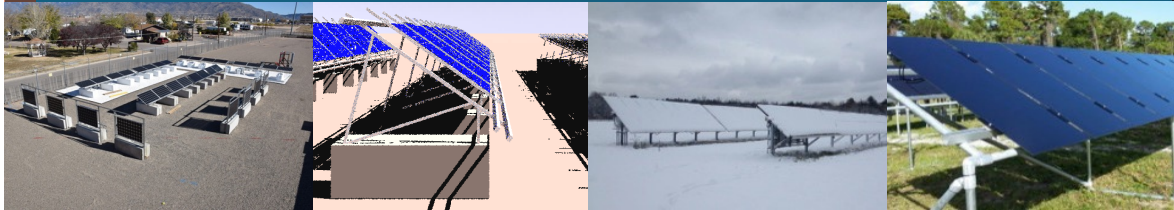




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# Approaches to Sky Image Based Single Axis Tracker Algorithms



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## Single axis tracking in varied weather conditions

- ❖ Most SAT algorithms (such as pvlib's) **only follow the Sun**
- ❖ This is optimal when there are **no clouds**
- ❖ Cloud covering the Sun = less direct, more diffuse
  - ❖ When it's very cloudy, **move trackers towards the horizontal to maximize diffuse**

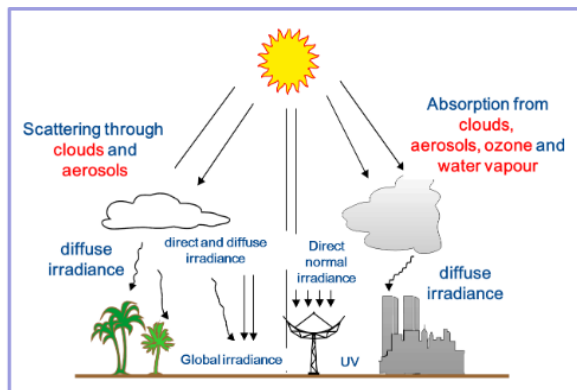
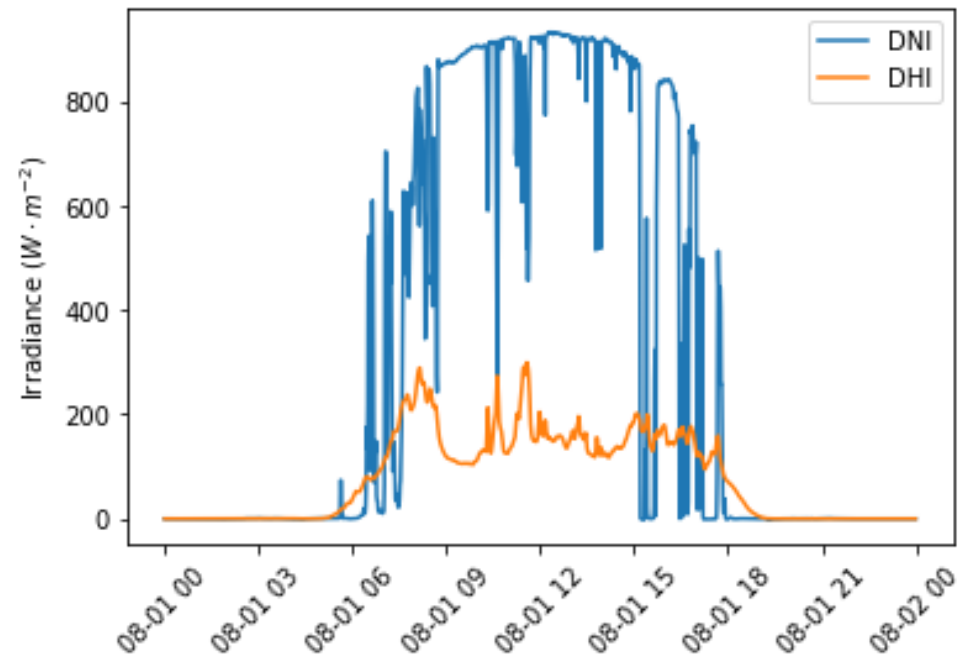


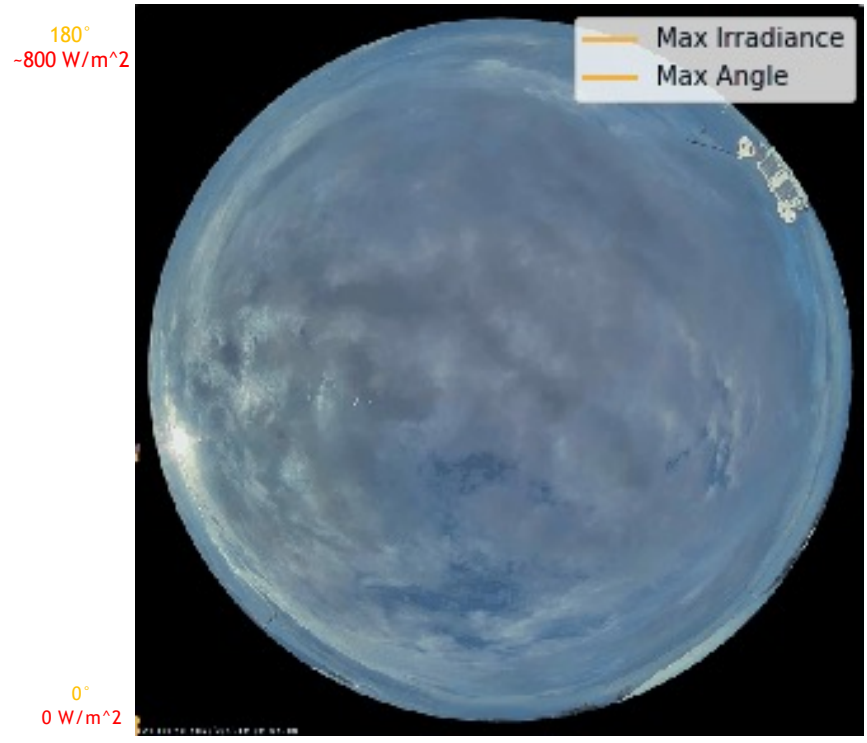
Figure: Copernicus Atmosphere Monitoring Service



## Relationship between angles, irradiance, and weather

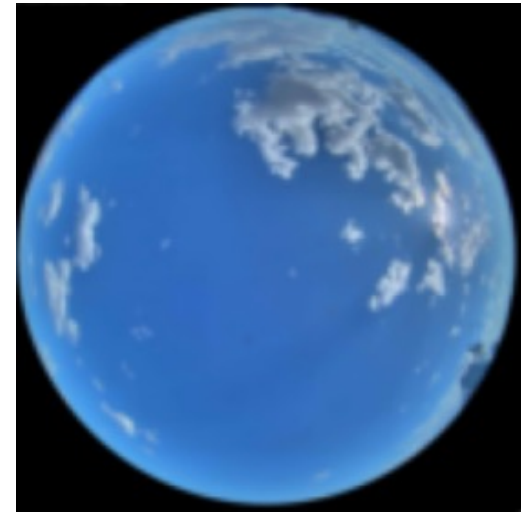


- ❖ Orange line: Normalized angle of max irradiance
- ❖ Red line: Normalized irradiance at max angle
- ❖ “Spiky” signal- angle of max irradiance would not be a good tracking strategy
- ❖ Short-term effects often not modeled due to coarser aggregations, but are impactful

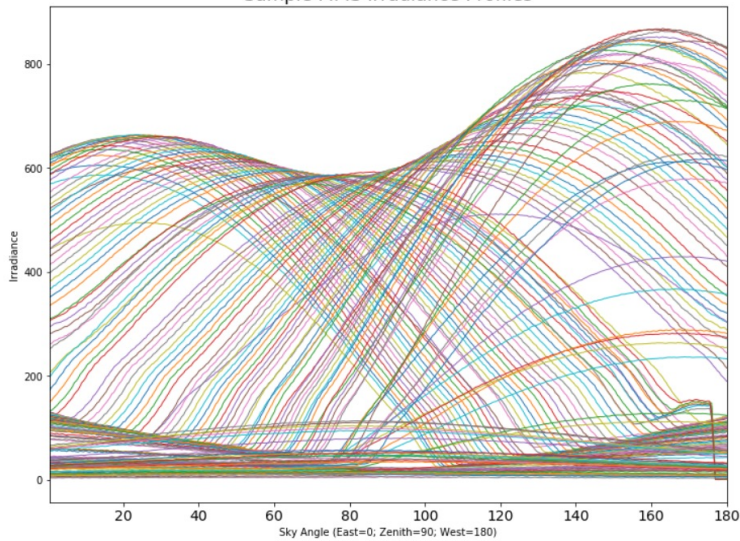


# Data collection and sensors

- ❖ Sky images collected in real time
- ❖ Validation data is collected with a Multi Planar Irradiance Sensor (MPIS)
  - ❖ Irrad. sensor rotating on same axis as tracker
- ❖ Physical MiniSATs as testbench



Sample MPIS Irradiance Profiles



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# Multiple possible approaches



- ❖ We plan to implement and test three different types of algorithms
  - ❖ Cloud coverage heuristic
  - ❖ Past- $n$  regression
  - ❖ Deep Reinforcement Learning

- ❖ Each approach uses a neural network of some type to do:
  - ❖ Cloud segmentation
  - ❖ Prediction of angle of *maximal irradiance*
  - ❖ Prediction of optimal *movement strategy*

} These are different, due to tracker movement costs, wear and tears, etc

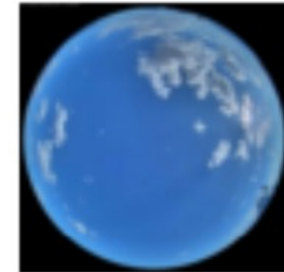
- ❖ Each has different drawbacks, such as
  - ❖ Manual input & bias for movement strategy
  - ❖ Reliant on accurate angle predictions
  - ❖ Difficult to train & generalize

} These two are also less explainable due to lack of explicit decision tree

# Cloud Coverage Heuristic

- ❖ Concept:
  - ❖ If extended cloud cover: **Move towards the horizontal by some amount**
  - ❖ Else, **follow the Sun**
  - ❖ Further conditions based on **system knowledge**
- ❖ Many methods of calculating cloud coverage in literature
  - ❖ Your sky camera probably has one already
  - ❖ I presented a **neural network** based model at PVSC
- ❖ Has additional parameters:
  - ❖ % **coverage** to be considered cloudy
  - ❖ **Number of previous timesteps** to consider
- ❖ Simulations find this algorithm to be a **~0.06-0.08% gain in ABQ, NM**
  - ❖ Grid search over parameter space yields highly reactive tracker
- ❖ Advantages: Simple, configurable
- ❖ Disadvantages: Site specific heuristics/parameters

Original

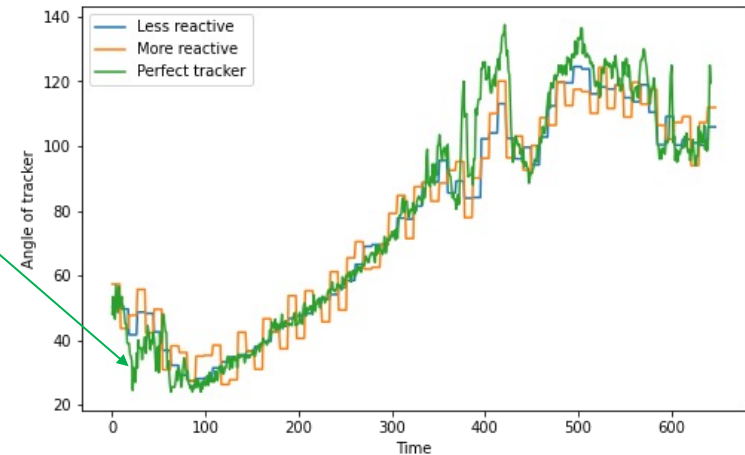
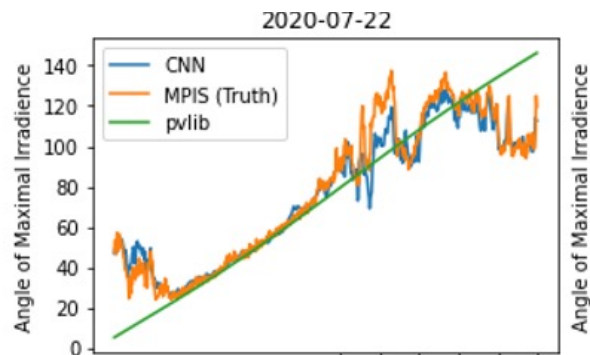


CAE prediction

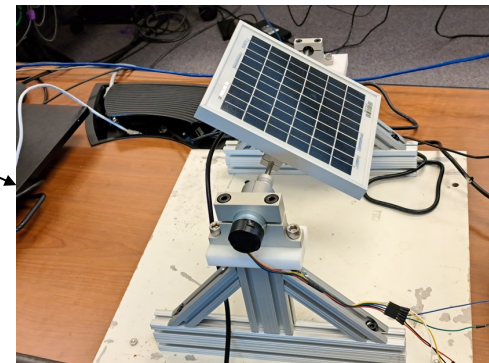


# Past- $n$ regression for tracker motion

- Use past  $n$  minutes of angles of maximal irradiance
- Move by **some threshold  $r$**  in direction of slope
- Update tracker **every  $k$**  minutes
- Advantages: explainable, adjustable
- Disadvantages: requires specialized device (eg MPIS) to find angle of max irradiance
  - Prototype sensor for wide deployment
  - Convolutional neural network (CNN)



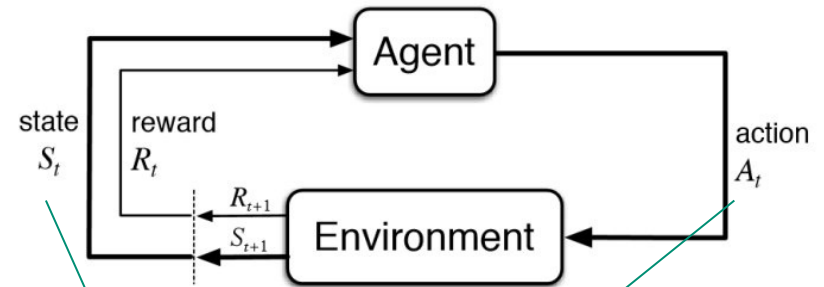
Algorithm can be adjusted by changing  $n$ ,  $r$ ,  $k$  to desired specificity



# Deep Q Learning for tracker motion



- Use Deep Q Learning, a type of reinforcement learning (RL) to predict **optimal movement strategy**
- Agent receives **rewards** (eg irradiance received) and **learns** based on expected future reward.
  - “What move will result in the maximal power received at the end of the day?”
- Approximate decision lookup table (function) with ANN
- Advantages: data-driven, adaptable
- Disadvantages: “black box”, computationally intensive to train



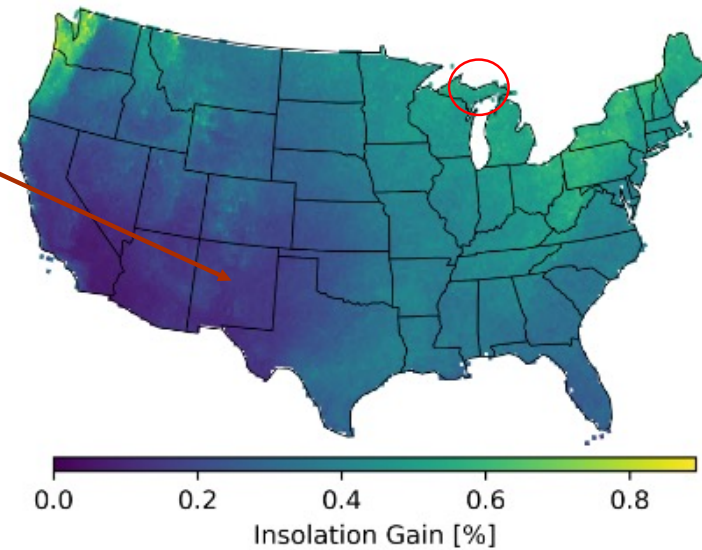
		actions			
		$a_0$	$a_1$	$a_2$	...
Sky image	states				
	$s_0$	$Q(s_0, a_0)$	$Q(s_0, a_1)$	$Q(s_0, a_2)$	...
	$s_1$	$Q(s_1, a_0)$	$Q(s_1, a_1)$	$Q(s_1, a_2)$	...
	$s_2$	$Q(s_2, a_0)$	$Q(s_2, a_1)$	$Q(s_2, a_2)$	...
	⋮	⋮	⋮	⋮	⋮

Expected movement reward



## Current Results & Next Steps

- ❖ Problem: **ABQ, NM is too good for PV!**
  - ❖ Extended periods of cloudiness are **rare** for much of the year
  - ❖ High overall irradiance dominated by direct component
- ❖ So, models behave “unrealistically” in most cases
  - ❖ Cloud coverage is **too reactive** (teleportation)
  - ❖ Past- $n$  regression **oscillates**
  - ❖ RL **doesn't move at all** (risk vs reward!)
- ❖ **Other conditions** must be considered
  - ❖ Snow shedding
  - ❖ Wind
  - ❖ Terrain
- ❖ Next step: **Install MPIS & Sky Camera at Michigan Tech RTU**



Anderson & Aneja PVSC 2022

Questions?

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