

SHORT-TERM SOLAR FORECASTING USING
SKY CAMERA BACKED BY A CONVOLUTIONAL
NEURAL NETWORK

By

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Thesis

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Statement of Originality

I hereby certify that the work embodied in the thesis is my own work, conducted under normal supervision. The thesis contains no material which has been accepted, or is being examined, for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made. I give consent to the final version of my thesis being made available worldwide when deposited in the University's Digital Repository, subject to the provisions of the Copyright Act 1968 and any approved embargo.

Joel Tze-Bean Wong, December 2022

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Abstract

A time series forecasting model based on a convolutional neural network, named “Solpred”, was developed to process images of the sky from a ground based camera, forecasting solar irradiance up to 15 minutes in the future. Accurate irradiance forecasts are a key factor in being able to proactively manage changes in energy output from solar power sources in an electricity grid, enabling a greater penetration of solar power. Solpred produced a deterministic forecast with a skill of 23.4% using RMSE vs naive persistence at a 2-minute forecast horizon of GHI, and a skill of 25.5% at a 15-minute forecast horizon of GHI. This was compared against a re-implementation of the SUNSET model proposed by Sun, Szűcs, and Brandt [1], which achieved 21.6% at a 2-minute horizon and 22.1% at a 15-minute horizon. The reasons for this difference in performance is investigated, with the absence of batch normalisation layers being found to produce the largest increase in performance.

Various input and output configurations were applied to test the limits of the Solpred architecture, with a key finding that sun-centred image cropping improved the skill of the model from 16.4% to 23.4% at a 2-minute forecast horizon. This suggests an easy improvement in performance for models, but also implies a limitation in how the architecture extracts spatial features using convolutional layers. The convolutional layers struggle to perform the spatial reasoning tasks required for solar forecasting, suggesting that they could be augmented with more flexible modules such as transformer encoders or recurrent modules when dealing with spatial reasoning tasks.

