Research Paper Presentation

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Title

Application of Machine Learning to Lightning Strike Probability Estimation.

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Abstract

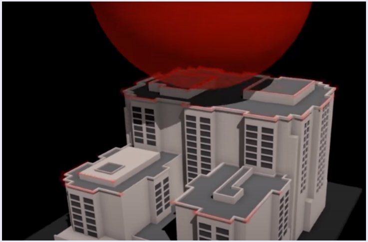
- The risk of a lightning strike to a structure is influenced by geometry, the type of material of the structure, and proximity to other structures.
- The probability of lightning strike to different points on an object can be determined by applying the concept of probability modulated collection volume using the dynamic electro-geometrical model (DEGM).
- The numerical computation of the DEGM is computer resource-intensive and requires extensive programming and analysis to implement, which may be difficult to apply by engineers in the field.
- This study explores the feasibility of applying artificial neural network (ANN) and predictive equation-based models developed using data pattern recognition and curve fitting techniques as easy to use alternatives to the numerical DEGM simulations.

Introduction

- Lightning is the discharge of transient, high energy current in the atmosphere. The lightning discharge process involves the downward movement of charges referred to as a **downward leader** via random conducting paths, from the cloud charge centres towards the ground, followed by an upward leader and then an upward return stroke, from the ground towards the cloud.
- The risk of a lightning strike to a structure is influenced by geometry, the type of material of the structure, and how it is exposed to lightning strikes relative to other nearby structures.
- **Striking distance** is a term that reflects the extent in terms of geometric distance, from which a point on a structure is exposed to downward leaders and may be struck by lightning. This has been used over time to estimate the protection zone of a lightning rod.
- **Lightning collection volume** is simply the region(volume) above the structure from where downward leaders can strike the structure.

Introduction

Rolling Sphere lightning protection concept



- A structure is deemed protected from lightning strikes using the rolling sphere concept if no point on the structure(except lightning rods and the ground) is touched by a sphere of a fixed radius corresponding to a specific protection level.
- However this analysis does not help in identifying high-risk points on the structure as it assumes that the probability of a strike to all points on a structure is the same, and it does not differentiate between strikes to ground, rods and transmission lines as validated by experimental analysis.

Introduction

DEGM

- The Dynamic Electro-Geometrical Model(DEGM) is a concept for evaluating the probability of lightning striking a structure, on a point-by-point basis.
- By creating meshes on the structure, the probability of strike to diff. points on the meshed structure can be determined using several rolling sphere radii, unlike the rolling sphere concept that uses a fixed radius.
- Although the DEGM provides more information for a better design of lightning protection systems for a structure, performing the DEGM analysis may be a major challenge due to the intricate level of programming, and computer resources required as several iterations are performed, which can take a few hours to compute even on advanced simulation computers.

Introduction

Concept of the DEGM

- The surface of the structure is meshed into several points to which a downward leader may attach. Also, since downward leaders descend towards the structure from above, spaces above the cuboid within the lightning collection volume of the structure are also meshed into multiple space points, as shown in figure 1.
- For each space point, the nearest surface point(s) on the structure or ground is determined as the likely strike point for any downward leader orientating from that specific point in space.
- The effective striking distance for each struck surface point is converted to a probability value by using an appropriate function. The cumulative probability of a lightning strike for each surface point is finally converted to a percentage of the total for the structure.

Introduction

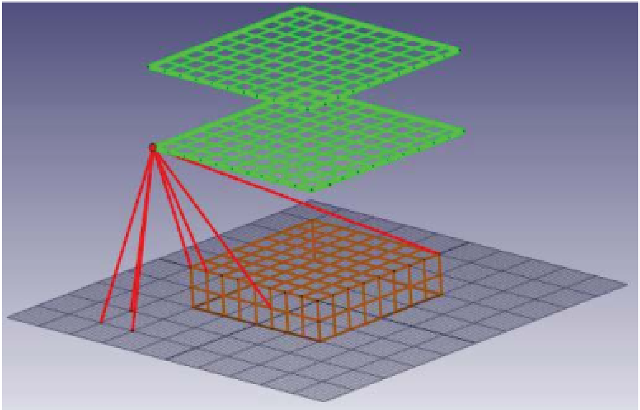


Figure: Illustration of meshed space points above, and surface points on the cuboid structure

Introduction

Artificial Neural Network

- The Artificial Neural Network (ANN) is a computational learning model that mimics the functioning of the neurons of the central nervous system.
- The ANN has artificial neurons called nodes, which can be used for evaluating a function based on given inputs, in order to produce a corresponding output.
- The nodes are usually interconnected and structured in layers referred to as hidden layers. From the input layer, the output of one neuron will become the input of the next neuron until the final output stage.

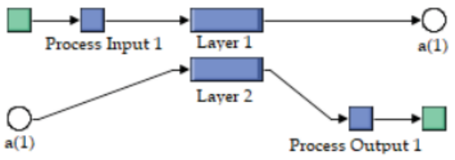


Figure: Two layer feed-forward ANN model

Artificial Neural Network (contd.)

- The neurons are interconnected by paths with a given weight value (w), which can be adjusted by a learning algorithm that tries to find the best weight value for each path in the model in order to accurately define the output values based on the set of inputs.
- The output of each node is triggered when the weighted input sum is processed by a preset activation function. This gives an output which is equivalent to an electrical potential in biological systems.
- The ANN learning process can be supervised, unsupervised or the hybrid mode, and it is very efficient for modelling non-linear systems.

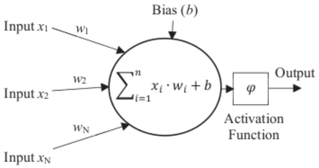


Figure: A model of an artificial neuron

The Methodology

- Two cuboids, Cuboid A and Cuboid B, with different roof surface areas (40m x 40m and 50m x 20m respectively) were considered and analyzed in this study.
- Numerical computations of the DEGM to the two cuboids as a case study was performed using the following heights, 10m, 20m, 30m, 40m and 50m, and the dataset (probability of a strike in percentage for each meshed point on the cuboid) is accumulated from these simulations.
- The dataset acquired using heights 10m, 30m, and 50m were used for training and validating the ANN model and equation-based models, and the data-set acquired using heights 20m and 40m were used to further test the extent to which their predictions can be generalized.

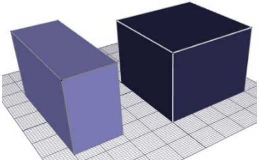


Figure: Cuboid A and Cuboid B

The Methodology

- To apply machine-learning techniques to a dataset, the inputs and outputs of the model must be well defined.
- In this case, the desired **output** is the **percentage probability of a strike to each point**(hereby referred to as target), which has been determined by DEGM analysis.
- There is a need to define the input features as independent variables that will define the desired output. To do this, attributes of the cuboid and the DEGM as a concept were considered to generate seven input features, as defined in the following section.

Firstly, the surface points on the cuboid structure were classified into five different types: sidewall (SW), corner (C), wall edge (WE), inner roof (IR), and roof edge (RE).

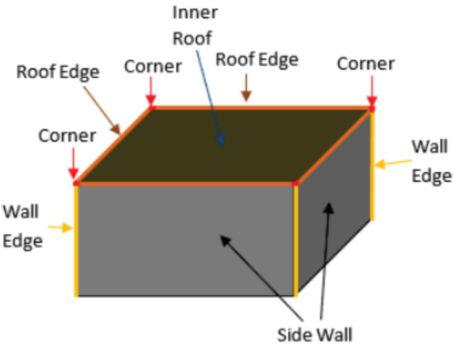
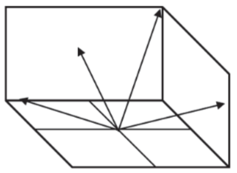


Figure: Types of surface points

Input Features

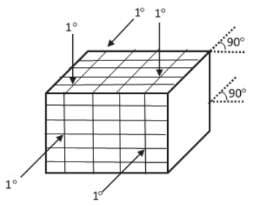
Feature A

This is the distance between each surface point and a reference point at the centre of the cuboid on the ground level. This parameter measures the relative displacement of each surface point from the datum point.



Feature B

This reflects the exposure of each type of surface points in angular terms using a single horizontal surface as a reference plane at each object height. For corners and wall edges, the exposure angle is 90°, while it is 1° for all other points.



Input Features

Feature C

Height of each discretized surface point above the ground.

Feature D

The type of surface point coded as follows: 1 for the SW, 2 for the WE, 3 for the C, 4 for the RE, and 5 for the IR.

Feature E

The surface area of the cuboid's roof(exposed top) in m^2

Feature F

The height of the cuboid.

Feature G

The total surface area of the four cuboid sides in m^2

The ANN Model

- To achieve an ANN-based DEGM, a **seven input** neural network model was developed using a **two-layer** feed-forward network comprising of **18 neurons**.
- The dataset containing **36900 samples** (e.g. $A = 29.4618$, $B = 1$, $C = 12$, $D = SW$, $E = 1600$, $F = 30$, and $G = 4800$) was randomly divided into three in the ratio, 70% for training, 15% for performance evaluation, and the remaining 15% for testing.
- The model was trained using the **Levenberg-Marquardt optimization algorithm** for **supervised learning** using the backpropagation rule.
- The analysis was carried out using the neural fitting tool on **MATLAB**.
- The training process is performed iteratively by feeding the inputs, updating the neural weights, and getting an output repeatedly until a preset limit is attained. Each of this iteration is referred to as an epoch, and in this study, the iteration was terminated after **1000 epochs**.

The ANN Model - Results

The simulation (training, validation, and testing) was completed in 2 minutes. The training status of the ANN model after completion is shown below

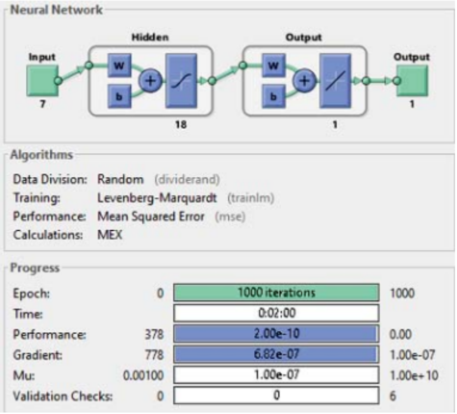


Figure: The Artificial Neural Network and training progress report

The ANN Model - Results

Error Histogram

- The error histogram is a plot of the error distribution, and it shows that highest error is around the central value of 5.09×10^{-6}, and the error decreases on both sides of the maximum error point, and this is a good indication of minimal predictive error.
- The performance of the model was evaluated using the **mean square error**(MSE) and **regression R^2 value**.

Figure: Error histogram

The ANN Model - Results

Mean Square Error(MSE)

- $$\text{MSE} = \frac{1}{\text{Sample Size(n)}} \times \sum_{i=1}^{n} (\text{Observed value}_i - \text{Predicted value}_i)^2$$
- The lower the MSE, the better the result. For the training process, the MSE observed is 2.000×10^{-10}, 2.103×10^{-10} for validation, and 2.138×10^{-10} for the testing.
- The performance validation in terms of the reduction of the MSE with successive iterations is shown below.

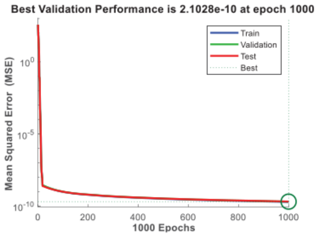


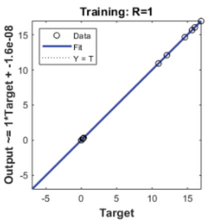
Figure: MSE trend

The ANN Model - Results

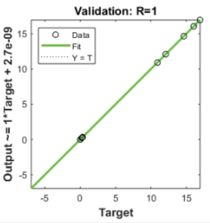
Regression R^2 value

- R^2 is a statistical measure of fit that indicates how much variation of a dependent variable is explained by the independent variable(s) in a regression model.
- $$R^2 = 1 - \frac{\text{Unexplained Variation}}{\text{Total Variation}}$$
- R^2 values are in the range from 0 to 1. Higher the R^2 value,the better the model results.
- The graphs on the next slide show the regression plots for training, validation, testing and the overall model performance.
- An **overall $\mathbf{R^2}$ value of 1 was achieved**, which indicates a good model fit.

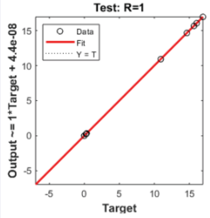
Regression Plots



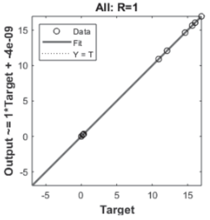
(a) Regression plot for the training data



(b) Regression plot for the validation data



(c) Regression plot for the test data



(d) Regression plot for the overall model

The ANN Model - Results

Overview

For an overview of the predictive ability of the ANN model, some samples of the predictions for Cuboid A, and Cuboid B from the five cuboid heights, i.e. 10 m, 20 m, 30 m, 40 m, 50 m are presented below

SN	Cuboid Type	Point Type	Target	ANN Prediction
1	A10	SW	0.00001	0.00002
2	A10	RE	0.29900	0.29893
3	A10	C	10.91782	10.91782
4	A30	IR	0.00288	0.00289
5	A30	RE	0.23580	0.23581
6	A30	C	14.65174	14.65174
7	A50	SW	0.00008	0.00008
8	A50	RE	0.20343	0.20340
9	A50	C	16.05324	16.05324
10	B10	IR	0.00705	0.00706
11	B10	RE	0.33125	0.33123
12	B10	C	12.09545	12.09545
13	B30	SW	0.00010	0.00011
14	B30	RE	0.25201	0.25202
15	B30	C	15.65919	15.65919
16	B50	C	16.94614	16.94614
17	B50	SW	0.00000	0.00000
18	B50	RE	0.21474	0.21474
19	A20	WE	0.00097	0.08164
20	A20	C	13.32972	13.22496
21	A20	RE	0.26071	0.26391
22	A40	SW	0.00007	-0.09099
23	A40	RE	0.21777	0.21473
24	A40	C	15.48832	15.52843
25	B20	C	14.41524	14.31642
26	B20	SW	0.00005	0.05884
27	B20	RE	0.28195	0.28757
28	B40	IR	0.00244	0.00436
29	B40	RE	0.23105	0.22936
30	B40	C	16.43327	16.46468

Figure: Comparison of the predicted results with the target value

The ANN Model - Results

Overview(contd.)

- The results from serial number 1 to 18 are from samples used in the ANN model development, i.e. 10 m, 30 m, and 50 m.
- In order to evaluate the ability of the model to predict for new data, data samples from 20 m, and 40 m, both for Cuboid A and Cuboid B which were not part of the ANN model development process were analyzed, and the results for few samples are shown comparatively from serial number 19 to 30.
- Although the predictions are not perfect, the result shows a close approximation to the target, especially for the roof edge (RE), the internal roof (IR), and the corner (C) points.

Equation-based Model

- As an alternative to the ANN approach, the possibility of deploying equations that reasonably model the attributes of the dataset for predictive analysis was explored.
- Only three key features were considered in the model, and these are feature A, feature C, and feature F. The addition of more features, only made the equations more complex without significant improvement in accuracy.
- Separate equations and analysis were developed for each type of surface point, i.e. WE, SW, RE, IR, and C, by exploring data fitting techniques using **ndCurveMaster**.
- Unlike the analysis for ANN, where the percentage of the probability of lightning strike was directly predicted, for the first equation-based model, the probability modulated collection volume(PMCV) (collection volume(which is infinite) is modulated to be 1 for roof surface points, and relative to that for other surface points.) will be predicted, and this will be converted to a percentage at the end of the analysis.

Equation-based Model - Results

For each of our different surface point types, we have an equation describing the predictive model for computing the PMVC for a surface point of that type, using variables A, C and F as inputs, and a figure presenting a visual view of the extent to which the predicted values are well fitted to the actual PMCV values.

Corner surface points

$$CornerP = k_0 + k_1 \times C^1 1 + k_2 \times F^0 .85, \tag{1}$$

where $k_0 = -461.24$, $k_1 = 5.6101x10^{-17}$, $k_2 = 305.341$, and CornerP is the PMCV of one corner surface point.

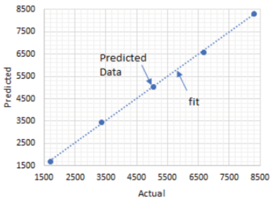


Figure: A fit of the predicted vs actual PMCV for corner points

Equation-based Model - Results

Roof edge surface points

$$RoofEdgeP = j_0 + j_1 \times C^4 + j_2 \times F^{2.4} + j_3 \times A^{0.93} \times C^{0.82} + j_4 \times A^{0.27} \times C^{1.2} \times F^{0.4}, \quad (2)$$

where $j_0 = 42.899$, $j_1 = -1.9446 \times 10^{-5}$, $j_2 = 0.01538$, $j_3 = -2.176 \times 10^{-14}$, $j_4 = 5.862 \times 10^{-14}$, and RoofEdgeP is the PMCV of one roof edge surface point.

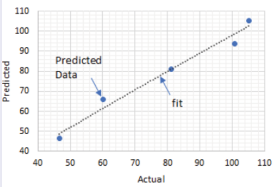


Figure: A fit of the predicted vs actual PMCV for roof edge points

Equation-based Model - Results

Wall edge surface points

$$WallEdgeP = m_0 + m_1 \times e^{2A} + m_2 \times C^{3.75} + m_3 \times e^{5F} + m_4 \times A^{-0.083} \times C^{4.8} + m_5 \times 2^A \times F^{-5.25} + m_6 \times C^{2.75} \times F^{0.01} + m_7 \times A^{-1.6} \times C^{10} \times F^{0.66}, \quad (3)$$

where $m_0 = 0.001029$, $m_1 = 2.7843 \times 10^{-51}$, $m_2 = 9.03 \times 10^{-6}$, $m_3 = 1.367 \times 10^{-112}$, $m_4 = -1.251 \times 10^{-7}$, $m_5 = -5.009 \times 10^{-10}$, $m_6 = -5.57 \times 10^{-5}$, $m_7 = 4.199 \times 10^{-16}$, and WallEdgeP is the PMCV of one wall edge surface point.

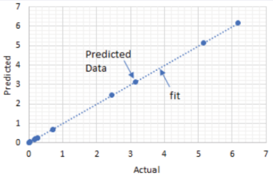


Figure: A fit of the predicted vs actual PMCV for wall edge points

Equation-based Model - Results

Sidewall surface points

$$\begin{aligned} SideWallP = n_0 + n_1 \times A^{14} + n_2 \times C^{4.25} + n_3 \times F^{1.8} \\ + n_4 \times A^{0.083} \times C^{0.69} + n_5 \times A^{15} \times F^{-3.3} \\ + n_6 \times C^{2.05} \times F^{0.067} + n_7 \times A^{0.01} \times C^{1.6} \times F^{0.1}, \end{aligned} \quad (4)$$

where $n_0 = -2.9218 \times 10^{-4}$, $n_1 = -4.0327 \times 10^{-27}$, $n_2 = -2.6635 \times 10^{-9}$, $n_3 = 3.5299 \times 10^{-7}$, $n_4 = 0.00036794$, $n_5 = 3.0598 \times 10^{-23}$, $n_6 = 0.00008559$, $n_7 = -2.2560 \times 10^{-4}$, and SideWallP is the PMCV of one roof edge surface point.

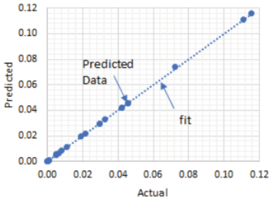


Figure: A fit of the predicted vs actual PMCV for sidewall points

Inner roof surface points

- This is the inner part of the roof which are exposed to vertical lightning strikes from space points directly above this region.
- The PMCV of each inner roof surface point should be 1.0, but in the computation of the DEGM, the analysis was performed up to 300 m (not ∞) above the roof, and the resulting PMCV is **0.991**. The value is constant for all inner roof surface points

Equation-based Model - Results

CubeSideP

- The value of the PMCV for each of the sidewalls and wall edge surface points are quite small in value, with some values in the order of 10^{-8}, and these small values were difficult to accurately predict by the model.
- A relationship between the PMCV of a corner point which was predicted accurately and the total PMCV of all surface points on the four side faces of the cuboid structure (i.e. CubeSideP) was developed as shown in (5).

$$CubeSideP = z_0 + z_1 \times CornerP^{3.8} + z_2 \times E^4 + z_3 \times G^{3.45} + z_4 \times \ln^4 F, \quad (5)$$

where $z_0 = 3.4407$, $z_1 = 6.681 \times 10^{-13}$, $z_2 = -4.4417 \times 10^{-14}$, $z_3 = 3.3648 \times 10^{-2}$, and $z_4 = -0.15141$.

- The total probability of a strike to the four sides of the cuboid structures, is typically less than 1.3% of the total probability, while surface points on the roof and corners account for the rest.

Equation-based Model - Results

Total PMCV

- The total PMCV for the whole structure is required to convert the results obtained using (1) to (4) to percentage probability values.
- The total PMCV is simply the summation of the PMCVs for all the corner points, the wall edge points, roof edge points, the four sidewall points (i.e. CubeSideP), and the inner roof. This can be computed using (6), where L is the length and B is the breadth of the cuboid.

$$\begin{aligned} Total\ PMCV = 4 \times CornerP + (2L + 2B - 4) \times RoofEdgeP \\ + (L-1) \times (B-1) \times 0.991 + CubeSideP \end{aligned} \tag{6}$$

Equation-based Model - Results

Percentage Probability

Our desired output (percentage probability of a strike to each point) can now be computed from the below formulae.

$$\text{Corner Probability}(\%) = \frac{CornerP \times 100}{Total\ PMCV} \tag{7}$$

$$\text{Roof Edge Probability}(\%) = \frac{RoofEdgeP \times 100}{Total\ PMCV} \tag{8}$$

$$\text{Inner Roof Probability}(\%) = \frac{0.991 \times 100}{Total\ PMCV} \tag{9}$$

$$\text{Side Wall Probability}(\%) = \frac{SideWallP \times 100}{Total\ PMCV} \tag{10}$$

Equation-based Model - Results

Direct Equation

- Further, an equation for directly predicting the percentage probability(target) of a lightning strike to the roof edge, corner, and inner roof area was developed.
- The sidewall and the wall edges were excluded from the analysis because of their small strike probability which reduces the accuracy of a general equation for all the five types of points.
- The result is directly in percentage using (11), and this is an alternative to the indirect analysis by calculating PMCV, and it applies A, B, C, D, and E as input variables.

$$\text{Target } (\%) = Q_1 + Q_2 + Q_3 + Q_4, \tag{11}$$

where Q_1, Q_2, Q_3, and Q_4 are defined on the next slide.

Equation-based Model - Results

Direct Equation(contd.)

$$Q_1 = t_0 + t_1 \cdot B^{0.24} + t_2 \times C^{-2} + t3 \times D^{5.9} + t_4 \times E^{0.96} + t_5 \times A^{2.95} \times B^{3.25} + t_6 \times A^{3.35} \times 6^{-C} + t_7 \times A^5 \times D^4$$

$$Q_2 = t_8 \times A^{1.55} \times E^{0.22} + t_9 \times B^{0.32} \times C^{-3.2} + t_{10} \times B^{0.77} \times E^{0.18} + t_{11} \times C^{-5.25} \times D^{16} + t_{12} \times C^{3.55} \times E^{0.44} + t_{13} \times \ln^3 D \times E^{0.167}$$

$$Q_3 = t_{14} \times A^{1.1} \times B^{4.8} \times C^{-2.75} + t_{15} \times B^{0.97} \times C^{3.4} \times D^{-4.9} + t_{16} \times C^{-0.125} \times D^{-5.55} \times E^{-0.65} + t_{17} \times A^{0.09} \times B^{-4.9} \times C^{2.75} \times 7^{-D}$$

$$Q_4 = t_{18} \cdot B^{-2.8} \cdot C^{0.07} \cdot D^{-1.45} \cdot E^6 + t_{19} \cdot A^{0.27} \cdot B^{2.75} \cdot C^{-2.5} \cdot D^{0.8} \cdot E^{3.25}$$

Where $\mathrm{t}_0 = -8.6018$, $\mathrm{t}_1 = 9.838205$, $\mathrm{t}_2 = -27.930$, $\mathrm{t}_3 = 0.0001855$, $\mathrm{t}_4 = 0.0012095$, $\mathrm{t}_5 = 2.1612 \times 10^{-11}$, $\mathrm{t}_6 = -0.088903$, $\mathrm{t}_7 = -4.351 \times 10^{-16}$, $\mathrm{t}_8 = 1.2513 \times 10^{-7}$, $\mathrm{t}_9 = 379.82078$, $\mathrm{t}_{10} = -0.08143$, $\mathrm{t}_{11} = 9.097 \times 10^{-9}$, $\mathrm{t}_{12} = 6.811 \times 10^{-12}$, $\mathrm{t}_{13} = -0.34028$, $\mathrm{t}_{14} = -2.398 \times 10^{-8}$, $\mathrm{t}_{15} = -1.8685 \times 10^{-5}$, $\mathrm{t}_{16} = 185702.9$, $\mathrm{t}_{17} = -1.466 \times 10^{-4}$, $\mathrm{t}_{18} = -4.4026 \times 10^{-20}$, and $\mathrm{t}_{19} = 2.242 \times 10^{-15}$.

Equation-based Model - Results

Overview

- Results from serial no. 1 to 18 are from samples used in the development of equations(from 10m, 30m, and 50m high cuboids), and results from 19 to 30 are from new surface points(from 20m and 40m high cuboids) to overview the ability of the model to predict for new data points.
- From the results, it is observed that the model was able to predict close results for samples used in developing the models, while for new data samples, there were slight deviations from the expected values.

SN	Cuboid Type	Point Type	Target	Indirect Equation (%)	Direct Equation (%)
1	A10	SW	0.00001	0.00001	–
2	A10	RE	0.29900	0.29901	0.29905
3	A10	C	10.91782	10.91819	10.91770
4	A30	IR	0.00288	0.00288	0.00295
5	A30	RE	0.23580	0.23580	0.23554
6	A30	C	14.65174	14.65165	14.65164
7	A50	SW	0.00008	0.00008	–
8	A50	RE	0.20343	0.20343	0.20360
9	A50	C	16.05324	16.05349	16.05312
10	B10	IR	0.00705	0.00705	0.00709
11	B10	RE	0.33125	0.33125	0.33115
12	B10	C	12.09545	12.09554	12.09533
13	B30	SW	0.00010	0.00010	–
14	B30	RE	0.25201	0.25201	0.25231
15	B30	C	15.65919	15.65903	15.65910
16	B50	C	16.94614	16.94634	16.94602
17	B50	SW	0.00000	0.00000	–
18	B50	RE	0.21474	0.21474	0.21452
19	A20	WE	0.00097	0.00101	–
20	A20	C	13.32972	13.93628	13.78360
21	A20	RE	0.26071	0.24414	0.24524
22	A40	SW	0.00007	0.00007	–
23	A40	RE	0.21777	0.22998	0.22135
24	A40	C	15.48832	15.03512	16.34327
25	B20	C	14.41524	15.02727	14.85685
26	B20	SW	0.00005	0.00005	–
27	B20	RE	0.28195	0.26325	0.26719
28	B40	IR	0.00244	0.00241	0.00453
29	B40	RE	0.23105	0.24459	0.23474
30	B40	C	16.43327	15.99009	16.33579

Figure: Comparison of the predicted results using equations with the target value

Conclusion

- Accurate design of lightning protection systems is vital for ensuring the safety of lives and properties. Air-termination networks must be positioned at high-risk points on a structure to ensure optimal lightning interception.
- The ANN model developed was able to show close approximations to expected results from DEGM with an overall regression R^2 value of 1.
- In terms of the ability of the models developed to predict accurate results for unfamiliar data samples, the ANN model performed far better than the equation-based model in predicting results for surface points on new cuboid structures.