Forecasting Ambient Air Temperature for Solar Photovoltaic Panel Predictive Maintenance in Kuala Kangsar, Perak, Malaysia

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Abstract
This study presents a forecasting approach to predict ambient air temperatures for the predictive maintenance of solar photovoltaic (PV) panels in Kuala Kangsar, Perak, Malaysia. Accurate temperature forecasting is critical as ambient air temperature significantly influences solar panel efficiency, performance, and maintenance requirements. A comprehensive dataset spanning 19 years (2005–2023) of hourly solar and weather variables, obtained from the Photovoltaic Geographical Information System (PVGIS), was analysed using advanced smoothing techniques, including exponential smoothing models. The study identified the Damped-Trend Linear Exponential Smoothing model as the most effective method based on Akaike and Bayesian Information Criteria. Forecast results for 2024 demonstrated good predictive accuracy, aiding the optimisation of maintenance schedules and the performance of solar PV systems. The findings underscore the importance of integrating advanced predictive techniques to enhance the sustainability and reliability of renewable energy projects.

Keywords: Time Series, Exponential Smoothing, Forecasting, Predictive Maintenance, Solar Energy

1. Introduction

In Malaysia, efforts to address the issue of global climate change are undertaken across various ministries, one of which is the Ministry of Energy and Natural Resources, which is the main driver for this effort. Through the ministry, one of the ways is to increase the capacity to generate electricity through renewable sources, such as solar energy. The ministry also gazetted the Sustainable Energy Development Authority Act in 2011 to establish the Malaysian Sustainable Energy Development Authority (SEDA). Through establishing SEDA, all functions and jurisdictions related to renewable energy development could be managed well and efficiently to ensure that the National Renewable Energy Policy can realise its vision to achieve a 20% Renewable Energy (RE) capacity mix by 2025. According to the 2022 SEDA Annual Report [1], which is shown in Figure 1, by the end of 2022, a total of 615.51 Mega Watts of installed capacity had been produced under the Feed-in Tariff (FiT) mechanism from various renewable energy resources, which is the most significant contribution of about 52% is from solar PV projects.

Figure 1: Yearly RE Installed Capacity 2012 - 2022

Sumber *Resources*	Tahun *Year* 2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Peratus % *Percentage %*
Biogas *Biogas*	7.41	11.73	12.83	20.23	35.69	61.79	69.94	102.76	110.59	124.3	137.6	22
Biojisim *Biomass*	52.3	50.4	55.9	76.7	87.9	95.55	70.65	70.65	70.65	70.65	58.65	10
Hidrokuasa Kecil *Small Hydropower*	15.7	15.7	15.7	18.3	30.3	30.3	50.3	70.3	70.3	87.8	96.8	16
Solar PV	26.32	115.56	169.88	219.89	284.74	315.34	320.52	322.44	322.55	322.52	322.46	52
Jumlah *Total*	101.73	193.39	254.31	335.12	438.63	502.98	511.41	566.15	574.09	605.27	615.51	100.00

Ekshibit *Exhibit* **20** **Kapasiti Terpasang TBB Tahunan hingga 2022**
Yearly RE Installed Capacity up to 2022

Perak is the second-largest state on the Malaysian Peninsula. It is known for its natural tropical beauty and rich cultural histories, such as during the British colonial era for tin mining and rubber wood. Under the Perak State Government, the state is divided into sixteen districts, of which Ipoh is the capital city and Kuala Kangsar is the Royal Town of Perak. Location-wise, the Chenderoh Community College, which resides in Kuala Kangsar, has a geo-location of 4.79° N and 101.898° E on the global map. Thus, having a high potential for sunlight intensity throughout the year, Perak, in which the solar panel rooftop installation, as shown in Figure 2, has vast prospects for solar energy harvesting into electricity. However, only 8% of solar projects have been operational and monitored in real-time by PV Monitoring System (PVMS), a national initiative to monitor the performance and reliability of selected grid-connected solar PV systems nationwide.

Figure 2: Solar Panel Rooftop Installation at Chenderoh Community College

2. Literature Review

Climate change significantly affects wind speed, primarily due to the rising ambient air temperature and shifting atmospheric patterns. A trend line considering these factors would generally show a change in average global wind speeds, though the trend is not universally consistent across regions.

2.1 Rising Ambient Air Temperature on Wind Speed

Following climate change, the rising ambient air temperature on wind speed imposes several effects: thermal gradient changes due to polar regions warming faster than the equator, thus reducing the gradient; changing ocean-atmosphere interaction due to warmer air temperatures affect ocean currents and surface temperatures, which disrupts natural cycles and influence wind speed patterns globally; increased incidence of extreme weather events in regions with more intense and frequent storms that increases the average wind speeds; and local influences in urban areas may experience altered wind speeds due to heat-driven convective currents, while deforestation potentially raising wind speeds at the surface level.

Although studies show mixed trends, the decrease in global wind speed has shown a “global stilling” phenomenon where global land wind speeds have decreased, particularly in mid-latitude regions [2]. This trend may be partly due to increased surface roughness from vegetation and urban expansion. However, a trend line considering climate change impacts on wind speed would likely show regional variation rather than a universal increase or decrease. Coastal areas and regions affected by extreme weather may experience an increase in wind speed, while inland and urban areas could observe a decrease due to surface roughness and atmospheric changes. Understanding these regional variations is crucial for effective solar panel maintenance and energy generation.

2.2 Rising Ambient Air Temperature on Solar Panel Performance

On the other hand, rising ambient air temperatures can significantly impact the performance of solar panels. Although solar panels are designed to convert sunlight into electricity, excessive heat can reduce efficiency. Several effects have been detailed below.

2.2.1 Decrease in Efficiency

Solar panels typically have a temperature coefficient, which indicates the efficiency drop per degree Celsius increase above a specific baseline (usually 25°C). Most standard silicon-based solar panels lose about 0.4-0.5% efficiency for every degree above this baseline. As a result, solar cells’ resistance increases with temperatures rise, reducing their ability to convert sunlight into electricity efficiently. This increase in thermal resistance causes power losses and limits current flow. Contrary to the issue, predictive analyses are recommended to enhance PV systems' efficiency, hence preventing PV arrays' failures [3].

2.2.2 Increased Heat Dissipation Needs

With higher ambient temperatures, solar panels absorb more heat from the surrounding environment, leading to excessive thermal load on the panel surfaces. Hence, enhanced cooling is required to maintain output performance. Solar installations in warmer regions may require additional cooling solutions, such as forced air or liquid cooling, which can add to installation and maintenance costs. However, the benefits of these solutions far outweigh the costs, as they can significantly improve the efficiency and lifespan of solar panels, making them a worthwhile investment in the long run.

2.2.3 Potential for Thermal Degradation

Continuous exposure to high temperatures exerts material stress, which can degrade the materials of the solar panel, especially the encapsulants, adhesives, and back sheets, potentially reducing the lifespan. This potential for thermal degradation is a significant challenge in solar panel maintenance, as it can lead to decreased efficiency and increased maintenance costs. Although cooling solutions address heat dissipation needs, they could also lead to high thermal cycling due to repeated heating and cooling, leading to micro-cracking of cells that potentially affects electrical connectivity and further decreases efficiency over time.

2.2.4 Shift in Peak Power Generation Times

Higher temperatures with poor ventilation may shift peak power generation from the sunniest period to slightly cooler when panels operate closer to optimal temperatures. Paradoxically, solar panels may generate less power during peak sunlight if temperatures are too high, as they lose efficiency when approaching their thermal limits. Contrary to the general belief that the warmer the panel becomes, the higher the electricity produced, it is indicative that the value of maximum power shifts in inverse proportion with the temperature change [4].

2.2.5 Impact on Power Electronics and Batteries

Rising temperatures also affect inverters, leading to possible efficiency drops and additional cooling needs for the inverter units. In particular, off-grid solar energy systems are paired with battery storage. Higher ambient temperatures can accelerate battery ageing/degradation and decrease storage capacity.

Considering Malaysia's ideal geo-location for renewable energy integration, where the government focuses on penetrating more solar photovoltaics into the utility market, ambient air temperature, cell temperature, and solar irradiance are crucial parameters in formulating predictive maintenance models [5]. These parameters represent the input variables to the model and define its efficiency to a great extent. The surface meteorological observation station (SMOS) provides the most accurate meteorological data; however, it is impossible to establish them at every location. The trade-off to SMOS data is that satellite-based data could provide a much greater continuity of data in space [6].

On that account, an optimised forecasting estimation for solar panel predictive maintenance at the location of the study was obtained through the observed-satellite data approach due to its long temporal, historical collection for better forecasting analysis. It also provides meteorological parameters such as the ambient air temperature and wind speed. However, it is essential to mention that other optical properties of the panel's components, such as the cell's material, glazing, encapsulant, back-sheets, the electrical efficiency of the cells and the heat transfer to the ambient (Koehl, et al., 2011), are also influential on the panel maintenance frequency.

3. Methodology

A collection of hourly satellite-based datasets on several solar resource parameters and weather variables, such as air temperature and total wind speed, from the Photovoltaic Geographical Information System (PVGIS) database was retrieved for a significant 19-year period from 1 January 2005 to 31 December 2023. This extensive data collection period was chosen to provide a comprehensive understanding of the long-term trends and patterns in solar resource parameters and weather variables, crucial for accurate forecasting and predictive maintenance of solar panels.

Further, the statistical analysis tool, JMP version 18.1.0 software, was used to save the dataset into a JMP data table file, which contains 166,536 entries of observations. The data set has eight series: date-time, system-rated power produced by 1000 Watt of installed PV crystalline panel measured in Watt, direct irradiance on the inclined plane of the panel array measured in Watt per square meter, diffuse irradiance on the inclined plane of the panel array measured in Watt per square meter, reflected irradiance on the inclined plane of the panel array measured in Watt per square meter, sun elevation angle, air temperature measured in degree Celsius and total wind speed measured in meter per second. Ambient air temperature, the focus parameter in this study, is a continuous time series variable, whereas date is a time variable.

As Malaysia lies in a temperate region, ambient air temperature is one of the critical factors affecting solar panel electrical performance. Four categories were outlined as the most common causes related to solar system malfunctioning: design, installation, operation, and maintenance-related problems [8]. Correct ambient temperature estimation can improve the efficiency of the predictive maintenance models, as Mohamed Bin Shams, et al. (2016) explain. Thus, ambient air temperature was extensively studied for forecasting purposes for 2024.

The forecasting work presented in this paper is divided systematically into the following sections: collection of hourly solar resources for nineteen years from 2005 through 2023, variation analysis of the distribution pattern of ambient air temperature, application of various advanced smoothing techniques such as moving average and exponential smoothing, and selection of the most suitable model based on information criteria, all of which were extensively described in the result and analysis part.

4. Result and Analysis

The dataset retrieved from the PVGIS database was about to forecast a univariate time series of the hourly ambient air temperatures. Observing the data's patterns and trends is crucial before performing a forecasting model by smoothing out the data before forecasting.

Smoothing is essential for accurate forecasting in time-series analysis, especially when trends or seasonality are present in the data. Exponential smoothing methods are instrumental because they apply decreasing weights to past observations, which helps capture the underlying pattern more effectively.

4.1 Summary Statistics of the Data Series

Summary statistics are crucial for understanding the essential characteristics of time series data. They provide insights into the data's central tendency, variability, and distribution, which can help decide the choice of smoothing and forecasting methods.

Figure 3: Variation of Air Temperatures from 2005 until 2023

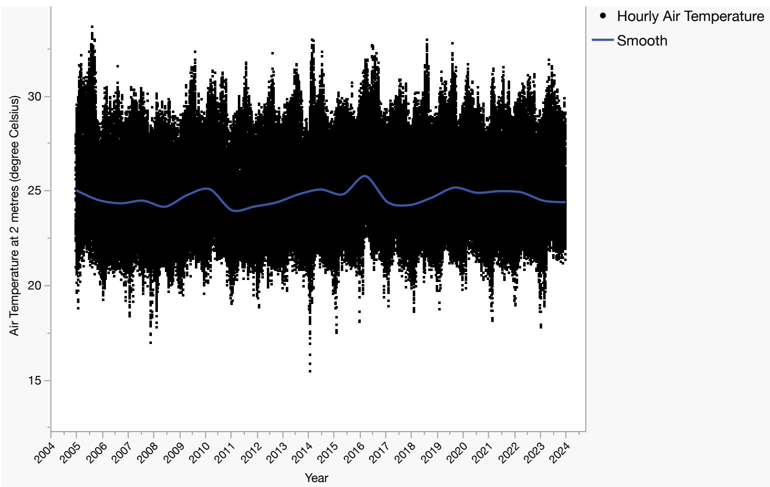

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Figure 3 shows the variation of air temperatures retrieved from the hourly solar resource data for a 19-year period. It can be observed that, due to having a considerably low standard deviation value, which indicates a uniform spread of data points, the temperatures were moderately volatile during the period. The generated smoothed curve showed that temperatures remained considerably stable, although some slight downward and upward movements were observed.

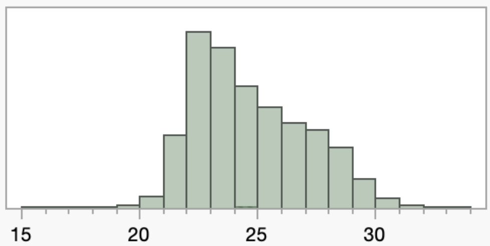
4.2 Visual Representation of the Data

The data distributions were analysed to identify trends, seasonality, or irregular ambient air temperature variation patterns.

Figure 4: Summary Statistics of Air Temperature Distributions

Distributions

Air Temperature (degree Celsius)



Quantiles

100.0%	maximum	33.67
99.5%		30.68
97.5%		29.49
90.0%		28.13
75.0%	quartile	26.42
50.0%	median	24.23
25.0%	quartile	22.81
10.0%		22.03
2.5%		21.28
0.5%		20.43685
0.0%	minimum	15.47

Summary Statistics

Mean	24.690812
Std Dev	2.3328668
Std Err Mean	0.0057166
Upper 95% Mean	24.702016
Lower 95% Mean	24.679607
N	166536
Skewness	0.5062115
Kurtosis	-0.548738
N Missing	0
Minimum	15.47
Maximum	33.67

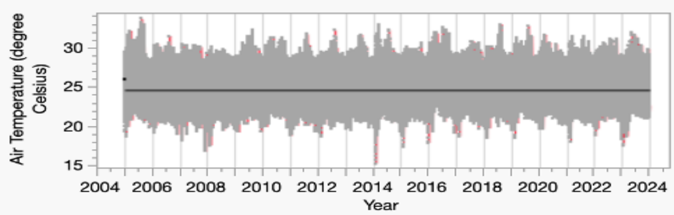
Figure 4 shows the summary statistics of ambient air temperatures. Other customised settings, such as skewness, kurtosis, minimum, and maximum, were added besides the default settings. The mean air temperature was 24.69 degrees Celsius, with a maximum of 33.67 degrees Celsius and a minimum of 15.47 degrees Celsius. Due to the mean and median values did not differ significantly, the temperatures were positively skewed, which shows the asymmetry of the data. However, as the data has a negative kurtosis, it reveals its tailedness, which means there were a few extreme values during the observed period. Hypothetically, the graph shown in Figure 3 indicates the need to apply smoothing techniques to the data before forecasting can be performed.

4.3 Time-series Representation of the Temperature Data

A time-series representation is one way to visualise how the temperature changes over time, which is fundamental in identifying trends, seasonality, and anomalies in the series. Hence, a time-series plot was carried out to interpret the underlying patterns in the data before applying any forecasting models.

Figure 5: Time-Series Output of Air Temperatures

Time Series Air Temperature (degree Celsius)



Mean	24.690812
Std	2.3328598
N	166536
Zero Mean ADF	-6.504663
Single Mean ADF	-70.22014
Trend ADF	-70.28221

Time Series Air Temperature (degree Celsius)

Time Series Basic Diagnostics

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
8597	0.1332	3.08e+8	<.0001*	8597	-0.0000
8598	-0.0358	3.08e+8	<.0001*	8598	0.0034
8599	-0.1861	3.08e+8	<.0001*	8599	0.0016
8600	-0.3095	3.08e+8	<.0001*	8600	-0.0007
8601	-0.4038	3.08e+8	<.0001*	8601	-0.0010
8602	-0.4691	3.08e+8	<.0001*	8602	-0.0014
8603	-0.5068	3.08e+8	<.0001*	8603	0.0018
8604	-0.5193	3.08e+8	<.0001*	8604	-0.0009
8605	-0.5073	3.08e+8	<.0001*	8605	-0.0003
8606	-0.4702	3.08e+8	<.0001*	8606	-0.0003
8607	-0.4052	3.08e+8	<.0001*	8607	0.0034
8608	-0.3112	3.08e+8	<.0001*	8608	0.0002
8609	-0.1879	3.08e+8	<.0001*	8609	0.0020
8610	-0.0375	3.08e+8	<.0001*	8610	-0.0024
8611	0.1319	3.08e+8	<.0001*	8611	0.0012
8612	0.3095	3.08e+8	<.0001*	8612	0.0028
8613	0.4795	3.08e+8	<.0001*	8613	-0.0000
8614	0.6231	3.08e+8	<.0001*	8614	0.0050
8615	0.7215	3.08e+8	<.0001*	8615	0.0040
8616	0.7586	3.08e+8	<.0001*	8616	-0.0040
8617	0.7216	3.08e+8	<.0001*	8617	-0.0041
8618	0.6236	3.09e+8	<.0001*	8618	0.0010
8619	0.4805	3.09e+8	<.0001*	8619	0.0041
8620	0.3109	3.09e+8	<.0001*	8620	-0.0009
8621	0.1336	3.09e+8	<.0001*	8621	-0.0009
8622	-0.0356	3.09e+8	<.0001*	8622	-0.0024
8623	-0.1861	3.09e+8	<.0001*	8623	0.0025
8624	-0.3096	3.09e+8	<.0001*	8624	-0.0026
8625	-0.4039	3.09e+8	<.0001*	8625	-0.0003
8626	-0.4691	3.09e+8	<.0001*	8626	0.0038
8627	-0.5066	3.09e+8	<.0001*	8627	0.0009
8628	-0.5189	3.09e+8	<.0001*	8628	0.0002
8629	-0.5069	3.09e+8	<.0001*	8629	0.0005
8630	-0.4696	3.09e+8	<.0001*	8630	-0.0000
8631	-0.4049	3.09e+8	<.0001*	8631	-0.0015
8632	-0.3110	3.09e+8	<.0001*	8632	0.0001
8633	-0.1878	3.09e+8	<.0001*	8633	0.0026
8634	-0.0373	3.09e+8	<.0001*	8634	0.0020
8635	0.1321	3.09e+8	<.0001*	8635	0.0005
8636	0.3097	3.09e+8	<.0001*	8636	-0.0011
8637	0.4796	3.09e+8	<.0001*	8637	-0.0028
8638	0.6230	3.09e+8	<.0001*	8638	0.0019
8639	0.7211	3.09e+8	<.0001*	8639	-0.0018
8640	0.7581	3.09e+8	<.0001*	8640	0.0031

Figure 5 shows the descriptive statistics of the time-series output, Auto Correlation Function (ACF), and Partial Auto Correlation Function (PACF) for air temperatures up to the 8640th lag. As per the line plot previously shown in Figure 3, the smoothed curve shows an upward or downward slope; therefore, the temperatures indicate a trend over time rather than seasonality or outlier.

4.4 Estimation of Various Smoothing Models

Estimating smoothing models is a crucial step for forecasting, mainly when the time series plot exhibits patterns like trends or seasonality. Various smoothing techniques were applied based on the smoothing models defined in Equation 1, apart from simple moving averages and state-space smoothing.

$$Yt = \mu t \; + \; \beta t\; t + S(t) + at \qquad (1)$$

Where,

μt = time-varying mean term
βt = time-varying slope term
$S(t)$ = one of the s time-varying seasonal terms
at = random shocks
For any models without a trend, the $\beta t = 0$, and nonseasonal models have $S(t) = 0$. The estimators for these time-varying terms are defined as follows:
Lt is a smoothed level that estimates μt
Tt is a smoothed trend that estimates βt
St - j for j = 0, 1,..., s - 1 are estimates of the s(t)
Figure 6 below shows the result of simple exponential smoothing, which includes a model summary, parameter estimates, and the forecast graph. The default settings for the two parameters remained unchanged: prediction intervals and constraints – two inputs required for exponential smoothing techniques.

Figure 6: Model Summary for Simple Exponential Smoothing

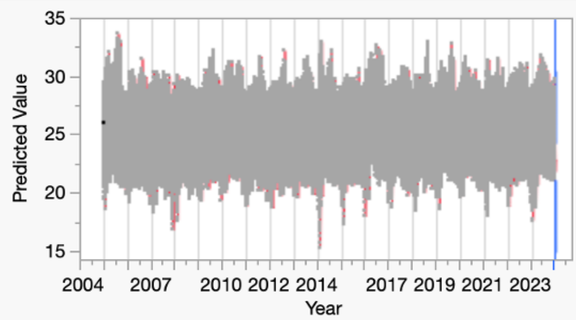
Model Summary

DF	166534	Stable	Yes
Sum of Squared Innovations	104233.247	Invertible	Yes
Sum of Squared Residuals	104233.247		
Variance Estimate	0.6258977		
Standard Deviation	0.79113697		
Akaike's 'A' Information Criterion	394573.829		
Schwarz's Bayesian Criterion	394583.852		
RSquare	0.88499209		
RSquare Adj	0.88499209		
MAPE	2.37719808		
MAE	0.59609986		
-2LogLikelihood	394571.829		

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	1.0000000	0.0023358	428.12	<.0001*

Forecast



4.5 Selection of the Best Smoothing Models

In order to appropriately select the best smoothing model, the same procedure as in section 4.4 was carried out for the other remaining exponential smoothing techniques, namely the Double Exponential Smoothing, Linear (Holt) Exponential Smoothing, Damped-Trend Linear Exponential Smoothing, Seasonal Exponential Smoothing and Winter's Model (Additive) for particularly compare on information criteria.

Figure 7: Six Smoothing Techniques Applied to the Temperature Data

Model Comparison

Report	Graph	Model	DF	Variance	AIC ^	SBC	RSquare	-2LogLH	Weights	.2 .4 .6 .8	MAPE	MAE
		Damped-Trend Linear Exponential Smoothing	2e+5	0.4082901	323431.01	323461.08	0.925	323425.01	1.000000		1.731161	0.428427
		Linear (Holt) Exponential Smoothing	2e+5	0.4752686	348724.63	348744.67	0.913	348720.63	0.000000		1.894426	0.471259
		Double (Brown) Exponential Smoothing	2e+5	0.4765732	349180.11	349190.13	0.912	349178.11	0.000000		1.902571	0.473147
		Seasonal Exponential Smoothing(12, Zero to One)	2e+5	0.4867071	352761.03	352781.07	0.911	352757.03	0.000000		2.244838	0.555076
		Winters Method (Additive)	2e+5	0.4866826	352768.86	352798.93	0.911	352762.86	0.000000		2.244685	0.555081
		Simple Exponential Smoothing(Zero to One)	2e+5	0.6258977	394573.83	394583.85	0.885	394571.83	0.000000		2.377198	0.596100

Figure 7 shows the model comparison list for all the estimated models. The Akaike Information Criterion (AIC) is a model selection metric that penalises model complexity and helps compare models.

Schwarz's Bayesian Criterion (SBC), on the other hand, is a statistical metric used to compare the goodness-of-fit of different models while penalising for model complexity.

Comparing the AIC or SBC values can help select the best smoothing model. The model that minimises the information criteria value is the most suitable, and the model that best fits the temperature data is the Damped-Trend Linear Exponential Smoothing.

4.6 Forecasting using the Most Suitable Smoothing Model

The Damped-Trend Linear Exponential Smoothing was selected as the most suitable model based on the information criteria. Figure 8 below shows the model summary of the lowest AIC and SBC values, which were 323431.01 and 323461.08, respectively. As per the forecast plot below, the forecasted data points indicated in red were close to the actual temperature values.

Figure 8: Model Summary for Damped-Trend Linear Exponential Smoothing

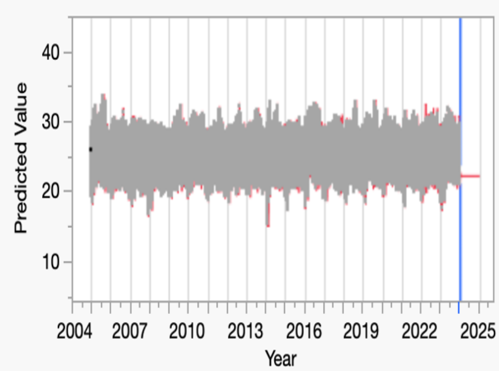
Model Summary

DF	166532	Stable	Yes
Sum of Squared Innovations	67993.3619	Invertible	Yes
Sum of Squared Residuals	67995.3909		
Variance Estimate	0.40829007		
Standard Deviation	0.6389758		
Akaike's 'A' Information Criterion	323431.008		
Schwarz's Bayesian Criterion	323461.077		
RSquare	0.92497588		
RSquare Adj	0.92497498		
MAPE	1.73116123		
MAE	0.42842701		
-2LogLikelihood	323425.008		

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Level Smoothing Weight	0.9285346	0.0042243	219.81	<.0001*
Trend Smoothing Weight	1.0000000	0.0138190	72.36	<.0001*
Damping Smoothing Weight	0.6459904	0.0030467	212.03	<.0001*

Forecast



4.7 Generating Forecast Values

A new data table containing the actual observations, predicted values and standard errors was generated after estimating the selected model. Since the dataset spans over 19 years of hourly data until 2023, the forecast horizon frequency was set to 8640 hours to predict the temperature in 2024. Table 1 below shows a couple of sets of generated values from the 8640 observations, starting at row 166537, representing the forecast of temperatures for every hour in 2024.

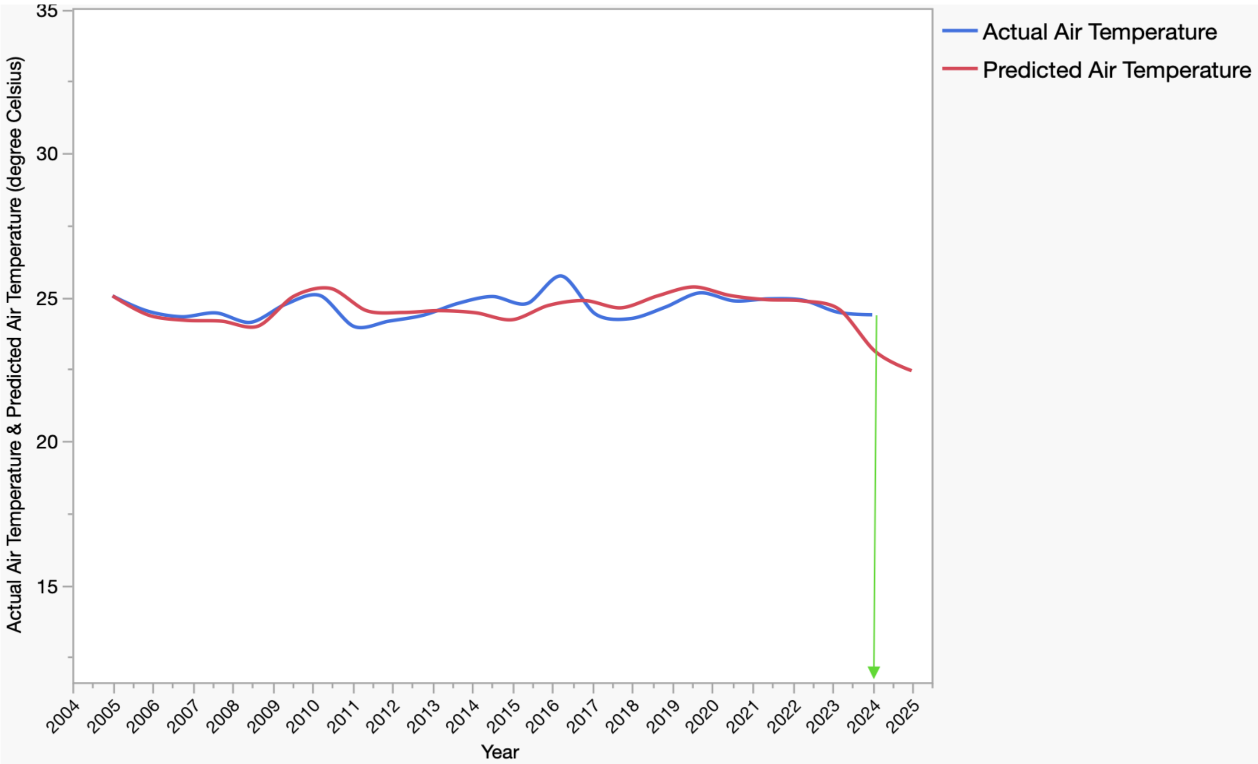
Table 1: Actual Observations, Predicted Values and Standard Errors

Actual vs Predicted (1-year of 8640 hours)

	Actual Air Temperature (degree Celsius)	Malaysia Time (formatted)	Predicted Air Temperature (degree Celsius)	Std Err Pred Air Temperature (degree Celsius)
166530	23.42	01/01/2024 1:30 AM	23.660743721	0.6389757975
166531	23.21	01/01/2024 2:30 AM	23.28140996	0.6389757975
166532	23.38	01/01/2024 3:30 AM	23.071627906	0.6389757975
166533	23.2	01/01/2024 4:30 AM	23.450247406	0.6389757975
166534	23.05	01/01/2024 5:30 AM	23.12739499	0.6389757975
166535	22.96	01/01/2024 6:30 AM	22.950652609	0.6389757975
166536	22.76	01/01/2024 7:30 AM	22.897188304	0.6389757975
166537	•	01/01/2024 8:30 AM	22.647371112	0.6389757975
166538	•	01/01/2024 9:30 AM	22.568280501	1.1670506096
166539	•	01/01/2024 10:30 AM	22.517188729	1.6913344142
166540	•	01/01/2024 11:30 AM	22.484183935	2.185495515
166541	•	01/01/2024 12:30 PM	22.462863157	2.6436451456
166542	•	01/01/2024 1:30 PM	22.449090139	3.0666494182
166543	•	01/01/2024 2:30 PM	22.440192902	3.4577010979
166544	•	01/01/2024 3:30 PM	22.434445373	3.8205769773
166545	•	01/01/2024 4:30 PM	22.430732524	4.1589331141
166546	•	01/01/2024 5:30 PM	22.42833406	4.4760442708
166547	•	01/01/2024 6:30 PM	22.426784675	4.7747382522
166548	•	01/01/2024 7:30 PM	22.425783787	5.0574130768
166549	•	01/01/2024 8:30 PM	22.425137223	5.3260853851
166550	•	01/01/2024 9:30 PM	22.424719549	5.5824465507
166551	•	01/01/2024 10:30 PM	22.424449736	5.8279162856
166552	•	01/01/2024 11:30 PM	22.424275439	6.0636898714
166553	•	02/01/2024 12:30 AM	22.424162845	6.2907780937
166554	•	02/01/2024 1:30 AM	22.42409011	6.5100402521
166555	•	02/01/2024 2:30 AM	22.424043124	6.7222111036
166556	•	02/01/2024 3:30 AM	22.424012772	6.927922711
166557	•	02/01/2024 4:30 AM	22.423993164	7.1277221122
166558	•	02/01/2024 5:30 AM	22.423980498	7.3220856083
166559	•	02/01/2024 6:30 AM	22.423972316	7.5114303366
166560	•	02/01/2024 7:30 AM	22.42396703	7.6961236739
166561	•	02/01/2024 8:30 AM	22.423963616	7.8764909045
166562	•	02/01/2024 9:30 AM	22.42396141	8.0528215031
166563	•	02/01/2024 10:30 AM	22.423959985	8.2253743074
166564	•	02/01/2024 11:30 AM	22.423959065	8.3943817989
166565	•	02/01/2024 12:30 PM	22.42395847	8.5600536641
166566	•	02/01/2024 1:30 PM	22.423958086	8.7225797742
166567	•	02/01/2024 2:30 PM	22.423957838	8.8821326906

Figure 9 below visualises the actual and predicted air temperature values. At 95% of the prediction interval, the actual and predicted curves in blue and red, respectively, show that the green arrow line shows the predicted temperature values for 2024. On remark, the blue curve does not end strictly at the end of the year 2023 because the PVGIS dataset observes the UTC zone, whereas in Malaysia, the corresponding time is leading by 8 hours apart (UTC+8).

Figure 9: Visualising Actual and Predicted Air Temperature Values



5. Discussion

Based on the findings in section 4.3, the ACF plot grew and decayed alternately, and the PACF plot showed stability for entire lags. The asymmetry characteristic of the data in section 4.2 makes it evident that the temperature series is nonstationary. Besides, a kurtosis value less than 3, that is, -0.55, indicates a platykurtic rather than a normal distribution due to fewer outliers [10].

As per the model comparison described in section 4.5, like the AIC, SBC helps prevent overfitting by discouraging unnecessary parameters. However, BIC applies a more substantial penalty for the number of parameters, making it particularly useful when selecting the best model among options with differing complexities.

Output data tabulated in Table 1 from section 4.7 set the forecast horizon frequency to 8640 hours to represent the forecast of temperatures for every hour in 2024. Particularly interesting to utilities and independent system operators (ISOs), forecasts for longer time horizons are helpful for unit commitment, scheduling, and improving balance area control performance [11] because there is a causal relationship between forecasting horizons, forecasting models and the related activities on the forecasting error [12].

Overall, while solar panels perform well under sunlight, high ambient temperatures can lead to performance losses, material degradation, and maintenance challenges. Adapting solar technologies and installation practices to mitigate heat impacts can optimise solar panel performance in a warming climate. Several strategies could be adopted to address the problem: panel positioning and ventilation, which improving airflow around panels and installing them at optimised angles can help reduce overheating; use of heat-resistant materials that include advanced solar materials, like perovskites or hybrid systems, are being developed to reduce temperature sensitivity; and selective cooling systems by implementing passive or active cooling that can help in high-temperature regions, though it comes at additional cost.

6. Conclusion

This study underscores the critical role of accurate forecasting of ambient air temperature in enhancing the predictive maintenance of solar photovoltaic (PV) panels, particularly in Kuala Kangsar, Perak, Malaysia. Through a thorough analysis of 19 years of satellite-based data, the application of advanced smoothing techniques, and the selection of the Damped-Trend Linear Exponential Smoothing model, this research demonstrates the importance of leveraging historical and observed data for cost-effective predictive maintenance in solar energy systems.

The findings highlight the challenges posed by high ambient temperatures on solar panel efficiency and the corresponding need for adaptive measures, such as optimised cooling systems and advanced materials. These strategies are essential for mitigating performance losses and ensuring the longevity of solar PV systems in tropical climates.

This work aligns with Malaysia's vision of achieving a 20% renewable energy mix by 2025. It provides a practical framework for integrating predictive maintenance into the country's expanding solar energy landscape. It offers valuable insights into addressing the challenges of climate change while advancing sustainable energy practices.

Since Malaysia has the highest average number of citations for research findings, which revealed a relatively high level of interest in artificial intelligence for renewable energy [13], future research could expand on this work by incorporating additional environmental variables or exploring the application of more robust machine learning models to enhance predictive accuracy and maintenance protocols further.

7. Appendix

The screenshot of the 2005-2023 PVGIS data set given below shows a partial view of all 166536 hourly satellite observations, the number of which is indicated in the lower right corner. It is worth noting that the dataset has zero values for the parameter "Int," which means no solar radiation values are being reconstructed.

	A	B	C	D	E	F	G	H	I	J	K
1	Latitude (decimal degrees):4.790	2005-2023 (19 years period), retrieved on 3 Nov 2024 by Mohd Ismi Aswaly Hanimi									
2	Longitude (decimal degrees):100.898										
3	Elevation (m):67										
4	Radiation database:PVGIS-ERA5										
5	PVGIS (c) European Union, 2001-2024										
6											
7	Slope: 40 deg.										
8	Azimuth: 0 deg.										
9	Nominal power of the PV system (c-Si) (kWp):1.0										
10	System losses (%):14.0										
11											
12	time	Malaysia Time (formatted)	P	G(i)	Gb(i)	Gd(i)	Gr(i)	H_sun	T2m	WS10m	Int
13	20050101:0030	01/01/2005 8:30 AM	228.34	299.67	222.37	73.15	4.15	14.11	20.91	0.9	0
14	20050101:0130	01/01/2005 9:30 AM	401.31	520.06	385.92	125.01	9.13	27.44	23.32	0.48	0
15	20050101:0230	01/01/2005 10:30 AM	537.43	716.48	580.54	122.19	13.75	40.1	24.83	0.21	0
16	20050101:0330	01/01/2005 11:30 AM	448.69	591.92	371.52	207.97	12.43	51.38	26.5	0.48	0
17	20050101:0430	01/01/2005 12:30 PM	585.38	797.93	566.1	215.09	16.74	59.66	27.06	0.34	0
18	20050101:0530	01/01/2005 1:30 PM	587.2	804.49	574.16	213.37	16.96	62.09	27.58	0.28	0
19	20050101:0630	01/01/2005 2:30 PM	506.84	683.5	412.27	256.65	14.58	57.34	27.84	0.34	0

Computed Data +

Ready Accessibility: Investigate Count: 166536

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9. Conflict of Interest

The author declares that no known competing financial interests or personal relationships could have appeared to influence the work reported in this paper.

10. Author's Biography

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