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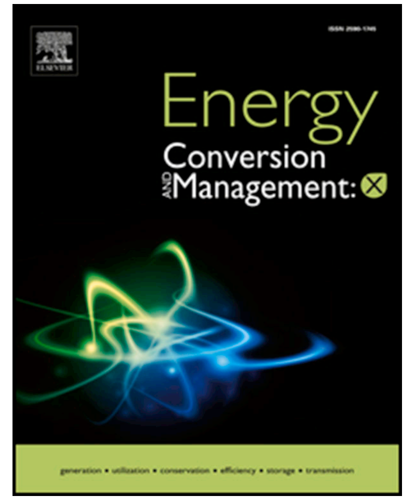

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Dust Impact on Photovoltaic Modules: Global Data, Predictive Models, Emphasis on Chemical Composition

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Abstract:

This study explores the influence of dust on optical properties such as transmittance, absorptance, and emissivity of photovoltaic (PV) modules using over 300 experimental readings from various dust types. These readings were collected during regional storms and ground sources, data encompass different weight levels. Incorporating 690 global datasets and leveraging Artificial Neural Networks (ANN) and Multiple Linear Regression (MLR) in MATLAB, the study integrates key dust chemical components (Si, Fe, Ca, Al) and weight to predict the PV optical properties. This approach enhances models' predictive accuracy across diverse environmental settings, which in turn enables more accurate forecasting of PV power output and thermal behavior under varying dust conditions, as these optical properties govern the module equations. Additionally, comparative analysis with existing literature shows superior accuracy, achieving Mean Squared Errors (MSEs) of 1.8 and 8.44, surpassing previous benchmarks. Results underscore the global efficacy of our methodologies in revealing dust's impact on PV module thermal behaviour and efficiency.

1. Introduction:

The development of PV technology, which involves converting sunlight into electricity, marks a significant shift in energy generation [1]. Although PV modules are typically tested under current environmental conditions at the manufacturing stages, their deployment in the real world presents unique challenges, particularly under the dust accumulation situation. The dust accumulation on the PV surface impacts the electrical, optical, and thermal characteristics of PV modules by obstructing the sunlight, which leads to a decrease in electrical output [2]. This impact varies based on different factors such as dust composition, quantity, PV module orientation, and environmental conditions.

It is crucial to understand how dust influences the optical properties of PV modules in terms of PV glass transmittance, absorbance and reflected light as well as emitting heat from its surface. The dust will absorb more light and, in turn, reduce efficiency and increase module temperature [3]. Additionally, the light transmittance and reflection due to dust accumulation play pivotal roles in PV performance which can lead to changing the output power. Moreover, dust emissivity, often overlooked, can influence thermal behavior in PV systems. The chemical composition and quantity of accumulated dust on PV modules could play an important factor in influencing the optical properties of PV.

Understanding the interaction between dust contamination and the PV modules is considered very essential for enhancing the efficiency of PV systems to optimize the use of solar energy. This understanding becomes increasingly vital as the global community shifts towards renewable energy sources. Therefore, Numerous studies have investigated the impact of dust deposition on PV system optical properties. For example, Piedra et al. [4] demonstrated that there is a linear correlation between the light transmission through PV modules with increasing dust accumulation. Another study revealed that adding just one gram of dust per square meter could result in a 4.1% reduction in light transmittance [5].

Most research in this area has primarily focused on dust's effect on transmittance, which directly impacts the electrical performance of PV modules. Gholami [6] conducted experiments on the reduction in transmittance coefficient due to dust accumulation on PV surfaces and formulated a specific equation that correlates between dust surface density and transmittance.

Diop et al. [7] investigated optical losses in PV modules due to Saharan dust deposition in Senegal. They have provided detailed insights into how dust thickness and deposits change the transmittance and reflectance percentages. This insight is crucial as it highlights the need for regular cleaning of solar panels in similar dusty environments to maintain energy efficiency. Elminir et al. [8] established an equation relating dust deposition density to the reduction in transmittance of PV modules in Egypt, highlighting regional variances in dust impacts.

Studies in Saudi Arabia by Said and Walwil [9] focused on dust fouling effects on PV module performance, detailing the chemical composition of dust and its correlation with reduced transmittance. The predominance of Calcium, Silicon, and Iron in the dust composition was emphasized. In China, Liu et al. [10] explored the power reduction mechanism of dust-deposited photovoltaic modules, revealing a significant decrease in transmittance with increasing dust density, indicating a threshold beyond which the impact on PV module performance stabilizes. This research quantified the power reduction mechanism in dust-deposited photovoltaic modules, correlating dust thickness and spectral composition with the percentage decrease in energy generation.

Wu et al. [11] introduced a mathematical model assessing the influence of dust particle shape on relative transmittance in photovoltaic systems. Validated through simulations and experiments, the model highlights that cubic dust particles induce a more significant reduction in transmittance compared to spherical particles. However, aspects like absorptance and emissivity, crucial for thermal behaviour, have received comparatively less attention in the literature. A wide range of experimental studies have investigated the impact of dust on light transmittance, and many of them have developed different mathematical modules to predict this impact on transmittance, as shown in Table 1.

Table 1. Comparative Models to Estimate Dust Impact on PV Panel Transmittance.

Study	Model Equation
[6]	$\Delta\tau\ (\%) = -0.001335\rho^6 + 0.04398\rho^5\ 0.5427\rho^4 + 3.05\rho^3 - 7.703\rho^2 + 11.19\rho - 2.25$

[8]	$\Delta\tau\,(\%) = 0.0381\rho^4 + 0.8626\rho^3 - 6.4143\rho^2 - 15.051\rho + 16.769$
[9]	$\Delta\tau(\%) = 0.004\rho + 0.0269$
[10]	$T = (1 - F^2)\, e^{(-am/p)}$
[12]	$T(\%) = 66.66exp(-0.038 \times \rho)$
[13]	$\tau = \tau c[1 - 0.3437erf(0.17\rho^{0.8473})]$
[14]	$\Delta\tau = 23.27\, ln(\rho) - 23.5$
[5]	$\Delta\tau = 4.1\rho$
[15]	$\Delta\tau = -43.156\, exp\,(-0.125\rho) + 43.152$
	$\Delta\tau = -0.208\rho^2 + 5.074\rho + 0.12$
Conceição et al. cited in [16]	$\Delta\tau = 1 - 0.02545\rho$
[17]	$\Delta\tau = 4.39\,\rho + 0.507$

Where ρ represents the dust density and is measured in grams per square meter.

to further optimize the performance of PV modules in dusty environments, it is essential to consider a broader range of environmental parameters that affect their characteristics. In particular, dust accumulation requires detailed modeling to fully understand its impact. For this reason, machine learning models like Artificial Neural Networks (ANN) and Multiple Linear Regression (MLR) offer powerful tools for predicting and optimizing PV module performance under varying conditions [18]. Comparing these methods' effectiveness could significantly enhance the accuracy of PV performance predictions in real-world scenarios [19].

Although previous studies on the impact of dust on PV systems have made significant contributions, there are several key limitations that this research aims to address:

- Region-specific restrictions: all the previous studies focus more on certain dust types that are partially dependent on some regions. Therefore, the results may not generalize in different environmental conditions.
- Consider only the dust weight: The current models have been considered mainly the one character of dust, which is the dust weight, and have neglected very important elements, which is the chemical composition of dust.
- Limited the optical properties: In fact, while the literature mainly investigated and developed different modules on the effect of dust on transmittance, all other important optical properties like absorbance and emissivity have been relatively neglected. Understanding these properties is essential for recognizing the thermal behaviour and hence the efficiency of the PV module.
- Prevailing research predominantly explores the impact of dust on transmittance, overlooking equally crucial optical properties like absorbance and emissivity. Understanding these properties is essential for comprehending the thermal behaviour and efficiency of PV modules.
- Simple analytical techniques: simple techniques such as curve fitting procedures may not well describe the complex relations between dust characteristics and the performance of optical PV systems.
- Limited mathematical models: The most commonly used models are limited within specific dust weight ranges which may result in inaccuracies whenever used in wider dust accumulation scenarios.

These gaps demonstrated the necessity for a more detailed and complicated analytical approach to accurately predict the impact of dust on PV optical properties. Therefore, the main aims and objectives of this study are:

- Broader applicability: This study would involve a wide range of dust types from different global locations; therefore, it is enhancing generalizability within multiple environmental dusty conditions.
- Considering chemical composition for optimal understanding: It extends the analysis to include the dust weight as well as the dust chemical composition (e.g., Si, Fe, Ca, and Al) into predictive models to thoroughly evaluate its impact on optical properties.
- In-depth optical evaluation: the study detailed analysis of not only the transmittance, but also absorbance, and emissivity for understanding the impact of dust on the optical characteristics of the PV systems.
- Advanced modeling techniques: it has been employing more complected modeling techniques such as ANN and MLR in MATLAB to develop new models that would be capable of predicting any changes in the optical properties caused by dust accumulation.
- Incorporating diverse datasets: the study utilizes a diverse multinational dataset which is covering a wide range of dust weights and chemical compositions to ensure the accuracy and applicability of mathematical models in various dust accumulation scenarios.

The study contributes to a significant improvement in predicting the PV optical properties when addressing these identified gaps, where it offers a more holistic perspective on how dust accumulation affects the optical properties of PV modules and provides practical tools for predicting the optical impact of dust accumulation on PV surfaces.

2. Methodology

This section demonstrates the methodology, highlighting in-depth dataset collection procedures. It illustrates how the experimental data from this study have been combined with previous experimental data from global research findings to create a detailed and extensive dataset. Additionally, the study demonstrates the utilization of complex analytical methods, specifically Artificial Neural Networks and Multiple Linear Regression in MATLAB. These methods provide a strong predictive base for evaluating the various optical characteristics of PV modules, considering varying dust deposition weights and types.

2.1 Collation of Dust Study Data and Sources

This research has followed the established testing protocols used by Almukhtar et al. [20] to guarantee uniformity in the data collection methods. Dust samples were carefully collected using a similar detailed method in previous studies. This involved using a large plastic sheet to gather samples during three regional dust storms. Additionally, ground-based samples from the same regions have been collected. In this approach, uniformity of data was ensured, maintaining direct comparison with the results of previous studies.

The experimental procedure included many analyses: X-ray fluorescence (XRF) and the INGLAS TIR100-2 device were used to determine the dust's chemical composition and emissivity. At the same time, UV-Vis spectroscopy assessed transmittance and absorptance on PV module surfaces. The optical properties were examined across different dust weights and compositions to represent real accumulation scenarios, aligning with the methodology outlined in Almukhtar et al. [20] These efforts aimed to extensively evaluate how dust affects the optical properties of PV modules and ensure consistency with prior methodologies for a thorough analysis.

Additionally, there was significant integration of data from external studies. This involved a thorough review and analysis of existing literature, adhering to specific inclusion criteria to guarantee its relevance and comparability with our experimental data. Emphasis was placed on studies investigating the chemical composition of dust, as this aspect was crucial for understanding its impact on PV modules. Prioritization was given to research providing both chemical composition and dust weight data, facilitating an in-depth analysis correlating the dust's chemical makeup with its weight. The selected studies exhibited a wide range of dust weights, from 0.7 to 42 g/m², ensuring a broad spectrum for analysis. Geographical diversity was maintained in study selection, analysing experimental work from various countries to gain a global perspective on dust characteristics under different climatic conditions. Over 700 samples from these selected studies were analysed, forming a reliable dataset that expanded the scope and depth of our extensive analysis. Table 2 presents the data sources and arrangement utilized for this study from previous research.

Table 2. demonstrates the number of data that will be collected from the investigation experimental for this study.

Study	Country	Data reading Size	Chemical Composition
[6]	Iran	560	Si:50.26%, Fe:7.23%, Ca:27.31%, Al:7.92% and other components.
[7]	Senegal	5	Si:50.1%, Fe:16.8%, Ca:10.6%, Al 0.5% and other components.
[8]	Egypt	48	Si: 49.25%, Ca: 35.55%, Al: 4.43%, Fe: 4.24% and other components.
[9]	Saudi Arabia	28	Ca: 47.0%, Si: 20.5%, Fe: 16.0%, Al: 4.0% and other components.
[10]	China	45	Ca: 10.4%, Si: 50%, Fe: 3.8%, Al: 26% and other components.
[20]	Iraq	4	Si (%) 30.31, 31.35 Al (%) 9.27, 9.80 Fe (%) 9.49, 9.70 Ca (%)34.78, 34.80 and other components.

Table 3 presents experimental readings for various optical properties categorized by different types of dust. Initially, samples from three distinct storms (types A, B, and C) underwent analysis for their transmittance and absorbance properties, involving six readings per type. Following this, a comparative analysis was conducted between dust collected during storms and ground-collected dust (A and G), comprising 33 readings each for transmittance, absorbance, and emissivity measurements. Lastly, a comparative study among the three storm types (A, B, and C) focused on emissivity properties, with 6 readings for each type.

Table 3. Experimental Readings of Optical Properties for Different Dust Categories - Storms A, B, C, and Ground-Collected Dust

Experimental Investigation	Dust Types	Number of Readings	Properties Analyzed
Dust from three distinct storms	A, B, C	18 (6 per type) *	Transmittance
Dust from three distinct storms	A, B, C	18 (6 per type) *	Absorbance
Comparative a nalysis: dust storm vs. ground collected	Aand G (Dust storm and ground)	66 (33 each)	Transmittance
Comparative analysis: dust storm vs. ground collected	A and G (Dust storm and ground)	66 (33 each)	Absorbance
Comparative analysis: dust storm vs. ground collected	A&G (Dust Storm and Ground)	66 (33 each) *	Emissivity
Comparative study: Three dust storm types	A, B, C	54 (18 per type)	Emissivity
Total		**306**	

*Specifically, for dust types A and B, only two sets of readings for transmittance, absorbance, and emissivity data were previously published in our work from [20].

2.2 Analytical Methods

The study leveraged MATLAB's computational capabilities for two complicated analytical methods: ANN and MLR. These methods played a crucial role in predicting the optical properties of dust-coated PV modules, accounting for both chemical composition and dust weight.

2.2.1 Artificial Neural Networks

ANNs served as the primary tool for predicting the optical properties of PV modules. These networks, inspired by the human brain, excel at identifying complex patterns within data. Leveraging MATLAB's neural network toolbox, the ANN process involved key steps:

- Data Input: The network was fed an extensive dataset comprising chemical composition and dust weights from various samples.
- Network Structure: This included multiple layers featuring an input layer, two hidden layers for computation (20 and 15 neurons, respectively), and an output layer for predictions, as illustrated in Figure 1. Due to a process of trial and error, these

choices were made to capture complex features and patterns from the input data while balancing model complexity and the risk of overfitting.

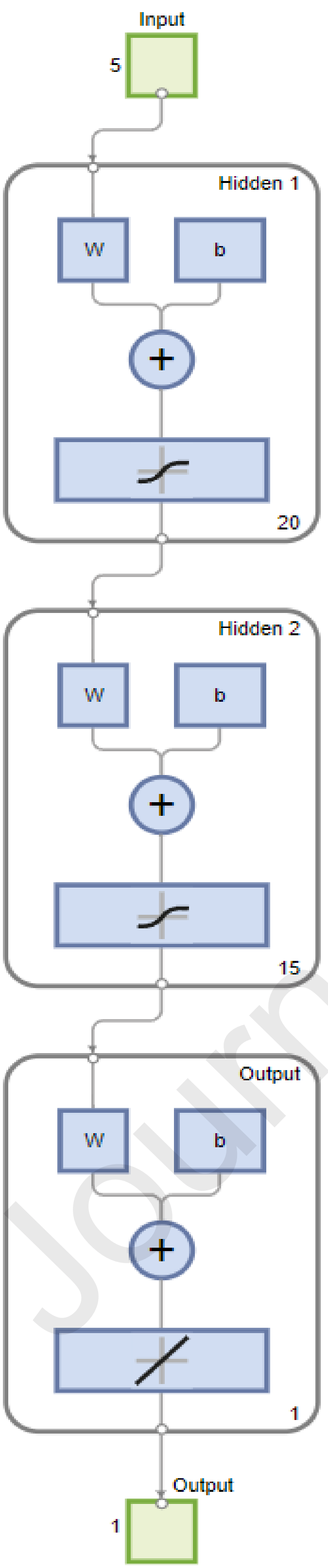

Figure 1. Structure of ANN with Two Hidden Layers (20 and 15 Neurons) Developed in MATLAB

Furthermore, the training and testing phases involved splitting the data into training (70%), validation (15%), and testing (15%) sets. This split ensures a well-rounded evaluation, helps prevent overfitting, and is commonly used by scholars. The network underwent training using Bayesian Regularization backpropagation (*trainbr* function) for 500 epochs, with a *max_fail* criterion of 10. The ANN training process stops when either the maximum of 500 epochs is reached or if validation performance does not improve for 10 consecutive checks, which helps prevent overfitting. The ANN proved particularly effective in handling non-linear relationships within the complex dataset.

2.2.2 Multiple Linear Regression

MLR served as a complementary analytical method to ANN. This statistical technique models the relationship between a dependent variable and multiple independent variables. The MLR process in MATLAB involved:

- Variable Identification: This study considers the independent variables, which are the chemical composition and dust weights, and their relation to the dependent variables, which are the optical properties.
- Model Development: A linear equation has been constructed to identify the optimal combination of independent variables for predicting the dependent variable using the film function.
- Coefficient Analysis: the study determines coefficients for each variable to understand their impact on the optical properties. This provides an understanding of the importance of chemical composition and dust weight in predicting the optical characteristics.

The integration of ANN and MLR in this study provides a detailed approach to the impact of dust on the optical properties of PV modules. The ANN is adept at handling complex data patterns, and MLR offers insights into linear relationships. Utilizing both ANN and MLR to predict the dust impact contributes to enhancing the precision of predictions. The flowcharts in Figure 2 detail each step of these analytical methods and offer a visual guide for enhanced clarity and comprehension.

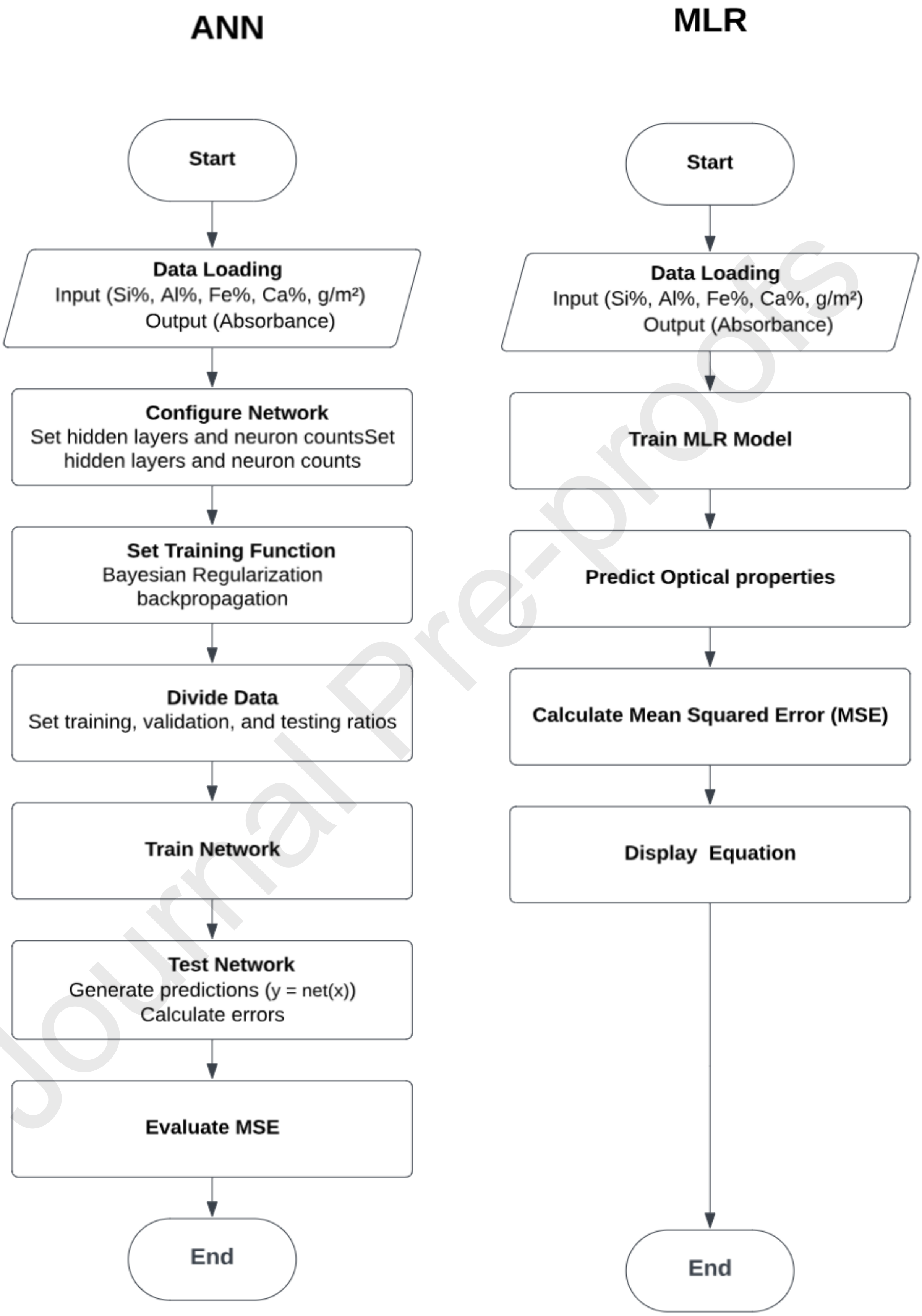

Figure 2. Demonstrates the analytical methods step-by-step flowcharts for clarity and comprehension.

2.3 Mean Squared Error (MSE) Calculation

The Mean Squared Error (MSE) is a commonly used metric to evaluate the performance of predictive models, particularly in regression analysis [21]. MSE quantifies the average squared difference between the observed actual outcomes and the outcomes predicted by the model. It is defined by the following equation:

$$MSE = \left(\frac{1}{n}\right)\Sigma\left(experimantal\ valu - \text{predicted values obtained from the model}\right)^2$$

Where: n is the number of observations. The MSE is a non-negative value, where a lower MSE indicates a better fit of the model to the data, implying higher accuracy in the model's predictions. A value of zero would indicate a perfect fit, where the predicted values are exactly equal to the observed values.

3. Results and Discussion

This section presents an analysis of the research findings. It combines the details of the impact of dust on PV modules. This includes considering various factors, which are the chemical composition and weight of dust and its diverse influence on optical properties. Additionally, the section discusses the practical implementation that comes with these findings.

3.1 Chemical Composition of Dust Samples

All examined dust samples have been analyzed to determine their chemical composition. Table 4 details the chemical composition of four dust types A, B, C and G. Types A and B have been previously published in a separate paper [20].

Table 4. The proportion of various elements and materials present in each dust type.

Element	Dust storm A	Dust storm B	Dust storm C	Ground-Dust G
Si (%)	30.31	31.35	29.16	46.03
Al (%)	9.27	9.8	8.50	1.20
Fe (%)	9.49	9.7	8.40	15.20
Ca (%)	34.78	34.8	36.11	20.29
Mg (%)	5.01	5.01	4.80	2.00

Na (%)	5.47	3.5	0.684	2.49
K (%)	2.69	2.82	2.819	0.75
S (%)	5.47	3.51	7.347	0.70
Ti (%)	0.969	1.137	0.985	0.34

These results contribute to understanding the material components and how they possibly influence PV optical characteristics. Table 4 provides a detailed quantitative analysis of the elemental composition in dust samples from different dust types. Key components, including Silicon (Si), Aluminium (Al), Iron (Fe), Calcium (Ca), Magnesium (Mg), Sulphur (S), and Potassium (K), are highlighted. The data reveals significant differences, especially between the dust storms and ground-collected dust in these elements, with notable levels of Si, Al, Fe, and Ca, which affect the dust's physical and optical properties. For example, high Silicon concentrations, especially in soil dust, indicate its possible influence on altering light absorption and scattering patterns. Understanding these differences in chemical composition is crucial for demonstrating how dust affects PV module performance, possibly affecting factors like transmittance, absorbance, emissivity, and general efficiency.

It's important to note that although the research focuses on elements found in high concentrations, the cumulative effect of all components, including those in small amounts, can still contribute to the overall behavior of dust and its impact on PV modules. However, to simplify the study in predicting optical properties using MATLAB, prioritizing the analysis of the critical elements offers a focused and relevant understanding of the impact of dust accumulation.

3.2 Influence of Dust Characteristics on PV Optical Performance

This section demonstrates the results from experimental tests on how different dust types and weights influence the optical performance of PV systems. The key findings related to the effects of dust on transmittance, absorbance, and emissivity are crucial factors impacting both PV efficiency and thermal behavior.

3.2.1 Experimental Results for the Optical Properties of PV Systems

This subsection provides a thorough analysis of the optical behaviors exhibited by PV systems under the influence of different types and weights of dust. The study distinctly emphasizes the impact of dust accumulation on absorption, transmittance, and emissivity within the dusty glass layer of PV modules. Visual representations of these relationships are illustrated in scatter charts (Figures 3-5).

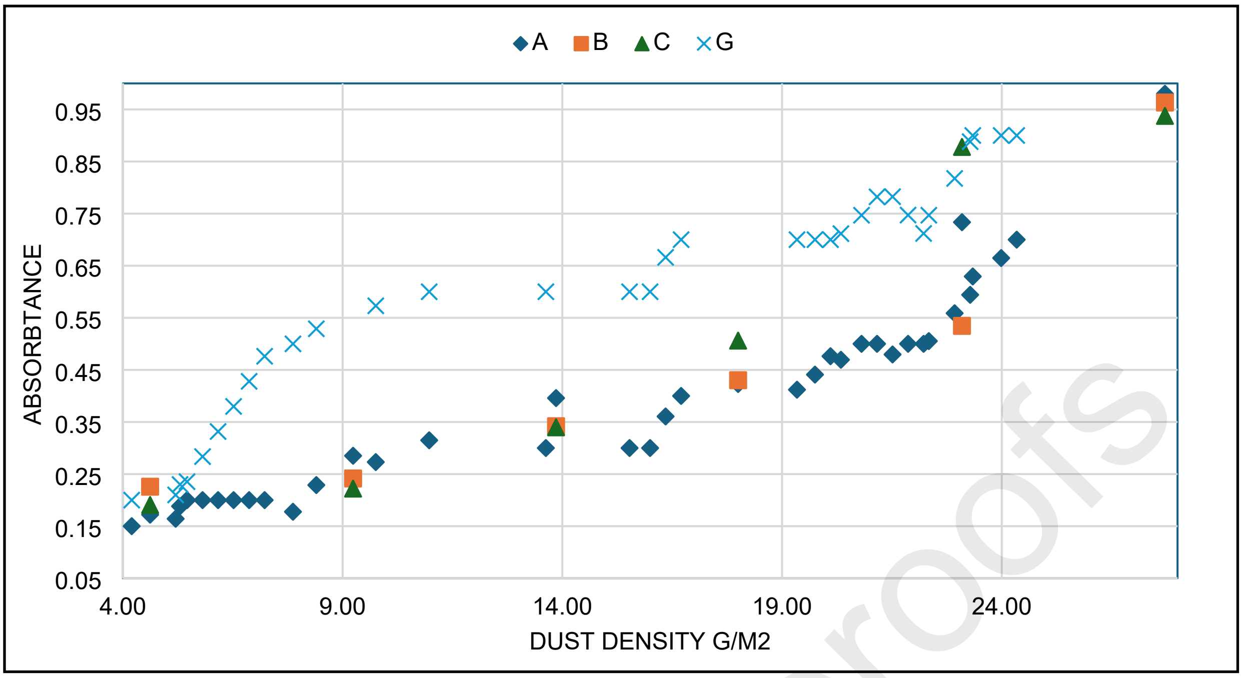

Figure 3. *Absorptance* Comparison Between Storm-Collected (*A, B, C*) and Ground-Collected (G) Dust. *For dust type A and B at the weight (9.2 and 18) g/m² from Ref. [20].

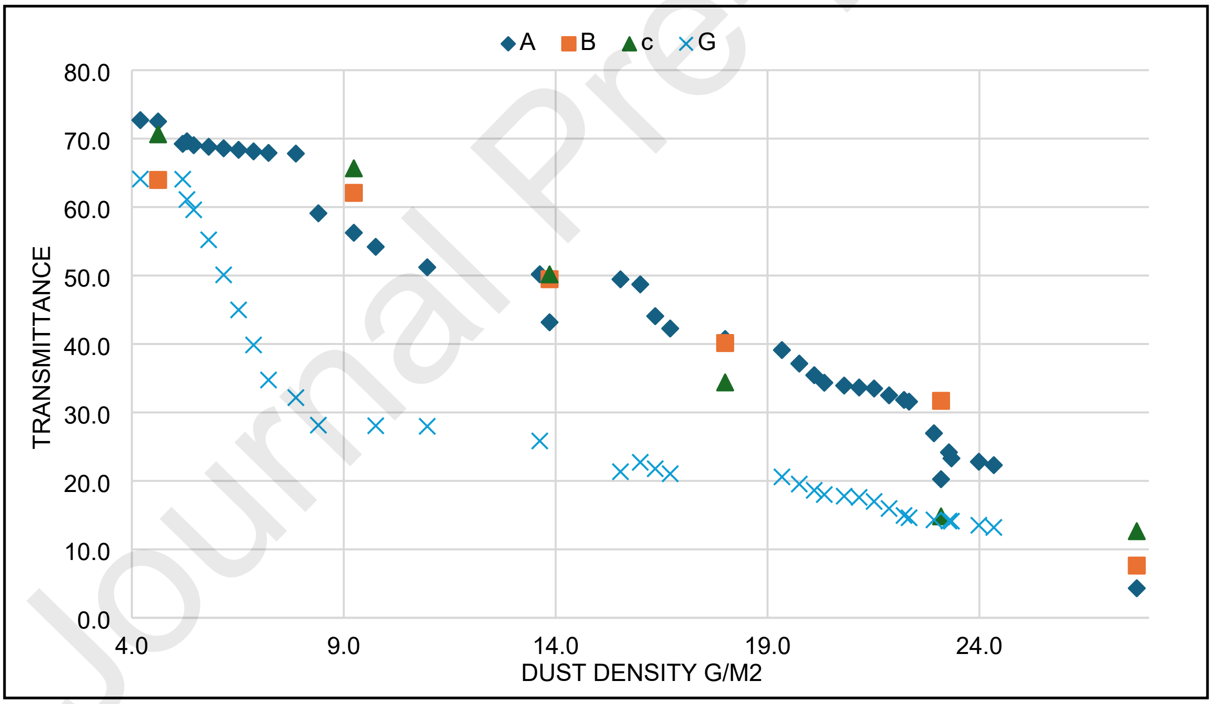

Figure 4. Transmittance Comparison Between Storm-Collected (*A, B, C*) and Ground-Collected (G) Dust. *For dust type A and B at weight (9.2, 18) g/m² from Ref. [20].

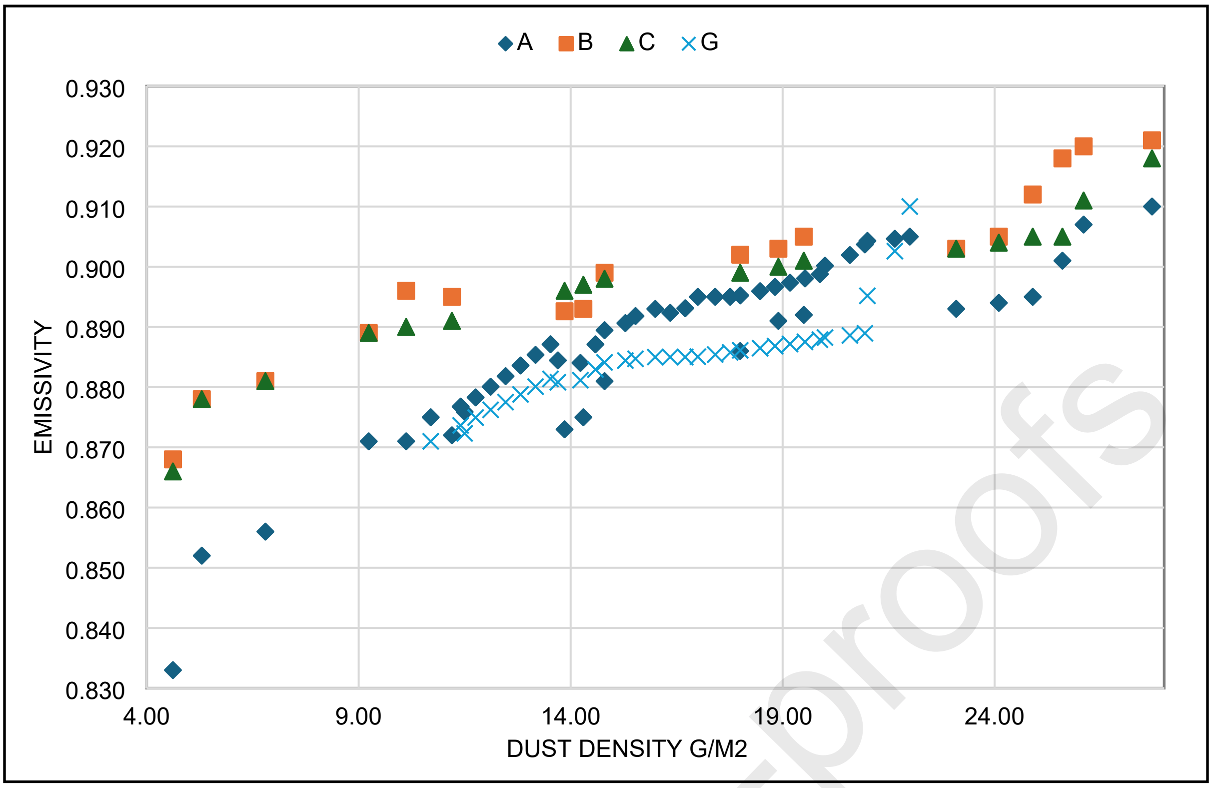

Figure 5. Emissivity Comparison Between Storm-Collected (*A, B, C*) and Ground-Collected (G) Dust.

*For dust type A and B at weight (9.2, 18) g/m² from Ref [20].

A notable finding reveals an inverse relationship between dust weight and transmittance. For example, Type A dust's transmittance decreases from 72.5% at 4.6 g/m² to 20.25% at 23.1 g/m² (Figure 3), indicating obstructed light passage. In contrast, both absorbance and emissivity increase with dust weight, suggesting enhanced light entrapment and increased radiation emission. Notably, Type G dust is more effective at blocking light than Types A, B, and C, leading to a substantial increase in absorbance values as its weight accumulates. However, Types A, B, and C also exhibit increased absorbance with heavier dust layers, with a plateau effect of around 27.71 g/m², suggesting a maximum threshold for light absorption. Anomalies in Type G dust, such as the absorbance value at 23.28 g/m², indicate possible variations in dust composition or aggregation.

The study further distinguishes optical properties between dust collected during storms and ground samples. For instance, storm-collected Type A dust at 11.5 g/m² shows a transmittance of 69.24% and absorbance of 0.164, contrasting with ground-collected Type G dust, which exhibits a transmittance of 64.07% and higher absorbance. The differences in optical properties between the dust collected from storms and the ground are due to their different physical and chemical properties. This research has found non-linear patterns and anomalies in transmittance, absorbance, and emissivity at specific dust concentrations. This highlighted how complex the interaction between dust and PV modules can be, and it points out the need for an in-depth analysis. Additionally, the study demonstrates the impact of dust on the optical characteristics of PV systems. Even a small amount of dust can lead to a significant impact on transmittance, absorbance, and emissivity. This influences the thermal behavior and efficiency of PV systems.

3.2.2 MATLAB Results

In this section, the study reveals the outcomes of applying ANN and MLR to estimate the impact of dust on the optical properties of PV modules.

3.2.2.1 Predicting Optical Characteristics of PV with ANN

The ANN has considered five inputs to predict different optical features. These include the most common chemical elements found in dust, which are silicon (Si%), Aluminium (Al%), Iron (Fe%), Calcium (Ca%), and the total dust weight per square meter (g/m2). Each optical property was analyzed using distinct datasets: 88 experimental samples for absorbance, 120 for emissivity, and over 700 samples from various nations for transmittance. The data were divided into training, validation, and testing subsets with ratios of 70%, 15%, and 15%. The training across all studies involved 500 epochs with a maximum failure criterion set at 10. The performance of the ANN for each optical property is summarized in Table 5.

Table 5. Summary of ANN Performance for Each Optical Property

Optical Property	Sample Size	Training R	Validation R	Testing R	Overall R	Best Validation Performance
Absorbance	88	0.990	0.986	0.981	0.988	0.057
Emissivity	120	0.967	0.954	0.878	0.957	0.053
Transmittance	>700	0.998	0.999	0.997	0.998	0.00192

3.2.2.2 Discussion and Comparative Analysis

The analysis exposes differing degrees of accuracy across the three optical properties:

- Absorbance: Demonstrated high accuracy, affirming the model's proficiency in comprehending the influence of dust composition and weight on absorbance.
- Emissivity: Displayed slightly lower R values but still presented substantial accuracy, indicating the model's effectiveness in predicting material emissivity.
- Transmittance: Attained the highest accuracy among the three, with exceptional R values, particularly in the validation phase.

The superior performance in transmittance analysis can be attributed to several factors:

- Larger Sample Size: The transmittance study utilized over 700 samples, significantly larger than the datasets for absorbance and emissivity. This extensive sample size likely contributed to the model's ability to generalize better and capture a broader range of scenarios.
- Dataset Diversity: The transmittance dataset includes data from different countries. This data provides a varied range of environmental conditions and dust compositions, which enhances the model's learning and predictive capabilities.

The outcomes highlight the flexibility and dependability of the ANN in examining different optical properties in various dusty scenarios. Although the prediction of the three properties demonstrated strong predictive abilities, the transmittance analysis was particularly notable. This emphasizes the capability of ANN models to manage large and varied datasets.

3.2.2.3 Predictive Optical Characteristics of PV with MLR

The MLR models were developed and executed in MATLAB. These MLR models offer straightforward, linear correlations to understand the impact of various dust levels on these optical properties. The models incorporate five inputs, including the highest concentration of chemical components of dust (Si%, Al%, Fe%, Ca%) and the dust weight per square meter (g/m^2).

Each MLR model is trained using the same dataset used with ANN, and the film function in MATLAB establishes a linear model between the input and the respective optical properties. It has evaluated the model performance using the Mean Squared Error (MSE). The performance details and equations of each MLR model are summarized in Table 6.

Table 6. MLR Model Performance and Equations Evaluated Using MSE

Optical Property	Sample Size	MSE	R-squared	Model Equation
Absorbance	88	0.0084	0.858	$Absorbance = -0.117 \times Si\% - 0.047 \times Al\% + 0.321 \times Fe\% + 0.021 \times Ca\% + 0.045 \times \rho$
Emissivity	120	2.6E-05	0.862	$Emissivity = 0.0205 \times Si\% + 0.0029 \times Al\% - 0.0218 \times Fe\% + 0.0117 \times Ca\% + 0.0020\rho$
Transmittance	>700	8.4	0.912	$Transmittance = 40.708 + 10.605 \times Si\% + 3.909 \times Al\% - 53.529 \times Fe\% + 102.728 \times Ca\% + 15.936 \times \rho$

3.2.2.4 Discussion and Comparative Analysis

Absorbance:

The low MSE of 0.0084 in the model, about absorbance, indicates its high accuracy in predicting absorbance changes. This accuracy is crucial for analyzing the thermal behavior of PV systems. Furthermore, the model boasts an R-squared value of 0.858. This means it successfully explains 85.8% of the variation in emissivity, underlining its effectiveness in the context of the variables utilized. Notably, the negative coefficients for Silicon (Si%) and Aluminium (Al%) suggest that an increase in these elements leads to lower absorbance. This could be due to their reflective properties. In contrast, the positive coefficient for Iron (Fe%) indicates that higher Iron concentrations enhance absorbance, likely because of Iron's darker color and greater capacity for heat absorption. Additionally, the positive coefficient for dust weight (g/m^2) is consistent with the expectation that more dust leads to increased absorbance.

Emissivity:

The emissivity model performed with an especially low Mean Squared Error (MSE) of 0.000026, representing its high precision in predicting changes in emissivity within PV systems. It has an R-squared value of 0.862, capturing 86.2% of emissivity variance, indicating a high fit level. The model equation shows positive coefficients for Si% and Calcium (Ca%), suggesting that increasing these elements correlates with higher emissivity. Silicon may enhance emissive properties due to being a major component of sand. A negative coefficient for Fe% implies that Iron reduces emissivity, possibly by retaining heat. A low positive coefficient for dust weight indicates that heavier dust accumulation marginally increases emissivity.

Transmittance:

The transmittance model, with a higher MSE of 8.4, indicates more variability in predictions, possibly due to a larger dataset size (>700 observations) and diversity in experimental conditions from various publications. It has the highest R-squared value of 0.912, explaining 91.2% of the variance in transmittance, and an adjusted R-squared of 0.911, confirming robustness despite numerous predictors. Unlike absorbance and emissivity, transmittance data comes from multiple sources, introducing variations. The model equation reveals a large negative coefficient for Fe%, indicating a substantial decrease in transmittance with increasing Iron content, due to its opacity and light-absorbing characteristics. In contrast, a high positive coefficient for Ca% suggests Calcium significantly increases transmittance, likely due to its light-scattering properties. Positive coefficients for Si% and Al% imply a moderate increase in transmittance with their concentration. The coefficient for dust weight indicates that heavier dust layers reduce transmittance, aligning with the understanding that thicker dust layers block more light.

3.3 Overall Implications

The variations in MSE across different optical properties underscore the distinct challenges in modeling each optical property, emphasizing the significance of selecting appropriate predictors for accurate modeling. While all models demonstrate good predictive capabilities, as indicated by their R-squared values, the variations highlight that some properties, such as transmittance, are more complex to predict. Understanding these interactions is crucial for developing more accurate predictive models, which can significantly enhance the prediction of PV module temperature and overall performance. Accurate modeling is essential not only for optimizing the design of PV systems in dusty environments but also for informing maintenance practices. By predicting when and how dust accumulation impacts performance and temperature, these models can guide the timing and necessity of cleaning interventions to avoid overheating that could damage or threaten the PV technology. This approach ensures that PV systems operate at peak efficiency with minimal downtime, ultimately improving the longevity and cost-effectiveness of solar installations in areas prone to dust accumulation.

3.3.1 Comparative Analysis of ANN and MLR Models for Predicting Optical Properties of PV Modules.

This section offers a comparative analysis of ANN and MLR models in predicting the influence of dust on the absorbance, emissivity, and transmittance of photovoltaic modules.

The performance of each model is evaluated using metrics like R-squared (R^2), Adjusted R^2, and Mean Squared Error (MSE), as detailed in Table 7.

Table 7. Comparative Performance of ANN and MLR Models for Optical Properties

Optical Property	Model Type	R^2 (%)	Adjusted R^2 (%)	MSE
Absorbance	ANN	98.751	98.741	0.004007
	MLR	85.8	85.1	0.008398
Emissivity	ANN	95.697	95.69	4.02E-05
	MLR	86.2	85.7	0.000026
Transmittance	ANN	99.778	99.777	1.8
	MLR	91.2	91.1	8.4

Figures 6, 7, and 8 compare the experimental results and the prediction values made by MLR and ANN models for transmittance, absorbance, and emissivity. This visual representation helps in understanding how closely each model is from the experimental data.

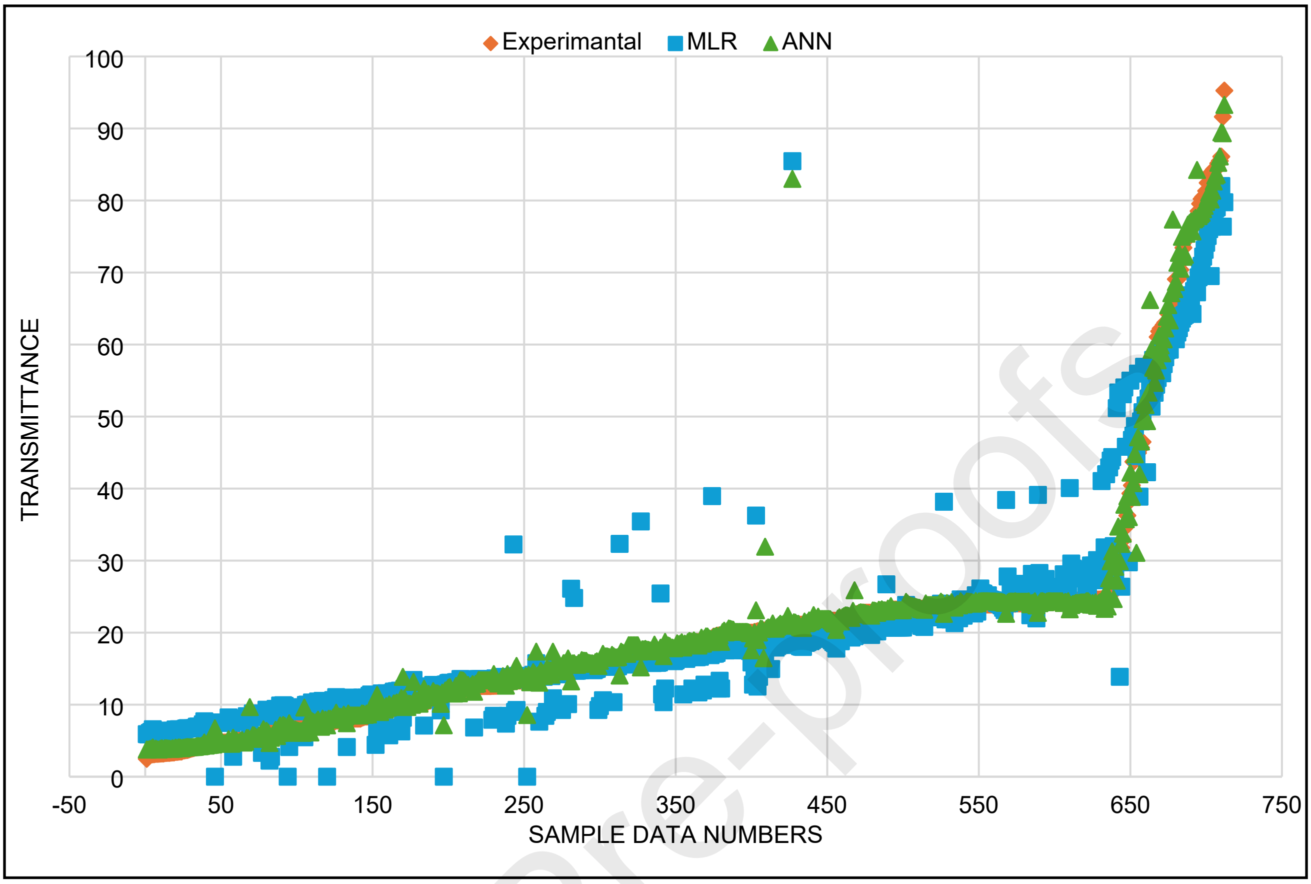

Figure 6. Transmittance Comparison: Evaluating Experimental Values Against MLR and ANN Forecasts

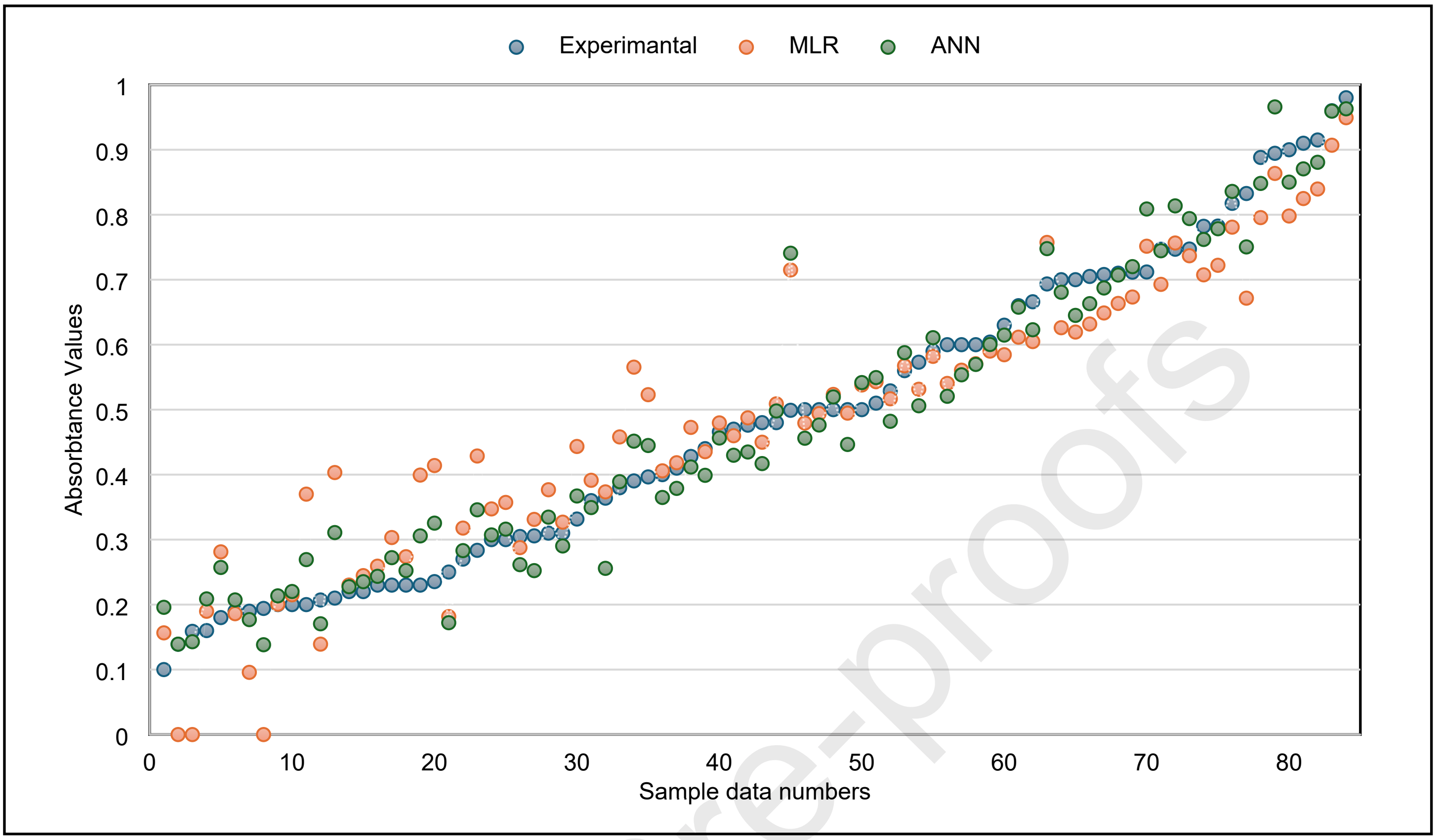

Figure 7. Absorbance Analysis: Experimental vs. Predicted (MLR & ANN)

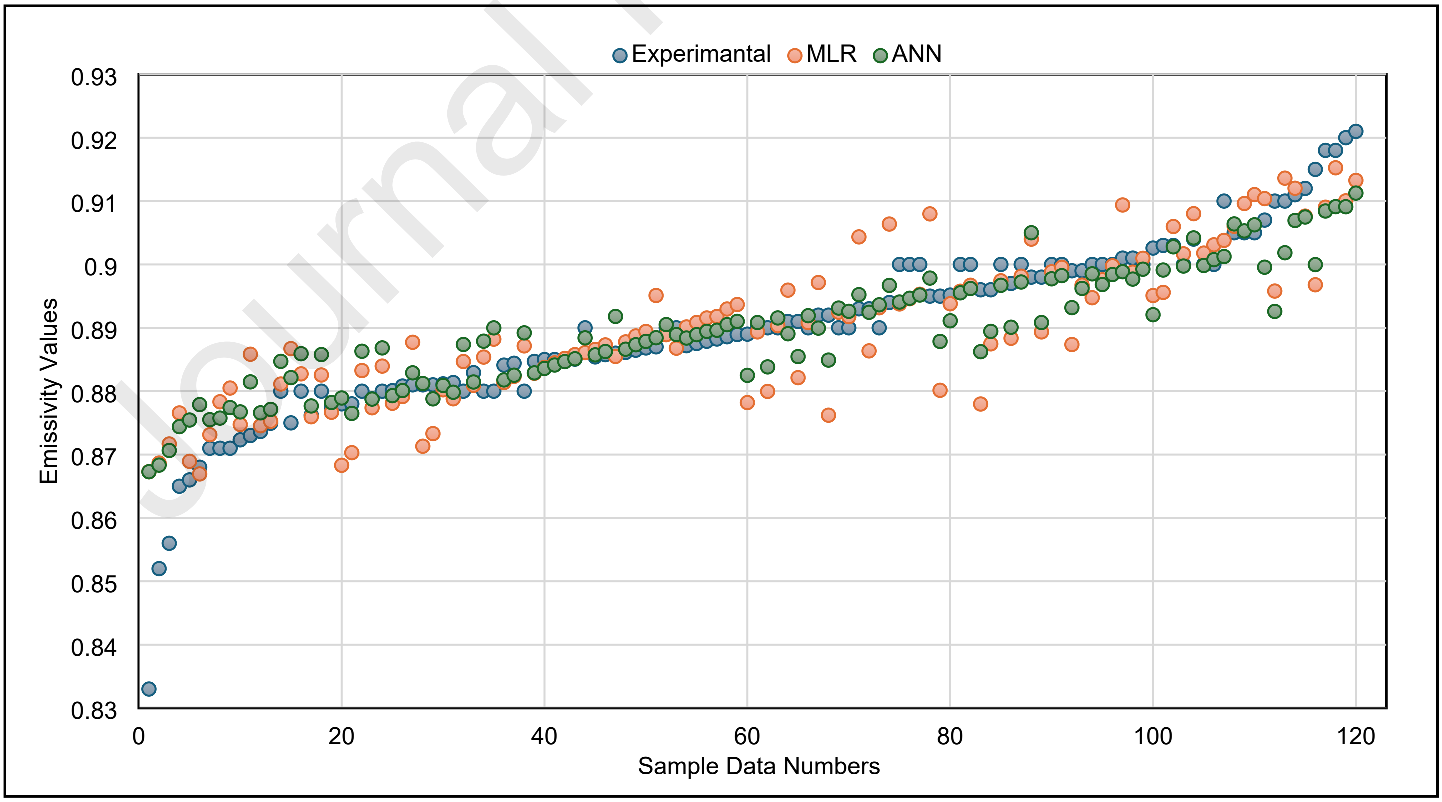

Figure 8. Emissivity Trends: Comparing Actual Data with MLR and ANN Predictions

The overall performance of ANN models demonstrates higher R^2 and Adjusted R^2 values across all optical properties, indicating a stronger fit to the data than MLR models. This superiority indicates that ANN is more efficient in capturing the complex, non-linear interactions between dust characteristics and optical properties. Additionally, lower MSE values in ANN models further demonstrate better predictive accuracy, particularly in capturing the variability within the data, as noted in the absorbance and emissivity models. Although the ANN models have shown superior performance, they are more complex and less interpretable than MLR models. The linear equations of MLR provide ease of understanding, making it beneficial for assessments or explanations between the input and output parameters.

3.4 Comparative Analysis of Transmittance Reduction Predictions

The study extensively compares the predictive capabilities of various models in estimating transmittance reduction due to dust accumulation on PV glass. It has compared the prediction values from this study and those from the published modules in Table 2 with experimental values listed in Table 3 and the experiment data from this study. Since there are many prediction values from the previous modules, the dataset underwent filtering to exclude values outside the 0-100% range, resulting in varying numbers of exclusions across different models. MSE values were then calculated for each model using the filtered dataset. The details of exclusions and MSE values are summarized in Table 8, and a scatter chart in Figures 9 and 10 visually compares these model predictions against actual data.

Table 8. Comparative Analysis of Excluded Values and Mean Squared Error (MSE) Across Various Models

Model Reference	Number of Values Excluded	MSE
MLR (Multiple Linear Regression)	0	8.4
ANN (Artificial Neural Networks)	0	1.8
[6]	80	7.792
[8]	73	12.965
[14]	153	31.974
[5]	5	34.001
[9]	0	387.115

[12]	0	669.309
[15] A	0	109.90
[15] B	5	192.39
[17]	9	120.76
Conceição et al. cited in [16]	1	663.75

This analysis is crucial for evaluating the reliability and precision of different predictive models in the context of PV system performance. Accurate predictions of transmittance reduction are essential for optimizing PV system maintenance, particularly in dusty environments.

The ANN model demonstrates the lowest MSE (1.8), indicating high accuracy and predictive performance. While the MLR model's MSE is higher than ANN's, it still shows commendable predictive capability. The calculated MSE for other equations indicates varying levels of accuracy, which are far away from the ANN and MLR.

This analysis provides a clear picture of each model's predictive accuracy. With its high accuracy and robustness, the ANN model is an excellent choice for complex scenarios in PV system analysis. The MLR model, though less precise, offers valuable predictions and is beneficial where interpretability is crucial. The variability in MSE, among other equations, underscores the need for careful model selection based on specific requirements and data characteristics in PV research and maintenance applications.

The experimental data, consistently depicted in blue, serves as a benchmark against which the predictions of other models are evaluated. Each chart contrasts the experimental data with one of the models, highlighting the deviation of model predictions from actual data. This analysis reinforces the findings discussed earlier, underscoring the superiority of the ANN model in terms of accuracy, as evidenced by its closer alignment with the experimental data. Likewise, the visual data supports the robust performance of the MLR model and highlights the variability in accuracy among the other models. Limitation

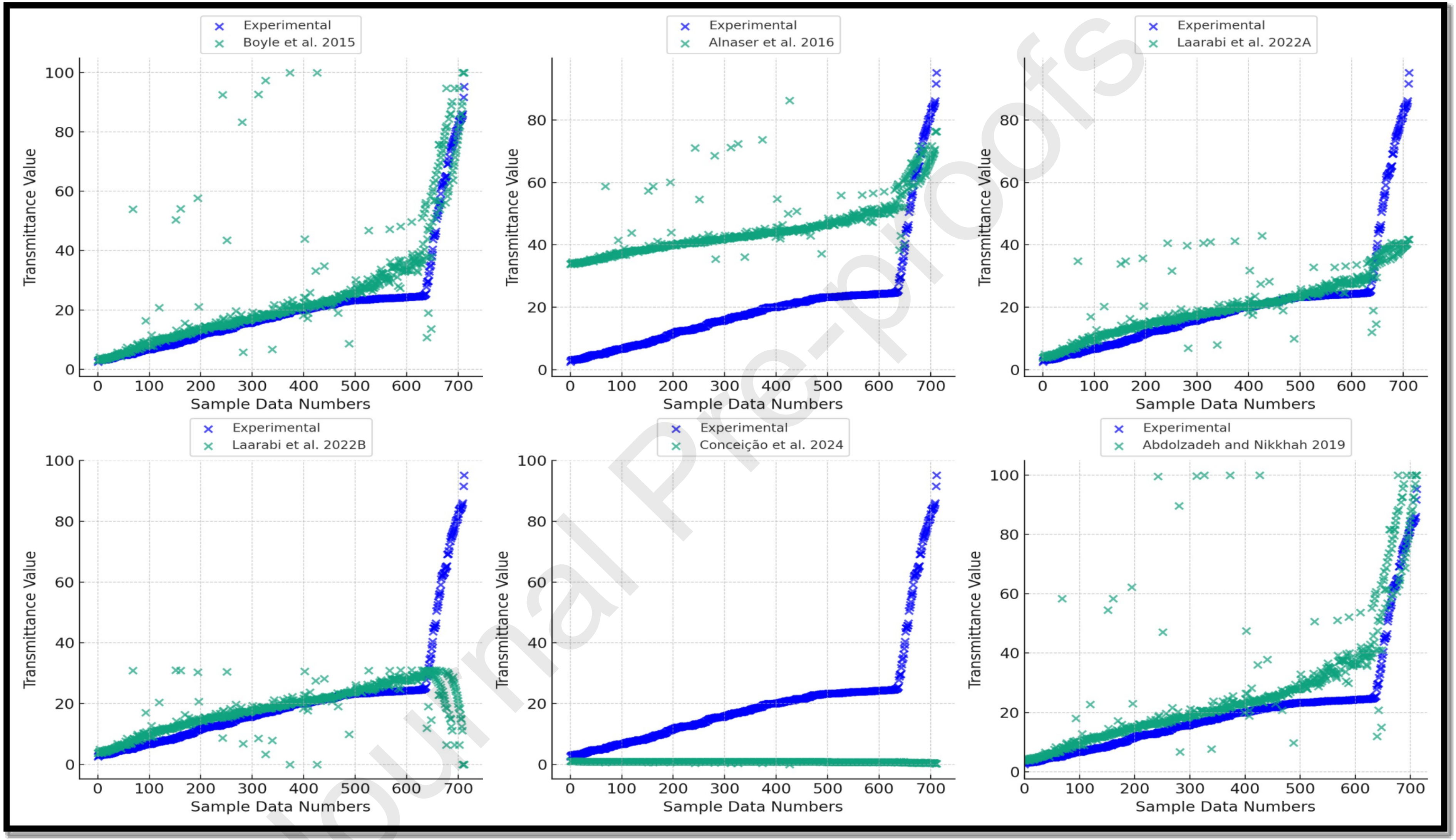

Figure 9 Scatter chart visualizing model predictions vs. experimental data* across diverse analytical methods * *The experimental data from different references as demonstrated in Table 2 as well as our experiments.*

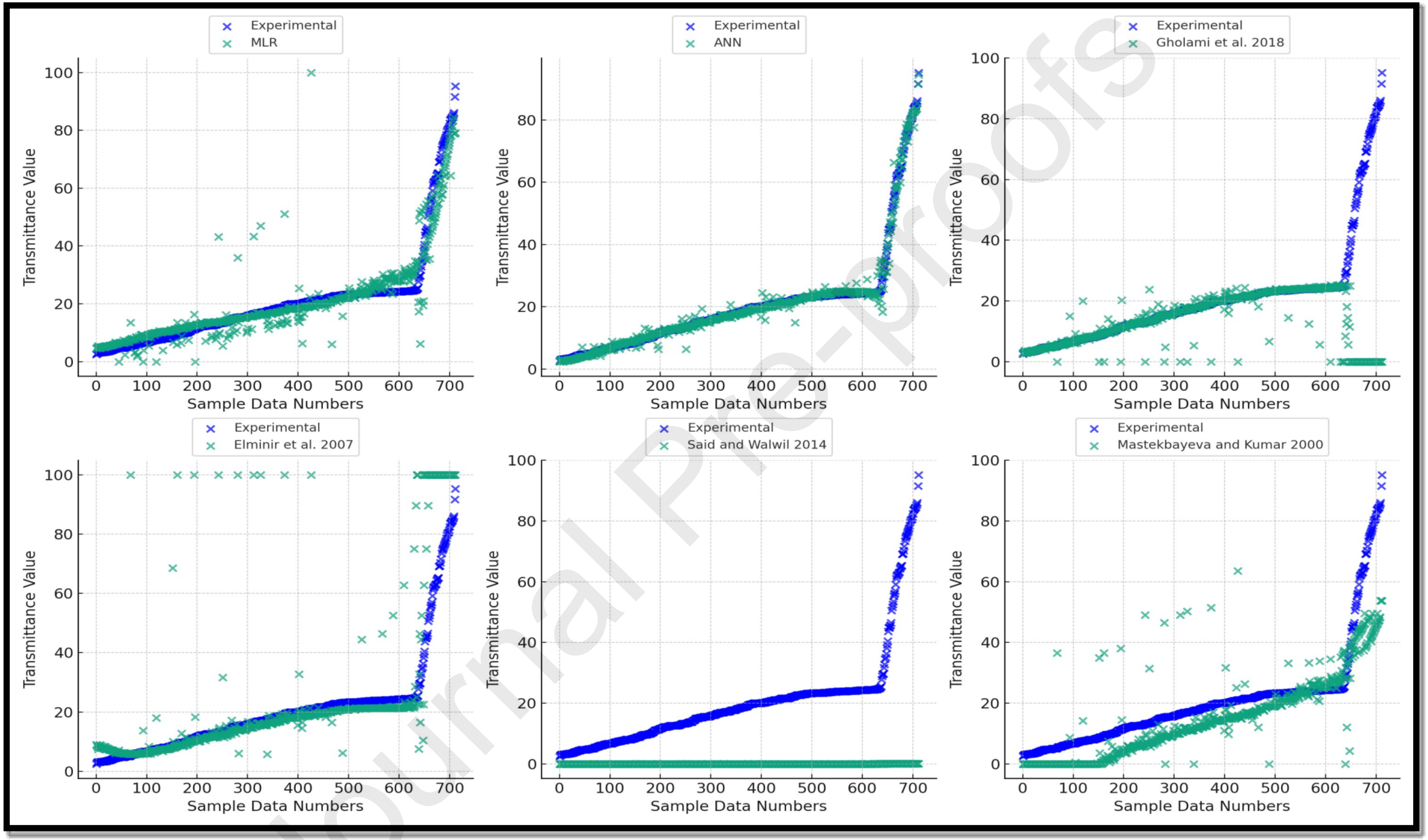

Figure 10. scatter chart visualizing model predictions vs. experimental data* across diverse analytical methods. * The experimental data from different references, as demonstrated in Table 2, as well as our experiments.

4. Conclusions

The study signifies a significant step forward in comprehending the effects of dust accumulation on the optical properties of PV glass. Through the integration of experimental investigations and more accurate predictive modeling utilizing ANN and MLR, the research sheds new light on how dust influences PV technology. Notably**,** the ANN model achieved a remarkably lower MSE of 1.8, while the MLR model achieved an MSE of 8.44, indicating high predictive accuracy. These findings, highlighting their superiority in predicting the impact of dust on PV optical properties, especially when compared with existing data, underscore the effectiveness of these methodologies in forecasting the consequences of dust accumulation on PV systems. The findings underscore the significance of precisely predicting the impact of dust on the optical properties of PV modules, which is crucial for anticipating thermal effects and ensuring the efficiency of PV installations.

For future research directions, expanding experimental sample sizes to include emissivity and absorbance data from diverse nations would contribute to a more extensive understanding of the impact of dust across various geographical conditions. Additionally, the research could delve into the diverse composition of dust, considering various component materials. It could further explore physical aspects, particularly focusing on the shape and size of particles. Understanding these interactions is paramount for developing more accurate predictive models and effective cleaning methodologies. Additionally, current models need more detailed consideration of dust particle size and shape, significantly affecting prediction accuracy. Addressing these factors may contribute to improving model precision.

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- Investigation of dust impact on optical properties of PV modules

- Utilization of ANN and MLR models in MATLAB for prediction
- Achieved predictive accuracy with MSE: 1.8 (ANN) and 8.44 (MLR)
- Combined novel and global data for comprehensive dust impact analysis
- Analysis of diverse dust chemical compositions and weight impacts