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In-situ Atmospheric Intelligence for Hybrid Power Grids: Volume 5 (Ambient vs. Panel Temperature in Photovoltaic Power Modeling)

by Gail Vaucher, Robert Jane, and Jessica Whitaker

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In-situ Atmospheric Intelligence for Hybrid Power Grids: Volume 5 (Ambient vs. Panel Temperature in Photovoltaic Power Modeling)

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14. ABSTRACT Reducing the vulnerability of remote electrical resources can be advanced through power diversity. To optimize this diversity, one strategy is to secure advanced knowledge of key atmospheric parameters. When solar energy (photovoltaic [PV] panels) is integrated into a hybridized grid, the critical meteorological elements include 1) solar radiation, which defines the maximum potential PV power production, and 2) PV panel temperature, which impacts power production efficiency. Examining temperature as a function of PV power generation, the study asked 1) Can ambient temperatures be used for PV panel temperatures? and 2) What is the optimal data reach-back and reach-forward for a neural network PV panel-temperature forecast model? Results showed that under overcast sky, the two temperatures performed equivalently. Under clear sky, grid optimization routines will need to assimilate the potential for midday excursions from actual power generation—the model using ambient temperature overestimated measured power, whereas using PV panel temperatures underestimated measured power. For neural network PV panel-temperature forecast modeling, the optimal reach-back/-forward was defined by temperature input thresholds. The next steps are to test the temperatures in other PV power models, and experiment with the hidden layer number, layer population, and/or neural net architecture.					
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Executive Summary

Power diversity has significant potential for reducing the vulnerability of remotely located electrical resources to continuity issues. The integration of renewable energy into a grid, such as combining photovoltaic (PV) power with traditional power, is just one application of this concept. The advantages gained in power hybridization rest on the ability to optimize the power distribution from the various resources without detracting from the system performance. Methods of optimization include exploiting a foreknowledge of grid power generation and load requirements.

Research documented in this report was constructed on the thesis that advanced knowledge of certain atmospheric conditions can significantly contribute to the optimization of an isolated hybridized power grid. As part of the investigation, PV power was included in the overarching grid design, along with traditional power resources. To determine the maximum power potential, PV power models were used. These models rely heavily on current and future atmospheric conditions, such as 1) solar radiation (SR), which defines the maximum potential PV power production, and 2) PV panel temperature, which impacts power production efficiency. While exploring the SR element is not within the scope of this report, temperature is.

Securing PV panel-temperature data is not always practical. Consequently, the first of two questions steering this study was the following:

- Can ambient temperature measurements be used in place of PV panel temperatures when modeling PV panel power generation?

For this Part 1, the ambient and PV panel temperature relationship was explored, where ambient temperature is the temperature of the local air. The study began with an investigation into various temperature sensor types. Diurnal ambient temperature time series were described as a function of global latitude and elevation. Finally, concurrent ambient and PV panel temperatures were compared, and a qualitative relationship defined. Results found the following when comparing ambient and PV panel temperatures:

- 1) Each day reported two times when the ambient and panel temperatures coincided (these are called neutral events, or brief times when the lower atmosphere is isothermal).
- 2) The panel temperature consistently showed lower values over the nighttime period and perpetually warmer values during the daylight hours than the ambient temperature.

- 3) The upward or downward trends of the higher-frequency oscillations are consistent between the matched data, with the magnitude of the panel temperature being more exaggerated (greater amplitude) than the ambient temperature and sometimes the timing being slightly asynchronous.

A physics-based PV power generation model, the Mahmoud, Xiao, and Zeineldin (M-X-Z) Model, was used to assess temperature effects on PV power calculations. Clear (CLR) and overcast (OVC) sky conditions were selected to explore the influences of minimal and maximum SR filtering, respectively. Measured power was included in the modeled PV power output graphics. Results showed little distinction when using ambient and panel temperatures in the M-X-Z Model for the OVC case. For the CLR case, during the peak SR hours, the sample case showed that modeled power—as a function of ambient temperature—overestimated the measured power. The modeled power—as a function of PV panel temperature—underestimated the measured power. The respective power curve characteristics were distinctive. When ambient temperature was used, the power curve features resembled the SR curve, including the few guywire shadow spikes. When PV panel temperature was used, the higher frequencies of the calculated power curve took on the equivalent PV panel-temperature features, as did the measured power curve.

Part 2 focused on advancing the machine learning (ML)/artificial intelligence (AI) temperature forecast model. The core question was, What is the optimal data reach-back/-forward for the neural network (NN) PV panel-temperature forecast model? This part began with a review of current panel-temperature usages in determining PV power. ML/AI techniques were explored, which included current and historical temperature data in forecasting future temperatures. Finally, experimentation with the historical temperature reach-back and forecast-forward intervals framed the determination of future PV power forecast modeling requirements.

An eight-step process was used to develop the AI/ML ambient temperature forecast algorithm. Ambient temperature modeling was pursued due to the availability of data and the premise that establishing the process was a constructive step forward toward answering the Part 2 question. Each algorithm development step is detailed in this report. Three variables were defined to facilitate the NN reach-back/forward capabilities:

- T_s , which represented the fundamental input/target feature *step size*,
- T_p , which represented the length of *past* measurement history when combined with the fundamental step size variable, and
- T_f , which represented the *future* measurement of the target.

Four cases were examined. The first two held the past temperature time interval constant:

- 1) $T_p = 15 \text{ min}$ and T_f was set to (5, 10, 20, 40, 80, and then 160 min),
- 2) $T_p = 30 \text{ min}$ and T_f was set to (5, 10, 20, 40, 80, and then 160 min).

The second two held the future temperature forecast time interval constant:

- 3) $T_f = 15 \text{ min}$ and T_p was set to (5, 10, 20, 40, 80, and then 160 min),
- 4) $T_f = 30 \text{ min}$ and T_p was set to (5, 10, 20, 40, 80, and then 160 min).

When the past history was held constant (T_p constant) to generate a prediction that spanned progressively larger timescales (T_f increased by doubled time intervals), the NN performance degraded, with the mean standard error (MSE) effectively doubled with the increased forecast target.

When T_f was held constant and T_p was varied (additional historical information was provided), the MSE values remained relatively constant (slight negative correlation) for both sky conditions.

The cases reviewed demonstrated thresholds for constructive input in both reach-back and reach-forward directions. Going beyond these empirical limits risks growing the overall AI/ML algorithm complexity. For an operational system that has processing/storage limitations, these thresholds are needed to frame future PV power forecast modeling requirements.

Future research in the ML/AI algorithm development will explore changes in the number of hidden layers, the population of layers, and/or the artificial neural network (ANN) architecture. Investigating a full Monte Carlo simulation using alternative architectures and sizes of the same type of feedforward ANN will also be informative.

1. Introduction

Ensuring the continuity of future electricity and reducing its vulnerability are achievable through the integration of multiple energy sources. The incorporation of available renewable resources is one method for safeguarding power production in potentially unstable or hostile environments. One strong candidate for this future hybridized power vision is solar energy. Converting the sun's energy into power is typically accomplished via photovoltaic (PV) technologies. Advanced knowledge of atmospheric conditions can help optimize the performance of PV power resources. This type of operational design is further strengthened through smart grid communications executed across the Internet of Things as a cyber-physical system while incorporating atmospheric knowledge.

1.1 Project Goals

The overarching project supporting this research was built on the thesis that optimized power distribution for an isolated hybridized grid is strengthened by analyzing and exploiting atmospheric intelligence. For isolated energy networks that utilize alternative energy resources, such as renewables, power diversity is essential and made operationally efficient through strategic energy management. Once successfully managed, the hybridized power design is capable of reducing one-time-use fuels and their cascading fuel supply requirements and logistics.

For grids using PV technologies, atmospheric predictions are a critical input for optimizing the energy acquisition and power production. There are multiple features that impact solar power production including solar irradiance, ambient and panel temperature, wind speed, wind direction, relative humidity, pressure, PV panel location and orientation with the sun, and multiple other contributing factors. For this study, the two primary meteorological components of interest include 1) the PV panel temperature, which affects power production efficiency, and 2) solar radiation (SR), which defines the maximum potential PV power production. While the latter is used to explain the context of the results, the PV panel temperature is the focus of this research. The specific research objectives pursued sought to answer two questions:

- Can ambient temperature measurements be used in place of PV panel temperatures when modeling PV panel power generation?
- What is the optimal temperature data reach-back (forward) for the neural network (NN) PV panel-temperature forecast model?

The motivation for these questions was to optimize hybridized grid performance through the determination of maximum available PV power generated. With smart real-time grid management, if one power source becomes unavailable, another power resource can be called into action. In a tactical or disaster relief scenario, ensuring power availability and reducing costs drive the need for onsite renewable power sources. With dependable power, uninterrupted field operations are possible. Knowledge and foreknowledge of atmospheric influences are critical requirements for determining and managing power availability.

1.2 Project Method

This study was divided into two major parts:

- Part 1: Determining the ambient and PV panel temperature relationship.
- Part 2: Advancing the machine learning (ML)/artificial intelligence (AI) temperature forecast model.

Part 1: The ambient temperature and PV panel temperature relationship study began with an investigation into various temperature sensor types. Ambient temperature was defined as the temperature of the local air. Diurnal ambient temperature time series were then described as a function of global latitude and elevation. Finally, concurrent ambient and PV panel temperatures were compared, and a qualitative relationship defined.

Part 2: Advancing the ML/AI temperature forecast model began with a review of current panel-temperature usages in determining PV power. ML/AI techniques for including current and historical temperature data into forecasting future temperatures were explored. Finally, experimentation with the historical temperature reach-back and forecast-forward intervals framed the determination of future PV power forecast modeling requirements.

The results from both research investigations are documented in this report.

2. Ambient and PV Panel Temperature Relationship

Ambient temperature is a quantified measure of warmth/coolness (temperature) for a local environment. To use ambient temperature in the PV panel power calculation, the sensor would need to be within a reasonable distance of the subject PV panel. For this study, that distance was about 6 m north-northwest of the PV panel. PV panel temperature is the warmth/coolness (temperature) of the physical PV panel, which is measured by attaching a temperature-sensing device to the panel. Before

comparing these two temperature types, a review of the temperature variable character and the acquisition methods was conducted.

2.1 Ambient Temperature Sensors

Per Vaucher et al. (2022), the average translational kinetic energy of the molecules in a mass is used as a metric for hotness and coldness, or “temperature” (Lower 2021). Slower-moving molecules are associated with coldness and faster collisions are linked with hotter temperatures. The common sensor used to quantify this variable is a thermometer (literally, a device that measures the thermal properties). Traditional thermometers used mercury or alcohol liquids within a marked glass tube with the level of fluid expansion/contraction corresponding to temperature values—such as freezing temperatures equaling 0 °C and the temperature at which water boils marked as 100 °C. One hundred equally distant gradient markings between these two anchor points constitute a thermometer’s temperature reading scale (in Celsius).

In contrast, a digital temperature sensor uses a resistance across a voltage drop (thermistors) to measure the temperature. Units of temperature include Fahrenheit, Celsius, or kelvin. Other methods/sensors used to report temperature follow (Young 2021).

Change-of-state sensors: These sensors use the response of a substance to the local environment’s warmth or coolness to measure temperature. These precalibrated devices are nonelectrical and rugged, and perpetually respond to their environment’s warmth. They are commonly packaged as temperature-labeled dots on a vertical strip.

Bimetallic device sensors: These devices operate on the principle that metal expands at different rates as a function of warmth/heat. In this sensor, two metals are bonded together, along with a “needle” that points to an appropriate ambient temperature value. As heat (or coolness) is applied to the area, the bimetallic strips expand (contract) uniquely, moving the needle to its appropriate temperature reading. Bimetallic devices are less accurate than electric sensors, but do not require a power supply.

Silicon diode sensors: This sensor is a linear device used for measuring extreme temperatures, such as in cryogenic applications. The conductivity of the diode increases linearly in response to changes in warmth and coolness. System requirements and integration techniques define the specific silicon diode sensor selection.

Infrared sensors: An infrared sensor is a remote, non-contact device that can measure temperature by sampling emitted radiation. This sensor has limitations, such as, in infrared ice water measurement, evaporation will produce a measurement less than 0 °C.

Thermocouple sensors: This sensor measures a voltage change in response to local warmth/coolness. Thermocouple output voltage rises as the temperature increases and lowers as output voltage decreases. These wire sensors are often housed within protective shields to protect them from their sampling environments. For atmospheric measurements, a sensor housed in a white ceramic cylinder is placed in the center of vertically stacked white-painted “pie plates” to minimize systematic solar heating and sample the temperature of the air flowing horizontally between the thinly separated pie plates.

Resistive temperature detector (RTD): RTD devices measure temperature as a function of resistance. Typically, RTDs are composed of nickel, copper, or platinum wires with a positive temperature coefficient, meaning that as the resistance rises, the temperature rises. Conversely, as the RTD resistance decreases, temperature decreases (Process Solutions 2022).

2.2 Ambient Temperature as a Function of Latitude and Elevation

Temperatures sampled around the Earth are characterized by multiple, repeatable patterns often captured in climatological studies. To better describe temperature, this variable was examined in the context of the northern hemisphere, using Earth latitudes and elevation (height above the ground). Five locations were chosen across the United States. Conventional three-letter code abbreviations were used for each site. Figure 1 maps the sites and associates their code names. Each site was selected based on its dominant thermodynamic character. For example, Sites 1 (Albuquerque, New Mexico [ABQ]) and 2 (El Paso, Texas [ELP]) were land-locked locations in the mid-latitudes. Sites 3 (Barrow, Alaska [BRW]) and 4 (Anchorage, Alaska [ANC]) were polar/coastal environments. Location 5 (Sterling, Virginia, a.k.a., Washington DC/Dulles [IAD]) was a mid-latitude site with a coastal character.



Fig. 1 Locations and three-letter definitions for the sampled rawinsonde observation (RAOB) launch sites

While it is beyond the intent of this report to describe the entire climatological makeup for each site's environment, a general understanding for the atmospheric character can be gleaned using a vertical temperature profile sampled over these locations. A balloon-borne rawinsonde package (a.k.a. radio observation with winds measurements or rawinsonde observation [RAOB]) is routinely launched and logged by the National Oceanic and Atmospheric Administration (NOAA)/Earth System Research Laboratories (ESRL). For most designated sites, this event is done twice a day, 12 h apart.

This launched package slowly rises using a helium-filled balloon. Pressure, temperature, relative humidity, wind speed, and wind direction are remotely transmitted at given time intervals during the balloon's rise into the atmosphere. The maximum height above the Earth that is sampled can be as high as the stratosphere (12–35 km). The resulting data are provided via a NOAA/ESRL website (NOAA/ESRL 2021). Figure 2 shows the website interface for the NOAA/ESRL Radiosonde Database. Figures 3 and 4 show examples of extracted raw RAOB data from ANC and processed RAOB data from ABQ. The exported RAOB data were reformatted and processed into an Excel table spreadsheet, which enabled the subsequent analyses.

NOAA/ESRL Radiosonde Database

General information about this database, access to station lists and other details is available on the [GSL website](#).

Recent Activities:

- June 2020: Updated and merged the 2018 and 2019 data from IGRA and GSL observations.
- July 2020: The station [inventory](#) has been updated.

I. Input Dates: (UTC units)

From: yr: 2020 mo: 6 dy: 7 hr: 0

Thru: yr: 2020 mo: 6 dy: 10 hr: 12

II. Sounding Specific Information

Hours of access: All Times Data levels: All Levels

Wind Units: Knots

III. Select Stations / Data

Select Radiosonde Sites by: WMO Station Identifier

Continue Data Request

Fig. 2 NOAA/ESRL RAOB database interface

254	0	7	JUN	2020		
1	26409	70273	61.17N	150.02W	45	2304
2	100	77	2850	169	99999	3
3		ANC			99999	kt
9	10020	45	160	90	270	3
4	10000	69	156	96	270	3
6	9723	304	99999	99999	245	7
5	9600	410	108	81	99999	99999
6	9371	609	99999	99999	275	5
5	9280	690	84	79	99999	99999
4	9250	722	84	65	215	5
5	9230	740	82	67	99999	99999
5	9200	767	92	12	99999	99999
6	9037	914	99999	99999	190	8
6	8707	1219	99999	99999	155	8
5	8680	1244	56	14	99999	99999
5	8620	1300	52	18	99999	99999
5	8570	1347	56	9	99999	99999
4	8500	1416	52	5	140	15
6	8388	1524	99999	99999	140	17
5	8290	1619	40	-40	99999	99999
6	8078	1828	99999	99999	130	13
5	7980	1926	12	-48	99999	99999
5	7880	2027	6	-74	99999	99999
6	7776	2133	99999	99999	140	14
5	7760	2149	-5	-55	99999	99999
5	7580	2335	-19	-79	99999	99999
6	7482	2438	99999	99999	145	11
5	7360	2567	-39	-87	99999	99999
5	7340	2588	-41	-111	99999	99999
5	7300	2631	-45	-105	99999	99999
5	7240	2696	-49	-129	99999	99999
6	7198	2743	99999	99999	140	11
4	7000	2967	-69	-129	140	11
6	6927	3048	99999	99999	140	12
6	6659	3352	99999	99999	140	14
5	6520	3515	-113	-148	99999	99999
5	6490	3550	-117	-165	99999	99999

Fig. 3 Example of ANC RAOB data (2020 June 7, 00z)

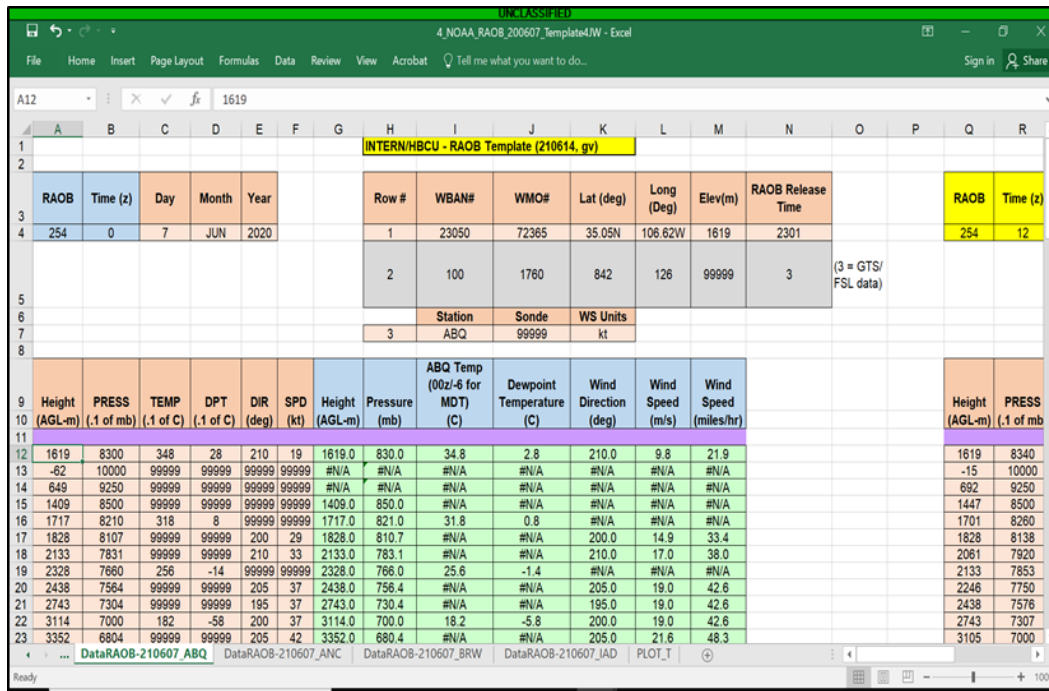


Fig. 4 Example of reformatted ANC RAOB data (2020 June 7, 00z)

The 2020 June 7 temperatures from all five RAOB sites are shown in Fig. 5. Appendix A shows additional temperature profiles from these five sites. These vertical temperature profiles include both the 00 Zulu* (z) and 12 z launch data sets. Zulu time is the military name for Universal Time Coordinated (UTC). UTC is the time at 0° longitude, formerly called the Greenwich Mean Time (or the time at the Royal Observatory in Greenwich, London, England) (“Greenwich Mean Time” 2022; “Universal Time Coordinated” 2022) To determine local times (LTs) for each site, an adjustment to the UTC time is needed. Since all sites are west of the 0° longitude line, the number of time zones west of 0° longitude is subtracted from UTC, taking into account daylight savings and standard time adjustments. As an example, the local time for ELP on 2020 June 7, 00z would be 2020 June 6, 1800 Mountain Daylight Time (MDT) (6 pm MDT) and the local ELP time for 2020 June 7, 12z would be 2020 June 7, 0600 MDT.

Inspecting Fig. 5, there are at least three general atmospheric layers observed from the vertical temperature measurements. Focusing on the polar site profiles (BRW/ANC), starting at the surface to about 2 km (planetary boundary layer), the 12z cases show profiles with brief sections of temperature increasing with height. This feature is called a “temperature inversion,” or simply an “inversion,” and is explained in a later paragraph. Between 2 and 10 km (troposphere), the temperatures consistently decrease with height. Above 10 km, there is a very short

region of isothermal conditions (tropopause), followed by the temperatures increasing with height (stratosphere).

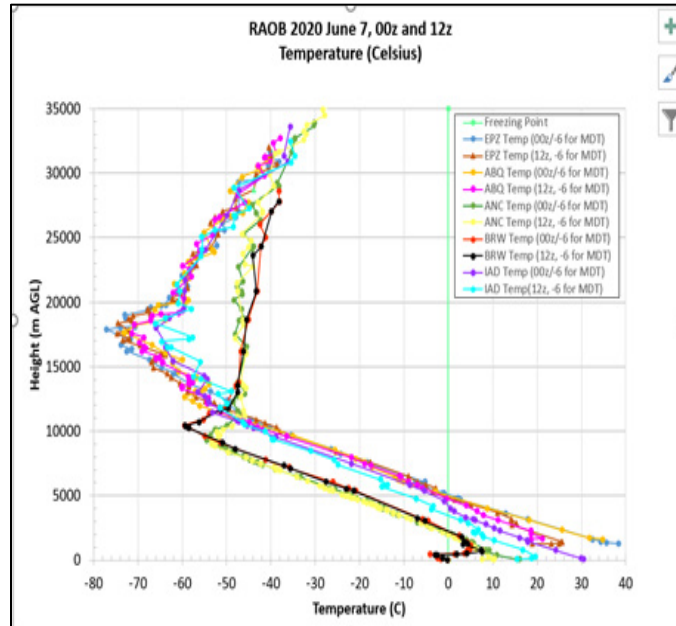


Fig. 5 Vertical temperature profiles from the five RAOB sites (00z; 12z)

Taking a closer look at the tropospheric layer, the lowest-level temperatures show two patterns. The dominant pattern is for temperature to decrease with height. However, for most 12z (0600 Mountain Standard Time [MST]) profiles, there is a shallow temperature inversion (temperature increases with height) before it abruptly shifts to the more common tropospheric pattern. To understand the inversion, consider the following: during the nighttime, under clear skies, the soil radiates out its warmth, leaving the air closest to the ground cooler than aloft. The resulting temperature inversion is often found in the local morning RAOB launch data (for ELP, this would be 12z) and at the top of the planetary boundary layer. The upper inversion separates the influences of surface friction and convective airflow associated with the ground from the more freely moving airflow of the mid-tropospheric region. Note: By the mid-morning/afternoon hours, the sun has warmed the ground sufficiently, replacing the inversion with the more typical temperature profile that decreases with height. Thus, the afternoon profiles do not show a surface temperature inversion.

The mid-tropospheric layer is characterized by a systematic cooling with height. This concept is easily validated by noting the climatologically colder (and often snowcapped) high-elevation mountains and warmer forest and grassland in lower elevation valleys (such as in the Rocky Mountain region). The rate at which the temperature decreases with height has been well established. For modelers, the rate

of change above the lowest layer (planetary boundary layer) is called the lapse rate. The dry lapse rate is $-9.8^{\circ}\text{C}/\text{km}$. In a moist environment, the temperature's vertical rate of change is $-6.5^{\circ}\text{C}/\text{km}$.

To test the lapse rate concept, temperature changes with height were calculated for each RAOB site. Table 1 shows an extracted sample of lapse rate calculations based on data from ABQ and ANC. An averaged lapse rate was then determined per location for the 00z and 12z RAOB cases (Table 2). While an in-depth study of the lapse rate was outside the goals of this study, the observation that temperature changes with height is a well-established characteristic of this thermal atmospheric parameter. Therefore, if one were comparing a PV panel temperature sampled from a PV panel mounted on top of a five-story building with an ambient temperature sampled 2 m above the ground, a systematic offset of magnitudes (per these lapse rates) can be expected.

Table 1 Lapse rate calculations for ABQ and ANC

Date (YYMMDD)	Time (z-zulu)	Location (AAA)	T (Top) (C-Celsius)	T(Bottom) (C)	Ht (top) (m - meter)	Ht (bottom) (m)	Delta T (C)	Delta z (m)	Lapse Rate (C/km)
210607	0	ABQ	-73	35	9630	1619	-108	8011	-13.5
210608	0	ABQ	-71	33	9927	1619	-104	8308	-12.5
210609	0	ABQ	-69	31	9821	1619	-100	8202	-12.2
210610	0	ABQ	-68	24	9789	1619	-92	8170	-11.3
210607	12	ABQ	-71	21	10160	1701	-92	8459	-10.9
210608	12	ABQ	-72	19	9590	1670	-91	7920	-11.5
210609	12	ABQ	-68	10	9450	1619	-78	7831	-10.0
210610	12	ABQ	-69	16	9795	1872	-85	7923	-10.7
210607	0	ANC	-55	16	9319	45	-71	9274	-7.7
210608	0	ANC	-53	17	9221	45	-70	9176	-7.6
210609	0	ANC	-59	10	10200	45	-69	10155	-6.8
210610	0	ANC	-57	11	10066	45	-68	10021	-6.8
210607	12	ANC	-53	10	9013	85	-63	8928	-7.1
210608	12	ANC	-55	11	9963	45	-66	9918	-6.7
210609	12	ANC	-59	9	10210	45	-68	10165	-6.7
210610	12	ANC	-58	10	10336	208	-68	10128	-6.7

Table 2 Average lapse rate results for the five continental US sites

Standard dry adiabatic lapse rate ($-9.8^{\circ}\text{C}/\text{km}$)		
Standard moist lapse rate ($-6.5^{\circ}\text{C}/\text{km}$)		
Location	Average lapse rate (00z)	Average lapse rate (12z)
ABQ	-12.36	-10.76
ELP	-7.22	-6.78
BRW	-6.78	-6.57
ANC	-12.55	-11.16
IAD	-9.41	-9.37

Each profile included a sharp shift from decreasing temperatures to increasing temperatures in the upper atmosphere. This right angle turn in the plot was labeled the tropopause. For this June sample, the polar regions reported the shift around 10 to 12 km, whereas the mid-latitudes showed it occurring much higher, around 18 km. Irrespective of location, there seemed to be two increasing temperature rates above the tropopause. Moving vertically, the slower rate starts this stratospheric layer, followed by a steeper rise in temperature. By 35,000 km, any correlation with the surface location seemed irrelevant, as seen in the convergent temperature magnitudes reported.

2.3 Ambient and PV Panel Temperature Comparison

A direct comparison of concurrent, co-located ambient versus PV panel temperatures was conducted. The initial investigation reviewed an isolated 24-h data sample. In this section, the atmospheric and power data resources are described, followed by a qualitative discussion of the temperature comparison results.

2.3.1 Temperature Data Resources

Comparison data for this study originated from a hybrid power testbed constructed in a southwestern US desert location. The testbed was specifically designed to co-locate power and atmospheric sensors. The power train consisted of a single PV panel, batteries, and a programmable load. A generator was simulated within the system design by adding the modeled generator output over the time of operation (in kJ) to the calculated battery state of charge (also in kJ), simulating a higher resultant battery charge level (D'Arcy 2022). A PV panel temperature probe was attached to the back (shaded white panel) of the PV panel. This Maxim DS18B20 digital thermometer reported measurements every minute.

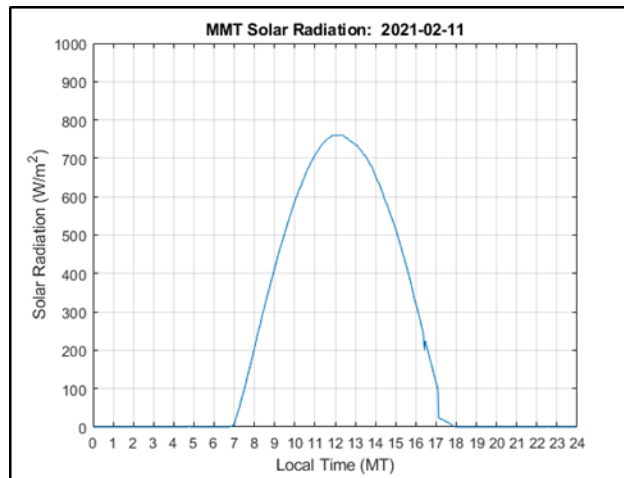
Independent of the testbed and located within 6 m of the PV panel temperature sensor was a suite of atmospheric instruments called the “Meteorological Measuring Tripod #2” (MMT2). Table 3 lists the MMT2 sensor specifications for the six atmospheric variables acquired at a 1-min sampling rate. These measurements included pressure, temperatures at three unique heights, relative humidity, SR, wind speed, and wind direction. For the core research, the Campbell Scientific T107 probe was used to measure the ambient temperature at 0.7 and 5.7 m above roof level (ArL), and the E+E Elektronik EE181 probe sampled both ambient temperature and relative humidity at 2 m ArL.

Table 3 MMT2 sensor suite

Variable	Sensor	Model	Height (m ArL)
Pressure	Barometer	Vaisala PTB110	1
Temperature	Thermometer	Campbell Scientific T107	0.7, 5.7
Temperature	Thermometer	E+E Elektronik EE181	2
Relative humidity	Hygrometer	E+E Elektronik EE181	2
SR	Pyranometer	Kipp/Zonen CMP3	2
Wind speed/direction	Anemometer	RM Young 05305	6

2.3.2 Qualitative Comparison Results

Temperature changes are directly linked to heat, which for the Earth is a product of the sun in the form of incoming SR. To minimize complexities, the initial PV panel temperature versus ambient temperature assessment was based on a consistently clear day, namely, 2021 Feb 11. As seen in Fig. 6, the SR magnitudes and smooth curve during the 2021 Feb 11 daylight hours in ELP reported no interruptions in the incoming SR over the sampling site. The one spike around 1630 LT was caused by a guywire shadow. The asymmetrical time series from 1630 LT to sunset was due to the jagged Organ Mountains along the western horizon. As the sun neared this horizon (sunset), the mix of direct and diffuse light sampled by the pyranometer, shifted to primarily diffuse light (light scatter around the jagged edges of the mountain peaks), thus creating an asymmetric pattern while still under a clear sky. The eastern horizon is relatively flat. Thus, the start of the daylight SR time series comes quickly and SR increases rapidly.

**Fig. 6** 2021 Feb 11 SR time series indicates a day of clear sky

A tabulated extract of the temperature data from this case study is presented in Tables 4 and 5. In both cases, the timestamp was converted into decimal hours (beige column) for plotting purposes. Note: The MMT data were sampled prior to

the MMT2 sensor update. For this suite, the 2-m ArL, temperature/relative humidity sensor was a Rotronics HC 2-S3; all other temperature measurements for this study used the same sensor model listed in Table 3. No sensor heights were changed in the MMT update (Vaucher 2016).

Table 4 Sample of the 2021 Feb 11 PV panel-temperature data

AIHPG	Panel-T	210211	Full				JD: 42	
ID	YYYY	MM	DD	hh	mm	ss	Time (Dec Hr)	AIHPG Panel-T (~1m ArL)
1	2021	2	11	0	0	1	0.000278	13.062
1	2021	2	11	0	1	2	0.017222	13.125
1	2021	2	11	0	2	1	0.033611	13.062
1	2021	2	11	0	3	1	0.050278	13.062
1	2021	2	11	0	4	1	0.066944	13.062
1	2021	2	11	0	5	1	0.083611	13.125
1	2021	2	11	0	6	1	0.100278	13.187
1	2021	2	11	0	7	1	0.116944	13.25
1	2021	2	11	0	8	1	0.133611	13.312
1	2021	2	11	0	9	1	0.150278	13.312
1	2021	2	11	0	10	1	0.166944	13.5
1	2021	2	11	0	11	2	0.183889	13.562
1	2021	2	11	0	12	2	0.200556	13.625
1	2021	2	11	0	13	2	0.217222	13.437

Table 5 Sample of the 2021 Feb 11 ambient atmospheric data

L-REAC®/MMT														
210211-MMT														
MMT Station #	MMT Julian Day	Local Time	Local Time	MMT Pressure	MMT Temp Hi (5.7m ArL)	MMT Temp Low (0.7m ArL)	MMT Temp Vaisala (2m ArL)	MMT RH Vaisala (2m ArL)	MMT WS (6m ArL)	MMT WD (6m ArL)	MMT Solar Radiation (2m ArL)	MMT Battery Datalogger	MMT Datalogger Panel T	
(number)	(number)	hhmm	(dec hr)	(mb)	(C)	(C)	(C)	(%)	(m/s)	(deg)	W/m^2	volts	(C)	
120	42	0	0.00000	869.62	15.198	15.004	15.182	16.21	5.328	325.78	-2.486	0	14.19	
120	42	1	0.01667	869.63	15.084	14.865	15.114	16.35	4.97	324.61	-2.821	0	14.18	
120	42	2	0.03333	869.59	14.905	14.687	14.98	16.61	5.191	327.81	-3.061	0	14.17	
120	42	3	0.05000	869.63	14.954	14.638	14.862	16.94	5.8	326.89	-3.297	0	14.14	
120	42	4	0.06667	869.62	15.039	14.77	14.913	16.87	5.432	321.99	-2.484	0	14.11	
120	42	5	0.08333	869.64	14.953	14.741	14.882	16.88	5.488	321.59	-2.616	0	14.09	
120	42	6	0.10000	869.64	15.019	14.737	14.861	17.01	5.124	319.55	-2.54	0	14.06	
120	42	7	0.11667	869.68	15.068	14.81	14.887	17.02	4.624	322.46	-2.248	0	14.03	
120	42	8	0.13333	869.65	14.94	14.708	14.848	16.84	5.142	316.88	-2.565	0	14	
120	42	9	0.15000	869.68	15.025	14.811	14.889	16.86	4.954	317.44	-2.489	0	13.97	
120	42	10	0.16667	869.67	15.181	15.012	14.98	16.92	4.635	316.69	-1.921	0	13.95	
120	42	11	0.18333	869.67	15.201	15.055	15.057	16.67	5.098	316.91	-1.737	0	13.92	
120	42	12	0.20000	869.65	15.389	15.157	15.101	17.26	4.84	316.53	-1.927	0	13.9	
120	42	13	0.21667	869.65	15.493	15.256	15.24	17.42	4.26	325.63	-1.545	0	13.88	
120	42	14	0.23333	869.65	15.529	15.245	15.266	17.37	4.51	318.44	-1.818	0	13.86	
120	42	15	0.25000	869.62	15.699	15.421	15.365	17.36	6.12	315.31	-1.848	0	13.85	
120	42	16	0.26667	869.65	15.714	15.572	15.537	16.89	4.787	319.37	-0.933	0	13.84	
120	42	17	0.28333	869.65	15.602	15.454	15.514	16.79	4.6	315.55	-1.692	0	13.83	

A graphical representation of the ambient versus PV panel temperature time series is shown in Fig. 7. This figure is purposefully large to assist the reader in observing details, which are described in the subsequent two sections. For reference, a red line

shows 1200 LT (ELP). Note: Solar noon for 2021 Feb 11 at the sampling site was actually 1220 LT. This time series is reproduced with a red grid overlay in Fig. 8 to facilitate an easier intercomparison with other coincident atmospheric variables.

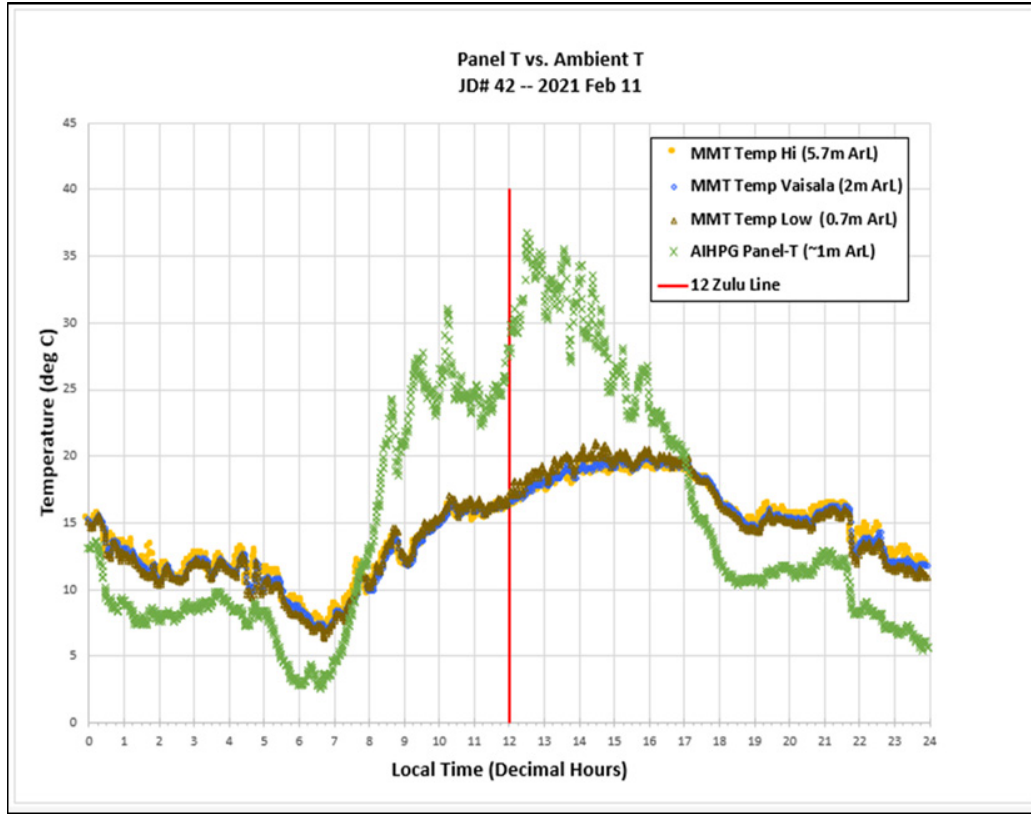


Fig. 7 2021 Feb 11 ambient and PV panel temperature time series

2.3.2.1 Ambient Temperature Patterns

Observing ambient temperature as a function of height, there was only a slight variation between the 0.7, 2, and 5.7 m ArL time series over this 24-h period. The three ambient temperature curves (denoted MMT in the legend in Fig. 7) display a very similar character. In a subtle manner, the temperatures closest to the surface were warmest in the daytime and coolest at night.

Two transition periods, called “neutral events,” are noted around local sunrise (0649 LT) and sunset (1750 LT). Surface neutral events are by definition a time when the lowest atmospheric layers are isothermal, due to the transition between sunless (night) to sun-filled (day) conditions (and vice versa). Under clear skies, the rule of thumb for these neutral events is clear sky neutral events in the southern US desert occur about 60 min after sunrise and approximately 40 min before sunset. In this Feb 2021 case, the standard seems to apply. Not surprisingly, the PV panel-temperature magnitudes appear to be close, if not equal to, the ambient

temperatures during these neutral events. Observing this pattern strengthens the confidence that the data are representing their respective sources.

2.3.2.2 PV Panel-Temperature Patterns

Building on the neutral event pattern confidence, the PV panel temperature shows a much wider diurnal range of values than the ambient temperature (see Figs. 7 and 8). During the nighttime period, the magnitude of the PV panel temperature is consistently less than the ambient temperature. The general oscillating shape of the night PV panel-temperature time series tracks the ambient curves, with about a 35% cooler offset.

Once the sun starts to heat the surface (daylight), the PV panel temperature is consistently greater than the ambient temperature and loosely imitates the Gaussian shape of a diurnal pyranometer time series (Fig. 8b). Since the sun is its primary heat source, this observation is not surprising. The jagged progression of the panel temperature contrasts the smoothness of the clear sky SR. Both ambient and panel temperatures show this “noisier” pattern when examined closely. The progression of rises/falls within the two temperature sources track one another well, though the extent (amplitude) of the rises and falls is significantly larger for the panel temperature than the ambient temperature. This pattern is bluntly observed when the sun initially begins to heat the surface (sunrise through 0830 LT). Aside: To better assimilate the atmospheric characteristics, Fig. 8 shows coincident atmospheric parameters overlaid with a red x-y grid.

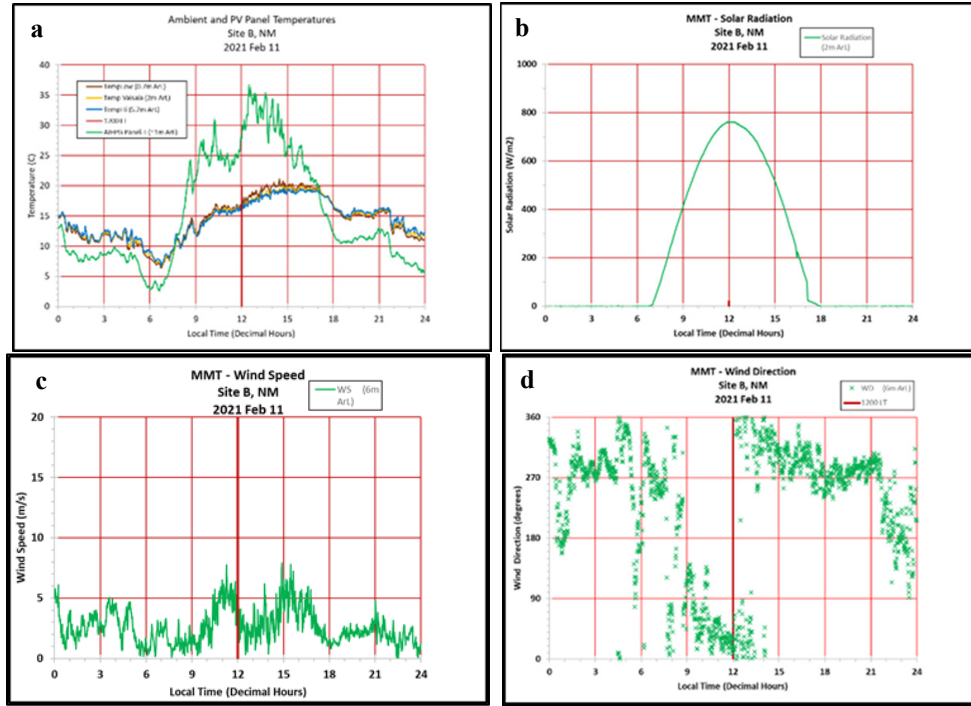


Fig. 8 Concurrent 2021 Feb 11 data include (a) ambient and panel temperatures, (b) SR, (c) wind speed, and (d) wind direction

The two temperature resources on this Feb 11 case show a net increase throughout the morning hours. Their crest for the day occurs at different times. Panel temperature peaks around 1230 LT, whereas the ambient temperatures reach their maximum closer to 1430 LT. To understand the periodic cooling cycles in both resources, one must consider the character of the medium through which the heat travels—the atmosphere. Beginning with wind speed and wind direction, there are many periods where winds decrease into a “light (wind speed) and variable (wind direction)” status. By definition, wind speeds less than 3.06 m/s are not quick enough to define a consistent direction from which the air is flowing, thus the “variable” label. Without a consistent horizontal movement of air, convection (vertical radiative heating) dominates and direct SR is able to heat surfaces quicker. Once the airflow resumes, surface warmth is mixed (brushed off surfaces) into the surrounding environment, enabling the surface to cool by ventilation. This scenario helps to explain the strong panel-temperature increase during the early morning “light and variable” periods.

Another factor in this explanation involves the direction from which the air is flowing. For this site, morning air from the north-northwest tends to be cooler. From 0900–1200 LT, the panel temperature’s warming trend is muted/slowed. Over this same period, winds were above the “light and variable” magnitude—bringing “new” air into the area—and the air was coming from the northern

quadrants. Just before and after the 1200 LT hour, winds slipped back into a “light and variable” state. Panel temperature magnitudes showed a significant rise over this same time. There was also a distinguishing separation initiated between the three ambient temperatures at this time, which persisted until the waning of the sun.

The afternoon hours sported winds strong enough to show a direction, starting from the north and then the west (sunset). The effects of the perpetual ventilation are seen in both temperature sources, though the panel temperature again shows a more exaggerated change in magnitudes, while it converges with the ambient temperatures at the neutral event.

2.4 Ambient and PV Panel Temperature Relationship

The 2021 Feb 11 case demonstrated the basic patterns to expect when comparing coincident ambient and PV panel temperatures. The comparison was then extended for a total of 48 nearly consecutive days. Appendix B presents the graphical results for 2021 Feb 11 through 2021 May 1 temperature comparisons. This slice of the year was selected based on the availability of the concurrent specialized data and the seasonally strong winds associated with the region, ensuring the maximum opportunity for sampling from a reasonably ventilated environment.

Reviewing the subsequent results reenforced the observations previously stated:

- 1) Each day reported two times when the ambient and panel temperatures coincided (neutral events).
- 2) The panel temperature consistently showed lower values over the nighttime period and perpetually warmer values during the daylight hours than the ambient temperature.
- 3) The upward or downward trends of the higher-frequency oscillations were consistent between the matched data, with the magnitude of the panel temperature being more exaggerated (greater amplitude) than the ambient temperature and sometimes the timing being slightly asynchronous.

When assimilating the major similarities and differences, the initial question regarding the interchangeability of these two measurements evolves into a more focused question of determining the impact of higher or lower temperature magnitudes on the PV power generation models.

3. PV Power Models

Two PV power generation models were used in this study: 1) the Mahmoud, Xiao, and Zeineldin (M-X-Z) Model (Mahmoud 2012) and 2) an “in-development” PV

array model. The former model was physics-based, whereas the latter was a developmental model designed to integrate ML/AI techniques for determining PV panel temperatures used by MATLAB/Simulink. Each power-calculating method is summarized in the following sections.

3.1 M-X-Z Model

The M-X-Z model (Mahmoud 2012) predicts the electrical power based on in-situ atmospheric and PV hardware parameters. More specifically, this module requires SR, panel temperature, and specific vendor-specified panel model parameters to calculate the current-voltage (I-V) curve of the panel. From that I-V curve, the maximum power is utilized to estimate the resulting PV panel generated power (Vaucher et al. 2020).

3.2 MATLAB/Simulink PV Array Model

The MATLAB/Simulink's PV array model uses two primary inputs: solar irradiance and panel temperature. The simulated system output is regulated by adjusting the output voltage, which in turn dictates the output current and therefore the PV array power generation. MATLAB's foundational Simscape's power systems use a block set capable of defining an "array made up of strings of modules connected in parallel; each string consisting of modules connected in series" (PV Array 2021). The MATLAB/Simulink PV array is capable of modeling both predefined PV arrays, as defined in the National Renewable Energy Laboratory (NREL) System Advisor Model (NREL 2018), in addition to custom PV arrays. Developing a ML/AI algorithm for the model's temperature input was the targeted application of Part 2 in this research.

4. Temperatures Applied to a PV Power Model

The physics-based model was exercised first to establish the effects of using ambient versus PV panel temperatures in calculating PV panel power. These results served as guidance for the subsequent ML/AI "panel temperature" algorithm development, which is described in Section 5.

Power generated by a PV panel is currently limited to the availability of SR, or daylight hours. PV panels acquire the sun's energy via direct and diffuse SR. To minimize the random nature of diffuse contributions, the M-X-Z Model was first tested using a clear sky scenario. With minimal filtering between the sun and the PV panel, the clear sky case best ensured a consistently strong direct solar source

for the radiation and thermal input. The diffuse SR contributions would be minimized and a function of identifiable, stationary local objects (i.e., guywires).

4.1 Clear Sky Case (2021 March 19)

The 2021 March 19 data were selected as an example of a clear sky case. Figure 9 displays the two significant model inputs (irradiance and temperatures) for this date as a function of time. The irradiance (upper-left plot) shows the persistently, unobstructed sky, with only two guywire shadow interruptions (just after midday and around 1630 LT). The original ambient and panel temperatures are plotted in the lower-left graph. The temperature time series follow the patterns described earlier. The model outputs, shown in the right plot, include power based on ambient temperature (orange) and power based on the PV panel temperature (yellow). Measured power (blue) is also included to help evaluate the modeled results.

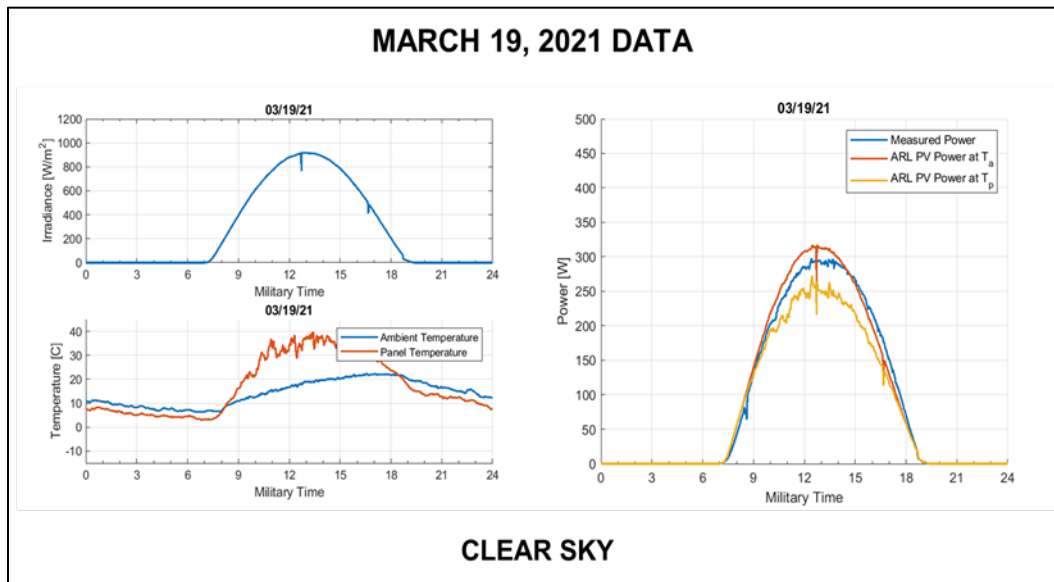


Fig. 9 Power conversion clear sky case

The first pattern noted is that the nighttime values correctly report 0 W/m² and all three power time series maintain a Gaussian-shaped curve during the daytime, much like the SR time series. The amplitudes of the power curves, however, are about 62% less than the SR curve. For a 315-W panel, this is very reasonable.

Continuing with the clear sky results, the measured power shows a noisy curve, especially during the midday hours. The power based on ambient temperature (T_a) has a smoothness that the other two curves do not. This result also preserves the

impact of the guywires. Power based on PV panel temperature (T_p) exhibits the rough character of the panel-temperature time series, along with the guywire spikes.

During morning hours, the three power time series are hard to distinguish. By midday, the T_p underestimates the measured values, whereas the T_a overestimates the measured power. This layering shifts around 1500 LT, when the T_a joins the T_p in underestimating the measured values. Near sunset, all three power values once again overlap. Nighttime values are appropriately zero for all methods of determining PV power.

4.2 Overcast Sky Case (2021 March 9)

While clear sky cases have no solar interruptions, overcast skies represent a total filtering of incoming SR. Consequently, the second case (2021 March 9) includes overcast conditions. The 2021 March 9 SR time series shows a general Gaussian curve shape. The daytime SR curve also has distinct periods of partly cloudy to overcast (0600–1230 LT), sunny skies (1230–1430 MT), and overcast skies (1430–1800 LT) (Fig. 10).

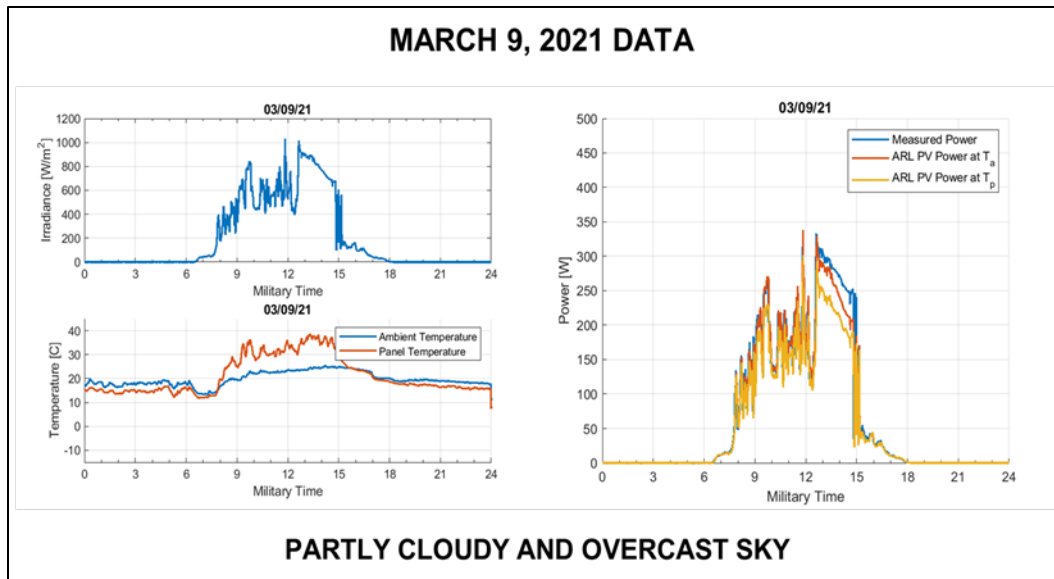


Fig. 10 Power conversion partly cloudy and overcast sky case

The ambient and PV panel temperatures report much closer magnitudes than the clear sky case. Not surprisingly, during the partly cloudy and overcast periods, it is difficult to visually separate the three power time series. Not until the clear sky returns (1230–1430 LT) is there the familiar afternoon pattern where both calculated power values underestimate the measured values and the power derived

from ambient temperature is closer in measured magnitudes. For additional examples of concurrent modeled and measured power comparisons, see Appendix C.

5. Advancing the ML/AI Temperature Forecast Model

The PV array model in development included the primary atmospheric variables (global irradiance and panel temperature) as input. As described earlier, SR dictates the maximum power available through the atmospheric medium. The panel temperature primarily determines the overall efficiency of the energy collectors. With a focus on energy efficiency, a set of AI/ML-based algorithms were pursued that were intended to be the PV panel or ambient temperature model input.

Advances in computational sciences, data analytics and storage, and universal connectivity of dissimilar distributed processes and networks have rejuvenated AI/ML-based algorithm development. Such algorithms are capable of learning both linear and nonlinear time series input and output relationships. Additionally, AI/ML is commonly used for image classification and recognition. Such algorithms can be computationally efficient and capable of running in near real time to real time, depending on the complexity of the algorithm architecture and available processing power.

Generally speaking, there is an eight-step process required to develop and deploy an AI/ML-based algorithm:

- 1) data assimilation and manipulation,
- 2) data segmentation,
- 3) input and target feature extraction or selection,
- 4) algorithm selection and definition,
- 5) learning/training algorithm selection,
- 6) algorithm training,
- 7) validation and testing/deployment, and
- 8) adaptation or retraining of the algorithms using alternative data set(s), which is required to improve algorithm robustness and extensibility.

Each of the eight steps is discussed in greater detail within the subsequent sections.

5.1 Data Assimilation and Manipulation

When generating AI/ML-based algorithms, one of the most important procedures is a careful selection of data for training, testing, validation, and adaptation. Not all data sets are alike, and, in many cases, the data need to be managed or modified (i.e., up sampled, down sampled, or filtered) to ensure high- or low-frequency noise is attenuated, and thus, the possibility of overtraining the AI/ML-based algorithms is reduced. An overtrained AI/ML algorithm can vastly reduce the robustness of the predictive algorithm. There are many different atmospheric data resources from which to develop the AI/ML algorithm. Three atmospheric data resources are highlighted here:

- 1) The National Solar Radiation Database (NSRDB) is a serially complete collection of hourly and half-hourly values for three of the most common solar measurements: SR-global horizontal, direct normal, and diffuse horizontal irradiance, as well as other meteorological data. The current NSRDB is modeled using multichannel measurements from geostationary satellites. The older versions of the NSRDB were modeled using cloud and weather information primarily acquired at airports. The NSRDB has a sufficient number of locations and temporal/spatial scales to accurately represent regional SR climates (NREL n.d.). This database, while coarse, is still good for long-term forecasting ranging from daily, to monthly, to yearly forecasts and spans multiple geographical locations.
- 2) Short-term forecasts are challenged by the coarse granularity of the NSRDB tool. Consequently, higher-resolution data resources were investigated. The US Army Combat Capabilities Development Command Army Research Laboratory's Atmospheric Intelligence for Hybrid Power Grid (AIHPG) Testbed and associated meteorological sensor suite were found to provide many of the same NSRDB measurement types, with one distinguishing attribute—the data measurements were sampled far more frequently (minutes vs. hours) (Vaucher et al. 2020).

The two impediments found when using the high-resolution data sets for the AI/ML algorithms were the long-term yearly trends were limited by the less than 10-year archive of data and the detailed single-site data set represented the local environment/climatic conditions. With the data being tied to a specific geographic location, any global adaptability of algorithms would require additional training data from a “new,” or equivalent, operational location. On the plus side, combining the NSRDB and DEVCOM Army Research Laboratory resources would allow the AI/ML algorithms to

service both long- and short-term forecasts from (equivalent) similar climatic locations.

- 3) The Measurement and Instrumentation Data Center (MIDC) is another atmospheric data source similar to the two previous ones. Operated by NREL, the MIDC is accessible from <https://midcdmz.nrel.gov/>. Sampling rates were equivalent to the AIHPG sensor suite (NREL n.d.).

As with AIHPG data, developing AI/ML algorithms using the MIDC produce results representing smaller geographic regions, which are not evenly spaced or logically oriented. Thus, AI/ML algorithms can only represent location-specific meteorological conditions. Also, any vision for a world-wide application will be a challenge for the higher resolution MIDC data set (Andreas and Wilcox 2011).

For this research, the MIDC Solar Technology Acceleration Center (SolarTAC) data resource was used (Andreas and Wilcox 2011). SolarTAC is available from <https://midcdmz.nrel.gov/apps/sitehome.pl?site=STAC>.

Aside: Ambient temperature modeling was pursued due to the availability of data and the premise that establishing the process was a constructive step forward toward answering the Part 2 question. Variables used included three derived SR values (global horizontal, direct normal, diffuse horizontal) and six measured variables (station pressure, air temperature, relative humidity, wind speed, wind direction, and solar zenith angle).

In terms of data manipulation, three custom variables were defined:

- T_s , which represented the fundamental input/target feature *timestep size*,
- T_p , which represented the *past time interval* in the measured variable (temperature) history when combined with the fundamental step size variable, and
- T_f , which represented the *future time interval* of the measured variable (temperature) target.

To create a more coarse and less noisy set of input and target features, T_s was increased and refined, accordingly. The impact of using a greater or lesser time history of input values was accomplished by changing a combination of the past (T_p) and step (T_s) input features. Finally, short-term forecasts (1 min into the future) and long-term temperature forecasts (24 h into the future) were developed by changing T_f in the AI/ML algorithm development.

As an example of how these three key variables controlled the amount of data used for reach-back, if $T_s = 1 \text{ min}$ step and $T_p = 5 \text{ min}$ in the past, then each input feature would be represented by a vector of length one by six, as shown in Eq. 1, where U_x represents a generic input feature and t represents time:

$$U_x(t - 5 \text{ min}), U_x(t - 4 \text{ min}), \dots, U_x(t - 0 \text{ min}) \quad (1)$$

If instead the fundamental step size was $T_s = 15 \text{ min}$ and $T_p = 60 \text{ min}$, then each input feature would be represented by a vector of length one by five, as shown in Eq. 2:

$$U_x(t - 60 \text{ min}), U_x(t - 45 \text{ min}), \dots, U_x(t - 0 \text{ min}) \quad (2)$$

Looking toward the future, if the future time history variable T_f was set to $T_f = 5 \text{ min}$ and $T_f = 60 \text{ min}$, respectively, then the corresponding targets for the inputs shown in Eqs. 1 and 2 would become Eqs. 3 and 4, respectively, where T_x represents a generic target feature:

$$T_x(t + 5 \text{ min}) \quad (3)$$

$$T_x(t + 60 \text{ min}) \quad (4)$$

The three variables were used in combination with custom functions to manipulate the input and target features. This capability enabled flexible experimentation with the different input feature variations so that it would be possible to identify the ideal data reach-back requirements for the AI/ML panel or ambient temperature forecast algorithm. Describing it more linearly, the technique helped define to what degree does using past measurement data help improve or degrade the AI/ML performance in predicting the target features.

5.2 Data Segmentation

Developing predictive AI/ML algorithms is largely dependent on having a sufficient quantity of data for training and validating results. While the AIHPG and MIDC data were invaluable resources for developing and testing the atmospheric and AI/ML algorithms, after iterative experimentation, the SolarTAC data set was selected for this study. The SolarTAC resource had been operational for more than a decade, which facilitated both short- and long-term forecasting. The intended strategy was to use a more complete data set and then adapt the pre-trained algorithms. The latter would be done after the algorithms were sufficiently trained and tested.

Two separate data sets from the SolarTAC data resource were downloaded. The first data set contained atmospheric measurements spanning from 2013–2019.

These data were termed the “training data set” and used exclusively for training, validation, and preliminary algorithm testing. The second data set was called the “testing data set” and consisted of the same atmospheric measurement types as defined by the training data set; however, the latter data had sample dates spanning from 2020 to 2021. An “adaptation” data set was extracted from the AIHPG resource, which ranged from 2019–2022, and was slated for future work.

5.3 Input and Target Feature Extraction/Selection

Before reaching this third step, a learning type (supervised, reinforcement, or semi-supervised learning) to train the AI/ML algorithms was needed. For this study, the supervised learning method was selected.

The input and target feature extraction and selection processes were critical steps in the algorithm development in that it was like designing the infrastructure for an organization. For algorithm development, the step required selecting input features that related to the target features. If the input features did not relate to the target features, the AI/ML based algorithms would likely fail to converge or identify relationships between input and target elements. For such cases, the algorithm’s extensibility and robustness was limited and likely to have exceedingly poor performance when applied to alternative data sets. Thus, selecting the proper input features with respect to the target feature was critical.

For this study, the target features included the ambient or panel temperatures. Other related variables included date (year, month, day), time (hour, minute, seconds), pressure, ambient temperature, relative humidity, wind speed, and wind direction. There were many different methods for determining feature selection. The two most common methods included 1) utilizing engineering intuition, empirical experiences and known relationships for the desired input/target features, and 2) using principal component analysis (PCA) on the applicable data set. Note: The AI/ML community is somewhat divided in regard to using PCA for feature selection.

5.3.1 Engineering Intuition

One of the most common input–target feature extraction/selection processes is engineering intuition. This intuition relies on the developer’s expertise in understanding the physical phenomenon being modeled. For example:

- In this study, the two primary contributors to solar power production were SR and cell or panel temperature. PV arrays are designed such that energy contained in light can be converted using solar collectors. These collectors convert the thermal energy into electrical energy. As a result of this conversion, SR measurements or forecasts are necessary for PV energy

production; therefore, they were defined as a required input feature for forecasting PV panel or cell temperature.

- The other primary feature impacting PV array performance was ambient temperature. As described earlier, the ambient temperature (heat) is linked to panel or cell temperature and the efficiency of PV power generation. The former characteristic is best described through the use of heat transfer concepts:
 - One-dimensional conductive and convective heat transfer rates are generally assumed to be governed by Eqs. 5 and 6, respectively, where ΔT represents a temperature difference, dx represents a change in length, k represents the thermal conductivity of a material or substance, h represents the heat transfer coefficient of a material or substance that is impacted by velocity of a fluid, and q_x'' and q_s'' represents the heat transfer rate through conduction or convection, respectively:

$$q_x'' = k \frac{\Delta T}{dx} \quad (5)$$

$$q_s'' = h\Delta T \quad (6)$$

- Equations 5 and 6 can be rewritten to form Eqs. 7 and 8, where L is now the length of a medium through which conduction will take place, A is the surface area through which convection will take place, $T_{surface}$ represents the surface of the material, T_a and T_b represent two different surfaces or boundaries of an object through which heat can transfer via conduction, and T_∞ represents the environmental temperature in which the material is placed or emersed:

$$q_{cond} = \frac{k}{L}(T_a - T_b) \quad (7)$$

$$q_{conv} = \bar{h}A(T_{surface} - T_\infty) \quad (8)$$

- Based on these equations, the velocity of the fluid can be inferred. The fluid direction can impact heat transfer rates (as observed in Section 2.3.1); thus, wind speed, wind direction, and ambient temperature were determined as features impacting the PV array performance.

Based on the net engineering intuition applied to this study, eight different features were defined for the input and target feature extraction/selection process:

- 1) time of year (ToY),
- 2) time of day (ToD),
- 3) station pressure,
- 4) either air temperature or panel temperature,
- 5) relative humidity,
- 6) wind speed,
- 7) wind direction, and
- 8) global horizontal irradiance.

Note: The order of the 1 ➔ 8 list used to create the NN Training Results (Appendix D) was the following:

- 1) station temperature,
- 2) station pressure,
- 3) relative humidity,
- 4) average wind speed,
- 5) average wind direction,
- 6) irradiance,
- 7) ToD, and
- 8) ToY.

The input features of ToD and ToY were computed from the data set variables: year, month, day and hour, minute, second. These features were added to explore the diurnal, monthly, and possibly annual environmental trends of a specific geographic location. Projecting forward, the observed trends held the possibility of being applicable to alternative locations.

5.3.2 Principal Component Analysis

Multivariate statistics are difficult to visualize when using many variables. Replacing a group of variables with a single new variable simplifies the issue. PCA is just such a simplification method.

PCA reduces the complexity of high-dimensional patterns by generating a new set of variables defined as the principal components (PCs). PCs are linear combinations

of the original variables. PCA is commonly used in image processing, pattern recognition, and ML for conducting feature extraction, identification, or selection.

PCA utilizes computer vision, pattern recognition, and ML to assess, analyze, and select the optimal feature set so as to not overcomplicate the algorithm creation. Data set features that are not constructively helpful in the algorithm development can lead to overfit algorithms. By using a minimal set of features, this product saves storage and computation time, and increases comprehensibility. PCA facilitates the selection of limited feature components from the original feature samples (Minitab 2021).

To determine the minimum number of PCs that can account for most data variations, one examines the proportion of variance that the components explain and the eigenvalues. The cumulative proportion can be used to determine the amount of variance that the PCs explain. The PCs that define an acceptable change level are retained. Note: Acceptable change levels are a function of the application.

PCs with the largest eigenvalues are also retained. Plotting the eigenvalues in an increasing order enables one to interpret each PC in terms of the original variables and identify the outliers.

The Pareto front visually explains what percentage of the variance within the supplied data is explainable by the PCs. Recall that the PCs are linear combinations of the selected eight inputs, including the ambient pressure, ambient temperature, relative humidity, wind speed, wind direction, irradiance, ToY, and ToD. The coefficients that result from the normalized input features representing the PCs are shown in Eq. 9. The matrix rows represent the input feature, and the columns represent the individual PCs.

$$\begin{bmatrix} -0.5607 & 0.1745 & -0.0362 & 0.0565 & 0.0422 & -0.0295 & -0.5579 & 0.5803 \\ 0.0324 & 0.6325 & -0.0602 & -0.0130 & 0.5912 & 0.4626 & 0.0032 & -0.1778 \\ 0.5852 & 0.0296 & 0.0292 & 0.0001 & 0.0390 & 0.1646 & 0.2081 & 0.7641 \\ -0.2554 & -0.5059 & 0.1412 & 0.1908 & -0.0339 & 0.7835 & 0.0849 & 0.0196 \\ -0.0492 & -0.3426 & -0.5808 & 0.4418 & 0.5200 & -0.2340 & 0.1381 & 0.0593 \\ -0.4970 & 0.1538 & -0.1895 & -0.3521 & -0.0861 & -0.0297 & 0.7230 & 0.1959 \\ -0.1544 & -0.0937 & 0.7740 & 0.1679 & 0.4451 & -0.2975 & 0.2191 & 0.0740 \\ -0.0595 & 0.4037 & 0.0437 & 0.7829 & -0.4125 & 0.0013 & 0.2198 & -0.0110 \end{bmatrix} \quad (9)$$

Within the provided matrix, values less than -0.5 or greater than 0.5 were deemed significant. Applying Eq. 9, the following observations were noted:

- Analysis of the first PC would indicate that the first PC explains 27.7% of the variance, which is negatively impacted by the ambient temperature and positively impacted by relative humidity.

- Analysis of the second PC would indicate that an additional 16.4% of the variance is positively impacted by the ambient pressure and negatively impacted by wind direction, thus explaining 44.1% of the variance.
- Analysis of the third PC would indicate that an additional 13.5% of the variance is negatively impacted by the wind direction and positively impacted by ToD, thus explaining 57.6% of the variance.
- Finally, analysis of the fourth PC would indicate that an additional 12.4% of the variance is positively impacted by ToY, thus explaining 70.0% of the variance.

Based on the PCA, to simplify the input features of the AI/ML-based algorithms, the eight input features could be exchanged and a fraction of the resulting PC transformations used. The result could potentially create a more computationally efficient set of AI/ML algorithms. Conversely, using the PCA performance of the algorithm could be reduced if certain input features or PCs were omitted.

5.4 Algorithm Selection and Architecture Definition

There are generally three types of NN architectures:

- 1) Shallow feedforward artificial neural networks (ANNs): The ANN includes general feedforward networks and networks with exogenous inputs (NARX) feedforward networks.
- 2) Deep neural networks: These networks include long-short term memory networks (LSTMNs), convolution neural networks (CNNs), residual neural networks, recurrent neural networks (RNNs), and multilayer perceptron.
- 3) Networks that include multiple different types of the pattern recognition, clustering, and image recognition algorithms.

AI/ML can be applied to multiple engineering and scientific applications. Certain sets of algorithms may be better suited to different applications, for instance, LSTMNs and NARX networks are expressly used for time series predictions and CNNs may be used for time series predictions or image classification, recognition, or clustering. For this research, the focus was on the general set of shallow feedforward ANNs.

The selected architecture definition used for each shallow ANN is shown in Fig. 11. The NN input was governed by a selection of input features, in addition to T_s and T_p . The initial NN input was passed through each individual hidden layer, culminating with an output layer that included a final prediction. The output was

designed to be either a forecasted ambient or panel temperature based on the previously established variable of T_f . As shown in Fig. 11, each hidden layer was populated by 10 hidden neurons, where the input signal was multiplied by a weight, added to a bias, and then run through the hyperbolic tangent function, which acted as an activation layer within each hidden layer.

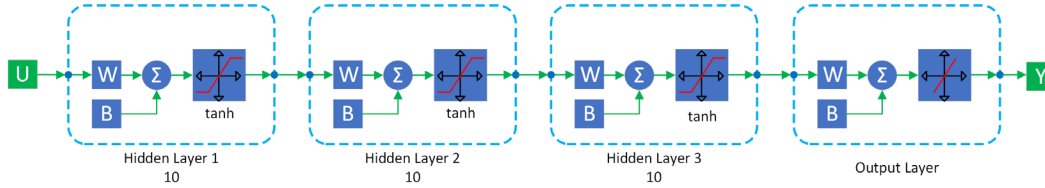


Fig. 11 Shallow ANN feedforward architecture

5.5 Learning/Training Algorithm Selection

AI is developed during the learning or training processes of an algorithm. During this step, the individual weights and biases as defined by each input, output, and layer (including hidden, convolution, LSTM, regression, or classification), and are iteratively solved with an optimization routine. During the learning process, some form of a gradient- or global optimization-based algorithm was deployed to minimize the selected performance function. The performance function describes the AI/ML algorithm's ability to predict the desired target correctly. Common types of performance functions include the mean squared error (MSE), mean absolute error (MAE), and so on.

5.5.1 Learning/Training Algorithm Selection

There are five fundamental types of learning/training that can be used to train AI/ML algorithms: supervised learning, unsupervised learning, reinforcement learning, transfer learning, and semi-supervised learning. For supervised learning, the algorithm development is governed by the architecture selection, input and target features, as well as large characterized and labeled data sets.

For unsupervised learning, an algorithm is provided a data set. From the data set, the ML algorithms discover connections forming intelligence, culminating in a classification or prediction. This type of learning is generally considered to be the most difficult and complex. It also requires significantly large uncharacterized data sets.

For reinforcement learning, reward metrics are defined. During the learning/training process, the metrics reinforce the input and output relationships.

For transfer learning, a set of AI/ML-based algorithms are pretrained on a similar but more general data set. This algorithm is then applied to a specific data set and adapted.

Finally, there is the semi-supervised learning, which is a combination of supervised and unsupervised training techniques.

5.5.2 Supervised Learning Used in this Research

Supervised learning was chosen to develop the ambient or panel temperature forecast models based on a need to define the algorithm set, as well as the input and target features. In the Section 5.6, the training method is described in the context of its application to this research.

5.6 Algorithm Training

The algorithm training began by extracting 80% of the training data set for initial algorithm development. The remaining 20% was withheld and used for preliminary testing. Data for the initial algorithm development was then randomly segmented, with 70% parsed for training, 15% for validation, and 15% for testing. MATLAB was used to segment the input and target features data in an attempt to minimize the possibility that the network may be overtrained or overfitted. The neural fitting (nftool) graphical user interface (GUI) was used to generate an advanced script featuring additional options and example code for generating a feedforward ANN. The code was modified to accommodate the selection of input and target features, which were then passed to the additional options and example code. The optimization routine used for training the NN was the Levenberg–Marquardt training algorithm. The MSE was used to evaluate the NN performance.

The training process of the feedforward NN was made visible through the NN training GUI (nntraintool), as shown in Fig. 12.

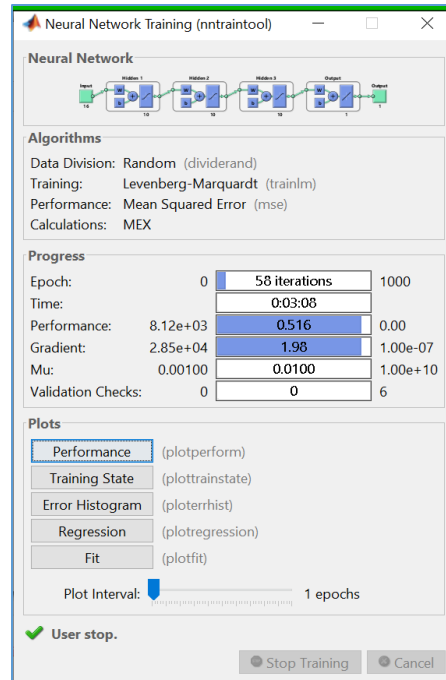


Fig. 12 NN training screen in MATLAB

The ANN training/learning process was halted after either a thousand iterations were completed or MATLAB validation checks interrupted the training.

The NN performance state was visualized through the performance graphics, as shown in Fig. 13. Using MSE, one could observe how many iterations were required before updating the individual ANN weights and biases during the learning or training process resulted in minimal significant improvements (i.e., MSE showed minimal changes with increasing epochs). In Fig. 14, there is little change within the performance function once it reaches epoch 22. Here, the NN can continue to train/learn, which may improve the AI/ML algorithm; however, there will be very little quantifiable improvement from the results. Persistence at this stage could result in overfitting. To prevent overfitting, MATLAB was coded to terminate if the validation checks exceed the tolerance.

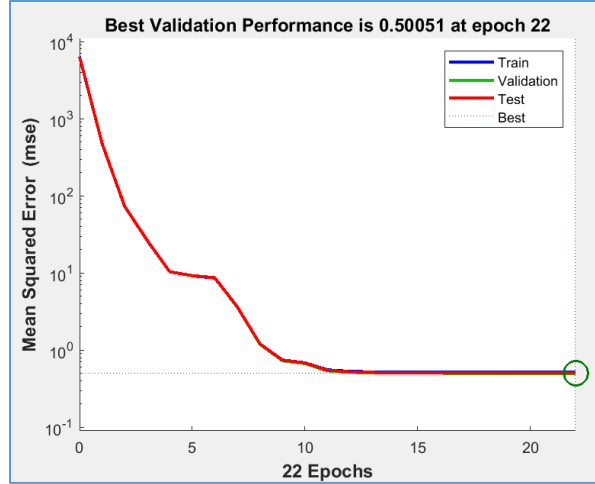


Fig. 13 Performance graph for NN training

The code was executed multiple times using multiple values for T_p and T_f . Each case supported the original goal to better understand the historical reach-back (forward) capabilities of the proposed AI/ML algorithms for predicting the ambient and panel temperatures.

5.7 Validation and Testing/Deployment

The preliminary algorithm validation and testing for this study was conducted on a set of atmospheric conditions characterized as either clear (CLR) or overcast (OVC) skies. As described earlier, a CLR SR time series has the general shape of a Gaussian bell-shaped curve centered on solar noon. The maximum CLR irradiance, for the area selected, ranged from 800–1200 W/m². The OVC cases tracked a similar irradiance curve; however, the time series was characteristically noisier and rarely exceeded 60% of the CLR irradiance over a 24-h period. Maximum surface SR is largely a function of latitude, longitude, solar declination, site elevation, and cloud cover. Four graphs for the CLR and OVC sky cases were created for all variables of T_p and T_f . Figures 14 and 15 show a sample of the MATLAB NN training for forecasted ambient temperature. Appendix D displays additional ambient temperature forecast results for CLR, OVC, and partly cloudy cases.

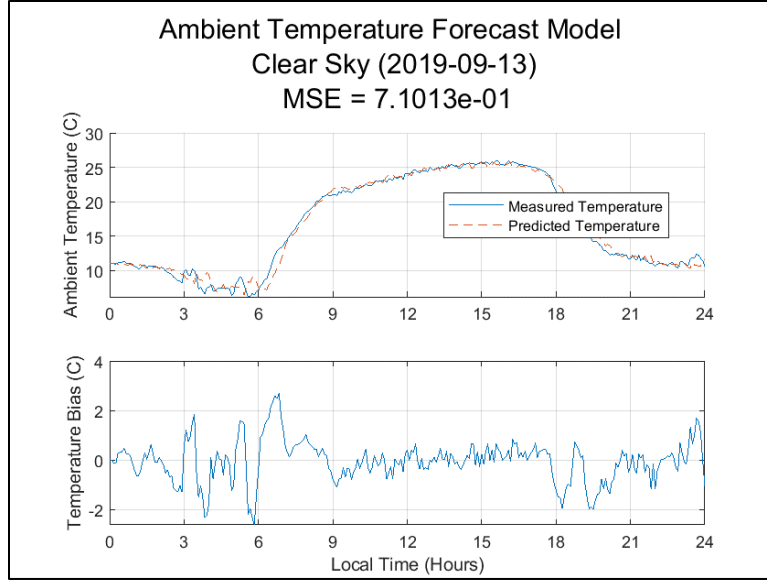


Fig. 14 NN training result for a CLR case

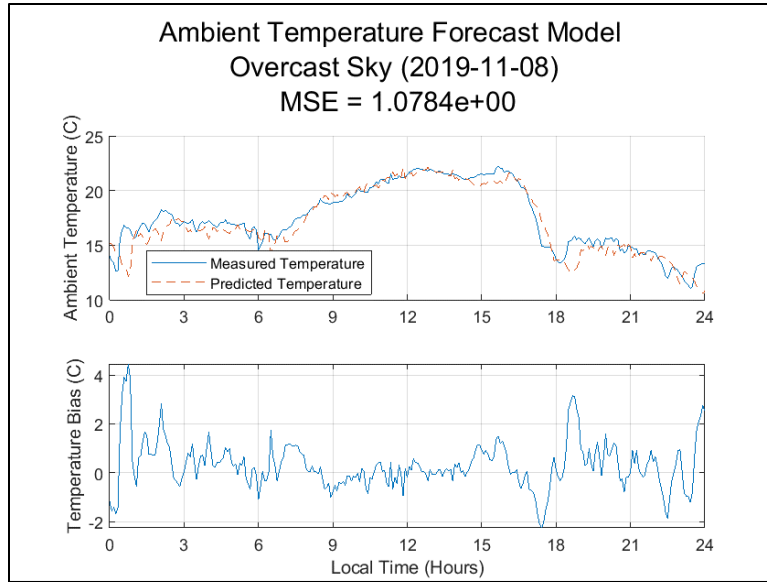


Fig. 15 NN training results for an OVC case

Note: The “bias” values shown in Figs 14 and 15 were calculated using a (measured power – forecasted power) formula. Thus, a negative bias shows a forecasted overestimation of the measured power; positive bias reports an underestimation of “truth.” The ideal bias is zero.

Table 6 presents tabulated results for these sample CLR and OVC cases. As described earlier, combinations of T_s and T_p variables were used to manage the amount of past time series data used by the NN. T_f designated the future target

feature, which for this example was predicting ambient temperatures. Aside: Due to time constraints, forecasting panel temperatures was left for a later project.

Table 6 Training performance results for CLR and OVC T_p and T_f values

T_f Value	T_p Value	MSE - OVC - 11/8/19	MSE - CLR - 9/13/19	T_f Value	T_p Value	MSE - OVC - 11/8/19	MSE - CLR - 9/13/19
min	min	°C	°C	min	min	°C	°C
5	15	0.11515	0.10995	15	5	0.51311	0.36904
10	15	0.32528	0.25733	15	10	0.51657	0.3798
20	15	0.63726	0.44854	15	20	0.54454	0.43282
40	15	1.2063	0.71113	15	40	0.47592	0.34266
80	15	2.4079	1.3066	15	80	0.50541	0.36941
160	15	5.6679	2.8694	15	160	0.48517	0.36143
5	30	0.10953	0.10555	30	5	1.0511	0.71747
10	30	0.29610	0.23051	30	10	1.0784	0.71013
20	30	0.64827	0.47026	30	20	0.985	0.60802
40	30	1.0279	0.43632	30	40	0.95295	0.59504
80	30	2.5624	1.229	30	80	0.84342	0.60464
160	30	4.9078	2.3795	30	160	0.89369	0.59979

To assimilate the NN reach-back capabilities, the input and target feature step sizes were individually kept constant. Four separate cases were created—two with T_p constant and the forecast interval iteratively doubled:

- 1) $T_p = 15 \text{ min}$ and T_f was set to (5, 10, 20, 40, 80, and 160 min).
- 2) $T_p = 30 \text{ min}$ and T_f was set to (5, 10, 20, 40, 80, and 160 min).

and two with T_f constant and the past interval iteratively doubled:

- 3) $T_f = 15 \text{ min}$ and T_p was set to (5, 10, 20, 40, 80, and 160 min).
- 4) $T_f = 30 \text{ min}$ and T_p was set to (5, 10, 20, 40, 80, and 160 min).

When the same amount of past time history was used (T_p was held constant), the NN performance decayed; MSE effectively doubled with the increasing forecast target. This result is reasonable. The probability that the future atmospheric conditions are impacted by the current set of meteorological conditions decreases as the air sampled to create the current measured values exits the area and is replaced with a new air mass (set of conditions).

When the forecast interval T_f was held constant and T_p was varied (additional historical information was provided), Table 6 shows the MSE values remained relatively constant (slight negative correlation) for both sky conditions. The observation that using more historical data generates minimal-to-no improvement in the algorithm's ability to predict the future temperature is a flag. Without

significant improvements, increasing T_p creates a risk for unnecessarily growing the overall complexity of the AI/ML algorithm. If an operational system has processing/storage limitations, this finding is especially notable for determining the appropriate historical data cut-off requirement for the application.

Only one set of ANN architectures and variations was tested. By changing the number of hidden layers, the population of the layers, and/or the ANN architecture, further improvement could be possible. For a more conclusive set of results, a full Monte Carlo simulation should be run using alternative architectures and sizes of the same type of feedforward ANN.

5.8 Adapting/Retraining of the Algorithms

At this time, the algorithms have not been adapted or retrained for alternative geographical locations. As the validating and testing process advances, the current set of algorithms will include alternative forms of AI/ML, such as CNNs, RNNs, and classifiers.

6. Summary

Reducing the vulnerability of remote-site electrical resources can be advanced through power diversity. To optimize this diversity, one strategy is to secure advanced knowledge of key atmospheric parameters. When solar energy is integrated into a remotely located grid using PV panels, the two critical atmospheric elements include 1) SR, which defines the maximum potential PV power production, and 2) PV panel temperature, which impacts power production efficiency. While SR was used for analysis context, temperature is the focus of this investigation. Power generation calculations require a PV panel-temperature input; however, such measurements are not always available. Consequently, the first of two questions steering this study was the following:

- Can ambient temperature measurements be used in place of PV panel temperatures when modeling PV panel power generation?

For this Part 1, the ambient and PV panel temperature relationship was explored. The study investigated various temperature sensor types, diurnal ambient temperature time series as a function of global latitude and elevation, and finally, concurrent ambient and PV panel temperatures were compared, with a qualitative relationship defined. Results found the following observations:

- 1) Each day reported two times when the ambient and panel temperatures coincided (also called, neutral events, or a brief time when the lower atmosphere is naturally isothermal).

- 2) The panel temperature consistently showed lower values over the nighttime period and perpetually warmer values during the daylight hours than the ambient temperature.
- 3) The upward or downward trends of the higher-frequency oscillations are consistent between the matched data, with the magnitude of the panel temperature being more exaggerated (greater amplitude) than the ambient temperature and sometimes the timing being slightly asynchronous.

Assessing the impact of the temperature on PV power calculations, the physics-based PV power model “M-X-Z” was used. CLR and OVC sky scenarios were selected to characterize min and max SR filtering on the PV panel. Real-world coincident PV power measurements scaled the results.

For the OVC case, the M-X-Z Model power results showed little distinction when using ambient and panel temperatures. For the CLR case, during the peak SR hours, the modeled power as a function of ambient temperature overestimated the measured power. The modeled power as a function of PV panel temperature underestimated the measured power. The power curve resembled the smoothness of the SR curve and included the few guywire shadow spikes when ambient temperature was used. When PV panel temperature was used, the higher frequencies within the calculated power curve took on the equivalent PV panel temperature character, as did the measured power curve.

Part 2 of the project focused on advancing the ML/AI temperature forecast model. The core question was, What is the optimal data reach-back for the NN PV panel-temperature forecast model? This second part reviewed current panel-temperature usages in determining PV power. ML/AI techniques were explored, which included current and historical temperature data in forecasting future temperatures. Finally, experimentation with the historical temperature reach-back and forecast-forward intervals framed future PV power forecast modeling requirements.

An eight-step process was used to develop the AI/ML temperature forecast algorithm:

- 1) data assimilation and manipulation,
- 2) data segmentation,
- 3) input and target feature extraction or selection,
- 4) algorithm selection and definition,
- 5) learning/training algorithm selection,
- 6) algorithm training,

- 7) validation and testing/deployment, and
- 8) adaptation or retraining of the algorithms using alternative data set(s).

Each step was discussed in this report. Aside: Ambient temperature modeling was pursued due to the availability of data and the premise that establishing the process was a constructive step forward toward answering the Part 2 question.

Three variables were defined to quantify the NN reach-back/forward capabilities:

- T_s represented the fundamental input/target feature *timestep size*,
- T_p represented the length of *past* measurement history when combined with the fundamental step size variable, and
- T_f represented the *future* measurement of the target.

Four cases were examined. In cases 1 and 2, the effects of forecasting forward were tested by holding the past temperature time interval (T_p) constant:

- 1) $T_p = 15 \text{ min}$ and T_f was set to (5, 10, 20, 40, 80, and then 160 min),
- 2) $T_p = 30 \text{ min}$ and T_f was set to (5, 10, 20, 40, 80, and then 160 min).

In cases 3 and 4, the effects of reaching back were tested by holding the future temperature forecast time interval (T_f) constant:

- 3) $T_f = 15 \text{ min}$ and T_p was set to (5, 10, 20, 40, 80, and then 160 min),
- 4) $T_f = 30 \text{ min}$ and T_p was set to (5, 10, 20, 40, 80, and then 160 min).

When the past history was held constant (T_p constant) to generate a prediction that spanned progressively larger timescales (T_f forecast interval was doubled), the NN performance declined; MSE effectively doubled with the increasing forecast target.

When T_f was held constant and T_p was varied (additional historical information was provided), the MSE values remained relatively constant.

Thresholds, where adding historical data no longer improved the temperature prediction, were noted due to their risk for growing the overall AI/ML algorithm complexity. In an operational setting, minimizing NN algorithm complexity is critical with respect to a system's processing/storage requirements.

7. Conclusions

Here, we answer the original research questions.

7.1 Can Ambient Temperatures Be Used for PV Panel Temperatures?

For OVC cases, the answer is yes. For CLR cases, grid optimization routines will need to assimilate the potential for midday excursions from actual power generation. Using ambient temperatures will likely result in an overestimated PV power forecast based on the given model, whereas PV panel temperatures will likely underestimate PV power over the peak PV energy intake periods (again, based on the given model). The next step is to test these findings against other PV power models.

7.2 What Is the Optimal Data Reach-Back (forward) for the NN PV Panel-Temperature Forecast Model?

Based on the ambient temperature modeling results, the cases reviewed demonstrated thresholds for constructive input in both reach-back and -forward directions. Since only one set of ANN architectures and variations were tested, there is still room for future investigations. Aside: Ambient temperature modeling was pursued due to the availability of data and the premise that establishing the process was a constructive step forward toward answering the Part 2 question.

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Appendix A. Rawinsonde Observation (RAOB) Temperature Profiles

Vertical temperature profiles characterize temperature as a function of elevation. Rawinsonde observation (RAOB) launches remotely sample the atmospheric from a balloon-borne package. To observe the impact of global latitude and climatological conditions, five unique RAOB stations were selected:

- 1) Desert, landlocked locations: El Paso, Texas (ELP), and Albuquerque, New Mexico (ABQ).
- 2) Polar, coastal locations: Barrow, Alaska (BRW), and Anchorage, Alaska (ANK).
- 3) Mid-latitude coastal location: Sterling, Virginia, Dulles Washington, DC (IAD).

The RAOB data were sampled on 2020 June 8–10, at 00 Zulu (z) and 12z. As a reference, a 0 °C line (freezing) was added to each plot. For a description of a vertical temperature profile, see Section 2.2.

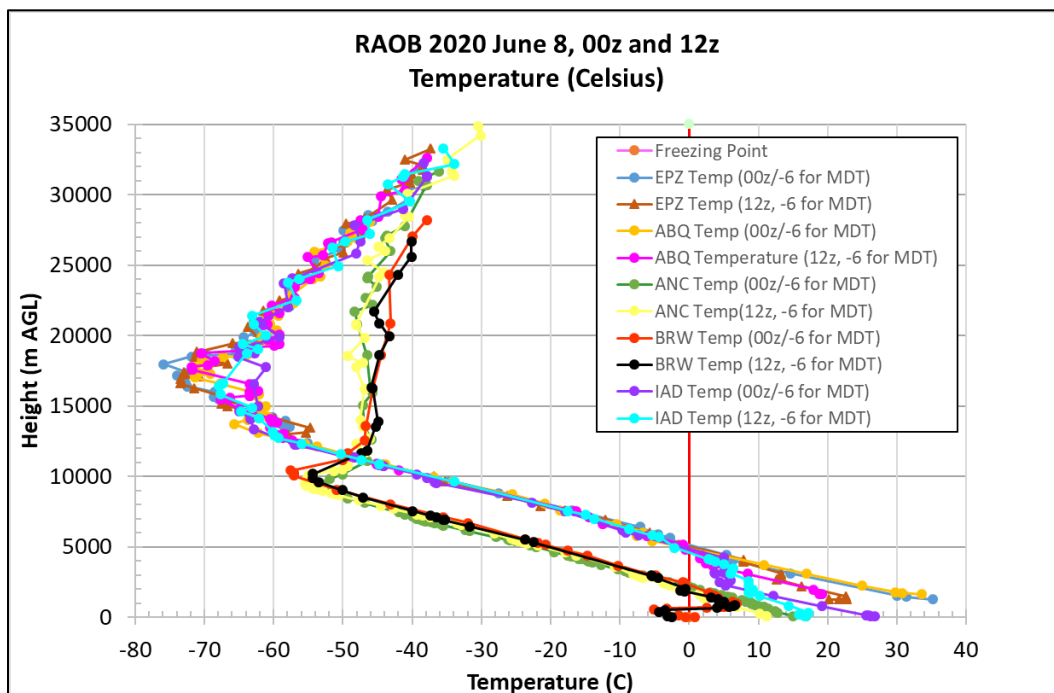


Fig. A-1 2020 June 8, 00z and 12z rawinsonde data from five US locations

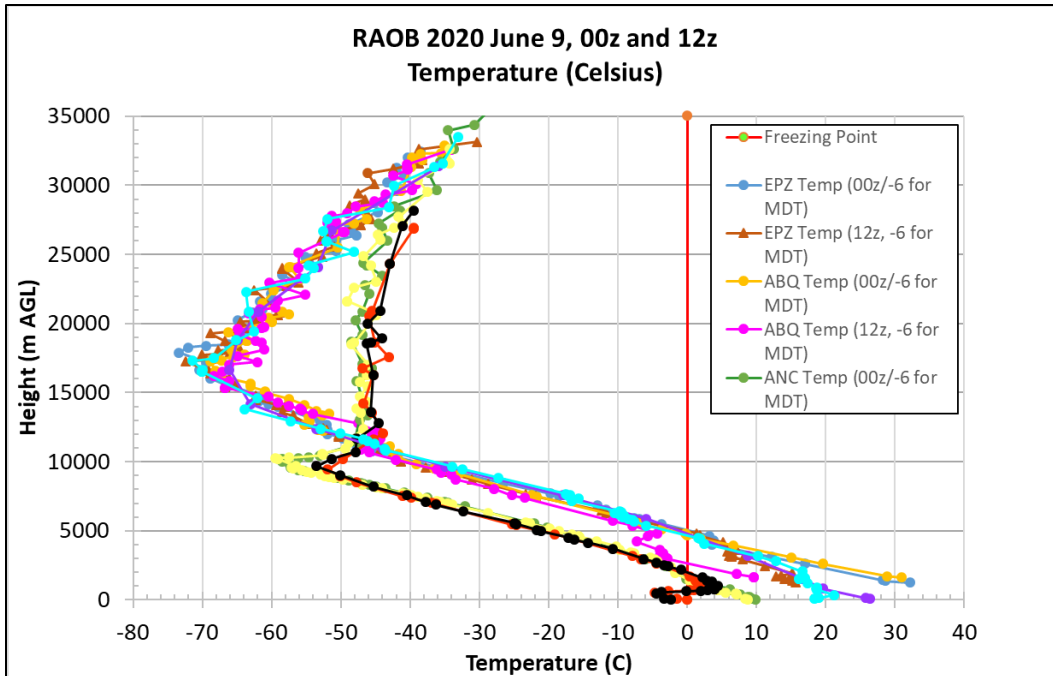


Fig. A-2 2020 June 9, 00z and 12z rawinsonde data from five US locations

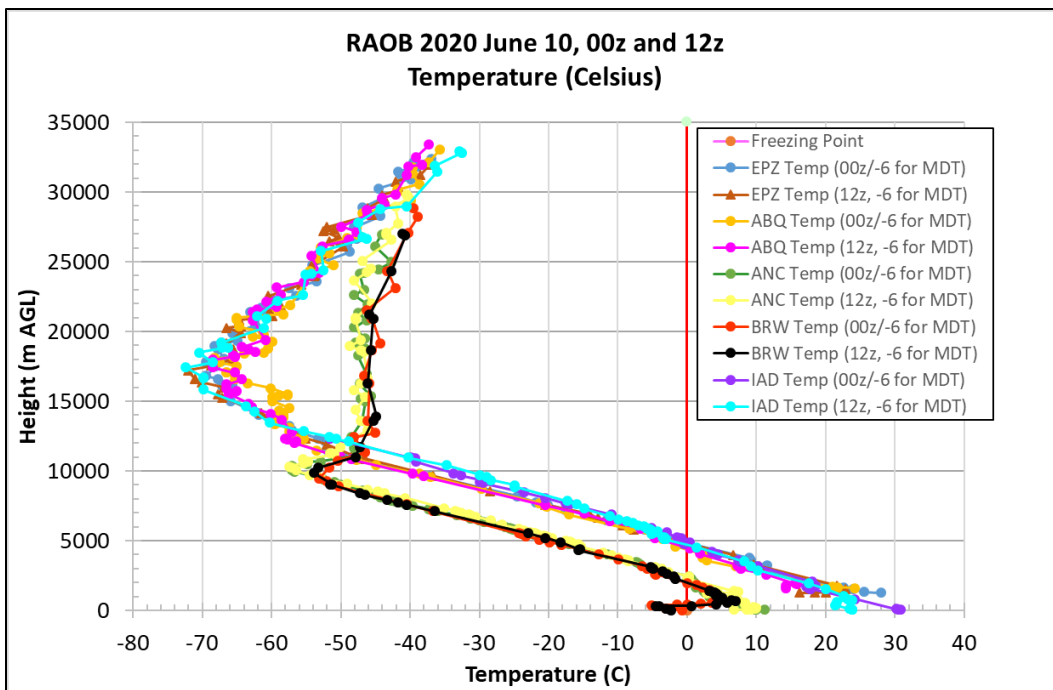


Fig. A-3 2020 June 10, 00z and 12z rawinsonde data from five US locations

Appendix B. Ambient versus Photovoltaic (PV) Panel Temperature Time Series

The following graphs display the photovoltaic (PV) panel versus ambient temperature from 2021 Feb 11 through 2021 May 1. This slice of the year was selected based on the availability of the concurrent data and the seasonally strong winds associated with the region, ensuring the maximum opportunity for sampling from a well-ventilated environment. For a detailed review of coincident panel versus ambient temperatures, see Section 2.2.

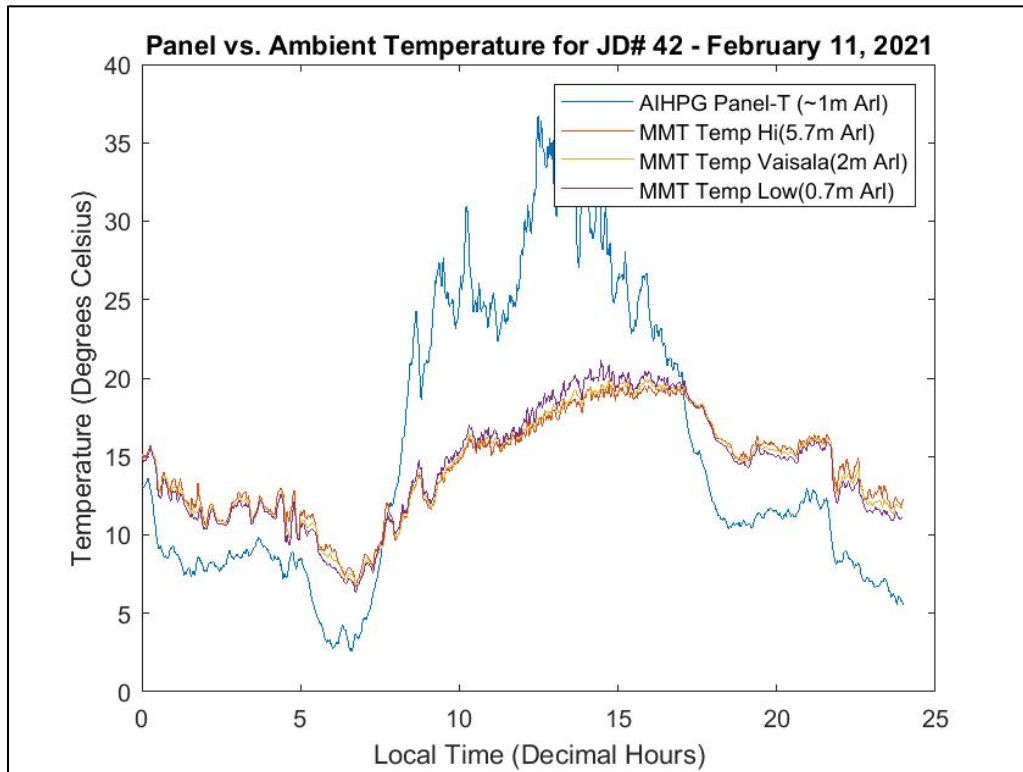


Fig. B-1 2021 Feb 11, panel vs. ambient temperature

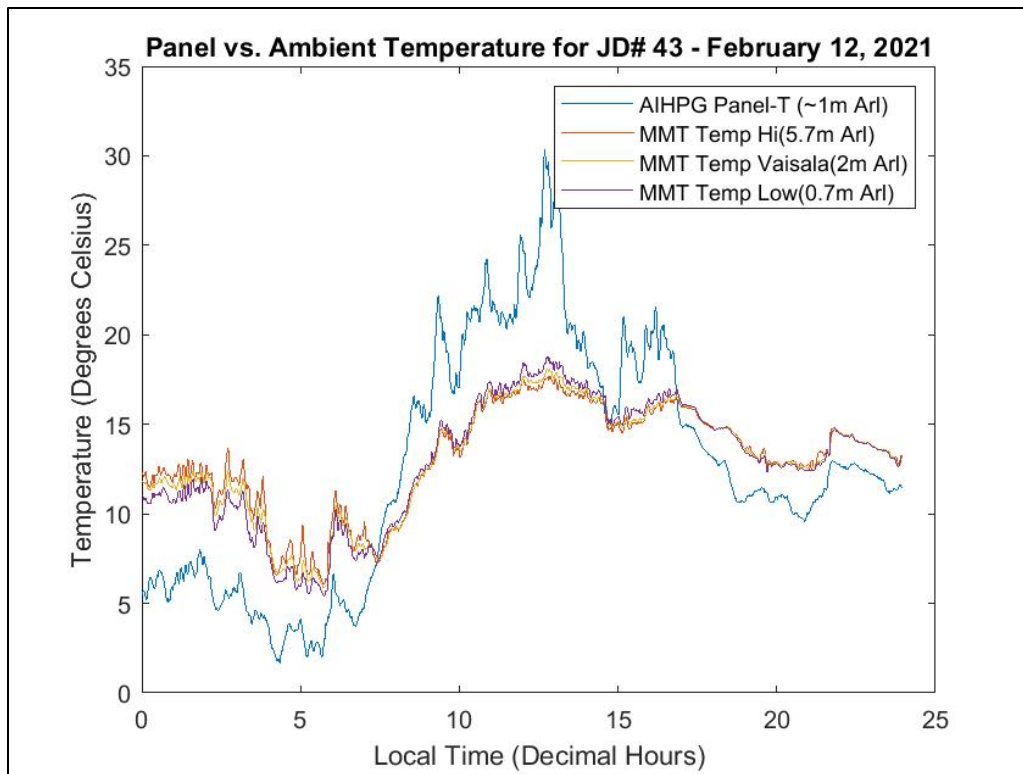


Fig. B-2 2021 Feb 12, panel vs. ambient temperature

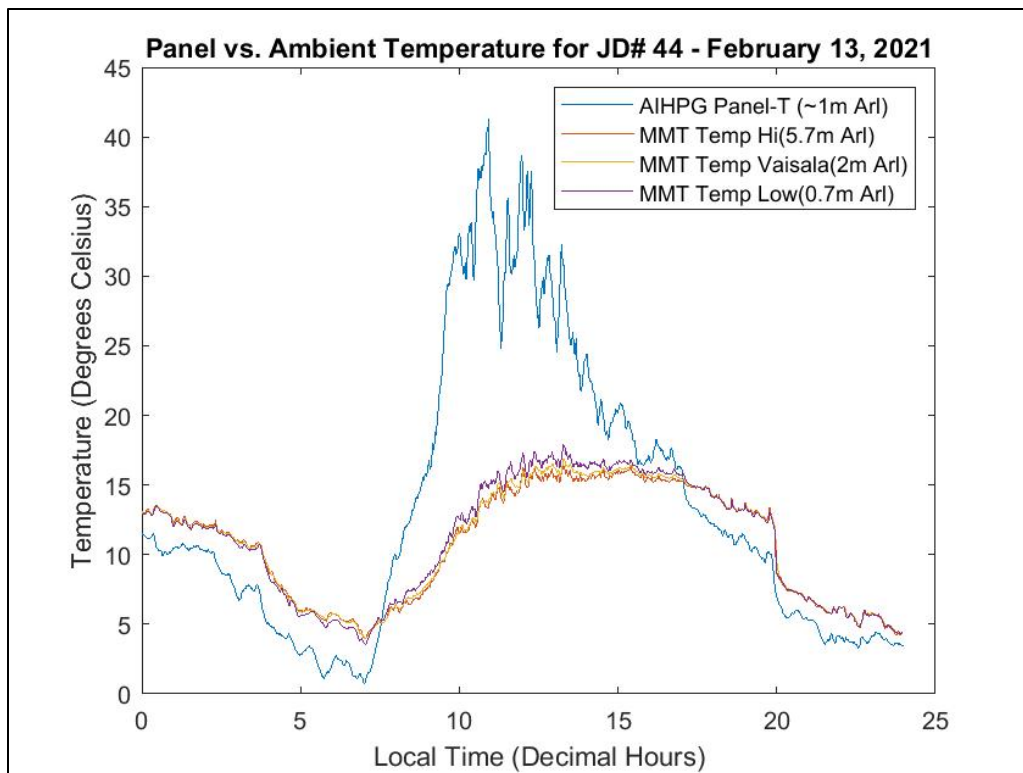


Fig. B-3 2021 Feb 13, panel vs. ambient temperature

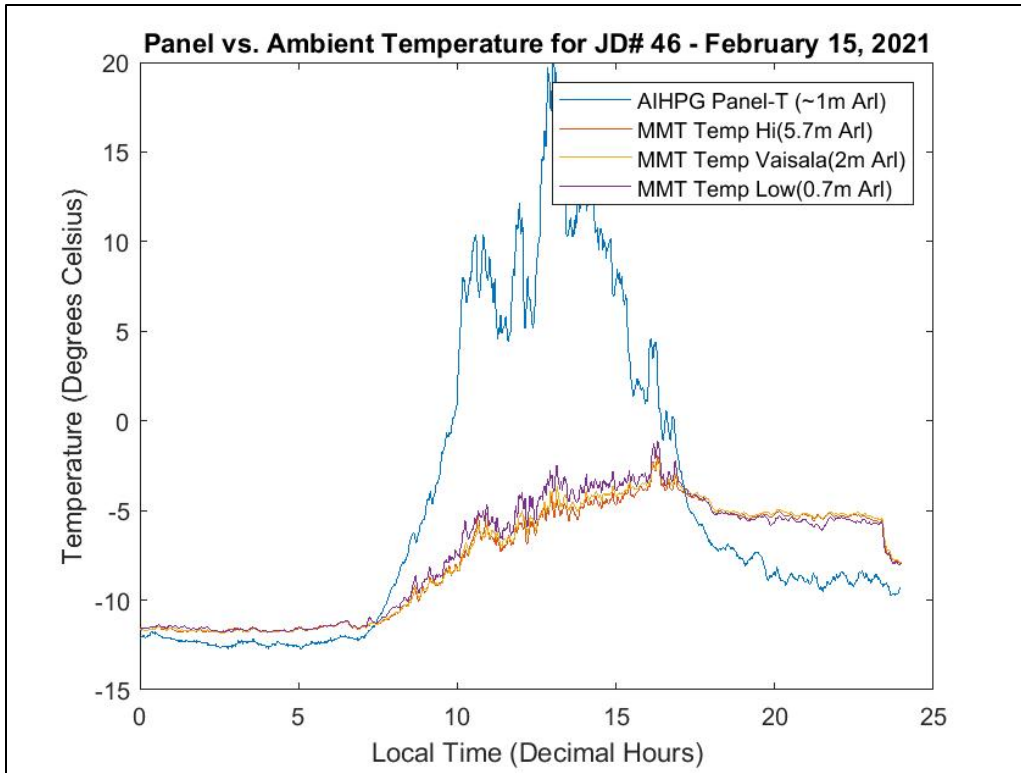


Fig. B-4 2021 Feb 15, panel vs. ambient temperature

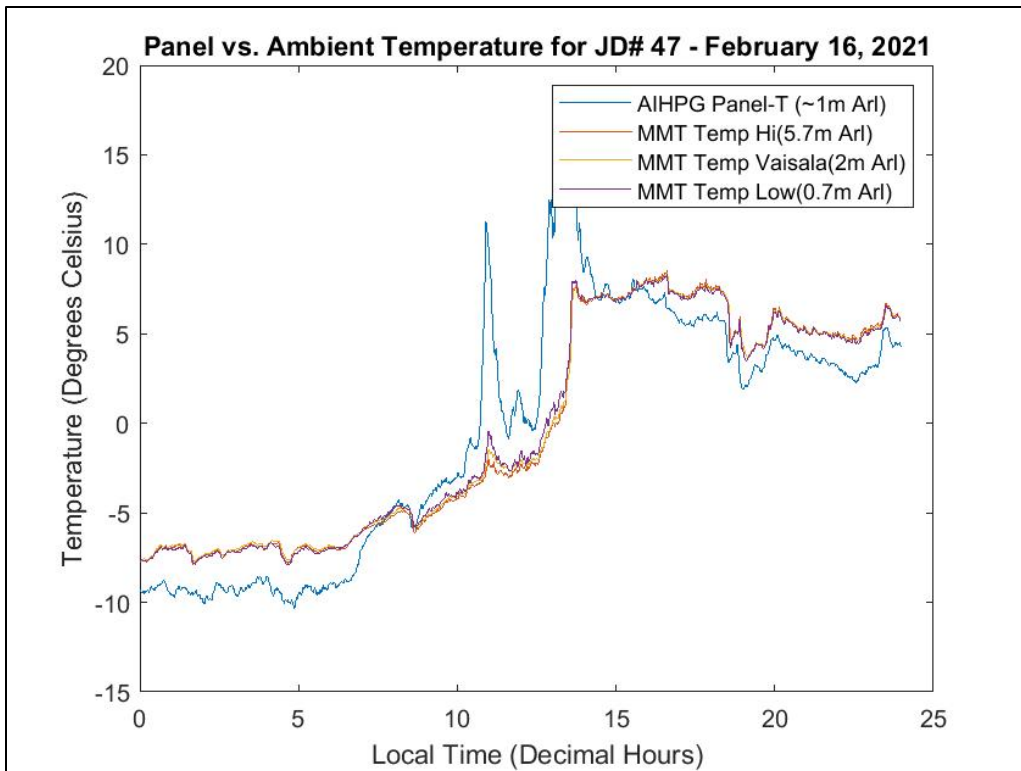


Fig. B-5 2021 Feb 16, panel vs. ambient temperature

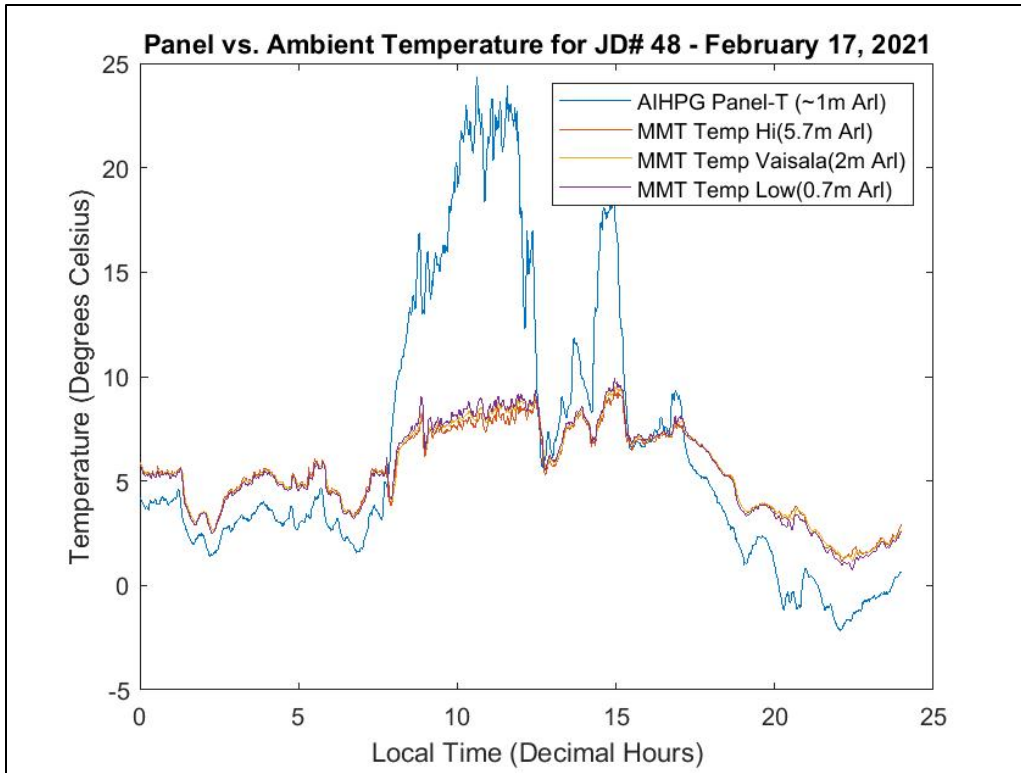


Fig. B-6 2021 Feb 17, panel vs. ambient temperature

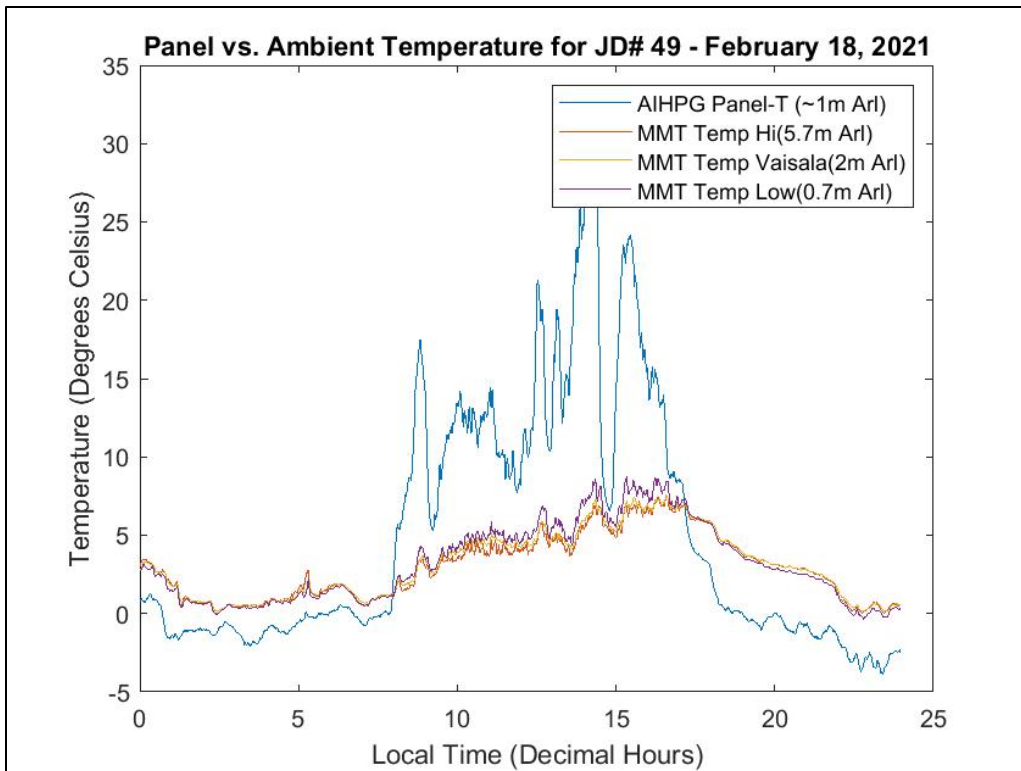


Fig. B-7 2021 Feb 18, panel vs. ambient temperature

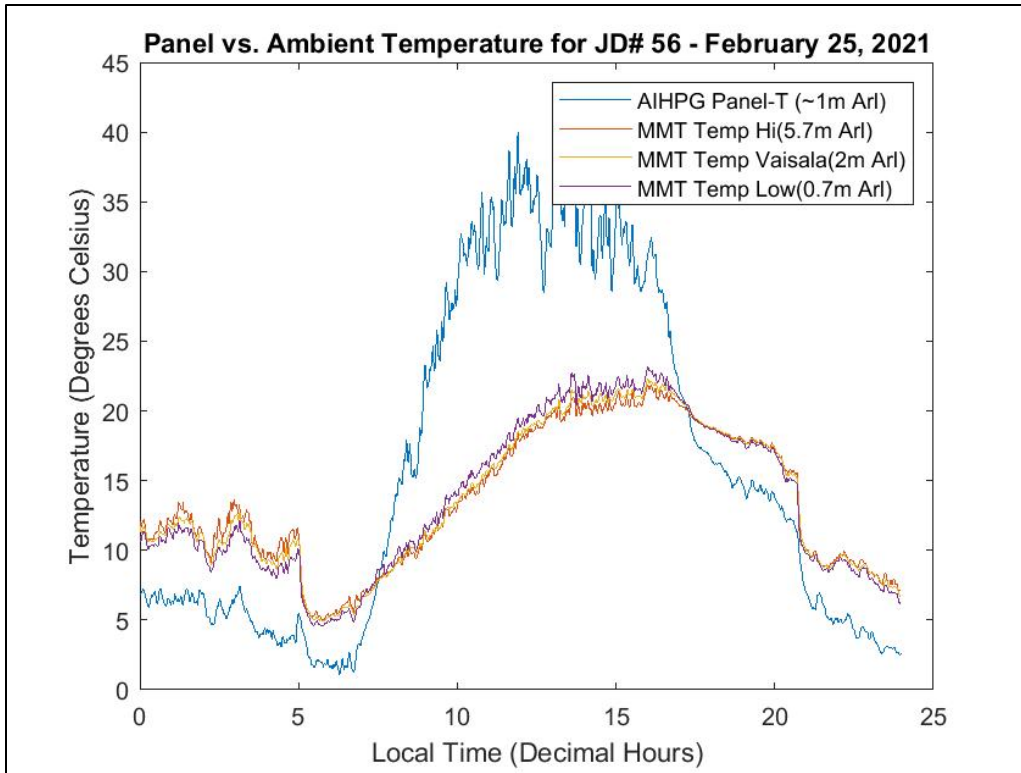


Fig. B-8 2021 Feb 25, panel vs. ambient temperature

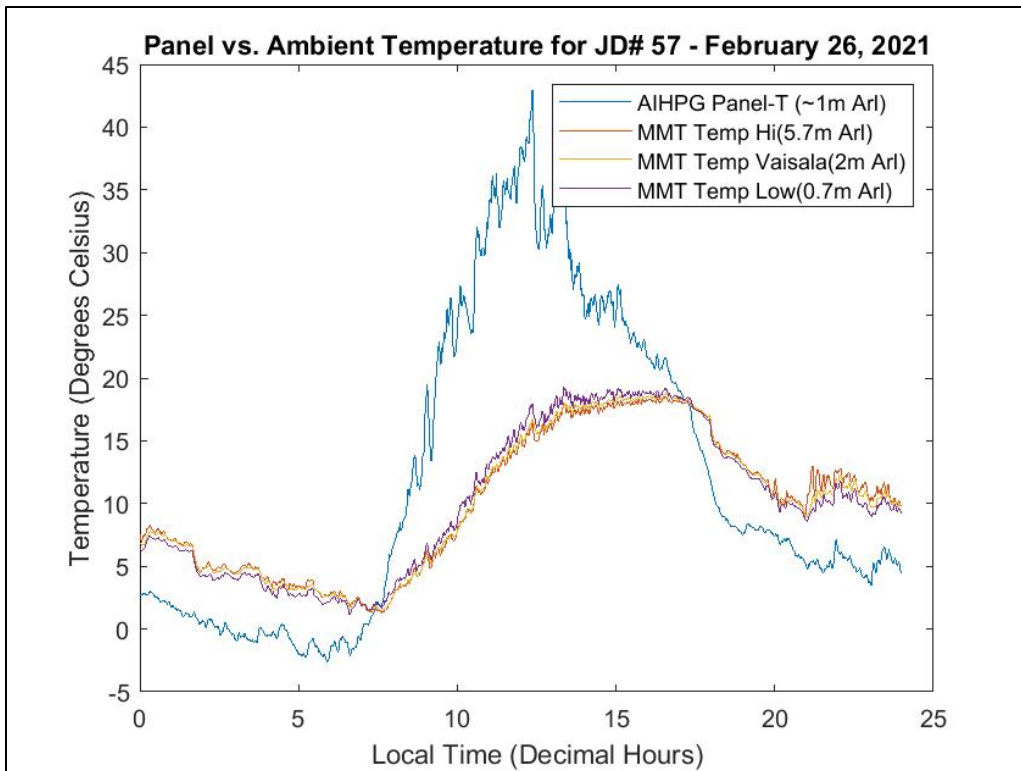


Fig. B-9 2021 Feb 26, panel vs. ambient temperature

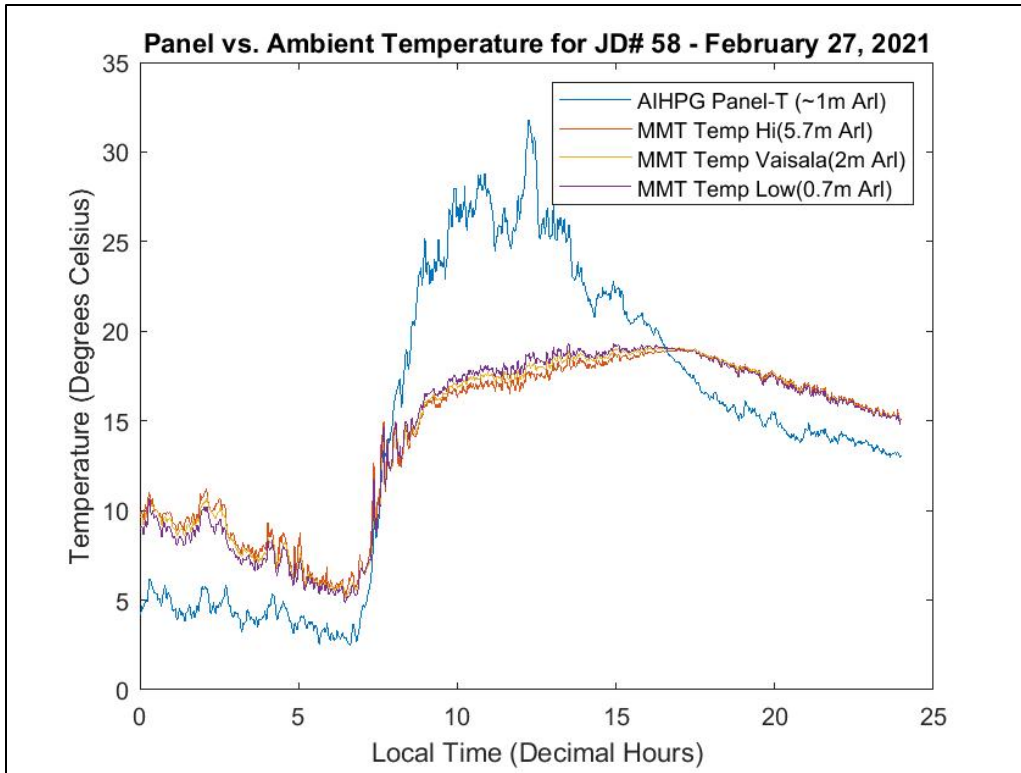


Fig. B-10 2021 Feb 27, panel vs. ambient temperature

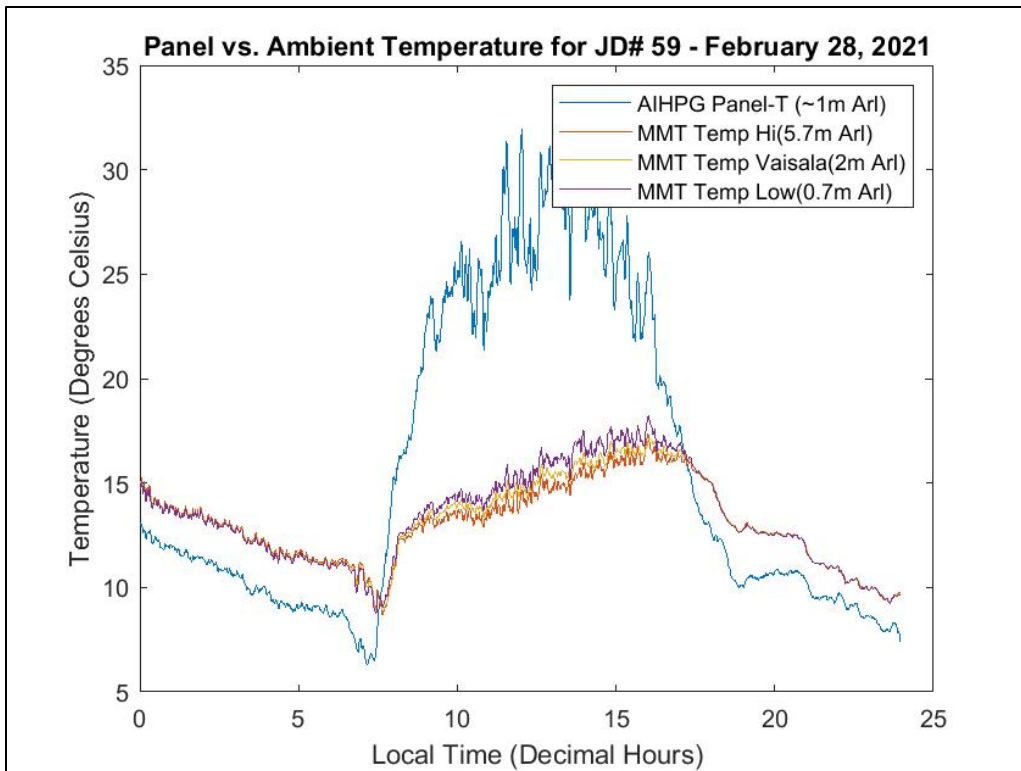


Fig. B-11 2021 Feb 28, panel vs. ambient temperature

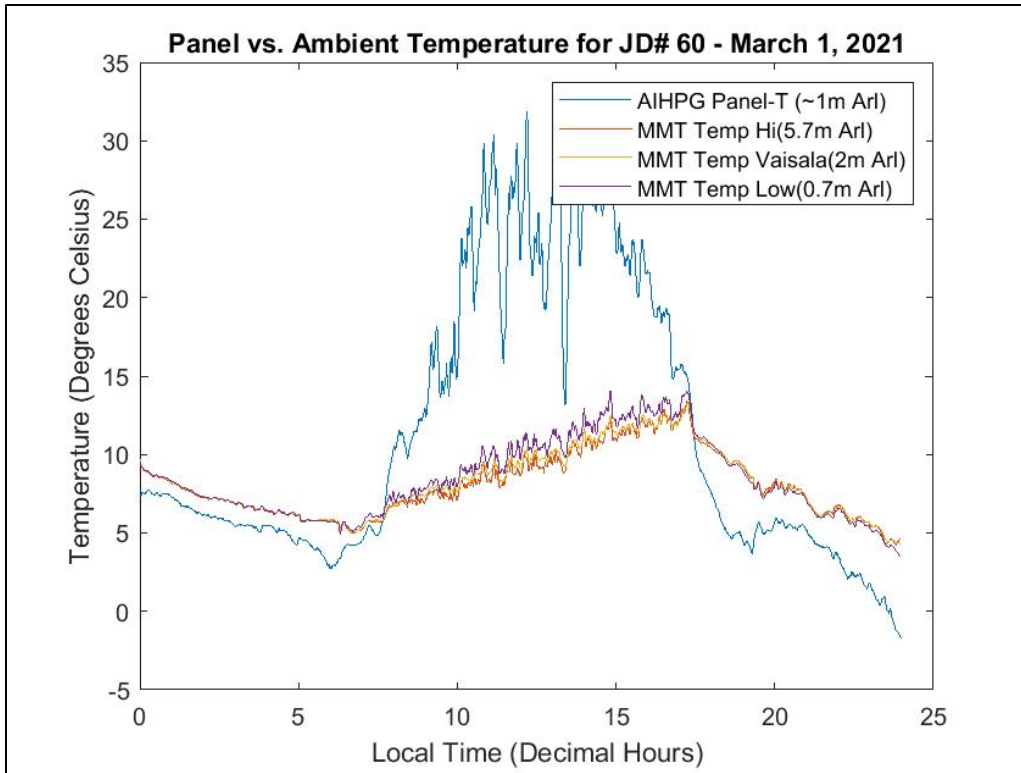


Fig. B-12 2021 Mar 1, panel vs. ambient temperature

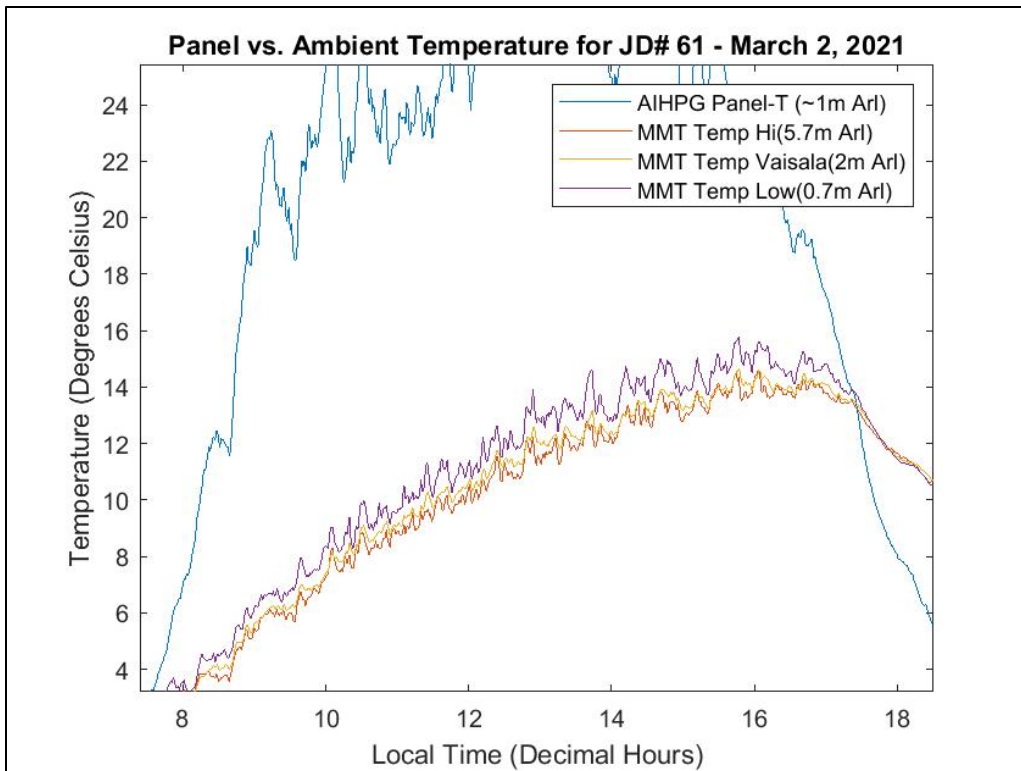


Fig. B-13 2021 Mar 2, panel vs. ambient temperature

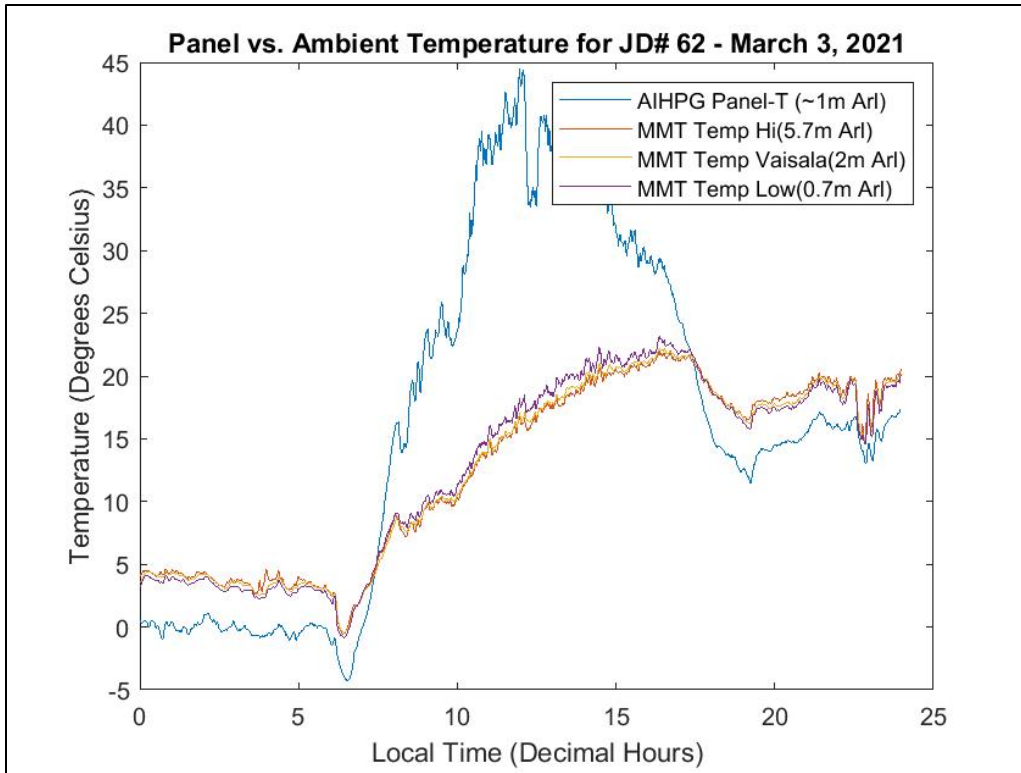


Fig. B-14 2021 Mar 3, panel vs. ambient temperature

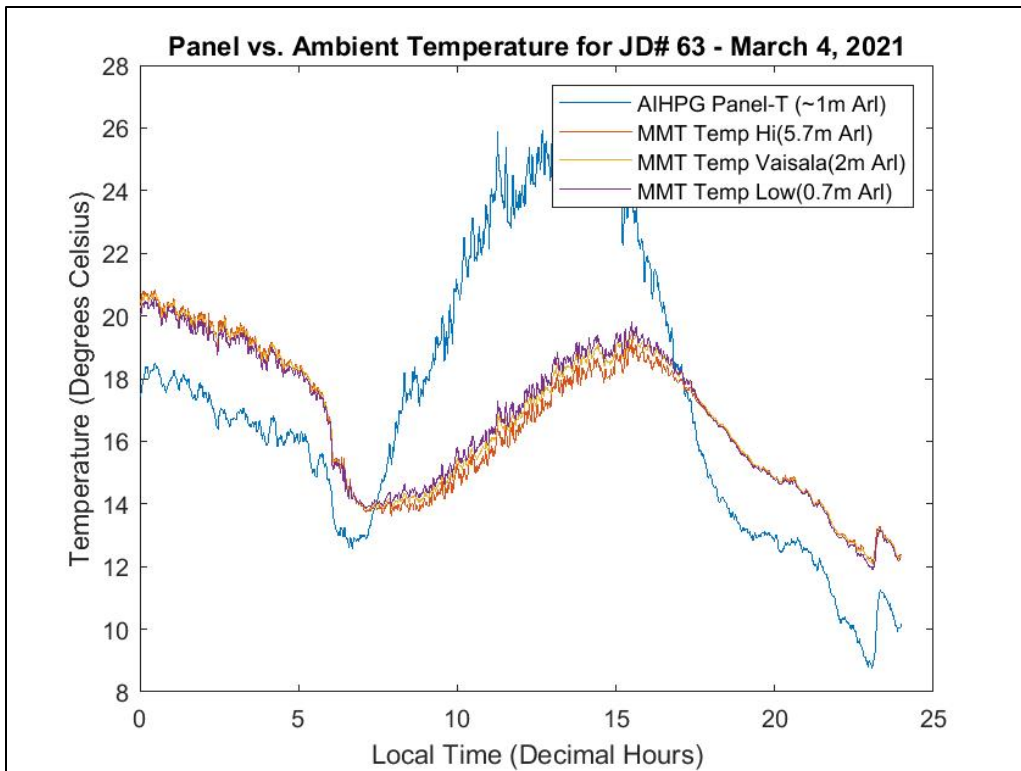


Fig. B-15 2021 Mar 4, panel vs. ambient temperature

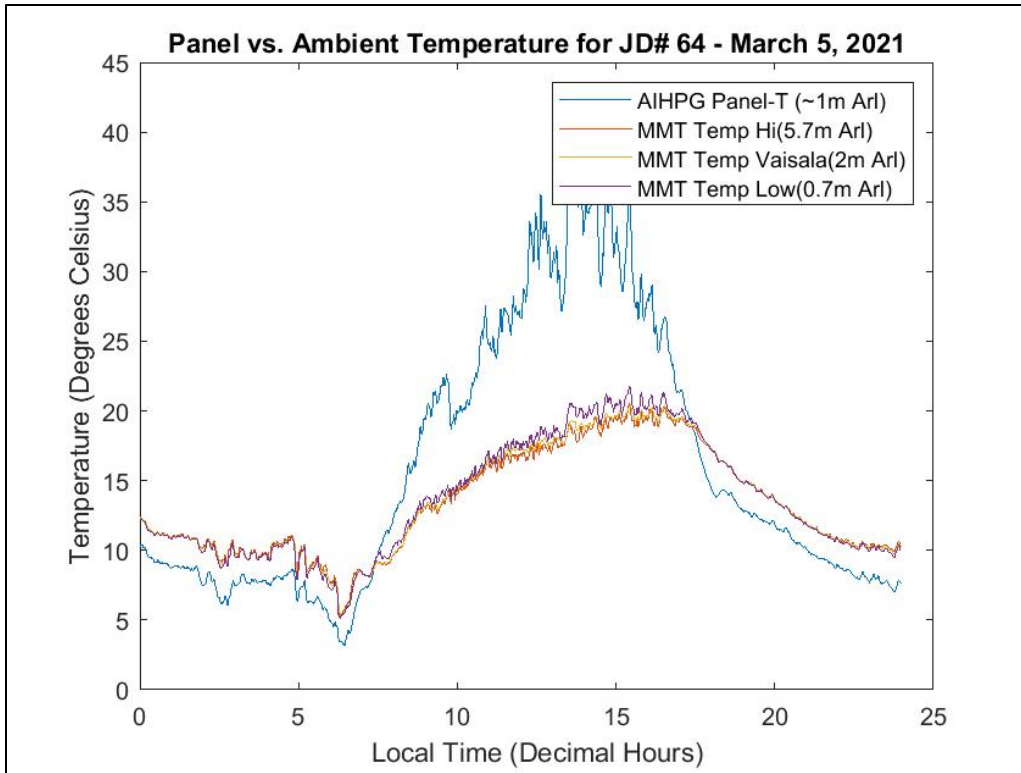


Fig. B-16 2021 Mar 5, panel vs. ambient temperature

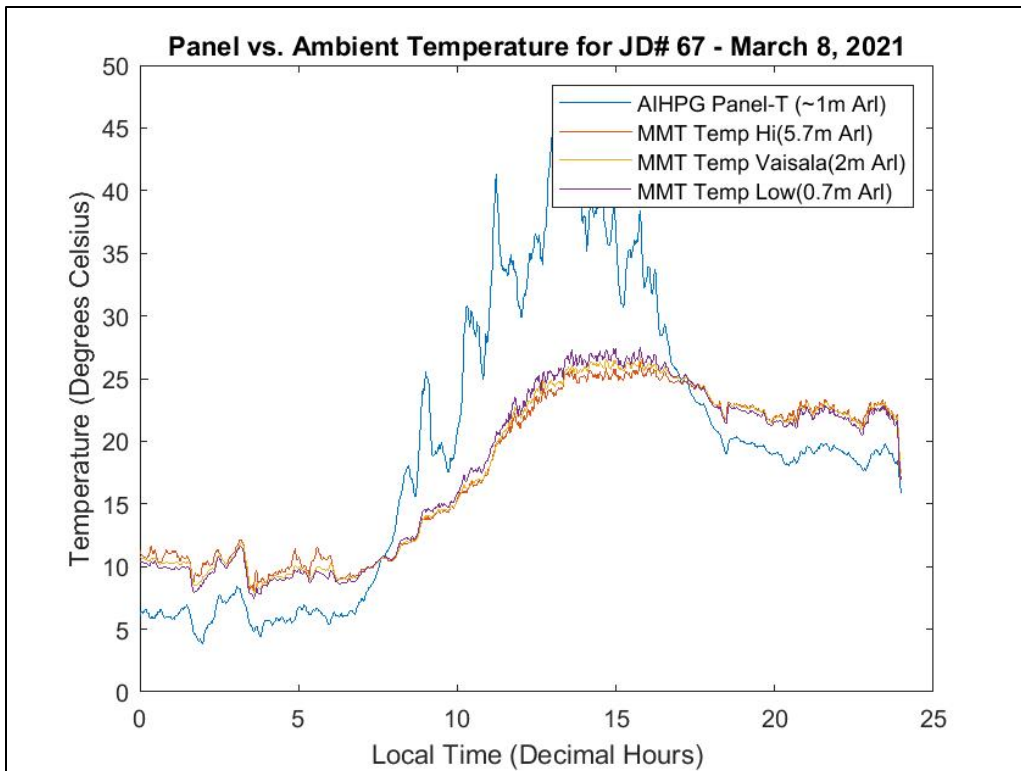


Fig. B-17 2021 Mar 8, panel vs. ambient temperature

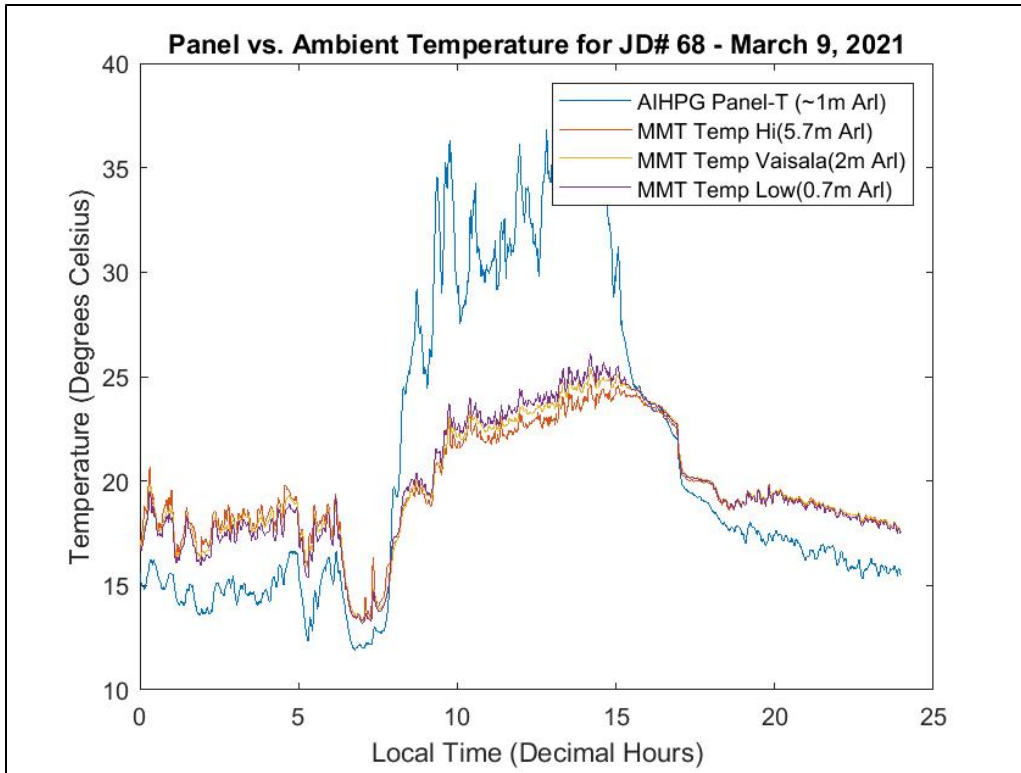


Fig. B-18 2021 Mar 9, panel vs. ambient temperature

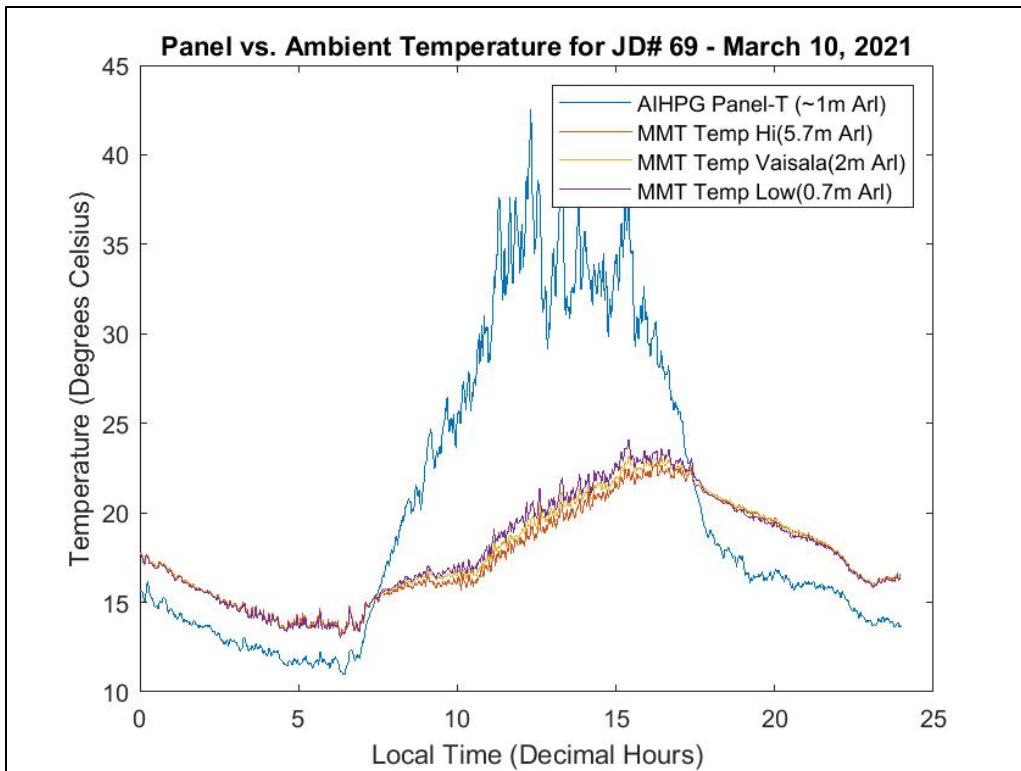


Fig. B-19 2021 Mar 10, panel vs. ambient temperature

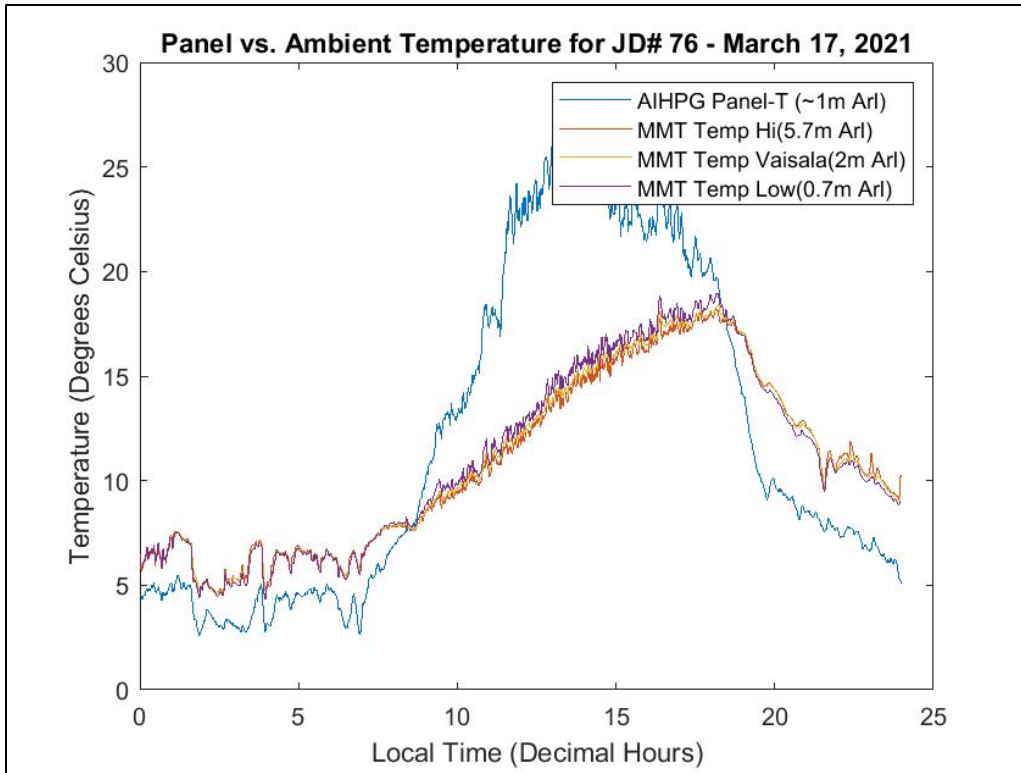


Fig. B-20 2021 Mar 17, panel vs. ambient temperature

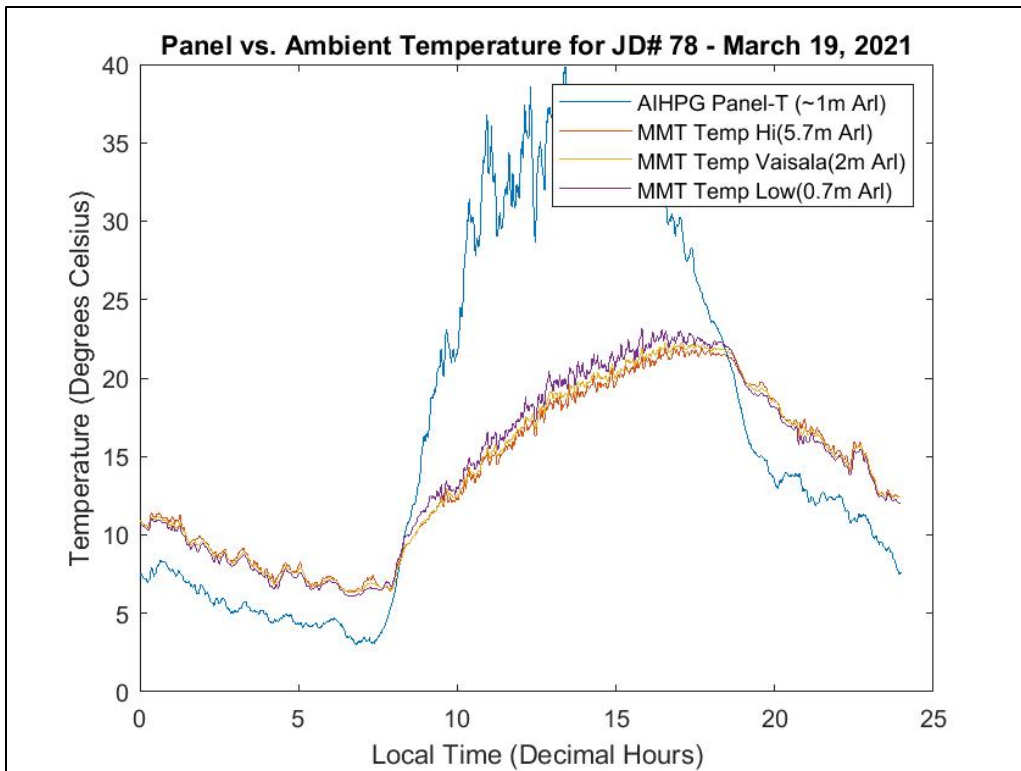


Fig. B-21 2021 Mar 19, panel vs. ambient temperature

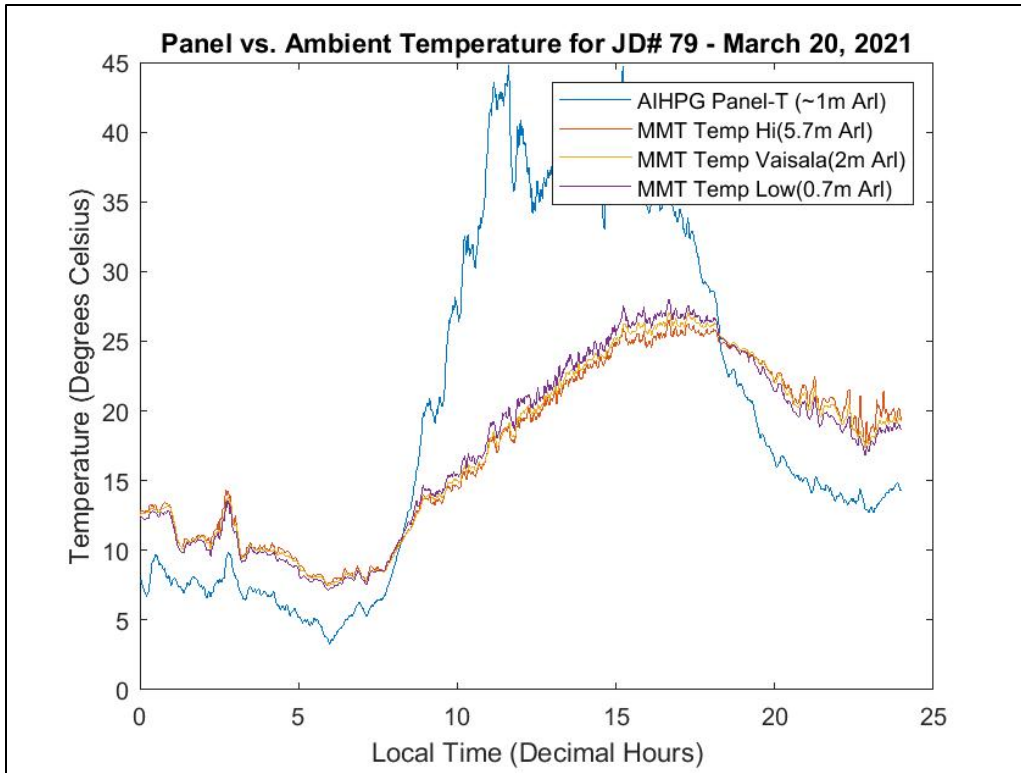


Fig. B-22 2021 Mar 20, panel vs. ambient temperature

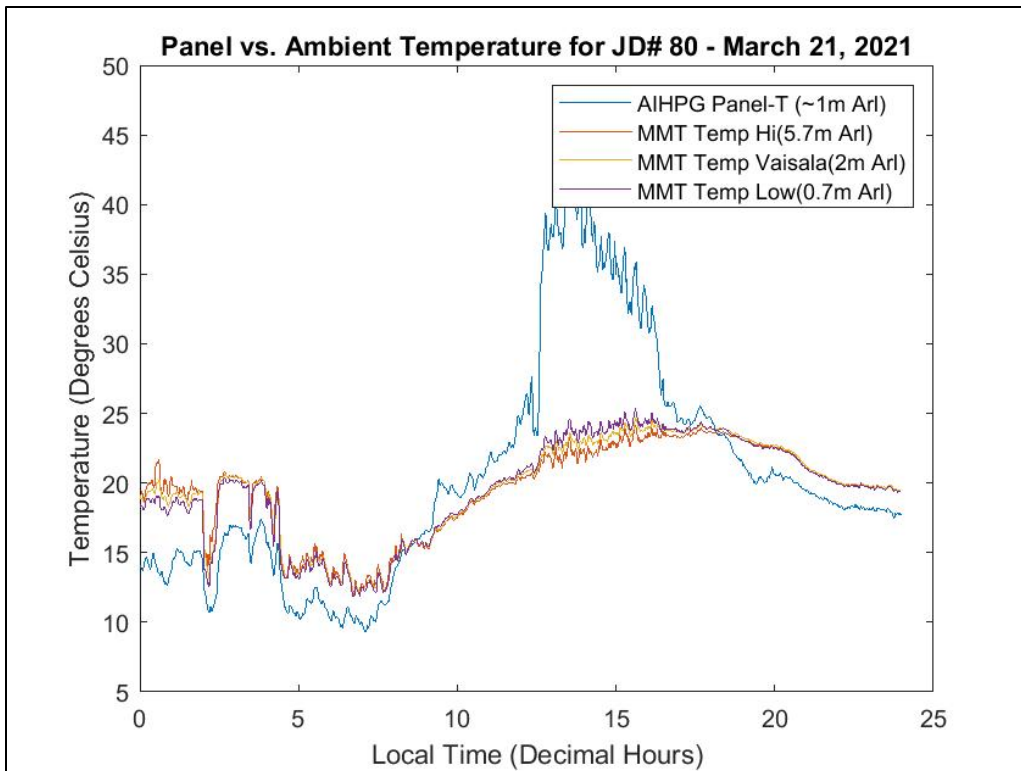


Fig. B-23 2021 Mar 21, panel vs. ambient temperature

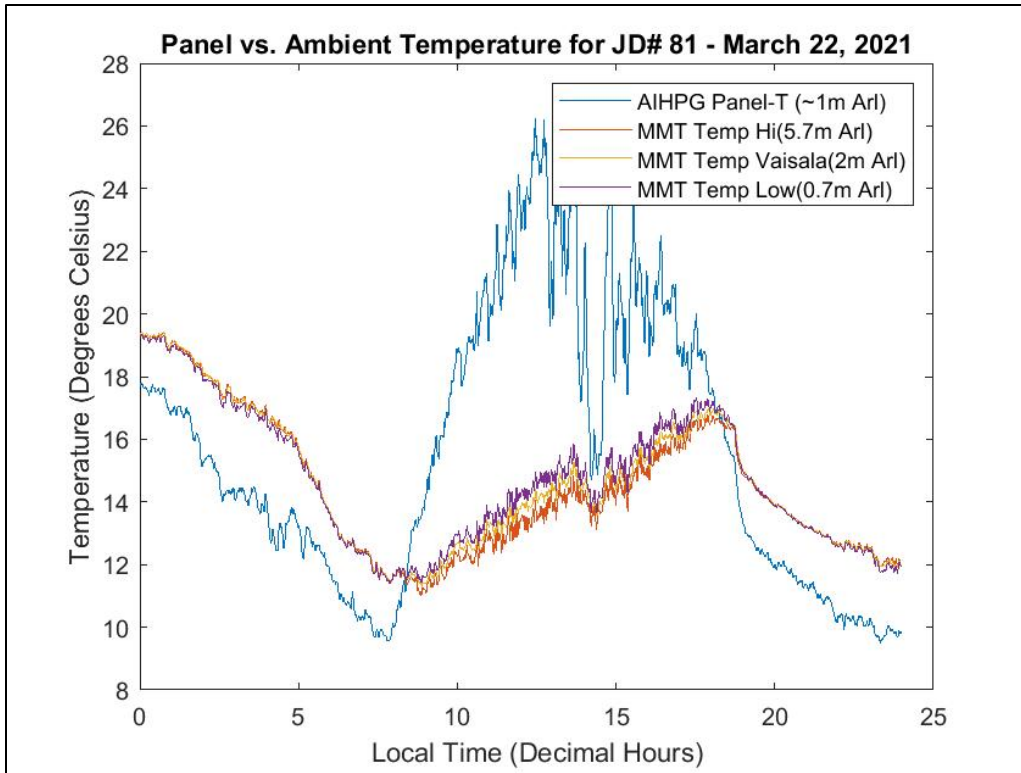


Fig. B-24 2021 Mar 22, panel vs. ambient temperature

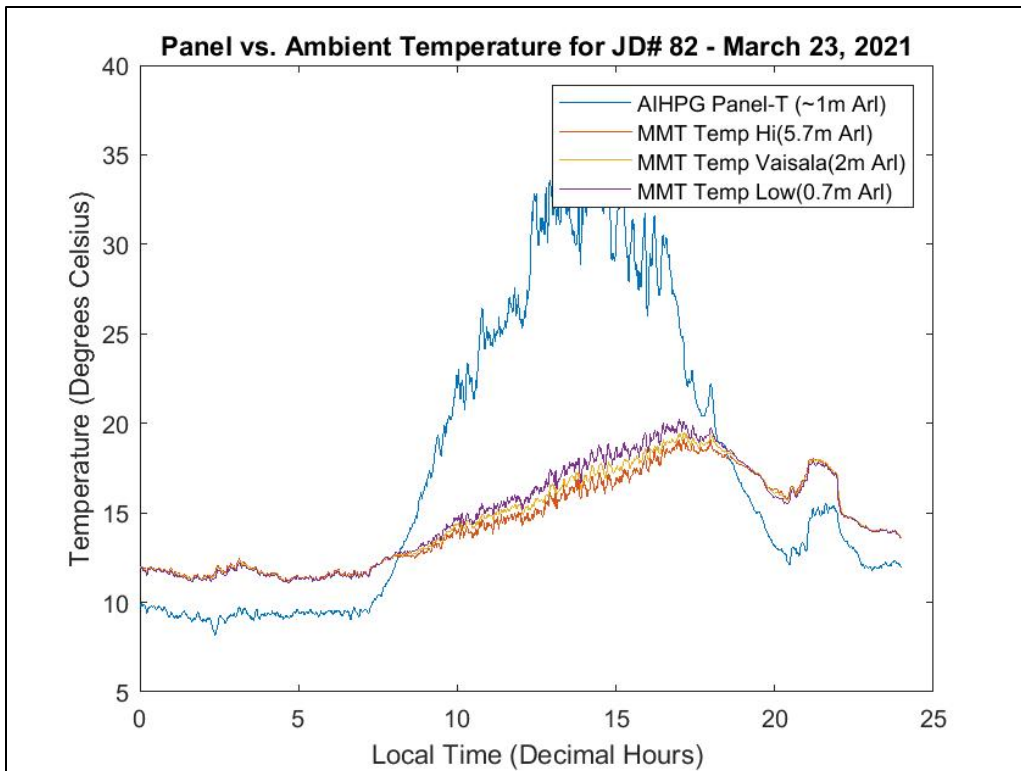


Fig. B-25 2021 Mar 23, panel vs. ambient temperature

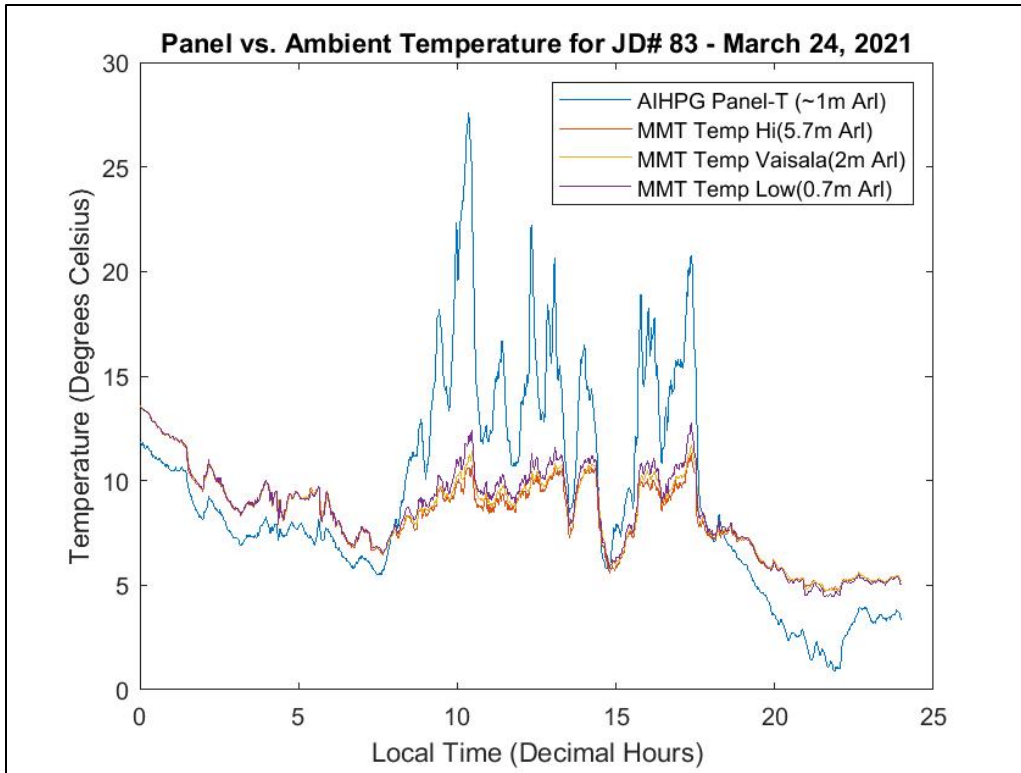


Fig. B-26 2021 Mar 24, panel vs. ambient temperature

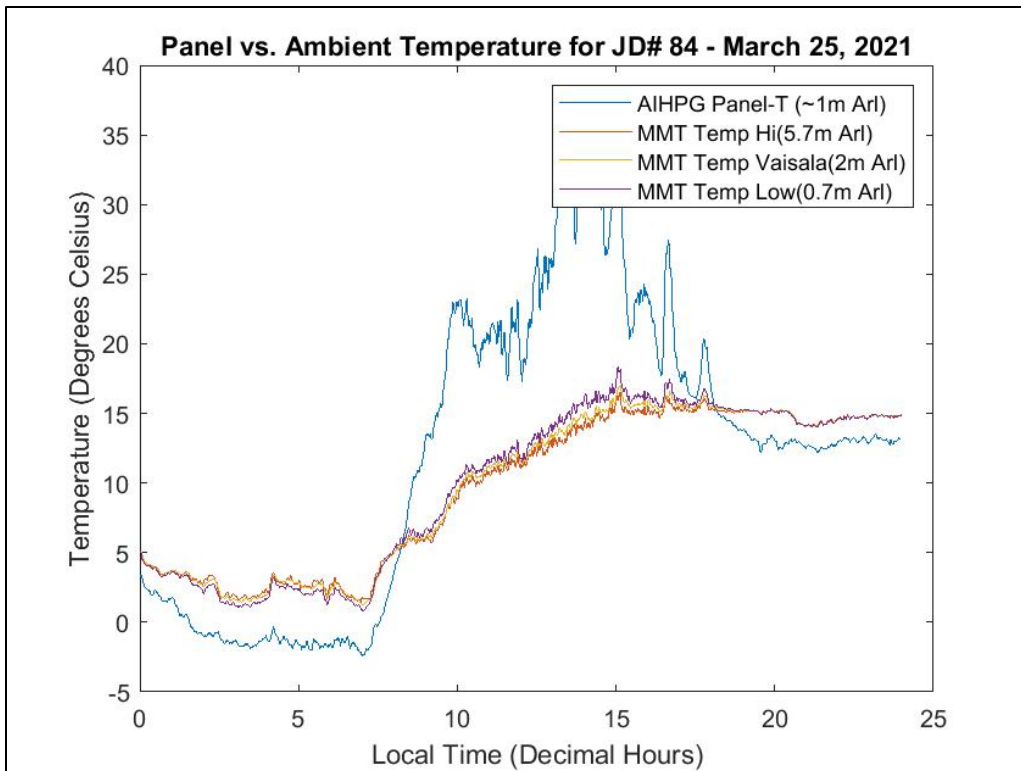


Fig. B-27 2021 Mar 25, panel vs. ambient temperature

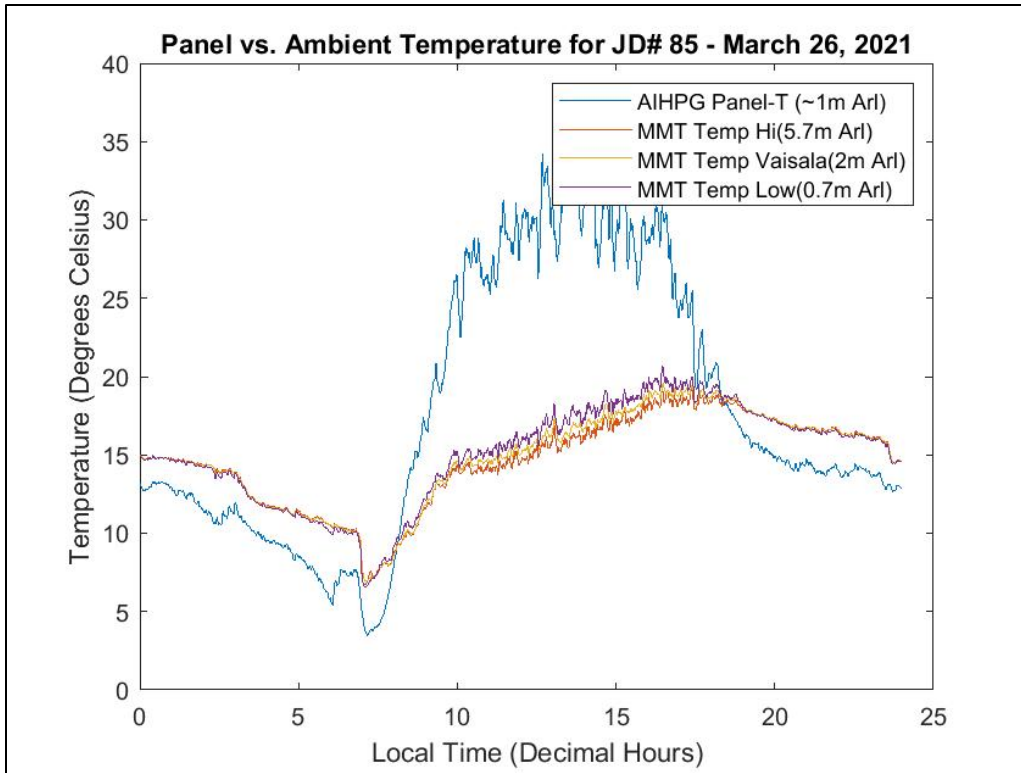


Fig. B-28 2021 Mar 26, panel vs. ambient temperature

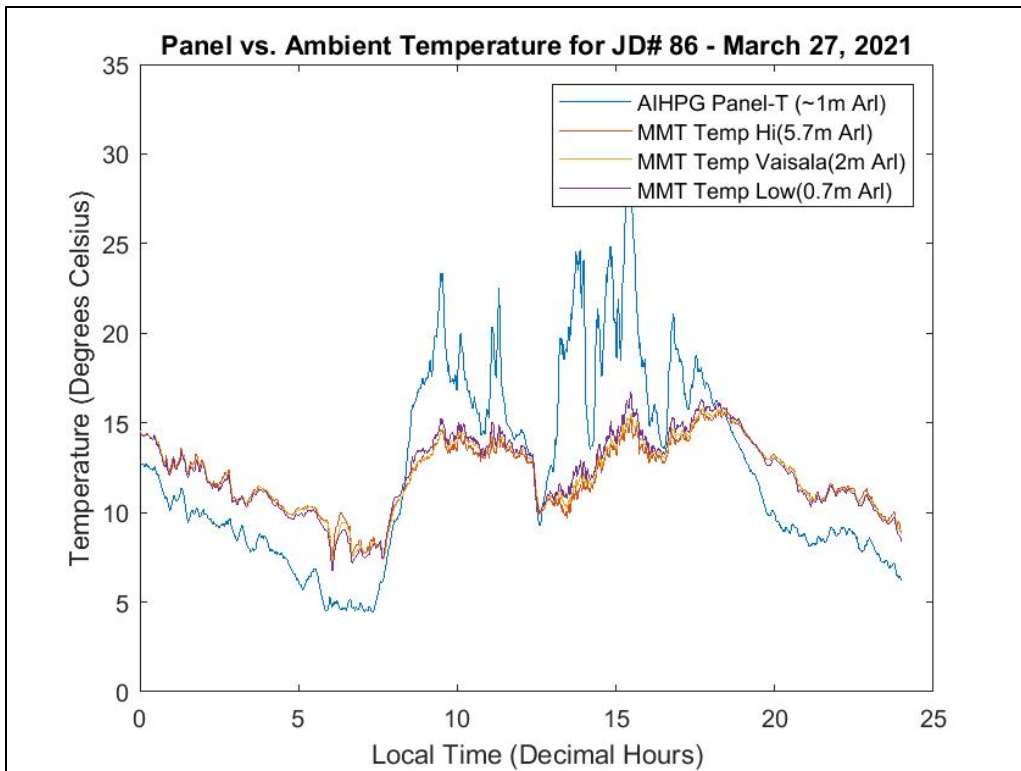


Fig. B-29 2021 Mar 27, panel vs. ambient temperature

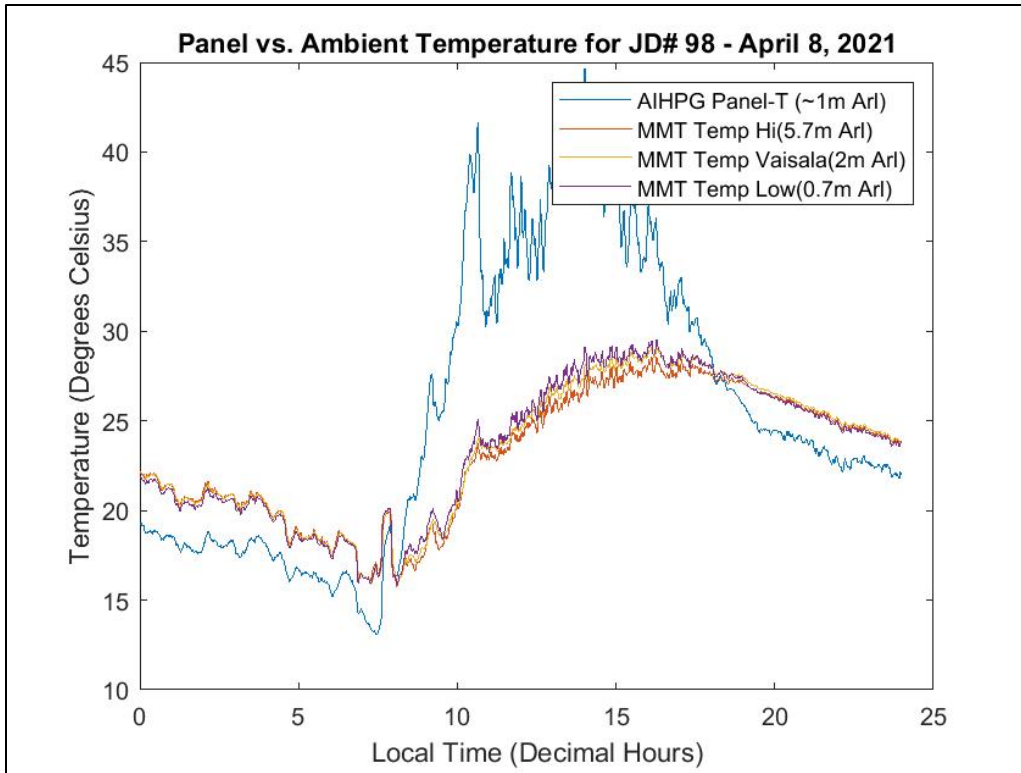


Fig. B-30 2021 Apr 8, panel vs. ambient temperature

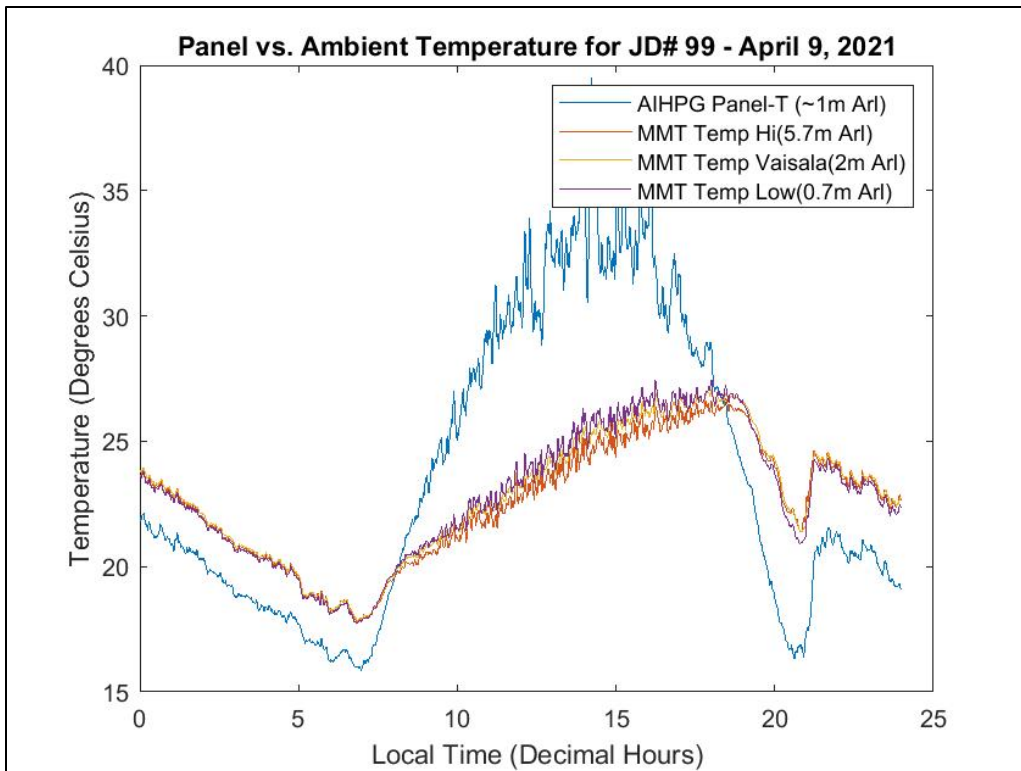


Fig. B-31 2021 Apr 9, panel vs. ambient temperature

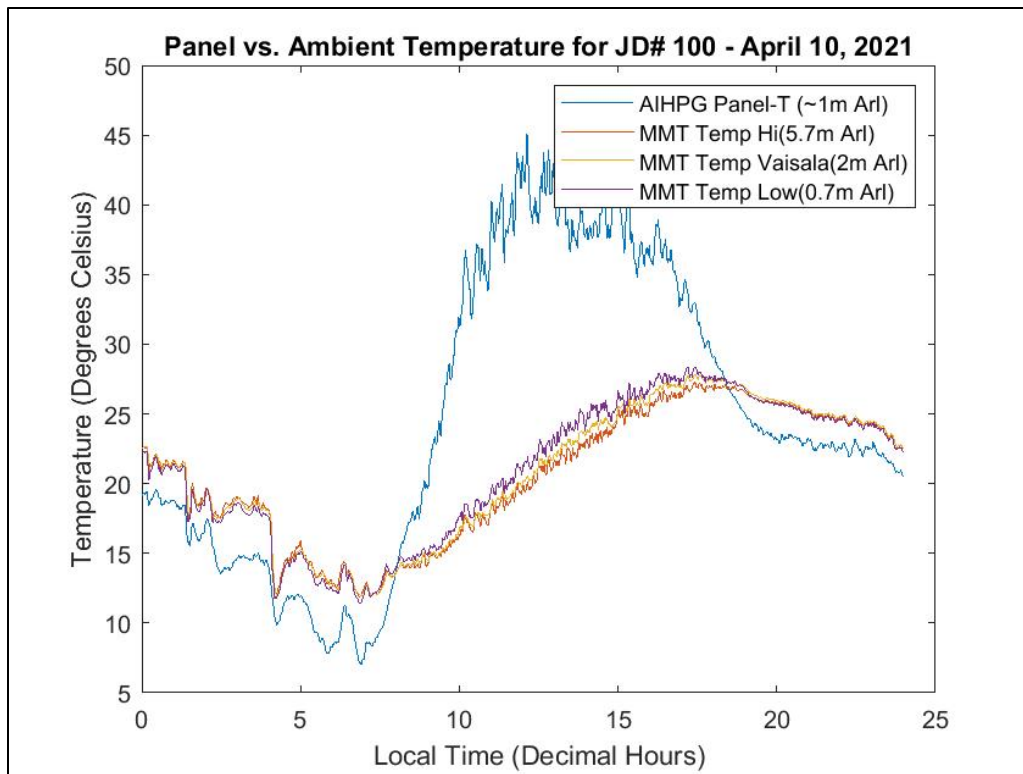


Fig. B-32 2021 Apr 10, panel vs. ambient temperature

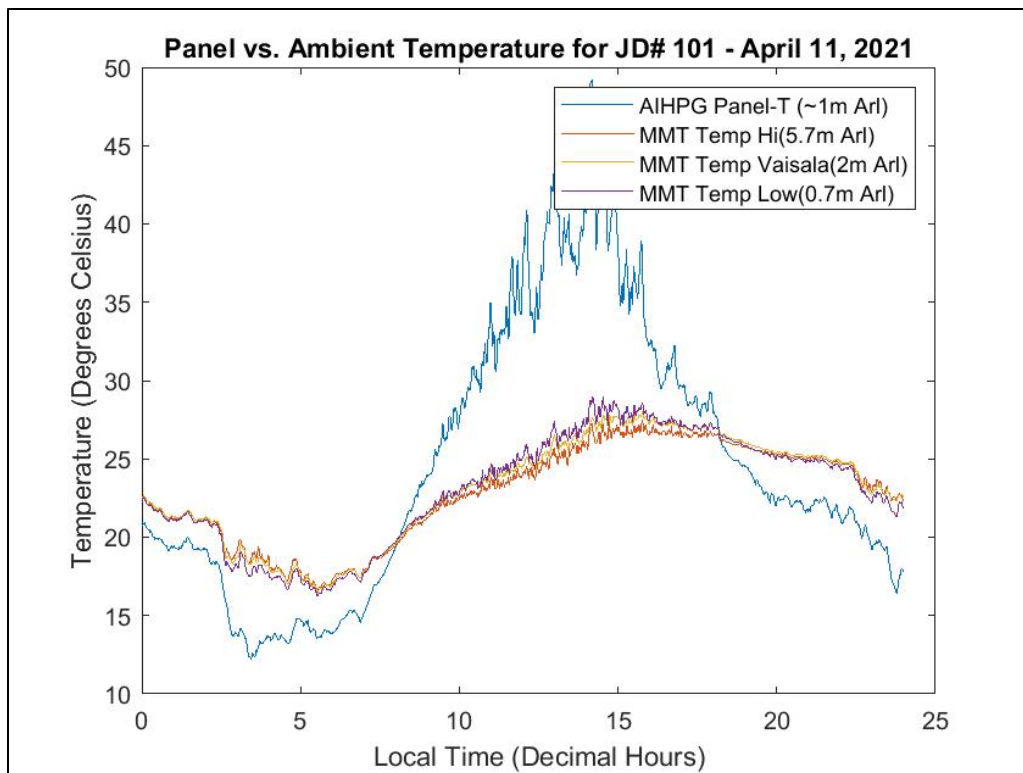


Fig. B-33 2021 Apr 11, panel vs. ambient temperature

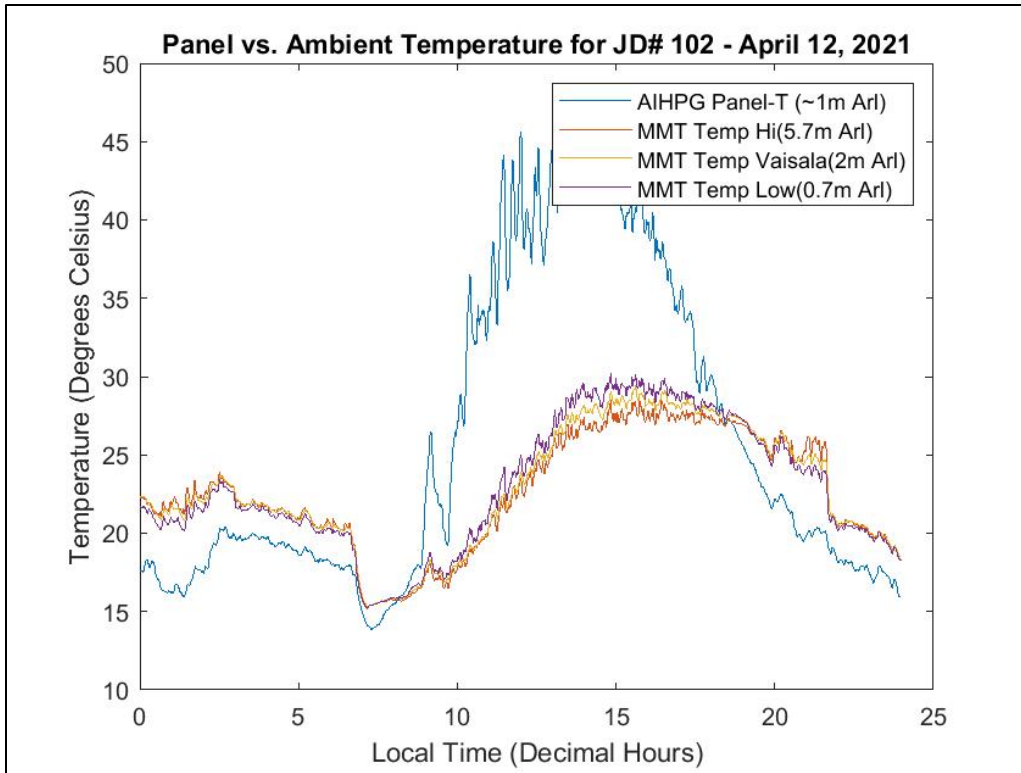


Fig. B-34 2021 Apr 12, panel vs. ambient temperature

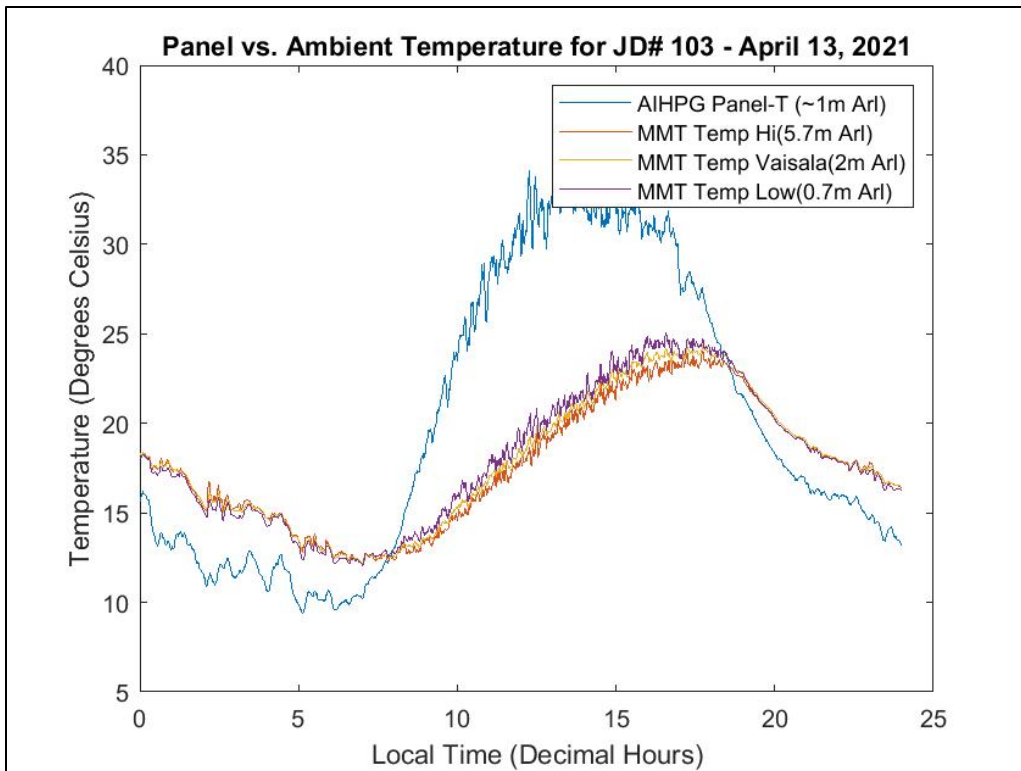


Fig. B-35 2021 Apr 13, panel vs. ambient temperature

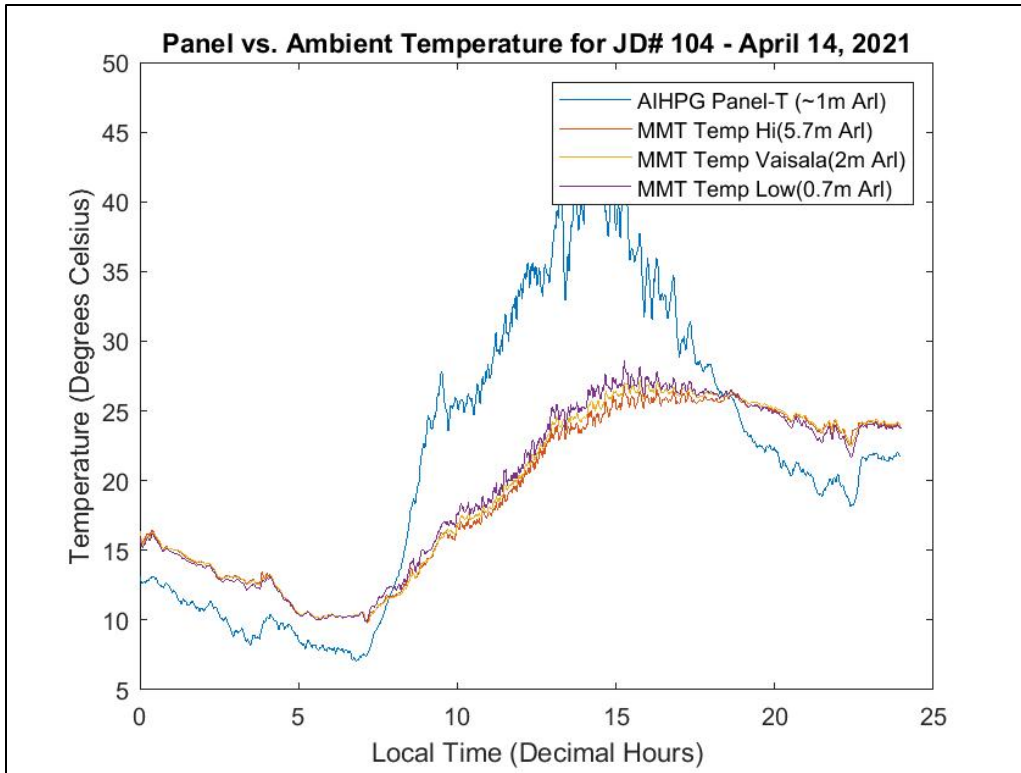


Fig. B-36 2021 Apr 14, panel vs. ambient temperature

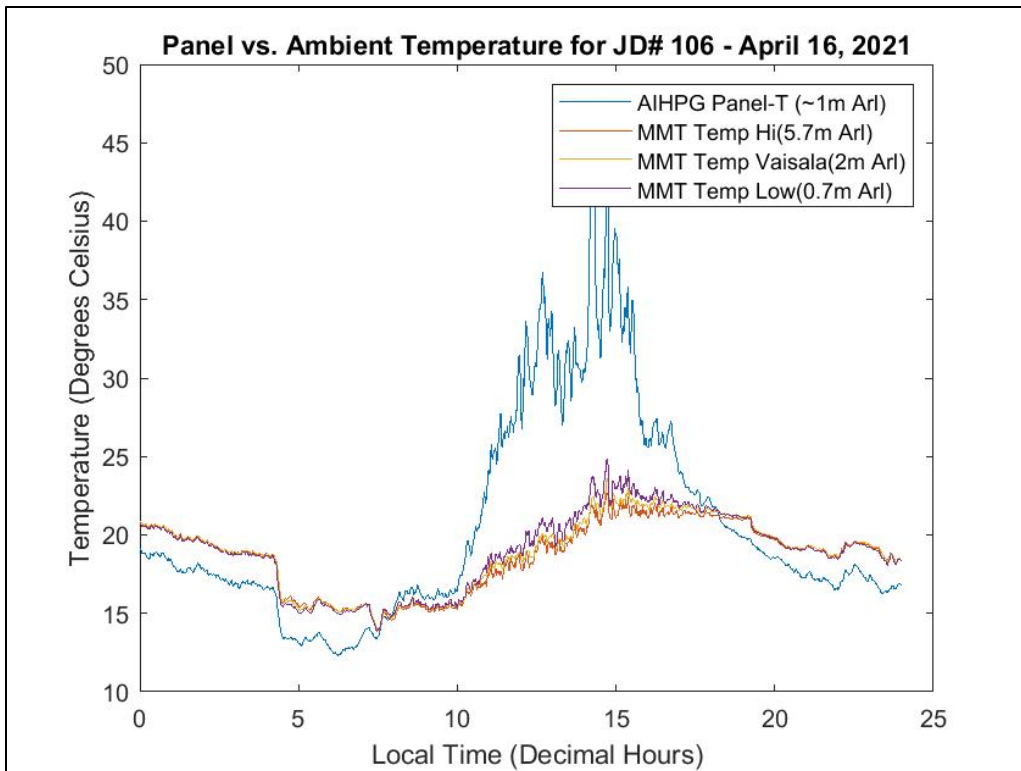


Fig. B-37 2021 Apr 16, panel vs. ambient temperature

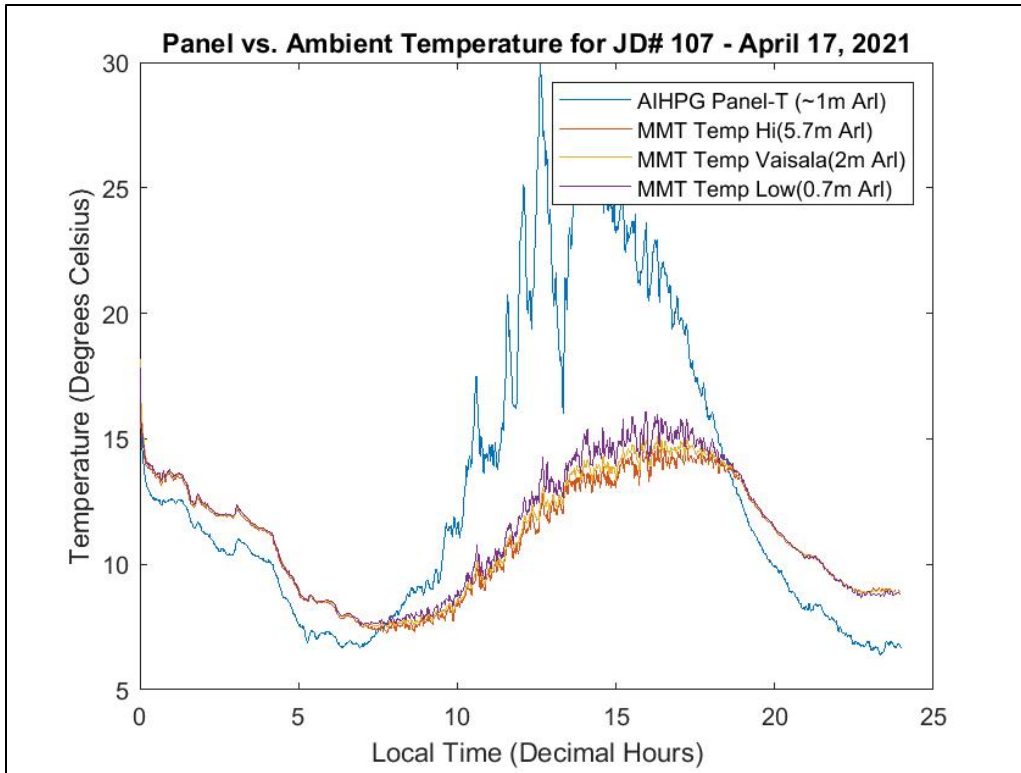


Fig. B-38 2021 Apr 17, panel vs. ambient temperature

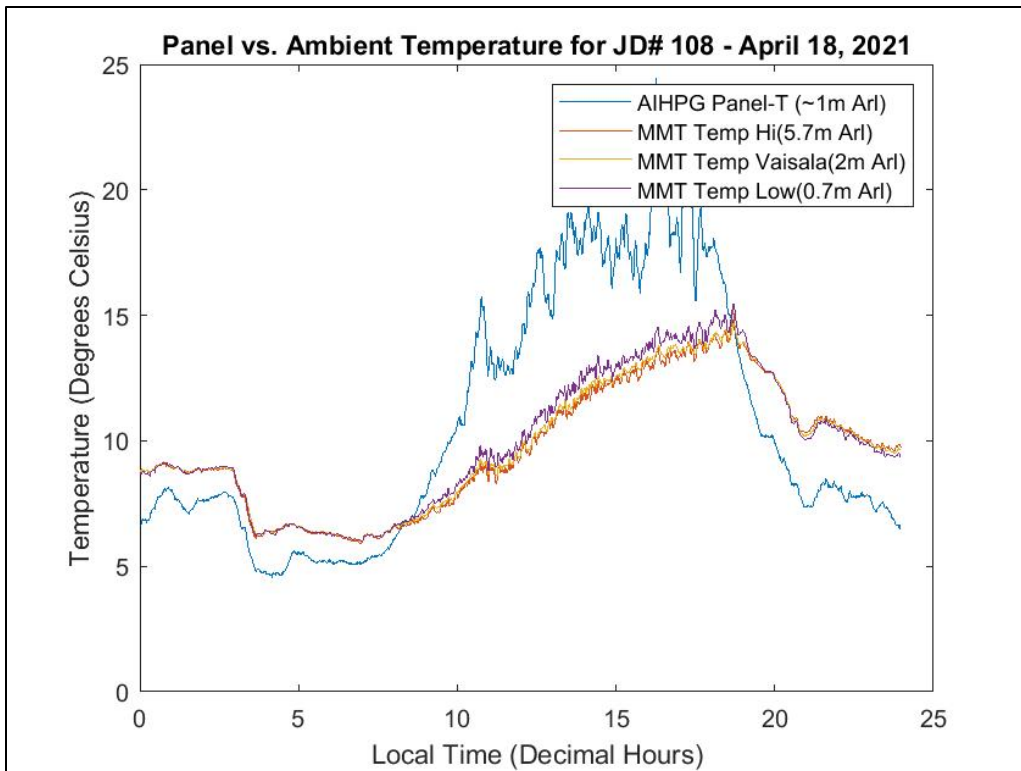


Fig. B-39 2021 Apr 18, panel vs. ambient temperature

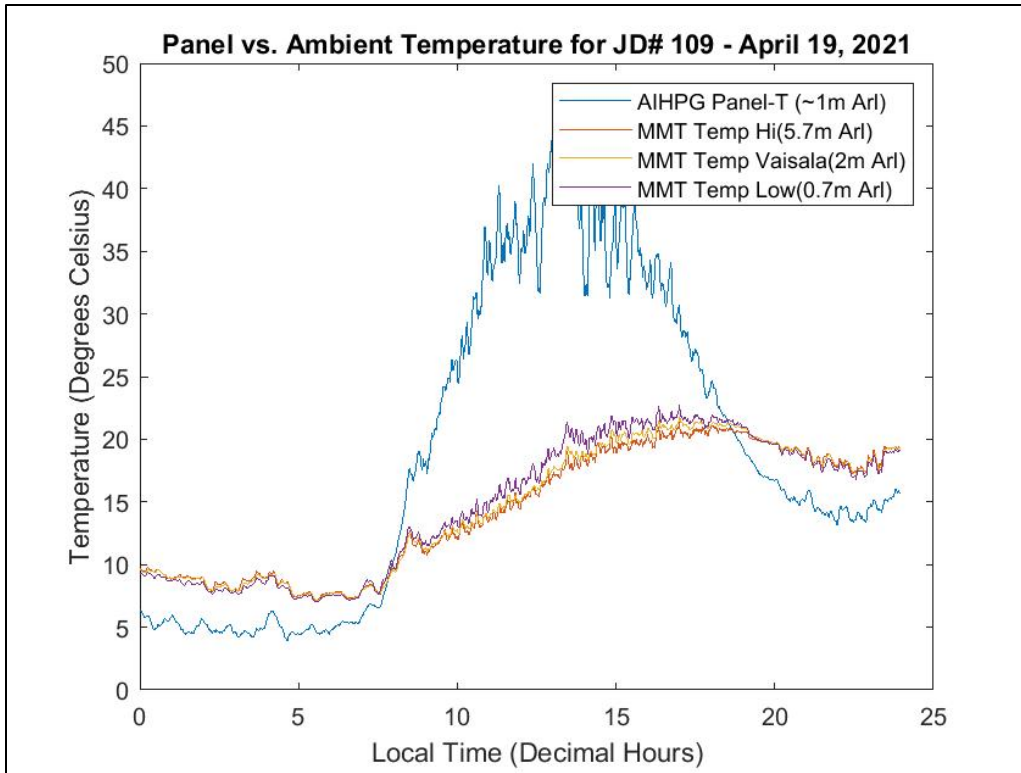


Fig. B-40 2021 Apr 19, panel vs. ambient temperature

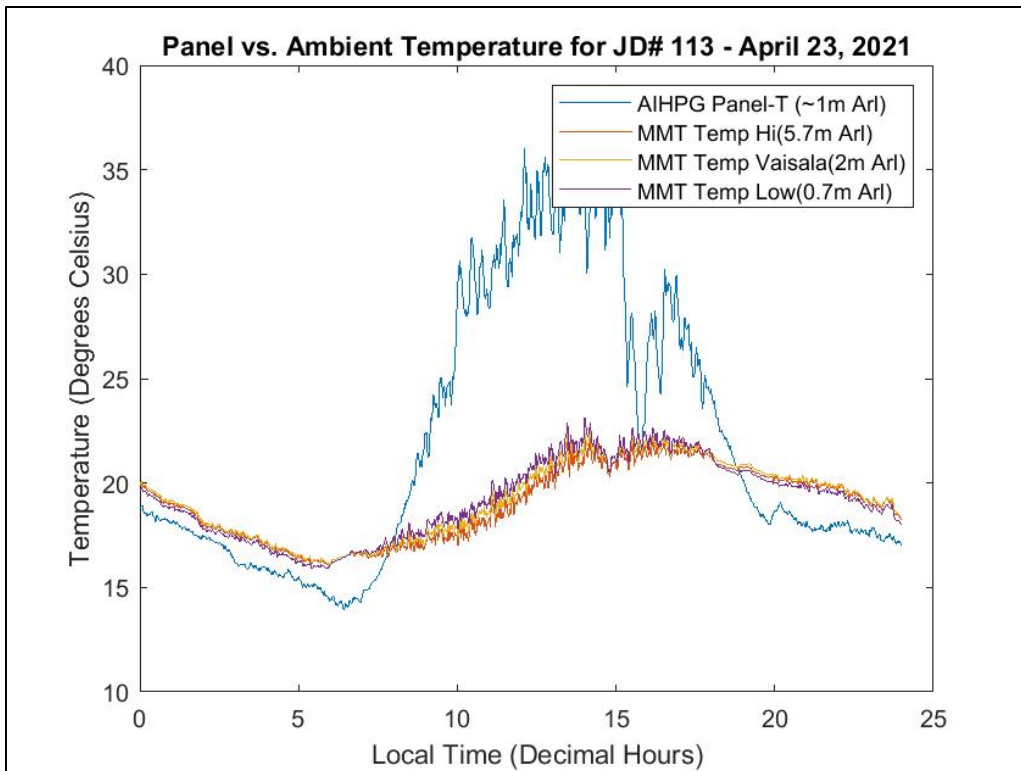


Fig. B-41 2021 Apr 23, panel vs. ambient temperature

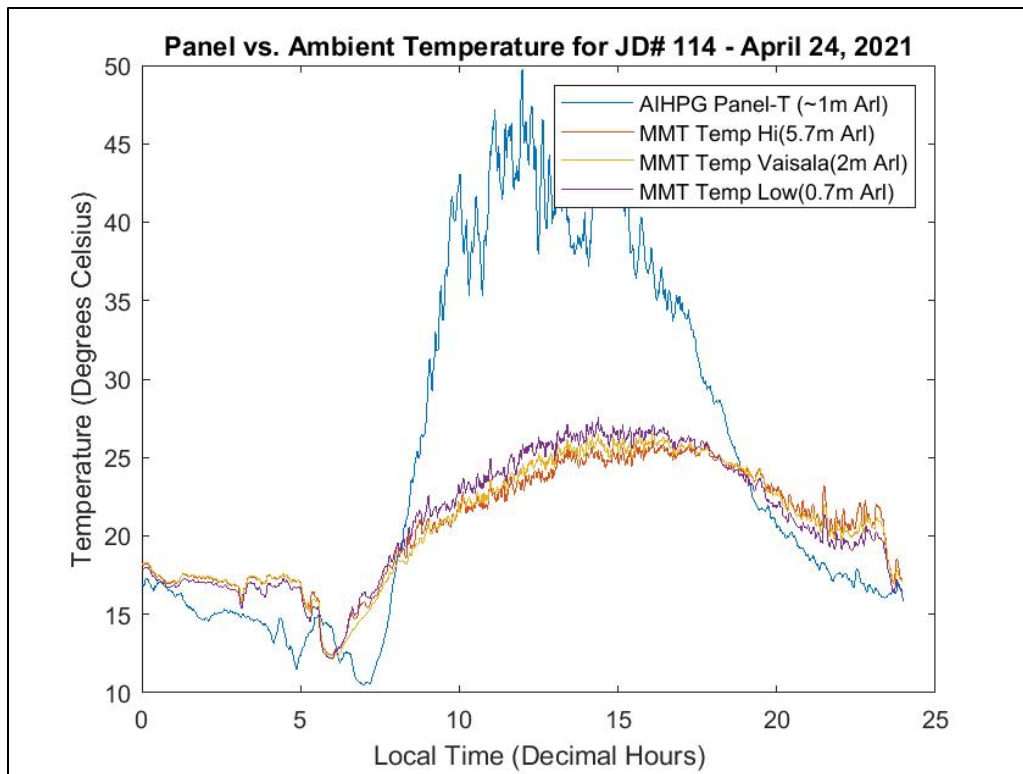


Fig. B-42 2021 Apr 24, panel vs. ambient temperature

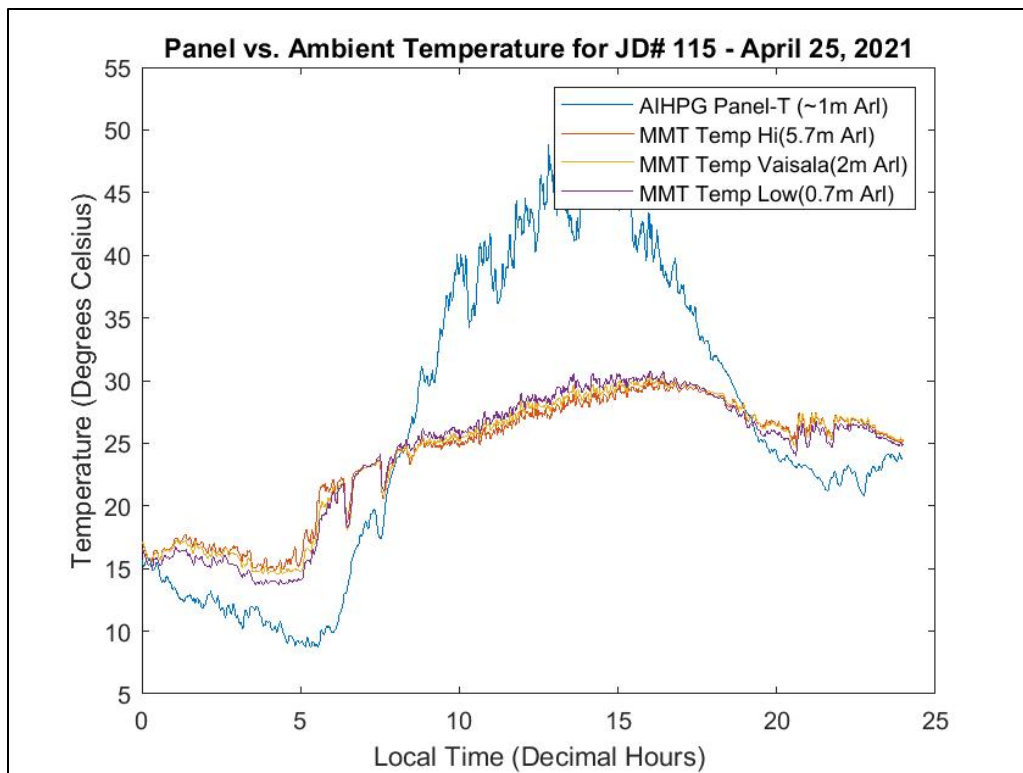


Fig. B-43 2021 Apr 25, panel vs. ambient temperature

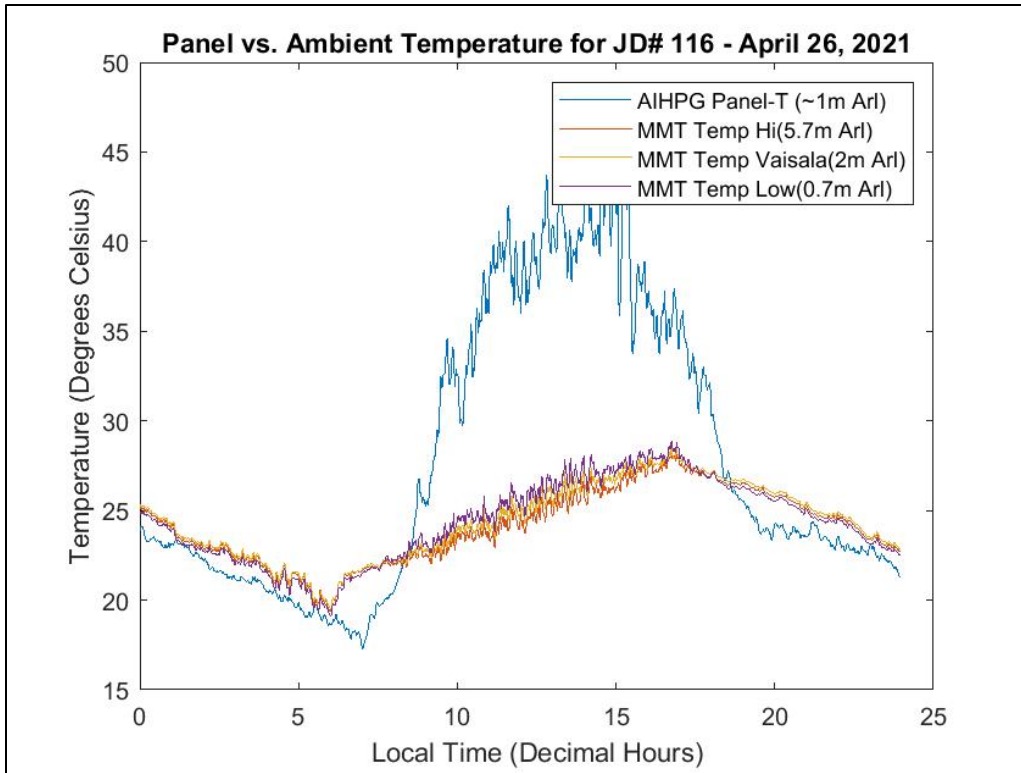


Fig. B-44 2021 Apr 26, panel vs. ambient temperature

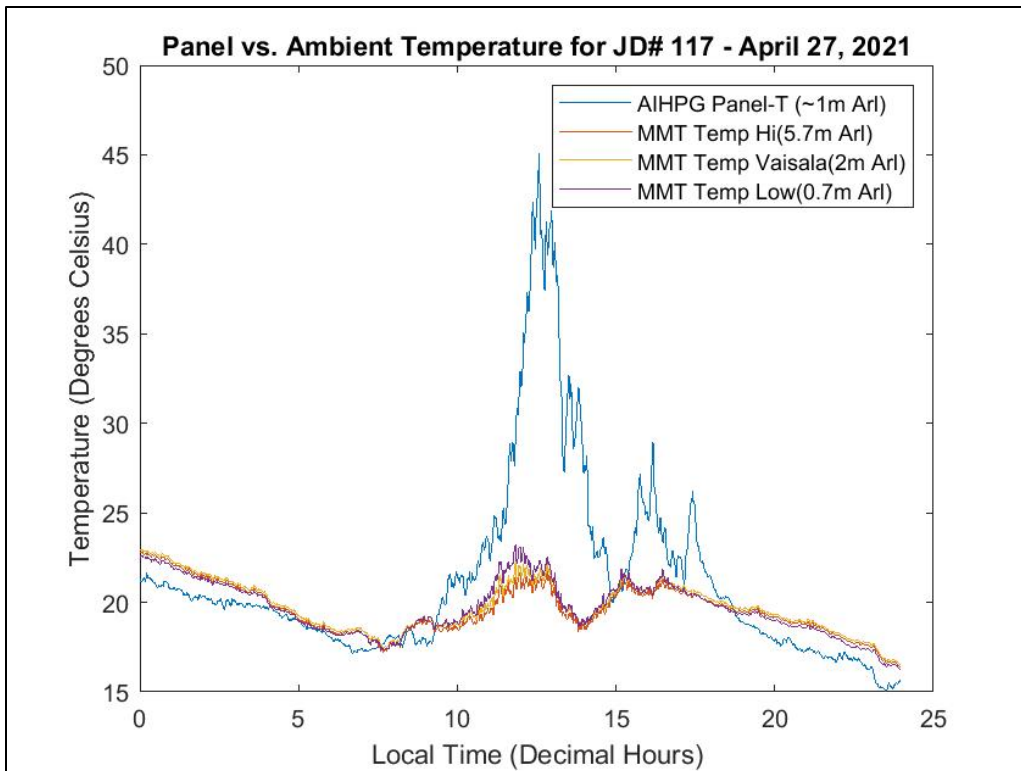


Fig. B-45 2021 Apr 27, panel vs. ambient temperature

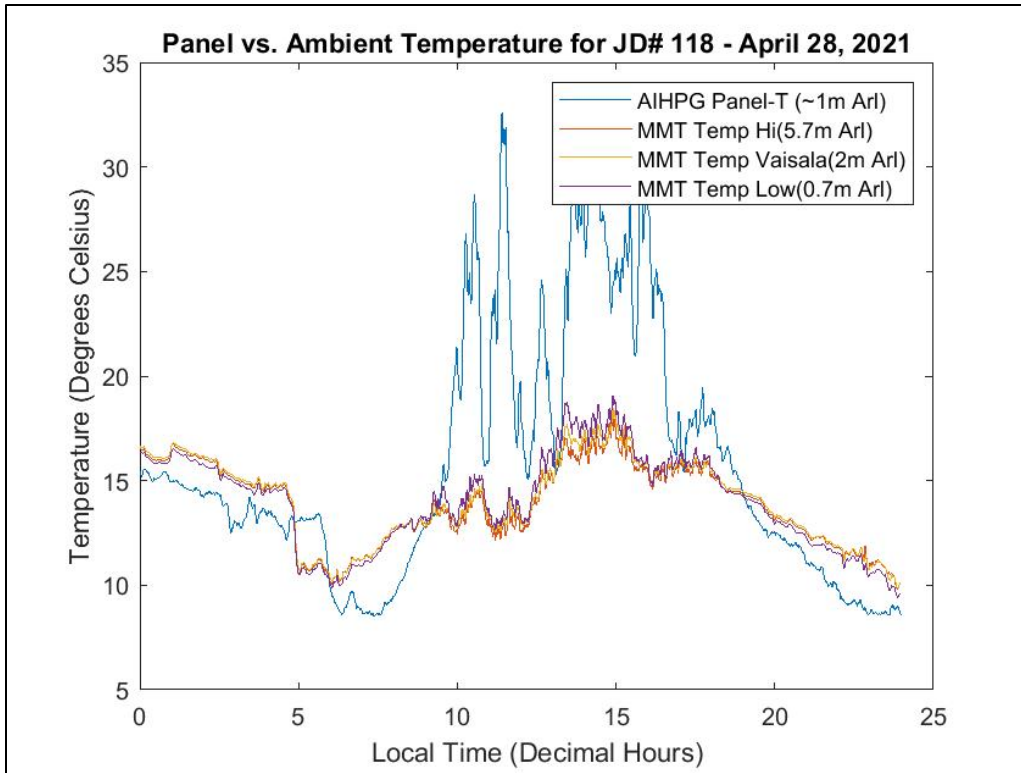


Fig. B-46 2021 Apr 28, panel vs. ambient temperature

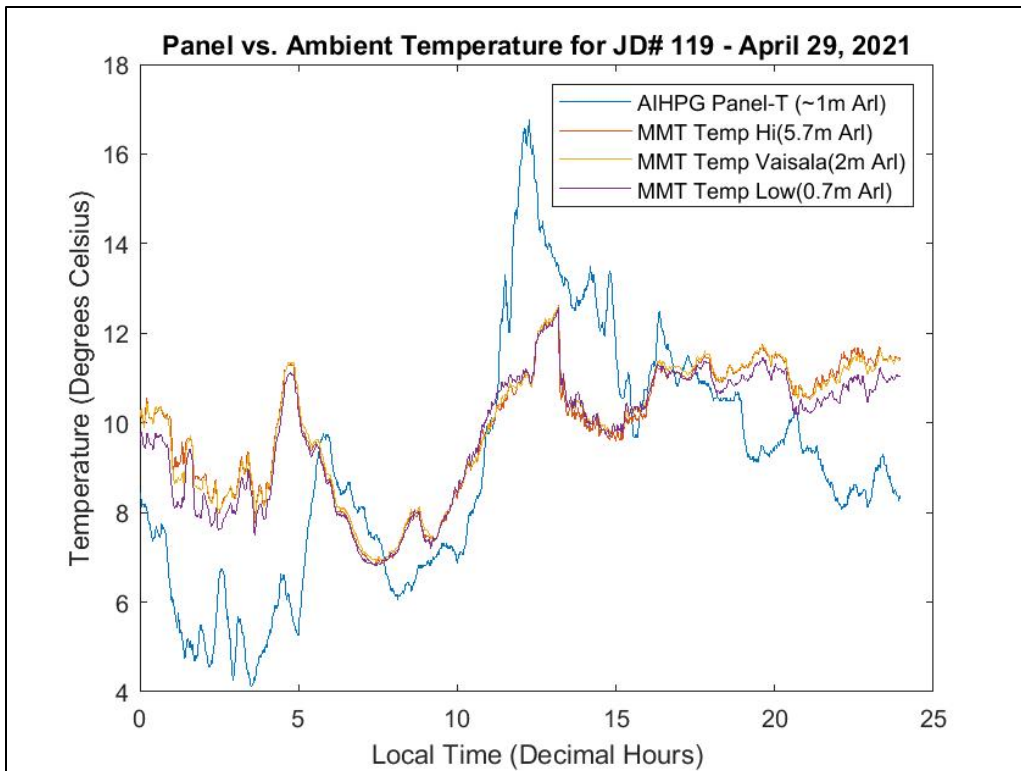


Fig. B-47 2021 Apr 29, panel vs. ambient temperature

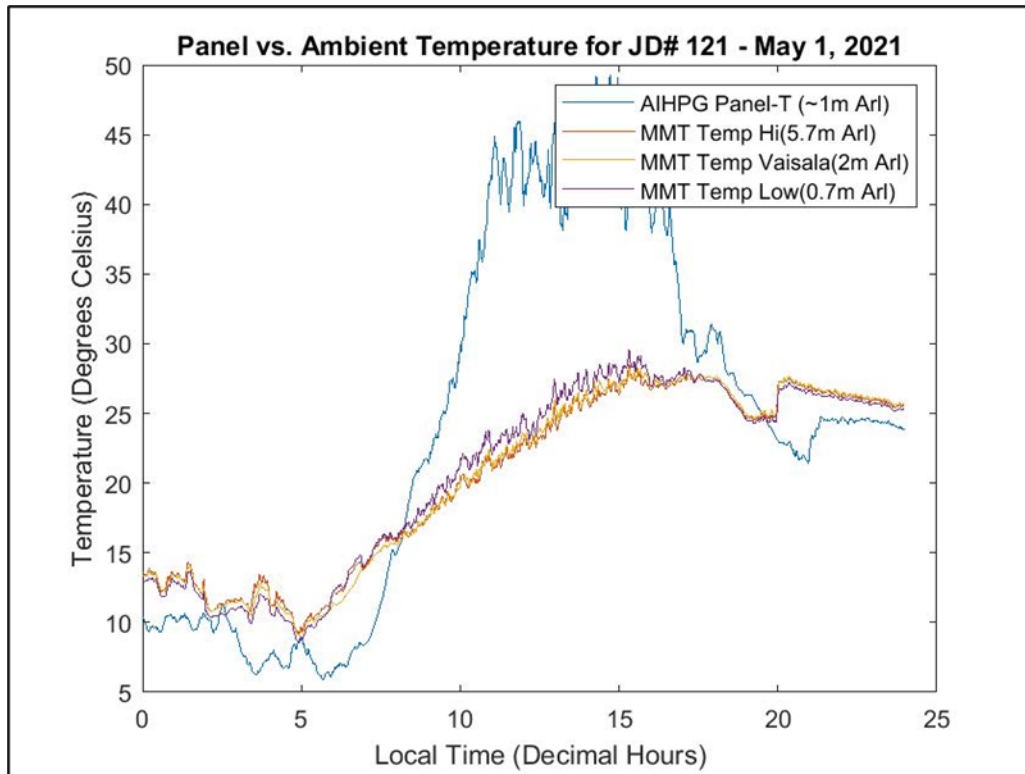


Fig. B-48 2021 May 1, panel vs. ambient temperature

Appendix C. Modeled and Measured Photovoltaic (PV) Power

The following graphs show the photovoltaic (PV) power calculated from the ambient (T_a) and PV panel temperatures (T_p) sampled during March 2021 over the southwestern New Mexico desert. To the left of the results are the solar radiation (SR) (irradiance) and raw T_a and T_p temperature time series for the same date and location. The general sky conditions are labeled at the base of the tri-graph display.

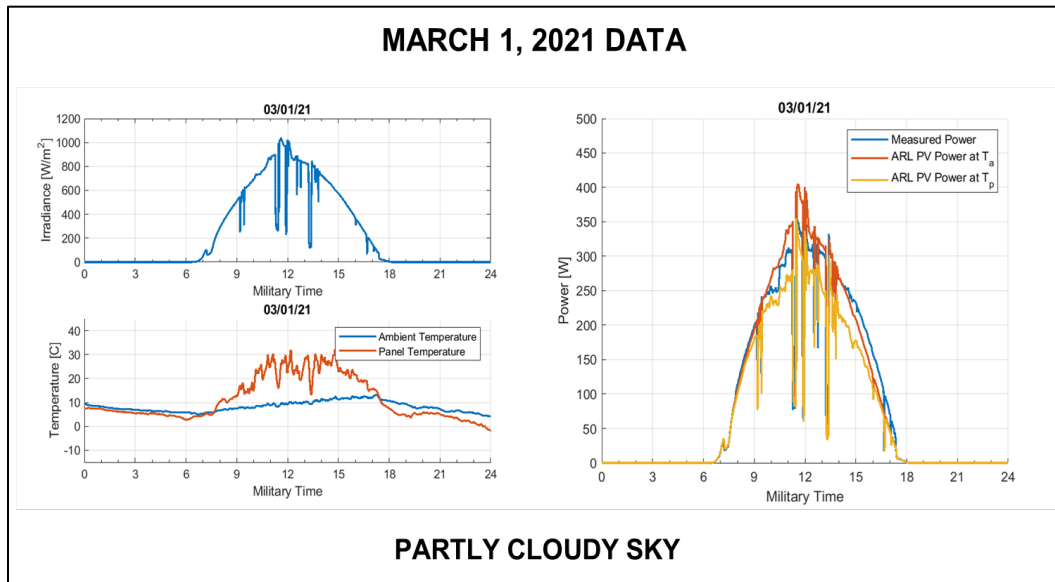


Fig. C-1 Partly cloudy - 2021 March 1; PV power measured and calculated from T_a and T_p . SR time series is included.

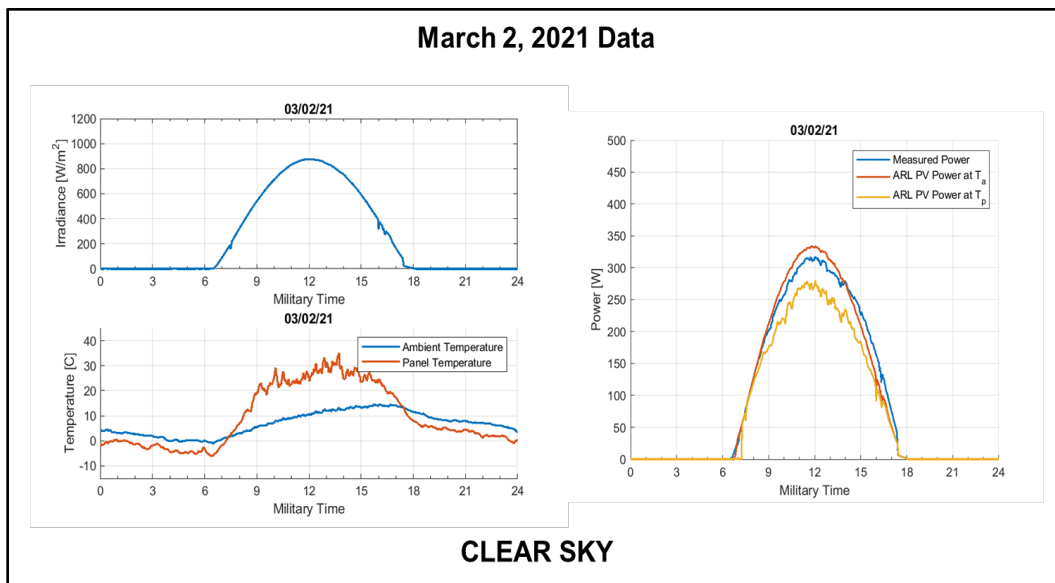


Fig. C-2 Clear (CLR) - 2021 March 2; PV power measured and calculated from T_a and T_p . SR time series is included.

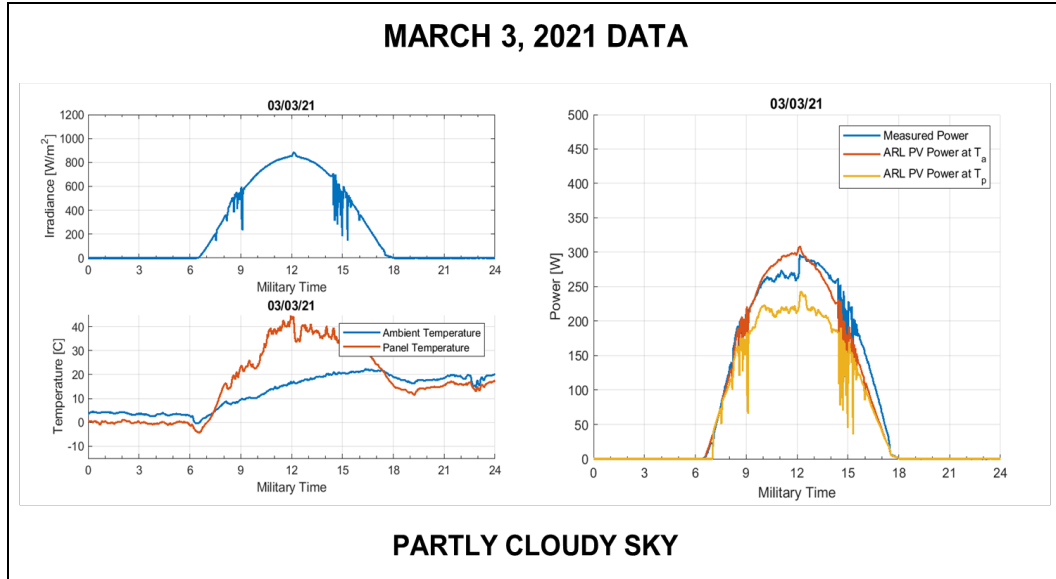


Fig. C-3 Partly cloudy - 2021 March 3, PV power measured and calculated from T_a and T_p. SR time series included.

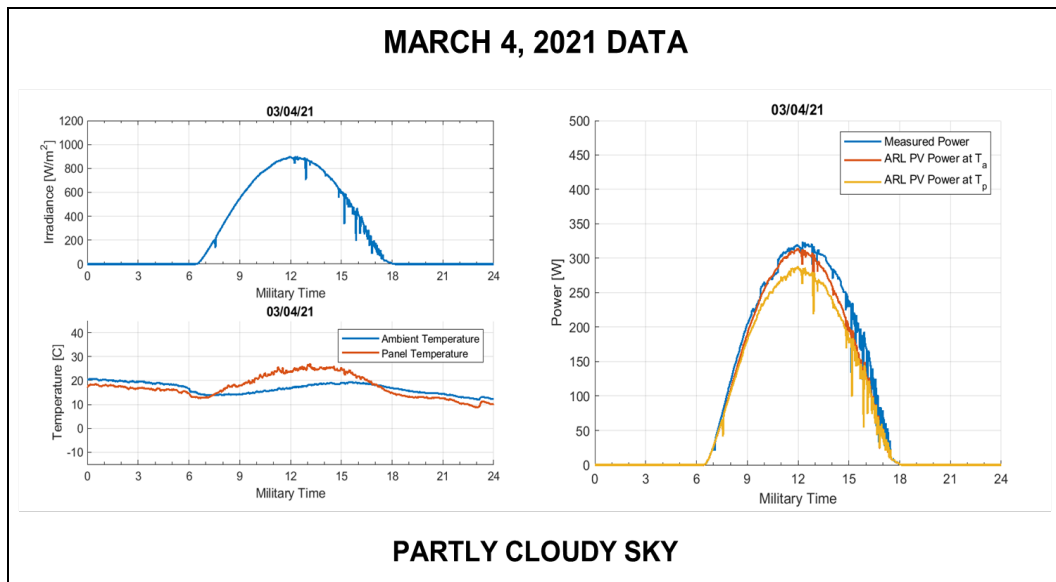


Fig. C-4 Partly cloudy - 2021 March 4, PV power measured and calculated from T_a and T_p. SR time series included.

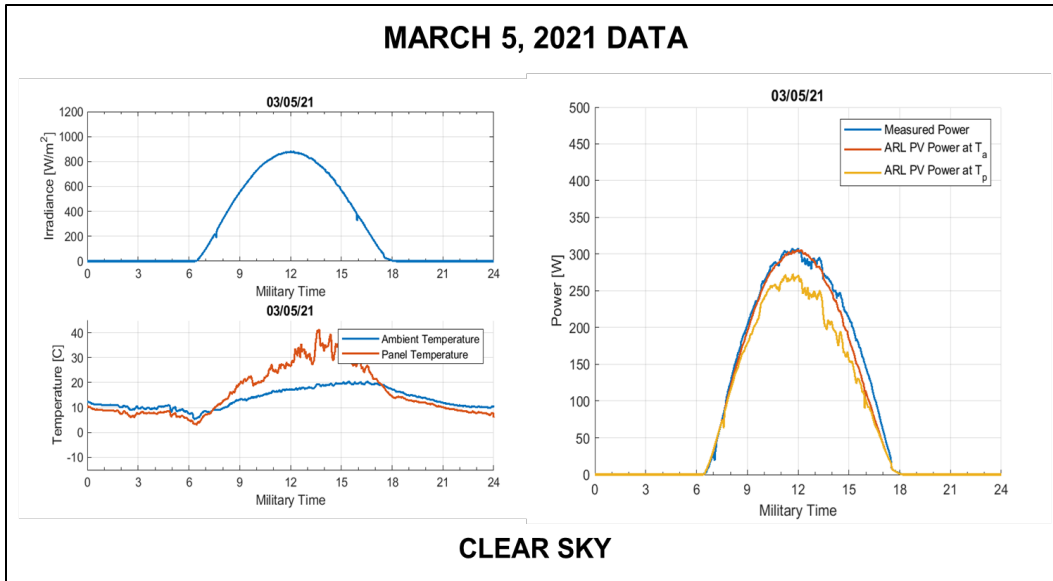


Fig. C-5 CLR - 2021 March 5, PV power measured and calculated from T_a and T_p . SR time series included.

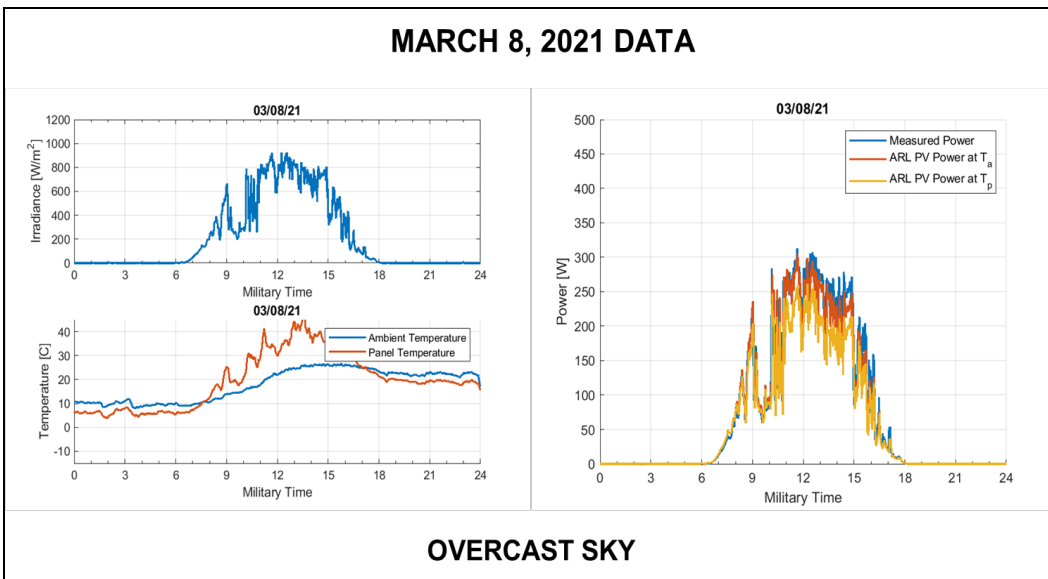


Fig. C-6 Overcast (OVC) - 2021 March 8, PV power measured and calculated from T_a and T_p . SR time series included.

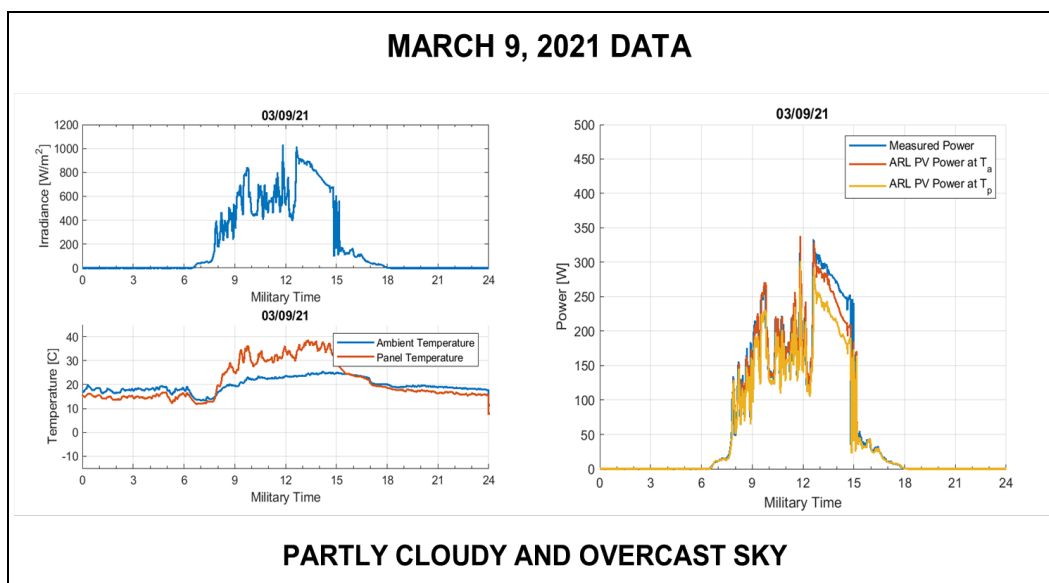


Fig. C-7 Partly cloudy and OVC - 2021 March 9, PV power measured and from T_a and T_p . SR time series included.

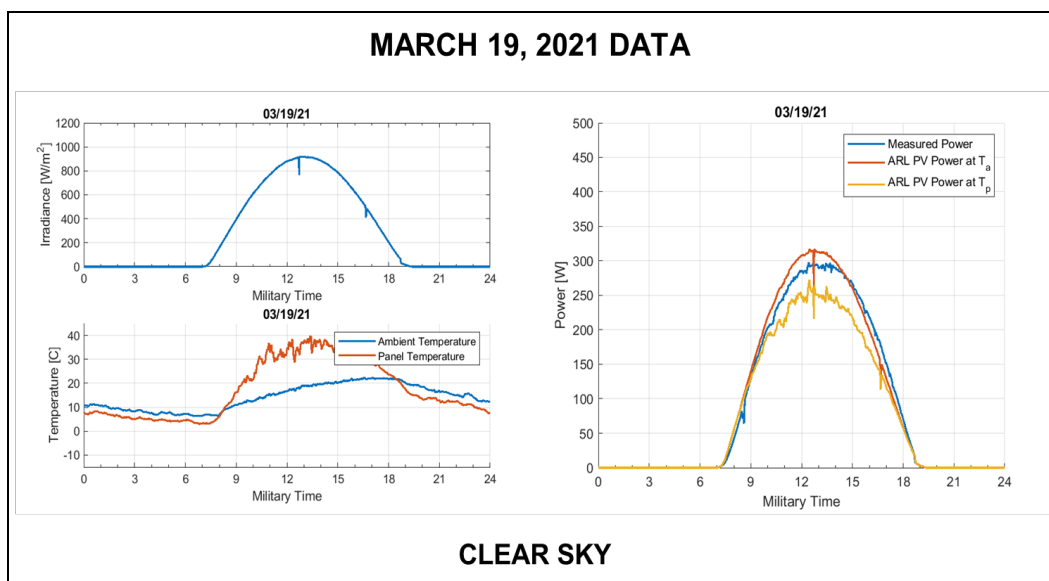


Fig. C-8 CLR - 2021 March 19, PV power measured and calculated from T_a and T_p . SR time series included

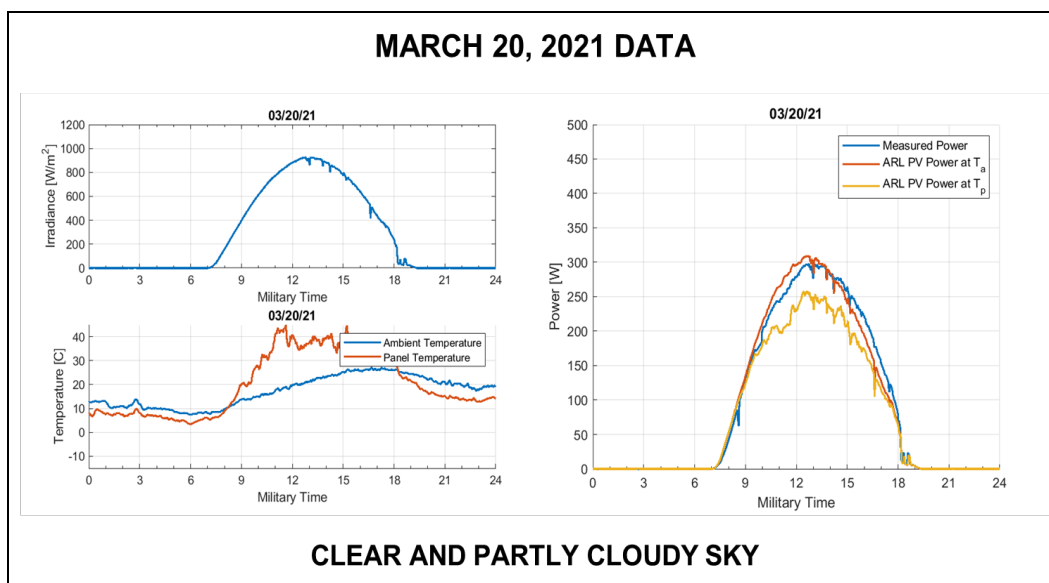


Fig C-9 CLR and partly cloudy - 2021 March 20, PV power measured and calculated from T_a and T_p . SR time series included.

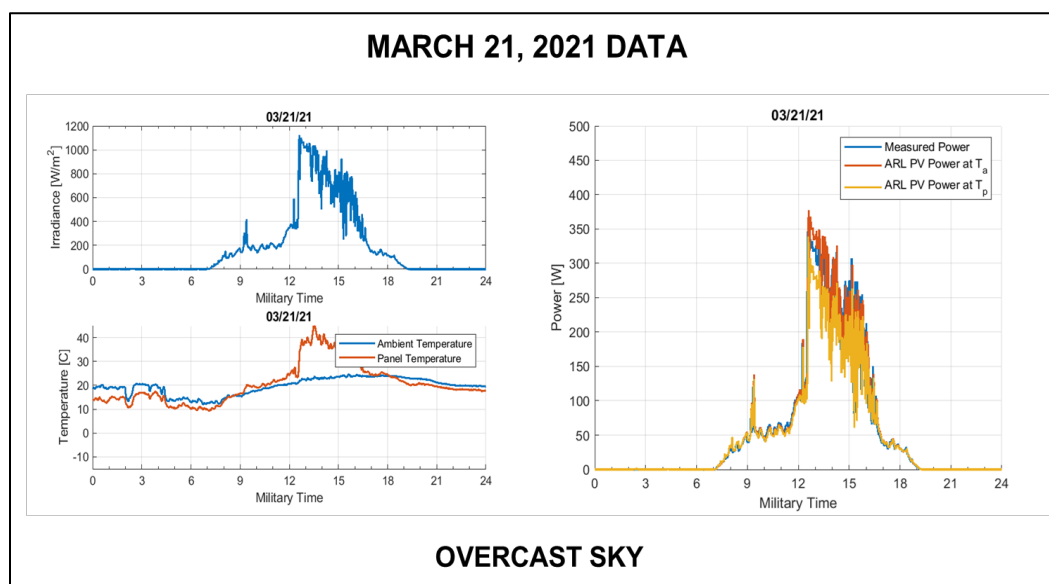


Fig C-10 OVC - 2021 March 21, PV power measured and calculated from T_a and T_p . SR time series included.

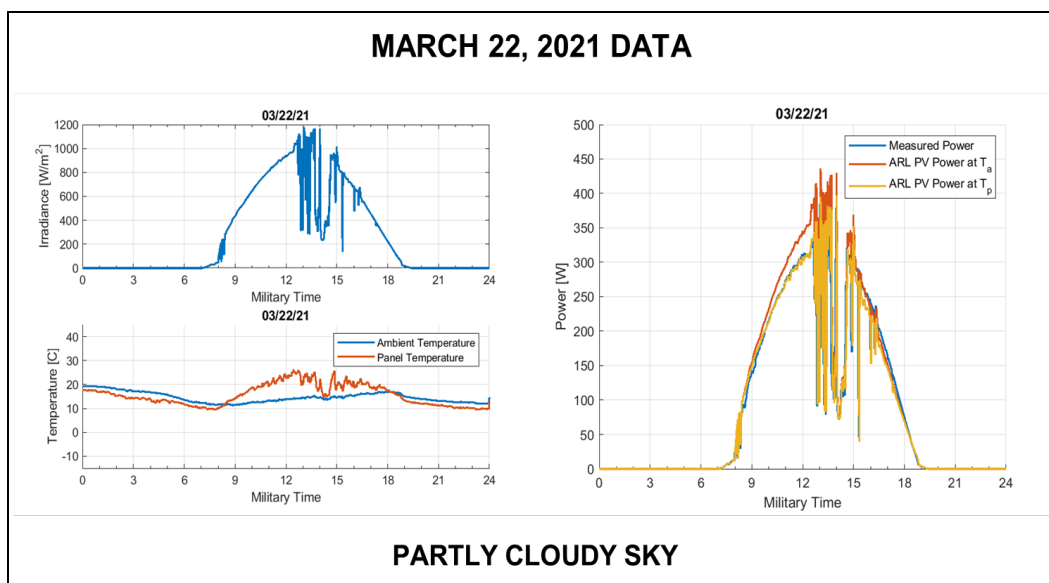


Fig. C-11 Partly cloudy - 2021 March 22, PV power measured and calculated from T_a and T_p . SR time series included.

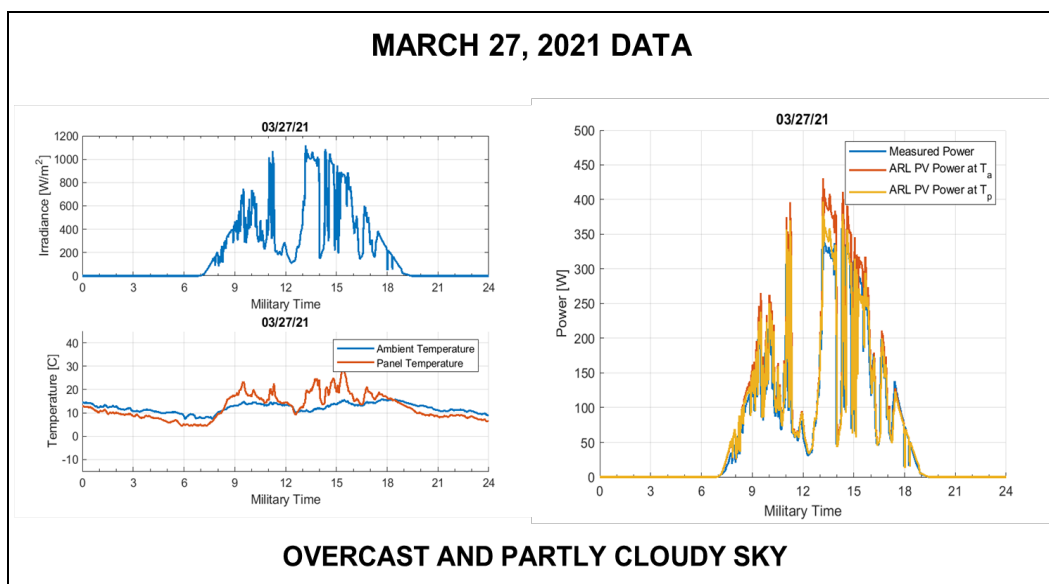


Fig. C-12 OVC and Partly cloudy - 2021 March 27, PV power measured and calculated from T_a and T_p . SR time series included.

Appendix D. Neural Network (NN) Training Input and Results

To assimilate the neural network (NN) reach-back capabilities, the input and target feature step sizes were individually kept constant. Four separate patterns were created—two with T_p constant and the forecast interval iteratively doubled:

- 1) $T_p = 15 \text{ min}$ and T_f was set to (5, 10, 20, 40, 80, and 160 min).
- 2) $T_p = 30 \text{ min}$ and T_f was set to (5, 10, 20, 40, 80, and 160 min).

and two with T_f constant, and the past interval iteratively doubled:

- (1) (3) $T_f = 15 \text{ min}$ and T_p was set to (5, 10, 20, 40, 80, and 160 min).
- (2) (4) $T_f = 30 \text{ min}$ and T_p was set to (5, 10, 20, 40, 80, and 160 min).

In this Appendix, past temperature inputs (T_p) are in units of minute; future temperatures (T_f) are in units of minutes. The plots are grouped in the following sequence:

- NN training graphical user interface (GUI) starts each section of results, followed by
- 4 clear sky case results (2019 Jan 14, July 2, Sep 13, Nov 20) and
- 4 overcast case results (2019 Jan 16, May 12, Sep 9, Nov 8).

The graphics include measured and predicted (modeled) temperatures, along with a plot of the power differences (bias) results. Note: The “bias” values were calculated using a (measured power – forecasted power) formula. Thus, a negative bias shows a forecasted overestimation of the measured power and a positive bias reports an underestimation of “truth.” The ideal bias is zero.

$$T_p = 15$$

$$T_f = 5$$

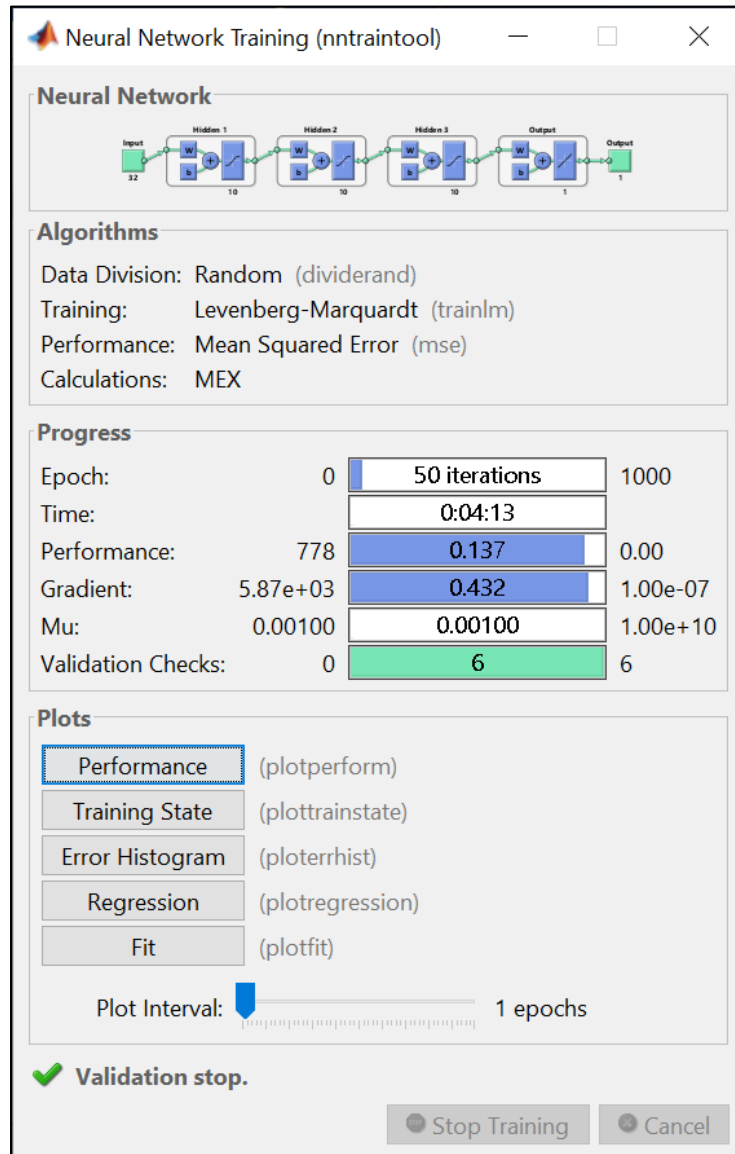


Fig. D-1 $T_p = 15$, $T_f = 5$ (Pattern 1)

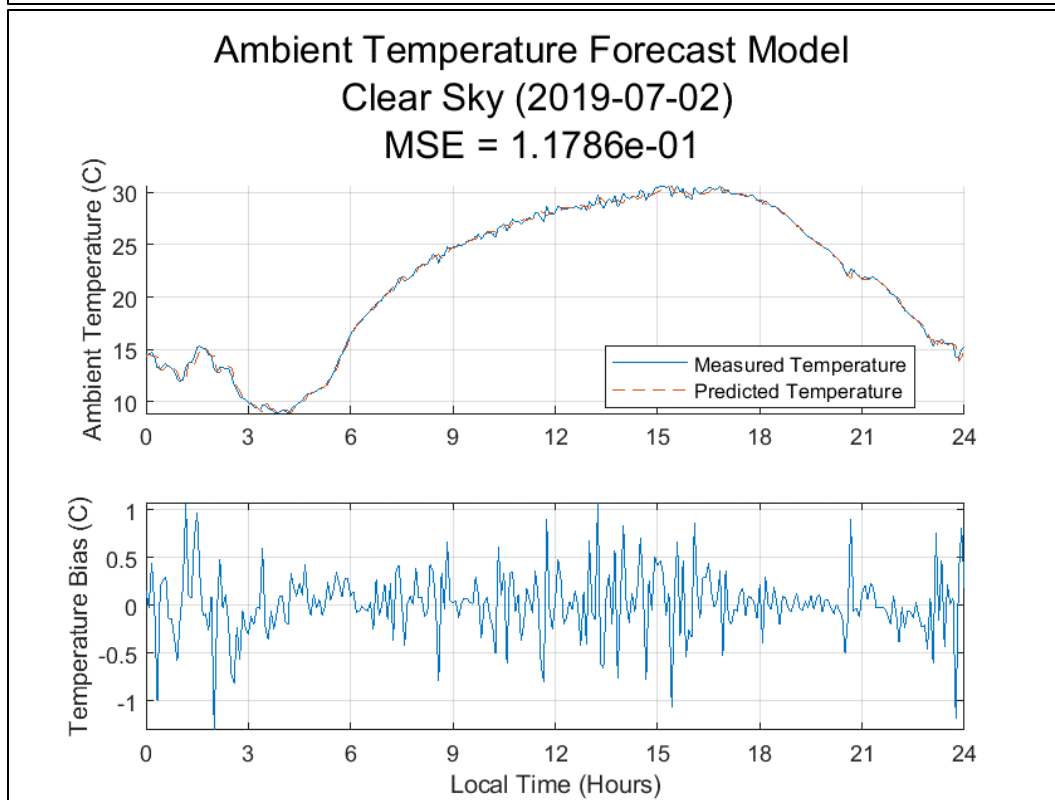
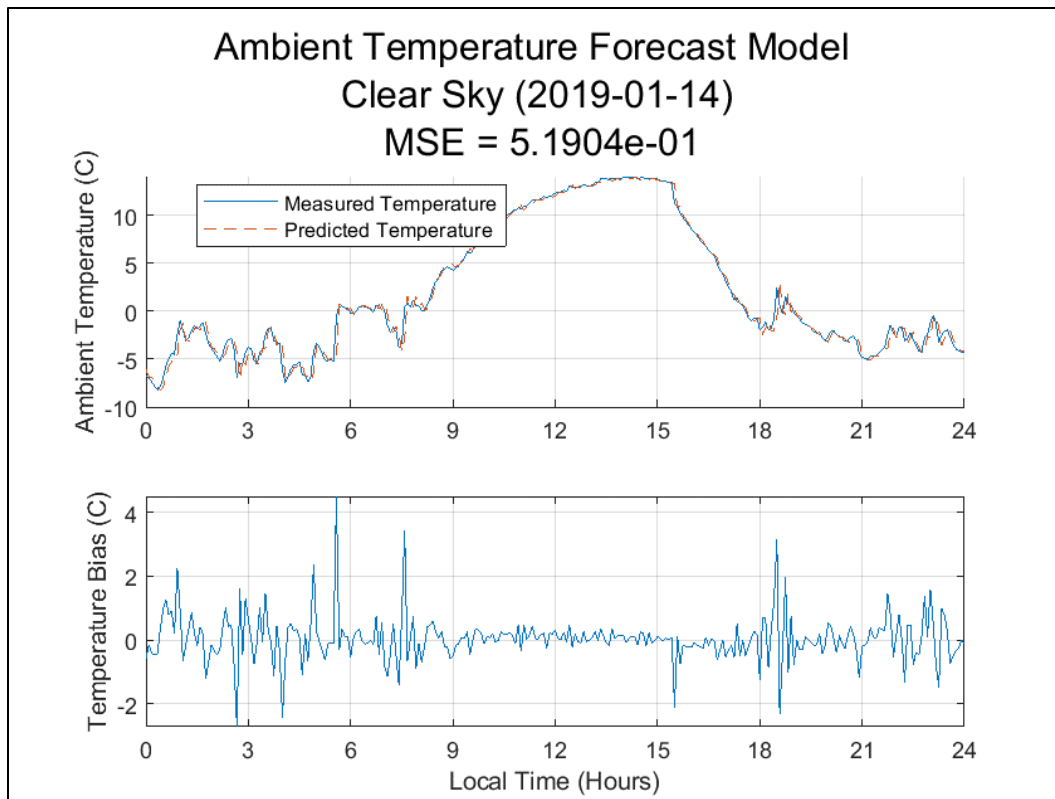


Fig. D-1 $T_p = 15$, $T_r = 5$ (Pattern 1) (continued)

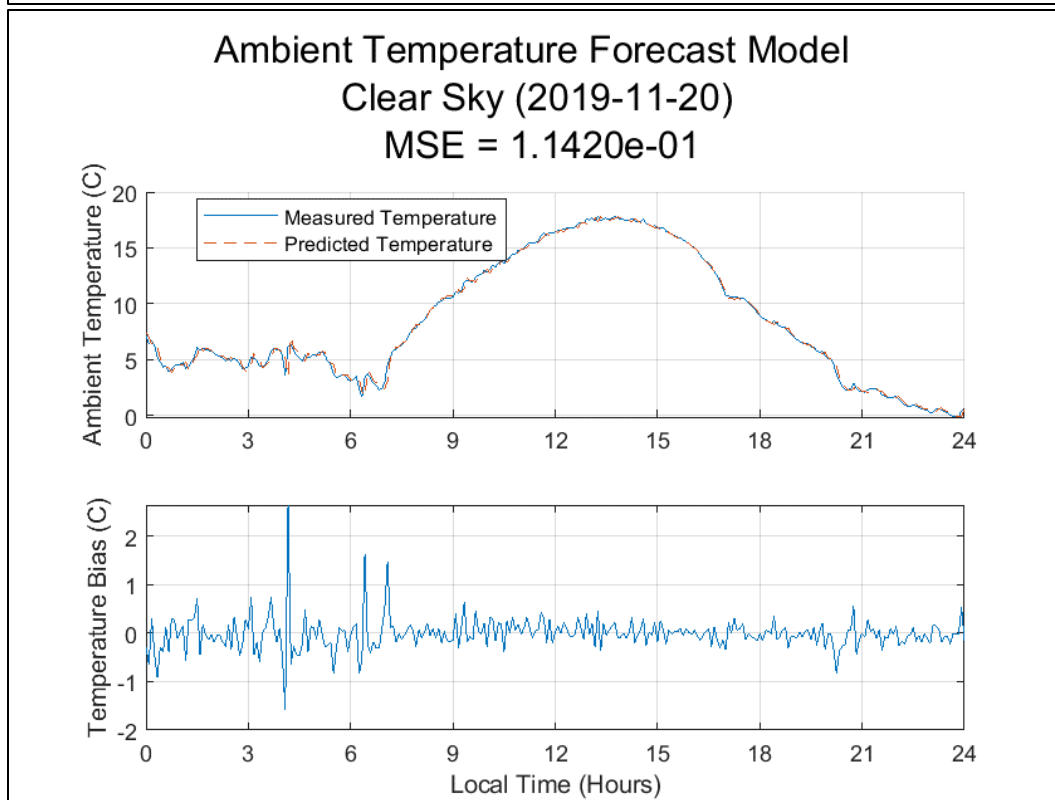
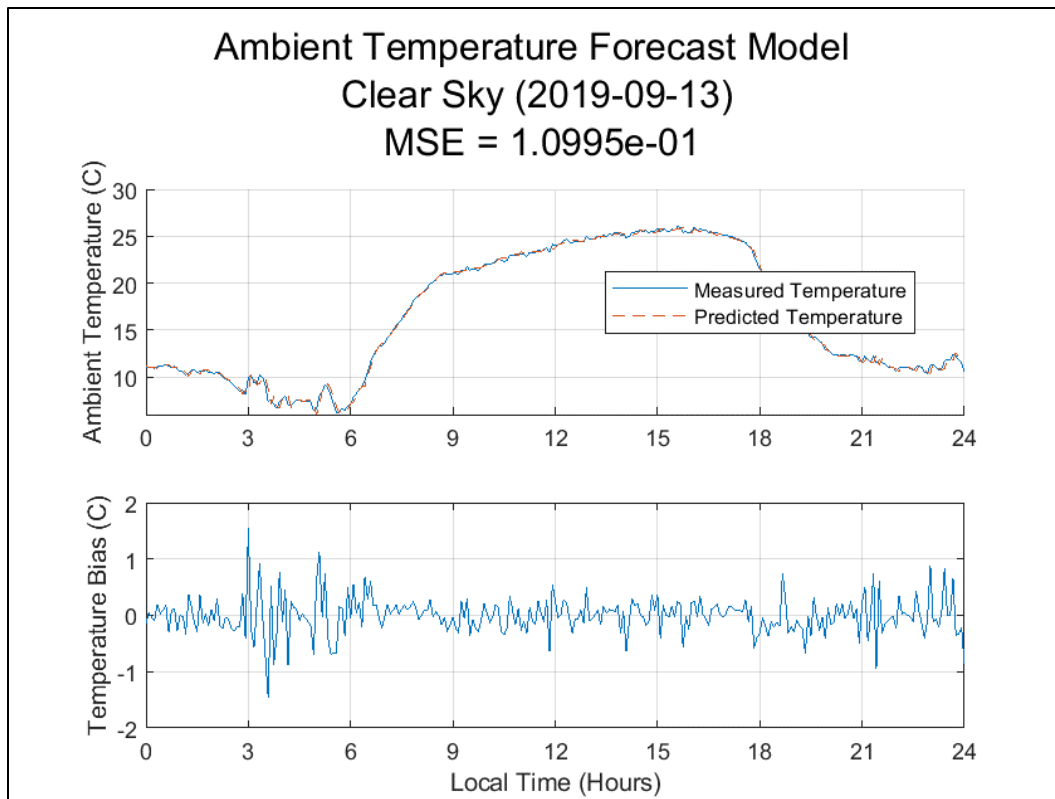


Fig. D-1 $T_p = 15$, $T_r = 5$ (Pattern 1) (continued)

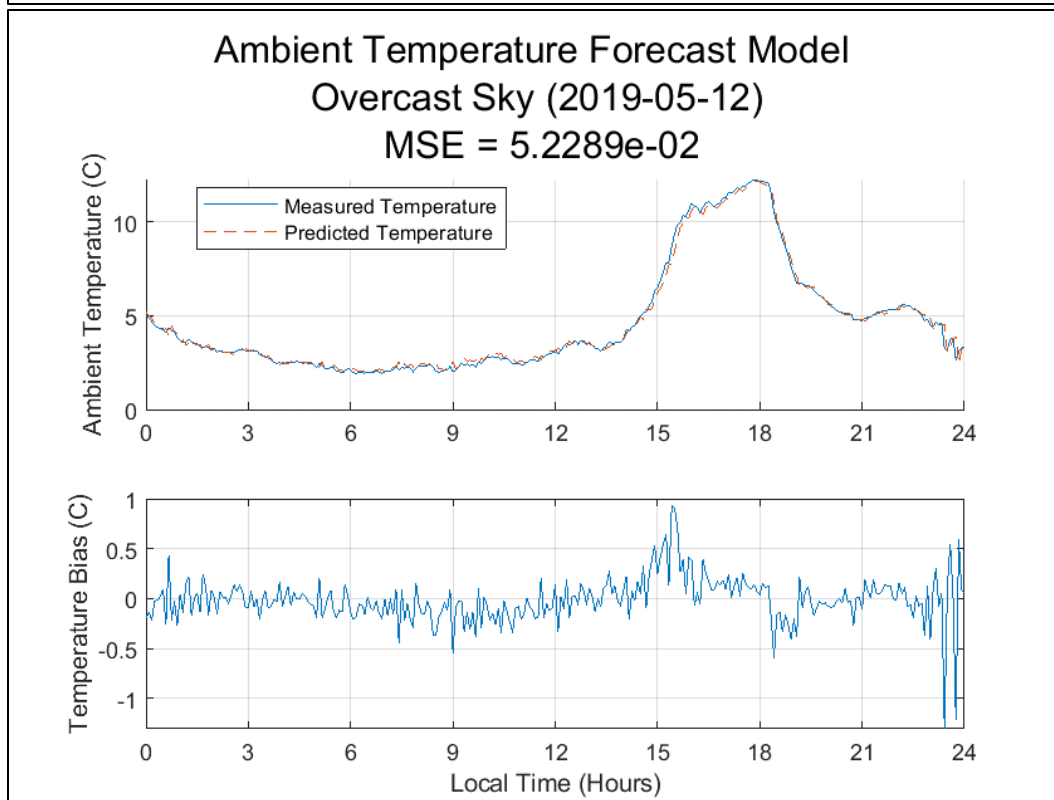
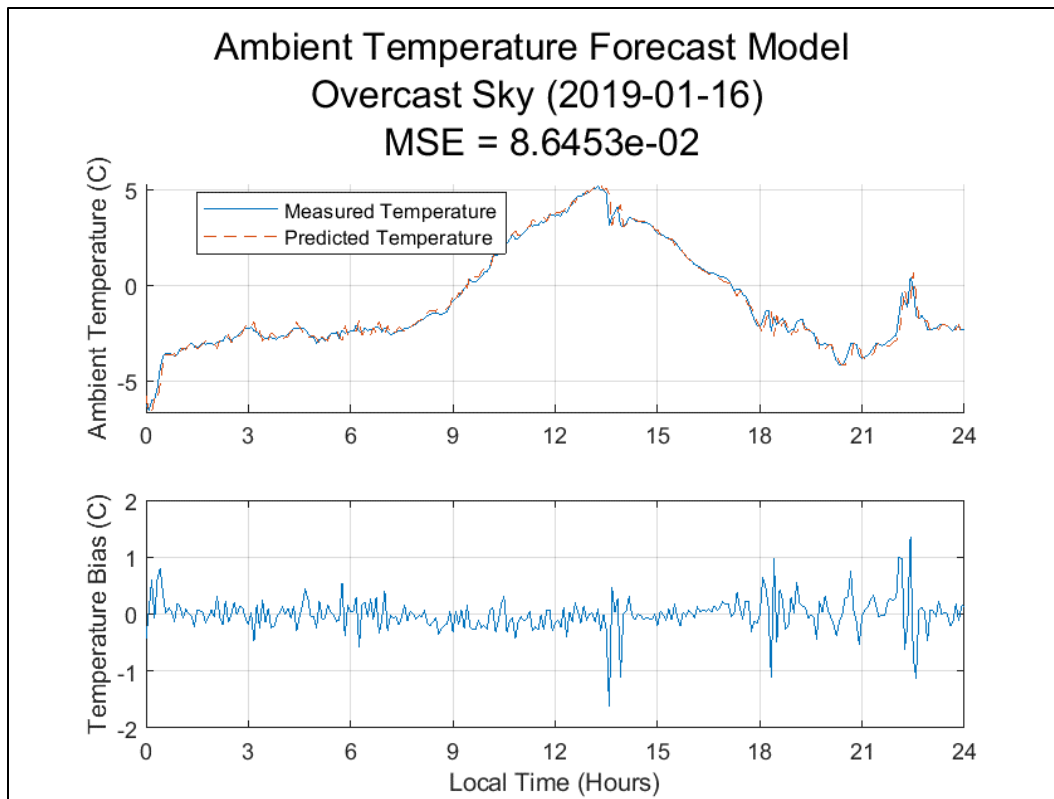


Fig. D-1 $T_p = 15$, $T_r = 5$ (Pattern 1) (continued)

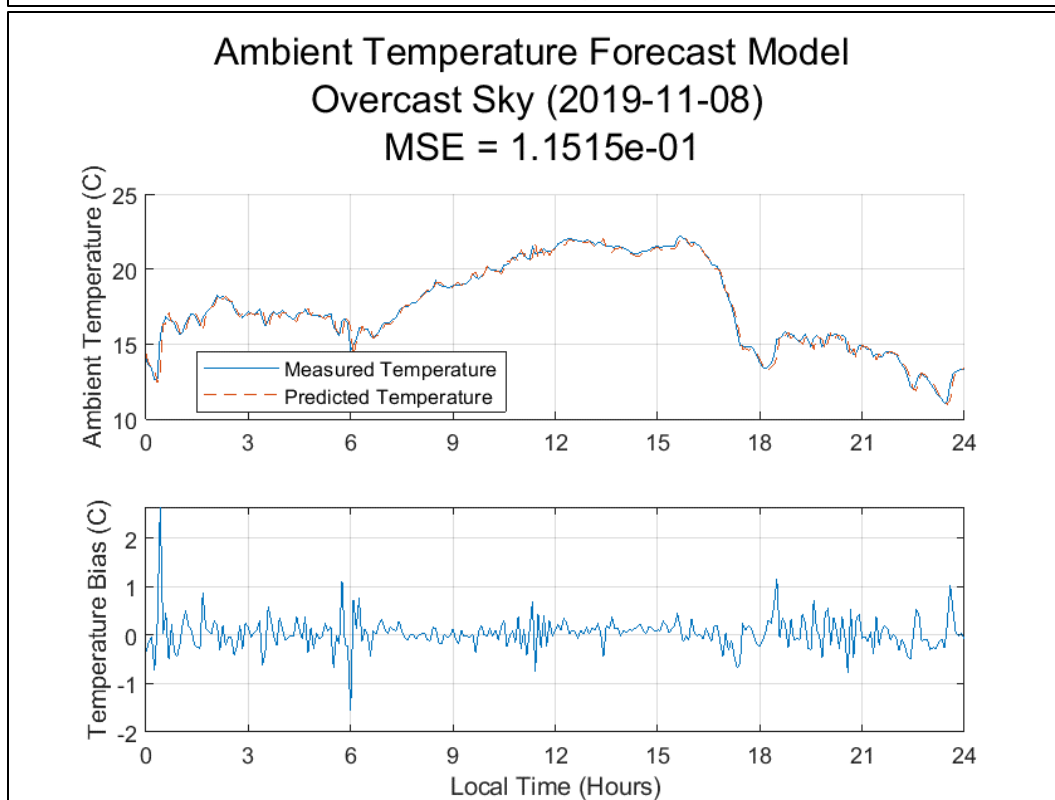
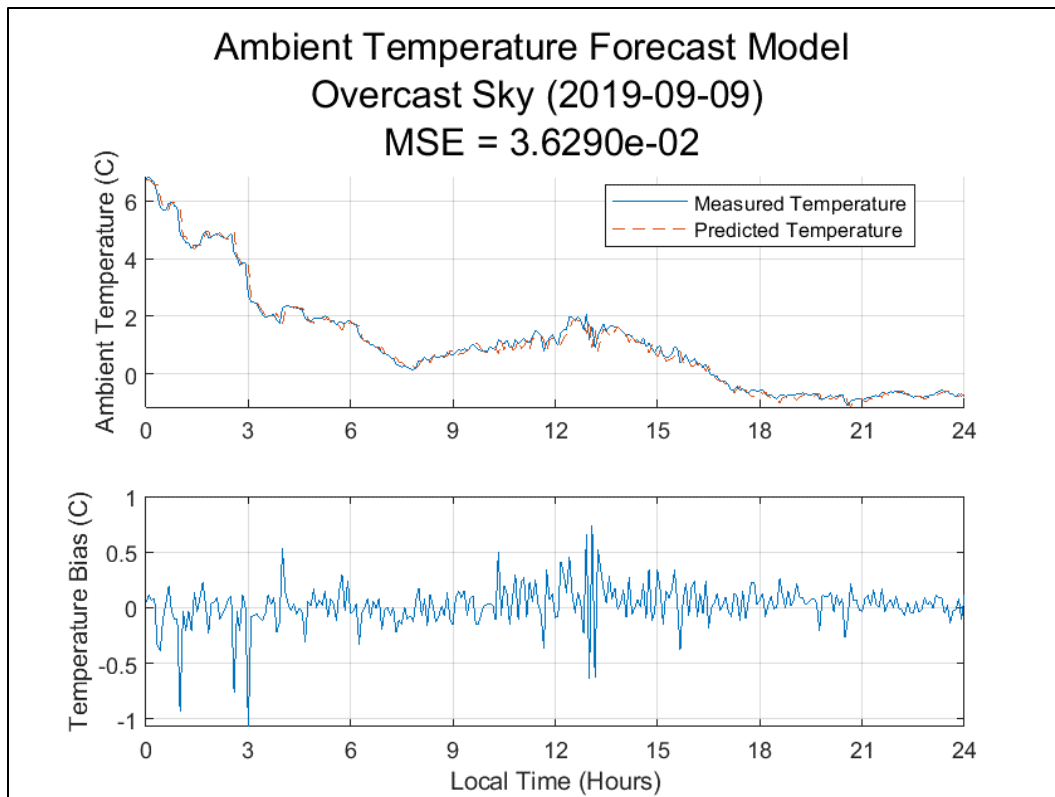


Fig. D-1 $T_p = 15$, $T_r = 5$ (Pattern 1) (continued)

$$T_p = 15$$

$$T_f = 10$$

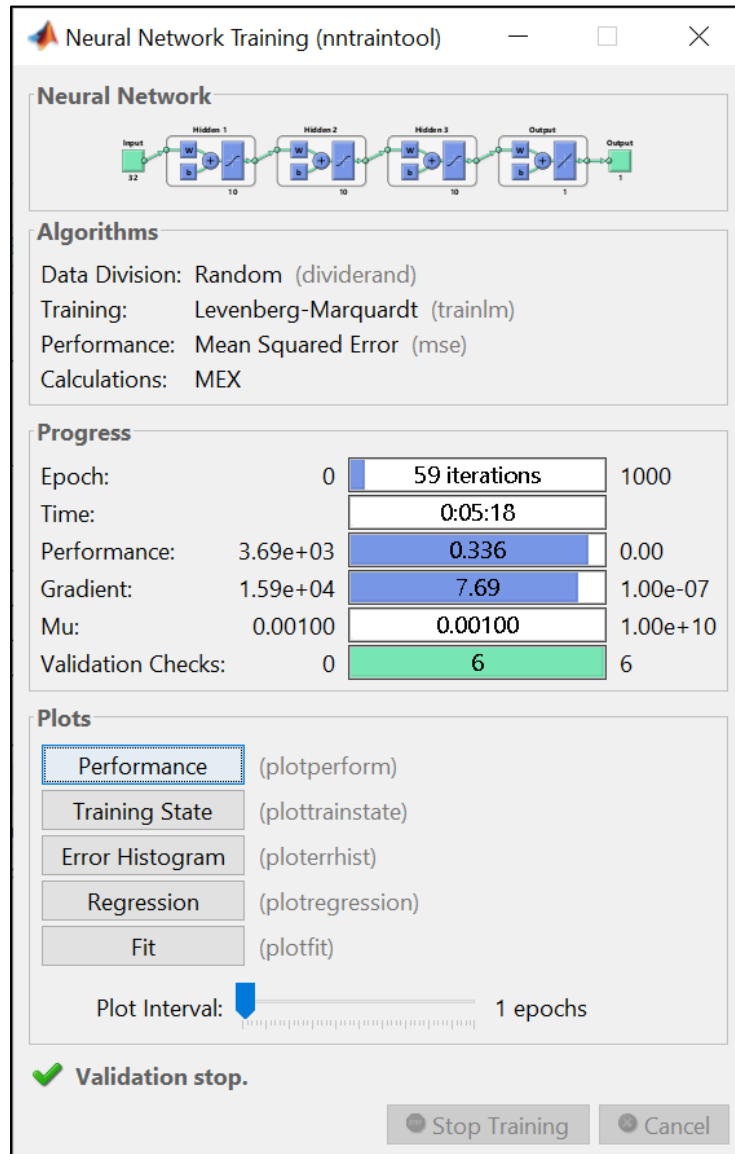


Fig. D-2 $T_p = 15$, $T_f = 10$ (Pattern 1)

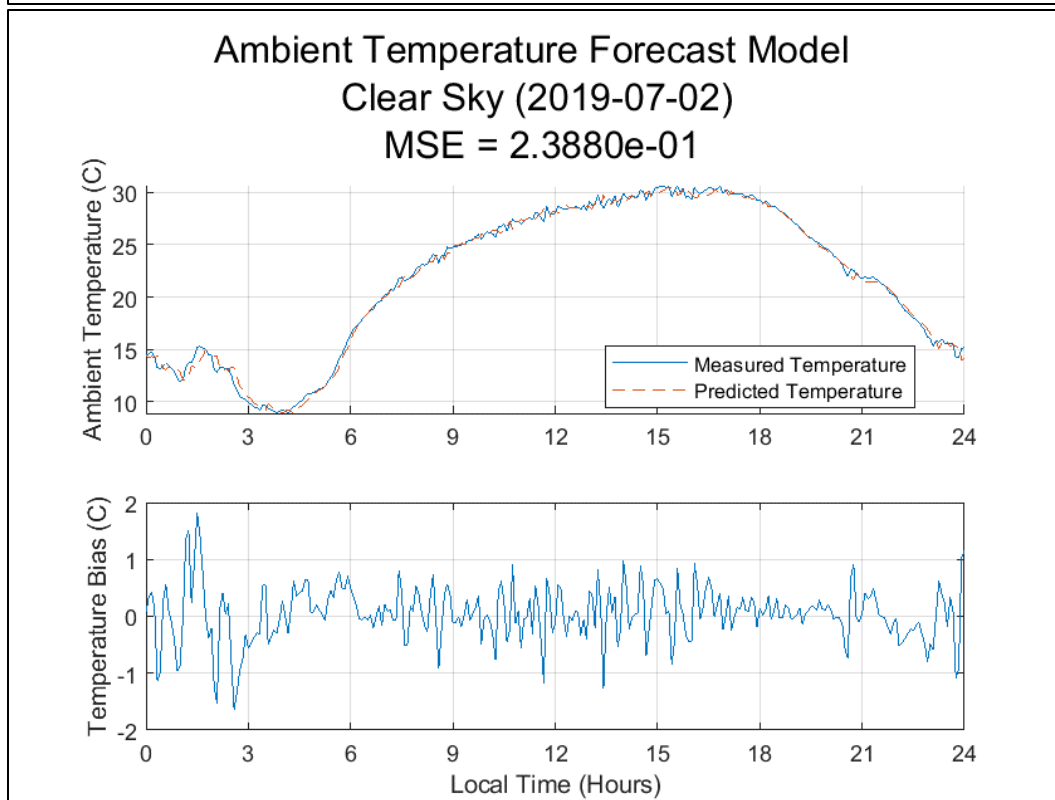
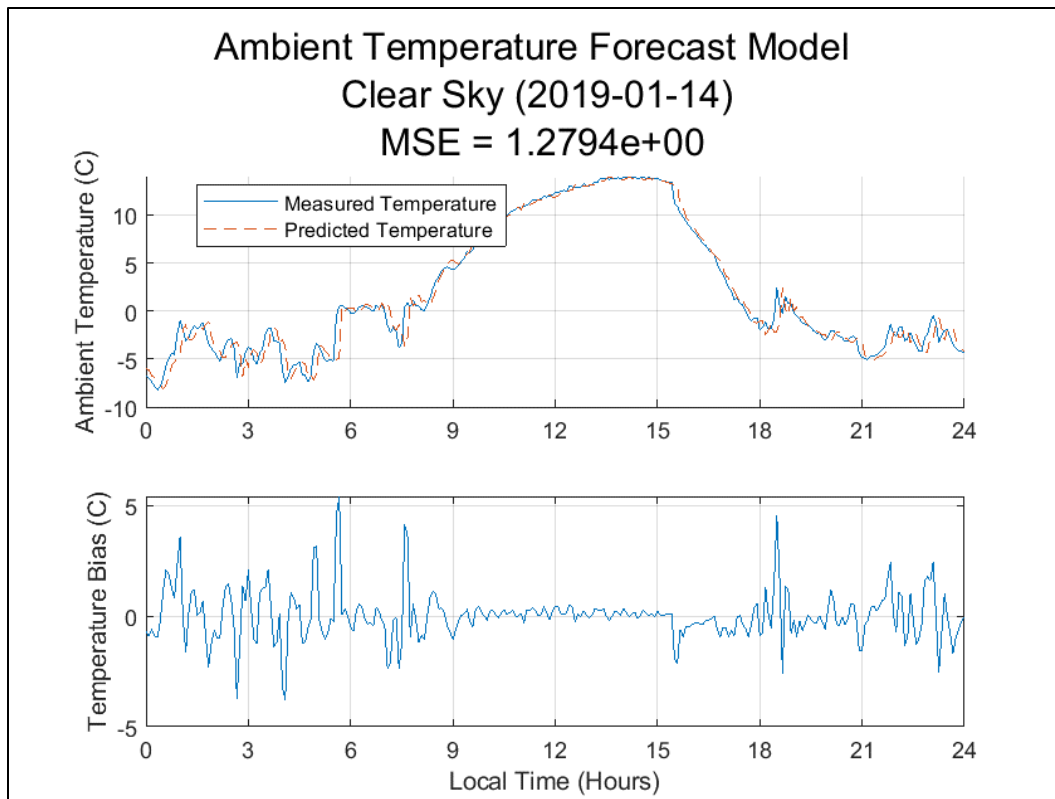


Fig. D-2 $T_p = 15$, $T_r = 10$ (Pattern 1) (continued)

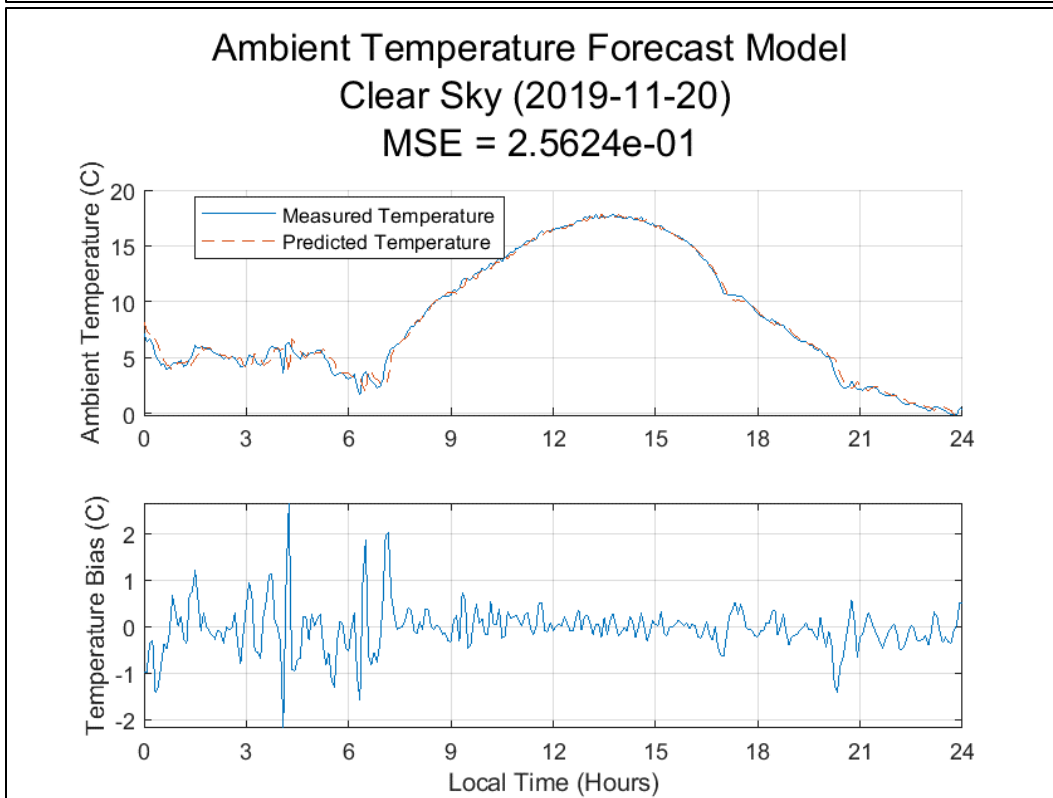
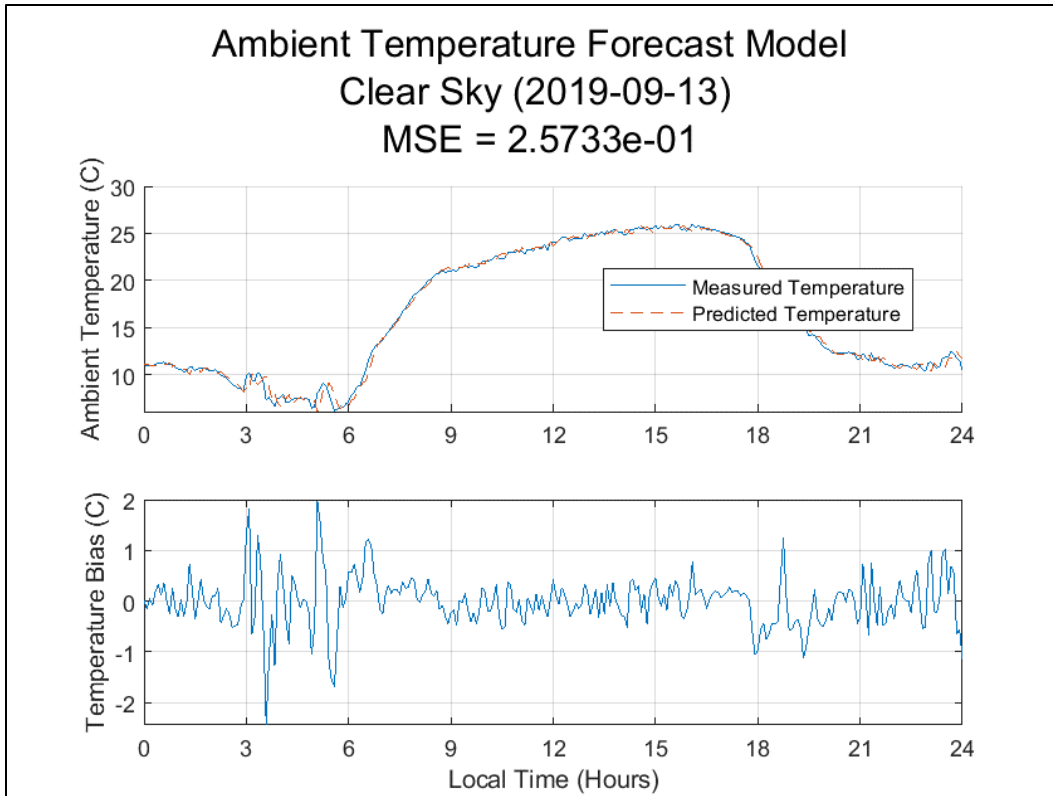


Fig. D-2 $T_p = 15$, $T_r = 10$ (Pattern 1) (continued)

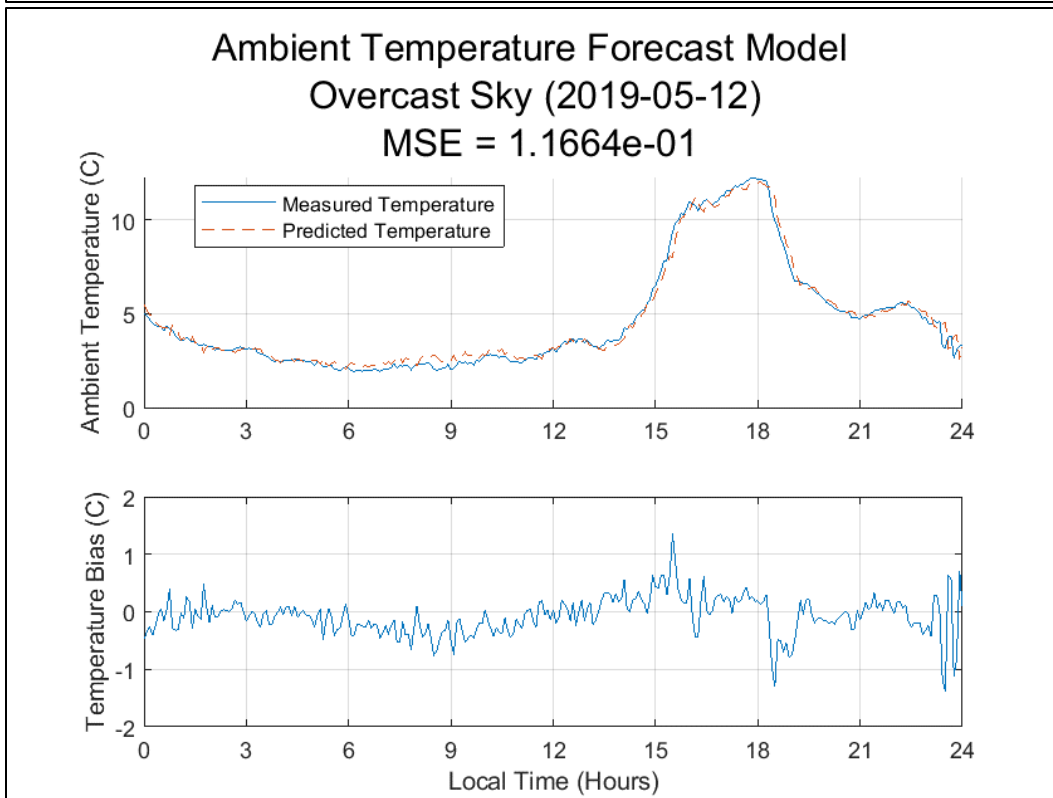
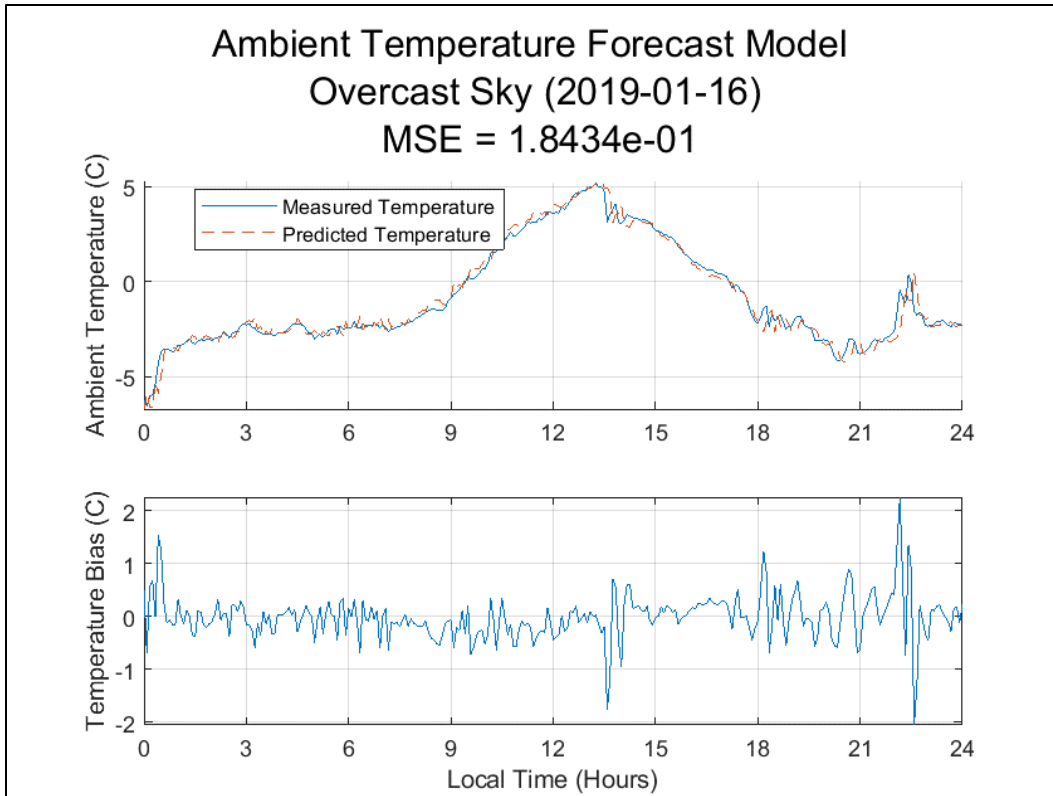


Fig.D-2 $T_p = 15$, $T_r = 10$ (Pattern 1) (continued)

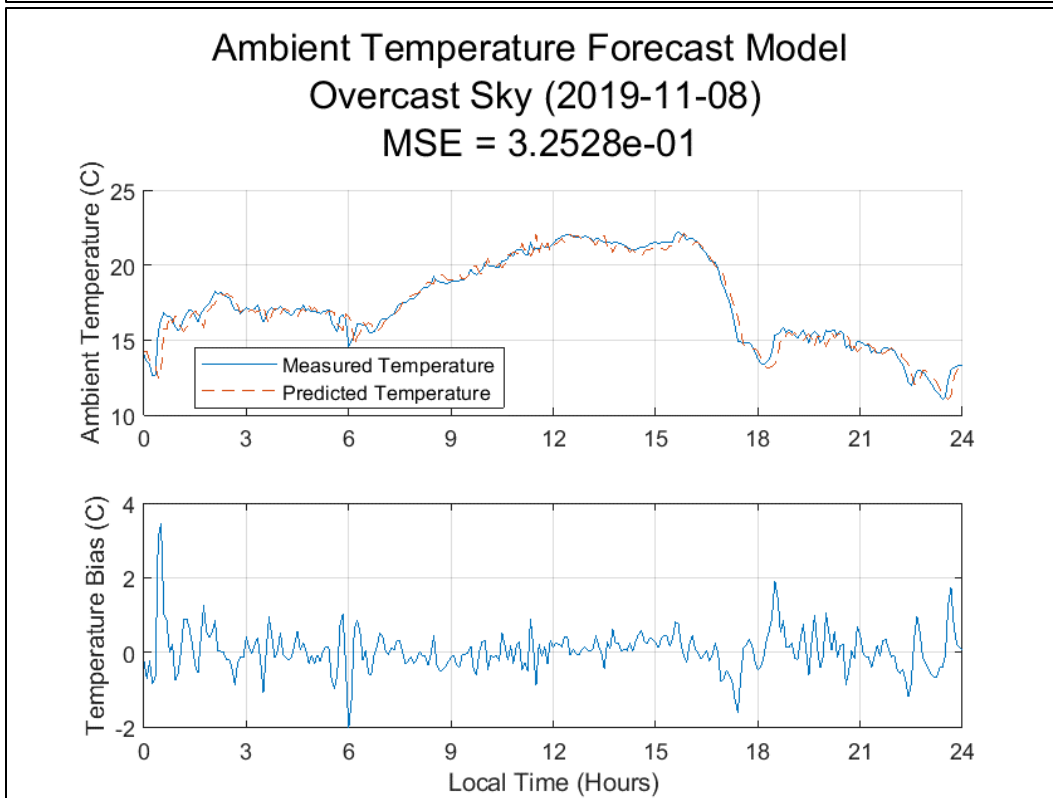
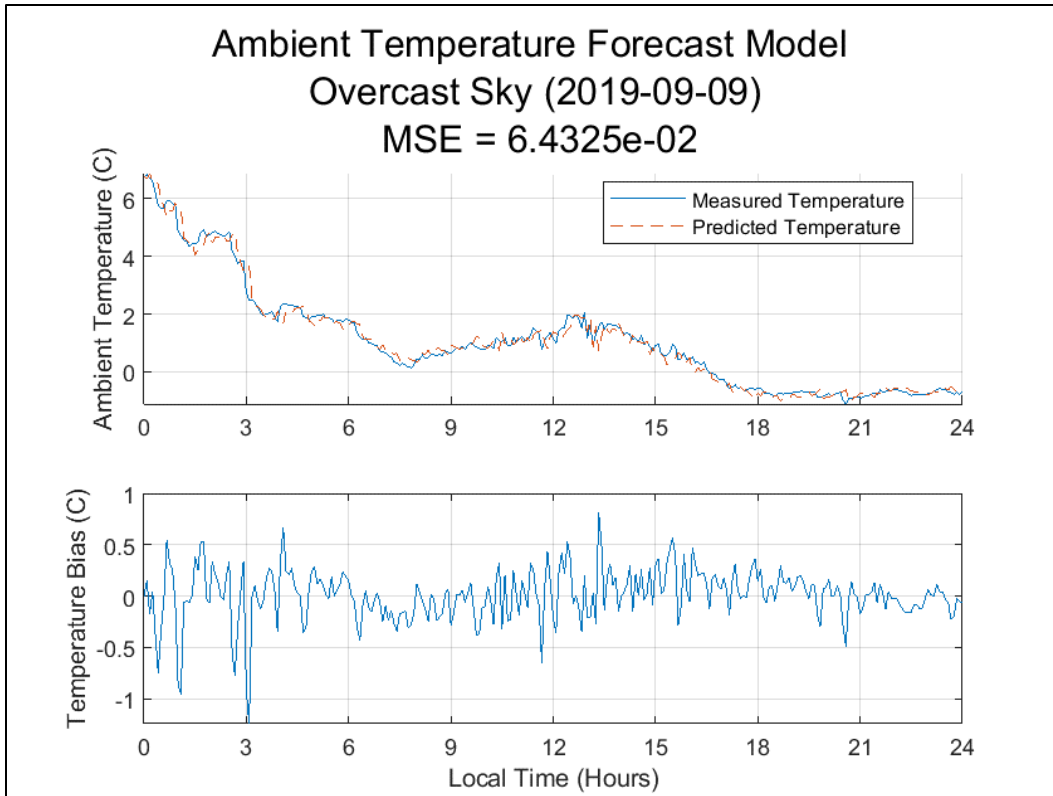


Fig.D-2 $T_p = 15$, $T_r = 10$ (Pattern 1) (continued)

$$T_p = 15$$

$$T_f = 20$$

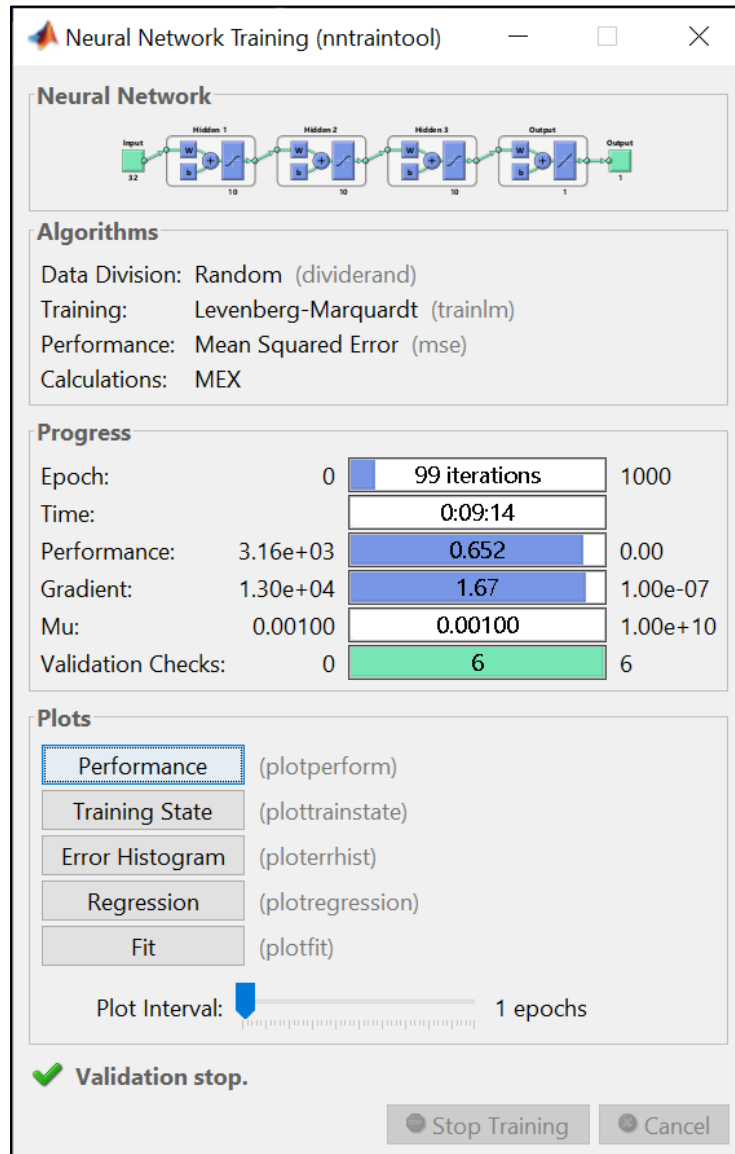


Fig. D-3 $T_p = 15$, $T_f = 20$ (Pattern 1)

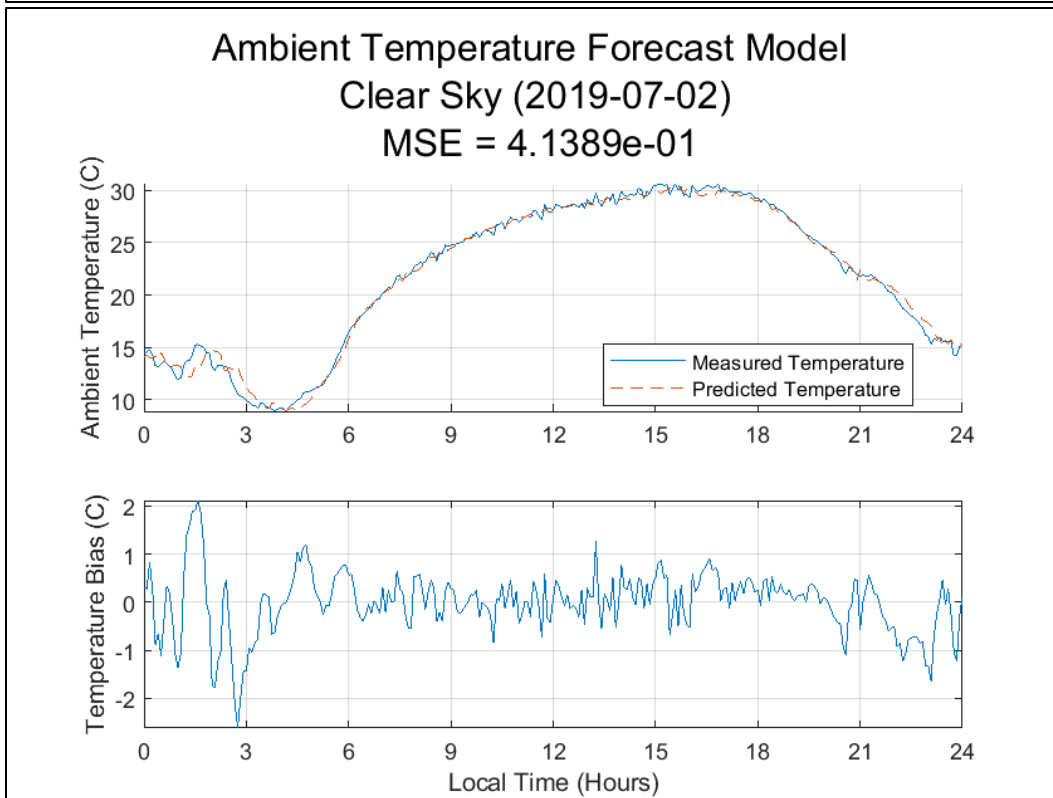
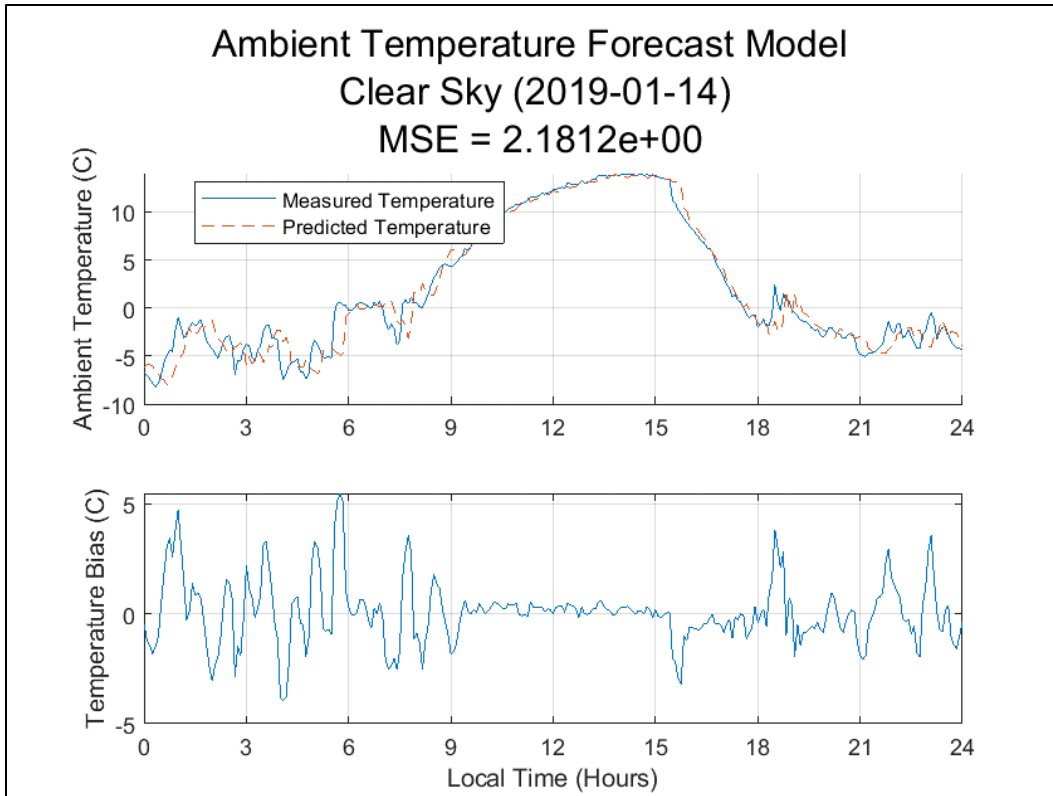


Fig. D-3 $T_p = 15$, $T_r = 20$ (Pattern 1) (continued)

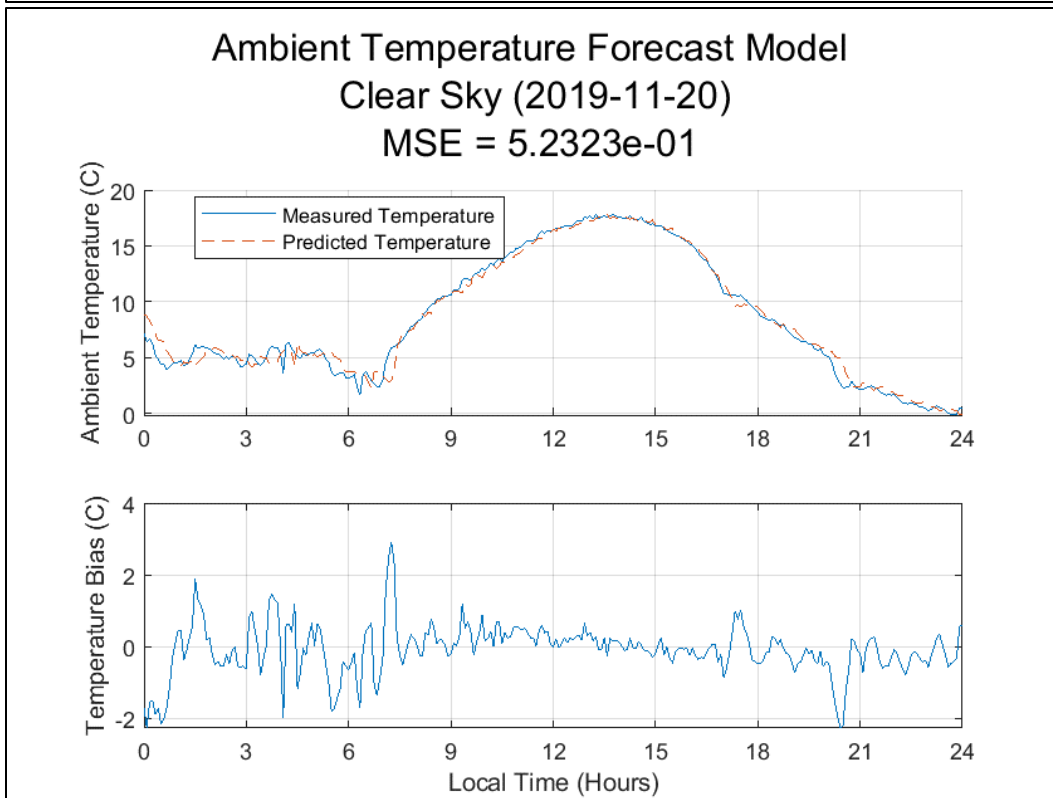
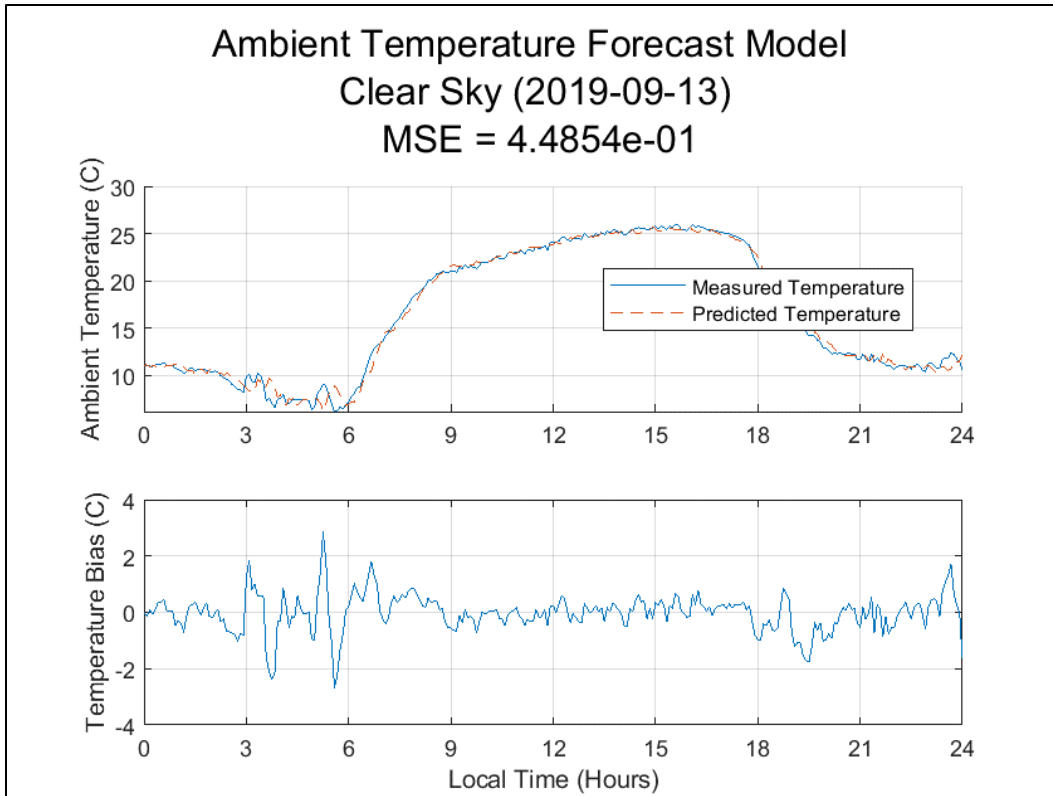


Fig. D-3 $T_p = 15$, $T_r = 20$ (Pattern 1) (continued)

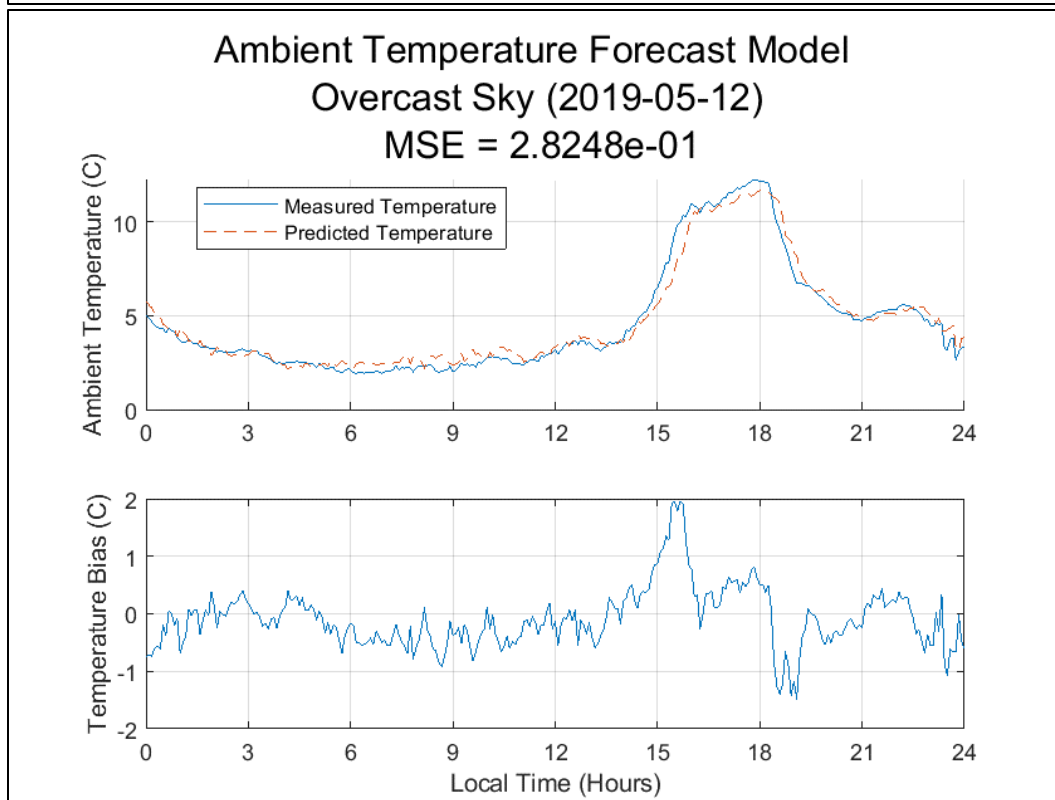
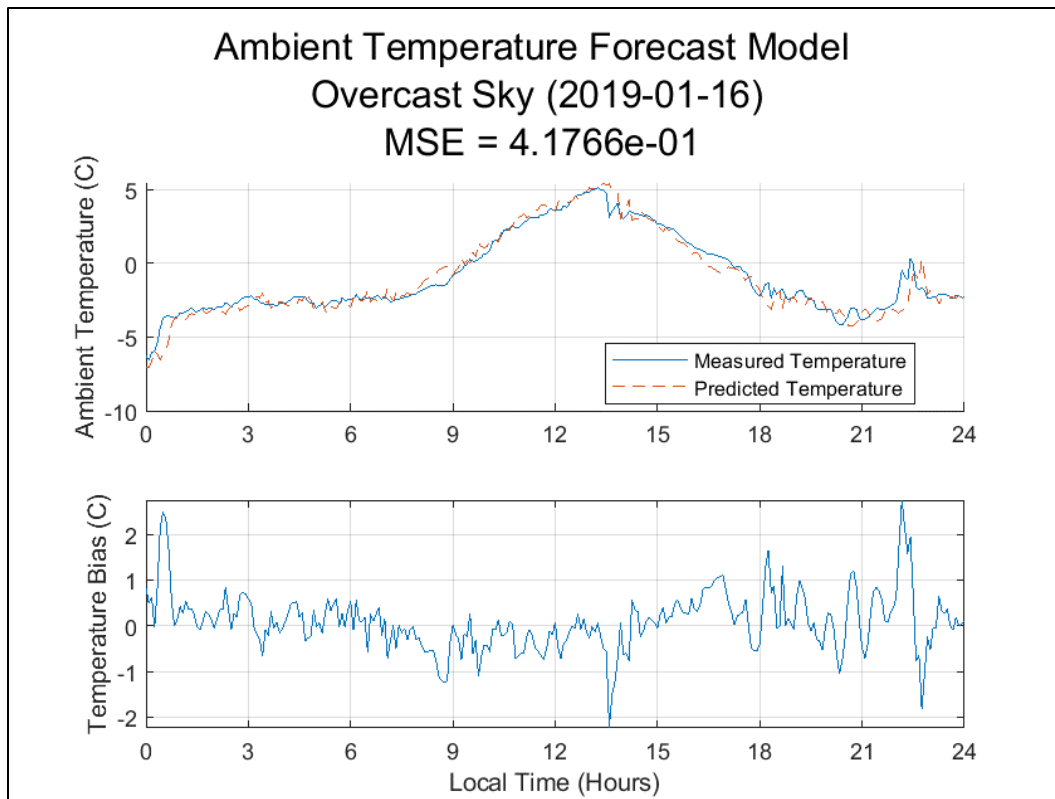


Fig. D-3 $T_p = 15$, $T_r = 20$ (Pattern 1) (continued)

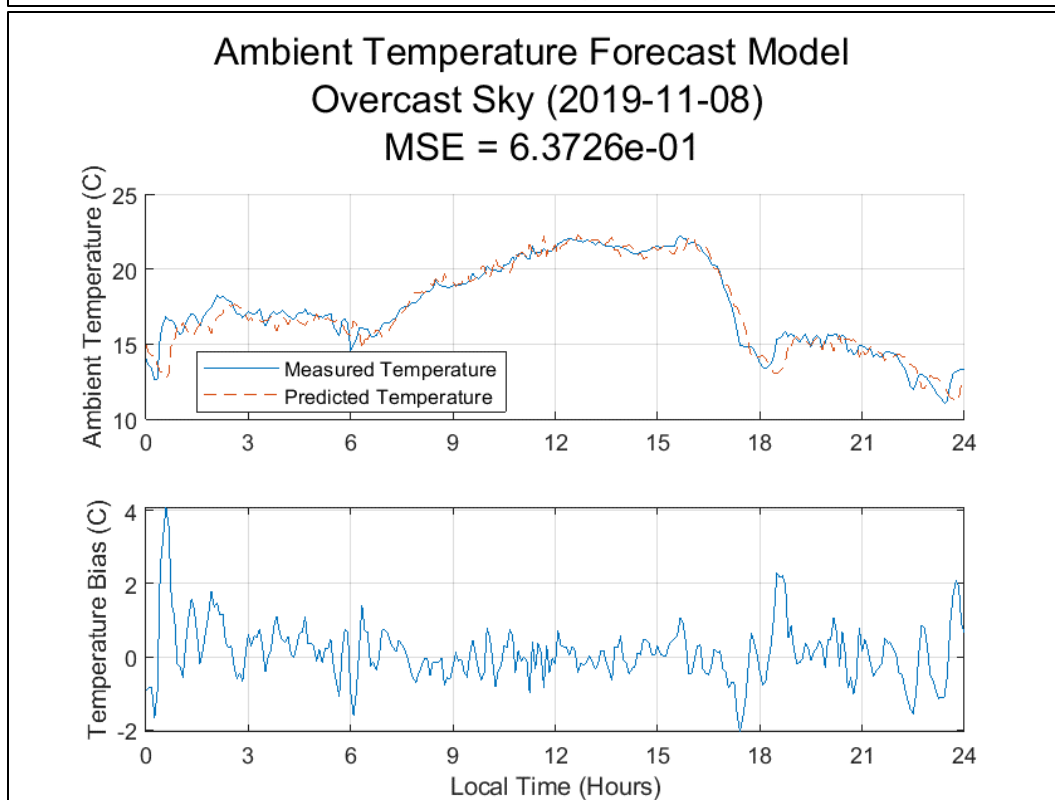
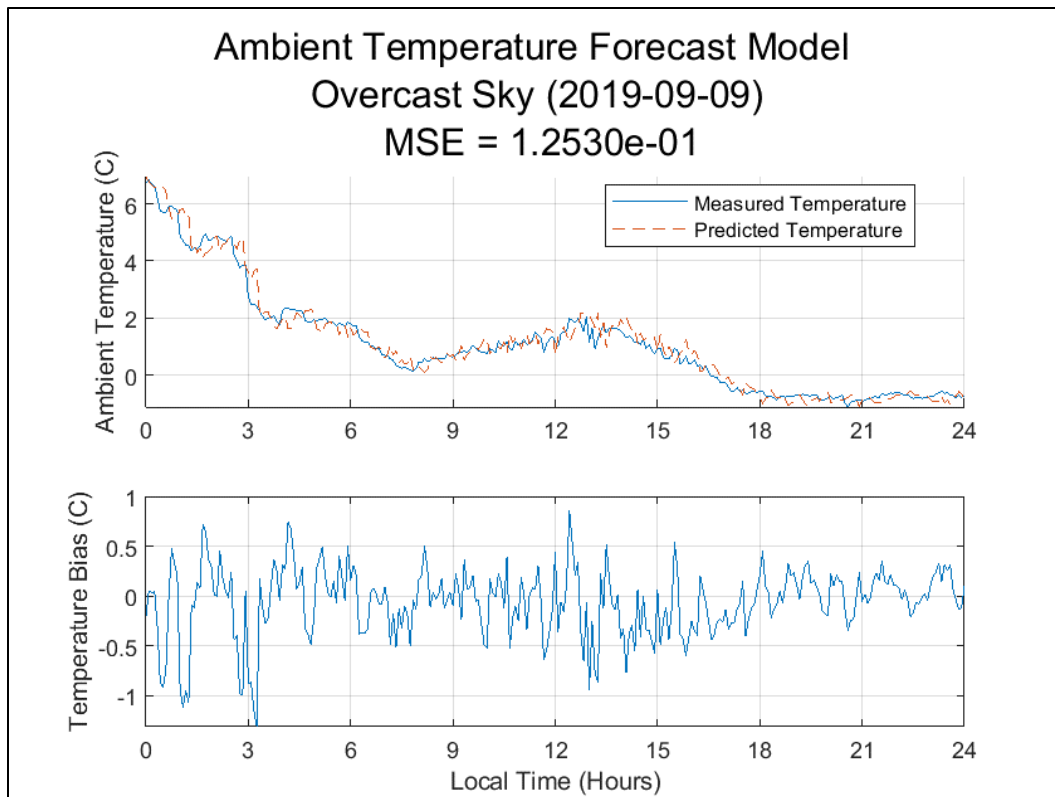


Fig. D-3 $T_p = 15$, $T_r = 20$ (Pattern 1) (continued)

$$T_p = 15$$

$$T_f = 40$$

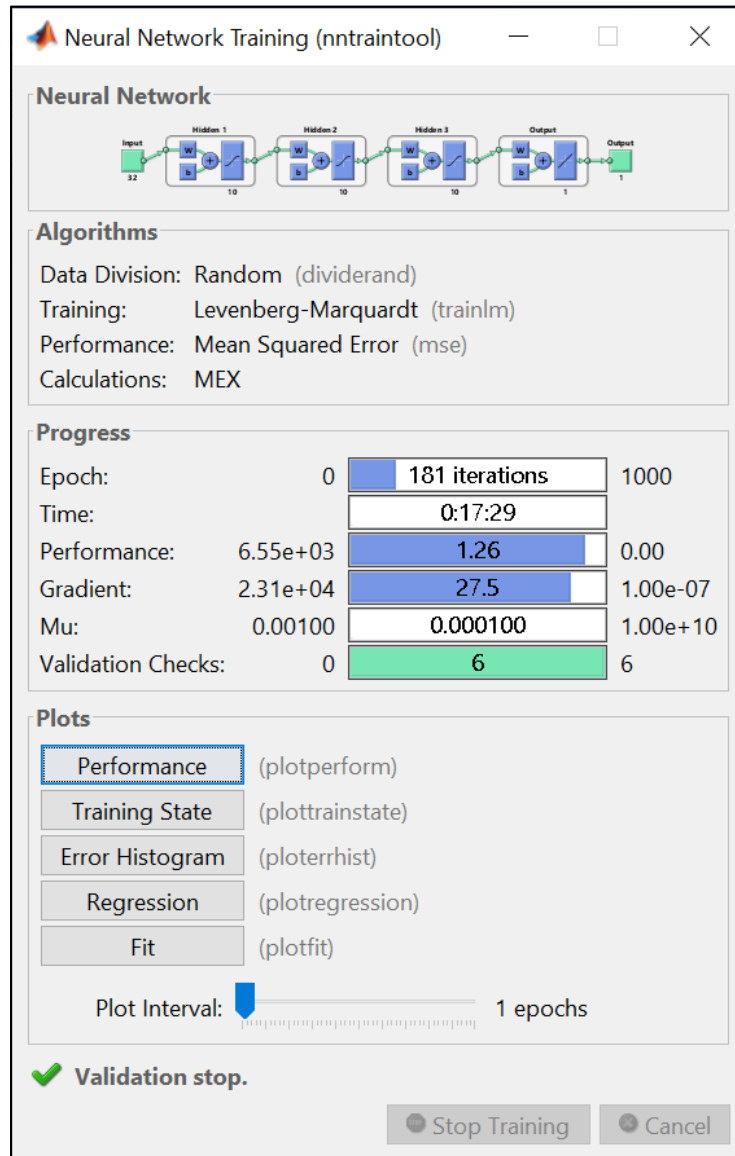


Fig. D-4 $T_p = 15$, $T_f = 40$ (Pattern 1)

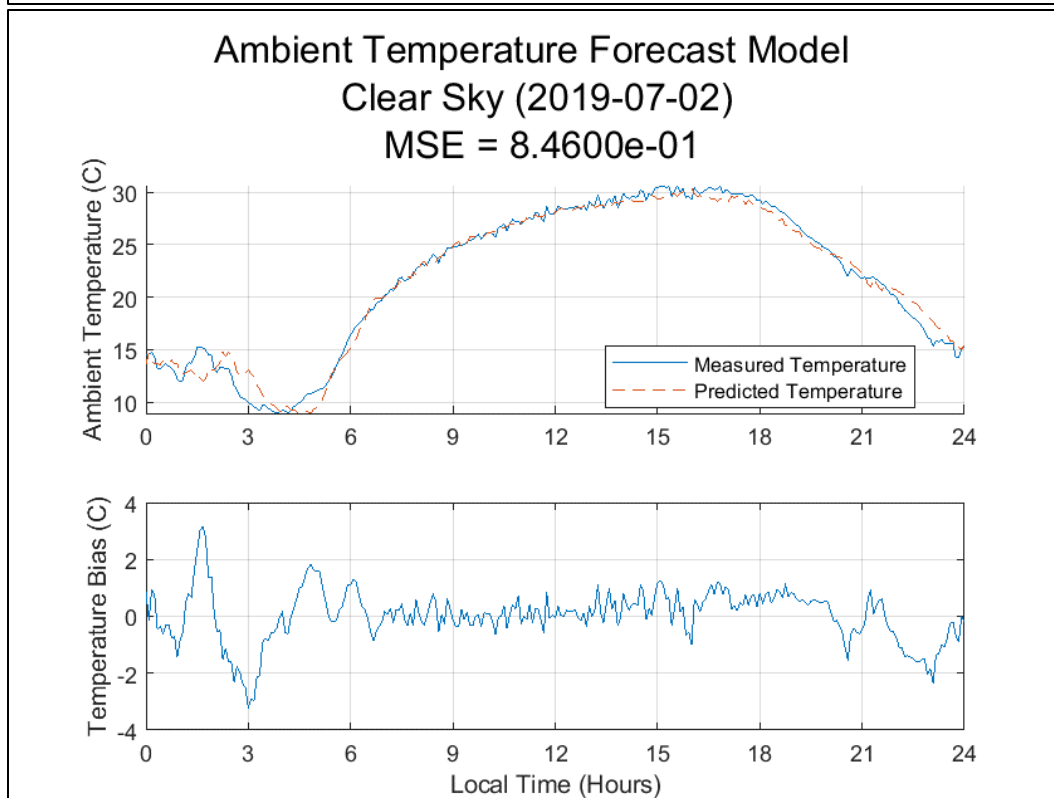
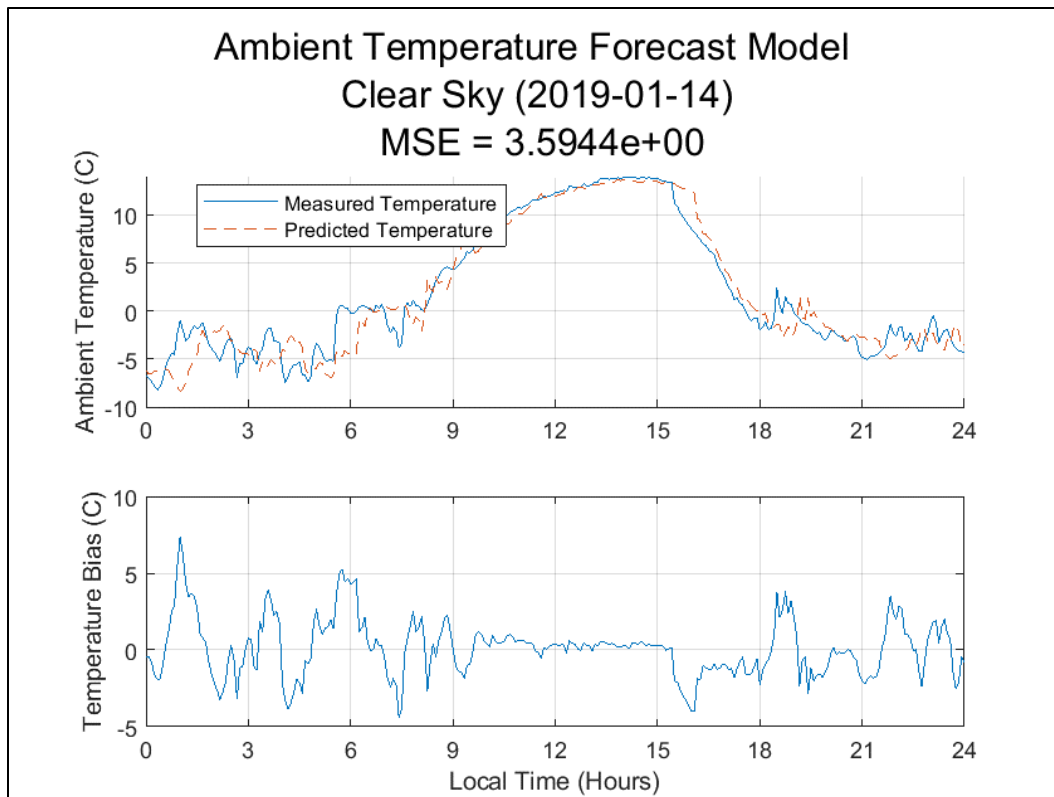


Fig. D-4 $T_p = 15$, $T_r = 40$ (Pattern 1) (continued)

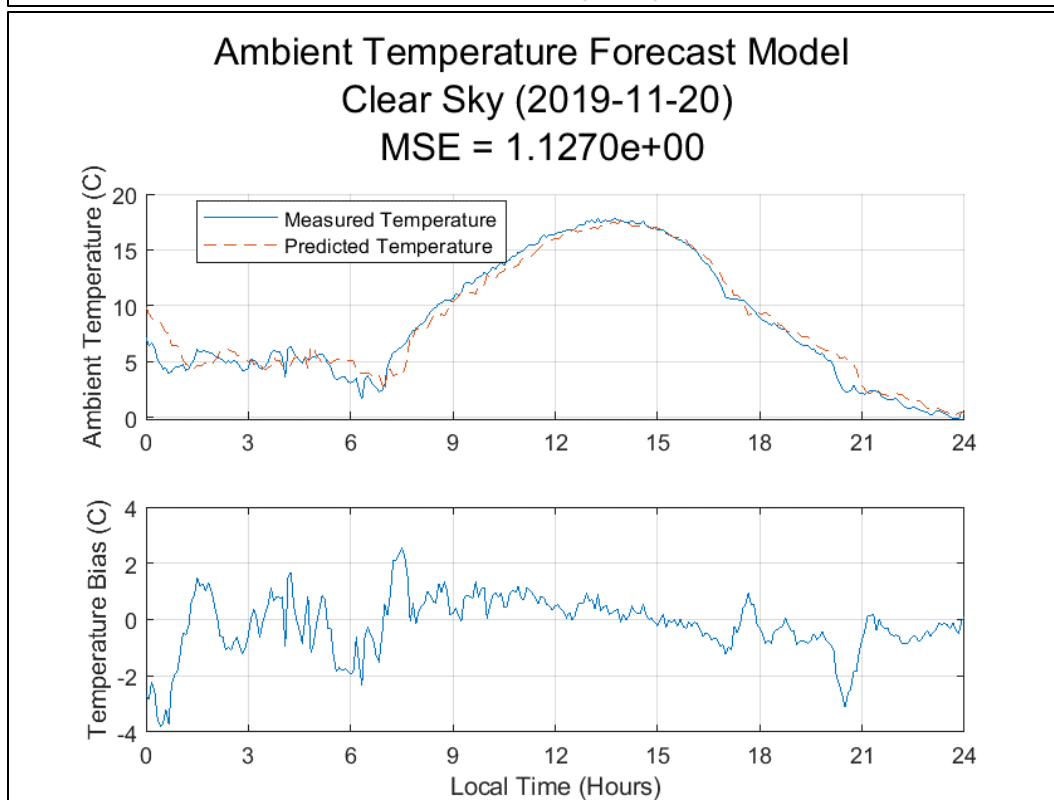
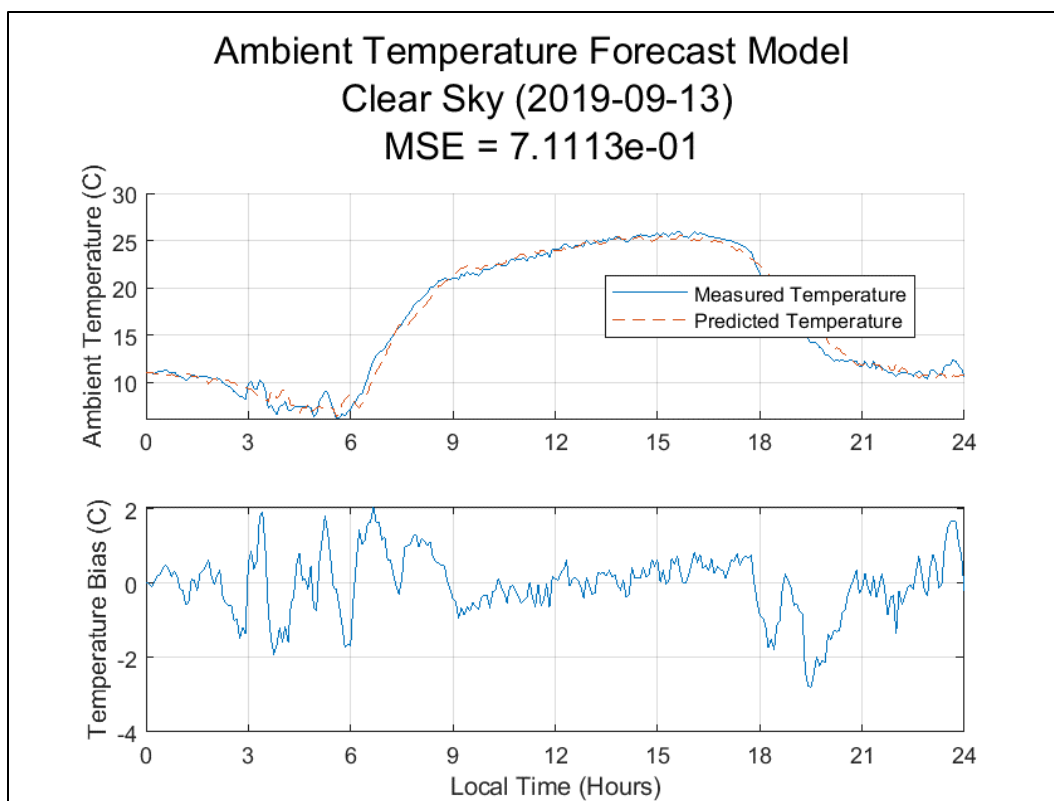


Fig. D-4 $T_p = 15$, $T_r = 40$ (Pattern 1) (continued)

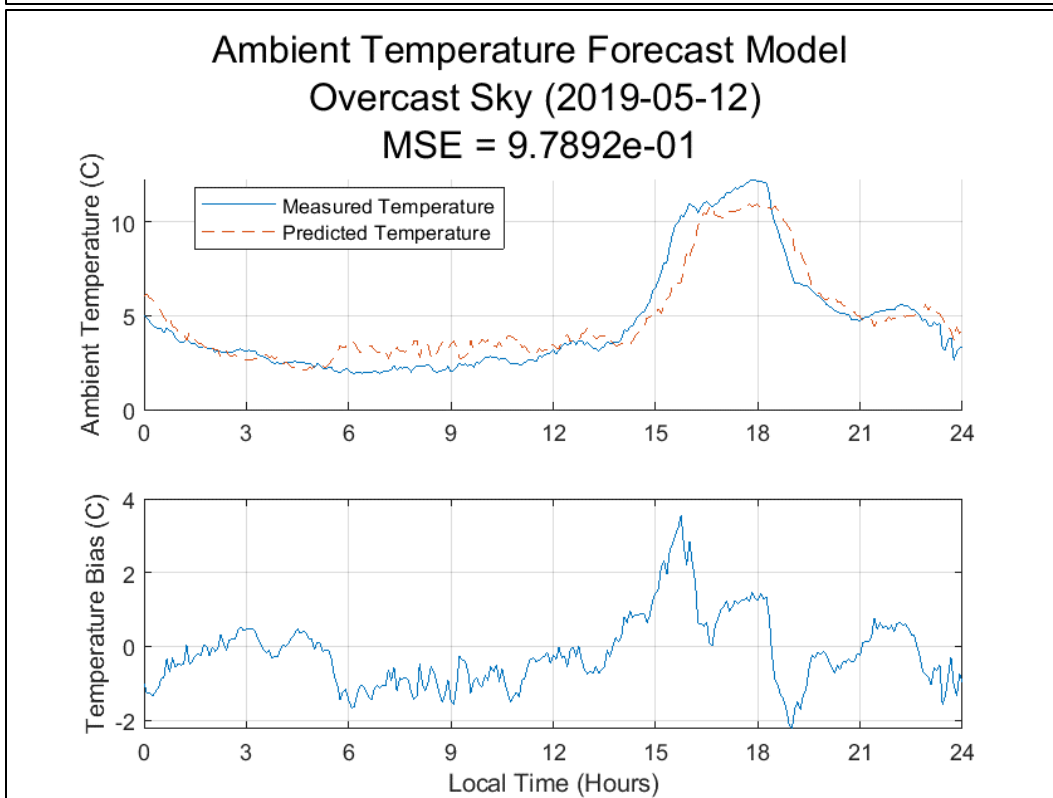
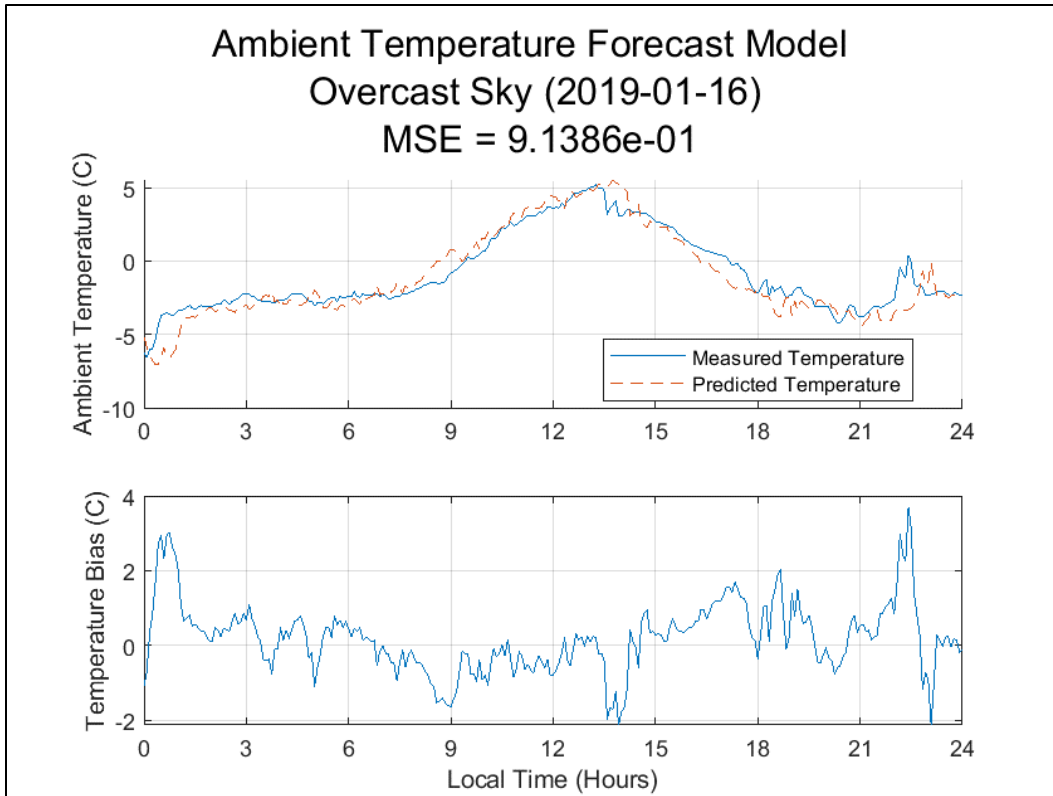


Fig. D-4 $T_p = 15$, $T_r = 40$ (Pattern 1) (continued)

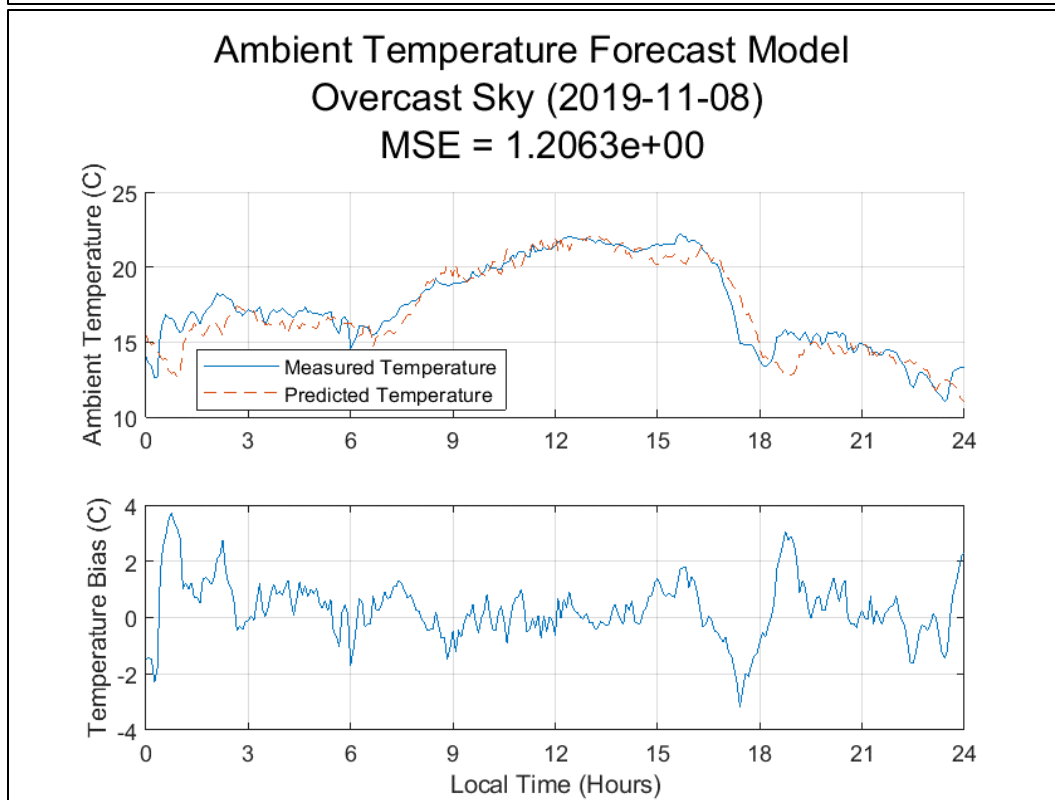
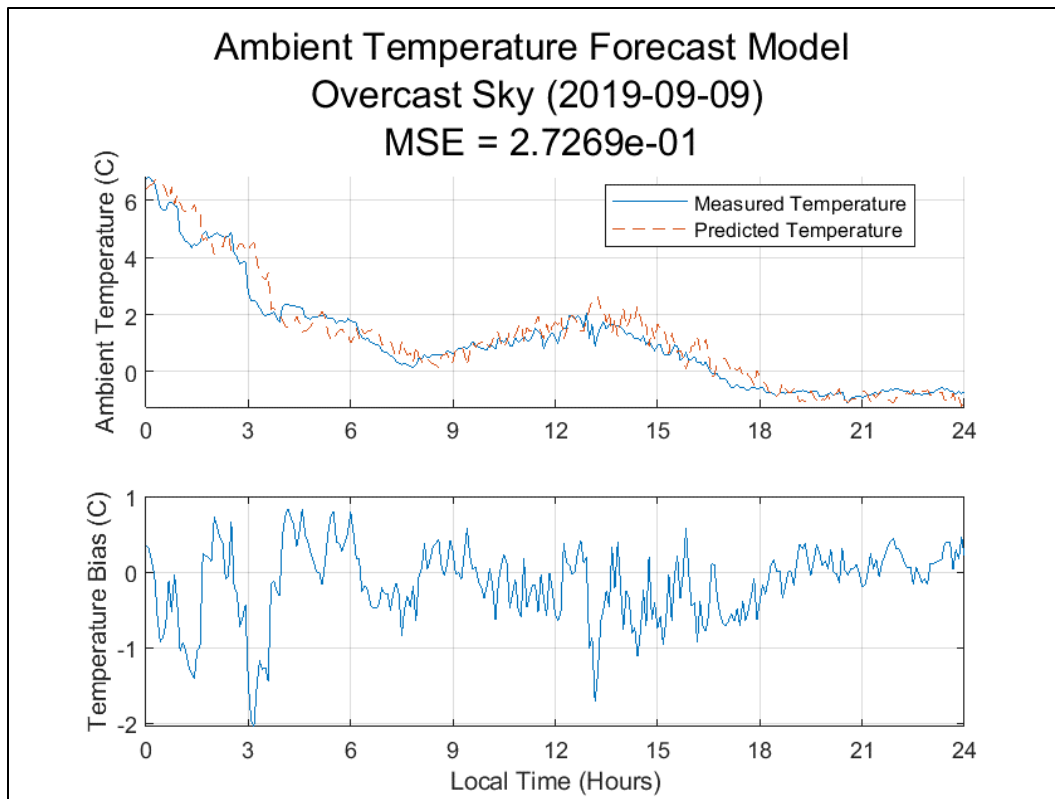


Fig. D-4 $T_p = 15$, $T_r = 40$ (Pattern 1) (continued)

$$T_p = 15$$

$$T_f = 80$$

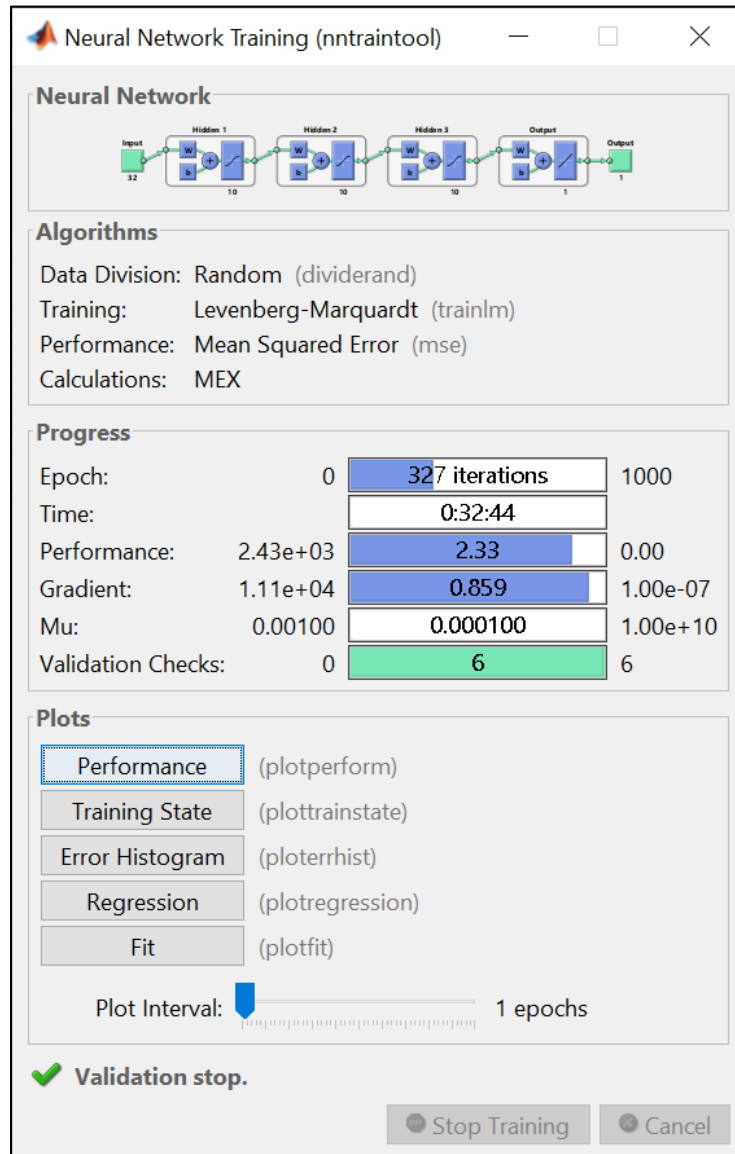


Fig. D-5 $T_p = 15$, $T_f = 80$ (Pattern 1)

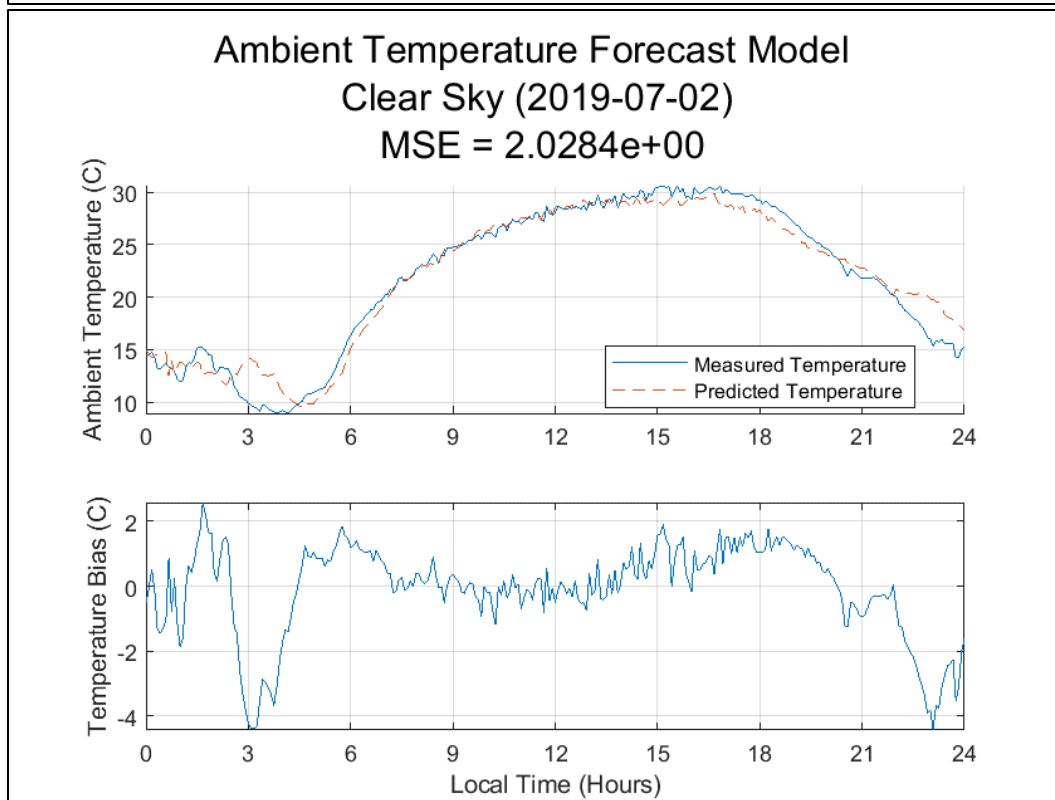
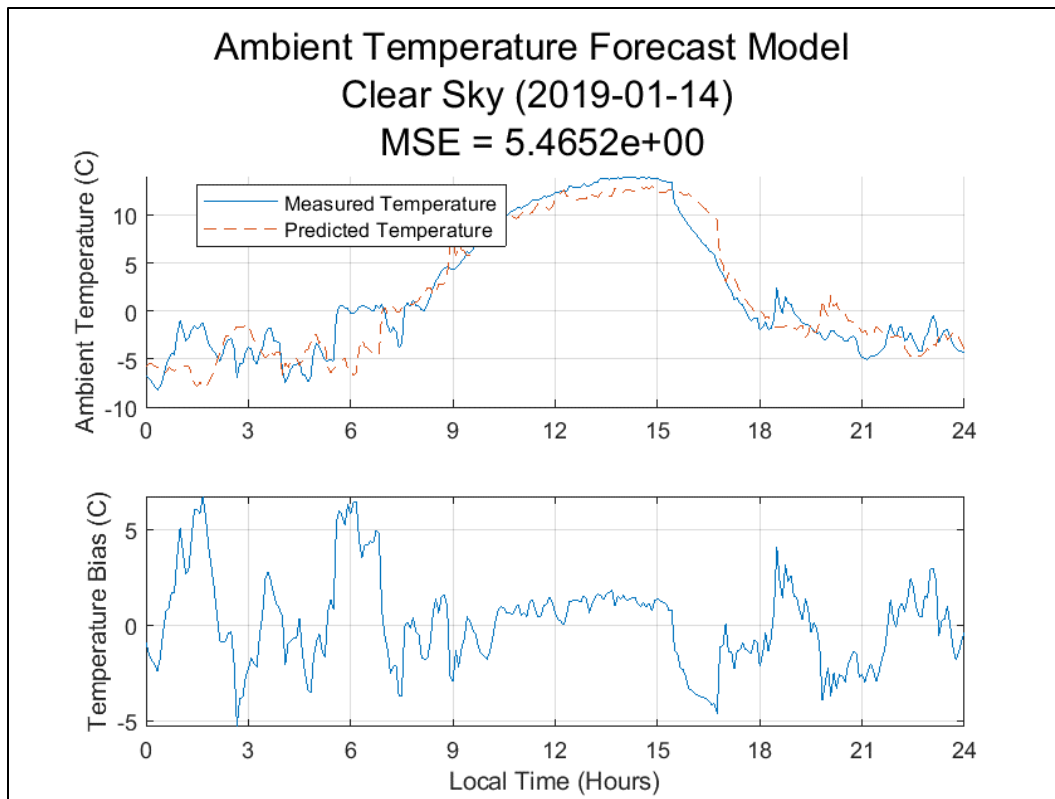


Fig. D-5 $T_p = 15$, $T_r = 80$ (Pattern 1) (continued)

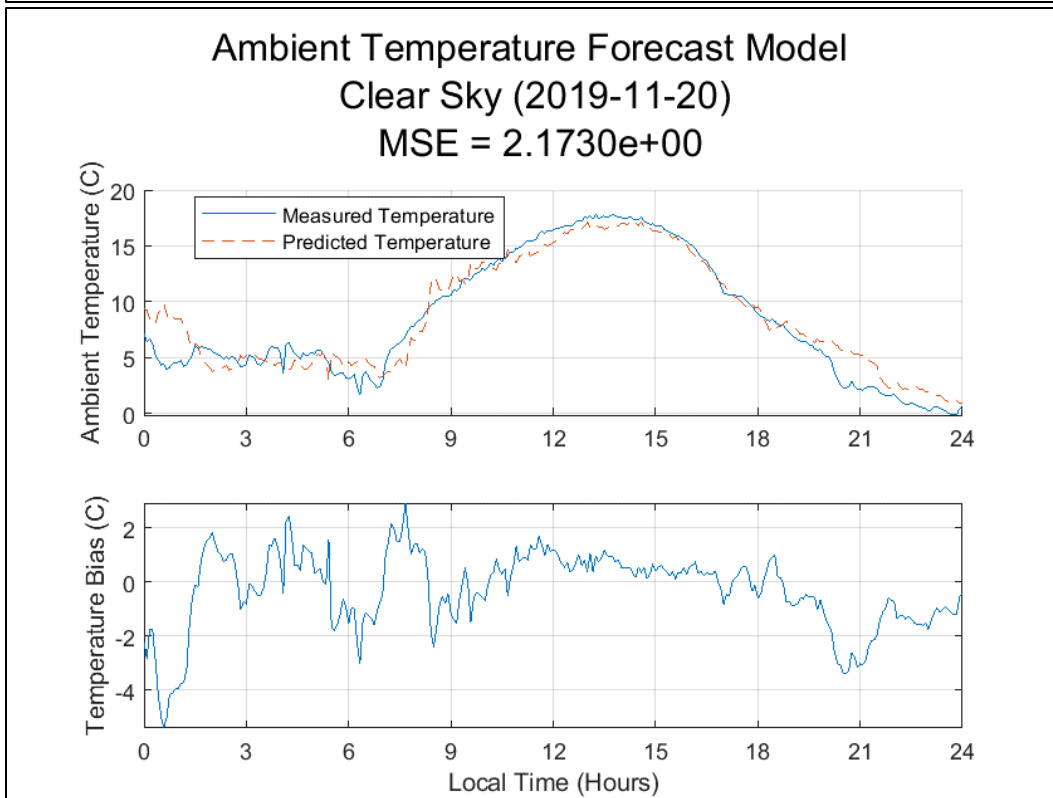
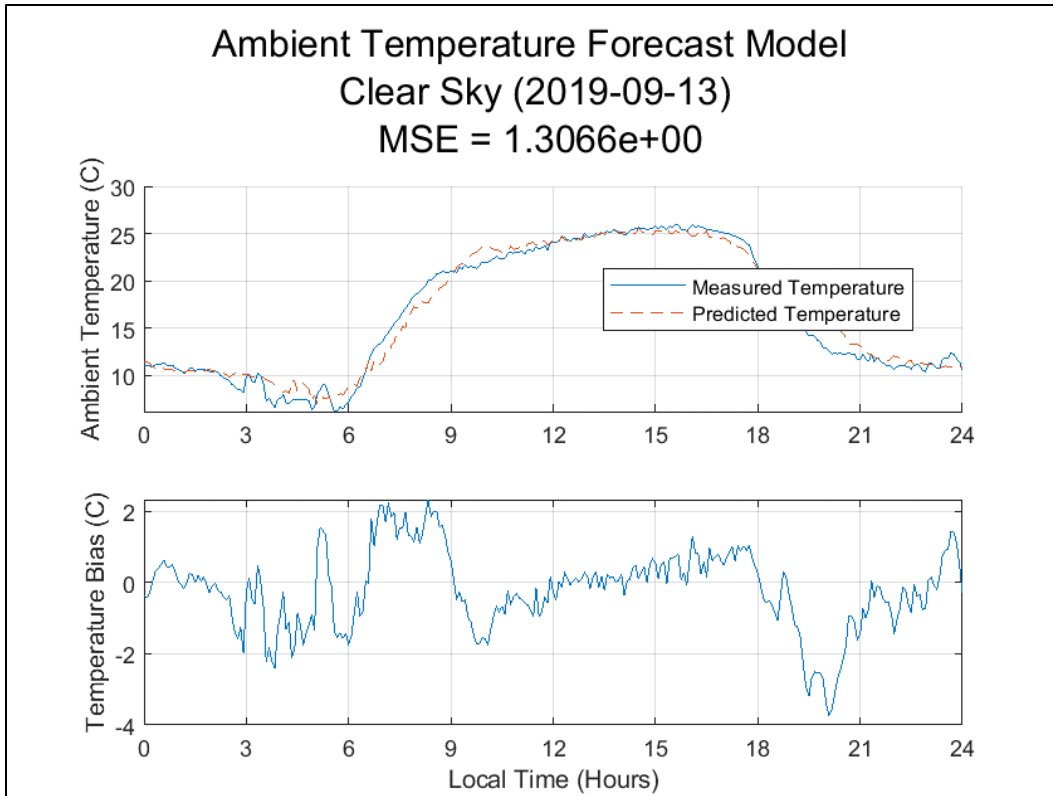


Fig. D-5 $T_p = 15$, $T_r = 80$ (Pattern 1) (continued)

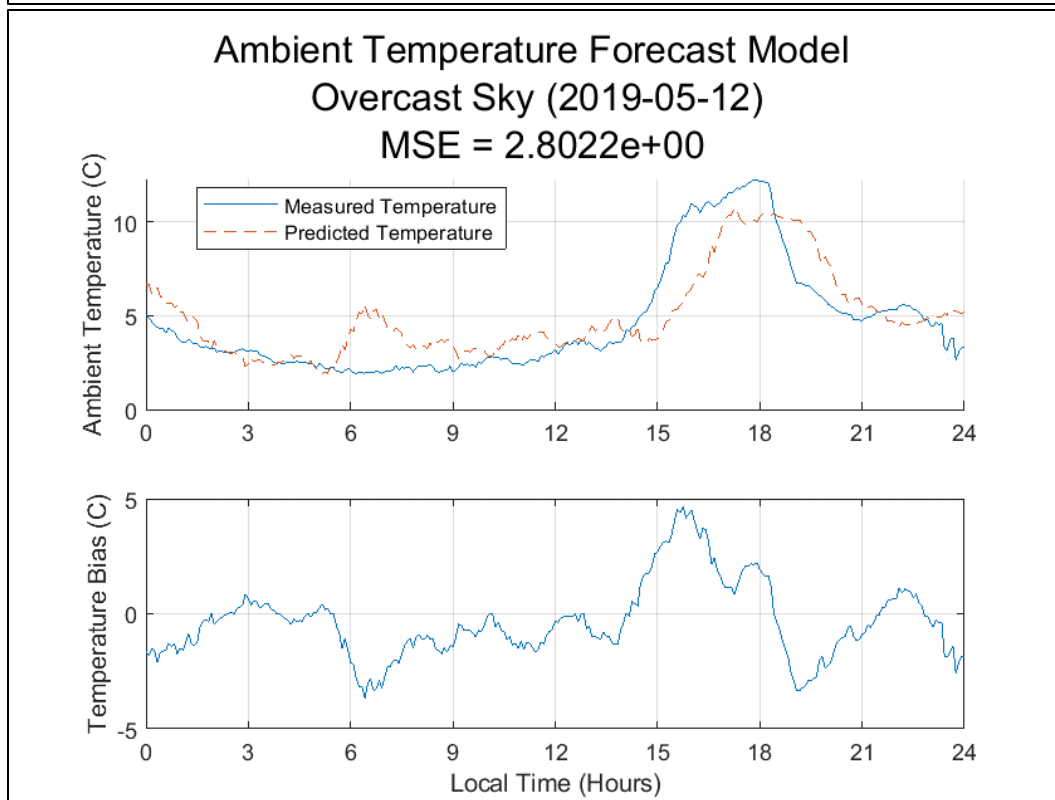
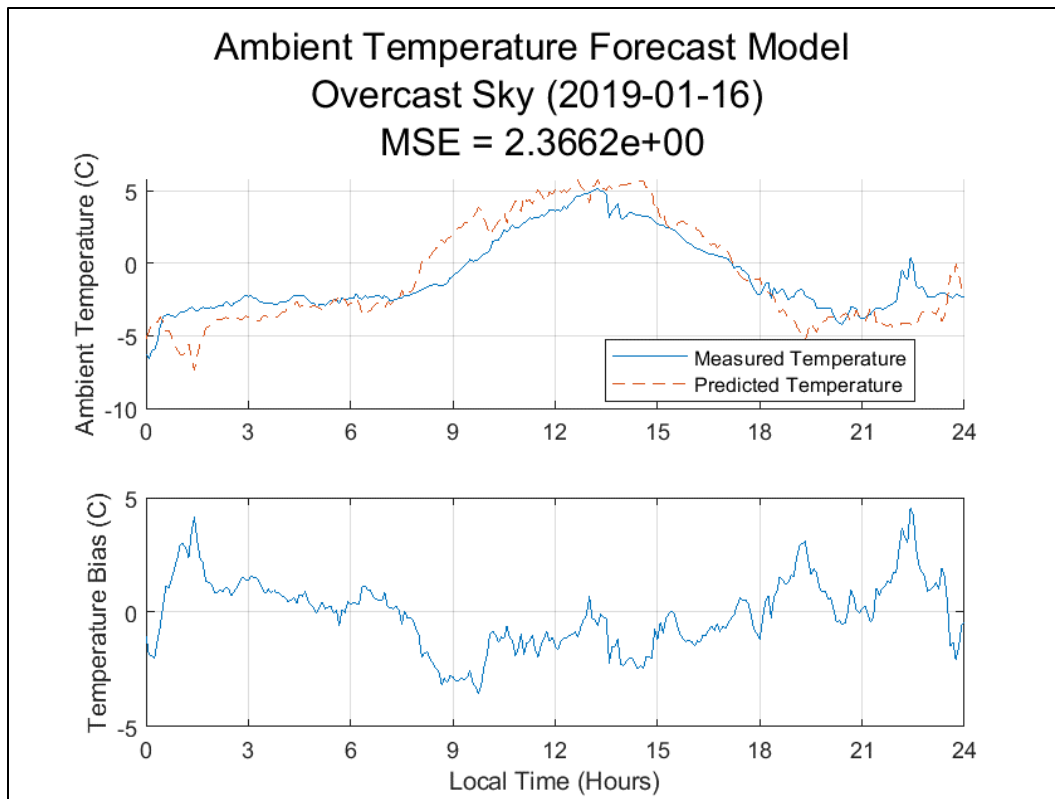


Fig. D-5 $T_p = 15$, $T_r = 80$ (Pattern 1) (continued)

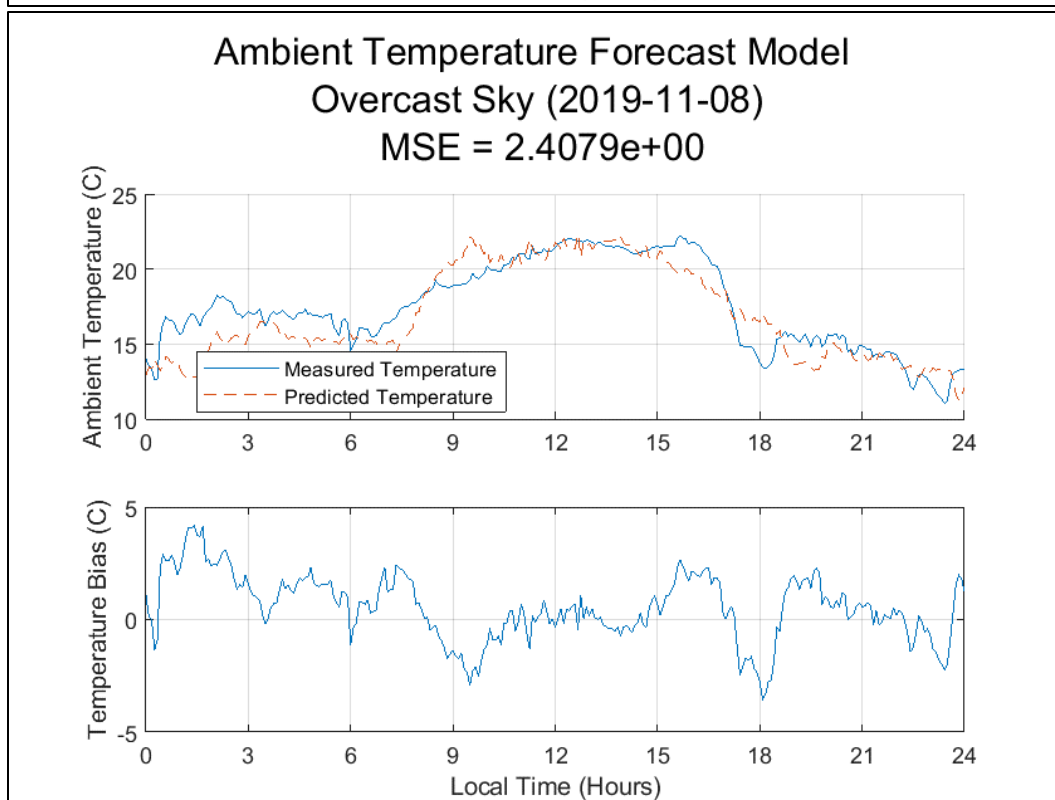
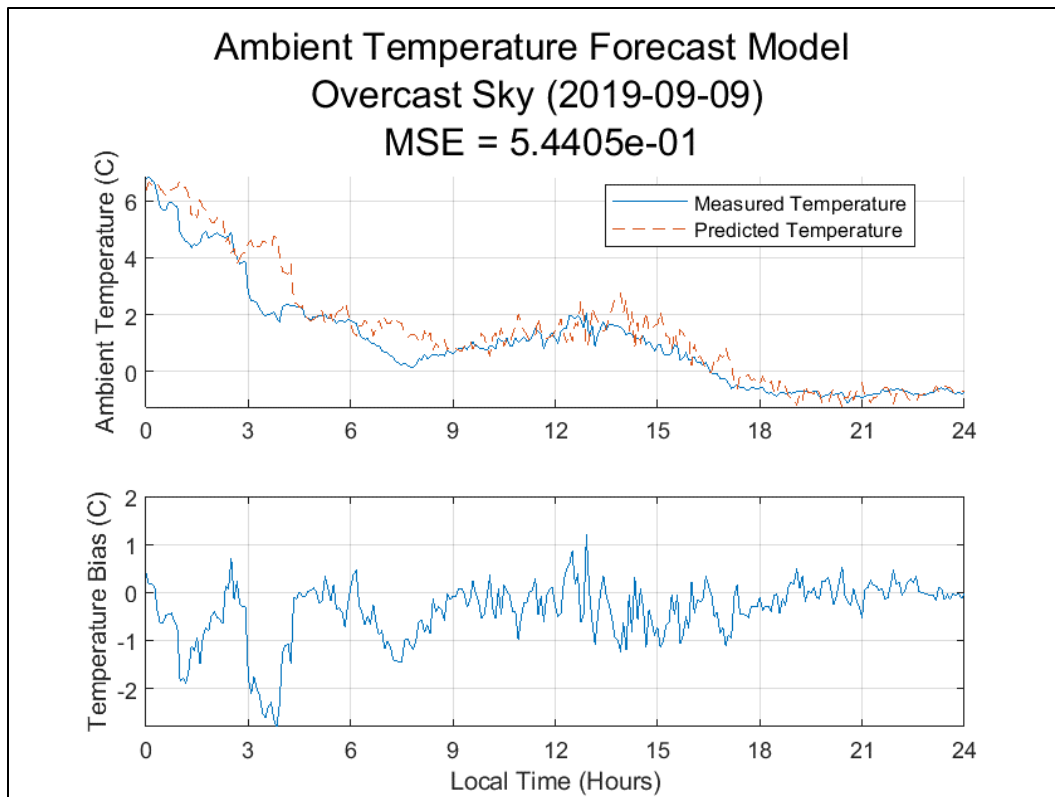


Fig. D-5 $T_p = 15$, $T_r = 80$ (Pattern 1) (continued)

$$T_p = 15$$

$$T_f = 160$$

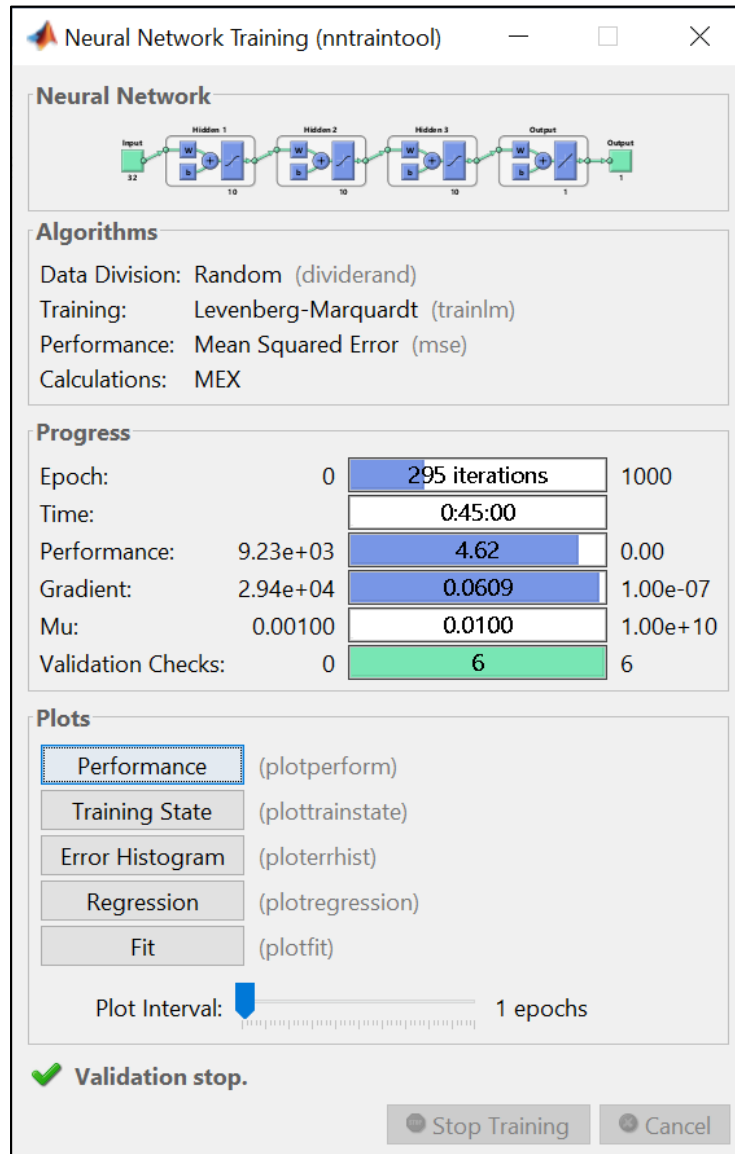


Fig. D-6 $T_p = 15$, $T_f = 160$ (Pattern 1)

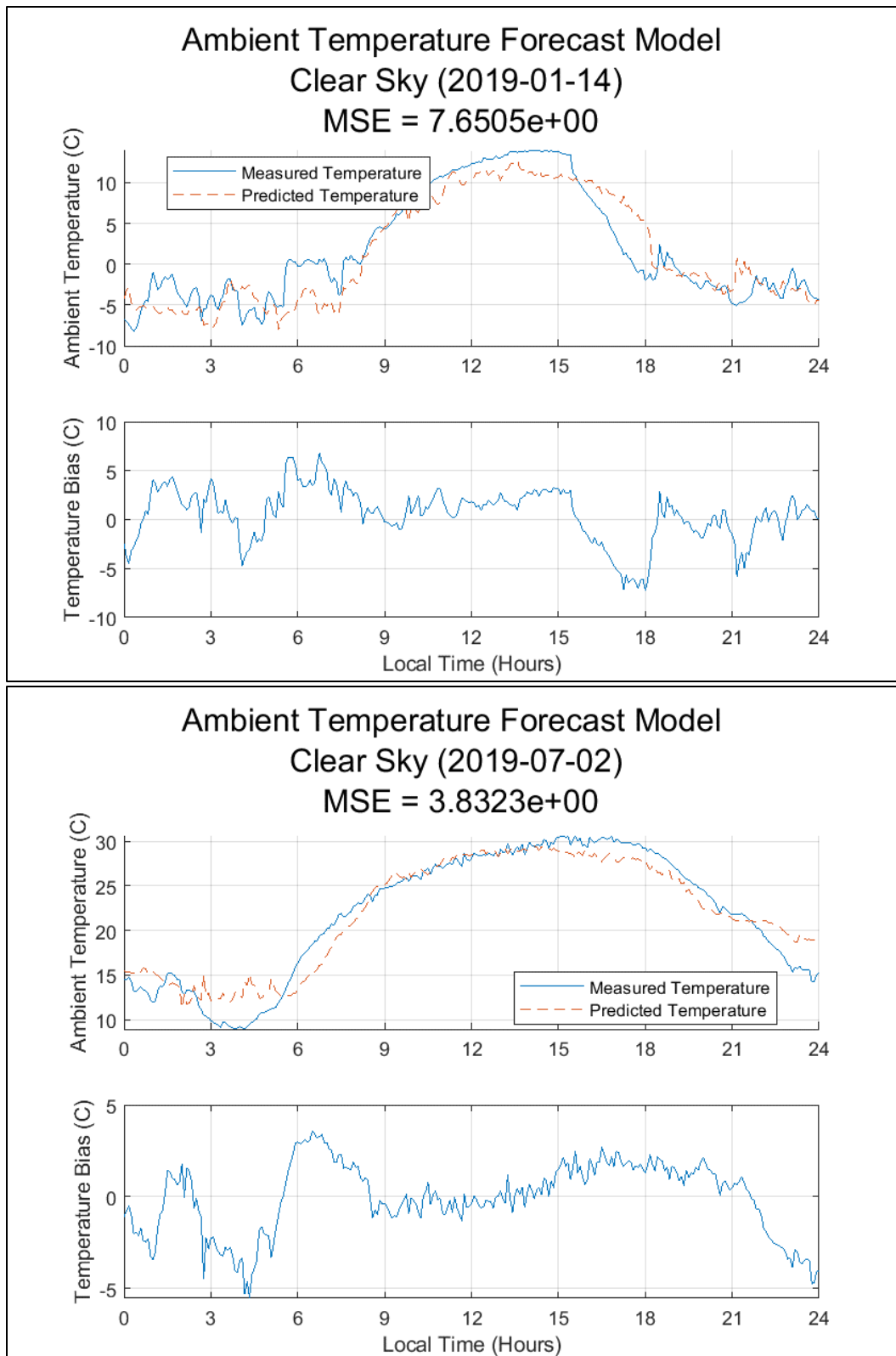


Fig. D-6 $T_p = 15$, $T_r = 160$ (Pattern 1) (continued)

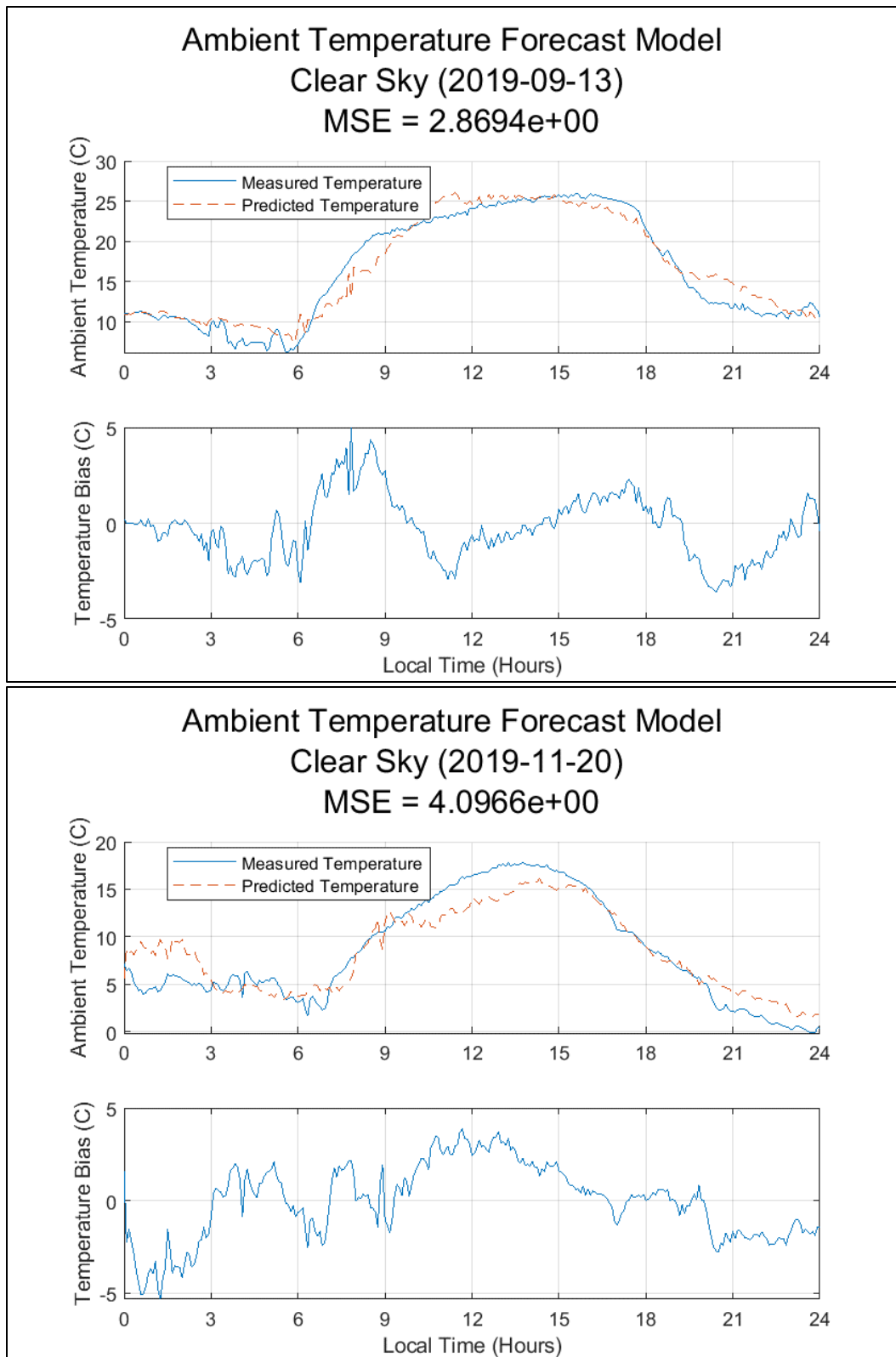


Fig. D-6 $T_p = 15$, $T_r = 160$ (Pattern 1) (continued)

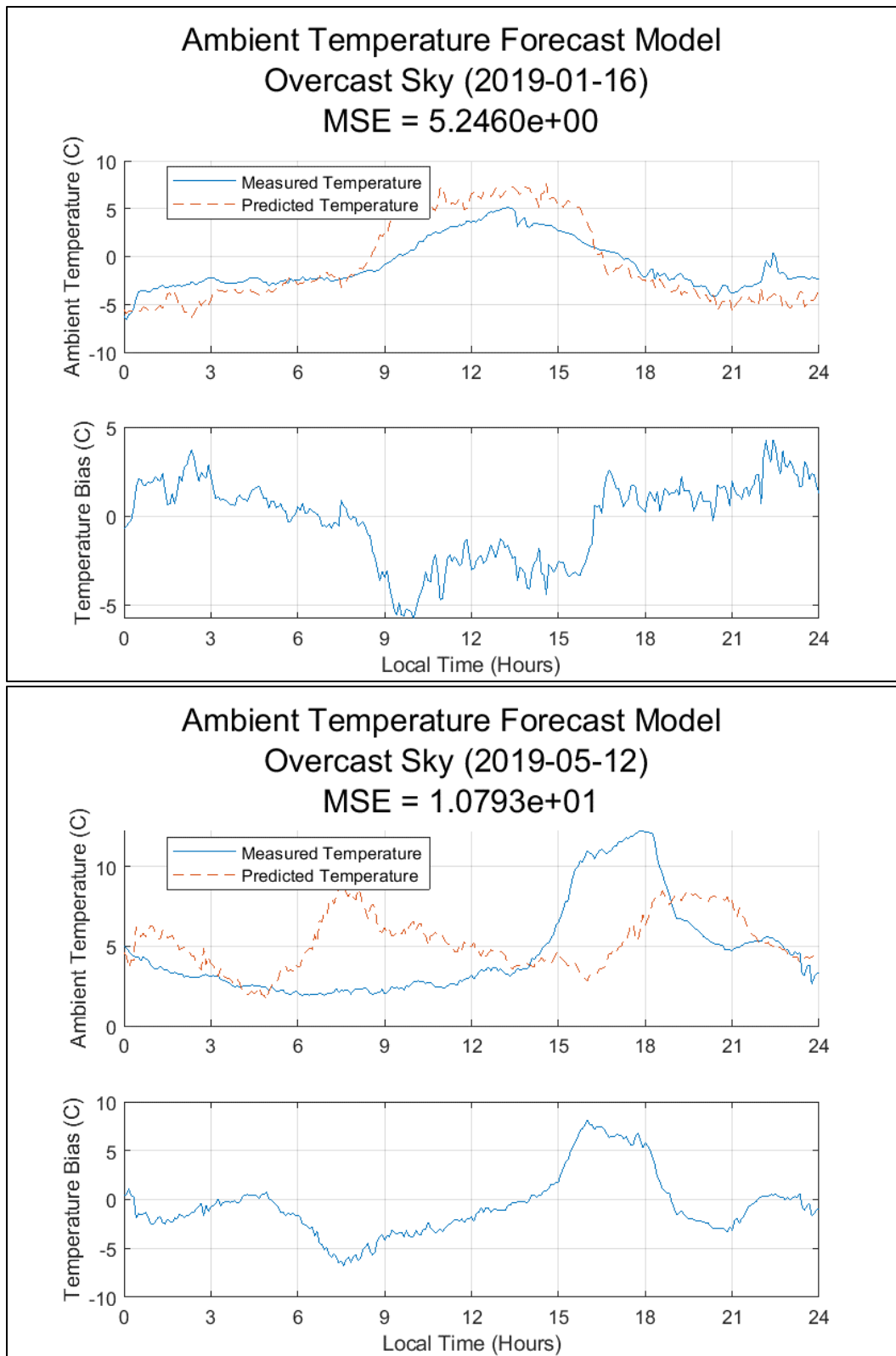


Fig. D-6 $T_p = 15$, $T_r = 160$ (Pattern 1) (continued)

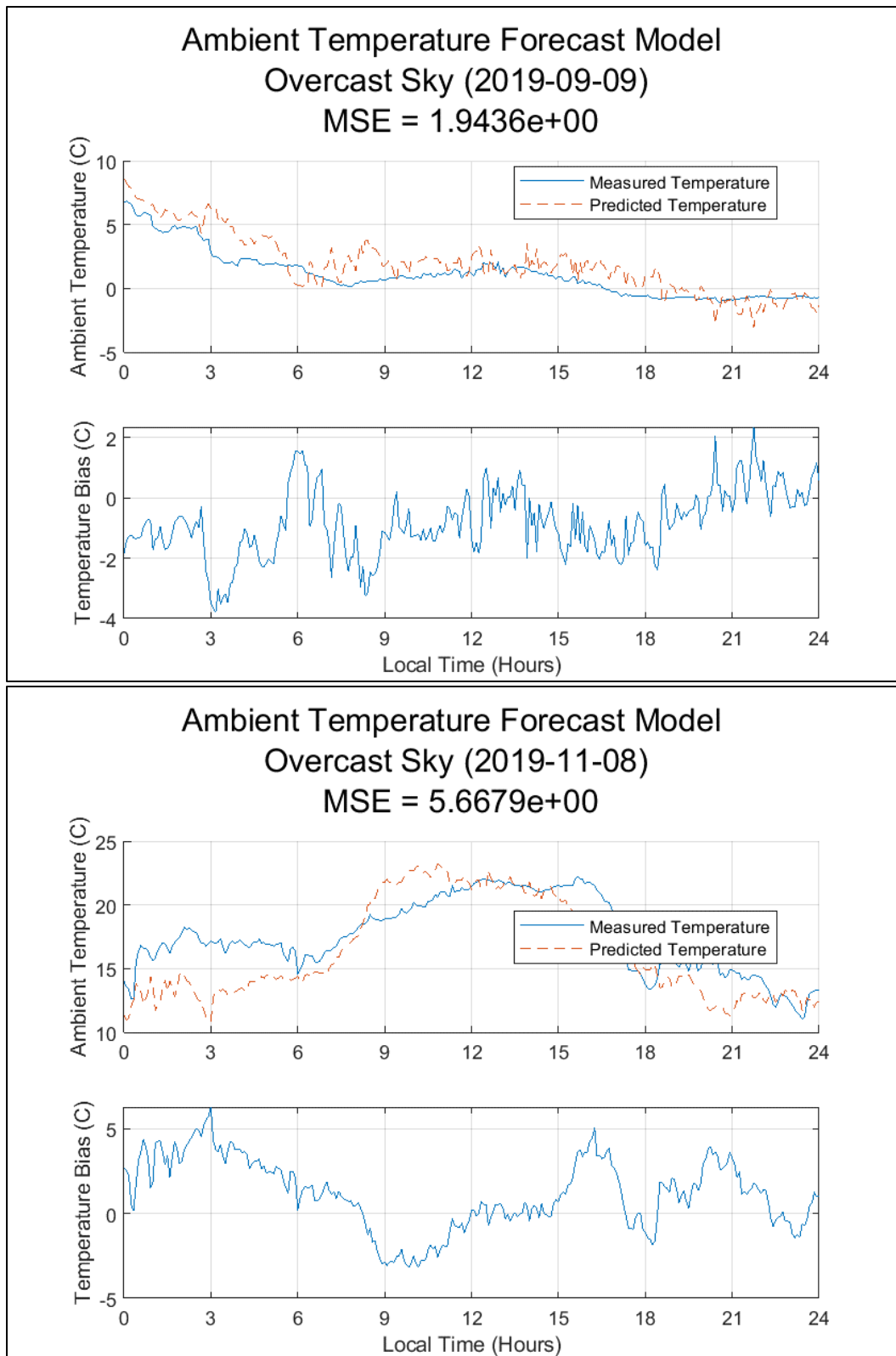


Fig. D-6 $T_p = 15$, $T_r = 160$ (Pattern 1) (continued)

$$T_p = 30$$

$$T_f = 5$$

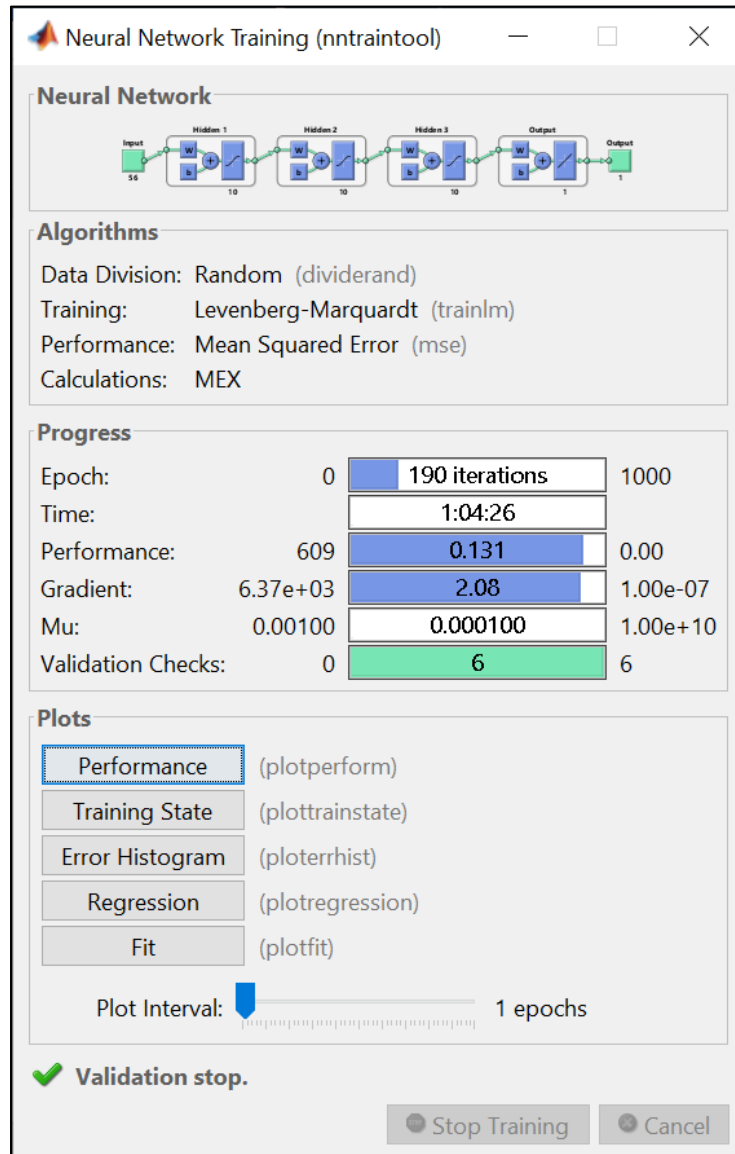


Fig. D-7 $T_p = 30$, $T_f = 5$ (Pattern 2)

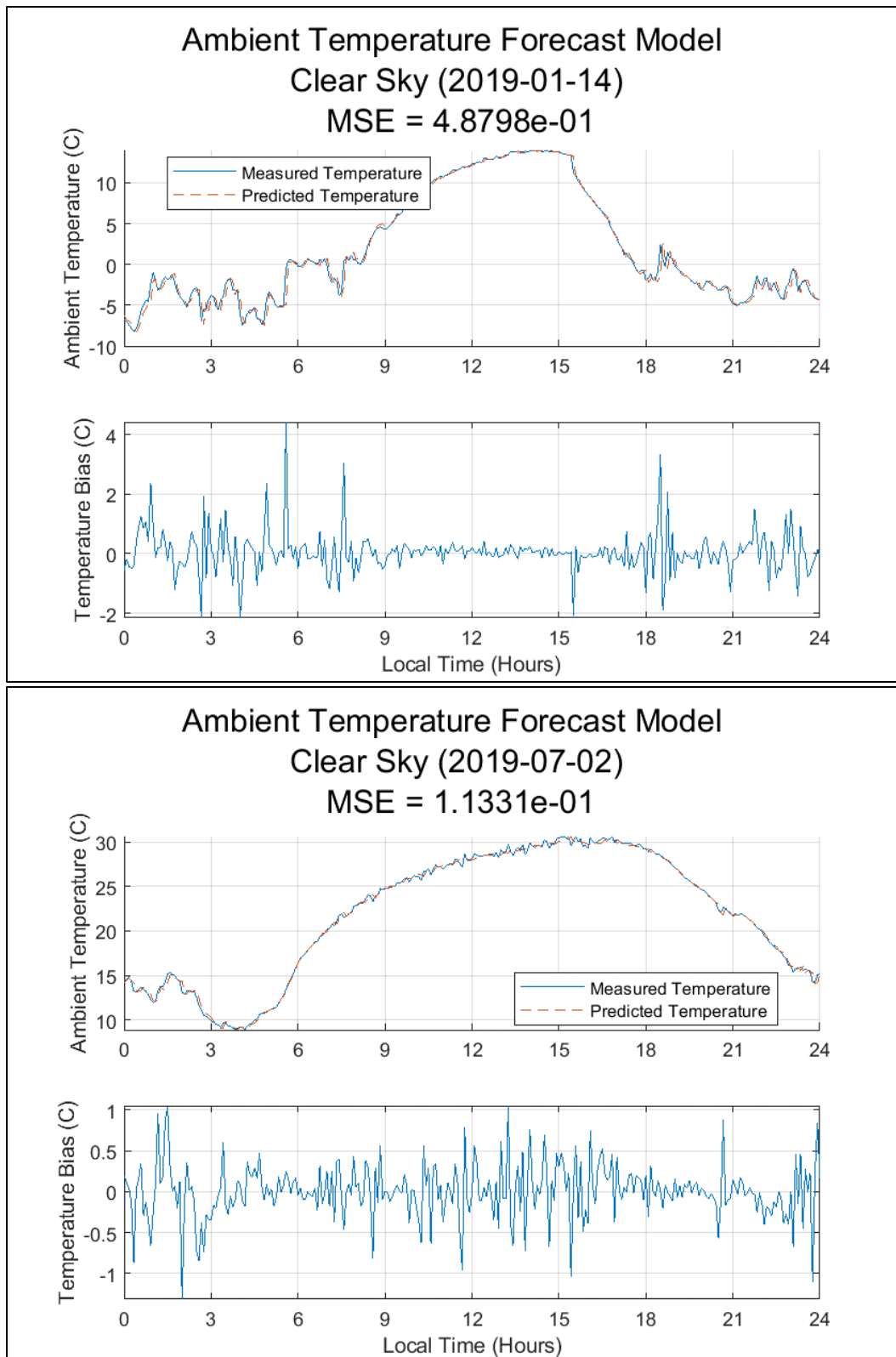


Fig. D-7 $T_p = 30$, $T_r = 5$ (Pattern 2) (continued)

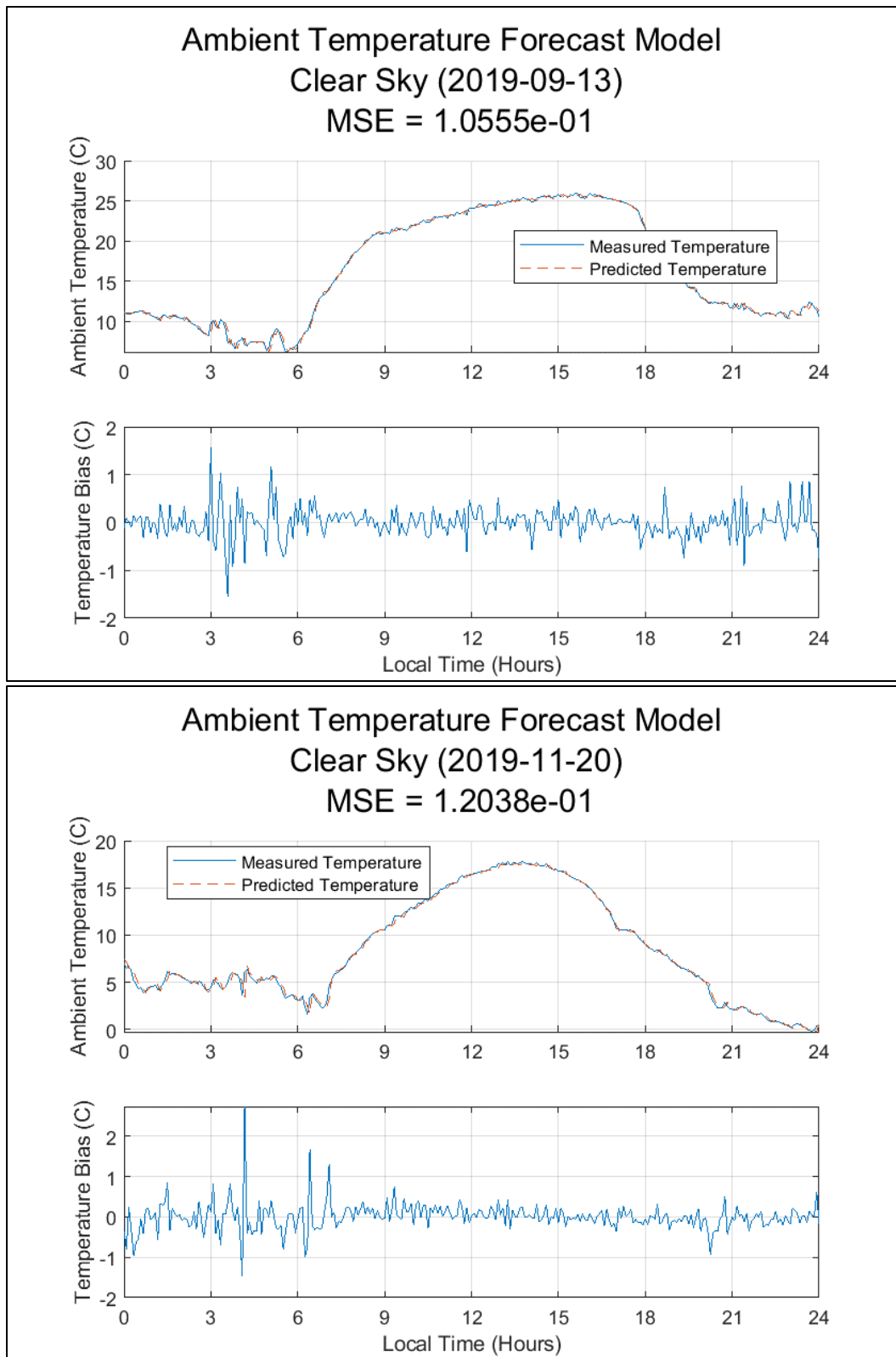


Fig. D-7 $T_p = 30$, $T_r = 5$ (Pattern 2) (continued)

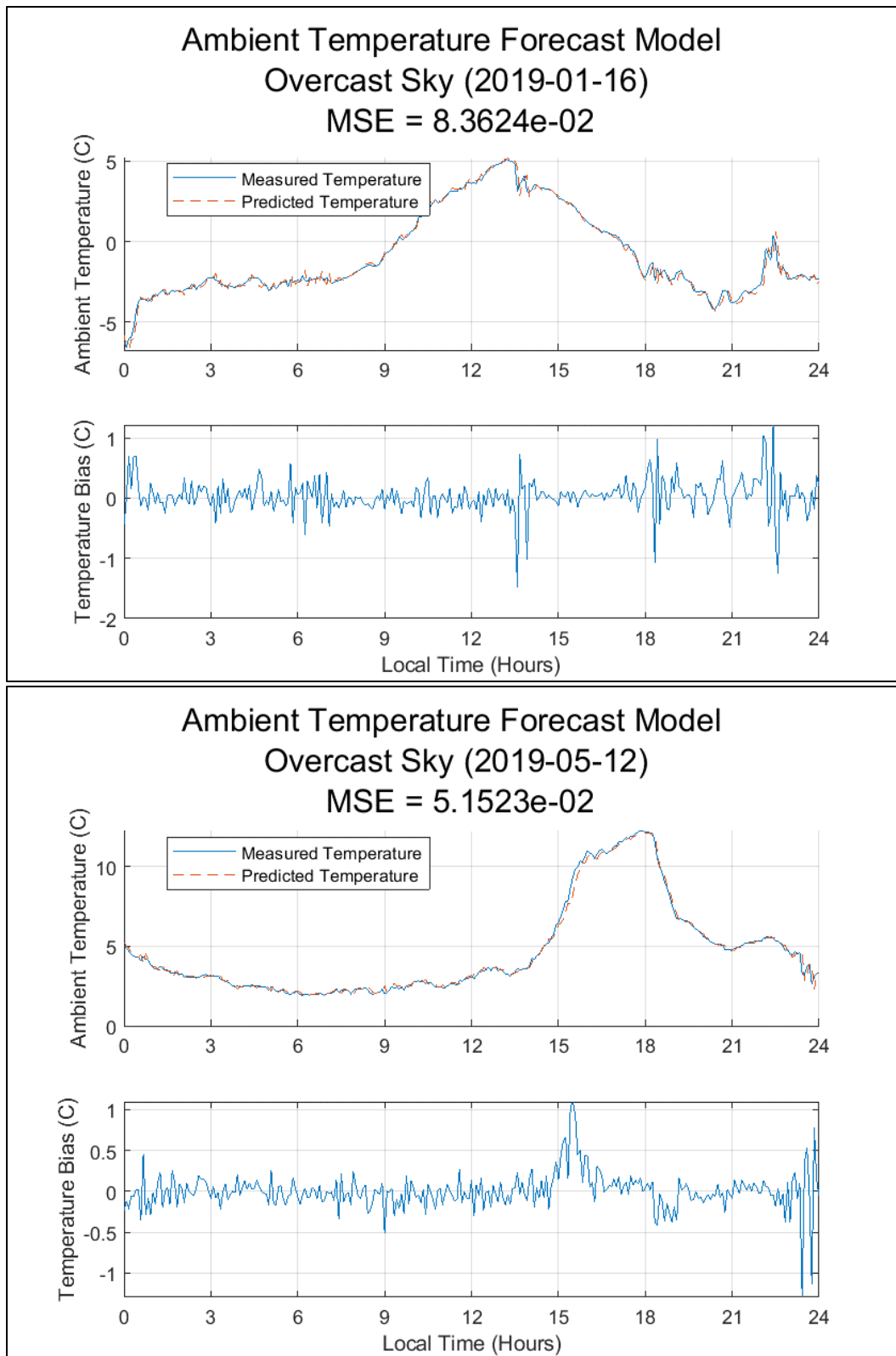


Fig. D-7 $T_p = 30$, $T_r = 5$ (Pattern 2) (continued)

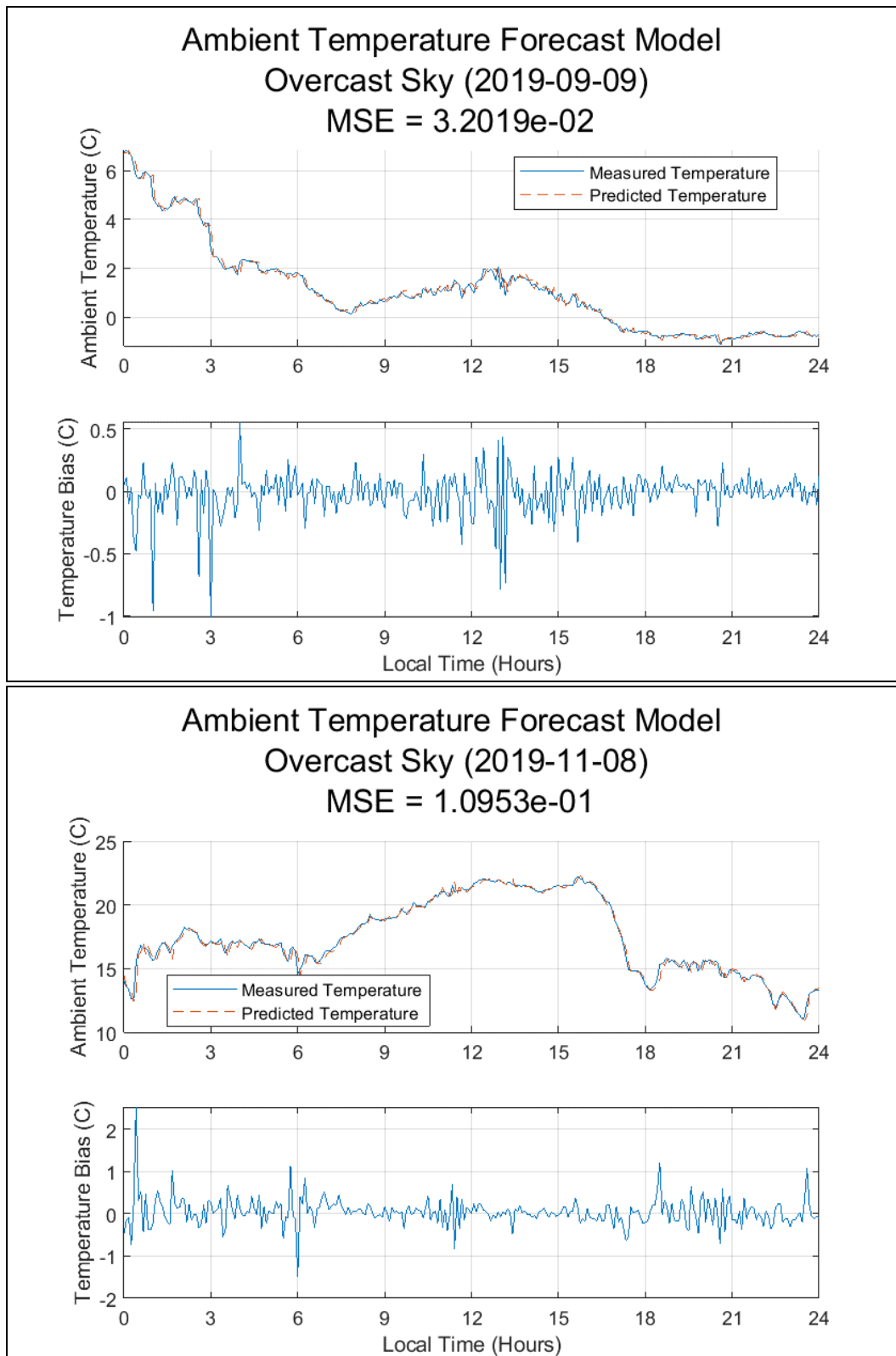


Fig. D-7 $T_p = 30$, $T_r = 5$ (Pattern 2) (continued)

$$T_p = 30$$

$$T_f = 10$$

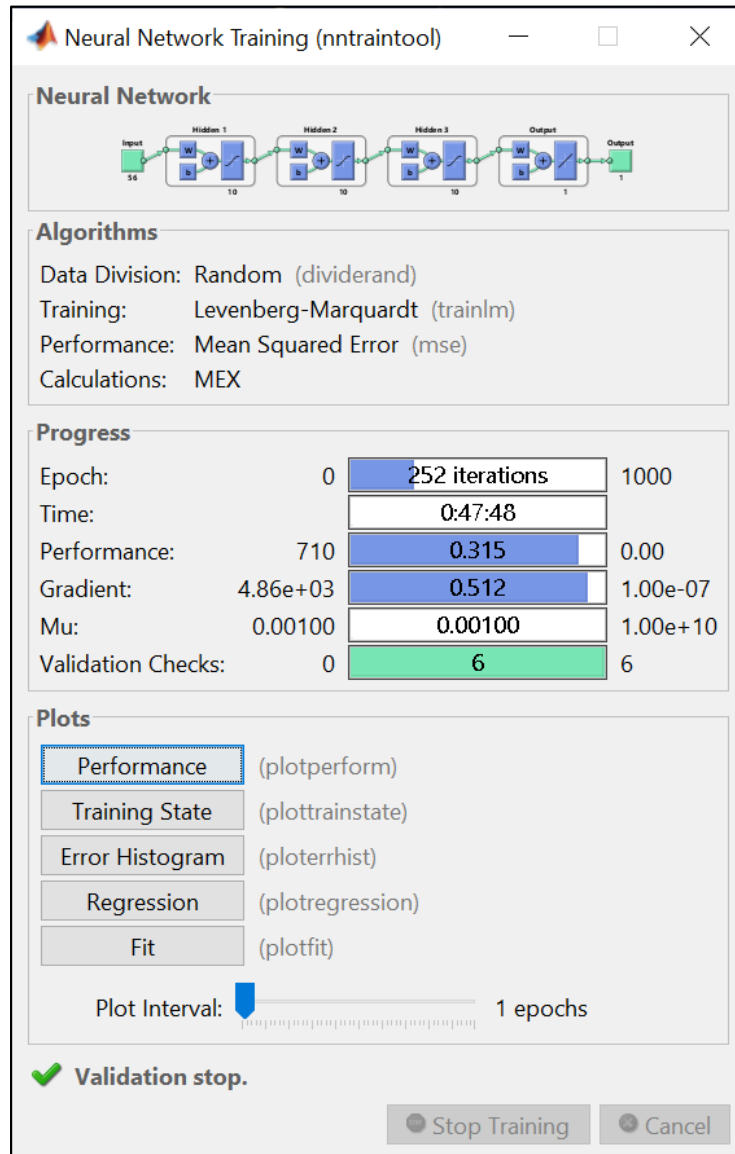


Fig. D-8 $T_p = 30$, $T_f = 10$ (Pattern 2)

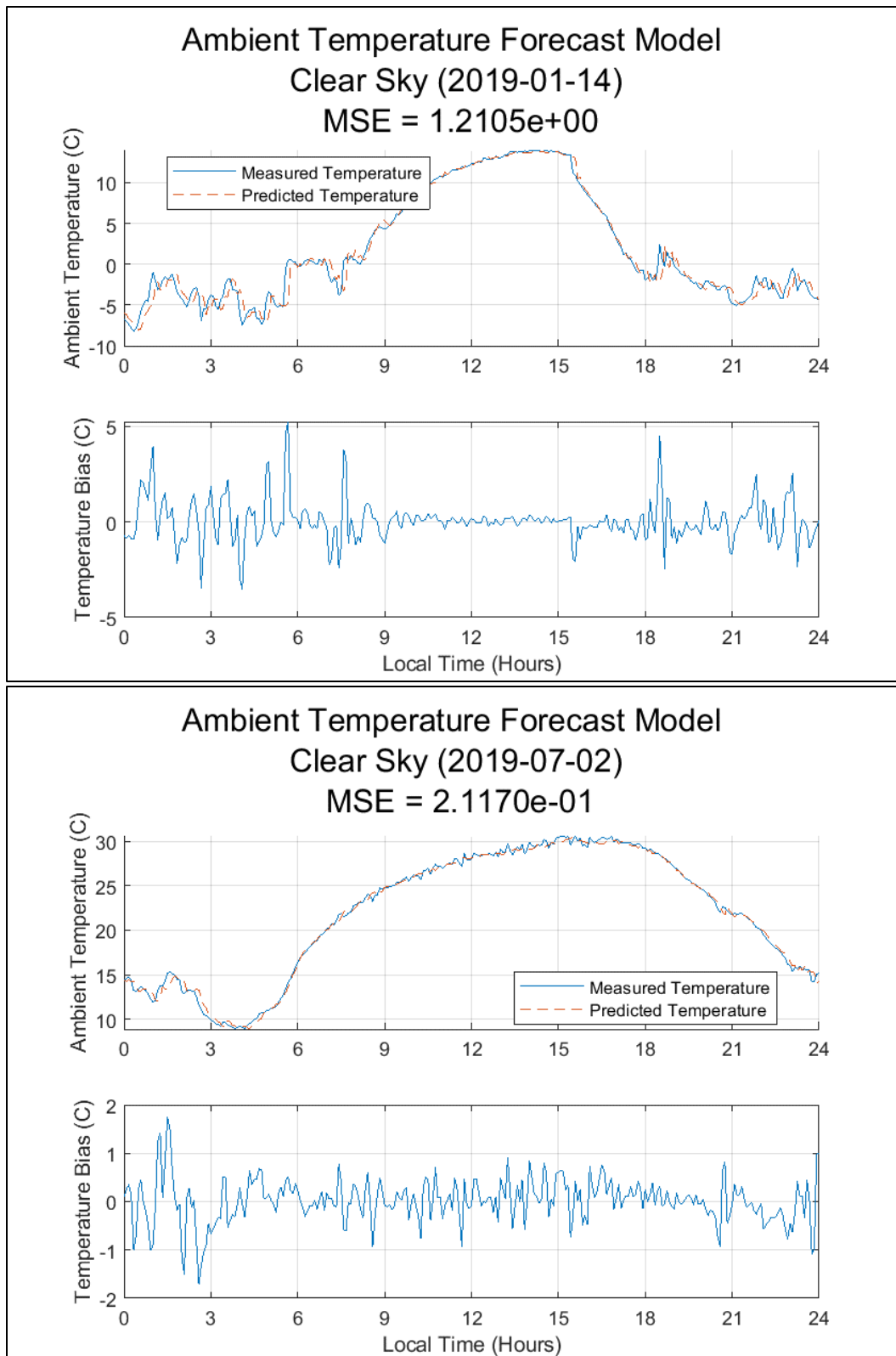


Fig. D-8 $T_p = 30$, $T_r = 10$ (Pattern 2) (continued)

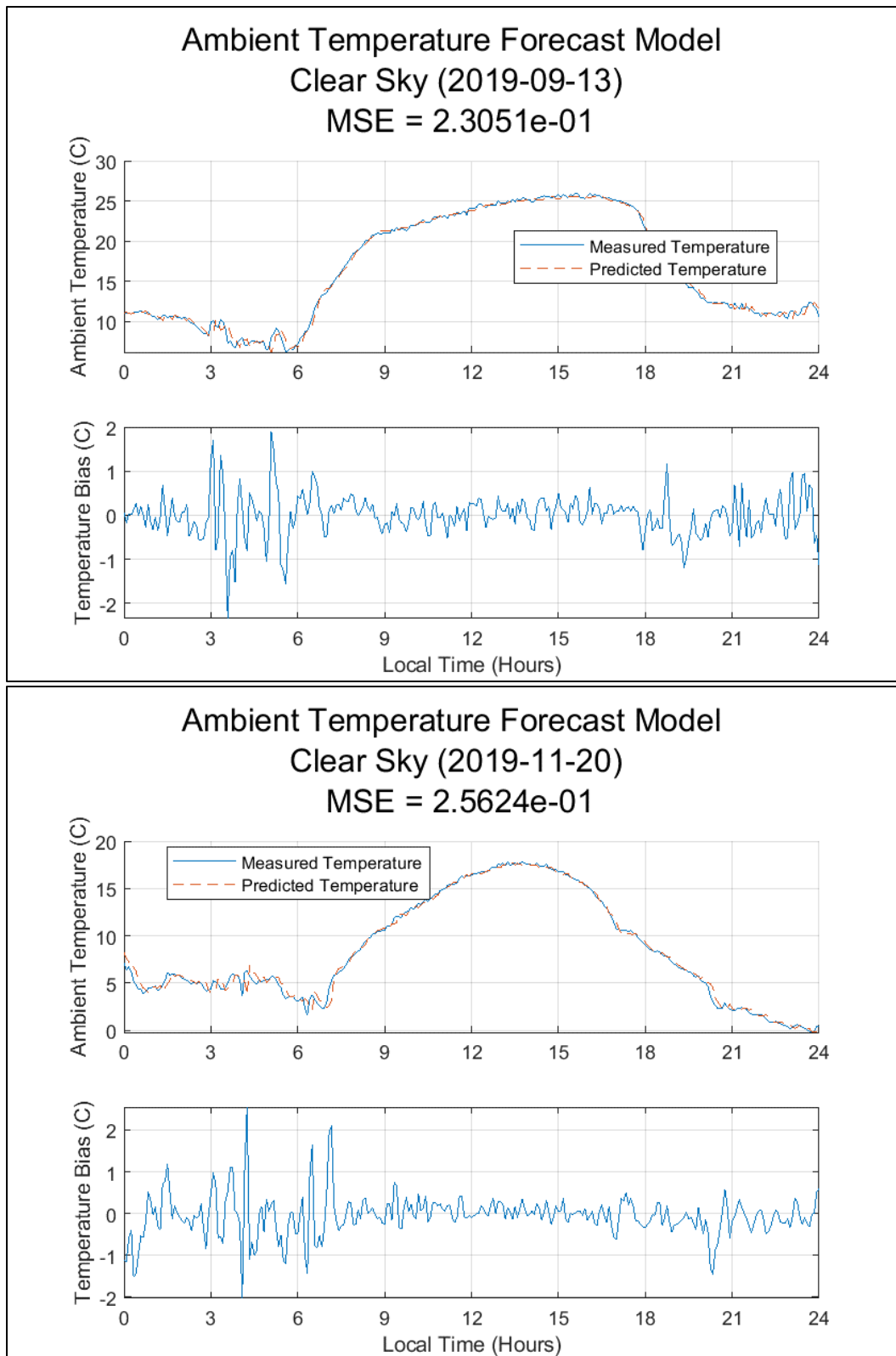


Fig. D-8 $T_p = 30$, $T_r = 10$ (Pattern 2) (continued)

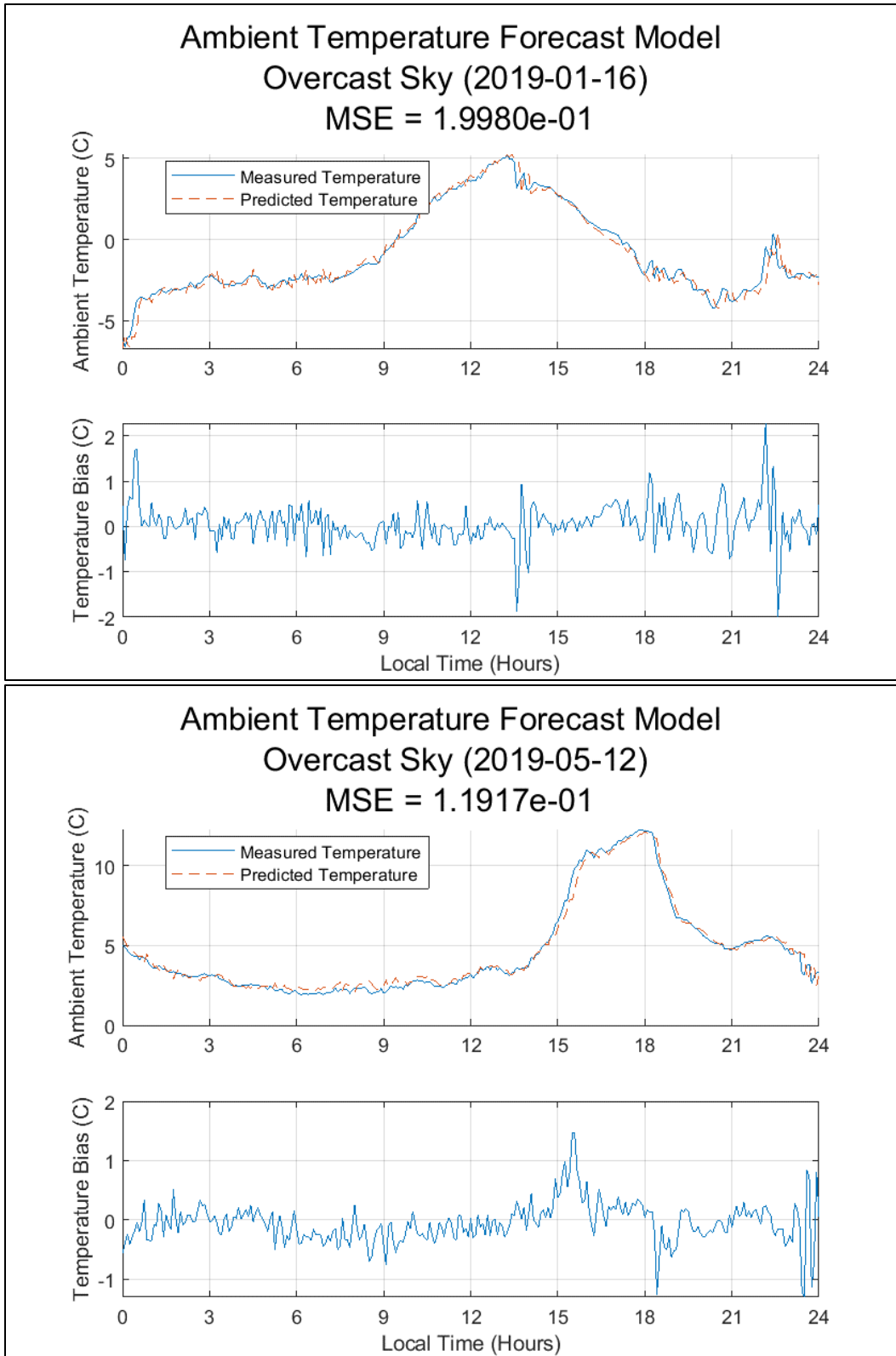


Fig. D-8 $T_p = 30$, $T_r = 10$ (Pattern 2) (continued)

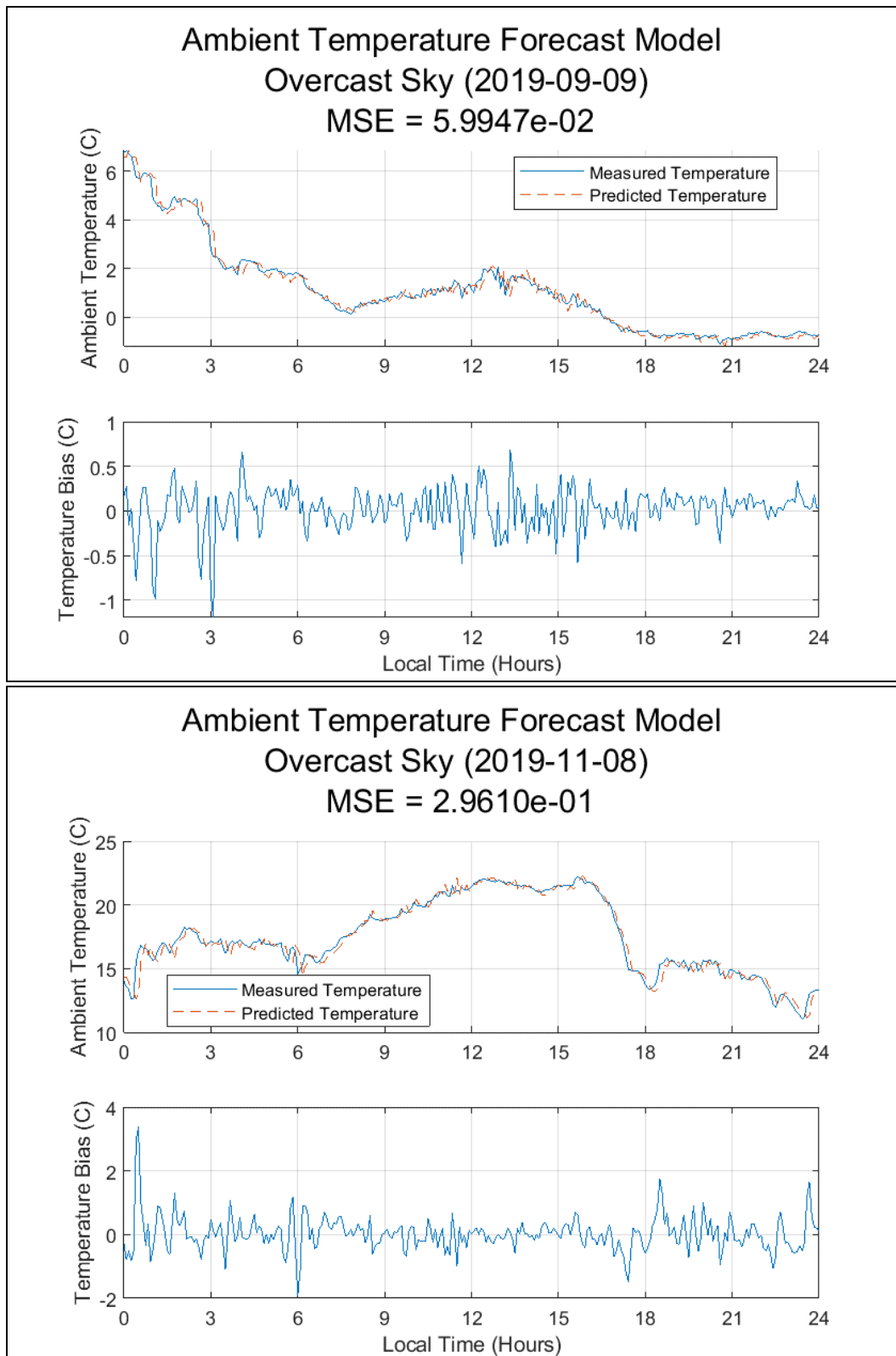


Fig. D-8 $T_p = 30$, $T_r = 10$ (Pattern 2) (continued)

$$T_p = 30$$

$$T_f = 20$$

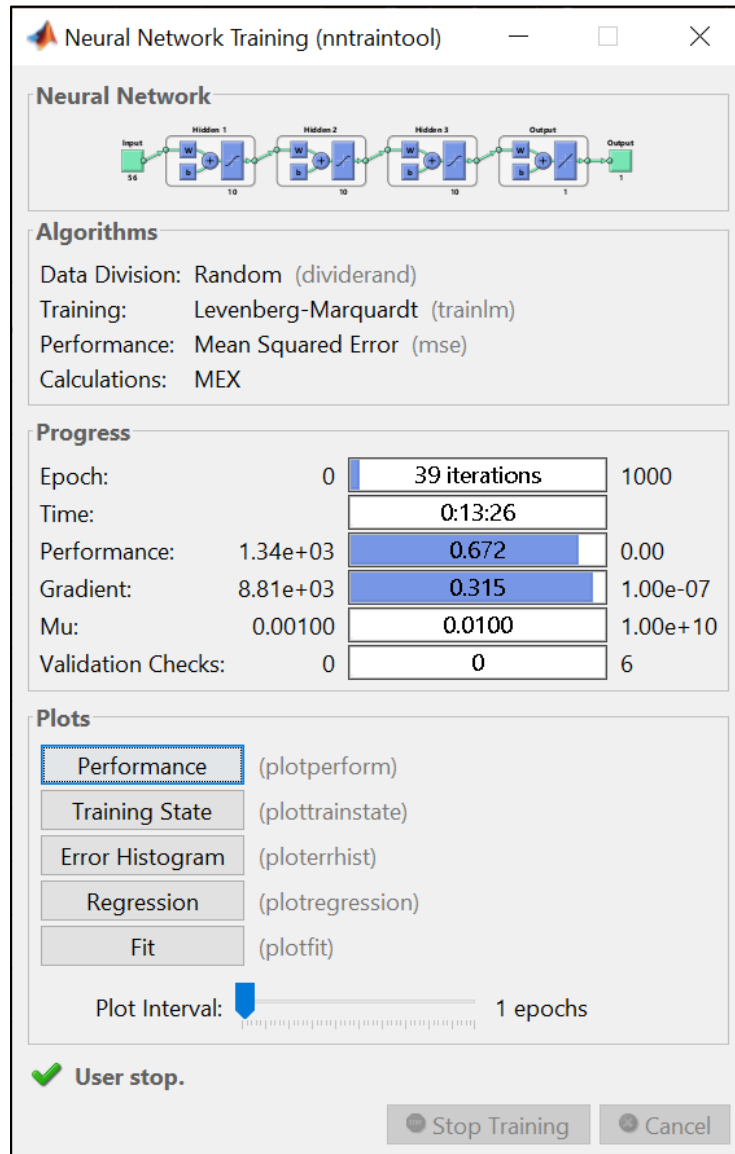


Fig. D-9 $T_p = 30$, $T_f = 20$ (Pattern 2)

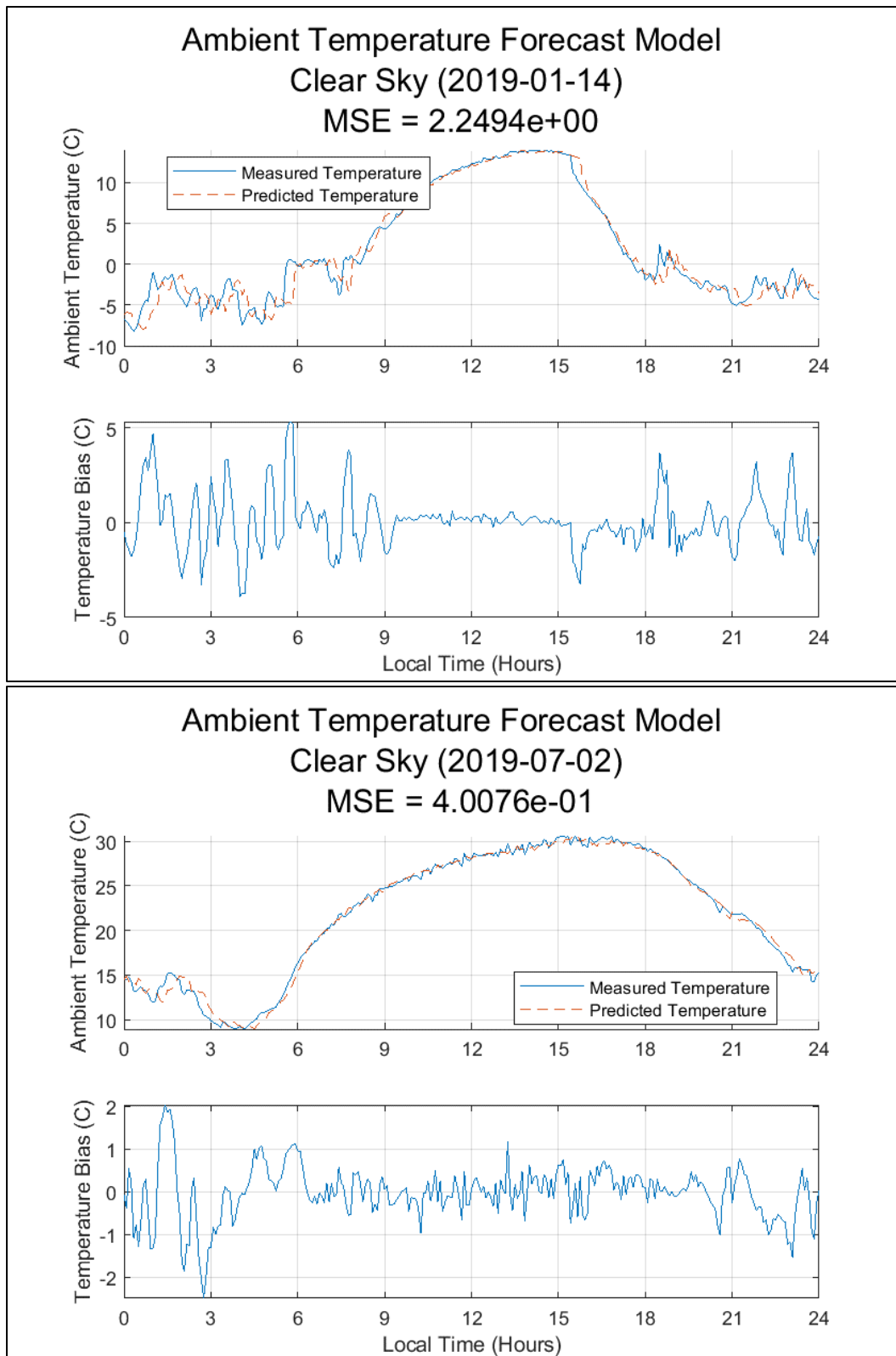


Fig. D-9 $T_p = 30$, $T_r = 20$ (Pattern 2) (continued)

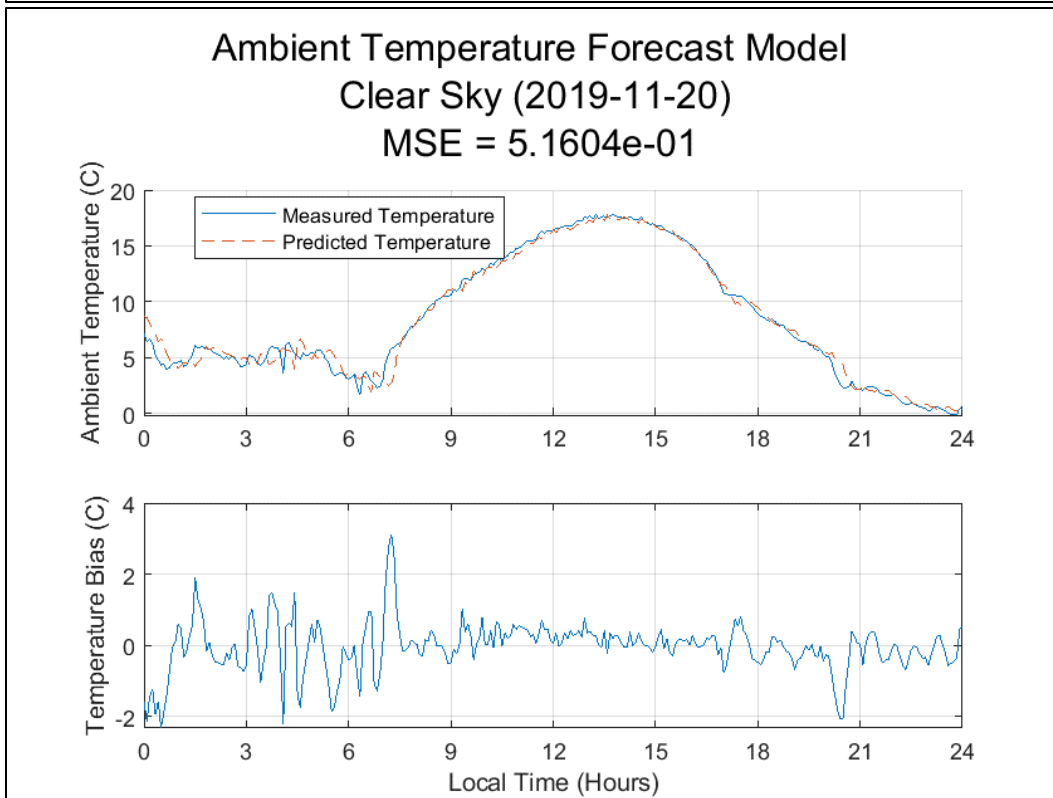
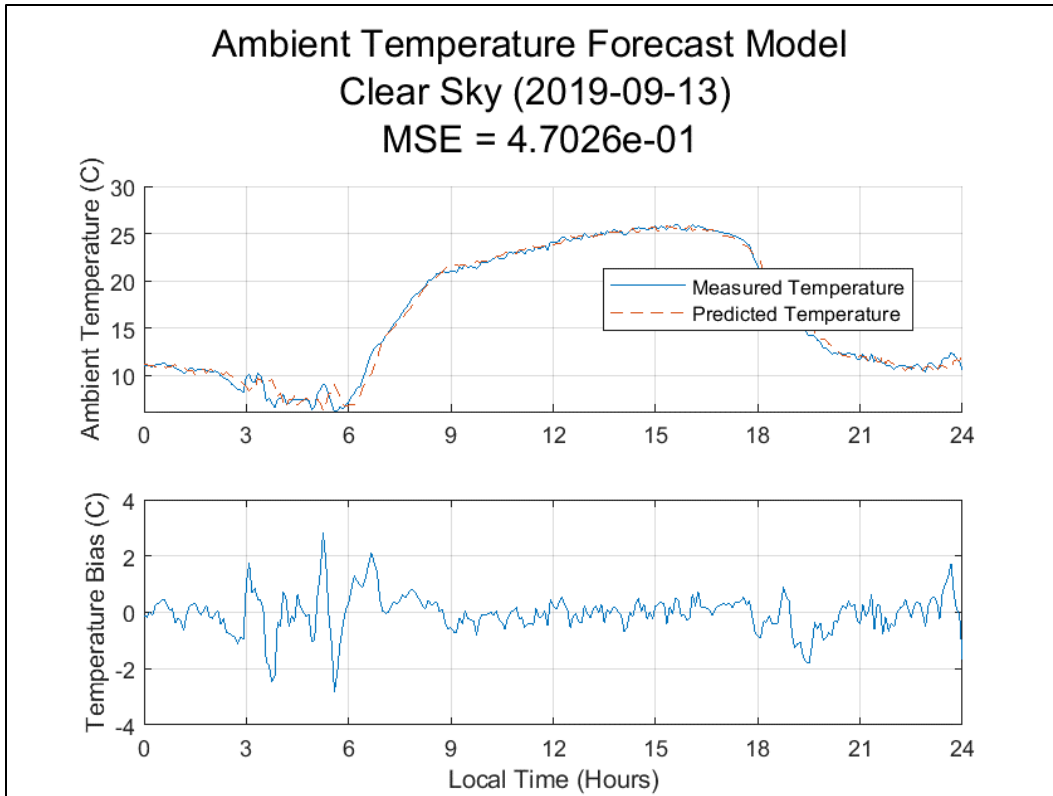


Fig. D-9 $T_p = 30$, $T_r = 20$ (Pattern 2) (continued)

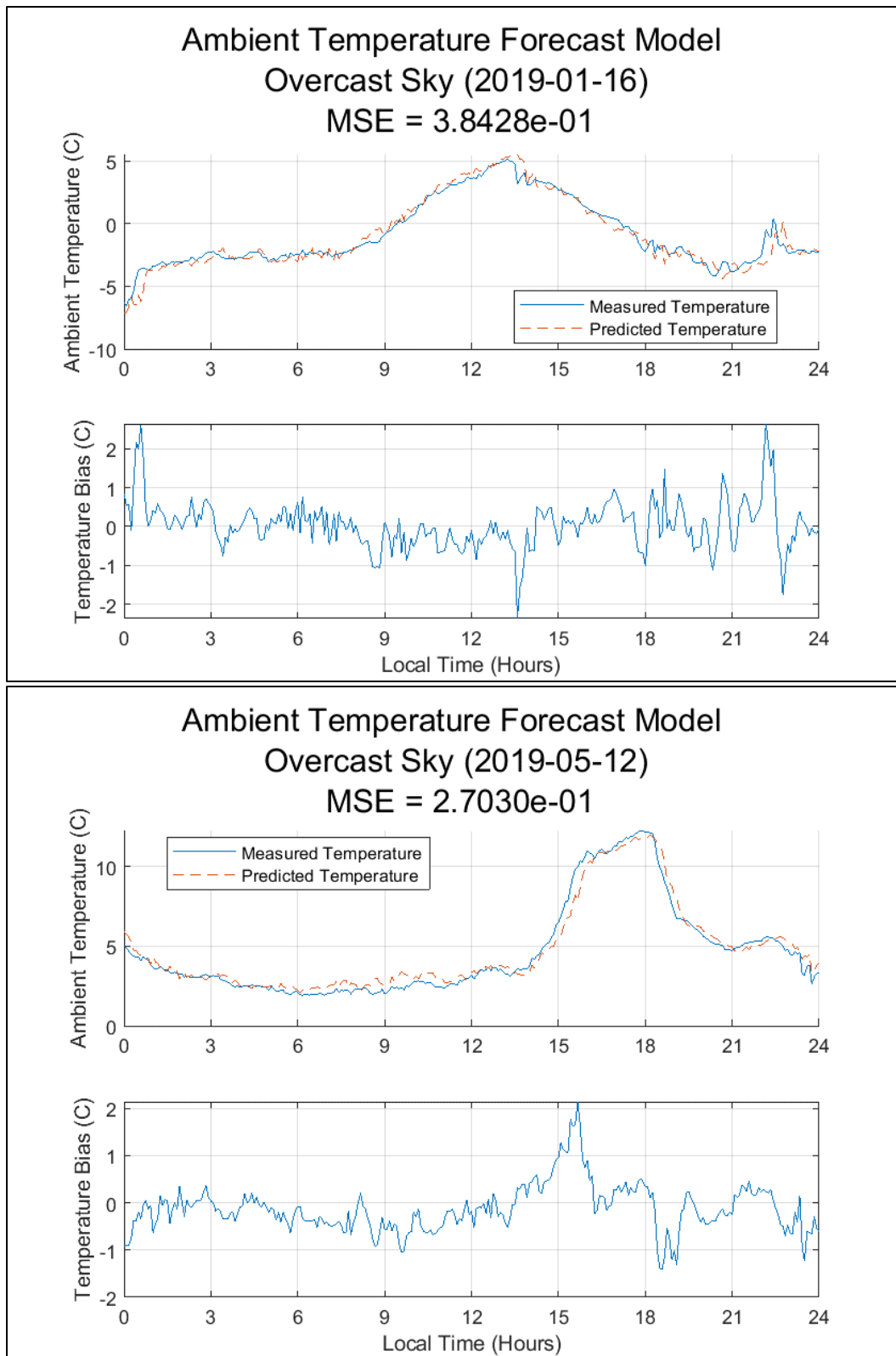


Fig. D-9 $T_p = 30$, $T_r = 20$ (Pattern 2) (continued)

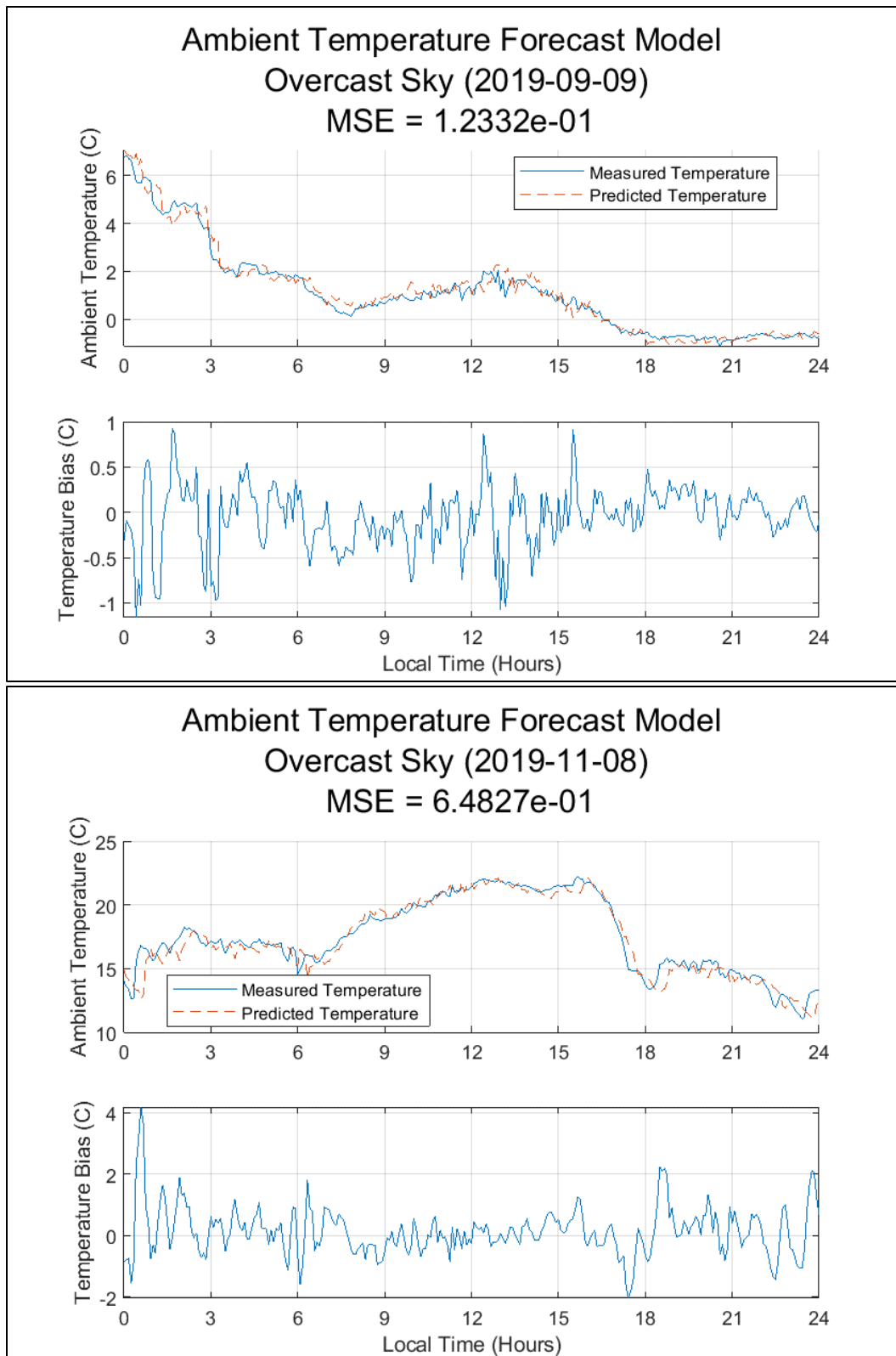


Fig. D-9 $T_p = 30$, $T_r = 20$ (Pattern 2) (continued)

$$T_p = 30$$

$$T_f = 40$$

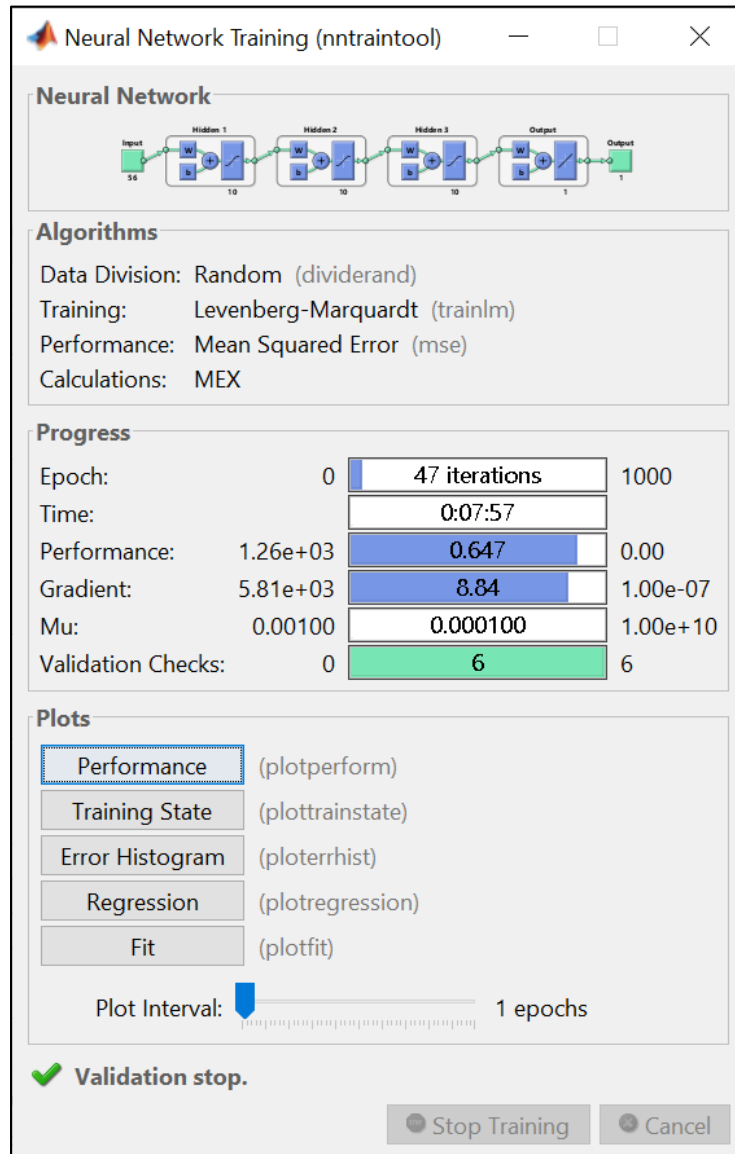


Fig. D-10 $T_p = 30$, $T_f = 40$ (Pattern 2)

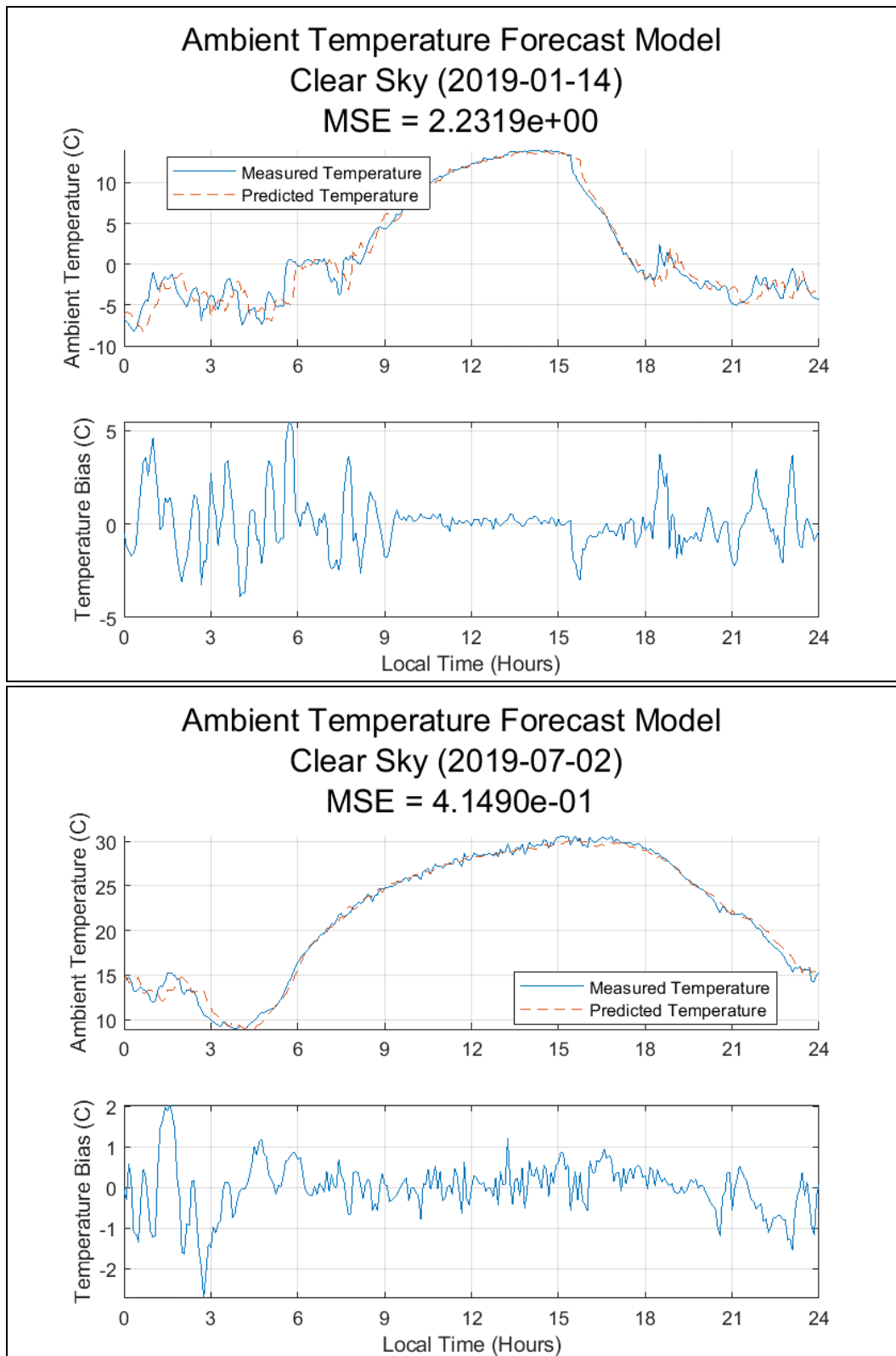


Fig. D-10 $T_p = 30$, $T_f = 40$ (Pattern 2) (continued)

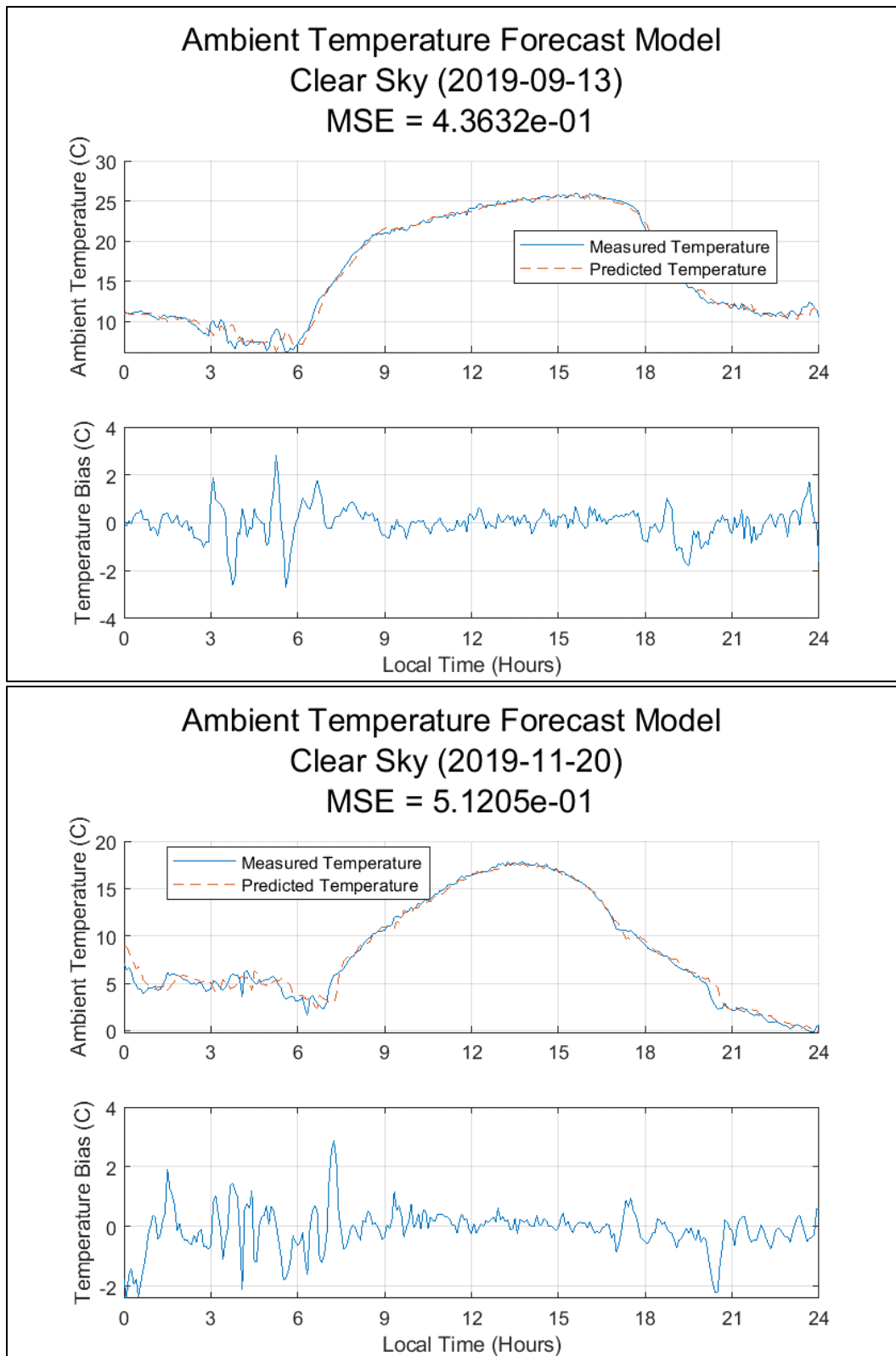


Fig. D-10 $T_p = 30$, $T_f = 40$ (Pattern 2) (continued)

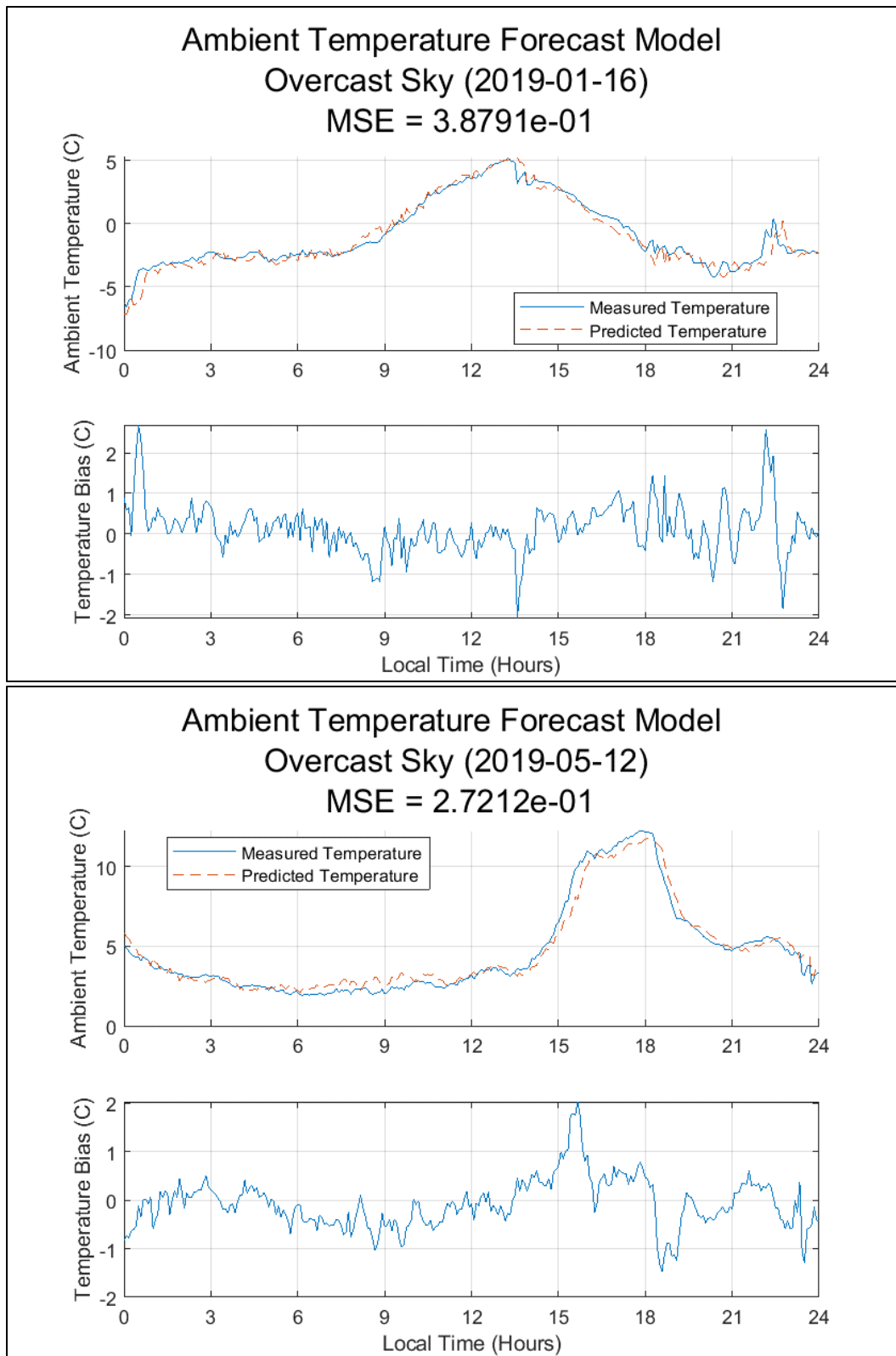


Fig. D-10 $T_p = 30$, $T_r = 40$ (Pattern 2) (continued)

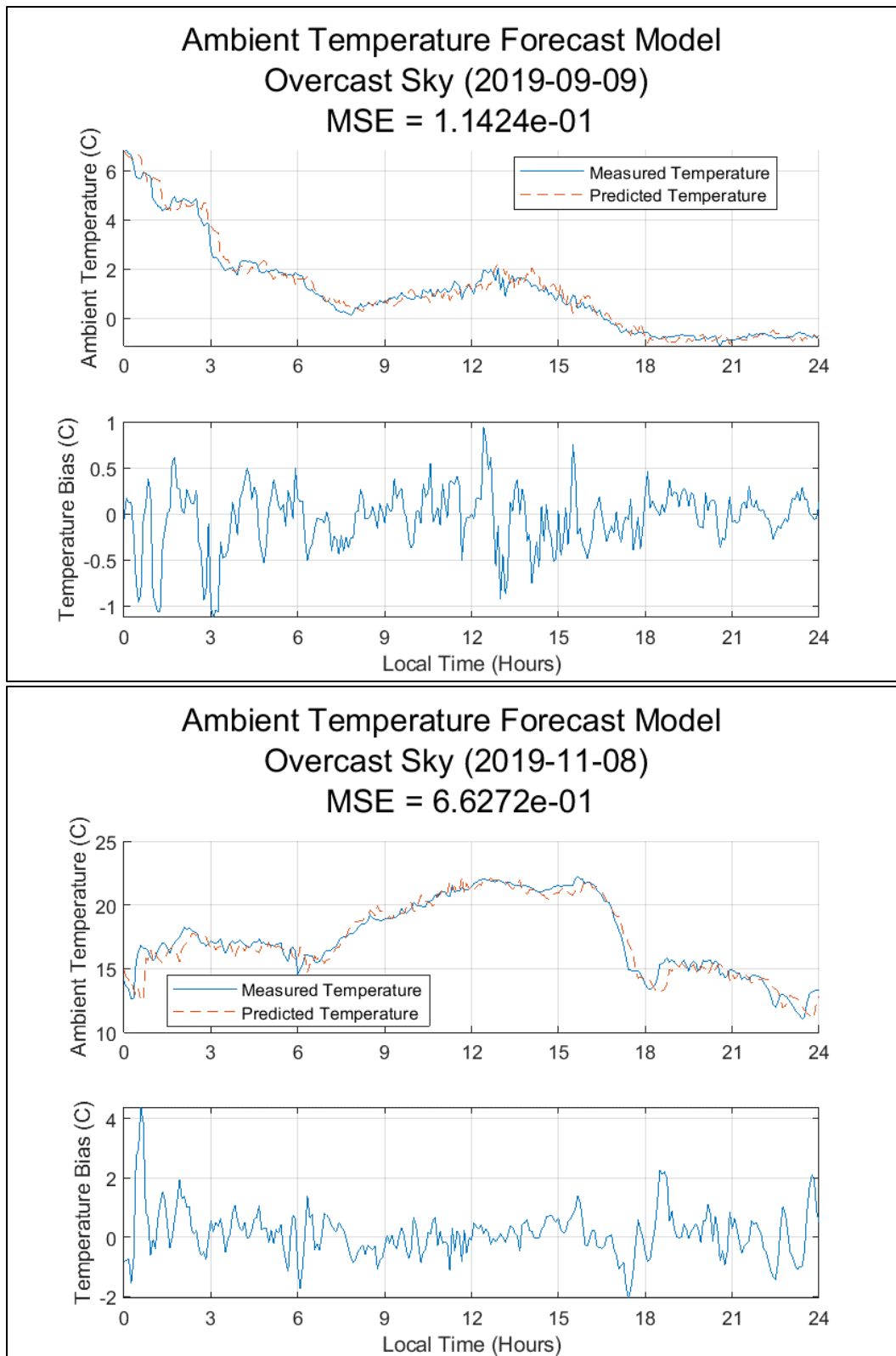


Fig. D-10 $T_p = 30$, $T_f = 40$ (Pattern 2) (continued)

$$T_p = 30$$

$$T_f = 80$$

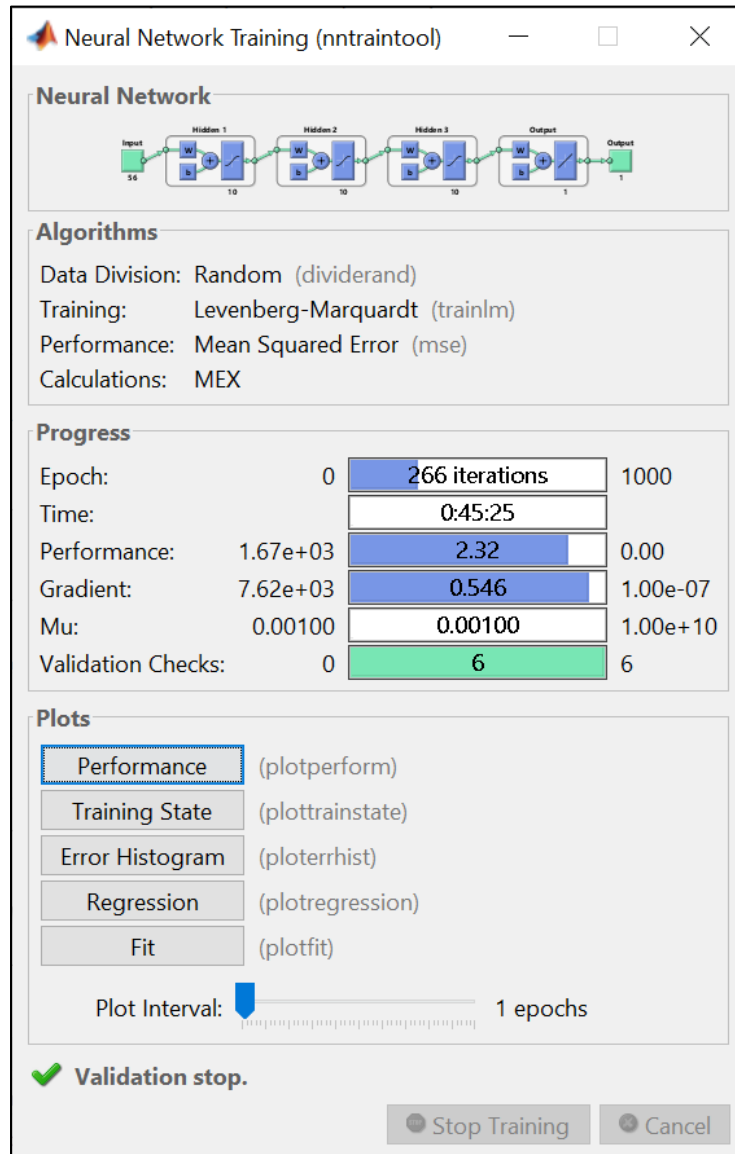


Fig. D-11 $T_p = 30$, $T_f = 80$ (Pattern 2)

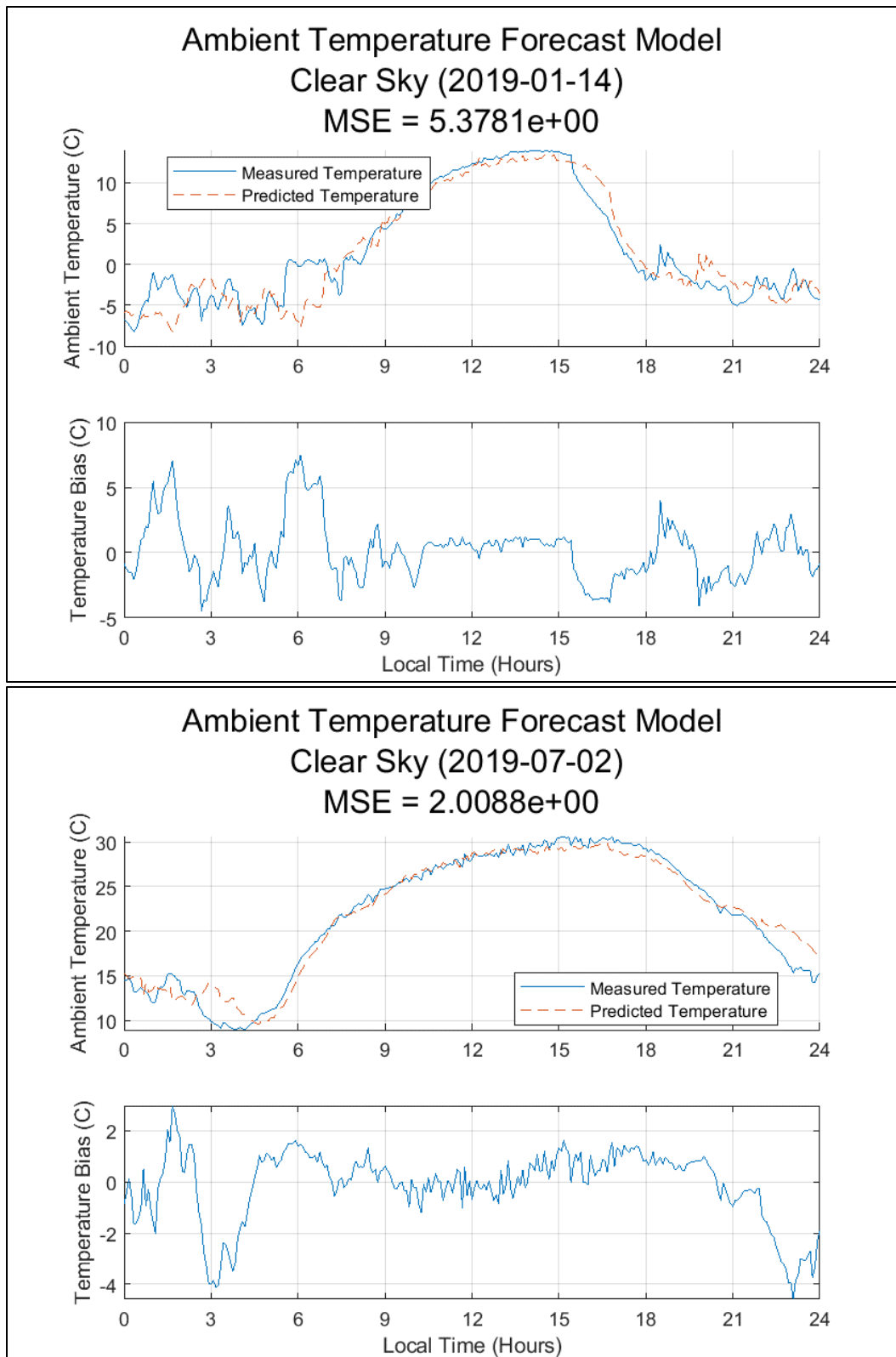


Fig. D-11 $T_p = 30$, $T_r = 80$ (Pattern 2) (continued)

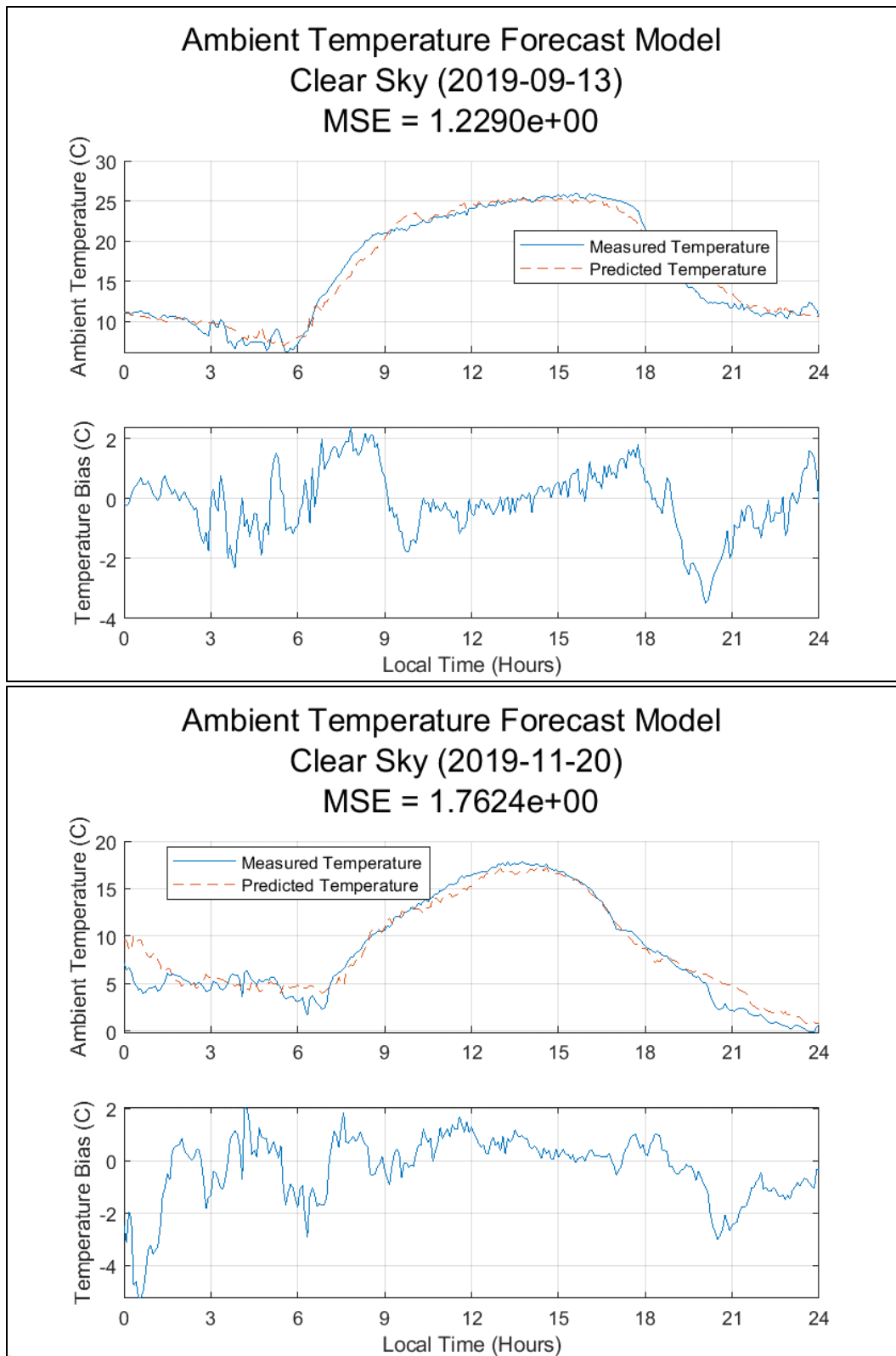


Fig. D-11 $T_p = 30$, $T_f = 80$ (Pattern 2) (continued)

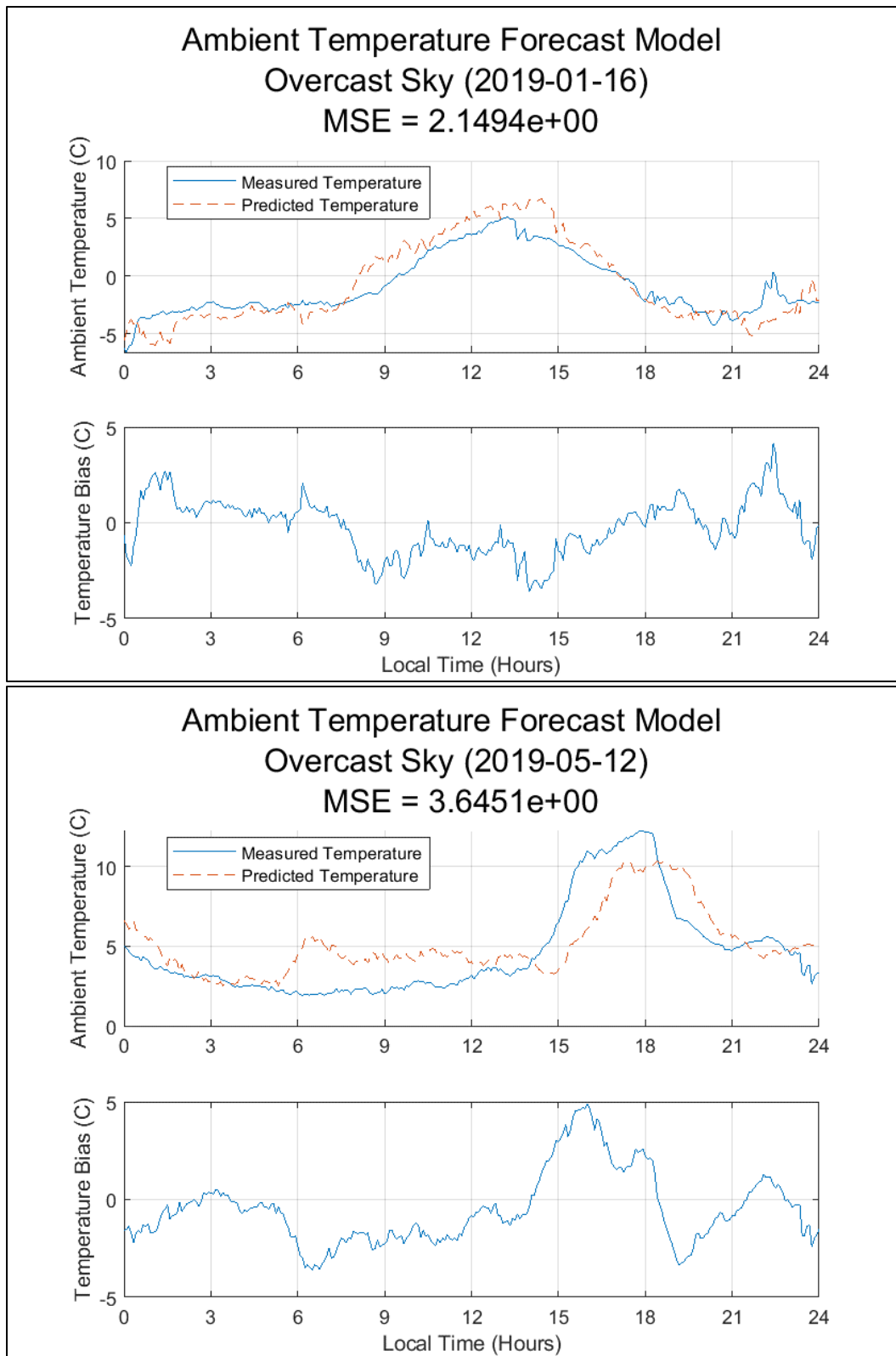


Fig. D-11 $T_p = 30$, $T_r = 80$ (Pattern 2) (continued)

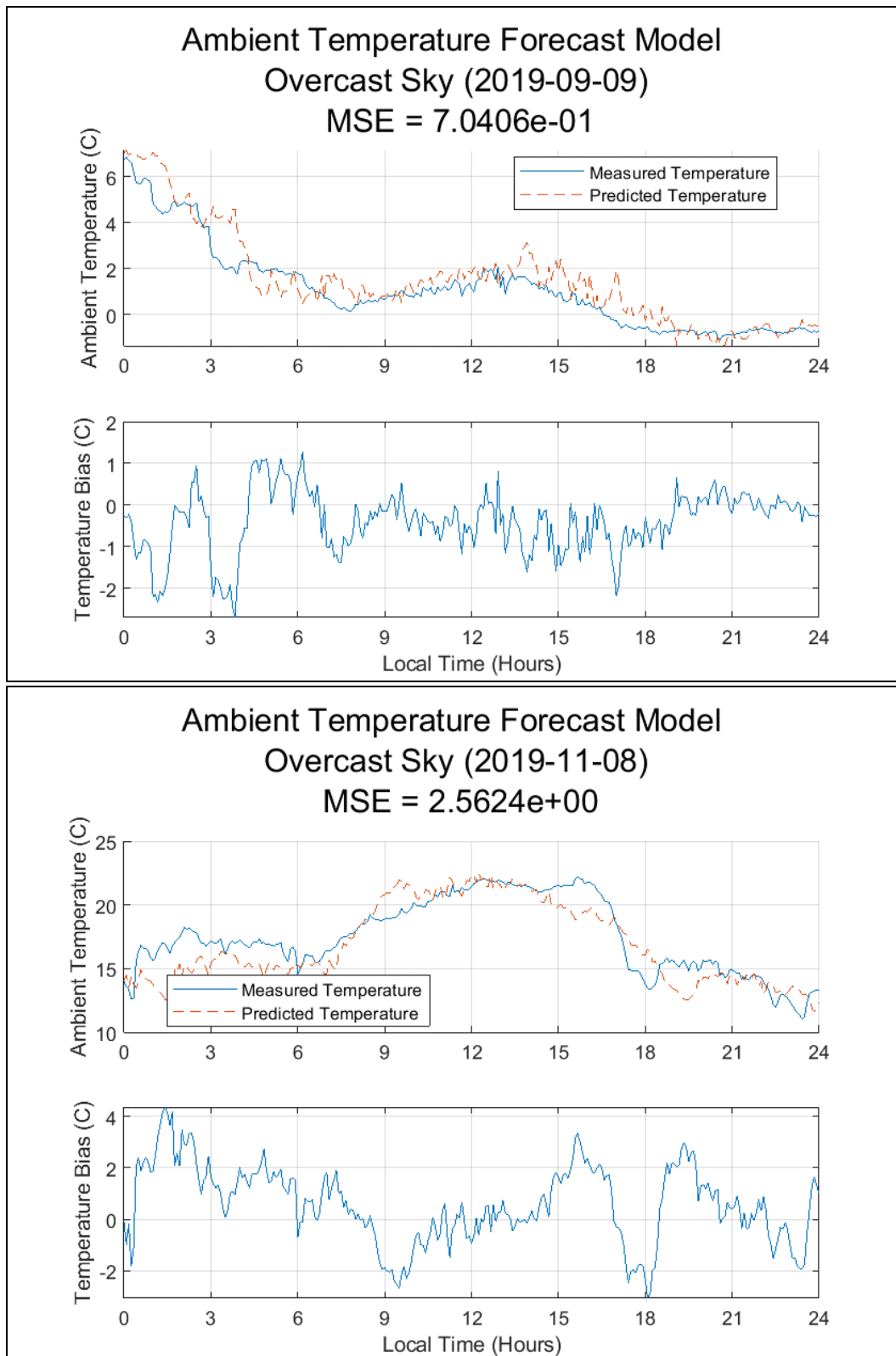


Fig. D-11 $T_p = 30$, $T_f = 80$ (Pattern 2) (continued)

$$T_p = 30$$

$$T_f = 160$$

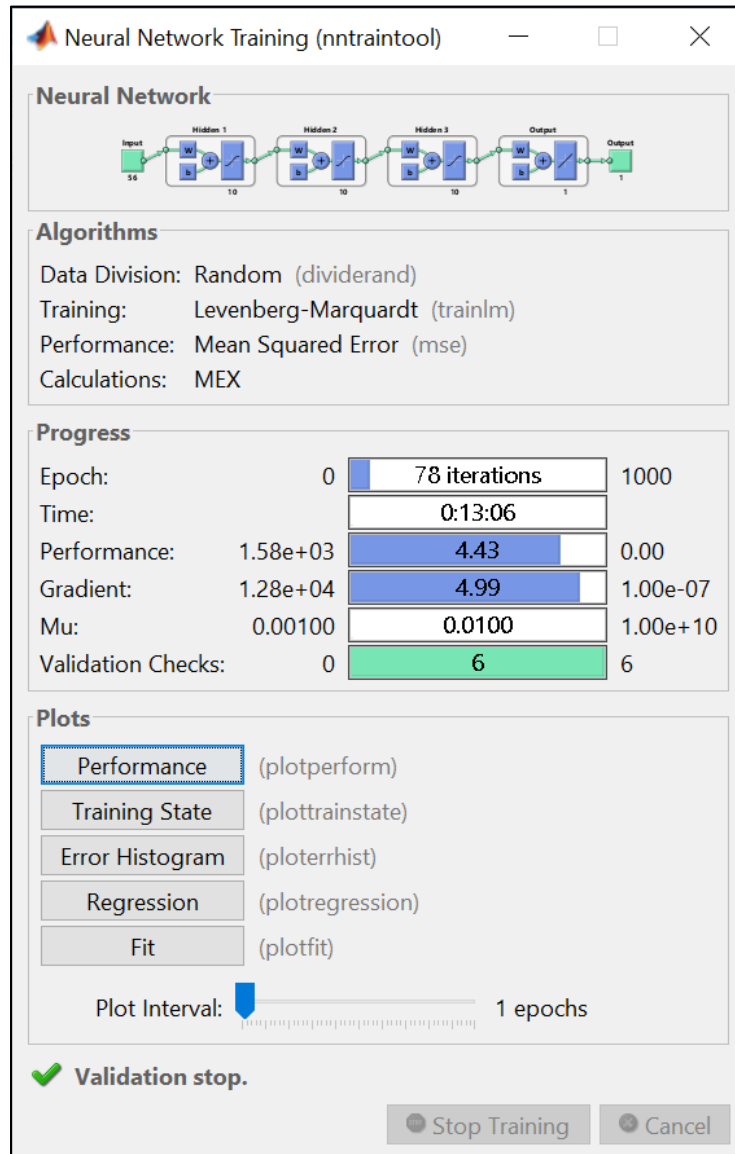


Fig. D-12 $T_p = 30$, $T_f = 160$ (Pattern 2)

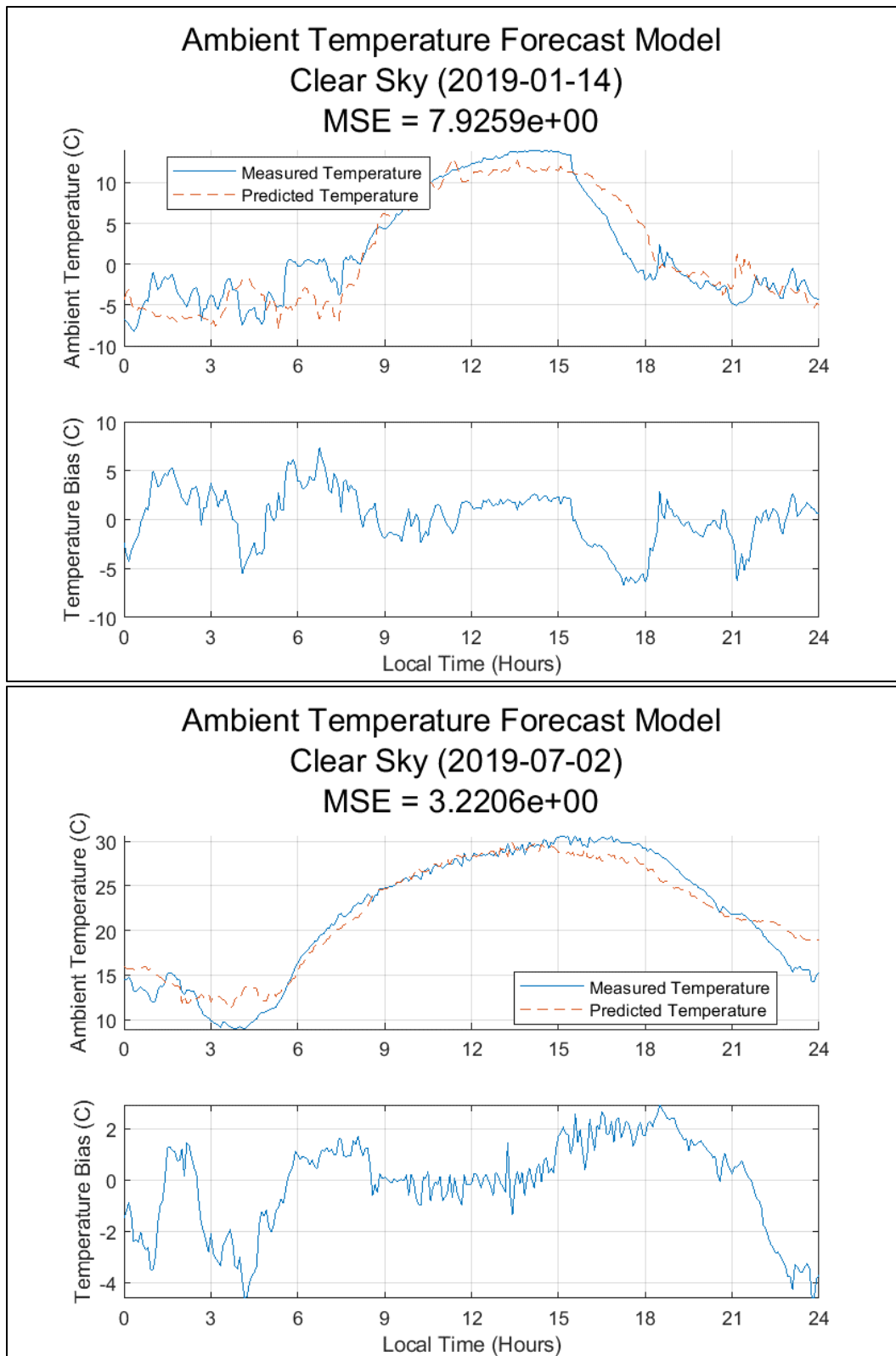


Fig. D-12 $T_p = 30$, $T_r = 160$ (Pattern 2) (continued)

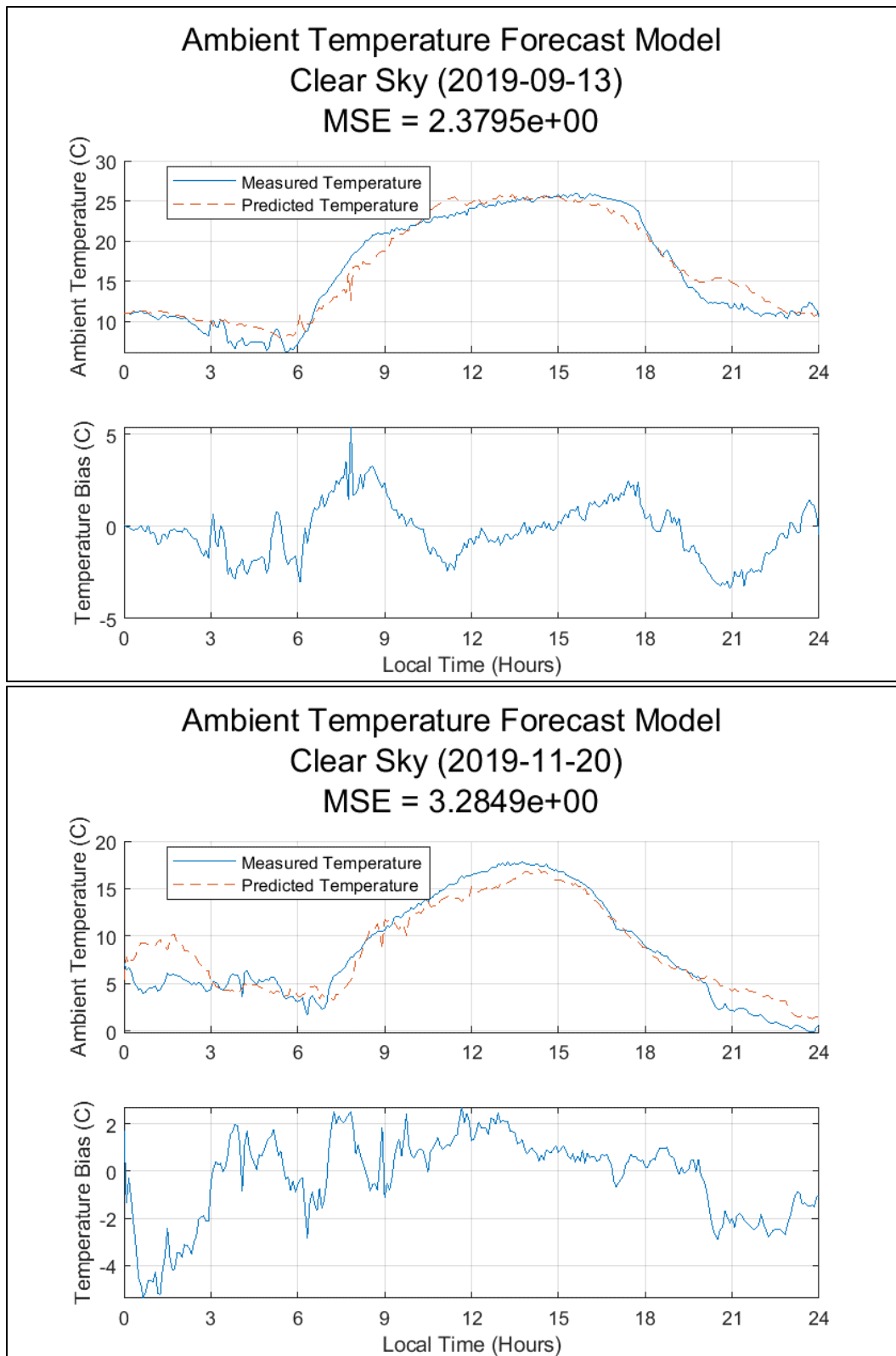


Fig. D-12 $T_p = 30$, $T_r = 160$ (Pattern 2) (continued)

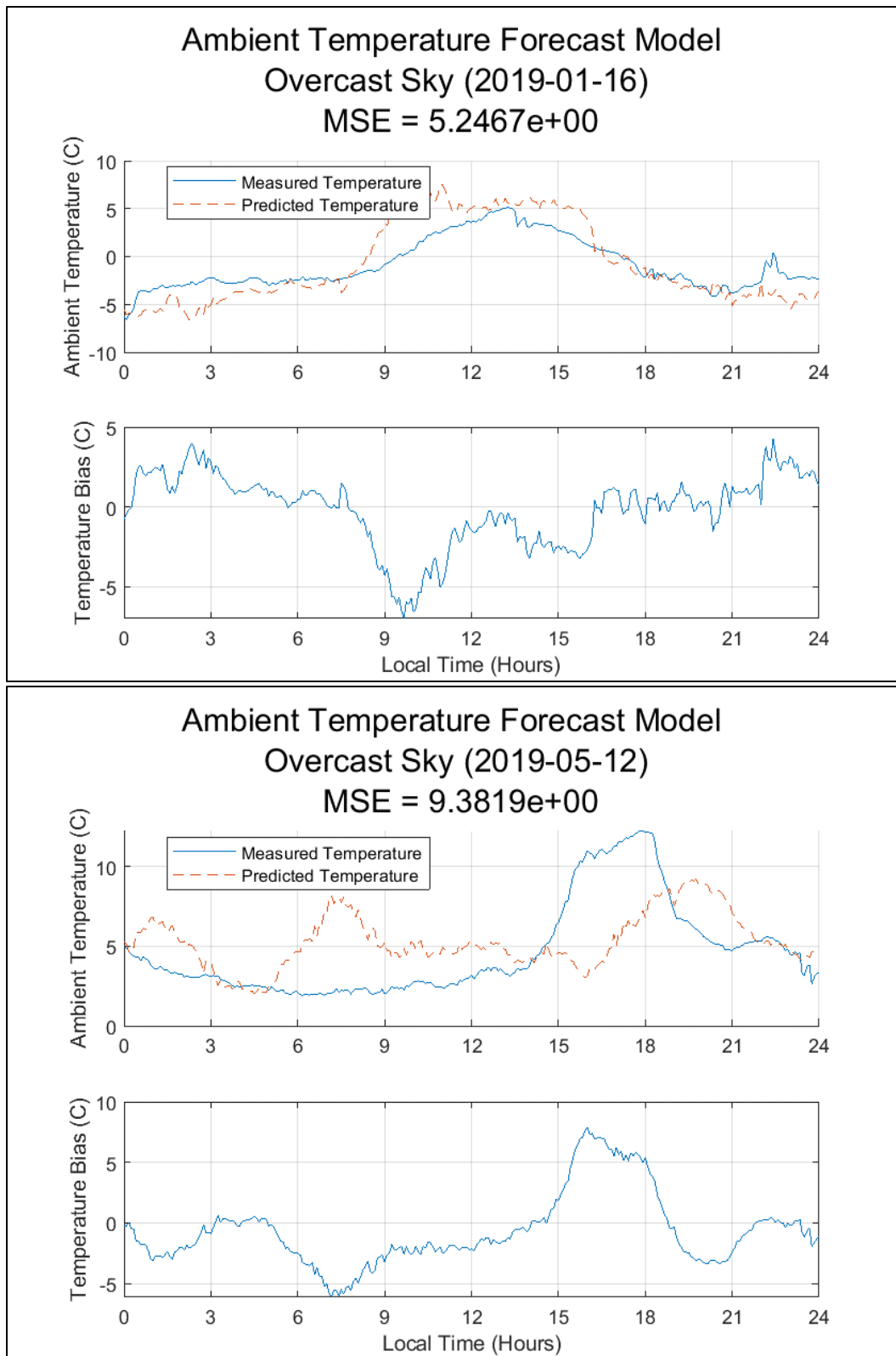


Fig. D-12 $T_p = 30$, $T_r = 160$ (Pattern 2) (continued)

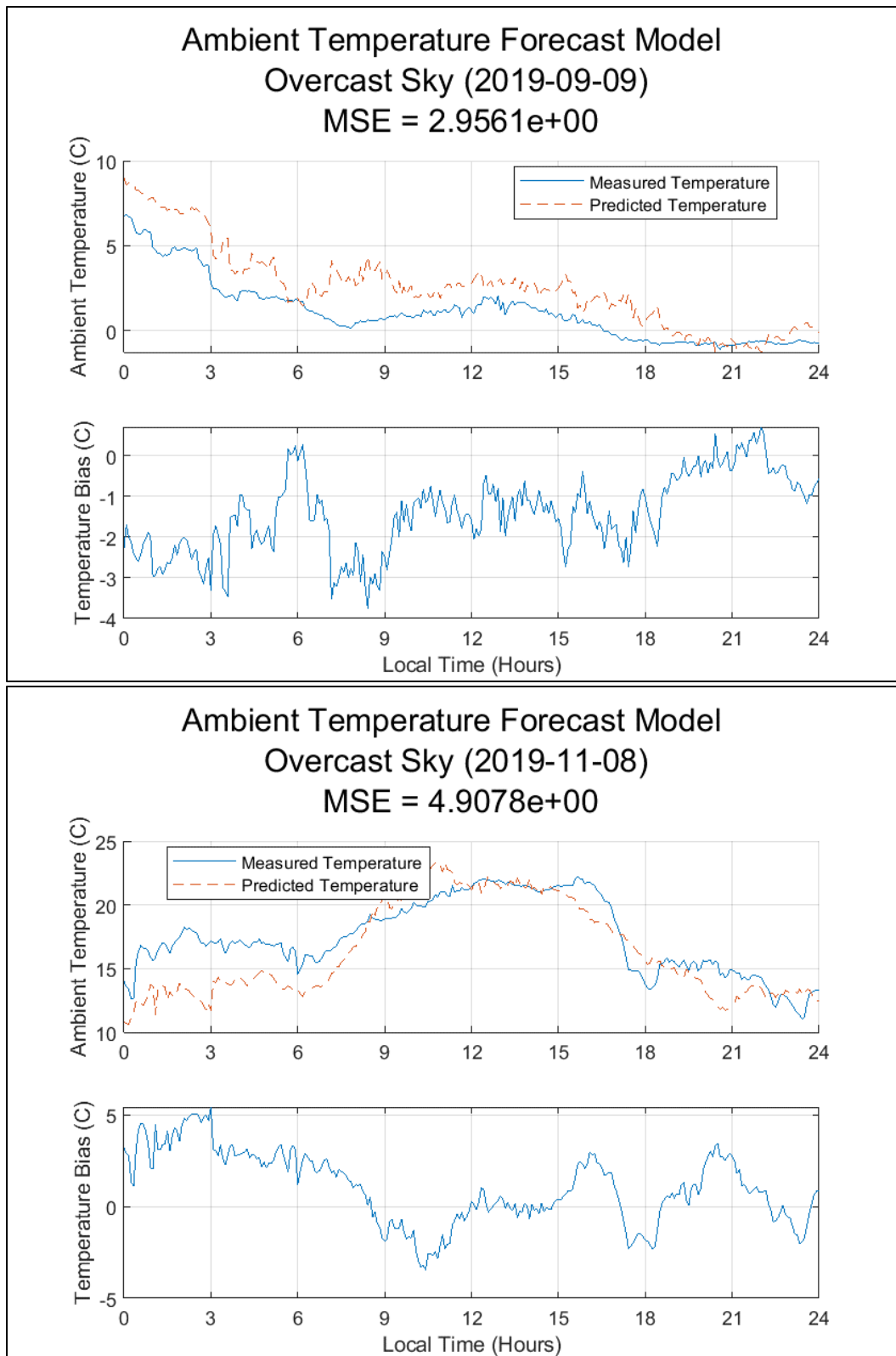


Fig. D-12 $T_p = 30$, $T_r = 160$ (Pattern 2) (continued)

$$T_p = 5$$

$$T_f = 15$$

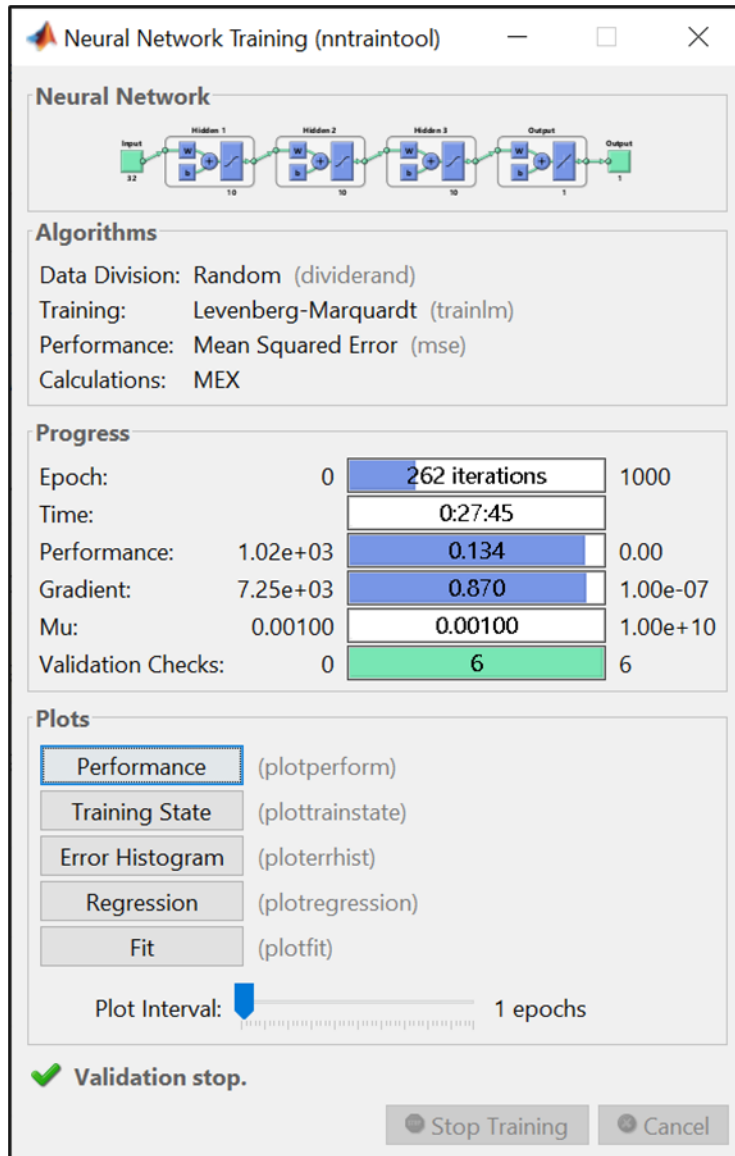


Fig. D-13 $T_p = 5$, $T_f = 15$ (Pattern 3)

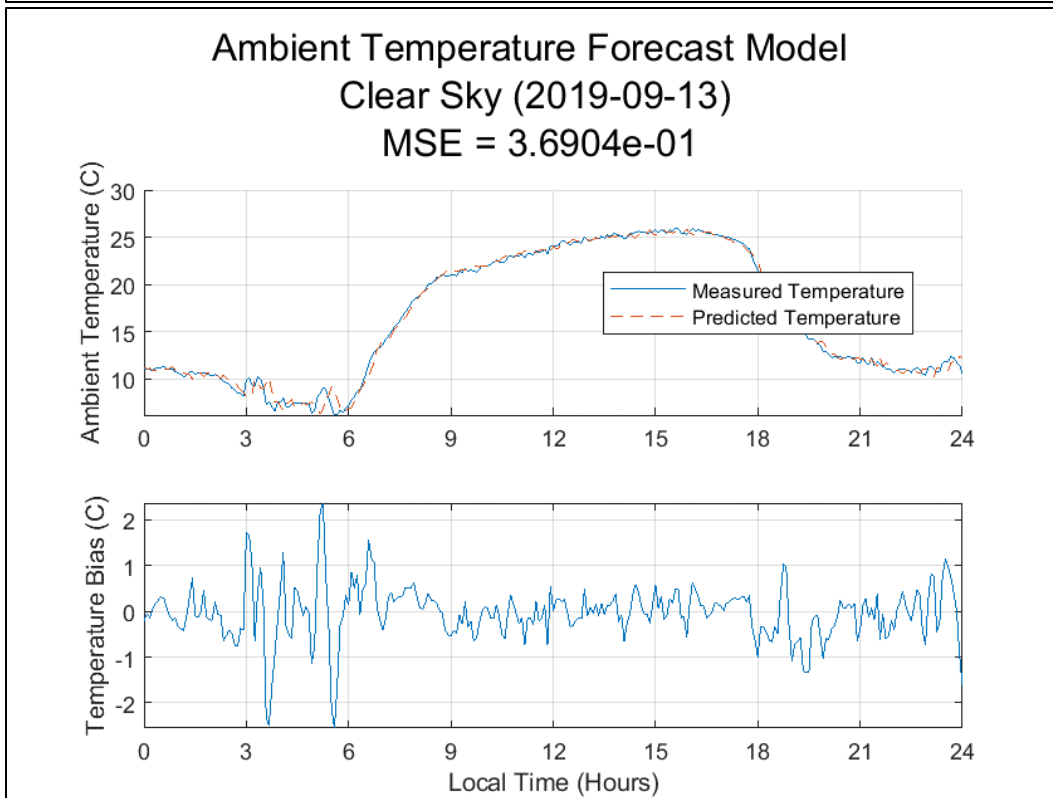
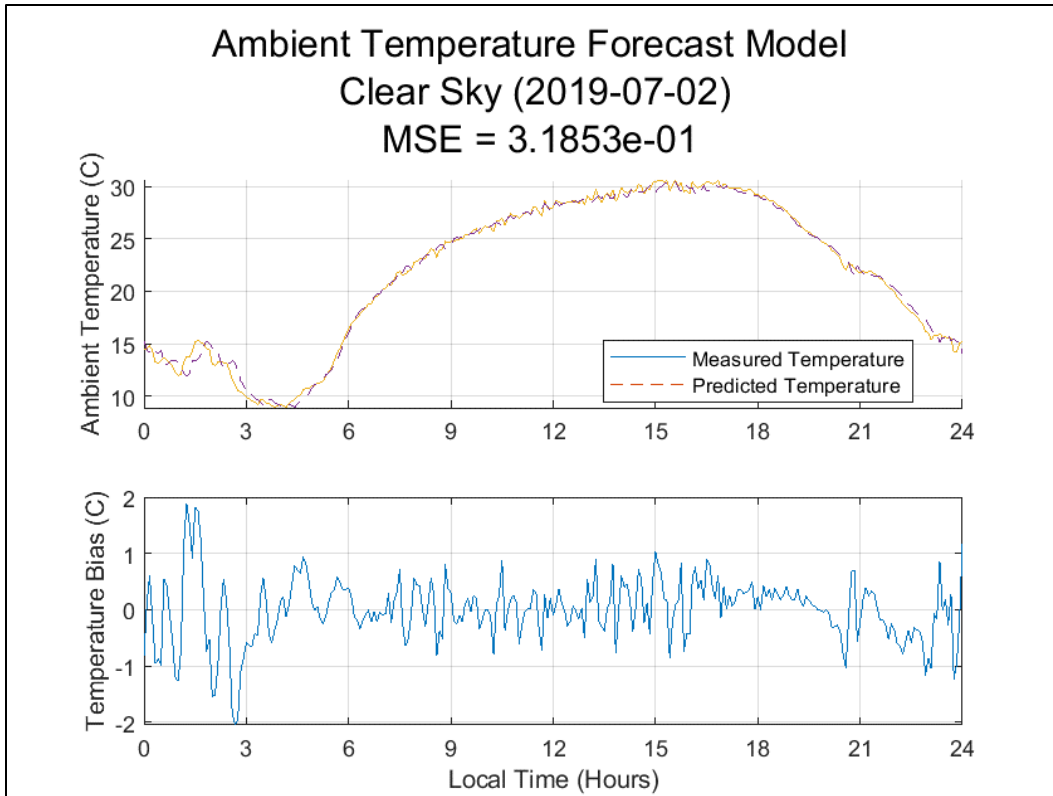


Fig. D-13 $T_p = 5$, $T_r = 15$ (Pattern 3) (continued)

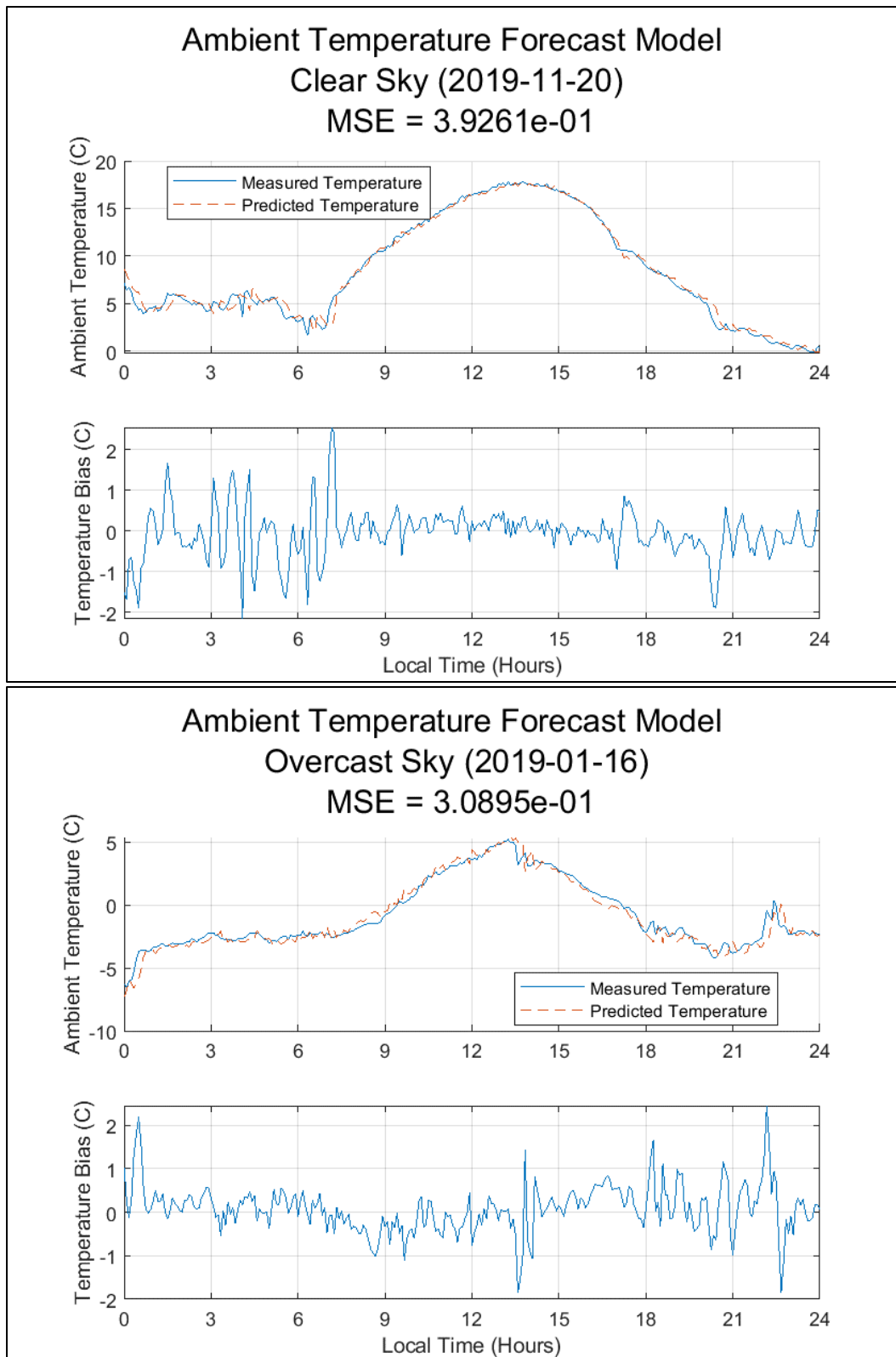


Fig. D-13 $T_p = 5$, $T_r = 15$ (Pattern 3) (continued)

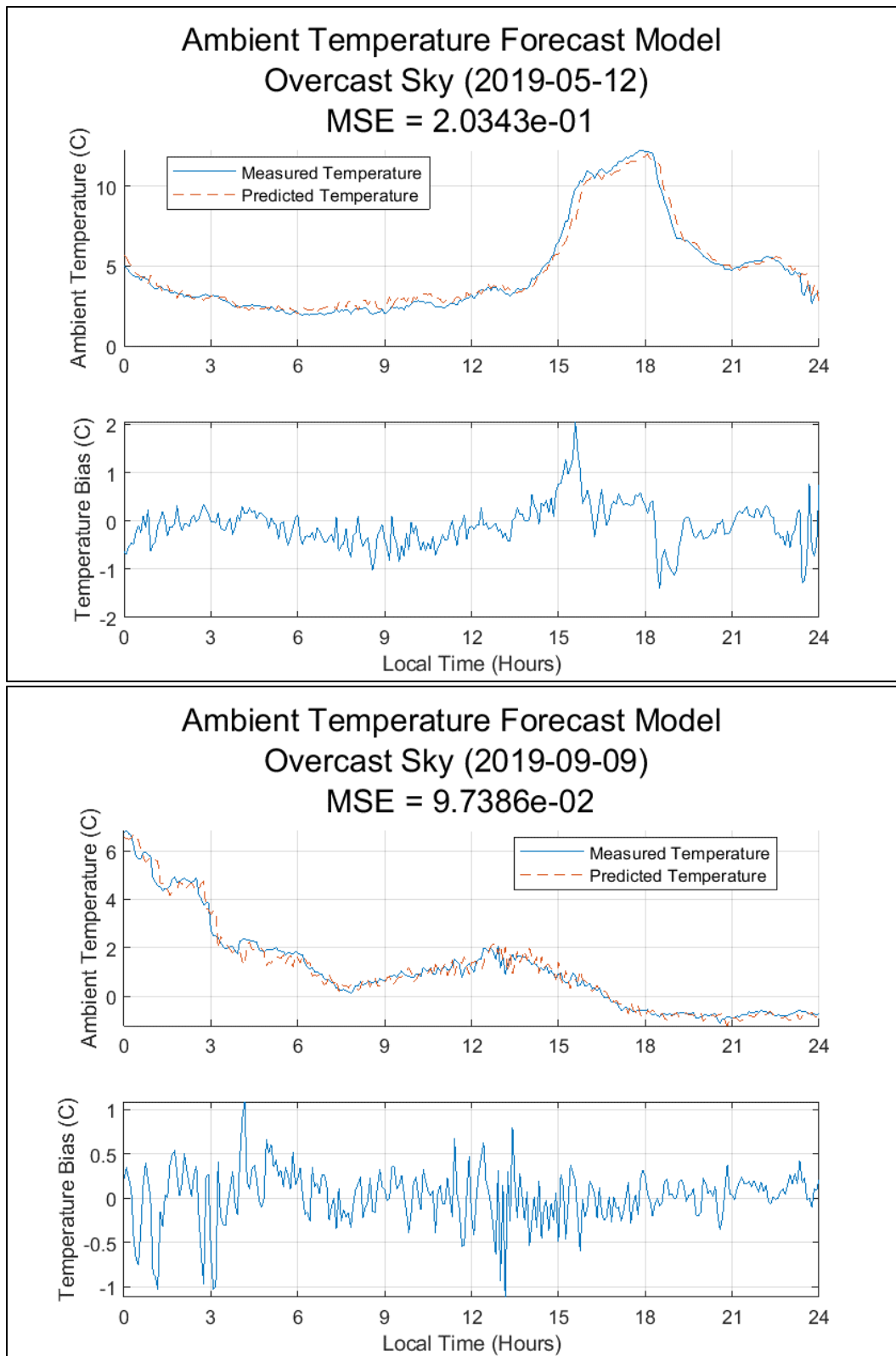


Fig. D-13 $T_p = 5$, $T_r = 15$ (Pattern 3) (continued)

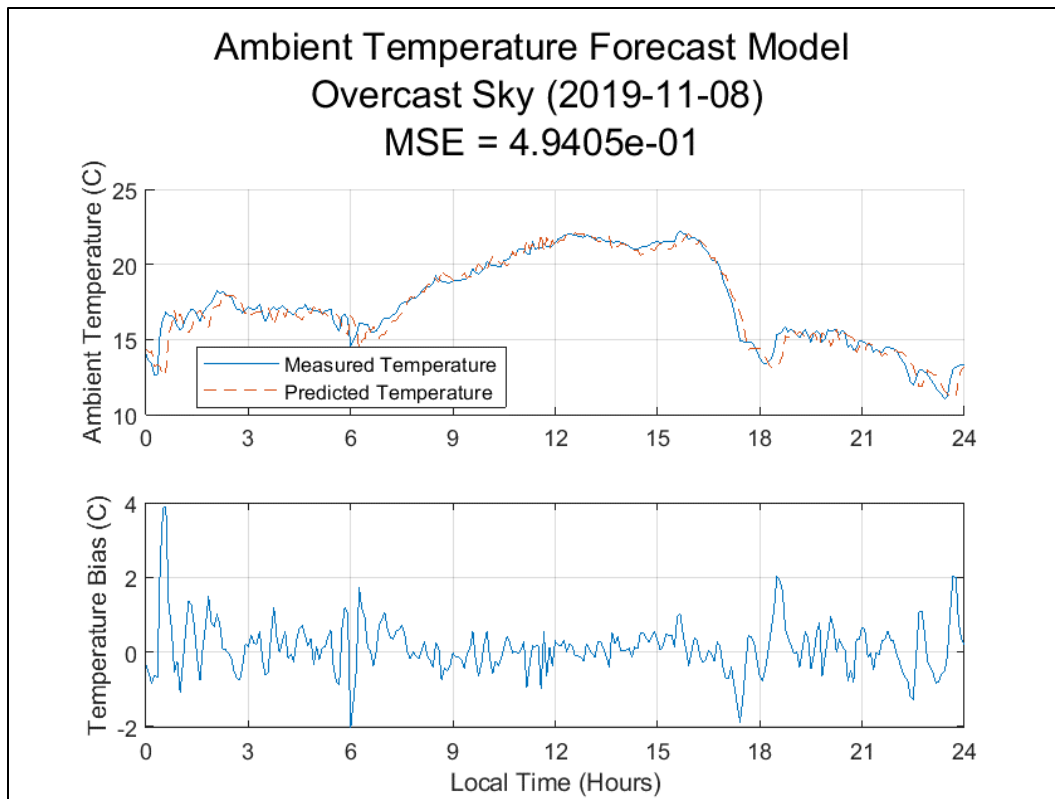


Fig. D-13 $T_p = 5$, $T_r = 15$ (Pattern 3) (continued)

$$T_p = 10$$

$$T_f = 15$$

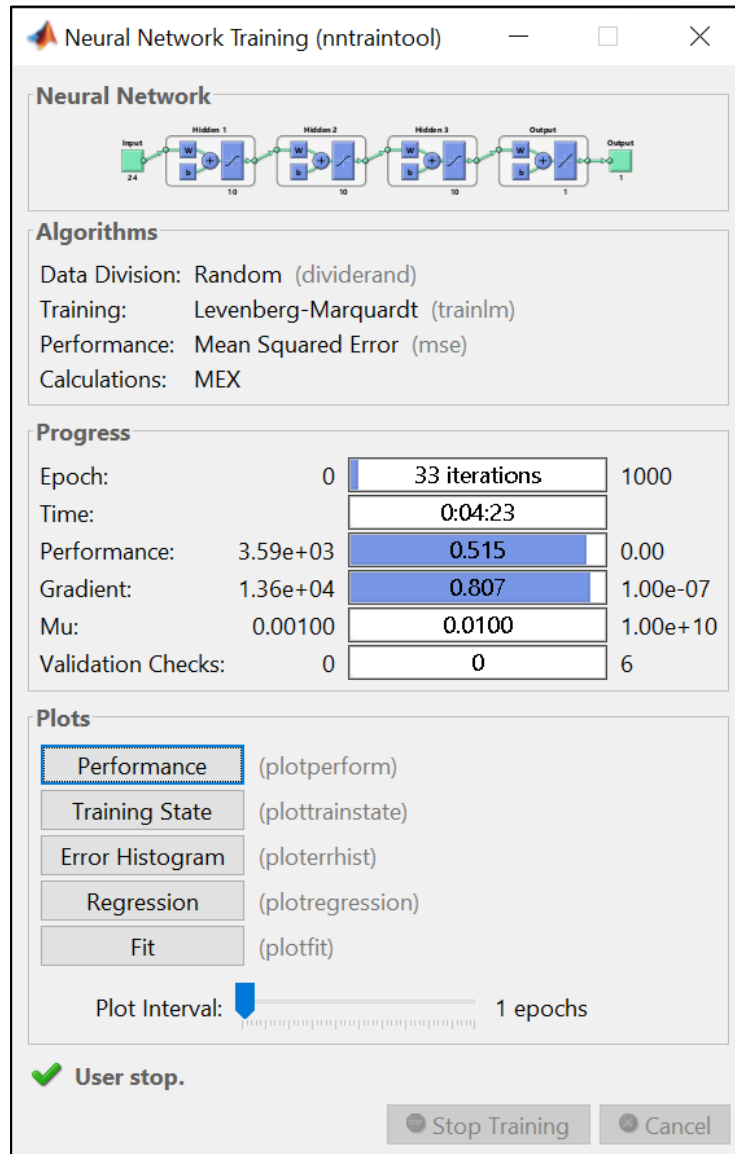


Fig. D-14 $T_p = 10$, $T_f = 15$ (Pattern 3)

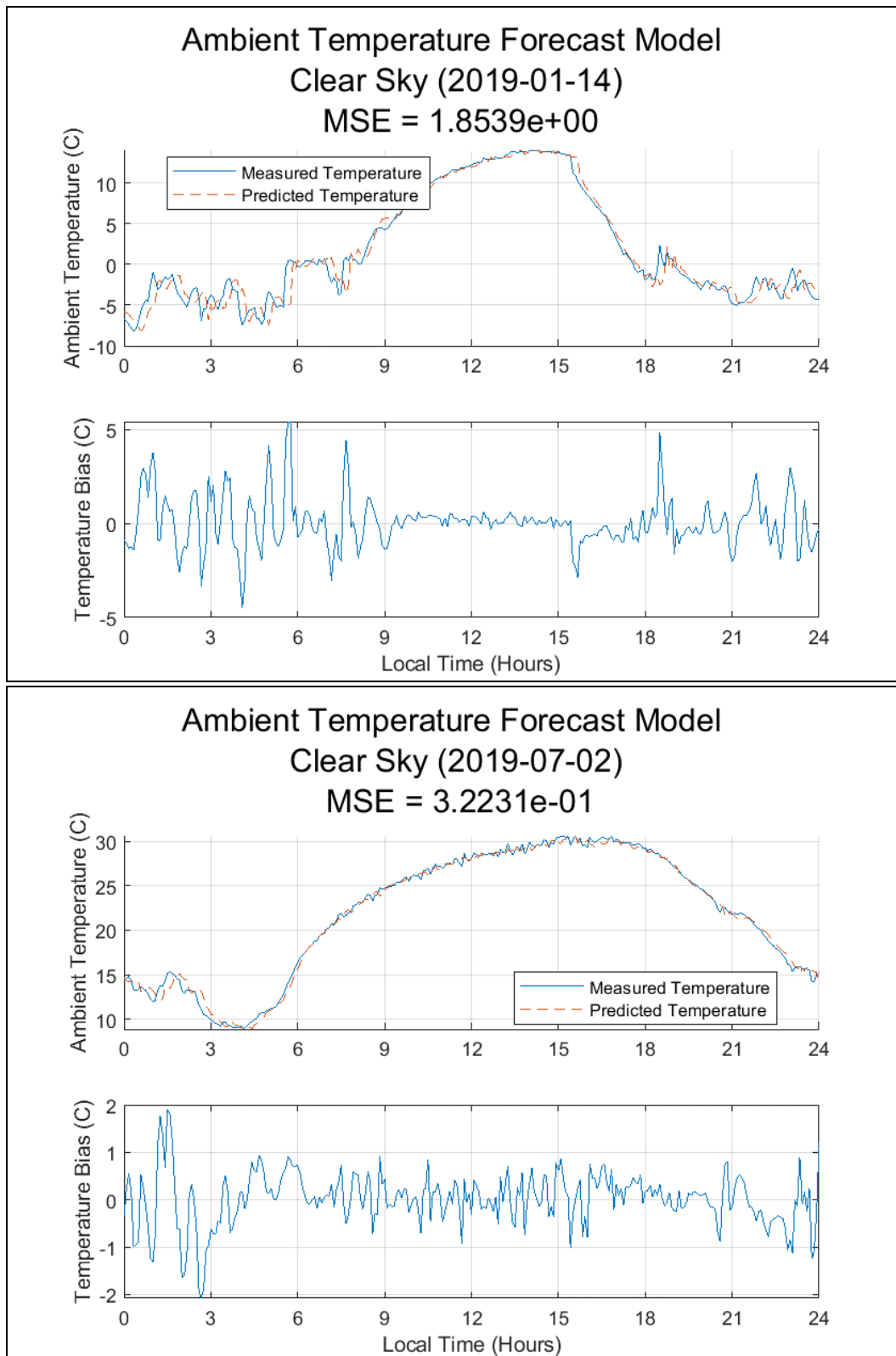


Fig. D-14 $T_p = 10$, $T_r = 15$ (Pattern 3) (continued)

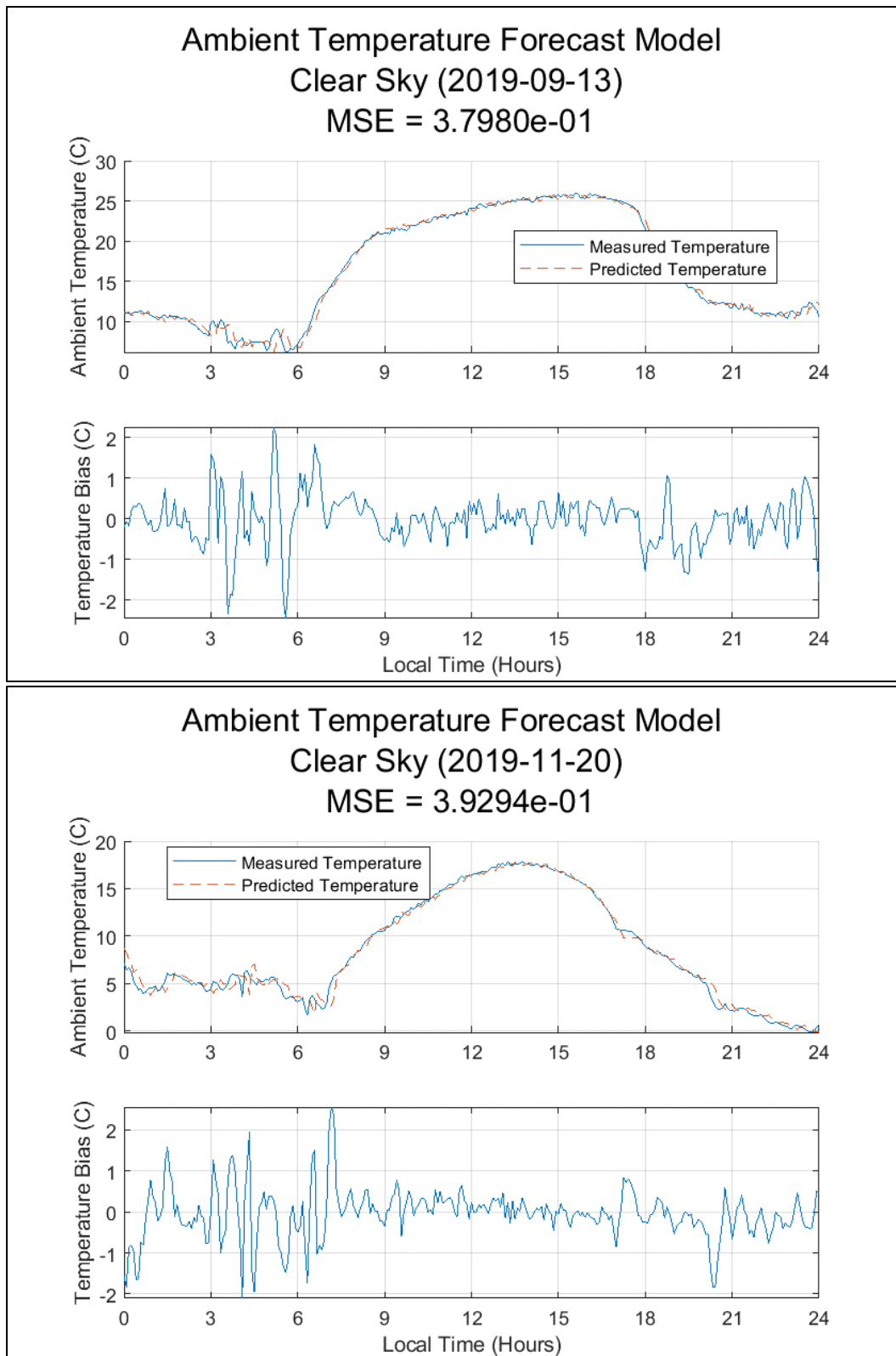


Fig. D-14 $T_p = 10$, $T_r = 15$ (Pattern 3) (continued)

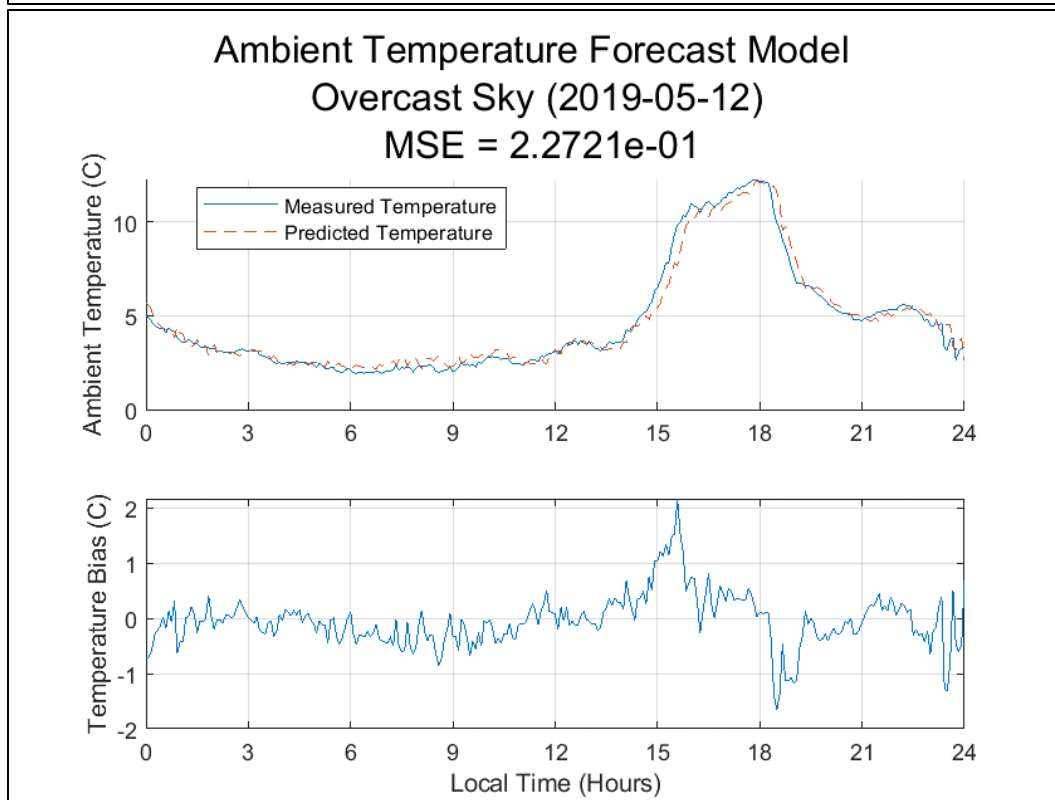
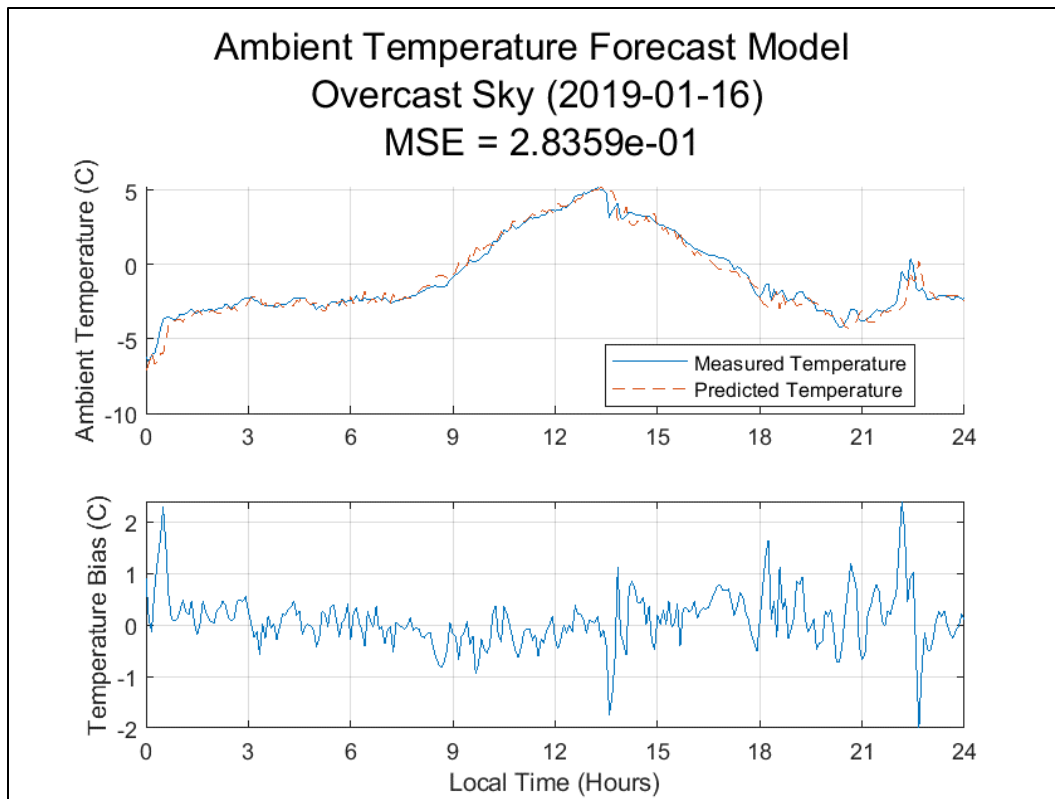


Fig. D-14 $T_p = 10$, $T_r = 15$ (Pattern 3) (continued)

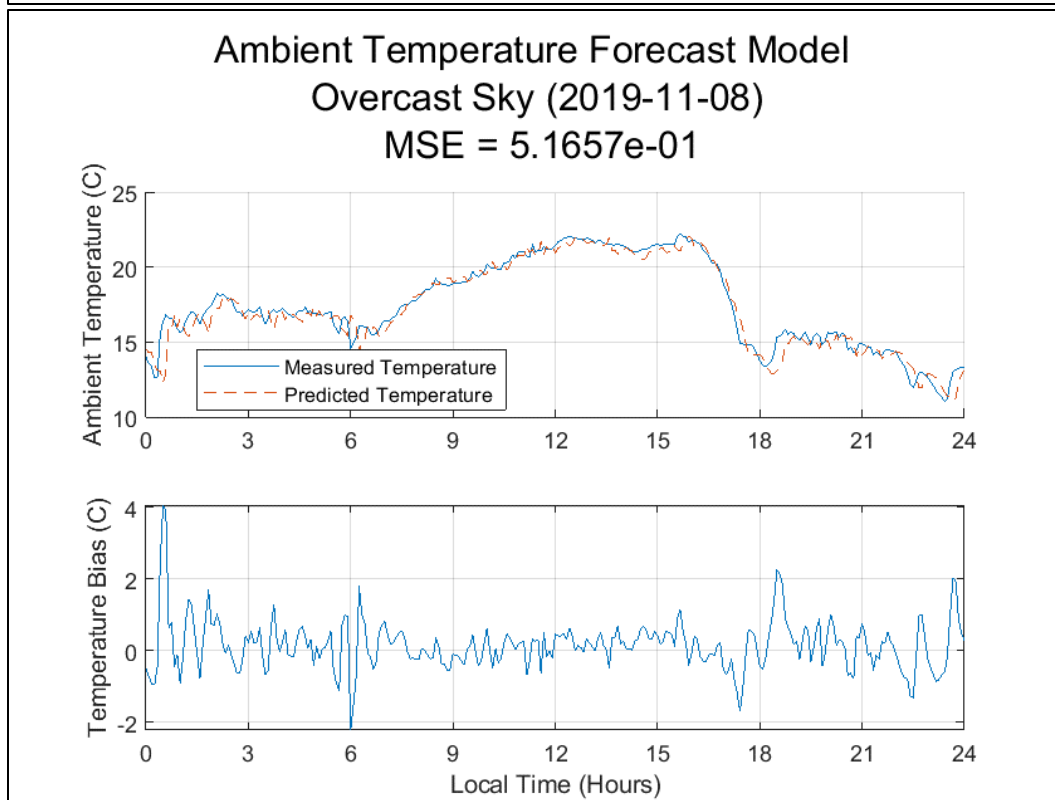
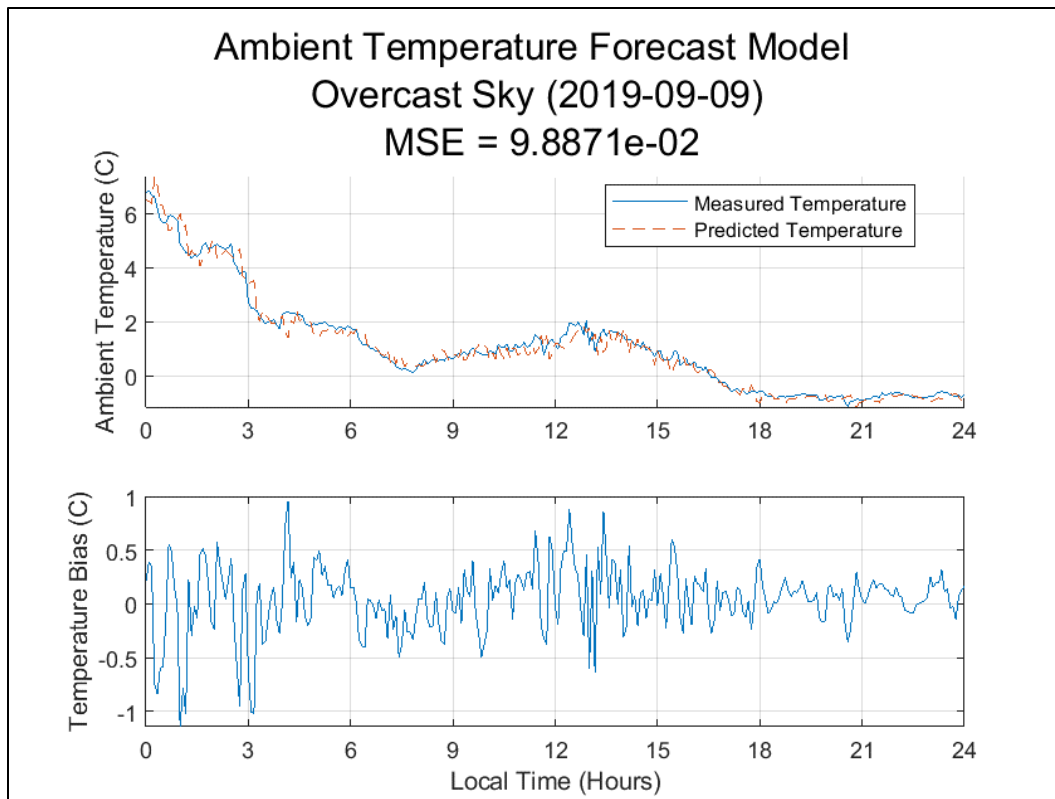


Fig. D-14 $T_p = 10$, $T_f = 15$ (Pattern 3) (continued)

$$T_p = 20$$

$$T_f = 15$$

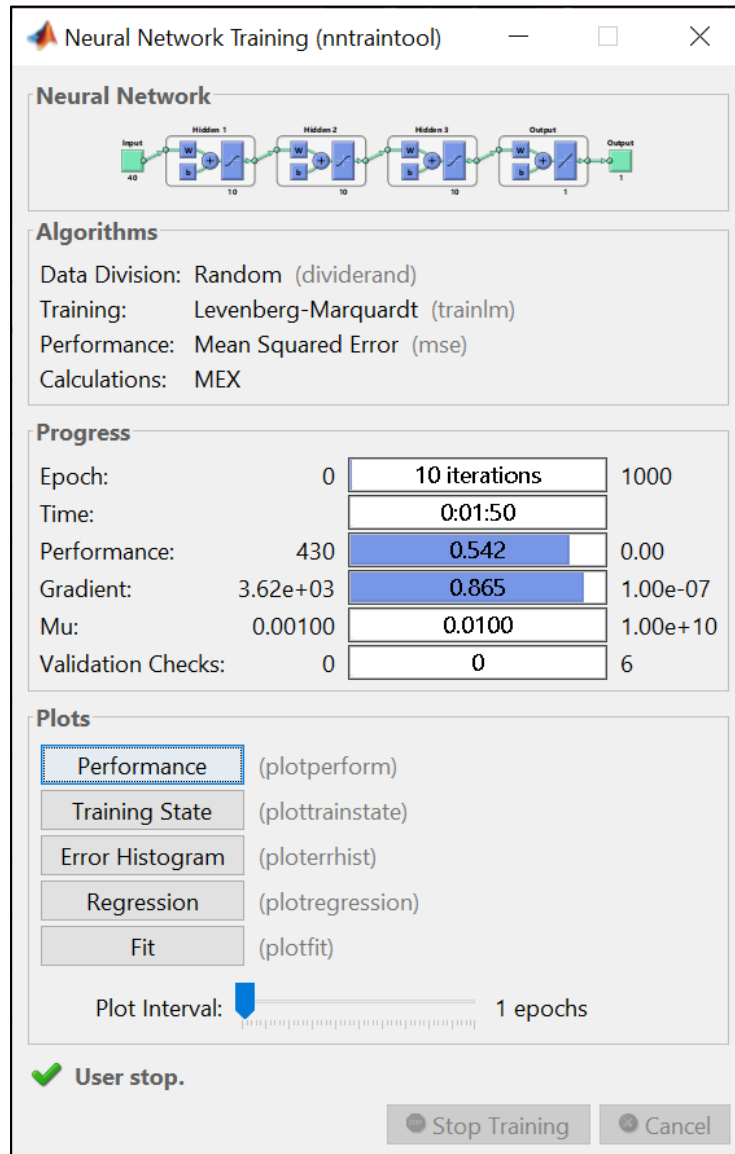


Fig. D-15 $T_p = 20$, $T_f = 15$ (Pattern 3)

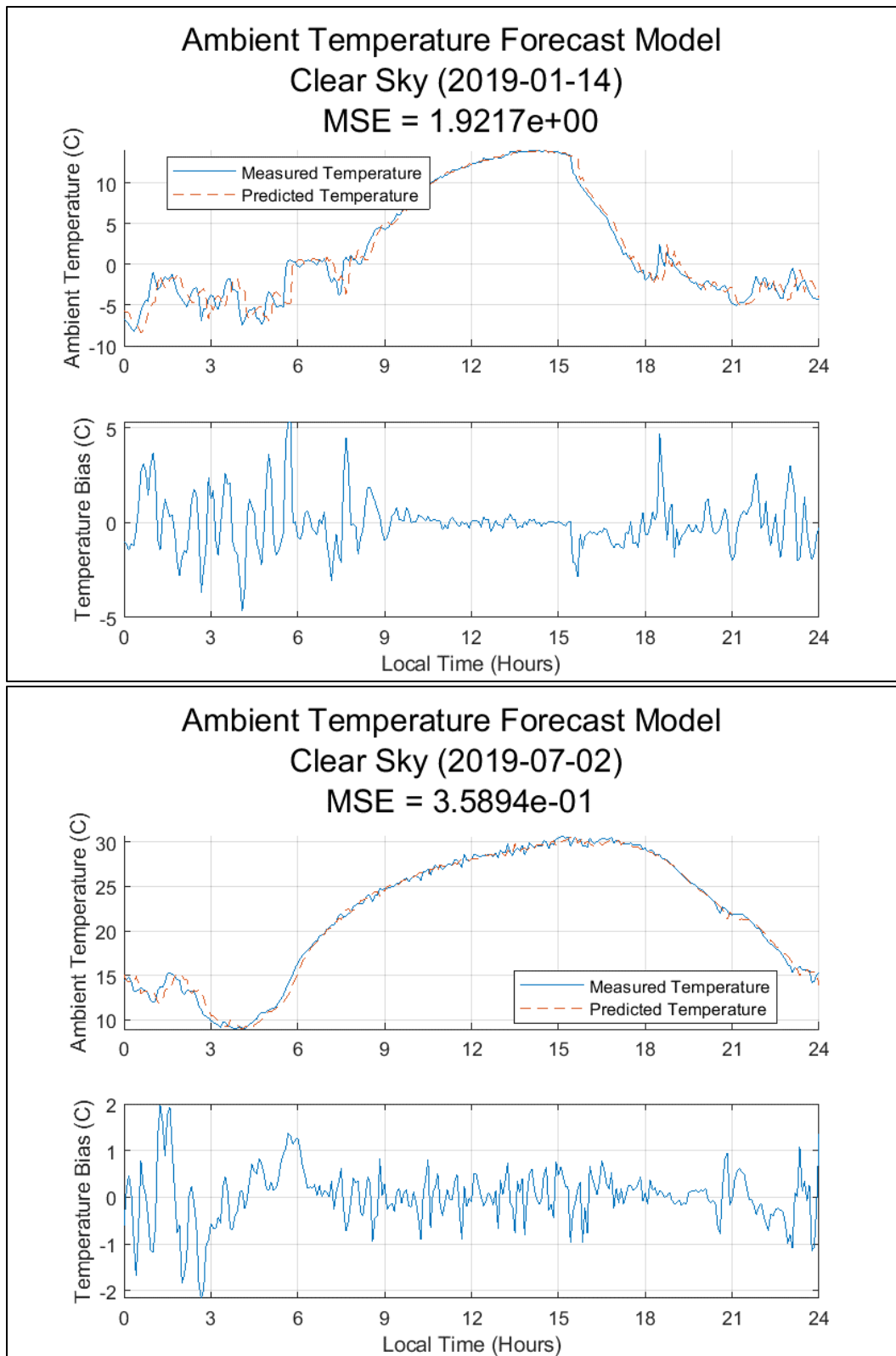


Fig. D-15 $T_p = 20$, $T_r = 15$ (Pattern 3) (continued)

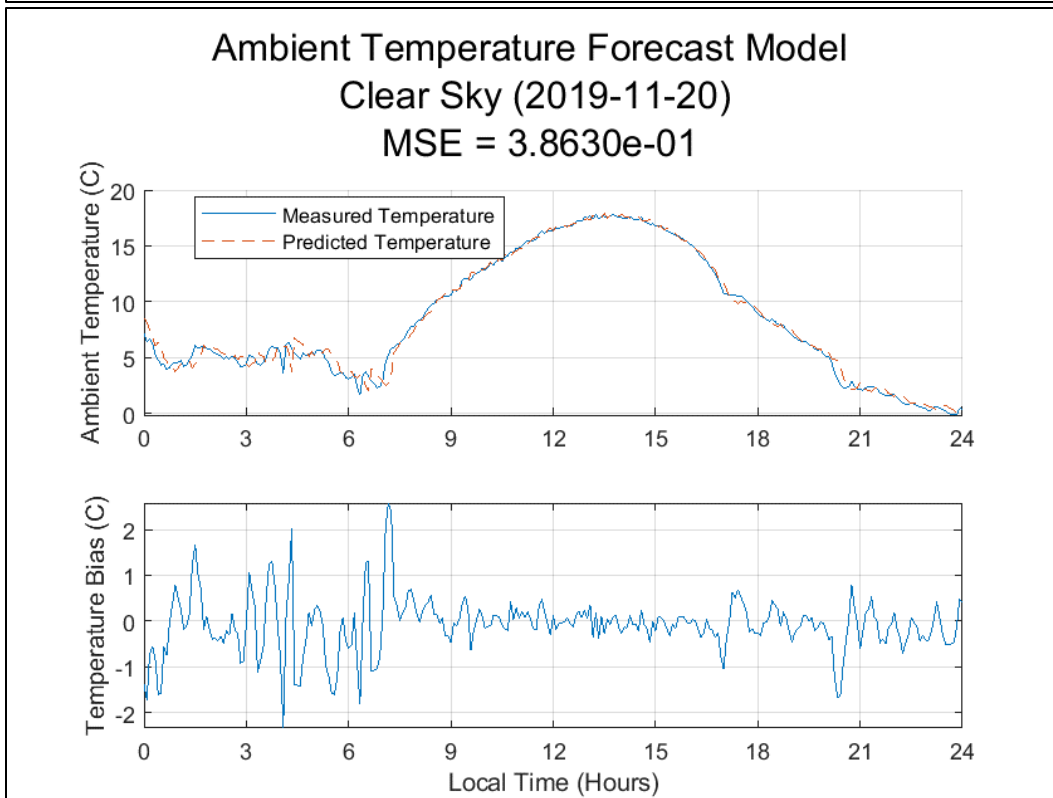
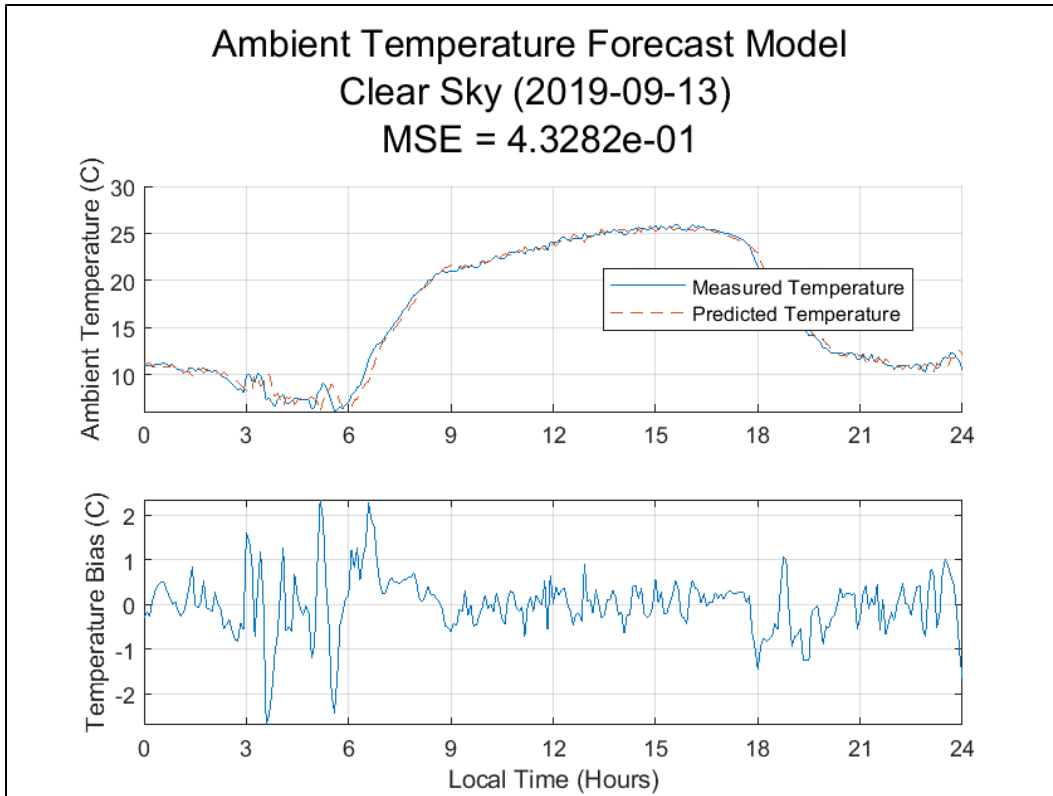


Fig. D-15 $T_p = 20$, $T_f = 15$ (Pattern 3) (continued)

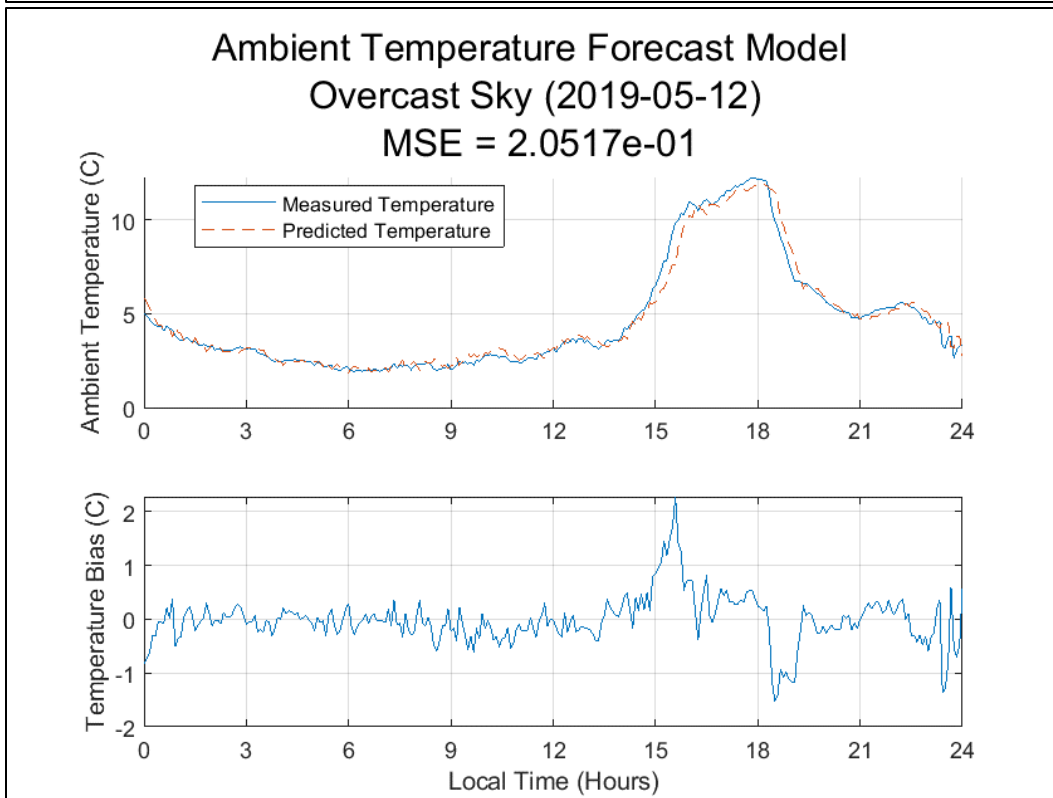
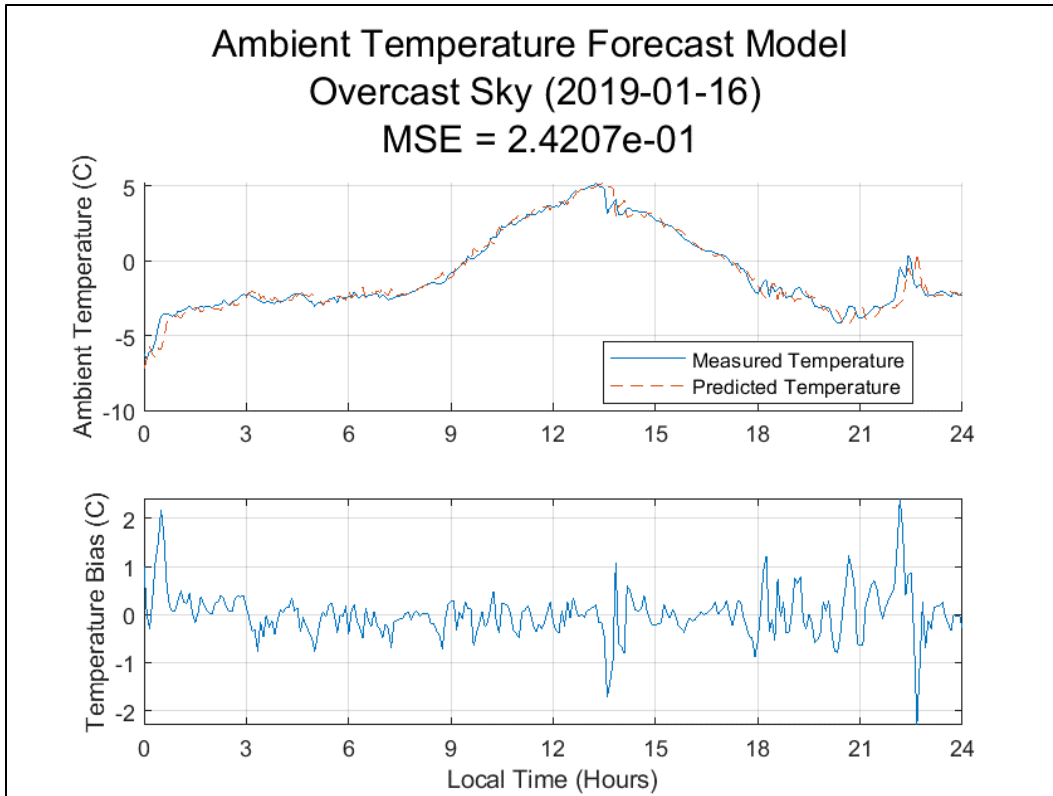


Fig. D-15 $T_p = 20$, $T_f = 15$ (Pattern 3) (continued)

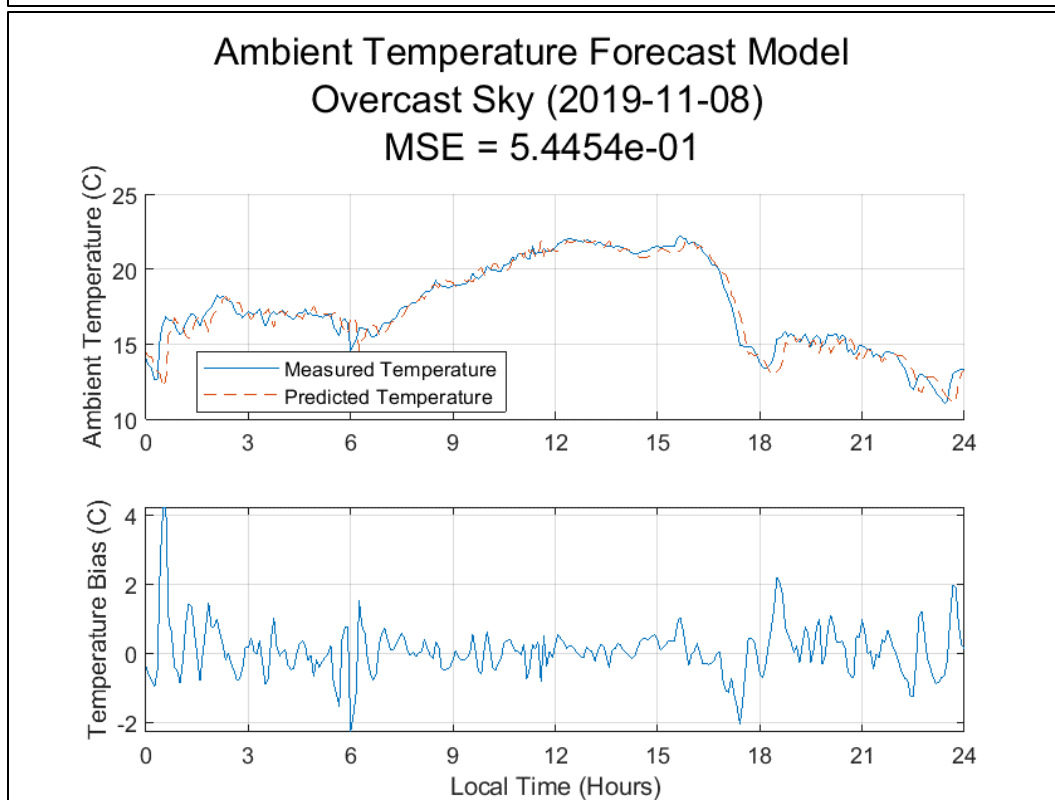
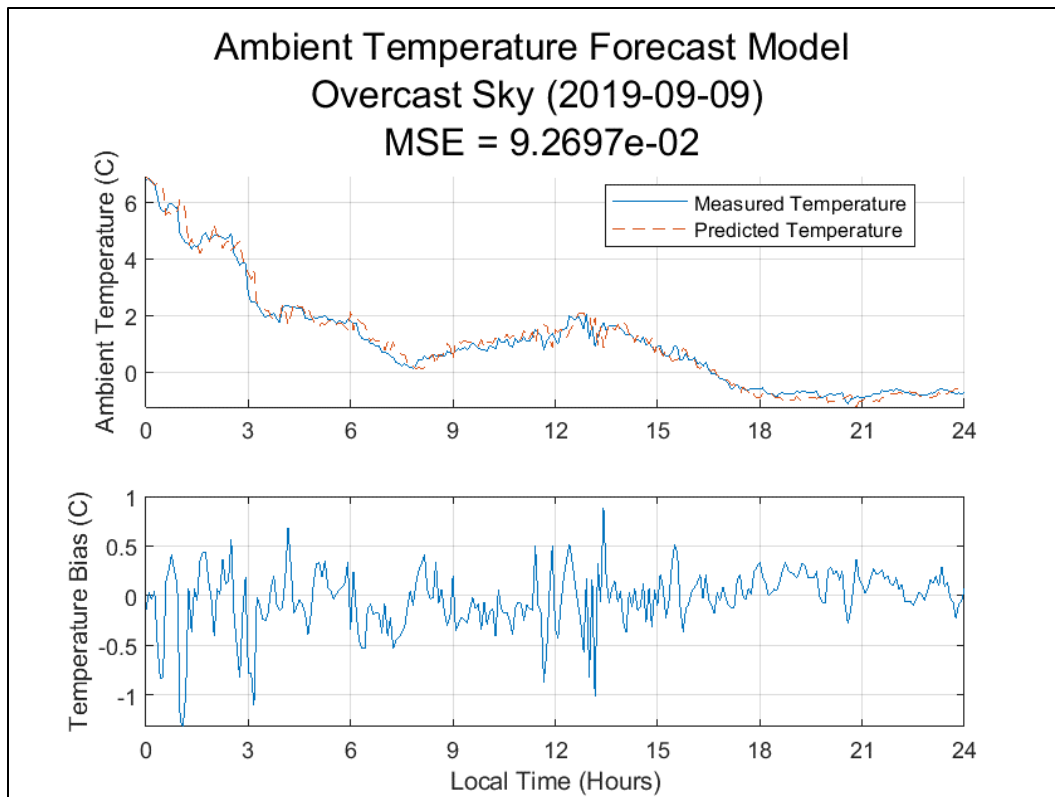


Fig. D-15 $T_p = 20$, $T_f = 15$ (Pattern 3) (continued)

$$T_p = 40$$

$$T_f = 15$$

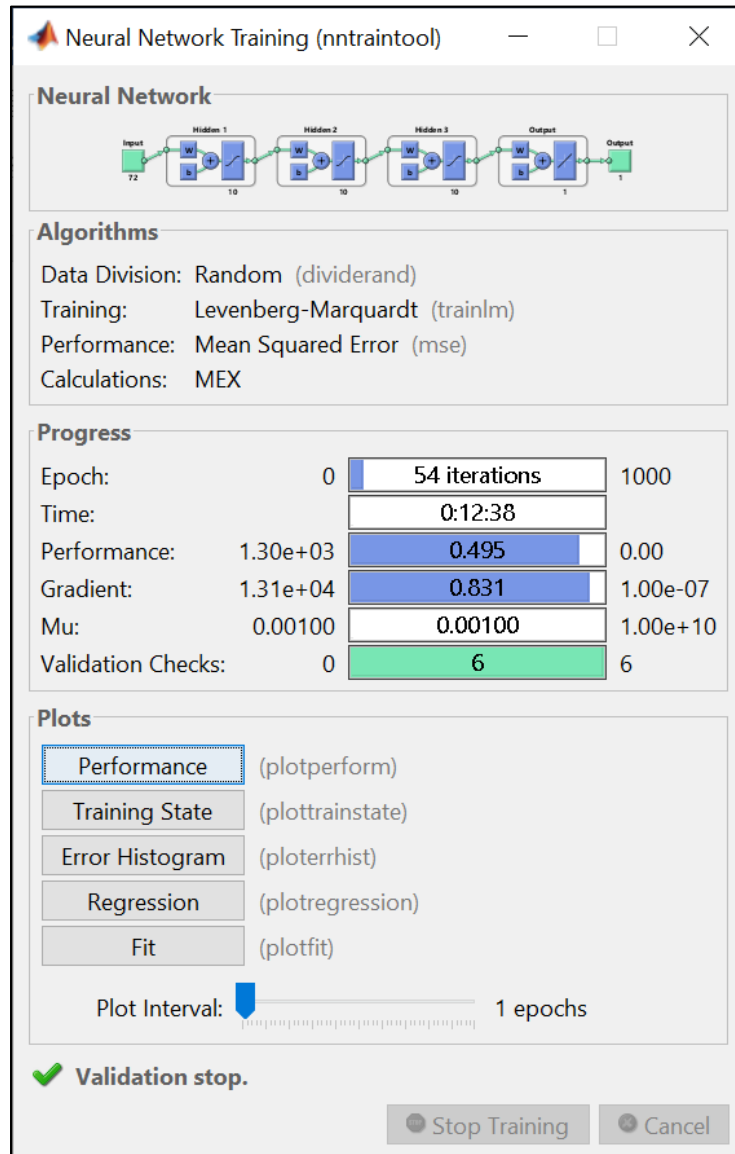


Fig. D-16 $T_p = 40$, $T_f = 15$ (Pattern 3)

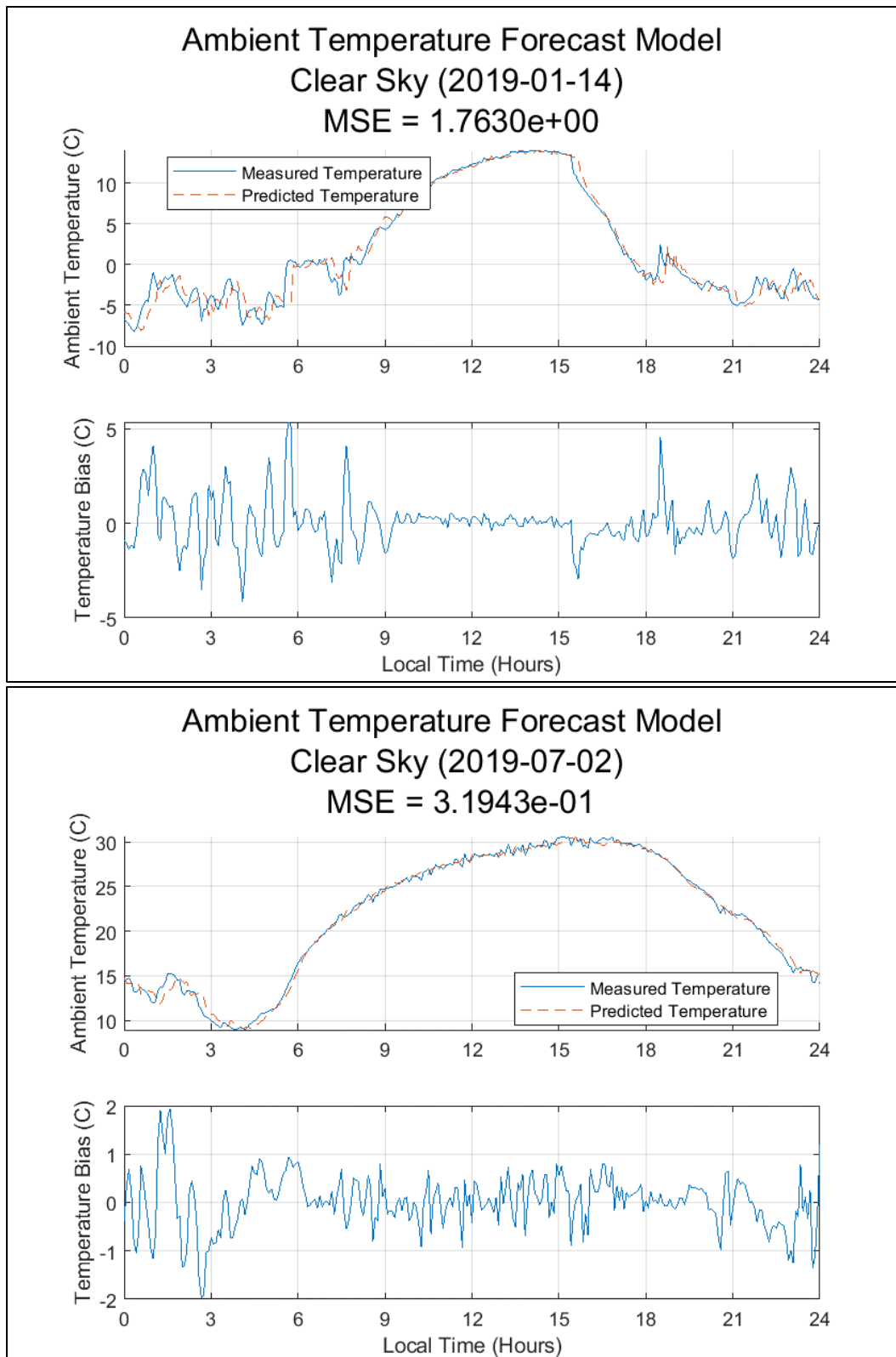


Fig. D-16 $T_p = 40$, $T_f = 15$ (Pattern 3) (continued)

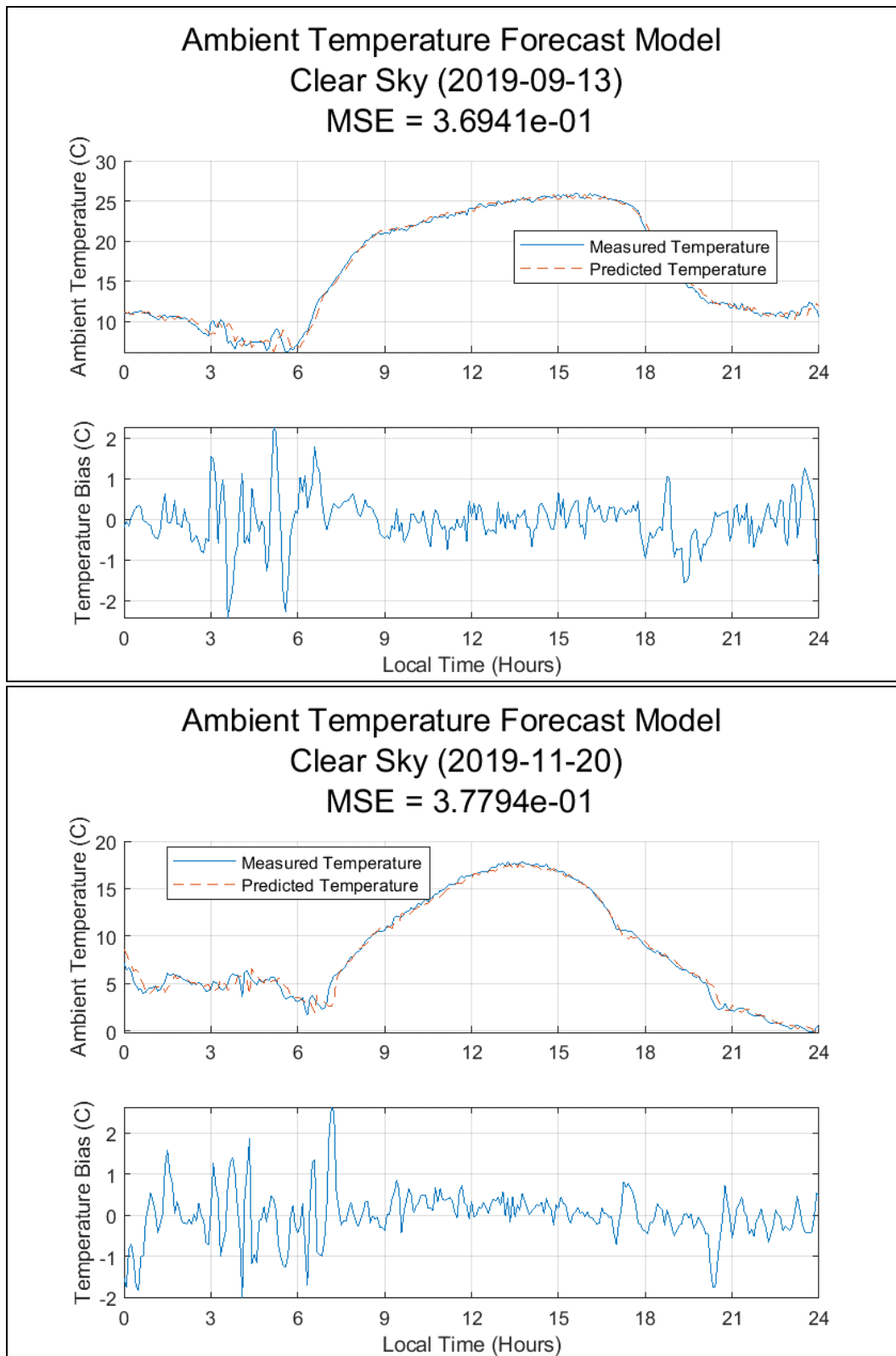


Fig. D-16 $T_p = 40$, $T_f = 15$ (Pattern 3) (continued)

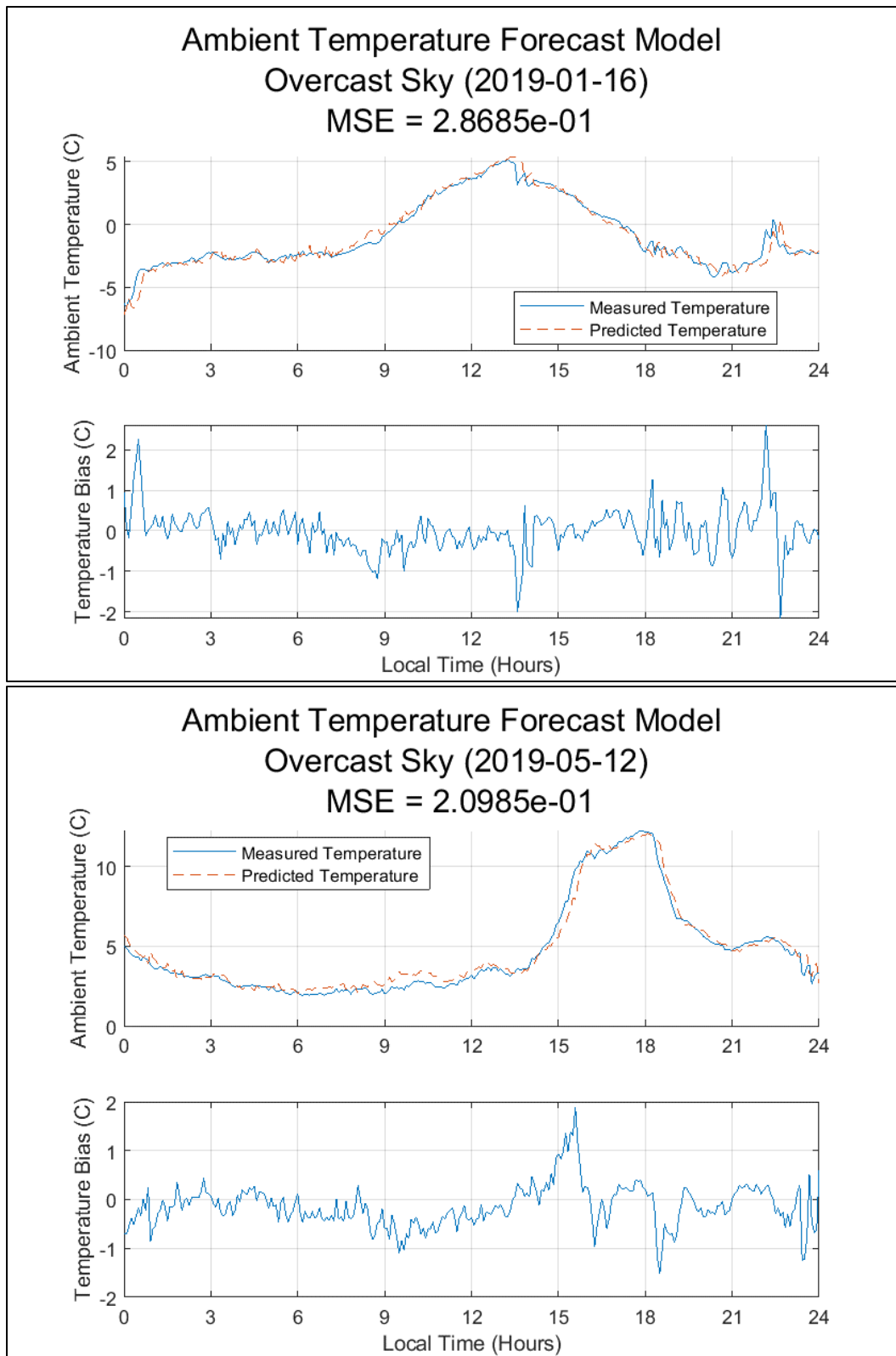


Fig. D-16 $T_p = 40$, $T_f = 15$ (Pattern 3) (continued)

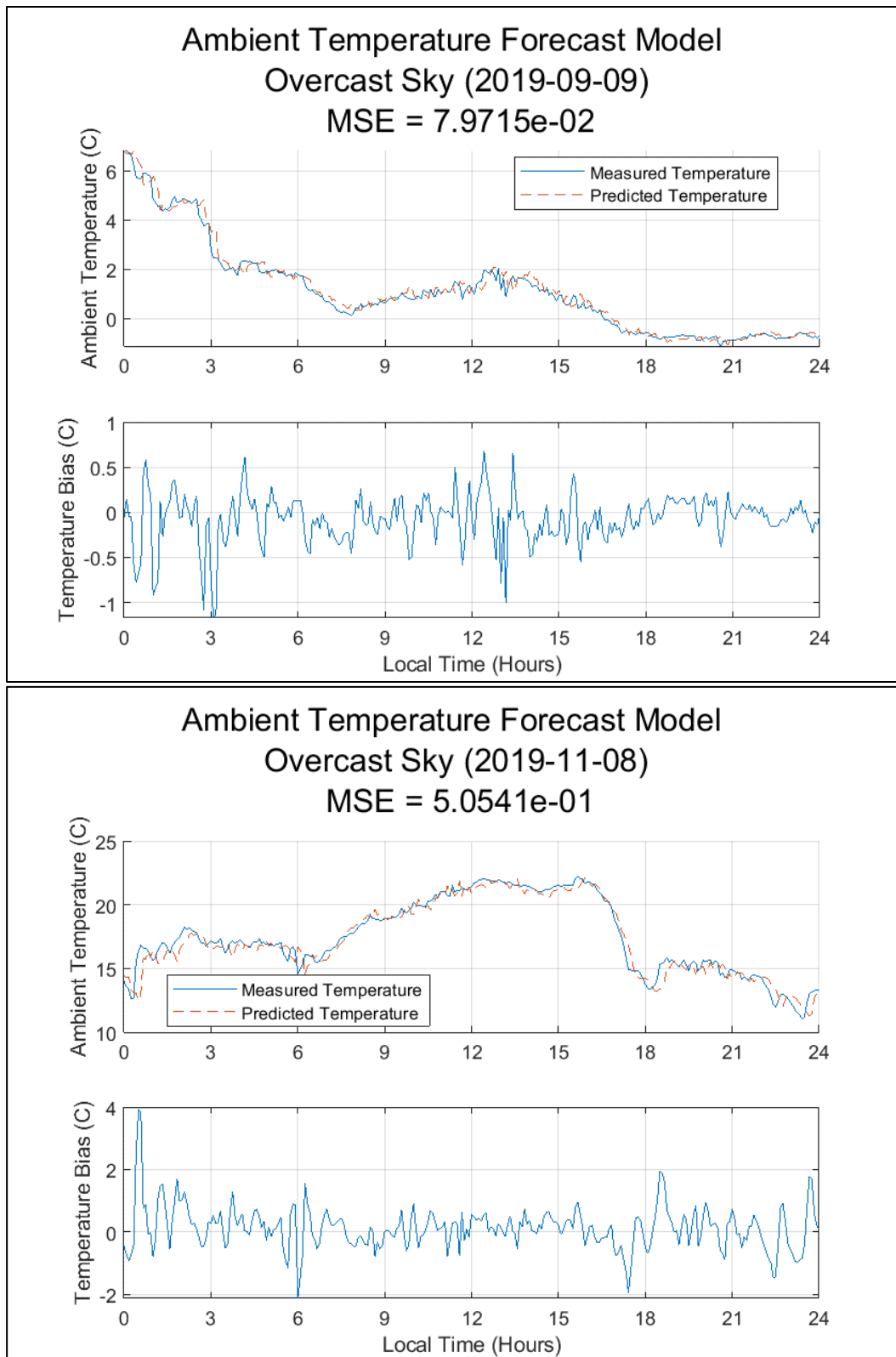


Fig. D-16 $T_p = 40$, $T_f = 15$ (Pattern 3) (continued)

$$T_p = 80$$

$$T_f = 15$$

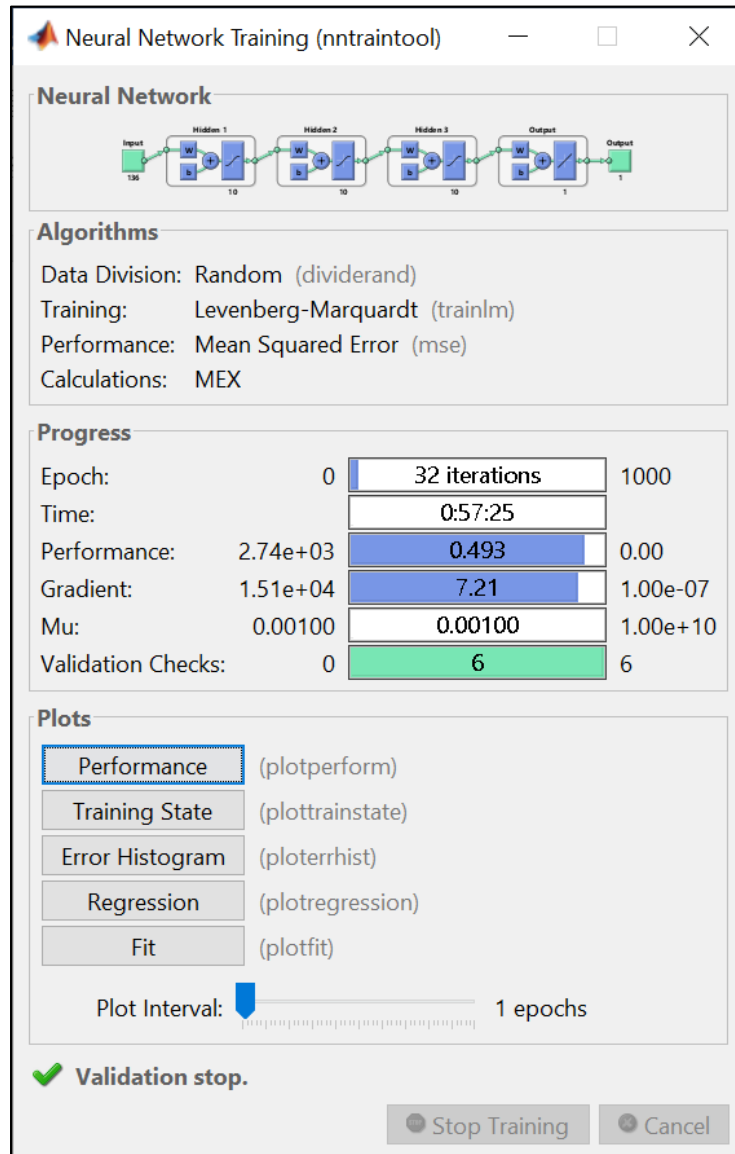


Fig. D-17 $T_p = 80$, $T_f = 15$ (Pattern 3)

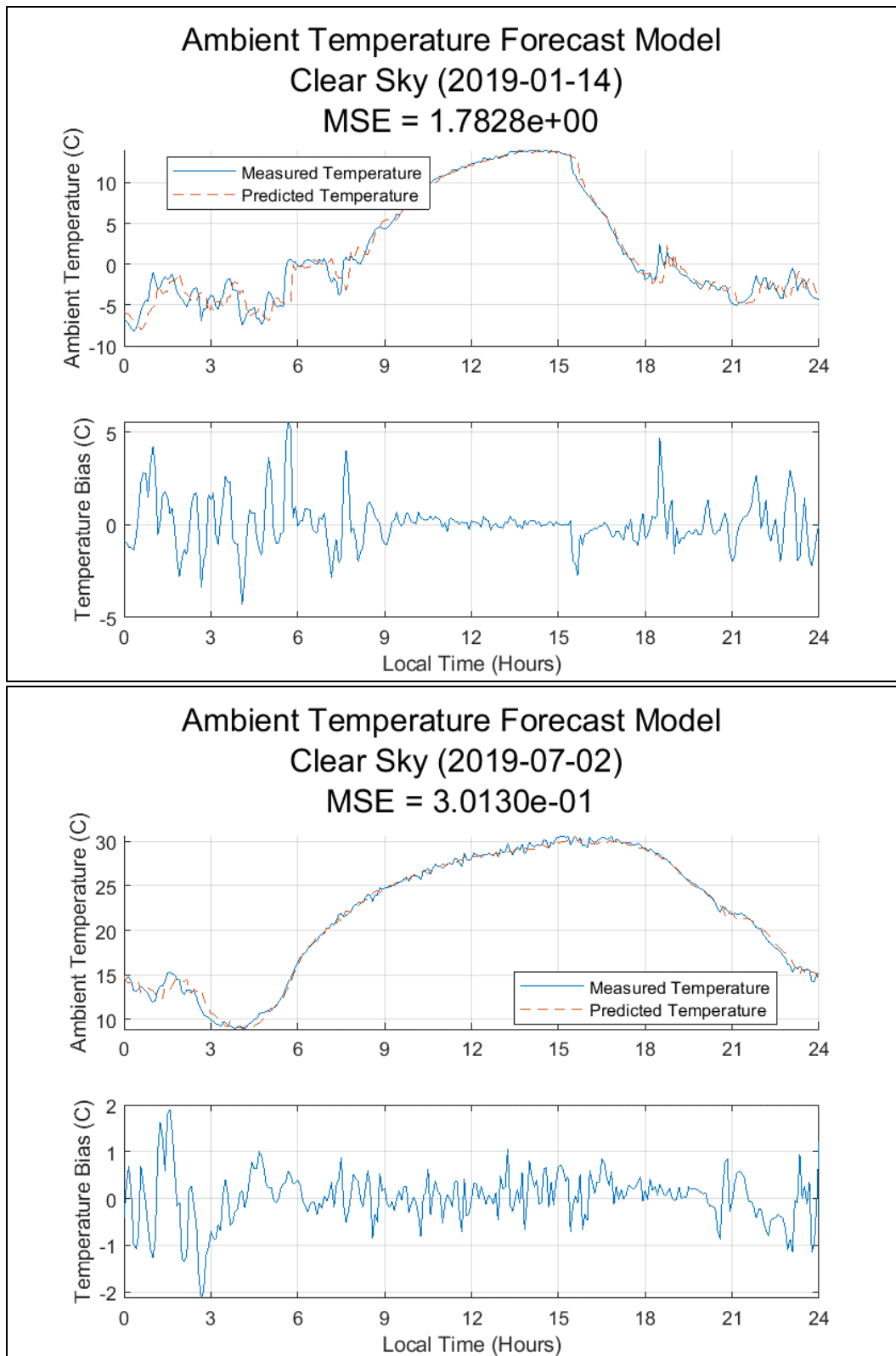


Fig. D-17 $T_p = 80$, $T_f = 15$ (Pattern 3) (continued)

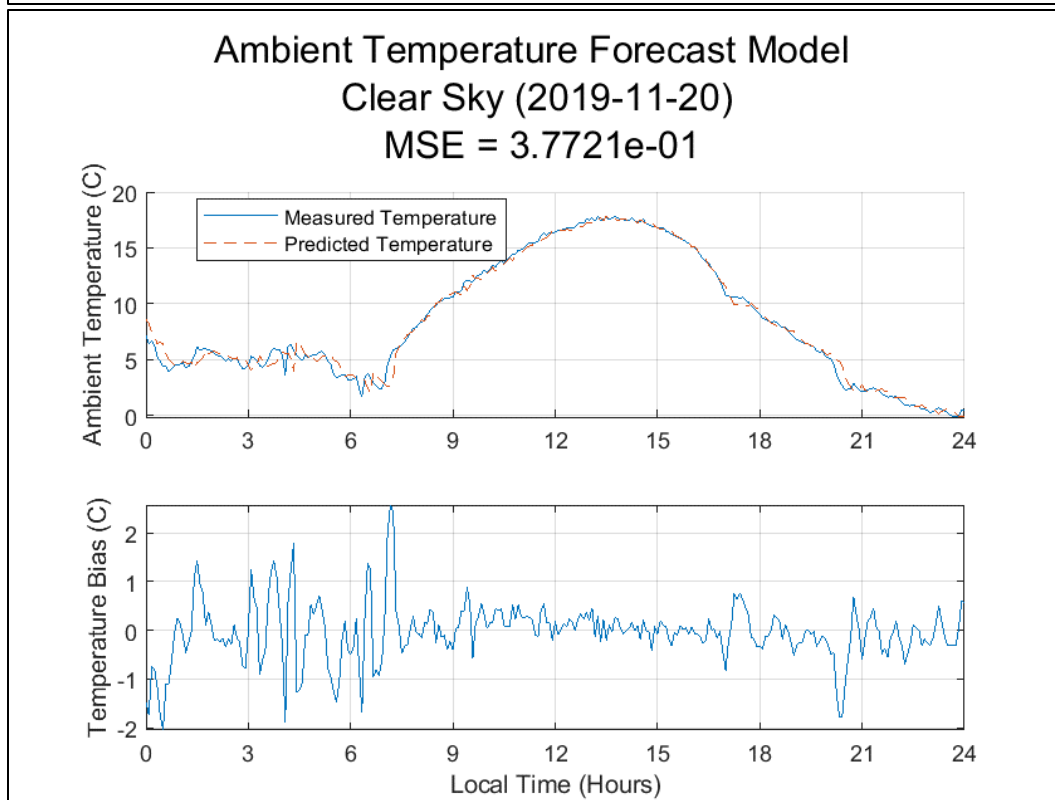
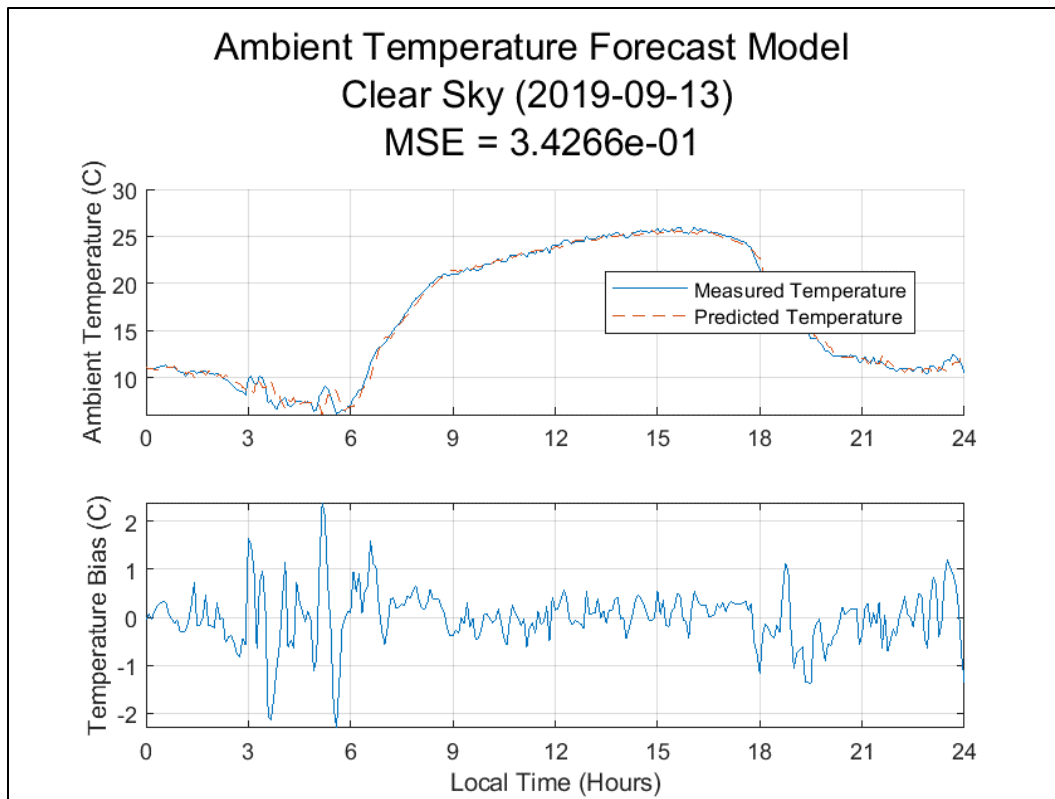


Fig. D-17 $T_p = 80$, $T_f = 15$ (Pattern 3) (continued)

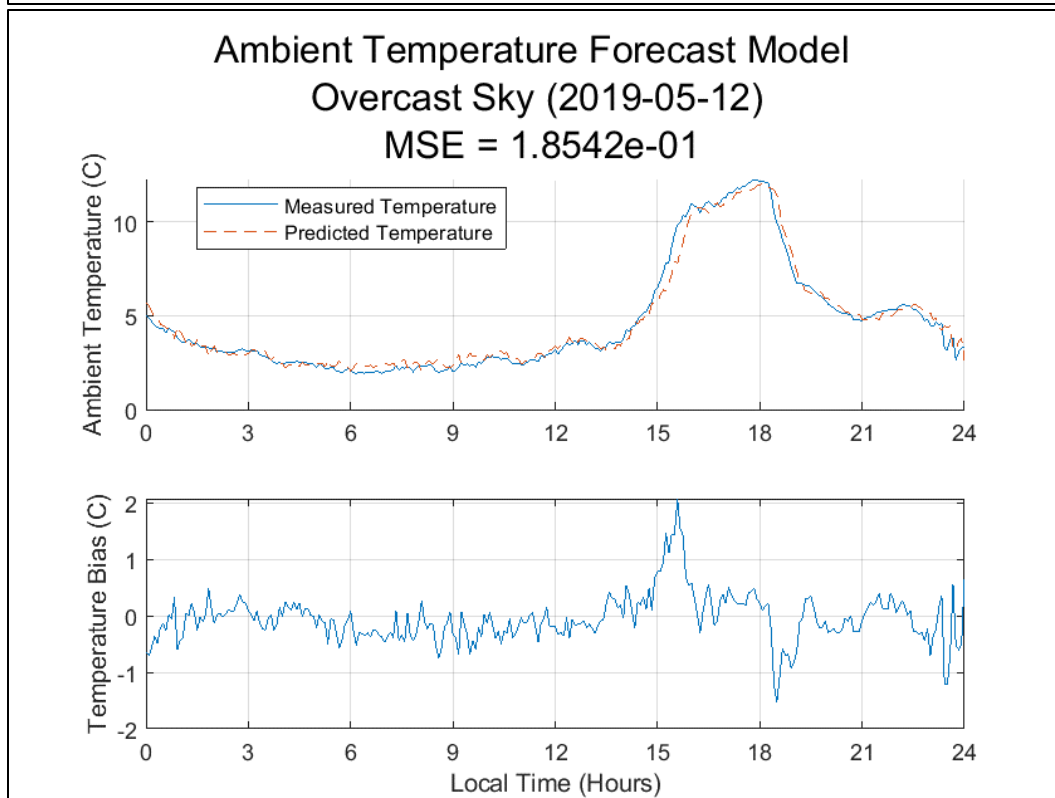
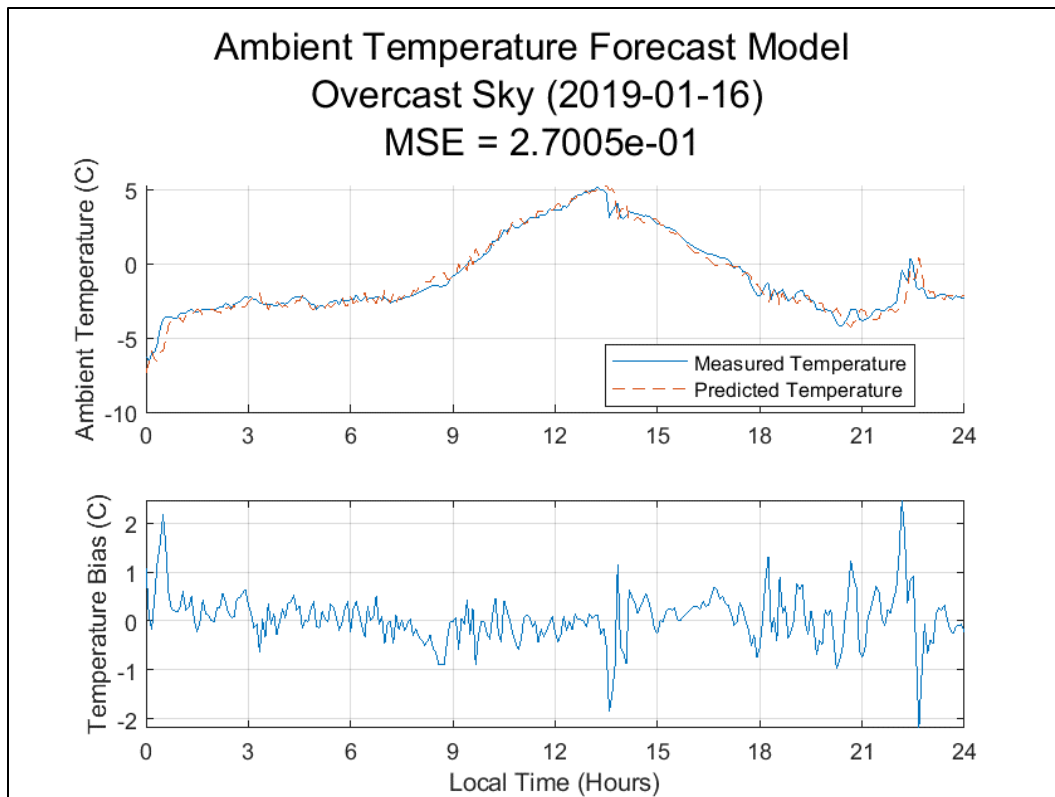


Fig. D-17 $T_p = 80$, $T_f = 15$ (Pattern 3) (continued)

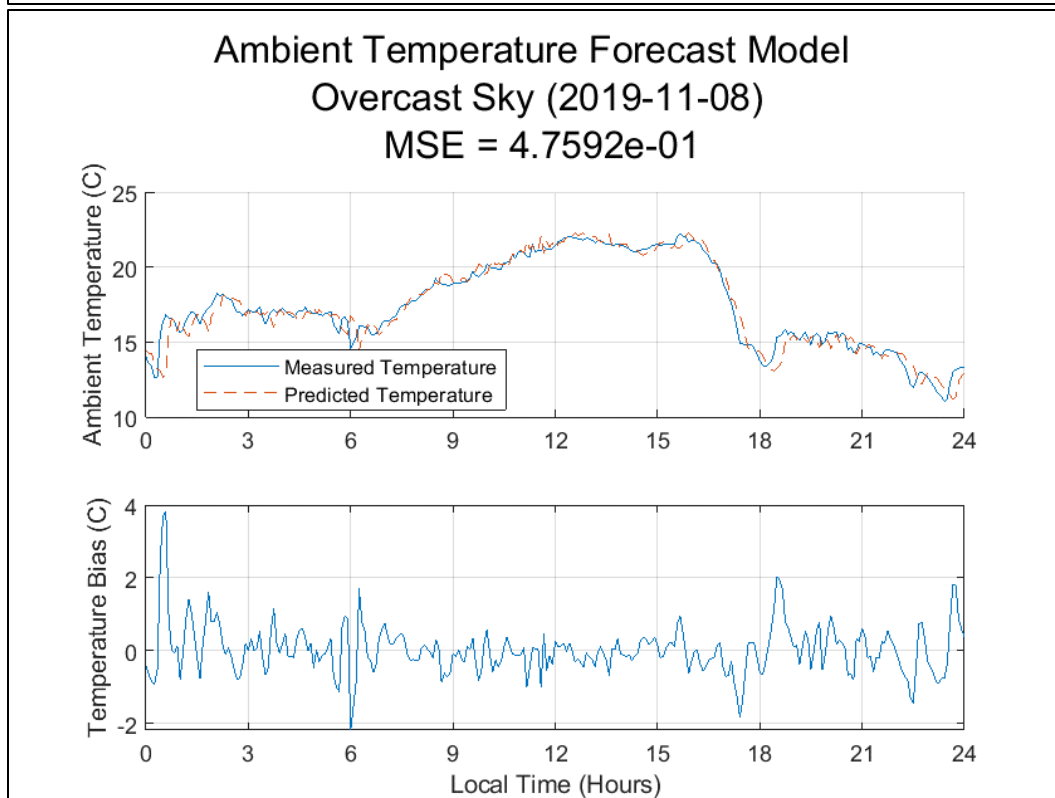
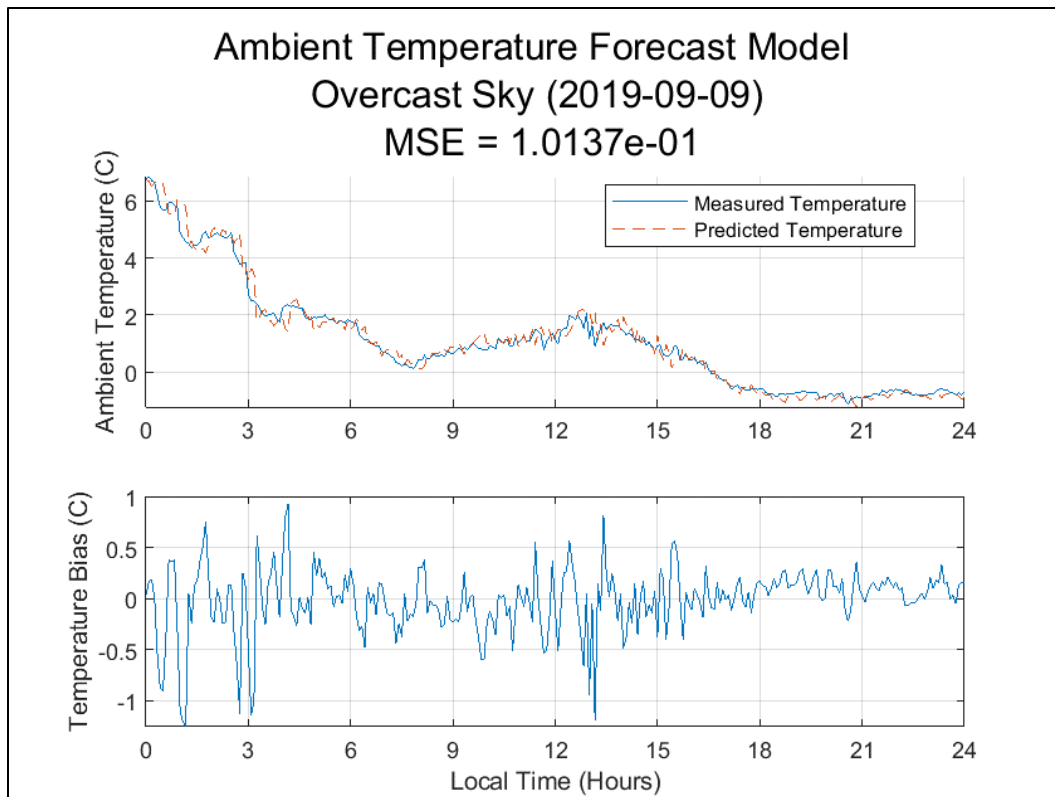


Fig. D-17 $T_p = 80$, $T_f = 15$ (Pattern 3) (continued)

$$T_p = 160$$

$$T_f = 15$$

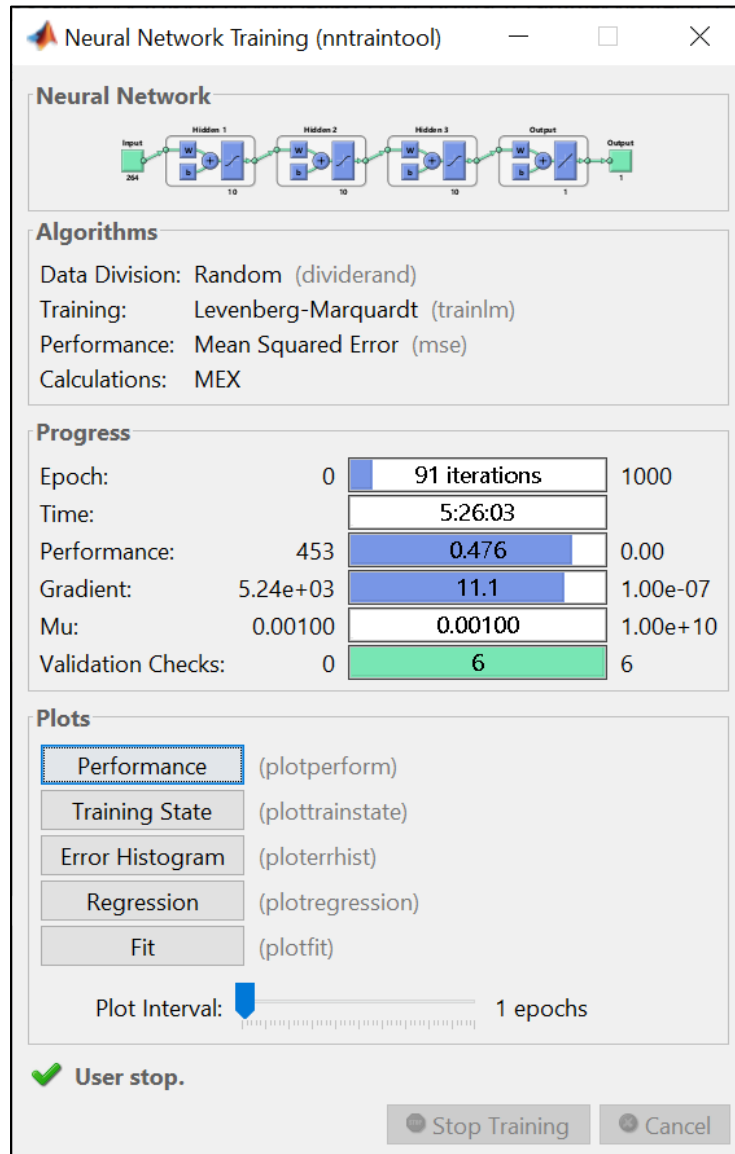


Fig. D-18 $T_p = 160$, $T_f = 15$ (Pattern 3)

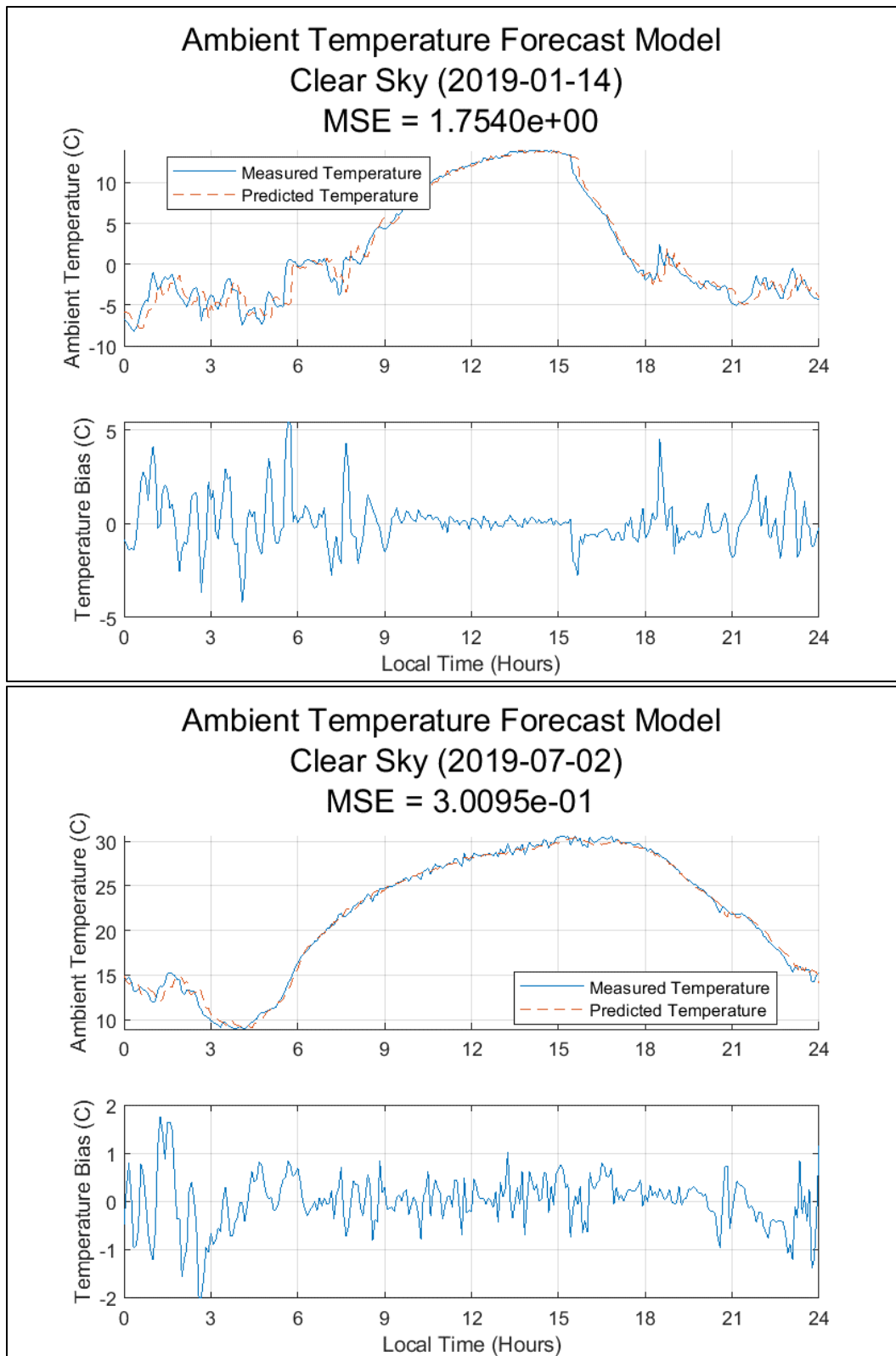


Fig. D-18 $T_p = 160$, $T_r = 15$ (Pattern 3) (continued)

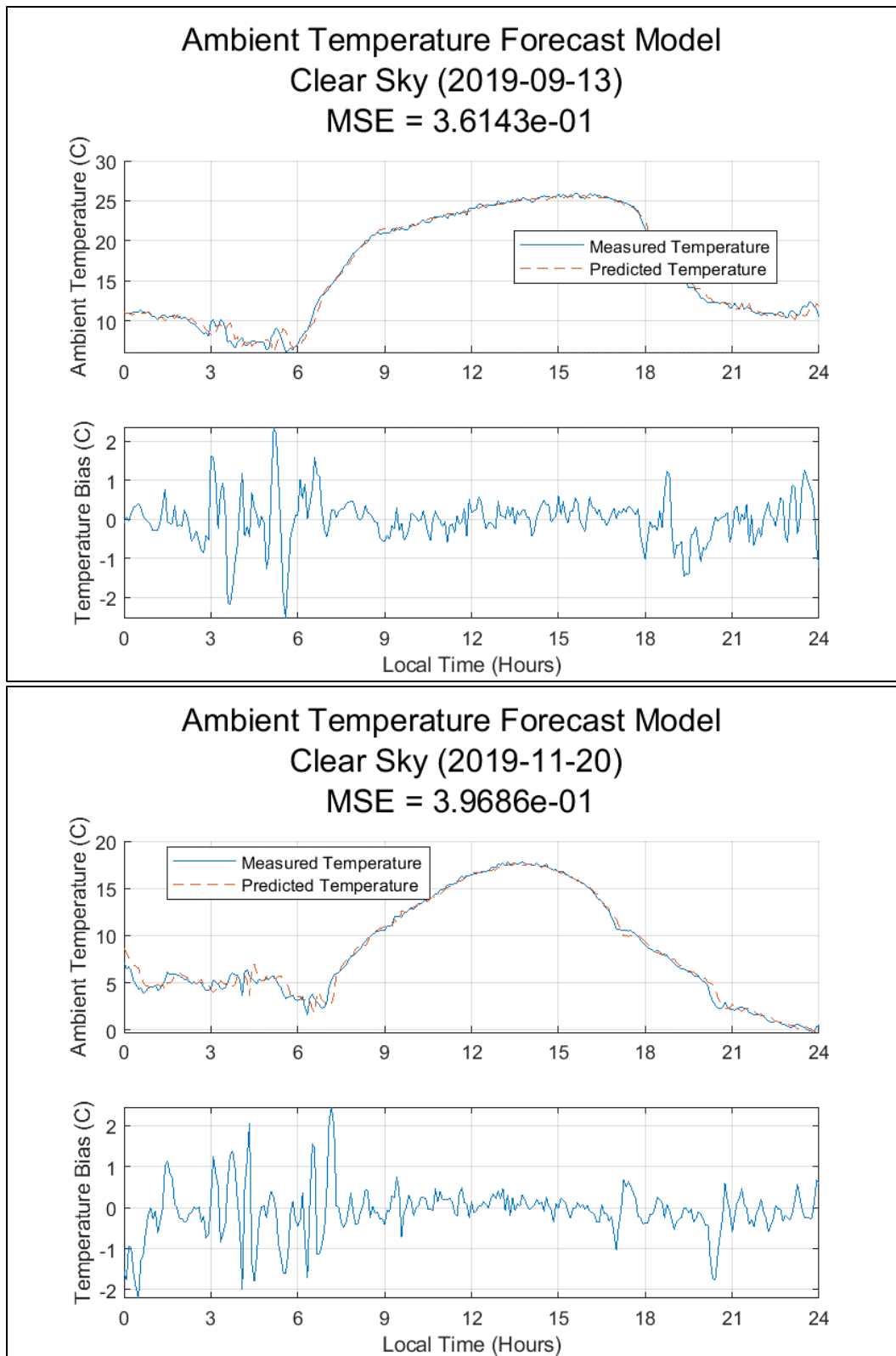


Fig. D-18 $T_p = 160$, $T_r = 15$ (Pattern 3) (continued)

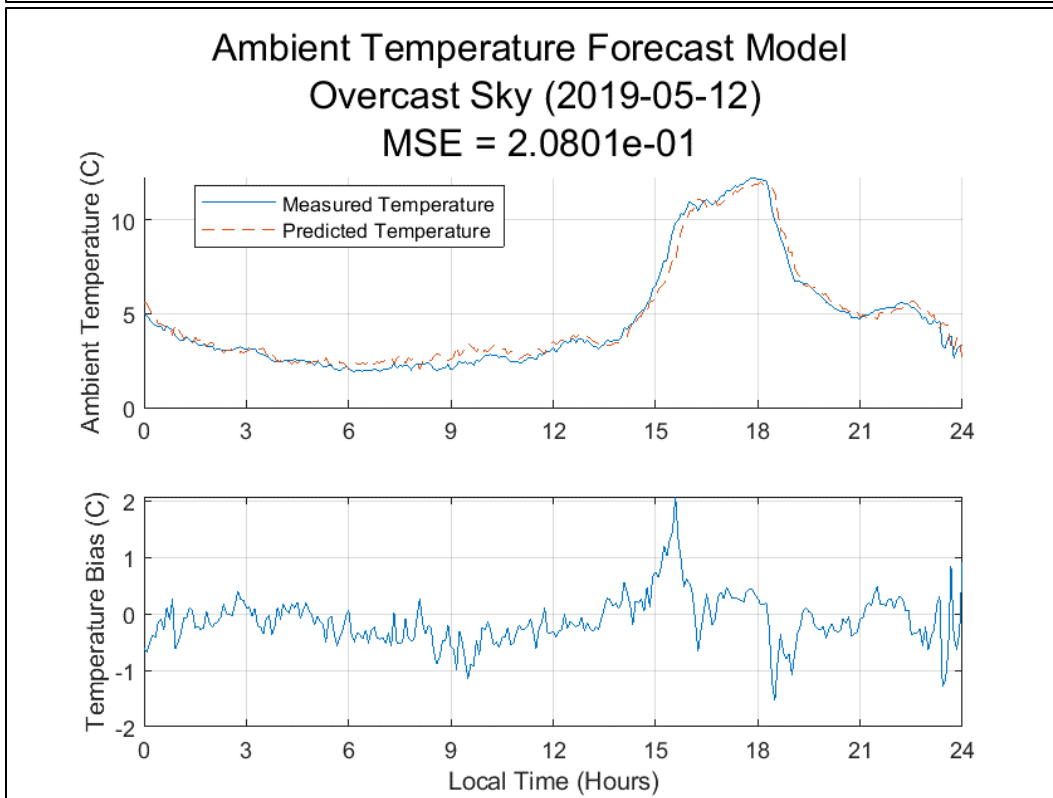
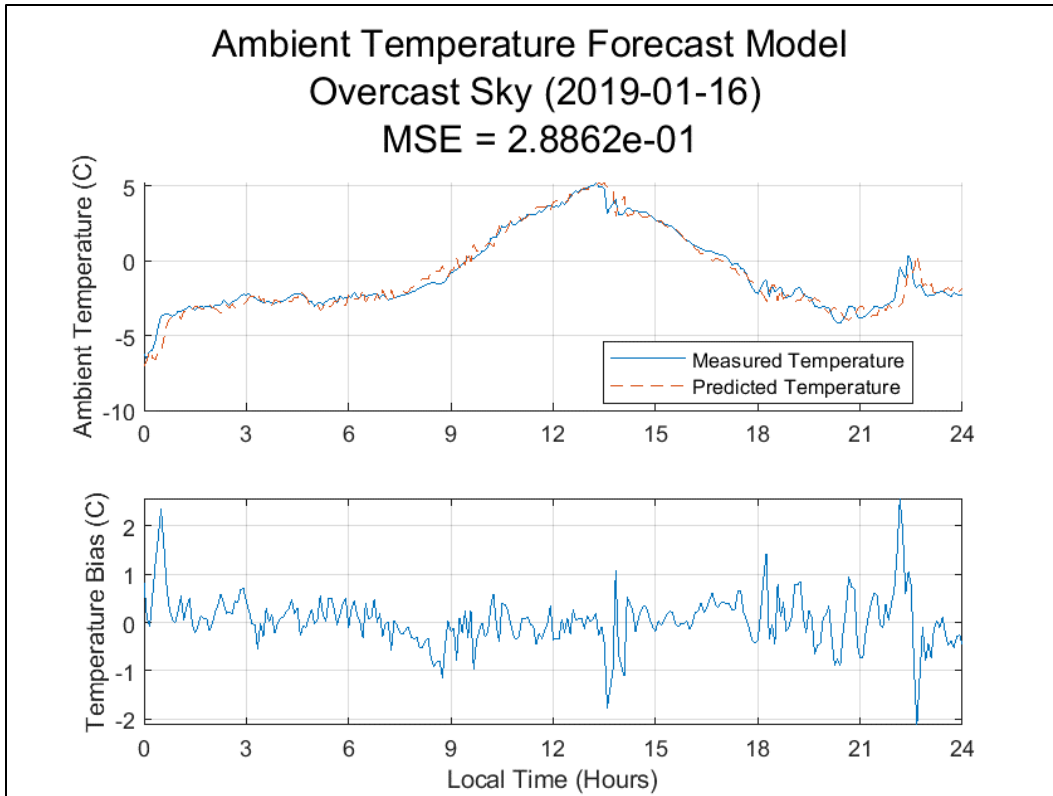


Fig. D-18 $T_p = 160$, $T_r = 15$ (Pattern 3) (continued)

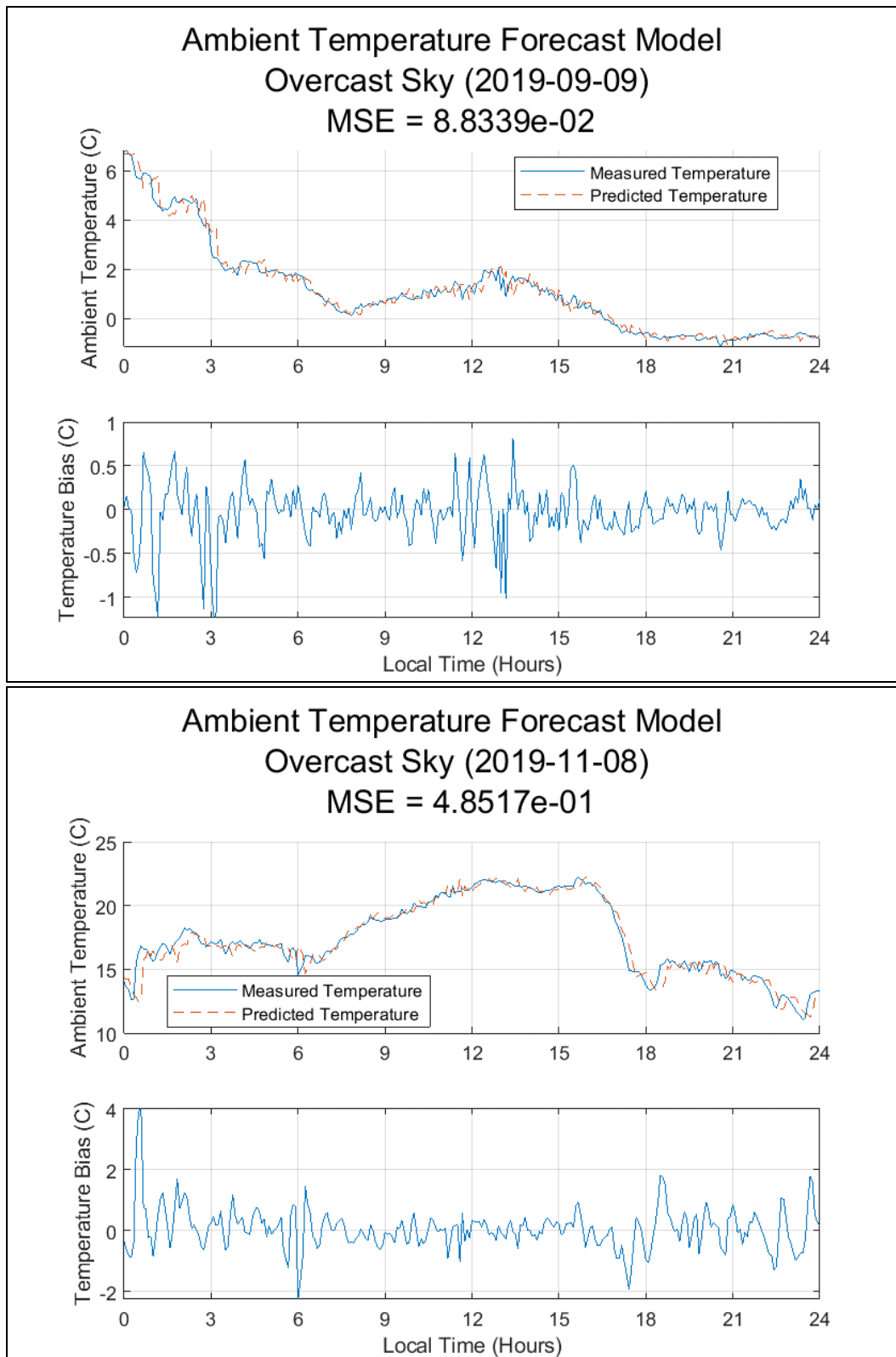


Fig. D-18 $T_p = 160$, $T_r = 15$ (Pattern 3) (continued)

$$T_p = 5$$

$$T_f = 30$$

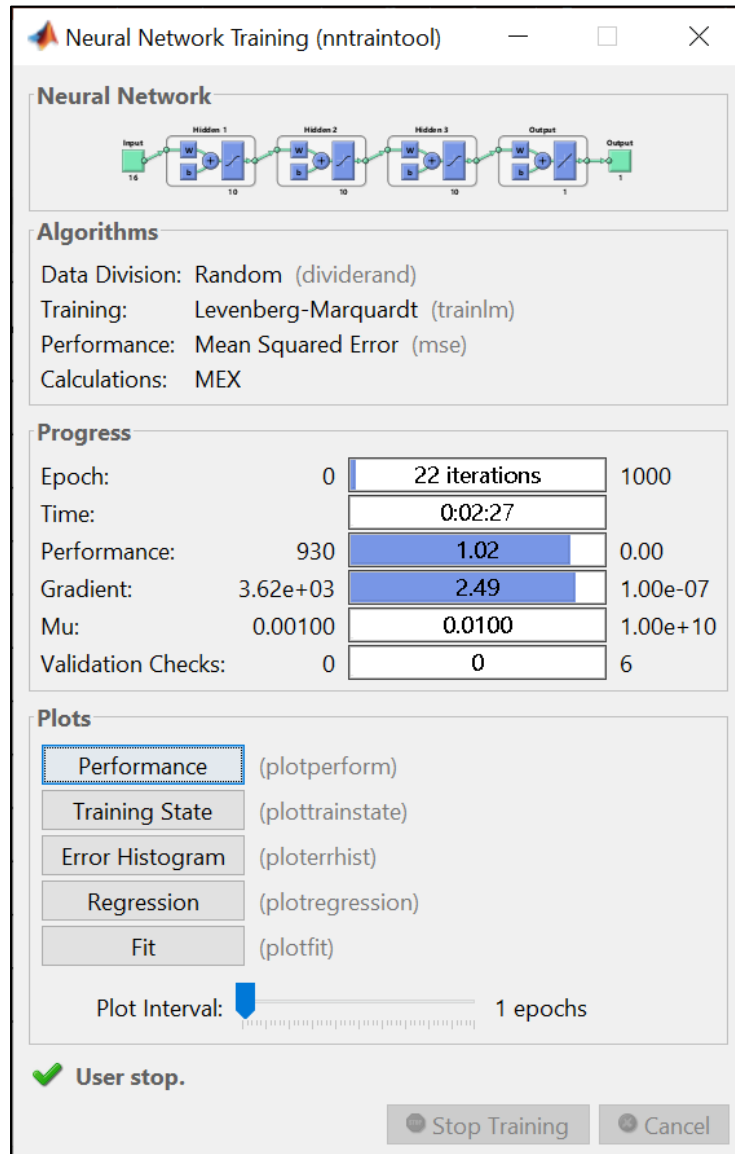


Fig. D-19 $T_p = 5$, $T_f = 30$ (Pattern 4)

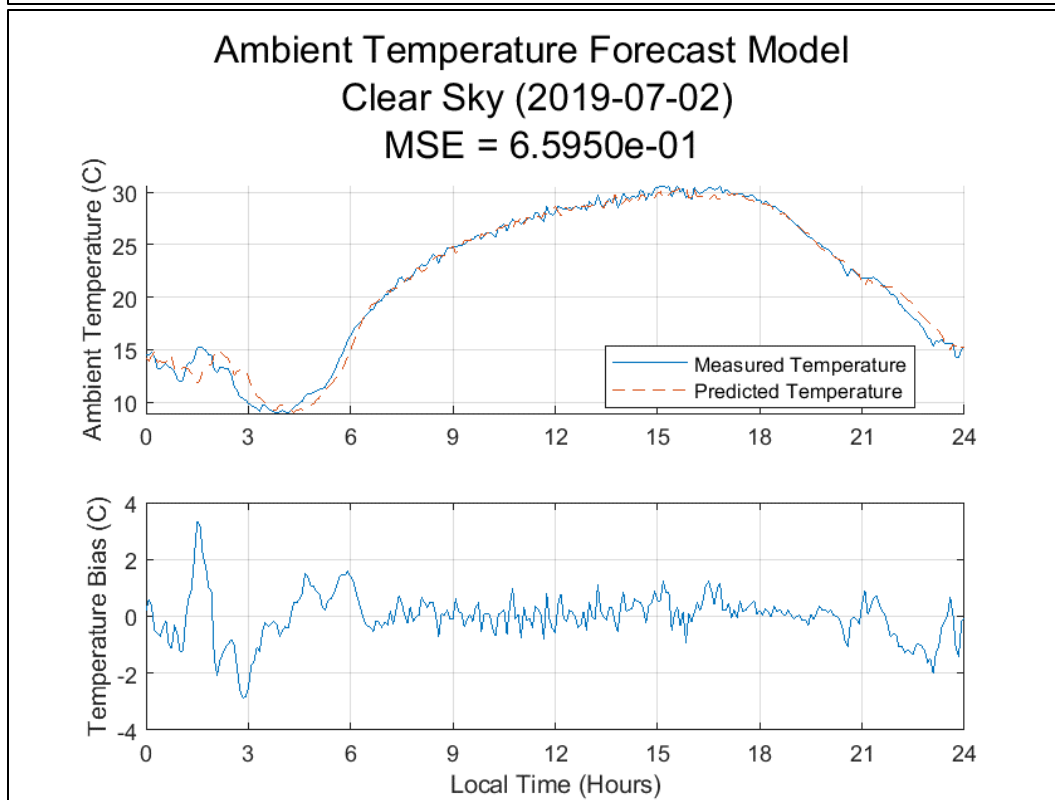
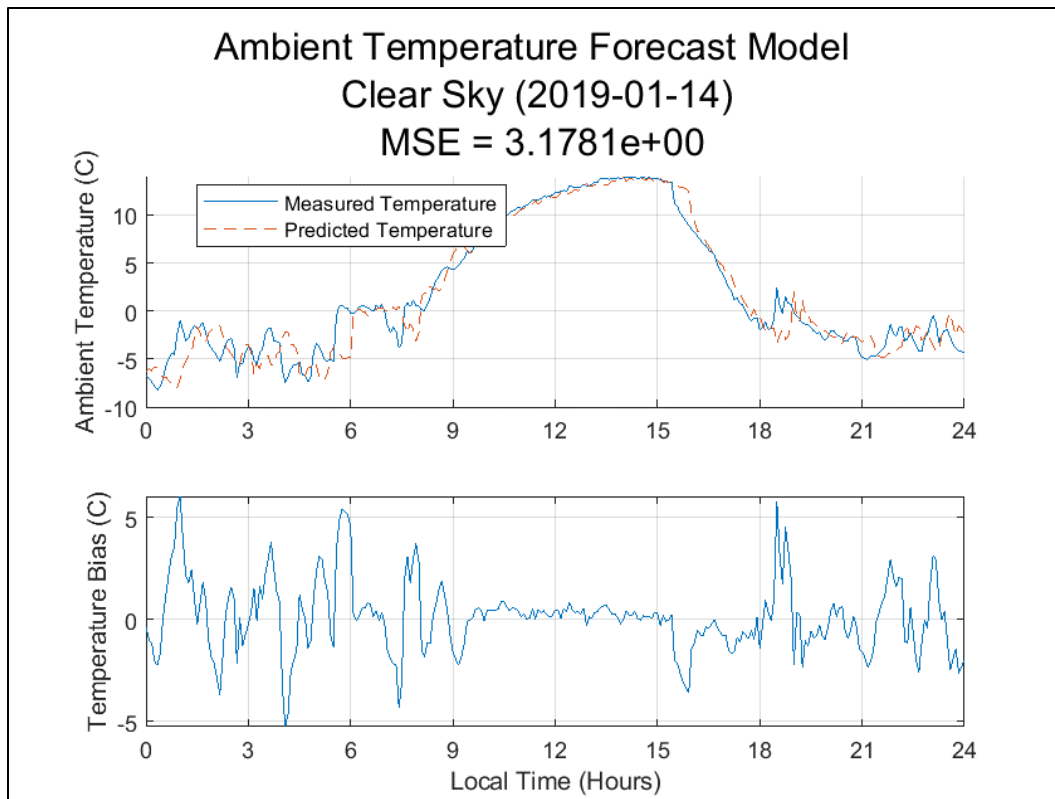


Fig. D-19 $T_p = 5$, $T_r = 30$ (Pattern 4) (continued)

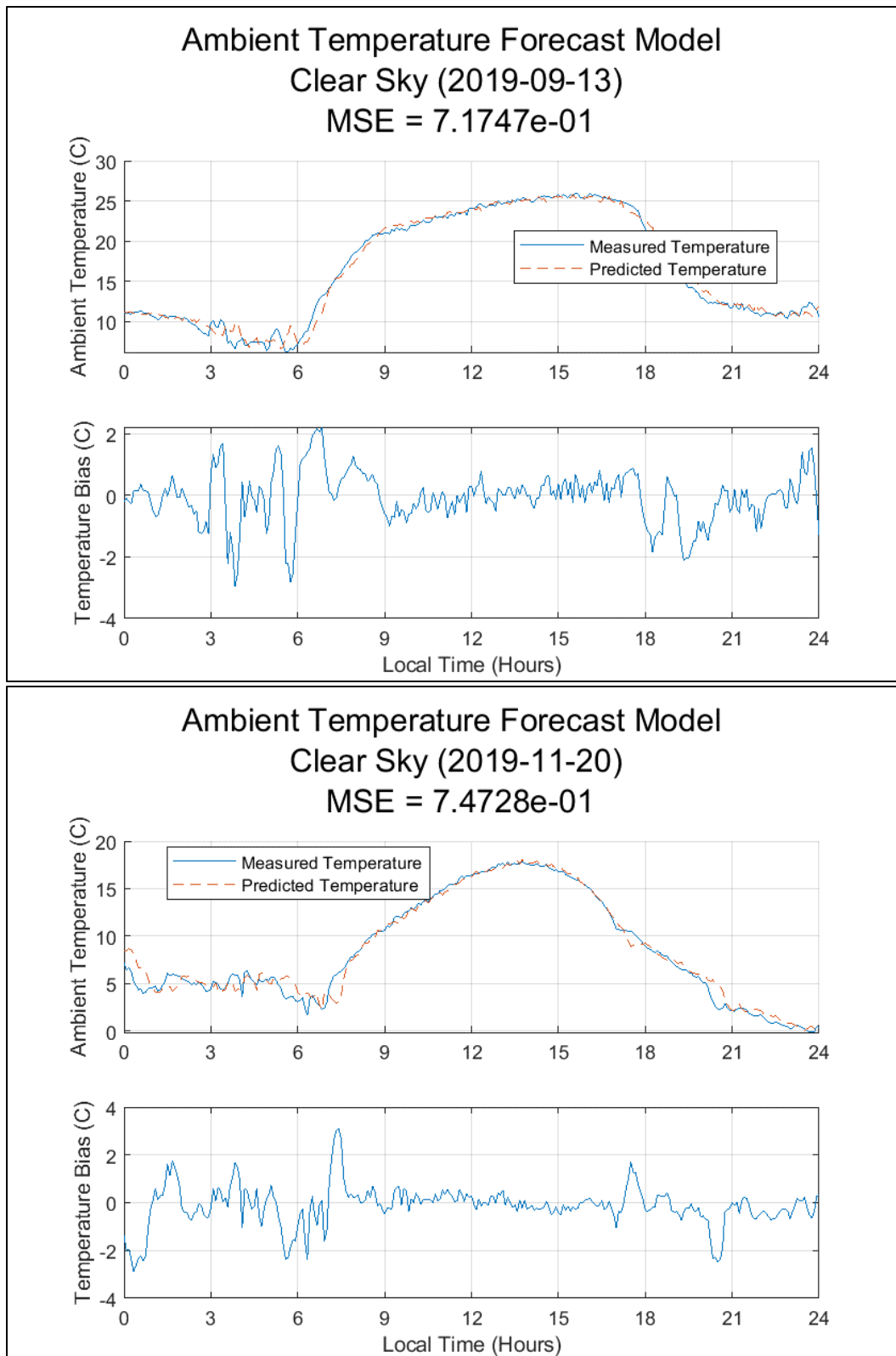


Fig. D-19 $T_p = 5$, $T_r = 30$ (Pattern 4) (continued)

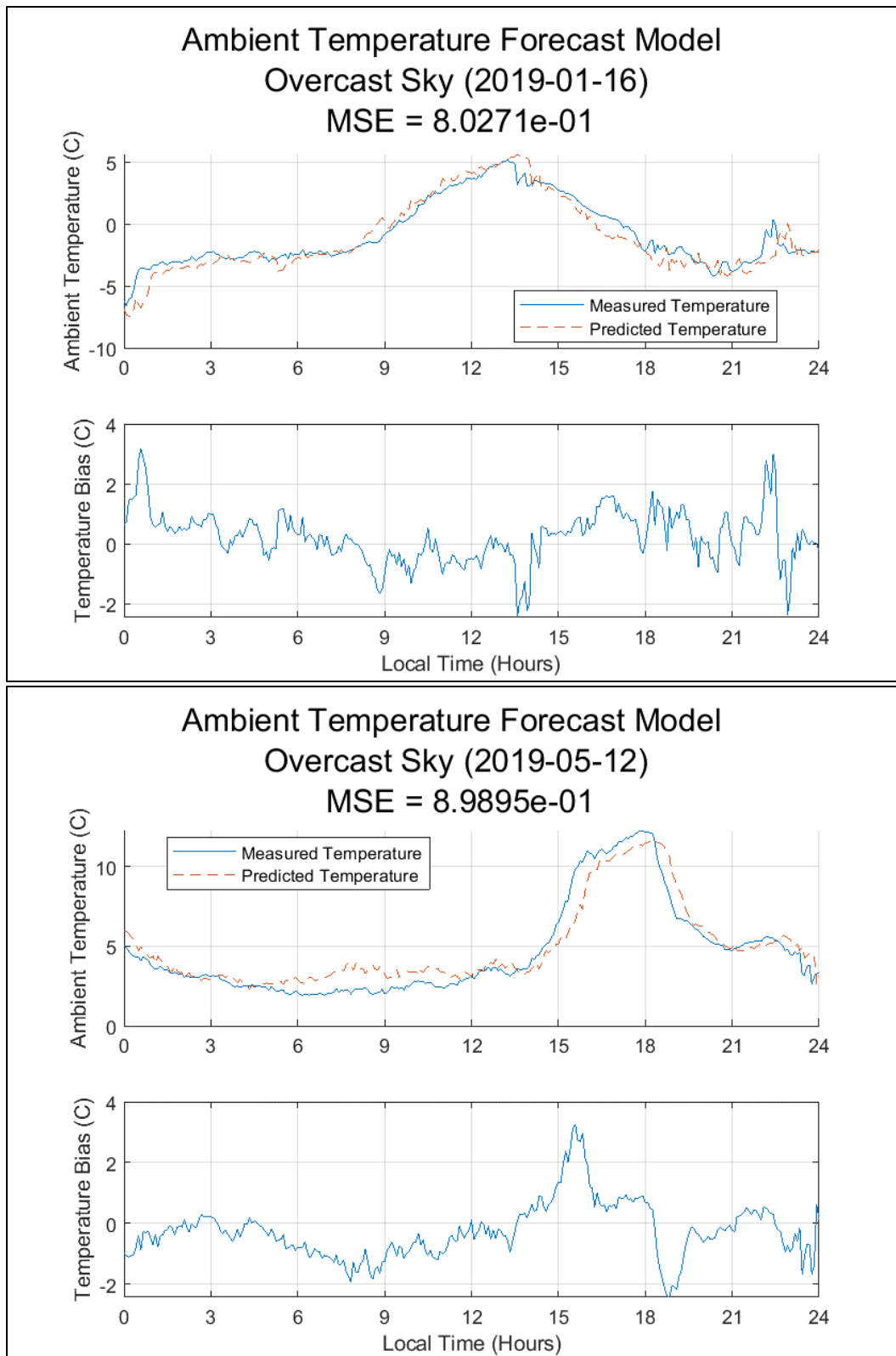


Fig. D-19 $T_p = 5$, $T_r = 30$ (Pattern 4) (continued)

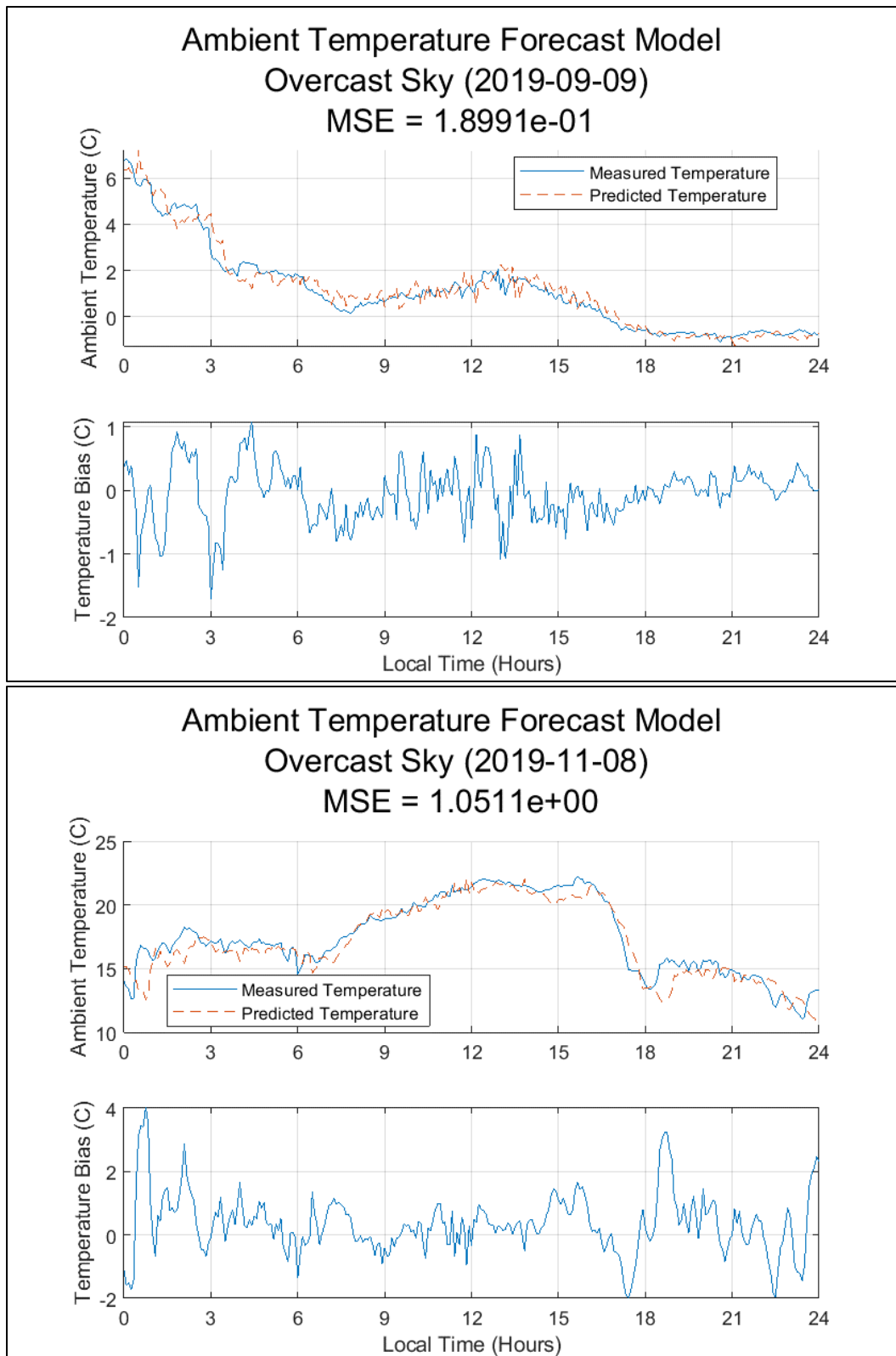


Fig. D-19 $T_p = 5$, $T_r = 30$ (Pattern 4) (continued)

$$T_p = 10$$

$$T_f = 30$$

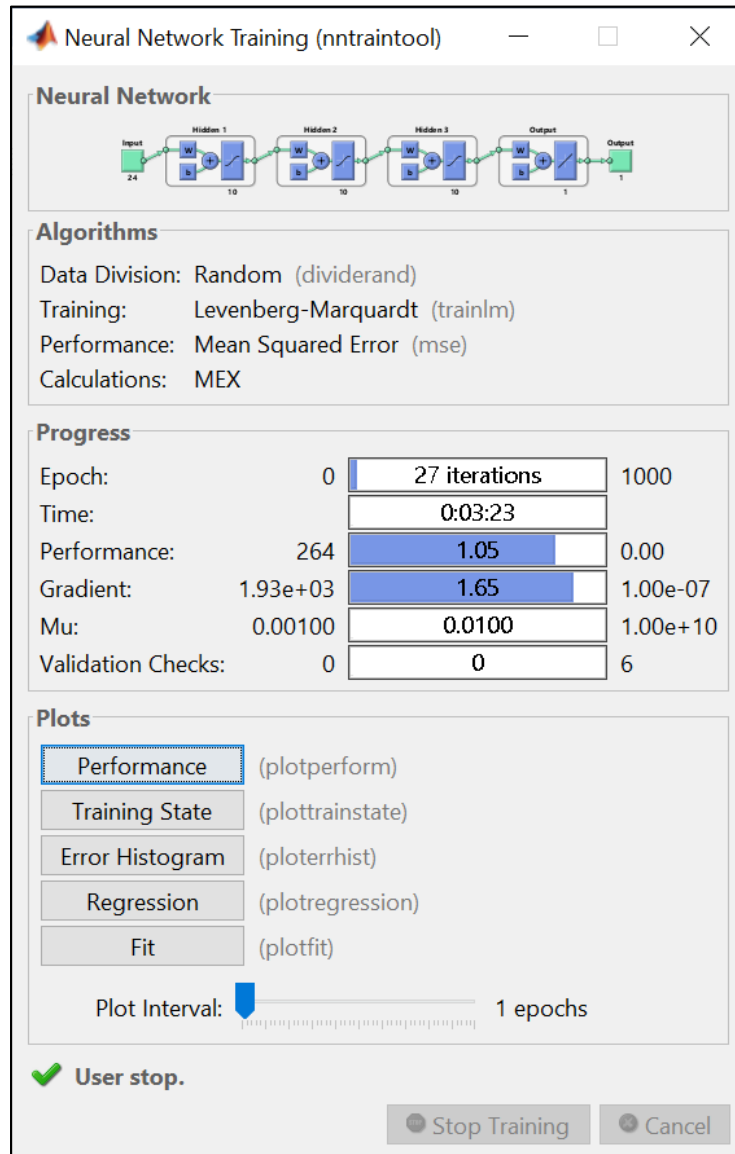


Fig. D-20 $T_p = 10$, $T_f = 30$ (Pattern 4)

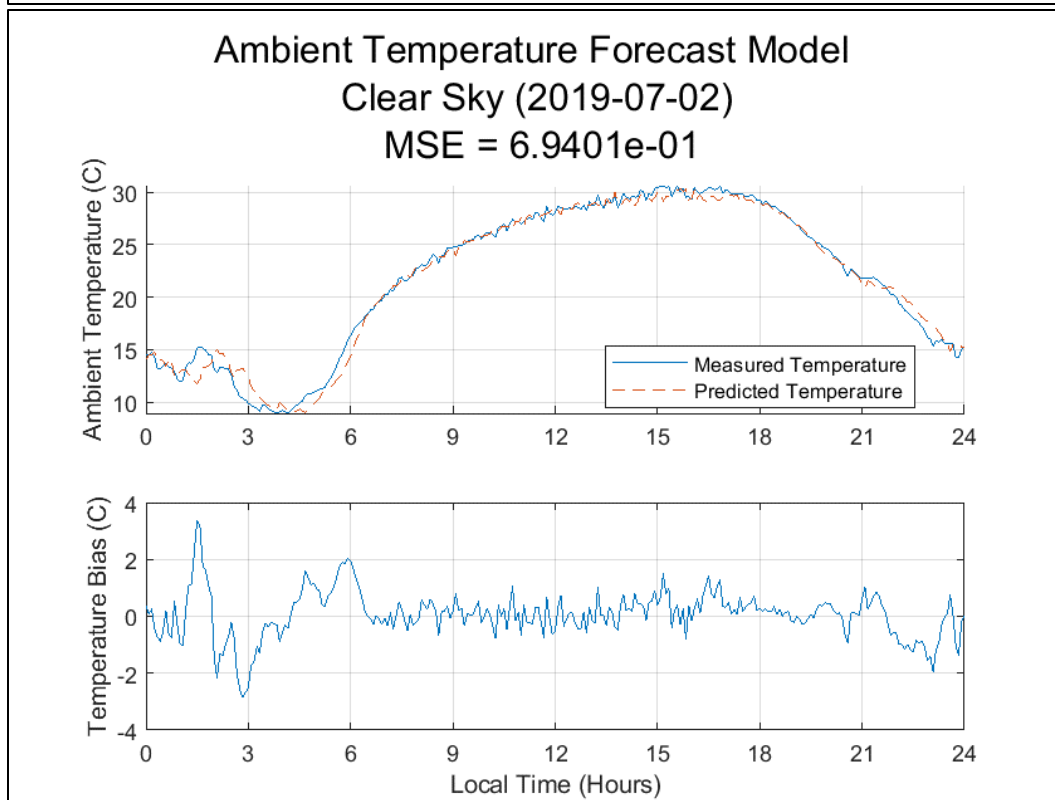
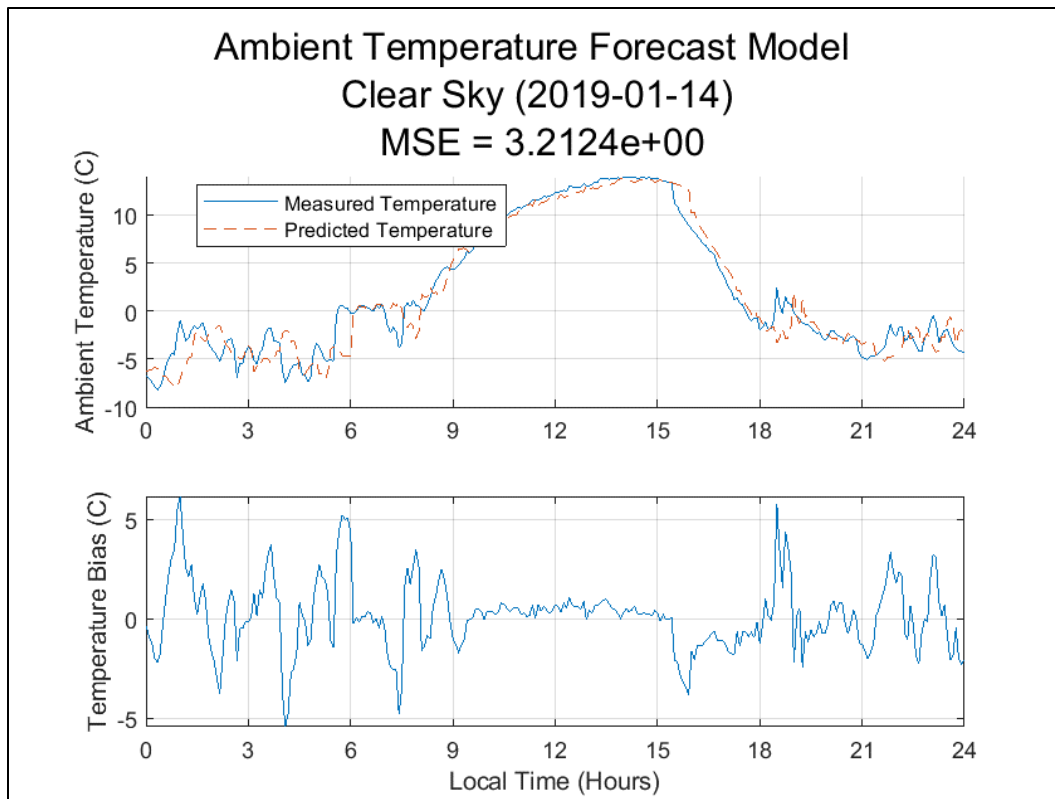


Fig. D-20 $T_p = 10$, $T_r = 30$ (Pattern 4) (continued)

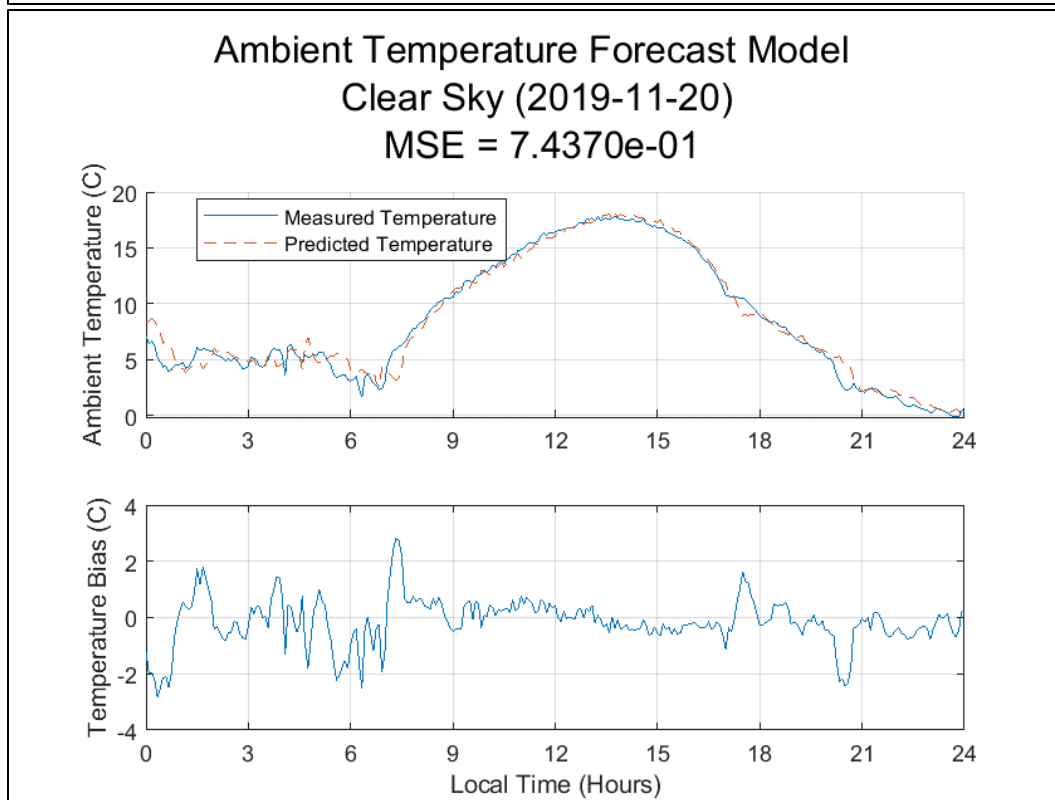
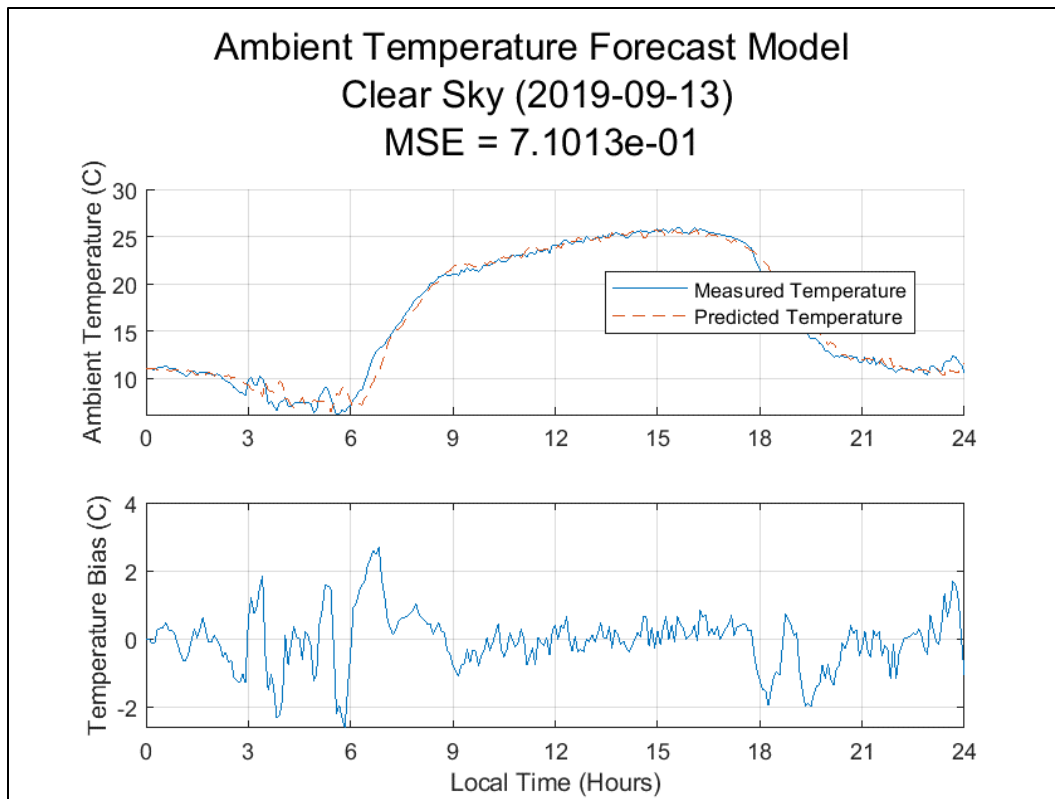


Fig. D-20 $T_p = 10$, $T_f = 30$ (Pattern 4) (continued)

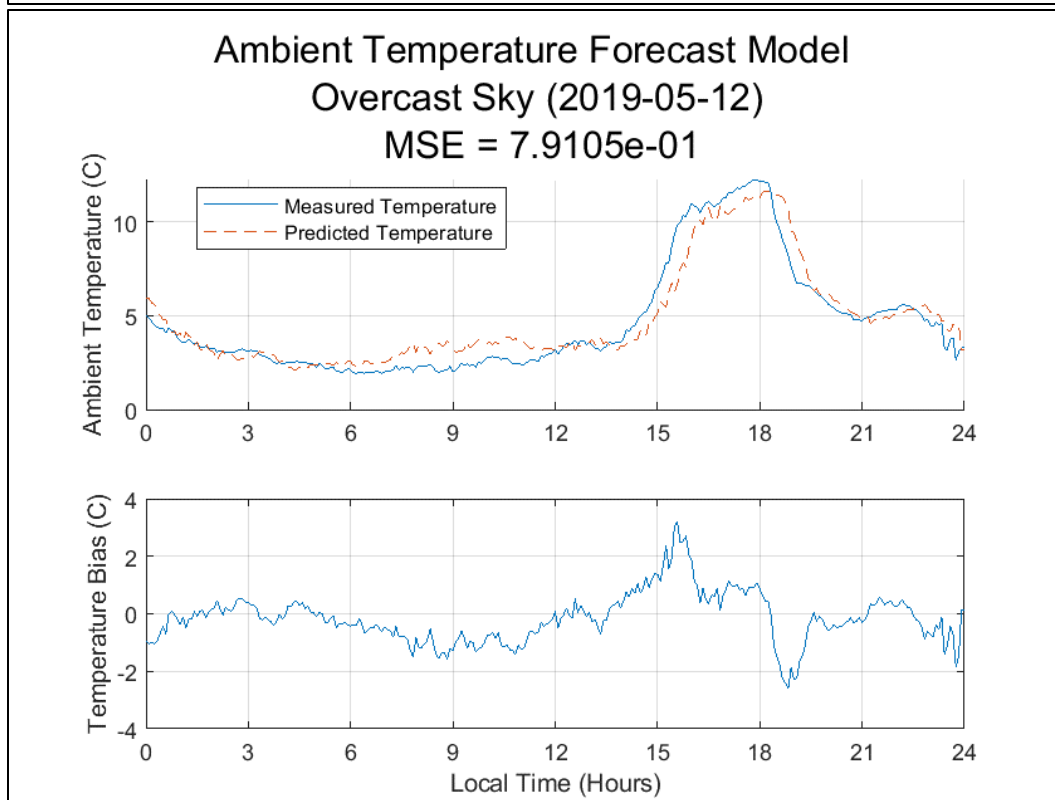
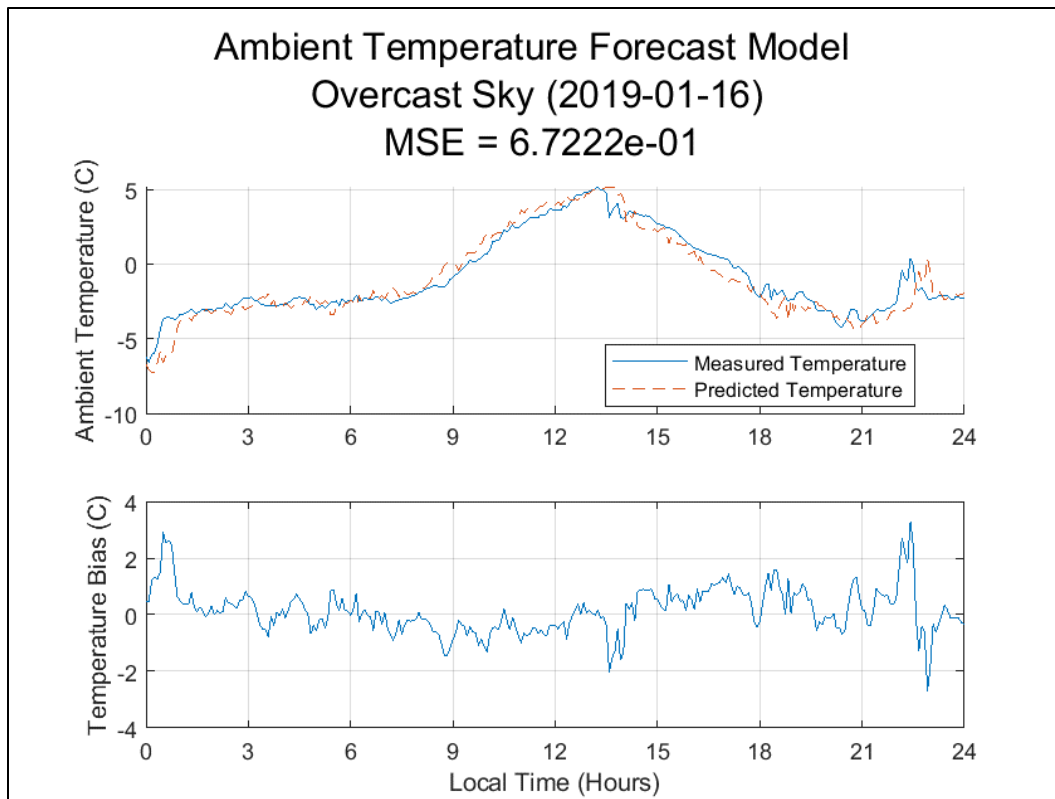


Fig. D-20 $T_p = 10$, $T_f = 30$ (Pattern 4) (continued)

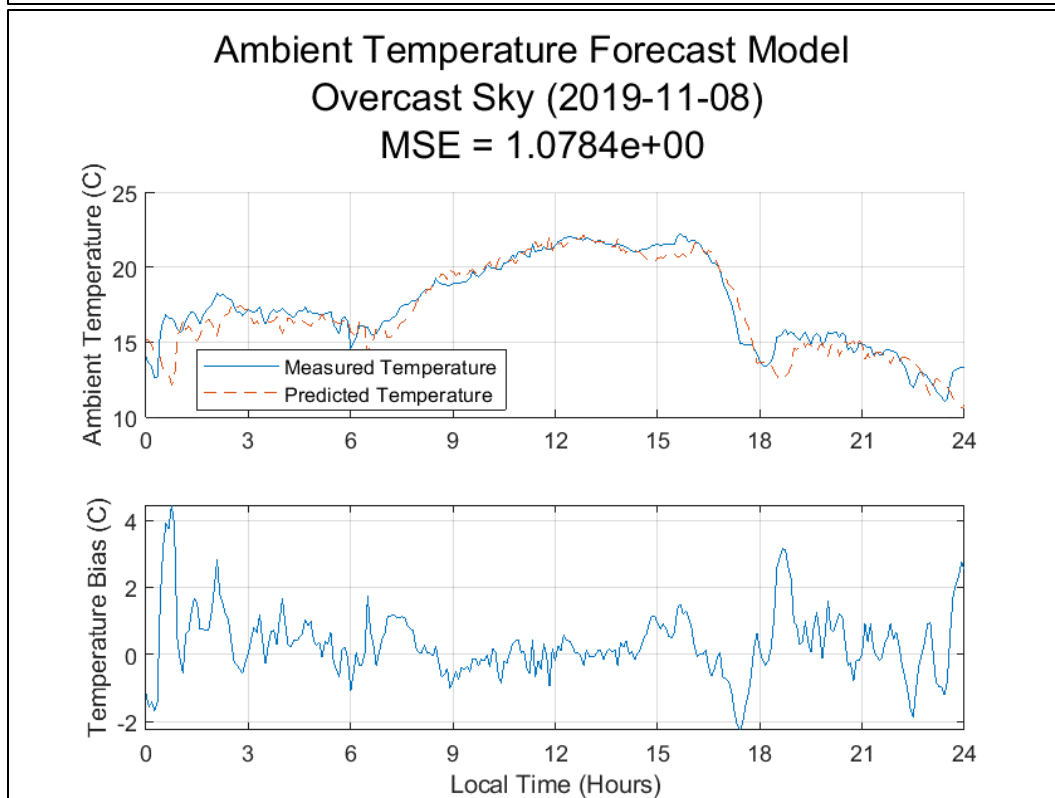
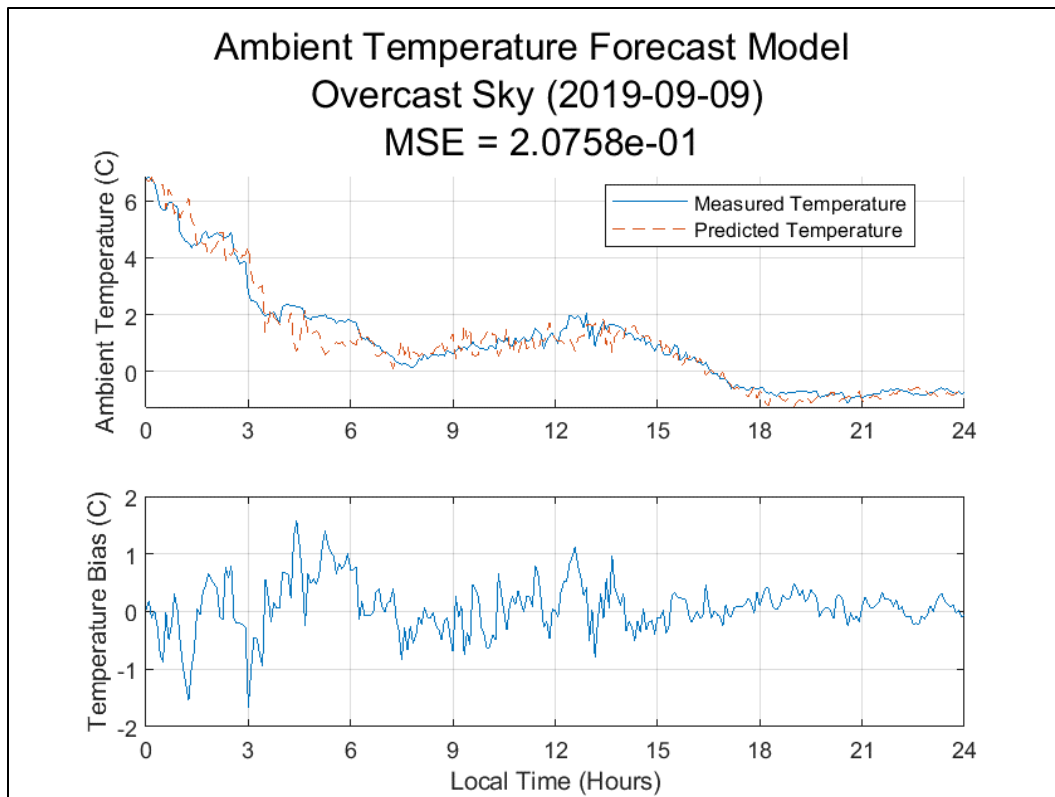


Fig. D-20 $T_p = 10$, $T_f = 30$ (Pattern 4) (continued)

$$T_p = 20$$

$$T_f = 30$$

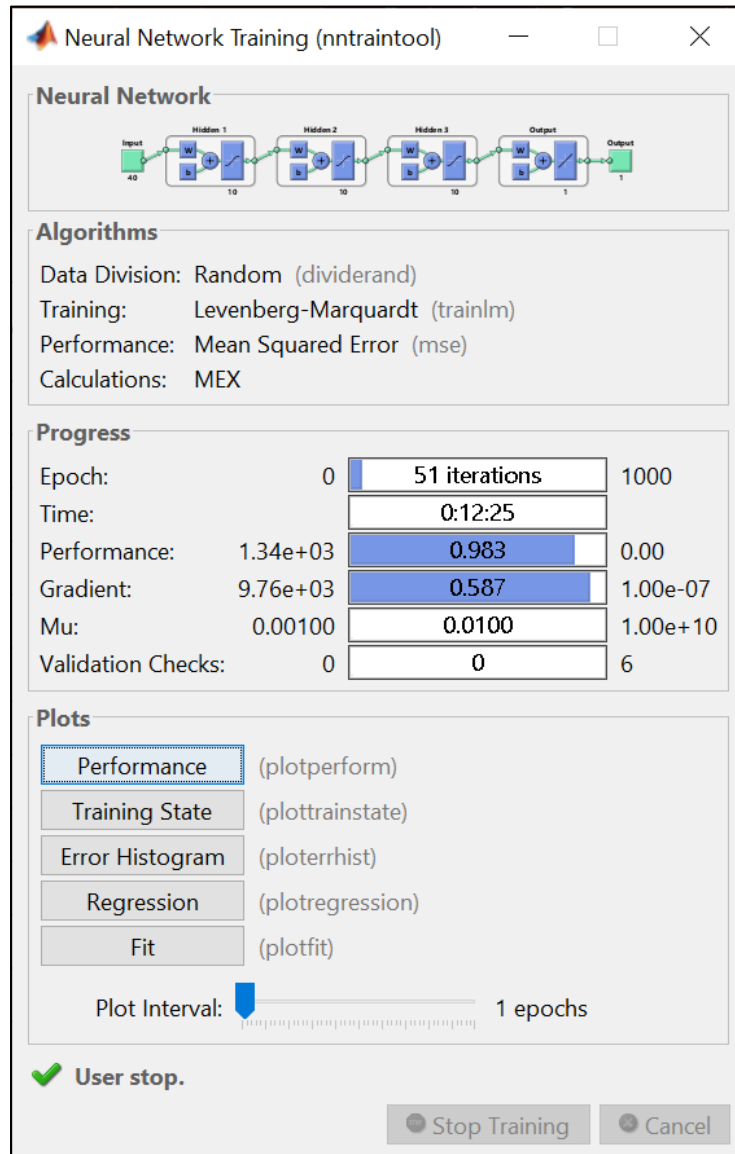


Fig. D-21 $T_p = 20$, $T_f = 30$ (Pattern 4)

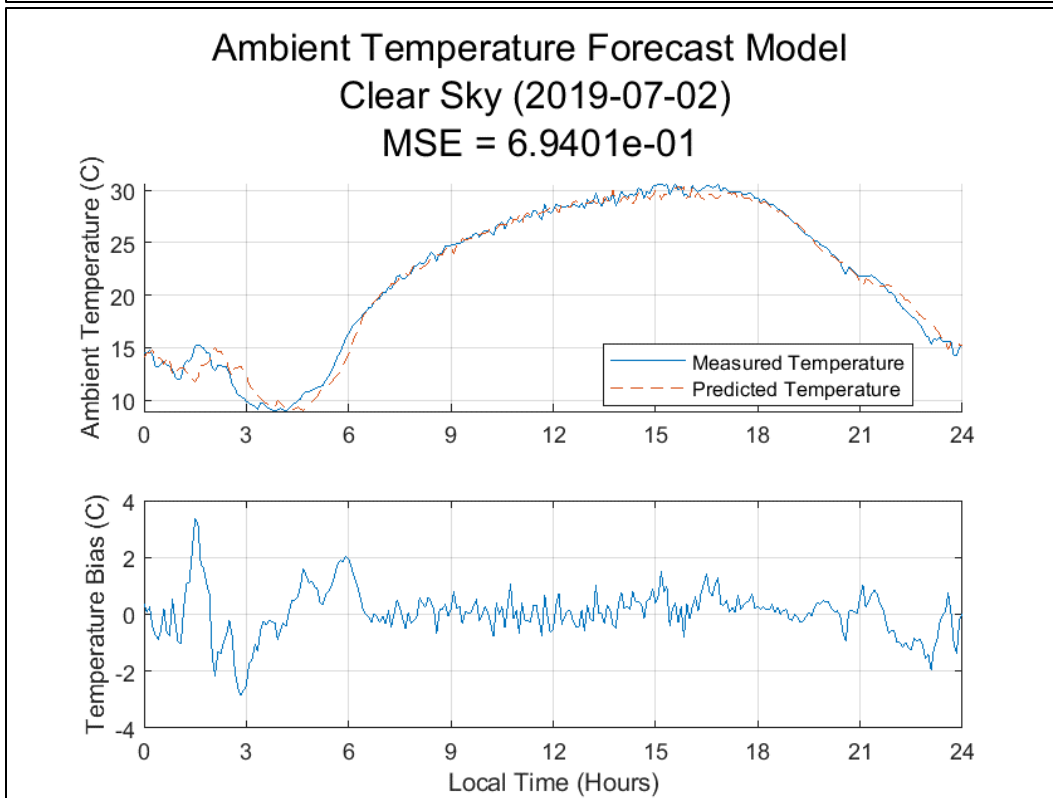
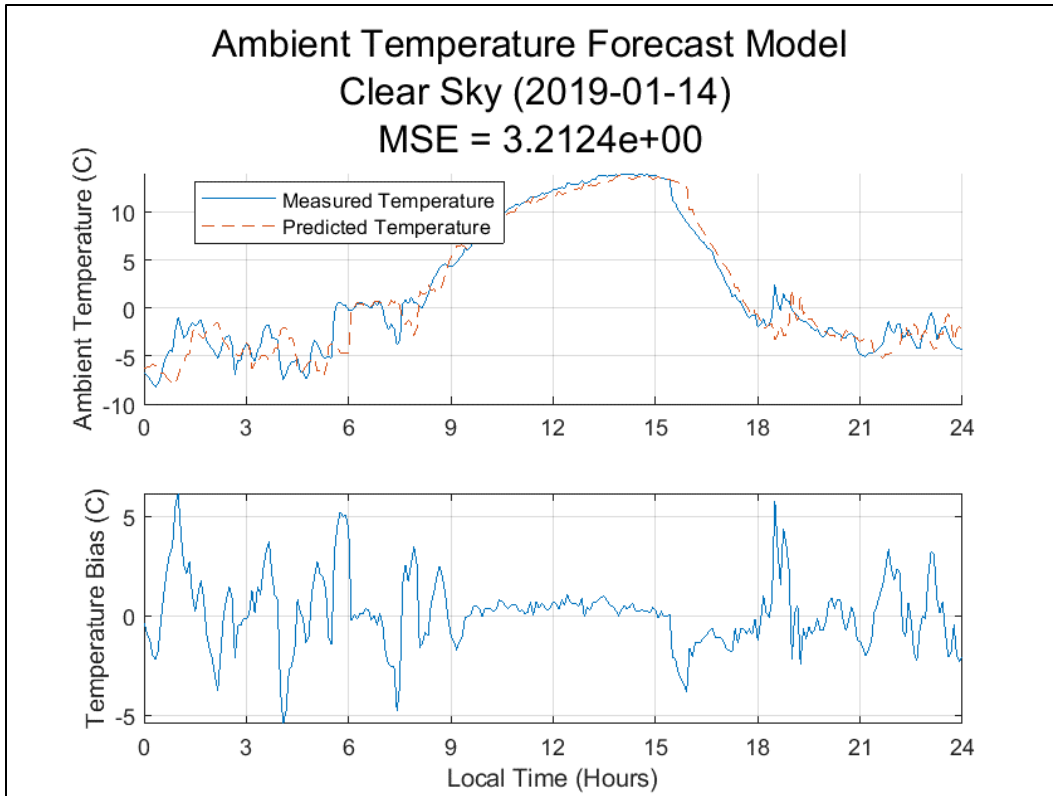


Fig. D-21 $T_p = 20$, $T_f = 30$ (Pattern 4) (continued)

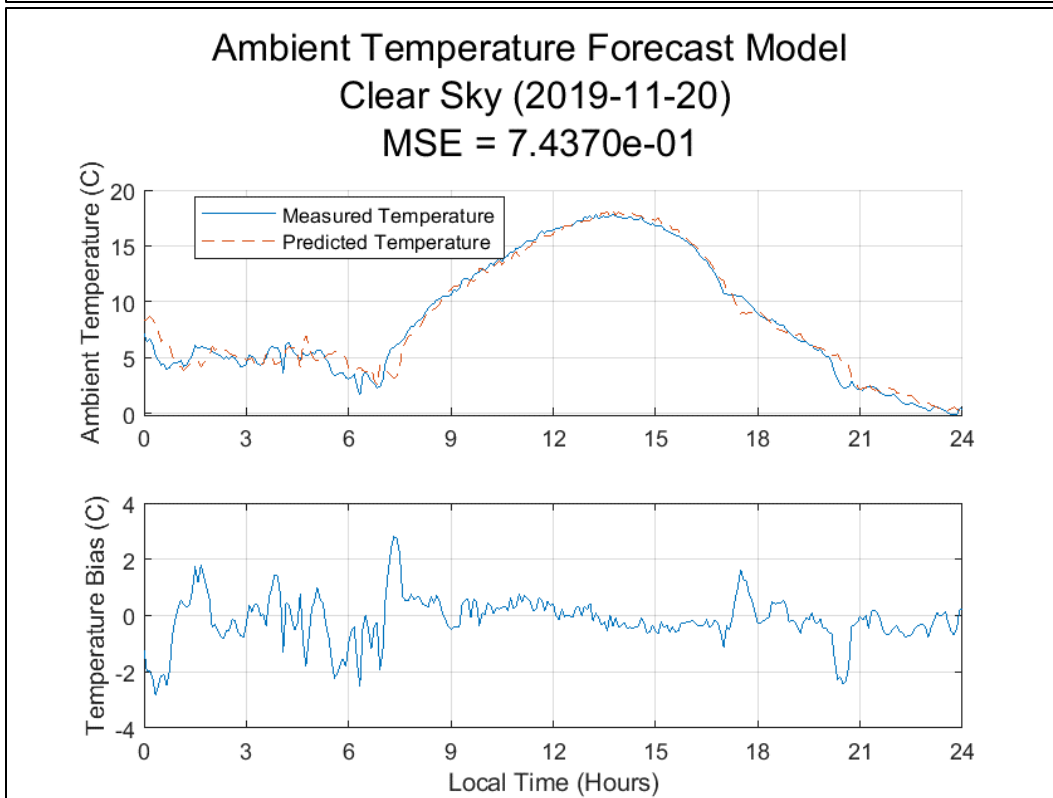
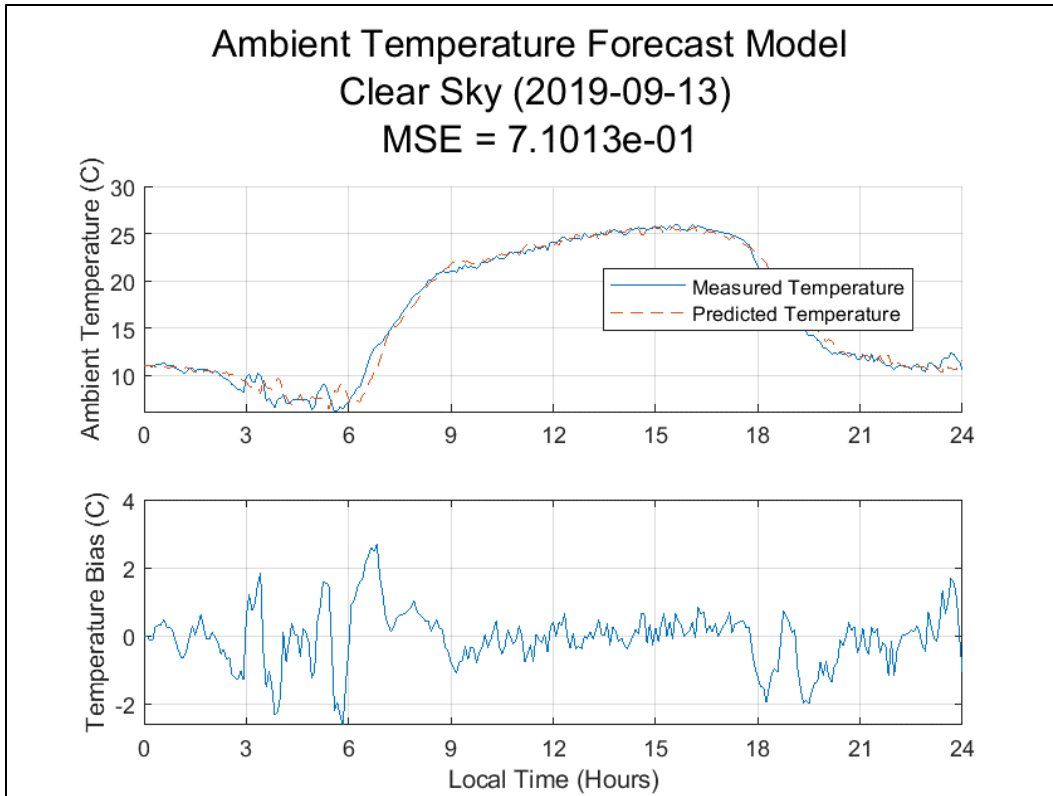


Fig. D-21 $T_p = 20$, $T_f = 30$ (Pattern 4) (continued)

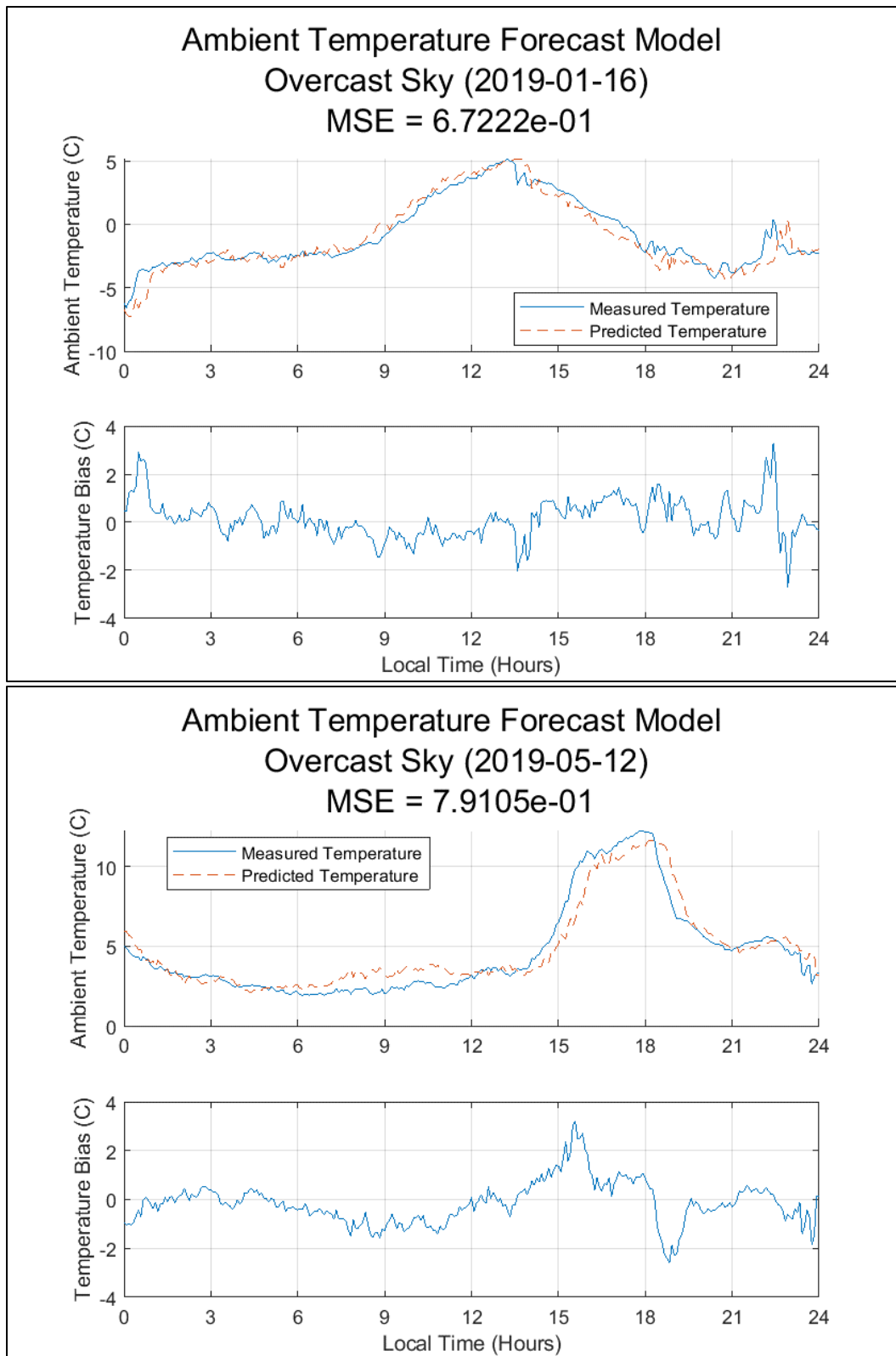


Fig. D-21 $T_p = 20$, $T_f = 30$ (Pattern 4) (continued)

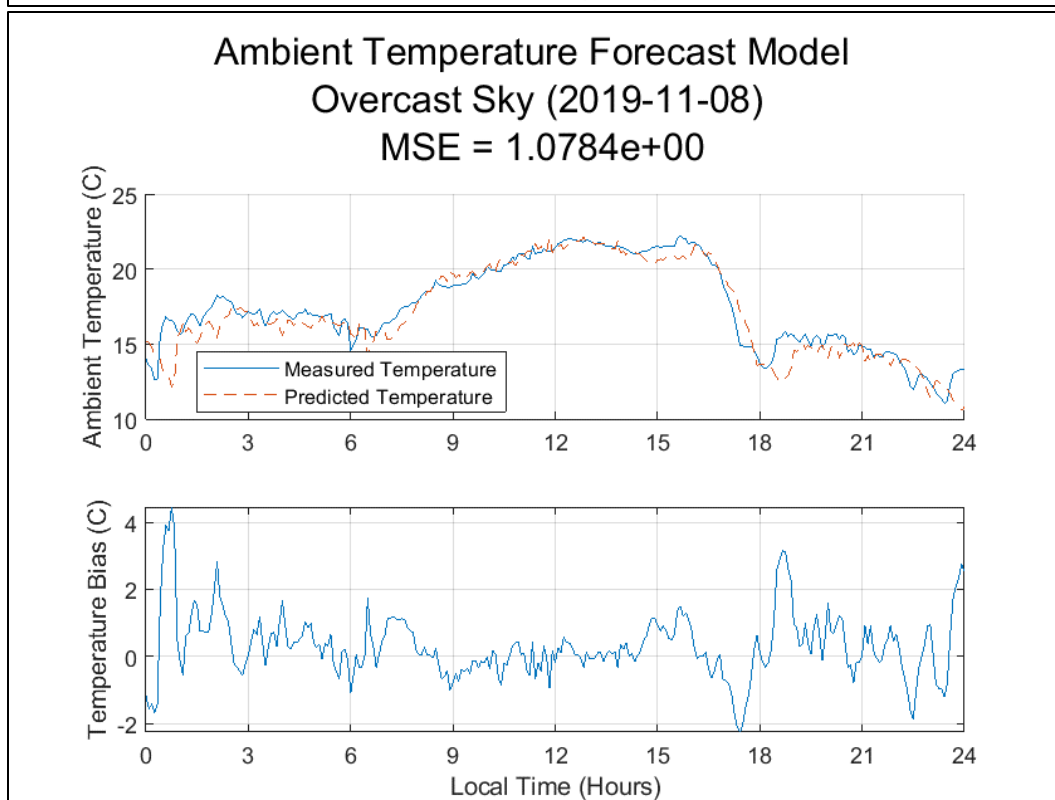
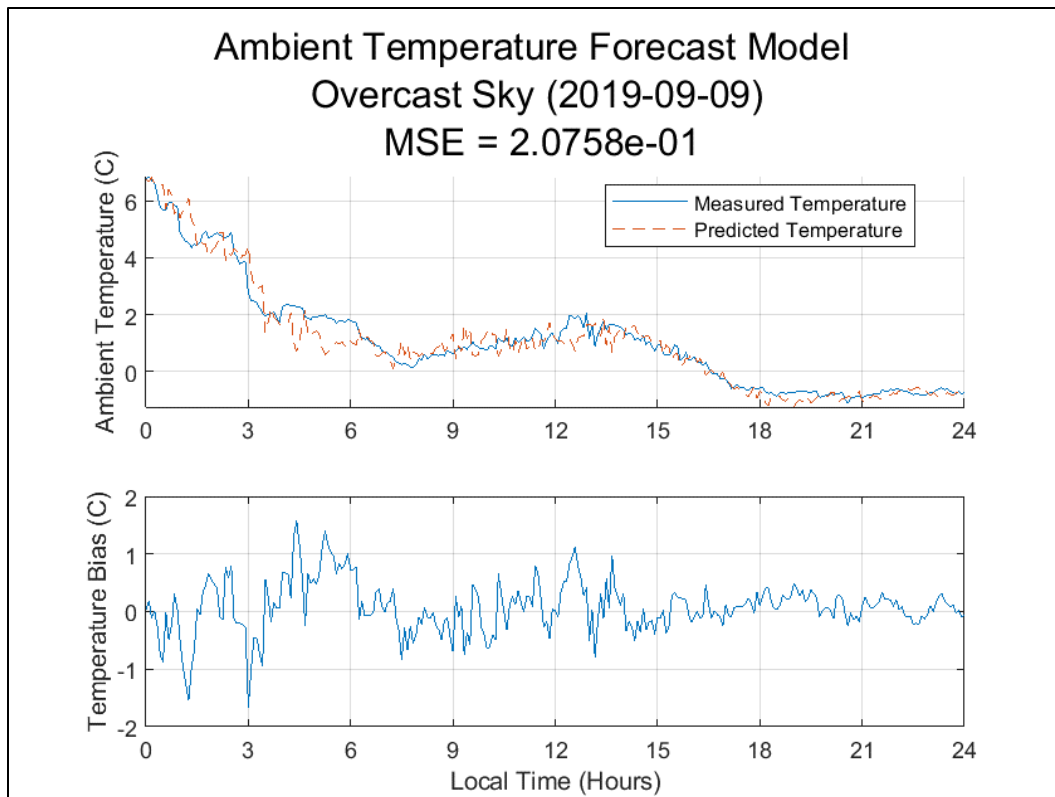


Fig. D-21 $T_p = 20$, $T_f = 30$ (Pattern 4) (continued)

$$T_p = 40$$

$$T_f = 30$$

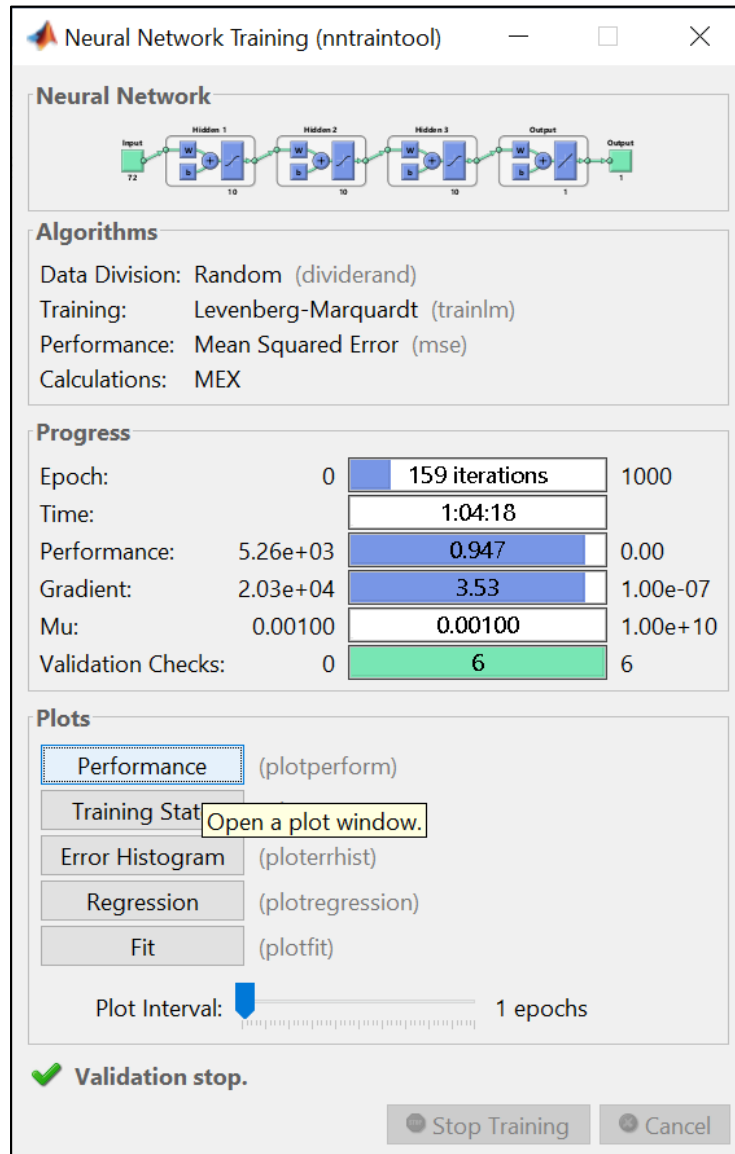


Fig. D-22 $T_p = 40$, $T_f = 30$ (Pattern 4)

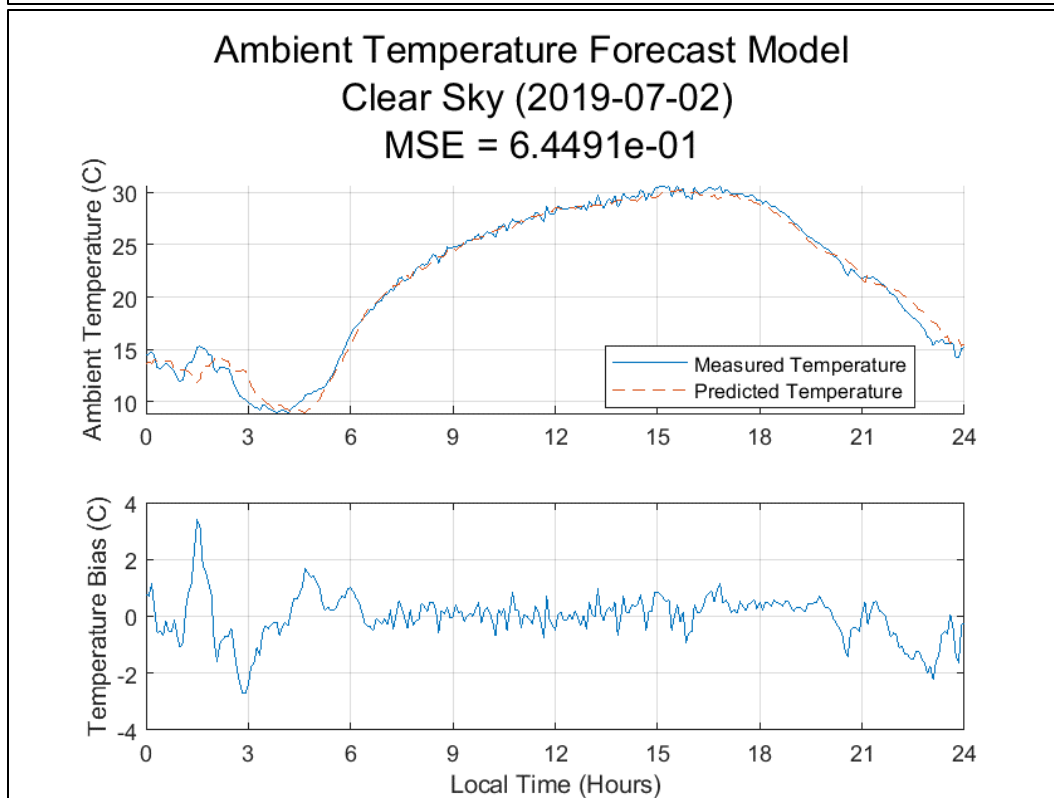
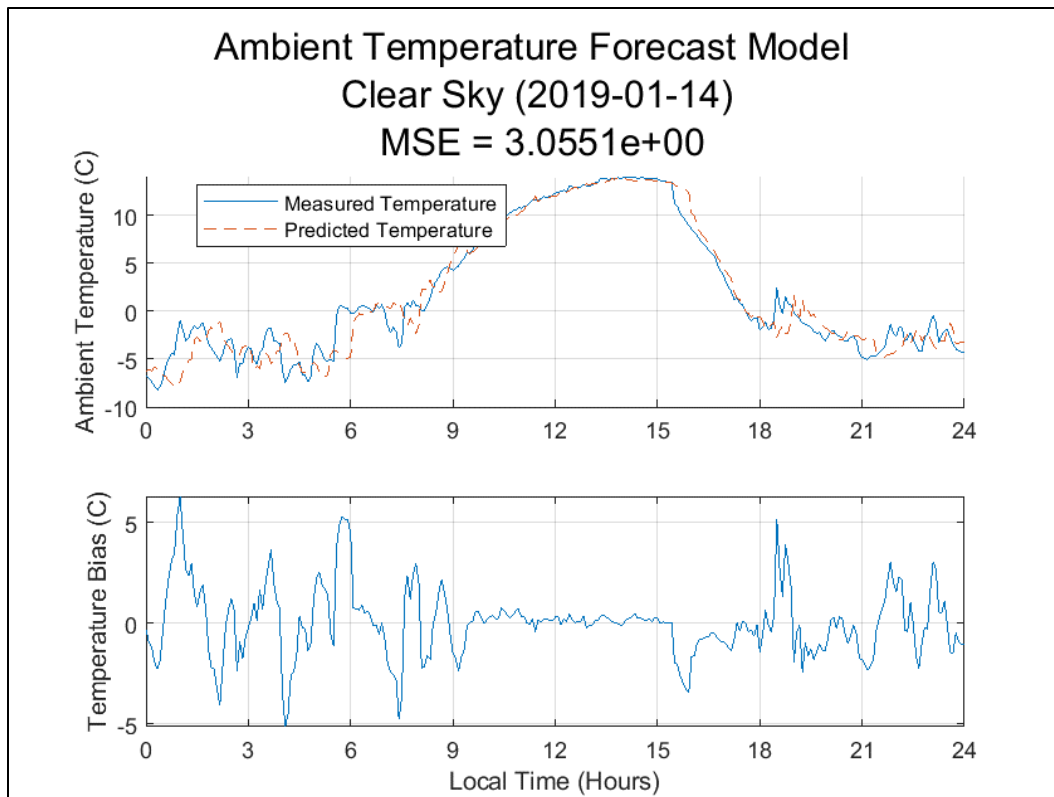


Fig. D-22 $T_p = 40$, $T_f = 30$ (Pattern 4) (continued)

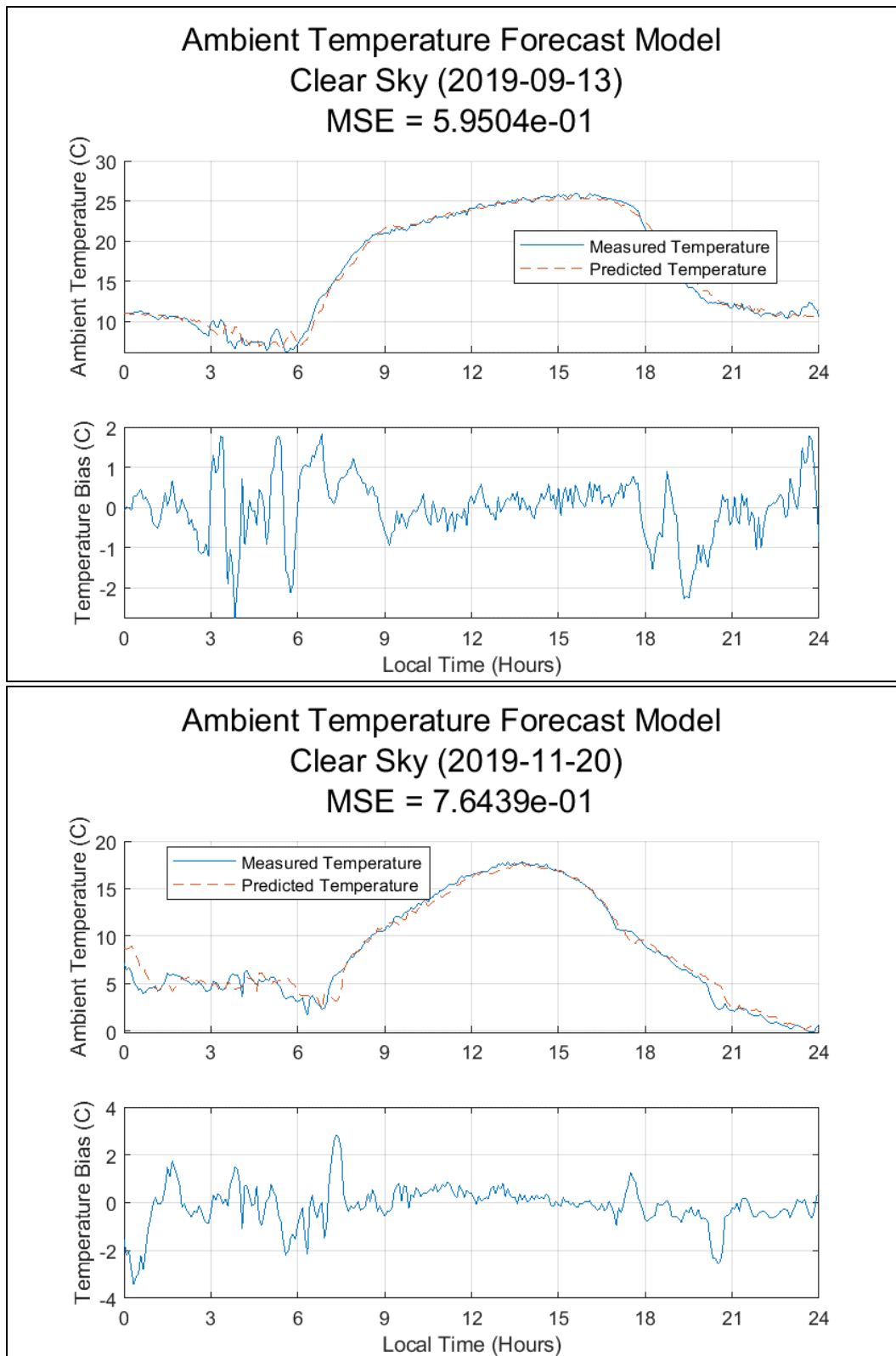


Fig. D-22 $T_p = 40$, $T_f = 30$ (Pattern 4) (continued)

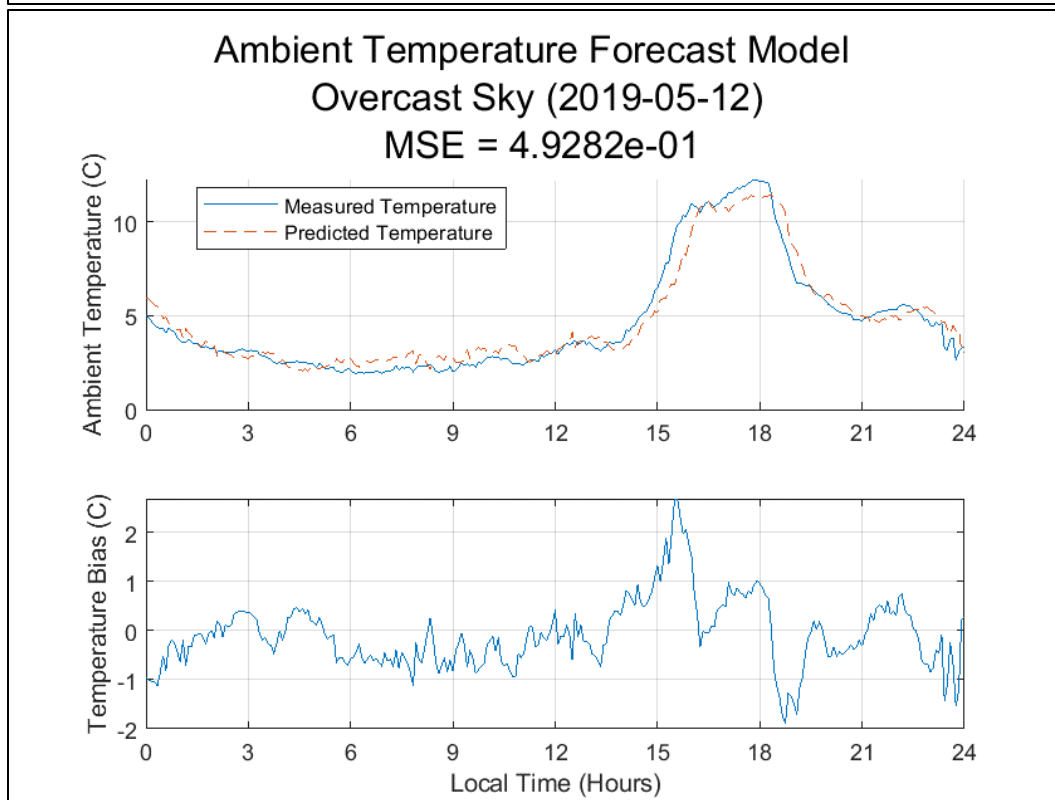
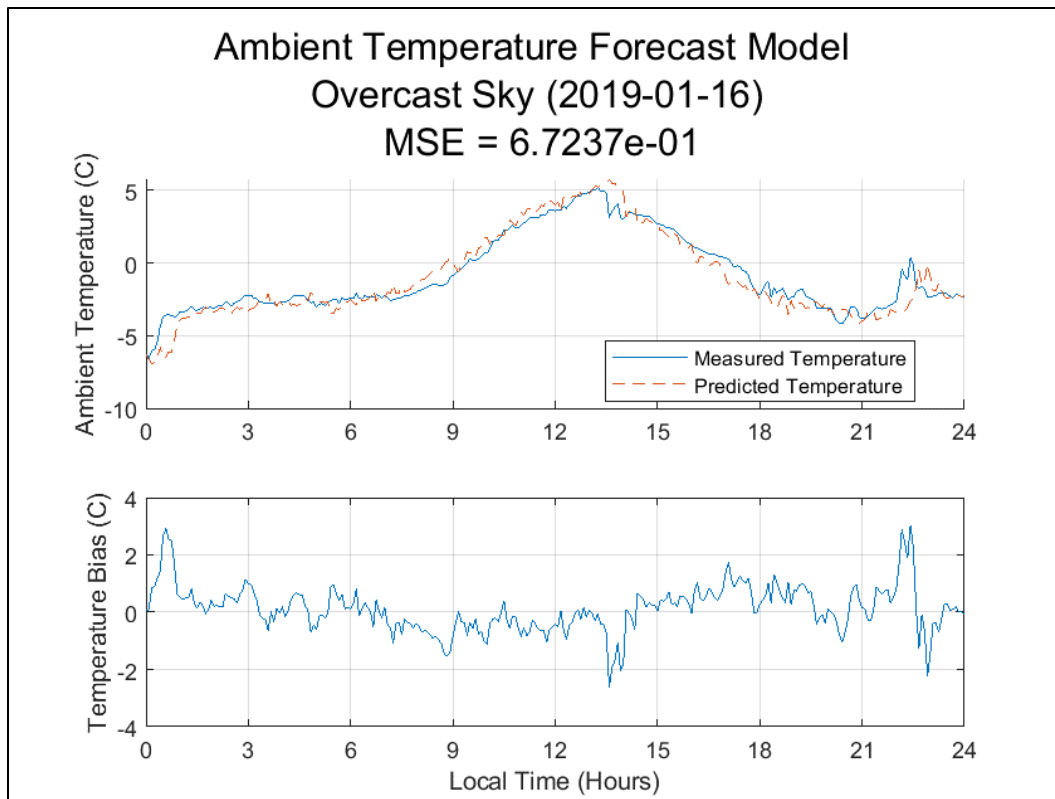


Fig. D-22 $T_p = 40$, $T_f = 30$ (Pattern 4) (continued)

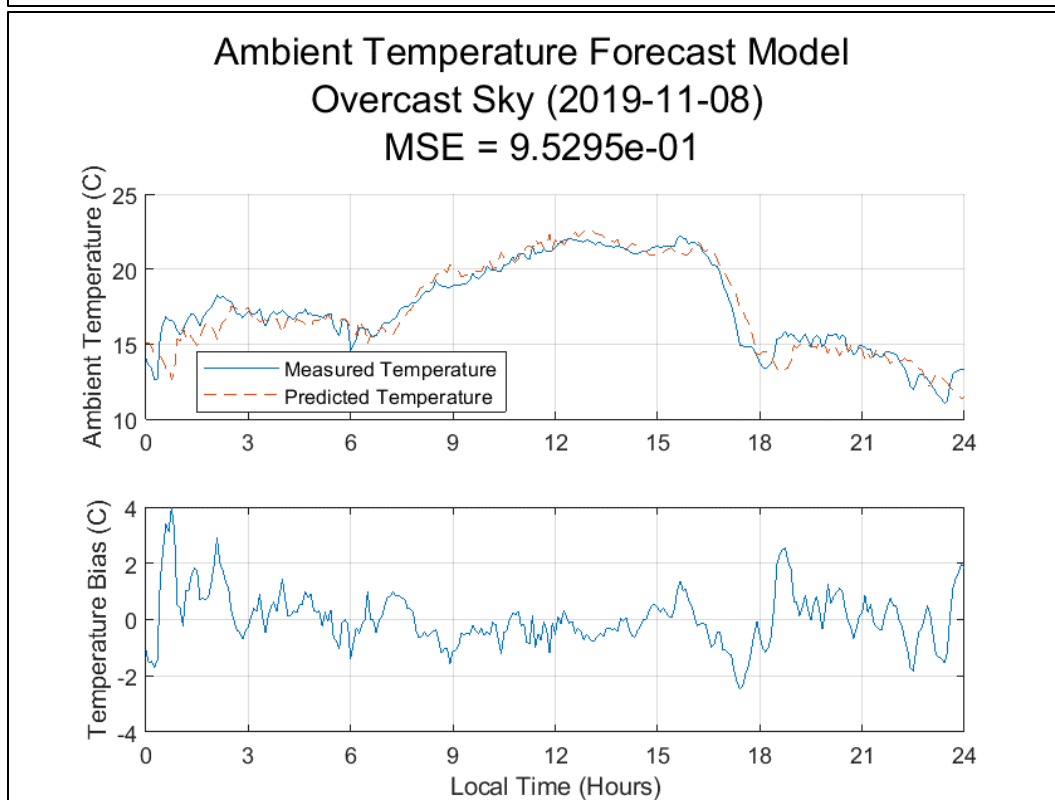
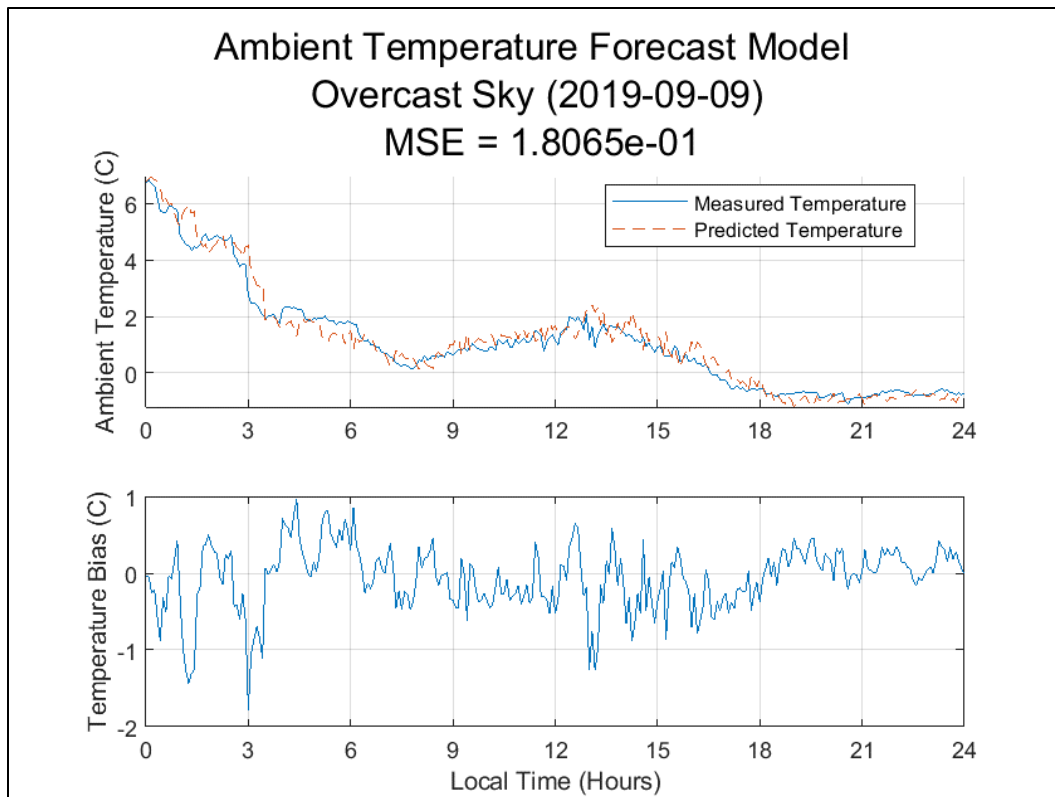


Fig. D-22 $T_p = 40$, $T_f = 30$ (Pattern 4) (continued)

$$T_p = 80$$

$$T_f = 30$$

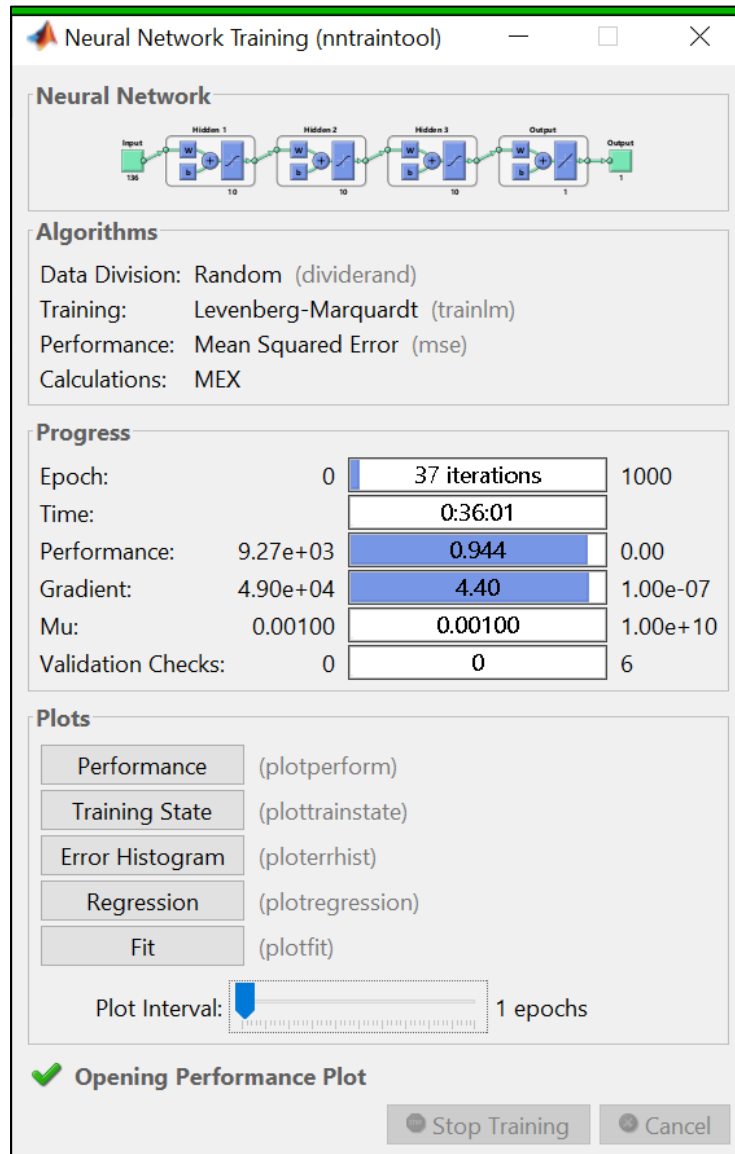


Fig. D-23 $T_p = 80$, $T_f = 30$ (Pattern 4)

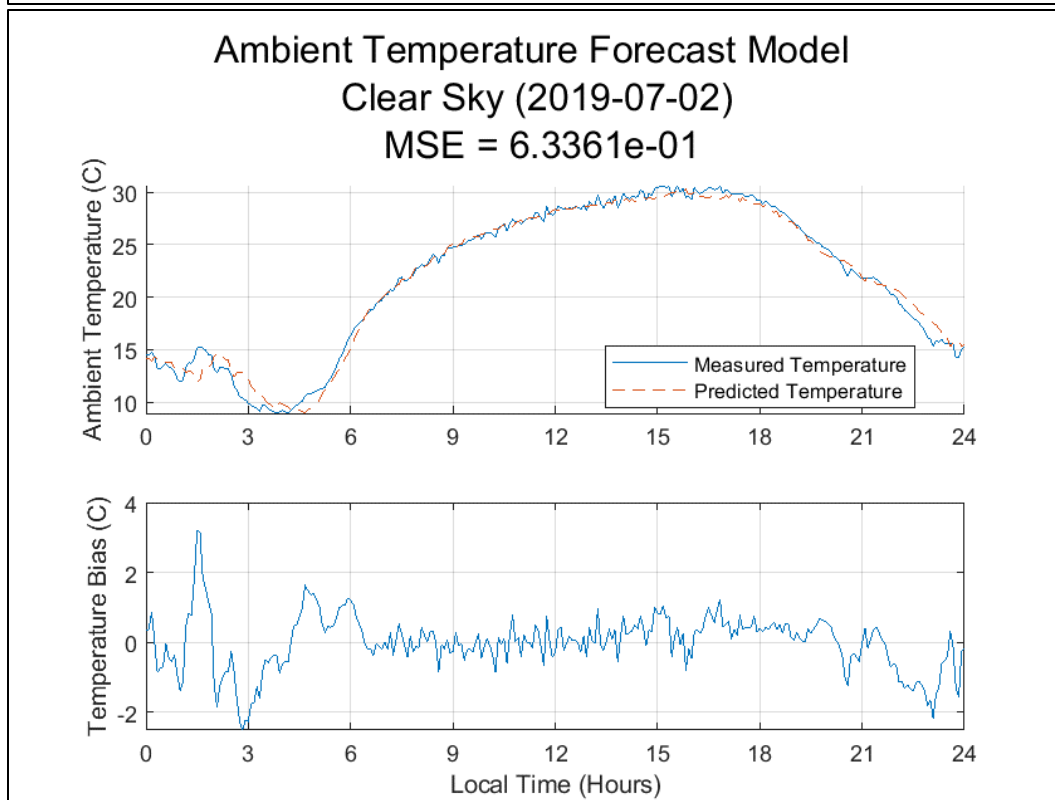
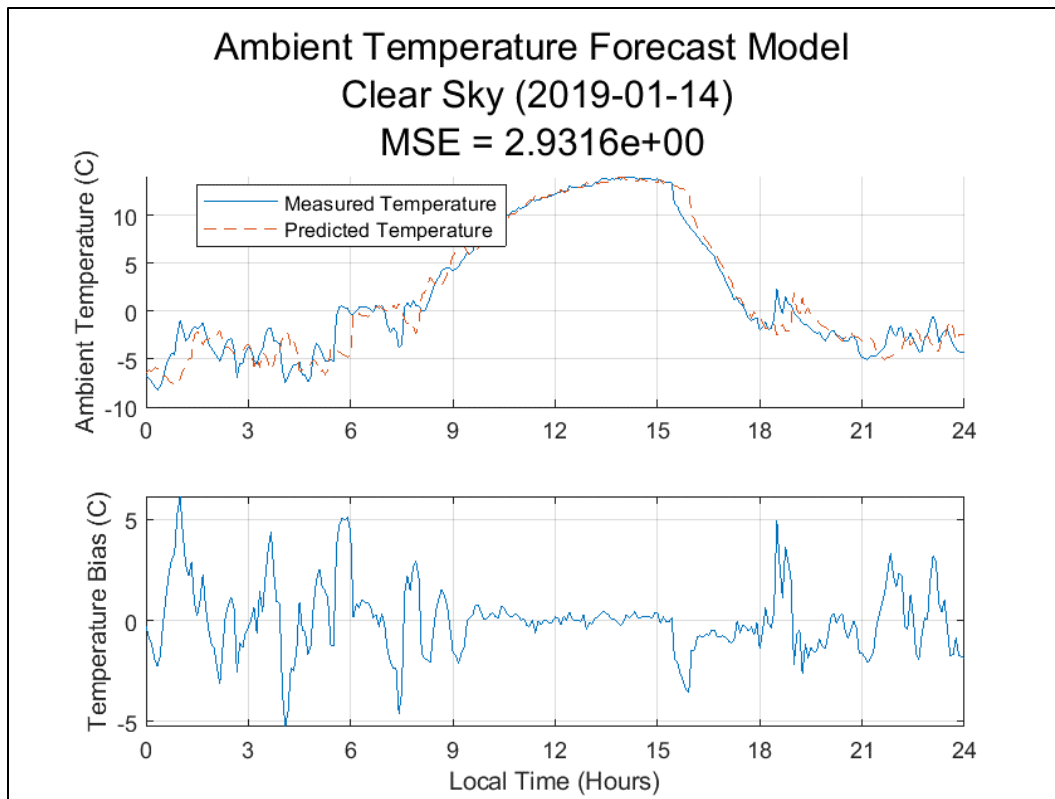


Fig. D-23 $T_p = 80$, $T_r = 30$ (Pattern 4) (continued)

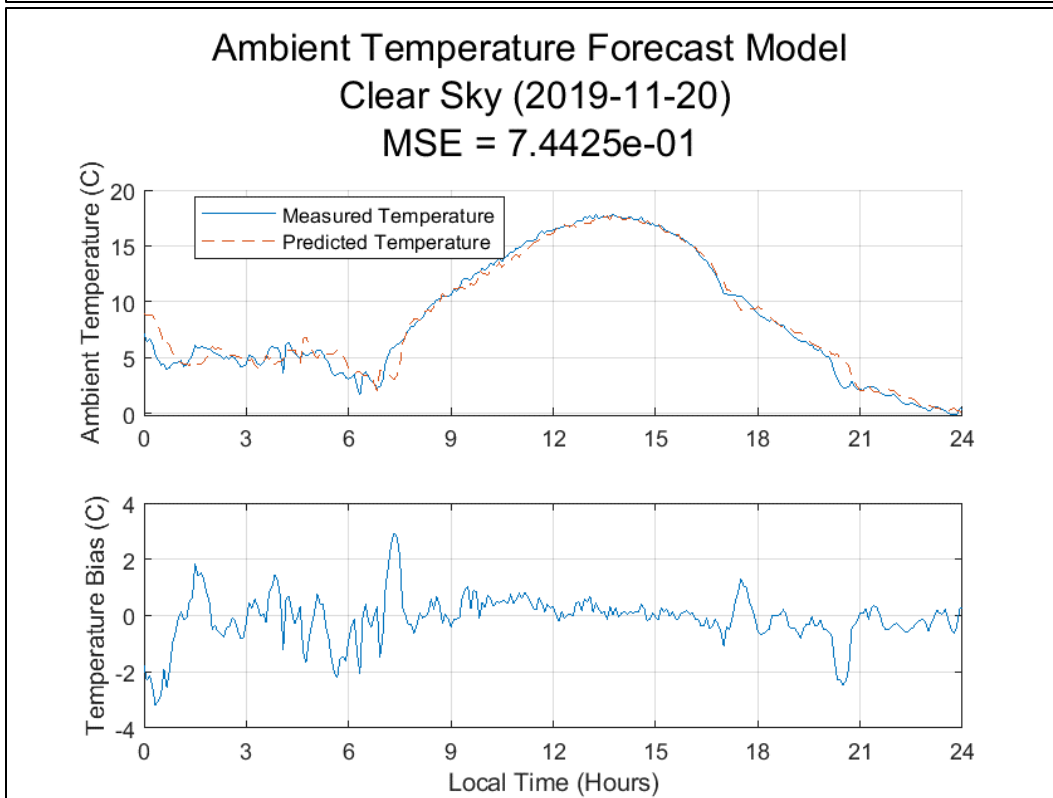
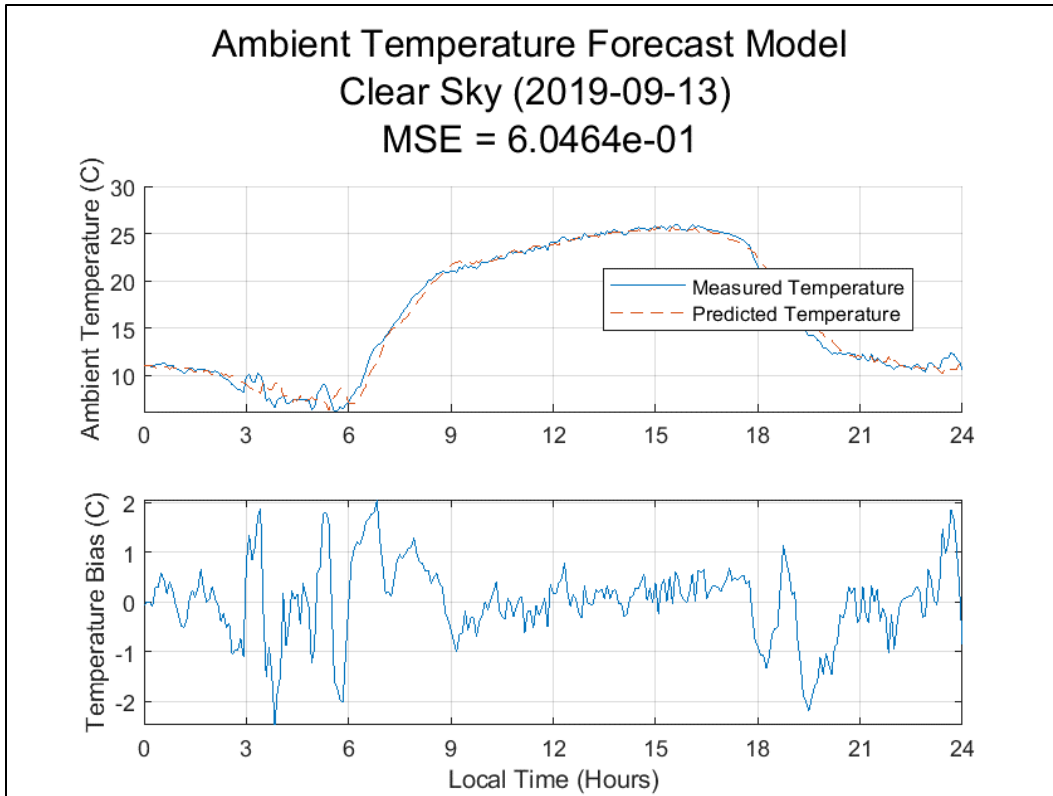


Fig. D-23 $T_p = 80$, $T_f = 30$ (Pattern 4) (continued)

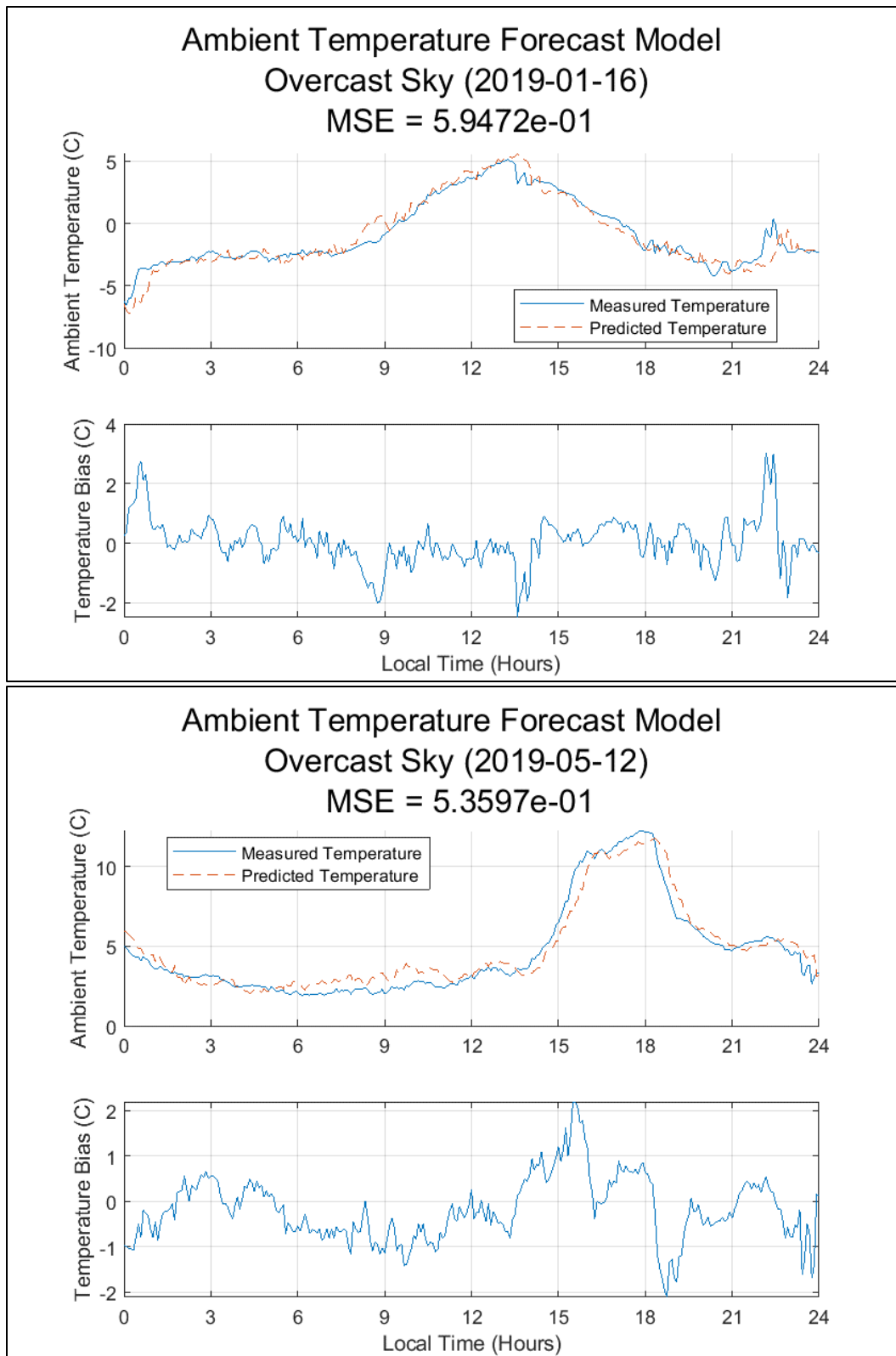


Fig. D-23 $T_p = 80$, $T_r = 30$ (Pattern 4) (continued)

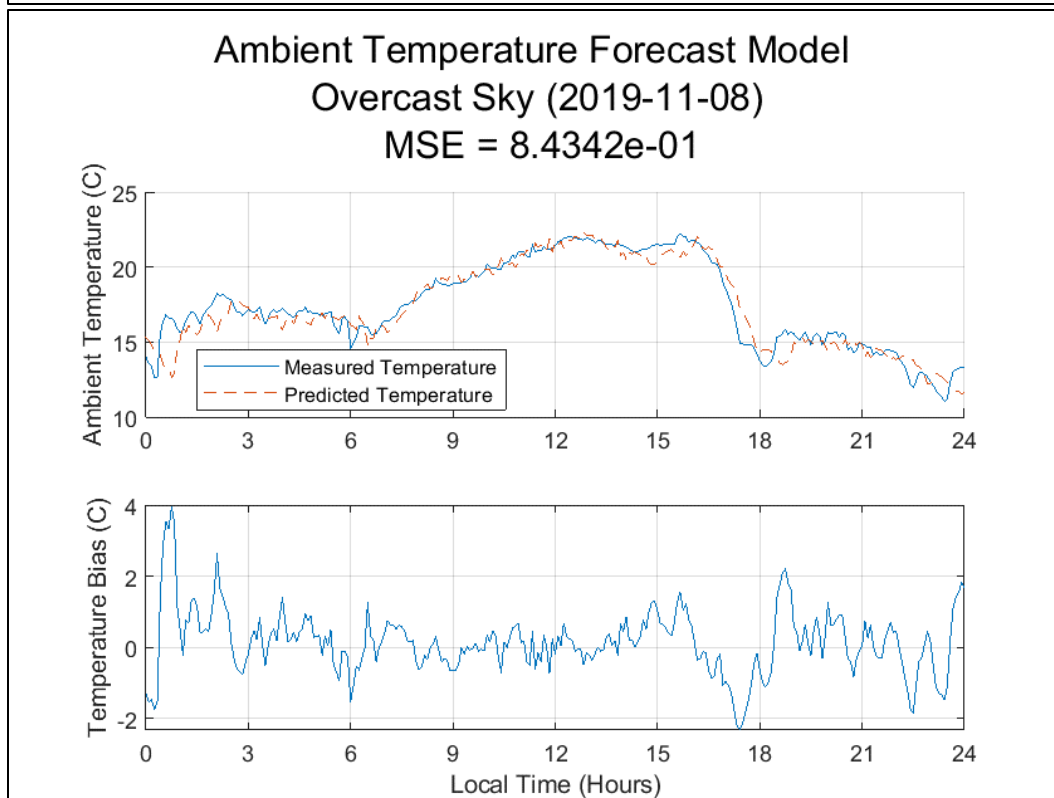
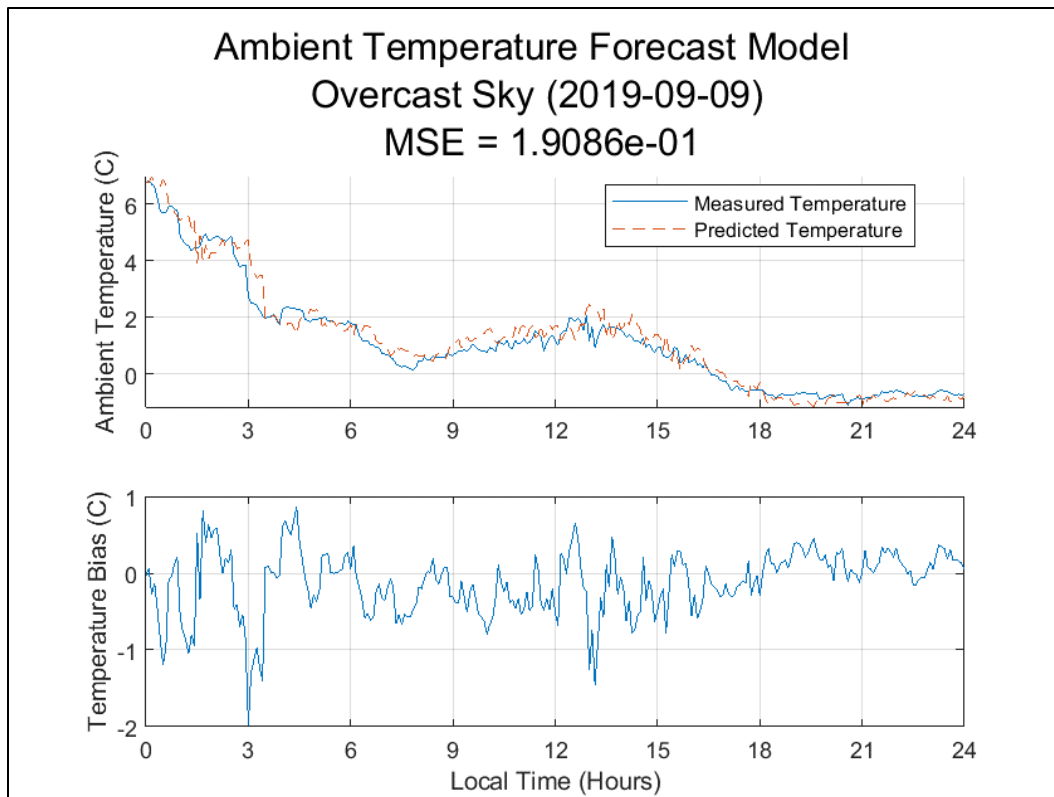


Fig. D-23 $T_p = 80$, $T_r = 30$ (Pattern 4) (continued)

$$T_p = 160$$

$$T_f = 30$$

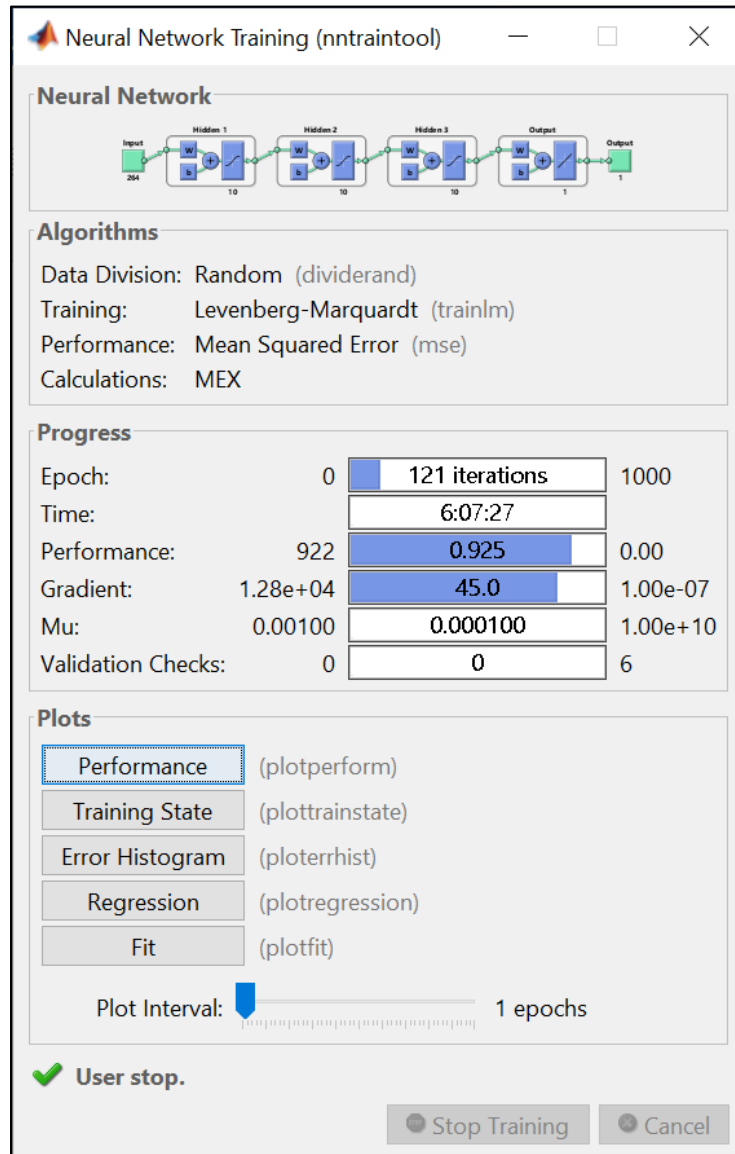


Fig. D-24 $T_p = 160$, $T_f = 30$ (Pattern 4)

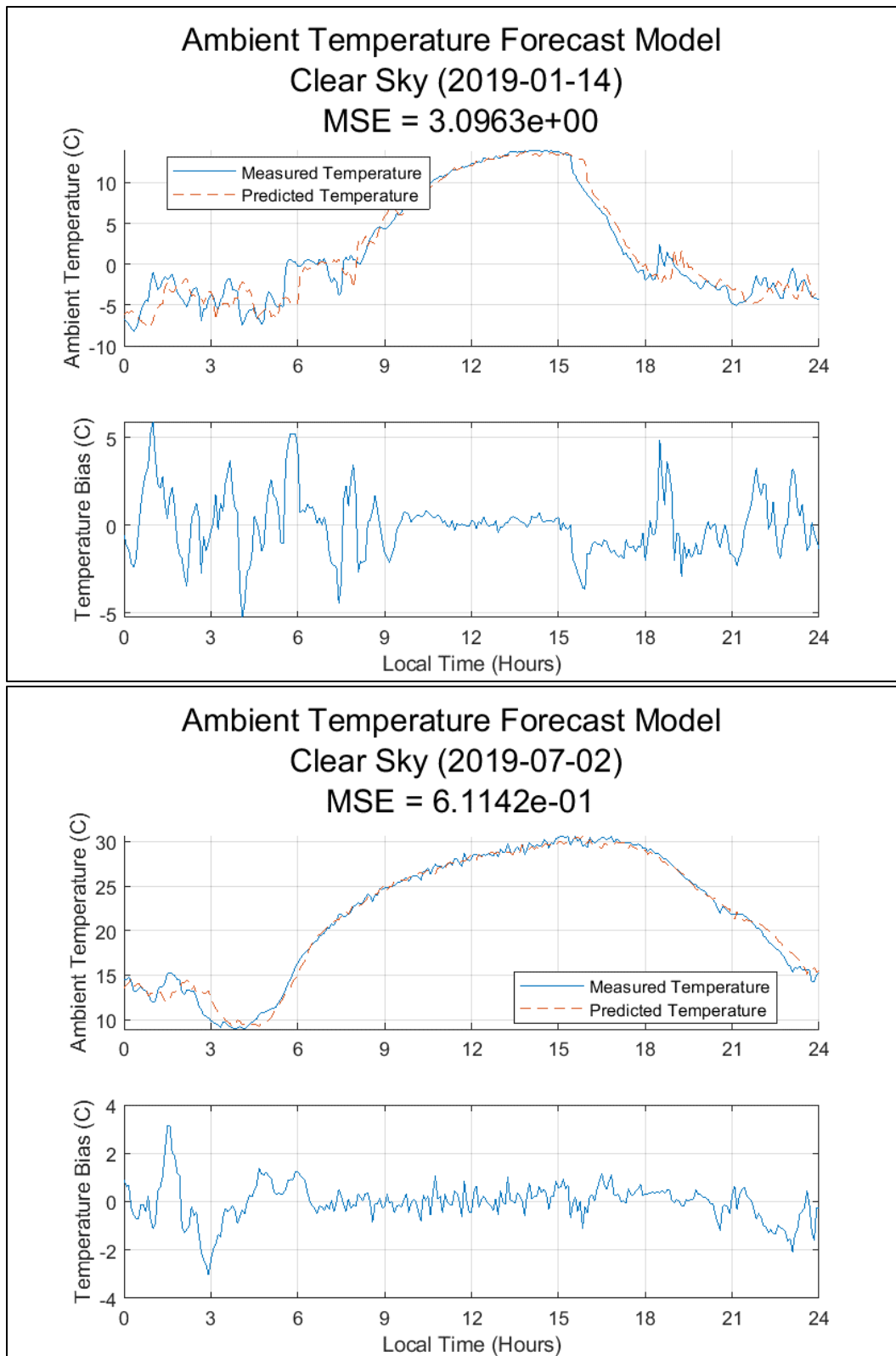


Fig. D-24 $T_p = 160$, $T_r = 30$ (Pattern 4) (continued)

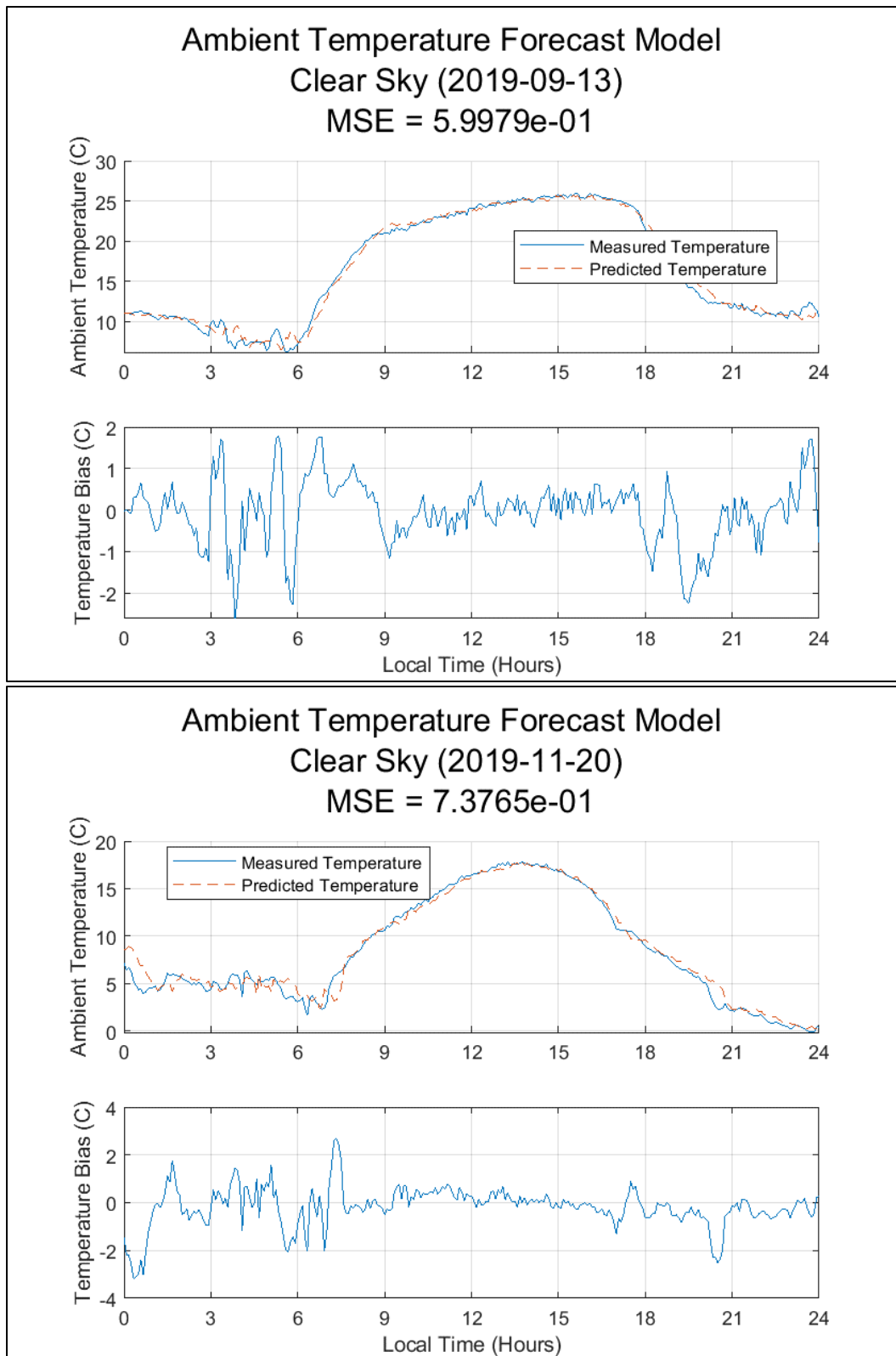


Fig. D-24 $T_p = 160$, $T_r = 30$ (Pattern 4) (continued)

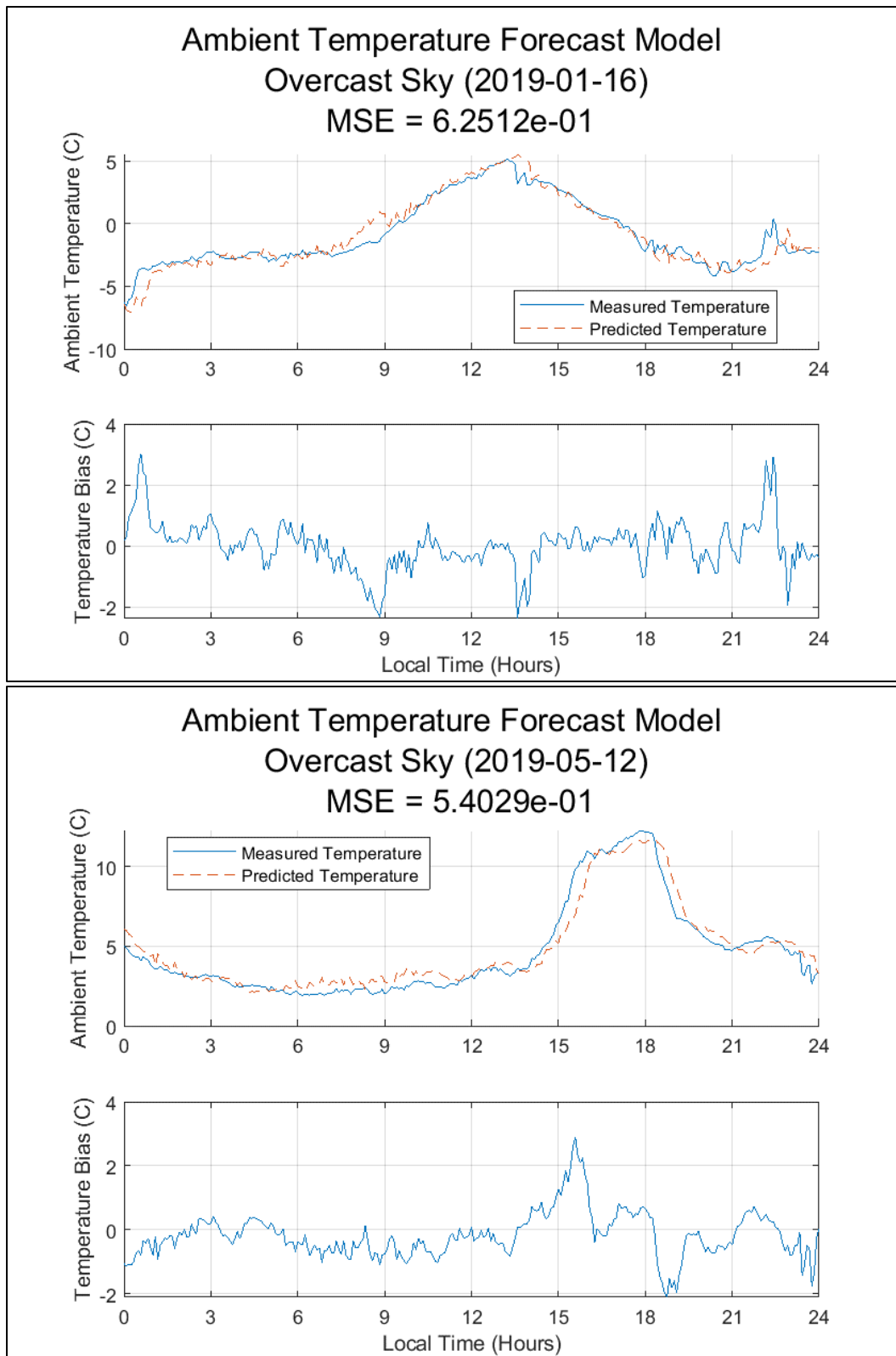


Fig. D-24 $T_p = 160$, $T_r = 30$ (Pattern 4) (continued)

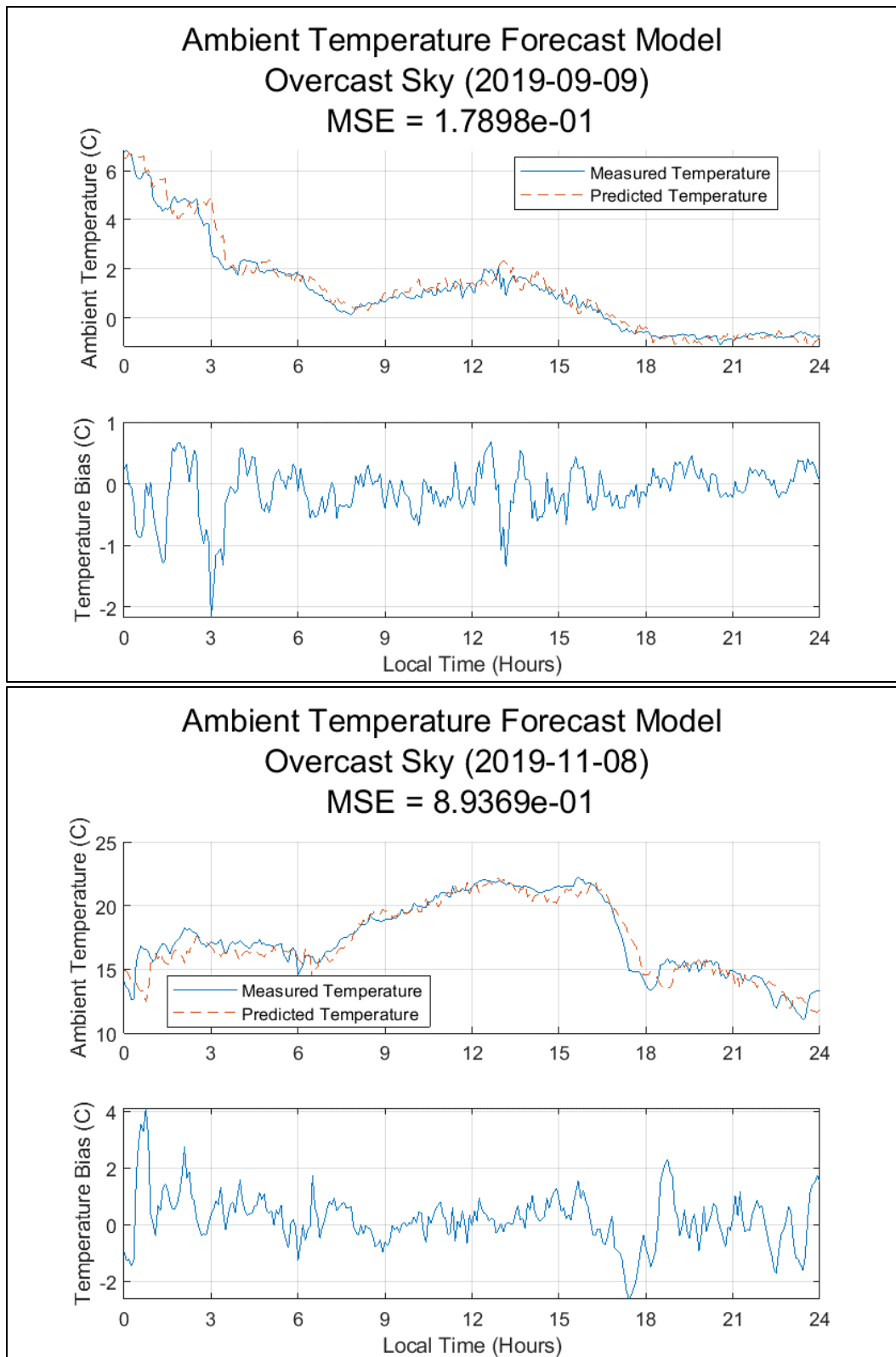


Fig. D-24 $T_p = 160$, $T_r = 30$ (Pattern 4) (continued)

List of Symbols, Abbreviations, and Acronyms

AI	artificial intelligence
AIHPG	Atmospheric Intelligence for Hybrid Power Grid
ABQ	Albuquerque, New Mexico
ANC	Anchorage, Alaska
ANN	artificial neural network
ARL	Army Research Laboratory
ArL	above roof level
BRW	Barrow, Alaska
CLR	clear
CNN	convolution neural network
DEVCOM	US Army Combat Capabilities Development Command
ELP	El Paso, Texas
ESRL	Earth System Research Laboratories
GUI	graphical user interface
IAD	Sterling, Virginia, Dulles Washington DC
LSTMN	long-short term memory network
LT	local time
MDT	Mountain Daylight Time
MIDC	Measurement and Instrumentation Data Center
ML	machine learning
MMT2	Meteorological Measuring Tripod #2
MSE	mean standard error
MST	Mountain Standard Time
M-X-Z	Mahmoud, Xiao, and Zeineldin
NARX	networks with exogenous inputs
NOAA	National Oceanic and Atmospheric Administration

NN	neural network
NREL	National Renewable Energy Laboratory
NSRDB	National Solar Radiation Database
OVC	overcast
PC	principal components
PCA	principal component analysis
PV	photovoltaic
RNN	recurrent neural network
RAOB	rawinsonde observation
RTD	resistive temperature detectors
SolarTAC	Solar Technology Acceleration Center
SR	solar radiation
ToD	time of day
ToY	time of year
UTC	Universal Time Coordinated
z	Zulu

1	DEFENSE TECHNICAL
(PDF)	INFORMATION CTR
	DTIC OCA
1	DEVCOM ARL
(PDF)	FCDD RLD DCI
	TECH LIB
1	ATEC
(PDF)	S STARTZ
3	INTERNS
(PDF)	S BERGEN
	H GOODMAN
	J WHITAKER
1	MTU
(PDF)	G PARKER
1	C5ISR
(PDF)	M BAILEY
1	GVSC
(PDF)	D RIZZO
12	DEVCOM ARL
(PDF)	FCDD RLC E
(5 HC)	B MCCALL
	T JAMESON
	FCDD RLC ED
	G VAUCHER (5 HC/1 PDF)
	C HOCUT
	R BRICE
	R RANDALL
	M LEE
	M S DARCY
	J RABY
	FCDD RLS RP
	M BERMAN
	B GEIL
	R JANE