Climate change is evident at present with threatening effects as intense hurricanes, rising sea level, increase number of droughts, and shifting weather patterns. Burning of fossil fuels and anthropogenic activities increase the greenhouse gases concentration in atmosphere, which is a major cause behind the climate change. Renewable energy as solar is a good source for combating the causes of climate change by producing clean energy.

The efficient integration of solar energy into electrical grids requires an accurate prediction of solar irradiance. The solar irradiance is the flux of radiant energy received per unit area of the earth from the sun. Existing techniques use basic stochastic (such Gaussian model, hidden Markov model, etc.) and ensemble neural network models for solar forecasting. However, recent literature reflects the potential of deep-learning models over the statistical model.

In this paper, we propose a deep-learning-based one-dimensional, multi-quantile convolution neural network for predicting the solar irradiance. The network employs dilation in its convolution kernel, which helps capturing the long-term dependencies between instances of the input climatic variables. Additionally, we also incorporate the attention mechanism between the input and learned representation from the convolution, which allows attending to the temporal instance of features for improved prediction. We perform both short-term (three hours ahead) and long-term (twenty-four hours ahead) solar irradiance prediction. We exhaustively present the forecast for all four seasons (spring, summer, fall, and winter) as well as for the whole year. We provide a point solar forecast along with forecast at different quantiles. Quantile forecast provides a range of estimates with varying confidence intervals, which allows better interpretation as compared to point forecast. This notion of confidence associated with each quantile makes the forecasting probabilistic.

In order to validate our approach, we consider two cities (Boulder and Fort Peck) from the SURFAD network and examine twenty climatic features as input to our model. Additionally, we learned embedded reduced input dimension using an autoencoder. The proposed architecture is trained with all the input features and reduced features, independently. We observe the prediction error for Boulder is higher than Fort Peck, which can be due to the volatile weather of Boulder. The proposed model forecasts the solar irradiance for winter with a higher accuracy as compared to spring, summer, or fall. We observe the correlation coefficients as 0.90 (Boulder) and 0.92 (Fort Peck) between the actual and predicted solar irradiance. The long-term forecast shows average
improvements of 37.1% and 33.1% in root mean square error (RMSE) over existing numerical weather prediction model for Boulder and Fort Peck, respectively. Similarly, the short-term forecast shows improvements of 33.7% and 34.2% for the respective cities.