A Case for Solar Energy System Dashboards to Validate Performance Warranties

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Abstract

Solar power generation has increased exponentially in the last decade. It is expected to play an essential role in generating renewable energy in the United States and the world in the future. One of the critical points for the return on investment of photovoltaic systems is to maximize energy generation. Yet, a problem exists in that solar energy systems do not have a monitoring system for all components, so there is no way to know, in real-time, if the solar energy system is performing as expected. This study proposes to evaluate the effectiveness of the PVWatts prediction calculator compared to actual real-world data obtained from the Solar Energy Research Institute (Keshena, WI). The results show that the PVWatts prediction of solar energy generation is statistically significantly different from the actual solar energy generation. Moreover, the actual solar energy generation varies year by year, and the theoretical vs. actual analysis demonstrates that this system is not working according to warranty expectations. Therefore, there is a need for a real-time monitoring system or another type of real-time preventive maintenance to know the performance of solar systems.

Keywords
Solar energy, real-time monitoring, energy industry, Photovoltaic system

1. Introduction
1.1 Motivation
Like many other systems, cars have *fuel economy labels* to inform the potential consumer of performance-related expectations. Similarly, solar panels have *data sheets* to inform the potential consumer of performance-related expectations. Cars have monitoring systems (e.g., car dashboards) to notify the owner of the car's performance. Unfortunately, solar energy systems do not have a monitoring system, so there is no way of knowing (in real-time) if the solar energy system is performing as expected.

There are three current approaches to address the problem. First, solar energy system owners can do manual calculations based on net-metering credit from the utility company to approximate solar energy system performance (taking into consideration the weather over the past 30 days). Yet, this approximation will offer limited accuracy when the solar energy system is performing poorly versus not performing at all, due to constant changes in temperature and solar irradiance. Second, solar energy system owners can hire an electrician to perform a quality check if they believe their system is performing poorly or simply as re-assurance the system is performing as expected. Yet, this can result in a biased diagnosis, especially if the problem is due to the electrician installation (e.g., mismatch, wiring, and/or connections). Third, solar energy system owners can purchase additional component-level monitoring for either the solar panels or the inverter. Yet, this only provides monitoring for one component and not the system as a whole. Additionally, this can result in a biased diagnosis, especially if the problem is due to the component being monitored.

1.2 Study Purpose

The purpose of this exploratory study is to test several hypotheses of which ultimately are used to quantify the difference (if any) between the predicted (e.g., PVWatts) to actual (e.g., using real-time generation performance sensors) to the theoretical (e.g., using real-time temperature and solar irradiance sensors).

The predicted performance, as quantified by the industry-standard PVWatts, uses TMY (typical metrological year) weather data to estimate anticipated solar energy generation for locations throughout the world. Since the weather is constantly changing, it is hypothesized that the predicted power will be statistically different from the actual power generated for each year of data collected. Moreover, it is hypothesized that the actual power generated will be statistically significantly different for each year.

The actual performance is then compared to the theoretical performance. The actual performance is obtained using real-time energy generation sensors, which show the actual energy generated for each hour across five years. The theoretical performance is obtained by calculating the energy generated based on the incoming temperature and solar irradiance. Anecdotal evidence and prior experience suggest these numbers may not match, implying a warranty issue with the solar panels or inverter.

2. Background

2.1 Predicted Estimation - Industry Standard Performance Estimator (PVWatts) Explained

Due to the increased use of solar panels, the National Renewable Energy Laboratory (NREL) has created various software to analyze photovoltaic energy systems (Psomopoulos, Ioannidis, Kaminaris, Mardikis, & Katsikas, 2015). Some of these softwares include RET Screen, SAM, PVGIS, HOMER Pro, PvPlanner, Solar Pro, and utilized in this study, PVWatts.

In this specific study, PVWatts was utilized to derive all actual performance data. The NREL PVWatts calculator is a web application developed by the NREL that estimates the electricity production of a grid-connected photovoltaic system based on a few simple inputs (Dobos, 2014). In 2013, NREL began the process of revamping the PVWatts online web application to update the visual appeal and functionality, consolidate versions to reduce the ongoing maintenance burden, and update the energy prediction algorithms to be in line with the actual performance of modern photovoltaic systems (Dobos, 2014). PVWatts combines several sub-models to predict overall system performance and includes several built-in parameters hidden from the user (Dobos, 2014). PVWatts has myriad applications, such as estimates of energy production and energy cost of grid-connected photovoltaic power systems. These applications allow homeowners, small business owners, installers, and manufacturers to quickly develop performance estimates for potential photovoltaic installations (Database, 2021).

PVWatts offers many benefits, such as the flexibility of the tool containing a wide range of applications, the public availability of a reasonable amount of documentation for the software, and the usefulness of the tool for analysis of energy systems in the context of sustainable development (Psomopoulos et al., 2015). Moreover, PVWatts provides many benefits including the following: pre-feasibility analysis of plants, technical sizing of multiple components, prediction of long-term system performance, and estimation of energy generation. Additionally, the influence of various technical parameters of solar systems can be analyzed: angle of inclination, orientation, photovoltaic technology in performance indexes, hourly, monthly, and annual, energy generation, the potential of solar radiation in a particular site, financial benefits of the system, among others (Kumar, 2017). PVWatts allows the user to input potential derate loss factors that may cause the solar energy system to perform lower than its predicted efficiency. These derate losses can include impacts from dirt, shading, snow cover, misalignment, wiring, connections, light-induced degradation, nameplate rating, system age, and operational availability (Dobos, 2014); the total loss can be calculated by multiplying the reduction due to each loss Li (%) as shown in Equation 1:

$$L_{total}(\%) = 100\left[1 - \prod_i \left(1 - \frac{L_i}{100}\right)\right] \quad (1)$$

PVWatt's default total system loss is calculated to be 14 % (Dobos, 2014). These losses may be represented by a derate factor applied to the amount of energy produced (Flowers et al., 2016). Losses associated with shading indicate blocking of the horizon due to large obstructions (Dufour & Belanger, 2014). The typical loss associated with shading is about 3%. Soiling is a phenomenon in which dust accumulates over a surface. Due to gravitation, dust particles from the air usually carried by the wind will settle on any surface, and these particles will settle down, and their density will keep increasing over time with the addition of other airborne dust particles settling in the same place (Jamil, Rahman, Shaari, & Desa, 2020).

2.2 Actual Performance - Solar Energy Research Institute Explained

A data set of power production and real-time weather was collected from the College of Menominee Nation's (CMN) Solar Energy Research Institute (SERI) through the Sunny Portal and Enphase Energy interface. The data set consists of 5 years' worth of data from the start of May 2014 to the end of May 2019 at hourly increments. The College of Menominee Nation's Solar Energy Research Institute was established in 2014 and consists of two main systems, a 3.0 kW microinverter system and a 13.2 kW central inverter system, in addition to performance and weather data collection systems. This study will focus on the smaller 3.0 kW microinverter system. The 3.0 kW microinverter system was installed in mid-April 2014 and consisted of twelve 250 W Solar World standard crystalline silicon panels, each with its own Enphase microinverter. The panels are positioned at a fixed tilt on a metal roof 6/12 pitch of 26.56 degrees at south facing orientation of 180 degrees. The performance-related data collection includes individual solar energy panel generation and inverter output in 1-hour time increments. The weather-related data collection (used to calculate theoretical performance in the next section) was available in 1-hour time increments and includes plane-of-array solar irradiance, module temperature, ambient temperature, wind direction, and wind speed.

2.3 Theoretical Calculations - Solar Energy Generation Model Explained

Solar energy, among other renewable sources of energy, is a promising and freely available energy source for managing long-term issues in energy crises (Kannan & Vakeesan, 2016). Solar electricity is generated from direct sunlight. However, solar cells individually produce very little energy, so to optimize their power, several cells are connected to create a solar module, also known as a solar panel (Boxwell, 2010). Equation 2 can be used to theoretically estimate the amount of power generated by a solar energy panel (Dobos, 2014).

$$P_{mod} = \frac{I_{mod}}{I_{STC}} * P_{max} * \left[1 + TCP_{mpp} * (T_{mod} - T_{STC})\right] \quad (2)$$

Where the terminologies are as follows:

- P_{mod} : module estimated alternating current (AC) power generation in watts (W)
- I_{mod}: module plane-of-array solar irradiance in watts per square meter (W/m2)
- I_{STC} : standard test condition (STC) solar irradiance in W/m2
- P_{max}: module rated maximum DC power in W
- TCP_{mpp} : module rated temperature coefficient in percent per Celsius degree (%/˚C)
- T_{mod} : module temperature in ˚C
- T_{STC} : STC temperature in ˚C

All the variables, except for temperature and solar irradiance, can be obtained from the manufacturer warranty datasheets. Although these data sheets vary from one manufacturer to another, all specification sheets typically include the following information: electrical data, mechanical data, I-V curve, tested operating conditions, warranties and certifications, and mechanical dimensions (Chowdhury et al., 2020). Under the category of electrical data, P_{max} (maximum power rating) is disclosed which is 275 W. Additionally, the tolerance of maximum power rating indicates that the power rating according to manufacturer standards will be at least 270 W and no more than 275 W (CER). Another essential component is the temperature coefficient. The temperature coefficient of P_{max} within the solar panels utilized within this study is -0.44%/ ºC meaning that as the ºC drops 1 degree, there is a decrease in efficiency of 0.44% (CER). Solar panel efficiency is also an essential factor to consider. Solar panel efficiency is a measurement of a solar panel's ability to convert sunlight into usable electricity, and currently, most solar panels are between 15 percent and 20 percent efficiency (Aggarwal, 2021). An additional important component of a specification sheet provides the solar panel's lifetime. For most solar panels, the lifetime warranty is up to 25 years (Chowdhury et al., 2020). However, this life can be affected by derating factors and difficulties associated with solar panel maintenance (Deb & Brahmbhatt, 2018).

3. Methods

3.1 Study Overview

The purpose of this exploratory study is to test several hypotheses of which ultimately are used to quantify the difference (if any) between the predicted (e.g., PVWatts) to actual (e.g., using real-time generation performance sensors) to the theoretical (e.g., using real-time temperature and solar irradiance sensors).

Part 1 - Predicted vs. Actual: The predicted performance, as quantified by the industry-standard PVWatts, uses TMY (typical metrological year) weather data to estimate anticipated solar energy generation for locations throughout the world. Since the weather is constantly changing, it is hypothesized that the predicted power will be statistically different from the actual power generated for each year of data collected. Moreover, it is hypothesized that the actual power generated will be statistically significantly different for each year.

Part 2 - Actual vs. Theoretical: The actual performance is then compared to the theoretical performance. The actual performance is obtained using real-time energy generation sensors, which show the actual energy generated for each hour across a five-year period. The theoretical performance is obtained by calculating the energy generated based on the incoming temperature and solar irradiance. Anecdotal evidence and prior experience suggest these numbers may not match, implying a warranty issue with the solar panels or inverter.

3.2 Data Analysis

The Statistics Package for Social Sciences (SPSS) was employed to analyze the data. Statistics were compared, t-test and graphical analysis of variables were performed.

4. Results

4.1 Part 1 - Predicted vs. Actual:

According to PVWatts solar energy generation prediction calculator, the descriptive statistics for PVWatts are provided in Table 1. The numbers are the same for every year because PVWatts uses TMY (typical meteorological year) historical data to predict annual generation; PVWatts assumes each year corresponds to the typical weather date, and it predicts the same results for each year.

TABLE 1. PREDICTED SOLAR ENERGY GENERATION DESCRIPTIVE STATISTICS BY YEAR (2015-2018)

Year	N	Mean	Std. Deviation
2015	8760	472.450	709.288
2016	8760	472.450	709.288
2017	8760	472.450	709.288
2018	8760	472.450	709.288

The actual data descriptive statistics are provided in Table 2. The sample size (N) varies slightly due to missing data points. The mean and standard deviation for the year 2015 is the highest with 429.8 and 711.9, respectively; the year 2018 is the lowest with 387.8 and 674.6, respectively.

TABLE 2. ACTUAL SOLAR ENERGY GENERATION DESCRIPTIVE STATISTICS BY YEAR (2015-2018)

Year	N	Mean	Std. Deviation
2015	8760	429.800	711.862
2016	8784	393.990	674.145
2017	8761	389.780	678.737
2018	8759	387.760	674.575

Based on the LSD post hoc analysis (summarized in Table 3), there is a statistically significant difference ($p < 0.001$) between 2015 and 2016, 2015 and 2017, and 2015 and 2018. This means the solar energy generated in 2015 is statistically different from 2016, 2017, and 2018.

Table 3. Actual Solar Energy Generation Post Hoc T-Test by Year (2015-2018)

	2015	**2016**	**2017**	**2018**
2015	NA	Mean Diff: 35.811 Std Error: 10.061 Sig.: <0.001	Mean Diff: 40.013 Std Error: 10.068 Sig.: <0.001	Mean Diff: 42.041 Std Error: 10.069 Sig.: <0.001
2016	Mean Diff: -35.811 Std Error: 10.061 Sig.: <0.001	NA	Mean Diff: 4.201 Std Error: 10.061 Sig.: 0.676	Mean Diff: 6.230 Std Error: 10.062 Sig.: 0.536
2017	Mean Diff: -40.013 Std Error: 10.068 Sig.: <0.001	Mean Diff: -4.201 Std Error: 10.061 Sig.: 0.676	NA	Mean Diff: 2.029 Std Error: 10.068 Sig.: 0.840
2018	Mean Diff: -42.041 Std Error: 10.069 Sig.: <0.001	Mean Diff: -6.230 Std Error: 10.062 Sig.: 0.536	Mean Diff: -2.029 Std Error: 10.068 Sig.: 0.840	NA

Figure 1 shows a visual comparison of the means by year (using the descriptive statistics provided in Table 1 and Table 2). There are two important takeaways from the visual. First, consistent with the hypothesis testing, we can visually see that the mean solar energy generation in 2015 differs from 2016-2018. This implies the actual generation from year to year varies. Second, we can visually see that the PVWatts predicted mean is substantially inflated for all Years (2015-2018). This implies the predicted and actual are also different. A paired samples t-test also confirms there was a statistically significant difference between the actual and predicted solar energy generation ($t_{40871} = -30.295$, $p<0.001$).

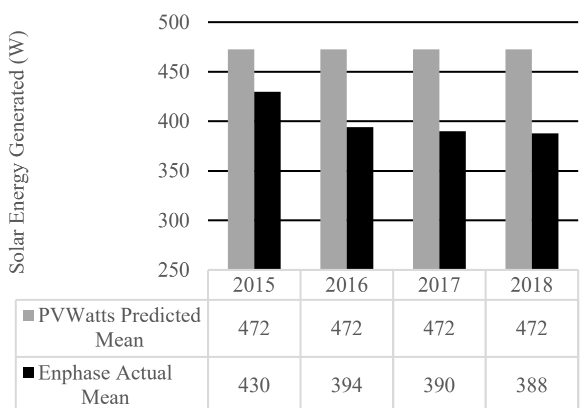

Figure 1. Solar Energy Generation Actual vs. Predicted by Year (2015-2018)

4.2 Part 2 - Actual vs. Theoretical:

Table 4 summarizes descriptive statistics for solar energy generation by year for both the actual and theoretical. The descriptive statistics show the means are substantially higher for the theoretical in comparison to the actual. The difference between actual and theoretical can also be visually observed in Figure 2. This implies the solar energy system is not working according to warrantied expectations.

Table 4. Theoretical vs. Actual by Year (2015-2016)

	Year	**N**	**Mean**	**Std. Deviation**	**Std. Error**
Enphase_Power_W (Actual)	**2015**	**8760**	**429.800**	**711.862**	**7.606**
	2016	**8784**	**393.990**	**674.145**	**7.193**
PmodMicroInverter (Theoretical)	**2015**	**8747**	**530.130**	**824.802**	**8.819**
	2016	**8783**	**494.770**	**790.545**	**8.435**

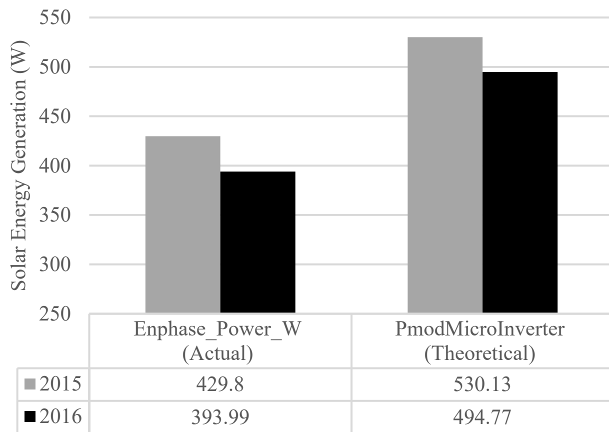

Figure 2. Solar Energy Generation Theoretical vs. Actual by Year (2015-2016)

5. Discussion

There are notable differences between the work done in this study and others of a similar nature, although many conclude the same results. Two solar panels were used to collect the data in the study, “Sustainable Cities and Society”. One panel was left to collect dust and soil every day, and another panel was cleaned every week (Shapsough, Takrouri, Dhaouadi, & Zualkernan, 2020). The panels were analyzed using an IoT-based IV Tracer, and similarly to this study, Pmax, Open Circuit Voltage (Voc), and Short Circuit Current (Isc) were measured on a month-to-month basis. Contrary to this study, that study focuses on the derate percentage of soiling, while this study includes soiling and other derate factors such as mismatch, wiring, connections, light-induced degradation, nameplate rating, age, and availability (Shapsough et al., 2020).

In another study, simultaneous measuring is implemented in maximum operating voltage and current on each module for both before and after washing the solar modules. Weekly water washing is performed through these months (February – May) to evaluate PV performance. So, the maximum current and voltage are measured at the terminal via the digital multi-meter device before and after washing to gain the maximum power at the operating point generated by the module. However, in this study, no washing was done on the solar panels during the period of analysis, providing an outlook with no maintenance work (Mohamed & Hasan, 2012).

In another study, “Effect of Shadow and Dust on the Performance of Silicon Solar Cell”, solar simulators were utilized to collect data for testing (Ibrahim, 2011). However, the utilization of solar simulators calls into question effective irradiance, pulse length for flash type solar simulators, uniformity of irradiance in the test area, uniformity of irradiance in the test area, and temporal instability of irradiance can affect the results of the study (Ibrahim, 2011). Contrastingly, this study utilized a solar panel that quantified outputs using outdoor measurements.

Similarly to this study, Mallor et al. (2017) utilized historical meteorological and satellite observation data (Mallor et al., 2017). The authors developed an unsupervised statistical method to monitor the variable range (maximum production in the whole set minus minimum production in the whole set for each time interval t) to detect significant variations in this range (Mallor et al., 2017). Large outliers in this range will thus be indicative of large production deviations among the different sets of PV panels and thus of the malfunctioning of at least one of them to detect outliers or abnormal behavior of working PV panel sets and what factors caused these outliers (Mallor et al., 2017). However, in Mallor et al.'s analysis, a 5% reduction in power production occurred by reducing the recorded production of one randomly chosen inverter by 5% (Mallor et al., 2017). In contrast to this study, no reduction was factored in as it was naturally reflected in the degradation seen in our data, making our results more conclusive, but still similar (Mallor et al., 2017).

In another study conducted by Bognár and colleagues (Bognár, Loonen, Valckenborg, & Hensen), the analysis was carried out using weather data, basic information about the site, and AC power. The necessary weather input utilized consists of solar irradiance, ambient temperature, and wind speed measurements gathered from a nearby meteorological station satellite. The AC power data was used to account for losses such as inverter efficiency, degradation, soiling, spectral effects, whereas in this study, these losses were actively calculated within PVWatts (Bognár et al., 2018). Similar to this study, these models were used to compare predicted data versus actual data, indicating that the solar panels used in the Bognár et al. study were not working at full efficiency (Bognár et al., 2018).

6. Conclusion

The purpose of this exploratory study was to test several hypotheses which ultimately are used to quantify the difference (if any) between the predicted (e.g., PVWatts) to actual (e.g., using real-time generation performance sensors) to the theoretical (e.g., using real-time temperature and solar irradiance sensors). In summary, PVWatt's prediction of solar energy generation is statistically significantly different from the actual solar energy generation. Moreover, the actual solar energy generation varies year by year. Finally, the theoretical vs. actual analysis demonstrates that this system is not working according to warranty expectations. For owners of solar energy systems, the results of this analysis are critical for (1) assessing the accuracy and decision making related to return on investment (via PVWatts prediction tool) and (2) evaluating real-world performance expectations (via on-site sensors, if available). More often than not, the "set it and forget it" approach to solar energy generation results in consumers *assuming* the return on investment and real-world performance is accurate when the data (as shown through this analysis) implies otherwise. This analysis supports the need for installing a real-time monitoring system to validate return on investment and warrantied real-world performance expectations.

Like all studies, this study has its limitations. First, the study only assessed one solar energy system site. It is recommended that future research evaluate other sites which may be considerably different within the environmental factors and conditions that could affect certain derate factors such as soiling, snow, and shading, therefore, creating the potential for different results and conclusions mentioned in this study. A second limitation is that the data is restricted to 5 years. Due to climate change and several other external factors, future research should continue to assess solar energy system performance from a longitudinal perspective, utilizing as much data as possible. Third, only one type of technology (e.g. mono-crystalline silicon) was assessed in this study. Future research should consider the evaluation of new technologies including organic, premium, and thin-film technologies. Moreover, future research should consider different configurations (e.g., angle and orientation) and a variety of derate factors.

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Biographies

Amaya McNealey is a current undergraduate student at North Carolina A&T State University studying Industrial and Systems Engineering. She is currently a member of Tau Beta Pi Engineering Honor Society, the Society of Manufacturing Engineers, and the Institute of Industrial and Systems Engineers. She has previously worked for companies including Procter and Gamble, Abbott Laboratories, Deloitte, and Inc-Query. She is also the founder of an organization called Your Health, Our Hope which aids to address inequities present in the healthcare system specifically pertaining to minority populations. After graduating this spring, she will be attending Georgia Institute of Technology to pursue her Ph.D. in Industrial and Systems Engineering.

Esteban Alexis Soto Vera received his industrial engineer degree (2014) and master's degree (2015) in industrial management from the University of Concepcion (UDEC), Chile. He is a current PhD candidate in technology at Purdue, where he is project coordinator for the Research Experience for Undergraduates (REU) Program, the goal of which is to provide underrepresented students with research experience. His main roles are to mentor students, co-teach modules, and track students' tasks. His doctoral research is framed in solar energy systems with the objective of analyzing Peer-to-Peer (P2P) models and evaluating the potential benefits. Before coming to Purdue, he was co-founder and CEO of Potencial, a startup dedicated to the design and development of "MPZero," an electrostatic device used to reduce emissions of particulate material. At UDEC, he was one of the founders of the AutoSolar project, whose car won the Atacama Solar Race, and a member of the CasaSolar team who built a solar-powered house. Esteban, a Fulbright Scholar, is president of the Purdue Fulbright Association and president of the Purdue Chilean Association. He is currently completing the Foundations in College Teaching Certificate and has participated in the Purdue-NSF I-Corps program. As a future faculty member, he vows to expand minority participation in engineering and technology and incorporate an entrepreneurial mindset in his courses.

Dr. Lisa Bosman, Ph.D. in Industrial Engineering, is an Assistant Professor at Purdue University. She is the founder of iAGREE Labs (Inclusive, Applied, and Grounded Research in Entrepreneurially-Minded Education), aimed to empower action through real-world solutions and evidence-based practices. Her research centers on developing the **entrepreneurial mindset**, defined as the "inclination to discover, evaluate, and exploit opportunities" (Bosman and Fernhaber, 2018 and 2021), in future leaders and innovators. One aspect of her research focuses on providing real-world applied learning opportunities for students to gain practical experience in academic lab-driven entrepreneurship. Dr. Bosman has obtained over $2 million in funding. Moreover, she has disseminated research through more than 60 peer-reviewed publications; of which more than 20 are co-authored with students. Dr. Bosman spent the first part of her career working as a manufacturing engineer for world-class companies including Harley-Davidson, John Deere, and Oshkosh Defense, before going back to graduate school and entering academia.