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Solar Power Generation Analysis and Forecasting Real-World Data Using LSTM and Autoregressive CNN

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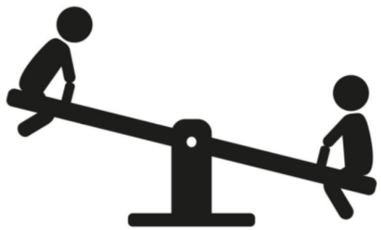
Background and Motivation

Supply



Demand

There are **571** registered solar power plants (6.166 MW) **(% 6,69)** [1]

There are **219** registered natural gas power plants(25.615 MW) **(% 27,81)** [2]

Meaning that distribution of PV systems being wide-spread over the country with small power range.

More PV penetration in grids. → Stability issues, Market problems. → PV generation forecast is required.

The reason: Generated power of PV is **volatile** and **susceptible** to environmental conditions.

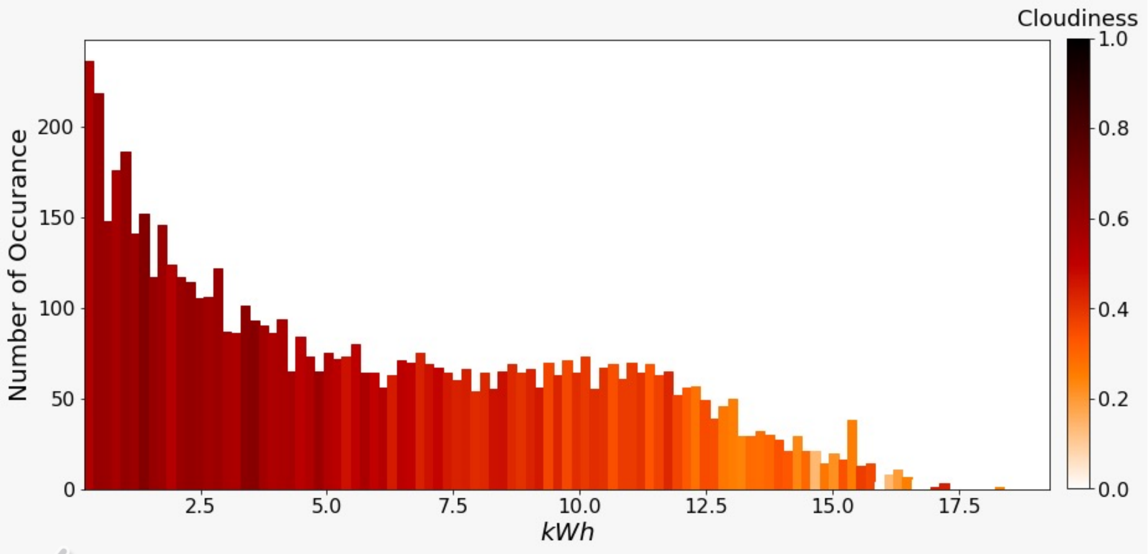
Background and Motivation

Solar power forecasting methods can be classified into three groups [4],

1. Time series-statistical
2. Physical
3. Ensemble.

- Physical methods, such as sky and satellite imagery requires additional hardware and computational complexity to capture and process these images.
- Distribution of PV systems being wide-spread over the country with small power ranges

Cost-free solutions are essential!



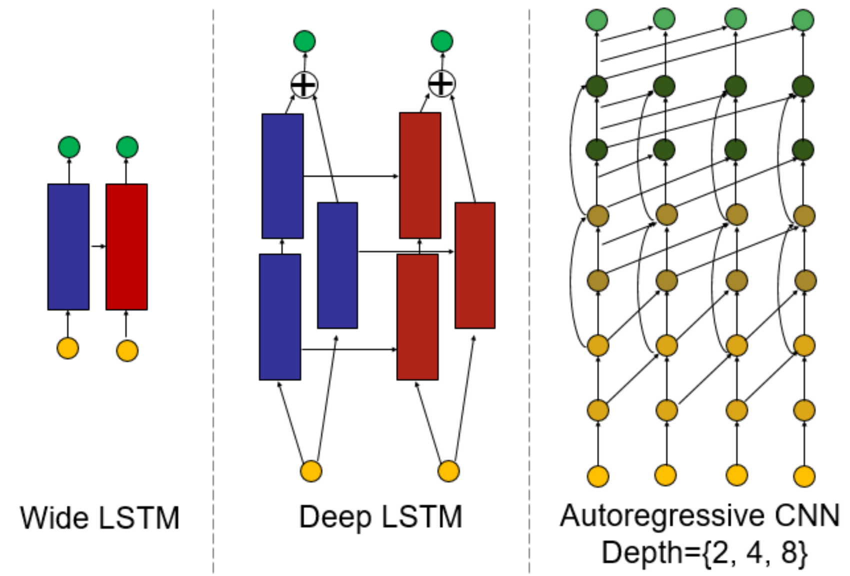
Trade of alert!!

Physical and ensemble methods can promise more accurate performance, however with a price cost!

Background and Motivation

Auto-regressive CNN has already used in time-series problems in the literature.

«WaveNet is a powerful new predictive technique that uses multiple Deep Learning (DL) strategies from Computer Vision (CV) and Audio Signal Processing models and applies them to longitudinal (time-series) data.» [5]

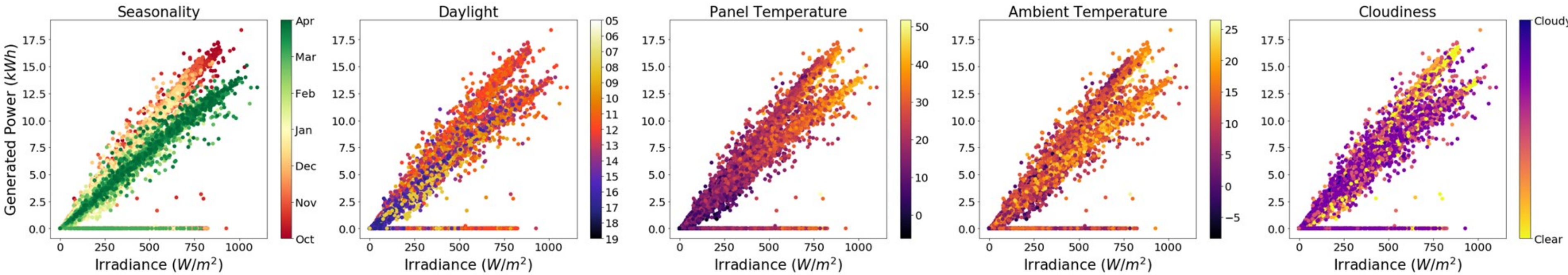


The best of our knowledge, different implementations like W-LSTM and Auto-Regressive CNN are not employed in PV generation forecast problems.

Sophisticated ML models are better in capturing the relation between the input variables and the PV power production compared to the more simple linear models. [6]

AIM: to **investigate the suitability of the WaveNets** in PV power forecasting problems

Analysis and Error Measures



(a) (b) (c) (d) (e)

Temperature effect can be understood by seasonality plot.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x-\hat{x}\right)^2}$$

Second order error measure.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|x-\hat{x}|$$

First order error measure, also comparison purpose [7].

$$EMAE = \frac{1}{n}\sum_{t=1}^{n}\frac{|x-\hat{x}|}{max(x,\hat{x})}$$

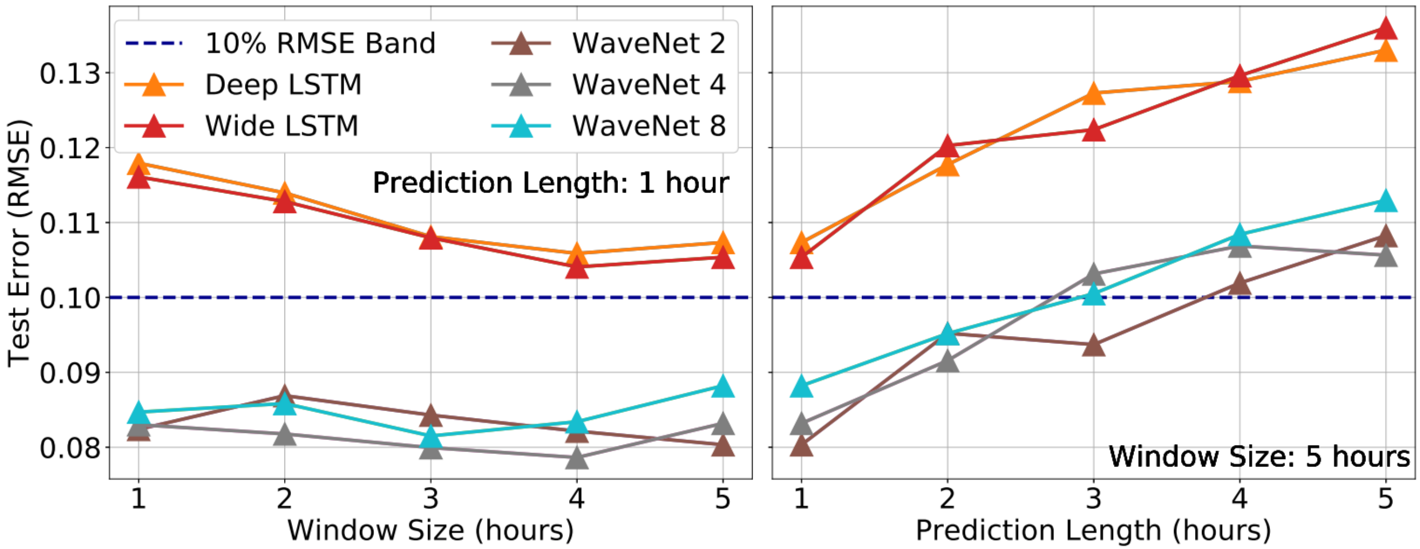
Comparison purpose [8], similar to MAPE.

Results and Discussion – Internal Comparison

TABLE II
THE NUMBER OF TRAINING PARAMETERS OF ALL MODELS.

Model Name	The number of training parameters
D-LSTM	1,064,193
W-LSTM	4,224,001
WaveNet-2	178,817
WaveNet-4	327,681
WaveNet-8	623,105

- Wavenets have better performance than LSTMs. Moreover, they have less training parameters.
- D-LSTM and W-LSTM have similar performance, although their the number of training parameters are differ.
- Stacking LSTM units can be better than one wider LSTM unit.



Results and Discussion - Benchmarks

First Benchmarking → Sophisticated ML models such as AR-CNN are better in than a classical statistical method like linear regression.

Second Benchmarking → There exists both long term and short term time dependencies. Memory is required! (Better than the classical ANN)

Third Benchmarking → Wavenets outperforms GRNN (another NN with memory.)

Results and Discussion

First Benchmarking

TABLE IV
MODEL PERFORMANCES WITH VARYING PREDICTION LENGTH AND ERROR MEASURES.

	Prediction length (h)				
	h = 1	h = 2	h = 3	h = 4	h = 5
RMSE					
Deep LSTM	0.1058	0.1177	0.1274	0.1274	0.1330
Wide LSTM	0.1052	0.1202	0.1222	0.1286	0.1359
WaveNet	0.0804[1]	0.0917[1]	0.0938[1]	0.1020[1]	0.1058[3]
L. Reg.	0.1224	0.1527	0.1759	0.1904	0.1926
MAE					
Deep LSTM	0.0515	0.0642	0.0658	0.0721	0.0741
Wide LSTM	0.0594	0.0679	0.0712	0.0782	0.0853
WaveNet	0.0470[1]	0.0451[1]	0.0665[1]	0.0618[3]	0.0645[1]
L. Reg.	0.0707	0.1007	0.1227	0.1339	0.1336
EMAE					
Deep LSTM	5.1542	6.4245	6.5830	7.2055	7.4065
Wide LSTM	5.9382	6.9112	7.115	7.825	8.529
WaveNet	4.6952	4.5068	6.6541	6.2709	6.4486
L. Reg.	7.0662	10.0662	12.2672	13.3894	13.3640

1: WaveNet 2
2: WaveNet 4
3: WaveNet 8

Second Benchmarking

TABLE V
THE PERFORMANCE (IN EMAE) COMPARISON OF CONSTRUCTED MODELS WITH ANN [20]

	D-LSTM	W-LSTM	WaveNeT	L. Reg.	ANN
1 h ahead	5.15	5.93	4.69	7.07	13.68
2 h ahead	6.42	6.91	4.51	10.06	16.25

Third Benchmarking

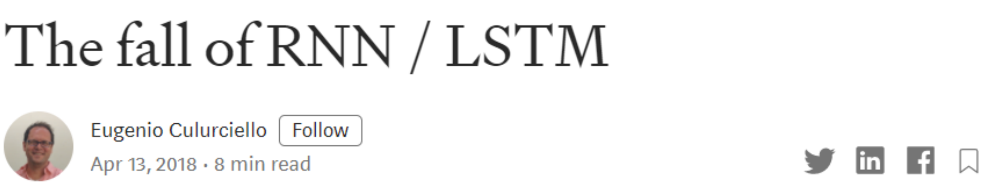
TABLE VI
THE PERFORMANCE (IN RMSE) COMPARISON OF CONSTRUCTED MODELS WITH [21]

	D-LSTM	W-LSTM	WaveNeT	L. Reg.	In [21]
1 h ahead	0.1058	0.1052	0.0787	0.1224	0.0861†
3 h ahead	0.1274	0.1222	0.0883	0.1759	0.1007†

†: maximum performance in fall, winter and spring season averages.

Conclusions

- AR-CNN algorithms i.e. WaveNets outperform LSTMs although they have less number of trainable parameters.
- RMSE values are higher than MAE and EMAE as in the other solar forecasting studies. This indicates that the reason for the error in the forecasting arise from high oscillations rather than trend fitting.
- Stacking multiple narrow LSTM units can be more computationally efficient than one wider LSTM block.
- There exists both long term and short term time dependencies, LSTMs or AR-CNN have better performance then classical ANN for solar power generation forecasting.
- AR-CNN' performance is not highly dependent on the window size like in Wide and Deep LSTM. (Quick note: LSTM's are dangerous! [9])



Recommendations/References

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