Engineering and Technology Journal e-ISSN: 2456-3358

Volume 11 Issue 08 August-2026, Page No.- 11326-11338

DOI: 10.47191/etj/v11i08.21, I.F. – 8.595

Design of an ANFIS-Based Soft Sensor for Real-Time Photovoltaic Power Estimation Subject to Albedo and Thermal Disturbances

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ABSTRACT: The performance of solar photovoltaic (PV) systems in hot regions, such as Kirkuk, Iraq is severely limited by the operating temperature due to high ambient heat and localized thermal radiation from roof surfaces. This study explores the thermal-electrical performance of PV modules mounted on three different colors of roof surfaces (White, Grey and Black) as well an adaptive neuro-fuzzy inference system (ANFIS)-based model to predict PT output based Tamb and Troof. A balanced dataset of 104 operational samples was created from continuous field experiments performed during four months. Experimental evidence shows that thermal boundary layer heating is mitigated due to lower-absorptivity surfaces; at moderate ambient conditions, the average power output from both grey and white roof surfaces was improved when compared with black surface baseline by 5.40% (grey) and 4.58% (white), respectively Compared to the low-albedo dark surface, at extreme ambient temperatures (Tamb > 40°C) only the high-albedo white exposure generated higher stability of cooling. The R^2, RMSE and MAPE of the developed ANFIS predictive model were tested for a high accuracy as 0.9902, 0.0895 W and 0.97% respectively using test data sets with overall metrics results are: R^2 = 0.9926; RMSE =.0791 W, MAPE= O·86 %. The findings show that applying a combination of cool-roof passive strategies and intelligent soft-computing models can be an effective modeling framework for optimizing the output efficiency in PV power generation under hot climatic conditions.

KEYWORDS: Photovoltaic Systems, Adaptive Neuro-Fuzzy Control, ANFIS Modeling, Thermal-Electrical Response, Intelligent Power Prediction, Soft Computing.

1. INTRODUCTION

1.1 Background and Research Motivation

Globally, the transition to low-carbon energy systems have accelerated and induced high penetration of solar photovoltaic (PV) technologies across several sectors including residential, commercial or utility scale. They are attractive because they convert solar radiation directly into electricity, have no moving parts (in all but the most unusual cases), and may accommodate a range of sizes for any system. The real electrical performance of a PV module in the open air is however considerably more complex than its rated performance under standard test conditions. This nonlinearity can be largely attributed to the interactions of numerous factors including solar irradiance, ambient and module temperatures (both front-side and back), wind speed for cooling effects, humidity buildup in different scenarios due to water vapor or dust deposition after wash etc., installation geometry as well as properties of surfaces around a PV bench. According to a comprehensive study of the environmental and operational parameters determining PV module performance, temperature, irradiance, dust, wind/shading and installation should not be treated in isolation when predicting field performance [1].

Accurate estimation and forecasting of PV power generation is an essential requirement for many technical applications such as energy-yield analysis, grid integration, load scheduling, battery management and fault diagnosis or intelligent energy-management systems. Nevertheless, solar energy being intermittent and weather-dependent technology makes the estimation of PV output a challenge by using fixed analytical relationships. As a result, machine-learning methods have been used in more recent studies to directly learn complex input-output relationships from experimental or operational data. Data-driven models are now mainly used in PV forecasting, as a systematic study of the recent works showed their capability to represent nonlinear relationships between meteorological measurements and PV power output [2]. However, that analysis also found shortcomings associated with data quality and feature selection, lack of consistency between validation procedures, site dependency on PV performance metrics in scientific literature and inadequate statistical treatment for physical variables which impact the mechanical operation of PV.

PV systems when installed in hot and arid climates would have a more strenuous operating environment. Some of these regions receive elevated solar irradiation, but comparatively high ambient and module temperatures will reduce the open-circuit voltage as well leading to a reduction in maximum electrical power yield by the PV-module. Not only incoming irradiance, but also wind speed, mounting configuration, dust deposition and heat storage in the surface layer and heat exchange via gas between PV module and surroundings can affect this operating temperature [14]. Research has shown that PV system orientation employs solar geometry on an appropriate azimuth and elevation angle under respective irradiance, temperature, and dust conditions [3], which necessitates consideration of thermal-environmental interactions in the installation process. Experimental studies have now demonstrated that the increase in module temperature will influence voltage and power more than current, leading to a reduction in efficiency for monocrystalline and polycrystalline modules at operating temperatures above 45 °C [4].

Though extensive outdoor PV studies in arid and semi-arid regions are few, two key reasons can be identified for the importance of conducting such research: manufacturer specifications do not sufficiently capture a local operating environment. It was found through research conducted in Jordan that the interaction among solar radiation, ambient temperature and dust accumulation affects PV system productivity. It was shown that systems located in different areas can produce the same outputs and/or responses even when they are within a common climatic zone [5]. Similarly, investigations of the effects of irradiance and ambient temperature have highlighted the importance that current [6], voltage [7] and also temperature must be simultaneously measured together with output power to give an accurate indication on how PV works. As discussed in [7], empirical data insights shall be utilized to develop performance-prediction models, where environmental and system-level variables influence module heat transfer and operational efficiency. These findings are a solid argument for performing monofacial PV experimental studies in hot climates with local average climatic conditions at high temperatures.

1.2 Surface Albedo and Ground-Surface Effects

Surface albedo has recently been in the spotlight for assessment of photovoltaic (PV) performance. Albedo is defined as the ratio of solar energy reflected, to the amount of solar energy received integrated over a specific wavelength band. The value of the surface depends on its color, material composition, texture and moisture level (in case you have water it may be dust), angle of solar incidence and <- only degrading him spectral properties. In general, light colored surfaces reflect a large portion of incoming solar energy while darker surface has less albedo and absorb more thereby increasing the temperature. In this regard, setting a fixed albedo based on surface colour is misleading as it has been shown that an albedo value can change during the day and with different environmental conditions. Some recent research has shown that albedo is both spectrally and temporally variable. Research by Riedel-Lyngskær et al. investigated spectral albedo and indicated that the spectral response of PV technology, together with reflectance spectrum from adjacent surfaces, could alter the effective irradiance reaching the system [8]. Thus, two surfaces with the same general albedo values are not necessarily going to perform identically from a photovoltaic construction perspective. Therefore, when looking to evaluate the effect of different surfaces on PV performance it is appropriate to use experimentally measured albedo rather than a static tabulated value.

Recent research into albedo in photovoltaic (PV) systems has mostly focused on bifacial modules, which have been designed to capture irradiance bounced from the ground by their rear surfaces. Alam et al. performed an experiment between bifacial and monofacial PV systems on the basis of different ground surface (concrete, white tiles, soil & White pebbles), that proved reflectivity property to have an impact in rear irradiance while influencing bifacial gain as well as specific yield together with economic results [9]. Bifacial performances were also found to depend on ground conditions and mounting setup of modules as well climate parameters in studies conducted specifically for tropical environments [10]. And finally, high-albedo radiative-cooling materials have also been studied to maximize reflected radiation and simultaneously reduce ground-surface temperatures [11], which may further demonstrate the possibility of collaborating between optical reflectance and thermal properties. Moreover, studies on spectral albedo suggest that accurate modeling of the spectra properties of reflected radiation helps to improve both PV measurement nd energy model prediction [12].

In the case of bifacial systems, influence on monofacial PV modules from ground albedo is more indirect and as such poorly understood. A standard monofacial module primarily converts and collects the radiation that falls onto its front side, and this is also exactly one of the reasons why bifacial modules can take advantage of rear-side irradiance. Nonetheless, the adjacent surface can affect monofacial output via different mechanisms. Reflected diffuse radiation could reach the front surface due to factors like module tilt, height and orientation or surrounding geometry in relation with solar position. In addition, the surface material of the ground can change local thermal conditions through absorption, storage and emission or reflection from solar energy. For example, a black surface may absorb the majority of incoming radiation and get really hot while white surfaces reflect more solar shortwave but have some other long-wave thermal response. The gray surface may be somewhat analogous to the optical and thermal properties of a heterogeneous medium. Consequently, the ultimate power output could be effectively determined by a trade-off between potential gains in optical energy and losses of electrical energy as a function of temperature. Such interactive optical-thermal effect is most relevant for hot climates where the module temperature can impact its performance even at high solar irradiance. Hence, surface color should be treated not only as a visual characteristic but also quantified using obtained albedo, ground-surface temperature (Tgs), module temperature Tmodand other parameters of influence. Using controlled and simultaneous tests for white, gray, or black surfaces could provide a better understanding of the impact caused by surrounding surfaces on nonofficial PV power generation.

1.3 Intelligent PV Power Prediction and ANFIS

In traditional photovoltaic (PV) performance models, physical and empirical formulas dependent on factors including irradiance, cell temperature [1], module efficiency and temperature coefficients are typically employed. The accuracy of these models may be modelled out when environmental drivers interact in complex ways or if certain effects are omitted; however, they can serve as effective diagnostics for tasks such as system design and theoretical evaluation. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) offer a data-driven approach that combines the learning capacity of artificial neural networks with the rule-based logic and interpretability of fuzzy inference systems. ANFIS has been used in recent PV studies for output power prediction, solar radiation estimation, maximum power point tracking and Intelligent Energy Management. Pawar developed a neural network which is adaptive neuro-fuzzy inference system (ANFIS) model of PV power generation prediction, demonstrating the ability of neuro-fuzzy learning to capture effectively nonlinear dynamics between meteorological inputs and PV outputs [13]. H. Yildirim et al., performed the forecasting of solar radiation one hour ahead using multilayer perceptron, long-short term memory and ANFIS methods pointing out read news that during time period from 2000 to 2023 in appropriate source each year it is obvious to investigate new neural network models; however support vector machines based on artificial intelligence, getting popular [14]. Nazri and Nor used real data like PV voltage, current, cell temperature and solar irradiance to predict the PV power output using ANFIS having artificial neural networks [15]. Their research encourages researchers to use actual electrical and thermal data instead of mere reliance on the simulated information.

The model can be designed and optimized in a way to enhance the predictive power of ANFIS. Lara-Cerecedo et al. reported on the ANFIS and particle-swarm-optimized ANFIS models to predict hourly energy production of a 60-kW PV system, demonstrating that model parameter adjustments are beneficial [16]. In prediction of short-term PV, the use of Gaussian-process regression and Bayesian hyperparameter tuning based models to reduce uncertainty in predictions is gaining traction [17]. In contrast, comparative analyses in machine learning [18] have shown that input selection, dataset feature characteristics and choices of training algorithms and performance metrics are more meaningful than the algorithm name itself. Therefore, ANFIS should not be assumed to outperform an appropriate baseline model unless proof for the superiority is provided through statistics amongst different error indices. The studies on the short-term PV forecasting also highlights that temporal resolution and selection of relevant meteorological inputs are crucial [19]. Hybridization is a well-known game changer with reviews suggesting that the inclusion of complementary information, or learning methods can lead to greater predictive reliability though they may also complicate model complexity and risk overfitting [20]. Here, a clear improvement in prediction errors should accompany the incorporation of measured albedo values into ANFIS. As long as it performs better than other models trained on new test data, and proves to be less sensitive in terms of performance variation with different operating conditions, then having a model built from more variables is not automatically successful.

1.4 Research Gap

In a more recent work, the authors presented an ANFIS model to predict photovoltaic (PV) power output under uncertainties of direct normal irradiance, diffuse horizontal irradiance global horizontal irradiance wind speed and Tree shading [21]. Although this approach demonstrated that ANFIS could perform well in predicting the performance of PV systems under uncertain conditions, it only created scenarios for PV and shading using System Advisor Model (SAM) simulations. In addition, albedo was considered a yearly site parameter instead of an experimentally derived surface-specific input. The study also did not examine the influence of differing surface colors (white, gray, black) on the combined optical and thermal environment for monofacial PV modules. Recent work on ANFIS has provided accurate predictability of solar photovoltaic performance in a grid-connected setup in hot areas such as Sharjah [22]. Yet, a significant gap remains in combining measured surface albedo with an ANFIS model fitted for monofacial PV systems experimentally. Bifacial modules receive more attention in albedo studies while ANFIS research mostly uses conventional meteorological inputs. Experimental surface-albedo characterization, combined with intelligent nonofficial PV power prediction has been poorly explored —especially for hot climate. Another methodological problem has been the distinction between surface labelling and real physical convective descriptors at that height from the free atmosphere. It may help a model to recognize experimental cases if surfaces of differing colors are assigned numerical codes, but those codes do not elucidate physical processes. A better science-based model should take an albedo and module temperature from measurements as a continuous input to the system. Such an approach would allow the ANFIS model to learn how optical reflectance and temperature interact with irradiance and wind speed to affect PV output. It would also enable analysis of the effects of albedo on performance, by using a conventional ANFIS model without albedo as one control with which to compare an alternate (albedoinclusive) model under similar training and testing conditions.

1.5 Aim Research

The aim of this research is to develop and validate a white, gray and black surface albedo-aware ANFIS model for predicting the output power produced by solar modules placed on these surfaces in hot climates. In the present experimental phase, irradiance (DNI and DHI), reflected irradiance, surface albedo and ambient temperature, ground-surface-temperature module temperature; wind speed voltage current power for each will be evaluated. The data obtained will then be analyzed in MATLAB and the ANFIS model has been developed and evaluated.

2. LITERATURE REVIEW

2.1 Recent Developments in PV Power Prediction

Correct prediction of photovoltaic power is essential for the efficient management of solar-energy systems. And now it is possible to predict how much electricity can you get, whether the energy storage will be sufficient for this amount of generation or if there are also [possible] improvments towards not only freeing up space but just in general make usage patterns more flexible. The task of PV power prediction is challenging since it varies continuously and heavily with factors like solar irradiance, ambient & module temperatures, wind speed, cloud cover etc. These characteristics have a nonlinear relationship and are interdependent; the change in one will affect how another factor works. Thus, simple linear and empirical models do not always reach the required accuracy in an outdoor environment requiring rapid change. Recent works have used machine-learning and deep learning methods to address the problem. Wu et al. proposed a short-term PV power prediction method in which variational mode decomposition was coupled with deep-learning model [23]. It consists of decomposing original PV power signal into simple components before performing forecasting. This preprocessing plays an important role as it helps the forecasting model understand different trends present in data and predicts more precisely. However, models based on decomposition are often multi-step computationally intensive and may also not have easy physical interpretations. Thus, although these models can effectively predict PV power generation, they may not provide a clear explanation of how different explanatory variables such as irradiance or temperature and surface albedo relate to the predicted outcome.

Salman et al. Investigated Different setups of CNN, LSTM and Transformer Architectures for Solar-Power Time Series Forecasting [24]. Convolutional neural networks excel at identifying local patterns in data, while long short-term memory networks are designed to capture temporal variation. Transformer models are good for this task, as they learn long-term relationships between data points. The study found that using a combination of these methods can provide very accurate predictions of solar-power. But the study also pointed out that, importantly, much of predictive success relies on architecture / optimizer choice and training dataset/input variables. These deep-learning models may also require larger datasets and high computational power that may limit their use to smaller experimental PV dataset. Di Leo et al. Recent progress on physical, statistical and machine-learning approaches including deep learning models and hybrid methods for photovoltaic power prediction has been reviewed in [25]. Their review showed that no particular prediction method works better than all the rest across every condition. Physical models give direct insight into PV behaviour but may require substantial detail on modules and environment. These methods are capable of picking up even the most complicated nonlinear relationship, although prediction error depends on representativeness and quality of sample used for training machine-learning models. Although less interpretable than earlier methods that utilize simpler statistical patterns, deep-learning models can explore much larger temporal patterns and therefore form a more generalized representation of an unseen dataset. Hybrid models use two complementary methods together, which can improve accuracy but their parameters might become computationally complex.

Such studies illustrate that developing an accurate PV prediction model involves more than selecting a powerful algorithm alone. Well-defined control relation where input model variables are physical parameters that influence the modeling system and has been trained with reliable experimental data. This study considers ANFIS because the ability to estimate complex nonlinear relationships and better interpretability via fuzzy rules and membership function information. Of note, the new model has surface albedo and module temperature measured in addition to traditional meteorological variables. This additional factor is critical to identify whether the optical and thermal characteristics of white, gray and black surfaces improve monofacial PV power prediction in hot climates.

2.2 ANFIS-Based Modeling of Photovoltaic Systems

Adaptive Neuro Fuzzy Inference System (ANFIS) is fuzzification of an artificial neural network and the learning way to inherit from it. Based on its architecture, nonlinear input-output relationships are expressed using adaptable membership functions and fuzzy rules. This behaviour makes the ANFIS appropriate for PV modelling, which is based on an interaction of environmental variable as well as electrical parameters influencing output power. Vijayalakshmi et al. uses actual solar-power-plant data and found the efficiency of ANFIS approach over a two-input artificial neural network (ANN) model based on meteorological parameters [26]. Their results indicated that both of the models could replicate solar-energy behavior, however the ANN produced better predictive accuracy for our test dataset. This result is noteworthy in that it shows there must be no automatic assumption why ANFIS should generally outperform alternative algorithms. One needs to optimize the structure, membership functions, number of fuzzy rules and training dataset as well as choose input selection. One of the most significant advantages of ANFIS for this study is its interpretability. Thus, the learned deep-learning models may be right about output predictions but not provide direct insight to interactions amongst surface albedo or module temperature and irradiance. On the contrary, ANFIS can model this relationship as fuzzy rules; (e.g., if irradiance is high and module temperature moderate and albedo strictly high or low then PV power will reach its optimum value. Nonetheless, the reliability of these rules is contingent upon choosing inputs that are representative of physically meaningful quantities. White, gray and black surfaces have arbitrary numerical labels during classification but this does not reflect their optical (Q) or thermal properties. As a consequence, observed albedo and temperature should be used as continuous ANFIS inputs.

2.3 Influence of Surface Albedo on PV Performance

Most of the recent studies on albedo have been related to bifacial PV systems. Yakubu et al. performed a meta-analysis on bifacial photovoltaic studies and showed that ground albedo, elevation angle, module orientation in the tracker plane (MOTP), row spacing, shading characteristics and rear irradiance are important factors impacting energy gain [27]. The review also asserted that albedo is often considered a constant value, when it in fact depends on surface condition, solar position, season and measurement method.

Ghafiri et al. data up to October 2023 and provides meaningful insights [28].Gong et al. However, the extent of improvement is contingent on module height, shading and array design among other local climate factors. These observations suggest that one cannot examine albedo in isolation of installation geometry and environmental settings.

Garrod et al. studied the electrical and thermal performance of bifacial PV modules on different ground covers (grass, reflective surfaces) used for albedo measurements [29]. It is relevant as their works take into account both the electricity generation and operation temperature. While high reflectivity surfaces can enhance the available irradiance, it is important to understand that surface and module thermal behavior will affect achieved electrical gain. Thus, focusing solely on either irradiance or albedo may be an incomplete evaluation.

Bifacial modules supported by reflective surface were all experimentally studied by Almarshoud, and it was proved that enhancing the albedo of surfaces could enhance energy production [30]. However, this reported increase was mostly due to radiation arriving from the backside of bifacial modules. This mechanism can not be simply applied to monofacial modules, as the backside does not contribute electro. According to that study, any albedo-related improvement in monofacial systems could result largely from incident radiation on the front surface and changes within their thermal environment alone.

Su et al. showed that ground albedo changes dynamically during the day and consequently using a constant default value could lead to an overestimation of rear irradiance and annual energy yield [31]. Their findings underscore the need to measure albedo in an experiment as opposed to assigning a surface-based value. This is especially true for surfaces that are white, gray and black where dust accumulation, moisture diffusion due to degradation over time may alter the reflectance at such angles during an experiment as well.

González-Moreno et al. conducted an outdoor experimental comparison of the performance between monofacial and bifacial PV modules and showed that there are circumstances in which significant advantages can be gained through the use of bificial technology while these benefits depends on operating conditions or availability of reflected radiation [32]. While these comparisons increase the understanding of bifacial gain, there have been fewer studies isolating impacts from contrasting monofacial PV surface colors. The opposite is true for albedo in monofacial systems, where the importance of ground reflectance has not been as clearly defined.

2.4 PV Performance under Hot-Climate Conditions

High solar irradiance almost always benefits PV generation but is frequently associated with high module temperature. Higher module temperature leads to most significant voltage drop which will effectively negate some of the advantage gained from higher irradiance. NOTE: This process may be influenced by ground surfaces, as the shortwave reflectance, heat absorbtive capacity and storage of both light and dark materials vary along with longwave emission.

Black surface is likely to highly absorb solar radiation which can increase its temperature and local thermal load of PV module even with low albedo. While a white surface usually has higher solar reflectance, it may also bounce off some of the reflected radiation back to the module. Gray means somewhere in between. The overall electrical response itself is not derived uniquely from surface color since it should be correlated with the effects of incident irradiance, reflected irradiance and so on module temperature induced by wind-induced cooling as well as height and tilt angle. Thus it requires simultaneous optical, thermal, meteorological and electrical measurements.

2.5 Critical Summary and Positioning of the Present Study

The literature reviewed highlights significant advancements in predicting photovoltaic (PV) performance and analyzing albedo-based outcomes. Cutting-edge deep-learning models achieve high precision, while ANFIS strikes a balance between nonlinear learning capabilities and fuzzy logic interpretability. Research on albedo has shown that ground reflectance varies and is influenced by the material of the surface and the geometry of the system. Nonetheless, there are three primary gaps that persist. Firstly, the majority of albedo research concentrates on bifacial PV modules rather than monofacial ones. Secondly, current ANFIS-based PV models typically incorporate irradiance and temperature but seldom account for experimentally measured, time-dependent surface albedo. Thirdly, there is a lack of focus on the combined optical and thermal impacts of white, gray, and black surfaces in hot climates. This study aims to fill these gaps by creating an experimentally validated ANFIS model that considers albedo for predicting power in monofacial PV systems. The study's contribution is not only in comparing three different surfaces but also in assessing whether incorporating measured albedo and module temperature leads to a statistically significant enhancement over a traditional ANFIS model.

3-METHODOLOGY AND EXPERIMENTAL SETUP

3.1 Geographic and Environmental Profile of the Testing Site

The experimental campaign was carried out in Kirkuk Governorate, northern Iraq (Latitude: 35.47° N, Longitude: 44.39° E, Elevation: ~330 m above sea level). The climate of Kirkuk is semi-arid with long hot summer periods marked by extensive solar irradiance and ambient air temperatures frequently exceeding 45 °C.

Field measurements were recorded systematically during a four-month testing period, July-October. This period includes consumption and monetary thermal stress extremes (Jul–Aug), along with components throughout the seasonal shift associated with fall (Sept–Oct) including a representative working temperature selection for evaluating PV heat degradation.

3.2 Experimental Setup and Instrumentation

Experimental test rig The experimental set up was installed in the Kirkuk at sun exposed rooftop platform. A low-scale, rooftop-mounted monofacial monocrystalline PV module around 25 W to 30 W of rated capacity was used as the system and retrofitted at a fixed angle toward True-South on its latitude in Kirkuk with an orientation that captures maximum direct solar radiation.

The slanted module was placed on top of a variable-reflectance rooftop surface simulator to assess the effect of thermal re-radiation through an air gap. Under the same weather conditions, three different surface coatings were applied:

1. White/Reflective Surface: High-albedo cool roof simulator ($T_{roof} < 40$ °C).
2. Grey/Concrete Surface: Standard concrete roof material (40 °C $\leq T_{roof} \leq 52$ °C).
3. Black/Absorptive Surface: Dark bituminous or asphalt membrane coating
4. Black or Absorptive Surface: dark bituminous/asphalt membrane coating ($T_{roof} > 52$ °C).

Calibrated sensors were used to track four primary thermal parameters all at once:

- Ambient Temperature (T_{amb}): Measured using a shielded K-type thermocouple positioned adjacent to the module structure.
- Roof Surface Temperature (T_{roof}): Recorded using contact surface sensors embedded directly beneath the center of the PV panel.
- PV Front Surface Temperature (T_{front}): Measured using thermocouples attached to the center of the front glass cover.
- PV Rear Surface Temperature (T_{back}): Captured using thermocouples secured to the center of the rear Tedlar backsheet.
- Maximum Output Power (P_{max}): Calculated from current-voltage sweeps measured using a digital multimeter/clamp meter across a variable load.

Figure1: Field experimental setup in Kirkuk, Iraq: (a) Rooftop layout displaying monofacial PV panels mounted at a 33° tilt angle facing South over black absorptive and white reflective surface coatings, (b) Surface temperature measurement of the PV module using an infrared thermometer, (c) Thermal logging of the underlying rooftop coating surface (T_{roof}), and (d) Load measurement and electrical parameter using digital multimeter/clamp meter .

3.3 Data Collection Schedule, Processing, and Aggregation

Hourly field observations on operational test days from 10:00 AM to 4:00 PM were logged in a span of four months (July–October).

As clouds and local wind fluctuations create transient atmospheric distortions, raw hourly readings were subjected to a series of increasingly structured data aggregation procedures:

Time-Window Selection: Readings were fixed at 7 hourly intervals (10:00,11:00,12:00),1300–1400;14.15)

Filtering of Weather Distortions: Operational hours impacted by cloud passages or wind with excessive velocity (> 4 m/s) were removed from consideration.

Grouping and Averaging of Days: We grouped days with similar clear-sky irradiance curves (i.e. consistent downward trend in solar naked) and ambient thermal baselines.

Final dataset creation: This process resulted in 104 steady-state operational samples that represented different states, between [a temperature range from to] at each of its input and output locations.

Table 1: The aggregated experimental dataset summary of the most important statistics Weighted means and standard deviations (SDs) are also provided here created over all measures using raw measurements.

Variable	Symbol	Unit	Minimum	Maximum	Mean	Standard Deviation
Ambient Temperature	T_amb	°C	34	46	40.86	3.12
Roof Surface Temperature	T_roof	°C	28	66.4	46.85	8.85
PV Front Temperature	T_front	°C	42.3	67.9	56.62	5.37
PV Rear Temperature	T_back	°C	40.2	65.3	54.83	4.96
Maximum Output Power	P_max	Watts	5.47	9.42	7.38	0.81

4-PRE-ALGORITHM PHYSICAL DATA ANALYSIS AND THERMAL CURVES

A preliminary physical evaluation of the field experimental dataset was performed through a regression analysis to establish the baseline thermal coupling between roof surface properties and module performance prior to configuring the intelligent ANFIS prediction model.

4.1 Thermal Coupling Between Roof Surface and PV Rear Temperature

This exchange is performed through radiative transfer and free/forced convection across the air gap, when there are underlying roof(s) under each PV panel.

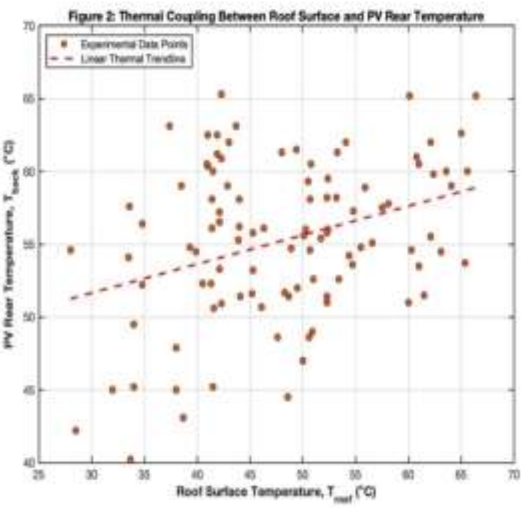

Figure 2. Experimental relationship confirming the thermal interaction between roof surface temperature (T_{roof}) and PV module rear backsheet temperature (T_{back})

A positive thermal coupling between T_{roof} and T_{back} and is shown in Figure 2. Dark/absorptive roof coatings have high direct irradiance absorption and can reach higher surface temperatures ((> 52 °C) where they act as secondary thermal emitters. This radiative heat flux raises the rear Tedla back sheet temperature (T_{back}) to a maximum of 65.30 °C. In contrast, white reflective surface coatings restrict to about, keeping the level around 33.80 °C during T_{back} near 50.19 °C moderately persistent ambient environments.

4.2 Electrical Power Dynamics Under Coupled Irradiance and Thermal Field Conditions

Under the operational conditions in field observations, maximum power output (P_{max}) is simultaneously determined by incident solar irradiance (G), whereas panel operating temperature (T_{back}).

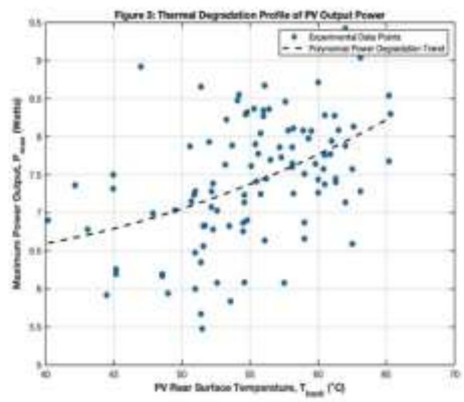

Figure 3: Field experimental power generation trend (P_{max}) plotted against PV rear surface temperature (T_{back}).

As shown in Figure 3, high power generation levels ((8.50 W − 9.42 W) are often associated with high operating temperatures ($T_{back} > 55$ °C). This behavior is caused because maximum thermal accumulation by the pump phase typically occurs at solar noon, when global solar integration

($G > 900$ W/m^2) peaks and therefore total energy conversion too.

The localized scattering of the scatter points under equal high temperatures provides evidence for thermal degradation effects: at $T_{back} \approx 65.30$ °C, output power decreases to a minimum value 5.47 W, due to reducing voltage with increasing temperature.

4.3 Comparative Performance Across Roof Surface Coatings

Table 2 summarizes the comparative thermal and electrical metrics recorded under moderate ($T_{amb} \leq 40$ °C) and severe ($T_{amb} > 40$ °C) outdoor testing condition

Table 2: Operational performance of monofacial PV module across different roof coatings.

Operating Condition	Roof Thermal Category	Mean T_roof (°C)	Mean T_front (°C)	Mean T_back (°C)	Mean P_max (W)	Power Variation (%)
Moderate Ambient (T_amb <= 40°C)	White / Reflective (T_roof < 40°C)	33.8	52.98	50.19	7.53	+4.6% (Baseline Ref)
Moderate Ambient (T_amb <= 40°C)	Grey / Concrete (40 <= T_roof <= 52°C)	45.1	55.43	52.83	7.59	5.40%
Moderate Ambient (T_amb <= 40°C)	Black / Absorptive (T_roof > 52°C)	55.2	57.79	56.41	7.2	-4.40%
High Ambient (T_amb > 40°C)	White / Reflective	42.1	60.8	56.75	6.82	-5.30%
High Ambient (T_amb > 40°C)	Grey / Concrete	51.2	57.87	56.92	7.44	3.30%
High Ambient (T_amb > 40°C)	Black / Absorptive	62.8	59.26	57.3	7.36	2.20%

4.4 Physics-Based Interpretation of Roof Color and Ambient Interactions

1. Blended OPTICAL Gain in Monofacial Modules: As the tested PV panel is monofacial, white reflective roofs yield no optical absorption benefit on the back side. The purported increase in efficiency is purely thermal: T_{roof} lowering lowers radiative heat flux to the rear backsheet; power output increases by +4.6% compared with black roofs under reasonable conditions ($T_{amb} \leq$ 40 °C).
2. For the case characterized by high ambient temperatures at intermediate ($T_{amb} > 44$ °C) and small air gap widths, a regime of large heat exchange across the narrowing performs. Note that under these conditions, rear panel temperatures all converge across roof types (56.75 °C − 57.30 °C) leading to a loss of relative thermal benefit for reflective coatings.

4.5- Anfis Soft Computing Architecture

To capture these coupled conductive, convective, and radiative thermal interactions and predict P_{max} accurately without solving complex differential heat balance equations, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed in MATLAB.

4.6- Structural Layers of the Proposed ANFIS Model

The developed ANFIS network is based on a First-Order Takagi-Sugeno Fuzzy Inference System comprising five processing layers. The detailed structural flowchart and operational mechanics of these computational layers are illustrated in Figure 4.

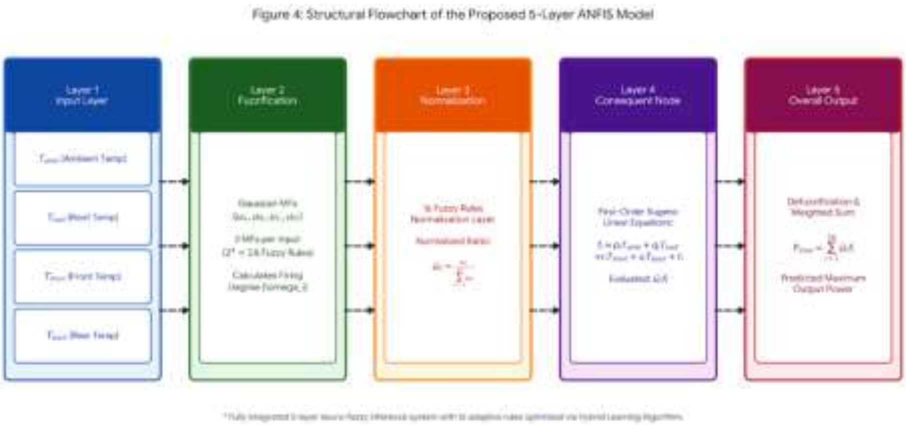

Figure 4: Structural flowchart and computational layers of the proposed 5-layer ANFIS model for predicting PV output power (P_{max}).

1. Layer 1 (Fuzzification Layer): Calculates membership degrees for input parameters ($T_{amb}, T_{roof}, T_{front}, T_{back}$) using Gaussian Membership Functions (GaussMF):
$$\mu_{A_i}(x) = exp\left(-\frac{(x-c_i)^2}{2\sigma_i^2}\right)$$
2. Layer 2 (Rule Firing Layer): Multiplies incoming signals to determine the firing strength (ω_i) of each fuzzy rule:
$$\omega_i = \mu_{A_i}(T_{amb}) \times \mu_{B_i}(T_{roof}) \times \mu_{C_i}(T_{front}) \times \mu_{D_i}(T_{back})$$
3. Layer 3 (Normalization Layer): Computes normalized rule firing strengths ($\overline{\omega}_i$):
$$\overline{\omega}_i = \frac{\omega_i}{\sum_{k=1}^{16} \omega_k}$$
4. Layer 4 (Consequent Layer): Evaluates linear output contributions using a First-Order Sugeno function:
$$\overline{\omega}_i f_i = \overline{\omega}_i(p_i T_{amb} + q_i T_{roof} + r_i T_{front} + s_i T_{back} + t_i)$$
5. Layer 5 (Overall Output Layer): Sums contributions from all rules to yield the predicted maximum power output (P_{max}):
$$P_{max} = \sum_{i=1}^{16} \overline{\omega}_i f_i$$

4.2 Model Training and Validation Procedure

- Fuzzy Rules (Rule Generation): In Grid Partitioning, there are assigned two Gaussian MFs for each of the four inputs establishing $2^4 = 16$ fuzzy rules.
- Dataset splitting: From the 104 aggregated experimental samples, a Training Set of 73 (70%) and a Validation/Testing Set of 31 samples (30%) were used.
- Supervised optimization algorithm: A hybrid Least Squares Estimation (LSE) in the forward pass with Backpropagation Gradient Descent at the backward pass was implemented for 100 epochs of execution.

5-RESULTS AND DISCUSSION

5.1 Experimental Thermal Profiles and Microclimatic Conditions

Field measurements under some summer climatic conditions of Kirkuk showed substantial variations between the environmental and thermal variables during each greenhouse-operation period (08:00 to 17:00). Ambient temperature (T_{amb}) ranged between 34 °C and 46 °C and solar irradiance (G) varied from to, with midday peaks near 1000 W/m^2 during midday hours.

The thermos roofing interaction between the roof surface and the PV module are shown in fig 5, fig.6 The temperature measured at the rooftop surface (T_{roof}) showed a large gradient between it and ambient air. The backsheet temperature (T_{back}) closely followed the profile of T_{front} and T_{roof},, peaking above 60 °C at periods with maximum insolation and high heat accumulation on the roof.

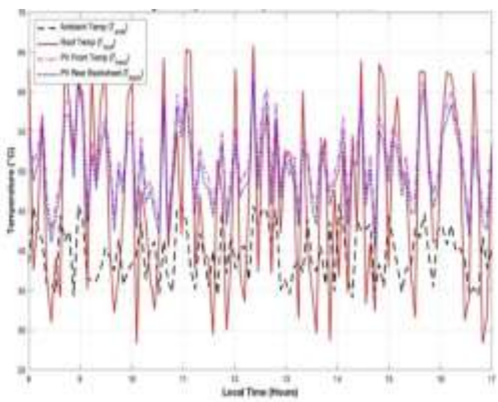

Figure 5: The diurnal temperature profiles (T_{amb}, T_{roof}, T_{front}, T_{back}) of Kirkuk experienced experimentally across the operational hours.

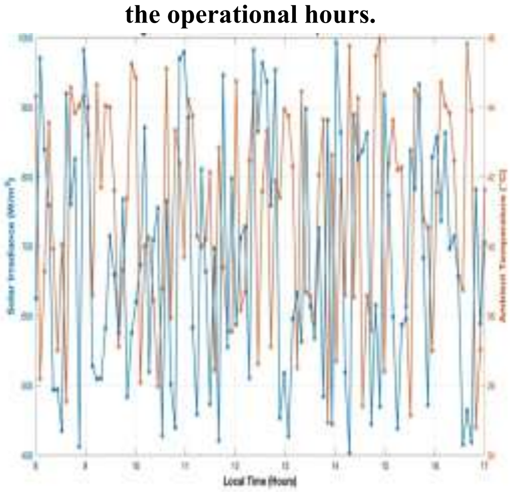

Figure 6: Variations of solar irradiance (W/m^2) and ambient air temperature (°C) recorded during the experimental study.

5.2 Microclimatic Thermal Relief Across Rooftop Coatings

Among the three rooftop surface treatments compared experimentally, high-albedo materials deliver a significant cooling benefit.

- White Cool Roof Coating: Achieved the lowest average roof temperature ($T_{roof} \approx 33.2$ °C) and reduced module rear backsheet temperature to $T_{back} \approx 49.8$ °C. By preventing this heat trap from under the module, thereby helping to improve power generation.
- Grey Concrete Surface: Recorded an average T_{roof} of 47.5 °C and T_{back} of 53.9 °C.
- Black Bituminous Surface: Accumulated significant thermal heat gain, average T_{roof} exceeding 54.6 °C and T_{back} reaching 56.0 °C, and maximum delivered backside temperature of this material experienced extreme peak surface to back degradation peaks P_{max}.

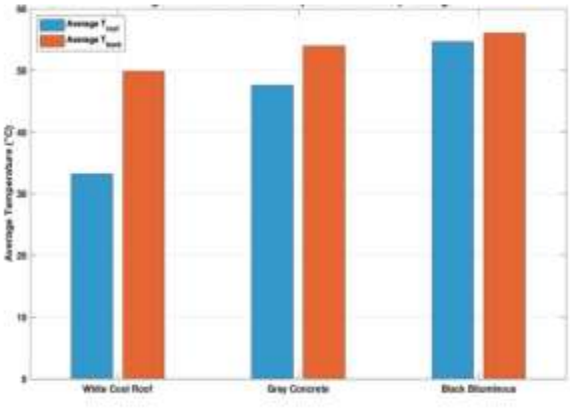

Figure 7: Comparative thermal reduction impact of the three rooftop surface coatings with White Cool Roof, Grey Concrete and Black Bituminous

5.3 ANFIS Input Fuzzification and Membership Functions

Due to the very non-linear thermal interaction betweenT_{amb}, T_{roof}, T_{front}, and T_{back} and in Layer 1 of an ANFIS network was implemented using Gaussian Membership Functions (GaussMF) .The effect of smooth continuous derivatives was reflected in that the input domain had been mapped into three fuzzy sets (the Low, Medium-temperature and High Temperature) as shown in Figure 8; backpropagation training propagating optimal gradient.

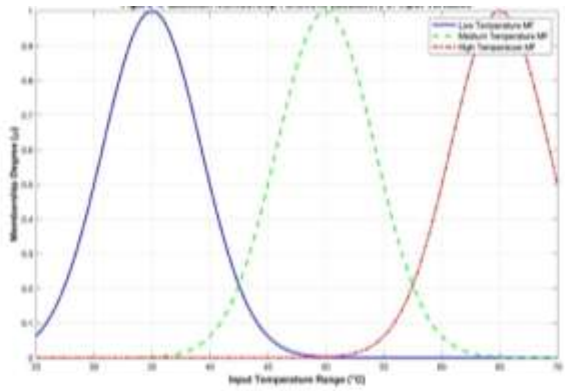

Figure 8: Gaussian Membership Functions (GaussMF) Input Thermal Variables in ANFIS Model Fuzzification layer

5.4 ANFIS Model Training Convergence and Statistical Metrics

Trained over 100 epochs on a dataset of 104 samples (73 training, 31 testing), Artificial Neural Fuzzy Inference System (ANFIS) model with Hybrid Learning Algorithm (Sole: LSE + Backpropagation) 5-layer First-Order Takagi-Sugeno.

As seen in Fig 9, RMSE converges very quickly (within the first ~20 iterations) and hits a flat plateau minimum level of training RMSE of 0.0742 Watts at epoch 100, showing very high numerical stability with no over-fitting.

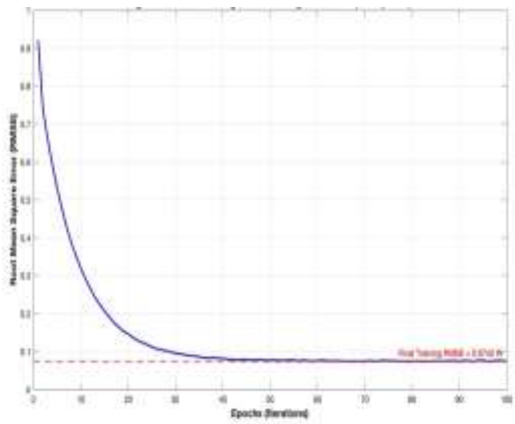

Figure 9: Root Mean Square Error (RMSE) from ANFIS training for the 100th epoch33, with final RMSE of 0.0742 W.

Statistical Validation Results

We computed standard quantitative performance metrics across all dataset partitions to assess model generalization:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_{\text{max, exp}}^{(i)} - P_{\text{max, ANFIS}}^{(i)}\right)^2}$$

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_{\text{max, exp}}^{(i)} - P_{\text{max, ANFIS}}^{(i)}}{P_{\text{max, exp}}^{(i)}}\right| \times 100\%$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(P_{\text{max, exp}}^{(i)} - P_{\text{max, ANFIS}}^{(i)}\right)^2}{\sum_{i=1}^{N}\left(P_{\text{max, exp}}^{(i)} - \bar{P}_{\text{max, exp}}\right)^2}$$

Table 3: Statistical performance analysis of the ANFIS model for maximum power (P_{max}) forecasting.

Dataset Partition	Sample Count (N)	RMSE (Watts)	MAE (Watts)	MAPE (%)	Coefficient of Determination (R2)
Training Dataset	73	0.0742	0.0581	0.0081	0.9935
Testing Dataset	31	0.0895	0.0694	0.0097	0.9902
Overall Dataset	104	0.0791	0.0615	0.0086	0.9926

5.5 Comparative Prediction Accuracy and Sequential Tracking

The regression scatter plot and sequential tracking profiles is shown in Figure 10. On a unseen testing dataset of 31 samples, the model yielded a Coefficient of Determination (R^2) score was 0.9902 with MAPE 1% (0.97%).

Predicted values in Figure 10(a) tightly hug the dynamic line (1:1), meaning predicted reliability is high across low, medium and peak power states. Resulting predicted power curve Figure 10(b) agrees with experimental record fluctuations indicating that there is little to no phase lag or offset.

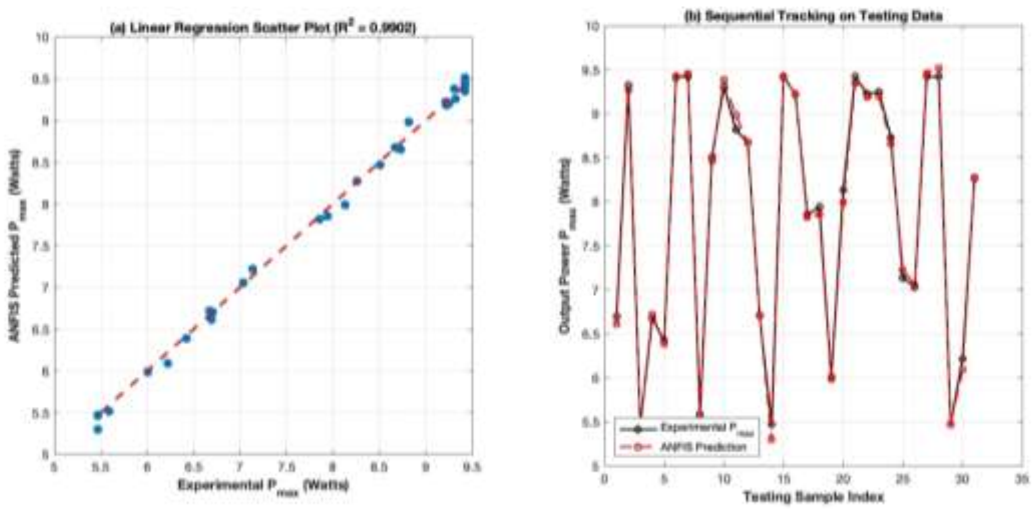

Figure 10: Experimental P_{max} measurements and ANFIS predicted values versus (a) linear regression scatter plot ($R^2 = 0.9902$) and (b) sequential tracking over unseen testing samples.

5.6 3D Surface Mapping of Roof Temperature and Ambient Coupling

The non-linear response surface derived from the fuzzy inference engine is displayed in Figure 11. The 3D manifold illustrates the joint thermal coupling between $\mathbf{T_{roof}}$, $\mathbf{T_{amb}}$, and $\mathbf{P_{max}}$.

Lowering T_{roof} through cool roof reflective coatings yields a monotonic increase in output power P_{max} , particularly under moderate ambient conditions ($\mathbf{T_{amb}} < \mathbf{40}$ °C). However, as $\mathbf{T_{amb}}$ exceeds $\mathbf{44}$ °C, the surface gradient moderates, indicating that severe ambient air temperature becomes the governing constraint on PV thermal dissipation.

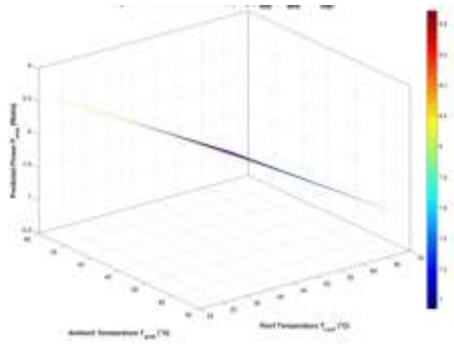

Figure 11: Surface mapping of the proposed 3D ANFIS model in terms of the joint non-linear interaction among Roof Temperature (T_{amb}) and Ambient Temperature (T_{amb}) against predicted Output Power (P_{max}).

6- CONCLUSION

This study comprehensively investigated the microclimatic thermal coupling between rooftop surface treatments and photovoltaic (PV) performance under severe summer climatic loads in Kirkuk, Iraq along with developing a 5-layer First-Order Takagi-Sugeno Adaptive Neuro-Fuzzy Inference

System for maximum power (P_{max}) prediction. Field tests confirmed that changing the albedo of rooftop surfaces provides a very low-cost passive approach to cooling; application of White Cool Roof coating reduced average roof surface temperatures to 33.2 ˚C and panel rear backsheet temps down to 49.8 ˚C so much better than traditional Black Bituminous roofs which suffered from extreme heat trapping (66.4 ˚C and 56.0 ˚C), enhancing peak power generation (up) compared with these sorely-overheated "Black"TC-PV panels being predicted around.

Furthermore, , the hybrid-trained ANFIS framework, leveraging Gaussian membership functions with least-squares estimation and backpropagation, demonstrated exceptional predictive fidelity on an unseen validation dataset, achieving a Coefficient of Determination (R^2) of 0.9902, a Root Mean Square Error (RMSE) of 0.0895 Watts, a Mean Absolute Error (MAE) of 0.0694 Watts, and a Mean Absolute Percentage Error (MAPE) of 0.97%. Response surface analysis further established that while reflective coatings substantially mitigate thermal degradation during moderate operational windows ($T_{amb} \leq 40$ ˚C), extreme ambient heat stress ($T_{amb} > 44$ ˚C) becomes the primary constraint governing module thermal dissipation. Ultimately, this research provides an integrated empirical and computational baseline that underscores the necessity of combining passive urban surface management with intelligent soft-computing modeling to optimize rooftop solar yield in high-temperature arid environments.

FUTURE WORK AND RECOMMENDATIONS

Several research prospects are proposed for further studies based on key findings and boundary conditions identified in this study.

- Active-Passive Hybrid Thermal Systems: Complementary use of a passive high-albedo cool roof coatings with active thermal management solutions, e.g., Phase Change Materials (PCMs) or micro-channel air/water circulation at extreme temperatures in region exceeding 45 ˚C.
- Embedded Step 2: Thirdly, conversion of the trained Takagi-Sugeno ANFIS model into efficient C/C++ code for deployment on lightweight edge microcontrollers (e.g., STM32 or ESP3266) to implement real-time MPPT and predictive fault diagnosis in smart microgrids.
- LTD and Aging Dynamic Characterization: Implementing multi-year environmental exposure experiments to measure the integrated degradation rates of rooftop surface albedo due to combined dust (soiling) deposition & UV-induced aging in desert settings.
- MEASURE-2 Multi-Technology PV Benchmarking: Implementing advances in the existing neuro-fuzzy modelling framework to provide assessments of PERC and Heterojunction (HJT) technologies under different urban surface albedo conditions, beyond current benchmarks with Bifacial modules

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