Probabilistic and Point Solar Forecasting Using Attention-Based Dilated Convolutional Neural Network

Moumita Saha, Bhalchandra Naik, Claire Monteleoni

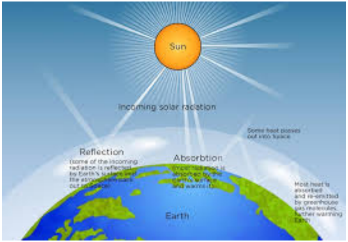
Department of Computer Science
University of Colorado Boulder, USA

EGU General Assembly, May 2020
Sharing Geoscience Online

Scope

Solar Irradiance

- Solar is a good source for renewable and clean energy
- Solar Irradiance is the flux of radiant energy received per unit area of the earth
- Solar irradiance has many significant applications:
  - the prediction of energy generation from solar power plant
  - the heating and cooling loads of buildings
  - climate modeling and weather forecasting



Importance of Solar Irradiance

- Climate change is evident and net damages are quite significant
- A high rise in greenhouse gases is a major cause for climate change

- Contributed with burning of fossil fuels and other anthropogenic activities
- Renewable energy sources like solar are a good source for clean energy production for combating climate change

Forecasting Solar Irradiance

- Efficient integration of solar energy into electrical grids requires an accurate prediction of solar irradiance

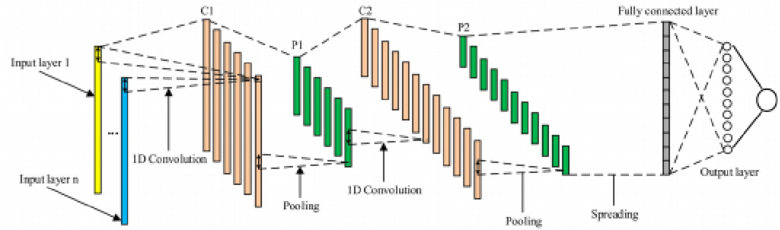
- Influences the production of solar energy at photo-voltaic plant
- Accurate prediction of irradiance helps in forecasting the energy production at a lead time
- Need for crucial decisions in scheduling harvesting and estimating power requirements for the future

Convolutional Neural Network for Solar Irradiance

- We aim to forecast downwelling global solar irradiance using a fixed history of the variables
- We propose a convolutional neural network with dilated kernel and attention-based mechanism for predicting the solar irradiance
- We present both probabilistic and point forecasts of solar irradiance at multiple lead times
- Forecast for all four seasons: Fall, Winter, Spring, and Summer

Convolutional Neural Network

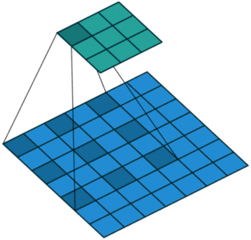
- Convolutional neural networks (CNN) are capable of extracting features from data that have local spatial relations
- We use CNN to map samples of sub-sequences from a time-series series to some observed value in the future



Dilated Kernel and Temporal Attention Method

- Dilation refers to cavities in the kernel, which allows looking for dependencies in non-adjacent cells

- We added dilation for capturing long-term dependencies



- Attention mechanism compels the model to focus on the parts of the input that bear a high impact on the output

- In our case, it emphasis the past states of input which have the highest impacts on the output solar irradiance

Model Training and Loss Function

- The input dimension is twenty-one and the output dimension is either the number of quantiles (probabilistic) or one (point)
- The quantile loss QL_α used in probabilistic forecasting is

$$QL_\alpha(\hat{y}, y|q) = \begin{cases} (y-\hat{y})(1-\alpha), & \text{if} \quad (y-\hat{y}) < 0 \\ (y-\hat{y})\alpha, & \text{if} \quad (y-\hat{y}) \geq 0 \end{cases}$$

- For point-forecasting, we use a $L2$ loss function

$$PL(y, \hat{y}) = (y-\hat{y})^2$$

Performance Metrics

- Root mean square error (RMSE) for point forecasting

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(y_t - \hat{y}_t)^2}{T}}$$

- Continuous Ranked Probability Score (CRPS) for probabilistic forecasting

$$\overline{CRPS} = \int_0^1 \frac{1}{T}\sum_{t=1}^{T} QL_\alpha(y_t, \hat{y}_t)d\alpha$$

Baseline Persistence Models

- Simple persistence (SP) model can be defined as:

$$I_p(t + \triangle t) = I(t),$$

where $I(t)$ is the solar irradiance at current time

- Smart persistence (SMP) model forecast the irradiance by multiplying the clear-sky index by the future clear-sky irradiance

$$I_{sp}(t + \triangle t) = k_t(t) * I_{clr}(t + \triangle t)$$

where $k_t(t)$ is the clear-sky index at current time and I_{clr} denotes the clear-sky irradiance

Point Forecasting for Solar Irradiance

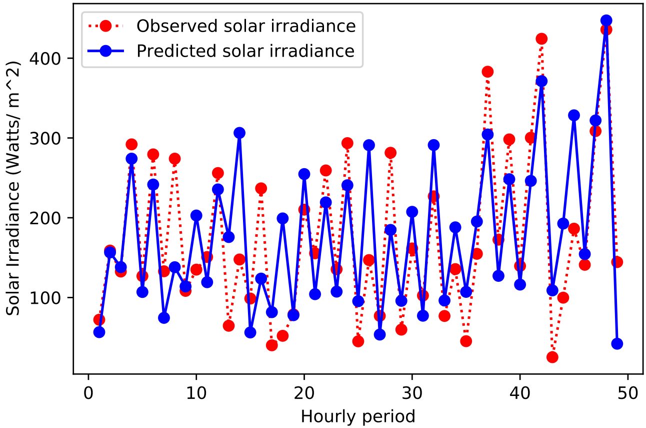
- The model shows higher performance for the fall and winter seasons

RMSE for point solar irradiance forecasting by CNN and simple persistence (SP) models at two different leads

Boulder-Colorado								
Leads	**Fall**		**Winter**		**Spring**		**Summer**	
	CNN	**SP**	**CNN**	**SP**	**CNN**	**SP**	**CNN**	**SP**
3 hrs	169	325	122	280	234	369	243	375
6 hrs	183	375	100	263	267	464	238	491
Fort Peck-Montana								
3 hrs	135	248	128	201	167	304	202	326
6 hrs	148	279	132	174	195	392	252	383

Point Forecasting for Solar Irradiance

Hourly observed and predicted solar irradiance for Boulder winter season



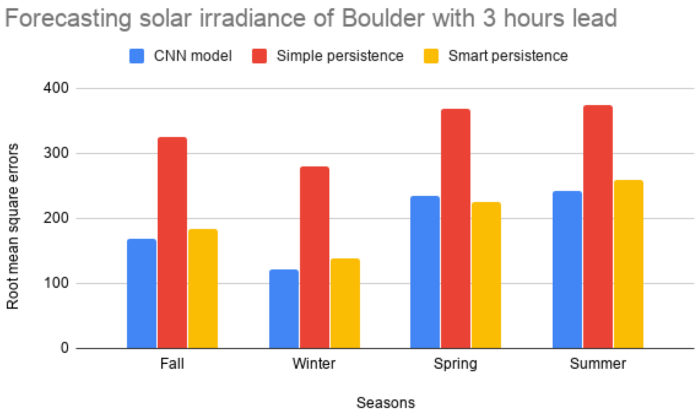
Probabilistic Forecasting of Solar Irradiance

- We use quantile regression for probabilistic forecasting
- We predicted solar at 19 different quantiles with $\alpha = [0.05, 0.10, 0.15, ..., 0.95]$
- Similar high performance observed for the winter and fall

CRPS for probabilistic solar irradiance forecasting

Boulder-Colorado				
Leads	**Fall**	**Winter**	**Spring**	**Summer**
3 hrs	182.3	130.4	242.2	261.7
Fort Peck-Montana				
3 hrs	138.3	122.3	181.6	235.8

Solar Forecasting by CNN and Persistence Models



Skill Score of CNN Model over Persistence Models

- CNN model shows high skill score over the baseline persistence models for both the lead times

Skill score for point solar irradiance forecasting over persistence models

Boulder-Colorado								
	Simple persistence				**Smart persistence**			
Leads	**Fall**	**Winter**	**Spring**	**Summer**	**Fall**	**Winter**	**Spring**	**Summer**
3 hrs	47.9	56.3	36.5	35	8.5	11.8	-3.6	6.2
6 hrs	51.8	61.8	42.4	51.5	13.3	16.9	9.5	11.6
Fort Peck-Montana								
3 hrs	45.3	36.1	44.8	24.2	8.2	11.7	6.4	7.2
6 hrs	47.1	23.9	50.0	38.7	13.2	15.2	9.2	11.6

Conclusion

- The CNN model learns the mapping from the past time-series of climatic variables to solar irradiance and predicts the irradiance at multiple lead times
- Dilated kernel and temporal attention aid to boost the forecast accuracy
- Adding past irradiance as an input improves the forecast
- Solar irradiance prediction for winter and fall seasons are better than other seasons

Future Work

- Apply a dual-stage attention mechanism which can learn the importance of input features and temporal history
- An adaptive temporal attention method can aid in detecting the number of attention steps to be considered
- Solar irradiance in finer grids over the United States to support power plants in crucial decision-making

References

1. ‘Validation of short and medium term operational solar radiation forecasts in the US,’Solar Energy, 2010
2. ‘Short-term probabilistic forecasts for direct normal irradiance,’ Renewable Energy, 2017
3. ‘Online short-term solar power forecasting,’ Solar Energy, 2009
4. ‘The SURFRAD Network. Monitoring Surface Radiation in the Continental United States,’ 2010
5. ‘Day-ahead solar irradiance forecasting for microgrids using a long short-term memory recurrent neural network:A deep learning approach,’ Energies, 2019
6. ‘CSRNet: Dilated convolutional neural networks for understanding the highly congested scenes,’ CVPR, 2018
7. ‘Neural machine translation by jointly learning to align and translate,’ arXiv:1409.0473, 2014
8. ‘A dual-stage attention-based recurrent neural network for time series prediction,’ IJCAI, 2017

Thank you

?