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In-situ Atmospheric Intelligence for Hybrid Power Grids: Volume 1 (Feasibility Study)

by Gail Vaucher, Sean D'Arcy, and Morris Berman

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In-situ Atmospheric Intelligence for Hybrid Power Grids: Volume 1 (Feasibility Study)

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14. ABSTRACT Envisioning future optimized and fully versatile tactical energy includes the integration of not-yet standardized resources, such as solar energy. Once successful, the net result could reduce the current dependency on one-time-use fuels, lessen battery requirements (lightening Soldier loads), and replace supply trains and logistics costs (human and fiscal) with longer-lasting, more durable materials that better optimize power utilization and generation. A separate US Army Combat Capabilities Development Command Army Research Laboratory (ARL) microgrid simulation study found that with a minimal set of atmospheric parameters, hybrid power fuel consumption could be reduced. Bridging the gap between simulations and real-world applications posed the question, Can the needed atmospheric intelligence be gleaned from in-situ-only resources and formatted for an isolated, tactical hybrid power distribution manager? The ARL in-situ Atmospheric Intelligence for Hybrid Power Grids (AI-HPG) Feasibility Study answered this question with an affirmative. This report documents the AI-HPG Test-bed design consisting of four primary elements: two on-site atmospheric measurements and two models. Methods used to calibrate the models are presented. The feasibility study not only confirmed that the on-site-only data limitations could be successfully overcome, but also discovered that the test-bed output could contribute to microgrid simulation validation research. Future work includes automating the data flow and streamlining technology and techniques.					
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Executive Summary

Advancing versatile tactical power and propulsion for future Multi-Domain Operations requires reliable and resilient electrical power resources. Diversifying power resources and optimizing that diversity capture the core strategy of the research being reported in this document. The new understandings gained by this investigation have strong relevancy in the development of constructive solutions for various isolated disaster relief scenarios as well.

Envisioning and planning the future optimized and fully versatile tactical energy supply includes the integration of the not-yet standardized renewable resources. Once successful, the net result will reduce the current dependency on one-time-use fuels, lessen battery requirements (lightening Soldier loads), and replace supply trains and logistics costs (human and fiscal) with longer-lasting, more durable materials that better optimize power utilization and generation.

Such a diversification of power resources begins with understanding the atmosphere's impact on alternative power resources. The US Army Combat Capabilities Development Command Army Research Laboratory (ARL) microgrid simulation study showed that having local atmospheric intelligence reduced fuel consumption for a hybrid power grid.¹ The study found that for grid optimization, a benefit was derived simply from the knowledge of a minimal set of atmospheric conditions and parameters. Building a bridge between simulations and “boots on the ground” applications prompted the question, Can one acquire and communicate the needed atmospheric intelligence to an isolated, tactical hybrid power distribution manager?

This reports documents the ARL in-situ Atmospheric Intelligence for Hybrid Power Grids (AI-HPG) Feasibility Study, the testing of a proposed method for DoD or disaster relief applications to optimize power distribution while requiring both timely and relevant meteorological input from only in-situ resources. Specifically, this report documents the AI-HPG Test-bed design, which consists of four primary elements:

- Two in-situ atmospheric measurements, photovoltaic (PV) panel temperature and sky documentation quantified by a simulated Whole Sky Imager. The latter in-house-built sensor uses cost-effective, contemporary materials to

¹ Jane R, Parker G, Vaucher G, Berman M. Using meteorological forecast to improve microgrid performance. Submitted to IEEE - Transactions on Smart Grid. 2019 Aug.

provide the atmospheric sky conditions required by the system's solar radiation model.

- Two models: a solar radiation model and a “solar radiation to power conversion” model. These two models ingest the in-situ measurements and calculate the PV power generation. The model output is formatted for use by microgrid optimization management software.

Models were created and tailored for this application, and then an end-to-end data flow was executed to test the feasibility of acquiring in-situ atmospheric intelligence and converting it into useful hybrid power grid management information. The feasibility study not only confirmed that the on-site-only data limitations could be successfully overcome, but also that the test-bed output could contribute to microgrid simulation validation research. Future work includes automating the data flow and streamlining technology and techniques.

1. Introduction

Future Multi-Domain Operations require forward-looking versatile tactical power and propulsion. Current and future tactical power grapple with the same challenges in their service to the Soldier: the provision of reliable and resilient electricity. Envisioning optimized and fully flexible power with minimal logistics demands anticipating diverse and dynamic tactical power resources. In the future, reaping energy from one's local environment will no longer be the exception, but the standard. Before this new standard can be realized, several key concepts need to be explored and converted into practical knowledge. The US Army Combat Capabilities Development Command Army Research Laboratory (ARL) in-situ Atmospheric Intelligence for Hybrid Power Grids (AI-HPG) Feasibility Study was executed from this framework, and its real-world milestones are described below.

1.1 Long-Term Vision

Future tactical power grids, whether flying a swarm of mini-drones or supporting a mobile community of people, will aim to exploit all available energy sources and optimization opportunities. Understanding the atmosphere's impact on alternative power resources is necessary to reveal unrealized opportunities that will reduce the current dependency on one-time-use fuels, lessen battery requirements (lightening Soldier loads), and replace supply trains and logistics costs (human and fiscal) with longer-lasting, more durable materials that better optimize power utilization and generation. Diversifying power resources alone reduces a current tactical vulnerability. Stabilizing transient sources will bring their application closer to becoming a standard operating procedure. These long-term possibilities motivate the exploration of current atmospheric impacts on power generation.

1.2 Short-Term Goals and Applications

To simulate the diversification of power resources, a simplified testbed was used, which included a single traditional power resource (batteries) and a less-traditional resource (photovoltaic [PV] power). The key goal was to exploit the atmospheric knowledge to optimize power grid distribution.

In a separate simulation study, using local atmospheric intelligence resulted in a reduction of fuel consumption for a Hybrid Power Grid (HPG) (Jane et al. submitted 2019). The study revealed that for grid optimization, a benefit was derived simply from the knowledge of a minimal set of atmospheric parameters—namely, solar radiation and PV panel temperatures. Since the foundational study used a simulation, the question arose, How would one acquire and communicate

the needed atmospheric intelligence to a real-world automated power distribution manager? The method proposed would need to ensure that the meteorological input was both timely and relevant. To service the tactical or even disaster relief applications, the solution would have to be limited to only in-situ resources.

A summary of the Feasibility Study is described through a review of the AI-HPG Test-bed in Sections 2 and 3. To calibrate the models, the AI-HPG Test-bed was supplemented with solar radiation sensors (pyranometers) and the ability to determine the actual power generated by the PV, batteries, and load for any given point in time. A sample of the calibration results is given in Appendix A. Appendix B explains how the zenith vs south-angled field of view impacts surface solar radiation sampled under a clear sky. A step-by-step review of the Feasibility Test process is summarized in Appendix C.

2. System Design

The AI-HPG Test-bed design investigated hybrid power generation and distribution, while concurrently and coincidentally sampling the basic and study-specific atmospheric parameters. A description of the overall system and each system element follows.

2.1 AI-HPG Test-bed

The test-bed for investigating the ingesting of atmospheric intelligence into an isolated HPG was designed around scientific and application ideals, as well as budget and labor restrictions. The ideal HPG test-bed vision for the power requirements consisted of multiple tactical generators, multiple banks of batteries, several PV panels, one or two wind turbines, and programmable loads to utilize and optimize power distribution. Budget and labor resources reduced this ideal into a conceptual HPG composed of one PV panel, a series of three 8-V batteries that would represent a 24-V resource, and a programmable digital load that would balance the PV power generation and battery storage capacity.

The atmospheric components consisted of PV panel temperatures and surface solar radiation (a.k.a. irradiance) values. The PV panel temperature sensor, described in a later section, had only a few options. The solar radiation measurement was acquired using a research-grade pyranometer. This specialized sensor was quickly determined to not be a practical solution for the tactical and disaster relief applications (see Section 2.4). Consequently, the pyranometer measurement was converted into a stand-alone solar radiation model with sub-elements that would generate the required in-situ model input. The sub-elements consisted of a simulated Whole Sky Imager (sWSI) and specialized image analysis. Using the

same computer platform, a “solar radiation to power” conversion model ingested the measured PV panel temperature and the computed solar radiation to calculate the current PV power generated values needed by an HPG power distribution manager. This baseline design included a vision for the added capability of forecasting power generation potential based on current and predicted meteorological conditions as well. The task of exploiting the atmospheric data to optimize the HPG power distribution was conducted by Jane et al. (2019), a parallel ARL HPG simulation project. (While the intention of the HPG test-bed data was to show the feasibility of acquiring timely and relevant in-situ atmospheric data for an HPG application, the test-bed data also showed potential for contributing to HPG simulation validation studies.)

In Section 2.2, power generated by the test-bed is computed at three locations within the AI-HPC system. These values provide “power truth” for the feasibility study.

2.2 Power Generation and Management

There were three active components in the AI-HPG system that produced or consumed power. These components were the PV panel (production), load (consumption), and battery (consumption and production). All power to/from each of these components was routed through a charge controller, allowing measurements at the charge controller to form a complete representation of the total system. The power to/from each system component was calculated by multiplying the measured current (I) and voltage (V) values.

Specifically, the AI-HPG Test-bed power generation was done with a single Sunmodule XL SW 315 Mono, 315-W nominal PV panel, feeding into a MidNite Solar Kid maximum power point tracking (MPPT) charge controller. The charge controller fed power to both a 24-V battery system and a BK Precision 8510 digitally controlled variable load. The voltage and current of all three components were measured as they entered/exited the charge controller, using a National Instruments (NI) CompactDAQ chassis with three analog voltage input modules and three Riedon 0.005-ohm precision shunts. These shunts allowed current to be calculated from a voltage measurement. Customized LabVIEW software read the NI DAQ data acquisition system and also allowed control over the load. Current and voltage measurements were sampled at a user-definable interval.

PV panels are characterized by I-V curves that are dependent on environmental conditions and panel materials. I-V curves can be approximated given the panel temperature, solar irradiance, and a PV panel's electrical characteristics. The energy generated by a PV panel can then be approximated from these curves. As part of

the test-bed design, the charge controller automatically managed the voltage of the extracted power to guarantee it occurred at the maximum power point. This ensured maximum power production from the PV panel for use by the load and battery.

The system management used the only component designed for user control—namely, the load. The same LabVIEW program that acquired power data also managed the load. This software adjusted the load to follow a preprogrammed current or power, which used feedback control to ensure that power generated and distributed were kept nearly balanced. This balance was a distinguishing attribute from the foundational Atmospheric Renewable Energy (ARE) field study design. (Vaucher et al. 2017; Vaucher and Welch 2018).

With “power truth” measurements established for the test-bed, the two in-situ AI-HPG atmospheric parameters needed for the on-site power conversion model are described next.

2.3 PV Panel Temperature

The first sampled element of the AI-HPG system was the PV panel temperature. PV panel power is dependent upon the PV cell temperatures; consequently, temperature is a critical contributor to the PV power conversion model. The AI-HPG Test-bed used a DS18B20 temperature sensor attached to the PV panel. Temperatures were measured every minute from 0500 Local Time (LT) (sunrise twilight) to 2100 (sunset twilight) and stored in a file for that day. After evaluating several weeks of measurements, it was determined that the thermistor-based sensor provided a reasonable approximation of the PV cell temperatures. The sensor’s digital output was communicated directly to the computer used for collecting the other sampled element, the whole sky images (see the next section).

2.4 Solar Radiation Model, Measurements, and Model Input

Solar radiation is the key “renewable” contributor to the PV-generated electricity. While measured values of solar radiation would satisfy the system design, the system application in a tactical environment makes that solution impractical. Research-grade sensors are expensive and require periodic calibration in order to remain a valid source of atmospheric intelligence. Consequently, a solar radiation model that could function on site, using only in-situ input, was pursued. The results are described next, followed by a description of the research-grade sensors used to calibrate the model.

2.4.1 Solar Radiation Model

Atmospheric forecasting for solar energy has evolved significantly due to projects such as the SunCast, a solar-power forecasting system that was developed through a public-private-academic partnership. The five major models developed from this consortium included Statistical Forecasting, a Multisensor Advection Diffusion NowCast, Total Sky Imager Forecast, Cooperative Institute for Research in the Atmosphere Forecast, and Weather Research and Forecasting-Solar (Haupt et al. 2016). A forecasting model based on machine learning was also generated by the IBM Thomas J Watson Research Center (Hamann 2015; Martin 2015). While important advances were made for the national power grid application, their dependency on large databases, powerful computers, and network communications seriously limited their application to the on-site-only atmospheric model needed for the current project. Consequently, a search was made for a solar radiation model able to stand on its own, using only in-situ atmospheric data for input. The investigation results identified a Solar Radiation Flux (SRF) model, originally developed by Ralph Shapiro in 1982 (Vaucher and Welch 2018). This model was transcribed into a contemporary code in 2017. For a detailed review of the model, see Walker and Vaucher (2017).

The SRF model input requirements included local time, location, ground albedo, and a cloud description (amount, type, and layer). Originally designed with a graphical user interface (Fig. 1), these input parameters were recoded to accept file input as well. The output included the solar radiation at the top of the atmosphere and at the surface. The automatically plotted time series ranged from midnight (0) to midnight (1).

Before using the model, the test-bed system needed to calibrate the model output against solar radiation measurements. In the next section, the data used to assess the model are described.

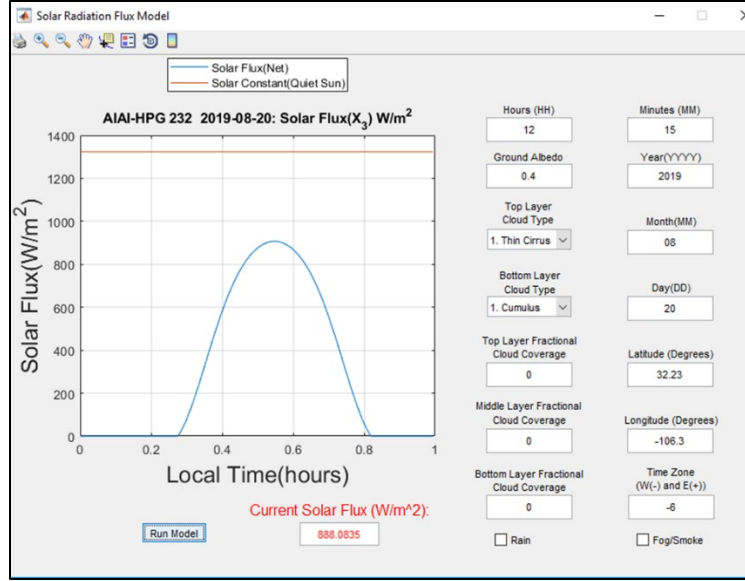


Fig. 1 Graphical user interface for the solar radiation flux model input

2.4.2 Solar Radiation Measurements and Model Validation

Linking solar radiation measurements with PV output began with a series of ARE field studies. In Vaucher et al. (2017), the ARE pyranometers were mounted on a PV panel and compared to a stand-alone suite of sensors located within 16 m of the PV panel. Pyranometers measure the total sum of direct and diffuse solar radiation received from a hemispheric field of view above the plane of the sensor. All sensors began in a zenith-facing orientation. Once the side-by-side calibration successfully served its purpose, one of the pyranometers was re-angled to align with a single south-facing PV panel. Subsequent data acquisition studies continued this pattern. The AI-HPG project was no exception.

Two pyranometers were mounted on the single AI-HPG Test-bed PV panel. Pyranometer 1 was mounted on the top-east corner of the PV panel; pyranometer 2 was mounted on the top-west corner of the PV panel. Both were about 1 m above roof level and about 1.17 m horizontally apart. In Appendix A, the side-by-side pyranometer calibration results are displayed for the 13–24 June 2019 time period.

An enlargement of the 17–18 June (Fig. 2) pyranometer time series is provided to better view the sensor sample alignments. On Julian day (JD) 168 (17 June 2019), the early morning was partly cloudy, as seen by the noisy Gaussian curve. From mid-morning through mid-day, the interrupted curve indicates that clouds dominated the sky, causing irradiance fluctuations. In the afternoon, clear skies persisted, as shown by the smooth time series. This smooth trend continued through the next day. Both zenith-facing sensors coincidentally captured the magnitude of a very brief, subtle sun occultation in the afternoon of JD 169 (18 June).

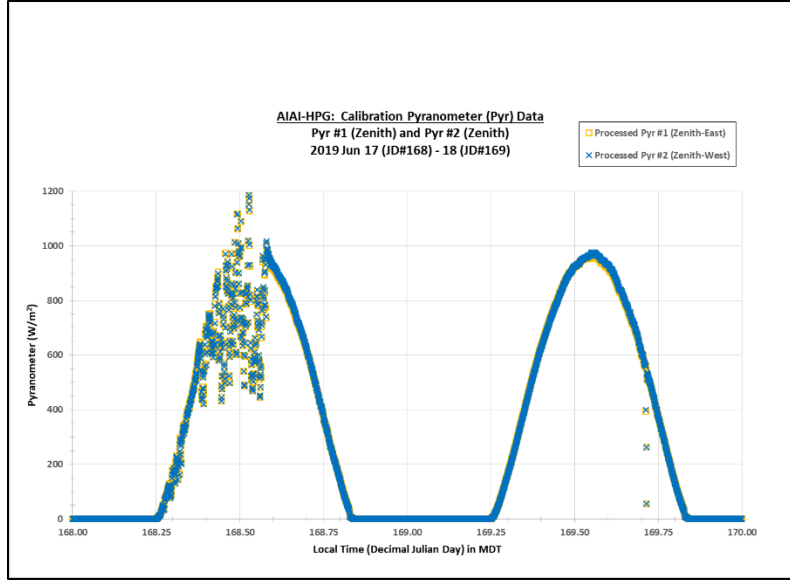


Fig. 2 Side-by-side pyranometer calibration results for partly cloudy (18 June 2019) and nearly clear (18 June/afternoon – 19 June 2019) sky conditions

Figure 3 compares the two pyranometers directly. The bright pink line shows a perfect fit. The near-linear alignment of the side-by-side zenith-facing pyranometer results instilled confidence in the dual AI-HPG pyranometer acquisition resources.

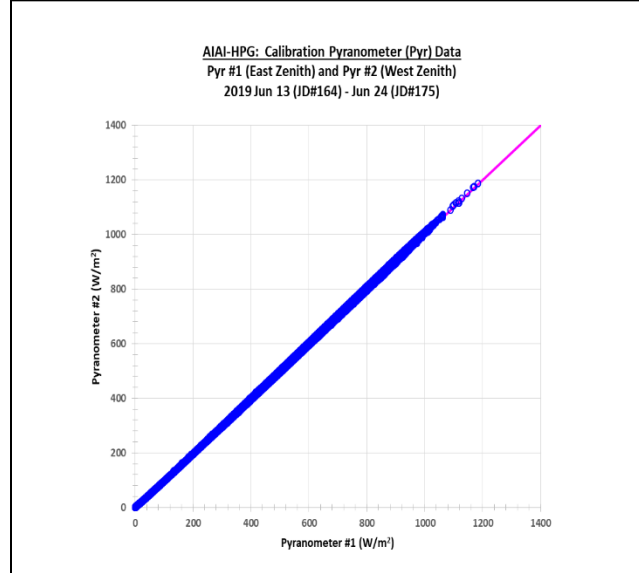


Fig. 3 Calibration results: comparing concurrent pyranometers over a 48-h period

Once confident in the sensors, the east mounted sensor was re-oriented to align with the south-facing PV panel's 32° angle above the surface. Data were periodically downloaded and reviewed for quality control purposes. Figure 4 shows an example of a full 24-h cycle of angled and zenith-facing pyranometer data. For this JD 206

(25 July) sample, the day implied some shadowing in the morning around 0700 LT but is predominantly clear for the rest of the day. A small interruption around the 1155 LT time period was picked up by both sensors, as was the increased cloudiness near sundown.

Of interesting note is that under clear skies, the angled pyranometer shows less solar radiation than the zenith sensor. Typically, a field of view angled to latitude (in this case, about 32° from the surface) will capture more sunlight than a zenith-facing field of view. However, for the 25 July case, the position of the sun in the sky was far enough north over the test-bed field site that the zenith pyranometer was closer to the ideal orthogonal orientation with the solar disc than the angled pyranometer (12° vs. 46° angle, as measured from sun). The net effect was a provision of more clear sky solar radiation for the zenith orientation than an angled perspective. For a more detailed explanation, see Appendix B.

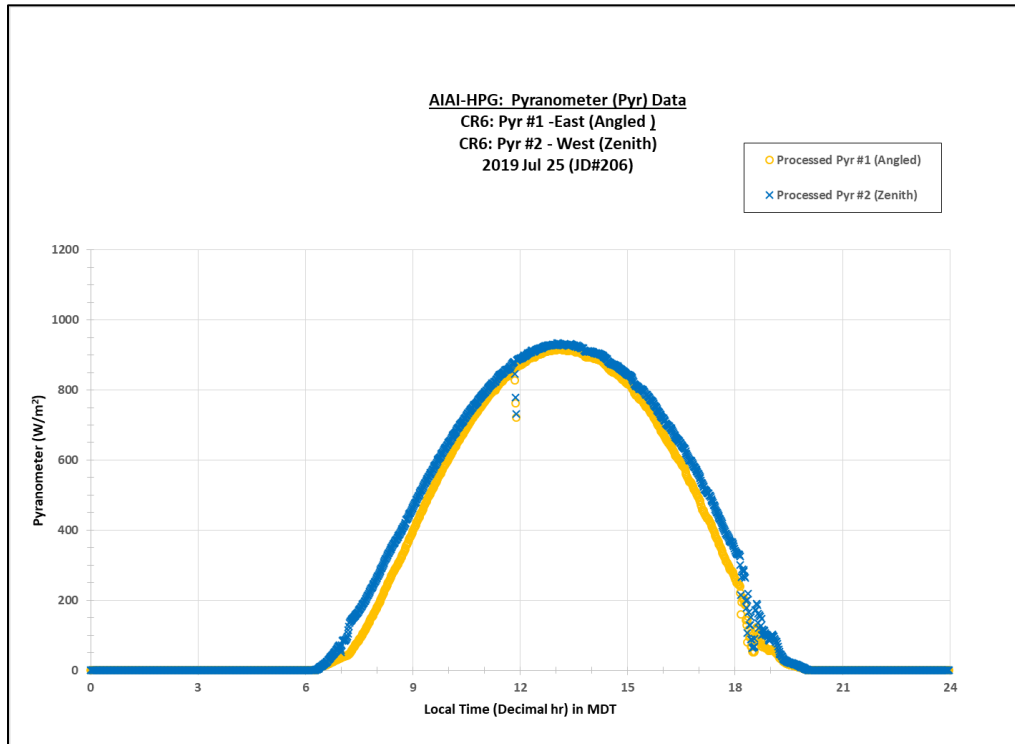


Fig. 4 AI-HPG pyranometers: pyranometer 1 (east side of PV panel) was mounted at the same angle as the PV panel; pyranometer 2 (west side) was zenith facing

In contrast, under cloudy skies, an angled pyranometer can exceed the zenith solar radiation values even in the summer months due to the stronger diffuse element of the hemispheric solar radiation being acquired. The feasibility test date/time selected was such a case.

(When the pros and cons of angled versus zenith-facing field of views for maximizing the solar radiation are weighed over a full year's time, the angled sensor will prove to have the greatest annual solar radiation intake [Boxwell 2013].)

2.4.3 Simulated Whole Sky Imager (sWSI)

Irradiance is largely a function of the date/time of the year and location. Consequently, these parameters are some of the required model input. The most significant inhibitors of solar radiation traveling from space to the Earth's surface are clouds and aerosols. Proportionally, clouds have the greater impact on the surface irradiance. For the solar radiation model selected, the key cloud attributes are cloud amount(s), type(s), and level(s). To determine these values with in-situ tools, one can use an upward-pointing camera with a fisheye lens, also known as a whole sky imager (WSI) or total sky imagers (TSIs). The challenge is photographing the sky while the sun is saturating the observer/tool with light. (Professional WSI and TSI systems generally include an occulting element to block the sun or moon. Since this feature was not included in this research's technology, the term "simulated Whole Sky Imager" was respectfully assigned to the device.)

During the ARE field studies, a photographic technique was developed whereby a human could adjust the exposure and aperture to optimize the photograph's details. A trained observer would then assess the amount of clouds viewed, along with the cloud type and level. The atmosphere was reduced to just three layers, and cloud types were simplified to three basic categories, each representing the dominant cloud type for a given layer (1 = cumulus, 2 = stratus, and 3 = cirrus), as explained in Vaucher et al. (2017). These values could be manually inserted into the model. For this project, the receiving model was designed to read in the parameters via a file.

The AI-HPG sWSI images were captured using a Raspberry Pi camera module, fitted with a 210° fisheye lens in an M12 mount. The software for image capture used the PiCamera libraries called from a Python script. Images were taken in 15-min intervals from 0500 to 2100 LT (sunlight hours). More frequent images were possible but not needed for this phase of the project. The assembly was mounted in a red plastic cylinder that created an easily discerned horizon and limited the sky image to 180° (hemispherical). The assembly was covered by a clear acrylic dome for weather protection.

2.4.4 sWSI Image Analysis

Once the sky was documented in an sWSI image, the next step was to convert this resource into cloud amount, type, and layer. (If the cloud type was defined, the layer could be inferred.)

While work continues in automating the process, the following description outlines the basic concepts. Using MATLAB software, there were three steps:

- 1) The circular disc of the whole sky image was extracted from the rectangular image via an “Image Segmenter” app.
- 2) Using the color thresholder app, the cloud features were isolated from the non-cloud features. For example, if the red-green-blue filter was used, one could reduce the red pixels from 250 units to 100, change the black areas to white using an inverted mask option, and export this mask for later use.
- 3) The Image Region Analyzer app was used to determine the area (in pixels) of the inverted mask (white), which represented the clouds. Dividing this value by the circular disc area from the Image Segmenter (the whole sky) and taking the percentage resulted in the percent of cloud cover for that image.

This method was not exact, since the lens can generate artifacts and the unblocked sun has a white “glory” that can be mistakenly categorized as cloud cover. However, for the sake of determining feasibility, the technique was considered reasonable.

2.5 Power Conversion Model

In this feasibility study, two power conversion models were used to ascertain the PV panel’s power output given PV panel temperature and the incident irradiance on the solar panel: the linear System Advisor Model (SAM) and the Mahmoud, Xiao, Zeineldin (M-X-Z) model. The linear SAM utilized a nominal I-V curve that was generated for the solar panel with the SAM (National Renewable Energy Laboratory 2019). The M-X-Z model generated I-V curves based on a simplified electrical model of the PV panel, irradiance, and panel temperature. The two models are shown in Fig. 5 (Mahmoud et al. 2012).

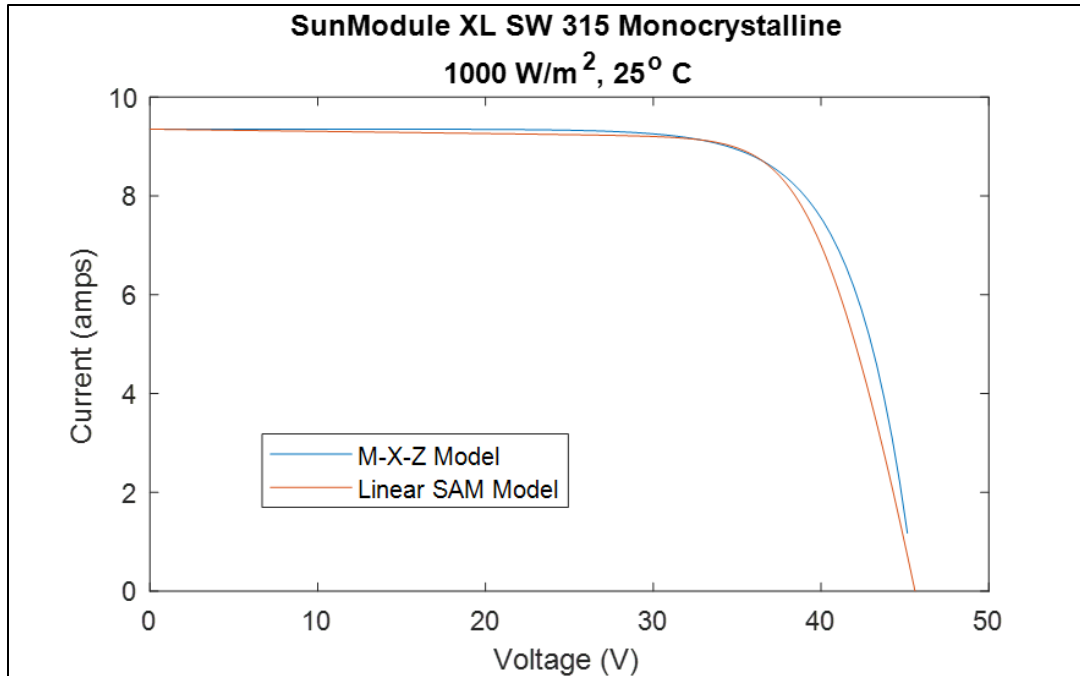


Fig. 5 Nominal I-V curves

For each irradiance and temperature measurement provided to the model, the maximum power point was used to predict the PV panel's power output. For this feasibility study, the irradiance and power were measured permitting an assessment of each power prediction algorithm. As shown in Fig. 6, the M-X-Z model more accurately approximated the power produced by the PV panel.

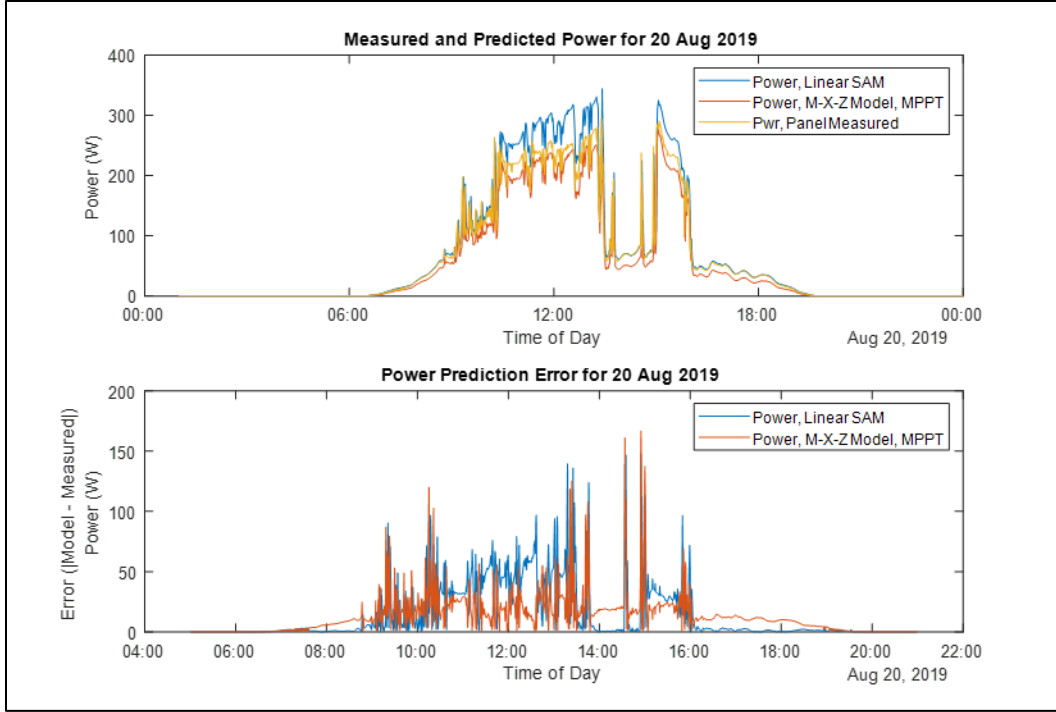


Fig. 6 PV power for the feasibility test: 20 August 2019 case (top) and error between predicted and measured power (bottom)

2.6 Hybrid Power Application

This research demonstrates the feasibility of utilizing meteorological data and predictions to drive a power output model. In its actual implementation, a microgrid controller would be receiving both real-time information (power, temperature, irradiance) from the PV panel and a forecast of how those quantities are expected to vary over the next time interval.

The microgrid controller incorporates an understanding of the load, forecast, and current conditions to determine an optimal grid configuration. Ideally, the controller could incorporate knowledge of how atmospheric conditions impact the load. For example, the heating, ventilation, air-conditioning (HVAC) loads vary based on solar loading and ambient temperature. In other cases, mission requirements may dictate certain load scenarios. There may also be other discretionary loads that can be varied in time, based on power availability. The controller combines these parameters, along with the known battery state, and determines an optimal power distribution solution that dictates grid configuration as well as discretionary load timing recommendations. These recommendations are a function of both the current and anticipated grid state, based on the atmospheric predictions. For instance, if a clear sky is anticipated, the controller may advise immediate execution of discretionary loads (such as laundry). However, if cloudy

skies are forecasted, the recommendation may delay those loads until a sufficient amount of energy has been stored in grid-based batteries.

3. Method: Testing the AI-HPG Proof of Concept

With all the AI-HPG test-bed elements defined, the next step was to test the data flow through each of these elements. A four-step process was used to test the feasibility of acquiring and converting the atmospheric intelligence into the critical input needed to optimize an HPG. The example below used to demonstrate this AI-HPG proof-of-concept feasibility test follows the step-by-step process documented in Appendix C. Data for this test were acquired on 20 August 2019. The test itself was conducted on 21 August due to the multiple locations participating.

3.1 Step 1: Acquire the Panel Temperature

Panel temperature for 20 August 2019, was plotted, and a single point (1215 Mountain Time [MT]) was extracted and saved from the time series. The panel temperature reported at the user-selected time was 47.4 °C.

3.2 Step 2: Acquire the Atmospheric Data

The 20 August 2019, 1215 MT whole sky image from the sWSI data resources was extracted. Using both a visual assessment and a software-derived assessment, the cloud cover percentage was determined to be between 20% and 30%. An averaged value of 25% cloud cover was determined for the solar radiation flux model input.

3.3 Step 3: Calculate Irradiance and Calibrate Results

Using 25% cloud cover, the solar radiation flux model calculated an irradiance of 844 W/m² for 20 August 2019 at 1215 MT. To calibrate this value, the coincident pyranometer data were plotted, and the solar radiation values at the user-selected time (1215 MT) were reported to be 847 W/m² and 802 W/m² for the angled and zenith field of view pyranometers, respectively. These values were accepted as reasonable, based on the partly cloudy conditions.

3.4 Step 4: Calculate Power and Calibrate Results

Employing the panel temperature and irradiance values, the linear SAM and M-X-Z models were used to calculate the expected PV power output. Results were 269 W and 203 W, respectively.

These power values were compared to the actual power, measured initially in current and voltage, and converted into a product. Since the time stamp of the power data was not centered on the minute, the two neighboring power values were noted—namely, using h:min:s

12:15:12 (232 W) and

12:14:42 (221 W).

Comparing the model versus the measured power, the linear SAM power model overestimated the measured value by about 16% and the M-X-Z model underestimated the sampled power by about 13%.

4. Lessons Learned

All pioneering projects create lessons learned that make the future versions of the project less encumbered and more fruitful. The following sections highlight some of these lessons learned from developing and testing the AI-HPG proof of concept.

4.1 Lessons Learned Regarding the System Elements

Power Train: The charge controller was designed not only to maximize PV input, but also to limit it, in order to prevent battery overcharge. This strategy challenges the execution of research in that there is a loss of information about PV panel performance. When the battery system goes into “float” mode, the charge controller will no longer attempt to use maximum power but will set the voltage to limit power instead. Thus, for research purposes, it is important to prevent the charge controller from going into float mode. (The ability to control the load has been very useful in ensuring that the system does not go into float while still allowing for battery charge and discharge as needed.)

sWSI: A more sophisticated sWSI exposure control would improve the accuracy of the cloud cover analysis by minimizing the overexposure near the solar disk (glory).

sWSI Image Analysis: A more seasoned approach for discerning cloud cover, type, and levels is being pursued. Resources being reviewed include the historical WSI accomplishments completed by the University of California–San Diego (Shields et al. 2019) and the ongoing work being conducted by the Total Sky Image Forecast work of the Brookhaven National Lab (Haupt et al. 2016).

Model - Solar Radiation:

- The choice to put the solar radiation model on a MATLAB platform was based on its future integration with a MATLAB-based simulation. The initial model used a graphical user interface to more efficiently view input/output. For this application, however, the input/output were expanded to include file options. Once the concept reaches an automation stage, the model design might better be served in a platform-independent format.
- The model has limitations. Areas for improvement include an expansion regarding the integration of cloud cover specification and the consequential solar radiation transmission/reflection (and absorption).

Model - Power Conversion:

- The simplified power conversion model appears to do a reasonable job estimating PV power output.
- The current power algorithm computes an I-V curve with each irradiance point, resulting in excess computational expense. Given panel parameters, an I-V surface could be precomputed, resulting in reduced real-time computational expense.

4.2 Lessons Learned Regarding the System

Automating the process will be a healthy catalyst for streamlining the individual elements into a single program. The efficiency of a single program will ensure the time-relevancy criterion is met. It will also enable the system to expand from being only a diagnostic tool into being both diagnostic and prognostic.

5. Conclusion and Recommendations

The purpose of this study was to prove (or disprove) that in-situ-only atmospheric intelligence could be acquired, processed, and converted into useful information for power grid management optimization. The usefulness of the meteorological data was confirmed in a separate study documented in Jane et al. (submitted 2019). The method for sampling and processing atmospheric data from on-site resources, then converting this critical intelligence into valuable power grid optimization manager input, has been shown and documented within this report. The next step is to refine and automate the process, leaning on the lessons learned, and experimenting with the new opportunities as they are revealed. Such advances blended with over-the-horizon (future) technology will ultimately prove the projected vision and steer the path toward its critical goal of empowering the tactical environment with fully reliable, consistent, uninterrupted electrical power.

6. References

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Appendix A. Pyranometer Calibration Data

The Atmospheric Intelligence for Hybrid Power Grids (AI-HPG) pyranometer calibration data plots below show that the side-by-side solar radiation values are within a reasonable magnitude. A statistical summary is provided in Table A-1. Raw data (Fig. A-1), ratio magnitudes (Fig. A-2), and pyranometer differences (Fig. A-3) describe the coincidentally sampled solar radiation values.

Table A-1 Statistical summary of the west minus east, zenith-facing pyranometer (Pyr) differences

	Difference = Pyr 2 – Pyr 1
Average difference	0.76 W/m ²
Standard deviation	4.52 W/m ²
Maximum difference	13.00 W/m ²
Minimum difference	–8.30 W/m ²
Number of samples	14761

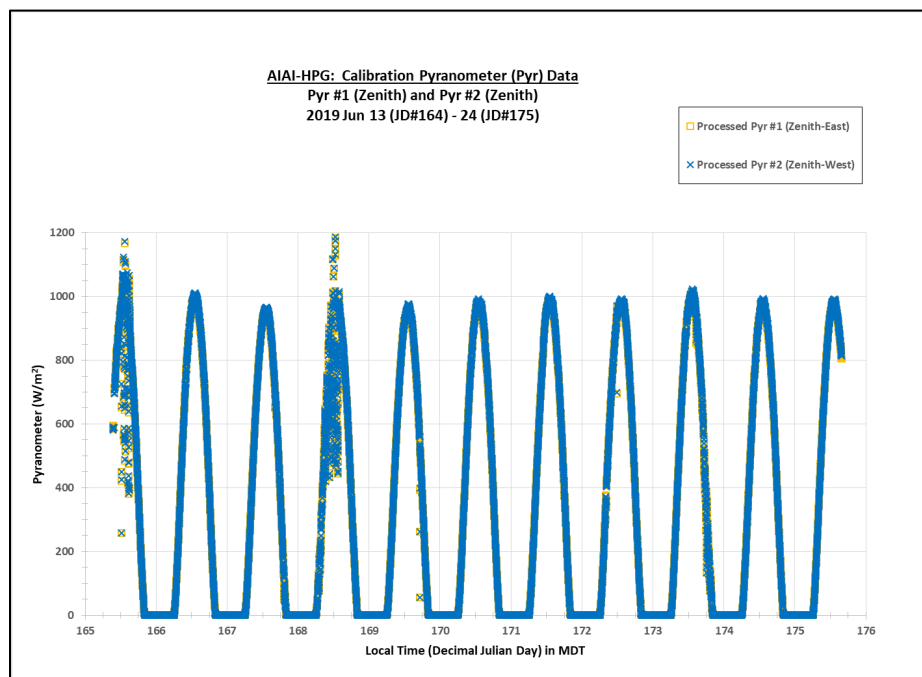


Fig. A-1 Side-by-side raw pyranometer calibration data for 13–24 June 2019

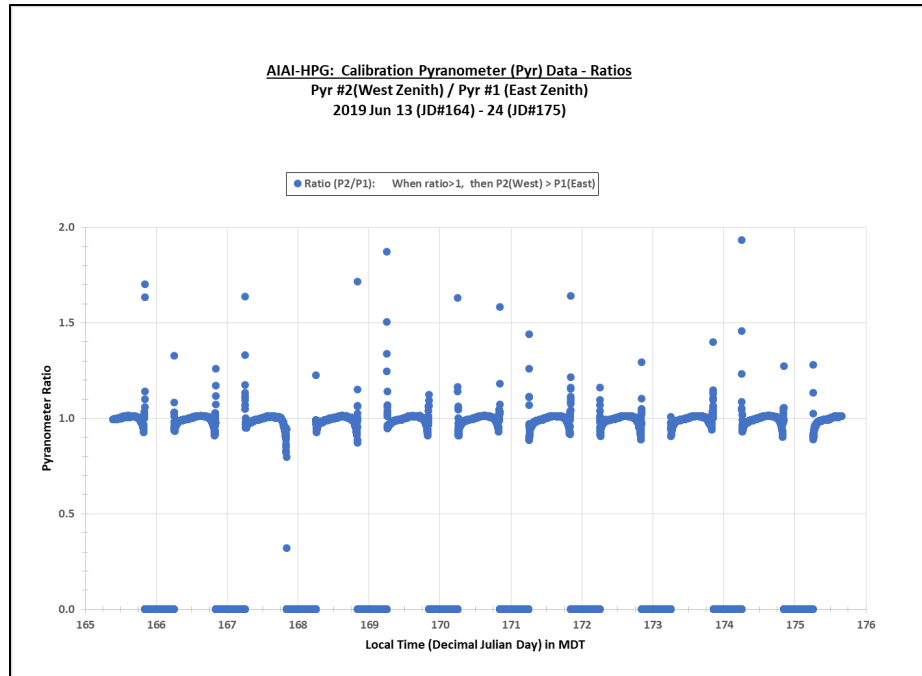


Fig. A-2 Calibration–ratio comparison: the west pyranometer 2 / east pyranometer 1. If the ratio is greater than 1, then the west pyranometer (2) is larger in value than the east pyranometer (1).

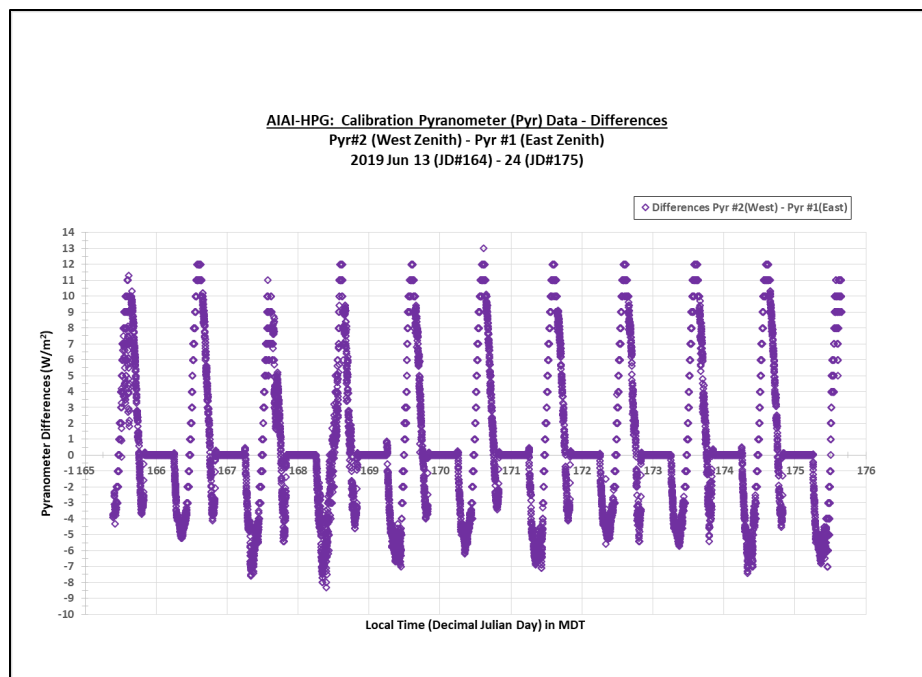


Fig. A-3 Calibration–differences comparison: the west pyranometer 2 minus the east pyranometer 1. If the result is greater than 1, then the west pyranometer (2) is larger in value than the east pyranometer (1). When the sun is in the west quadrant, the west side pyranometer tends to report greater values (and vice versa).

Appendix B. Solar Angle Impact on Surface Solar Radiation

During the Atmospheric Intelligence for Hybrid Power Grids (AI-HPG) Feasibility Study, two pyranometers were mounted on the west and east top corners of the AI-HPG Test-bed photovoltaic (PV) panel. The “west” pyranometer field of view was zenith facing (straight up). The “east” pyranometer was mounted at about a 32° angle—the same angle as the PV panel. In Fig. 4, the Julian day (JD) 206 (July 25) 24-h pyranometer time series data are shown. A description of this clear sky sample case was provided in Section 2.4.

Under the JD 206 clear skies, the angled pyranometer shows less solar radiation than the zenith. Typically, the reverse is expected.¹ However, since the July 25 sun position is near that of the summer solstice, the sun is far enough north over the test site that it affects the solar radiation magnitude.

Specifically, on 25 July at local noon, the sun was located at a point in the sky that is about 12° south of the zenith (Fig. B-1). The angled pyranometer was aimed at a point in the southern sky that was 32° above the local horizon (measured starting from the horizon), or about 58° south of the zenith (measured starting from the zenith). (The greatest annual solar radiation is acquired by a sensor angled at latitude.¹) Consequently, the local angle between the position of the sun in the sky and the angled pyranometer viewpoint was about $58^\circ - 12^\circ = 46^\circ$. In contrast, the zenith-facing pyranometer was only 12° away from the sun, which explains why, for this date, under clear sky, the angled pyranometer showed less solar radiation than the zenith pyranometer.

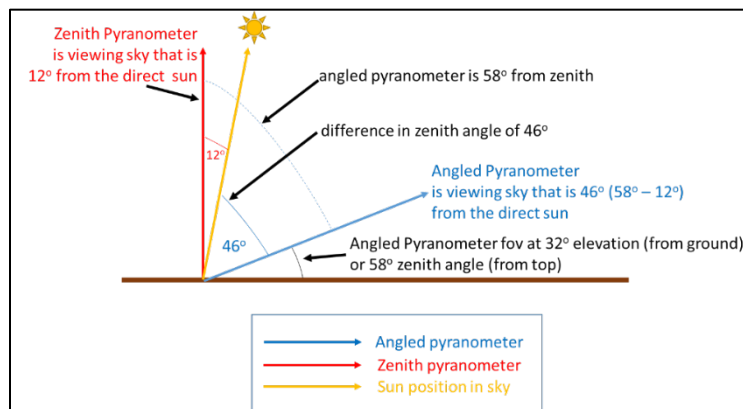


Fig. B-1 Angled vs. zenith-facing pyranometers. On July 25, at solar noon, the sun position is 12° south of the zenith-facing pyranometer. A pyranometer angled at 32° above the local horizon will be 46° away from the sun.²

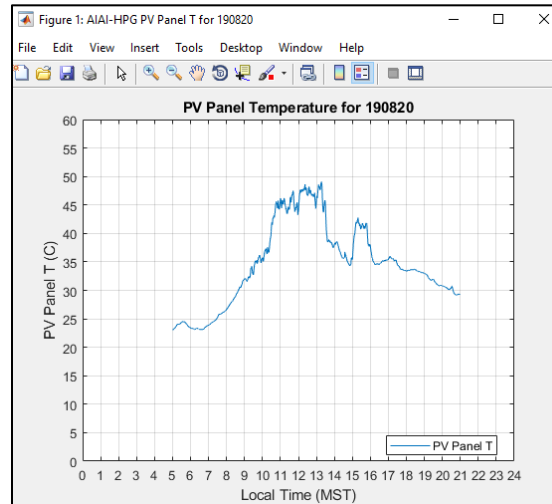
¹ Boxwell M. Solar electricity handbook, 2013 edition: a simple, practical guide to solar energy - designing and installing photovoltaic solar electric systems. 7th ed. London (UK): Greenstream Publishing; 2009–2013.

² Raby J. CCDC Army Research Laboratory, White Sands Missile Range, NM. Personal communication, 2019 Oct 23. Angled vs. zenith-facing pyranometers.

Appendix C. Atmospheric Intelligence for Hybrid Power Grids (AI-HPG) Feasibility Test

The purpose of the Atmospheric Intelligence for Hybrid Power Grids (AI-HPG) Feasibility Test was to prove (or disprove) that in-situ atmospheric intelligence could be acquired, processed, and converted into useful information for power grid management optimization. The test data were acquired on 20 August 2019 under partly to mostly cloudy skies in southern New Mexico. The execution of the single-point extraction, processing, and conversion of on-site atmospheric data to power grid input occurred on 21 August 2019, due to the multiple locations of participants. The following sequence documents each step of the AI-HPG Feasibility Test.

STEP 1: Acquire In-situ Atmospheric Data (Panel Temperature). A photovoltaic (PV) panel temperature time series for 20 August 2019 was plotted (Fig. C-1a). Using an AI-HPG system program, the specific date/time of 20 August 2019 at 1215 Mountain Time (MT) was selected from the 24-h time series to test the data flow feasibility (Fig. C-1b).



(a)

```

Command Window
New to MATLAB? See resources for Getting Started.

>> ReadPlotSelectData_PanelT(190820)

Select a specific PV Panel T datapoint? y

Current data date is: 190820
Enter hour in local time? 12
Enter minute in local time? 15

Power data for 190820, 1215LT is:
Panel T = 47.375

...PanelT Output File < 190820_1215_PanelT.txt > saved.

End PanelT Function

```

(b)

Fig. C-1 a) PV panel temperature for 20 August 2019 and b) PV panel temperature for 20 August 2019, 1215 MT, was 47.4 °C

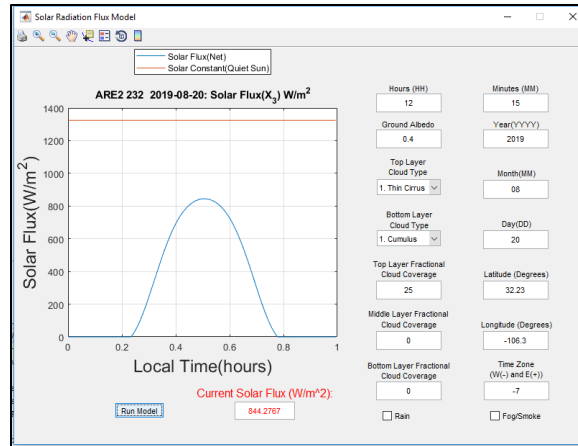
STEP 2: Acquire In-situ Atmospheric Data (Cloud Cover). A simulated Whole Sky Imager (sWSI) image for 20 August 2019, 1215 MT, was retrieved (Fig. C-2) and a meteorologist visually estimated cloud cover to be between 2/10 and 3/10. For the AI-HPG Feasibility Test, the estimated cloud cover was taken as the averaged value, 25%. Later, an image analysis professional independently equated the numeric method described in the text (pixel ratio) and determined the cloud amount to be about 30%.



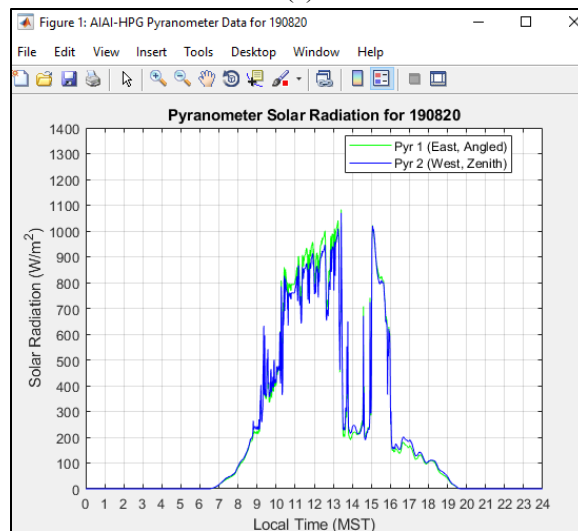
Fig. C-2 A cropped sWSI image sample for the 20 August 2019, 1215 MT, case

STEP 3a: Run Solar Radiation Model Using In-situ Atmospheric Data. The required in-situ data for the Shapiro Solar Radiation Flux (SRF) model were entered, and a solar radiation value of 844 W/m^2 for 1215 LT was calculated (Fig. C-3a).

STEP 3b: Calibrate Solar Radiation Model Output with Measured Data. The 24-h time series of the solar radiation sampled by the angled and zenith facing pyranometers were plotted. A value of 847 W/m^2 was extracted for the angled pyranometer at 1215 MT (Fig. C-3b), and the zenith field of view was noted.



(a)



(b.1)

```

Command Window
New to MATLAB? See resources for Getting Started.

>> ReadPlotSelectData_Pyr(190820)

Do you want to select solar radiation data point?y

Current data date is: 190820

Enter hour in local time? 12
Enter minute in local time? 15

Solar Radiation data for 190820, 1215LT is:
Solar Radiation (East Pyr1/Angled fov) = 847.000
Solar Radiation (West Pyr2/Zenith fov) = 802.000

...Pyranometer Output File < 190820_1215_Pyr.txt > saved.

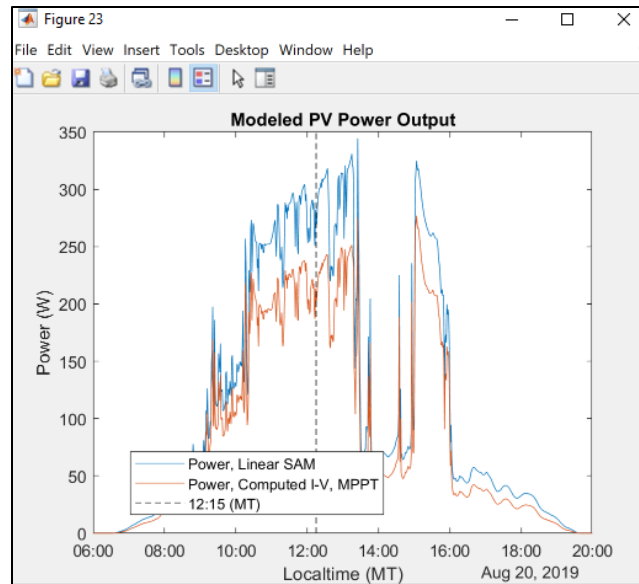
End Pyr Plotting Function

```

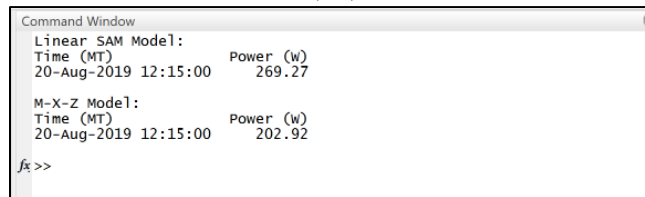
(b.2)

Fig. C-3 a) SRF model input and graphical results; b.1) 24-h pyranometer data time series acquired on 20 August 2019; and b.2) the angled solar radiation value extracted for 1215 MT, 20 August 2019, was 847 W/m^2

STEP 4a: Convert Solar Radiation into PV Power. The modeled solar radiation output was provided to the Solar Radiation to Power conversion models as a 24-h solar radiation time series. Using both the linear System Advisor Model (SAM) and Mahmoud, Xiao, and Zeineldin (M-X-Z) models, 24-h power-generated time series were calculated (Fig. C-4a.1). Extracting the power calculated for 1215 MT yielded the value of 269 W for the linear SAM model and 203 W for the M-X-Z model (Fig. C-4a.2).



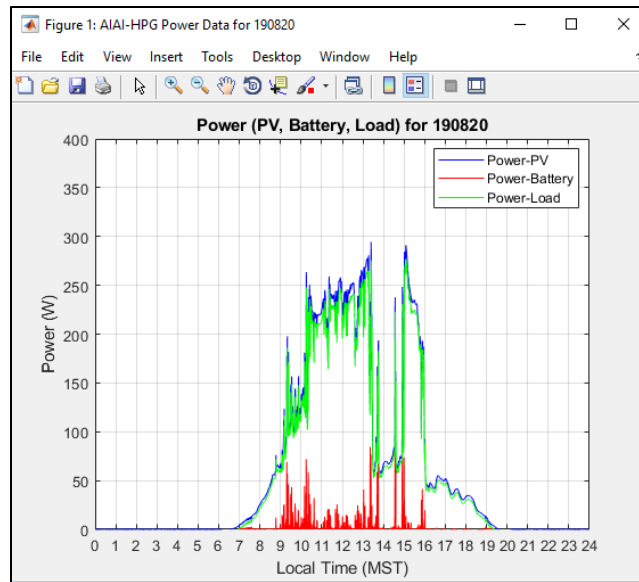
(a.1)



(a.2)

Fig. C-4 a.1) M-X-Z model and linear SAM model power time series for 20 August 2019. a.2) The extracted power values at 1215 MT, 20 August 2019, was 269 W for the linear SAM model and 203 W for the M-X-Z model.

STEP 4b: Calibrate Modelled Power by extracting Measured Power. Three power data time series (PV, battery, load) for 20 August 2019 were plotted (Fig. C-4b.1) after multiplying their respective measured currents and voltages. The 1215 MT single PV power value was extracted and documented in a screen shot (Fig. C-4b.2). Comparing modeled versus measured PV power, the M-X-Z model underestimated the sampled power by about 13%. The linear SAM power model overestimated the measured by about 16%.



(b.1)

```

Command Window
New to MATLAB? See resources for Getting Started.

Current data date is: 190820
Enter hour in local time? 12
Enter minute in local time? 15

Power data for 190820, 1215LT is:
PV Current = 7.182
PV Voltage = 32.349
PV POWER = 232.331

Batt Current = 0.360
Batt Voltage = 25.257
BATT POWER = 9.093

Load Current = 8.540
Load Voltage = 24.748
LOAD POWER = 211.348

...Power Output File < 190820_1215_Power.txt > saved.

End Power Plotting Function

```

(b.2)

Fig. C-4 b.1) Three power time series (PV, battery, and load) calculated from measured current and voltages for 20 August 2019. b.2) Actual PV power extracted for 20 August 2019 at 12:15:12 was 232 W. Note: At 12:14:42, the actual PV power was 221 W.

List of Symbols, Abbreviations, and Acronyms

AI-HPG	Atmospheric Intelligence for Hybrid Power Grids (a non-automated version of the AIAI-HPG System)
AIAI-HPG	Automated In-situ Atmospheric Intelligence for Hybrid Power Grids
ARE	atmospheric renewable energy
ARL	Army Research Laboratory
CCDC	US Army Combat Capabilities Development Command
DAQ	Data Acquisition System
HPG	Hybrid Power Grid
HVAC	Heating, Ventilation and Air-Conditioning
I	current
JD	Julian day
LT	Local Time
MT	Mountain Time
MPPT	maximum power point tracking
M-X-Z	Mahmoud, Xiao, and Zeineldin
NI	National Instruments
PV	photovoltaic
Pyr	pyranometer
SAM	System Advisor Model
SRF	Solar Radiation Flux
sWSI	simulated Whole Sky Imager
TSI	total sky imager
WSI	whole sky imager
V	voltage

1 DEFENSE TECHNICAL
(PDF) INFORMATION CTR
DTIC OCA

1 CCDC ARL
(PDF) FCDD RLD CL
TECH LIB

20 CCDC ARL
(10 PDF, FCDD RLC ED
5 HC, G VAUCHER (5 CD, 5 HC)
5 CD) C HOCUT
R RANDALL
S DARCY
J RABY
FCDD RLS DP
M BERMAN
B GEIL
R JANE
D PORCHET
FCDD RLS SE
S HU

1 MTU
(PDF) G PARKER

1 WEST POINT
(PDF) C JAMES