RECURRENT NEURAL NETWORK FOR FORECASTING SOLAR ENERGY PRODUCTION

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Background

Solar Power

- Cleanest and most abundant renewable energy source [1]
- Energy production volatility reduces solar power efficiency [2]
- Need for solar energy production **forecasting methods** [2]

Recurrent Neural Networks

- Special class of neural network which keeps history of previous inputs [4]
  - Time-based (accepts sequences of data)
  - Popular for forecasting

Methodology

Our model used historical **solar irradiance** and **cloud coverage** data to predict future **solar irradiance** (Solar irradiance, cloud coverage linked to solar energy production) [3]

Training

- Preprocessed data, implemented model and training mechanisms, incorporated optimization framework, and configured connection to computing clusters
- Searched for the best model over these configurations:
  - **RNN Type** (standard RNN [4], LSTM [5], or GRU [6])
  - Number of stacked **RNN layers** (1-4)
  - Number of **neurons per layer** (32, 64, or 128)

Results

I trained and optimized a **recurrent neural network** to **forecast solar irradiance**

Conclusions

- Best performing model: **1-layer GRU** with **32 neurons**
- Promising results for **hyperlocal solar energy production forecasting** using edge computing with Argonne's Waggle sensors

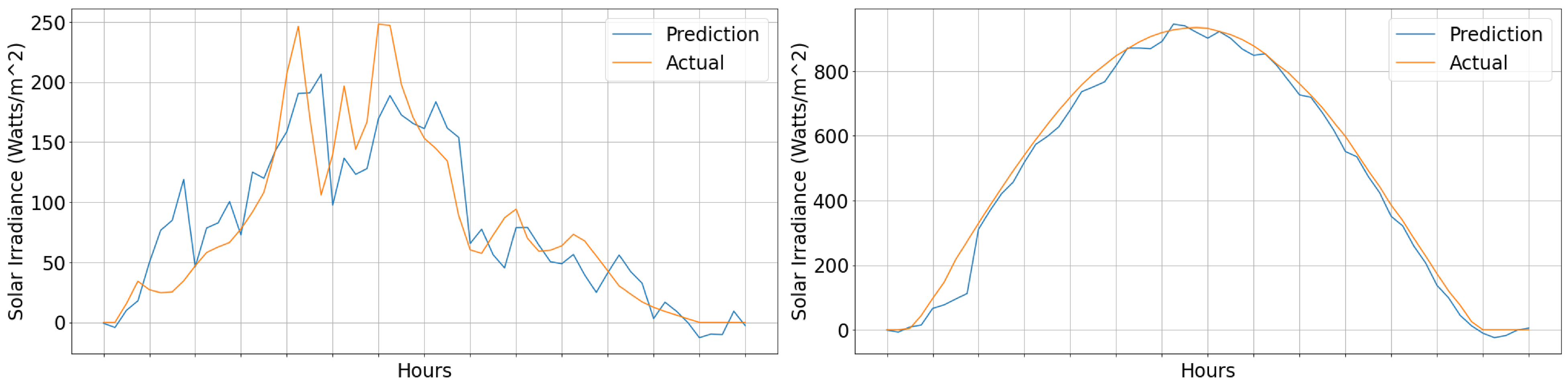

Fig. 1: Solar irradiance prediction by the best performing model, a 1-layer GRU with 32 nodes with a 15-minute resampling frequency. Each hour (tick on x-axis) is predicted using the data of the 4 hours prior. **Left:** Solar irradiance prediction on a cloudy day. **Right:** Solar irradiance prediction on a sunny day.

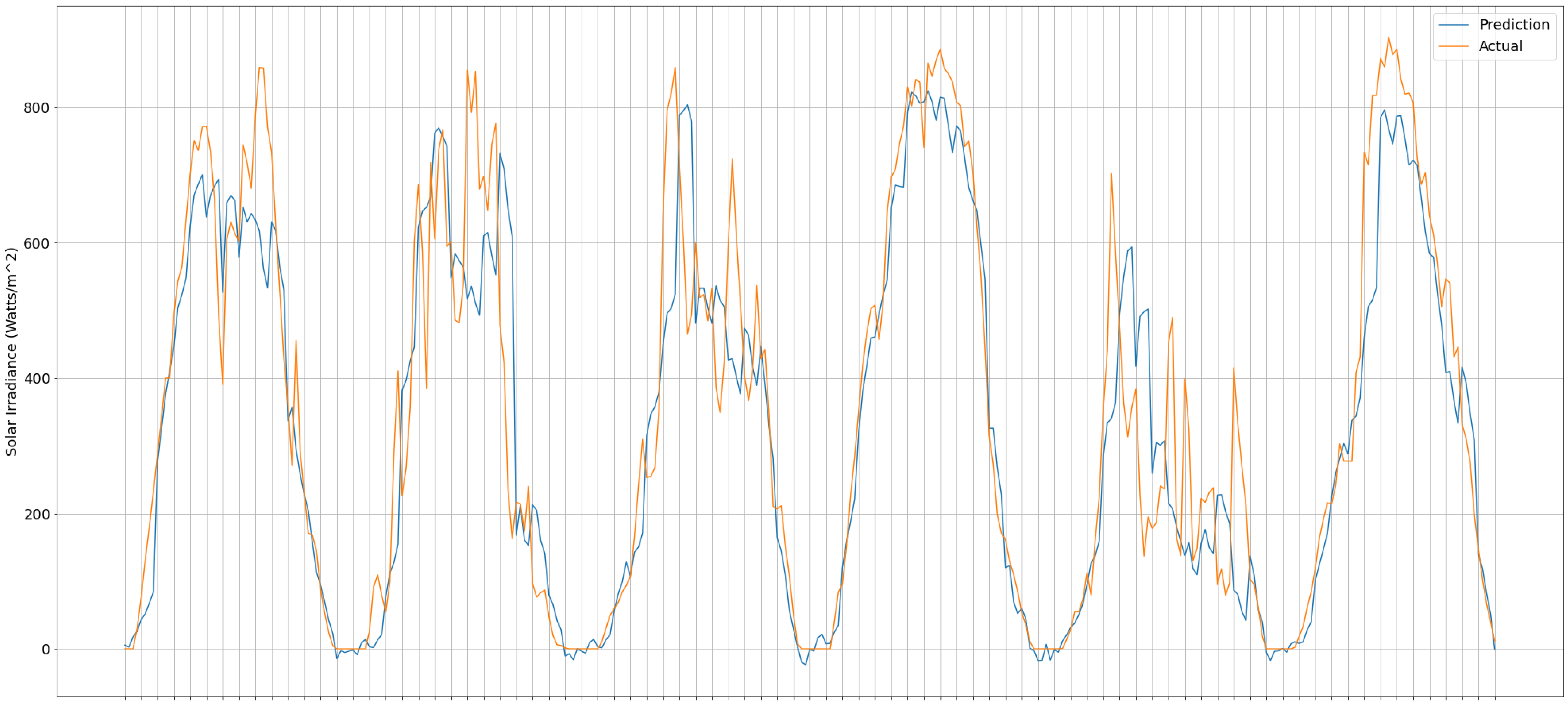

Fig. 2: Solar irradiance prediction over a six-day stretch., including a variety of cloud conditions, by the best performing model, a 1-layer GRU with 32 nodes with a 15-minute resampling frequency. Each hour (tick on x-axis) is predicted using the data of the 4 hours prior. Note that nightfall is not included in the data; thus, each day is less than 24 hours.

rank	cell type	layers	neurons	loss
1	GRU	1	32	0.004806
2	GRU	2	32	0.004825
3	LSTM	4	32	0.004837
4	GRU	1	32	0.004866
5	LSTM	4	32	0.004895
6	GRU	1	32	0.004949
7	RNN	2	32	0.004961
8	RNN	1	128	0.005107
9	RNN	1	64	0.005218
10	RNN	2	64	0.005225
11	RNN	2	128	0.005234
12	GRU	2	32	0.006033
13	LSTM	2	32	0.006210
14	GRU	2	32	0.006322
15	GRU	3	128	0.006343
16	GRU	2	32	0.006347
17	RNN	3	32	0.006533
18	GRU	1	64	0.006539
19	GRU	4	128	0.006561
20	GRU	1	64	0.006635
21	GRU	2	128	0.006650
22	LSTM	2	128	0.006661
23	GRU	2	32	0.006686
24	GRU	3	32	0.006708
25	LSTM	3	32	0.006824
26	LSTM	3	32	0.006867
27	LSTM	3	32	0.006891
28	LSTM	1	128	0.006966
29	GRU	3	64	0.006978
30	LSTM	4	32	0.006979
31	RNN	3	128	0.007135
32	GRU	4	32	0.007163
33	GRU	1	128	0.007219
34	GRU	1	128	0.007246
35	LSTM	4	32	0.007266
36	GRU	4	32	0.007295
37	GRU	2	64	0.007326
38	LSTM	4	32	0.007399
39	LSTM	4	32	0.007428
40	LSTM	4	32	0.007452

Table 1: Accuracy results for each trial. Hyperparameters were chosen using a TPESampler. Thus, values were selected unequally

Future Directions

- Dockerize for usage in **Waggle sensors**
- Compare models' resource usage and speed for **edge computing** in Waggle sensors
- Consider training for different time intervals

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Sources: **[1]** Z. Pang, F. Niu, and Z. O'Neill, "Solar radiation prediction using recurrent neural network and artificial neural network: A case study with comparisons," *Renewable Energy*, vol. 156, pp. 279–289, Aug. 2020, doi: 10.1016/j.renene.2020.04.042. **[2]** D. Kaur, S. Islam, A. Mahmud, E. Haque, and Z. Y. Dong, "Energy Forecasting in Smart Grid Systems: A Review of the State-of-the-art Techniques," *arXiv*, Nov. 2020, doi: 10.48550/arXiv.2011.12598 **[3]** S. Park, Y. Kim, N. J. Ferrier, S. M. Collis, R. Sankaran, and P. H. Beckman, "Prediction of Solar Irradiance and Photovoltaic Solar Energy Product Based on Cloud Coverage Estimation Using Machine Learning Methods," *Atmosphere*, vol. 12, no. 3, p. 395, Mar. 2021, doi: 10.3390/atmos12030395. **[4]** C. Goller and A. Kuchler, "Learning task-dependent distributed representations by backpropagation through structure," *Proceedings of International Conference on Neural Networks (ICNN'96)*, 1996, pp. 347-352 vol.1, doi: 10.1109/ICNN.1996.548916. **[5]** S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, vol. 9, no. 8, p. 1735-1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735 **[6]** K. Cho, B. Merrienboer, D. Bahdanau, and Y. Bengio, "On the Properties of Neural Machine Translation: Encoder-Decoder Approaches," *arXiv*, Sep. 2014, doi: 10.48550/arXiv.1409.1259