Short-Term PV Forecasting at High Latitudes using a Distributed Sensor Network

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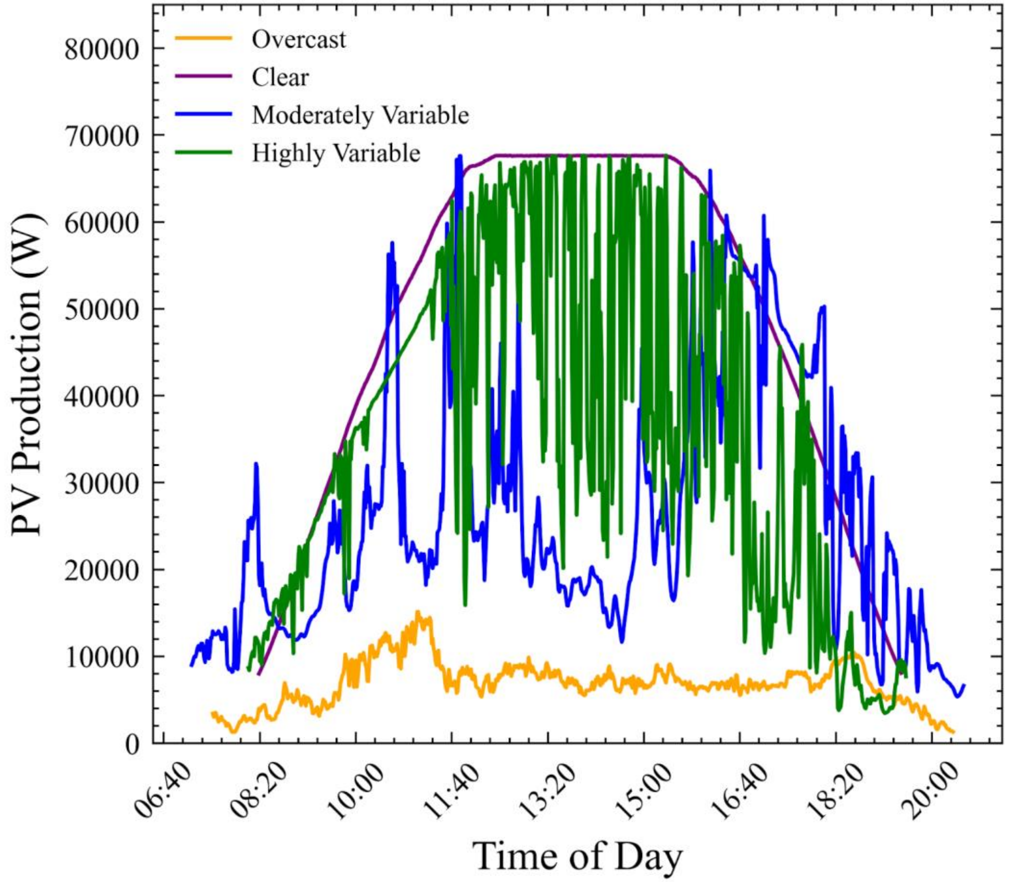
Why PV Forecasting is Useful

- Sudden changes (“ramps”) in PV production caused by clouds are bad for grid stability, especially in microgrids.

- Microgrids need to maintain a lot of spinning reserve, usually with diesel generators.
  - **1-2 minutes to start and sync a diesel generator.**
  - Cannot be run below ~30% capacity
  - Fuel/maintenance is expensive, especially for rural microgrids.

- Energy storage can help but is expensive.



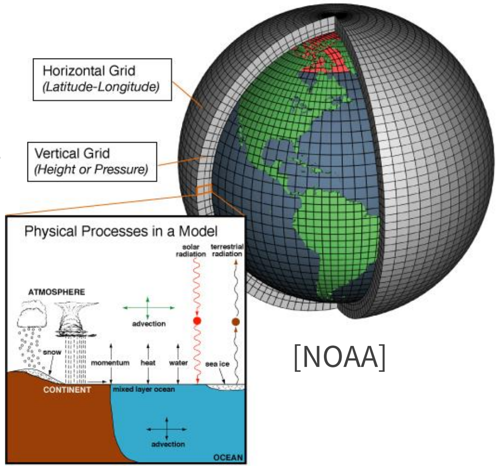
A Potential Solution

- **Short-term forecasting:** what if grid operators/control systems could predict PV production **1-2 minutes** into the future?
  - Leave more generators offline?
  - Smaller energy storage systems?

Options for PV Forecasting

Numerical Weather Prediction (NWP)

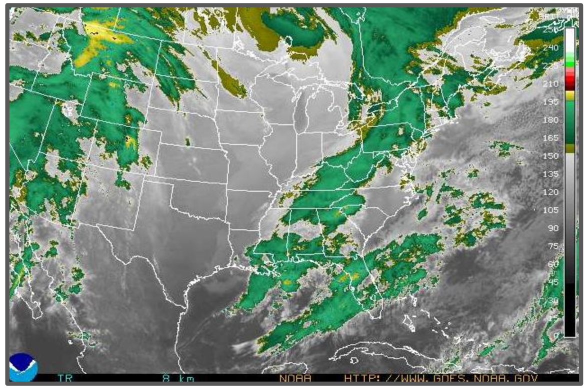
- Time horizons of hours to days.
- Computationally intensive.
- Used for larger-scale regional forecasts.



[NOAA]

Satellite Imaging

- High data bandwidth requirements.
- Limited spatial/temporal resolution
- Very limited data at high latitudes.



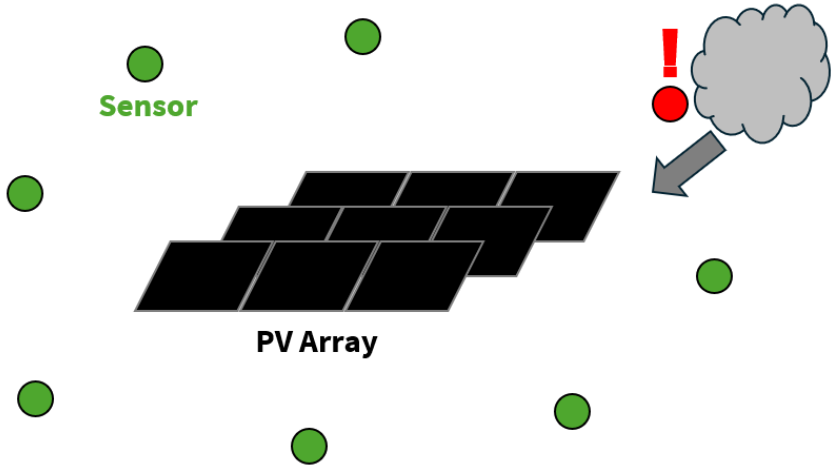
Sky Cameras (TSI)

- Can be expensive, difficult to maintain [1]
- Reduced accuracy below 5-minute time horizon due to shadow band [2].
- High data bandwidth.

[NOAA]

Distributed Sensor Networks

- Sensors collect irradiance data from around PV array.
- Shown to outperform TSI in 1-2-minute horizon range [3].
- Lower cost than TSI systems [4]



Sensor Design

Design Requirements

- Operate wirelessly on their own power.
- Transmit data over several kilometers.
- Survive in a high-wind environment with temperatures as low as -40 °C.
- Not too expensive.

Final Specifications

- Arduino microcontroller.
- 1-watt PV panel for sensing irradiance and powering the device.
  - Plus a non-rechargable battery (too cold for standard Li-ion).
- LoRaWAN radio communications.
- **$450 USD (~SEK 4600, €415)** per sensor.
- Measures data every 2-seconds.
- Programmed only to transmit when a ramp of a certain size is detected.
- Can only transmit 10 data points (20 seconds) every 2 minutes to preserve battery.
  - This led to discontinuous "choppy" data.

One of the sensors deployed near the Kotzebue, Alaska

Sensor Network

- 10 sensor deployed in Kotzebue, Alaska (67° N).
- Centered around 575-kW community PV array.
- Locations based on max distance a cloud could travel in 2 minutes.
- Central node near PV array intakes live sensor transmissions and uploads them to internet.
- PV production and meteorological data were measured on-site at 1-minute resolution.

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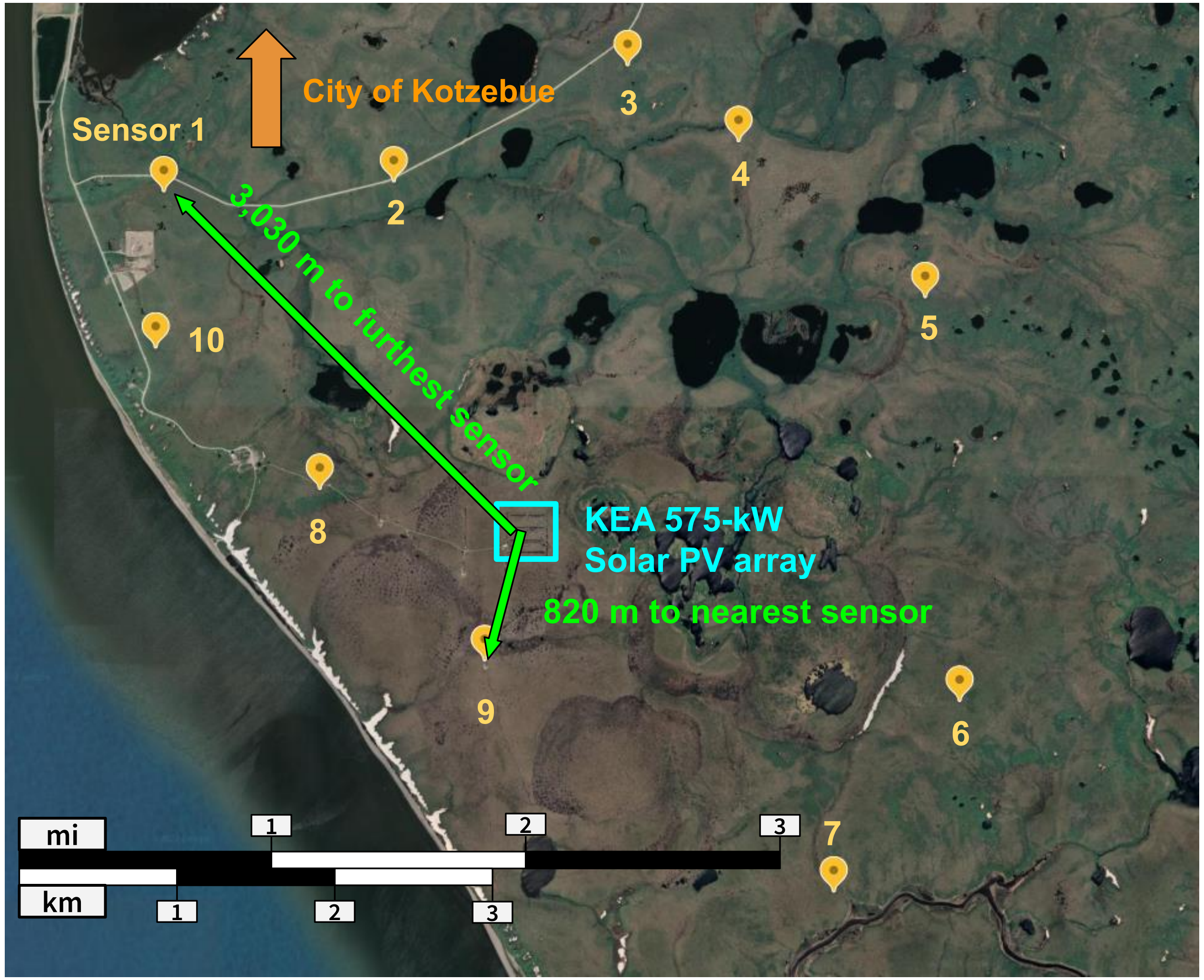
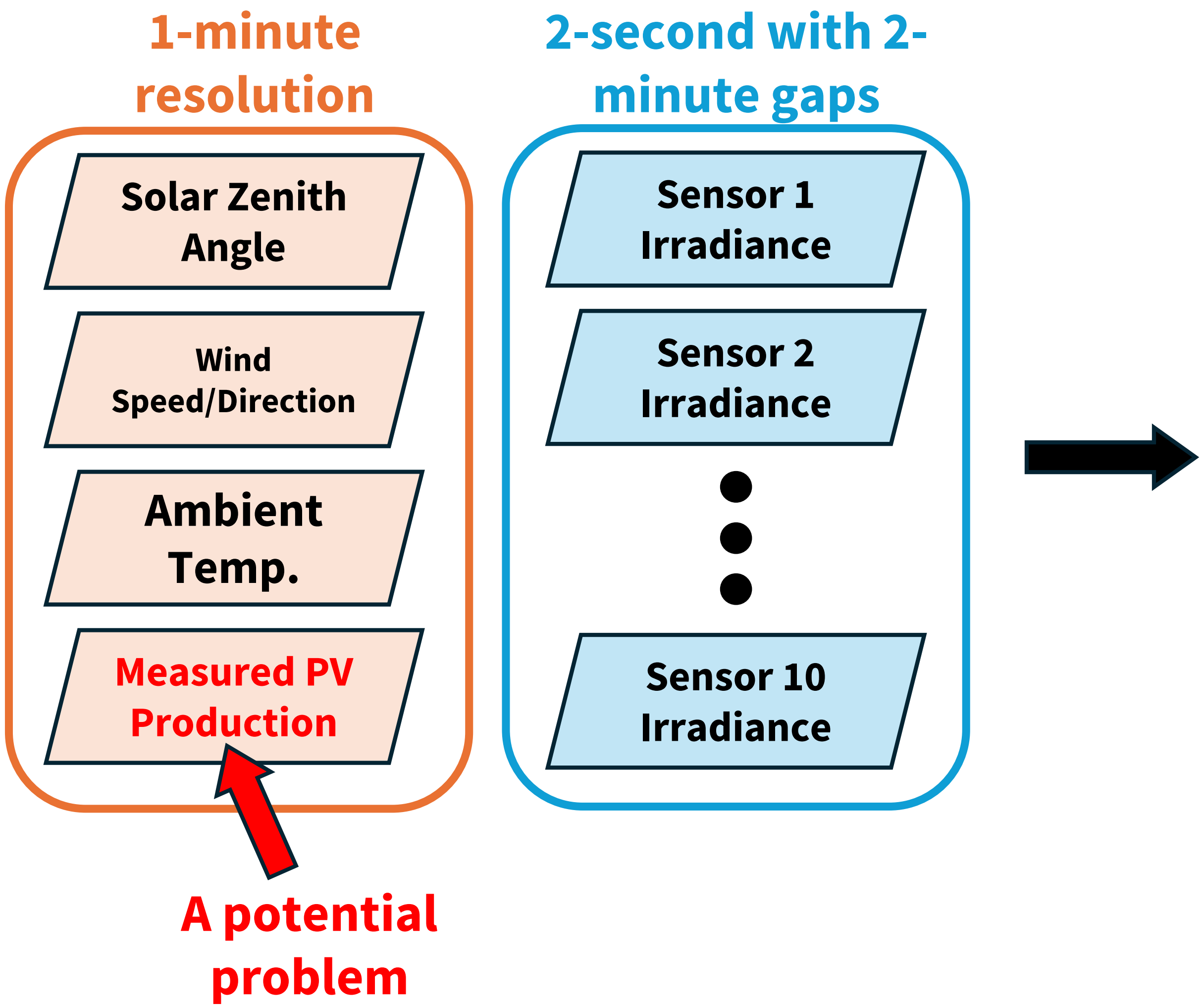


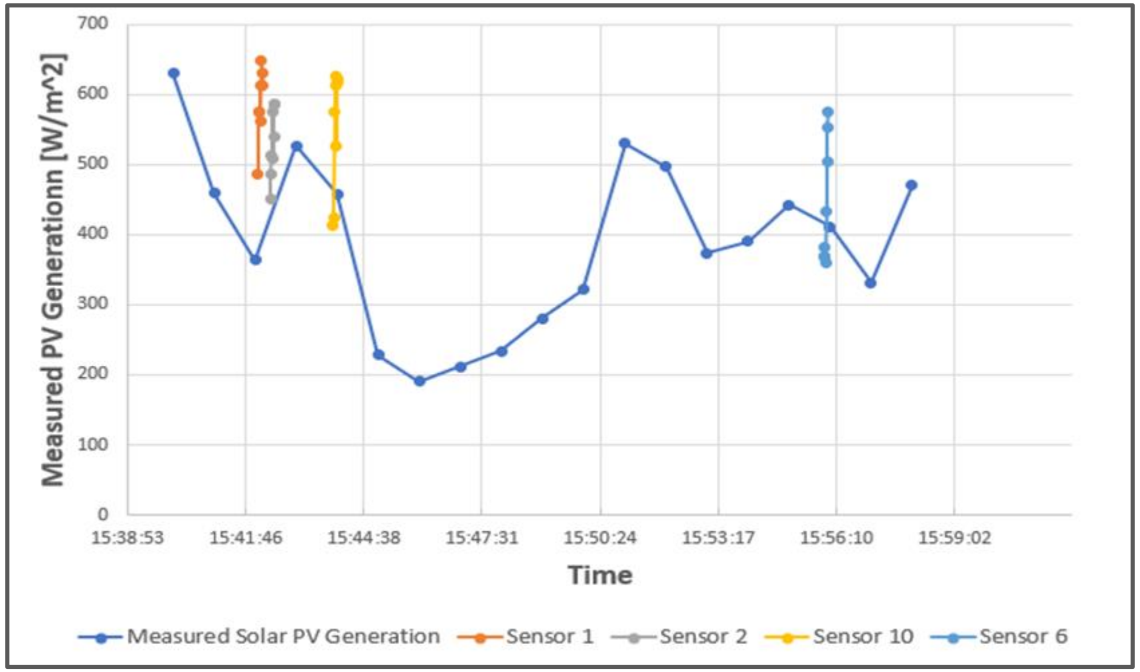
Locations of the 10 sensors deployed around the Kotzebue community PV array.

Turning the Data into a Forecast

Data Formatting



- This produced a discontinuous data set with varied time resolutions.



- Data were resampled and rearranged to make a continuous, 1-minute data set.

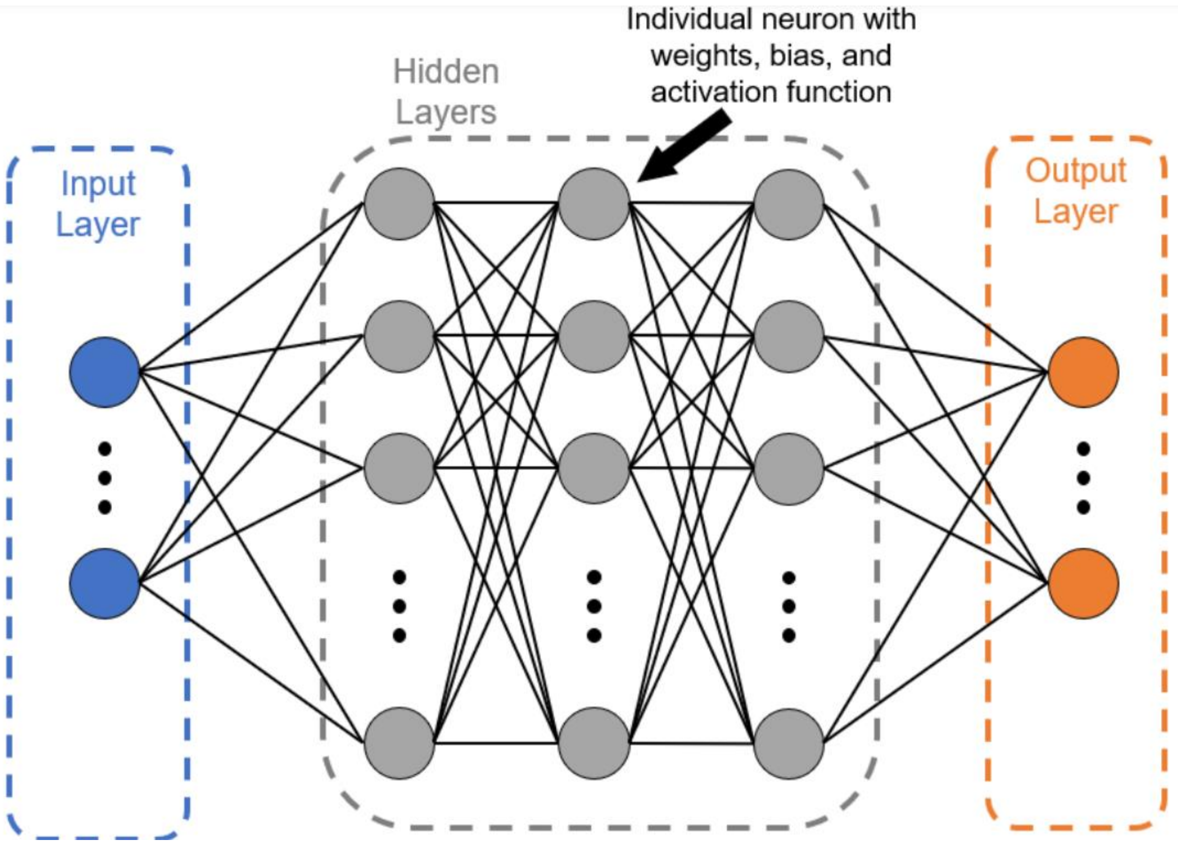
Turning the Data into a Forecast

What model structure to use?

- Previous works using sensor networks typically use one of two types of algorithm:
  - **Peak Matching**
  - **Wavelet Decomposition**

- Both require high-resolution, continuous data sets.

- **Neural networks** have shown promise for PV forecasting applications.
  - Very little research into the combination of neural networks and sensor networks for PV forecasting.
  - Able to learn complex relationships in between input data fields.
  - Better suited to our mismatched data set.



An example of a basic neural network structure.

Neural Networks

Convolutional

- 1-dimensional (**Conv1D**) commonly used in time series forecasting.
- Used to reduce dimensional complexity of input data.

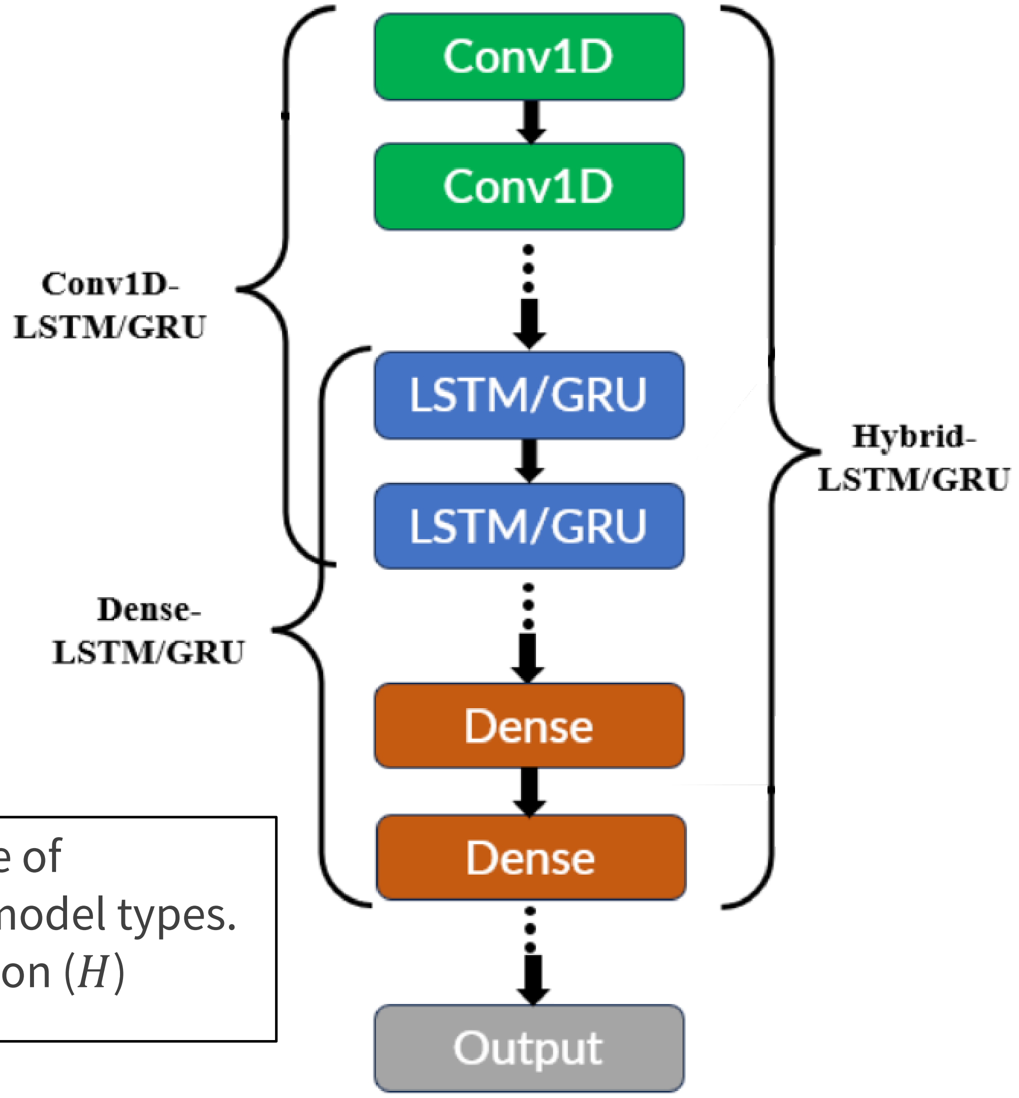
Recurrent

- Specialized for sequential data like time series.
- 2 Types:
  - Long Short-term Memory (**LSTM**)
  - Gated Recurrent Unit (**GRU**)

Dense

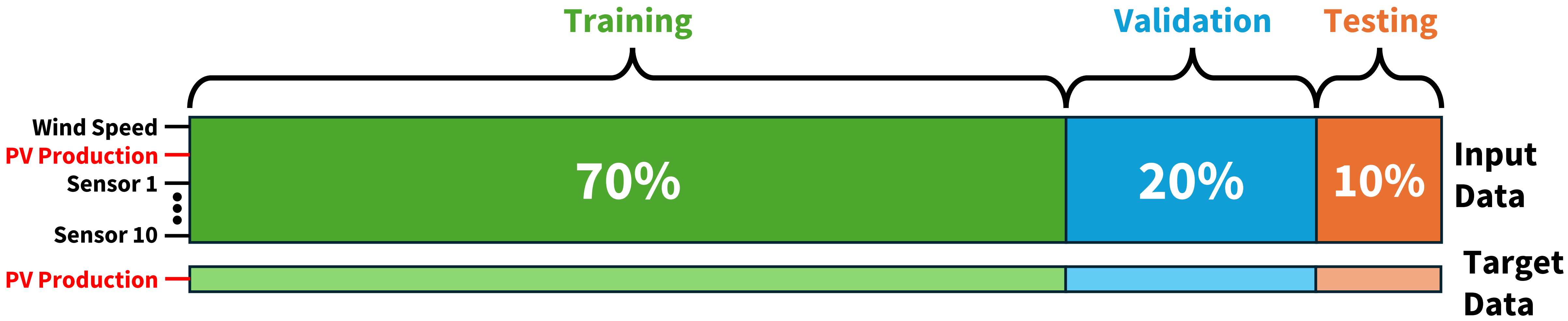
- More generic neural network.
- Used to add model processing capabilities as needed.

- 8 different models made of combinations of these model types.
- **2-minute** forecast horizon (H)



How the Neural Network Models Use the Data

- Models iteratively update their internal parameters in a process called "training."
- Training is repeated until forecast stabilizes.
- Validation data used to stop "overfitting."
- Due to technical issues, only 71 days of data were available in total.



- Models use a window of input data points at previous time steps to try and predict the current time step

Performance Metrics

Standard Error Metrics

- How close are the actual (y) and forecasted ($\hat{y}$) time series?

- **Mean Absolute Error (MAE)**
- **Mean−Square Error (MSE)**
- **Root-Mean-Square Error ($RMSE$)**
- r^2
- $skill$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

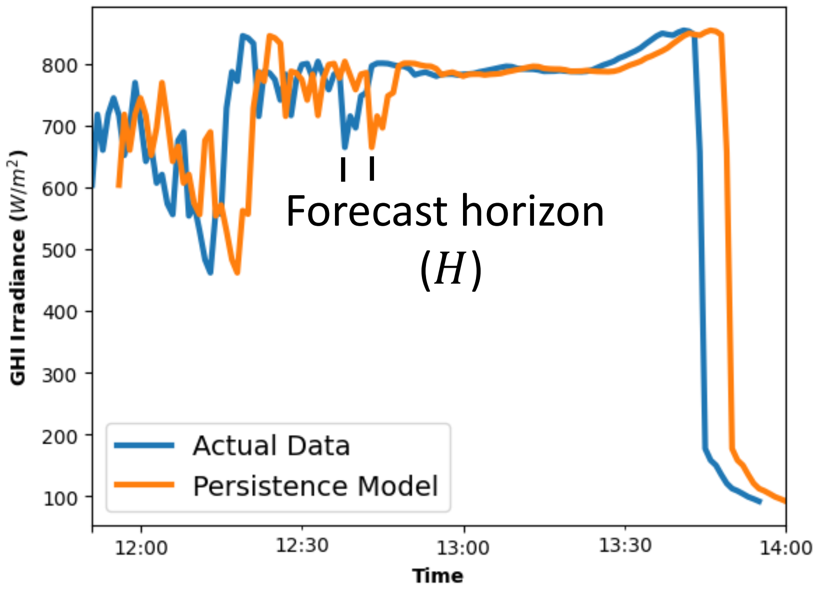
$$r^2 = 1 - \frac{\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{N}(y_i-\bar{y}_i)^2}$$

$$skill = 1 - \frac{RMSE_{forecast}}{RMSE_{persistence}}$$

Persistence model:

$$\hat{y}_{t+H} = y_t$$

*Notoriously hard to beat for short time horizons



Event-based Metrics

- How good are the models at detecting individual ramp events?
- Three useful metrics:
  - **Precision (PR)**
  - **Recall (RE)**
  - F_β ($\beta = 1$ for this analysis)

$$PR = \frac{hits}{hits + false\ alarms}$$

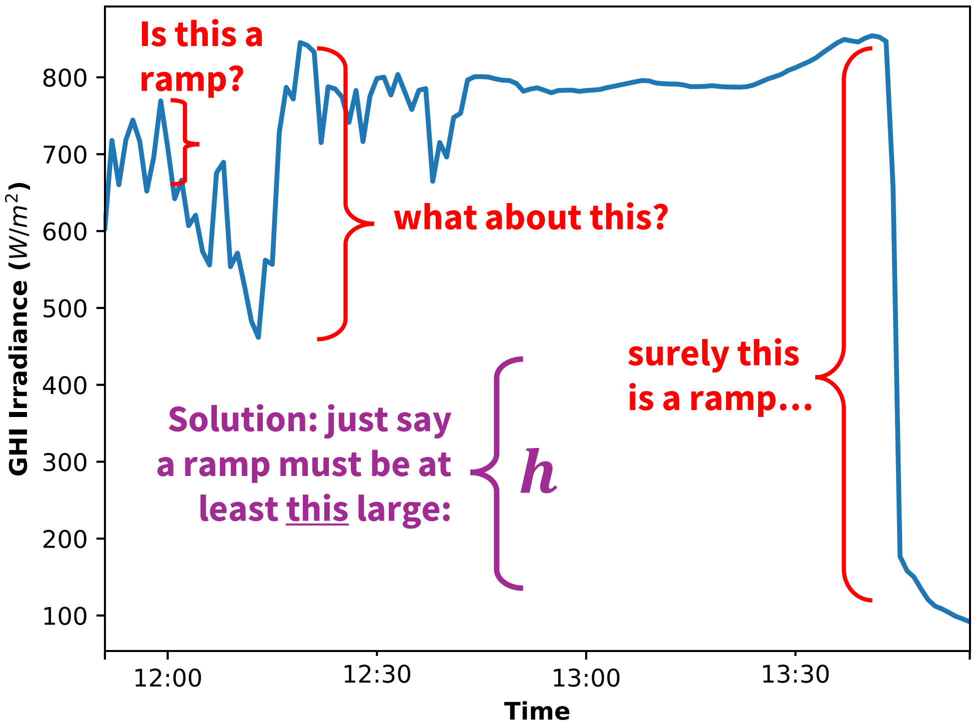
$$RE = \frac{hits}{hits + misses}$$

$$F_\beta = (1 + \beta^2) \cdot \frac{PR}{\beta^2 \cdot PR + RE}$$

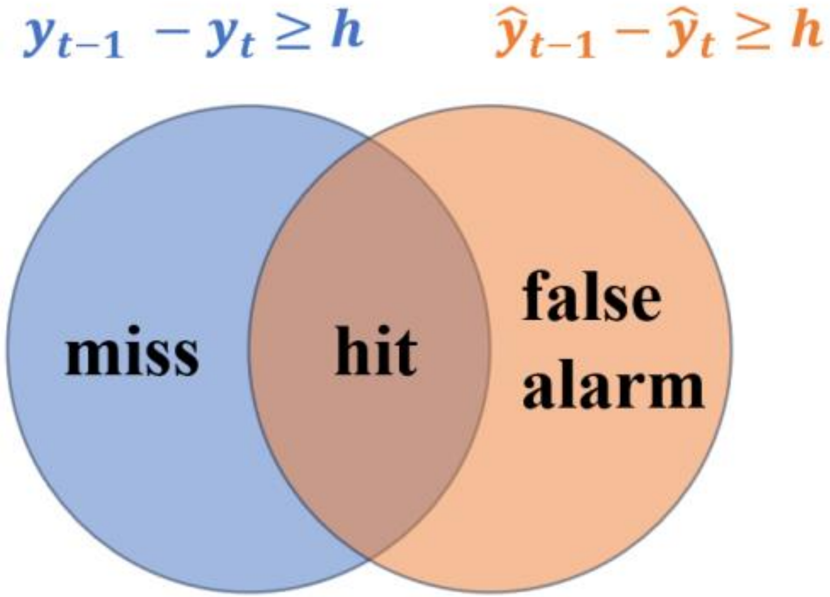
Using the Event-based Metrics

What is a ramp?

- There is no standard definition of a "ramp."
- A common approach is to choose an arbitrary threshold difference between y_t and y_{t-1} (or $\hat{y}_t$ and $\hat{y}_{t-1}$)



- We chose an arbitrary threshold h to define minimum ramp size.
  - **Units of (% of max PV output per minute).**
- Only evaluated downwards ramps.
  - In theory, these matter more since you can always curtail.

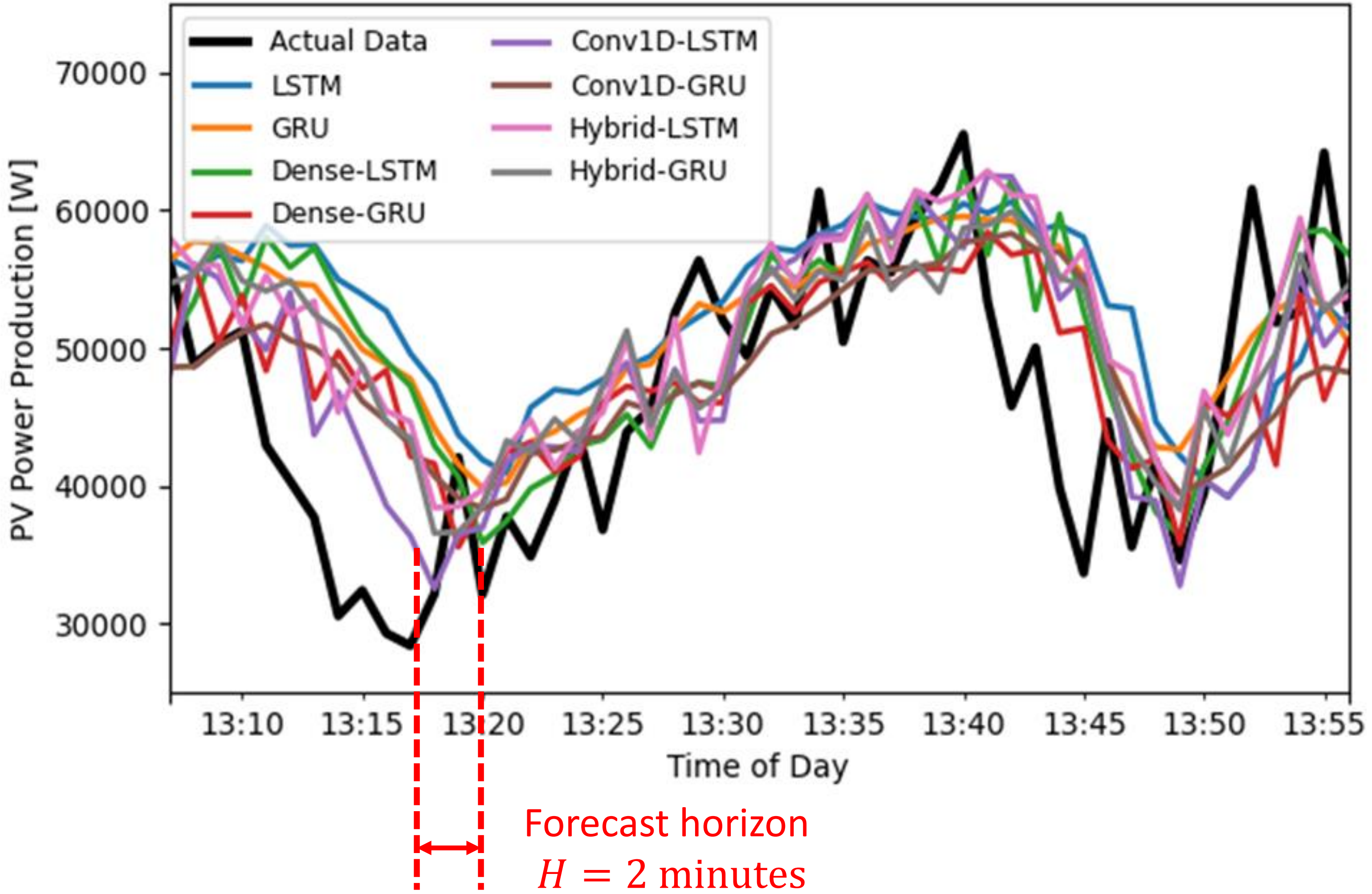


Model Performance

- Once the models were trained, 10% (7 days) of the data were used to generate forecasts for analysis.

- A clear systematic lag of 2 minutes.
    - All of the models are "learning" to copy persistence models.

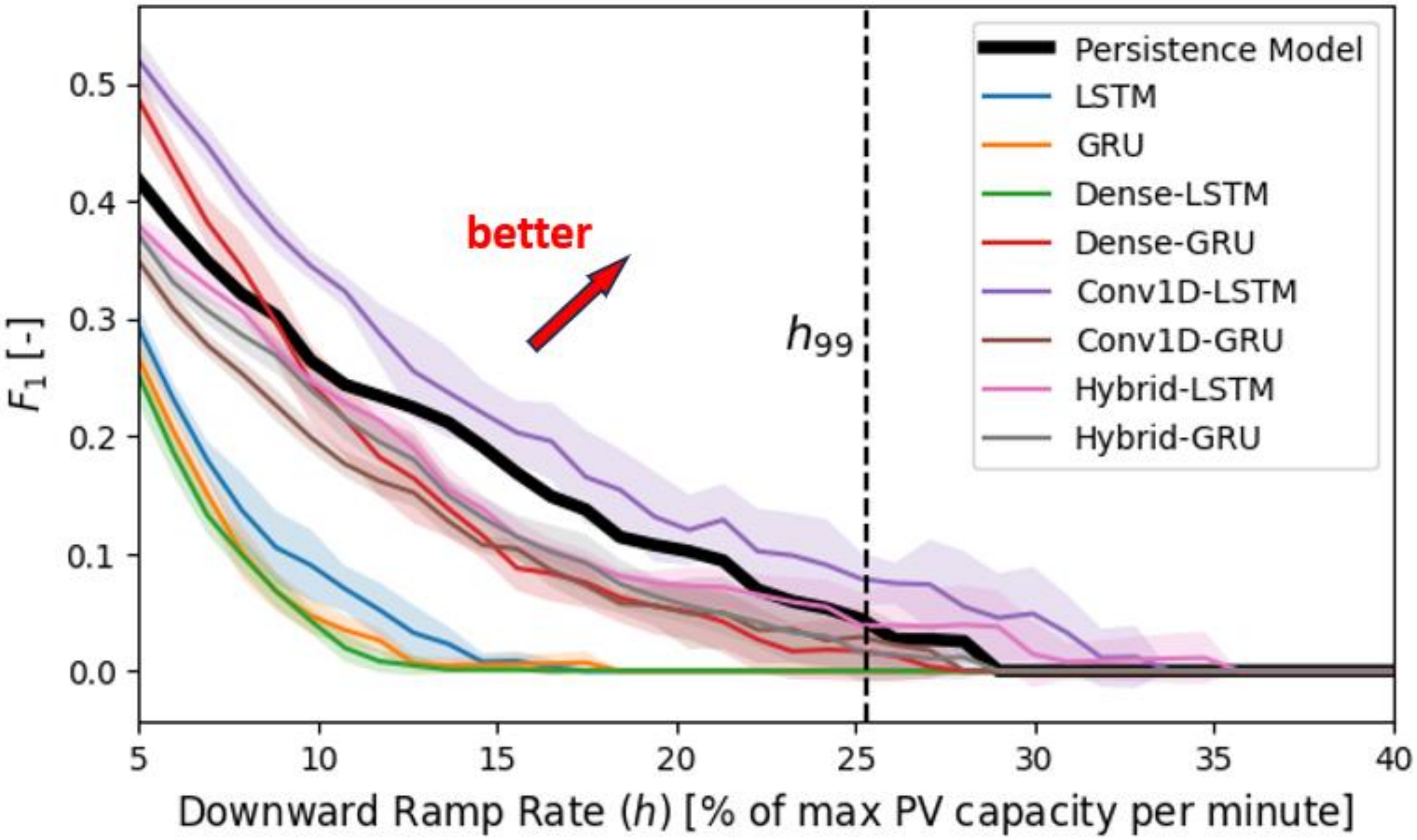
- This is a commonly observed issue in the literature with models which use their target variable as input.



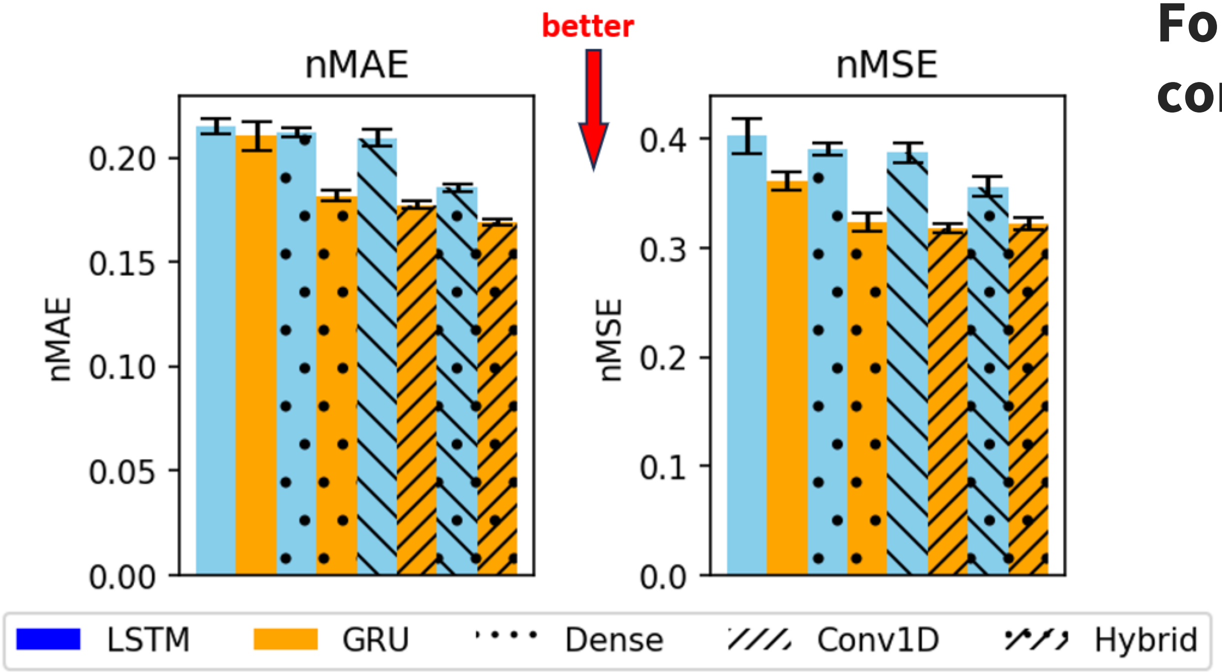
Event-based Results

- Our goal is to detect ramps which could threaten grid stability.
- How big that ramp is (h) is highly dependent on the state of the given grid.

- Only the Conv1D-LSTM model structure was able to reliably beat a persistence model in terms of F_1.
- Less complex models performed noticeably worse.
- Performance across all models was lacking.
- Small sample size of ramp events due to lack of data.

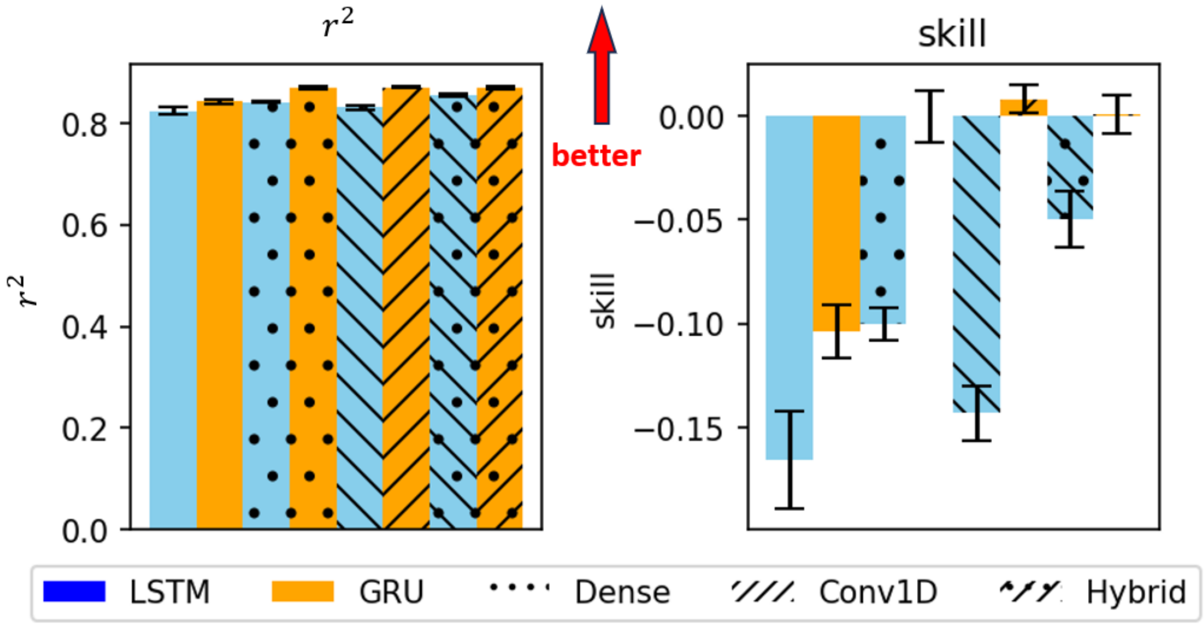


Standard Error Metric Results



Forecasts from the same 7 test days compared using standard error metrics

- *skill* values are low compared to literature
  - **0.30** to **0.95** [3]
  - **-0.26** to **0.54** [5]
  - **-0.05** to **0.20** [8]
- r^2 scores are about on-par with literature.



- nMAE and nMSE values are high compared to literature.
  - nMAE: **0.04** to **0.15** [5, 6]
  - nMSE: **0.02** to **0.20** [3, 7]

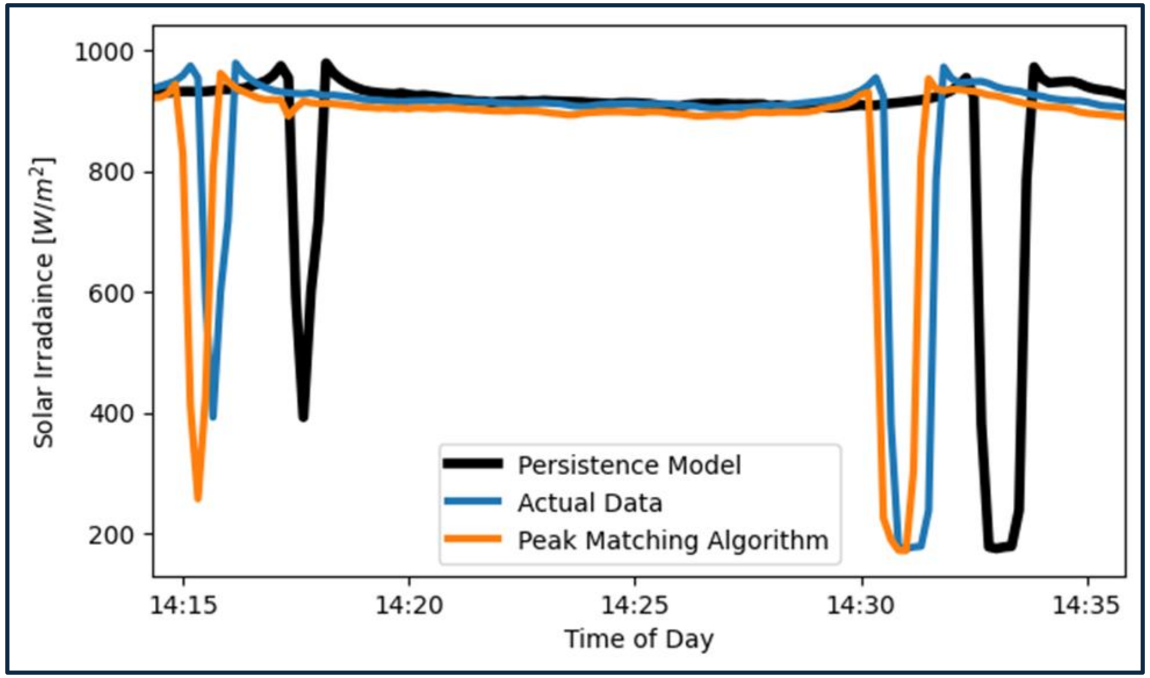
Conclusions and Ideas for the Future

Lessions Learned

- Using PV production as both input and target caused it to dominate the forecast.
- The sensors only being able to transmit 20 seconds every 2 minutes caused some ramps to go undetected.
- Having only 71 days of data potentially limited the capability of the models to extract patterns and reliably generate forecasts.

Next Steps

- Developing sensors which can meet design requirements ***and*** transmit more frequently.
  - Theoretically possible within U.S. FCC radio transmission limits.
- Testing peak-matching/wavelet decomposition on Kotzebue data.



Peak-matching algorithm [3] used on data from NREL Oahu solar measurement grid [9]

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Questions or Comments?

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