FINAL REPORT

Soitec 1MW Concentrated Photovoltaic (CPV) Demonstration Projects for On-Site Distributed Power Generation

ESTCP Project EW-201301

FEBRUARY 2018

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Soitec Solar, Inc.

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

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1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From - To)*
02/02/2018	ESTCP Final Report	6/20/2013 - 6/19/2018

4. TITLE AND SUBTITLE
Soitec 1MW Concentrated Photovoltaic (CPV) Demonstration Projects for On-Site Distributed Power Generation

5a. CONTRACT NUMBER
Contract: 13-C-0032

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Patrick Rowe

5d. PROJECT NUMBER
EW-201301

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Soitec Solar Development, LLC
11682 El Camino Real
San Diego, CA 92130

8. PERFORMING ORGANIZATION REPORT NUMBER
EW-201301

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Environmental Security Technology Certification Program
4800 Mark Center Drive, Suite 17D03
Alexandria, VA 22350-3605

10. SPONSOR/MONITOR'S ACRONYM(S)
ESTCP

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
EW-201301

12. DISTRIBUTION/AVAILABILITY STATEMENT
Distribution A; unlimited public release

13. SUPPLEMENTARY NOTES

14. ABSTRACT
The Project's objectives were to demonstrate to the DoD the reliability and cost-effectiveness of Soitec's CPV technology in the harsh desert climates with high Direct Normal Insolation (DNI), or direct sunlight a majority of the year. Additionally, the solar forecasting system, a component of the Project, was intended to produce a direct, measurable benefit to the DoD due to cost-effective ways to manage and distribute on-site solar generation resulting in increased energy quality and security.

15. SUBJECT TERMS
Soitec 1MW Concentrated Photovoltaic (CPV), On-Site Distributed Power Generation, Alternating Current, Concentrator Photovoltaic, Concentrated Solar Power, Concentrix, Direct Normal Irradiance, Photovoltaic, Solar Cell Assembly

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Patrick Rowe
UNCLASS	UNCLASS	UNCLASS	UNCLASS	202	19b. TELEPHONE NUMBER *(Include area code)* 858-888-3137

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FINAL REPORT

Project: EW-201301

TABLE OF CONTENTS

Page

EXECUTIVE SUMMARY ES-1

1.0 INTRODUCTION 1

1.1 BACKGROUND 1

1.2 OBJECTIVE OF THE DEMONSTRATION 1

1.3 REGULATORY DRIVERS 2

2.0 TECHNOLOGY DESCRIPTION 3

2.1 TECHNOLOGY OVERVIEW 3

2.2 TECHNOLOGY DEVELOPMENT 3

2.3 ADVANTAGES AND LIMITATIONS OF THE TECHNOLOGY 6

2.3.1 Advantages 6

2.3.2 Limitations 7

3.0 PERFORMANCE OBJECTIVES 9

3.1 SUMMARY OF CPV SYSTEM PERFORMANCE OBJECTIVES 9

3.2 PERFORMANCE OBJECTIVES DESCRIPTIONS 10

3.2.1 Performance Objective 1: Technology Installation Time 10

3.2.2 Performance Objective 2: Preventive and Reactive O&M Labor. 11

3.2.3 Performance Objective 3: Energy Model Validation. 12

3.2.4 Performance Objective 4: CPV Power Plant Availability 13

3.2.5 Performance Objective 5: Performance Degradation 14

3.2.6 Solar Forecasting Performance Objective 15

4.0 FACILITY/SITE DESCRIPTION 17

4.1 FACILITY / SITE LOCATION AND OPERATIONS 17

4.2 FACILITY/SITE CONDITIONS 18

5.0 TEST DESIGN 19

5.1 CONCEPTUAL TEST DESIGN 19

5.2 BASELINE CHARACTERIZATION 19

5.3 DESIGN AND LAYOUT OF TECHNOLOGY COMPONENTS 24

5.3.1 CPV Module 24

5.3.2 Dual-Axis CX-S530Tracker 24

5.3.3 Balance of System 26

5.4 OPERATIONAL TESTING 27

5.5 SAMPLING PROTOCOL 28

5.6 SAMPLING RESULTS EQUIPMENT CALIBRATION AND DATA QUALITY ISSUES 29

TABLE OF CONTENTS (Continued)

Page

6.0 PERFORMANCE ASSESSMENT 31
6.1 PERFORMANCE OBJECTIVE 1: TECHNOLOGY INSTALLATION TIME 31
6.2 PERFORMANCE OBJECTIVES 2 AND 3: PREVENTIVE AND REACTIVE O&M LABOR 32
6.3 PERFORMANCE OBJECTIVE 4: ENERGY MODEL VALIDATION 35
6.4 PERFORMANCE OBJECTIVE 5: CPV POWER PLANT AVAILABILITY 37
6.5 PERFORMANCE OBJECTIVE 6: LONG TERM PERFORMANCE DEGRADATION 37
6.6 SOLAR FORECASTING PERFORMANCE OBJECTIVE 40
7.0 COST ASSESSMENT 43
7.1 COST MODEL 43
7.2 COST DRIVERS 44
7.2.1 CPV System Costs 44
7.2.2 CPV Installation Costs 44
7.2.3 Civil Work Costs 46
7.2.4 Shipping, Handling and Treatment Costs 47
7.2.5 O&M Costs 48
7.2.6 Performance Costs 49
7.3 COST ANALYSIS AND COMPARISON 49
7.3.1 Installation Cost Exclusions: 50
7.3.2 Installation Cost Assumptions: 51
7.4 LIFECYCLE COST APPROACH 51
7.4.1 Project Development Costs 51
7.4.2 Project Pre-Construction Costs 52
7.4.3 Equipment Procurement Costs 52
7.4.4 Installation Costs 52
7.4.5 Annual O&M costs 57
7.5 LIFECYCLE COST ANALYSIS 59
8.0 IMPLEMENTATION ISSUES 63
8.1 DUAL-AXIS DRIVE 63
8.2 SOITEC'S LONG-TERM VIABILITY 63
8.3 OPERATIONS AND MAINTENANCE (O&M) COSTS 64
8.4 LACK OF COMMERCIALIZATION OF CPV SYSTEM COMPONENTS 64
8.5 PERMITTING AND REGULATIONS 64
8.6 IMPLEMENTATION ISSUES CONCLUSION 64
9.0 REFERENCES 67
APPENDIX A POINTS OF CONTACT A-1
APPENDIX B DNV-GL ENGINEERING REPORT B-1
APPENDIX C SOLAR FORECASTING REPORT C-1

TABLE OF CONTENTS (Continued)

Page

APPENDIX D NREL LETTER D-1
APPENDIX E NREL INITIAL SITE VISIT REPORT E-1
APPENDIX F NREL FOLLOW-ON REPORT F-1

LIST OF FIGURES

Page

Figure 1. Concentrator Photovoltaic Solar Cell Assembly (SCA) 3
Figure 2. Increased Module Size and Efficiency 4
Figure 3. Increased Tracker Size 5
Figure 4. High DNI Areas 6
Figure 5. Power curve of Californian Grid 6 Aug 2008 and Production Curves in Seville Spain 1 May 2008 6
Figure 6. CPV vs. Conventional PV Efficiency 7
Figure 7. USTA Process Concept 10
Figure 8. USTA Field Setup with Tracker Structure Mounted on Specialized Trailer 11
Figure 9. Fort Irwin National Training Center Location in California 17
Figure 10. Site Location and Layout on Goldstone Road at the Fort Irwin National Training Center (GoogleEarth) 18
Figure 11. CPV Plant at Fort Irwin 18
Figure 12. South Africa Plant Availability 21
Figure 13. South Africa Plant Production Ratio 21
Figure 14. Spain Plant #1 Performance Ratio 21
Figure 15. Spain Plant #1 Availability 22
Figure 16. Spain Plant #2 Production Ratio 22
Figure 17. US Plant Production Ratio and Availability Record 23
Figure 18. Comparison of Multi-year Module Production under Similar Weather Conditions . 23
Figure 19. Soitec M-500 CPV Module 24
Figure 20. Soitec CX-S530 Tracker 25
Figure 21. CPV System Major Component Illustration 25
Figure 22. CPV Power Plant Schematic Showing Balance of System 26
Figure 23. Fort Irwin CPV Power Plant Layout 27
Figure 24. Fort Irwin 1MW CPV Project Phase Gantt Chart 28
Figure 25. Graphical Display of CPV System Assembly, Installation and Commissioning 32
Figure 26. Reactive and Preventive Maintenance Percentages 33
Figure 27. Preventive and Reactive Maintenance Hours/CPV System/Year 34
Figure 28. CPV System Reactive Maintenance Hours 35
Figure 29. CPV System Soiling Test 1 Results 38
Figure 30. CPV System Soiling Test 2 Results 39
Figure 31. CPV System Soiling Test 1 Results 39
Figure 32. CPV System Soiling Test 2 Results 39
Figure 33. Tracker Table Assembly Process 44
Figure 34. Tracker Table Lift and Installation on the Mast 45
Figure 35. Completion and Commissioning of the CPV System 45

LIST OF FIGURES

Page

Figure 36. Labor Percentage Breakdown on Fort Irwin CPV System Assembly 46
Figure 37. Pre-drilling and driving CPV masts 47
Figure 38. Typical Conventional PV Pier Driving Machine 47
Figure 39. O&M Average Costs 2015 49
Figure 40. Fort Irwin 1MW CPV EPC Cost Percentage Breakdown 53
Figure 41. Fort Irwin 1MW CPV EPC and CPV BOM Cost Breakdown 54
Figure 42. Future 1MW CPV Plant Cost Breakdown 54
Figure 43. EPC vs. CPV BOM Future Project Cost Breakdown 55
Figure 44. DOD Irwin CPV Power Plant O&M Cost Category Breakdown 58
Figure 45. Power Purchase Agreement (PPA) Rate Trend Chart 60
Figure 46. Dual-Axis Drive 63

LIST OF TABLES

Page

Table 1. Executive Summary of Performance Objectives and Results 1
Table 2. Performance Objectives Summary Table 9
Table 3. Forecast Performance of Current Techniques versus Target Values at the End of the Project by Time Horizon 16
Table 4. Forecast Performance Result Values at the End of the Project 16
Table 5. Baseline Characteristics for Each Performance Objective 20
Table 6. Sample Collection Approach for Each Performance Objective 29
Table 7. Record of CPV System (tracker) Assemblies/Day 31
Table 8. Forecast Performance of Current Techniques versus Target Values at the End of the Project by Time Horizon 40
Table 9. Forecast Performance Result Values at the End of the Project 41
Table 10. 1MW CPV Demonstration System (Fort Irwin) Cost Table 43
Table 11. Ideal Site Requirements for CPV and Conventional PV Power Plants 50
Table 12. Conventional CPV Module Prices (Q1 2017) 56
Table 13. Cost Estimate for Various Sizes of CPV and Conventional PV Power Plants 57
Table 14. Lifecycle Cost Analysis 61

ACRONYMS AND ABBREVIATIONS

AC	Alternating Current
CPV	Concentrator Photovoltaic
CSP	Concentrated Solar Power
CX	Concentrix
DNI	Direct Normal Irradiance
DC	Direct Current
DoD	Department of Defense
ESTCP	Environmental Security Technology Certification Program
IEEE	Institute of Electrical and Electronics Engineers
IRR	Internal Rate of Return
HASP	Hour-Ahead Scheduling Process
kW	Kilowatt
kWh	Kilowatt Hour
LCOE	Levelized Cost of Energy
MW	Megawatt
NAVFAC	Naval Facilities
NEM	Net Metering
NREL	National Renewable Energy Laboratory
O&M	Operations and Maintenance
PV	Photovoltaic
RFP	Request for Proposal
ROI	Return on Investment
RTD	Real-Time Dispatch
RUFMA	Rotational Unit Field Maintenance Area
SCA	Solar Cell Assembly
SCE	Southern California Edison
SDG&E	San Diego Gas & Electric
UCSD	University of California, San Diego

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ACKNOWLEDGEMENTS

Soitec would like to acknowledge the following individuals and organizations that contributed to this demonstration and this report. Point of contact information is provided in Appendix A.

Fort Irwin Military Installation - Mr. Muhammed Bari, Mr. Christopher Sayer, Mr. Christopher Woodruff, Mr. William Schaefer

University of California San Diego (UCSD) – Mr. Carlos Coimbra, Mr. Hugo Pedro

National Renewable Energy Laboratories (NREL) – Ms. Sarah Kurtz, Mr. Matthew Muller, Mr. Chris Deline

Soitec Solar – Mr. Marc Jeanson, Mr. Clark Crawford

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EXECUTIVE SUMMARY

Soitec constructed a one (1) MW_{AC} power plant ("Project") at the U.S. Army's installation at Fort Irwin, California, to demonstrate its Concentrix® concentrating photovoltaic (CPV) technology and address ESTCP's objective of cost effective on-site distributed energy generation. The Project employed forty (40) Soitec CX-S530 CPV systems and included third party performance validation by the National Renewable Energy Laboratory (NREL) and solar forecasting development expertise by the University of California at San Diego (UCSD). The data collection and observation period ran from 28 July 2015 to 28 July 2017 (24 months).

CPV technology converts sunlight into electricity with state-of-the-art Fresnel silicone on glass lenses concentrating sunlight onto high performance multi-junction solar cells. The modules are mounted on dual axis trackers that follow the sun's trajectory throughout the day. Fresnel lenses concentrate the sun by a factor of approximately 500 onto a small solar cell, thereby reducing the size and amount of costly cell material required.

The Project's objectives were to demonstrate to the DoD the reliability and cost-effectiveness of the CPV technology in the harsh desert climates with high Direct Normal Insolation (DNI), or direct sunlight a majority of the year. Additionally, the solar forecasting system, a component of the Project, was intended to produce a direct, measurable benefit to the DoD due to cost-effective ways to manage and distribute on-site solar generation resulting in increased energy quality and security.

Specific demonstration objectives and results are show in Table 1 below.

Table 1. Executive Summary of Performance Objectives and Results

Performance Objectives	Metric	Success Criteria	Results
1. Technology Installation Time	Number of days needed to install and commission the CPV systems.	Two systems per day	**MET OBJECTIVE**
2. Preventive O&M Labor	Cumulative number of man-hours	$\leq$ one man-hour annually per CPV System	**DID NOT MEET OBJECTIVE**
3. Reactive O&M Labor	Cumulative number of man-hours	$\leq$ two man-hours annually per CPV System	**DID NOT MEET OBJECTIVE**
4. Energy Model Validation	Energy produced (MWh or kWh generated by the power plant and the CPV systems).	Within 2% of baseline model or expected value	**MET OBJECTIVE**
5. CPV Power Plant Availability	Energy produced (MWh or kWh) and system downtimes and failures.	Power plant availability is greater than 98%	**DID NOT MEET OBJECTIVE**
6. Long Term Performance Degradation	Energy produced (MWh or kWh generated by the power plant and the CPV systems)	Power output change after two years of operations is within measurement accuracy	**MET OBJECTIVE**

Implementation Issues: Soitec has found most end-user concerns with CPV revolved around the financeability of the CPV technology. These concerns are categorized as such:

1. **Dual-axis drive.** The drive unit, though composed of a standard housing, slewing rings, worm gearing, reduction gearbox and AC motor, was a source of end-user concern. Major worries were how the drive would handle the immense tracker loads, especially during wind or seismic events, if the drive's precision would support the exact pointing requirements of the CPV tracker (especially over time as the gear teeth experienced wear) and the general lifecycle of the drive.

2. **Soitec's Long-Term Viability.** End users, developers and investors were concerned about what would happen if Soitec went bankrupt or abandoned its solar business.

3. **Equipment and Implementation Costs.** Equipment costs for this Project were over $1.20/watt. During the same time period, conventional PV module efficiency has risen moderately and prices have fallen precipitously. Support technologies, such as 3rd party single-axis trackers and inverters have seen a shakeout in the industry, with quality rising and prices falling.

4. **Operations and Maintenance (O&M) Costs.** End-users were concerned at the lack of real O&M cost data, realizing that the CPV technology was unproven and would require intensive preventive and reactive maintenance over the life of the plant.

5. **Lack of Commercialization of CPV System Components.** At the time of construction of the DOD Fort Irwin project, the Soitec Bill of Materials were a combination of standard commercial off-the-shelf (COTS), a custom-built prototype, or newly commercialized.

In late 2016 Soitec sold its CPV technology to Saint-Augustin Canada Electric Inc. (STACE), a world-class supplier of large electrical equipment in the power generation industry. With this acquisition, STACE became the technological leader of the CPV industry and stated it would continue to improve the technology and maintain the collaboration with the recognized Fraunhofer Institute for Solar Energy Systems ISE, based in Freiburg, Germany.

1.0 INTRODUCTION

1.1 BACKGROUND

Soitec constructed a one (1) MW_{AC} power plant ("Project") at the U.S. Army's installation at Fort Irwin, California, to demonstrate its Concentrix® concentrating photovoltaic (CPV) technology and address ESTCP's objective of cost effective on-site distributed energy generation. The Project employed forty (40) Soitec CX-S530 CPV systems, which represented the fifth generation of Soitec's CPV technology and included third party performance validation by the National Renewable Energy Laboratory (NREL) and solar forecasting development expertise by the University of California at San Diego (UCSD).

The demonstration period ran from 28 July 2015 to 28 July 2017 (24 months). At the same time of the construction of the power plant, January 2015, Soitec developed a strategic plan to refocus its activities around its core business of electronics. Soitec restructured to begin divesting itself of its solar division and the solar division experienced massive personnel layoffs and asset divestitures. However, a skeletal group of individuals remained to continue the demonstration and maintenance of the power plant at Fort Irwin.

1.2 OBJECTIVE OF THE DEMONSTRATION

The Project's objectives were to demonstrate to the DoD the reliability and cost-effectiveness of Soitec's CPV technology in the harsh desert climates with high Direct Normal Insolation (DNI), or direct sunlight a majority of the year. Additionally, the solar forecasting system, a component of the Project, was intended to produce a direct, measurable benefit to the DoD due to cost-effective ways to manage and distribute on-site solar generation resulting in increased energy quality and security.

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6. Long Term Performance Degradation	Energy produced (MWh or kWh generated by the power plant and the CPV systems)	Power output change after two years of operations is within measurement accuracy	**MET OBJECTIVE**

1.3 REGULATORY DRIVERS

San Diego Gas and Electric (SDG&E), in its "Net Metering 2.0" model, recently shifted its peak hours from 11AM-6PM to 4PM-9PM[1]. This is a result of plentiful renewable power in the old peak hours. The new peak hours reflect the changing energy markets and capture a portion of daylight hours when conventional PV power production has decreased significantly or stopped completely due to the lower horizon of the setting sun. Other utilities are expected to follow suit.

As discussed further in Section 2.3, CPV more closely matches matching peak load demands than conventional PV. CPV ramps up early in the morning and, more importantly, produces more energy in the peak demand period from approximately 2PM to 6:30PM when conventional PV ramps down production.

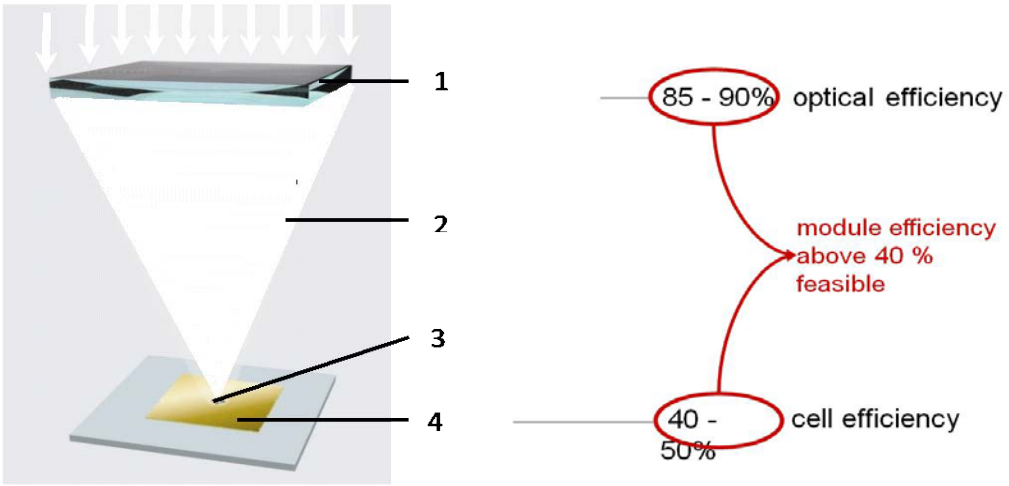
Other technologies to extend the renewable power production hours, such as battery storage and molten salt have been constructed and operated on test and commercial scales, but the cost and complexity barriers are still high. CPV is a proven technology that would today provide utilities with renewable energy when they most need it.

[1] Robert Walton. 2017. *California regulators propose shifting peak period for SDG&E TOU rates. Utility Dive.* Online.

2.0 TECHNOLOGY DESCRIPTION

2.1 TECHNOLOGY OVERVIEW

As shown on Figure 1 below, Soitec's Concentrix® CPV technology converts sunlight into electricity with state-of-the-art Fresnel silicone on glass lenses concentrating sunlight onto high performance multi-junction solar cells. The modules are mounted on dual axis trackers that follow the sun's trajectory throughout the day. Fresnel lenses concentrate the sun by a factor of approximately 500 onto a small solar cell, thereby reducing the size and amount of costly cell material required.



1. Silicone on glass Fresnel lens
2. Concentrated light
3. Multi-junction III-V solar cell
4. Heat spreader

Figure 1. Concentrator Photovoltaic Solar Cell Assembly (SCA)

Each CPV system is comprised of twelve (12) CX-M500 CPV modules, one (1) CX-T030 tracker, one (1) CX-TC2 tracker control unit, and one (1) air drying unit CX-AD1 component. The innovative module design, high tracker accuracy of ±0.1 degree and the new air-drying unit represented some of Soitec's recent R&D efforts at the time. At the time of the proposal, Soitec's new factory in San Diego had recently begun producing fifth generation CPV modules with enhanced features and performance characteristics to meet the demands of the North American market while employing the same proven reliable materials as previous generations.

2.2 TECHNOLOGY DEVELOPMENT

Prior to the field demonstration, the Concentrix CPV (formerly termed FLATCON) technology had been developed by the Fraunhofer Institute for over 10 years and had been field tested since 2005 with commercial power plants in operation since 2008. Global installations included 21 demo installations in 10 countries (0.273 MW), 8 commercial installations in 6 countries (4.4 MW) and 7 commercial plants under construction (6.8 MW). Soitec CPV modules had a cumulative 1 million months of operation and no measurable degradation.

Evolutionary improvements over time included:

- Increase concentration ratio and decreased cell material
- Less expensive materials and less redundancy while maintaining quality
- 12 CX-M500 modules per tracker vs. 168 CX-M400 modules per tracker
- Increased module efficiency and size (see Figure 2 below)
  - Increased power rating from 59 watts to 2.34 kW
  - Increased glass surface area from 2.8 ft2 to 7.5 ft2
  - Increased number of cells per module, from 150 to 2,400
  - Increased concentration ratio from 385x to 500x

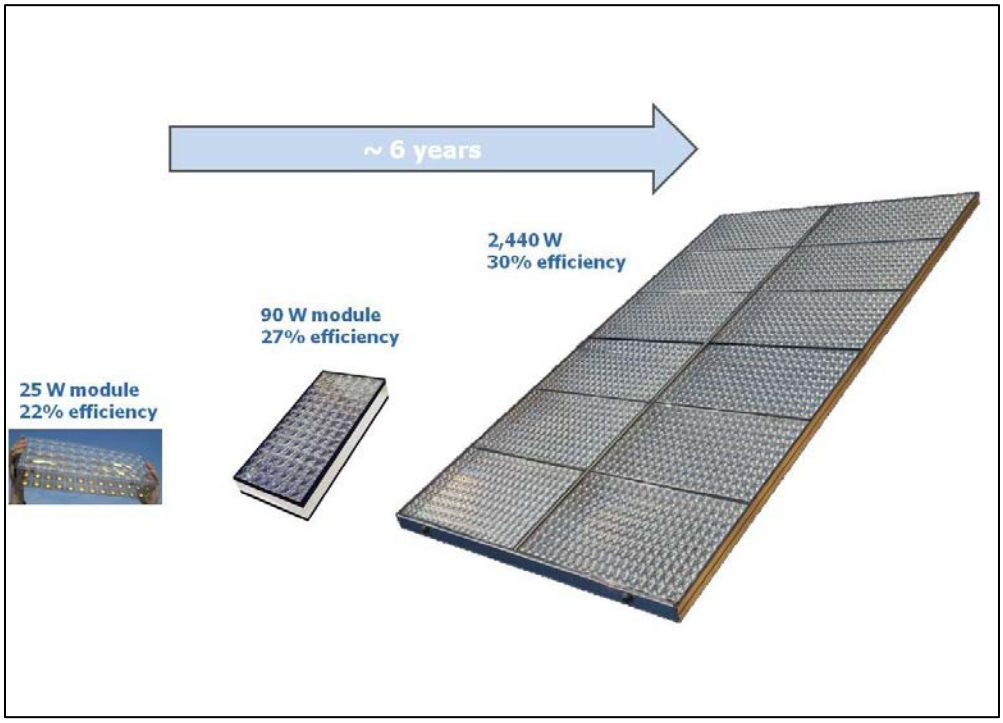


Figure 2. Increased Module Size and Efficiency

- Increased tracker size to strike a balance between material requirements and installation cost (see Figure 3 below). The first CX-T030 tracker was installed in July 2011 and was immediately subjected to accelerated life cycle testing.

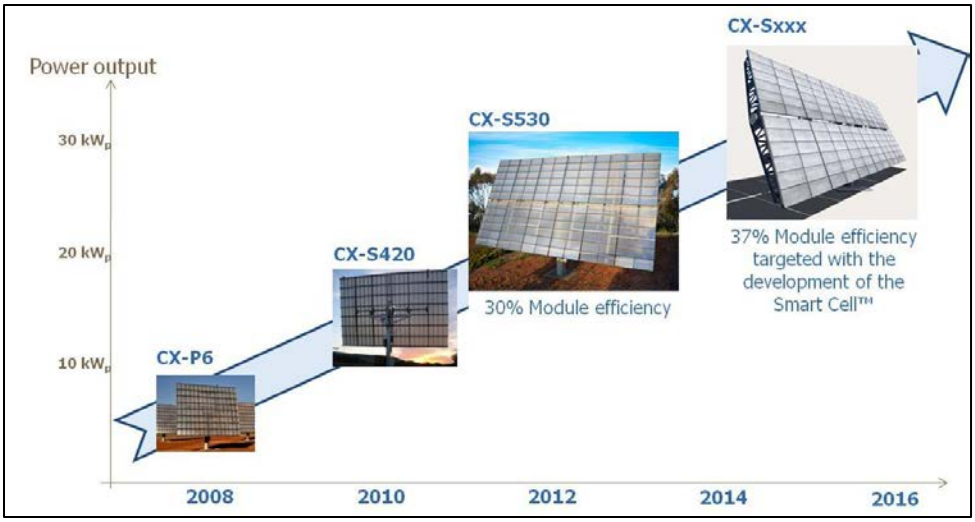


Figure 3. Increased Tracker Size

Concentrix was purchased by Soitec, a French semi-conductor company, in 2009. Soitec commissioned third party tests and independent engineering reports from reputable engineering firms such as KEMA in 2009 and SAIC/R.W. Beck (now Leidos) in 2011.

In particular, the findings from the SAIC/R.W. Beck engineering report were as follows:

- *Soitec has previously demonstrated the capability to manufacture its CPV modules using proven techniques and supply its Concentrix CPV systems.*
- *Soitec has also demonstrated the capability to qualify the suppliers of the system components that it does not manufacture internally.*
- *Soitec has successfully applied previous lessons learned into its design and manufacturing processes.*
- *Soitec's CX-P6, CX-S420, and the demonstration CX-S530 systems have been proven to work under their rated conditions and it is expected that commercial CX-S530 CPV systems are capable of operating as intended.*
- *To date, Soitec's CPV systems have operated without significant issues and based on this fact, it is expected that the CX-S530 CPV system will also operate without significant issues.*
- *During the course of the review SAIC did not identify any significant technical risks with the CX-P6 system that could not be mitigated by proper O&M practices.*

2.3 ADVANTAGES AND LIMITATIONS OF THE TECHNOLOGY

2.3.1 Advantages

CPV competes with conventional crystalline-silicon PV systems to produce energy from utility, commercial and residential power plant installations. Due to the fact that CPV uses dual-axis tracking, the electricity produced by CPV technology is consistently high in high DNI regions (>1800 kWh/m²), such as the US Southwest, Southern Europe, Northern & Southern Africa, the Middle East and Australia. The cell technology is based on III-V materials which maintain energy output at high temperatures (1/3 the losses of silicon) and with long life expectancies.

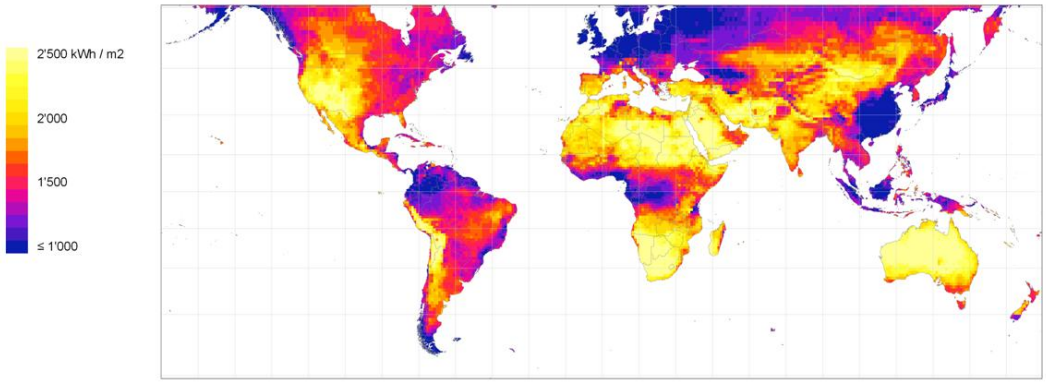


Figure 4. High DNI Areas

CPV more closely matches matching peak load demands than conventional PV. Figure 5 below shows how energy produced from CPV ramps up early in the morning and, more importantly, produces more energy in the peak demand period from approximately 1400 – 1830 when conventional PV ramps down production.

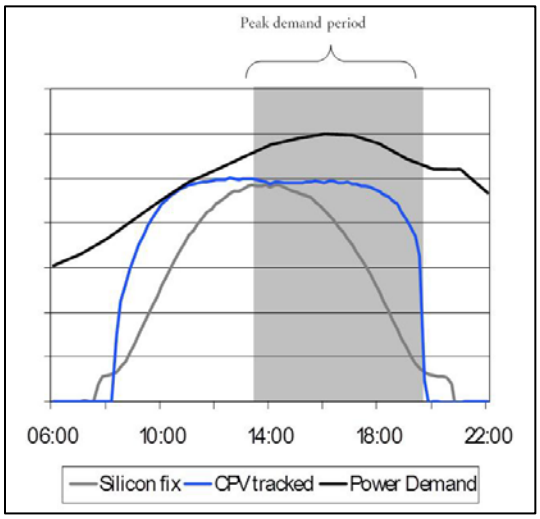


Figure 5. Power curve of Californian Grid 6 Aug 2008 and Production Curves in Seville Spain 1 May 2008[2]

[2] . Sources: California Independent System Operator, Concentrix Solar, Abengoa Solar

As shown in Figure 6 below, CPV is more efficient than conventional crystalline-silicon PV systems, particularly in the high temperature desert conditions of the Southwest U.S. Cell efficiency is over 40% and module efficiency is almost 30% which at the time was 2-3 times the efficiency of PV technology and was proposed as one of the most efficient and cost-effective solar power technologies with the lowest environmental impact.

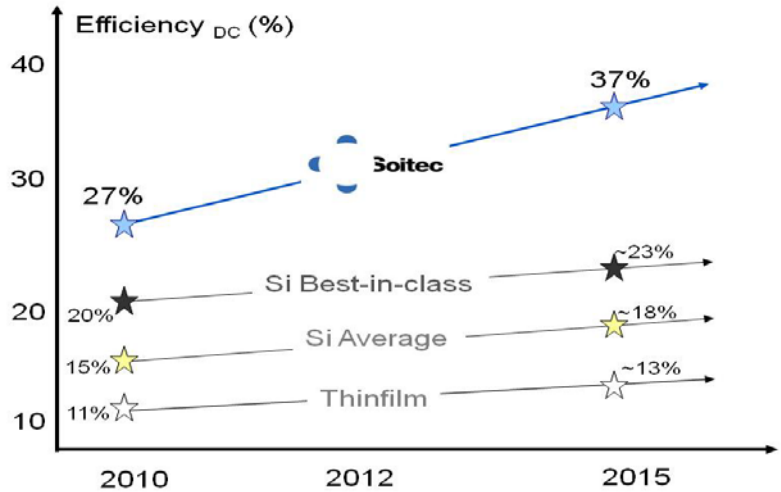


Figure 6. CPV vs. Conventional PV Efficiency

Like PV, but unlike concentrated solar thermal power (CSP), there is no water needed for operations except for panel cleaning on an as-needed basis.

2.3.2 Limitations

As with any technology CPV has its limitations and constraints, some of which have been addressed during this demonstration:

1. CPV experiences more significant energy fluctuations based on cloud cover versus conventional PV. CPV energy production relies upon DNI whereas conventional PV relies on both DNI and Global Horizontal Insolation (GHI). Therefore, CPV performance is not optimal in low DNI areas with frequent clouds.
2. High wind events limit energy production due to the wind stow function necessary to protect the CPV Systems from damage. The dual-axis trackers stow at approximately 33 mph winds and it requires approximately 10 minutes to reach stow from the steepest tracker position. During movement to stow position, stow position and movement back to operation, power production is virtually zero.
3. Excessive rocky soil or sloped sites may limit economical foundation options, as the 16,000 lb. tracker table requires robust foundations to withstand wind and seismic events. CPV cannot be used on landfills or any location where cap penetration is an issue.
4. Due to the tracker weight and wind signature, CPV is not ideal for rooftops or other similar structures.

5. CPV CAPEX and OPEX costs are higher than those of conventional photovoltaic solar technology. This is discussed in more detail in Section 7 (Cost Assessment).
6. There is a current lack of traction in the marketplace, as many CPV providers have departed the business or have declared insolvency.
7. There is a current lack of government policy supporting CPV Technology
8. There is a difficulty overcoming the more established photovoltaic solar technology
9. CPV has a much more limited performance track record than conventional photovoltaic solar technology.
10. There remains a lack of familiarity of financial institutions about CPV, resulting in inadequate financing options for CPV power plant projects.
11. Additional implementation challenges are discussed in Section 8 (Implementation Issues).

3.0 PERFORMANCE OBJECTIVES

3.1 SUMMARY OF CPV SYSTEM PERFORMANCE OBJECTIVES

Performance objectives for the CPV technology's installation, operations and maintenance (O&M), energy production, availability, and performance degradation are summarized in Table 2. Soitec has provided a broad overview of the test design and data analysis to provide insight into the methodology.

Table 2. Performance Objectives Summary Table

Performance Objectives	Metric	Data Requirements	Success Criteria	Results
1. Technology Installation Time	Number of days needed to install and commission the CPV systems.	Time studies of the installation from construction start to commissioning completion.	≥ Two systems per day.	**MET OBJECTIVE** 2.9 systems per day
2. Preventive O&M Labor	Cumulative number of man-hours needed to perform annual preventive maintenance.	Maintenance logbook of the different maintenance activities.	≤ one man-hours per CPV System annually.	**DID NOT MEET OBJECTIVE** 154 hours, which is 1.93 man-hour per CPV system annually.
3. Reactive O&M Labor	Cumulative number of man-hours needed to perform annual reactive maintenance.	Event and maintenance logbook of the different activities required to repair equipment in the field.	≤ two man-hours per CPV system annually.	**DID NOT MEET OBJECTIVE** 393 hours, which is 4.92 man-hours per CPV system annually.
4. Energy Model Validation	Energy produced (MWh or kWh generated by the power plant and the CPV systems).	Meter readings of energy produced by installation and CPV systems.	Within 2% of baseline model or expected value	**MET OBJECTIVE** 99% (within 1% of expected)
5. CPV Power Plant Availability	Energy produced (MWh or kWh) and system downtimes and failures.	Meter readings of energy and status of main power plant equipment (CPV systems and inverters)	Power plant availability is greater than 98%	**DID NOT MEET OBJECTIVE** CPV System 96.3%. Power Plant availability 95.6%.
6. Long Term Performance Degradation	Energy produced (MWh or kWh generated by the power plant and the CPV systems)	Meter readings of energy produced by CPV systems.	Power output change after 24 month operation is within measurement accuracy	**MET OBJECTIVE** Improved 1.6% (within %5 measurement accuracy)

Note: No Solar Forecasting performance objective is included in Table 2, however, a Performance Objective for Solar Forecasting is discussed below in Section 3.2.6.

3.2 PERFORMANCE OBJECTIVES DESCRIPTIONS

Each of the performance objectives is described in detail below.

3.2.1 Performance Objective 1: Technology Installation Time

Purpose: Soitec's goal was to significantly decrease the time required to assemble, install and commission the CPV systems compared to previous installations. Steps included (1) tracker table assembly process; (4) tracker table installation on the mast, and (5) completion and commissioning of the CPV system.

Soitec performed the first full-scale trial of its Utility Scale Tracker Assembly (USTA) process. As conceptually shown below in Figure 7 and in the field in Figure 8, the USTA process employs a field-adapted centralized assembly production line concept which enables the delivery of tracker components to a central, protected assembly area equipped with specialized equipment utilizing streamlined, repetitive assembly movements. This results in a faster, safer, and less expensive tracker assembly process. The trackers are assembled on a specialized trailer which transports the tracker table to its designated mast where a crane installs it. Processes were balanced to minimize waiting time between tracker assembly operations.

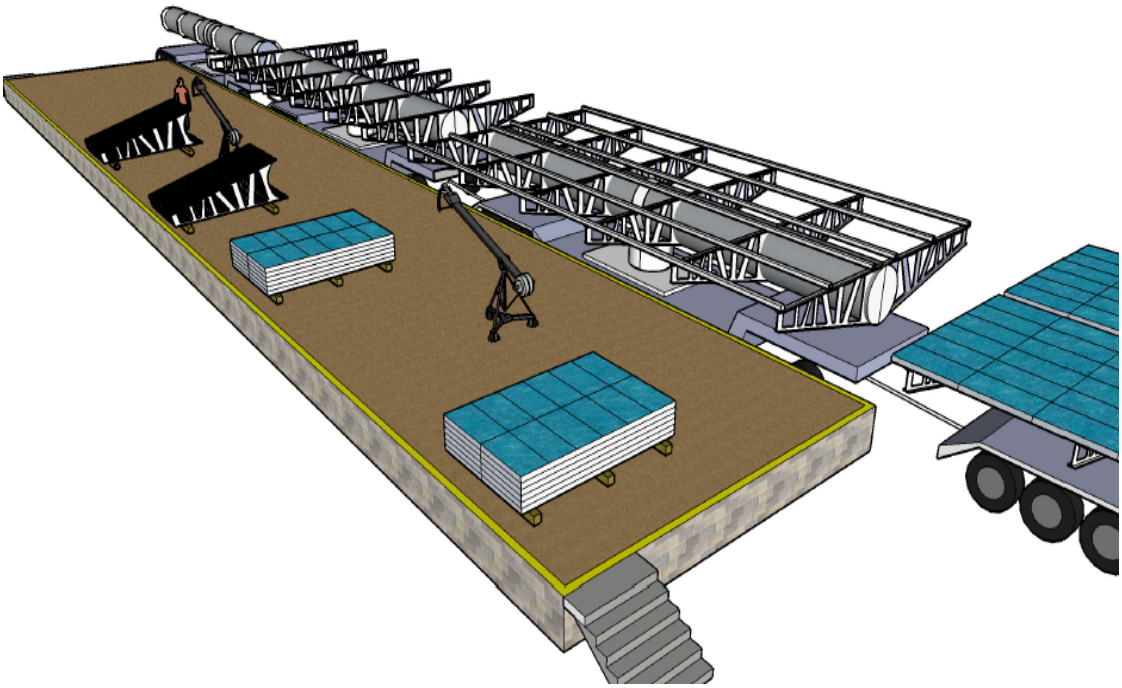


Figure 7. USTA Process Concept

Figure 8. USTA Field Setup with Tracker Structure Mounted on Specialized Trailer

Metric: Soitec conducted a time study with help of a stopwatch in order to document the time required to assemble and erect the trackers.

Data: The data required include number of trackers completed and time required to complete.

Analytical Methodology: The analytics for this objective were straightforward. See Section 6 for graphical data in Excel format.

Success Criteria: The goal was to assemble and erect two trackers per day. As the previous record was one tracker per two days, this represented a 200% increase in the current baseline.

Result: The assembly of the forty (40) solar tracker tables started 20 Jan 2015 and was completed 5 February 2015 (12 work days). Tracker installation averaged **3.33/day**. However, commissioning and completion was dependent upon the Balance of Plant schedule, since full commissioning requires AC power and a DC power load draw. Therefore, since commissioning was not completed directly after tracker installation, it was nearly impossible to track the time. However, trackers were commissioned, on average, at the same rate as installation. If conducted back-to-back with installation, this would normally lag installation by two days and result in an overall time, start to finish, of 14 days, yielding **2.9 trackers/day.**

3.2.2 Performance Objective 2: Preventive and Reactive O&M Labor.

Purpose: Preventive maintenance is performed on a regular schedule and consists of systematic inspection, detection, and correction of incipient failures before they occur or develop into major defects. Reactive maintenance is carried out on an as-needed basis, typically after a failure is detected, and is aimed at restoring the CPV system to a condition in which it can perform its intended function. Soitec intended to reduce the number of man-hours needed to perform preventive and reactive maintenance, which is necessary to be competitive when comparing CPV levelized cost of energy (usually over 25 years) to PV.

Metric: Soitec recorded the number of hours that field maintenance personnel spend performing annual preventive and reactive maintenance, as well as the cost of equipment used.

Data: The data recorded included the task, date and time. The data was recorded in a Computerized Maintenance Management System (CMMS) and categorized by different types of maintenance activities.

Analytical Methodology: See Section 6 for graphical data in Excel format.

Success Criteria: The goal is for preventive maintenance activities on each CPV system was to be no more than one man-hour annually. The goal is for reactive maintenance activities on each CPV system was to be no more than two man-hours annually.

Result:

Preventive Maintenance – **DID NOT MEET OBJECTIVE**; preventive maintenance over two years totaled **154 man-hours**, which was**1.93 man-hours** per CPV system annually.

Reactive maintenance - **DID NOT MEET OBJECTIVE;** recorded reactive maintenance over two years totaled 316 hours, which was 3.9 man-hours per CPV system annually. However, there was an approximately 6-month gap in reactive maintenance records between September 2016 and March 2017. Reactive maintenance averaged 12.96 hours/month, so assuming a fairly level pattern, this would represent an additional 80 hours of reactive maintenance, making the total **393 man-hours**, or **4.92 man-hours** of reactive maintenance per tracker.

The main causes of reactive maintenance were:

1) Failed drive encoders
2) Failed limit switches
3) Failed control boards
4) Failed 4Q sensors
5) Variable frequency drive overcurrent, undervoltage or over-temperature
6) Failed DC connectors

3.2.3 Performance Objective 3: Energy Model Validation.

Purpose*:* Soitec used the industry-leading PV simulation software PVSyst to calculate the energy output of its CPV power plants. This model duplicated the expected energy production based on the actual onsite weather conditions and allows it to be compared to actual energy production. Actual energy production of CPV power plants depends on onsite specific meteorological conditions, as well as plant components, layout, and assembly. As actual energy production is closely correlated to plant revenues and requires a high level of predictability. In order to validate the energy production model, NREL provided an assessment of Soitec and PVSyst findings.

Metric: Energy produced (kWh/MWh) by the CPV systems. Since this consisted of assessing pure performance, the expected energy production when a CPV system was not available (i.e. not producing power) was reduced proportionally.

Data: Meter readings of energy produced by the CPV Systems as well as weather station measurements (DNI, temperature, and wind speed).

Analytical Methodology: The PV energy simulation data (with actual meteorological inputs) were compared to actual energy production data.

Success Criteria: Energy produced must be within 2% of baseline model or targeted value, when the outliers are removed from the full data population.

Result: **MET OBJECTIVE** - Within the limitations of the available data, the power plant demonstrated capability to produce 99% of model predicted energy, which exceeds the target 98% of model predicted energy.

3.2.4 Performance Objective 4: CPV Power Plant Availability

Purpose: It is assumed that in a typical utility scale solar power project a certain small portion (usually 0 - 2%) of energy production will be lost due to maintenance and repair downtime. The objective of the availability assessment was to evaluate how long it took to maintain and repair the CPV Systems, how much corresponding energy was lost, and how long the trackers were not operated. The analysis enabled the assessment of the amount of energy lost due to the unavailability of the CPV systems, the inverters, and the remaining balance of plant equipment.

Metric: The availability definition used for this analysis is a ratio of the number of online records and the total number of records:

Availability= (Number of records with trackers online)/(Total number of records)

Two types of availability were considered:

System availability – This is an "all-in" availability that considers all sources of downtime regardless of cause.

CPV availability – This is an "in-scope" availability that excludes site-wide events that are not within the scope of the operator.

To reduce uncertainty and avoid counting tracker production during invalid DNI data recordings, only records with a DNI>500 W/m2 were considered in the calculation.

To avoid sensor error and tracker performance from impacting the availability calculation, Soitec used an online/offline threshold of 1,000 kW. The data points above the threshold are considered online records. Using this threshold ensures that the calculation is a measure of availability, not dependent on performance.

This is consistent with the methodology that Soitec has historically used for other power plants[3]:

$$\text{Availability (missing data excluded)} = \frac{n_avail}{n_unavail + n_avail}$$

[3] Tobias Gerstmaier, Tobias Zech, Michael Röttger, Christian Braun and Andreas Gombert. *Large-Scale and Long-Term CPV Power Plant Field Results*. 2015. AIP Conference Proceedings of the 11th International Conference on Concentrator Photovoltaic Systems CPV-11, Aix-les-Bains, France.

where:
n_avail = enough data for DNI and average DC power of system >= 1kW
n_unavail = enough DNI data and enough data for system and DNI>=500 W/m² and average DC power of system < 1kW

Data: Hourly average values of DNI and DC power, measured individually for each CPV System.

Analytical Methodology: Calculated by using two years of actual weather conditions programmed into PVSyst.

Success Criteria*:* CPV Systems available ≥ 98%.

Result:

Overall Power Plant Availability – **DID NOT MEET OBJECTIVE**; 95.6%.

CPV System Availability - **DID NOT MEET OBJECTIVE**; 96.3%,

Results are discussed in further detail in Section 6.4 below.

3.2.5 Performance Objective 5: Performance Degradation

Purpose: There are two types of performance degradation may impact a solar energy system:

- Short-term degradation - Primarily is caused by soiling on the modules, which reduces power output performance.
- Long-term system performance degradation – Results from materials failure and is of greater concern for power plant owners, utilities, financiers and other stake-holders.

Metric: Energy (MWh/kWh) generated by the CPV systems.

Data: Meter readings of energy produced by the CPV Systems as well as weather station measurements (DNI, temperature, and wind speed). Also, onsite personnel were to document the local soiling conditions regularly and clean the trackers and sensing equipment as necessary.

Analytical Methodology:

- Short Term Degradation: As further detailed in Section 6.5, Soitec conducted intensive soiling studies at a 1.5 MW CPV Power plant in Newberry Springs, CA, about 70 miles south of Fort Irwin in the spring of 2014. Soitec compared the performance changes in clean CPV Systems (the control) and naturally soiled CPV System (the variable).
- Long Term Degradation: Production degradation was verified by comparing performance on clear days near the start and end of the evaluation period.

Success Criteria:

- Short-term performance degradation - NREL's recommended cleaning frequency is less than once every six weeks.

- Long-term system performance degradation - Power output change after two years of operations is within measurement accuracy of the performance index.

Result:

- Short-term performance degradation - Soitec's conclusion was that the soiling loss factor could not be determined as it was within the measurement accuracy; however, NREL did not have the opportunity to analyze this objective.
- Long-term performance degradation - **MET OBJECTIVE** - Performance appeared to improve by 1.6%, which is within the estimated 5% measurement uncertainty of the performance index.

3.2.6 Solar Forecasting Performance Objective

Purpose: With future incorporation of the CPV power plant and the Solar Forecasting System into an on-base grid management system, optimal plant operation (storage dispatch, curtailment, demand response, etc.) could be further achieved and potentially enable the effective capture of demand related savings.

Metric: The metric used for this assessment was the forecasting skill (s) developed by the UCSD team. This metric provides a path to assess the accuracy of solar forecast by allowing for comparison of forecast skill across different sites, timesteps, and irradiance versus power.

The metric *s* is defined as the the ratio: $s = \frac{V-U}{V} = 1 - (\frac{U}{V})$

where uncertainty U is defined as the standard deviation of a model's forecast error divided by the estimated clear sky solar irradiance I_{clr} over a subset time window of N_w data points.

The solar irradiance variability V is represented by the standard deviation of the step-changes of the ratio of the measured solar irradiance to that of I_{clr}.

Data: The quality and accuracy of the forecast provided by UCSD was monitored and documented using data from the Project. Due to difficulties with accessing data from the Project's inverter Shark 200 meters and unavailability of instantaneous CPV System data, real-time data analysis was not possible. Soitec downloaded energy production data from the CPV Systems and provided it to UCSD.

Analytical Methodology: A measure of the improvement of a forecast method with respect to the persistence forecast based on the clear sky index is defined by the ratio U/V. s = 1 means that the solar irradiance or solar power output is perfectly forecasted, and when s = 0 the forecast error is as large as the variability. By definition, the persistence forecast has a forecast quality measure of s = 0. The metric *s* evaluates the variability that is efficiently reduced by the forecasting models by taking the difference between U and V. Since the uncertainty U depends on meteorological conditions it increases as complex weather develops. It also increases with the temporal resolution of the forecast (e.g. minute-by-minute forecast from a sky imager versus hourly average forecast from NWP), the *s*' normalization by V controls the variability impact providing comparability across different geographic regions and temporal resolutions.

Success Criteria: The forecasting component of this project was to be considered a success if the target values in Table 3 below were achieved.

Table 3. Forecast Performance of Current Techniques versus Target Values at the End of the Project by Time Horizon[4]

Horizon	**< 1 hr (RTD)**	**1 hr (HASP)**	**1-6 hrs**	**24-36 hrs (DAM)**	**>36 hrs**
Averaging period	1 min	5 min	15 min	1 h	1 d
Current *s*	0.12-0.32	0.15-0.29	0.08-0.14	0.08-0.39	0.19
Target *s*	0.25-0.45	0.40	0.30	0.30	0.40

Result: Results are shown below in Table 4. For shorter time horizons (< 1 hour and 1 hour), the targeted forecasting skills were not fully achieved. However the obtained values are in agreement with the best performing forecasting models published in current literature[5]. For the forecast time window 1-6 hours, the Result s (DNI) of 0.25 to 0.39 (average of 0.32) exceeded the Target s of 0.30, meaning the average accuracy of the DNI forecast exceeded the target. With respect to longer horizons the demonstration exceeded the targets. More detail on the results can be found in Section 6.6 and UCSD's full final report can be found in Appendix C.

Table 4. Forecast Performance Result Values at the End of the Project

Horizon	**< 1 hr (RTD)**	**1 hr (HASP)**	**1-6 hrs**	**24-36 hrs (DAM)**	**>36 hrs**
Averaging period	1 min	5 min	15 min	1 h	1 d
Result *s (DNI)*	0.24-0.32	0.24-0.32	0.25-0.39	0.34	.41
Success Criteria Met?	No	No	Yes	Yes	Yes

[4] Note the current and project values of forecast skill in the table above also increase with the averaging period. For example, 24-36 hour forecasts are hourly averages while the 1-6 hour forecasts have 15-minute resolution. This and the decrease in accuracy of the reference (persistence) causes the 24-36 hour forecast to have higher skills.

[5] J. Antonanzas, N. Osorio, R. Escobar, R. Urraca, F. J. Martinez-de Pison, and F. Antonanzas-Torres. 2016. *Review of Photovoltaic Power Forecasting*. Solar Energy. 136:78–111.

4.0 FACILITY/SITE DESCRIPTION

4.1 FACILITY / SITE LOCATION AND OPERATIONS

After evaluating DOD installations that meet the project criteria of a minimum average daily direct normal irradiance of 6.0 kWh/m^2, Soitec located the solar power plant at the Fort Irwin Military Installation in San Bernardino County, California.

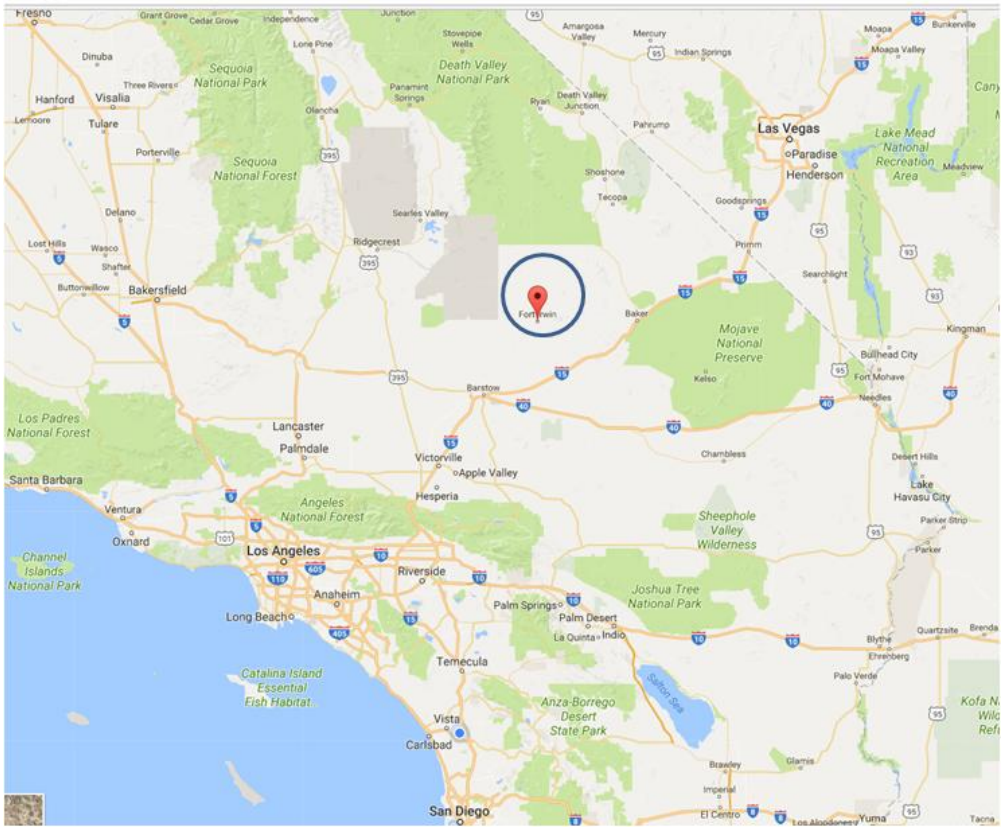


Figure 9. Fort Irwin National Training Center Location in California

Soitec used approximately 6 acres of land of the Fort Irwin National Training Center, CA (Department of Army). Fort Irwin is located roughly halfway between Las Vegas, NV and Los Angeles, CA.

The project site is located on Goldstone Road, approximately 1 mile from the center of the Fort Irwin cantonment area. It is bordered on the east by a water treatment plant, on the south by a RV/camping area and on the west by old garrison horse stable area. Figure 10 below shows the location and plant layout about one mile from the garrison center at Fort Irwin.

Figure 10. Site Location and Layout on Goldstone Road at the Fort Irwin National Training Center (GoogleEarth)

4.2 FACILITY/SITE CONDITIONS

The location is representative of arid desert environments in which CPV technology performs at the highest level. The adjacent water treatment, RV park and horse stable facility operations did not significantly impact the operation of the solar plant.

Figure 11. CPV Plant at Fort Irwin

5.0 TEST DESIGN

The broad technical approach of the proposed project was comprised of five activities:

1) Site-specific system design - described in detail in Section 5.3.
2) System construction, installation and commissioning – described in Section 3.2.1.
3) System operation and maintenance – described in Section 3.2.2.
4) System performance monitoring and validation – described in Section 3.2.3, Section 3.2.4 and Section 3.2.5.
5) Deployment of solar DNI forecasting – described in Section 3.2.6.

5.1 CONCEPTUAL TEST DESIGN

The primary scope of work involved the installation of a CPV demonstration power plant at Fort Irwin, followed by the monitoring and reporting of the operations and energy production at this plant.

a) Soitec recorded system assembly and installation times in the field using a dedicated manager witnessing crew assembly and commissioning times.
b) Soitec recorded measurements of energy and energy production performance using DC energy meters in the control units of each tracker. Recorded information captured major power plant downtime periods and outages.
c) Soitec logged O&M activities by on-site personnel entered their activities into a Computerized Maintenance Management System (CMMS) which allows data extraction and reporting.
d) UCSD provided solar forecasting services for the project. UCSD's forecasting engines are based on multi-layered data processing and machine learning algorithms, and its integrated load and solar generation forecasts have been extensively refined over the past few years for intra-hour, one to six hours, and up to 36 hours ahead.
e) NREL provided independent monitoring and validation services over the duration of the project.

5.2 BASELINE CHARACTERIZATION

Soitec installed the 1.12MW_{DC} power plant at Fort Irwin because of the reference conditions, which included:

1. Average DNI (Direct Normal Irradiance) of at least 6.0 $kWh/m^2/day$.
2. Dry, arid conditions
3. Good construction site composed of flat ground with good soil characteristics for supporting the tracker masts and which would support rapid installation of the trackers without slopes or excessive vegetation
4. Readily available grid distribution system for tie-in.

5. The Fort Irwin installation's maximum 30MW energy demand and minimum 10MW energy demand

Baseline characteristics for each of the performance objectives were as follows:

Table 5. Baseline Characteristics for Each Performance Objective

Performance Objectives	Metric	Baseline
1. Technology Installation Time	Number of days needed to install and commission the CPV systems.	CPV systems were previously installed one system every two days.
2. Preventive O&M Labor	Cumulative number of man-hours needed to perform annual preventive maintenance.	N/A; due to lack of recorded and available data for a CPV power plant of this size and location
3. Reactive O&M Labor	Cumulative number of man-hours needed to perform annual reactive maintenance.	N/A; due to lack of recorded and available data for a CPV power plant of this size and location
4. Energy Model Validation	Energy produced (MWh or kWh generated by the power plant and the CPV systems).	See below. Performance Index for Soitec's power plants had proven to be up to 106.2% over 4 years.[6]
5. CPV Power Plant Availability	Energy produced (MWh or kWh) and system downtimes and failures.	See below. Availability for Soitec's power plants had proven to be up to 98.8% over 4 years.[7]
6. Long Term Performance Degradation	Energy produced (MWh or kWh generated by the power plant and the CPV systems)	See below. No discernible degradation over 7 years using modules with similar components and technology.[8]

At the beginning of the demonstration, Soitec had almost 80MWp of cumulative capacity installed and although the bulk of this installation had just begun operation Soitec had over six years of field performance data from three plants, two in Spain and one in South Africa. Soitec also had a year of data from a 1MW plant in the US that utilized the CX-S530 CPV system. The energy model validation was supported by the results below:

The South Africa Plant (77kWp, 10 CPV systems) had an availability of 98.8% and a daily performance ratio of 79.7%. Comparing the actual AC energy (from plant meters) to the target AC energy (from PVSyst), the plant performed at 106.3% of expected production, as the actual AC energy exceeded the target AC energy by 6.3%.

[6] Tobias Gerstmaier, Tobias Zech, Michael Röttger, Christian Braun and Andreas Gombert. 2015. Large-Scale and Long-Term CPV Power Plant Field Results. AIP Conference Proceedings of the 11th International Conference on Concentrator Photovoltaic Systems CPV-11, Aix-les-Bains, France.
[7] Ibid.
[8] Andreas Gombert. 2015. *Soitec's Concentrator Photovoltaic (CPV) Long-Term and Large-Scale Track Record.* Soitec Corporate Presentation.

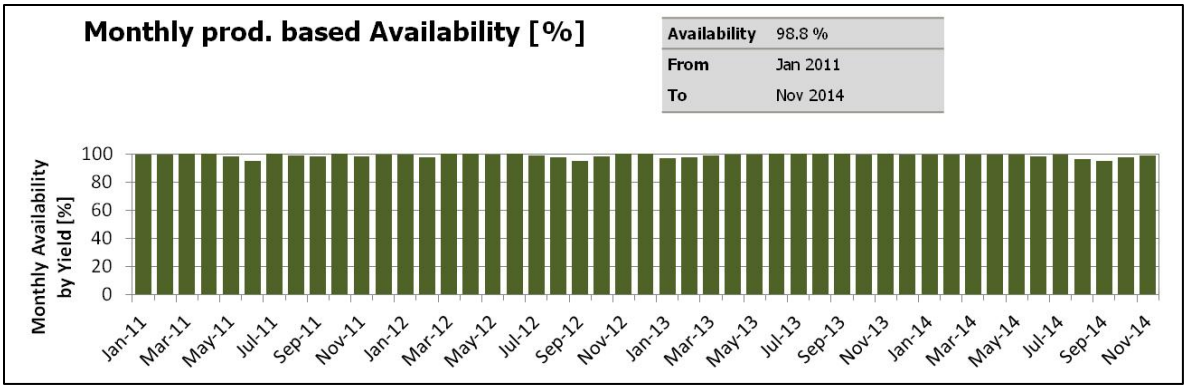


Figure 12. South Africa Plant Availability9

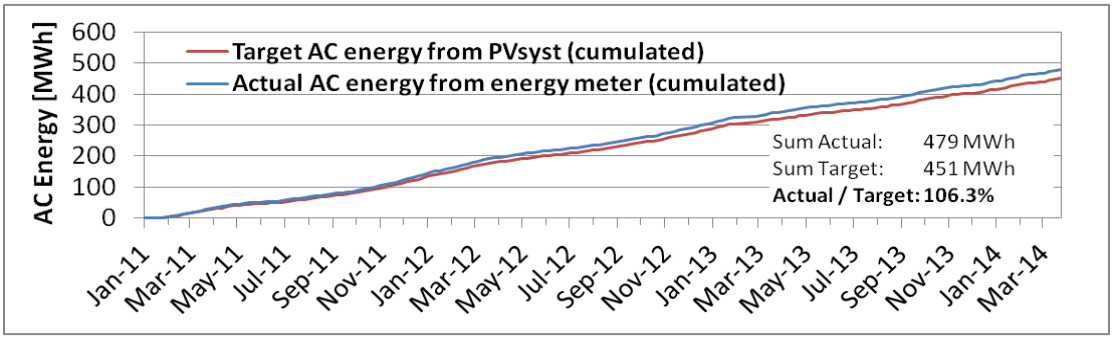


Figure 13. South Africa Plant Production Ratio[10]

Plant #1 in Spain (263kW, 36 CPV Systems) had performance ratio of 74.1% and an availability of 97.7%, despite being used for firmware/software tests and insufficient customer maintenance. Comparing the actual AC energy (from plant meters) to the target AC energy (from PVSyst), the plant performed at 103.3% of expected production, as the actual AC energy exceeded the target AC energy by 3.3%.

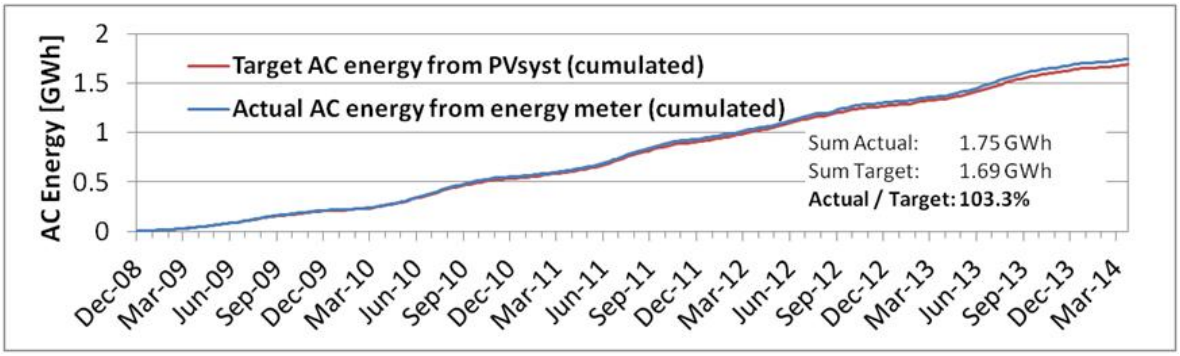


Figure 14. Spain Plant #1 Performance Ratio[11]

[9] Ibid, pg. 12.
[10] Ibid, pg 23.
[11] Ibid, pg 21.

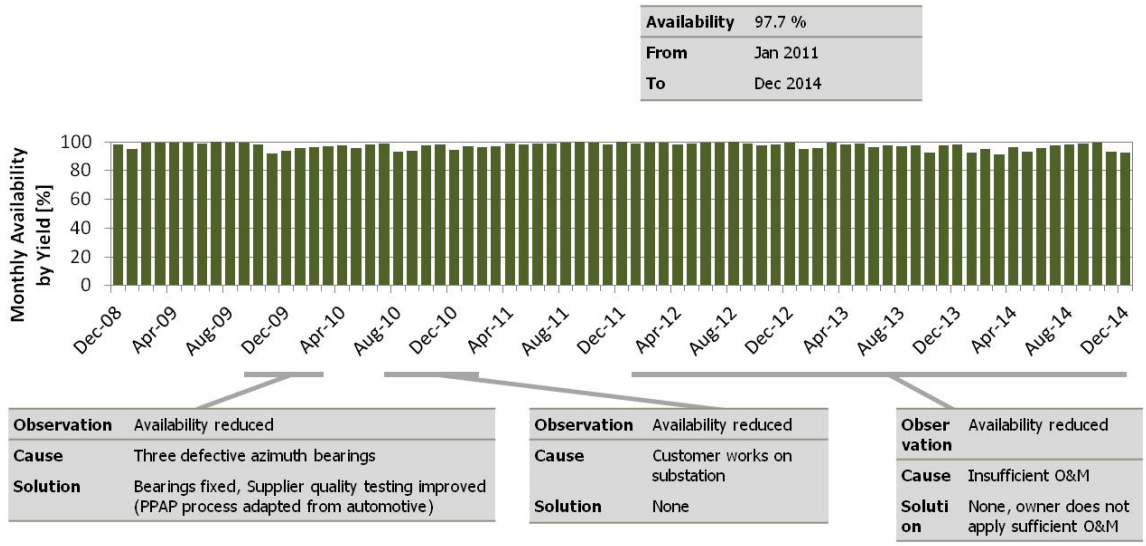


Figure 15. Spain Plant #1 Availability[12]

Plant #2 in Spain had a performance ratio of 72.8% and 96.9% availability from December 2008 to December 2014. Comparing the actual AC energy (from plant meters) to the target AC energy (from PVSyst), the plant performed at 102.6% of expected production, as the actual AC energy exceeded the target AC energy by 2.6%.

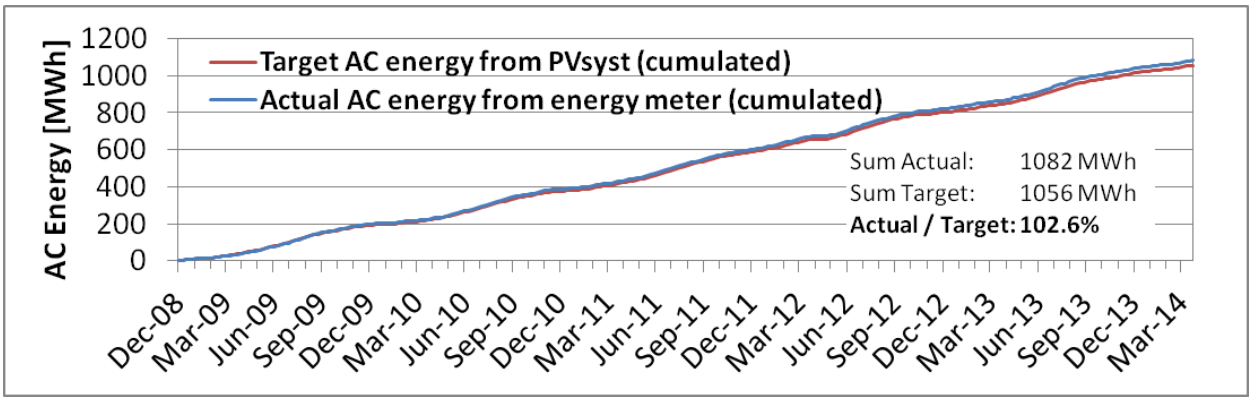


Figure 16. Spain Plant #2 Production Ratio[13]

The US plant experienced numerous issues with inverters, AC meter data compilation and was used to support other tests; however, when operated normally the daily AC actual to target AC ratio was 100.8%. The availability at the same time was 98.1%.

[12] Ibid, pg 15.
[13] Ibid, pg 22.

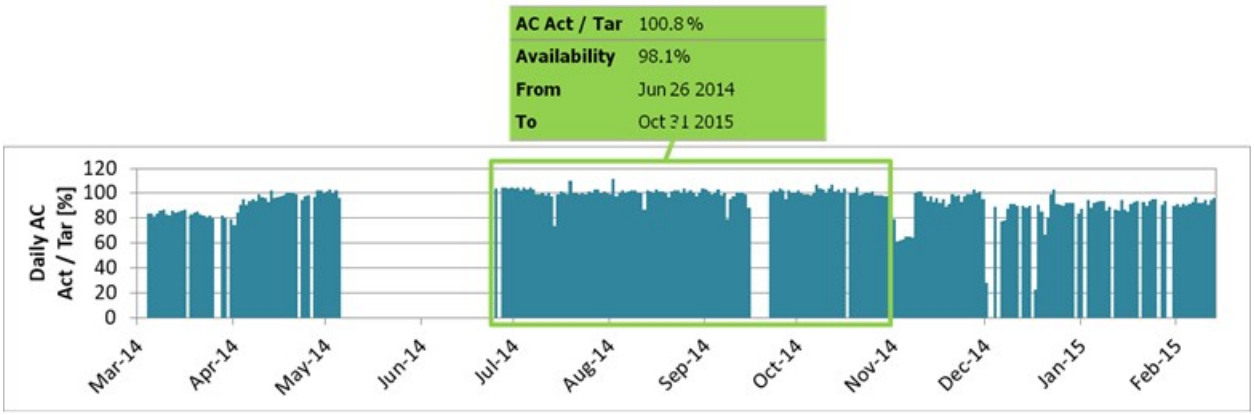


Figure 17. US Plant Production Ratio and Availability Record[14]

A detailed comparison of days with similar weather conditions reveals no degradation over 7 years for CPV modules from three operating power plants.

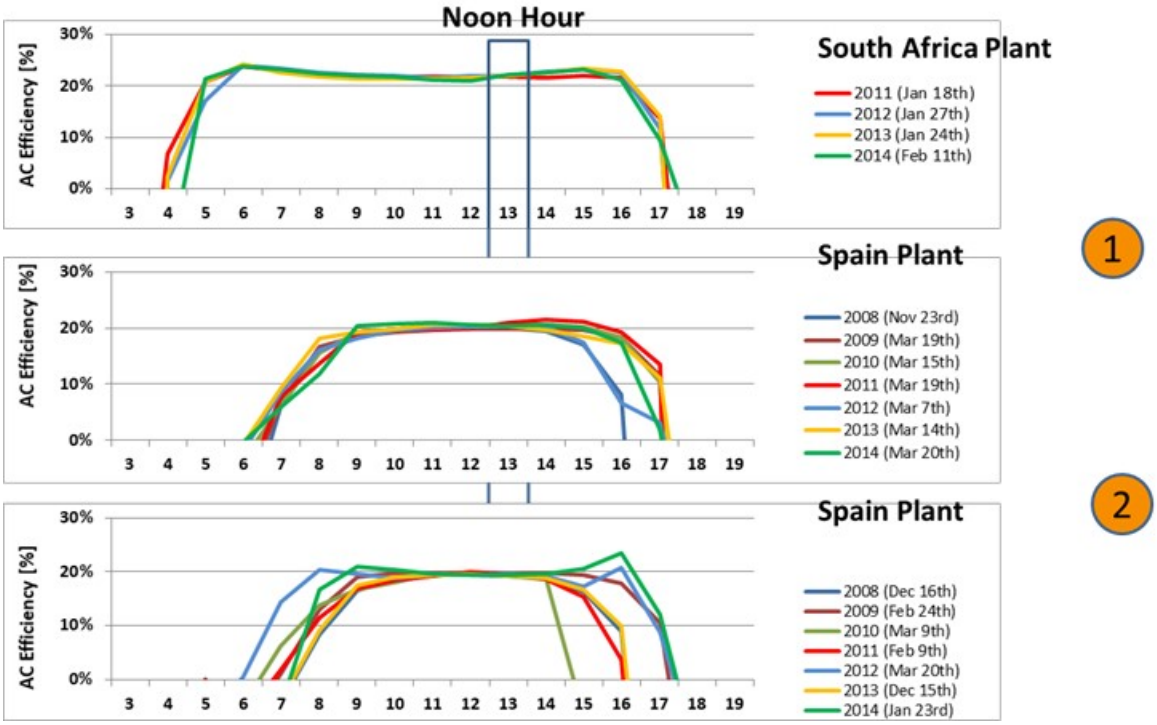


Figure 18. Comparison of Multi-year Module Production under Similar Weather Conditions[15]

[14] Ibid, pg 27.
[15] Ibid, pg 19.

In conclusion, at the beginning of the demonstration Performance Ratio and Availability for Soitec's power plants had proven to be high and stable over 6+ years and day-by-day AC efficiency comparison of 7 consecutive years had not revealed measurable module degradation.

5.3 DESIGN AND LAYOUT OF TECHNOLOGY COMPONENTS

5.3.1 CPV Module

At the heart of the system is the M-500 CPV module, which has the specifications:

- Dimensions: 12.0 ft x 7.84 ft x 0.335 ft
- Characteristics:
  - 2,400 Solar Cell Assemblies ("SCA") per M500 (12 sub-modules, 200 SCAs each)
  - One air tube inlet and one outlet valve
  - One junction box located on short edge for portrait assembly
- Certification: IEC62108

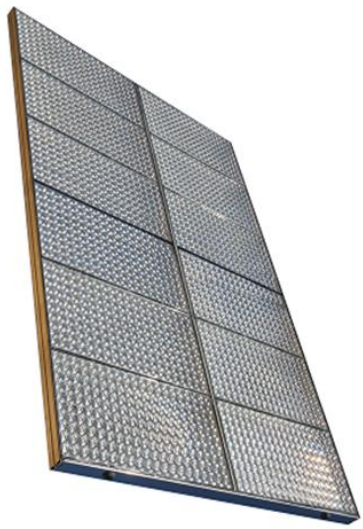


Figure 19. Soitec M-500 CPV Module

5.3.2 Dual-Axis CX-S530Tracker

The CX-S530 main components are grouped into parts and named as follows:

- Thirty Stringers (1)
- Two Main tubes (2)
- One dual-axis drive (3)
  - Elevation gear reduction box and motor (5)
  - Azimuth gear reduction box and motor (4)
- Twelve ribs (6)
- One Air Drying Unit (ADU) (7)

- One Tracker Control Unit (TCU) (8)

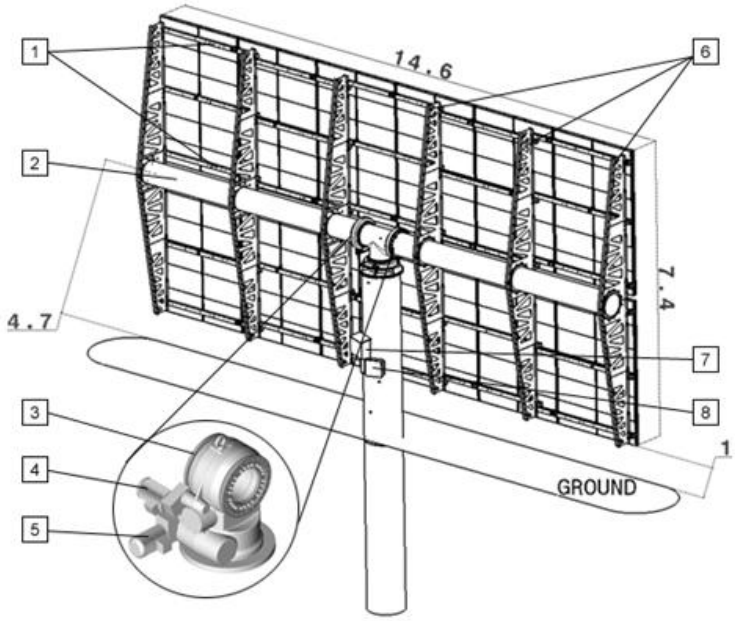


Figure 20. Soitec CX-S530 Tracker

The tracker has the following specifications:

- Dimensions: 47.9 ft x 24.7 ft
- Aperture: 110 m^2
- Two-axis tracking, rotational elevation
- Mast height above ground: 12ft
- Elevation movement: 5 to 90°
- Azimuth movement: +/- 150°

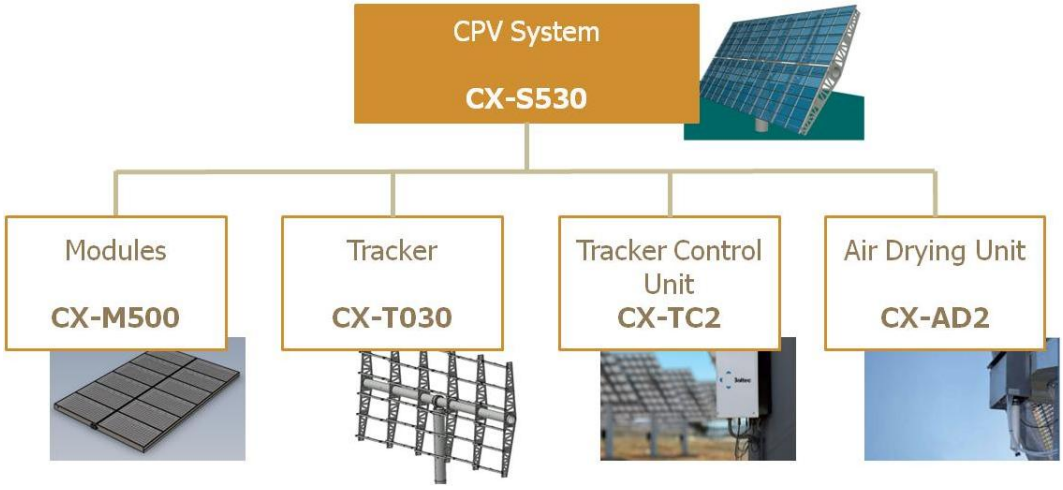


Figure 21. CPV System Major Component Illustration

5.3.3 Balance of System

As illustrated below in Figure 22, the Balance of System (BOS) of the power plant is the electrical collection system, which collects the DC power produced by each of the trackers and transports it to the power conversion station, also known as the inverter station. The inverter station converts the DC electrical power to AC electrical power and a transformer increases the voltage to medium-voltage (MV) AC electrical power. Additional electrical collection equipment transports the AC power to the substation, or energy delivery point, where another transformer increases the MV AC power to high voltage (HV) AC power. At the point, the electrical power is placed on the transmission or distribution lines of the utilities' grid, where it is a commodity ready for use.

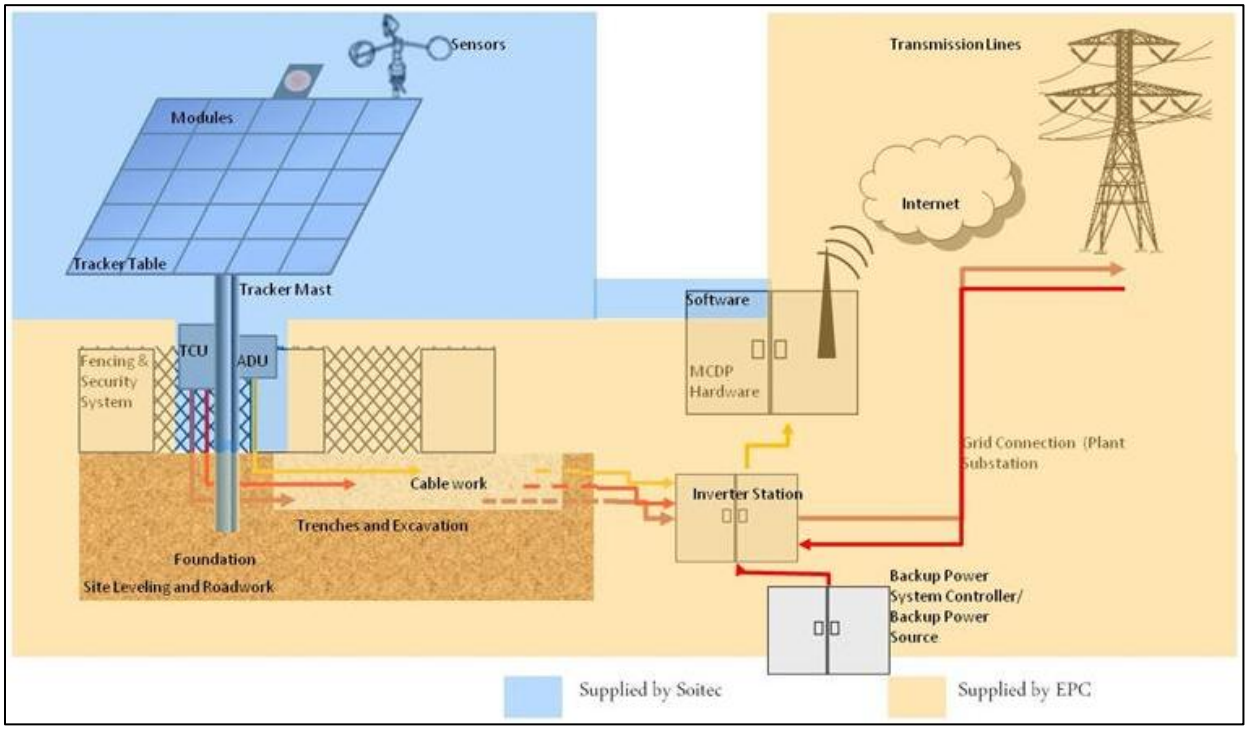


Figure 22. CPV Power Plant Schematic Showing Balance of System[16]

Figure 23 shows the layout of the 1MW Fort Irwin CPV Plant, with forty (40) CPV Systems around a central inverter station containing 2 AE 500TX (500kW) inverters. The plant AC station contains equipment from Soitec and from the utility, Southern California Edison and is the point of delivery to the utility's grid system on the military installation.

[16] Note the color coding is a typical scope of work division between Soitec and EPC for a CPV Power Plant.

Figure 23. Fort Irwin CPV Power Plant Layout

5.4 OPERATIONAL TESTING

Phase I of the project was the project development and permitting by Soitec and the physical construction by an Engineering, Procurement, Construction (EPC) contractor under Soitec's supervision. Phase 1 consisted of installing 40 trackers on a bus cabling system feeding into DC combiner box, which in turn feed into a central inverter station. Two AE-500TX (500kW) inverters are housed in one location, sharing a 1MW transformer with two low voltage windings.

During Phase 1, Soitec was able to evaluate and confirm the tracker assembly process employing a field-based centralized assembly production line concept which enabled the assembly of modules onto tracking rigs, ready for transportation and attachment to the mast.

Phase 2 of the project was the operational data gathering and analysis of the power plant. The size of the demonstration power plant project is 1.12MW_{DC} which allowed Soitec to evaluate and confirm:

1) O&M costs and their subsequent impact on the economic viability of the technology and the availability of the power plant;
2) Total energy and power production as a function of actual conditions and time of day throughout the duration of the project life;

3) No measurable degradation in energy production performance during project life;
4) The CPV system's capability to integrate with advanced DNI forecasting systems (UCSD).

Phase 3 of the project was the final report development and transfer of the property (power plant) over to the host site, Fort Irwin National Training Center.

The phases are shown below in a Gantt chart format in Figure 24.

	Task Name	Duration	Cal Days Start	Cal Days Fin	Start	Finish
	Milestone Summary Schedule	**1300 dys**	**0**	**0**	**Fri 6/28/13**	**Fri 6/22/18**
Phase 1	Milestone 1:Submit Table 1, Performance Objectives and Demonstration Plan	1 dy	-447	-446	Fri 6/28/13	Fri 6/28/13
	Milestone 2: Long Lead Time Equipment Ordered	1 dy	-414	-413	Wed 7/31/13	Wed 7/31/13
	Milestone 3: Q1 Report	1 dy	-322	-321	Thu 10/31/13	Thu 10/31/13
	Milestone 4: Development Design Completed and Submitted	0 dys	0	0	Thu 9/18/14	Thu 9/18/14
	Milestone 5: Materials and Equipment Needed For Installation on Site	0 dys	85	85	Fri 12/12/14	Fri 12/12/14
	Milestone 6: Q2 Report and Site Preparations	0 dys	113	113	Fri 1/9/15	Fri 1/9/15
	Milestone 7 (Equipment Installation and Certification Underway)	0 dys	145	145	Mon 2/9/15	Mon 2/9/15
	Milestone 8: Metering Equipment Installed and Operational	0 dys	285	285	Tue 6/30/15	Tue 6/30/15
	Milestone 9: Q3 Report and Project Inspected, Approved and Commissioned	0 dys	313	313	Tue 7/28/15	Tue 7/28/15
Phase 2	Milestone 10: Q4 Report	0 dys	-49	-49	Thu 7/31/14	Thu 7/31/14
	Milestone 11: Q5 Report; Six Months of Operation Demonstrated and Raw Data Monitoring	0 dys	134	134	Fri 1/30/15	Fri 1/30/15
	Milestone 12: Q6 Report	0 dys	134	134	Fri 1/30/15	Fri 1/30/15
	Millestone 13: Q7 Report	0 dys	224	224	Thu 4/30/15	Thu 4/30/15
	Milestone 14: Q8 Report	0 dys	316	316	Fri 7/31/15	Fri 7/31/15
	Milestone15: Q9 Report	0 dys	407	407	Fri 10/30/15	Fri 10/30/15
	Milestone 16: Q10 Report	0 dys	498	498	Fri 1/29/16	Fri 1/29/16
	Milestone 17: Q11 Report	0 dys	680	680	Fri 7/29/16	Fri 7/29/16
	Demonstration 50% Complete	0 dys	651	651	Wed 6/29/16	Wed 6/29/16
	Demonstration 75% Complete	0 dys	819	819	Wed 12/14/16	Wed 12/14/16
	Demonstration Complete and Initiate Property Transfer	0 dys	1015	1015	Wed 6/28/17	Wed 6/28/17
Phase 3	Milestone 18: Submit Draft Final, Cost and Performance Report	0 dys	1184	1184	Fri 12/15/17	Fri 12/15/17
	Receive Final Report & C&P Report Comments	0 dys	1222	1222	Mon 1/22/18	Mon 1/22/18
	Submit Revised Final Report	0 dys	1248	1248	Fri 2/16/18	Fri 2/16/18
	Milestone 19: Q12 Report and Receive Final Report Approval, C&P Report Approval	0 dys	1276	1276	Fri 3/16/18	Fri 3/16/18
	Property Transfer Complete to Fort Irwin	0 dys	1373	1373	Fri 6/22/18	Fri 6/22/18

Figure 24. Fort Irwin 1MW CPV Project Phase Gantt Chart

5.5 SAMPLING PROTOCOL

The sampling protocol for each performance objective is listed below in Table 6.

Table 6. Sample Collection Approach for Each Performance Objective

Performance Objectives	Sample Descriptions	Number of Samples	Type of Samples	Methodology	Quality Assurance Sampling	Calibration
1. Technology Installation Time	Number of trackers completed per day. NOTE: Soitec did not count the first five trackers because they served as the learning curve for the EPC contractor, who had never assembled one of these trackers before.	40	Number of trackers completed per day.	Soitec assigned a dedicated on-site project manager to perform the data collection and summary.	Project management supervision	N/A
2. Preventive O&M Labor	Cumulative number of man-hours needed to perform annual preventive maintenance.	Multiple	Hourly logs	Maintenance logbook entries	Maintenance supervision	N/A
3. Reactive O&M Labor	Cumulative number of man-hours needed to perform annual reactive maintenance.	Multiple	Hourly logs	Maintenance logbook entries	Maintenance supervision	N/A
4. Energy Model Validation	Energy produced (MWh or kWh generated by the power plant and the CPV systems).	Multiple	DC meter readings of energy produced	See details below.	Cleaning of DNI sensors	Calibration of DNI sensors
5. CPV Power Plant Availability	Energy produced (MWh or kWh) and system downtimes and failures.	Multiple	DC meter readings of energy produced	See details below	Cleaning of DNI sensors	Calibration of DNI sensors
6. Long Term Performance Degradation	Energy produced (MWh or kWh generated by the power plant and the CPV systems)	Multiple	DC meter readings of energy produced.	See details below	Cleaning of DNI sensors	Calibration of DNI sensors

5.6 SAMPLING RESULTS EQUIPMENT CALIBRATION AND DATA QUALITY ISSUES

During the demonstration there were a few instances of data unavailability that affected the data collection; however, in most cases engineering, separate observations/studies and assumptions were used to supplement the findings.

Issue: Inverter Meter Data.

Discussion: It was planned to record data from the Shark 200 inverter meters, specially selected and installed to incorporate into Soitec's SCADA system, during the demonstration; however, due to Soitec's decision to leave solar industry and the subsequent personnel drawdown the data linkage never happened.

Solution: The DC energy data from the CPV Systems were used in all calculations and analysis. This type of data is commonly used for the performance objectives' supporting calculations.

Issue: Real-Time Performance Data.

Discussion: Soitec was not able to provide UCSD with real-time data for solar forecasting analysis due to the lack of knowledgeable IT personnel.

Solution: UCSD performed their analysis with Fort Irwin performance data provided by Soitec with a delay and compare this to their forecast models.

Issue: Soiling Data and Module Washing Frequency

Discussion: Due to resource shortages, Soitec was not able to conduct module washings and soiling studies.

Solution: Soitec conducted a detailed soiling study at a 1.5MW CPV Power plant in Newberry Springs, CA which is about 70 miles south of Fort Irwin and located in a similar environment in the Mohave Desert. In Section 6.5, Soitec provides the findings of this soiling study in lieu of data at Fort Irwin.

Issue: Missing O&M Recorded Hours

Discussion: Soitec technicians failed to record all O&M data from approximately October 2016 to February 2017 (5 months).

Solution: Soitec assumed certain CPV System and BOS reactive and preventive maintenance hours would have been consistent with the remainder of the performance period and factored in these estimated hours into the calculations.

Issue: Half the CPV System's Energy Measured by TCU DC Energy Meter

Discussion: Only six (6) CPV modules (half of the twelve total modules on the CPV System) are connected to the TCUs so as to not exceed their NEC code current constraints. Therefore, the DC meters only measure half of the energy produced by the tracker. This is also the case with other Soitec CPV power plants with this type of CPV System in the US.

Solution: On December 17, 2015 Soitec IT made a software change to double the measured energy from each CPV System. Prior to this date, the DC energy was recorded as measured. The change assumes that each half of the CPV System (6 modules) are performing exactly the same as the other. To obtain consistent data throughout the demonstration, DNV multiplied the energy measured prior to December 17, 2015 by two.

6.0 PERFORMANCE ASSESSMENT

6.1 PERFORMANCE OBJECTIVE 1: TECHNOLOGY INSTALLATION TIME

This was a straightforward performance objective to monitor and record. Table 7 below shows the number of CPV Systems (also called trackers) assembled and installed per day. As mentioned in Section 3.2.1, commissioning did not take place immediately after installation due to the power plant schedule. Tracker assembly and installation averaged **3.33/day**. When combining the commissioning rate this would result in an overall time, start to finish, of 14 days, yielding **2.9 trackers/day.** The tracker assembly station was comprised of 3 bays with transport trailers. Each bay had an equipment operator (lift vehicle) and approximately 5 workers. There were three commissioning teams with two workers to each team. The number of teams and the composition of teams would have a significant effect on the assembly, installation and commissioning rates. For larger power plants, EPC firms would normally make a larger investment in equipment, stations and workers to increase throughput. Figure 25 below shows the ramp-up and ramp-down of the installation process. As the workers became more practices, the rate increased. Towards the end the EPC contractor began shutting down bays and de-mobilizing lift equipment to save money, slowing down the process on the last few trackers.

Table 7. Record of CPV System (tracker) Assemblies/Day

Day #	Date	# of Trackers Assembly Completed	# of Trackers Installed	# of Trackers Commissioned and Completed (est.)
1	20th Jan	1	0	
2	21st Jan	2	0	
3	22nd Jan	2	5	
4	23rd Jan	4	0	
5	26th Jan	4	7	5
6	27th Jan	4	0	0
7	28th Jan	5	9	7
8	29th Jan	4	0	0
9	2nd Feb	4	7	9
10	3rd Feb	4	5	0
11	4th Feb	4	0	7
12	5th Feb	2	7	5
13	6th Feb			0
14	7th Feb			7
		40	40	40
	Average of Assembly and Install	**3.3**	**3.3**	
	Total	14	days	
	Total	40	trackers	
	Total (incl. commissioning)	2.9	average trackers / day	

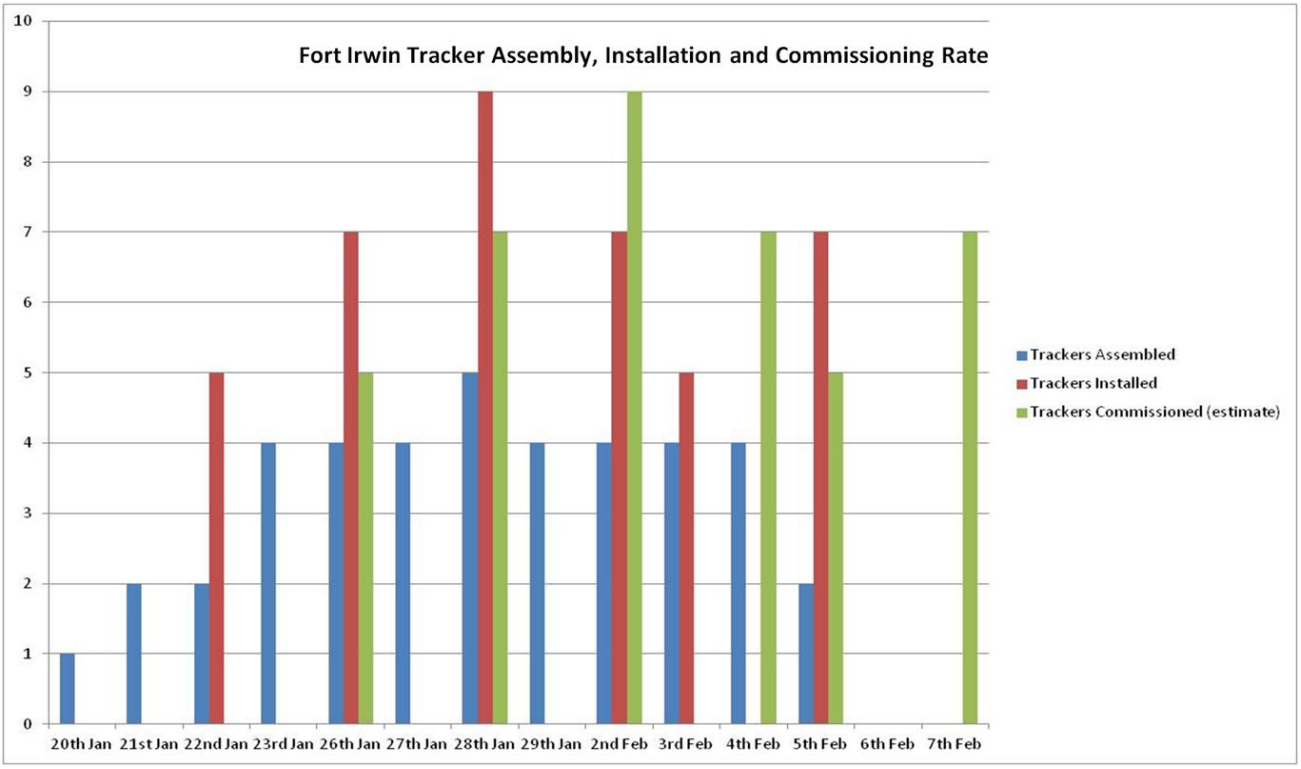


Figure 25. Graphical Display of CPV System Assembly, Installation and Commissioning[17]

6.2 PERFORMANCE OBJECTIVES 2 AND 3: PREVENTIVE AND REACTIVE O&M LABOR

As mentioned previously, Soitec recorded technicians' hours performing reactive and preventive maintenance on a CMMS system. Soitec found that the majority of O&M hours were spent on reactive maintenance on the CPV Systems (see Figure 26).

[17] Note: NREL has not reviewed construction/installation data.

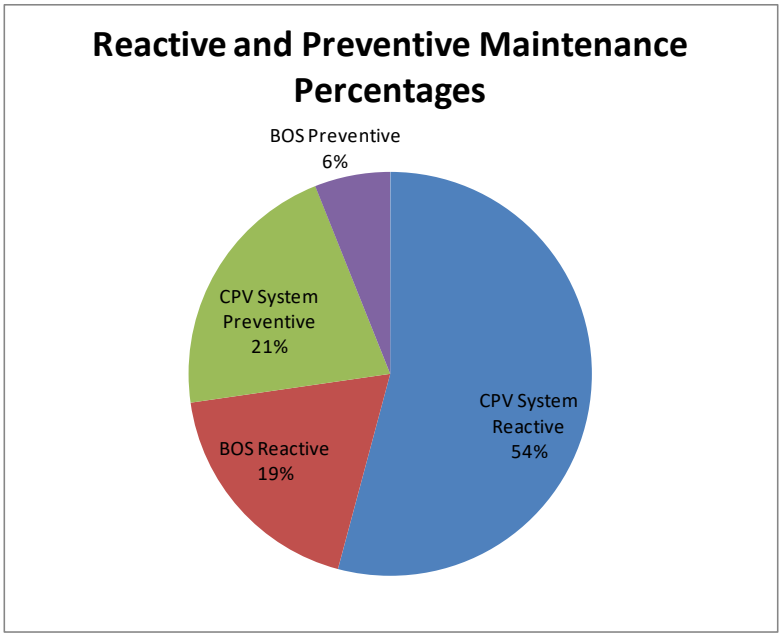


Figure 26. Reactive and Preventive Maintenance Percentages

The main causes of reactive maintenance on the CPV Systems were:

1) Failed drive encoders
2) Failed limit switches
3) Failed control boards
4) Failed 4Q sensors
5) Variable frequency drive overcurrent, undervoltage or over-temperature
6) Failed DC connectors
7) Loose hardware bolts (likely from installation)

The majority of the CPV System preventive maintenance was related to the annual CPV System inspection and the bi-annual dual-axis drive regreasing. This is normally referred to as Scheduled Maintenance but for reporting purposes was considered as Preventive Maintenance.

BOS reactive maintenance was mostly comprised of troubleshooting faulty communications to the site. This could have involved the Verizon services, routers, modems, etc.

BOS preventive maintenance was performed by 3rd party specialist contractors on the AE inverters, the Caterpillar backup generator and the AC switchgear and other electrical hardware.

The performance objectives specifically pertained to the CPV Systems, so the results are highlighted in Figure 27 below.

Preventive Maintenance – **DID NOT MEET OBJECTIVE**; preventive maintenance over two years consumed 154 hours, which is 1.93 man-hours per CPV system annually. Eliminating the Scheduled Maintenance activities of the annual CPV System inspection and the bi-annual dual-axis drive regreasing would dramatically reduce this metric to .23 man-hour per CPV system annually and would meet the objective.

Reactive maintenance - **DID NOT MEET OBJECTIVE**. Reactive maintenance over two years was 393 hours, which is 4.92 man-hours per CPV system annually.

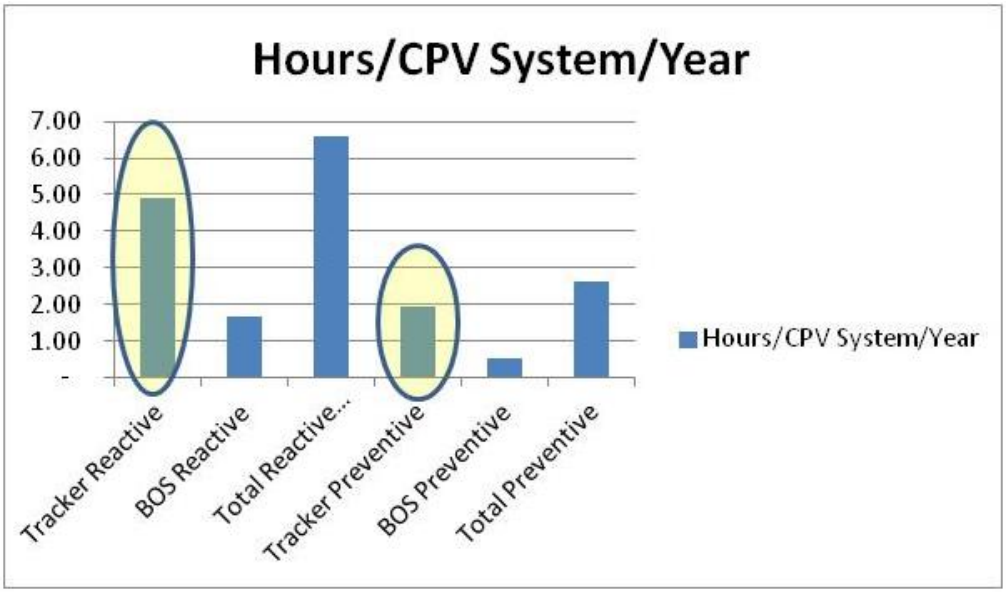


Figure 27. Preventive and Reactive Maintenance Hours/CPV System/Year

As mentioned in Section 5.6 and as shown below in Figure 28, there was an approximately 5-month gap in CPV System reactive maintenance records between October 2016 and March 2017. Soitec assumed certain CPV System and BOS reactive and preventive maintenance hours would have been consistent with the remainder of the performance period and factored in these estimated hours into the calculations.

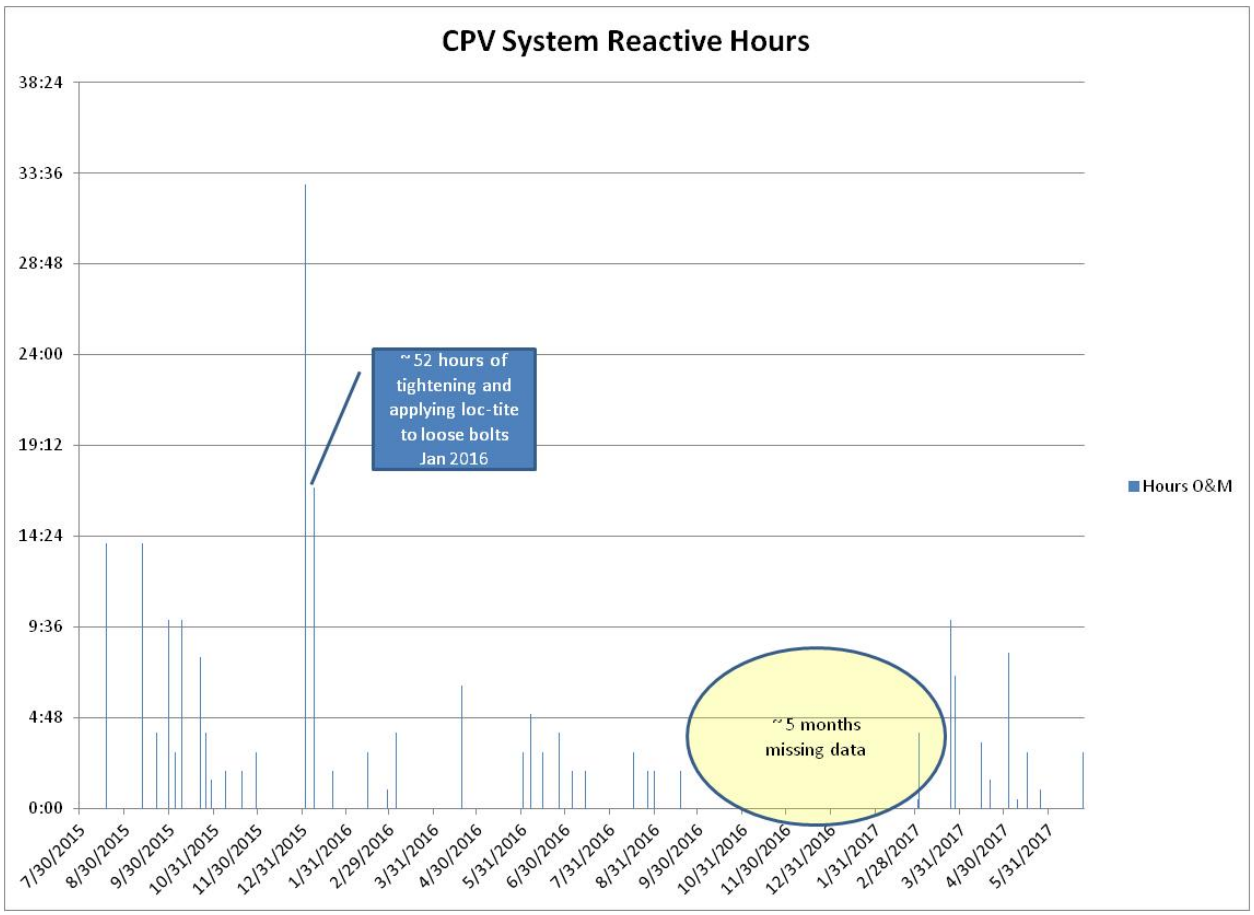


Figure 28. CPV System Reactive Maintenance Hours

6.3 PERFORMANCE OBJECTIVE 4: ENERGY MODEL VALIDATION

The performance assessment was performed by DNV-GL and confirms that the Soitec CPV Systems did perform as predicted. The completed PVSyst prediction that was completed at the beginning of the test was modified to reflect the weather data measured during the two years of the project, as variability of the weather adds complexity to any solar-related performance assessment. DNV GL compared energy production with expected production as predicted using measured weather as input to the PVsyst performance simulation model as supplied by Soitec.

Results: DNV-GL's report is shared in Appendix B. In summary, the performance objective was met.

NREL was involved in this process from a verification standpoint via the following steps:

- **NREL Initial Verification of Model:** At the beginning of the test, NREL and Soitec verifed that NREL and Soitec both obtained the same prediction from PVSyst. This required alignment of all of the inputs to the model. The duplication of the modeling will ensure that no changes are made to the model between the initial application and the final application.

- **NREL Site Visit October 2015:** NREL visited the site shortly after the completion of construction to inspect the location and installation of all sensors, initial sensor calibration certificates, the one-line drawings ad site conditions. The inspections confirmed the identity and accuracy of what is being measured by each meter and sensor, as well as confirming the direct relevance of the measured data to the input and output data of the PVSyst model[18]. Major observations were:
  - Module Alignment:
    - Observation. 35% of the modules inspected were noted to not be in the optimal alignment position. NREL estimated energy losses due to misalignment to be in the 1-2% range.
    - Resolution: Due to resource constraints, Soitec was not able to correct the module alignment during the demonstration.
  - DNI sensor misalignment and soiling
    - Observation: One DNI sensor was not within the alignment specifications of Kipp & Zonen (the equipment manufacturer) while both sensors had visual soiling present.
    - Resolution: Soitec cleaned the DNI sensors periodically, though unfortunately only a few records indicate the date cleaned.
  - Predicted vs. measured DC performance data
    - Observation: NREL found modeled and measured performance were in close agreement between 9 am and 3 pm. Outside that window PVsyst underestimated the output outside these hours while the simple model overestimated the output, possibly because PVsyst overestimated the shading or spectral losses while the simple model overestimated performance as it did not include either of these effects.
    - Resolution: Modeled and measured performance was compared for all daylight hours and the result is an average of the comparison.

See Appendix E for the NREL initial report which contains more detail on the issues listed above.

NREL Follow-On Report 4/17/2017. NREL also submitted a follow-on report on April 17, 2017 from six months of data (June 2016 to December 2016)[19]. Major observations were:

  - DNI sensor misalignment and soiling
    - Observation: One DNI sensor alignment sunspot for DNI sensor (SN 140003) was still not within the alignment specifications of Kipp & Zonen (the equipment manufacturer) while both sensors had visual soiling present.
      - Both issues can result in a false low DNI readings, which made the measured power seem higher than the PVSYST energy predictions.
      - Comparison with a NREL Measurement and Instrumentation Data Center (MIDC) station in Las Vegas showed the DNI in Las Vegas in September 2016 was nearly 9% higher than in Ft. Irwin, which is not typically expected for clear sky conditions at each of these sites.

[18] Matthew Muller, Sarah Kurtz and Chris Deline. 2015. *Fort Irwin 1 MW Soitec CPV Field Inspection*. National Renewable Energy Laboratory (NREL) Report.
[19] Matthew Muller, Sarah Kurtz and Chris Deline. 2017. *Fort Irwin 1 MW Soitec CPV Performance Validation Report*. National Renewable Energy Laboratory (NREL) Report.

    - Comparison with a Las Vegas DNI sensor suggested that the site sensor could be under reporting DNI by nearly 6%. This is consistent with other soiling studies for PV systems in southern California which show annual energy losses (uncleaned systems) on the order of 2-6%.
  - Resolution: Soitec's engineer DNV-GL conducted a correction in the calculations to correct for excessive soiling. For the alignment issue, if the DNI sensors were within 5% of each other, Soitec used an average of the two. If the DNI sensors were greater than 5% of each other, Soitec used the higher DNI value.

See Appendix F for the NREL follow-on report which contains more detail on the issues listed above.

NREL Review of DNV-GL's Approach and Calculations. NREL reviewed DNV's report including:

- The original PVSyst prediction of electricity generation;
- The original solar resource that was used for the PVSyst prediction;
- The measured solar resource;
- The modified PVSyst prediction based on measured weather data;
- The measured electricity generated by the trackers;
- The uncertainty found in the modified prediction and the measured electricity.

NREL agreed with DNV-GL's major findings, as signified by their approval letter in Appendix C.

6.4 PERFORMANCE OBJECTIVE 5: CPV POWER PLANT AVAILABILITY

This performance assessment CPV Systems did not meet the Availability target of 98%. The overall Power Plant Availability was 95.6% and the CPV System Availability was 96.3%.

Detailed results are shown within the DNV-GL technical report in Appendix B.

6.5 PERFORMANCE OBJECTIVE 6: LONG TERM PERFORMANCE DEGRADATION

Though this performance objective title specifies long-term performance degradation, the details in the Demonstration Plan also labeled a criteria for short-term module degradation caused by soiling.

DNV-GL performed the analysis for the long-term performance degradation and the results are located in Appendix B. In summary, performance actually appeared to improve by 1.6%, which is within the estimated 5% uncertainty of the performance index.

For short term module degradation caused by soiling, as mentioned in Section 5.6, Soitec was not able to conduct module washings at the Fort Irwin CPV plant due to resource shortages. However, Soitec did conduct intensive soiling studies at a 1.5 MW CPV Power plant in Newberry Springs, CA[20].

[20] *Newberry Soiling Analysis March 18th to April 14th 2014*. 2014. Internal Presentation, Soitec Solar Energy Business Unit.

Newberry Solar 1 is about 70 miles south of Fort Irwin and is also located in the Mojave Desert with approximately the same atmospheric conditions. Soitec conducted the soiling analysis at Newberry over the time span March 18th – April 14th 2014 to determine the monthly soiling loss factor for financing a larger CPV project.

The approach was to clean one CPV System regularly (the control) and leave one CPV System to soil naturally and clean manually only when the rest of the trackers within the power plant were cleaned. The two CPV Systems were located adjacent to each other.

Soitec conducted two tests of this nature. The results are show below in Figures 29 - 32.

Test 1	
Start date:	March 18, 2014
End date:	April 14, 2014
Control Tracker:	T_3.35
Unwashed Tracker:	T_3.29

Test 1			
	Units	*Unwashed Tracker*	*Control Tracker*
Energy Produced on hour 20 with DNI >= 200W/m2	KWh	294.505	294.791
Total Energy Produced	KWh	2728.070	2688.908
Baseline Offset	-0.097%		
Soiling Rate	-1.553%		

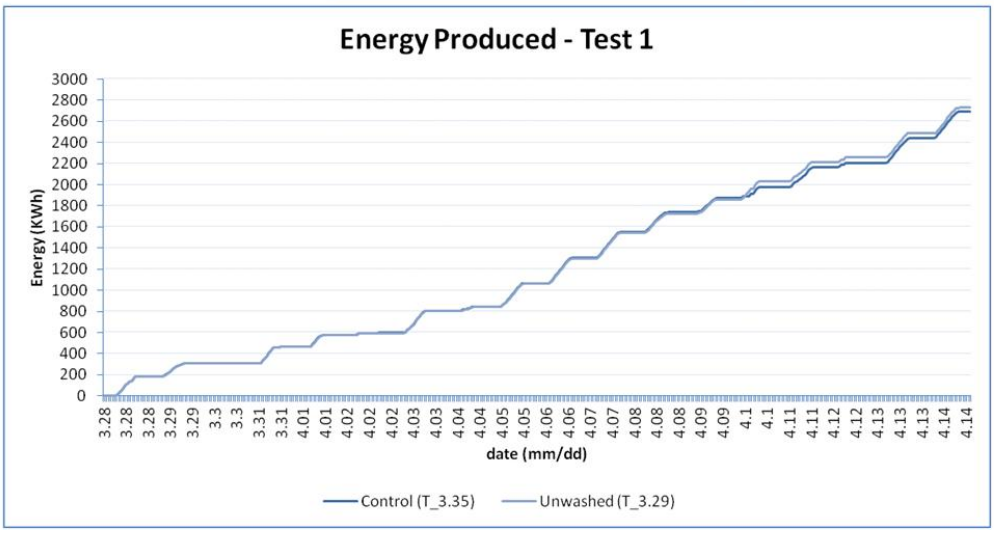


Figure 29. CPV System Soiling Test 1 Results

Test 2	
Start date:	March 18, 2014
End date:	April 14, 2014
Control Tracker:	T_3.36
Unwashed Tracker:	T_3.37

Test 2			
	Units	*Unwashed Tracker*	*Control Tracker*
Energy Produced on hour 20 with DNI >= 200W/m2	KWh	305.366	284.650
Total Energy Produced	KWh	2882.196	2682.207
Baseline Offset	7.278%		
Soiling Rate	-0.179%		

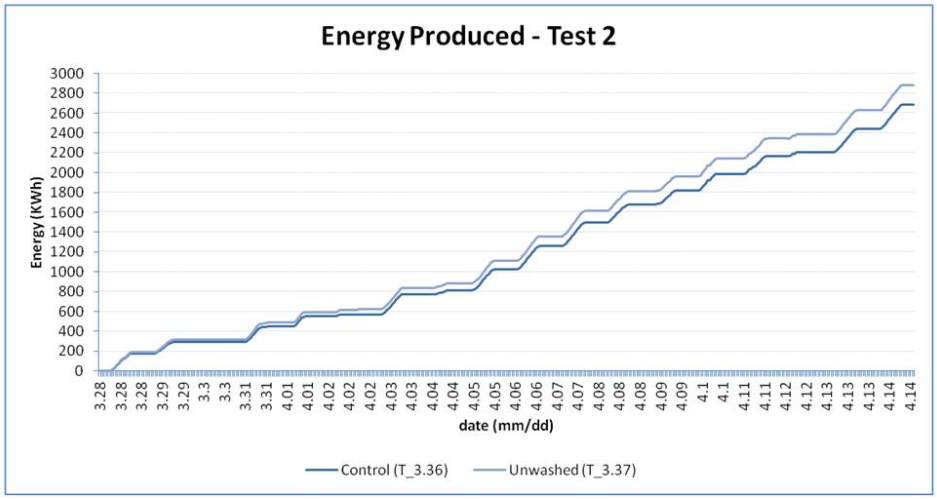


Figure 30. CPV System Soiling Test 2 Results

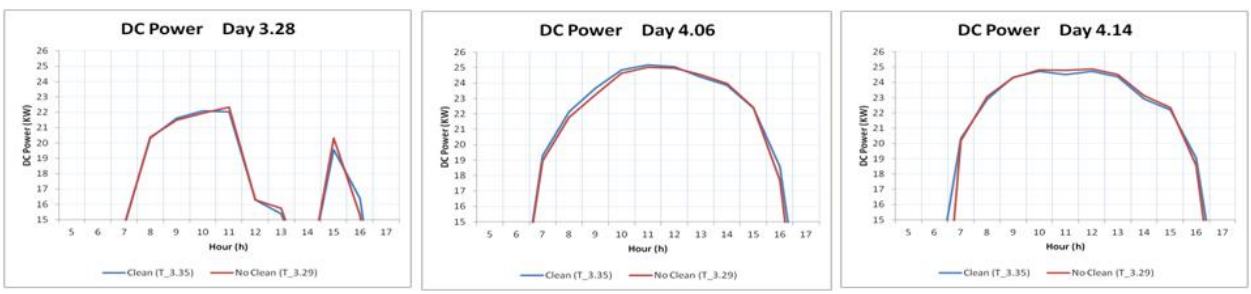


Figure 31. CPV System Soiling Test 1 Results

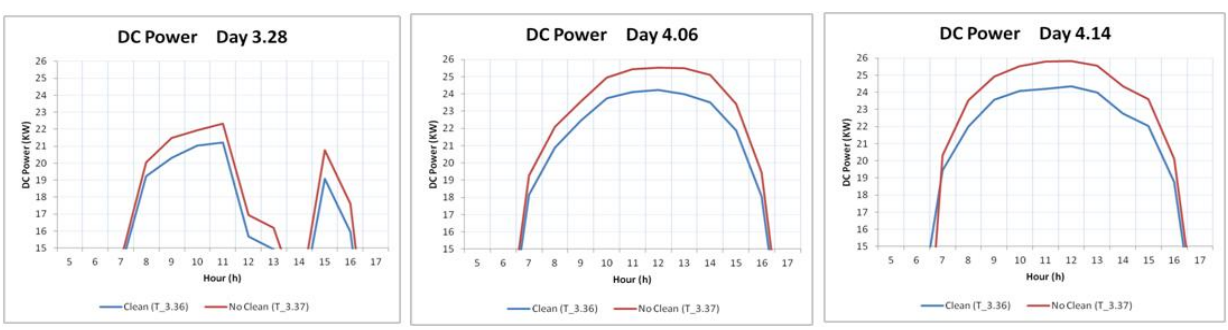


Figure 32. CPV System Soiling Test 2 Results

Soitec's conclusion was that the soiling loss factor could not be determined, with the following possible explanations:

- Short test duration

- Depending on the atmospheric conditions, cleaning may actually induce soiling since after washing the water residue collects air particles.
- Error induced by measuring half of the tracker
- DC board measurement accuracy of 2% was higher than soiling effect

Furthermore, at the Newberry and Fort Irwin facilities, Soitec management decided that the energy gained by cleaning the CPV Systems was not worth the cost in manpower and equipment. This, of course, may be different from plant to plant as plant location, proximity to other power plants, labor costs, etc. may vary significantly. The M-500 modules at the Newberry and Fort Irwin facilities have not been washed for years (other than natural precipitation events) with no significant visual accumulation of dirt or dust. The humidity levels in the high desert elevation reduce the dust's ability to adhere to the modules and the frequent high wind events and blowing sand remove any accumulation that does occur.

Therefore, it is Soitec's conclusion that the short-term degradation due to soiling does not require a cleaning frequency less than once every six weeks.

6.6 SOLAR FORECASTING PERFORMANCE OBJECTIVE

Success Criteria: The forecasting component of this project was to be considered a success if the target values in Table 8 below were achieved.

Table 8. Forecast Performance of Current Techniques versus Target Values at the End of the Project by Time Horizon[21]

Horizon	**< 1 hr (RTD)**	**1 hr (HASP)**	**1-6 hrs**	**24-36 hrs (DAM)**	**>36 hrs**
Averaging period	1 min	5 min	15 min	1 h	1 d
Current *s*	0.12-0.32	0.15-0.29	0.08-0.14	0.08-0.39	0.19
Target *s*	0.25-0.45	0.40	0.30	0.30	0.40

Result: Results are shown below in Table 9. For shorter time horizons (< 1 hr. and 1 hr. forecast time window), the targeted forecasting skills were not fully achieved since the Result *s* was not higher than the Target *s*. This means that the accuracy of the forecast (an *s* value closer to 1 is more accurate) did not meet the target accuracy, about 70-75% of the time they were innacurate and the actual DNI and Power values did not match the forecasted DNI and Power values. However, the obtained values are in agreement with the best performing forecasting models published in current literature[22]. The results of the effort show the great difficulty in forecasting short-term DNI from on-site sky camera data due to nature of rapidly changing atmospheric conditions and the relatively limited field of view of the cameras.

[21] Note the current and project values of forecast skill in the table above also increase with the averaging period. For example, 24-36 hour forecasts are hourly averages while the 1-6 hour forecasts have 15-minute resolution. This and the decrease in accuracy of the reference (persistence) causes the 24-36 hour forecast to have higher skills.

[22] J. Antonanzas, N. Osorio, R. Escobar, R. Urraca, F. J. Martinez-de Pison, and F. Antonanzas-Torres. 2016. Review of Photovoltaic Power Forecasting. Solar Energy. 136:78–111.

With respect to longer horizons the demonstration met or exceeded the target values. For the forecast time window 1-6 hours, the Result s (DNI) of 0.25 to 0.39 (average of 0.32) exceeded the Target s of 0.30, meaning the average accuracy of the DNI forecast improved over two times the baseline level and exceeded the target accuracy. The forecast time window 24-36 hours ahead saw the greatest increase in accuracy with a Result s (DNI) of 0.34 which exceeded the Target s of 0.30. The forecast accuracy of the 48 hours (>36 hours) ahead forecast time window doubled during this exercise, just exceeding the target of 0.40, meaning 41% of the time the forecasts were accurate.

Improvements in accuracy forecasts for longer intra-day (1-6 hours) and day(s)-ahead horizons were greater as these forecasts incorporated satellite images and national cloud cover forecasts versus only sky images from on-site cameras. The cloud cover information contained within the on-site camera images is good for not much more than an hour and is a very weak predictor of conditions for the next day.

The 24 to 36-hour and the 48 hour forecasts are important for regulating entities and independent system operators whose job is to schedule resources ahead of time to balance electric grids.

Table 9. Forecast Performance Result Values at the End of the Project

Horizon	**< 1 hr (RTD)**	**1 hr (HASP)**	**1-6 hrs**	**24-36 hrs (DAM)**	**>36 hrs**
Averaging period	1 min	5 min	15 min	1 h	1 d
Result *s (DNI)*	0.24-0.32	0.24-0.32	0.25-0.39	0.34	.41
Result *s* (Power)	0.24-0.32	0.20-0.24	0.17-0.35	0.38	.43
Success Criteria Met?	No	No	Yes	Yes	Yes

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7.0 COST ASSESSMENT

Soitec performed this section with internal knowledge of Fort Irwin's cost and cost proposals for larger CPV plants that were never constructed due to lack of financing. However, the cost proposals were in the final stages in 2014/2015 and should serve as a reliable estimate. Soitec also relied upon employee knowledge of conventional PV costs from the external experience within that industry and from recent online research. However, it is important to note that these are only reasonable estimates. Soitec has not been active in securing better pricing from suppliers nor reducing installation costs since early 2015 due to Soitec's decision to depart from the solar business within that timeframe.

7.1 COST MODEL

In Table 10 below, Soitec has provided a simple cost model for the 1MW CPV System at Fort Irwin. In Section 7.3 these costs will serve as the basis of a lifecycle cost analysis.

Table 10. 1MW CPV Demonstration System (Fort Irwin) Cost Table

DESCRIPTION	% of Total	Cost	Cost/ watt
Mobilization	4.09%	$ 97,070	$ 0.09
Site Logistics	3.84%	$ 91,174	$ 0.08
Site Grading and Trenching	2.98%	$ 70,673	$ 0.06
Tracker Assembly Area Grading	2.08%	$ 49,331	$ 0.04
Access Road	2.44%	$ 57,862	$ 0.05
Construction Entrance	1.56%	$ 37,105	$ 0.03
Dust control	3.12%	$ 73,935	$ 0.07
Erosion Contrl	1.60%	$ 38,052	$ 0.03
Seeding	1.32%	$ 31,415	$ 0.03
Fencing and Gate	4.76%	$ 112,848	$ 0.10
Security and Lighting	4.06%	$ 96,226	$ 0.09
Drive Piers/Masts	1.96%	$ 46,403	$ 0.04
Surveys	0.38%	$ 9,080	$ 0.01
Water Supply Equipment (Tank, etc.)	0.34%	$ 7,991	$ 0.01
Fire Control Equipment	0.25%	$ 5,902	$ 0.01
Backup Generator	0.77%	$ 18,161	$ 0.02
DC Cabling and Hardware	8.82%	$ 209,179	$ 0.19
Inverter Installation	15.68%	$ 372,076	$ 0.33
AC Cable and Hardware	5.05%	$ 119,694	$ 0.11
SCADA/Panel Installation	1.83%	$ 43,519	$ 0.04
Tracker Assembly	3.27%	$ 77,509	$ 0.07
Tracker Installation	2.68%	$ 63,529	$ 0.06
Tracker Terminations	0.32%	$ 7,607	$ 0.01
Tracker Commissioning	0.81%	$ 19,274	$ 0.02
Indirect Cost	26.00%	$ 616,783	$ 0.55
Insurance, Contingency, Bonding, OH&P	INCLUDED IN PRICE BREAKDOWN		
EPC Total		**$ 2,372,400**	**$ 2.12**
Non-DOD reduction (%)			
Substation and Gen-Tie	18.25%	$ 433,000	**$ 0.39**
Subtotal		**$ 2,805,400**	**$ 2.50**
BOM Cost		$ 1,346,429	$ 1.20
Owner PM		$ 104,566	$ 0.09
TOTAL Construction Cost		**$ 4,256,395**	**$ 3.80**
Engineering Cost		$ 150,000	$ 0.13
Development and Land Cost		$ 233,667	$ 0.21
Subtotal		**$ 4,640,062**	**$ 4.14**
ESTCP Pre-Construction Compliance (Legal)		$ 82,743	$ 0.07
Total Cost		**$ 4,722,805**	**$ 4.22**

7.2 COST DRIVERS

Below Soitec has listed and described some of the major cost drivers of this project, as well as anticipated cost drivers that should be considered when selecting the technology for future implementation.

7.2.1 CPV System Costs

The cost of manufacturing CPV components is still higher than conventional flat plate technology due to lack of high volume manufacturing of CPV components and modules needed to achieve cost competitiveness versus conventional flat plate solar. Conventional PV single-axis tracker prices are at $.10 to $0.21/watt[23] and conventional crystalline-silicone PV solar panels are dipping $0.35/watt at the factory gate to $0.40 to $0.53/watt cost to integrators[24].

Each CPV tracker requires its own control unit, which adds to the CPV system cost. With some conventional PV single-axis tracking system, trackers within an approximate area of a football field are controlled by a single control box.

Each CPV module must be humidity-controlled on the inside to prevent condensation and moisture damage to sensitive wiring components. This requires air-drying units and air tubing to each module. The additional AC power requirements for the air-drying equipment causes increased AC wiring and hardware sizing and costs.

7.2.2 CPV Installation Costs

CPV installation costs are typically higher than conventional PV due to several reasons. First, assembly and installation requires heavy crane equipment, as the tracker tables with modules weigh approximately 16,000 lbs and must be mounted on an 11' mast. This makes installation vulnerable to wind speeds over 20mph, causing expensive delays.

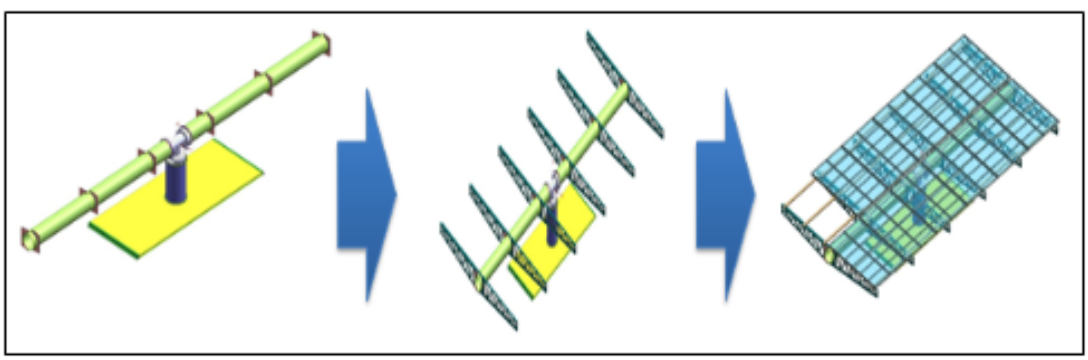

Figure 33. Tracker Table Assembly Process

[23] Ran Fu, David Feldman, Robert Margolis, Mike Woodhouse, and Kristen Ardani. 2017. *U.S. Solar Photovoltaic System Cost Benchmark: Q1 2017*. National Renewable Energy Laboratory (NREL) Report.
[24] Ibid, pgs. 13- 19.

Figure 34. Tracker Table Lift and Installation on the Mast

Figure 35. Completion and Commissioning of the CPV System

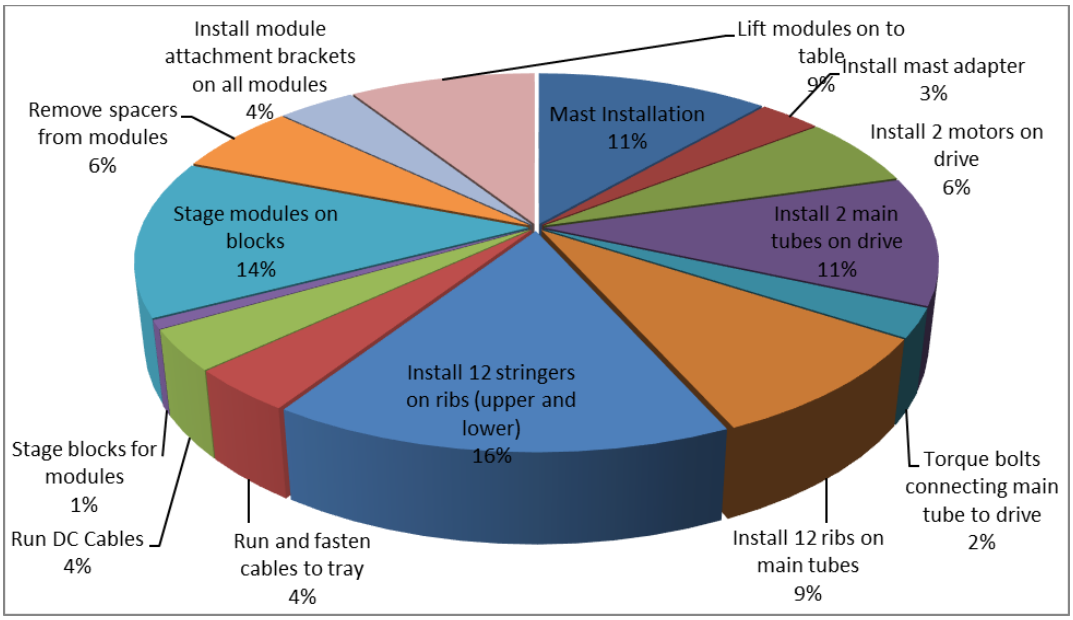

Figure 36. Labor Percentage Breakdown on Fort Irwin CPV System Assembly

Second, Soitec and the CPV industry as a whole has not had the opportunity to invest in automated equipment on a large scale because the majority of power plants have been under 10MW and only a few (Alamosa at 30MW and Touwsrivier at 44MW) have approached the 50MW mark.

Third, the industry has engineered out installation costs and has gained overwhelming experience in conventional PV installation. There are thousands of workers and construction superintendents that have worked with systems from First Solar, SunPower, Nextracker and Array Technologies. Fourth, the masts (or piers) required to support the massive tracker tables must themselves be either driven or vibrated into the ground with large, custom equipment or require massive amounts of excavation and concrete for foundations. In contrast, there are hundreds of specialized pier-driving machines and experienced operators for conventional PV piers. Entire companies that specialize in designing and installing piers have emerged and that portion of the power plant installation is very competitive. This has contributed to utility-scale conventional PV systems achieving 2020 Sunshot cost targets three years early in 2017[25].

7.2.3 Civil Work Costs

CPV is more susceptible to higher costs when the soil is rocky, loose, corrosive, has a higher water table. Because the masts (up to 30" or higher in diameter) must be driven deeper into the soil (at least 15' or more), they are adversely affected when rocks, caliche or water are found at shallower levels. By comparison, most conventional PV piers are driven 5-8' deep. CPV mast weigh at least 1,000 lbs. and require large equipment to ship, transport and maneuver around the construction site. The masts require full-scale excavator platforms with custom equipment to pre-drill holes of the required diameter and drive the ½ ton masts into the ground (Figure 37). These machines are very expensive to mobilize, have a high per hour rate and require skilled operators.

[25] Ibid, Pg 9.

Figure 37. Pre-drilling and driving CPV masts

Figure 38. Typical Conventional PV Pier Driving Machine

7.2.4 Shipping, Handling and Treatment Costs

CPV modules weigh approximately 500 lbs. each, making them more expensive to ship and handle. They require forklifts and special attachments to move a single module on site. By comparison, conventional CPV modules are shipped and moved around the construction site in stacks of 30-40 modules.

The CPV tubular masts and horizontal main tubes are difficult to ship efficiently due to the weight and the volume of air inside the masts that takes up space and minimizes the amount that can fit on a truck or inside a shipping container. The large size of the masts limits the number of vendors who have adequate facilities to perform hot-dip galvanization for corrosion protection on the masts.

There are a few components of the tracker table that can be moved by hand, such as the ribs and stabilizers; however the mast, drive, horizontal main tubes and modules require a forklift to maneuver.

7.2.5 O&M Costs

Soitec researched industry publications for O&M costs and found:

- Single-axis conventional PV O&M costs are 10-20% higher than fix-tilt arrays[26].
- Smaller systems (<1MW) can be 2-4x more expensive to maintain compared to large sites (≥10MW)[27]. For purposes of this report, Soitec assumes a 30% increase in O&M costs for a small conventional PV power plant.
- Due to the size of the CPV System components and complexities involved with dual-axis tracking, Soitec estimates the O&M costs for CPV dual-axis CPV Systems are at least 20-30% higher than single-axis conventional PV. There are several reasons for this:
- The large tracker components, such as the drive, requires crane equipment for replacements.
- Because the drive unit, motors, modules and DC string cabling are located 12-15' off the ground, a boom lift is needed frequently to allow crews to troubleshoot, inspect or repair components at that level.
- The CPV module requires a reach forklift and special lifting equipment for replacements. Conversely, conventional CPV O&M crews rarely need more than a service truck and manpower for replacing or repairing PV modules.
- The control units of dual-axis CPV trackers are more complex because the pointing accuracy limits are more stringent. Each CPV tracker requires its own control box and each control box is susceptible to communications failure and component failure. This requires additional maintenance crew travel and troubleshooting time.
- Washing modules on a 28' tall tracker requires more time and specialized equipment.
- The CPV dual-axis drives require re-greasing and re-oiling every two years and a total lubricant change every 10 years. This requires significant manpower, boom lift equipment, lubricant and lubricant storage and disposal costs.

Figure 39 below validates this, showing CPV estimated O&M costs to the right of the graph, approximately 21% higher than crystalline silicone PV.

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[26] Charles W. Thurston. *Trackers Thaw Solar Freeze.* 2016. PV Magazine, Issue 10-2016. Online.
[27] Nadav Enbar, Dean Weng, Geoff Klise. 2015. Budgeting for Solar PV Plant Operations and Maintenance: Practices and Pricing. EPRI/Sandia National Laboratories Report.

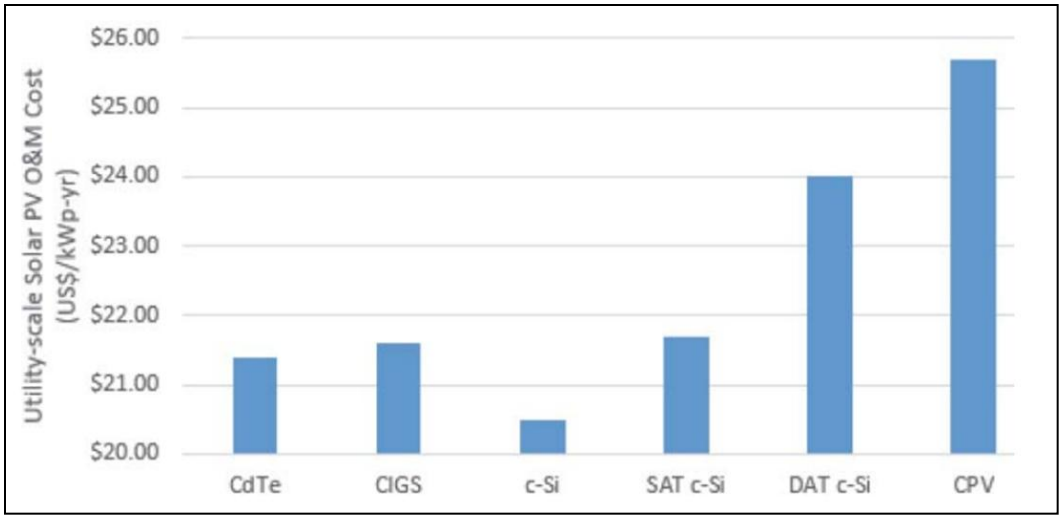

Figure 39. O&M Average Costs 2015[28]

7.2.6 Performance Costs

CPV modules are more efficient than conventional PV modules. However, CPV modules produce energy only when provided with Direct Normal Insolation (DNI). High wind events (typically both CPV and conventional PV trackers will stow at 32-38mph winds) will cause CPV power production to go to zero. Clouds will have the same effect. After a high wind or cloud event, trackers need anywhere from a few minutes to 30 minutes to return to the sun, depending on the length of the event. Conventional single-axis PV trackers will continue producing power, albeit at a reduced level, during these events and will resume pointing within a few minutes of a wind event. When analyzing CPV projects for Levelized Cost of Energy (LCOE) and Return on Investment (ROI), analysts and investors must factor in added impact of wind velocity history and cloud events.

7.3 COST ANALYSIS AND COMPARISON

Soitec included project development costs, equipment/BOM costs, installation costs and operations and maintenance (O&M) costs when developing the CPV lifecycle cost analysis.

For the conventional PV comparison, Soitec only considered single-axis crystalline-silicon PV, not fixed tilt PV. A tilted single axis tracking system provides energy gains in the range of 30-40% compared to a tilted fixed PV panel[29] and 20+% for non-tilted panel[30].

Ideal site requirements are listed below in Table 11. The table shows applicability to CPV, PV or both.

[28] Ibid, pg.10.
[29] S. P. Singh, K. Srikant and K. S. Jairaj. 2017. Performance Comparison and Cost Analysis of Single Axis Tracking and Fixed Tilt PV Systems. School of Energy and Environmental Studies, Devi Ahilya University. Pg. 6.
[30] Charles W. Thurston. 2016. *Trackers Thaw Solar Freeze* (Dan Shugar (NextTracker) quote). PV Magazine, Issue 10-2016. Online.

Table 11. Ideal Site Requirements for CPV and Conventional PV Power Plants

Requirements	CPV	PV	Comments
Located in an area with at high direct irradiation (>1800 kWh/m^2)	X		Conventional PV does not require high DNI regions; therefore, provides more geographical options
Relatively flat and well-drained with minimal grading required	X	X	
Does not contain excessively rocky or loose soils within 20' of surface	X		Conventional PV piers are not driven as deep (normally 5-8')
Bedrock and water table lower than 20' from top of ground	X		Conventional PV piers are not driven as deep (normally 5-8')
Minimal vegetation clearance required	X	X	
No surrounding structures (trees, buildings, mountains) which may shade the solar modules	X	X	
Within ¼ mile from utility point of delivery or grid connection point (substation, distribution line)	X	X	
Near or containing water source for washing modules	X	X	
No permitting restrictions (e.g. solar trackers up to 30' high allowed)	X		Conventional PV is more low-profile.
Not located in an acute flood zone (e.g. 100-year floodplain)	X	X	
Non-corrosive, well-graded soils (assumed soil conditions)	X	X	

7.3.1 Installation Cost Exclusions:

- Location and/or demolition of any existing site utilities
- Costs associated with existing underground utilities (location, removal, alteration)
- Costs associated with concrete footings for masts/piers
- Removal of any hazardous materials (including any required abatement).
- Standard fencing (6' chain link with 3 strands of barbed wire)
- Premium for off-hours work or accelerated schedule.
- Site storm drainage above and beyond standard SWPPP.
- Construction of any paved permanent access, fire access or perimeter roads.
- Upgrades of existing utility or meter equipment.
- Annual SCADA/DAS monitoring agreement subscription costs.
- O&M services
- O&M building and/or infrastructure
- Cathodic or other corrosion protection for foundation mast/piers (other than hot-dipped galvanization)
- Sales tax for all materials and equipment.
- Hazardous material testing, investigation, removal or dispoal
- Off-site improvements

- Payment and performance bonds

7.3.2 Installation Cost Assumptions:

- Driven mast/pier installation only
- Site conditions as indicated above
- Workmanship Guarantee of two (2) years from the Substantial Completion Date
- Direct-buried, aluminum cable
- Use native soil for all backfill with no required import or export of soils
- Non-union, non-prevailing wage job site
- On-site water source for dust control

7.4 LIFECYCLE COST APPROACH

7.4.1 Project Development Costs

Soitec used historical project development costs in the lifecycle cost model. These costs would be applicable to CPV and conventional PV and include:

- Permitting (Major Use Permit)
  - Costs of supporting studies, surveys and reports (i.e. geotech, visual impacts, traffic, environmental)
  - Fees
- Interconnection Agreement (IA)
  - Costs of supporting studies, surveys and reports (i.e. interconnect upgrade survey)
  - Fees
- Power Purchase Agreement (PPA) costs (normally paid to the utility)
  - Costs of supporting reports and applications
  - Fees
- Legal Fees
- Consultant Costs
- Real Estate Fees (easements, rights of way)
- Engineering costs to support project development efforts

Project development costs typical add $0.03 to $12/watt to the cost of the project, depending on the size of the project and the situation[31]. They would be approximately similar for CPV or conventional PV.

[31] Ran Fu, David Feldman, Robert Margolis, Mike Woodhouse, and Kristen Ardani. 2017. U*.S. Solar Photovoltaic System Cost Benchmark: Q1 2017*. National Renewable Energy Laboratory (NREL). Pg 39.

7.4.2 Project Pre-Construction Costs

These costs would include:

- Value engineering costs
- More detailed soils analysis
- Site plan approvals and building permits
- Purchase of long-lead items (e.g. main transformers, gen-tie poles/towers)
- Contract development costs (EPC, separate installation contractors)

7.4.3 Equipment Procurement Costs

These costs would vary widely between CPV and conventional PV, for reasons previously stated. These costs would normally include shipment to the construction site and any customs fees.

7.4.4 Installation Costs

The majority of these costs involve payments to an Engineering, Procurement and Construction (EPC) company who fills the role of a general contractor. This is normally the majority of the project's capital expense (CAPEX). Every project will have differences in the EPC's scope, for example who provides major components such as trackers, modules, inverters and cabling. This depends on the preferences of the owner aor which entity can utilitize the most advantageous purchasing power with suppliers. For this lifecycle cost analysis, Soitec has assumed that the major Balance of System component costs (inverters, cabling) will be borne by the EPC, while modules and trackers will be provided by the Owner.

The EPC Cost Breakdown for the Fort Irwin is shown in Figure 40. As this was 2013 pricing, it is evident that inverter procurement/installation costs, indirect costs and cable procurement/installation were major contributors. Indirect costs include project management costs, general conditions (construction trailers, life support items, office equipment) travel, specialty tools, and temporary power and water. The percentage of indirect costs to the entire CAPEX cost is generally higher on small projects because although they rise with the size of the project, there is a baseline cost that is spread out over fewer megawatts.

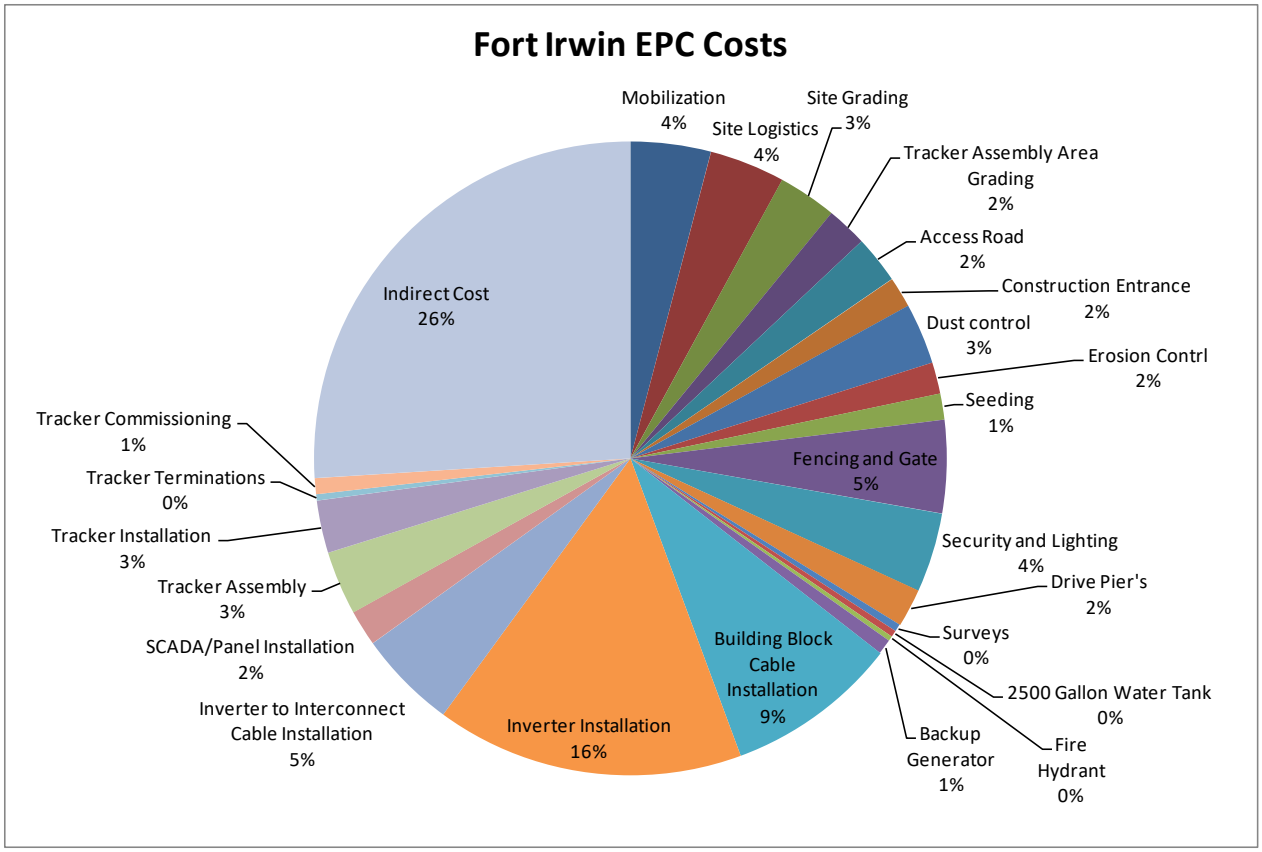

Figure 40. Fort Irwin 1MW CPV EPC Cost Percentage Breakdown

For Fort Irwin, the modules, trackers, internal wiring and auxiliary equipment (Soitec monitoring system and sensors) comprised approximately 36% of the project, as shown in Figure 41. This figure would remain consistent with estimated cost breakdown of future projects (Figure 42), indicating that EPC cost reductions and Soitec BOM cost reductions would be approximately the same.

This ratio is consistent with conventional PV (Figure 43) for the same reason: the costs of conventional PV BOM components (modules, trackers, internal wiring) are lower, but so are the EPC costs.

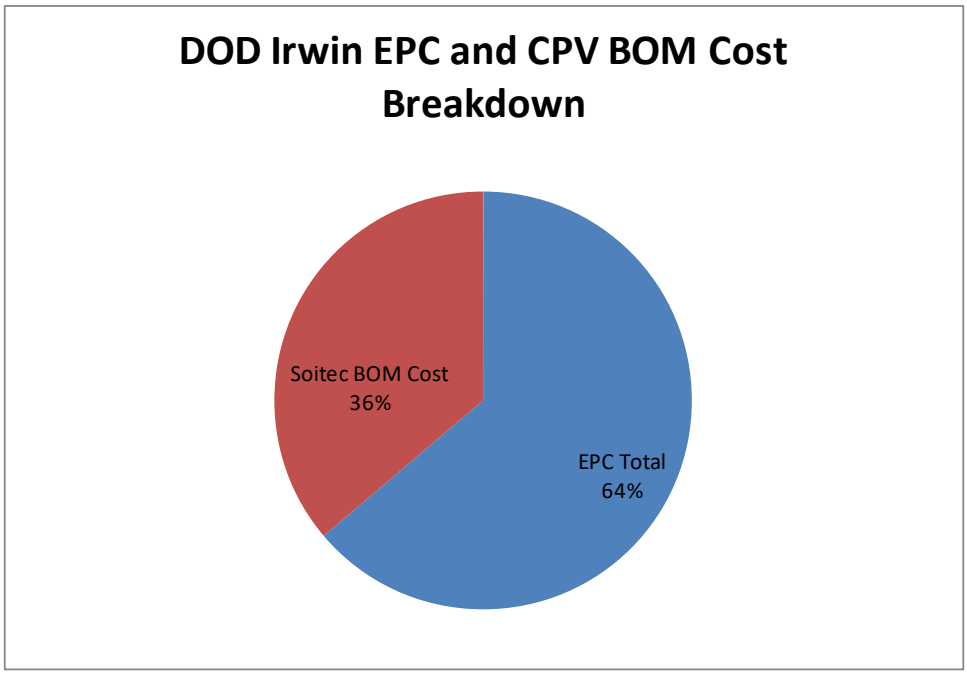

Figure 41. Fort Irwin 1MW CPV EPC and CPV BOM Cost Breakdown

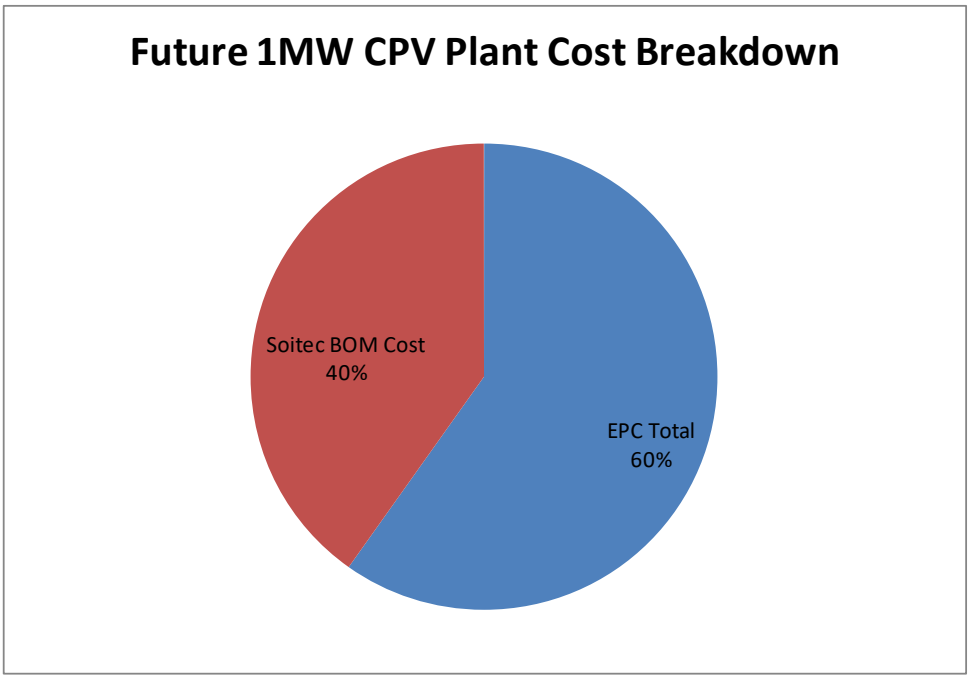

Figure 42. Future 1MW CPV Plant Cost Breakdown

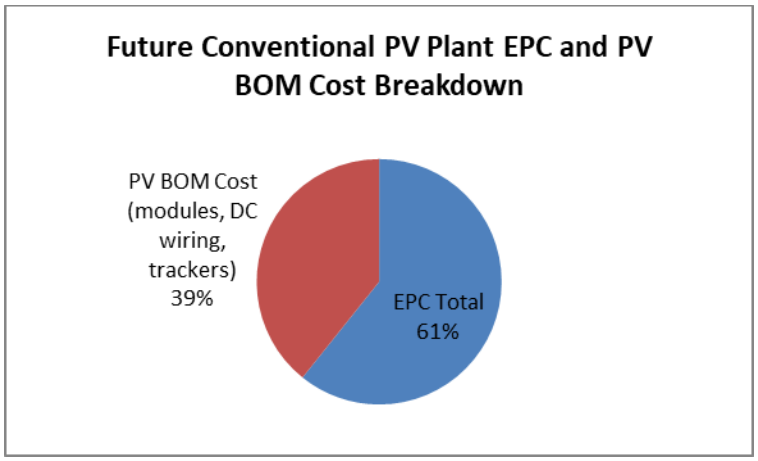

Figure 43. EPC vs. CPV BOM Future Project Cost Breakdown

The reason for the lower EPC costs on a conventional commercial PV plant is that eight plus years of intense competition and the concentration of specialized vendors who have honed techniques and prices on conventional utility-scale PV power plants have driven pricing down dramatically. A few examples are:

- Companies who specialize in pier installation have developed specialized machines that are easily mobilized and demobilized and use the latest technology to efficiently drive piers.
- AC and DC cable manufacturers have been under intense competition to create unique products that allow direct burial of cable without conduit protection.

Additionally, those in the solar industry are well-acquainted with the race to the bottom on pricing for module and tracker components.

- Fixed and single-axis tracker manufacturers have developed trackers that in some cases eliminate the need for AC cabling to the trackers and have designed products that install quickly in the field, requiring only forklifts. They have reduced the quantity of steel, taken advantage of off-the-shelf subcomponents and have leveraged competition among a multitude of sub-assembly suppliers.
- The most significant shift in pricing has been with conventional PV module manufacturers. According to NREL, average module prices were ~ \$0.40 per $watt_{dc}$ during Q1/2017[32].
- Average single-axis tracker structure pricing is \$.015/$watt_{dc}$[33]

Another large cost reduction contributor that would affect both CPV and conventional PV is that inverter manufacturers have developed larger inverters that do not require expensive climate-controlled enclosures or shade and have dropped prices dramatically with foreign labor and simplified designs, down to \$0.06 to \$0.08/$watt_{dc.}$[34]

[32] Ibid, pg 39.
[33] Ibid, pg 39.
[34] Ibid, pg 39.

Table 12. Conventional CPV Module Prices (Q1 2017)[35]

2.4 U.S. Polysilicon, Wafer, Cell, and Module Prices, Q1 2016-Q1 2017

	Q1 2016	Q2 2016	Q3 2016	Q4 2016	Q1 2017
Polysilicon ($/kg)	$14.17	$16.44	$15.29	$14.98	$16.78
Wafer ($/W)	$0.21	$0.20	$0.15	$0.15	$0.15
Cell ($/W)	$0.32	$0.30	$0.23	$0.21	$0.20
Module ($/W)	$0.63	$0.59	$0.49	$0.39	$0.40

In summary, both installation costs and solar component costs have fallen at consistent rates, leading to overall lower costs for conventional PV plants. The average price of a 100MW single-axis tracker project in Q1 2017 is about $1.05 per watt[36]; however, this is an average price and will generally be higher for power plants under 10-20MW, where indirect costs are spread out over more MW. Soitec estimates that a 1MW conventional PV plant would cost between $1.28 and $1.35/watt. Smaller plants cost more because generally the same permits must be obtained, the same designs must be engineered, fees and taxes must be paid and the EPC's general conditions (trailers, life support, etc.) are more expensive per watt.

Installations requiring prevailing wage, such as on DOD installation, easily adds 10-25% to the EPC's overall cost[37]. By that same rationale, Soitec estimates a 1MW conventional PV plant on a DOD installation would cost between $1.60 to $1.70/watt. See Table 13 below for a breakdown of costs.

[35] Christian Roselund. 2017. U.S. utility-scale solar falls below US$1 per watt . PV-Magazine. Online.
[36] Fu, op. cit., pg 38.
[37] Ibid.

Table 13. Cost Estimate for Various Sizes of CPV and Conventional PV Power Plants

Scenario	1. 2015 Fort Irwin CPV		2: 2017 1MW DOD CPV		3. 2017 1MW CPV (non-DOD)		4. 2017 20MW CPV		5. 2017 1MW PV		6. 2017 20MW PV	
DESCRIPTION	**Cost**	**Cost/ watt**	**Cost**	**Cost/ watt**	**Cost**	**Cost/ watt**	**Cost**	**Cost/watt**	**Cost**	**Cost/watt**		
Mobilization	$ 97,070	$ 0.09	$ 77,656	$ 0.06	$ 77,656	$ 0.06	$ 517,705	$ 0.02	$ 54,359	$ 0.04	$ 388,278	$ 0.014
Site Logistics	$ 91,174	$ 0.08	$ 72,939	$ 0.05	$ 72,939	$ 0.05	$ 486,262	$ 0.02	$ 51,058	$ 0.04	$ 486,262	$ 0.018
Site Grading and Trenching	$ 70,673	$ 0.06	$ 49,471	$ 0.04	$ 49,471	$ 0.04	$ 659,615	$ 0.02	$ 49,471	$ 0.04	$ 659,615	$ 0.024
Tracker Assembly Area Grading	$ 49,331	$ 0.04	$ 34,532	$ 0.03	$ 34,532	$ 0.03	$ 230,214	$ 0.01	$ 3,453	$ 0.00	$ 46,043	$ 0.002
Access Road	$ 57,862	$ 0.05	$ 46,290	$ 0.03	$ 46,290	$ 0.03	$ 617,198	$ 0.02	$ 46,290	$ 0.03	$ 617,198	$ 0.023
Construction Entrance	$ 37,105	$ 0.03	$ 35,250	$ 0.03	$ 35,250	$ 0.03	$ 176,251	$ 0.01	$ 35,250	$ 0.03	$ 176,251	$ 0.006
Dust control	$ 73,935	$ 0.07	$ 59,148	$ 0.04	$ 59,148	$ 0.04	$ 591,481	$ 0.02	$ 59,148	$ 0.04	$ 591,481	$ 0.022
Erosion Contrl	$ 38,052	$ 0.03	$ 26,636	$ 0.02	$ 26,636	$ 0.02	$ 133,182	$ 0.00	$ 26,636	$ 0.02	$ 133,182	$ 0.005
Seeding	$ 31,415	$ 0.03	$ 21,990	$ 0.02	$ 21,990	$ 0.02	$ 109,952	$ 0.00	$ 21,990	$ 0.02	$ 109,952	$ 0.004
Fencing and Gate	$ 112,848	$ 0.10	$ 95,921	$ 0.07	$ 95,921	$ 0.07	$ 479,605	$ 0.02	$ 95,921	$ 0.07	$ 479,605	$ 0.018
Security and Lighting	$ 96,226	$ 0.09	$ 81,792	$ 0.06	$ 81,792	$ 0.06	$ 408,960	$ 0.02	$ 81,792	$ 0.06	$ 408,960	$ 0.015
Drive Piers/Masts	$ 46,403	$ 0.04	$ 46,403	$ 0.03	$ 46,403	$ 0.03	$ 928,053	$ 0.03	$ 23,201	$ 0.02	$ 403,501	$ 0.015
Surveys	$ 9,080	$ 0.01	$ 9,080	$ 0.01	$ 9,080	$ 0.01	$ 45,402	$ 0.00	$ 9,080	$ 0.01	$ 45,402	$ 0.002
Water Supply Equipment (Tank, etc.)	$ 7,991	$ 0.01	$ 7,991	$ 0.01	$ 7,991	$ 0.01	$ 39,954	$ 0.00	$ 7,991	$ 0.01	$ 39,954	$ 0.001
Fire Control Equipment	$ 5,902	$ 0.01	$ 5,902	$ 0.00	$ 5,902	$ 0.00	$ 30,000	$ 0.00	$ 5,902	$ 0.00	$ 30,000	$ 0.001
Backup Generator	$ 18,161	$ 0.02	$ 18,161	$ 0.01	$ 18,161	$ 0.01	$ 181,608	$ 0.01	$ -	$ -		$ -
DC Cabling and Hardware	$ 209,179	$ 0.19	$ 125,508	$ 0.09	$ 125,508	$ 0.09	$ 2,510,152	$ 0.09	$ 100,406	$ 0.07	$ 2,510,152	$ 0.092
Inverter Installation	$ 372,076	$ 0.33	$ 148,830	$ 0.11	$ 148,830	$ 0.11	$ 2,480,508	$ 0.09	$ 148,830	$ 0.11	$ 2,480,508	$ 0.091
AC Cable and Hardware	$ 119,694	$ 0.11	$ 71,817	$ 0.05	$ 71,817	$ 0.05	$ 1,436,333	$ 0.05	$ 57,453	$ 0.04	$ 1,436,333	$ 0.053
SCADA/Panel Installation	$ 43,519	$ 0.04	$ 34,815	$ 0.03	$ 34,815	$ 0.03	$ 174,077	$ 0.01	$ 34,815	$ 0.03	$ 174,077	$ 0.006
Tracker Assembly	$ 77,509	$ 0.07	$ 54,256	$ 0.04	$ 54,256	$ 0.04	$ 1,085,127	$ 0.04	$ 32,554	$ 0.02	$ 361,709	$ 0.013
Tracker Installation	$ 63,529	$ 0.06	$ 44,470	$ 0.03	$ 44,470	$ 0.03	$ 889,401	$ 0.03	$ 26,682	$ 0.02	$ 296,467	$ 0.011
Tracker Terminations	$ 7,607	$ 0.01	$ 5,325	$ 0.00	$ 5,325	$ 0.00	$ 106,498	$ 0.00	$ 3,195	$ 0.00	$ 26,624	$ 0.001
Tracker Commissioning	$ 19,274	$ 0.02	$ 13,492	$ 0.01	$ 13,492	$ 0.01	$ 269,842	$ 0.01	$ 8,095	$ 0.01	$ 89,947	$ 0.003
Indirect Cost	$ 616,783	$ 0.55	$ 462,587	$ 0.34	$ 462,587	$ 0.34	$ 1,541,957	$ 0.06	$ 370,070	$ 0.27	$ 1,541,957	$ 0.057
Insurance, Contingency, Bonding, OH&P	INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED		INCLUDED	
EPC Total	**$ 2,372,400**	**$ 2.12**	**$ 1,650,263**	**$ 1.21**	**$ 1,650,263**	**$ 1.21**	**$ 16,129,335**	**$ 0.59**	**$ 1,353,644**	**$ 1.00**	**$ 13,533,458**	**$ 0.50**
Non-DOD reduction (%)				**$ -**	**10%**	**$ 0.00**	**10%**		**10%**		**10%**	
				$ -	**$ 1,485,237**	**$ 1.09**	**$ 14,516,401**	**$ 0.53**	**$ 1,218,280**	**$ 0.90**	**$ 12,180,112**	**$ 0.45**
Substation and Gen-Tie	$ 433,000	**$ 0.39**	$ 433,000	**$ 0.32**	$ 300,000	$ 0.22	$ 900,000	$ 0.03	$ 300,000	$ 0.22	$ 900,000	$ 0.03
Subtotal	**$ 2,805,400**	**$ 2.50**	**$ 2,083,263**	**$ 1.53**	**$ 1,785,237**	**$ 1.31**	**$ 15,416,401**	**$ 0.57**	**$ 1,518,280**	**$ 1.12**	**$ 13,080,112**	**$ 0.48**
BOM Cost	$ 1,346,429	$ 1.20	$ 1,360,000	$ 1.00	$ 1,360,000	$ 1.00	$ 27,200,000	$ 1.00	$ 752,857	$ 0.55	$ 15,057,143	$ 0.55
Owner PM	$ 104,566	$ 0.09	$ 104,566	$ 0.08	$ 50,000	$ 0.04	$ 500,000	$ 0.02	$ 50,000	$ 0.04	$ 500,000	$ 0.02
TOTAL Construction Cost	**$ 4,256,395**	**$ 3.80**	**$ 3,547,829**	**$ 2.61**	**$ 3,195,237**	**$ 2.35**	**$ 43,116,401**	**$ 1.59**	**$ 2,321,137**	**$ 1.71**	**$ 28,637,255**	**$ 1.05**
Engineering Cost	$ 150,000	$ 0.13	$ 150,000.00	$ 0.11	$ 150,000	$ 0.11	$ 600,000	$ 0.02	$ 150,000	$ 0.11	$ 600,000	$ 0.02
Development and Land Cost	$ 233,667	$ 0.21	$ 233,667	$ 0.17	$ 250,000	$ 0.18	$ 1,400,000	$ 0.05	$ 250,000	$ 0.18	$ 1,400,000	$ 0.05
Subtotal	**$ 4,640,062**	**$ 4.14**	**$ 3,931,496**	**$ 2.89**	**$ 3,595,237**	**$ 2.64**	**$ 45,116,401**	**$ 1.66**	**$ 2,721,137**	**$ 2.00**	**$ 30,637,255**	**$ 1.13**
ESTCP Pre-Construction Compliance (Legal)	$ 82,743	$ 0.07	$ 82,743	$ 0.06	0	$ -	0	$ -		$ -	$ -	$ -
Total Cost	**$ 4,722,805**	**$ 4.22**	**$ 4,014,239**	**$ 2.95**	**$ 3,595,237**	**$ 2.64**	**$ 45,116,401**	**$ 1.66**	**$ 2,721,137**	**$ 2.00**	**$ 30,637,255**	**$ 1.13**
System Cost (Total Cost - Development Cost)		$ 4.01		$ 2.78		$ 2.46		$ 1.61		$ 1.82		$ 1.07
O&M Cost	$ 25.76		$ 24.29		$ 24.29		$ 17.00		$ 22.10		$ 17.00	

7.4.5 Annual O&M costs

Soitec calculates that annual O&M costs for the Fort Irwin 1MW CPV project to be $25.76/kW$_{dc}$-yr or $28.85 /kW$_{ac}$-yr which is approximately 14% higher than the $22.10/kW-yr for a small conventional single-axis PV plant[38]. Some of the special cost drivers in this case are:

- There are no existing warranties on the Fort Irwin power plant equipment.
- Due to the remote location of the site, Soitec assumed response distance to the site would be 50 miles for a contract O&M employee for a typical O&M company under contract.
  - 10 hour workdays (2 hours overtime) due to the remote location and base access requirements
  - Travel costs (service truck maintenance and mileage)
- Two module cleanings per year
- $25/hour labor
- 23 year project life (25-year PPA minus 2 years already operated)
- No full-time site personnel

[38] Ibid, pg. 42.

Other typical cost drivers for any CPV plant O&M are:

- 10 year extensive dual-axis drive re-lubrication requirement. Due to the height of the module this requires special lifting equipment, such as bucket trucks or boom lifts and greasing equipment (automatic greasing equipment, air compressors).
- Reactive maintenance costs are higher. As seen in Figure XX below, reactive maintenance costs comprise 56% of the annual O&M budget. This is due to the autonomously-controlled trackers and the complexity of the individual tracker control units to keep the dual-axis trackers focused on the sun.
- Component replacement is more expensive due to the heavier components and the height of the components. This requires lifting equipment such as cranes, forklifts and boom lifts.

In general, for 1 MW+ systems, preventive maintenance consumes 70-85% of available budget is while 15%-30% is allocated to reactive maintenance[39]. However, Figure 44 shows the O&M category breakdown for the 1MW Fort Irwin CPV plant and reactive maintenance is unusually high in comparison to preventive maintenance. This is due to the unique requirements and complexities of Soitec's dual axis CPV System. It will be crucial to reduce this cost category in order to be competitive in the future.

Also, usually module washing requires an allocation of $0.80 to $1.30/kW-yr[40]; however, in this case cleaning is 9% of the total, or $2.19/kw-yr.

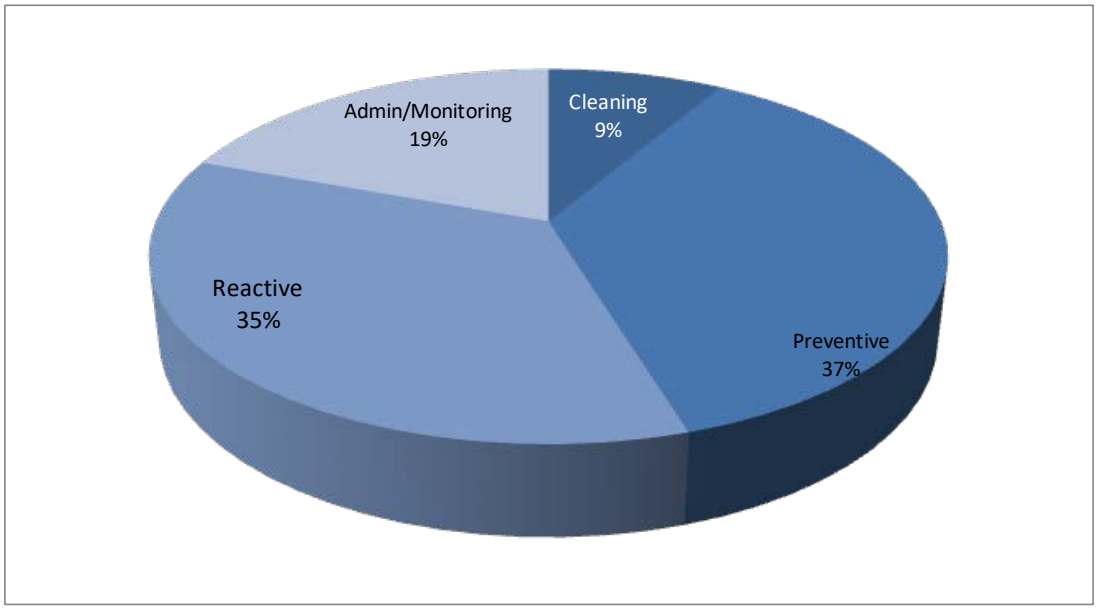

Figure 44. DOD Irwin CPV Power Plant O&M Cost Category Breakdown

[39] Enbar, op. cit., pg.12.
[40] Ibid, pg. 11.

For a typical 1MW CPV power plant (non-DOD installation) in 2017 with the provisions below, Soitec estimates annual O&M costs would reduce somewhat to \$24.29/kW_{dc}-yr or \$27.21 /kW_{ac}-year:

- Five-year inverter warranty, 10-year module warranty, 2-year general plant equipment workmanship warranty
- 25-year project life

There are a few major reasons for the difference between CPV and conventional PV O&M costs:

- Simplicity of equipment, especially with fixed-tilt trackers where there are no moving parts.
- Depending on the location, module cleanings are conducted once a year or less, since the PV modules are not as affected as CPV modules, which require DNI.
- Improved module quality
- Better personnel management and the fact that CPV requires a higher skilled worker
- Better plant and data management
- Robust logistics chain geared to the conventional PV industry

7.5 LIFECYCLE COST ANALYSIS

Soitec calculated the lifecycle cost of California CPV and PV power plants of various sizes, both on DOD installations and for a typical non-DOD Independent Power Producer (IPP). The scenarios are as follows:

- DOD Irwin 1MW CPV (2015 installation)
- DOD 1MW CPV (2017 installation)
- Non-DOD 1MW CPV (2017 installation)
- Non-DOD 20MW CPV (2017 installation)
- Non-DOD 1MW Conventional PV (2017 installation)
- Non-DOD 20MW Conventional PV (2017 installation)

For all scenarios, Soitec used the following assumptions:

- \$70/MWh peak PPA, \$40 off-peak PPA price
- 25 year system lifetime
- 30% Investment Tax Credit
- 5% residual value
- \$0.025/w inverter major repair cost after 13 years
- 3% discount rate during construction
- 2.2% discount rate during operations

- Depreciation
  - 90% - five year MACRS
  - 5% - fifteen year MACRS
  - 0% - twenty year MACRS
  - 5% – fifteen year S/L
  - 0% - twenty year S/L
- 8.25% state tax rate
- 35% federal tax rate
- 2% annual escalator
- 32% on-peak production
- 2,269 kWh/kWp ratio

The Power Purchase Agreement (PPA) rate Soitec used for all scenarios is quite generous by today's standards. Prices offered by the utilities have fallen dramatically over the past 10 years, with California prices near $150/MWh as late as 2010 and 2017 prices near $40/MWh (see Figure 45)[41]. This represents a 75% decrease over 7 years. However, PPA prices structures vary widely across states and regions, as they are influenced by the peak power requirements, percentages of solar energy vs. round-the-clock conventional power sources and state policies.

Figure 45. Power Purchase Agreement (PPA) Rate Trend Chart

For the 2017 1MW and 20 MW installations, Soitec used a 1.36 DC/AC ratio instead of the 1.12 DC/AC ratio for the DOD Irwin project. This is a more efficient DC/AC ratio. The Fort Irwin DC/AC ratio was due to contract constraints at the time.

[41] Mark Bolinger, Joachim Seel, Kristina La Commare. 2017. *Utility Scale Solar 2016: An Empirical Analysis of Project Cost, Performance and Pricing Trends in the United States*. Lawrence Berkeley National Laboratory. pg. 32.

Fort Irwin had no land costs, but extensive development and legal costs. Scenarios 1-5 feature a land cost, assuming 8 acres/MW and $5,000/acre.

For module degradation rates, Soitec used the maximum guaranteed rate from its limited module warranty (0.7%)[42] and the maximum guaranteed rate from SunPower's module warranty (0.4%)[43]. Even though in reality module degradation rates are closer to 0.5%[44], developers and lending institutions would use the maximum guaranteed rate in a lifecycle cost analysis.

Inputs specific to each scenario are shown in Table 14 below. Lifecycle cost analysis results are also shown in Table XX are described as follows:

- Net Present Value (NPV) – defined by Investopedia as "the difference between the present value of cash inflows and the present value of cash outflows. NPV is used in capital budgeting to analyze the profitability of a projected investment or project. A positive net present value indicates that the projected earnings generated by a project or investment (in present dollars) exceeds the anticipated costs (also in present dollars). Generally, an investment with a positive NPV will be a profitable one and one with a negative NPV will result in a net loss".
- Internal Rate of Return (IRR) – defined by Investopedia as "measuring the profitability of potential investments. Internal rate of return is a discount rate that makes the net present value (NPV) of all cash flows from a particular project equal to zero". Basically, this is the break-even point. Developers and investors look for a minimum of 7-8% IRR.
- Payback Period – also known as Return on Investment (ROI) - defined by Investopedia as "the length of time required to recover the cost of an investment". Payback period completely disregards the time value of money, as it is simply concerned with how many years it takes to recover the capital investment.

Table 14. Lifecycle Cost Analysis

Scenario	1	2	3	4	5	6
LCC Input/ Assumption Description	**DOD Irwin 1MW CPV**	**2017 1MW DOD CPV**	**2017 1MW CPV (non-DOD)**	**2017 20MW CPV**	**2017 1MW PV**	**2017 20MW PV**
System Size (MW DC)	1.12	1.36	1.36	27.20	1.36	27.20
System Cost ($/w dc)	$ 4.01	$ 2.78	$ 2.46	$ 1.61	$ 1.82	$ 1.07
O&M Costs ($/kWh)	$ 25.76	$ 24.29	$ 24.29	$ 17.00	$ 22.10	$ 17.00
Development Cost ($/w d	$ 0.21	$ 0.17	$ 0.18	$ 0.05	$ 0.18	$ 0.05
Annual Module Degradati	0.70%	0.70%	0.70%	0.70%	0.40%	0.40%
NPV ($)	($1,209,031)	($722,237)	($564,671)	$4,000,723	($119,781)	$10,997,870
IRR (%)	-2.61%	-0.97%	-0.51%	3.54%	1.51%	7.00%
Payback Period (years)	40	40	40	14	20	10

[42] *Soitec CPV Module CX-M500 Product and Performance Limited Warranty*. 2013. Soitec Solar GmbH Corporate Document.
[43] *SunPower Limited Product and Power Warranty for PV Modules.* 2012. Sunpower Document#: 503170 Rev A. Online.
[44] Bolinger, op. cit., Pg. 38.

The lifecycle cost analysis results show that CPV power plants of any size today would have great difficulty getting financed due to the low IRR that is driven by the high construction and operating costs. The IRR are negative for small CPV plants (1MW) and are still low for CPV power plants at least up to the 20MW size, using the constraints and settings of this model. Even small conventional PV power plants (~1 MW) present a financing challenge and would have to be supplied with higher PPAs and/or other financial incentives to provide an attractive IRR. At the 20MW size, using the constraints and settings of this model, conventional PV power plants start to become attractive in terms of IRR, with an IRR of 7.0% using the constraints and settings of this model. The surrounding circumstances and specific incentives of each power plant can vary significantly and changing these inputs to the model can move the needle materially in terms of NPV and IRR. To summarize, in general there is much progress needed on closing the gap between CPV construction and operating costs and conventional PV construction and operating costs in order for CPV technology to be an attractive technology selection for future photovoltaic power plants.

8.0 IMPLEMENTATION ISSUES

In addition to the limitations of CPV technology discussed in Section 2.3, Soitec has found most end-user concerns revolved around the financeability of the CPV technology. These concerns are categorized as such:

8.1 DUAL-AXIS DRIVE

The drive unit, though composed of a standard housing, slewing rings, worm gearing, reduction gearbox and AC motor, was a source of end-user concern. Major worries were how the drive would handle the immense tracker loads, especially during wind or seismic events, if the drive's precision would support the exact pointing requirements of the CPV tracker (especially over time as the gear teeth experienced wear) and the general lifecycle of the drive. Soitec notes that the dual-axis drives on other, larger projects have functioned quite well for several years without a single internal drive issue with the slewing rings and worm drives.

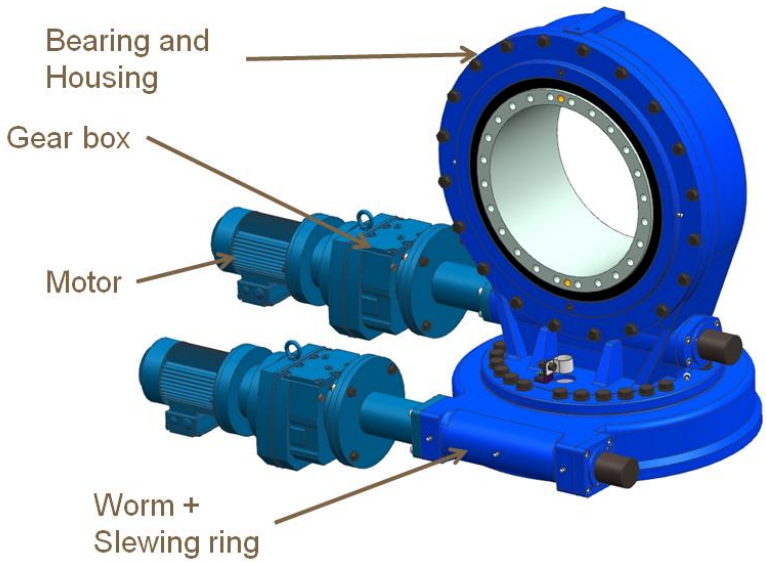

Figure 46. Dual-Axis Drive

8.2 SOITEC'S LONG-TERM VIABILITY

End users, developers and investors were concerned about what would happen if Soitec went bankrupt or abandoned its solar business. Major concerns related to this were:

- Module warranty issues. Soitec's modules were proprietary and Soitec was the exclusive manufacturer and supplier. Customers were concerned about where they would get warranty service and replacement modules.
- Custom proprietary tracking system, software and source code. Customers were concerned about a lack of future software support.
- CPV Component Suppliers. Customers also demanded "step-in" rights for Soitec's suppliers so that they could ensure continuous supply of spare or replacement parts.

8.3 OPERATIONS AND MAINTENANCE (O&M) COSTS

End-users were concerned at the lack of real O&M cost data, realizing that the CPV technology was unproven and would require intensive preventive and reactive maintenance over the life of the plant. This was especially acute given the exact pointing requirements of the trackers and the immediate reduction in energy production if the pointing accurancy criteria were exceeded for any reason.

8.4 LACK OF COMMERCIALIZATION OF CPV SYSTEM COMPONENTS

At the time of construction of the DOD Fort Irwin project, the Soitec Bill of Materials were a combination of standard commercial off-the-shelf (COTS), a custom-built prototype, or newly commercialized. The majority of the major equipment (CPV module, tracker structure and auxiliary equipment) were either newly commercialized with less than 400 tracker units produced for the US at the time and most of the COTS items are fastening hardware and represent a nominal portion of the overall CPV system cost.

8.5 PERMITTING AND REGULATIONS

The only major concerns with permitting/regulations are height restrictions which may exist in some locations. Most of the project sites permitted by Soitec fell within the AHJ-imposed height ceiling of 35 feet, as the trackers are approximately 28 feet high at the steepest angle.

8.6 IMPLEMENTATION ISSUES CONCLUSION

Soitec expects this demonstration would alleviate end-users' concerns with initial warranty claims and chronic problems, as the power plant did not require an inordinate amount of spare parts or experience any abnormal issues. However, concerns about the long-term viability of the CPV technology would remain given the 24-month demonstration duration was less than 10% of the average Power Purchase Agreement (PPA) life.

Also, at the time this power plant was commissioned (summer 2015), Soitec announced its exit of the solar business and subsequent inability to sell the business. Therefore, over the past two years Soitec has not moved forward with project, supplier or technology development/refinement and until recently most CPV development has stalled. Other CPV suppliers have experienced a similar fate, such as:

- Amonix closed its Las Vegas production facility in 2012 (now renamed and operating in a smaller capacity as Arzon Solar).
- SolFocus closed in 2013.
- GreenVolts went out of business in 2012.
- Energy Innovations, Soliant, Concentrator Optics, SunPower's C7 and Skyline Solar's low-concentration PV (LCPV) are no longer operating[45]

[45] Eric Wesoff. 2014. *Sources: Concentrated PV Startup Solar Junction Acquired by Saudis.* Greentechmedia.com. Online.

During the same time period, conventional PV module efficiency has risen moderately and prices have fallen precipitously. Support technologies, such as 3rd party single-axis trackers and inverters have seen a shakeout in the industry, with quality rising and prices falling. Third party O&M providers and performance monitoring companies have also refined their offerings and dropped prices significantly. Conventional PV power plants design techniques have improved. Therefore, Soitec expects CPV technology would face even stiffer competition with conventional PV today.

Paths forward that Soitec envisions for CPV that would allow it to approach the economic offering of conventional PV power plants would be:

- A breakthrough in the multi-junction cell efficiency, which would allow fewer trackers to provide the same amount of power, thereby reducing CAPEX costs.
- Improvements in tracking software and firmware
- Streamlined tracker control unit with software redundant protection systems
- Reduction in reactive maintenance costs
- Elimination or severe reduction in module washing
- Introduction of secondary optics in CPV modules to allow for looser pointing accuracy criteria
- New tracker design that reduces the amount of steel and hardware
- Commercialization of currently custom-built parts

In late 2016 Soitec sold its CPV technology to Saint-Augustin Canada Electric Inc. (STACE), a world-class supplier of large electrical equipment in the power generation industry. With this acquisition, STACE became the technological leader of the CPV industry and stated it would continue to improve the technology and maintain the collaboration with the recognized Fraunhofer Institute for Solar Energy Systems ISE, based in Freiburg, Germany[46].

[46] Saint-Augustin Canada Electric Inc.(STACE) acquires Soitec solar CPV technology. 2017. News Release. www.stacelectric.com.

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APPENDIX B DNV-GL ENGINEERING REPORT

The report from engineering firm DNV-GL covers the performance index, availability and long-term degradation performance objectives.

DNV·GL

FORT IRWIN SOLAR PROJECT

Fort Irwin Assessment

Soitec Solar Industries, Inc.

Document No.: 10058783-HOU-R-01
Issue: B, Status:
Date: 8 November 2017

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Project name:	Fort Irwin Solar Project	DNV GL - Energy
Report title:	Fort Irwin Assessment	Advisory Americas
Customer:	Soitec Solar Industries, Inc.	DNV KEMA Renewables, Inc.
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Date of issue:	8 November 2017	Tel: +1 206 387 4200
Project No.:	10058783	Enterprise No.: 26-2535197
Proposal Reference:	152247-HOU-P-01-B	
Document No.:	10058783-HOU-R-01	
Issue/Status	B/DRAFT	

Task and objective:

This report presents the results of analysis conducted by DNV GL on behalf of Soitec Solar Industries, Inc..

Prepared by:	Verified by:	Approved by:
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Keywords:
Solar, availability, performance, degradation

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Issue	Date	Reason for Issue	Prepared by	Verified by	Approved by
A	28 September 2017	Draft	S. Starnes	S. Smith	
B	8 November 2017	Updated draft	S. Starnes, J. Newmiller	S. Smith	

Table of contents

EXECUTIVE SUMMARY V

1 INTRODUCTION 1
1.1 Project Description 1
1.2 Objective and scope of review 1

2 METHODOLOGY AND RESULTS 1
2.1 Energy Model Validation 1
2.2 Availability Review 20
2.3 Degradation Analysis 25

3 CONCLUSIONS 28

4 REFERENCES 29

List of tables

Table 2-1. Monthly distribution of meteorological quality marks 9
Table 2-2. Monthly distribution of 40-Tracker performance data quality 11
Table 2-3. Monthly distribution of 36-Tracker performance data quality 13
Table 2-4. Files used in Fort Irwin Soitec CPV system model 15
Table 2-5. Overall summary of energy performance metrics 19
Table 2-6. Post-2015 energy performance metrics 20
Table 2-7 Annual availability results 23
Table 2-8. Evaluation Period Summary 27

List of figures

Figure 2-1. Trend of supplied performance data 3
Figure 2-2. Daily P95 per month irradiation values for three sites 5
Figure 2-3. Apparent pyrheliometer soiling 6
Figure 2-4. Best estimates of meteorological data 8
Figure 2-5. Quality trends for 40-tracker performance index inputs 10
Figure 2-6. Quality trends for 36-tracker performance index inputs 12
Figure 2-7. Comparison of DNI sensor readings 14
Figure 2-8. Trend of ratio of DNI1/DNI2 14
Figure 2-9. Agreement Plots of Measured vs. Modeled DC power 16
Figure 2-10. Trends of Performance Index 17
Figure 2-11. Performance Index Around 24 July 2017 Rain Event 18
Figure 2-12. Monthly DC Performance Index for subsets of data 19
Figure 2-13 Monthly data coverage 21
Figure 2-14 Representative power versus DNI plot 23
Figure 2-15 Monthly system and tracker availability 24
Figure 2-16 Tracker Availability excluding Trackers 2, 17, and 24 25
Figure 2-17. First degradation evaluation interval 26
Figure 2-18. Second degradation evaluation interval 27

EXECUTIVE SUMMARY

At the request of Soitec Solar Industries, LLC, DNV GL performed an independent analysis of the Fort Irwin 1MW Solar Project. The purpose of this review was to assess the performance of the Project during its first two years of operation with respect to energy production, equipment availability, and production degradation.

The Project, located in Ft. Irwin, CA, consists of 40 solar dual-axis tracker units that feed power to the grid. The tracker units use concentrator photovoltaic (CPV) panels to directly convert solar irradiance into direct current (DC) electrical power.

DNV GL compared energy production with expected production as predicted using measured weather as input to the PVsyst performance simulation model as supplied by Soitec. Within the limitations of the available data, the power plant demonstrated capability to produce 99% of model predicted energy, which exceeds the target 98% of model predicted energy.

DNV GL assessed overall system availability as well as tracker availability, which excludes the impact of site-wide outages. Overall system availability and tracker availability was found to be 95.2 and 96.7%, respectively, which is less than the target 98%. Much of the tracker downtime was a result of encoder failures. Following a design upgrade to the tracker encoders the monthly availability exceeded 98% consistently. DNV GL determined that throughout the period, 1.5% of the downtime was a result of just three trackers. Excluding these three trackers yielded an availability of 98.2% which exceeds the target availability.

Production degradation was verified by comparing performance on clear days near the start and end of the evaluation period. Performance appeared to improve by 1.6%, which is within the estimated 5% uncertainty of the performance index.

1 INTRODUCTION

At the request of Soitec Solar Industries, LLC ("Soitec" or the "Customer"), DNV Kema Renewables, Inc. ("DNV GL") performed an independent analysis of the Fort Irwin 1MW CPV Solar Project ("Fort Irwin" or the "Project"). This work was carried out pursuant to DNV GL proposal 152247-HOU-P-01-B Fort Irwin Assessment. The purpose of this review is to assess the performance of the Project during its first two years of operation.

1.1 Project Description

The Project, located in Ft. Irwin, CA, consists of 40 solar dual-axis tracker units that feed power to the grid. The tracker units use concentrator photovoltaic (CPV) panels to directly convert solar irradiance into direct current (DC) electrical power.

1.2 Objective and scope of review

As part of this analysis, DNV GL has performed the following tasks:

- Energy Model Validation: DNV GL calibrated the Project's PVsyst energy model with typical year weather and analyzed the resulting discrepancies to actual performance (subject to limitations of quality/availability of existing measured data, follow approach of IEC62670-2).
- Availability Analysis: Calculated overall System Availability and Tracker Availability. A reasonable downtime power threshold was selected by DNV GL and agreed upon with Soitec, with the

concurrence of the National Renewable Energy Laboratory (NREL; acting as independent validation entity). The overall System Availability includes all downtime sources including tracker downtime, inverter outages, and grid outages; Tracker Availability excludes inverter and grid outages.

- Degradation Review: DNV GL identified performance data records corresponding to clear-sky exposure and full system availability within 2 months of start of review period and 2 months of end of review period. DNV GL estimated magnitude and uncertainty of power capacity estimates, and of the derived degradation estimate.

2 METHODOLOGY AND RESULTS

2.1 Energy Model Validation

2.1.1 Methodology

The following subsections describe the methodology used for the energy model validation including a description of the dataset and data quality treatment.

2.1.1.1 Data Intake

Performance data were supplied in 21 Microsoft Excel files extracted from the power plant Supervisory Data and Control (SCADA) system, with various columns and time periods covered [1]. Scripted import of these files was used to merge the results reproducibly, and clear-sky estimated irradiance was computed based on site location and timestamps found in the data files and compared with measured data to confirm time-alignment of irradiance data. Channels provided included one DC power per each of 40 trackers, two pyrheliometer readings, two ambient temperature readings, and two wind speed readings.

Figure 2-1 illustrates that the IrrDNI1 sensor readings (Kipp and Zonen pyrheliometer serial number 140003 mounted on Tracker 17) were missing in late 2015, were essentially mostly zeroed (off-sun) between 9 January 2017 and 23 February 2017 (system downtime due to manpower shortage) and again from 2 April 2017 until 20 April 2017 (system downtime due to grease seal retrofit/replacement activities on site). Thus, there is a significant reliance on irradiance measurements IrrDNI2 (Kipp and Zonen pyrheliometer serial number 140029 mounted on Tracker 32). Data for channel 1 (Tracker 17) of the ambient temperature and

wind speed were missing prior to 8 December 2015, though the channel 2 data were mostly reasonable.

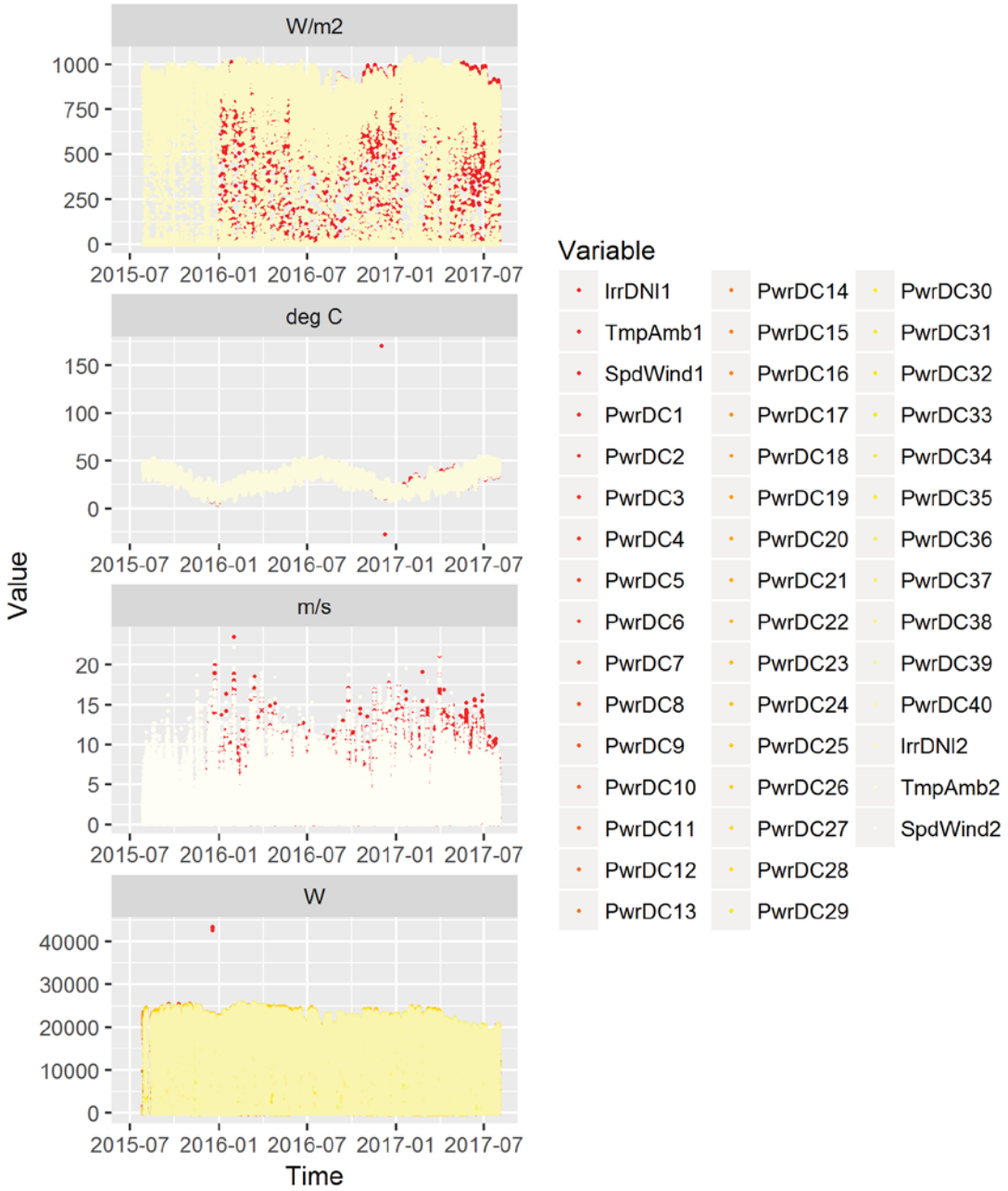

Figure 2-1. Trend of supplied performance data

We note that a fundamental limitation of this data set is that the power sensors were connected to one-half of the modules on each tracker. On 17 December 2015 a multiplier of 2 was added to the plant SCADA configuration so values reported after that time would be indicative of the power being produced by the whole tracker. Upon data import, DNVGL applied a retroactive factor of two prior to that date for simplicity of analysis.

Another fundamental limitation of this data was that no AC power or energy data were recorded by the SCADA system during this period of evaluation, so the analysis is all performed at the array-to-inverter interface rather than the more typical revenue meter interface.

All Fort Irwin performance data were reported in 15-minute data records. The UNLV and DRA data was supplied in 1-minute records which we aggregated to 15-minute basis.

2.1.1.2 Synthesized Data

The redundancy of meteorological station data supports sanity checking and "best estimate" values to be used when either of a pair of sensors fails to report valid (or any) data. For measured irradiance, the approach used for each data record was to mark individual sensor readings as missing (empty cell), night (≤0) or IrrHi (>1400), or otherwise valid (Ok) for comparing with other sources of data. For extracting a redundant best estimate of irradiance, one additional criterion was applied: IrrLow (<500W/m^2), and then among the readings still marked as valid we chose the sensor with the greatest value for reasons discussed below. For temperature and wind speed, a similar missing and range approach was used ($-4oC < T_a < aoC$ and $o\ mjs < ws < 1oo\ mjs$), but the mean of the valid values for that parameter was used. To simplify graphs, in some plots below the term "Invalid" is used to represent any of the conditions "Night", "IrrHigh", or "IrrLow".

Since the pyrheliometers were installed at the bottom edge of their respective trackers to facilitate regular cleaning, they were also typically shaded before 9am and after 3pm.

Onsite irradiance data appeared to be lower than expected, most likely due to some combination of alignment error or soiling. We compared clear day irradiance with two publicly-accessible solar meteorological stations: University of Nevada Las Vegas, or UNLV, and the SURFRAD station at Desert Rock, Nevada). Each of these stations is about 100 miles north-northeast of the Fort Irwin project site, with Desert Rock at about the same 1000m elevation and UNLV at around 650m above sea level. Clearly, the timing of cloud patterns will not be the same in these locations as at the project site, but to the extent that clear days in both locations have similar discrepancies we considered the discrepancies to be most likely indicative of impaired measurement at the project site. For most of the test period the SURFRAD Desert Rock (DRA) site reported clear day irradiance values about 4% higher than UNLV, except for the last few months when DRA dropped noticeably lower than UNLV, perhaps due to a tracking issue.

To identify and compare the clearest days in each month during the evaluation period, the daily irradiation value for which 95% of the values are smaller was chosen. (The maximum value is often more influenced by interfering effects than the P95 value is.) The monthly P95 daily irradiation values (in each of four quality categories) are shown in Figure 2-2 for the individual pyrheliometers and combined best estimate irradiance for the Fort Irwin (FTI) project site, along with the corresponding DRA and SURFRAD data in Figure 2-2. (Each site is identified with different symbol shapes, while the at-site multiple sources are distinguished using color.) Most of the irradiation is collected during "Ok" quality times, but the "invalid" (primarily below 500W/m2) quality category accounts for about 10% of the irradiation when individual sensors are used but is negligible when best-estimate combined irradiance data are used. The preliminary soiling estimates are obtained by computing the ratio of the Ok quality, best-estimate (combined) FTI P95 daily irradiation values (for which days are likely to be clear) with similar values obtained from the UNLV data. Due to data quality problems at the project site, some months appear to have some unexpectedly low best-case days so a floor of 80% was imposed to prevent overcompensation for soiling in early 2017.

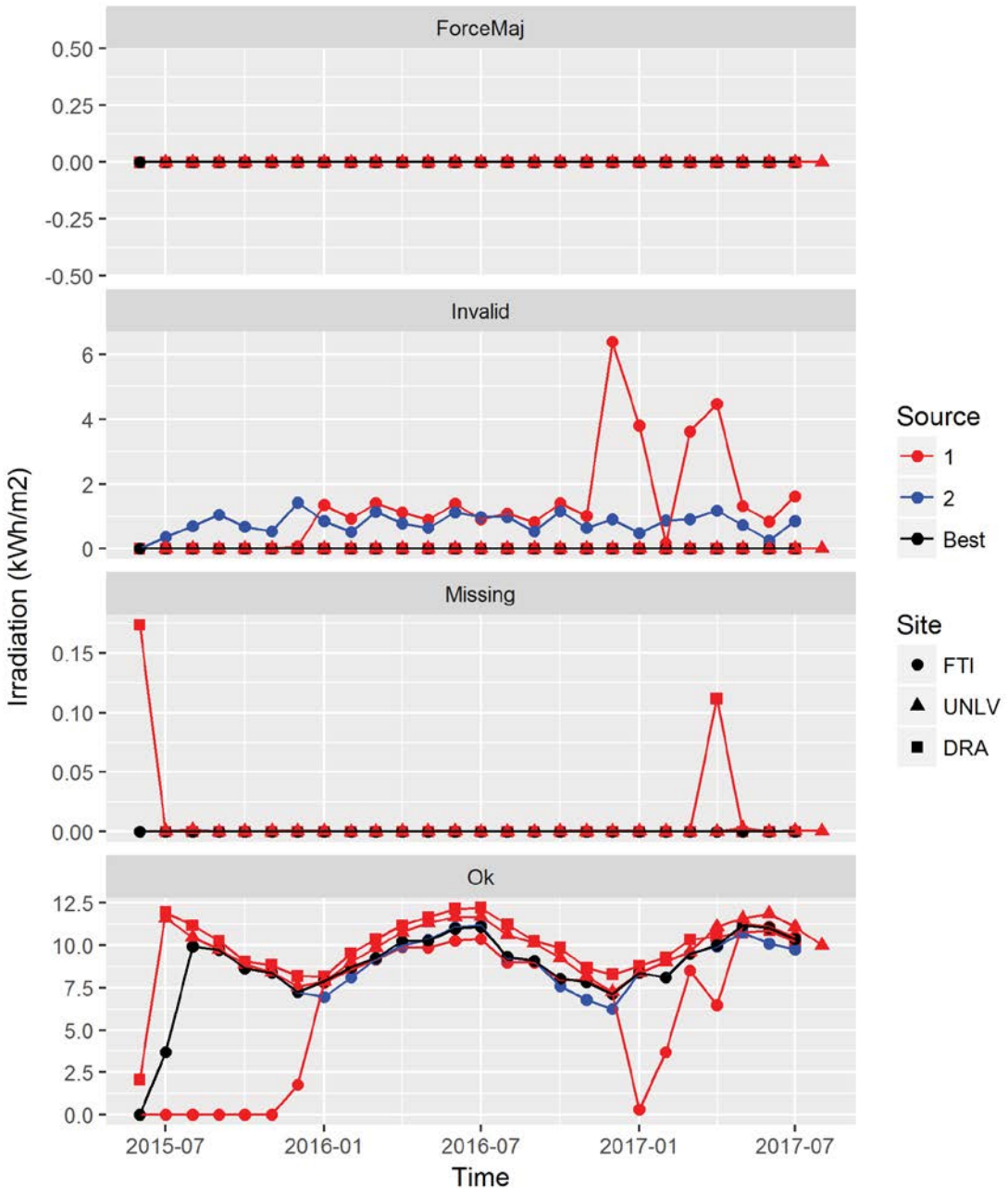

Figure 2-2. Daily P95 per month irradiation values for three sites

The preliminary soiling estimate and constrained soiling estimate appear in Figure 2-3. The 80% constraint rule prevents application of soiling corrections to the measured irradiance by more than 20%, and it only affects July 2015. Note the general trend downward, as typical of dust accumulation trends, interrupted in November 2016 by improved output from the pyrheliometers for three months and then some erratic variations starting in February 2017. Between the relatively simple seasonal changes in the UNLV P95 daily irradiation and our observations of rain-correlated performance index changes discussed later it appears that the variations in discrepancy are related to the FTI site measurements. Even though this soiling trend mostly looks consistent with the site inspection report discussion, this monthly correction is susceptible to interference by non-soiling mechanisms so introduces possible bias high in the available irradiance if we correct for it. The true value of irradiance is likely between the raw value and the corrected value. For this reason, we show performance index computations below using both non-soiling-corrected ("Raw") and soiling-corrected ("Corr") irradiance data.

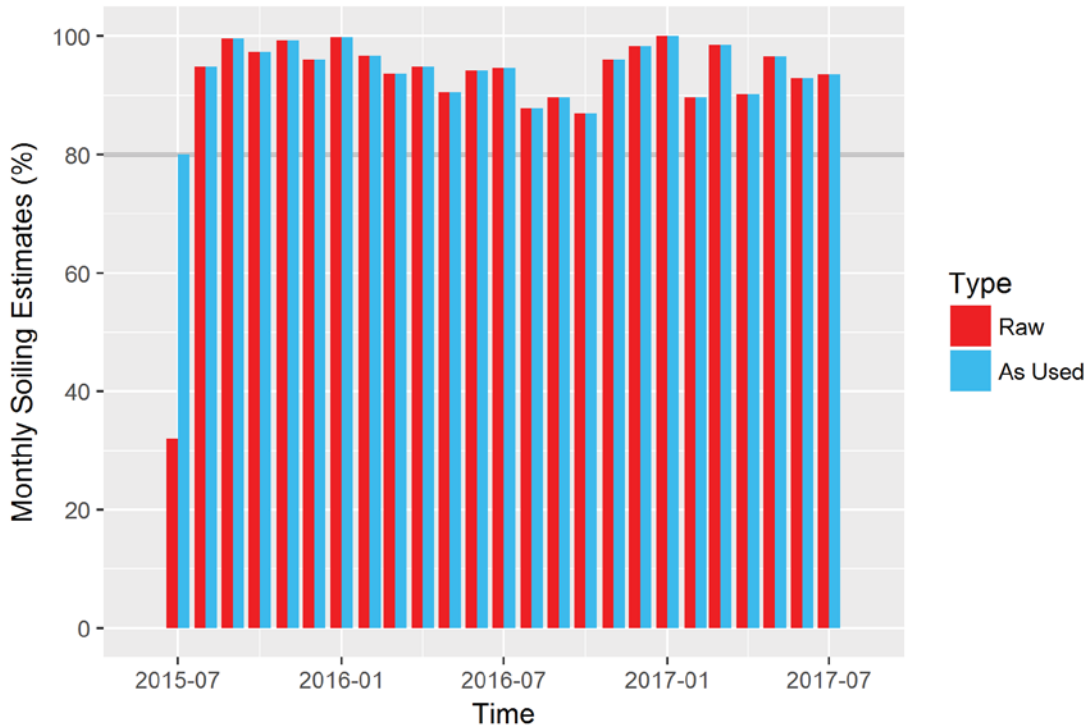

Figure 2-3. Apparent pyrheliometer soiling

2.1.1.3 Quality Control

Quality control was applied to the data by creating a marking column for each input and computed parameter. The quality marking is implemented in order, so that later categories only apply to Ok records, and do not change previous non-Ok marks. For a given set of criteria, each record in the combined 15-minute-interval data set is assigned a unique quality characterization.

Raw Sensor Quality

Individual sensor readings can in some cases be identified as having quality problems with no reference to other sensors.

- Quality marks for each of the power data columns `PwrDC1` through `PwrDC40` are set to `SiteIssue` where site outage time periods occur. Negative power readings (typically though not always at night) are marked as `RevPwrDC`, and power readings greater than 30kW are marked as `HiPwrDC`
- Input data (sensor readings) are marked as missing data or out of range,
- Time-intervals with known per-sensor operations issues were marked,
- Low irradiance (less than $\mathrm{soo\ W/m^2}$) data was marked as `IrrLow` for `IrrDNI1` and `IrrDNI2`,
- The `IrrDNI1` and `IrrDNI2` qc marks are set to `IrrDiff` if both sensor values were ok but their readings were more than 5% different from each other

Redundant Sensor Quality

When best estimates for parameters are obtained by referring to multiple redundant sensor readings, the combined parameter is regarded as having Ok quality unless all inputs fail their individual quality evaluations. This maximizes the number of records for which the parameter can be relied on.

- A redundant (best-estimate) `IrrDNI` estimate is computed by selecting the mean of the Ok values at each timestep, unless they differ by more than 5% in which case the maximum value is selected (under the premise that the lower value is likely affected by soiling).

- Redundant (best-estimate) `TmpAmb` and `SpdWind` estimates are computed by computing the mean of all Ok values at each timestep (under the premise that their discrepancies are random).

Non-Redundant Sensor Quality

Where multiple sensors are needed to obtain a quantity such as total DC power, any one sensor being invalid means the combined value is invalid.

- A total dc output `PwrDCA40` (DCA representing direct current at the array level) is computed as the equally-weighted sum of the 40 individual power values when all inputs are quality marked as Ok.
- An alternate "most of system" `PwrDCA36` value was computed by summing all dc power values except for `PwrDC2`, `PwrDC17`, `PwrDC24` and `PwrDC25` and scaling that sum up by 40/36. The corresponding quality mark omits dependence on the qc marks for those four excluded power values.

Performance Metric Quality

When applied to computing a performance metric, all relevant parameters should have Ok quality. If any do not, then the quality of the performance metric is marked according to the first identified non-Ok quality mark. It is then possible to plot all of the input data for that quality metric but color-code it according to different performance metric quality marks. This means for example that a best-estimate DNI value may be regarded as Ok for the purposes of one metric (where temperature or power are also Ok) but not for another metric (where either temperature or power are not Ok).

- A `40`-tracker quality mark for the performance index computed using `PwrDCA40` was determined by choosing the first non-Ok mark from among the quality marks for `PwrDCA40` and the quality marks for the best-estimate meteorological quantities `IrrDNI`, `TmpAmb` and `SpdWind`.
- A similar `36`-tracker quality mark was computed for the PI calculated with `PwrDCA36` and the quality marks for the best-estimate meteorological quantities `IrrDNI`, `TmpAmb` and `SpdWind`.
- A `MET` qc mark was generated based on the marks for the best-estimate meteorological quantities `IrrDNI`, `TmpAmb` and `SpdWind`.
- For reference, some results are computed with no quality mark checking.

2.1.1.4 Data Coverage

Figure 2-4, Figure 2-5, and Figure 2-6 show the combined quality marks applicable for using all best- estimate meteorological data, for adding all dc power values (e.g. computing performance index with all sensors), and ignoring four trouble-prone trackers in order to gain access to a greater quantity of internally- consistent data records (black data points) at the cost of neglecting the performance in a subset of the system.

Table 2-1, Table 2-2, and Table 2-3 summarize monthly distribution of marks corresponding to 24h/day all month.

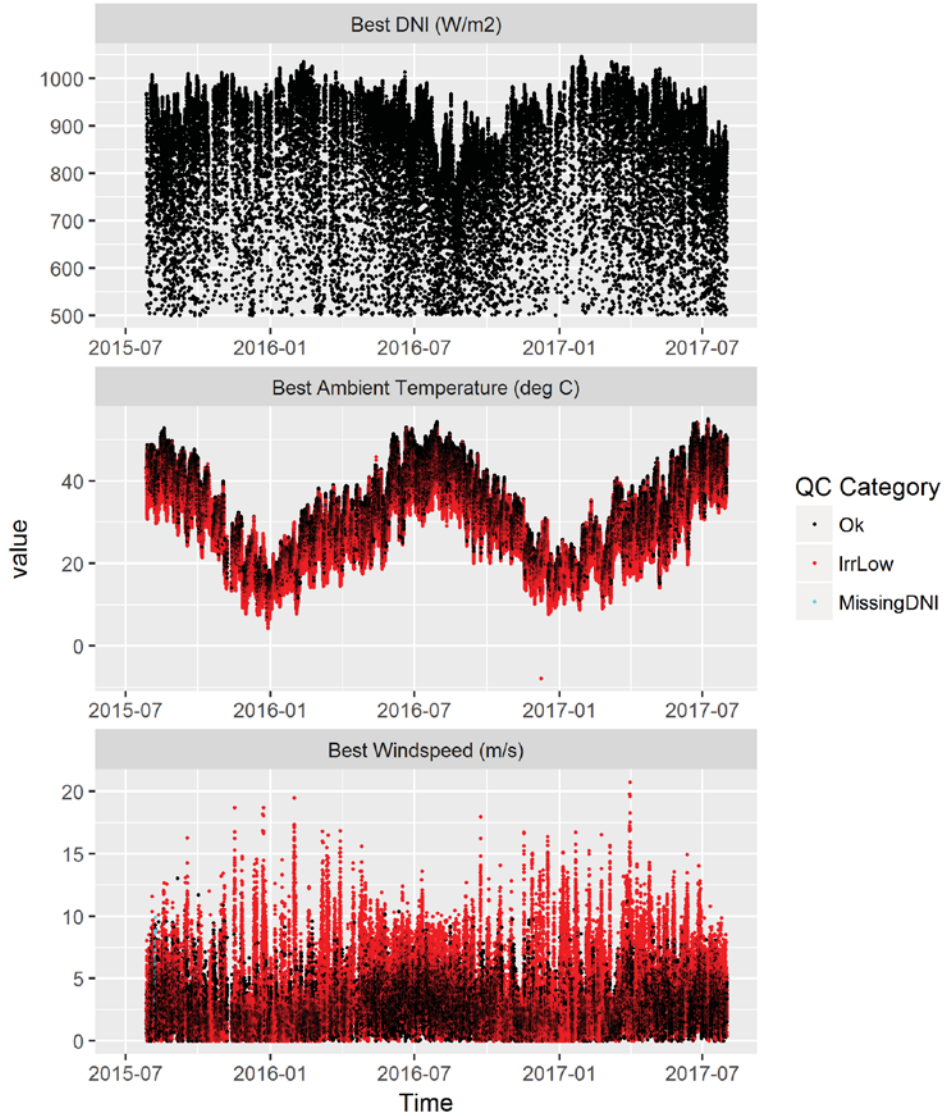

Figure 2-4. Best estimates of meteorological data

Table 2-1. Monthly distribution of meteorological quality marks

Month	Ok	IrrLow	MissingDNI
2015-06-01	-	-	100.0
2015-07-01	3.0	11.8	85.2
2015-08-01	38.4	54.0	7.6
2015-09-01	35.5	64.5	-
2015-10-01	25.9	74.1	-
2015-11-01	22.9	59.4	17.6
2015-12-01	21.6	78.3	0.2
2016-01-01	17.8	82.2	-
2016-02-01	33.2	66.8	-
2016-03-01	23.8	76.2	-
2016-04-01	22.9	60.3	16.8
2016-05-01	39.1	60.7	0.2
2016-06-01	44.0	56.0	-
2016-07-01	45.2	54.8	0.0
2016-08-01	41.5	58.4	0.1

2016-09-01	38.1	61.9	-
2016-10-01	27.9	72.1	-
2016-11-01	29.2	70.8	-
2016-12-01	16.8	83.1	0.0
2017-01-01	18.0	82.0	-
2017-02-01	18.2	81.8	-
2017-03-01	31.2	68.8	-
2017-04-01	31.8	67.1	1.1
2017-05-01	39.3	60.1	0.5
2017-06-01	42.4	56.5	1.0
2017-07-01	40.2	59.8	0.0

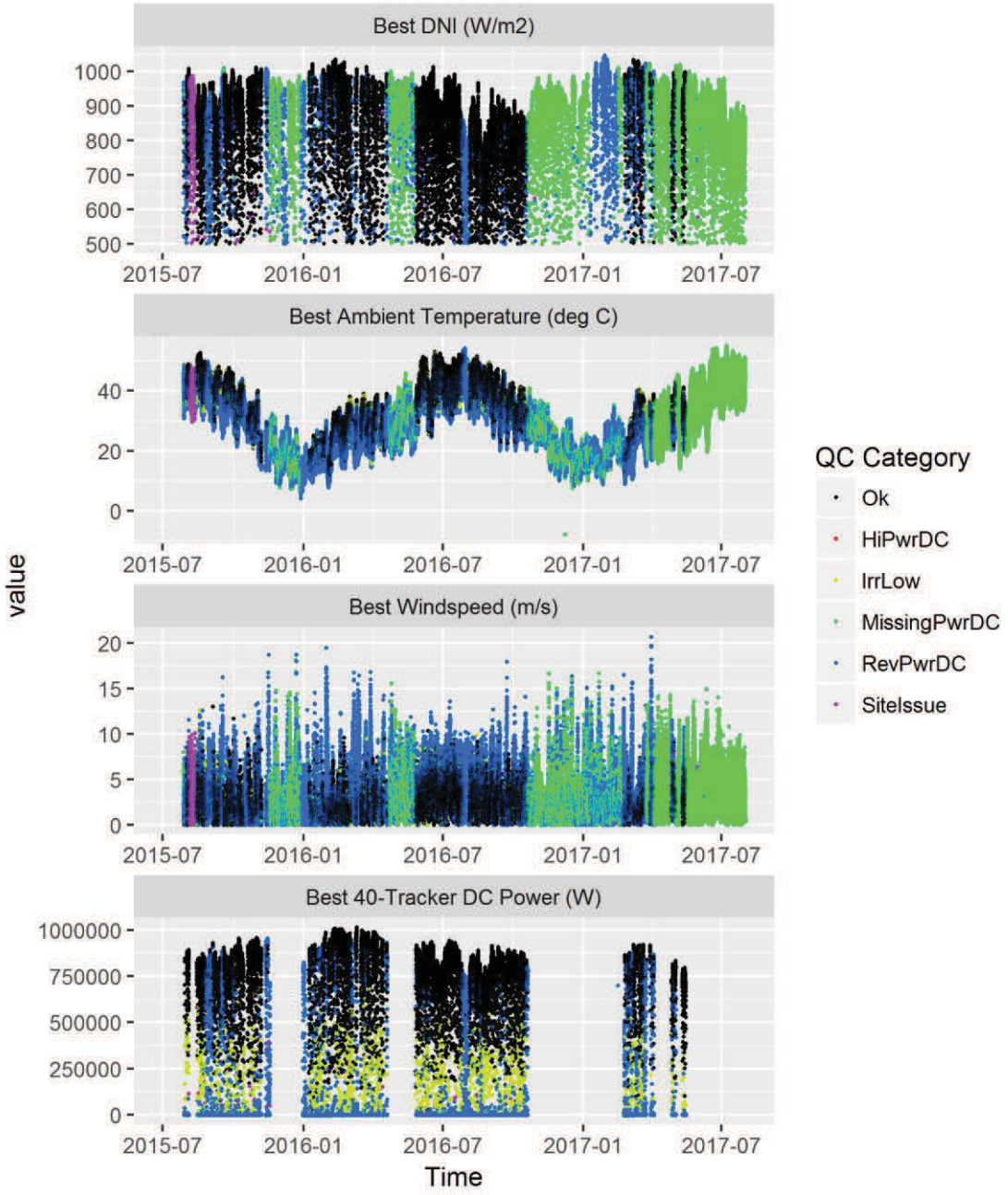

Figure 2-5. Quality trends for 40-tracker performance index inputs

Month	Ok	HiPwrDC	IrrLow	MissingPwrDC	RevPwrDC	SiteIssue
2015-06-01	-	-	-	100.0	-	-
2015-07-01	0.4	-	0.4	87.2	11.9	-
2015-08-01	21.2	-	3.2	0.1	42.7	32.8
2015-09-01	27.5	-	3.9	0.5	68.0	0.1
2015-10-01	24.5	-	2.9	0.2	72.2	0.1
2015-11-01	5.4	-	0.4	34.8	41.6	17.8
2015-12-01	-	0.1	-	67.4	32.3	0.2
2016-01-01	11.1	-	4.2	0.6	84.0	0.0
2016-02-01	30.7	-	2.9	0.1	66.2	0.0
2016-03-01	20.1	-	5.1	-	74.7	-
2016-04-01	13.1	-	2.8	19.9	47.3	16.8
2016-05-01	8.0	-	0.8	59.5	31.1	0.5
2016-06-01	42.8	-	5.8	-	51.0	0.5
2016-07-01	37.7	-	2.8	0.0	59.4	0.1
2016-08-01	35.5	-	4.8	0.3	59.2	0.1
2016-09-01	36.6	-	3.0	-	60.3	0.1
2016-10-01	17.8	-	3.6	28.3	50.3	0.0
2016-11-01	-	-	-	83.4	16.6	-
2016-12-01	-	-	-	74.5	25.4	0.0
2017-01-01	-	-	-	57.6	42.4	0.0
2017-02-01	2.3	-	0.2	44.1	53.4	-
2017-03-01	16.3	-	3.5	16.3	63.9	0.0
2017-04-01	6.6	-	0.7	75.4	16.1	1.2
2017-05-01	7.6	-	0.4	79.4	12.4	0.2
2017-06-01	-	-	-	98.9	-	1.1
2017-07-01	-	-	-	100.0	-	0.0

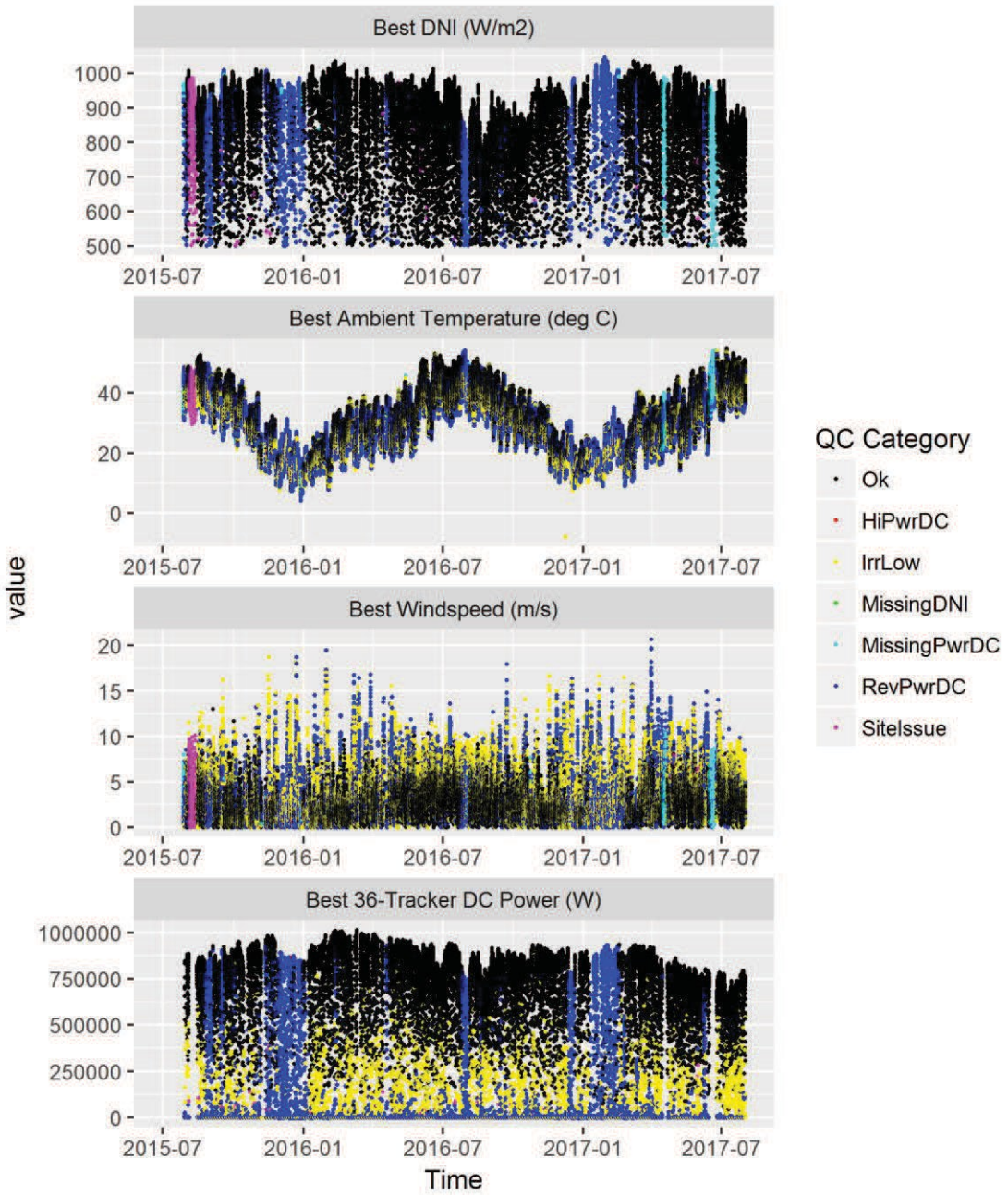

Figure 2-6. Quality trends for 36-tracker performance index inputs

Table 2-3. Monthly distribution of 36-Tracker performance data quality

MBegin	Ok	HiPwrDC	IrrLow	MissingDNI	MissingPwrDC	RevPwrDC	SiteIssue
2015-06-01	-	-	-	-	100.0	-	-
2015-07-01	0.4	-	4.7	-	87.3	7.6	-
2015-08-01	21.2	-	30.1	-	0.1	15.8	32.8
2015-09-01	28.2	-	48.0	-	0.4	23.3	0.1
2015-10-01	24.6	-	50.8	-	0.1	24.3	0.1
2015-11-01	16.3	-	42.0	-	0.1	23.7	17.8
2015-12-01	2.0	0.1	50.7	-	2.6	44.4	0.2
2016-01-01	17.0	-	57.4	-	0.1	25.5	0.0
2016-02-01	31.5	-	52.0	-	0.1	16.4	0.0
2016-03-01	23.5	-	50.9	-	-	25.6	-
2016-04-01	21.1	-	38.5	-	-	23.6	16.8

2016-05-01	38.1	-	42.2	-	0.4	18.7	0.5
2016-06-01	43.4	-	40.7	-	-	15.5	0.5
2016-07-01	37.7	-	38.6	0.0	0.0	23.6	0.1
2016-08-01	35.7	-	44.3	-	0.3	19.6	0.1
2016-09-01	36.9	-	46.6	-	-	16.5	0.1
2016-10-01	27.5	-	53.5	-	0.2	18.8	0.0
2016-11-01	29.0	-	54.3	-	-	16.7	-
2016-12-01	11.9	-	57.1	-	0.1	30.8	0.0
2017-01-01	4.2	-	53.7	-	-	42.1	0.0
2017-02-01	6.5	-	51.1	-	0.1	42.2	-
2017-03-01	28.5	-	47.2	-	-	24.3	0.0
2017-04-01	25.0	-	36.5	-	15.4	21.9	1.2
2017-05-01	39.0	-	40.6	0.5	0.0	19.6	0.2
2017-06-01	25.4	-	24.4	-	29.0	20.0	1.1
2017-07-01	40.2	-	44.3	-	0.0	15.4	0.0

Figure 2-7 confirms that the agreement between the two sensors is largely within a ±5% calibration band, and Figure 2-8 shows how the agreement drifts over time in 2016, and is occasionally reset (presumably by the actions of re-alignment cleaning).

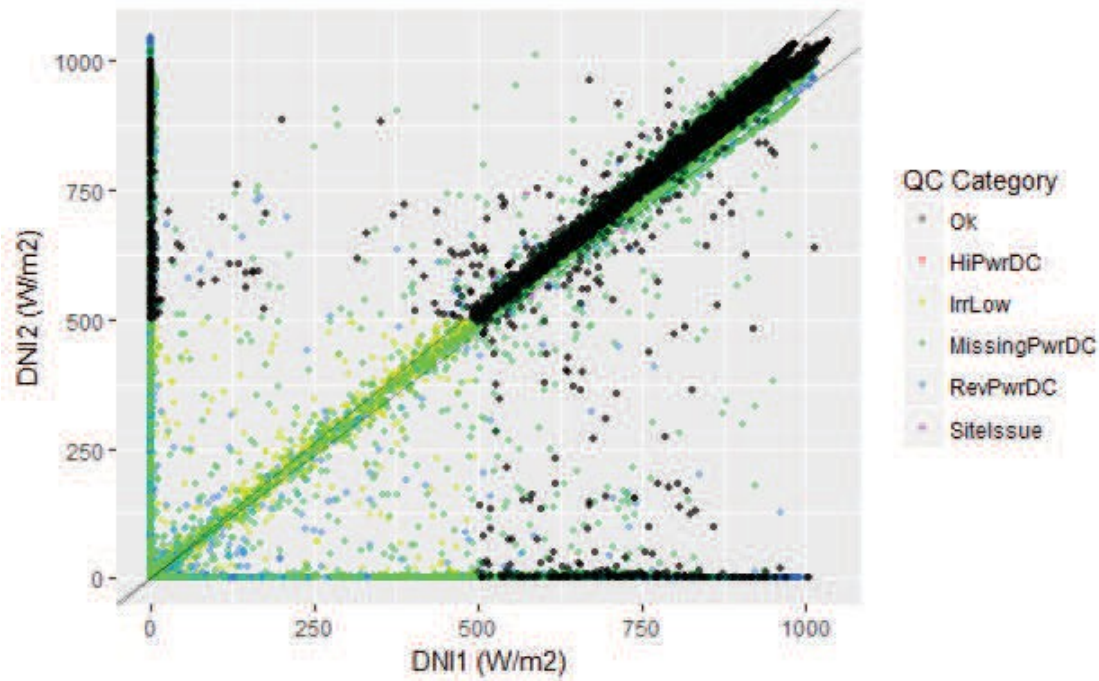

Figure 2-7. Comparison of DNI sensor readings

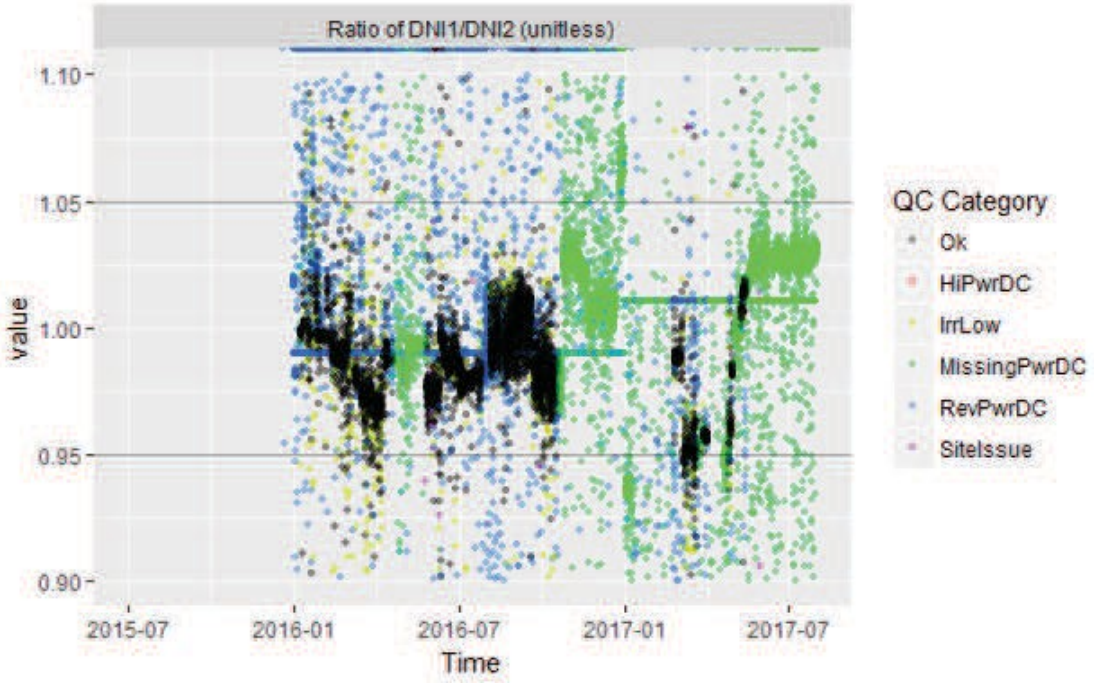

Figure 2-8. Trend of ratio of DNI1/DNI2

2.1.1.5 Reference Model

The reference model used was a set of PVsyst model files developed by Soitec for this project. The original (reference) simulation was run under PVsyst version 5.66.

Table 2-4. Files used in Fort Irwin Soitec CPV system model

Application_Note_PVSyst_v31_EN_2014-07-11.pdf	General guidance for design of PVsyst models with Soitec CPV modules
CX-M500_2335Wp_MOD-99009_1_0.PAN	Modeling parameters for module used at Fort Irwin
SMA_Central500CP.OND	Modeling parameters for inverters used at Fort Irwin
FORT IRWIN.MET	Typical meteorological data used in reference simulation
DOD Fort Irwin.PRJ	PVsyst project site assumptions file
DOD Fort Irwin.VC0	PVsyst project PV system assumptions file
DOD Fort Irwin approximated layout.SHD	PVsyst shade configuration
DOD Fort Irwin.SIT	PVsyst location specification file for this project

2.1.1.6 Simulated Generation

A total of six 8760-record[1] input files (2 sets of 3 years) were generated using the best estimate meteorological data above, one set with ("Corr") and the other set without ("Raw") the soiling correction applied to the irradiance data. Empty or missing data fields in the field meteorological data were filled with zeros in the PVsyst input files, with the understanding that each record has been marked per its quality so that records not marked "Ok" will be discarded. The PVsyst version used was v6.63 rather than the original v5.66, but typical annual production was verified to still be 2,543 MWh as it was in the original estimate.

Figure 2-9 shows the two sets of dc power (EArray as computed using either as-measured "Raw" DNI or soiling-corrected "Corrected" DNI) generated by PVsyst plotted versus the measured dc power, filtered per four different data quality approaches. Using the Raw DNI leads to measured power often exceeding modelled power. Using the Corrected DNI values equalizes or shifts the measured data down relative to the modelled values. Estimating total "measured" DC power using all 40 trackers (half of modules installed) leads to the fewest available data points, while using 36 of the most reliable trackers (45% of installed modules) allows system performance to be evaluated in more data records. For purposes of estimating the impact of availability the data quality can be relaxed to the level where all reasonable meteorological data that can be used to estimate a valid power production value is used. Finally, all data (no quality constraints) is shown for completeness. For each of the first three combinations, only "Ok" data points not marked for some quality issue are shown.

[1] Data on 29 February 2016 was not modeled since PVsyst standard input files are non-leap year size.

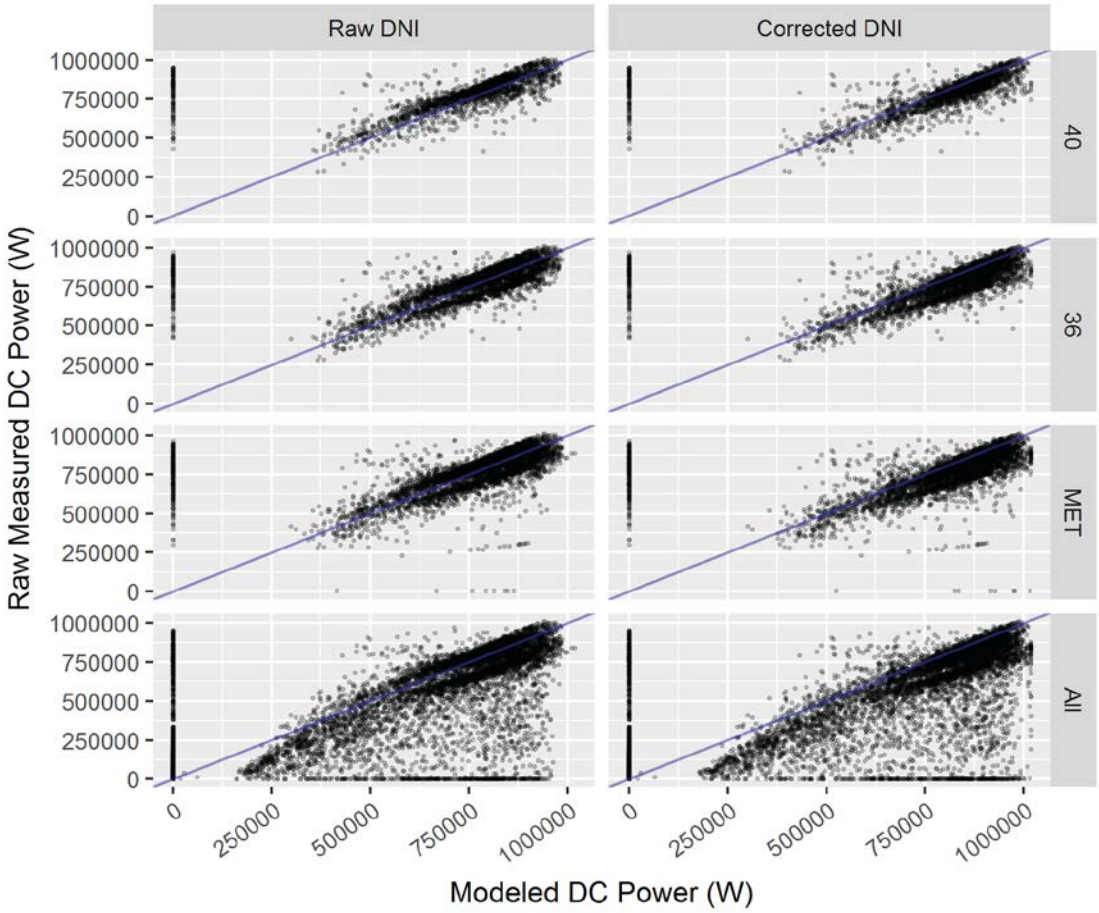

Figure 2-9. Agreement Plots of Measured vs. Modeled DC power

2.1.1.7 Performance Index

Performance Index is the ratio of actual to expected production, where in this case the expected production is set by the PVsyst model using measured meteorological inputs. For any given data record, this can be interpreted as the slope of a line in Figure 2-9 drawn from the origin to a data point. Trends of performance index over time can be used for diagnostic purposes, and the performance over a time interval can be computed using the ratio of energy produced over energy expected or the energy performance index. In this case, we have various concerns about data quality by time and tracker, so long-term energy estimates may be computed with different data quality restrictions as long as the same restrictions are used for excluding data in both the numerator and denominator of the ratio.

Figure 2-10 shows the trends of performance index computed using the data presented in Figure 2-9. No manual cleaning events were recorded in the operations logs, but a rainfall of 0.26 inches was recorded by Weather Underground on 24 July 2017 near the very end of the performance period. The performance index recovers quite distinctly at that point (visible at the end of the evaluation interval in Figure 2-10 but seen more clearly in the approximately 8% “level shift” between midday 22 July 2017 to 28 July 2017 in Figure 2-11), suggesting that soiling was a significant cause of the apparent downward trend in performance during the evaluation period.

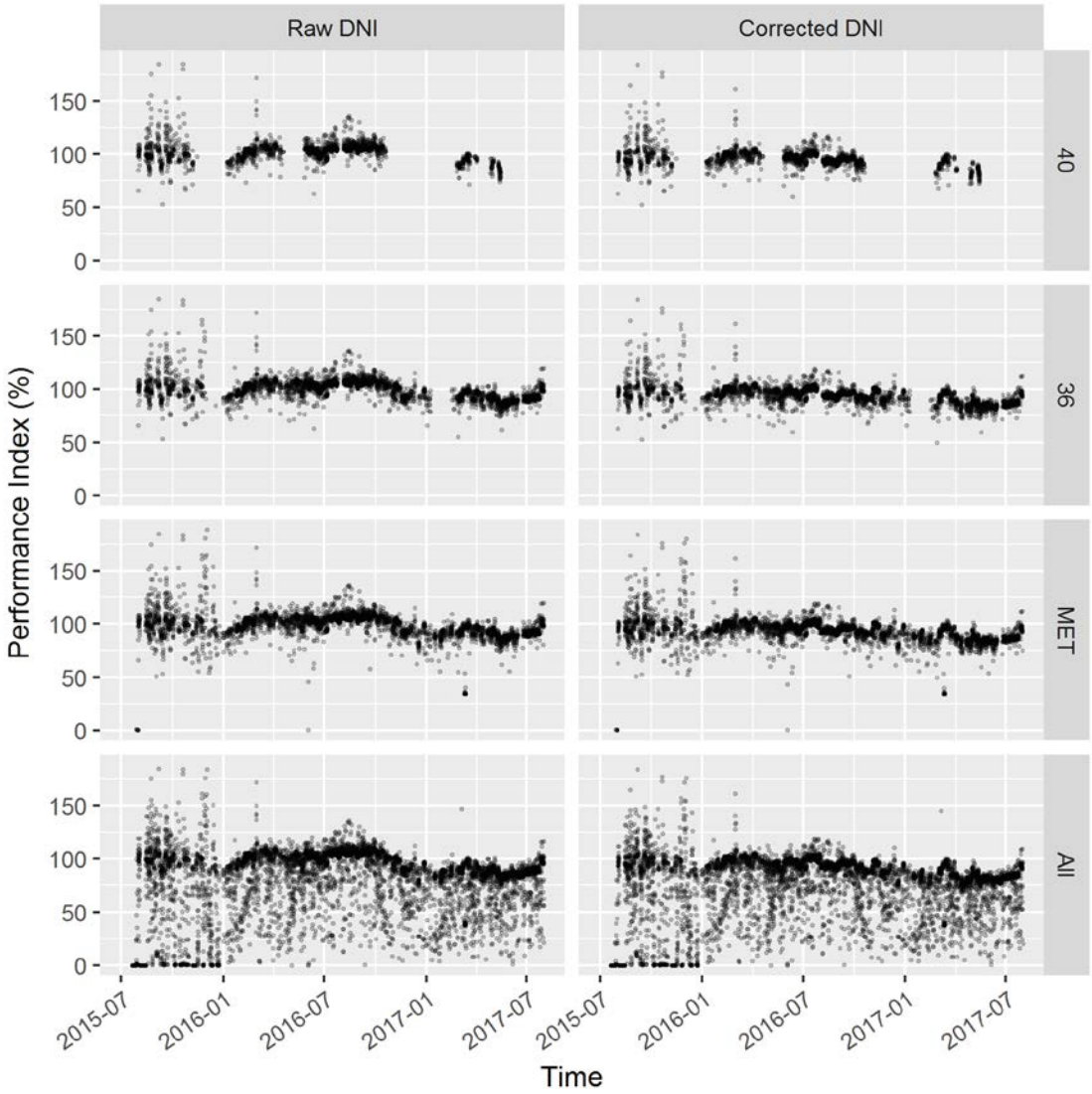
Raw DNI
Corrected DNI
40
36
MET
All
Performance Index (%)
150
100
50
0
2015-07
2016-01
2016-07
2017-01
2017-07
Time

Figure 2-10. Trends of Performance Index

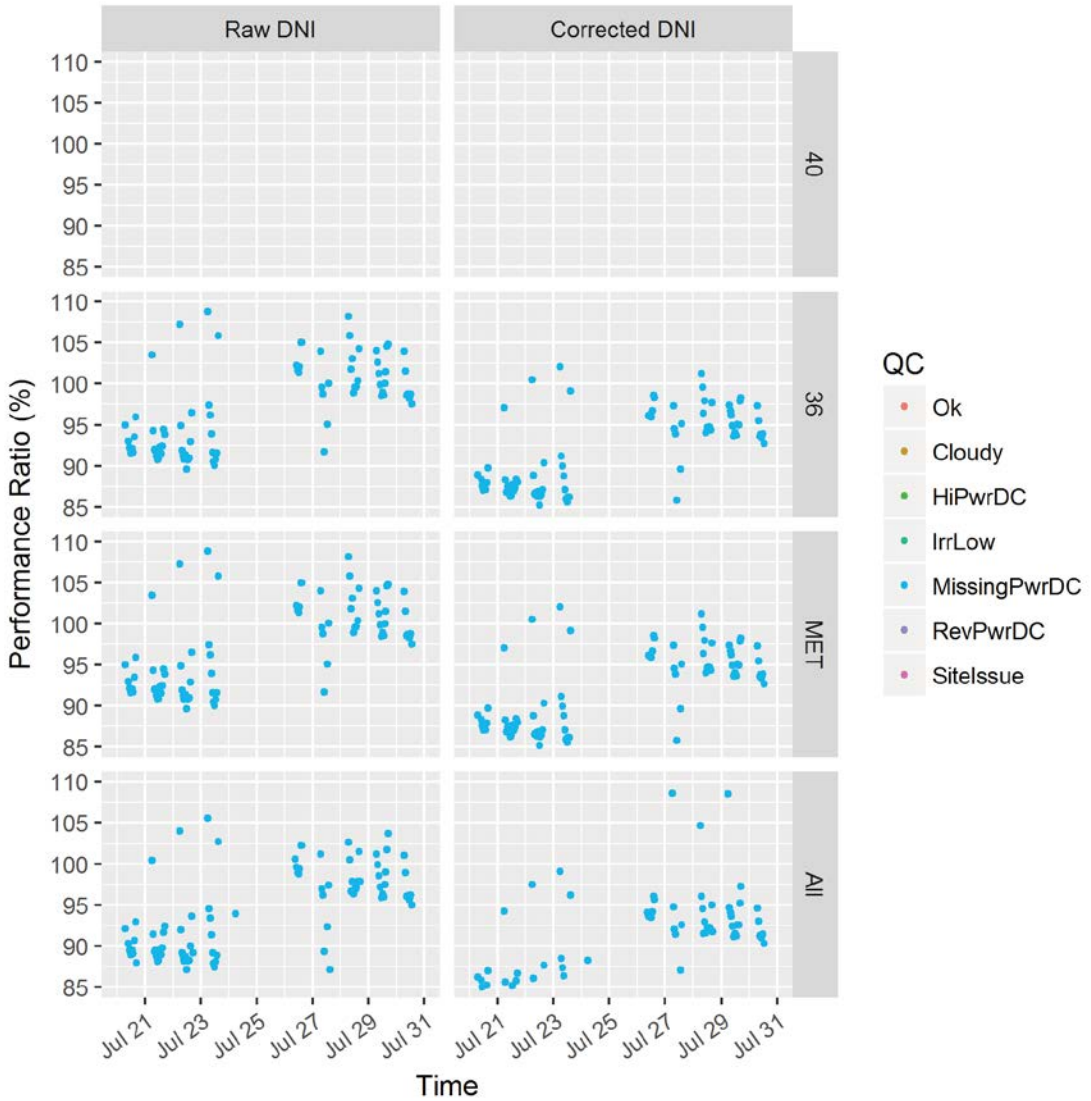

Figure 2-11. Performance Index Around 24 July 2017 Rain Event

For avoidance of doubt: the intent of using the Corrected DNI is to avoid setting the target production inappropriately low (which would lead to inappropriately high PI values), and is not used here to correct for soiling on the array itself.

2.1.2 Results

The accuracy of an energy production model such as the Fort Irwin PVsyst energy would ideally be judged on the total energy produced over the test interval. However, in practice, PV systems and their monitoring systems are composed of subsystems, not all of which may be functioning at once. For example, comparing all of the available energy produced with the energy prediction from the original typical-year model is an all- effects considered approach to verifying the original production estimate but if the weather conditions during the test interval were significantly different than the long-term average then PI metric is likely to inform the observer better regarding equipment function than the raw data will.

In the methods section above we discussed a couple of energy production expectations for power production and four approaches to quality control (40 trackers power, scaled-up power for 36 trackers, limiting only to

acceptable meteorological data, and all data considered). To the second set of options we add here summaries drawn directly from the reference simulation (TMY) for comparison.

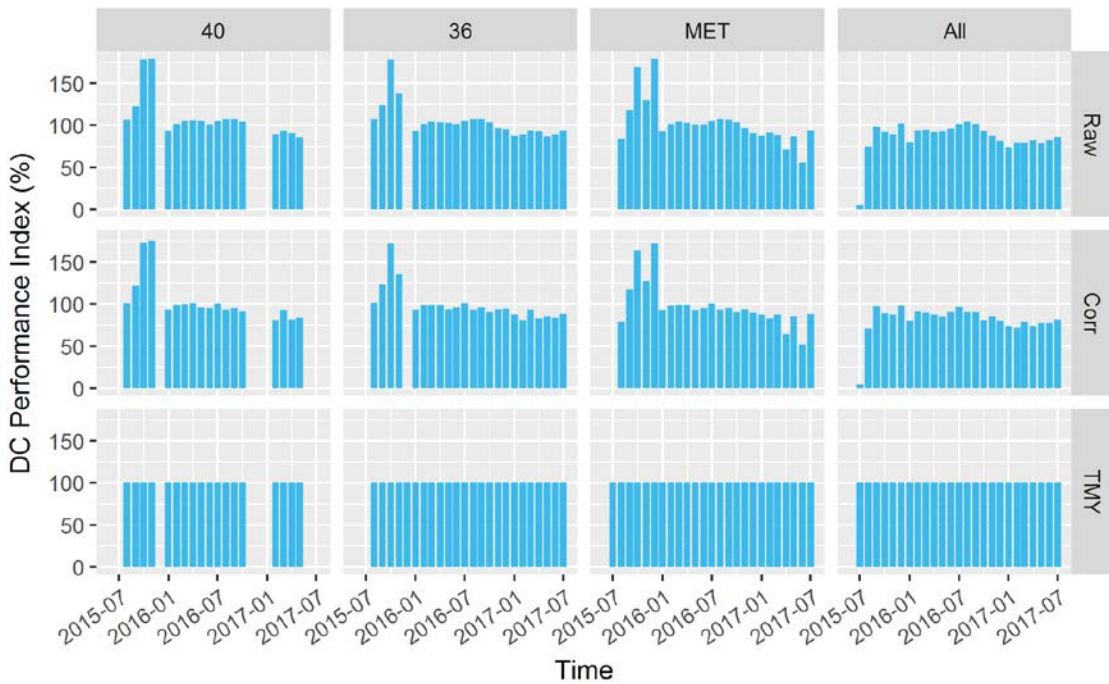

Figure 2-12. Monthly DC Performance Index for subsets of data

Of the above combinations, the best long-term estimate of overall system production relative to expectations is DC performance index using corrected irradiance and 36 trackers, at 97.2%. However, this metric includes the uncertain estimate of soiling magnitude obtained by comparison with non-co-located reference weather sites, and depends on measurements of only 45% of the modules in the system. An alternate metric for overall system performance is the Corrected-DNI 40-tracker performance index at 101.3%, but this omits some low performance periods later in the evaluation period. Neither of these metrics includes performance during reduced system availability, so the weather-only data quality used in the MET quality category includes all data records where expected power production could be estimated, including low availability periods.

Table 2-5. Overall summary of energy performance metrics

Type	QC	Measured (kW)	Modeled (kW)	Irradiation (kWh/m2)	DC Yield (kWh per kWh/m2)	PR_{dc}	PI_{dc}
Raw	40	1697511	1574517	1847	1514	82.0	107.8
Raw	36	2805916	2721764	3119	2503	80.2	103.1
Raw	MET	3233414	3298535	3843	2884	75.1	98.0
Raw	All	3961497	4485696	5151	3534	68.6	88.3
Corr	40	1697511	1675964	1967	1514	77.0	101.3
Corr	36	2805916	2885285	3318	2503	75.4	97.2
Corr	MET	3233414	3493784	4082	2884	70.7	92.5
Corr	All	3961497	4757211	5470	3534	64.6	83.3
TMY	40	1508298	1508298	1658	1345	81.2	100.0
TMY	36	2530357	2530357	2771	2257	81.4	100.0
TMY	MET	3114820	3114820	3423	2779	81.2	100.0
TMY	All	5266612	5266612	6044	4698	77.7	100.0

To avoid the erratic 2015 performance data apparent in Figure 2-12, Table 2-6 provides the same summaries as Table 2-5 but excludes 2015 performance.

Table 2-6. Post-2015 energy performance metrics

Type	QC	Measured (kWh)	Modeled (kWh)	Irradiation (kWh/m2)	DC Yield (kWh per kWh/m2)	PR_{dc}	PI_{dc}
Raw	40	1332666	1300268	1441	1189	82.5	102.5
Raw	36	2378781	2403604	2647	2122	80.2	99.0
Raw	MET	2625111	2791330	3079	2342	76.1	94.0
Raw	All	3221962	3599536	4118	2874	69.8	89.5
Corr	40	1332666	1393547	1551	1189	76.7	95.6
Corr	36	2378781	2557960	2834	2122	74.9	93.0
Corr	MET	2625111	2969021	3294	2342	71.1	88.4
Corr	All	3221962	3831189	4403	2874	65.3	84.1
TMY	40	1164658	1164658	1283	1039	81.0	100.0
TMY	36	2128841	2128841	2334	1899	81.4	100.0
TMY	MET	2485242	2485242	2730	2217	81.2	100.0
TMY	All	4017558	4017558	4601	3584	77.9	100.0

The evaluation of energy production capability is that "energy produced is within 2% of baseline model or targeted value, when the outliers are removed from the full data population." The targeted generation modelled with Corrected DNI provides least bias error regarding instrumentation soiling, and the measured generation extracted from 36 working trackers excludes tracker availability outliers, and evaluating post-2015 performance avoids erratic (over-) performance identified at the beginning of the evaluation period, so the best metric for operating performance is a PI of 93.0%. However, if the soiling on the array is comparable with the soiling on the pyrheliometer, then the Raw 36 PI of 99.0% would have reduced bias error in representing array performance absent soiling but have greater random uncertainty due to possible soiling discrepancies between the measurement system and the power system.

2.2 Availability Review

2.2.1 Methodology

The following section describes the methodology used for the availability review including a description of the dataset and the availability definitions.

2.2.1.1 Data Intake

Soitec provided the following data for the period of August 2015 through July 2017:

- 15-minute Supervisory Control and Data Acquisition (SCADA) data including power, direct normal irradiance (DNI), temperature, and wind speed [1]; and
- Annual summary for all work undertaken at the Project [3].

2.2.1.2 Synthesized Records

DNI data was provided from two sensors and was synthesized into a single value for the purpose of this analysis. To synthesize the value, the difference between the two DNI readings was calculated. Where the sensors agreed within 90% of each other, the average value was used. If the sensors did not agree, due to a bad sensor reading, the higher of the two values was used. During the period of 8 December 2015 through

29 December 2015, both DNI sensors were reading low values, virtually zero, for the entire period. DNV GL expects that these low readings are due to sensor error, and thus has considered this as zero data coverage and excluded the period from this analysis.

DNV GL identified periods where power readings were null for a single tracker, while data was available for the other trackers. It is expected that this loss of data is due to tracker downtime. Because of this, DNV GL assumed a synthesized power value of 0kW for periods when a single tracker was missing data. During periods when all trackers were missing power data, DNV GL expects that there was a site-wide outage. Thus, during these periods, a power value of 0 kW was assigned to all trackers.

2.2.1.3 Data coverage

Data coverage is a measure of how much valid data is within a given dataset. The data coverage for the dataset is shown in Figure 2-13 by month. The DNI data coverage reflects the synthesized DNI value as discussed above with the period of 8 December 2015 through 29 December 2015 considered to have zero data coverage.

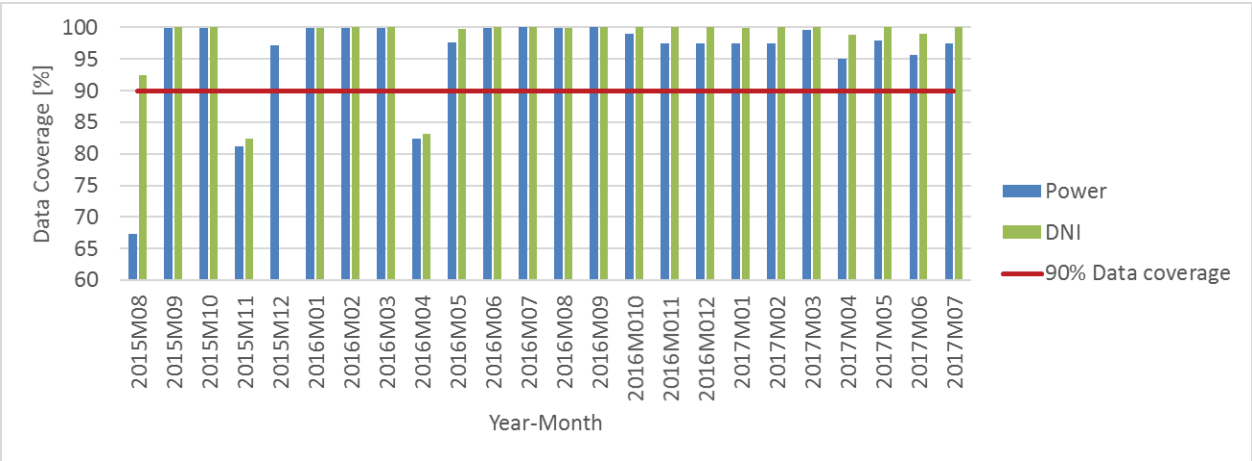

Figure 2-13 Monthly data coverage

DNV GL noted that during some periods there was no valid power or DNI data. It is expected that at least some of these periods of missing data are due to site-wide outages. Because these periods of missing data are essential excluded from the analysis due to no data coverage, the overall plant availability results may be slightly higher than the actual performance. However, these periods are excluded from the tracker availability and do not affect the results.

2.2.1.4 Availability Calculation

The availability definition used for this analysis is a ratio of the number of online records and the total number of records:

$$\text{Availability} == \frac{\text{Number of records with trackers online}}{\text{Total number of records}}$$

Two types of availability are considered:

- System availability – This is an “all-in” availability that considers all sources of downtime regardless of cause.

- Tracker availability – This is an “in-scope” availability that excludes site-wide events that are not within the scope of the operator.

DNV GL reviewed plots of power versus DNI plots for the tracker at the Project to determine an appropriate threshold for online/offline periods. Figure 2-14 shows a representative plot from Tracker 2. DNV GL notes a clearly defined horizontal grouping of points of 0 kW to ~400 kW at the bottom of the plot. These points represent periods when DNI resource was available, but the tracker was not producing.

Above these points there is some scatter, then a strong trend of average power versus DNI is apparent (shown with the blue line on the plot). This line represents the expected power, which is approximately equal to 20xDNI. Between the expected power and the online/offline threshold there are periods of scatter, some of which can be attributed sensor error due to the distance between the DNI sensor and the tracker. Other scatter is a result of poor performance by the tracker. Despite the lower power in this scatter area, DNV GL considers the tracker to be online during these periods. To avoid sensor error and tracker performance from impacting the availability calculation, DNV GL selected an online/offline threshold of 1,000 kW. The data points above the threshold are considered online records. Using this threshold ensures that the calculation is a measure of availability, not dependent on performance.

The yellow box below, shows records where little to no DNI is measured, yet the tracker is producing. DNV GL considers these points to be a result of invalid DNI readings. To remove these points and other noise from start-up/shutdown periods, only records with a DNI>500 W/m^2 were considered in the calculation; this is marked with the red line in the plot below.

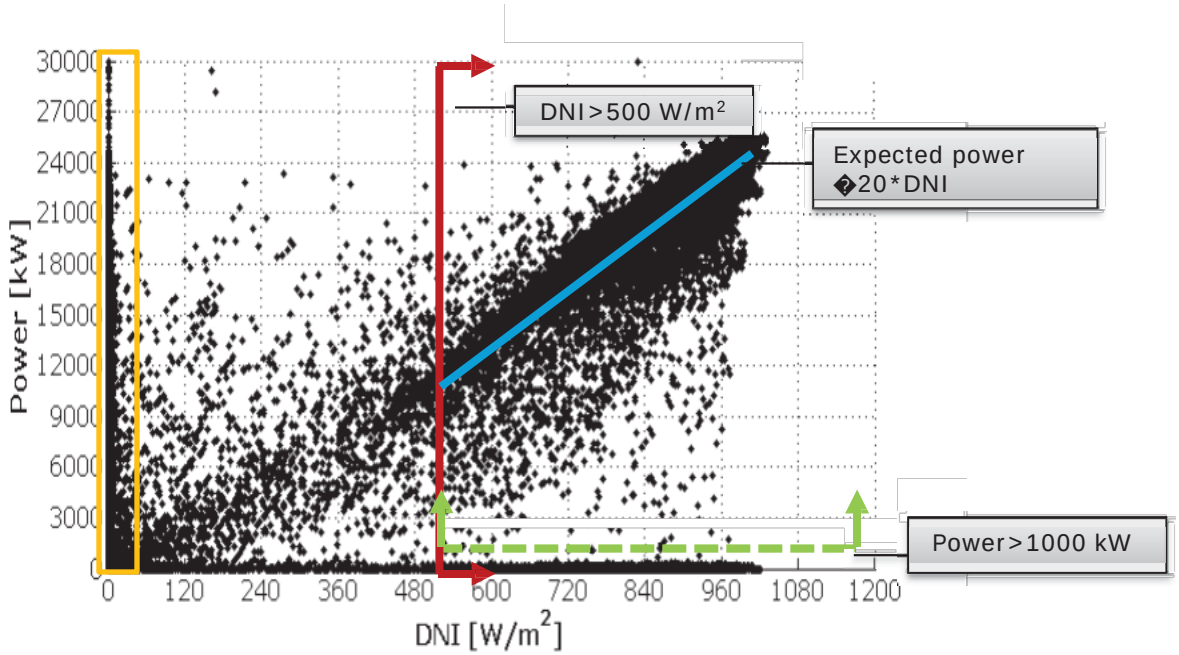

Figure 2-14 Representative power versus DNI plot

2.2.2 Results

Using the methodology described above, DNV GL calculated the system and tracker availability. The overall System and Tracker Availability was 95.2% and 96.7%, respectively. The difference between the two values suggests that 1.5% of the downtime was a result site-wide events; however, as noted previously, the System Availability may be skewed high due to missing data during site-wide outages. DNV GL understands that the Project had a target availability of 98%. Using the described method, the Project failed to meet the target for both System and Tracker Availability. The annual results of these calculations are shown in the table below.

Table 2-7 Annual availability results

Year	System Availability [%]	Tracker Availability [%]
2015	88.7	95.7
2016	97.7	98.0
2017		
Overall	95.2	96.7

The monthly system and tracker availability is shown in the plot below with a line indicating the target availability of 98%.

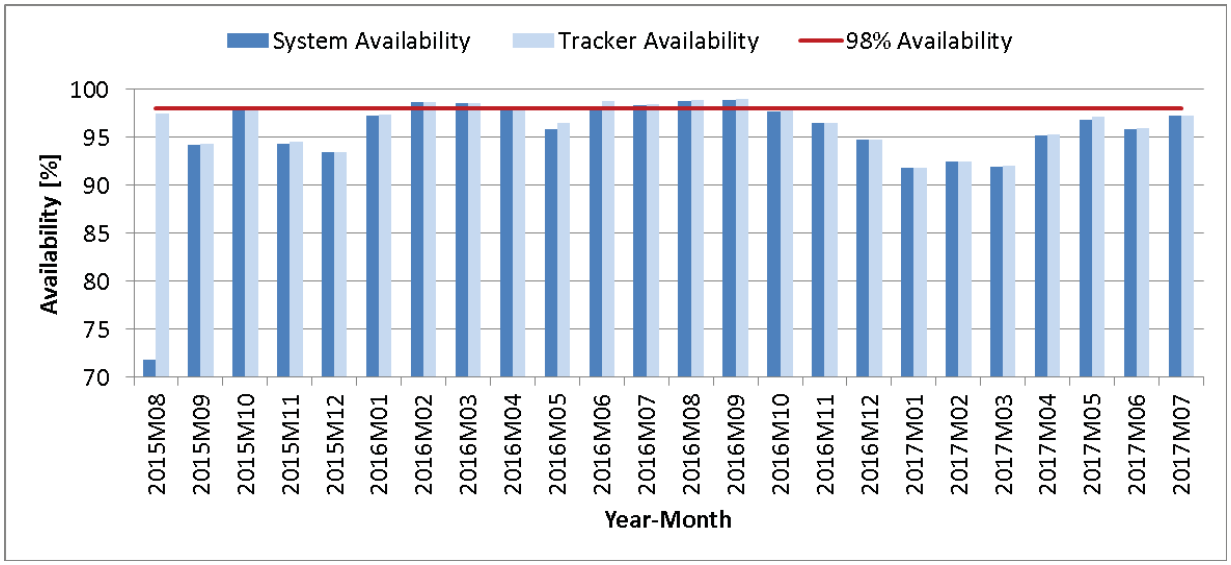

Figure 2-15 Monthly system and tracker availability

To further understand the availability of the Project, DNV GL reviewed the causes of downtime for months with lower availability. The following was noted:

- September 2015 – troubleshooting of faulted trackers occurred throughout the month. Additionally, Tracker 1 and Tracker 24 were offline for much of the month.
- May 2016 – Tracker 24 offline for most of the month.
- November 2016 – Tracker 24 offline for the entire month
- December 2016 – Tracker 24 offline the entire month; Tracker 2 periodically offline for much of the month. Trackers 26, 27, and 30 offline for a week.
- January 2017 – Tracker 24 offline the entire month; Tracker 2 periodically offline for much of the month. Tacker 38 offline for much of the month.
- February 2017 – Tracker 2 periodically offline throughout the month; Tracker 17, Tracker 24, and Tracker 38 offline for much of the month.
- March 2017 – Tracker 2 offline for most of the month; Tracker 17 offline for much of the month; many trackers were faulted 3/12-3/13.
- April 2017 – Tracker 2 offline for most of the month; Tracker 17 offline for most of the month.
- May 2017 – Tracker 2 offline for most of the month.
- June 2017 – Tracker 2 offline for the entire month; Tracker 12 offline for part of the month.
- July 2017 – Tracker 2 offline for the entire month.

DNV GL notes that much of the tracker downtime was due to only three trackers: 2, 17, 24. The Project reported that much of the extended tracker downtime is due to encoder failures. A retrofit was installed in February and March 2017 to address the encoder failures. Tracker 2 was down due to a unique failure that

has taken an extended time to repair. If this tracker is excluded, the resulting availability is 97.3% for the period. Excluding the three worst trackers yields an availability of 98.2%, which is above the target availability. Thus, approximately 0.7% of the availability loss is due to just Tracker 2 and of 1.5% of the downtime is a result of just three trackers. With those three trackers excluded, much of the remaining downtime is s result of encoder failures. DNV GL notes that following the retrofit installed to address this issue, the availability target was met each month. This is shown in Figure 2-16 below.

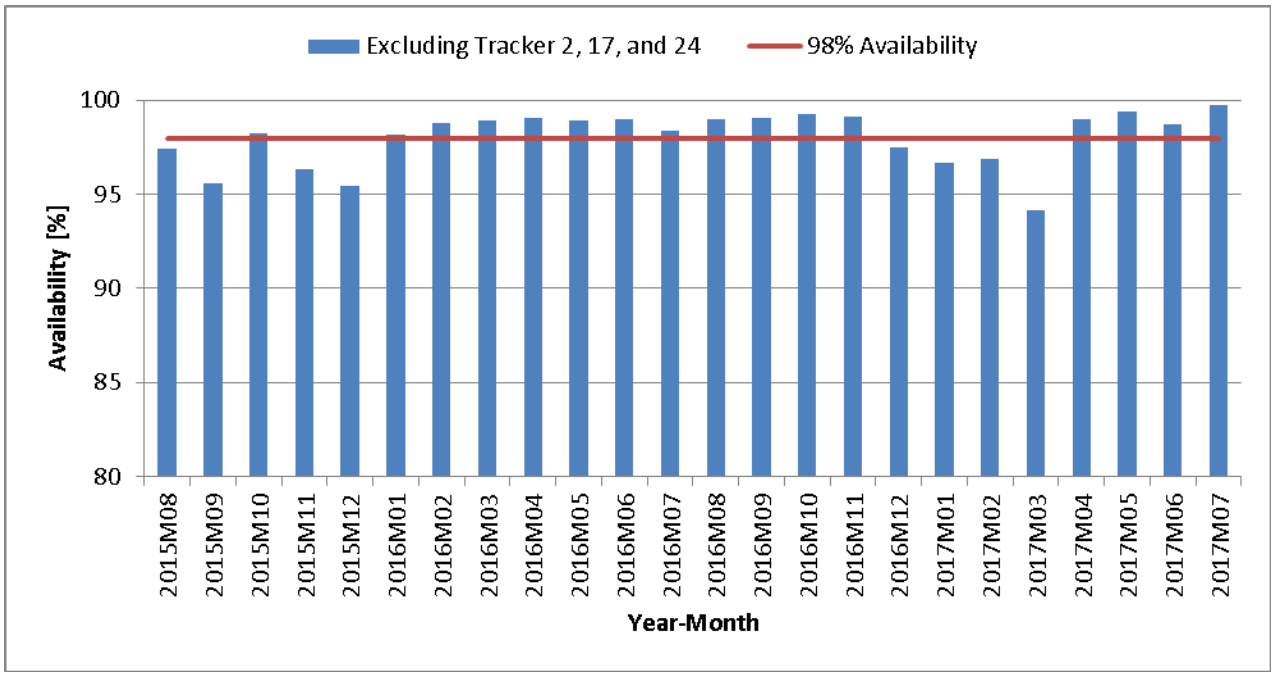

Figure 2-16 Tracker Availability excluding Trackers 2, 17, and 24

2.3 Degradation Analysis

Degradation is the overall change in production capacity of the equipment over time.

2.3.1 Methodology

Due to the evident array soiling, the trend of performance index values over time is not a reflection of changes in the production capacity of the power plant equipment. For this reason, the change in performance index observed during two short evaluation periods near the start and end of the evaluation period is used to indicate the change in equipment capacity.

For the purposes of estimating system capacity in this section we add to the quality control criteria used in the energy model validation, a `Cloudy` criterion wherever the best measured DNI estimate is less than the clear-sky DNI modeled using the apparently-conservative Laue 1970 [1] method.

To minimize the uncertainty introduced by use of the irradiance soiling correction, both short evaluation periods need to occur when the pyrheliometer and array soiling are negligible. The array and instrumentation were cleaned prior to the time of installation, and 16 August 2015 was the first available

clear day with good data quality. The array and instrumentation experienced a strong rain (0.26 inches in one day on 24 July 2017) near the end of the evaluation period, and 28 July 2017 was the day with best quality data available prior to the end of evaluation on 31 July 2017.

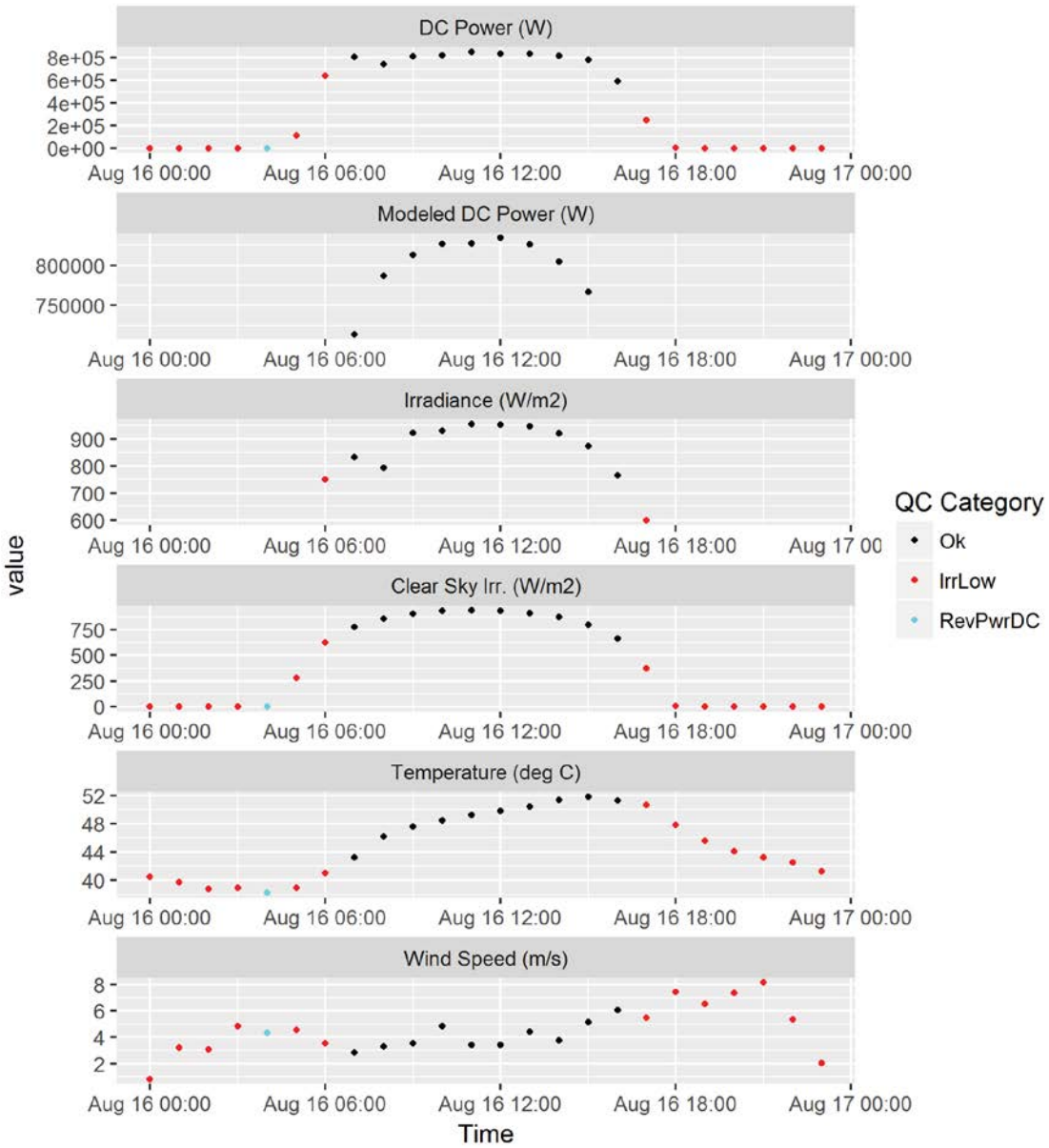

Figure 2-17. First degradation evaluation interval

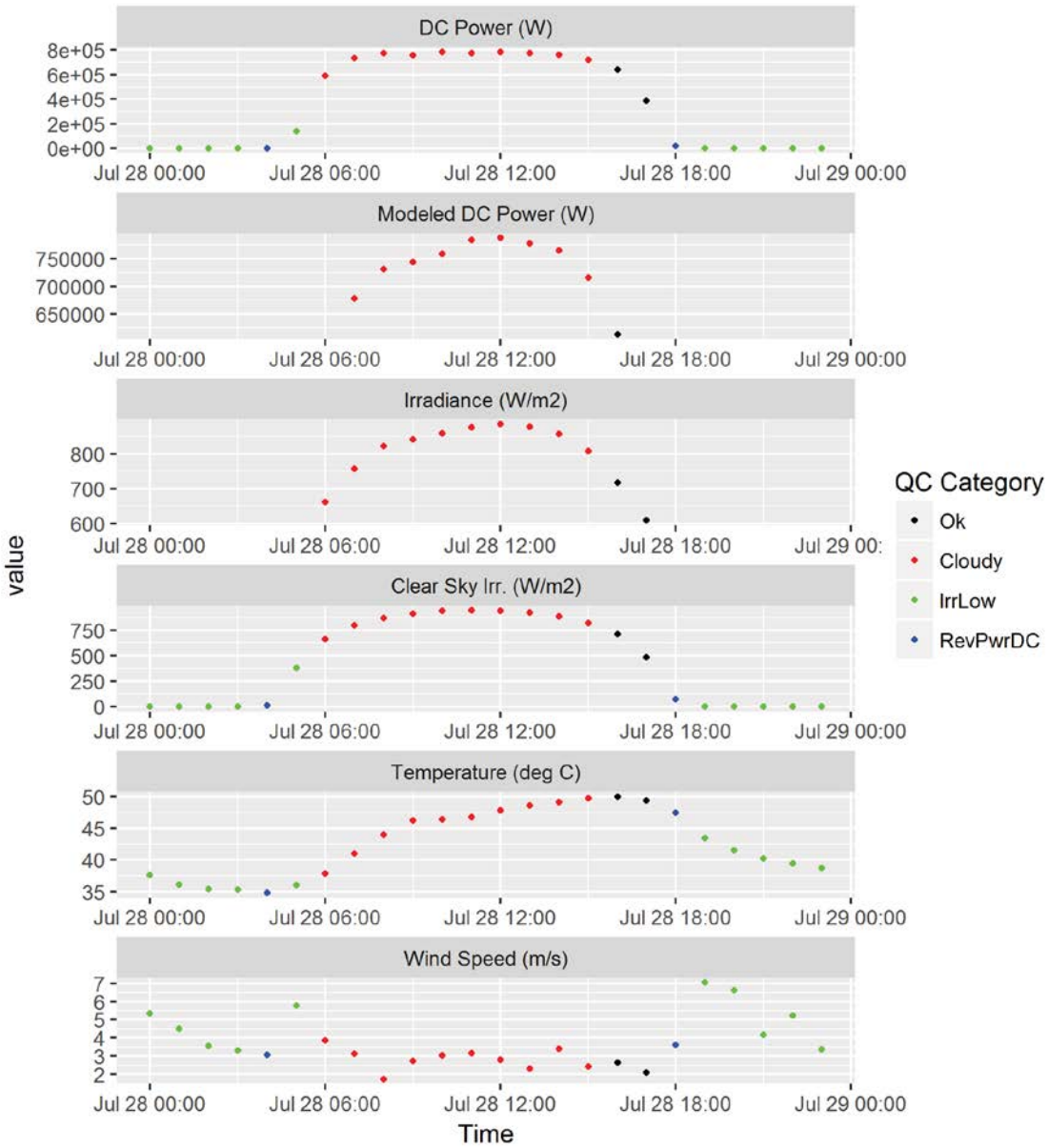

Figure 2-18. Second degradation evaluation interval

2.3.2 Results

Table 2-8. Evaluation Period Summary

Interval	Measured Energy (Wh)	EArray_Raw_36 (Wh)	DNI (kWh/m^2)	PI_{dc}
First	7903	7857	8.888	100.6
Second	1025	1003	1.325	102.2

This suggests an improvement in performance over time of +0.8%/yr , which is within the measurement uncertainty of 5%/yr of the expected -0.7%/yr. With a longer evaluation period the uncertainty of the performance index values (dominated by the irradiance uncertainty) could be amortized over more years and a more significant result could be obtained. However, this result does not suggest any cause for concern regarding module degradation.

3 CONCLUSIONS

Subject to the limitations of the data collection system, the best estimate for evaluating energy production capability of the equipment during the evaluation period is 99% of the modeled prediction, which is within the margin of 2% of expected energy production. Note that this estimate assumes that the soiling on the irradiance instruments is comparable to the soiling on the whole array, and omits low availability and poor data quality time intervals.

Overall system availability and tracker availability was found to be 95.2 and 96.7%, respectively, which is less than the target 98%. Much of the tracker downtime was a result of encoder failures, and following a design upgrade to the tracker encoders the monthly availability exceeded 98% consistently. Excluding the three lowest performing trackers yielded an availability of 98.2% for the period, which exceeds the target availability.

Reviewing performance during clear-sky conditions near the start and end of the evaluation period, the performance appeared to improve by 1.6%, but this is well within the 5% estimated uncertainty of the performance index. That is, there does not appear to be any cause for concern that significant degradation occurred during the evaluation period.

4 REFERENCES

[1] Excel files with SCADA data including direct normal irradiance, wind speed, ambient temperature, and power, provided by Soitec, 21 August 2017.

[2] PVSys model files, provided by Soitec, 21 August 2017.

[3] Annual summary of work undertaken, provided by Soitec, 21 August 2017.

[4] E. G. Laue, "The measurement of solar spectral irradiance at different terrestrial elevations," Solar Energy, 13(1), pp. 43-50, 1970.

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APPENDIX C SOLAR FORECASTING REPORT

The report from the University of California San Diego (UCSD) covers the solar forecasting performance objectives.

Proposal Number: 13 EB-EW2-077

Title: Concentrated PV Forecast System for On- Site Distributed Generation

Phase 5: Final Report

August 15,2017

Table of Contents

1 PROJECT DESCRIPTION 4

2 PHASE 5: FINAL REPORTING 4

3 PHASE 1.0 PRELIMINARY SOLAR RESOURCE ANALYSIS AND INSTRUMENTATION5

3.1 DATA COLLECTION, DE-TRENDING, FORECAST ENGINE TRAINING AND ANALYSIS 5

3.2 DEMONSTRATION OF FORECAST SYSTEM 9

4 PHASE 2.0 DETAILED SHORT-TERM SOLAR FORECAST DEVELOPMENT 10

4.1 TASK 2: STOCHASTIC LEARNING, CLOUD CLASSIFICATION AND SEGMENTATION ALGORITHMS.....10

4.1.1 Subtask 2a: Train algorithms using resource data from Task 1 10

4.1.2 Subtask 2b: Evaluate sky-imaging data and develop dedicated forecast for location.... 12

4.1.3 Subtask 2c: Automate sky imager forecast provision and supervise operation 13

4.1.4 Subtask 2d: Analyze short-term forecasting skills..... 14

4.1.5 Subtask 2e: Evaluate forecasting uncertainty..... 16

5 PHASE 3.0 INTRA-DAY SOLAR FORECASTING.....17

5.1 TASK 3.1: REMOTE SENSING ENHANCED BY STOCHASTIC LEARNING ALGORITHMS 17

5.1.1 Subtask 3a: Develop a regional sector model for the Fort Irwin location..... 18

5.1.2 Subtask 3b: Validate model with ground telemetry 18

5.1.3 Subtask 3c: Apply stochastic learning tools for output post-processing..... 20

5.1.4 Subtask 3d: Deliver intra-day forecasts to PI system (or equivalent) 21

5.1.5 Subtask 3e: Deliver intra-day forecasts to Web portal..... 21

6 PHASE 4.0: SOLAR AND POWER OUTPUT FORECASTING 21

6.1 TASK 4.1: DAY AHEAD SOLAR AVAILABILITY FORECASTS.....22

6.1.1 Subtask 4.1a: Train algorithms using locally generated and our own solar resource data 22

6.1.2 Subtask 4.1b:Develop 24 to 36 hour ahead solar forecast generated at 10 a.m. each day 25

6.1.3 Subtask 4.1c:Apply stochastic learning tools for output post-processing..... 27

6.2 TASK 4.2: PROSPECTIVE POWER FORECASTING.....27

6.2.1 Subtask 4.2a: Develop plant power output model for time horizons in phases 2 to 4 ... 27

6.3 TASK 4.3: 48-HOUR AHEAD DNI AND PO FORECASTS 32

6.3.1 Subtask 4.3a: Train algorithms using locally generated and our own solar resource data 32

6.3.2 Subtask 4.3b: Validation of the 48-hour ahead forecast models..... 33

7 CONCLUSION 34

APPENDIX 36

A ERROR METRICS.....36

B CLEAR SKY MODEL 37

C FORECAST MODELS.....38

C.1 Persistence model 38
C.2 MACHINE LEARNING MODELS 38
REFERENCES 41

1 Project Description

SOITEC constructed one 1 MWAC power plant at the U.S. Army's installation at Fort Irwin, California, to demonstrate its Concentrix concentrating photovoltaic (CPV) technology. This project will address ESTCP's objective of cost effective on-site distributed energy generation using CPV technology.

The project is comprised of six activities: site-specific system design; system assembly; system installation and commissioning; system deployment of in-situ DNI forecasting; performance monitoring and validation of forecasting algorithms.

UCSD provided solar forecasting services for the project. UCSD's forecasting engines are based on multi-layered data processing and machine learning algorithms, and its integrated load and solar generation forecasts have been extensively refined over the past few years for intra-hour, one to six hours, and up to 36 hours ahead.

The goal of this forecasting project is to provide high fidelity resource (DNI) and power output (PO) forecasts for CPV installation to be demonstrated at Fort Irwin. The intent is to demonstrate a direct, measurable benefit to the DoD by facilitating cost-effective ways to manage and distribute on-site solar generation, resulting in increased energy quality and security.

UCSD has demonstrated the next generation, intelligent forecasting platform that integrated publicly available, privately owned and proprietary real-time meteorological, generation and load data from high frequency sensor networks, satellite and ground based imaging, and meter telemetry. Improvements over traditional state-of-the-art forecasts provided increased visibility while reducing uncertainty.

2 Phase 5: Final Reporting

Demonstration Study Closure: UCSD provided input to the Demonstration Plan and a completed Final Report detailing the results of this project and its effectiveness for integration of distributed generation at Department of Defense facilities.

In this document we report on the technical activities pursued to achieve the project's objectives. The description of the technical activities and the forecasting results follows the project structure in the Demonstration Plan.

A general overview for the forecasting models produced in this project is given in Figure 1. The target variable (DNI or PO) is forecasted for horizons grouped in three categories: intra-hour (FH < 1 hour), intra-day (1 hour $\leq$ FH < 6 hours) and day-ahead (24 hours $\leq$ FH < 36 hours, and FH ≥ 36 hours). The forecast horizon is the length of time into the future for which forecasts are to be prepared. These forecasts differ in terms of issuing time: intra-hour and intra- day forecasts are produced continually every 15 minutes (a time-step equal to the data granularity). Day-ahead forecasts are produced only once daily at 10 am PST (Pacific Standard Time) in the case of the 24- to 36-ahead forecasts, in the case of ≥ 36 hours the forecasts are issued at 00:00 PST using daily averaged data.

The forecasts also differ in terms of predictors. Figure 1 indicates some of those variables for the different forecasts. For instance, intra-day forecasts make use of information derived from sky images, but day-ahead forecasts do not, as the information contained in the images is a very weak predictor of conditions for the next day.

In the sections below we explain in detail the predictors used to forecast DNI and PO for each forecasting horizon category and quantify in detail the resulting forecasting accuracy.

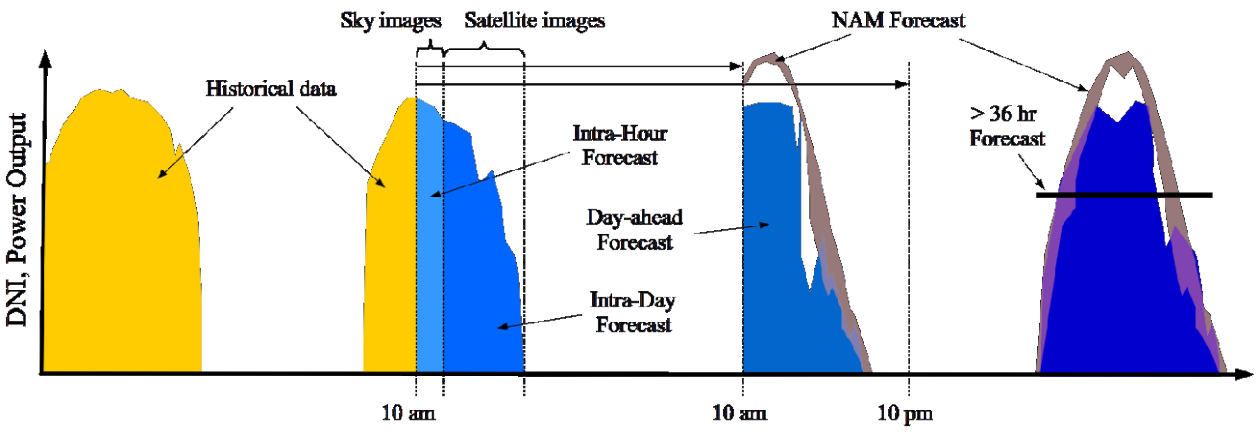

Figure 1: Forecast windows targeted for a forecast produced at 10 am (local time).

3 Phase 1.0 Preliminary solar resource analysis and instrumentation

3.1 Data Collection, De-Trending, Forecast Engine Training and Analysis

To demonstrate DNI and PO forecasts for Fort Irwin, we identified relevant inputs or predictors from historical data, historical satellite images and ground instruments. Data quality control and input selection were conducted for all data streams from ground sensors, plant power output, sky imagers, satellite images, and Numerical Weather Prediction (NWP) models, when appropriate.

After analyzing the data available from SOITEC instrumentation already installed on site, it was decided that the only additional instruments necessary were two sky cameras. UCSD provided SOITEC the hardware and technical assistance necessary to install and maintain the sky cameras.

Table 1 lists all the data sources used in this project and how they were obtained. The first six data sources comprise the local telemetry used in the project. Ambient data (DNI, temperature and wind speed) were obtained from instruments installed by SOITEC for monitoring the solar plant. The PO and solar tracker data were acquired by SOITEC from their plant monitoring tools. These data were transmitted to UCSD via email throughout the course of this project. Sky images were obtained from two sky cameras acquired by UCSD and deployed at the power plant by SOITEC, as mentioned. The cameras captured sky images and transmitted them via FTP to a server at UCSD (see Figure 2).

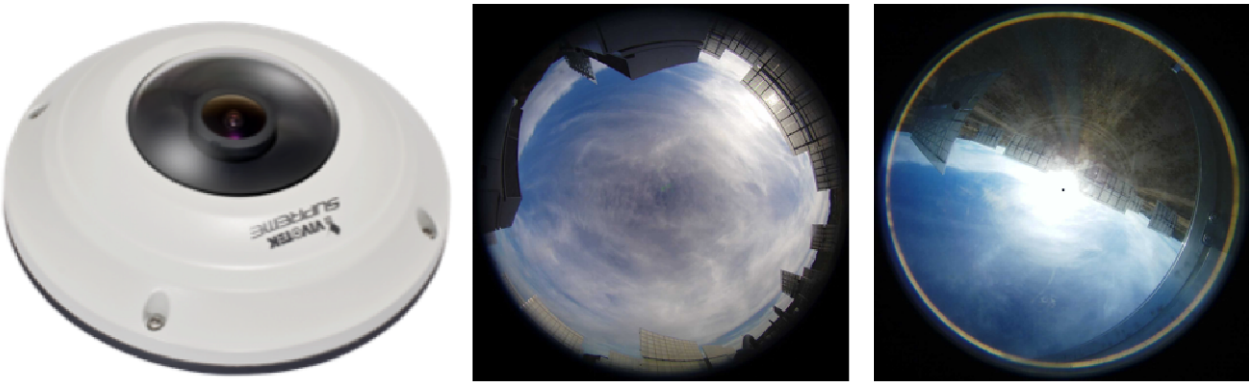

Figure 2: *Left:* Sky camera deployed at Fort Irwin. Two of these cameras were deployed on site. *Center:* Example of sky image obtained from the fixed, zenith-centered camera. *Right:* Example of sky image obtained from the tracker mounted, sun-centered camera.

The remaining two data sets listed in Table 1 originate from publicly available data streams and comprise the remote sensing data used in this project. The first one originates from forecasts produced by the North America Mesoscale Model (NAM). The NAM is a numerical weather prediction (NWP) model provided by the National Oceanic and Atmospheric Administration (NOAA) on a 12 km × 12 km spatial grid that covers the continental United States (CONUS). Forecasts are generated four times daily at 00Z, 06Z, 12Z and 18Z, with hourly temporal resolution for 1–36 hour horizons and 3 h resolution for 39–84 hour horizons. From all the NAM nodes that cover CONUS we select the ones nearest to Fort Irwin. Figure 3 shows the 13 NAM nodes selected.

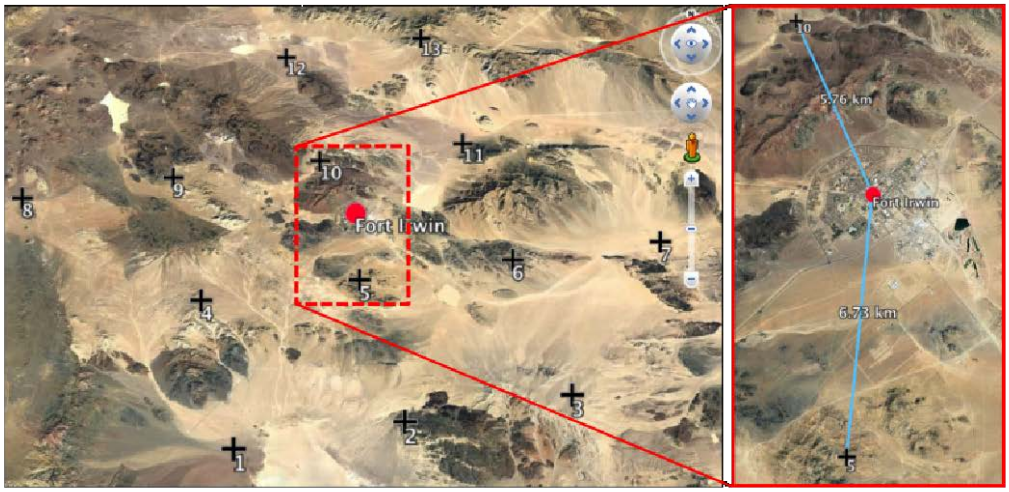

Figure 3: Nearest NAM nodes to Fort Irwin. The zoom on the right identifies the two nodes closest to the location of interest.

The NAM simulations produce a large amount of forecasted variables (e.g. wind speed, pressure at different altitudes, precipitation, etc.). For the purpose of this work we use only two variables that are closely related to the solar resource:

1. The downward shortwave radiative flux (DSWRF) [W/m2] at the surface, a synonym for GHI.
2. The total cloud cover (TCDC) [%], where the entire atmosphere is treated as a single layer.

The final remote sensing data set consists of satellite images acquired by the Geostationary Operational Environmental Satellite system (GOES), operated by the United States' National Environmental Satellite, Data, and Information Service (NESDIS). The motivation to include these images in the analysis is related to the fact that images obtained from the sky cameras have a limited field of view. Figure 4 shows examples of the GOES images used in this project.

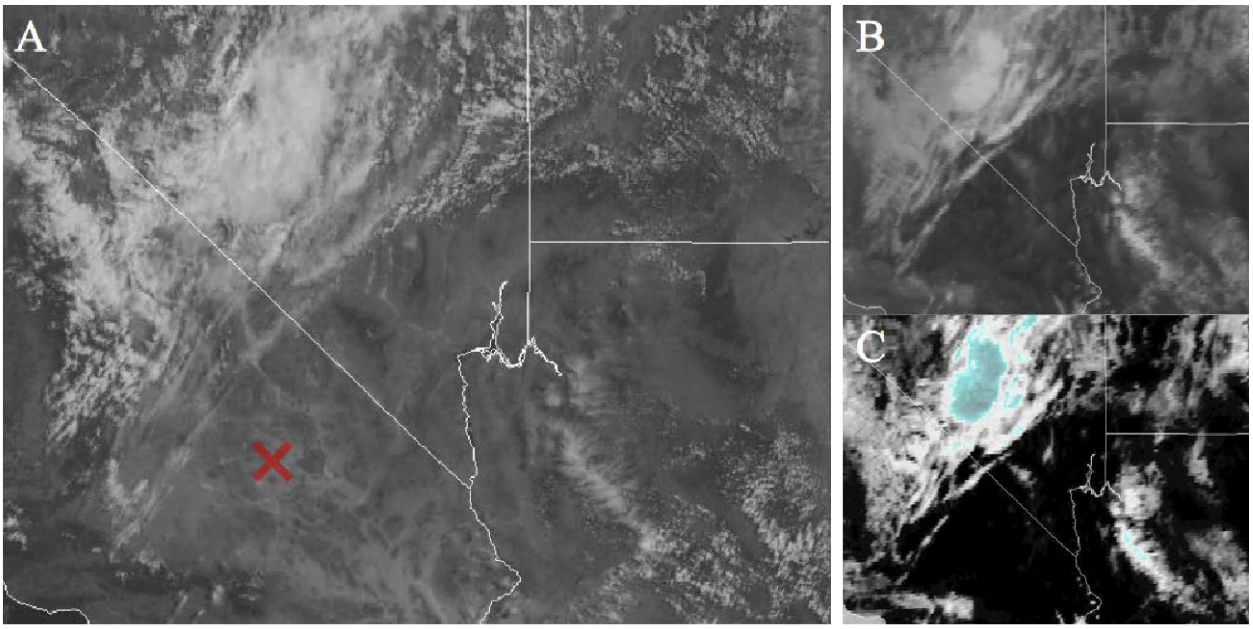

Figure 4: Examples of GOES images. (A) Image obtained with the visible (VIS) channel. (B) Image obtained with the infra-read (IR) channel. (C) Enhanced IR image to better distinguish clouds. VIS images are only available during the day. IR images are available day and night but have lower resolution than VIS images. The red cross in (A) identifies the location of Fort Irwin.

Table 1: List of data used in this project.

Data	Type	Description
DNI	Local	DNI data from two sensors installed and maintained by SOITEC. Data range: 2016-06-01 to 2017-05-30; Data resolution: 15 min.
Temperature	Local	Ambient temperature data from two sensors installed and maintained by SOITEC. Data range: 2016-06-01 to 2017-05-30; Data resolution: 15 min.
Wind Speed	Local	Wind speed data from two sensors installed and maintained by SOITEC. Data range: 2016-06-01 to 2017-05-30; Data resolution: 15 min.
Sky image	Local	Images captured with two sky cameras acquired and set up by UCSD with the assistance of SOITEC. One camera is mounted in a fixed zenith-centered position. The other camera is mounted in the solar tracked resulting in a sun-centered image. Image resolution: 2MP; Frequency: one image per minute; Range: 2017-04-15 to 2017-07-31.
PO for the whole plant	Local	Data obtained from SOITEC monitoring tools. Data range: 2016-06-01 to 2017-05-30; Data resolution: 15 min.
Solar tracker data	Local	Data for each one of the 40 solar trackers. Data obtained from SOITEC monitoring tools. Data range: 2016-06-01 to 2017-05-30; Data resolution: 15 min.
Satellite images	Remote	Satellite images from NOOA's GOES West satellite for the visible and infrared channel. Data range: 2016-06-01 to 2017-05-30; Frequency resolution: one image every 30 minutes.
NWP forecasts	Remote	Numerical weather forecasts from the North America Mesoscale Model (NAM) for the continental USA (CONUS). NAM forecasts provide GHI and cloud cover predictions out to 48 hours ahead of time at 1 hour resolution. Data range: 2016-06-01 to 2017-05-30; Data resolution: 1 to 3 hours; Spatial resolution: 12×12 km.

3.2 Demonstration of Forecast System

For this project we developed a web application to display the forecasts in real time using data from Folsom, CA. The website can be accessed at http://coimbra.ucsd.edu/projects/FIW/ (see Fig. 5).

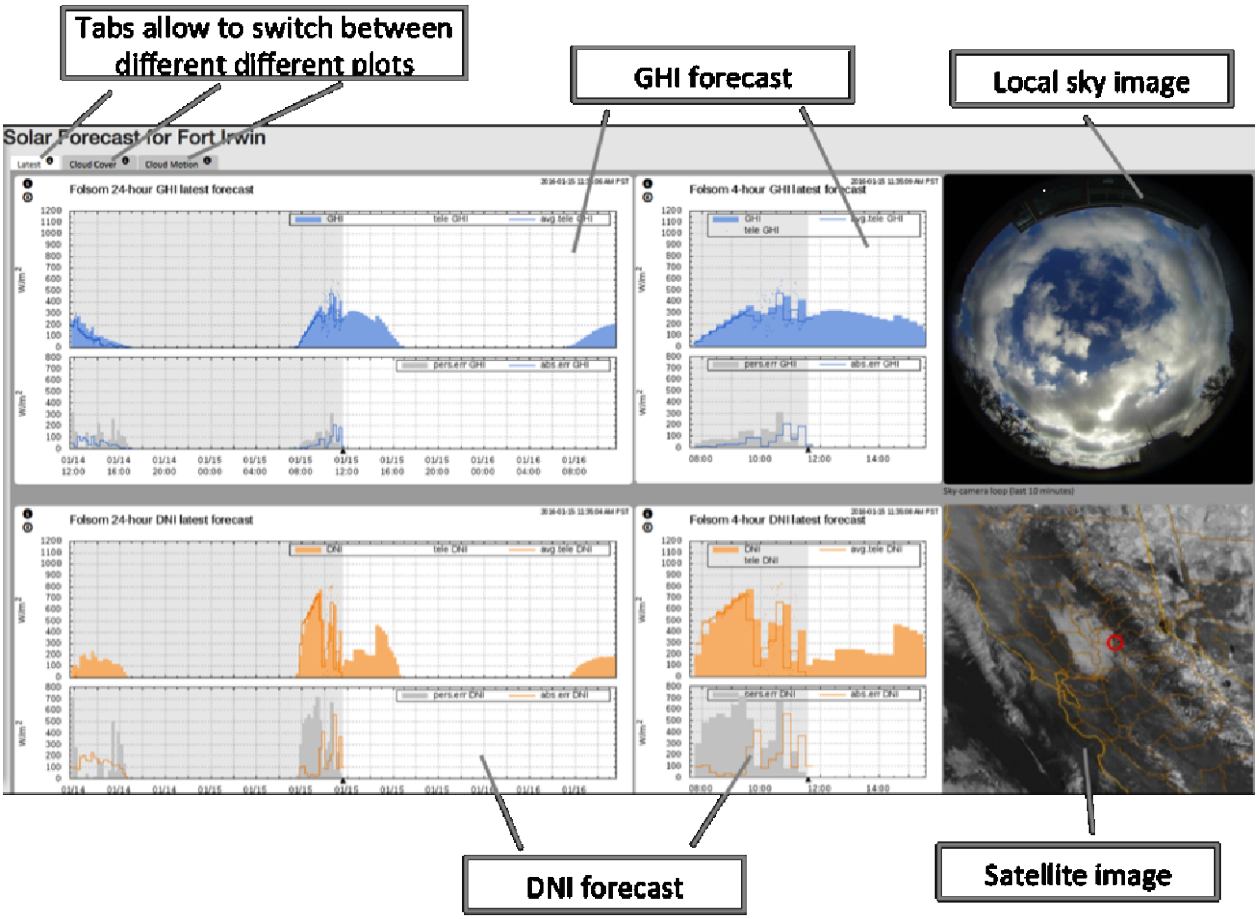

Figure 5: Prototype website to display the irradiance and power output forecasts developed in sub-task 2. Irradiance data used in the prototype is for Folsom, CA.

The web portal illustrates the forecasting output in real-time. New data is received from the local instruments and ingested by the forecast algorithms. We then produce several products (figures, tables, etc.) that show the forecasted values and forecasting accuracy based on the latest available telemetry.

4 Phase 2.0 Detailed short-term solar forecast development

4.1 Task 2: Stochastic learning, cloud classification and segmentation algorithms

In this task we used local telemetry to develop intra-hour irradiance forecasts. The intra-hour forecast includes the shortest forecasting horizons in this work, but it is the most challenging type of forecast in solar energy applications. This results from the fact that at these very short horizons we are not only interested in predicting the average behavior of the solar irradiance and power generation, but also in predicting their large and sudden changes: the ramps. Given that clouds moving in and out of the solar field are the key factor in determining these ramps, the intra-hour models rely on sky images. These images are essential to track the cloud motion and predict fluctuations in the solar generation. The activities for this phase are divided in 5 subtasks. Below we report on the activities for each one.

4.1.1 Subtask 2a: Train algorithms using resource data from Task 1

In this subtask we used the data obtained in Phase 1 to create intra-hour forecasts for DNI. For this horizon the most relevant data sources include the most recent irradiance measurements and sky-images.

At this location we have deployed two sky cameras: one centered at the zenith and another centered at the sun. Figure 6 illustrates how the images from these cameras are processed to extract information about clouds moving towards the power plant. The image processing is explained in more detail in Section 4.1.2.

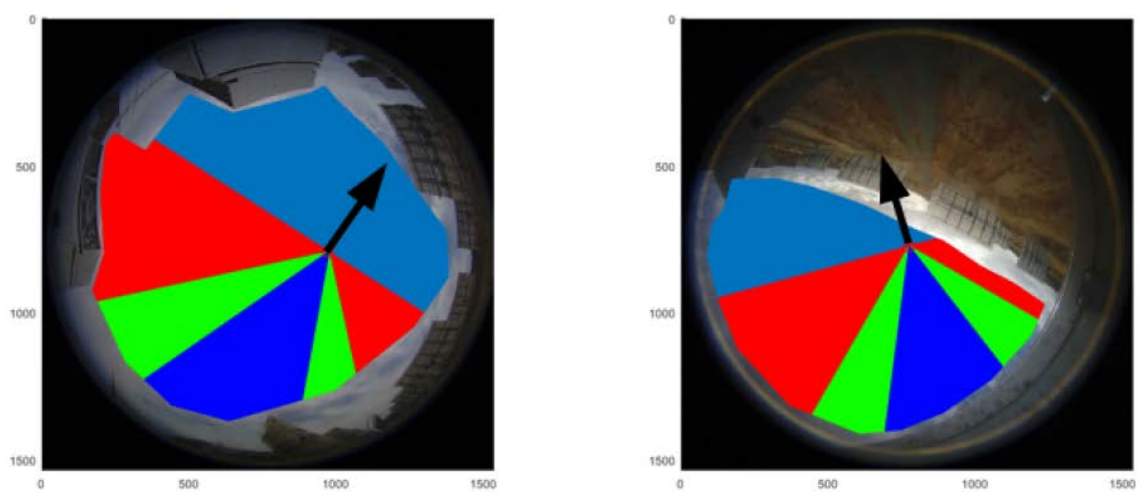

Figure 6: *Left:* zenith-centered sky image. *Right:* sun-centered sky image.

The benchmark model used for the intra-hour forecast is the clear-sky persistence model explained in Appendix C.1. The model assumes that the DNI clear-sky index (k_D) remains constant in the forecasting window $t_{issue} + [15, 45]$ minutes.

We also applied machine-learning tools to predict DNI for these horizons. We used the k-nearest-neighbors (kNN) model to predict DNI from its historical behavior (see Appendix C.2). The kNN model uses historical data to identify instances in the past (the neighbors) that resemble the conditions at the forecasting issuing time. The kNN predictions are created from the target variables (DNI or PO) in the historical data that correspond to the nearest neighbors. In this case the kNN neighbors are defined in terms of the following variables:

- DNI data and derived variables thereof. These consist of:
    a. The average (AVG) and standard deviation (STD) of k_D for the 30-, 60-, 90- and 120- minutes that precede t_{issue}.
    b. The *min* (MIN), *max* (MAX) and the slope (SLOPE) *max* − *min* values of k_D in the same time intervals.
- PO data and derived variables thereof. These consist of the same variables as in the case of DNI.
- Clear-sky index from the 40 trackers for the time t_{issue}.

The kNN model was optimized using the exhaustive search method explained in the Appendix C.2. The target variable for this forecast is not the DNI in the future but the step change between $t_{issue} + [15, 45]$ and t_{issue}. This approach makes the model more sensitive to large changes in the irradiance and produces better forecasts. The actual predicted DNI is calculated as:

$$\boldsymbol{\widehat{D}_{kNN}(t) = (\delta_{knn}(t) + k_D(t_{issue})) \times D_{clr}(t)} \quad (1)$$

where the step change $\delta_{knn}(t)$ is computed with the kNN model, and $D_{clr}(t)$ is the theoretical clear-sky DNI computed with the model explained in Appendix B. The model was trained and optimized with the data shown in blue in Figure 7.

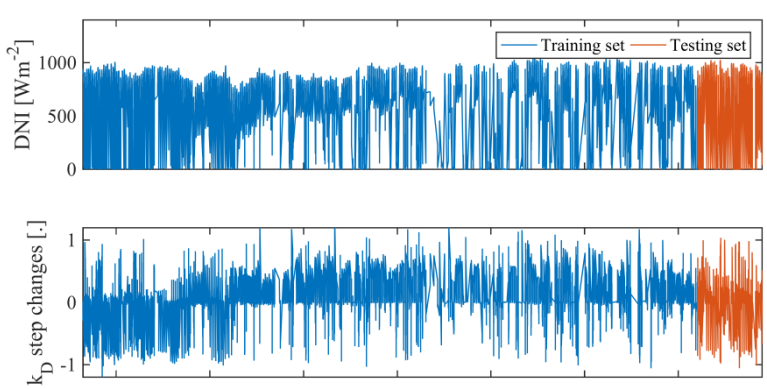

Figure 7: Top: DNI for training and testing sets. Bottom: the k_D step changes that were used in training the kNN model for the same sets as in the top figure.

The optimal kNN model is not the same for the 15-, 30- and 45-minute horizons. It differs in terms of the set of variables to use as neighbors and the number of neighbors used to forecast the step changes. Table 2 lists the optimal parameters for each case.

Table 2: Parameters for the optimal kNN model for the intra-hour DNI forecast. STD(k_D,60) denotes the standard deviation of k_D in the 60 minutes that precede t_{issue}. $TRKR_{11}$ denotes the clear-sky index for the PO at tracker 11 measured at t_{issue}.

FH	List of selected inputs	k
15	$k_P(t_{issue})$, $k_D(t_{issue})$, STD(k_D,60), $TRKR_{11}$, $TRKR_{26}$, $TRKR_{32}$, $TRKR_{39}$	14
30	MAX(k_P,30), MAX(k_D,30), MAX(k_D,60), SLOPE(k_D,60), $TRKR_{11}$, $TRKR_{20}$, $TRKR_{34}$	27
45	STD(k_P,120), MIN(k_P,120), AVG(k_D,120), STD(k_D,60), MAX(k_D,90), SLOPE(k_D,120), $TRKR_1$, $TRKR_{10}$, $TRKR_{11}$, $TRKR_{31}$, $TRKR_{33}$	12

4.1.2 Subtask 2b: Evaluate sky-imaging data and develop dedicated forecast for location

The sky-images were evaluated to create meaningful inputs for the forecasting algorithms. The first task to achieve this objective was to translate the image data into some numerical values that the forecasting algorithms can ingest. To do so, the three color channels – Red (R), Green (G) and Blue (B), and the ratio of Red to Blue were processed using the following operators: average, standard deviation and entropy. Figure 8 illustrates how the average and entropy values can be used to identify the type of cloud cover. The figure shows a clear demarcation for these values between cloudy periods and clear-sky periods.

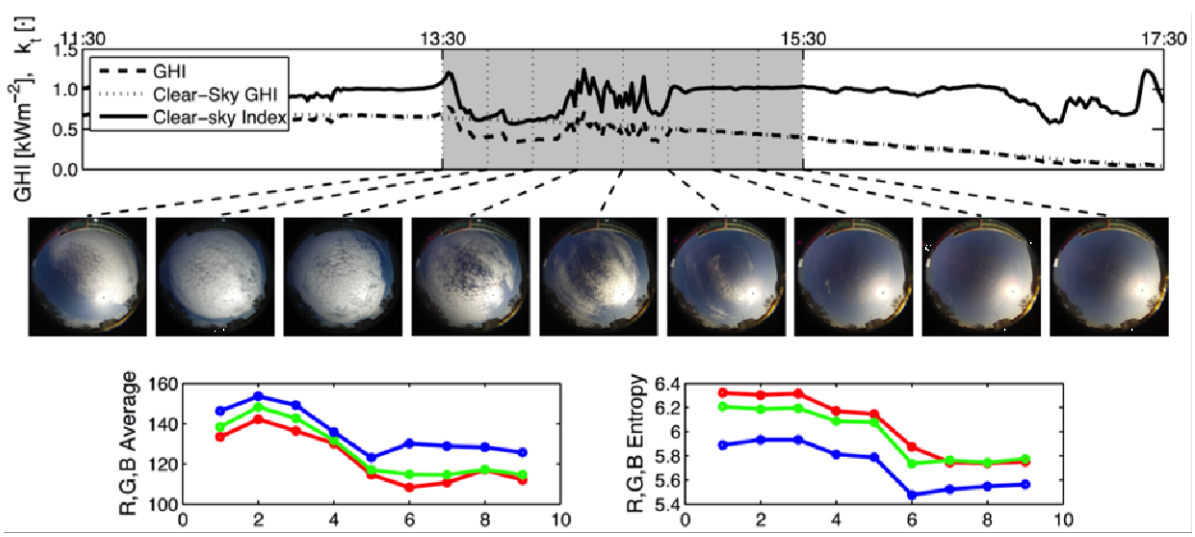

Figure 8: Top: Solar irradiance, Middle: nine sky images, Bottom: average and entropy for the R, G and B channels for the nine images.

In this example the image features were computed for the entire sky regardless of the cloud motion. However, we expected that sections in the sky image that show clouds moving toward the sun were better predictors for the DNI in the intra-hour horizons. To take this into account, for each image we determined the apparent cloud direction by comparing the image against the preceding one. The outcome of this algorithm is a velocity vector that characterizes the average cloud motion as illustrated in Figure 9. With this knowledge we computed the image features introduced above for different sections of the sky image as shown in Figure 6 above.

Figure 9: Example of how cloud motion detection is implemented in this work. By using two consecutive images (image at $t_{issue} - 1$ minute in the left panel and image at t_{issue} in the center panel) we can determine the cloud direction (red arrow in the center panel). Using this information we compute the image features for the portion of the sky that will influence DNI and PO in the next minutes (area highlighted in blue in the right panel).

These image features were then used to discriminate between clear and cloudy periods. We used this information to update the optimal kNN forecasts.

4.1.3 Subtask 2c: Automate sky imager forecast provision and supervise operation

In this subtask we created several scripts to register and manage the sky images received from the remote sky cameras. The sky cameras are configured to record images every minute and transmit them via FTP to our servers at UCSD. Once the images are available at the server, dedicated scripts move the images into a tree structure to facilitate image retrieval. The image files are organized in folders that follow the structure: location or camera id >year >month >day (see Fig. 10). The image path and respective UTC timestamp are also inserted into a MySQL database. Forecasting scripts retrieve the necessary images using the database and process them following the algorithm explained in Section 4.1.2.

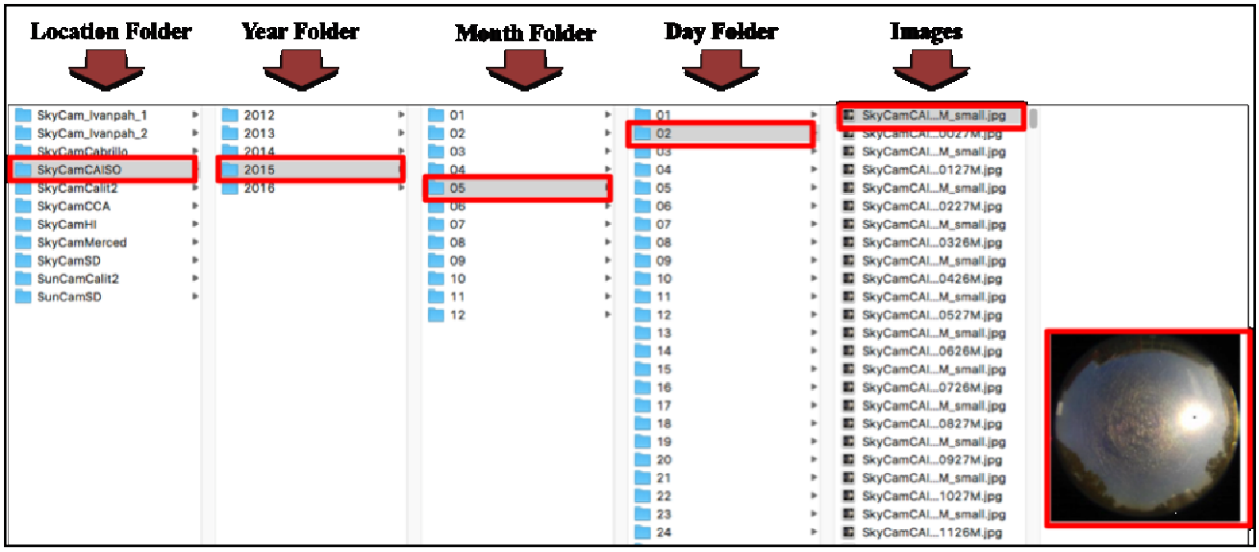

Figure 10: View of the sky image repository at UCSD.

4.1.4 Subtask 2d: Analyze short-term forecasting skills

In this section we assessed the forecasting performance of the forecasting models that predict DNI 15, 30 and 45 minutes ahead of time. In total we created three models in this task:

- The persistence forecast denoted as $\widehat{D}_{per}$;
- The kNN model introduced in Section 4.1.1 and denoted as $\widehat{D}_{kNN}$;
- The kNN model that uses sky image features to discriminate between clear and cloudy periods, denoted as $\widehat{D}_{kNN+IMG}$.

The forecasting performance for these models was analyzed for the testing set (data in orange in Figure 7). A single month was selected for testing the forecast given that is the only period for which we had sky images. However, in that month the data shows all levels of variability as the k_D step changes show in the bottom plot of Figure 7. The forecasting performance was quantified using the error metrics described in Appendix A. The error metrics for the testing set are listed in Table 3. The listed values show that the kNN model without image information already shows substantial forecasting skill (above 20 %). When image features are included in the forecasts that skill improves by 1 to 2%.

Another deliverable for this task is the assessment of the forecasting performance for ramp control. Ramps are sudden step changes in the irradiance and power generation that result from passing clouds. For DNI and CPV power generation, such events can result in changes of more than 50% in the irradiance value and are very difficult to predict. Nevertheless, a good forecasting model should perform well for such events. In order to assess the performance of the kNN model used in this project we computed the ramp magnitude (the absolute value of step changes in the DNI clear-sky index time series). Then we computed the root-mean-square error (RMSE) for forecasts binned by the ramp magnitude value. RMSE is a frequently used measure of the differences between values predicted by a forecasting model the values actually observed. The

results for this analysis are listed in Table 4 for the ramp bins: 10 to 25%, 25% to 50%, and 50% to 100%. A 50% ramp in the 30-minute forecast, for instance, means that $|k_D(t_{issue} + 30\ min) - k_D(t_{issue})| = 0.5$.

We define the ramps in terms of clear-sky index in order to remove deterministic variations from this analysis. Otherwise deterministic DNI variations at low solar elevations would be recorded as ramps.

Model	MBE	rMBE	MAE	rMAE	RMSE	rRMSE	skill
			FH = 15 minutes				
$\hat{D}_{per}$	8.9	0.9	73.2	7.3	190.6	19.1	-
$\hat{D}_{kNN}$	1.6	0.2	69.4	6.9	148.3	14.8	22.2
$\hat{D}_{kNN+IMG}$	2.3	0.2	67.9	6.8	145.2	14.5	23.8
			FH = 30 minutes				
$\hat{D}_{per}$	17.0	1.7	103.6	10.4	234.8	23.5	-
$\hat{D}_{kNN}$	-2.2	-0.2	81.1	8.1	164.7	16.5	29.9
$\hat{D}_{kNN+IMG}$	3.4	0.3	82.1	8.2	159.4	15.9	32.1
			FH = 45 minutes				
$\hat{D}_{per}$	15.8	1.6	109.9	11.0	244.1	24.4	-
$\hat{D}_{kNN}$	-0.6	-0.1	85.6	8.6	169.0	16.9	30.8
$\hat{D}_{kNN+IMG}$	4.8	0.5	85.8	8.6	165.9	16.6	32.0

Table 3: Bulk error metrics (in Wm^{-2} for the absolute values and % of maximum DNI, 1000 Wm^{-2}, for the relative values) for the different DNI intra-hour forecasting models.

	FH = 15 minutes			**FH = 30 minutes**			**FH = 45 minutes**		
Ramp [%]	10-25	25-50	50-100	10-25	25-50	50-100	10-25	25-50	50-100
N. Instances	63	52	52	81	51	96	95	53	131
					RMSE [Wm^{-2}]				
$\hat{D}_{per}$	169.8	365.9	750.3	169.4	357.1	743.3	152.5	362.6	741.2
$\hat{D}_{kNN}$	185.6	293.6	576.8	189.9	303.8	494.1	166.0	277.0	430.7
$\hat{D}_{kNN+IMG}$	176.7	300.8	562.9	194.9	292.0	473.2	163.1	286.6	414.6

Table 4: RMSE for several forecasting models as a function of ramp magnitude and forecasting horizon.

The first row in the table indicates the number of ramps in each bin. As expected large ramps are more frequent for larger forecasting horizons. The RMSE errors listed are much larger than the ones in Table 3 since they reflect the models' performance in rarer but extreme events. The results show the Persistence model has smaller RMSE than the kNN for small ramps. But as these increase the accuracy of the kNN model surpasses persistence by a large margin. For the largest ramps the kNN model with images reduces the error by 30 to 55% relative to persistence.

4.1.5 Subtask 2e: Evaluate forecasting uncertainty

Another goal for this project is to estimate the prediction intervals (PI) for the forecast. A PI is an estimate of the interval in which a future measured value will fall, given by a lower and an upper bound. The PI combined with the point forecasts PI provide information about the forecasting uncertainty and are very important for operational planning. Popular approaches to quantify PIs often rely on the assumption of normality, but in this case such assumption is not always true. For example, whenever irradiance or power output approach their natural limits the distribution of possible outcomes will tend to asymmetric distributions such as the gamma, or the exponential distributions. For this reason, we defined the PIs empirically using the extreme values for the individual forecasts produced by the kNN forecasting model.

In order to assign a confidence level to these intervals we computed the PI coverage probability (PICP), that is, the probability that the actual irradiance is within the range defined by the PI. A second metric used to measure the quality of the prediction intervals is the PI normalized average width (PINAW). If PINAW is large and approaches the maximum possible range, the PI will have little value: it is trivial to say that the future irradiance will be between its possible extreme values. Thus, the goal is to maximize PICP while minimizing PINAW. Figure 11 indicates how the PIs are calculated and gives examples of good and bad PIs.

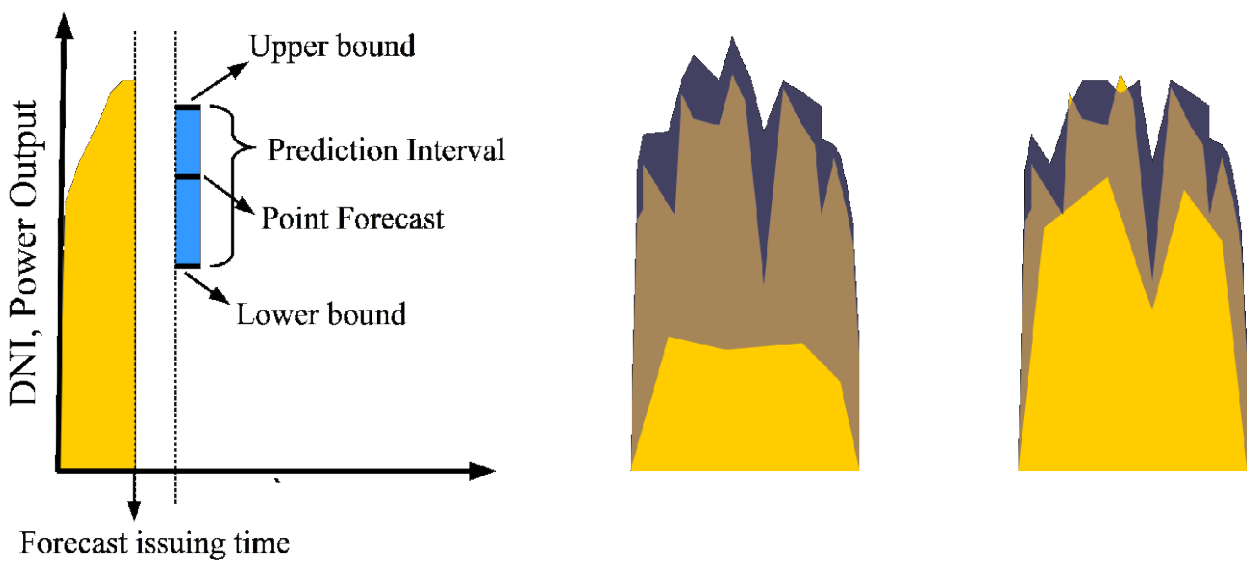

Figure 11: *Left:* Schematic that explain the meaning of the prediction interval. *Middle:* Example of PIs (the blue shaded area) that cover all the observed data (PICP=100%) but that are too wide (large PINAW). *Right:* Example of better PIs. These do not always cover all the observed data (PICP < 100%) but are much narrower (lower PINAW). Good PIs should be are narrow as possible while maintaining a good coverage.

Table 5 lists the PICP and PINAW obtained for the kNN model with sky image features. For comparison the table also lists those values for the persistence model. In that case the PIs are created by using the standard deviation of the DNI time series in the 120 minutes that precede t_{issue}. Figure 12 shows the kNN forecasts in solid blue and the respective intervals for three days in the testing data set.

Table 5: Performance metrics for the prediction intervals obtained with persistence and kNN models.

Model	FH = 15 minutes		FH = 30 minutes		FH = 45 minutes	
	PINAW	PICP	PINAW	PICP	PINAW	PICP
$\hat{D}_{per}$	31.5	79.7	31.0	70.0	30.5	65.6
$\hat{D}_{kNN+IMG}$	22.2	88.5	25.5	84.5	26.6	85.6

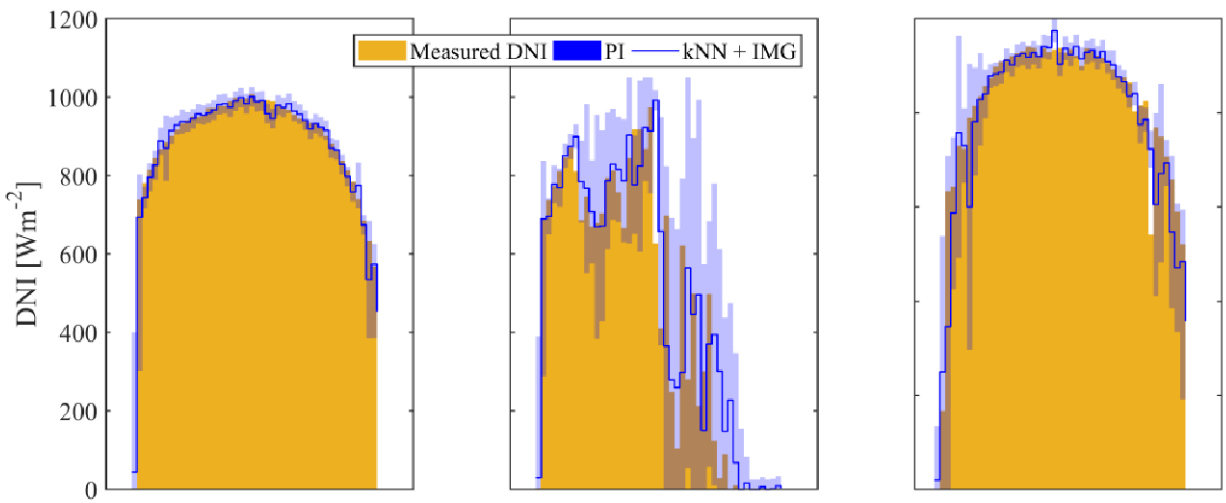

Figure 12: Measured and forecasted time-series and the corresponding PIs for DNI. The figure shows three days that cover different weather conditions, from overcast to clear days in the testing data set.

5 Phase 3.0 Intra-day solar forecasting

5.1 Task 3.1: Remote sensing enhanced by stochastic learning algorithms

Similarly to the intra-hour forecast presented in the previous section, the intra-day solar forecast also targets the forecasting of ramps in the solar resource. However, for these horizons the cloud information in sky images is too short-lived (sky images are useful for horizons below 30 to 45 minutes). An alternative to sky images that allows for a much larger field of view are the images acquired by the Geostationary Operational Environmental Satellite system (GOES) as

explained in Section 3. Another source of relevant data for the intra-day forecast comes from numerical weather prediction (NWP) models. Specifically, we use data from the North American Mesoscale Forecast System (NAM). Thus, the set of predictors includes local telemetry and remote sensing (satellite images and NAM forecasts).

In this task we seek to create DNI forecasts for 60 to 360 minutes using these two data sources. The activities for this task are divided in 5 subtasks. Below we report on the progress of each one.

5.1.1 Subtask 3a: Develop a regional sector model for the Fort Irwin location

In this subtask we have developed two models to predict DNI in 15 min steps out to 360 minutes:

1. An artificial neural network (ANN) model that ingests NAM data to produce DNI forecasts from 30 to 360 minutes. The ANN models uses the NAM data introduced in Section 3.
2. A kNN model similar to the one used to forecast DNI intra-hourly in the previous section. The only difference in that in this task we replaced the information from the sky images with information retrieved from satellite imagery.

The inclusion of the ANN model that uses NAM data only is an important benchmark: it will allow us to quantify forecasting accuracy when no local telemetry is available. Figure 13 shows the DNI data used in this task and identifies training data and testing data. Contrary to the intra-day forecasts, all the data sources are available at every time instance, thus we segregate training days from testing days randomly in order to include data from every season in those sets.

5.1.2 Subtask 3b: Validate model with ground telemetry

In this subtask we validated the forecasting models using ground telemetry (data shown in orange in Figure 13).

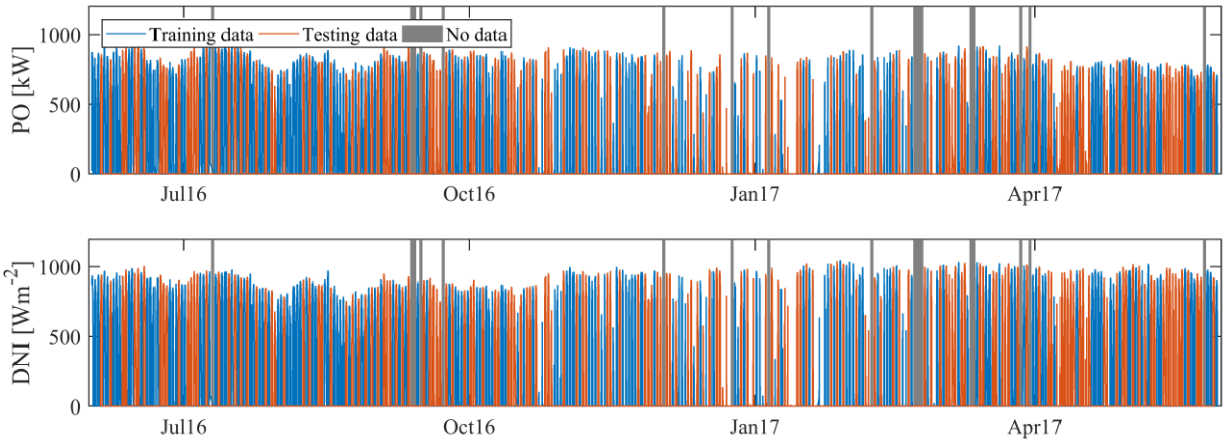

Figure 13: PO (top) and DNI (bottom) data from Fort Irwin. The different colors indicate data used in the training of the machine learning models and data used to validate the forecasts. Grey bars indicate days for which there is no data available.

Again we used the persistence model introduced in Appendix C.1 as a reference model. Table 6 lists the error metrics for the models. Again, by using local telemetry and selecting the optimal set of predictors the kNN model shows substantial forecasting skill. The ANN model with NAM data shows poor skill compared to the kNN model highlighting the importance of local telemetry and predictor selection in obtaining the best forecasting performance possible.

Model	MBE	rMBE	MAE	rMAE	RMSE	rRMSE	skill
			FH = 60 minutes				
$\hat{D}_{per}$	-3.8	-0.4	98.0	9.8	212.1	21.2	0.0
$\hat{D}_{ANN}$	-3.8	-0.4	140.0	14.0	238.2	23.8	-12.3
$\hat{D}_{kNN}$	-0.3	-0.0	87.7	8.8	168.7	16.9	20.5
$\hat{D}_{MOS}$	2.7	0.3	81.9	8.2	159.7	16.0	24.7
			FH = 120 minutes				
$\hat{D}_{per}$	-9.9	-1.0	111.1	11.1	232.6	23.3	0.0
$\hat{D}_{ANN}$	-3.1	-0.3	125.2	12.5	235.0	23.5	-1.1
$\hat{D}_{kNN}$	-6.2	-0.6	93.0	9.3	180.8	18.1	22.3
$\hat{D}_{MOS}$	0.7	0.1	85.1	8.5	165.0	16.5	29.0
			FH = 180 minutes				
$\hat{D}_{per}$	-14.7	-1.5	115.8	11.6	243.5	24.4	0.0
$\hat{D}_{ANN}$	-3.4	-0.3	115.1	11.5	216.8	21.7	11.0
$\hat{D}_{kNN}$	-7.6	-0.8	90.2	9.0	181.1	18.1	25.6
$\hat{D}_{MOS}$	-1.2	-0.1	80.9	8.1	163.2	16.3	33.0
			FH = 240 minutes				
$\hat{D}_{per}$	-18.5	-1.8	112.9	11.3	244.1	24.4	0.0
$\hat{D}_{ANN}$	-7.4	-0.7	97.2	9.7	200.2	20.0	18.0
$\hat{D}_{kNN}$	-5.4	-0.5	86.7	8.7	179.0	17.9	26.7
$\hat{D}_{MOS}$	0.3	0.0	76.3	7.6	158.1	15.8	35.2
			FH = 300 minutes				
$\hat{D}_{per}$	-19.0	-1.9	106.1	10.6	240.2	24.0	0.0
$\hat{D}_{ANN}$	-1.0	-0.1	89.4	8.9	182.8	18.3	23.9
$\hat{D}_{kNN}$	-6.1	-0.6	72.9	7.3	161.9	16.2	32.6
$\hat{D}_{MOS}$	-2.3	-0.2	66.7	6.7	147.4	14.7	38.6
			FH = 360 minutes				
$\hat{D}_{per}$	-18.3	-1.8	93.1	9.3	224.9	22.5	0.0
$\hat{D}_{ANN}$	-5.2	-0.5	73.1	7.3	169.3	16.9	24.7
$\hat{D}_{kNN}$	-2.9	-0.3	62.3	6.2	147.1	14.7	34.6
$\hat{D}_{MOS}$	-2.1	-0.2	59.7	6.0	137.9	13.8	38.7

Table 6: Bulk error metrics (in Wm^{-2} for the absolute values and % of maximum DNI, 1000 Wm^{-2}, for the relative values) for the different DNI intra-day forecasting models.

5.1.3 Subtask 3c: Apply stochastic learning tools for output post-processing

In this subtask we applied model output statistics (MOS) post-processing to further improve the forecasting performance. The idea behind this task is to take advantage of the error analysis for the different forecasting models in order to improve the accuracy.

In this project we combine all the different forecasts available (persistence, ANN, kNN) using a least-squares minimization to obtain a new forecast:

$$\boldsymbol{\hat{D}_{MOS} = w_1\hat{D}_{per} + w_2\hat{D}_{ANN} + w_3\hat{D}_{kNN} + \alpha} \qquad (2)$$

The goal of the least-squares is to find the weights (w1, w2 and w3) and constant α that minimize the error between $\widehat{D}_{MOS}$ and the measured DNI. This process was applied to the training data and the performance of $\widehat{D}_{MOS}$ was, as before, assessed using the testing data set. The error metrics for this model are also listed in Table 6. These results show that model output post-processing improves forecasting skill over the other models and should be used in the real-time forecasting.

5.1.4 Subtask 3d: Deliver intra-day forecasts to PI system (or equivalent)

The purpose of this task was to transmit the intra-day forecast to the plant managers, for instance, by inserting the forecast into a PI system historian. From there the interested parties could assess the forecast. To accomplish this goal, once the forecast was created every 15 minutes, we made available at the web portal the forecasted data in a comma separated values (csv) file. Figure 14 explains how the file can be accessed and shows a preview of the csv file contents.

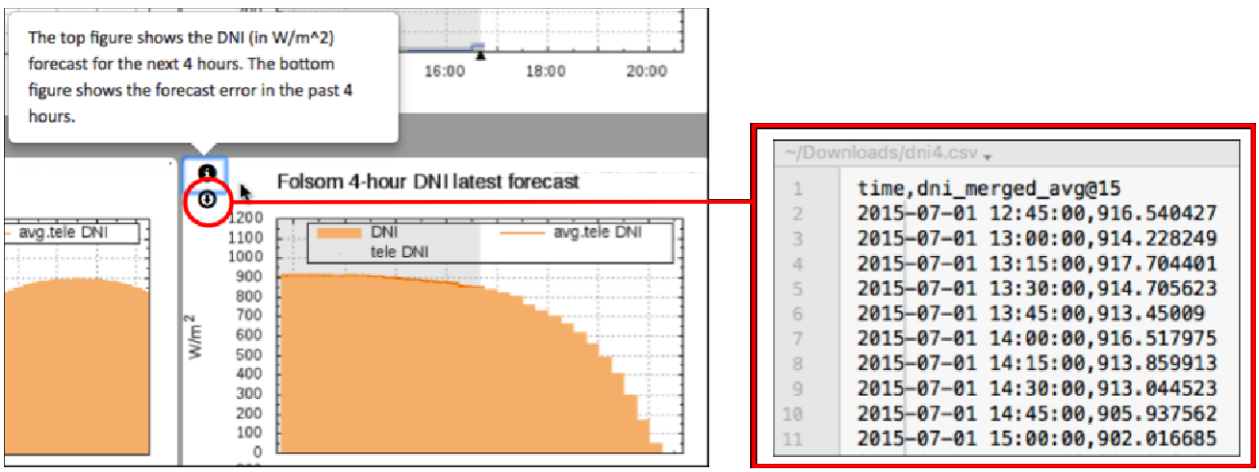

Figure 14: *Left*: snapshot of the web portal developed for this project. By clicking in the button the forecast is downloaded in csv format. *Right*: a snapshot of the content of the csv file containing the intra-hour forecast.

5.1.5 Subtask 3e: Deliver intra-day forecasts to Web portal

The models explained here were deployed in real time in our servers at UCSD. The output of the forecasting models was saved into a MySQL database. Several other plotting and error quantification scripts were then ran to create plots and diagnose tables for displaying in the web portal. Figure 5 (above in Section 3.2) illustrates real-time data shown in the web portal developed for this project.

6 Phase 4.0: Solar and Power Output forecasting

6.1 Task 4.1: Day ahead solar availability forecasts

This task consists of models that predict DNI and power output (PO) for the next day. The goal for these models was not to predict these variables to a fine granularity; instead the models predict longer trends in the target variables. For instance, forecast the aggregated level of DNI or PO for the following day, the onset and length of cloudy periods for the next day, etc. Such predictions are very important to determine the expected power generation for the next day as requested by the regulating entities and independent system operators whose job is to schedule resources to balance the electric grids.

Specifically the goal of this task was to create DNI forecasts at 10 am (local time) for the next 24 to 36 hours, as exemplified in Fig. 15. The data granularity for these forecasts is 1 hour. The forecasting algorithm uses historical data available at the issuing time and also data from numerical weather prediction models (NWP) that cover the 24 to 36 forecasting window. The activities for this phase are divided in three subtasks. Below we report on the activities for each one.

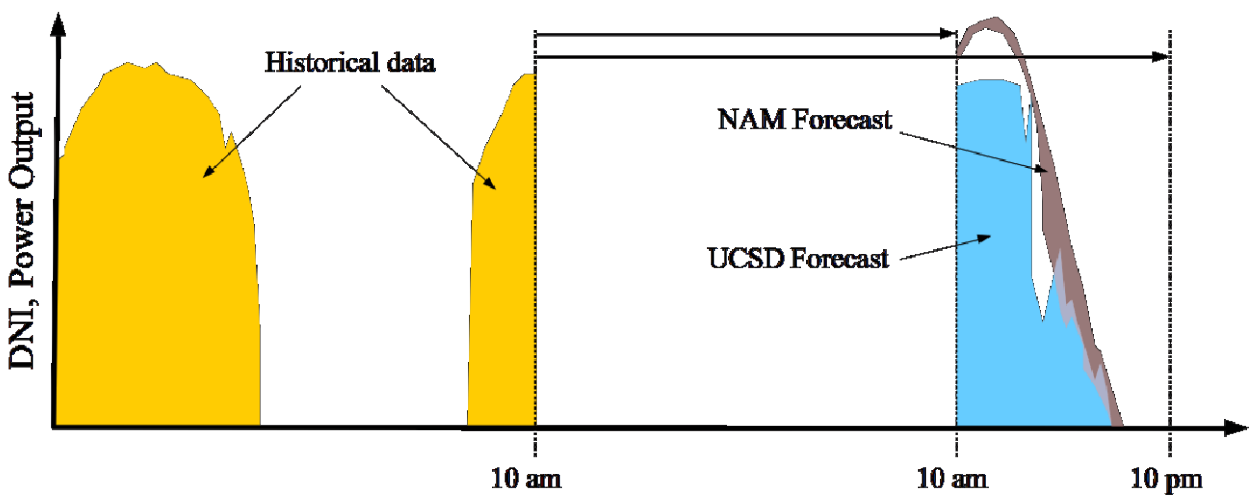

Figure 15: 15-minute day-ahead forecasting for 24 hours $\leq FH <$ 36 hours. The forecast is issued at 10 am local time for the next 24 to 36 hours.

6.1.1 Subtask 4.1a: Train algorithms using locally generated and our own solar resource data

As in previous cases, we started this subtask by assembling several data sets necessary for the day-ahead forecast as indicated by Fig. 15. In the first place, we acquired from SOITEC DNI measurements. The data set was then augmented with forecasted data from the NAM model introduced in Section 3. Given that the goal of this task was to produce day-ahead solar DNI forecasts at 10:00 PST (18:00 UTC) we used only the NAM forecasts produced in the last daily update (18Z).

Figure 13 above in Subtask 3b shows the DNI data obtained from the sensors at Fort Irwin. Data in blue was used for training the different forecasting algorithms. Data in orange was used to assess the forecasting performance.

To illustrate the relationship between NAM's GHI data and local DNI data Figure 16 shows the DNI data for a few days and the corresponding GHI forecasted data obtained from the NAM model for the 13 nodes nearest to Fort Irwin.

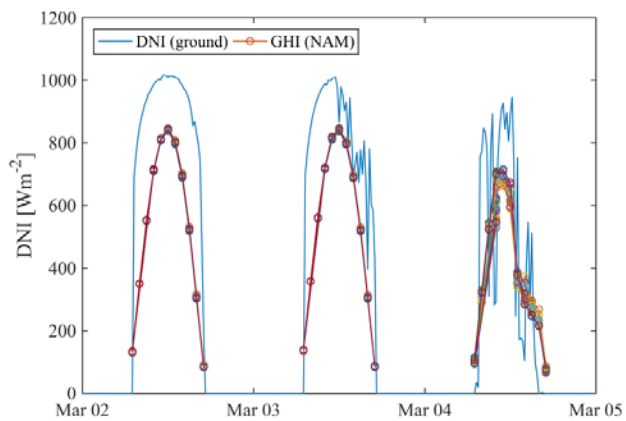

Figure 16: Example of GHI data obtained from the NAM model.

After collecting the data, the different irradiance variables (NAM's GHI and DNI) were normalized using the clear-sky model described in Appendix B. This operation removes deterministic trends from the training data and usually improves the forecasting performance.

Forecasting Models

In this section we explain the different forecasting models developed in this subtask. The first model used is the persistence algorithm given by Equation 10 in Appendix C.

Given that the assumption of persistence is not very accurate for the day-ahead forecast we also create a non-linear model from the NAM forecasted data. This model uses the GHI NAM predictions for the nodes closest to Fort Irwin. Using the training data set we normalized NAM's GHI for the 13 nodes using clear-sky GHI values and then averaged this variable across all nodes. The resulting value is denoted as $\langle k_G \rangle$.

By plotting measured DNI against $\langle k_G \rangle$ as in Fig. 17 we estimated the best curve that maps NAM's data into the target variable. This process resulted into the following piecewise function:

$$\widehat{D}_{NAM} = \begin{cases} 796.3\langle k_G \rangle^{3.487}, & if\ \langle k_G \rangle < 1.08 \\ 1050, & otherwise \end{cases}$$

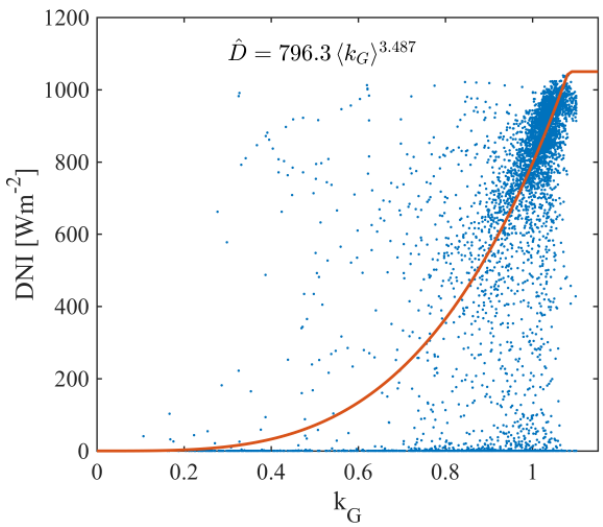

Figure 17: Measured DNI as a function of the average normalized GHI from the 13 nearest nodes to Fort Irwin.

The final class of models trained in this task consists of machine learning models, more specifically, the kNN model. In this model neighbors are defined in terms of the NAM's GHI and cloud cover forecasts for the 13 nodes. Time instances that exhibited similar behavior in terms of NAM forecast were tagged as neighbors. Then, using the DNI data from the training set that corresponds to those neighbors we computed the predicted irradiance for the next 24 to 36 hours by aggregating the measured DNI data. The optimal kNN model was then obtained using the algorithm explained in the Appendix C.2.

The optimization process indicated that, out of the 26 variables available, the kNN achieved the lowest forecasting error if only 17 are used (Fig. 18(right)) and that the optimal number of neighbors is 10. Figure 18(left) shows the convergence of this optimization process. Figure 18(right) shows the NAM data selected to establish the optimal set of neighbors.

After determining the best set of neighbors the kNN DNI forecast is calculated as

$$\boldsymbol{\hat{D}_{kNN}(t) = \frac{1}{10}\sum_{i=1}^{10} k_D(\tau_i) \times D_{clr}(t)} \qquad \textit{(3)}$$

where $k_D(\tau_i)$ is the DNI clear-sky index from the training data set that corresponds to the neighbors identified by the time τ_i.

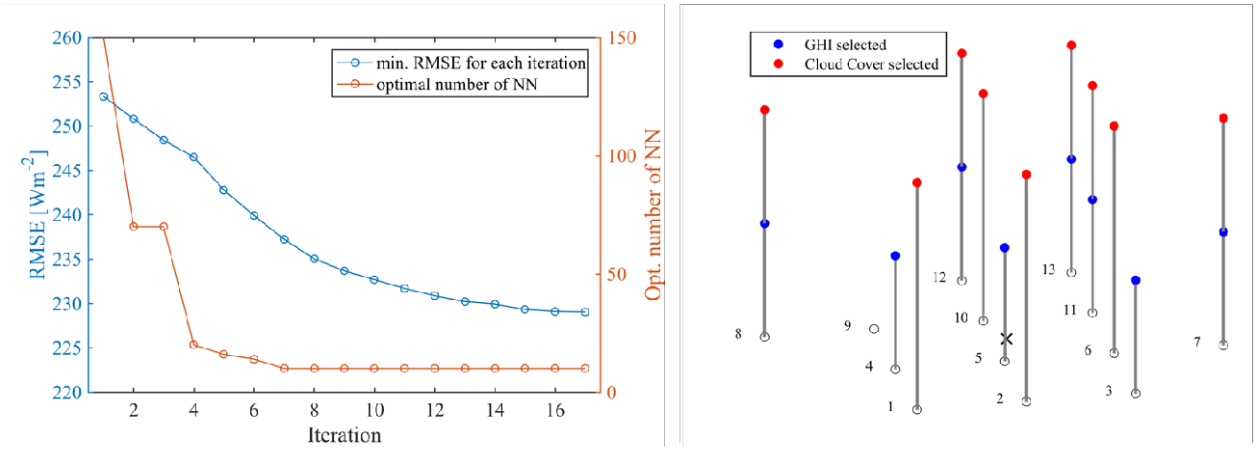

Figure 18: *Left*: convergence of the kNN optimization. As iterations progress the forecasting RMSE decreases until it stabilizes (blue curve). The number of neighbors (red curve) also stabilizes rapidly. *Right*: The NAM data selected per NAM node for the best kNN forecast. The blue dots indicate that the NAM GHI data is selected for the node identified below the dot. The red dots indicate that the NAM cloud cover is selected.

6.1.2 Subtask 4.1b:Develop 24 to 36 hour ahead solar forecast generated at 10 a.m. each day

The three models explained in the previous section were then applied to the data set presented above. The NAM model and the kNN model were determined using the training data set and then applied to the testing data set. Each model produces forecasts valid for $t \in [t_{issue} + 24h, t_{issue} + 36h]$ where t_{issue} 10 am local time.

The forecasting performance is established using the error metrics explained in Appendix A. In the results shown below we report on the error metrics applied to the testing data set since those are the results representative of the models' performance when applied to live data.

Table 7 lists these metrics for the three models described in the previous section irrespective of the forecasting horizon. The error metrics are in Wm^{-2} 2. We also list the values relative to the maximum measured DNI (1050 Wm^{-2}). Those values are denoted by the prefix "r".

Table 7: Bulk error metrics for the different forecasting models for day-ahead DNI.

Model	MBE	rMBE	MAE	rMAE	RMSE	rRMSE	skill
$\hat{D}_{per}$	-20.2	-1.9	191.1	18.2	317.5	30.2	-
$\hat{D}_{NAM}$	-66.8	-6.4	160.2	15.3	265.9	25.3	16.3
$\hat{D}_{kNN}$	3.7	0.4	127.5	12.1	216.0	20.6	32.0
$\hat{D}_{MOS}$	3.7	0.4	131.6	12.5	208.4	19.9	34.4

Finally, we also assessed how the models perform as a function of the forecasting horizon. To do so, we segregated the forecasted data into the 24, 25, . . . 36 horizons. Then we computed the error metrics for each horizon.

Figure 19 shows the forecasting skill obtained in this analysis. For horizons larger than 33 hours (that is 7 pm local time in the day after the issuing time) there are no data points due to the low solar elevation. The figure shows that the kNN model ($\widehat{D}_{kNN}$) achieves skills close to or above 30% for all horizons except for 31 hours where that values drops to 7%. The NAM model ($\widehat{D}_{NAM}$) achieves skills close to or above 20% for horizons lower than 31 hours. It then drops to negative skills.

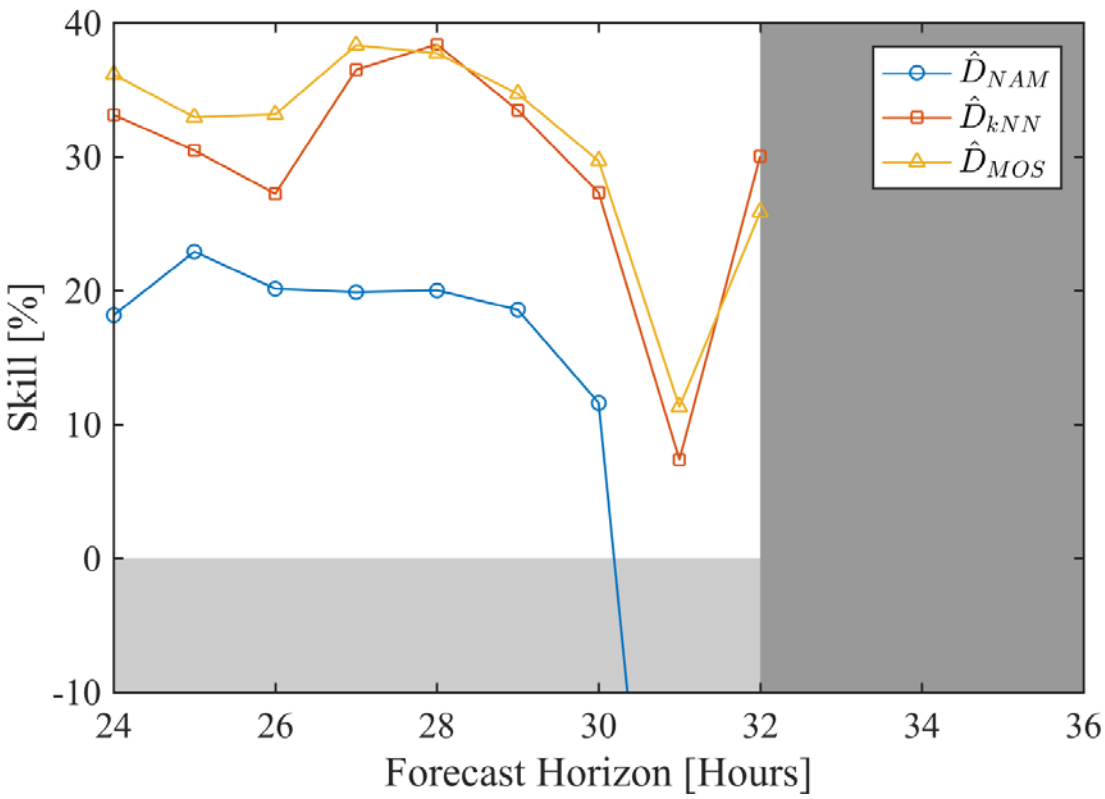

Figure 19: Forecast skill for the $\hat{D}_{NAM}$, $\hat{D}_{kNN}$ and $\hat{D}_{MOS}$ as a function of the forecasting horizon. The light shaded area indicates negative skill. The darker shaded area indicates forecasting horizons for which there is no data available (nighttime).

As mentioned in the introduction to this phase, the day-ahead forecast is most useful to predict the solar availability for the following day. Irradiance availability is computed by integrating DNI over the forecasting window $t \in [t_{issue} + 24h, t_{issue} + 36h]$, which yields a value in Whm^{-2}. By computing this value for the measured and forecasted data we can then access the forecasting performance when predicting solar availability. The results from this analysis are listed in Table 8. These results again highlight the superiority of the kNN model.

Table 8: Error metrics (in Whm^{-2}) for the daily DNI availability. The first row shows the averaged availability for the testing data set.

DNI	Mean	MBE	MAE	RMSE	skill
Measured	4750.01	-	-	-	-
$\hat{D}_{per}$	4918.38	-168.38	1292.57	1965.74	-
$\hat{D}_{NAM}$	5265.46	-515.45	906.09	1334.96	32.1
$\hat{D}_{kNN}$	4717.59	32.42	571.86	827.41	38.0

6.1.3 Subtask 4.1c:Apply stochastic learning tools for output post-processing

In this subtask we applied model output statistics (MOS) post-processing to further improve the forecasting performance. Here we proceeded as in Section 5.1.3 and combined all the different forecasts available (persistence, NAM, kNN) using a least-squares minimization to obtain a new forecast:

$$\boldsymbol{\hat{D}_{MOS} = w_1\hat{D}_{per} + w_2\hat{D}_{NAM} + w_3\hat{D}_{kNN} + \alpha} \qquad (4)$$

The free parameters w_1, w_2, w_3 and α are determined using the training data. The forecasting skill as a function of the horizon for this model is shown in Fig. 19, and its error metrics are listed in the last row of Table 7. These results show that model output post-processing improves forecasting skill over the other models and should be used in real-time forecasting.

6.2 Task 4.2: Prospective power forecasting

In this task we developed forecasting models to predict the power output (PO) at Fort Irwin for the following forecasting horizons: Intra-hour, Intra-Day, Day-ahead and Days-ahead. Figure 1 shown towards the beginning of this report illustrates the different forecasting windows and indicates some of the exogenous data (sky images, satellite images, NAM data) used for the different horizons. The models used to predict PO mirror what was done for DNI and explained in the previous sections. The activities for this phase are divided in 3 subtasks. Below we report on the activities for each one.

6.2.1 Subtask 4.2a: Develop plant power output model for time horizons in phases 2 to 4

Intra-hour forecasts

In this subtask we used PO, DNI and solar tracker data obtained from SOITEC to produce PO forecasts 15, 30, and 45 minutes ahead of time. Another source of information for this forecast consisted of the features derived from sky images. The models used in this case are the ones presented in Section 4.1.1 for the intra-hour DNI forecast.

The error metrics for the different models for intra-day PO forecast are shown in Table 9 as a function of the forecasting horizon. The error metrics are in *kW*. We also list the values relative to the plant capacity (1000 *kW*). Those values are denoted by the prefix "r".

Table 9: Bulk error metrics (in kW for the absolute values and % for the relative values) for the different PO intra-hour forecasting models.

Model	MBE	rMBE	MAE	rMAE	RMSE	rRMSE	skill
			FH = 15 minutes				
P_{per}	-2.7	-0.3	41.8	4.2	100.1	10.0	-
P_{kNN}	-1.9	-0.2	42.1	4.2	93.6	9.4	6.4
$P_{kNN+IMG}$	0.2	0.0	40.8	4.1	79.8	8.0	20.3
			FH = 30 minutes				
P_{per}	-6.4	-0.6	61.3	6.1	133.6	13.4	-
P_{kNN}	-2.3	-0.2	57.6	5.8	118.7	11.9	11.2
$P_{kNN+IMG}$	2.5	0.3	56.7	5.7	104.6	10.5	21.7
			FH = 45 minutes				
P_{per}	-9.7	-1.0	69.9	7.0	149.5	14.9	-
P_{kNN}	-4.2	-0.4	63.8	6.4	128.5	12.8	14.1
$P_{kNN+IMG}$	1.9	0.2	63.1	6.3	115.6	11.6	22.7

The results for PO are similar to the results for DNI. However in this case, the kNN model without images shows lower skill predicting PO than DNI. When information from the sky-images is included in the model the forecast improves markedly.

Intra-day forecasts

In this subtask we developed models to predict PO in 15 min steps from 60 minutes out to 6 hours following the methodology described in Section 5 for DNI.

We also applied model output statistics (MOS) to further improve the forecasting skill. The error metrics for the different intra-day PO forecasting models are shown in Table 10 as a function of the forecasting horizon. The results in this table show the good forecasting performance for the kNN and MOS models. That is, the error metrics for these models are substantial lower than the respective values for the reference model.

Table 10: Bulk error metrics (in kW for the absolute values and % for the relative values) for the different PO intra-day forecasting models.

Model	MBE	rMBE	MAE	rMAE	RMSE	rRMSE	skill
			FH = 60 minutes				
P_{per}	-10.5	-1.1	77.1	7.7	150.3	15.0	-
P_{kNN}	2.8	0.3	67.6	6.8	127.4	12.7	15.3
P_{MOS}	1.4	0.1	66.1	6.6	125.1	12.5	16.8
			FH = 120 minutes				
P_{per}	-15.4	-1.5	90.4	9.0	173.5	17.4	-
P_{kNN}	6.4	0.6	71.7	7.2	135.0	13.5	22.2
P_{MOS}	1.0	0.1	65.6	6.6	128.7	12.9	25.9
			FH = 180 minutes				
P_{per}	-19.7	-2.0	93.0	9.3	183.7	18.4	-
P_{kNN}	6.8	0.7	69.0	6.9	132.0	13.2	28.1
P_{MOS}	-1.3	-0.1	62.3	6.2	127.1	12.7	30.8
			FH = 240 minutes				
P_{per}	-23.7	-2.4	90.8	9.1	184.3	18.4	-
P_{kNN}	8.0	0.8	63.0	6.3	123.9	12.4	32.8
P_{MOS}	1.3	0.1	55.6	5.6	120.2	12.0	34.8
			FH = 300 minutes				
P_{per}	-25.0	-2.5	84.2	8.4	180.4	18.0	-
P_{kNN}	21.5	2.1	78.3	7.8	145.9	14.6	19.2
P_{MOS}	-4.5	-0.4	65.4	6.5	133.1	13.3	26.3
			FH = 360 minutes				
P_{per}	-25.2	-2.5	72.9	7.3	165.1	16.5	-
P_{kNN}	18.5	1.8	63.5	6.4	130.8	13.1	20.8
P_{MOS}	-2.8	-0.3	53.6	5.4	116.6	11.7	29.4

Day-ahead forecasts

The day-ahead forecasting models for PO were developed using the framework presented in detail in Section 6.1. The only difference is that in this case we used measured PO data as the target instead of DNI.

In this case we also developed a model that uses the GHI NAM predictions for the nodes closest to Fort Irwin. By plotting measured PO against $\langle k_G \rangle$ as in Fig. 20 we can estimate the best curve that maps NAM's data into the target variable. The model is described by the following piecewise function:

$$\widehat{P}_{NAM} = \begin{cases} 6.646 \times 10^5 \, \langle k_G \rangle^{6.675}, & if \ \langle k_G \rangle < 1.047 \\ 9.031 \times 10^5, & otherwise \end{cases} \quad (5)$$

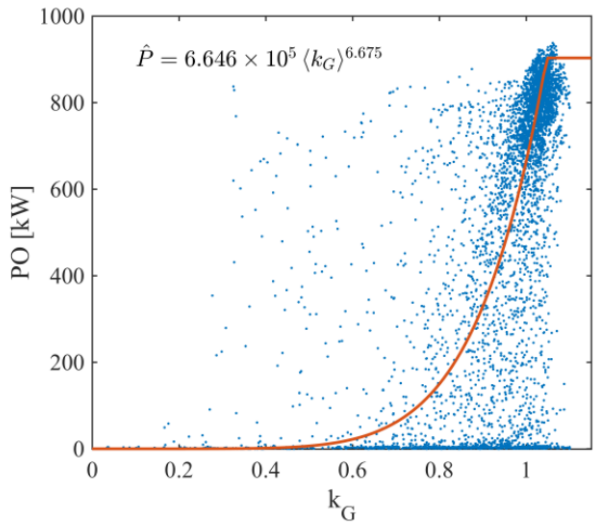

Figure 20: Measured PO as a function of the average normalized GHI for the 13 NAM nodes nearest to Fort Irwin (only training data).

The optimization of the kNN model indicates that, out of the 26 variables available, the kNN achieves the lowest PO forecasting error if only 16 are used (Fig. 21(right)) and that the optimal number of neighbors is 10.

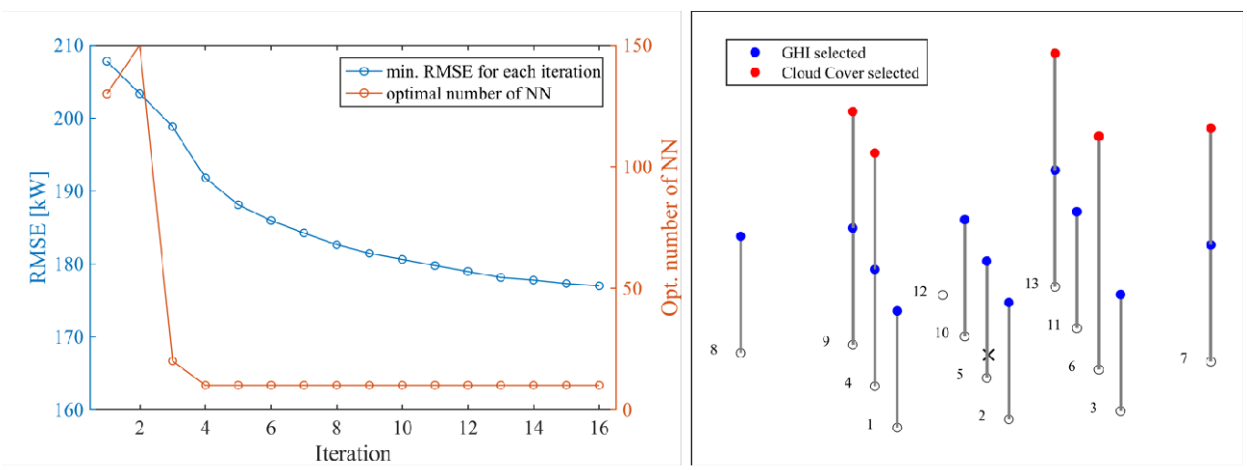

Figure 21: *Left*: convergence of the kNN optimization. As iterations progress the forecasting RMSE decreases until it stabilizes (blue curve). The number of neighbors (red curve) stabilizes faster and converges to 10. *Right*: The NAM data selected per NAM node for the best PO kNN forecast. The blue dots indicate that the NAM GHI data is selected for the node identified below. The red dots indicate that the NAM cloud cover is selected.

Table 11 lists the metrics for the three models considering all forecasting horizons. Figure 22 shows the forecasting skill as a function of the forecasting horizon. The results are very similar to the ones presented above for DNI day-ahead forecast. The figure shows that the kNN model

($\hat{P}_{kNN}$) achieves skills above 30% for all horizons. The NAM model ($\hat{P}_{NAM}$) achieves skills close to or above 20% for horizons lower than 31 hours. It then drops to negative skills.

Table 11: Bulk error metrics (in kW or %) for the different forecasting models for day-ahead PO.

Model	MBE	rMBE	MAE	rMAE	RMSE	rRMSE	skill
$\hat{P}_{per}$	-51.9	-5.2	177.2	17.7	287.8	28.8	-
$\hat{P}_{NAM}$	-55.1	-5.5	164.7	16.5	249.6	25.0	13.3
$\hat{P}_{kNN}$	-19.0	-1.9	102.9	10.3	185.8	18.6	35.5
$\hat{P}_{MOS}$	-3.8	-0.4	105.7	10.6	177.9	17.8	38.2

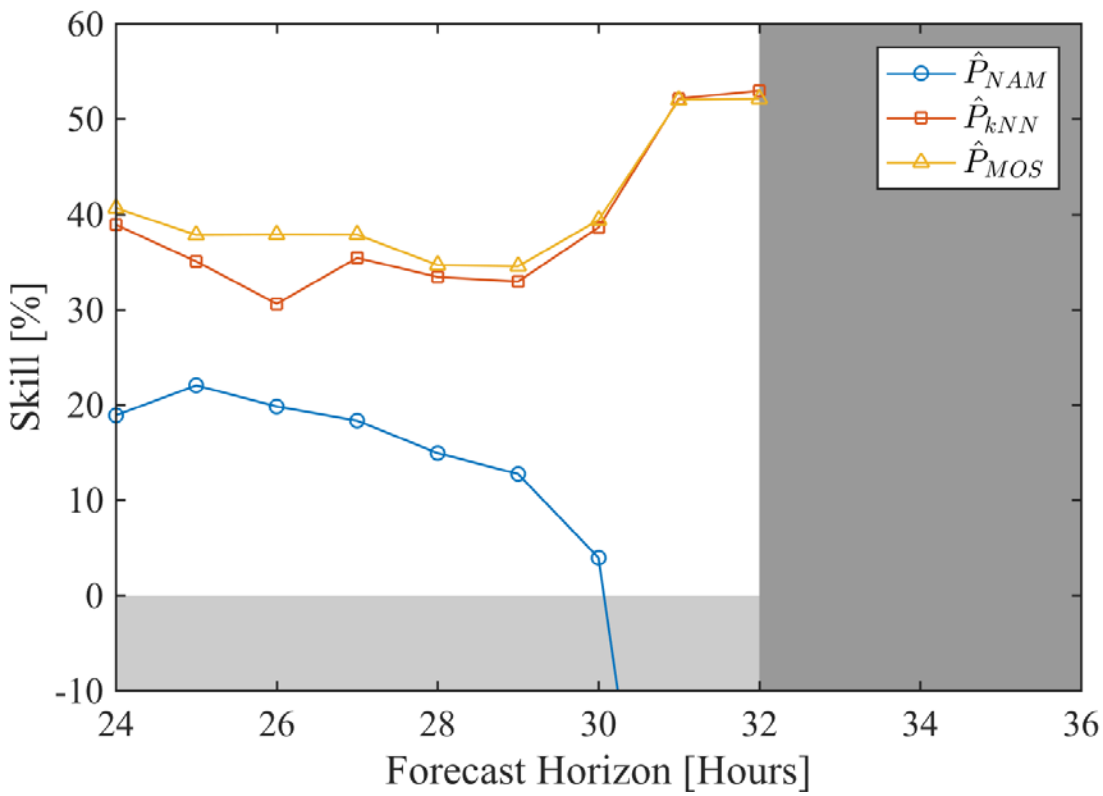

Figure 22: Forecast skill for the $\hat{P}_{NAM}$, $\hat{P}_{kNN}$ and $\hat{P}_{MOS}$ as a function of the forecasting horizon. The light shaded area indicates negative skill. The darker shaded area indicates forecasting horizons for which there is no data available (nighttime).

Here we also studied the models' performance in predicting next-day PO availability. To do so, we integrated PO over the forecasting window $t \in [t_{issue} + 24h, t_{issue} + 36h]$, which yielded a value in Wh. By computing this value for the measured and forecasted data we can then access the forecasting performance at predicting power availability. The results from this analysis are listed in Table 12.

Table 12: Error metrics (in kWh) for the daily PO availability. The first row shows the average availability for the testing data set.

PO	Mean	MBE	MAE	RMSE	skill
Measured	4135.2	-	-	-	-
$\hat{P}_{per}$	4551.0	-415.8	1292.7	1881.5	-
$\hat{P}_{NAM}$	4558.9	-423.7	1037.3	1377.8	26.8
$\hat{P}_{kNN}$	4276.3	-141.1	493.4	818.8	56.5
$\hat{P}_{MOS}$	4162.0	-26.7	534.8	787.3	58.2

Just as in the previous case, here we also explored MOS to further improve the forecasting performance. MOS was applied to the training data and the performance of $\hat{P}_{MOS}$ was assessed using the testing data set. The forecasting skill as a function of the horizon for this model is shown in Fig. 22 above, and the error metrics for this model are listed in the last row of Table 11 above.

6.3 Task 4.3: 48-hour ahead DNI and PO forecasts

The final task in this project consists of developing models that predict the daily average DNI and PO two days ahead of time. These models were treated differently than the ones presented above since they deal with daily averaged data (night time values excluded). As such, these models provide no information about short-lived DNI and PO dynamics but are useful to anticipate daily averages two days ahead of time. As in the 24 to 36-hour forecasts, such predictions are important for regulating entities and independent system operators whose job is to schedule resources to balance the electric grids.

Specifically the goal of this task was to create DNI and PO forecasts at 00:00 (local time) two days in the future, as exemplified in Fig. 23. The data granularity for these forecasts is 1 day, and the forecast produces as single value: the daily average of DNI or PO. As in the previous cases, the forecasting algorithm used historical data available at the issuing time and also data from numerical weather prediction models (NWP) that cover the 48-hour forecasting window.

6.3.1 Subtask 4.3a: Train algorithms using locally generated and our own solar resource data

In this task, the ground telemetry used corresponds to the DNI and PO data illustrated in Fig. 13. The only difference was that the data was aggregated into daily average values (excluding

night time). The input data set was also augmented with forecasted data from the NAM model introduced in Section 3. These data were also aggregated into daily average values. All variables were normalized using the clear-sky model described in Appendix B.

In terms of models used to produce the 48-hour ahead forecasts, we used two models: the baseline persistence model and an optimized ANN model (algorithm explained in the Appendix C.2).

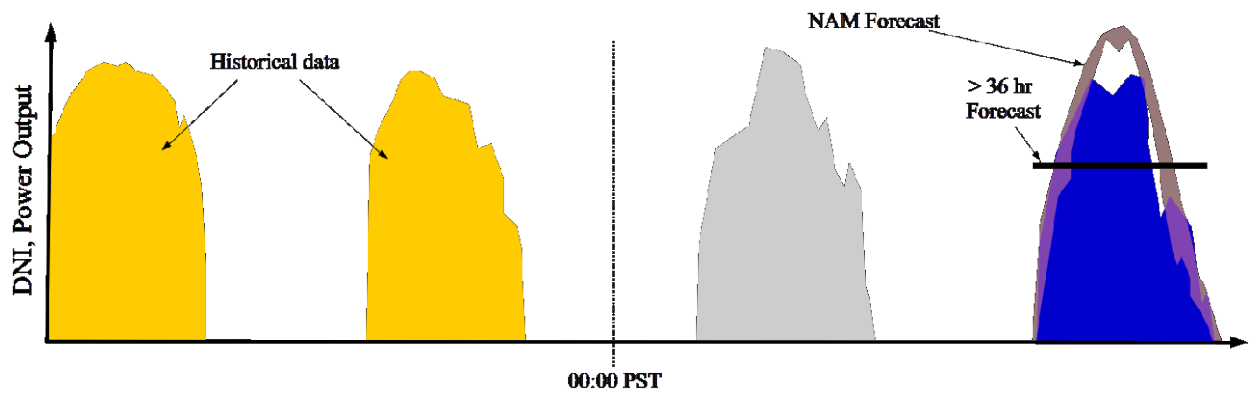

Figure 23: 48-hour ahead forecasting. The forecast is issued at 00:00 local time for the next 48 hours. The forecast produces daily average values for DNI and PO.

6.3.2 Subtask 4.3b: Validation of the 48-hour ahead forecast models

After training the ANN forecasts data was produced for the holdout validation data set. As in the previous cases, the models' performance was determined using the suite of metrics introduced in the Appendix A. The bulk error metrics are listed in Table 13 for both DNI and PO. The results are similar to the ones presented above for DNI and PO day-ahead forecast. The table shows that the ANN model ($\hat{P}_{ANN}$) was achieves skills above 40% for both variables.

Table 13: Bulk error metrics for the different DNI and PO 48-hour ahead forecasts. Absolute values are in kW and Wm^{-2} for PO and DNI, respectively. Relative values are in %.

Model	MBE	rMBE	MAE	rMAE	RMSE	rRMSE	skill
			Target Variable = DNI				
P_{per}	61.7	6.2	226.5	22.6	305.5	30.6	-
P_{ANN}	-16.4	-1.6	120.0	12.0	180.0	18.0	41.2
			Target Variable = PO				
P_{per}	22.2	2.2	190.0	19.0	254.4	25.4	-
P_{ANN}	-38.5	-3.9	103.0	10.3	146.1	14.6	42.5

7 CONCLUSION

This document describes the technical tasks performed by UCSD for the grant "Concentrated PV Forecast System for On-Site Distributed Generation". The goal of this project was to create fore- casting models for DNI and CPV power generation for intra-hour, intra-day and day-ahead horizons. The models use both remote sensing data (satellite images and NAM forecasts) and local telemetry (irradiance sensor, sky images, etc.) to create optimized machine learning forecasts with good forecasting skill.

Table 14 lists the status for the milestones and deliverables achieved in this project.

Table 14: List of deliverables and respective status

Deliverable	**Status**
Phase 1	
Collection and analysis of historical irradiance, imaging, power output data	✓
Develop necessary scripts and configure data base servers to collect on going data streams	✓
Deployment of sky imagers	✓
Cyber Secure, ICCP transfer of data to forecasting engine	✓
Phase 2	
Intra-hour DNI forecasts based on cloud tracking	✓
Analyze intra-hour operational forecasts for ramp control	✓
Success Metric: 20% skill improvement and over-persistence	**Achieved**
Phase 3	
Intra-Day DNI forecasts based on sector remote sensing	✓
Success Metric: 15% skill improvement and over-persistence	**Achieved**
Phase 4	
Day-ahead DNI forecasts based on stochastic learning and NWP models	✓
Prospective power output from Soitec power plant (intra-hour intra-day and day-ahead)	✓
48-hour ahead DNI and power output forecasts	✓
Demonstrate cyber secure, ICCP compliant, online forecast delivery platform for optimized monitoring, planning and market participation	✓
Success Metric: 20% skill improvement and over-persistence	**Achieved**

Finally, Table 15 lists the success criteria in terms of the forecast skill metric s as defined in the in the Demonstration Plan. The metric s is defined as the ratio: $s = (V\text{-}U)/V = 1 - U/V$. The uncertainty U is defined as the standard deviation of a model's forecast error and the variability V is the standard deviation of the solar irradiance step changes. As demonstrated in [1] this metric can be approximated by $s = 1 - \mathrm{RMSE}/\mathrm{RMSE}_{per}$, where RMSE is the forecast error for the new models developed in this project and RMSE_{per} is the error for the reference persistence

model. Thus, the values listed in Table 15 correspond the forecasting skill values for the best model in the tables above for the intra-hour, intra-day and day-ahead DNI and PO forecast.

Table 15: List of deliverables and respective status

Horizon	**<1 hr (RTD)**	**1 hr (HASP)**	**1-6 hrs**	**24-36 hrs (DAM)**	**> 36 hrs**
Averaging Period	1 min	5 min	15 min	1 h	1 d
Current s	0.12-0.32	0.15-0.29	0.08-0.14	0.08-0.39	0.19
Target s	0.25-0.45	0.4	0.3	0.3	0.4
		s values obtained in this project			
DNI	0.24-0.32[1]	0.24-0.32[1]	0.25-0.39	0.34	0.41
	Table 3	Table 3	Table 6	Table 7	Table 13
PO	0.20-0.23[1]	0.20-0.23[1]	0.17-0.35	0.38	0.43
	Table 9	Table 9	Table 10	Table 11	Table 13

[1] These values were obtained with 15 min data since 1-min and 5-min data were not available for this Demonstration project.

For shorter time horizons the targeted forecasting skills were not fully achieved. However the obtained values are in agreement with the best performing forecasting models published in the literature [2]. With respect to longer horizons the Demonstration Plan exceeded the targets.

Appendix A

Error metrics

The forecasting performance was established by analyzing the forecasting error, that is, the difference between the measured and forecasted data. We evaluated the models using error metrics commonly found in forecast literature: mean absolute error (MAE), mean bias error (MBE), root mean square error (RMSE), and forecasting skill (*s*) [1, 3].

MBE is a measure of systematic errors (or bias). An unbiased forecasting model, that is, one that on average does not under or over predicts the target variable, will have a MBE value close to 0. It is an important metric because understanding the overall forecasting bias (over or under-forecasting) would allow power system operators to better allocate resources for compensating forecasting errors in the dispatch process.

MAE is the magnitude of the forecasting error. In this metric all errors contribute equally regardless of their magnitude.

RMSE is a measure of random errors and, unlike MAE, it penalizes larger errors. In this sense this is a very important metric since one of the goals of this project is to reduce the instances of large error associated with large ramps.

Forecast skill s is a convenient way to benchmark new forecasting models. It measures the models' performance relative to the persistence model. It is a good metric to compare models applied to different variables (DNI and PO) since the intrinsic variability of the data is reflected in the RMSE for the persistence model: low RMSE for the persistence model implies low variability data whereas high RMSE implies high variability. For example, a model that returns very low RMSE for a data set comprised of only clear-sky days will have a very low skill since the RMSE for the persistence model will also be very low. The ideal forecast will have a low RMSE and high forecasting skill.

Mathematically these error metrics are defined as:

$$\boldsymbol{MAE = \frac{1}{m}\sum_{i=1}^{m}|y_i - \hat{y}_i|} \tag{6}$$

$$MBE = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i) \tag{7}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{8}$$

$$s = 1 - \frac{RMSE}{RMSE_p} \tag{9}$$

where y is the true value, $\hat{y}$ is the forecasted value and RMSE_p is the RMSE of the reference model: persistence forecast. These metrics can be applied to any subset of the data. In all the results presented above nighttime values are discarded.

Clear Sky Model

The clear-sky model returns irradiance and power for a given geographical location and time when clouds are absent. However, even in this condition the irradiance at ground level is influenced by other environmental conditions such as the aerosol content and precipitable water, which are quantified through the atmospheric turbidity. Several turbidity parameters have been introduced with the most popular being the Linke turbidity factor. Many models have been developed to estimate the clear-sky irradiance and comprehensive comparisons of some of the most popular models can be found in [4, 5]. In this work we used the clear-sky model proposed by Ineichen and Perez [6], as it is one of the best performing models, and one of the simplest. It requires as inputs the solar elevation and the Linke turbidity. The solar elevation for a given latitude and longitude is computed from the sun's orbital elements. The Linke turbidity is obtained from the worldwide monthly averaged maps available at [7] which were created based on the algorithm proposed by Remund et al [8]. Figure 24(top) compares the measured DNI against the DNI obtained with the Ineichen model for three days Fort Irwin (blue curve). The bottom figure compares measured and clear-sky PO (blue curve). Clear-sky PO is obtained from the clear-sky DNI by multiplying this value by 960.

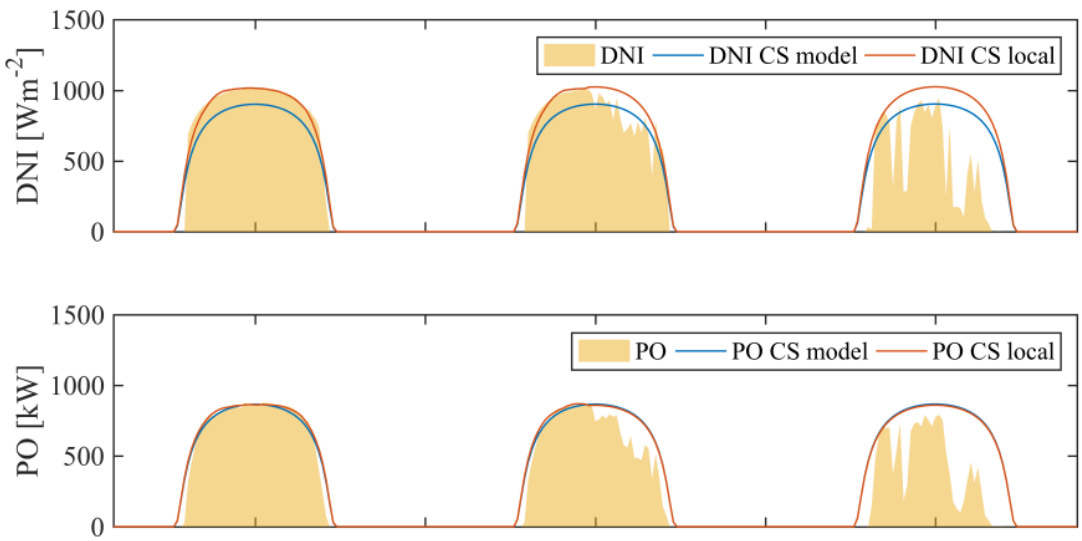

Figure 24: *Top*: DNI and clear-sky DNI irradiance for a period of three days. The clear-sky model in blue was computed with Ineichen's model [6] with monthly averaged Linke turbidity obtained from [7]. The orange curve was obtained by adjusting Ineichen's DNI with local telemetry. *Bottom*: Same as above but for the PO.

The figure shows that the DNI clear-sky model obtained with global turbidity factors shows the correct shape but not the correct magnitude. This suggests the following improvement: for each time instance we identified the preceding clear-sky instances using the algorithm provided in [9]. Then we computed a corrective factor that adjusts the Ineichen model to match the measured clear-sky DNI and PO. The resulting clear-sky model is shown in orange. As the figure illustrates, by taking into account local telemetry we can obtain a clear-sky model that approximates measured clear-sky data (first day and the first half of the second day) much more closely.

Forecast Models

Persistence model

The reference model used throughout this work is the persistence model. Persistence assumes that the DNI and PO clear-sky indexes (the ratio between the measured DNI and PO and their theoretical clear-sky values) over the forecasting window are the same as those values at the forecasting issuing time. Under this assumption, we calculated the persistence model according to the following expression:

$$\hat{\boldsymbol{y}}_{\boldsymbol{per}}(\boldsymbol{t}) = \boldsymbol{k}_{\boldsymbol{y}}(\boldsymbol{t}_{\boldsymbol{issue}}) \times \boldsymbol{y}_{\boldsymbol{clr}}(\boldsymbol{t}), \quad \boldsymbol{t} \in \boldsymbol{\Omega} \qquad (10)$$

where y denotes the variable to forecasts (DNI or PO), $\hat{y}_{per}$ denotes the forecasted value and y_{clr} denotes the theoretical clear-sky value. Intra-hour and intra-day forecasts are issued continuously throughout the day in 15-minute steps, thus t_{issue} is an increasing variable in 15-minute steps. The 24- to 36-hour ahead forecasts are issued one time daily at 10 am PST, resulting in $t_{issue} =$ 10 am (PST), whereas the 48-hour ahead forecasts are issued at $t_{issue} =$ 00:00 (PST). Finally Ω denotes the forecasting window for each forecast category:

- Intra-hour forecast **Ω** = [t_{issue}+ 15 min, t_{issue}+ 45 min];
- Intra-day forecast **Ω** = [t_{issue}+ 1 hour, t_{issue}+ 6 hours];
- Day-ahead forecast **Ω** = [t_{issue}+ 24 hours, t_{issue}+ 36 hours] for the 24- to 36-hour ahead forecast, and **Ω** = [t_{issue}+ 24 hours, t_{issue}+ 48 hours] for the 48-hour ahead forecast.

Machine Learning Models

In this section we explain in broad strokes the machine learning models used in this project. Figure 25 illustrates the process used to train and validate the models. In the training stage we used historical data to determine a function that maps the input variables or predictors into the output extracted from current and past satellite or sky images, etc. Output data includes the data we want to forecast. In this case DNI or PO at the targeted forecasting horizons.

In the training process we also included the preprocessing of the data. That includes techniques as the normalization of DNI and PO with a clear-sky model.

In the testing stage we assessed the forecasting performance by analyzing the forecasting error (the difference between the forecasted data and the testing target). Appendix A provides detailed information about the quantification of the forecasting error.

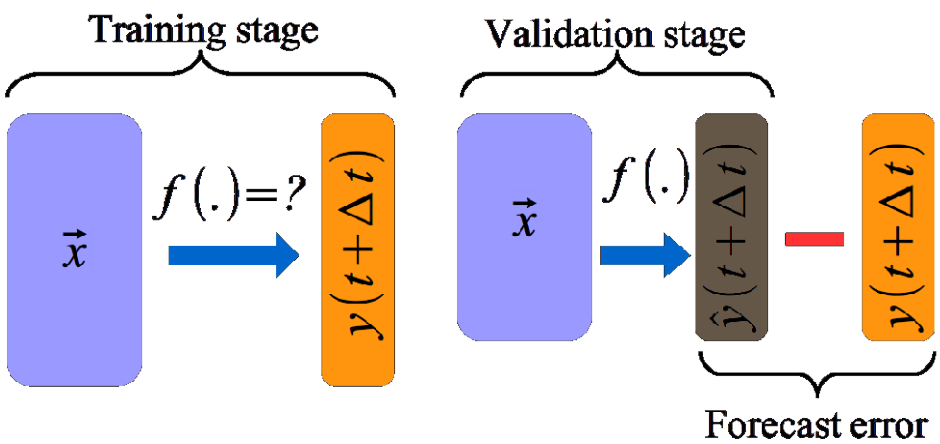

Figure 25: The forecasting algorithm is determined in the training stage using known input and output data. In the testing stage the model is evaluated using data not used during the training.

The key step in this process relies in obtaining the appropriate mapping function $f(\cdot)$. The input data x is used to forecast the output variable $\hat{y}$ (DNI or Power output) at time $t + FH$. In the training stage a mapping function $f(\cdot)$ is determined. In this work we explore a large family of stochastic tools to determine $f(\cdot)$. These include: k-nearest-neighbors (kNN), artificial neural networks (ANN) and least squares minimization.

In the kNN model neighbors are defined in terms of the various predictors available (current telemetry, NAM forecasts, etc.) Time instances that exhibit similar behavior in terms of predictors are tagged as neighbors. Then, using the DNI or PO data from the training set that corresponds to those neighbors we compute the predicted values for the targeted forecasting horizon by aggregating the historical data.

Depending on the case we can have more than 100 variables that can be used as predictors (such as in the case of the intra-hour forecast). In general, the set of variables that defines the optimal neighbors (the ones the minimize forecasting error), is a subset of all available variables. To determine this set we use an exhaustive search method in which all variables and combinations thereof are tested using the training data. Another parameter tested is the number of neighbors used in calculating the forecast. Practice shows that using the closest neighbor results in poor results, and that a pool of neighbors should be used instead.

After determining the best set of neighbors the kNN forecast for a target variable y (DNI or PO) is calculated as

$$\hat{y}_{kNN}(t) = \frac{1}{k}\sum_{i=1}^{k} k_y(\tau_i) \times y_{clr}(t), \quad t \in \Omega \qquad (11)$$

where $k_y(\tau_i)$ is the clear-sky index from the training data set that corresponds to the neighbors identified by the time τ_i, and Ω is as defined above for the persistence model.

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APPENDIX D NREL LETTER

The attached letter from the National Renewable Energy Laboratory (NREL) contains the results of NREL's review of the performance objective data collection and technical analysis methodologies used in the development of the Final Report and the Cost &Performance Report.

NATIONAL RENEWABLE ENERGY LABORATORY

Date: Monday, November 27, 2017

To: Patrick Rowe, Soitec

From: Chris Deline, NREL
Matt Muller, NREL / Leidos

Subject: Soitec 1MW Ft Irwin Project Final Report Approval

Dear Patrick,

I have been able to review the final report on the Soitec 1MW Ft Irwin project in collaboration with our subject matter expert Matt Muller, who is now working at the 3rd-party engineering firm Leidos INC. NREL's background on this project was to configure the initial energy production model, and to confirm that initial system performance was within expectation, based on a 2015 site visit, a 2015 performance report and a 2017 follow-on report.

DNV-GL provided data analysis and performance reporting for the 2017 Final Report, including:

- Final measured vs expected energy generation and system availability
- Performance degradation assessment

NREL has reviewed the methodology used by DNV-GL, and agrees with the major conclusions of the report, namely that over its first 24 months of operation, the Soitec Ft Irwin project has experienced negligible degradation (within measurement uncertainty), and has generated energy within 1% of modeled expectation. The methodology used to calculate system availability and O&M labor man-hours appears sound, with reported O&M labor slightly above the target (2-5 man-hours per CPV system annually vs. < 2 man-hours target) and system availability below the target (96.3% system availability vs 98% target). These results are consistent with our understanding of the site maintenance requirements and of the reported failures of 2-axis tracker drive sensors and components.

The Solar Forecasting methodology and results from UCSD have not been reviewed by NREL.

Sincerely,

Chris Deline
Engineer, Manager DOE Regional Test Center – NREL site

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Phone 303-275-3000

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Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

APPENDIX E NREL INITIAL SITE VISIT REPORT

The attached report from the National Renewable Energy Laboratory (NREL) contains the results of NREL's initial review of the CPV power plant installation in October 2015.

Fort Irwin 1 MW Soitec CPV Field Inspection

Inspection and Report completed by:

Matthew Muller, NREL, 16253 Denver W Parkway, Golden, CO 80401, phone: 303-384-6164, email: matthew.muller@nrel.gov

Report Reviewed by:

Sarah Kurtz and Chris Deline, NREL, sarah.kurtz@nrel.gov, chris.deline@nrel.gov

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Office of Energy Efficiency and Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

Contents

Introduction and Objectives 3
Plant Location and Equipment Details 3
General Inspection of the CPV plant, plant equipment, and wiring 4
General inspection of meteorological equipment and factors that can impact plant performance 10
System Performance Validation 15
Site Inspection and System Performance Summary 18

Introduction and Objectives

ESTCP (the U.S. Department of Defense's environmental research arm) contracted with Soitec to install a
1 MW CPV plant at Ft. Irwin in California which was connected to the grid in September 2015. As part of that contract it was agreed that during the operational testing phase (Phase 2), a third party would provide a performance review for the first 2 years of the project. Through communication with both ESTCP and Soitec, NREL agreed to serve as this third party. The performance review comprises measurements of energy and energy production performance using a combination of revenue grade meters, meteorological measurement equipment and data storage equipment which has been installed by Soitec. Soitec is responsible for delivering an internal PVsyst model, site meteorological data, plant performance data and O&M data to NREL for this evaluation.

NREL's assessment will be documented with an initial site inspection report and with two annual reports. The main activities proposed to be performed by NREL include:

- A site visit after installation to verify field conditions (power plant installed, locations of the meteorological stations, power plant functionality);
- On-going data quality reviews to ensure data collected is accurate and complete during the testing period;
- Final review of maintenance logs, calibration status and documentation of soiling;
- Detailed data analysis including energy model validation, system availability, degradation analysis and soiling loss analysis;
- Preparation of performance/validation reports on an annual basis.

The following report documents NREL's site inspection that was conducted on October 12, 2015. The performance data is also analyzed for the day of the inspection to further validate that the power plant was installed and is functioning as expected. The first annual report (due in 2016) will provide a more in depth analysis of the PVsyst model that Soitec has provided to NREL as well as the detailed data analysis as described above.

Plant Location and Equipment Details

Fort Irwin 1 MW Soitec CPV Installation, (U.S Army National Training Center)	
latitude/longitude	35.2464° N, 116.6819° W
tracking	40 individually controlled dual axis trackers
modules	12 CX-M500 modules per tracker (2335 Watts at CSTC)
system rating at CSTC	40*12*2335 = 1,121,000 Watts
grid connection	(2) 500 kW Advanced Energy Inverters (AE500 TX)
backup power for tracker stow	(1) Caterpillar generator
direct normal irradiance	(2) Kipp & Zonen CHP1
global normal irradiance	(2) NES measurement systems (SOZ1-03)
wind speed	(2) Adolf Thies GmbH&Co KG
internal module humidity and temperature	(2) Michell PCMini52-3-x25

General Inspection of the CPV plant, plant equipment, and wiring

Figure 1 Plant view from the east side. All trackers were on sun throughout the inspection period.

Figure 2 Plant view from the west side. The ground cover is small compacted sand/aggregate (1-2 mm size). The site slopes downward from west to east and includes the drainage ditch shown paralleling one row of trackers.

Figure 3 Erosion in the aggregate due to a recent storm. The shoe shown in the picture provides a relative scale for judging the erosion. Plant maintenance personnel indicated that recent storms were strong for the region.

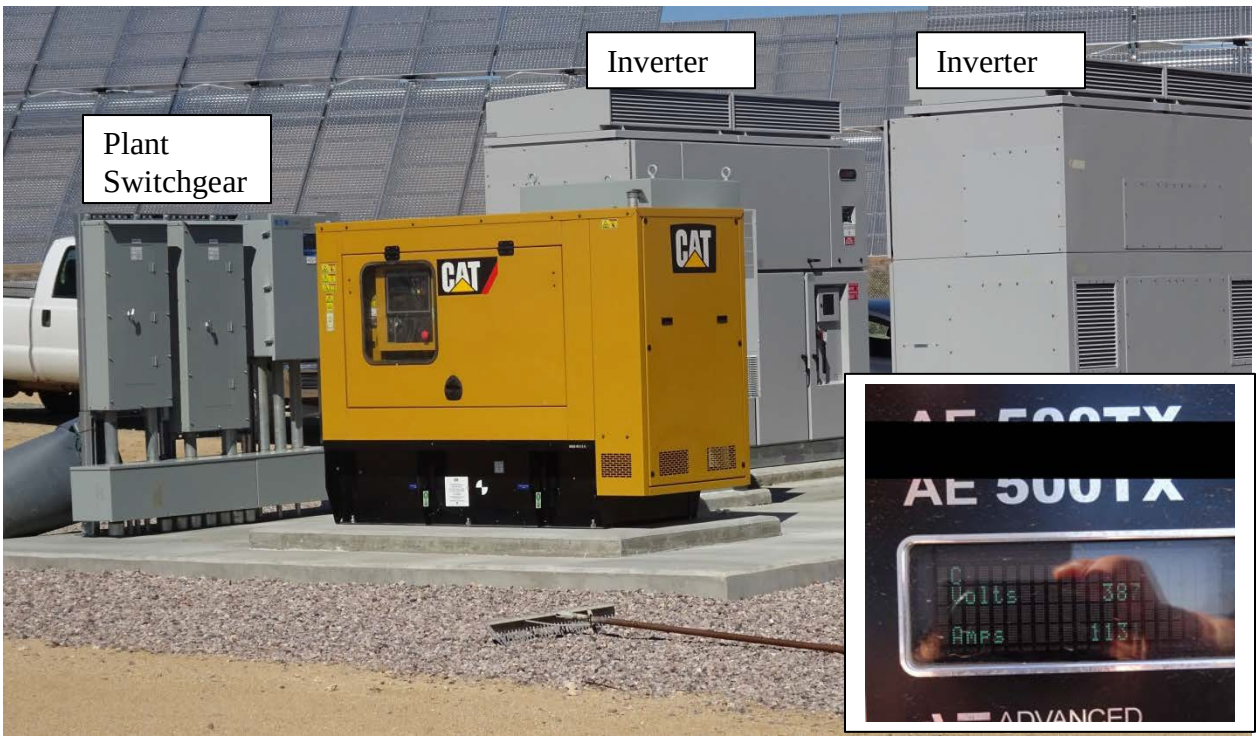

Figure 4 A centrally located concrete pad supports two inverters, the plant switchgear and a Caterpillar generator. Both inverters were online during the inspection period. In the inset in the lower right corner one inverter is reading 387 volts and 1,131 amps. Assuming the same output for the second inverter the

plant is outputting 0.875 MWs at the time of the photograph. The Caterpillar generator is wired into the system switchgear to provide tracker stow capabilities in the event that grid power is lost in a high wind event. The inverter pad is surrounded by coarse road grade aggregate and includes a road of the same aggregate which leads from the entrance gate to the inverter pad.

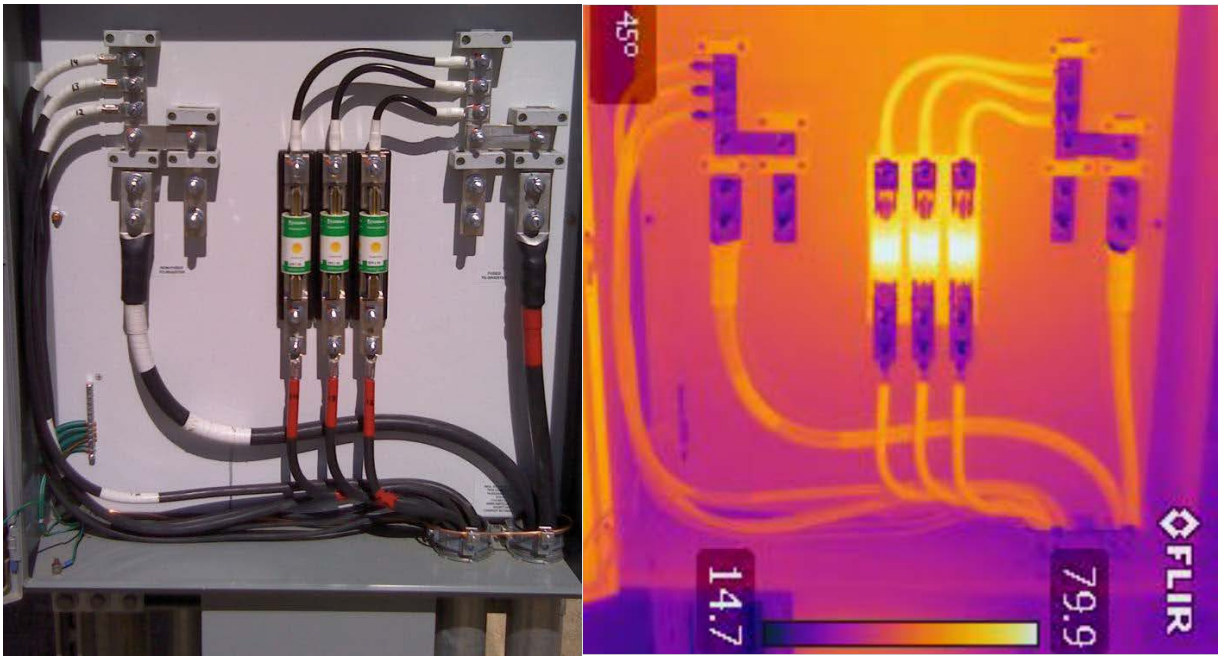

Figure 5. (Left) Photograph of the wiring inside system combiner box 2A. (Right) Infrared image of the wiring inside the same combiner box. As expected the fuses are at an elevated temperature compared to the wiring while all temperatures are within expectations. This combiner box is representative of others in the field.

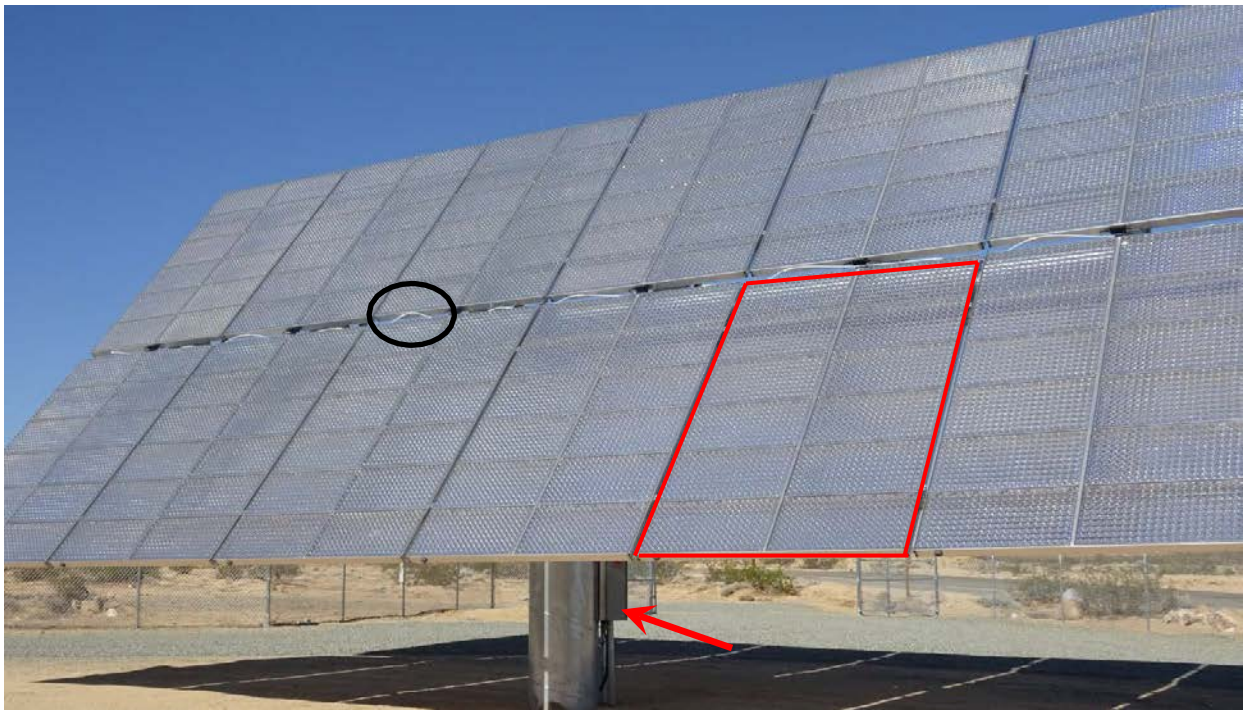

Figure 6. One of the 40 dual axis trackers that comprise the 1 MW plant. A red box outlines one of the 12 CX M500 modules that are part of the tracker array. A black circle highlights tubing that runs to each module to provide air drying for the internal module cavity. A red arrow points to the tracker control box. Each tracker has its own control box.

Figure 7 (Left) Each tracker is labeled per its control box enclosure. To the right of the control box is an additional enclosure housing air drying equipment shared by 3 trackers. An air filter can be seen protruding from the bottom of the air handling enclosure. (Right) A close up of the air handling equipment which is used to maintain module internal air at sufficiently low humidity levels.

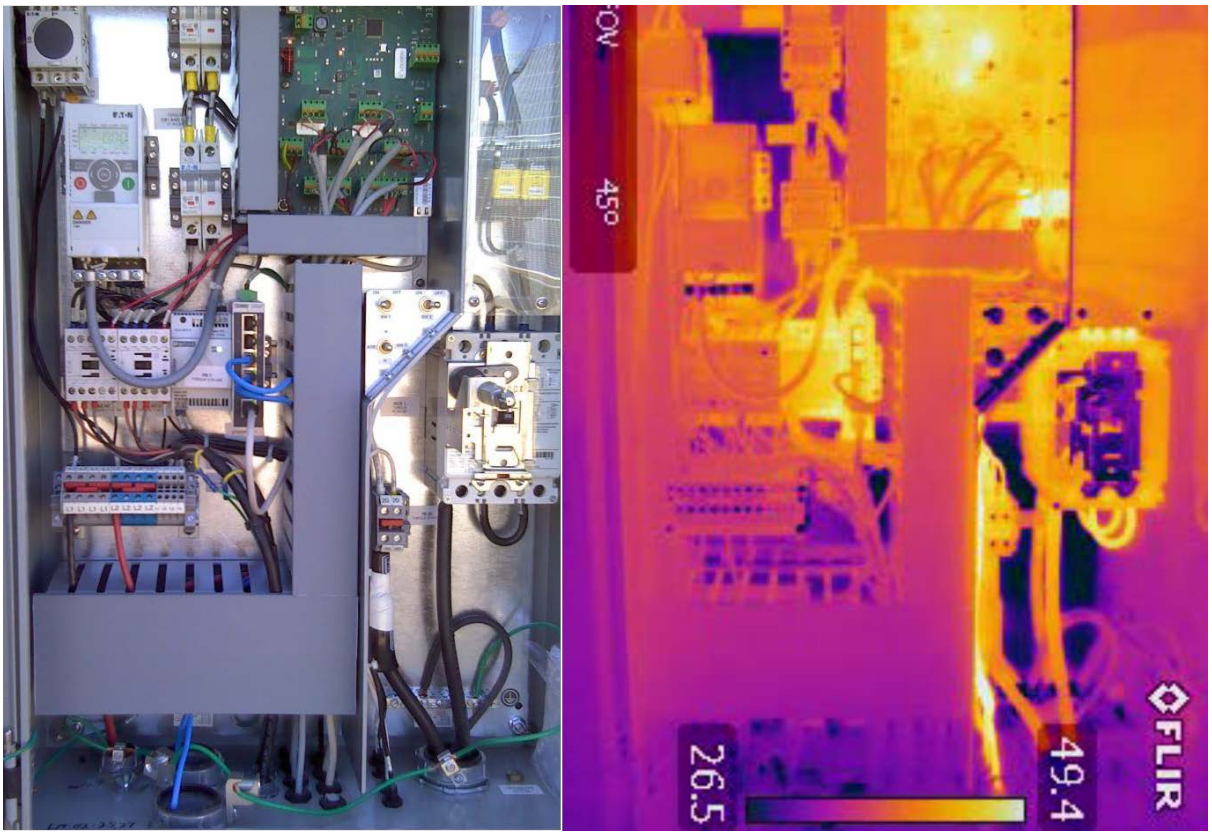

Figure 8. (Left) The internal visible image of one of the tracker control boxes. On the lower right of the image two large black wires are seen exiting the enclosure. These wires are the current carrying conductors that lead to system combiner boxes. Immediately to the left of these large black wires are smaller incoming DC wiring from the tracker array strings. One of the tracker array strings is used to provide feedback for the tracker controller for periodic optimization of tracker sun alignment. In other words the tracker controller optimizes alignment by maximizing output of this string. Note that in other Soitec installations the controller uses the complete output of all array strings for feedback but due to electrical requirements at the Ft. Irwin site only one string is used. The typical CX M500 module internal wiring was modified so the voltage was reduced by one third and the current was increased by one third. The controller was not designed to accommodate the increased array current and therefore one string was used as feedback rather than the complete array. (Right) The infrared image corresponding to the visual image on the left. All wiring and connections in this control box and the other 39 control boxes showed acceptable temperature ranges. In this infrared image the DC current carrying conductors incoming from the tracker array are one of the hottest items in the box. This is representative of all 40 control boxes.

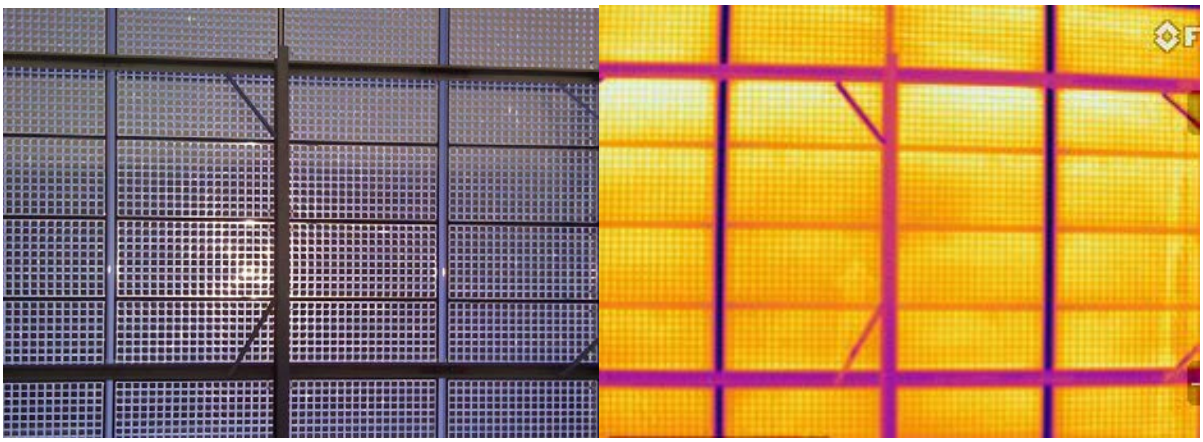

Figure 9 (Left) Visual image from the back of a representative sample of on-sun modules. (Right) The corresponding infrared image for the modules on the left. In this image the relative color scale is identical to Figure 8 but the scale is not shown here because the absolute temperatures are not representative. For this type of broad ranging image with the sun in the background the camera fails to accurately measure the absolute temperature. For example the second row (from the top) of modules appears hotter than other modules but this is assumed to be an artifact of camera distance and angle when the image was recorded. What can be concluded from this infrared image is that, as expected, the heat sink behind each cell is hotter than the surrounding backplate and the modules have a general temperature uniformity. The general reason for recording this and other module infrared images was to look for any hot spots. No module hot spots were found.

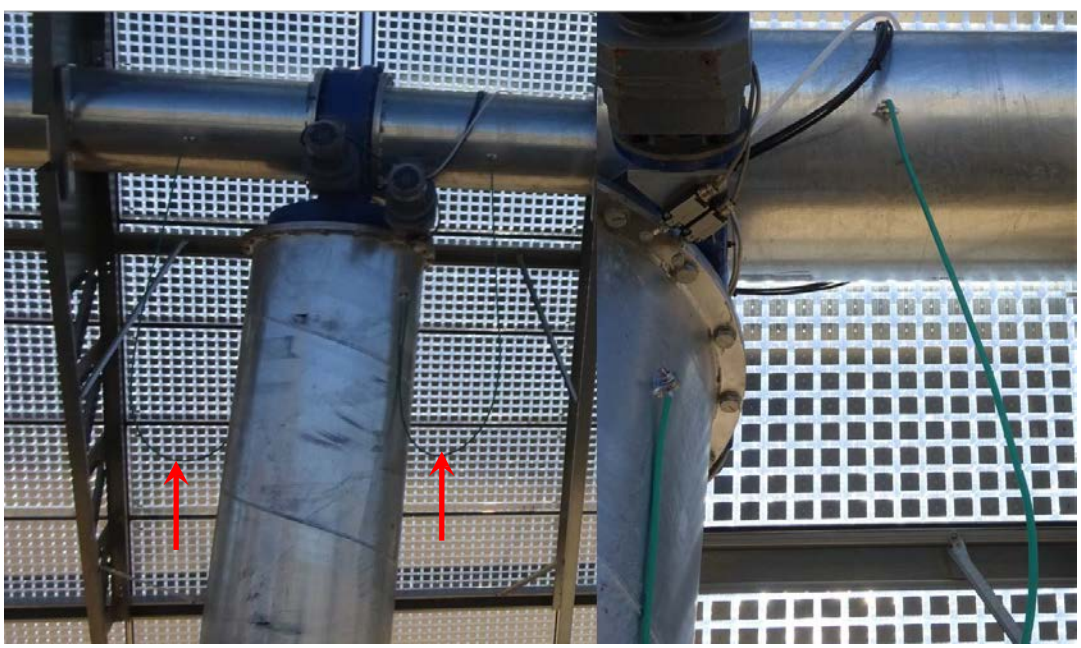

Figure 10. (Left) Red arrows point to grounding wires that connect the tracker pedestal to the left and right horizontal yoke tube that supports the array structural ribs. Although not shown here it was verified that each CX M500 module also was grounded.

General inspection of meteorological equipment and factors that can impact plant performance

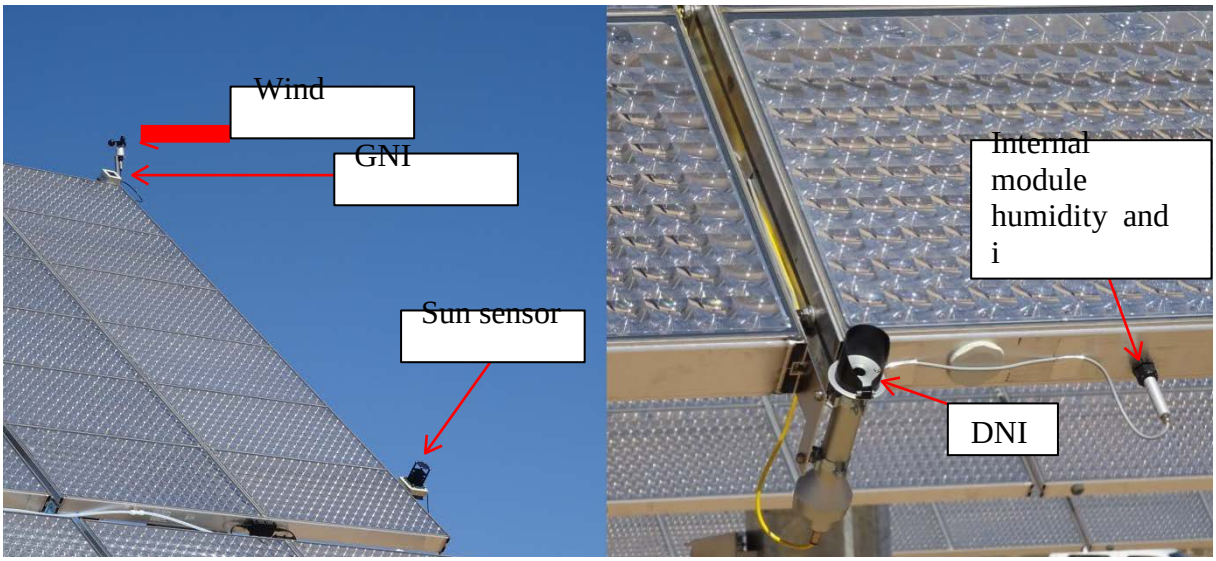

Figure 11 Two trackers within the 1 MW plant include meteorological equipment. The tracker labels are A1-A17 and B1-B32 where A1-A17 is located in the northeast corner of the plant and B1-B32 is centrally located on the southern side of plant. Each of these trackers contains a global normal irradiance sensor and a wind speed sensor on their upper right corner and on the lower central edge is a direct normal irradiance sensor and a sensor measuring one module's internal humidity and internal air temperature. Although not in the pictures, the same trackers also include measurements of module backplate temperature and ambient temperature. The meteorological data acquisition equipment is housed within a separate enclosure attached to the pedestal of each of these trackers. Every tracker includes a four quadrant sun sensor that it is used as part of the tracking control algorithm. Note that Soitec has informed NREL that the SCADA system is currently recording the meteorological measurements from one of the two trackers. It is unknown if the data from the other tracker is being recorded by alternate means or if this data could be made available.

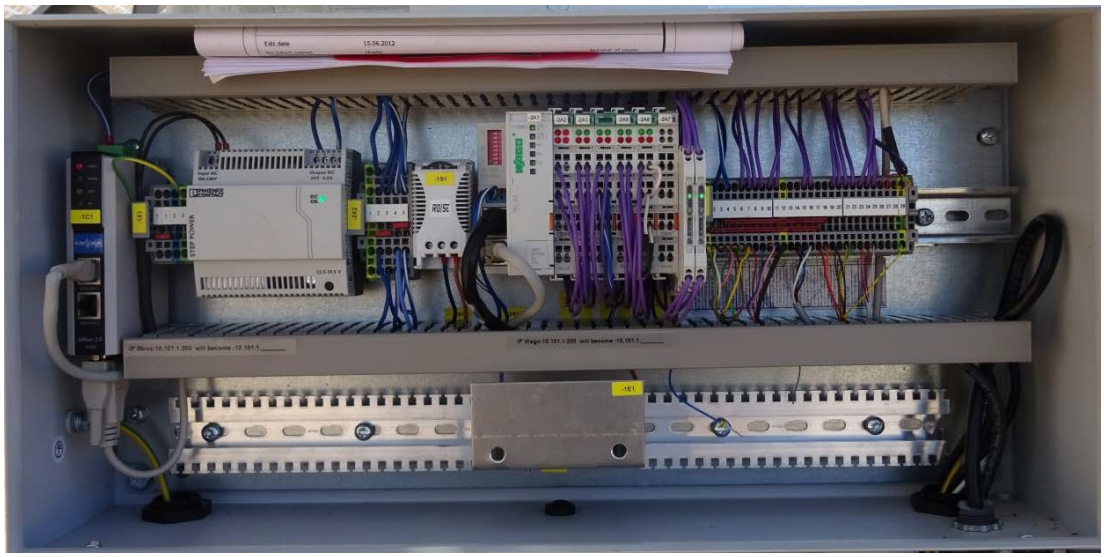

Figure 12. A picture of one of the two meteorological data acquisition enclosures.

Figure 13 Pictures of the serial numbers and calibration information for the two DNI sensors

Figure 14 Pictures of the serial numbers and calibration information for the two internal module humidity and air temperature sensors.

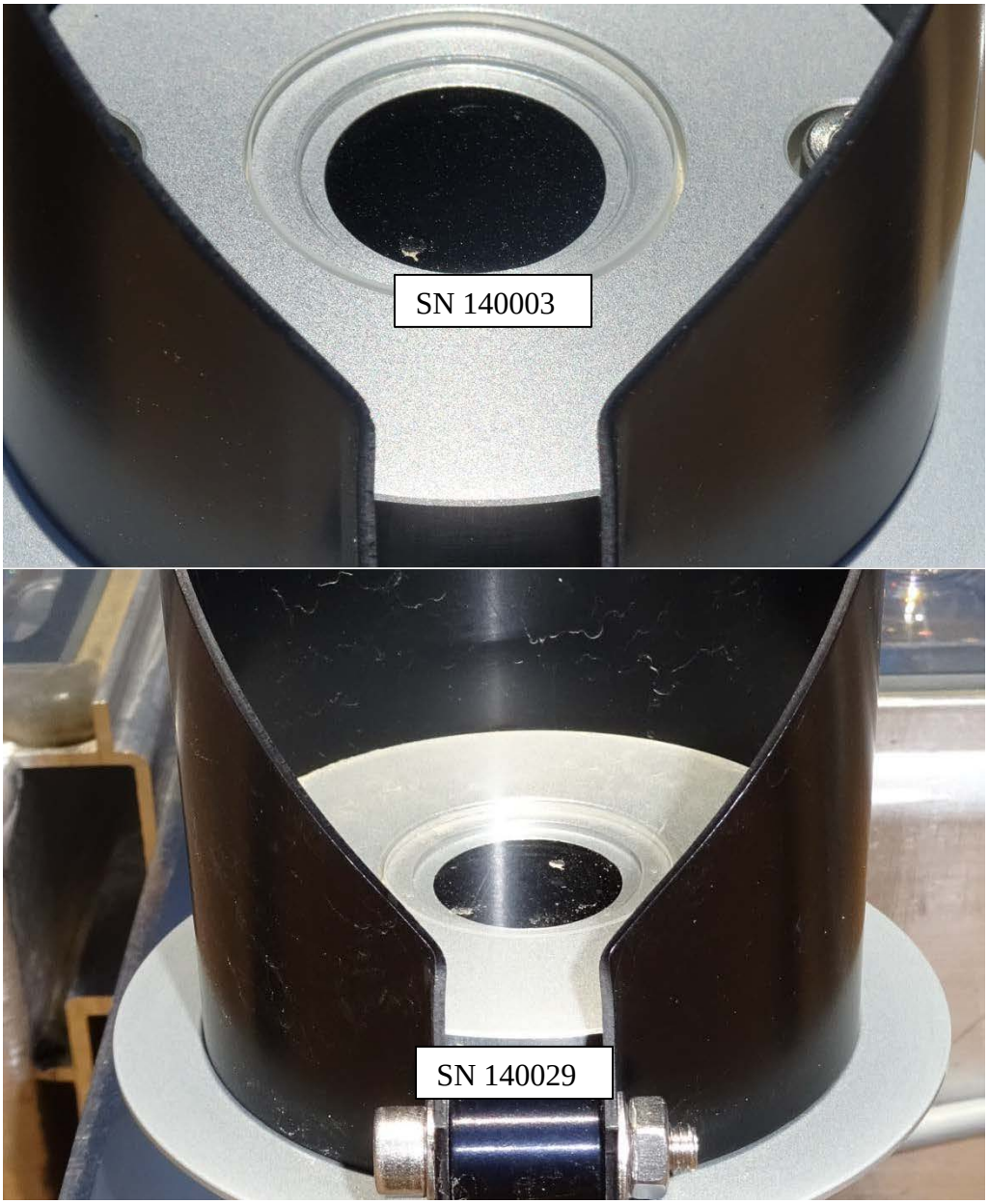

Figure 15. Both DNI sensors show soiling that will impact the resource measurements and performance evaluation for the plant. In the picture of SN 140003 it is difficult to see but minor soiling is noted. SN 140029 has readily visible soiling in the photograph that is estimated to be in the 1-3% loss range.

Figure 16. The alignment sunspot for DNI sensor (SN 140003), the cleaner of the two sensors in Figure 15. This misalignment is outside the Kipp and Zonen alignment specifications which can result in a false low reading for DNI. Note that the modules on this tracker indicated that the array was accurately aligned with the sun while the DNI sensor was misaligned with the sun. SN 140029 was within alignment specifications.

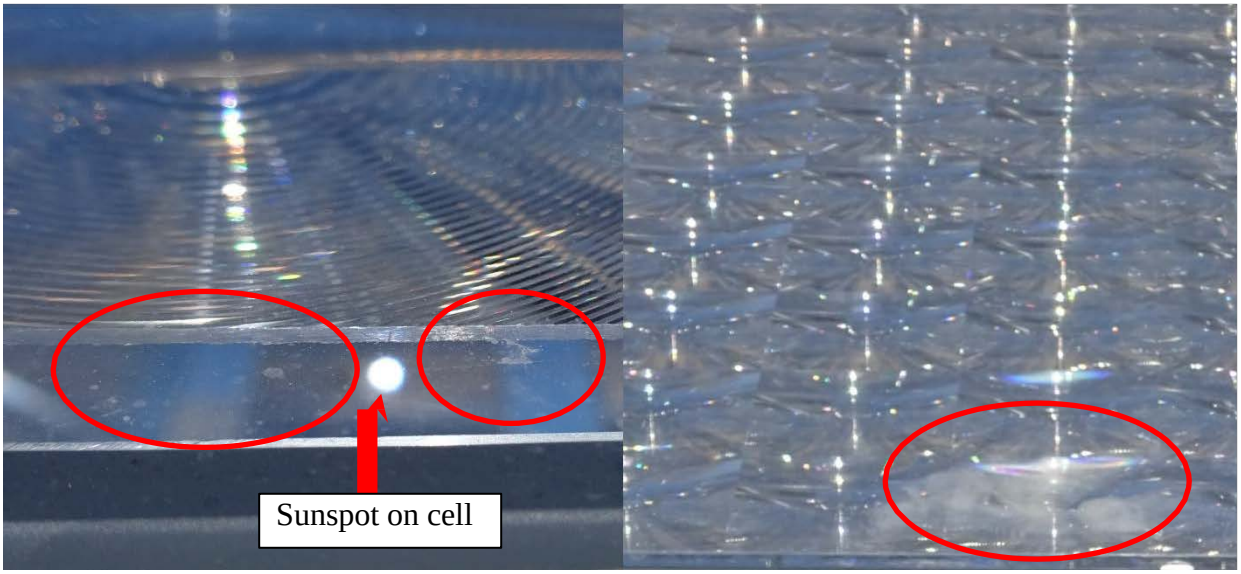

Figure 17. (Left) Very light system soiling is present as circled in red. This minor soiling is estimated to result in less than a 1% loss in power output. This level of soiling is generally representative for all the trackers. The spots are more visible on the lens edge as they better contrast the clear glass as compared to the facets of the silicone on glass. (Right) A small number of modules showed the hazy soil spots like circled in this image. Maintenance personnel indicated that the plant had not been cleaned since commissioning other than by rain events.

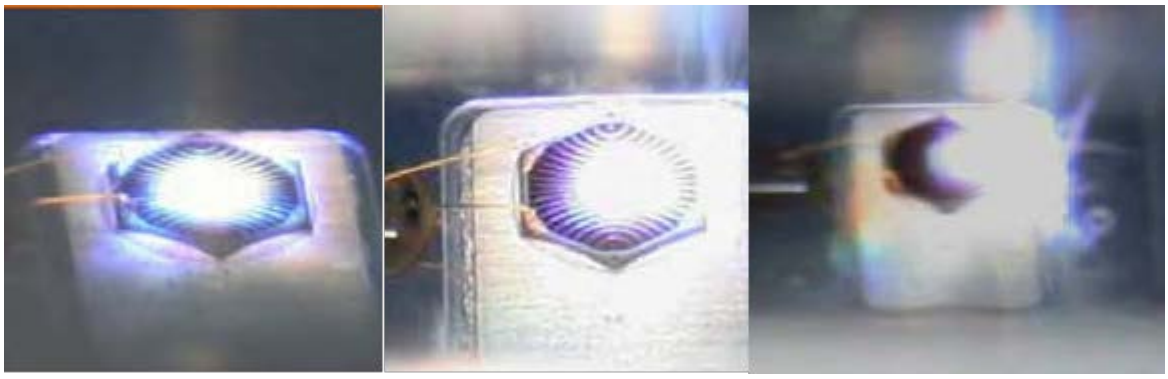

Figure 18. From left to right as copied from Soitec's installation manual are pictures of a "perfectly centered", "sufficiently centered" and "not acceptable" alignment for the solar cells within the CX M500 modules. For 10 of the trackers, the first row of submodules within each CX M500 was visually inspected for cell alignment. Cell alignment for ~65% of the submodules were within the perfect and sufficiently aligned categories while ~35% were unacceptable (the center of the sunspot was near or on the edge of the cell). If a 5% loss is assumed for these misaligned modules and the 35% approximation is assumed representative for upper rows on the trackers and the other 30 trackers, this equates to a 1.8% loss for the plant due to misalignment. Note that only 10 trackers were inspected as the tracker elevation position increased throughout the inspection period and the remaining 30 trackers were too high for a visual alignment inspection without the aid of a ladder. Also note that pictures were taken to record the cell/sunspot misalignment (see Figure 17) but the associated images were blurry due to glare and camera angle.

System Performance Validation

Soitec provided NREL access to Ft Irwin system and meteorological data and to the pan files Soitec developed for applying PVsyst modeling software to Soitec CPV systems. Although future reports will provide more details of system performance over time, current analysis is only presented for the day of inspection (October 12, 2015). The skies were clear the entire inspection day, making this an ideal day for comparing predicted performance with measured performance. It should be noted that due to the current and voltage changes in the CX M500 module detailed earlier, DC performance for half of each tracker is measured and the total plant performance is assumed to be twice the measured value. Currently only DC measurement data has been provided to NREL, and therefore only DC performance analysis is conducted.

Figure 16 demonstrated that there was misalignment of one of the DNI sensors and figure 15 demonstrated that there was soiling on both sensors. As the DNI is the primary solar resource and has direct implications on any modeling, figure 19 compares system DNI data with DNI data from a meteorological station in Las Vegas. The skies were also clear in Las Vegas on the date of inspection. The Las Vegas data was shifted by six minutes in order to account for the difference in sunrise time between the two locations. Figure 19 also includes the normalized system power divided by DNI over the course of the day.

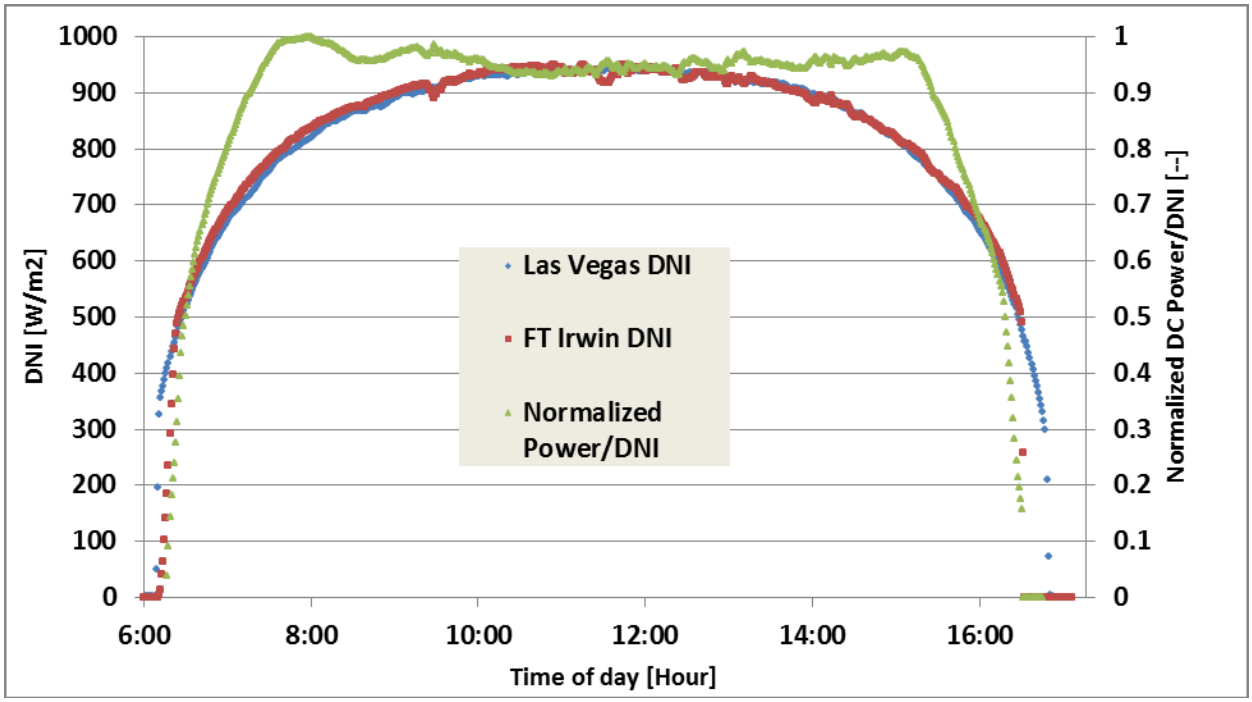

Figure 19, Ft. Irwin DNI compared to Las Vegas DNI for the date of the inspection. The Ft Irwin data set did not indicate which DNI sensor was used for the data set. The state of soiling of the Las Vegas sensor is not known but the Las Vegas meteorological station is expected to be cleaned on a weekly basis. There is no consistent shift between the two DNI measurements. Although the two measurements are at two different locations the consistency between the measurements provides a broad level check on the validity of the Ft. Irwin DNI measurement.

The comparative DNI data provided in Figure 19 indicates that the Ft Irwin DNI sensor is performing as expected for this type of sensor. It is noted that the Ft. Irwin data has some minor noise in the middle hours of the day as compared to the Las Vegas data. It is expected that these small up and down movements of the DNI in the middle of the day are an artifact of the alignment and system tracker performance at the Ft. Irwin site whereas the Las Vegas measurements are on a very high accuracy meteorological tracker. Between the hours of 6 and 7 am and 4 and 5 pm the Las Vegas DNI data show non-zero values for DNI while the Ft. Irwin data show zero values. These periods are indicative of either regions that are outside the Soitec tracker limits or

row to row shading of the DNI sensor(the DNI sensors are on the bottom edge of the trackers). The DNI that is not captured by the Ft. Irwin sensor is approximately 1% of the daily total.

Figure 19 also provides the normalized DC output power divided by DNI over the course of the inspection day. As expected the normalized performance peaks in the morning and also in the late afternoon when spectral conditions lead to current matching between the top and middle cells within the Soitec modules. The morning peak is higher than the afternoon peak due to the cooler morning temperatures. From 9 am to 3 pm the normalized performance is somewhat noisy and varies between 0.93 and 0.97. The DNI is stable during this time period so it is likely that this performance variation is due to variation in sun alignment of the 40 trackers.

Figure 20 provides a comparison between the measured average hourly DC output on October 12, 2015 and predicted average hourly output using PVsyst and an alternative simple model. The simple model applies a temperature correction based on backplate temperature and the nameplate power (-0.15%/C is assumed for the power temperature coefficient). The model than assumes a constant 10% DC loss to account for wiring losses, current mismatch and other losses. No spectral or shading losses are accounted for in the simple model. The results show that between 9 am and 3 pm both models are in close agreement with the measured data. In the early morning and in the late afternoon the simple model overestimates power while PVsyst underestimates power. This suggest that shading and spectral corrections are needed in the model but that for this particular clear sky day PVsyst has overly aggressive values for either spectral or shading losses.

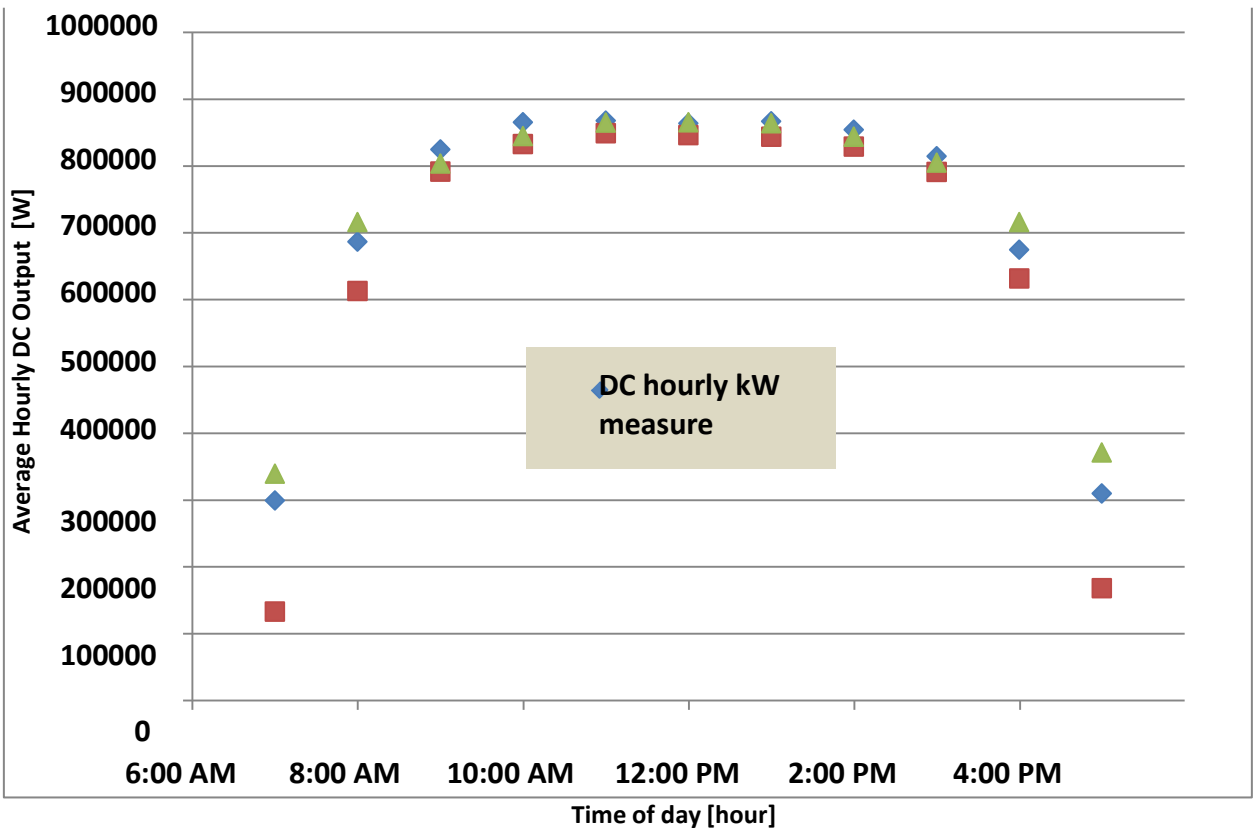

Figure 20 Comparison of the average measured system DC output with predicted average hourly DC output using PVsyst and a simple model. The simple model is a temperature correction based on the module backplate temperature (-0.15%/C temperature coefficient) and a constant 10% DC loss (wiring, current mismatch, etc.)

Site Inspection and System Performance Summary

The 1 MW Ft. Irwin Soitec CPV system was visually inspected on October 12, 2015. All information recorded during the inspection, including the images provided above, document that the system was installed according to the governing electric codes and to safety protocols. Site personnel were not able to indicate if tracker alignment was considered in the final state for the project but ~35% of the modules inspected were noted to not be in the optimal alignment position. Based on acceptance data measured at NREL for a sub-unit of a CX- M500 module and the assumption that 35% is representative for the entire plant, misalignment losses are estimated to be in the 1-2% range. Concerns were noted for DNI sensors capturing the solar resource data for the plant. One sensor was not within the alignment specifications of Kipp & Zonen (the equipment manufacturer) while both sensors had visual soiling present. The site maintenance personnel were notified of these findings and a request was made to correct the alignment and to clean the sensors weekly or biweekly.

For the date of October 12, 2015 measured DC performance data was compared against predicted system performance from PVsyst and a simple model (measured meteorological data were input into both models). The modeled and measured performance were in close agreement between 9 am and 3 pm. PVsyst underestimated the output outside these hours while the simple model overestimated the output. For these hours it assumed that PVsyst is overestimating shading or spectral losses while the simple model overestimated performance as it did not include either of these effects.

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APPENDIX F NREL FOLLOW-ON REPORT

The attached April 17, 2017 report from the National Renewable Energy Laboratory (NREL) contains the results of NREL's review of the first six months of site performance data (June 2016 to December 2016).

Fort Irwin 1 MW Soitec CPV Performance Validation Report 4/21/2017

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Office of Energy Efficiency and Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

Contents

Introduction and Objectives 3
Plant Location and Equipment Details 3
General Review of the Data Provided to NREL 4
System Performance Validation 6
System Performance Summary 10
Appendix (PVSYST REPORT) 11

Introduction and Objectives

ESTCP (the U.S. Department of Defense's environmental research arm) contracted with Soitec to install a 1 MW CPV plant at Ft. Irwin in California which was connected to the grid in September 2015. As part of that contract it was agreed that during the operational testing phase (Phase 2), a third party would provide a performance review for the first 2 years of the project. Through communication with both ESTCP and Soitec, NREL agreed to serve as this third party. The performance review comprises measurements of energy and energy production performance using a combination of revenue grade meters, meteorological measurement equipment and data storage equipment which has been installed by Soitec. Soitec is responsible for delivering an internal PVsyst model, site meteorological data, plant performance data and O&M data to NREL for this evaluation.

NREL's assessment includes an initial site inspection report and two annual reports. This report concludes the first annual report. The main activities by NREL have included:

- A site visit after installation to verify field conditions (power plant installed, locations of the meteorological stations, power plant functionality);
- On-going data quality reviews to ensure data collected is accurate and complete during the testing period;
- Final review of maintenance logs, calibration status and documentation of soiling;
- Detailed data analysis including energy model validation, system availability, degradation analysis and soiling loss analysis;
- Preparation of performance/validation reports on an annual basis.

The following report documents NREL's evaluation of plant performance compared to the PVsyst model that Soitec has provided to NREL for the period of 6/1/2016 through 1/18/2017. No operations and maintenance logs were provide to NREL and therefore NREL is unable to provide the complete set of analysis that was originally proposed.

Plant Location and Equipment Details

Fort Irwin 1 MW Soitec CPV Installation, (U.S Army National Training Center)	
latitude/longitude	35.2464° N, 116.6819° W
tracking	40 individually controlled dual axis trackers
modules	12 CX-M500 modules per tracker (2335 Watts at CSTC)
system rating at CSTC	40*12*2335 = 1,121,000 Watts
grid connection	(2) 500 kW Advanced Energy Inverters (AE500 TX)
backup power for tracker stow	(1) Caterpillar generator
direct normal irradiance	(2) Kipp & Zonen CHP1
global normal irradiance	(2) NES measurement systems (SOZ1-03)
wind speed	(2) Adolf Thies GmbH&Co KG
internal module humidity and temperature	(2) Michell PCMini52-3-x25

General Review of the Data Provided to NREL

Plant data were provided to NREL for the period of 6/1/2016 – 1/18/2017 for the purpose of validating plant performance. The data set included DC power measurements for half of the array for each of the 40 trackers on the site, two direct normal irradiance (DNI) measurements, 2 wind speed measurements, and 2 ambient temperature measurements. These data are consistent with instrumentation that was documented in the previous inspection report as shown in Fig. 1.

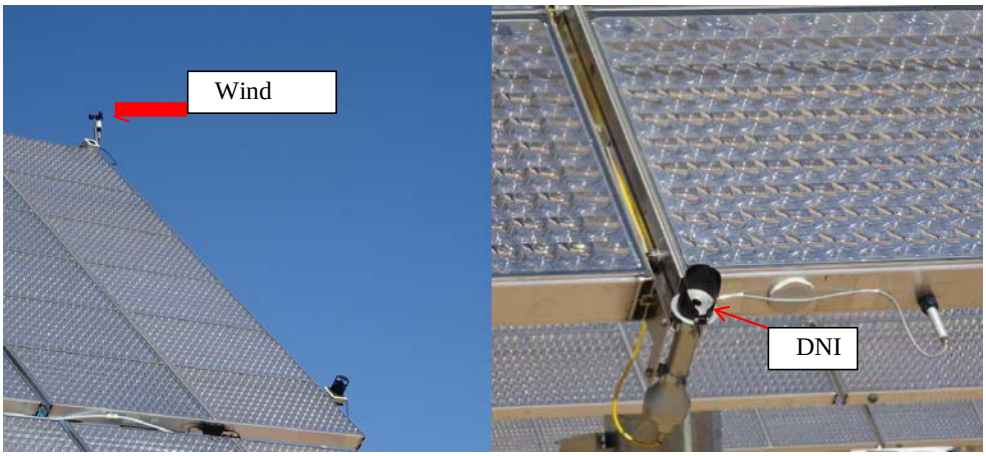


Fig. 1. DNI and wind sensors are mounted on two trackers within the 1 MW plant. The tracker labels are A1-A17 and B1-B32 where A1-A17 is located in the northeast corner of the plant and B1-B32 is centrally located on the southern side of plant. Each of these trackers contains a global normal irradiance (GNI) sensor but GNI data were not provided to NREL. The original inspection report noted that data were not available for one of the trackers but this problem was fixed as the two data streams were included in the data sent to NREL.

The data set was reviewed for basic quality issues resulting in the following findings:

1) Power for one of the 40 trackers was reported as "NaN" (Not a Number) from 10/20/16 -1/18/17. It is unknown if the tracker or array was having performance issues or if this was the result of a data acquisition issue.

2) For ~6% of the measured data points, realistic data were not reported for one DNI sensor or the other.

3) Although it was noted in the site inspection report that the DNI sensors were being allowed to unacceptably soil and one was misaligned (see Figs. 2 and 3), there is no indication that these problems were addressed or that regular cleaning occurred in the time period under examination. The DNI data suggest that each sensor potentially soiled differently over time. The irradiance was summed over the data collection period and one sensor reported approximately 2% more available solar energy than the other sensor. As it is not expected for a DNI sensor to over report DNI, the higher reported irradiance for each time interval was used for performance validation. Additional discussion on sensor soiling is included in the validation section.

4) In the case of wind speed and ambient temperature, the two measurements were averaged for each time interval for use in the PVSYST validation modeling.

Fig. 2. (From site inspection) Both DNI sensors show soiling that will impact the resource measurements and performance evaluation for the plant. In the picture of SN 140003 it is difficult to see but minor soiling is noted. SN 140029 has readily visible soiling in the photograph that is estimated to be in the 1-3% loss range.

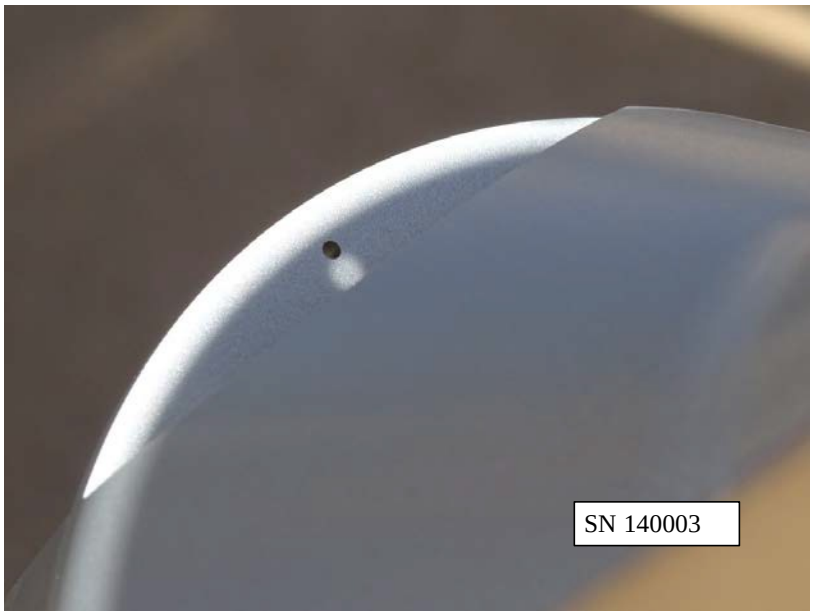


Fig. 3. (From site inspection) The alignment sunspot for DNI sensor (SN 140003), the cleaner of the two sensors in Figure 2. This misalignment is outside the Kipp and Zonen alignment specifications which can result in a false low reading for DNI. SN 140029 was within alignment specifications.

System Performance Validation

Soitec provided NREL access to Ft Irwin 15-minute system and meteorological data (described above) and to the .PAN files Soitec developed for applying PVsyst modeling software to Soitec CPV systems. 15-minute data were averaged to create hourly files for input to PVSYST. The PVSYST model was run using the provided .PAN files and the generalized PVSYST report has been included in the appendix (note that the report outputs must be multiplied by 2 in order to reflect the entire plant). The hourly output from PVSYST was then compared with the measured plant output. Values reported outside the appendix have been scaled by 2 to represent the entire plant. Fig. 4 presents comparative results for a series of clear sky days in June versus September. In June PVSYST and measured power closely agree while in September measured power is approximately 7% above the PVSYST predictions. Although there are a number of variables that could drive this variation, analysis of the DNI sensors suggest sensor soiling or misalignment is a likely cause. Fig. 5 compares the ground based DNI measurements at Ft. Irwin versus an NREL Measurement and Instrumentation Data Center (MIDC) station in Las Vegas. The DNI in Las

Vegas is nearly 9% higher than in Ft. Irwin, which is not typically expected for clear sky conditions at each of these sites. The DNI resource was integrated for the entire reporting period for both Ft. Irwin and Las Vegas. The Las Vegas sensor showed 5.8% more available irradiance than the Ft. Irwin sensor. Although this is not conclusive, this is consistent with observations during the Ft. Irwin site inspection that the sensors were not being cleaned and Soitec had no log or other evidence to indicate that the sensors were cleaned during the time period used in this analysis. Further, the Las Vegas station is expected to be cleaned on at least a weekly basis.

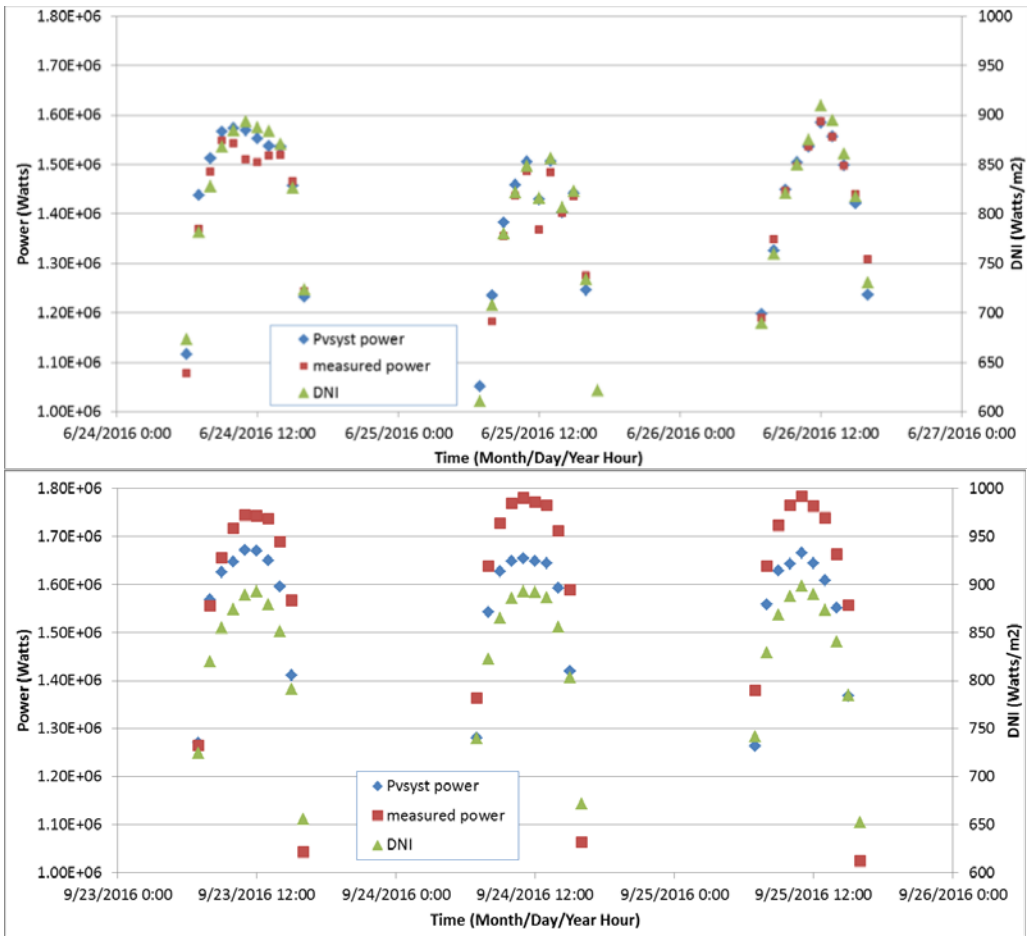


Fig. 4. A comparison of the PVSYST predicted power against measured power in two different months. In June PVSYT and measured power are similar while in September the measured power is approximately 7% above the PVSYST modeled power.

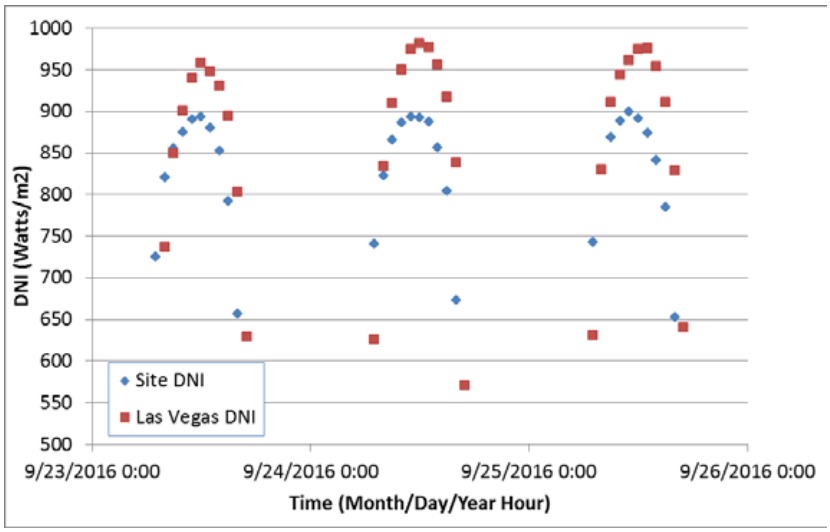


Fig. 5. A comparison of the ground DNI measurement at Ft Irwin versus the DNI measurement at a MIDC station at the University of Las Vegas. The two locations are approximately 160 km apart. The DNI is approximately 9% higher for the Las Vegas station, which is not expected on a clear sky day considering both locations are in a similar DNI environment. This is not conclusive but suggests the Ft. Irwin DNI sensor may have significant soiling or be misaligned.

Over the entire evaluation period the plant produced 2,725 MWh's (assuming scaling by 2 as only half to modules on each tracker are monitored) while PVSYST (based on the site DNI measurements) predicted that the plant would produce 2,676 MWh's. This is a 1.8% performance improvement above the model prediction when no uncertainty is taken into account. There are not enough data to provide an accurate uncertainty estimate but the given evidence suggests that the uncertainty is likely dominated by error in the site DNI resource. The site inspection (see Figs. 2, 3) showed that the DNI sensors were likely under reporting the DNI by 1-3% from soiling and/or from misalignment. Comparison with a Las Vegas DNI sensor suggested that the site sensor could be under reporting DNI by nearly 6%. This is consistent with other soiling studies for PV systems in southern California which show annual energy losses (uncleaned systems) on the order of 2-6%. Soiling and misalignment of the DNI sensor are not expected to be constant over time and therefore it is reasonable to assume that the DNI sensor is under reporting the total available energy by 1-6%. Considering this range, the Soitec system could be over performing by 0.8% or under-performing by as much as 4.2%. Note the following when considering validity of the above numbers:

1) PVSYST pan file already assumes a 3% loss due to soiling.

2) These performance numbers depend on the assumption that the second half of each tracker array is performing like the measured half. No data are available on the truth of this assumption beyond Soitec of DoD verifying that AC metered output is in line with the expectations by the DC measurements. NREL has been provided no AC data and therefore cannot complete this verification step. Furthermore, it is suggested that for improvement in future validation efforts, that the site DNI sensors be cleaned on a weekly basis and that the cleaning dates be maintained in a maintenance log.

3) "NaN" was recorded for one of the trackers from 10/20/16 – 1/18/17 . If this tracker was producing energy that was not recorded the measured plant energy production could be approximately 1% higher

To further investigate plant performance, the individual DC outputs from each tracker were compared. Fig. 6 provides the MWhs that were produced from half of the array from each of the 40 trackers. Data were reported as "NaN" after 10/20/17 for tracker number 8 and it is unknown if this is due to data acquisition problems or problems with the tracker or array. The statistics are as follows for the other trackers when number 8 is excluded. The mean output is 34.1 MWhs, the standard deviation is 0.8 MWhs, and the range is from 31.4 through 35.6 MWhs. This range represents an 11.8% variation from the best to worst performing tracker. It was noted in the site inspection that not all trackers were optimally aligned and therefore this could be a potential cause of the underperforming tracker. Other potential causes are non-uniform soiling across the plant, higher degradation of modules on the weak tracker, measurement issues, non-optimum tracking, or other unknowns. It is recommended that trackers 8, 28, 33, and 38 (as by the order given in the data file) be visually inspected to determine if there is a simple explanation and potential remedy for the underperformance.

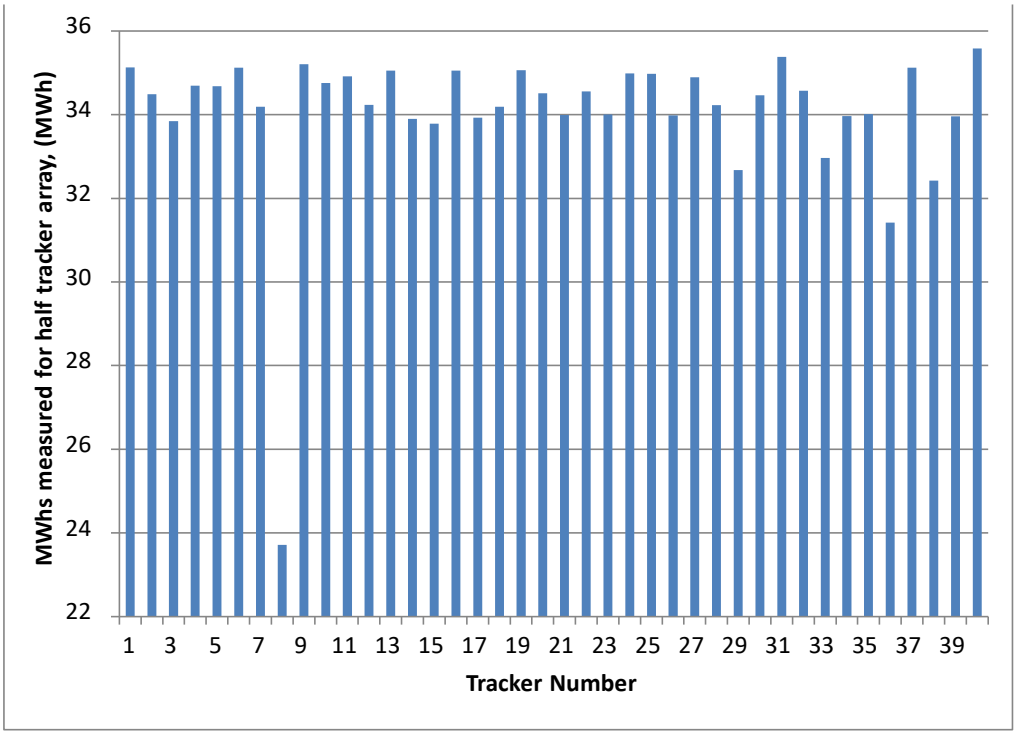


Fig. 6. Each bar shows the measured MWhs as produced by half of the array for each of the 40 trackers of the Soitec plant at Ft. Irwin.

System Performance Summary

Performance data from the 1 MW Ft. Irwin Soitec CPV system were provided to NREL spanning 6/1/2016 through 1/18/2017. The data were reviewed for any quality issues and then an hourly meteorological file was generated for running a PVSYST performance simulation. The measured energy output from the plant was 1.8% more than the PYSYST modeled output. The model potentially underreports plant output 1-6% due to a suspected soiling and/or misalignment of the plant DNI sensors. Consistent cleaning of the irradiance sensors would substantially reduce the uncertainty in the validation results. It is recommended that for future validation efforts that the plant DNI sensors be cleaned on a weekly basis and that the cleaning dates are recorded. It is also recommended that some indication of the AC output of the plant be shared with NREL in order to validate the assumption that the plant DC output is twice the measured DC

output (In other words no gross failure has been ignored). The data analysis also showed that several of the 40 trackers were underperforming relative to the average. The recommendation is that these trackers should be visually inspected to determine if there is a simple cause and remedy to the underperformance. The energy measurement for one of the trackers is being reported as “NaN” and therefore an effort should be made to determine the root cause of this problem.

Appendix (PVSYST REPORT)

PVSYST V6.39		24/04/17	Page 1/4

Grid-Connected System: Simulation parameters

Project :	**DOD Fort Irwin**			
Geographical Site	**DOD Fort Irwin**		Country	**USA**
Situation	Latitude	35.3°N	Longitude	116.7°W
Time defined as	Legal Time	Time zone UT-8	Altitude	756 m
	Albedo	0.20		
Meteo data:	**DOD Fort Irwin**	Imported - ASCII file		

Simulation variant :	**DOD Fort Irwin**			
	Simulation date	24/04/17 16h05		

Simulation parameters

Concentration System	Concentration Factor	500 x	Diffuse Acceptance	0 %
	Full Acceptance Angle	0.5 °	Limit Angle	1.0 °
Tracking plane, two axis	Minimum Tilt	0°	Maximum Tilt	85°
Rotation Limitations	Minimum Azimuth	-150°	Maximum Azimuth	150°
Models used	Transposition	Perez	Diffuse	Erbs, Meteonorm
Horizon	Free Horizon			
Near Shadings	According to strings		Electrical effect	25 %

PV Array Characteristics

PV module	GaInP2/GaAs/Ge	Model	**CX-M500 MOD-99009 1.0**	
Custom parameters definition		Manufacturer	Soitec	
Number of PV modules	In series	1 modules	In parallel	480 strings
Total number of PV modules	Nb. modules	480	Unit Nom. Power	2335 Wp
Array global power	Nominal (STC)	**1121 kWp**	At operating cond.	1078 kWp (50°C)
Array operating characteristics (50°C)	U mpp	624 V	I mpp	1728 A
Total area	Module area	**3761 m²**	Cell area	3756 m²
Inverter	Model	**Sunny Central 500CP**		
	Manufacturer	SMA		
Characteristics	Operating Voltage	430-820 V	Unit Nom. Power	500 kWac
Inverter pack	Nb. of inverters	2 units	Total Power	1000 kWac

PV Array loss factors

Array Soiling Losses			Loss Fraction	3.0 %
Thermal Loss factor	Uc (const)	14.4 W/m²K	Uv (wind)	1.1 W/m²K / m/s
Wiring Ohmic Loss	Global array res.	0.70 mOhm	Loss Fraction	0.2 % at STC
Serie Diode Loss	Voltage Drop	0.7 V	Loss Fraction	0.1 % at STC
Module Quality Loss			Loss Fraction	0.0 %
Module Mismatch Losses			Loss Fraction	3.2 % at MPP
Incidence effect, ASHRAE parametrization	IAM =	1 - bo (1/cos i - 1)	bo Param.	0.05

User's needs : Unlimited load (grid)

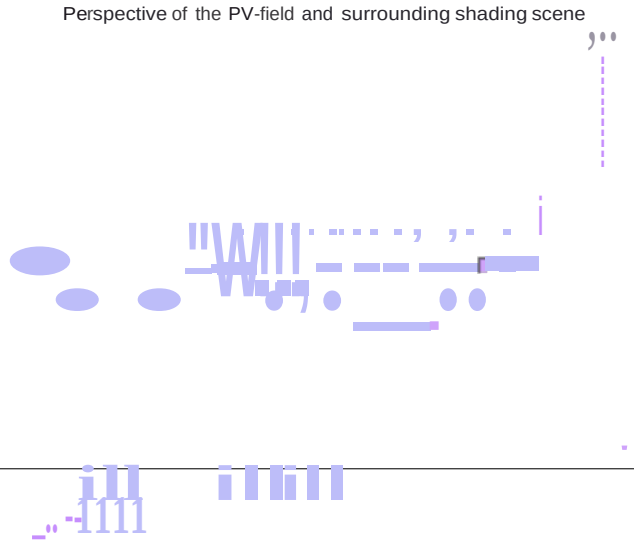
Grid-Connected System: Near shading definition	24/04/17	Page 2/4

Project : **DOD** Fort Irwin

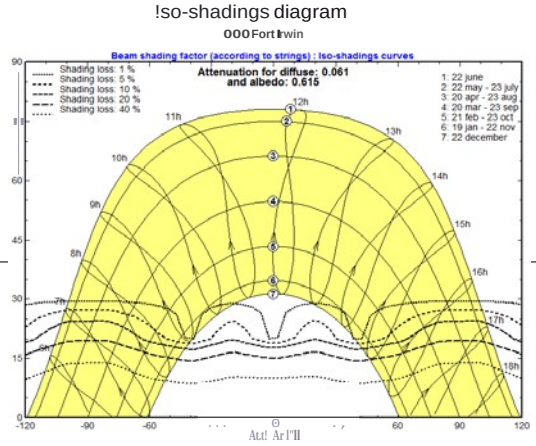
Simulation variant : **DOD** Fort Irwin

Main system parameters	System type	Grid-Connected		
Near Shadings	According to strings		Electrical effect	25%
PV Field Orientation	Tracking two axis	Concentration	Accept. angle	0.5°/Lim 1.0°
PV modules	Model	CX-M500 MOD-99009 1.0	Pnom	2335 Wp
PV Array	Nb. of modules	480	Pnom total	1121 kWp
Inverter	Model	Sunny Central 500CP	Pnom	500 kWac
Inverter pack	Nb. of units	2.0	Pnom total	1000 kW ac
User's needs	Unlimited load (grid)			

Perspective of the PV-field and surrounding shading scene



Iso-shadings diagram



Grid-Connected System: Main results

Project: DOD Fort Irwin

Simulation variant : DOD Fort Irwin

Main system parameters	System type	Grid-Connected		
Near Shadings	According to strings		Electricaleffect	25%
PV Field Orientation	Tracking two axis	Concentration	Accept. angle	0.5° /Lim 1.0°
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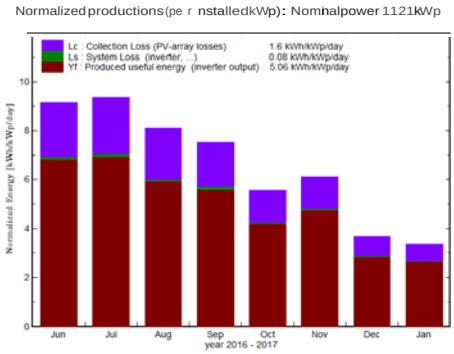
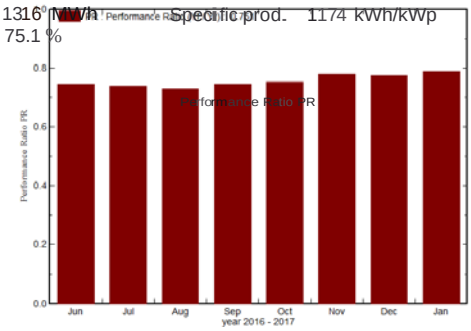
PVArray	Nb. of modules	480	Pnom total	1121 kWp
Inverter	Model	Sunny Central 500CP	Pnom	500 kWac
Inverter pack	Nb. of units	2.0	Pnom total	1000 kW ac
User's needs	Unlimited load (grid)			

Main simulation results

System Production	Produced Energy	1316 MWh	Specific prod.	1174 kWh/kWp
	Performance Ratio PR	75.1 %		





OOO Fort Irwin

Balances and main results

	GlobHor kWh/m²	TAmb °C	BeamInc kWh/m²	BeamEff kWh/m²	EArray MWh	E_Grid MWh	EffArrB %	EffSysB %
June 16	245.5	40.53	265.1	251.3	225.2	221.6	22.6	22.3
July 16	261.1	41.83	290.5	274.2	245.0	241.1	22.5	22.1
Aug. 16	227.1	40.98	251.5	236.3	209.2	205.9	22.2	21.8
sep. 16	182.7	35.14	225.9	210.2	191.7	188.7	22.6	22.2
oct. 16	133.3	30.06	173.1	161.0	148.7	146.3	22.9	22.5
Nov. 16	111.1	24.27	183.5	171.1	163.1	160.4	23.7	23.3
Dec. 16	74.7	17.91	113.7	106.5	100.5	98.8	23.5	23.1
Jan. 11	42.3	17.95	80.8	58.6	54.5	53.8	23.9	23.5
Period	1278.3	31.79	1563.9	1467.2	1337.8	1316.3	22.8	22.4

legends:

GlobHor	Horizontal global irradiation	EArray	Effective energy at the output of the array
TAmb	Ambient Temperature	E_Grid	Energy injected into grid
BeamInc	Beam incident on coll. plane	EffArrB	Effic. Eout array / Beam incid.
BeamEff	Normal Beam effective	EffSysB	Effic. Eout system / Beam incid.

Grid-Connected System: Loss diagram

Project: **DOD** Fort Irwin

Simulation variant : **DOD** Fort Irwin

Main system parameters	System type	Grid-Connected		
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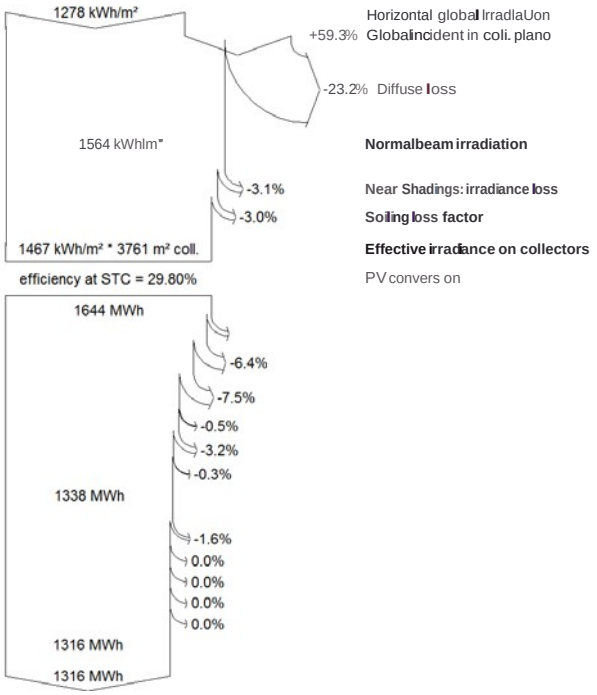
Inverter pack	Nb. of units	2.0	Pnom total	1000 kW ac
User's needs	Unlimited load (grid)			

Loss diagram over the whole year



-2.3%

Array nominal energy (at STC effie.) PV loss due to irradiance level

PV loss due to temperature

CPV specific loss

Shadings: Electrical Loss ace. to strings
Module array mismatch loss
Ohmic wiring loss
Array virtual energy at MPP

Inverter Loss during operation (efficiency) Inverter Loss over nominal inv. power Inverter Loss due to power threshold Inverter Loss over nominal inv. voltage Inverter Loss due to voltage threshold Available Energy at Inverter Output

Energy Injected Into grid