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Solar Power Forecasting Based on Ensemble Learning Methods

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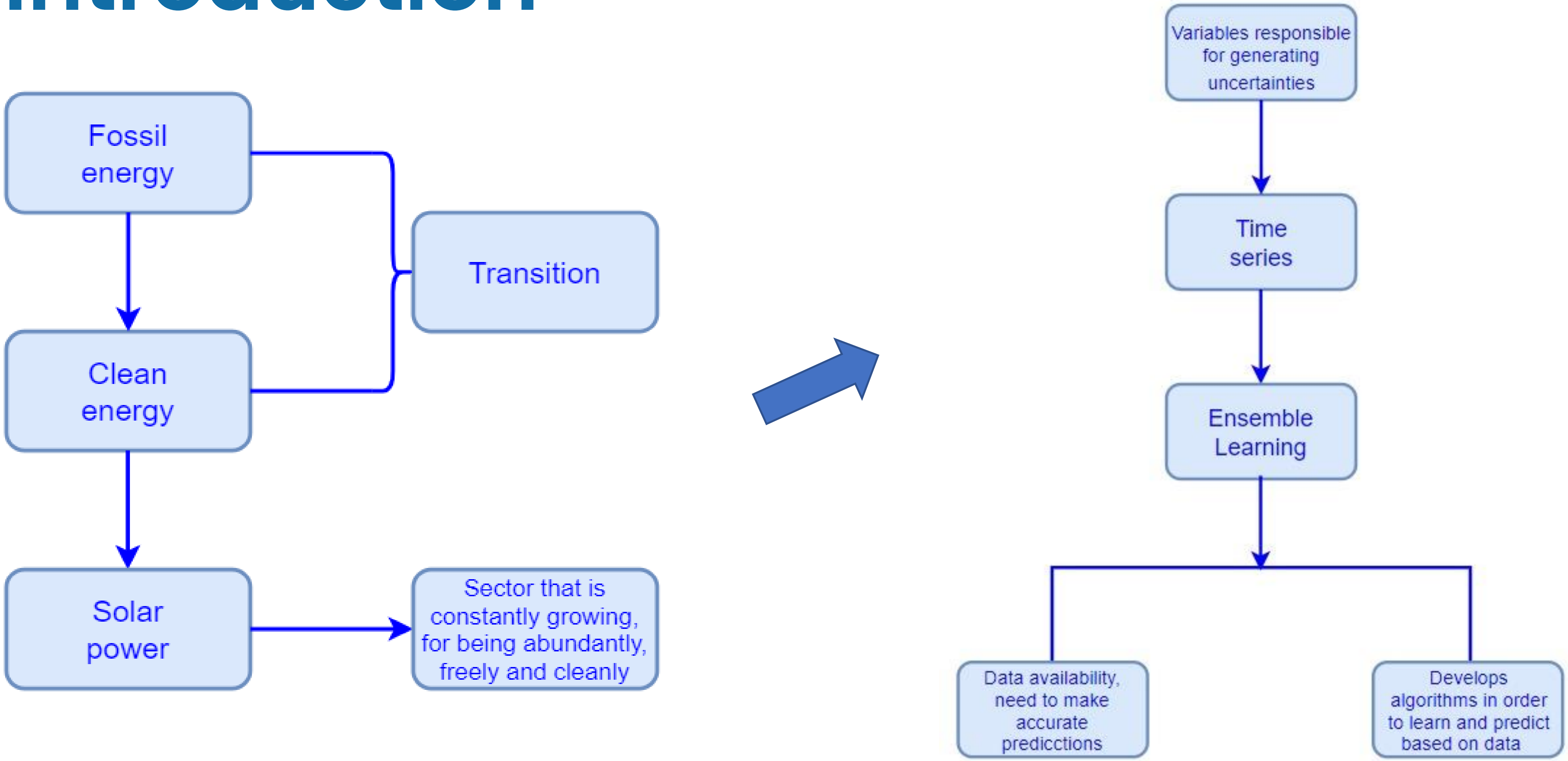
Agenda

- Introduction
- Objectives
- Material
- Methods
- Methodology
- Results
- Conclusion
- Acknowledgments

Introduction



Objectives

MAIN OBJECTIVE:

- Forecasting solar power generation.

SPECIFIC OBJECTIVES:

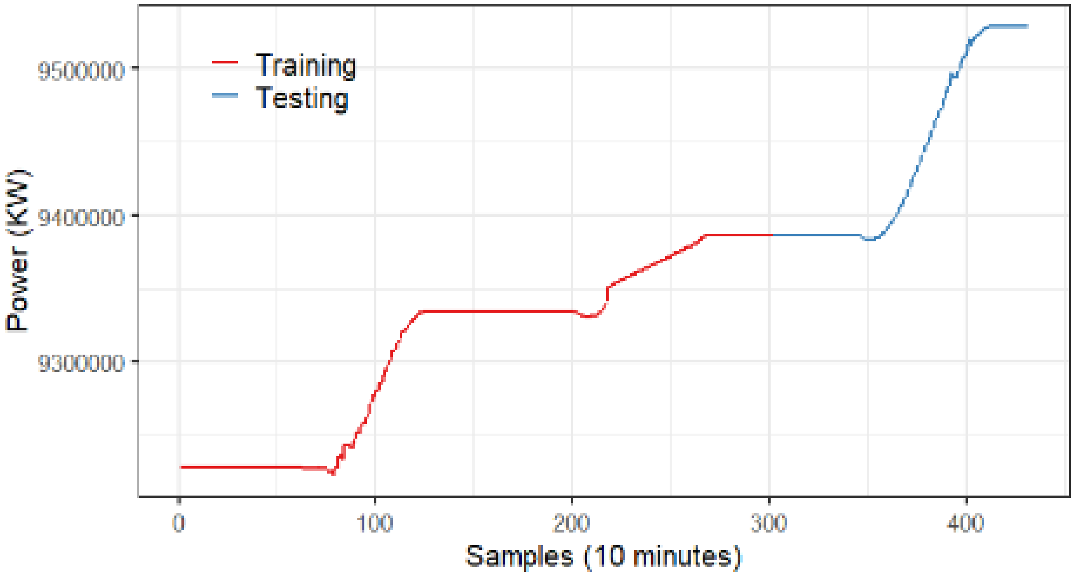
- Applying regression approaches;
- Developing a model to forecast solar power generation;
- Identifying suitable machine learning techniques;
- Improving the forecasting accuracy of solar power generation.

Material

- Photovoltaic plant of 26.35 MWp;
- Location: Artigas, Uruguay;
- No. of samples: 432;
- Period: 04/14/2018, 00:00h to 04/16/2018, 23h50;
- Collection: every 10 minutes;

Material

- The dataset was split into training (70%) and test (30%) sets:



- The system inputs and output (3 variables) are described in the following table:

INPUTS AND OUTPUT OF THE SYSTEM

Type	Description	Unit Measure
Input	Temperature	C°
Input	Radiation	W/m^2
Output	Power	kW

Methods

- Stacking-Ensemble Learnig (STACK);

Models used in the STACK method:

- CUBIST;
- Multivariate Adaptive Regression Splines (MARS);
- Linear Model (LM);
- Bayesian Regularized Neural Network (BRNN);
- Support Vector Regression with Linear, and Radial Basis Function kernel (SVRL and SVRR).

Methods

Pre-processing techniques:

- Principal Component Analysis (PCA);

(DU; ZHU, 2019)

- Correlation Matrix (CORR)

(KUHN; JOHNSON, 2013)

Methods

Performance Measures:

Relative Root Mean Square Error (RRMSE)

- $RRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\frac{1}{n}\sum_{i=1}^{n} y_i}$

Determination Coefficient (R^2)

- $R^2 = 1 - \frac{\sum_{i=1}^{n}[y_i(t) - \hat{y}_i(t)]^2}{\sum_{i=1}^{n}[y_i(t) - \bar{y}_i(t)]^2}$

Symmetric Mean Absolute Percentage Error (sMAPE)

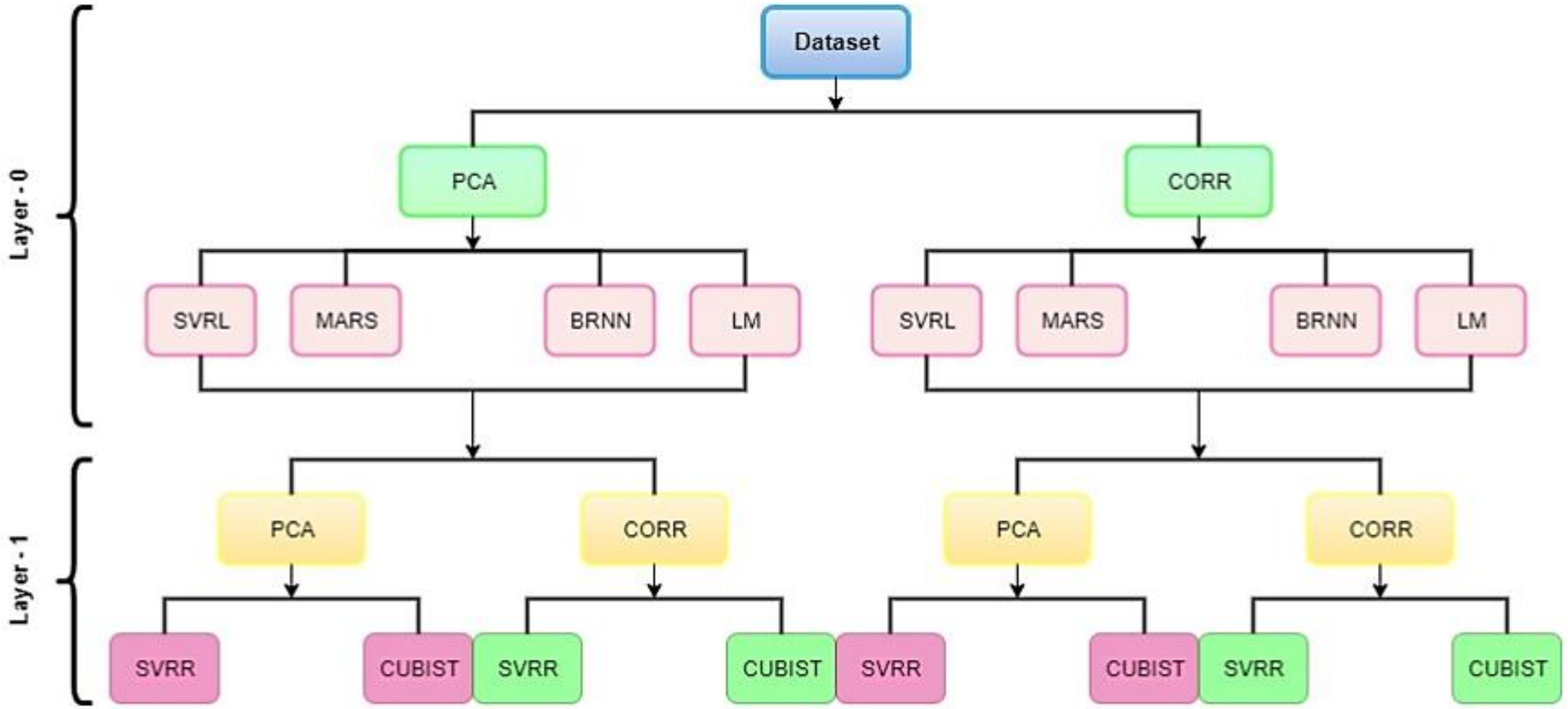
- $sMAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{|y_i| + |\hat{y}_i|/2}\right|$

Statistical test:
Diebold-Mariano test

$$\mathrm{DM} = \frac{\frac{\sum_{n}^{i=1}[d_i]}{n}}{\sqrt{\frac{\mathrm{var}(d_i)}{n-1}}}$$

Methodology

Steps for developing the proposed model:



Results

- CORR models presented better results than PCA models due to the fact that CORR removed the high correlated features;
- The combination CORR-LM obtained best results of the single models;
- The CORR-CORR-CUBIST-STACK obtained best results of the STACK models;
- Comparing best single and STACK models, the CORR-LM presented better performance.

PERFORMANCE MEASURES RESULTS OF THE MODELS

METRIC METHODS \Layer-0				METRIC METHODS STACK \Layer-1			
	sMAPE	RRMSE	R^2		sMAPE	RRMSE	R^2
PCA-SVRL	9.449549e-04	9.779133e-04	0.9997	PCA-PCA-SVRR-STACK	0.0108	0.0145	0.7025
PCA-MARS	9.473985e-04	1.018069e-03	0.9984	PCA-PCA-CUBIST-STACK	0.0056	0.0083	0.3338
PCA-BRNN	1.742184e-03	2.488815e-03	0.9946	PCA-CORR-SVRR-STACK	0.0103	0.0131	0.5773
PCA-LM	1.851099e-04	2.111932e-04	0.9998	PCA-CORR-CUBIST-STACK	0.0057	0.0084	0.4026
CORR-SVRL	1.074919e-03	1.171680e-03	0.9999	CORR-PCA-SVRR-STACK	0.0117	0.0147	0.6002
CORR-MARS	2.798447e-05	6.844400e-05	0.9999	CORR-PCA-CUBIST-STACK	0.0039	0.0059	0.9489
CORR-BRNN	1.969842e-03	3.000576e-03	0.9959	CORR-CORR-SVRR-STACK	0.0101	0.0132	0.4232
CORR-LM	**1.100414e-05**	**2.372946e-05**	**0.9999**	CORR-CORR-CUBIST-STACK	0.0014	0.0024	0.9874

Results

DIEBOLD-MARIANO TEST RESULTS

Model	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	(L)	(M)	(N)	(O)	(P)
(A) PCA-PCA-SVRR-STACK	-	8.8299*	8.9003*	8.7990*	1.2679	8.6965*	8.8302*	8.6453*	8.6432*	8.6432*	8.6451*	8.6432*	8.6432*	8.6432*	8.6467*	8.6432*
(B) PCA-PCA-CUBIST-STACK	-	-	-8.7708*	-1.757726	-8.9679*	7.2834*	-8.8186*	7.2895*	7.2863*	7.2860*	7.2895*	7.2866*	7.2861*	7.2866*	7.2870*	7.2866*
(C) PCA-CORR-SVRR-STACK	-	-	-	8.7187*	-9.2565*	8.5678*	-9.9921*	8.4939*	8.4909*	8.4908*	8.4937*	8.4909*	8.4909*	8.4909*	8.4958*	8.4909*
(D) PCA-CORR-CUBIST-STACK	-	-	-	-	-8.9366*	7.8333*	-8.7683*	7.6795*	7.6726*	7.6724*	7.6789*	7.6729*	7.6725*	7.6729*	7.6813*	7.6729*
(E) CORR-PCA-SVRR-STACK	-	-	-	-	-	8.8166*	9.2023*	8.7595*	8.7572*	8.7572*	8.7593*	8.7572*	8.7572*	8.7572*	8.7611*	8.7572*
(F) CORR-PCA-CUBIST-STACK	-	-	-	-	-	-	-8.6131*	7.2270*	7.2159*	7.2150*	7.2258*	7.2168*	7.2150*	7.2168*	7.2181*	7.2168*
(G) CORR-CORR-SVRR-STACK	-	-	-	-	-	-	-	8.5384*	8.5353*	8.5353*	8.5382*	8.5354*	8.5353*	8.5354*	8.5403*	8.5354*
(H) CORR-CORR-CUBIST-STACK	-	-	-	-	-	-	-	-	6.8960*	6.8658*	4.8139*	6.9226*	6.8642*	6.9228*	-7.4720*	6.9229*
(I) PCA-SVRL	-	-	-	-	-	-	-	-	-	-2.1311**	-6.8965*	10.2051*	-8.3503*	10.2451*	-7.1830*	10.2507*
(J) PCA-MARS	-	-	-	-	-	-	-	-	-	-	-6.8604*	6.6480*	-4.4925*	6.6627*	-7.1694*	6.6631*
(K) PCA-BRNN	-	-	-	-	-	-	-	-	-	-	-	6.9237*	6.8613*	6.9240*	-7.4023*	6.9240*
(L) PCA-LM	-	-	-	-	-	-	-	-	-	-	-	-	-9.5986*	4.4538*	-7.1964*	8.5665*
(M) CORR-SVRL	-	-	-	-	-	-	-	-	-	-	-	-	-	9.6156*	-7.1692*	9.6163*
(N) CORR-MARS	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-7.1965*	1.3622
(O) CORR-BRNN	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	7.1965*
(P) CORR-LM	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Note: *1% significance level; **5% significance level.

Conclusion

- In this case all single models presented better results when compared to STACK models, obtaining satisfactory values in all performance measures.
- And the single model CORR-LM obtained the best results of them all, in the three performance measures.
- As proposed for future research:

(i) Using different algorithms in both STACK layers;

(ii) Increasing the number of steps ahead for forecasting;

(iii) Using other renewable energy sources - such as wind and biomass - for comparative studies.

Acknowledgments

CAPES

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Thank you!