Subseasonal Solar Power Forecasting via Deep Sequence Learning

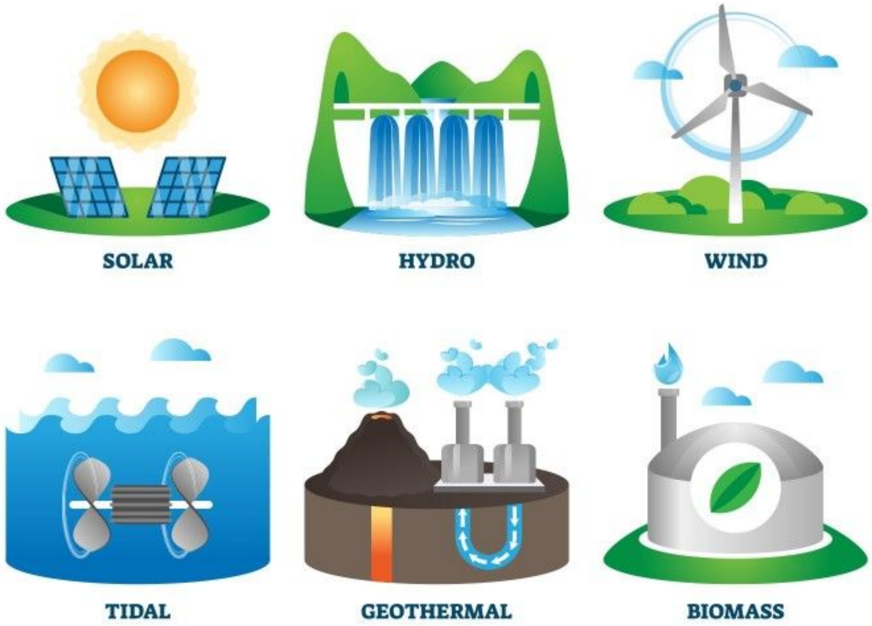
Saumya Sinha[1], Bri-Mathias Hodge[1,2], Claire Monteleoni[1]

Saumya.Sinha@colorado.edu

[1]University of Colorado, Boulder
[2] National Renewable Energy Laboratory (NREL)

Motivation

To help mitigate climate change, power systems are rapidly integrating renewable energy sources.



*https://www.inspirecleanenergy.com/blog/clean-energy-101/types-of-renewable-energy-sources

Motivation

- These resources, such as solar, are *variable* and *uncertain* in nature.

- To enable reliable integration, photovoltaics (PV) systems need *accurate solar irradiance forecasting.*

*https://energy.mit.edu/news/the-future-of-solar-energy-a-summary-and-recommendations-for-policymakers/

Contributions

- Deep sequence learning methods that provide forecasts for a significantly long horizon: *approximately 2-week lead time.*
- Forecasts that include *uncertainty estimates* via probabilistic prediction.
- Experiments demonstrate improved performance over various benchmarks that show promise for applications in future power systems storage operations.

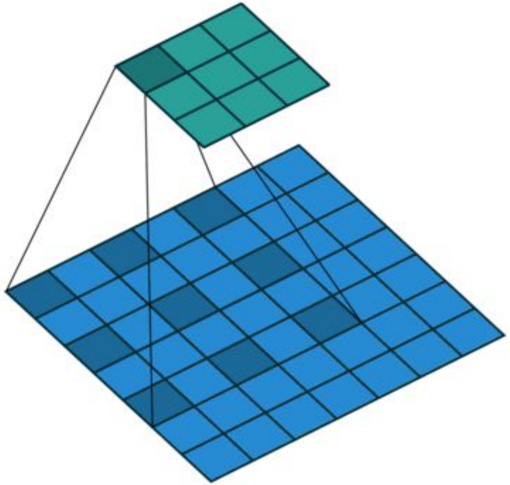
Method

We show the potential of following deep multivariate sequence models:

- Temporal CNN (TCN)
- Temporal CNN with Attention
- Transformer

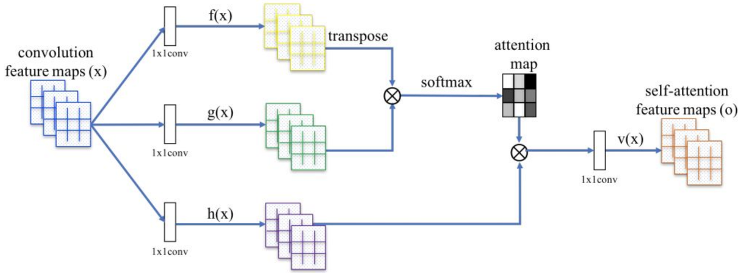
Method

Temporal CNN(TCN)



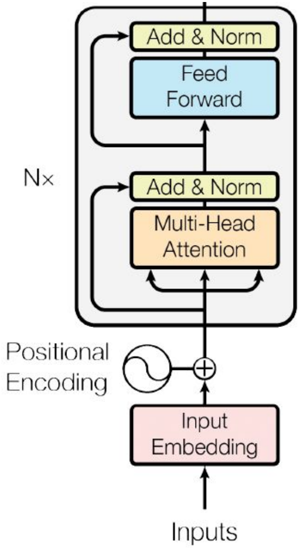
Dilated convolutions

TCN+Attention



Self-Attention module

Transformers



Transformer encoder

*https://github.com/vdumoulin/conv_arithmetic ; Self-attention generative adversarial networks, Zhang et al. 2019; Attention is all you need, Vaswani et al. 2017

Data

- NOAA’s SURFRAD network
  - **Ground-truth** : Global Horizontal Irradiance (GHI) (Watts/m2)
  - **Meteorological measurements** : e.g zenith angle, wind, pressure, temperature

- Models trained on years 2016-2017 and evaluated on 2018.

- Inputs are converted to an hourly resolution, and only the daytime values are considered.

Baseline models

- LSTM

- NgBoost : Natural gradient boosting
  ML-based probabilistic model (benchmark in short-term solar forecasting)

- Benchmarks from the solar energy literature:
  - Hourly Climatology (HC)
  - Complete history Persistence ensemble (CH-PeEN)

* Ngboost: Natural gradient boosting for probabilistic prediction, Duan et al. 2020 ;
Benchmark probabilistic solar forecasts: Characteristics and recommendations, Doubleday et al. 2020

Results: Point forecasting

	Ngboost		LSTM		TCN		TCN+Attention		Transformer	
	SP	HC	SP	HC	SP	HC	SP	HC	SP	HC
Sioux Falls, SD	28.5	17.53	19.08	6.51	**29.59**	**18.79**	28.51	17.54	28.09	16.91
Fort Peck, MT	28.02	28.8	23.21	23.83	30.02	30.85	**30.66**	**31.48**	29.99	30.56
Bondville, IL	27.66	12.1	17.59	-0.06	29.23	14.33	**29.95**	**15.2**	26.97	11.26
Penn State, PA	26.88	14.48	22.42	9.26	**26.91**	**14.51**	26.19	13.67	25.27	12.6
Boulder, CO	30.69	15.72	26.42	10.65	28.01	12.45	29.93	14.8	**30.79**	**15.95**
Desert Rock, NV	28.1	40.46	22.45	35.56	25.07	37.95	29.25	41.41	**32.23**	**43.68**
Goodwin Creek, MS	31.8	18.26	24.09	8.75	31.54	17.94	30.82	17.09	**32.95**	**19.4**

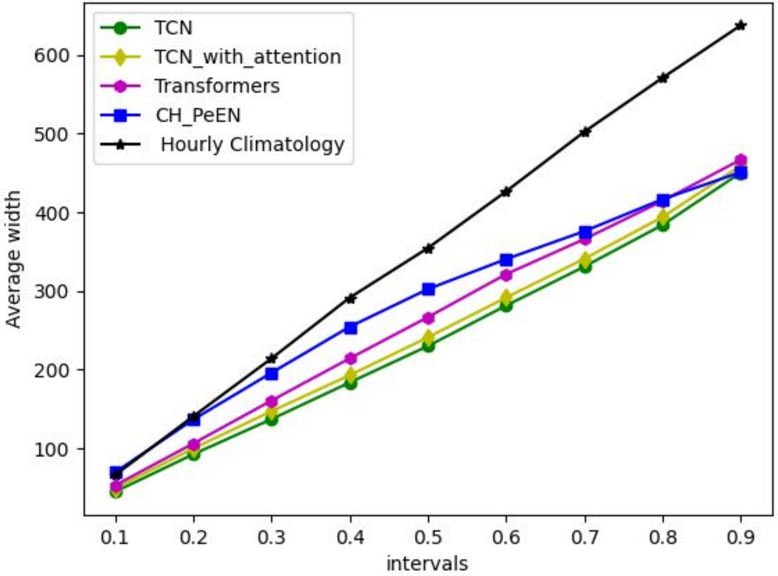
Results in terms of skill score(%) based on RMSE
(the higher the better)

Results: Probabilistic forecasting

	HC	CH-PeEN	Ngboost	LSTM	TCN	TCN+Attention	Transformer
Sioux Falls, SD	123.08	91.49	98.58	94.51	91.68	93.03	**87.42**
Fort Peck, MT	126.78	80.88	84.6	82.75	78.58	78.28	**77.69**
Bondville, IL	129.5	103.11	108.63	120.97	101.23	**100.52**	104.71
Penn State, PA	123.93	100.9	106.32	111.19	103.13	102.7	**100.52**
Boulder, CO	122.26	**90.11**	95.76	98.96	94.29	94.58	91.5
Desert Rock, NV	104.35	44.33	49.63	**43.56**	46.3	45.37	44.99
Goodwin Creek, MS	124.45	95.66	99.0	105.26	97.24	97.97	**95.48**

Results in terms of Continuous Ranked Probability Score or CRPS scores
(the lower the better)

Results



Plot comparing the sharpness of probabilistic models for Penn State station
(TCN and Transformers are sharper than CH_PeEN)

Conclusion

- We show the potential of deep learning methods for long-term point and probabilistic forecasting

- Proposed models: TCN, TCN+Attention, Transformers, outperform baselines

- Results comparable to Ch-PeEN benchmark in terms of CRPS, but better in terms of forecast sharpness

- Future work: Include NWP model ensemble outputs as input features to our models to observe enhanced performance

THANK YOU!