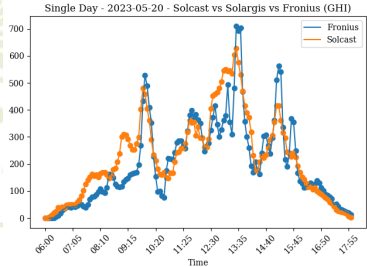
Figure: Measured GHI from Solcast and Fronius

Figure: Parameters after the pre-process

Tests methodology

Firstly, a **Normalization** between 0 and 1 is applied to all datasets and subsequently four sets of tests are carried out.

Test set 1	
Objective	To select the best predictor among those compared
predictor	LSTM, GRU, XGB
Input samples	One
Output samples	One
Dataset	Solcast
Tests done	Three (1A, 1B, 1C)

Table: Test set 1 description

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Tests methodology

Since XGB was the best predictor, the next test sets are developed with this one.

Test set 2	
Objective	To select the data organization to feed the predictors
predictor	XGB
Input samples	Thirteen/Seven/One hundred thirty
Output samples	One/One/Thirteen
Dataset	Solcast
Tests done	Three (2A, 2B, 2C)

Table: Test set 2 description

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Tests methodology

Since using thirteen samples to predict the next one proved to be the most effective technique for feeding the predictors; the subsequent tests are conducted using this methodology.

	Test set 3
Objective	To evaluate the method on different datasets
predictor	XGB
Input samples	Thirteen
Output samples	One
Dataset	Ideam, Fronius, Jenna
Tests done	Three (3A, 3B, 3C)

Table: Test set 3 description

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Tests methodology

Finally, hour predictions are made using a different model.

	Test set 4
Objective	To evaluate an hourly model methodology
predictor	XGB
Input Samples	Thirteen
Output Samples	One
Dataset	Solcast, Jenna
Tests done	Two (4A, 4B)

Table: Test set 4 description

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RESULTS: Test set 1

Single Input Single Output - Solcast dataset						
predictor	**Training**			**Testing**		
	MBE (w/m^2)	**RMSE** (w/m^2)	**R2**	**MBE** (w/m^2)	**RMSE** (w/m^2)	**R2**
LSTM	21.17	179.62	0.55	23.21	186.53	0.55
GRU	23.08	182.52	0.54	24.75	189.53	0.53
XGB	**0**	**174.52**	**0.57**	**2.51**	**183.11**	**0.56**

Table: Set tests 1 results

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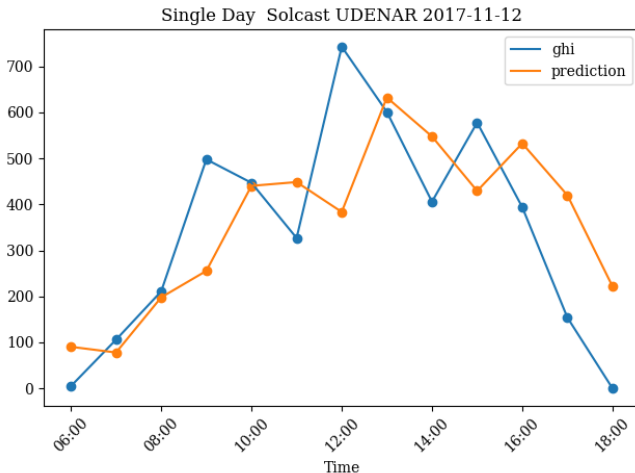NACIONAL
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RESULTS: Test set 1

Figure: Measured GHI vs predicted GHI using XGB

RESULTS:Test set 2

The number of samples used in the first and third tests is determined based on the recommendation given by [9], while the number of samples in the second test is determined by applying correlation measurements, obtaining the following results.
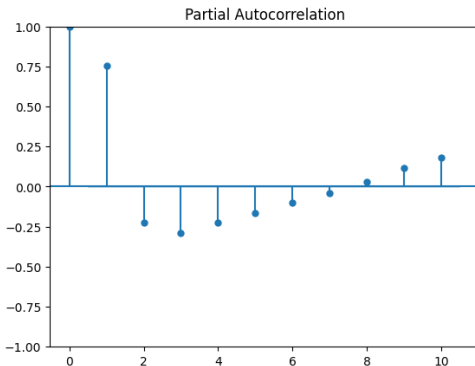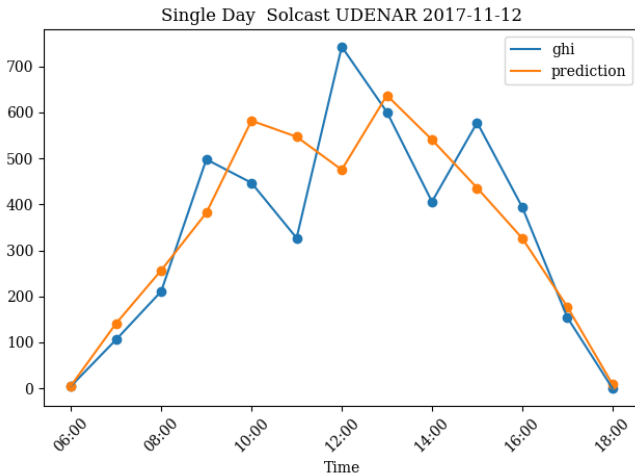

Figure: Solcast autocorrelation

RESULTS: Test set 2

XGB - Solcast dataset						
Input Samples/ Output Samples	**Training**			**Testing**		
	MBE (w/m^2)	**RMSE** (w/m^2)	**R2**	**MBE** (w/m^2)	**RMSE** (w/m^2)	**R2**
13/1	**0.02**	**130.46**	**0.76**	2.73	**140.38**	**0.74**
7/1	0.04	138.31	0.73	**-1.48**	147.97	0.72
130/13	0	151.31	0.68	3.77	168.64	0.63

Table: Set tests 2 results

RESULTS: Test set 2

Figure: Measured GHI vs predicted GHI using 13 samples to predict the next one

RESULTS: Test set 3

Multiple Input Single Output-XGB						
Dataset	**Training**			**Testing**		
	MBE (w/m^2)	**RMSE** (w/m^2)	**R2**	**MBE** (w/m^2)	**RMSE** (w/m^2)	**R2**
Ideam	**0**	128.49	0.78	-2.38	**139.66**	**0.72**
Fronius	0	**100.72**	**0.84**	**-2.23**	151.87	0.59
Jenna	0	1.37	0.98	0.031	1.48	0.97

Table: Set tests 3 results

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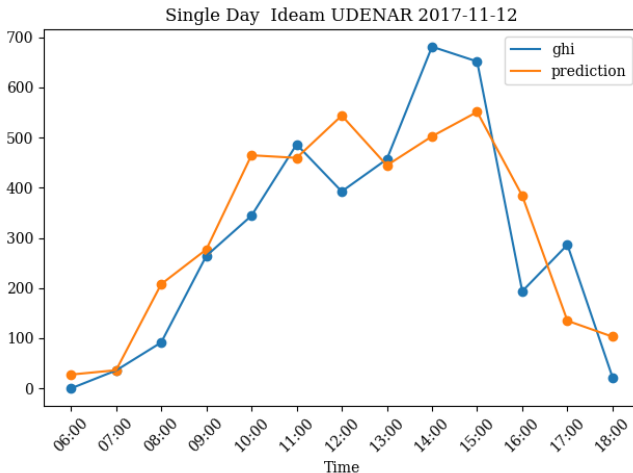
RESULTS: Test set 3

Figure: Measured GHI vs predicted GHI on IDEAM

RESULTS: Test set 4

Multiple Input Single Output-XGB-Model per hour						
Dataset	**Training**			**Testing**		
	MBE	**RMSE**	**R2**	**MBE**	**RMSE**	**R2**
Solcast (w/m^2)	-0.03	78.63	0.73	1.81	121.69	0.4
Jenna (℃)	0	1.73	0.95	0.22	2.56	0.86

Table: Set tests 4 results

RESULTS: Test set 4
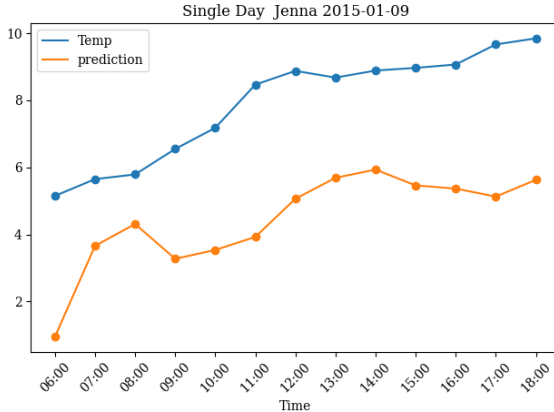
Figure: Measured Temperature vs predicted Temperature on Jenna

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Final discussion Solcast

Tests summary - Solcast - XGB						
Test set	**Training**			**Testing**		
	MBE (w/m2)	**RMSE (w/m2)**	**R2**	**MBE (w/m2)**	**RMSE (w/m2)**	**R2**
1C	**0**	174.52	0.57	2.51	183.11	0.56
2A	0.02	130.46	**0.76**	2.73	140.38	**0.74**
4A	-0.03	**78.63**	0.73	**1.81**	**121.69**	0.4

Table: Solcast Results Summary

Final discussion Solcast
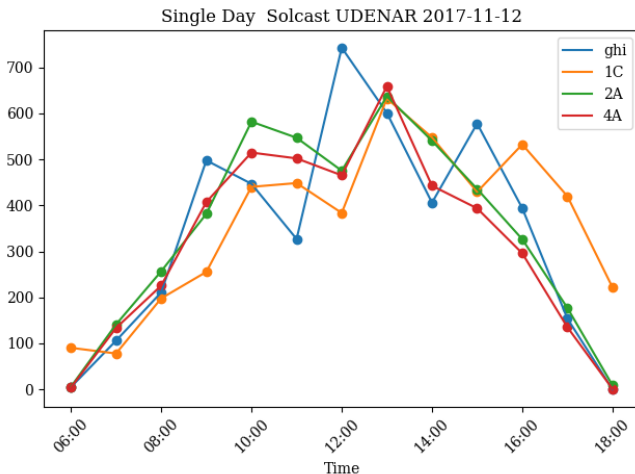

Figure: Measured GHI vrs predicted GHI with different methods

Final discussion Jenna

Tests summary - Jenna - XGB						
Test set	**Training**			**Testing**		
	MBE (w/m2)	**RMSE (w/m2)**	**R2**	**MBE (w/m2)**	**RMSE (w/m2)**	**R2**
3C	**0**	1.37	0.98	0.03	1.48	0.97
4B	0	1.73	**0.955**	0.22	2.56	**0.86**
[18]	-	**0.80**	-	**-**	**0.87**	-

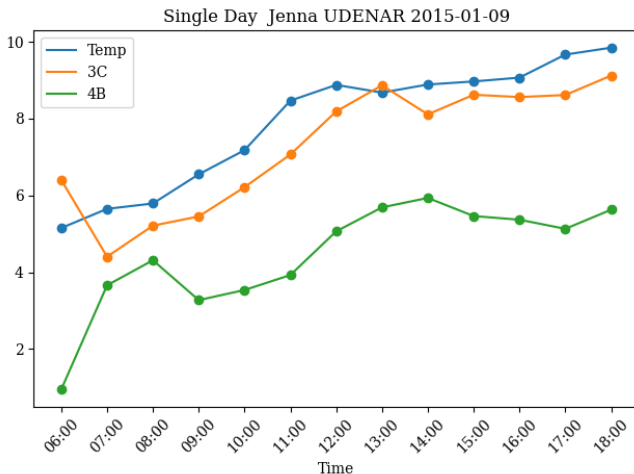Table: Jenna Results Summary

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Final discussion Jenna

Figure: Measured Temperature vrs predicted Temperature with different methods

Final discussion

The most important results are the following:

- As shown in set tests 2, using several samples to predict the next one significantly improves the results if compared to using only one previous sample.

- According to set tests 4 it is concluded that it is better to use a different model for each hour instead of using only one model to predict the GHI the next thirteen hours. Moreover, predicting all the values (multiple output) in a day decreases the accuracy of the prediction as seen in test 2C.

- Comparing Test 2A and Test 2B, it is concluded that if a window approach with a different analysis is carried out, it improves the accuracy.

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Future work

As further research the next tasks are proposed:

- To evaluate other methods such as: Gaussian process, hybrid methods, transformers.
- To find a relationship between Solcast and Ideam Data to take advantage of the two kind of data.

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References I

[1]   Noor Bariah Mohamad, An-Chow Lai, and Boon-Han Lim. "A case study in the tropical region to evaluate univariate imputation methods for solar irradiance data with different weather types". In: **Sustainable Energy Technologies and Assessments** 50 (2022), p. 101764.

[2]   Gabriel Narvaez et al. "The impact of climate change on photovoltaic power potential in Southwestern Colombia". In: **Heliyon** 8.10 (2022).

[3]   Jwaone Gaboitaolelwe et al. "Machine learning based solar photovoltaic power forecasting: a review and comparison". In: **IEEE Access** 11 (2023), pp. 40820–40845.

[4]   Abbas Mohammed Assaf et al. "A review on neural network based models for short term solar irradiance forecasting". In: **Applied Sciences** 13.14 (2023), p. 8332.

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References II

[5]   Laith Abualigah et al. "Wind, solar, and photovoltaic renewable
        energy systems with and without energy storage optimization:
        A survey of advanced machine learning and deep learning
        techniques". In: **Energies** 15.2 (2022), p. 578.

[6]   Meenu Ajith and Manel Martínez-Ramón. "Deep learning al-
        gorithms for very short term solar irradiance forecasting: A
        survey". In: **Renewable and Sustainable Energy Reviews**
        182 (2023), p. 113362.

[7]   Qingsong Wen et al. "Time series data augmentation for deep
        learning: A survey". In: **arXiv preprint arXiv:2002.12478**
        (2020).

[8]   Abdulrahman Almarshoud et al. "Validation of satellite-derived
        solar irradiance datasets: a case study in Saudi Arabia". In:
        Future Sustainability 2.2 (2024), pp. 1–7.

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References III

[9]   Laura S Hoyos-Gómez, Jose F Ruiz-Muñoz, and Belizza J Ruiz-Mendoza. "Short-term forecasting of global solar irradiance in tropical environments with incomplete data". In: **Applied Energy** 307 (2022), p. 118192.

[10]   Gentiana Alija, Armend Ymeri, and Nexhmi Krasniqi. "Study aspects for the solar-photovoltaic system with installation Capacity of 60.3 kwp". In: (2021).

[11]   K Venkatachalam et al. "DWFH: An improved data-driven deep weather forecasting hybrid model using Transductive Long Short Term Memory (T-LSTM)". In: **Expert systems with applications** 213 (2023), p. 119270.

[12]   Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu. "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019". In: **Applied soft computing** 90 (2020), p. 106181.

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References IV

[13] Pratima Kumari and Durga Toshniwal. "Deep learning models for solar irradiance forecasting: A comprehensive review". In: **Journal of Cleaner Production** 318 (2021), p. 128566.

[14] Hanjin Zhang et al. "A novel hybrid transformer-based framework for solar irradiance forecasting under incomplete data scenarios". In: **IEEE Transactions on Industrial Informatics** (2024).

[15] Rui Guo et al. "Degradation state recognition of piston pump based on ICEEMDAN and XGBoost". In: **Applied Sciences** 10 (Sept. 2020), p. 6593. DOI: 10.3390/app10186593.

[16] Garazi Etxegarai et al. "An analysis of different deep learning neural networks for intra-hour solar irradiation forecasting to compute solar photovoltaic generators' energy production". In: **Energy for Sustainable Development** 68 (2022), pp. 1–17.

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References V

[17] Bryan Lim and Stefan Zohren. "Time-series forecasting with deep learning: a survey". In: **Philosophical Transactions of the Royal Society A** 379.2194 (2021), p. 20200209.

[18] Hemant Yadav and Amit Thakkar. "NOA-LSTM: An efficient LSTM cell architecture for time series forecasting". In: **Expert Systems with Applications** 238 (2024), p. 122333.

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