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Satellite-Based Dust Deposition Monitoring for Power Quality Enhancement in Solar PV Systems: A Case Study from Oman

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Abstract. Solar Photovoltaic (PV) systems offer a sustainable energy solution, particularly in regions with high solar irradiance, such as Oman. However, their performance is often compromised by dust accumulation, which reduces efficiency and increases the need for maintenance. This study explores a satellite-based monitoring approach to assess dust deposition and its impact on PV performance in Oman's arid environment. Using remote sensing data, the research maps dust patterns and correlates them with solar radiation to evaluate efficiency losses. The proposed method provides a cost-effective alternative to ground-based monitoring, enabling the timely detection of dust buildup. This allows operators to plan targeted cleaning interventions, improving power output while reducing maintenance frequency and costs. The approach supports proactive system management by optimizing cleaning schedules and minimizing unnecessary operations. Ultimately, the study enhances understanding of environmental effects on solar energy production and offers a scalable solution for dust-prone areas. It contributes to improving solar PV performance and aligns with Oman's Vision 2040 goals for sustainable energy by promoting efficient and reliable solar power systems.

Keywords. Dust Deposition, Satellite Monitoring, Solar Photovoltaics, Power Quality, Machine Learning.

Nomenclature

AOD	Aerosol Optical Depth
DUEXTTAU	Dust Extinction Optical Thickness
DUSMASS	Dust Aerosol Mass Concentration
MAE	Mean Absolute Error
MERRA-2	Modern-Era Retrospective analysis for Research and Applications, Version 2
MSE	Mean Squared Error
PV	Photo Voltaic
R^2	Coefficient of Determination
FI_j	Feature Importance
RMSE	Root Mean Squared Error

1. Introduction

Dust accumulation on photovoltaic (PV) panels poses a serious challenge to solar energy production, especially in arid regions like Oman, where frequent dust storms exacerbate the problem [1]. This accumulation impairs panel efficiency by blocking sunlight, resulting in reduced energy output and increased maintenance costs. As the world shifts towards renewable energy, maintaining optimal performance of PV systems becomes essential for meeting sustainability goals. In this context, satellite-based monitoring emerges as a scalable and efficient solution for detecting and predicting dust deposition over large areas. By enabling targeted cleaning schedules, this approach optimizes energy production while reducing operational expenses, thereby enhancing the overall viability of solar installations in dusty environments [2].

Incorporating technologies such as IoT sensors and computer vision systems with satellite data further automates the monitoring process. This ensures consistent maintenance of PV panels, maximizes power generation, and aligns with the global push toward clean energy. The issue of dust deposition affects several aspects of PV system operation. Performance degradation, for instance, is significant, with even a 1-micron dust layer causing substantial efficiency losses. Studies indicate that prolonged exposure can reduce power output by over 20%, primarily due to the obstruction of solar radiation. Short-circuit current and maximum power output are notably affected, leading to considerable revenue losses [3-4].

Installation parameters also influence dust accumulation. The tilt angle of panels plays a crucial role, with steeper angles generally minimizing dust deposition. Proper spacing between panels reduces airflow disruption and mutual interference, while wind direction relative to panel orientation further dictates deposition rates [5]. Environmental variability, including particle size distribution and seasonal wind patterns, adds complexity to managing dust accumulation. Larger particles tend to settle on closely spaced panels, while smaller particles persist on isolated ones, requiring dynamic monitoring strategies to respond to shifting environmental conditions. Additionally, limitations in manual cleaning and dependency on inconsistent rainfall further highlight the necessity for automated, data-driven solutions [6].

To address these challenges, a range of innovative mitigation techniques have been proposed. Dust shields with optimal angular configurations can significantly reduce deposition by altering airflow, especially when designed with air gaps to enhance draft effects. Nano-coatings and dual-layer coatings prevent dust adhesion by modifying surface characteristics, thereby improving power output. Active solutions such as electrostatic dust removal systems use electrical charges to repel particles, proving particularly effective in windy settings. Hydrophilic coatings that facilitate water-based cleaning are also used, though their effectiveness is limited in water-scarce regions like Oman depicted in Fig. 1. A promising trend is the integration of passive and active methods, combining anti-soiling surfaces with active dust removal systems for maximum efficiency.

Fig.1 Satellite-based geographic overview of oman and study sites [7].

Despite these advancements, several research gaps remain. Existing studies often overlook the interaction between dust accumulation and pre-existing panel defects, which can compound efficiency losses. Regional differences in dust composition and particle size are frequently ignored, leading to generalized solutions that may not be effective in specific environments. The reliance on rainfall for passive cleaning limits applicability in arid regions, while mitigation designs often fail to scale for elevated installations such as rooftops or light poles. Moreover, predictive models for cleaning schedules often overlook dynamic environmental factors, leading to ineffective maintenance timing.

The proposed approach, as reflected in the title "Satellite-Based Dust Deposition Monitoring for Power Quality Enhancement in Solar PV Systems: A Case Study from Oman," introduces a novel and scalable strategy for addressing dust-related performance issues. By leveraging satellite data for real-time, region-specific dust tracking, the study enhances power quality and contributes valuable data specific to Oman a region underrepresented in existing literature. The integration of computational tools and predictive models to optimize cleaning routines presents a practical, cost-effective solution to a pervasive problem in solar energy systems. Overall, this research represents a significant step forward in ensuring reliable and efficient solar power generation in harsh, dust-prone environments.

2. Methodology

Overview methodology is illustrated in Fig. 2. Methodology for the study utilizes MERRA-2 aerosol data from 2020 to 2024 to build a predictive model addressing dust deposition impacts on solar PV systems in Oman. The approach begins with the collection of high-resolution aerosol optical depth (AOD) and related atmospheric parameters from the MERRA-2 dataset. This satellite-derived data provides a global overview of dust concentration and deposition, which is further supported by ground truth data collected from solar PV installations in Oman. This local data includes performance metrics such as energy output, maintenance records, and documented efficiency losses attributed to dust accumulation. Following data collection, the preprocessing stage involves cleaning and filtering the MERRA-2 dataset to isolate dust-specific variables while eliminating unrelated aerosol types. To ensure accurate analysis, spatial and temporal alignment is carried out between satellite observations and the operational timelines of ground-based PV systems. MERRA-2 aerosol data was filtered to isolate dust-specific variables. Zero values are filtered, time features are transformed to capture seasonality, data format transformation for example netcdf to CSV for ease of training. Feature engineering is then performed to derive relevant environmental parameters such as wind speed, humidity, temperature, and particle size factors known to influence dust deposition dynamics.

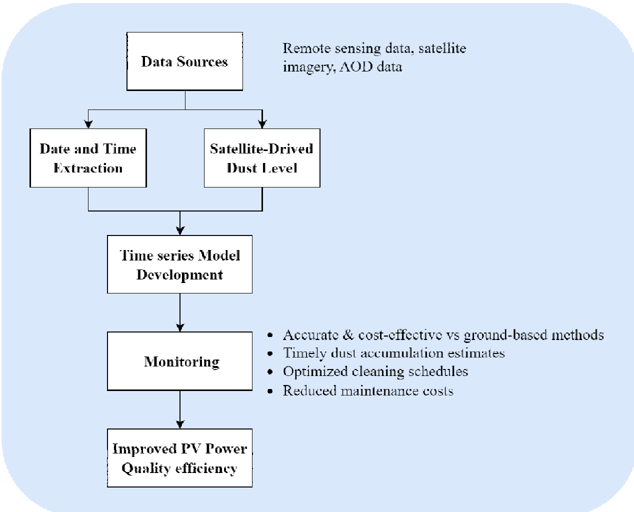

Fig. 2. Overview methodological framework for satellite-based dust deposition monitoring.

In the model development phase, the machine learning Neural Networks method is employed to train predictive models using the engineered features. These models incorporate both seasonal patterns and spatial variability, including proximity to dust sources such as deserts and urban areas. Neural networks were chosen for their ability to capture complex, non-linear relationships between environmental variables and dust deposition. The model achieved strong performance without explicit comparison to regression or decision trees. The models are further trained to correlate dust deposition predictions with PV performance indicators such as power output declines and frequency of cleaning interventions. the inputs included time features (hour, month, day of year, day of week, and their sine/cosine transforms) and satellite dust data (DUEXTTAU, DUSMASS). the Neural Network' used is a multi layer perceptron regressor with the following parameters hidden layer sizes=64, 32,32, 16 , max iteration of 1500, random state of 42 and early stopping set to true.

Validation of the model is achieved by comparing predicted values with actual recorded data from solar farms in Oman, using statistical metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared to assess model accuracy and reliability. Once validated, the predictive model is deployed as part of a decision-support system that integrates real-time PV system data with satellite-based forecasts. This system provides practical recommendations, such as optimized cleaning schedules or adjustments to installation parameters like tilt angle, to mitigate dust effects. Additionally, the MERRA-2 aerosol dataset is initially acquired in NetCDF format and later converted to CSV for ease of processing. Key columns of interest include variables directly tied to dust activity and atmospheric conditions that are relevant for the modeling process, which are the DUEXTTAU and DUSMASS.

3. Results

The statistical results for the MERRA-2 dust data show a range of values that describe the characteristics of both DUEXTTAU and DUSMASS datasets in Table 1. For DUEXTTAU, the mean value is 0.198, with a median of 0.171, indicating a relatively consistent distribution, though the mean is slightly higher than the median, suggesting a slight positive skew. The standard deviation of 0.138 reflects moderate variability in the data. The minimum value of 0.004 and the maximum value of 1.937 show a wide range in aerosol optical depth, with the skewness value of 1.937 suggesting a rightward skew, meaning there are more smaller values with a few extreme outliers. The kurtosis of 10.04 is very high, indicating that the distribution has heavy tails and is more peaked compared to a normal distribution, suggesting extreme values occur more frequently than expected.

Table 1. Statistical Summary of MERRA-2 Satellite-Derived Dust Deposition Data for Oman.

	DUEXTTAU	DUSMASS
Mean	0.198023	1.25E-07
Median	0.170791	1.02E-07
Std	0.138453	9.18E-08
Min	0.004146	5.56E-10
Max	1.937027	1.51E-06
Skew	1.936893	0
Kurtosis	10.04193	17.78693

For DUSMASS, the mean is 1.25E-07, and the median is slightly lower at 1.02E-07, with a very small standard deviation of 9.18E-08, indicating minimal variability in the dust mass measurements. The minimum value is 5.56E-10, and the maximum is 1.51E-06, reflecting a very narrow range. The skewness is 0, indicating a symmetric distribution, and the kurtosis value of 17.79 suggests a significantly peaked distribution with heavy tails, implying the occurrence of extreme values in the dust mass data as well. These statistical measures offer insights into the variability and distribution of aerosol and dust mass data, which are crucial for understanding dust deposition trends in the region.

Fig. 3 displays the averaged variation of the dust parameters over the year, month and day and hour. Additionally, Fig. 4 shows the variation of over dust and the distribution of the data utilized for this study over the years. Fig.4 shows the correlation between variables. Fig. 5 illustrates the correlation between input features. This helps identify which features are related, avoid redundancy, and select the most relevant variables for the model.

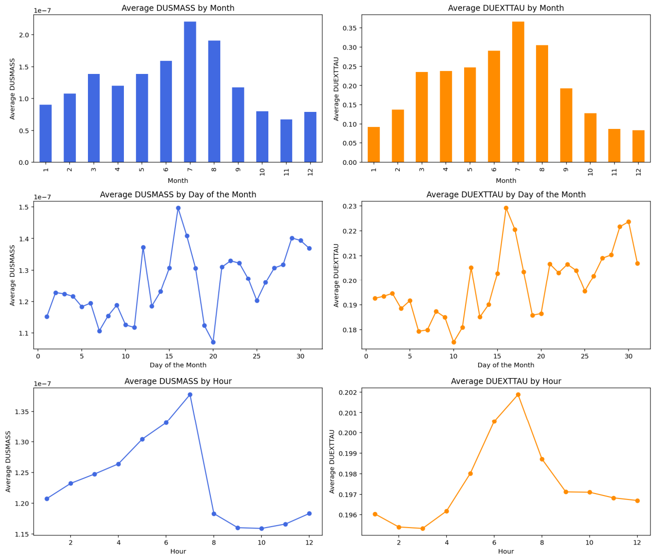

Fig. 3 Temporal variation of satellite-derived dust deposition: monthly and daily averages.

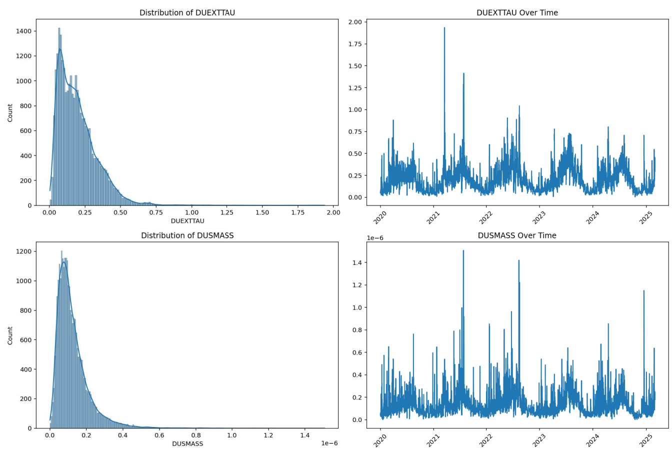

Fig. 4 Annual trends and variable distributions of dust deposition in oman.

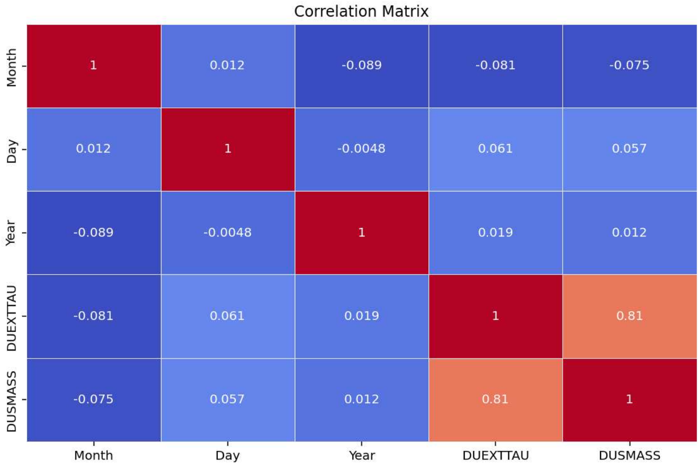

Fig.5 Correlation matrix of dust deposition, meteorological factors, and power quality metrics.

During training the results show a significant range in the model's error, with a maximum relative error of 855.44% and an average relative error of 16.32%. The high maximum relative error suggests that there may have been certain instances or outliers where the model's prediction was far off from the actual values. This could be due to unusual environmental conditions or data anomalies not captured by the model. On the other hand, the average relative error of 16.32% indicates that, on average, the model's predictions were reasonably accurate, with a modest deviation from actual values. The R-squared value of 0.8864 suggests that the model explains approximately 88.64% of the variance in the dust deposition data from MERRA-2 DUSMASS and DUEXTTAU as shown in Fig. 6. This is a strong indicator of the model's predictive ability, as it shows a high level of correlation between the predicted and observed data.

The results of the model training and prediction for DUEXTTAU and DUSMASS provide important insights into the accuracy and efficiency of the model in predicting dust deposition in relation to solar PV systems in Oman, as summarized in Table 2. For DUEXTTAU, the training time was approximately 7.27 seconds, with a relatively quick prediction time of 0.15 seconds, showing the model's efficiency. The Mean Squared Error (MSE) of 0.0023 and Root Mean Squared Error (RMSE) of 0.047 indicate a reasonable error in predictions. However, the R-squared value of 0.886 shows a strong fit between the model's predictions and actual values, suggesting the model explains 88.6% of the variance in dust optical depth. The model's feature importance analysis revealed that month, day of year, and day of week have the most significant influence on the predictions, with month_cos having the highest feature importance.

For DUSMASS, the training time was 7.43 seconds, with a slightly faster prediction time of 0.12 seconds. The MSE of 2.33E-15 and RMSE of 4.82E-08 are extremely low, indicating minimal error in the dust mass predictions. The R-squared value of 0.721 suggests a moderate fit, with the model explaining about 72% of the variance in dust mass data. Feature importance analysis for DUSMASS indicated that day of year_sin and day of year_cos were the most influential variables, highlighting the importance of seasonal and temporal factors in predicting dust mass. These results indicate that the models are effective in predicting dust-related parameters for PV systems in Oman, with DUEXTTAU showing stronger predictive power compared to DUSMASS. The feature importance analysis further emphasizes the role of temporal factors in dust accumulation, which is crucial for optimizing solar PV performance and scheduling cleaning interventions.

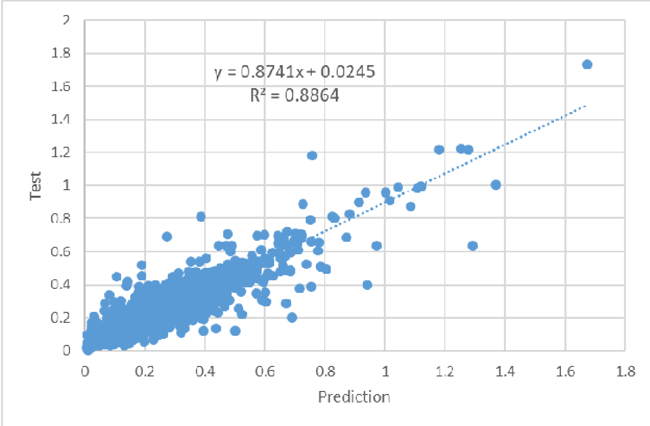

Fig. 6 Model goodness-of-Fit: R-squared values for dust deposition impact predictions.

Table 2. Performance metrics and results of predictive models for dust deposition effects on solar PV systems.

	DUEXTTAU	DUSMASS
Training Time	7.27	7.43
Prediction Time	0.15	0.12
MSE	0.00	0.00
RMSE	0.05	0.00
MAE	0.03	0.00
R^2	0.89	0.72
cv RMSE mean	0.06	0.00
cv RMSE std	0.01	0.00
FI_j hour	0.02	0.03
FI_j month	0.00	0.00
FI_j day of year	0.11	0.17
FI_j day of week	0.08	0.08
FI_j hour sin	0.02	0.04
FI_j hour cos	0.02	0.03
FI_j month sin	0.00	0.00
FI_j month cos	0.36	0.02
FI_j day of year sin	0.12	0.19
FI_j day of year cos	0.16	0.30
FI_j day of week sin	0.07	0.08
FI_j day of week cos	0.05	0.07

The feature month 35.6% importance captures seasonal dust patterns, while day_of_year 11.7% reflects intra-annual deposition cycles. These features encode temporal periodicity, which is critical for dust prediction in arid climates. Cross-validation was used, with a mean CV-RMSE of 0.062 ± 0.014; however, hyperparameter tuning was not conducted.

The ground data from Omani PV installations, such as energy output and maintenance records, do not sufficiently validate the satellite-derived dust estimates because these datasets lack the necessary spatial and temporal resolution, consistency, and direct measurement of dust parameters. Ground-based PV performance metrics can be influenced by multiple factors beyond dust accumulation, such as temperature fluctuations, shading, and equipment degradation, making them unreliable as standalone validation for satellite dust data. Therefore, without direct ground measurements of dust concentration or deposition, the satellite-derived dust estimates remain unconfirmed. Thus, No, the findings have not been conclusively validated with actual PV performance data from Oman.

4. Conclusion

This study presents a comprehensive analysis of dust accumulation on Solar Photovoltaic systems in Oman, leveraging satellite-based MERRA-2 data to predict dust deposition and dust mass. The findings demonstrate the ability of machine learning models to accurately predict dust accumulation using aerosol data, providing valuable insights into the factors that affect solar PV performance in arid regions. The DUEXTTAU model demonstrated strong predictive performance, with an R-squared value of 0.886, indicating that it can explain 88.6% of the variation in dust deposition patterns. In contrast, the DUSMASS model, although still accurate, exhibited a more moderate performance with an R-squared value of 0.721, indicating that dust mass prediction is slightly more complex and may require further refinement. The feature importance analysis revealed that temporal factors such as the month, day of year, and day of week played crucial roles in predicting both dust deposition and dust mass. These factors are indicative of seasonal variations and diurnal patterns in dust accumulation, which are critical for improving cleaning schedules and maintaining the efficiency of PV systems. Additionally, the models demonstrated efficient training and prediction times, suggesting that they can be integrated into real-time monitoring systems for operational optimization.

Based on the findings of this research, the following recommendations are made:

- Optimize Cleaning Schedules: Regular dust cleaning is crucial for maintaining optimal energy output from solar PV systems. The integration of satellite-based monitoring systems can assist operators in predicting when dust accumulation is significant enough to warrant cleaning, thereby optimizing schedules and reducing unnecessary interventions.
- Tilt angle optimization is acknowledged as a key dust mitigation factor. The model can recommend tilt adjustments based on predicted dust loads, though implementation details require further study.
- Further Model Refinement: While the models provide strong predictive accuracy, further improvement is recommended, particularly for the DUSMASS model. Incorporating additional variables, such as wind patterns, local dust storms, and geographical features, could enhance its performance and allow for more precise predictions of dust mass.
- Real-Time Monitoring Integration: The developed models could be incorporated into a real-time monitoring system for solar PV farms in Oman. This would provide operators with timely estimates of dust accumulation levels, enabling them to make proactive maintenance decisions and reduce the risk of efficiency losses due to dust accumulation.
- Scaling the Approach: The methodology used in this study, based on satellite data and machine learning, could be scaled to other regions with similar environmental conditions, such as desert climates in the Middle East and North Africa region, where dust accumulation poses significant challenges to solar energy production.
- Policy and Industry Alignment: This research aligns with Oman's Vision 2040 for sustainable energy development. It is recommended that policymakers and solar PV operators in Oman adopt the use of satellite-based dust monitoring and machine learning models to improve the efficiency and longevity of solar PV systems, contributing to national energy goals.

- By addressing these recommendations, solar PV systems in Oman and similar regions can achieve enhanced performance, lower operational costs, and contribute to the overall goal of sustainable energy development.

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