

Comparison of Cloud Speed Data for Solar Ramp Rate Analysis

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Motivation

For a power utility or transmission system operator (TSO) solar PV ramp rates are important for system planning, namely for:

1. Grid Frequency/Voltage Regulation
2. PV Deployment Studies
3. Bulk Generation Planning for Near/Far Term

The **Wavelet Variability Model (WVM)** calculates the average irradiance over a plant given plant geometry, an irradiance source, and cloud speed. It models the smoothing effect of uneven irradiance as clouds transit a solar PV plant.

Improving the cloud speed input may allow for more accurate ramp rate estimations. Cloud speed (CS) measurement methods in development with higher frequency cloud speeds were used with the WVM to estimate ramp rates to assess the potential improvement.

Cloud Speed Methods

NAM (baseline): The *North American Mesoscale Model* is a weather model. CS is extrapolated by finding the alt. of max humidity and using the modeled wind speed/dir. as the cloud speed and dir. Example seen in Fig. 1.

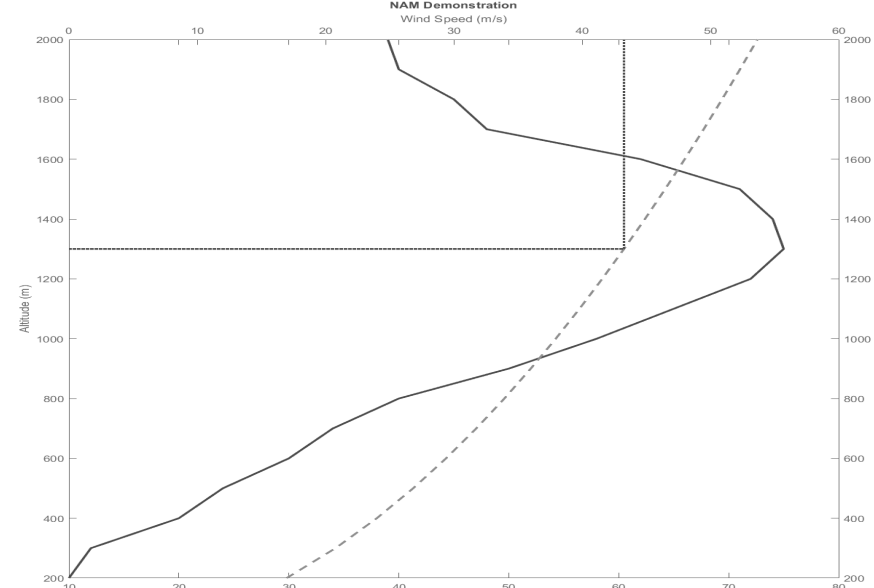


Figure 1: Demo NAM Method

CSS: The *Cloud [Shadow] Speed Sensor* was developed at UCSD. It has an array of photodiodes as seen in Fig. 2. From this array it calculates cloud speed and dir. by fitting the corresponding delay and direction for each photodiode pair to a cosine curve. The phase shift/amplitude of the cosine function informs cloud speed and dir.—Fig. 3.

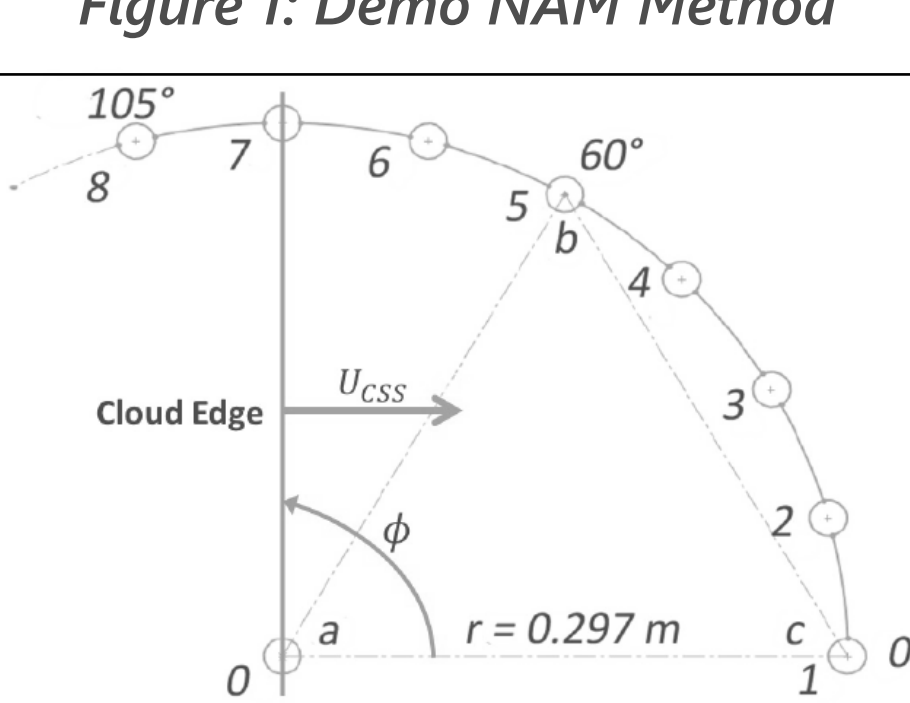


Figure 2: CSS Photodiode Layout

MCC: The *Macro Cloud Continuity Method* uses readily-available plant data at the combiner level. Using 15 sec. timeseries data, shading for 1 and 2 minute periods at a timestep are collected. Cloud motion is the translation of the shading. A linear fit is used to calculate cloud speed and direction as seen in Fig. 4.

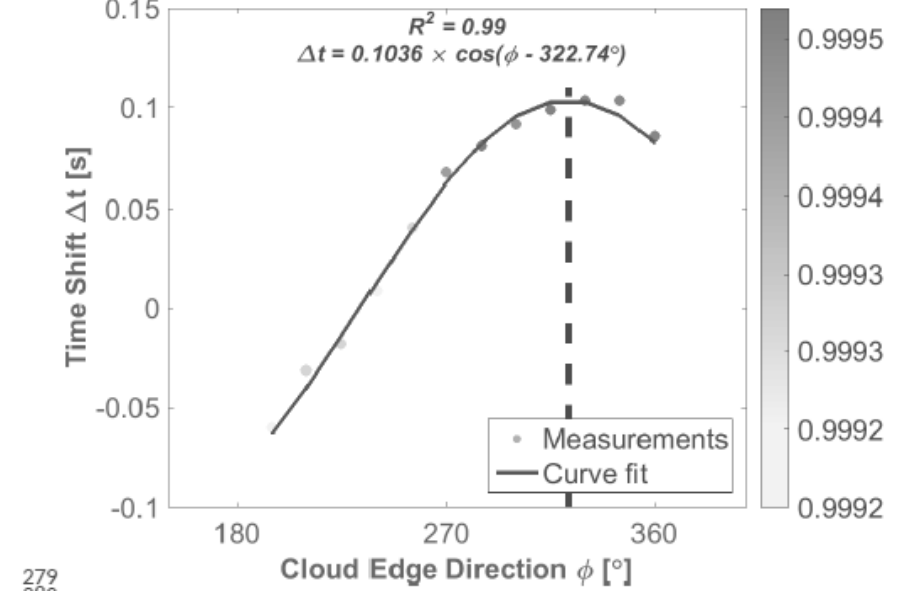


Figure 3: CSS Curve Fitting Method

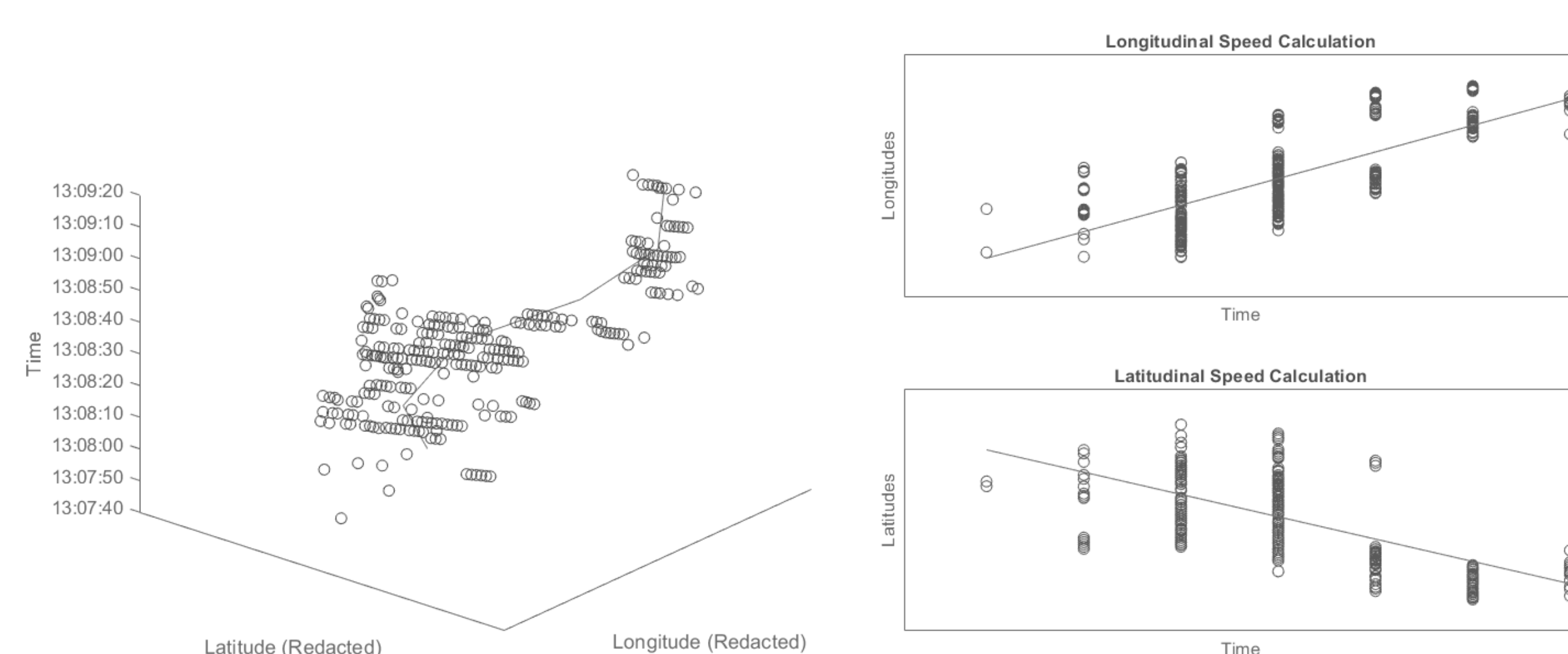


Figure 4: MCC Linear Regression Method. Left plot shows the first shading instance for each shaded region in the plant. Right plots show Long. and Lat. speed calculation.

WVM Analysis Methods

The **WVM** was modified to allow variable resolution cloud speed. The variability reduction factor calculation was modified to allow various cloud speeds at different frequencies.

The **3 cloud speed methods** were compared as inputs to the WVM for various averaging periods, including: 1h, 2h, 3h, 4h, 6h, 12h, 24h, Weekly, Monthly, and Period.

The **Methods** were compared to each other and actual ramp rates for each aggregation period.

CS Method Results

Notable Observations:

1. Fig. 5 shows the average daily CS for each hour over the period. Reasonable agreement can be seen.
2. Fig. 6 demonstrates that the MCC outperforms others for 1 min. ramps. The MCC can capture more clouds and works over larger distances, potentially yielding more cloud speeds than the CSS, resulting in potentially more robust hourly CS averages.
3. Fig. 6 shows that the CSS outperforms the NAM for 1 min. ramps.
4. Fig. 6 shows CSS and NAM varying less with aggregation period.
5. Fig. 7 shows that at longer ramp rate periods, differences in methods disappear—likely due to the effect of CS being diminished and ramps being driven by the diurnal solar cycle.

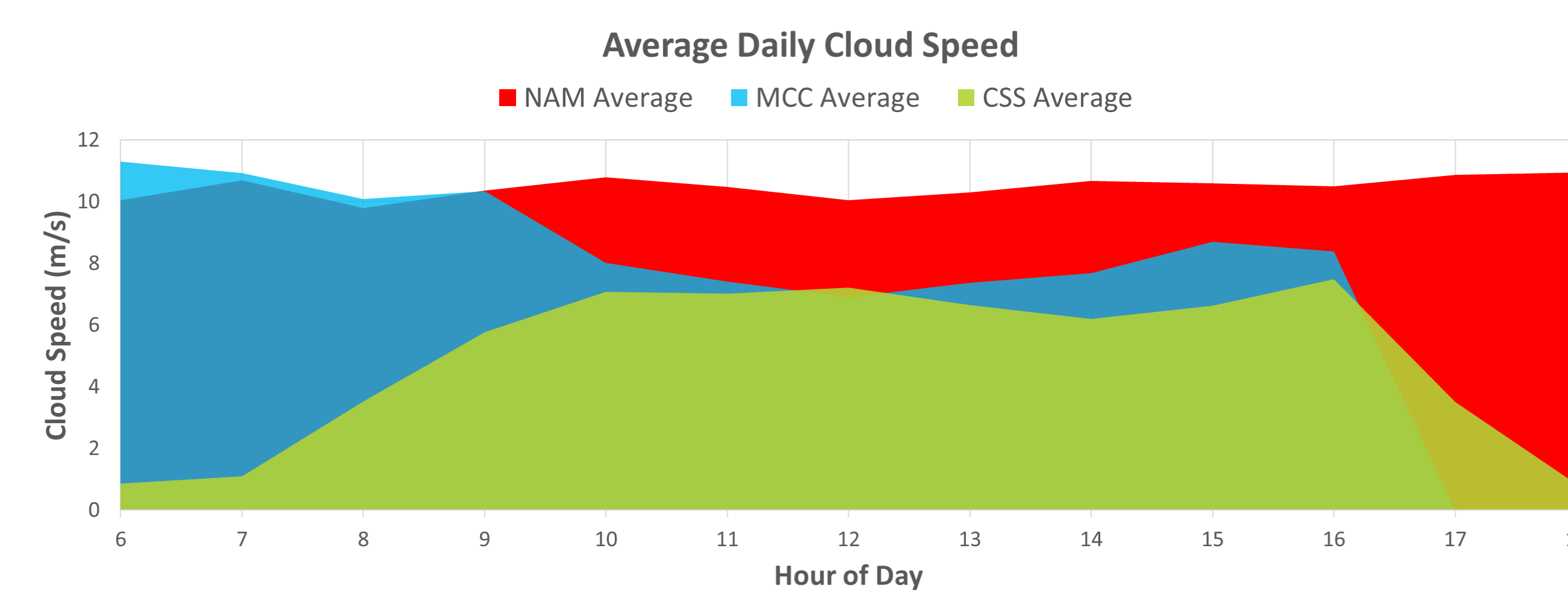


Figure 5: Daily average cloud speed profiles for the four methods.

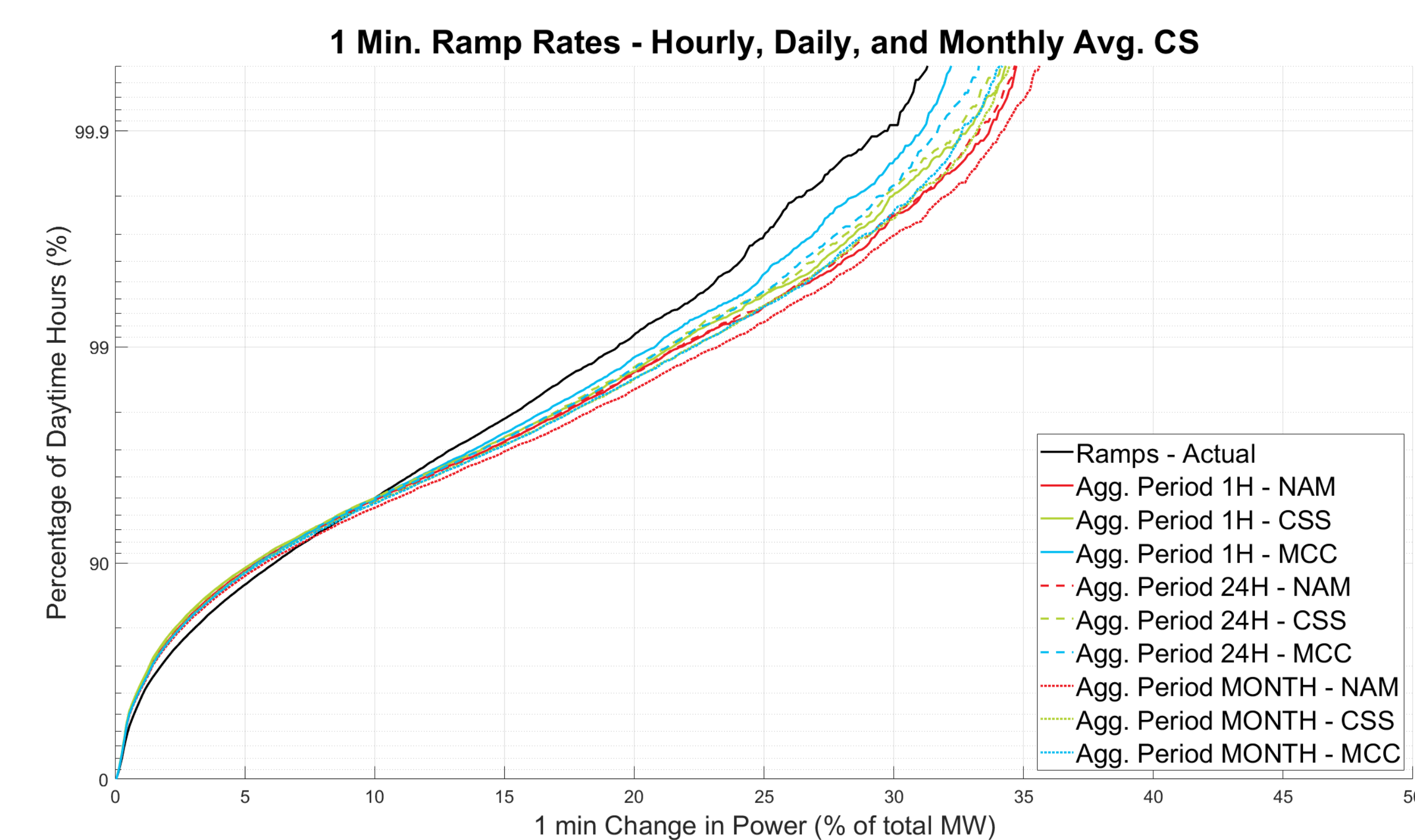


Figure 6: Comparison of modeled ramp rates with different CS aggregation periods.

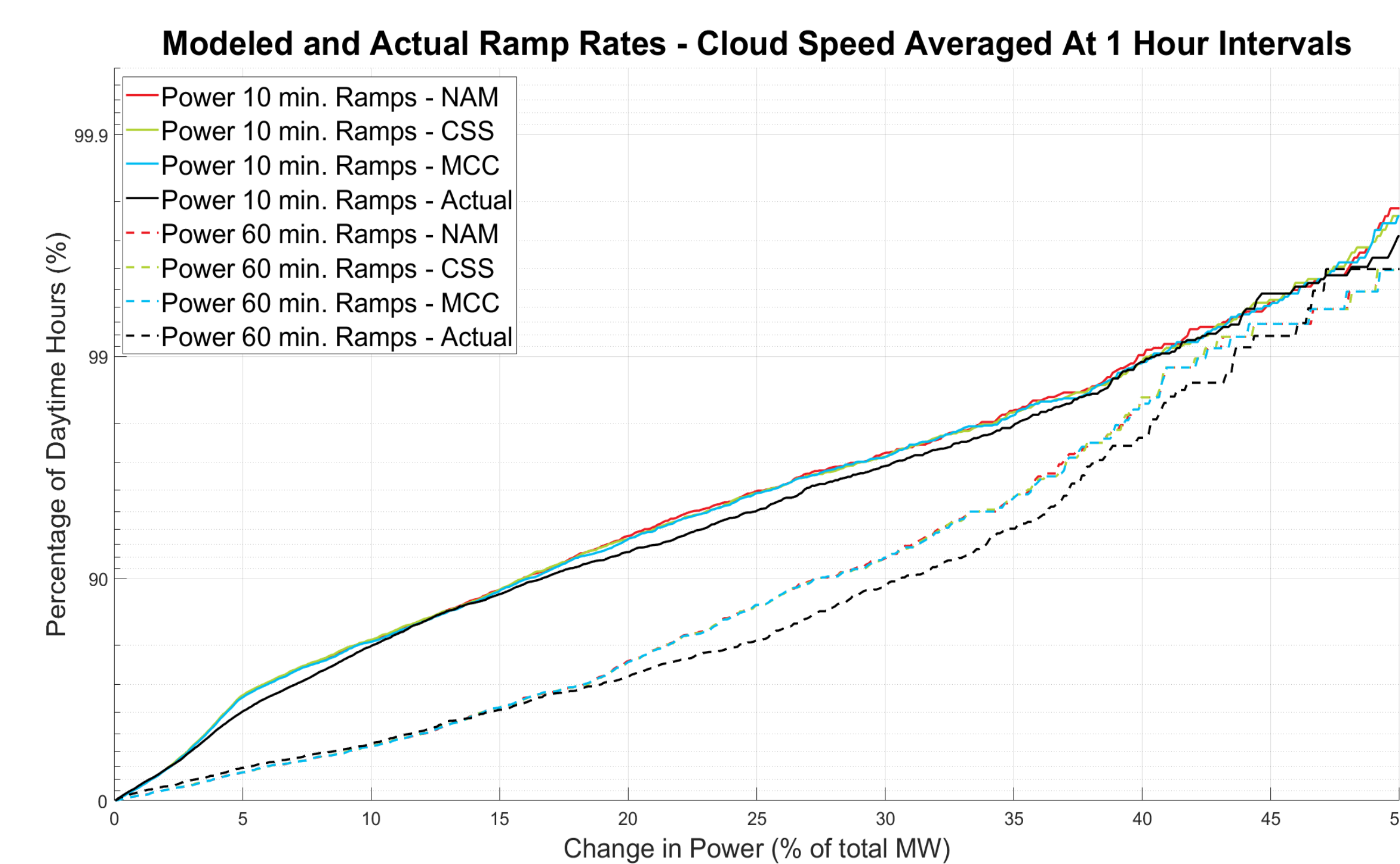


Figure 7: Modeled 10 minute and 60 minute ramp rates for 1 hour aggregate CS. Shows less variance between methods, in particular for 60 minute ramps.

CS Period Results

Notable Observations:

1. Fig. 8 shows a significant benefit to higher frequency CS using the MCC for 1 min. ramps.
2. Fig. 9 shows aggregate data can best predict 10 min. ramps over a long period, implying the value of high frequency CS is for extreme ramp rate modeling. For 95th percentile estimations, aggregated data may be more accurate because of canceling seasonal biases.
3. Fig. 10 shows that for daily 95th percentile ramp rate modeling, higher frequency CS can improve modeling.

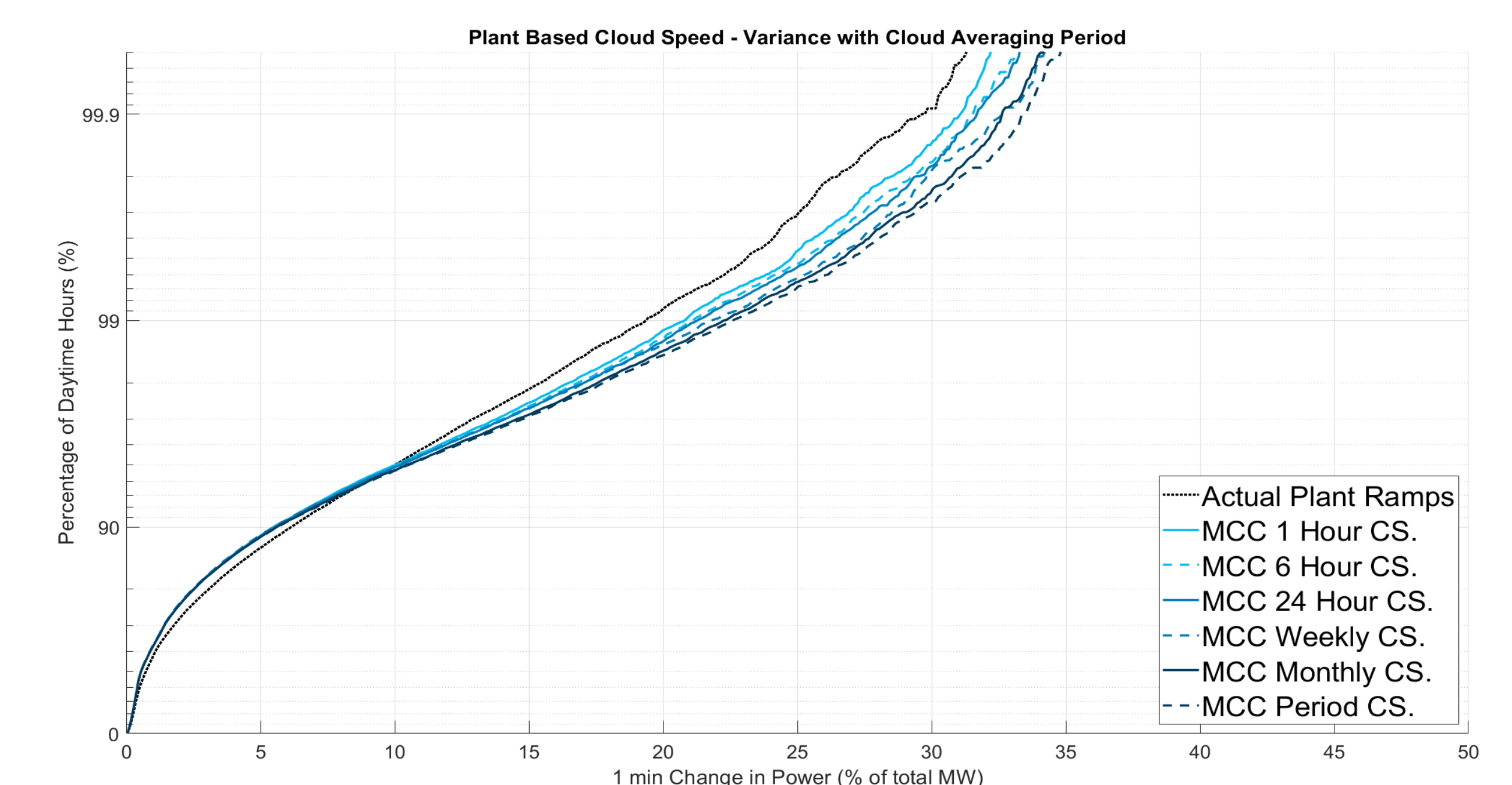


Figure 8: Modeled ramp rates using the MCC method for different CS aggregation periods.

| Cloud Speed Method | 1h | 6h | 24h | Week | Month | Period |
|--------------------|------|------|------|------|-------|--------|
| NAM | 9.22 | 8.01 | 7.38 | 5.82 | 4.91 | 4.55 |
| CSS | 7.23 | 7.26 | 6.73 | 7.3 | 5.97 | 5.83 |
| MCC | 7.32 | 7.03 | 6.7 | 7.27 | 5.56 | 5.61 |

Figure 9: Heatmap of the relative error of the 95th percentile of 10 minute ramps over the entire period for each CS method and aggregation period.

| Cloud Speed Method | 1h | 6h | 24h | Week | Month | Period |
|--------------------|-------|-------|-------|-------|-------|--------|
| NAM | 13.74 | 12.7 | 12.79 | 13.58 | 13.69 | 13.82 |
| CSS | 13.03 | 13.16 | 13.21 | 13.58 | 14.51 | 13.99 |
| MCC | 13.62 | 13.98 | 14.23 | 14.03 | 14.15 | 14.22 |

Figure 10: Heatmap of the median daily relative error for each CS method and aggregation period. Shows daily modeling is somewhat improved using high frequency CS, despite noise.

General Conclusions

Ramp Rate Modeling using the WVM can be improved with empirical and higher frequency cloud speed measurements.

Cloud Speed derived from plant data can be used to improve ramp rate modeling, which suggests the method is reasonably accurate.

1 min. ramp modeling can be improved with improved CS methods.

Higher frequency CS measurements may be most applicable to extreme ramp rate modeling (e.g. freq./volt. regulation & near-term generation planning).

Aggregate data may offer better results for long term planning.

References

1. M. Lave, J. Kleissl. "Cloud Speed Impact on Solar Variability Scaling—Application to the Wavelet Variability Model"
2. M. Lave, J. Kleissl. and J. Stein "A Wavelet-Based Variability Model (WVM) for Solar PV Power Plants"
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4. J. Stein et al. "PVLIB: Open Source Photovoltaic Performance Modeling Functions for MATLAB and Python"