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Inception 1D-convolutional neural network for accurate prediction of electrical insulator leakage current from environmental data during its normal operation using long-term recording

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ABSTRACT

Contamination flashover remains one of the biggest challenges for power grid designers and maintenance engineers. Insulator leakage current contains relevant information about their state so that continuous monitoring is considered the most effective way to prevent contamination flashover. In this work, we attempted to accurately predict insulator leakage current in real time during normal operations based on environmental data using long-term recordings.

We first confirmed that the history of environmental data also contained relevant information to predict leakage current by conditional Granger analysis and determined that 20 was the optimal number of previous samples for this purpose. We then compared the performance of typical regression models and convolutional neural network (CNN), when using both current and the last 21 samples as input features. We confirmed that the model with the last 21 samples might perform significantly better. Input features pre-processing by cascaded inception architecture was fundamental to capture the complex dynamic interaction between environmental data and leakage current and significantly improved the model performance. CNN based on inception architecture performed much better, achieving an average R^2 of 0.94 ± 0.03. The proposed model could be used to predict leakage current in both porcelain insulators with or without coatings and silicone composite insulators.

Our results pave the way for creating an on-line pre-warning system adapted to individual installations, can anticipate the negative consequences of weather and/or pollution deposits and is useful for designing a strategic high-voltage electrical insulator preventive maintenance plan for preventing contamination flashover and thus increase power grid reliability and resilience.

1. Introduction

High voltage electrical insulators play a fundamental role in energy transmission and distribution grids, although they can also cause catastrophic unplanned power outages generating serious socio-economic consequences (Ahmed et al., 2020; Thanh et al., 2021; Zhi-yi, 2003). During an insulator's life it is subjected to numerous stresses, such as electrical, mechanical and environmental (pollution deposits) which have a great impact on its reliability (Ahmed et al., 2020). Pollution deposits themselves do not cause a drastic change in surface conductivity and leakage current if the insulator surface is dry. However, pollution deposits moistened by light rain, fog, or dew, can create a conductive layer that considerably increases the leakage current (Gençoğlu and Cebeci, 2008; Rahal and Huraux, 1979). The insulator surface is then heated by the Joule effect, giving rise to the appearance of a dry band (Alston and Zoledziowski, 1963) due to a local increase of the electric field, thus initiating partial discharges that could trigger a flashover. This process is commonly referred to as *contamination flashover* and continually threatens power grid reliability (Ahmed et al., 2020; Gu et al., 2016; Li et al., 2010; Salam et al., 2013) and remains one of the greatest challenges for power grid designers and maintenance engineers.

Insulator leakage current (ILC) is an integral reflection of the weather, pollution deposits, applied voltage, and surface damage (Kim et al., 2001; Ramos et al., 1993) and can objectively reveal the entire process of converting insulator pollution deposits to contamination flashover (Thanh et al., 2021). Leakage current is considered one of the most significant and effective parameters for preventing contamination flashover, as it provides relevant information on the state of the electrical insulator and indicates how close the insulator string is to flashover (De Santos and Sanz Bobi, 2020). Considering the root-mean-square

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value, the leakage current during the entire process of contamination flashover is divided into three stages: the security stage, forecast stage and danger stage (Ahmed et al., 2020). In dry weather it is considered safe up to 5 mA. In humid conditions, current peaks up to 50 mA have been observed and are considered safe for operations (Ahmed et al., 2020). Leakage current over 150 mA–200 mA is considered dangerous according to the classification guide (Li et al., 2010). As early detection of anomalous signs in the security stage is the best way to design contamination flashover pre-warning systems (Li et al., 2010), continuous monitoring of leakage current is essential to design an effective strategy adapted to the special weather conditions of individual installations for the proper maintenance of high voltage electrical insulators to minimize contamination flashover and unplanned power outages. The development of a robust and accurate leakage current prediction model would be valuable to power generating companies, since it could anticipate the negative consequences of weather and/or pollution deposits and contribute to designing effective preventive strategies by increasing power grid reliability and resilience. It would also allow the optimization of both human and material resources for its maintenance.

Numerous studies have focused their efforts on developing ILC prediction models using environmental data (Araya et al., 2021; Castillo-Sierra et al., 2018; Castillo Sierra et al., 2015; Gao et al., 2018b; Pinotti and Meyer, 2017), the most commonly used data being relative humidity, temperature, wind direction and speed. The relationship between leakage current and relative humidity has been widely described (Bueno-Barrachina et al., 2021; Matsuoka et al., 2002; Waluyo et al., 2021). By contrast, there is some controversy about the influence of environmental temperature on the insulator leakage current (Amin et al., 2009; Rodriguez et al., 1985; Waluyo et al., 2021). In coastal installations, wind direction and speed are especially relevant to estimate ILC, as the accumulation rate of saline solution, the rate of diffusion and penetration, and the distance from the sea are closely related factors (Hussain et al., 2017; Venkataraman et al., 2008). Regarding ILC prediction, Vosloo and Holtzhausen attempted to predict the daily leakage current of porcelain insulators and obtained an R^2 that varies between 0.43 and 0.88 for the linear model, 0.56 and 0.95 for the non-linear model for 7-day recordings (Vosloo and Holtzhausen, 2002). Zhao et al. confirmed that the exponential regression equation can be used to predict the weekly leakage current, while the regression coefficients must be dynamically adjusted according to the pollution deposits in long-term 8-month recordings (Zhao et al., 2011). Other authors who attempted to use the exponential regression model to predict leakage current obtained an R^2 of 0.606, 0.633, and 0.678 for the ceramic, hybrid and polymeric insulator for 28-day recordings, respectively (Pinotti and Meyer, 2017). Linear multivariate regression (MVR) has also been proposed to predict insulator leakage current, obtaining an R^2 ranging from 0.674 to 0.938 in short-term-recordings (<3 months) (Ahmad et al., 2003; Castillo-Sierra et al., 2018).

Recent studies have proposed using more advanced processing techniques to model the complex non-linear interaction of leakage current with environmental data. A neural network was proposed to predict leakage current in both exposed ceramic (Khafaf and El-Hag, 2018) and silicone rubber insulators (Jahromi et al., 2006; Khafaf and El-Hag, 2018) to salt-fog (laboratory data). Ghiasi et al. used ANN to predict the leakage current of polymeric insulators from laboratory data under non-uniform fan-shaped contamination, achieving an error of 5% (Ghiasi et al., 2022). Bahramiazar and Oskuoee proposed using artificial neural networks (ANN) for 20-h recordings, obtaining an R^2 of 0.98 (Bahramiazar and Oskuoee, 2014). Multilayer feedforward neural networks were used to predict insulator leakage current in short-term recordings, obtaining an average absolute error of 9.11% for testing data (Kazemi et al., 2008). The backpropagation neural network was also proposed to predict insulators leakage current with partial success (Gao et al., 2018a). Their models were only able to fit the measured data well for large leakage currents, while there was a significant deviation between the prediction and the measured data for small leakage currents (Gao et al., 2018a). By contrast, Xia et al. suggested that the exponential model performed better than ANN to estimate leakage current of polluted insulators from laboratory data with a variable composition of equivalent salt deposit density (ESDD) and non-soluble deposit density (Xia et al., 2012). Other authors used the support vector machine (SVM) to classify categorical levels of insulator leakage current, reaching an accuracy of 87% (Cho and Lin, 2015).

To sum up, the different models for predicting ILC from environmental data based on MVR, ANN and SVM have achieved only a limited success, obtaining good results for short-term recordings with a low generalization capability to new incoming data ‘never’ seen by the model. To date, no evidence has been found of the feasibility of predicting leakage current in electrical insulators during normal operations in long-term recordings.

Deep learning, and especially convolutional neural networks (CNN), have obtained very promising results in facial recognition (Lu et al., 2020), image classification (Wang et al., 2019), handwriting text recognition (Bora et al., 2020), natural language processing (Zhang, 2021) and biomedical engineering (Alaskar, 2018). It is the latest achievement of the machine learning age and initially performed similarly to human and even superhuman abilities in many applications (Kiranyaz et al., 2021). CNN is a multilayer learning architecture that can automatically extract the relevant characteristics using cascading convolutional and pooling layers with minimal human interaction or expert knowledge, and then feeds them to multiple fully-connected layers in a daisy-chain mode to solve the classification task (Li et al., 2020). CNN was originally proposed for image classification, which was also called two-dimensional CNN (2D-CNN). A modified version of 2D-CNN has been developed to process one-dimensional input data (text or time series data), namely 1D-CNN, for both classification and regression tasks (Abdeljaber et al., 2017; Avci et al., 2017; Ince et al., 2016; Kiranyaz et al., 2019, 2016). The main difference lies in that the kernel convolution only moves in the time dimension, which forces the kernel size to match the number of input time series. To date, 1D-CNN has obtained promising results in different applications, including: automatic speech recognition (Abdel-Hamid et al., 2014), vibration-based structural damage detection in civil infrastructures (Yu et al., 2018) and biomedical engineering (Kiranyaz et al., 2016).

In this work, we aimed to develop robust and accurate models for high-voltage ILC prediction based on environmental data during normal operations to create a new on-line early-warning system that anticipates possible negative weather consequences and/or pollution deposits, among others. For the first time we introduced the inception 1D-CNN to accurately predict electrical insulator leakage current using environmental data during its normal operation, and showed that it outperformed MVR and support vector regression (SVR). We also reported for the first time that the past environmental data also contain relevant information for predicting ILC. We designed and validated our model using 30-month long-term recordings from both porcelain insulators with and without coating, as well as silicone composite insulators located in a specific outdoor substation to achieve robust and generalizable models. The proposed method can be easily adapted to other insulators or substations, since it only involves recordings of environmental data that can be obtained from conventional weather stations (temperature, relative humidity, wind direction and speed), with no need to measure the pollution index, rainfall and ultraviolet radiation or other factors.

2. Materials and methods

2.1. Data acquisition

Since the accumulation of pollution deposits on insulator surfaces under natural conditions is a long-term process and can vary from

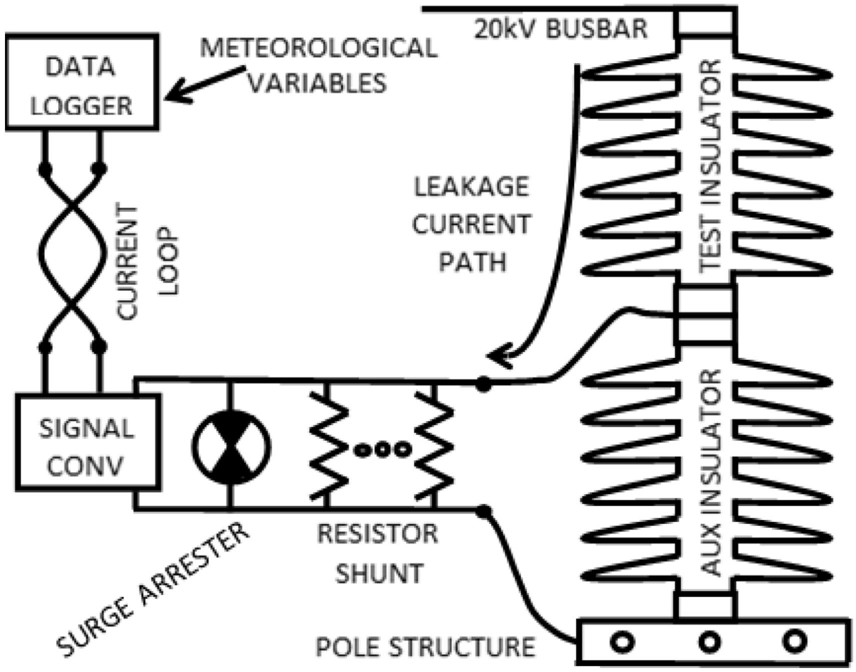

Fig. 1. Diagram block of the experimental setup.

months to years (CIGRE, 2008), we used 30-month long-term recordings to cover all the relevant stages of pollution deposits as well as the effect of natural self-washing by rain. We measured both the surface and capacitive components of the leakage current of the seven insulators connected to the same phase of a 20 kV busbar during normal operations using the experimental setup shown in Fig. 1. The auxiliary insulator on the pole structure was used to restrain the leakage current to the measurement system. The leakage current flowed into the measurement system through an insulator copper cable connected to a plate with shunt resistors, this latter being protected from possible short-circuit currents to the ground by a surge arrester. The shunt resistors were configured to measure leakage current from 600 μA to 4000 μA. A 4–20 mA current loop circuit connected to the input of a CR1000× commercial data logger specially designed for extreme outdoor conditions (Campbell Scientific Company) was used to process the voltage at the shunt resistor terminals. A CR Basic programming language software was designed to continuously compute the root-mean-square of leakage current every 250 ms. We stored the average value of the signal in 5-min windows on a microSD card.

We also simultaneously recorded the environmental data (temperature, relative humidity, wind direction and speed) with the leakage current in the seven insulators, with a sampling rate of one sample every 5 min by means of a METSENS600 meteorological station integrated with a Campbell Scientific data logger through an SDI-12 port for environmental data monitoring.

Table 1 shows the main characteristics of the insulators installed in a test panel in an outdoor substation on the Mediterranean coast with a high level of saline contamination. Specifically, we compared the insulator leakage current and its predictability from environmental data in: 1 porcelain insulator without coating, 5 porcelain insulators with room temperature vulcanization (RTV) silicone rubber coating and 1 silicone composite insulator. RTV coatings are usually used in applications in polluted environments to improve the insulator performance and increase its lifespan and power reliability (Jamaludin et al., 2017) due to their good dielectric properties and flexibility over a wide temperature range, combined with excellent resistance to ultraviolet, chemicals, thermal degradation and corona discharge (Aschwanden et al., 2020).

The RTV coatings used in this work are made up of a silicone base, fillers and pigments, to which we added volatile elements with a proportion ranging from 25% to 65% (according to the manufacturer). To avoid possible damage of the coating during transport, we conducted the vulcanizing process in-situ by spraying the material on the clean insulator surface using paint guns to achieve a layer thickness of between 450 and 500 μm. Likewise, The vulcanizing process was carried out at an environmental temperature between 10 °C and 40 °C, with a relative humidity less than 80% and the temperature of the insulator surface was at least 3 °C higher than the dew temperature.

2.2. Data analysis

2.2.1. Cause–effect analysis using conditional Granger causality

The instantaneous relationship between ILC and environmental data based on correlation analysis such as temperature, humidity, wind direction and wind speed has been widely described (Amin et al., 2009; Amin and Salman, 2006; Bueno-Barrachina et al., 2021; Hussain et al., 2017; Schindelholz and Kelly, 2012; Waluyo et al., 2021), although to date there has been no study on whether past values of environmental data provide relevant information for predicting leakage current. Physically, this phenomenon could be related to the delayed effect of moisture absorption and drying of the insulator surface (Wang et al., 2017; Zhang et al., 2013). For this, we analysed the cause–effect relationship of the environmental data with the leakage current recorded from each insulator using conditional Granger causality (Barnett and Seth, 2014). This latter can be interpreted as the degree to which the past of Y (for example temperature) helps to predict X (leakage current), beyond the degree to which X is already predicted by its own past and the past of the conditioned variable Z (humidity, wind direction and speed). Conditional Granger causality can be used to detect the real interaction between each environmental data and leakage current avoiding false causality due to the underlying 'hidden' interaction between the different environmental data (Waluyo et al., 2021). A vector autoregressive (VAR) model was first carried out on each insulator for the prediction of leakage current based on the previous P (model order) samples of its own information and the controlled variables from the past. Another VAR model was then built including the past information of the variable Y under analysis (Barnett and Seth, 2014). The conditional Granger causality is thus defined as the natural

Table 1
Characteristic of the tested insulators.

Insulator number	Insulator base material	Insulator coating
1	Porcelain	A type (Medium silicone proportion + filler) manufacture 1
2	Porcelain	B type (High silicone proportion + filler)
3	Porcelain	Without coating
4	Porcelain	C type (Medium silicone proportion + filler) manufacture 2
5	Porcelain	D type (Medium silicone proportion + filler) manufacture 3
6	Porcelain	E type (Medium silicone proportion + filler) manufacture 4
7	Silicone composite	–

logarithm of the covariance matrix of the residual errors of both models (Barnett and Seth, 2014).

The order of the VAR model contains information on the temporal dependence of the data and could be used to determine the number of environmental data in the previous sample to predict ILC. In this work, we used the commonly used Bayesian Information Criterion (BIC) to determine the optimal VAR model order to achieve a compromise between model precision and complexity, thus avoiding the overfitting of a finite data sequence (Barnett and Seth, 2014). Since the optimal order of the VAR models may change for different insulators, we used the average optimal P order of the 7 insulators (P previous samples) to further develop leakage current prediction models. We also analyzed the statistical significance of the estimated conditional Granger causality to determine whether each of the environmental data contains relevant information to predict leakage current (Barnett and Seth, 2014).

2.2.2. Prediction of leakage current based on environmental data

To avoid overfitting the model and obtain a robust and generalizable model for the new incoming data, we randomly divided the total database into three datasets by the holdout technique: training (70%), validation (15%) and test (15%). We used the training and validation datasets to develop the model by optimizing the hyperparameters of the algorithm, and the test dataset was used to determine the real generalization capability for the new incoming data never seen by the model. To minimize bias due to the randomness of the holdout technique, we conducted the holdout techniques 10 times, thus generating 10 folders to determine the average performance and its variability. It should be noted that all the models were developed and evaluated with the same folders, so that the differences in model performance are due exclusively to the prediction models and not to random data partition.

As mentioned previously, moisture absorption and drying may have a delayed effect on the leakage current (Wang et al., 2017; Zhang et al., 2013). We compared the model performances using only the current samples of environmental data or the last P + 1 samples (previous P + current sample) as input features.

2.2.2.1. Multivariate regression. We carried out a global linear MVR model on the insulators to predict the leakage current from environmental data: temperature, relative humidity, wind direction and speed. Since MVR only admits one-dimensional input features, we reshaped the last P + 1 samples of the 4 environmental data into a feature vector of dimension $1 \times (4 \cdot \mathrm{P} + 4)$. Since there is no need to adjust the hyperparameters in the model, we worked out each feature's weight using the training data, and then applied it to the validation and test datasets to determine the model's performance.

2.2.2.2. Support vector regression. Since the interaction between the environmental data and the leakage current may be non-linear, we conducted a global regression model for each insulator using the support vector regression (SVR), a specific application of the support vector machine (SVM) for data regression, which consisted of transforming the input data into a higher dimension space by the kernel function, in which the data best fits a straight line, namely hyperplane (Wang et al., 2020). In other words, the largest number of samples should fall into the hyperplane or within a margin of error ϵ. We used the radial basis function kernel, since this latter is one of the most frequently used non-linear kernels.

We also carried out two SVR models for each insulator using only current samples or the last P + 1 samples reshaped into a vector feature of dimension $1 \times (4 \cdot \mathrm{P} + 4)$. The hyperparameters of the models were optimized using the 10-folder hold-out technique for training and validation datasets: the parameter γ of the kernel function, the regularization parameter C and margin of error ϵ. The performance of the model was then determined for the test datasets.

2.2.2.3. 1D-CNN. Theoretically, CNN has the advantage of merging the feature extraction processes and the classification and/or regression task into a single learning architecture, so that they can learn to optimize features during the training phase directly from the raw input (Kiranyaz et al., 2021). This property makes it ideal for our application due to the complex underlying mechanism between environmental data and leakage current for long-term recordings. Instead of standard convolutional layers, we tested a variant of the convolutional layer based on inception architecture which was introduced by the GoogLeNet, the 2014 edition winner of the large-scale visual recognition Imagenet competition (Russakovsky et al., 2015). Its main objective was to achieve high precision at a low computational cost (Szegedy et al., 2015). Szegedy et al. confirmed the possibility of developing more accurate image classifiers with even 12 times fewer parameters than the Krizhevsky's 2012 winning architecture (Krizhevsky et al., 2012). Other authors demonstrated the superiority of the inception architecture with respect to the state of the art in the field of artificial vision, obtaining a 3.5% error in the Top-5 of the validation set and a 17.3% error in Top-1 of the validation set (Szegedy et al., 2016). The basic idea of convolution is to determine both the local structure and its spatial distribution of the input data. In general, convolution with kernel $K = 1$ is used to determine the local structure of the input data (Lin et al., 2013). There are also more complex features that should take into account the neighboring information that requires convolution with a larger kernel ($K = 3$ and $K = 5$). In general, the number of complex features tend to reduce with increasingly larger regions (Szegedy et al., 2015), and can be represented sparsely in most regions (Arora et al., 2013).

We adapted the inception architecture for 1D-CNN to predict leakage current using environmental data (see Fig. 2). This consists of 3 convolutional streams in parallel in which the previous layer is common to all of them. The first stream only consisted of a simultaneous convolution with 64 filters with kernel size $K = 1$. The second stream consisted of 2 cascaded convolutional layers with kernel size $K = 1$ and $K = 3$ in the first and second layer, respectively. Again, we established the number of filter banks at 64 in both layers. We used the same padding technique to preserve the dimensionality of the feature map and the ReLU activation function. The application of $K = 1$ before $K = 3$ would considerably reduce the computational cost thanks to the dispersed data representation of the ReLU activation function. The third stream is very similar to the second, with two cascading convolutional layers of kernel size $K = 1$ and $K = 5$ in the first and second layers, respectively. The 3 streams later converge to form a single output by concatenating their outputs. In this way, both local and regional information was extracted on the same features map. We repeated the inception architecture 4 times in cascade to achieve a deeper network,

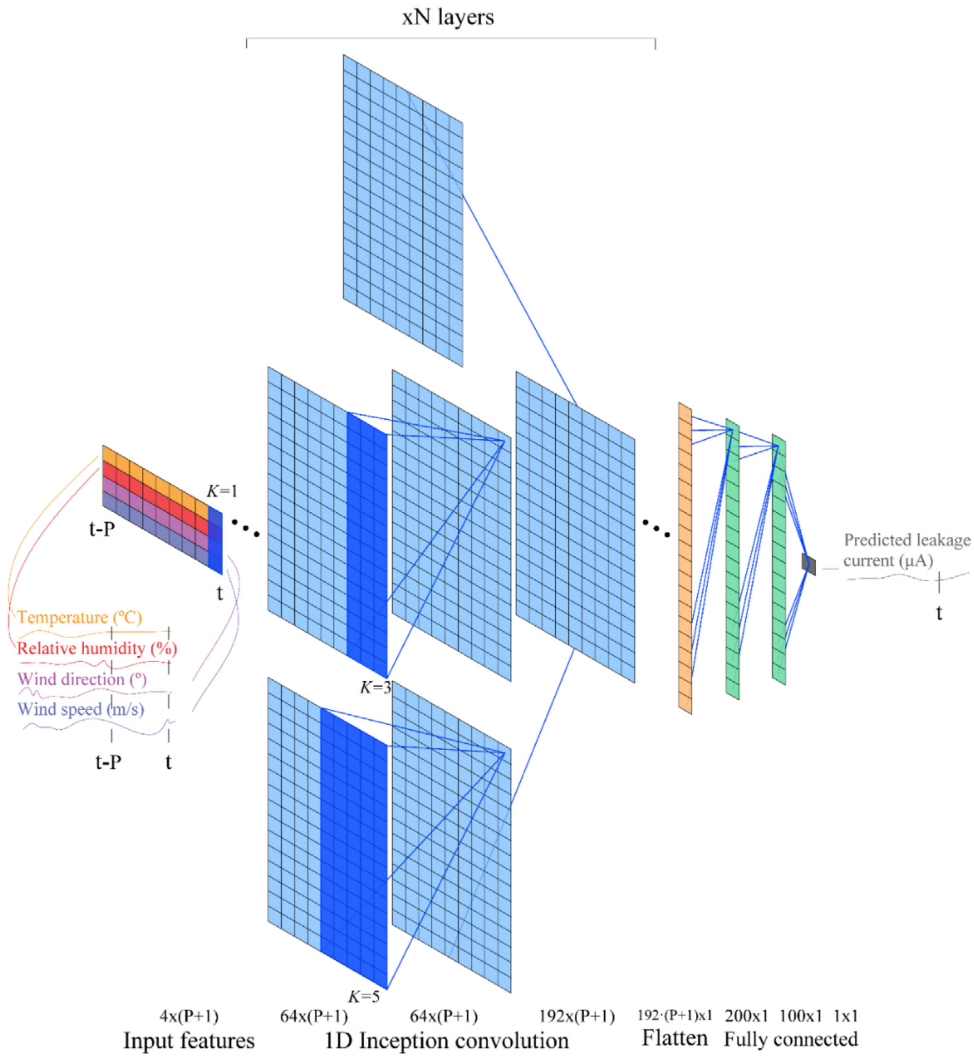

Fig. 2. Flowchart of the CNN based on N = 4 layers of Inception architecture for predicting insulator leakage current, in which the input features are the last (P + 1) samples of environmental data.

which made it possible to extract information from increasingly larger regions (distant time horizon).

The output of the last convolutional layer based on inception architecture was reshaped to a feature vector by flattening. Next, we used two fully connected layers with 200 and 100 neurons respectively as regression head, both with the ReLU activation function. Finally, the regressive output that provides the prediction of the leakage current was formed by a neuron with linear activation. It should be noted that we did not configure any pooling layers due to the low dimensionality of the input features (as shown below). Both the filter number and the number of neurons in the fully-connected layers were determined experimentally to achieve a compromise between model accuracy and computational cost. The Adam optimizer (Kingma and Ba, 2014) was used to train the model, in which the loss function is the R^2 of the regression. We used a batch size of 128 samples and the "early stopping" technique in the validation group to avoid overfitting the model. This consisted of stopping the algorithm if it failed to improve the objective function (R^2 of the validation group) in 15 successive iterations.

Analogously, we compared the model's performance based on 1D-CNN when using only current samples and the last P + 1 samples as input features. For this, we also adapted this architecture for the current sample as input features, in which the convolution with $K = 3$ and $K = 5$ should be necessarily replaced by $K = 1$.

2.2.2.4. Evaluation of model performance. Model performance was assessed by the commonly used regression metrics: coefficient of determination R^2, normalized mean square error (NRMSE). R^2 was calculated as a function of the total variation of data from the prediction outcome (also termed as sum of square residual) and the total variation of data from the mean value (total sum of squares). Since R^2 is in the range 0–1, the larger the R^2, the more accurate the prediction. By contrast, NRMSE should be as close as possible to 0% for accurate model prediction.

$$R_i^2 = 1 - \frac{\text{sum square residual}}{\text{total sum of squares(SST)}} = 1 - \frac{\sum_{k=1}^{N}\left(X_i[k] - \hat{X}_i[k]\right)^2}{\sum_{k=1}^{N}\left(X_i[k] - \overline{X}_i\right)^2} \quad (1)$$

$$NRMSE_i = \frac{\frac{1}{N}\sum_{k=1}^{N}\left(X_i[k] - \hat{X}_i[k]\right)^2}{\frac{1}{N}\sum_{k=1}^{N}\left(X_i[k]\right)^2} \cdot 100(\%) \quad (2)$$

where $\overline{X}_i = \frac{1}{N}\sum_{k=1}^{N} X_i[k], \forall i = 1\ldots7$. The annotation of $\overline{X}_i$ refers to the average value of the leakage current recorded from the insulator i, while $\hat{X}_i$ is the prediction of the leakage current for the insulator i estimated by the model.

As for the testing dataset which represents the new incoming data never seen by the model, for each insulator we conducted a comparative study between different input features (current sample vs. last P + 1 samples) using the Wilcoxon signed rank test ($\alpha = 0.05$). We also compared the model's achieved performance using different regression

Table 2
Conditional Granger causality of environmental data with leakage current of each insulator and the optimal order of the VAR model. Statistically significant causality is shaded in grey.

Insulator	Optimal order	Temperature	Humidity	Wind direction	Wind speed
1	19	0.0032	0.0189	0.0003	0.0005
2	17	0.0032	0.0160	0.0002	0.0005
3	18	0.0022	0.0146	0.0002	0.0014
4	21	0.0015	0.0056	0.0001	0.0004
5	31	0.0014	0.0048	0.0002	0.0006
6	17	0.0018	0.0083	0.0001	0.0003
7	20	0.0006	0.0036	0.0001	0.0004
Total	20.4±4.9	0.002±0.001	0.0103±0.006	0.0002±0.0001	0.0006±0.0004

techniques when using the current and the last P + 1 samples by the Friedman test ($\alpha = 0.05$) for the 7 insulators. If so, we used the Wilcoxon signed rank test to determine the significant difference between each pair of techniques ($\alpha = 0.05$).

3. Results

Table 2 shows the degree of interaction between each environmental data item and the leakage current recorded from each insulator, controlling the other environmental data by conditional Granger causality. The causality between the different environmental data and the leakage current is statistically significant for all the insulators, except for wind direction, which only obtained statistical significance for insulators 1–3 and 5. Humidity also obtained a higher Granger causality than wind speed, followed by temperature and wind direction. The optimal order of the VAR models varied from 17 for insulator 2 to 31 for insulator 5, with the average optimal order 20. In addition to current samples, we therefore also used the last 21 samples (20 previous+current sample) of the environmental data for predicting the ILC.

Table 3 gives the performance of the test dataset of the different leakage current prediction models based on MVR, SVR and 1D-CNN, respectively. Fig. 3 shows the box and whisker plot of different leakage current prediction model performance for the test dataset of the 7 insulators. In general, a higher R^2 value is associated with lower NRMSE. Model performance variability between partitions was low. When the current samples were used as input features, the prediction model performance obtained by MVR was relatively low, the average R^2 of the 7 isolators being about 0.40 ± 0.13 and the average NRMSE 18.20 ± 9.08%. Insulators 1 and 2 achieved the best results, obtaining an average R^2 of 0.55 and NRMSE of less than 10%. Insulator 6 performed slightly worse (R^2: 0.46 ± 0.01). For insulators 3–5, the average R^2 varied from 0.30 to 0.40 and the average NRMSE oscillated between 20–31%. The worst performance of the model was obtained for insulator 7 with an average R^2 of 0.22. When using the last 21 samples as input features, the MVR-based prediction models obtained better statistically significant results, regardless of the insulator. The average R^2 of the 7 insulators was 0.42 ± 0.13 and the average NRMSE was 17.45 ± 8.63%, which indicated that the MVR-based models could not accurately predict ILC. Again, insulator 7 performed worst (R^2: 0.23 ± 0.01) and the best results were obtained for insulators 1 and 2. These results suggest that the relationship between environmental data and ILC is non-linear in nature. There was also great variability between different insulators in the predictability of the leakage current from environmental data.

The problem is partially mitigated by the SVR technique, which obtained substantially better results, with an average R^2 of 0.70 ± 0.13. In general, using the last 21 samples as input features obtained practically the same results as the current samples, with no significant differences between them. We also found a large difference in the leakage current predictability for the different insulators (R^2 of insulator 1, 2 > 6 > 3–5 > 7). Again, the worst performance was obtained by insulator 7 (R^2 < 0.50 and NRMSE > 16%) and the best results were obtained by insulator 1 (R^2~0.85 and NRMSE~3.30%). Statistical analysis indicated that the SVR model performed significantly better than the MVR, obtaining significantly higher R^2 and lower NRMSE. Even though SVR improved the performance of the leakage current prediction model based on environmental data, it did not reduce the variability between the different insulators.

The performance of the 1D-CNN-based model using only current samples was moderately good. The average R^2 was 0.68 ± 0.14 for the test dataset, which was significantly inferior to that of the SVR model. Similarly, the best results were obtained in insulators 1 and 2 (R^2: 0.83 ± 0.01 and 0.80 ± 0.01 respectively), and insulator 7 performed worst (R^2: 0.43 ± 0.03). By contrast, the performance of the model improved considerably when using the last 21 samples as input features, this difference being statistically significant. The average R^2 was 0.94 ± 0.03 and the average NRMSE was 1.71 ± 1.22%. Similarly, insulators 1 and 2 performed best ($R^2 = 0.98 \pm 0.00$), although the other porcelain insulators (3–6) also obtained excellent performances (R^2 > 0.92). Insulator 7 again performed worst, obtaining an average R^2 of 0.88 ± 0.02, which was still quite accurate. The 1D-CNN model with the last 21 samples performed significantly better than other regression techniques such as MVR, SVR, achieving significantly higher R^2 and lower NRMSE.

Fig. 4 show the scatter plot of the leakage current prediction based on 1D-CNN using the last 21 samples versus target leakage current. Regardless of the insulator, the data cloud was located close to the 45° reference straight red line, with an almost random distribution around it. The model tends to underestimate only the case of abnormal leakage current peaks due to extreme adverse environmental conditions such as rain and frost. Again, these results confirmed the model's goodness for predicting leakage current from environmental data.

Trace (A) of Fig. 5 shows the time evolution of the leakage current recorded from a silicone composite insulator (n° 7) and its prediction by the 1D-CNN using the last 21 samples. Trace (B) shows the time evolution of the prediction error. Traces (C) and (D) show the same figure for 3-month recordings in summer and in winter, respectively. In general, the model reliably reproduces the leakage current regardless of the time of year, except for the presence of anomalous current peaks. Specifically, the percentile 99% of the absolute prediction error was 6.9 μA. These results reaffirmed the model's goodness for predicting leakage current from environmental data.

4. Discussion

4.1. Past environmental data for predicting ILC

In this work, we aimed to develop robust and accurate leakage current prediction models from environmental data during the normal operation of electrical insulators. Our results suggested that in addition to the current environmental data, their past (20 previous samples, equivalent to 100 min) also contained relevant information to predict ILC. We believe that this is to some extent related to the delayed effect of moisture absorption on the insulator surface. Previous lab studies determined that moisture absorption time increases with the concentration of soluble substances and varies between 5–30 min,

Table 3
Mean and standard deviation of the leakage current prediction model's performance for test dataset. Statistically significant differences when using current and the last 21 samples are shaded in grey.

Insulator n°	MVR				SVR				1D-CNN			
	Current sample		Last 21 samples		Current sample		Last 21 samples		Current sample		Last 21 samples	
	R^2	NRMSE (%)	R^2	NRMSE (%)	R^2	NRMSE (%)	R^2	NRMSE (%)	R^2	NRMSE (%)	R^2	NRMSE (%)
1	0.55±0.01	9.69±0.21	0.58±0.01	9.04±0.20	0.85±0.00	3.34±0.13	0.85±0.01	3.30±0.15	0.83±0.01	3.74±0.28	0.98±0.00	0.51±0.07
2	0.55±0.00	7.15±0.11	0.57±0.00	6.85±0.11	0.81±0.00	2.94±0.09	0.81±0.01	2.97±0.10	0.80±0.01	3.08±0.17	0.98±0.00	0.37±0.06
3	0.37±0.00	30.97±0.23	0.42±0.00	28.59±0.26	0.70±0.01	14.65±0.37	0.73±0.00	13.14±0.24	0.71±0.01	14.21±0.32	0.97±0.01	1.53±0.32
4	0.35±0.02	20.10±1.22	0.37±0.02	19.51±1.23	0.63±0.07	11.56±2.36	0.63±0.03	11.40±1.20	0.61±0.03	12.01±1.24	0.93±0.02	2.25±0.73
5	0.31±0.02	23.98±1.63	0.33±0.02	23.37±1.64	0.66±0.04	11.94±1.90	0.66±0.03	11.93±1.37	0.63±0.04	12.94±1.76	0.92±0.02	2.75±0.86
6	0.46±0.01	10.69±0.42	0.47±0.01	10.33±0.42	0.75±0.01	4.86±0.26	0.74±0.01	5.02±0.32	0.73±0.02	5.42±0.36	0.95±0.01	0.92±0.17
7	0.22±0.01	24.80±1.31	0.23±0.01	24.48±1.30	0.49±0.06	16.04±1.68	0.45±0.07	17.37±2.51	0.43±0.03	18.05±1.74	0.88±0.02	3.64±0.84
Total	0.40±0.13	18.20±9.08	0.42±0.13	17.45±8.63	0.70±0.12	9.33±5.50	0.70±0.13	9.30±5.56	0.68±0.14	9.92±5.82	0.94±0.03	1.71±1.22

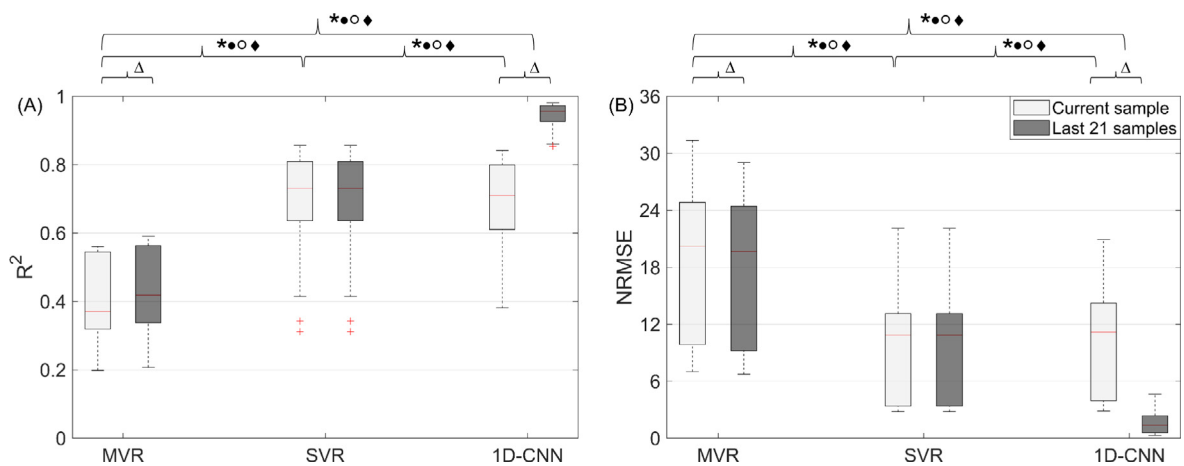

Fig. 3. Box and whisker plot of different leakage current prediction model performance for test dataset of the 7 insulators. *•∘♦ indicates statistical significance between different regression techniques when using current samples and the last 21 samples, respectively. Δ indicates statistical significance between using current samples and the last 21 samples for each technique.

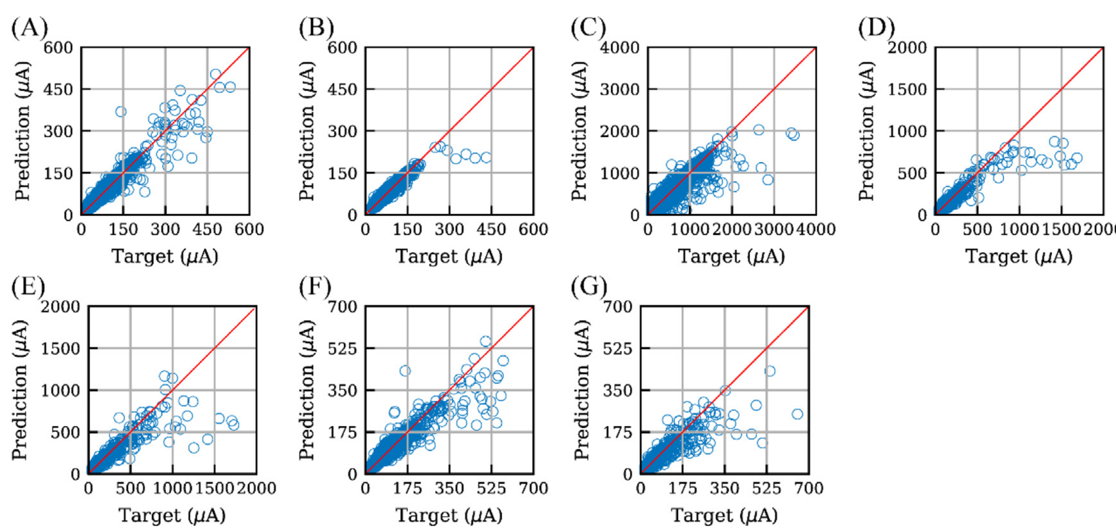

Fig. 4. Scatter plot of leakage current prediction based on 1D-CNN using the last 21 samples vs. target leakage current. Red line is the reference straight line if the model predicts the exact leakage current. (A) Insulator 1. (B) Insulator 2. (C) Insulator 3. (D) Insulator 4. (E) Insulator 5. (F) Insulator 6. (G) Insulator 7.

according to Zhang et al. (2013). Temperature also plays an important role in the moistening process (Dai et al., 2011; Zhang et al., 2013). Zhang et al. found that moisture absorption time increases at higher temperatures (Zhang et al., 2013). The difference between the insulator temperature and the environmental dew point greatly influences the leakage current magnitude (Dai et al., 2011). In this regard, the insulator temperature may depend mainly on the past air temperature due to thermal inertia. The environmental dew point depends on current information of ambient temperature and humidity. This could explain why including past environmental data improves the performance of the leakage current prediction model. Wang et al. found that the water absorption of the pollution deposits is directly proportional to the temperature difference between the environment and the insulator at medium humidity levels (60%–75%) (Wang et al., 2017). In addition, the amount of water absorbed achieved its maximum value after 1 h for a 25 °C ambient temperature and 70% humidity (Wang et al., 2017). The difference in moisture absorption time is probably due to the test conditions in the cited works. Long-term recordings may show a complex interaction between temperature, humidity, wind direction and speed and the indeterminate and variable composition of pollution deposits (De Santos and Sanz Bobi, 2020), which could lead to an even longer absorption time. In the present work we did not measure the moisture absorption time itself but determined the temporal structure of the data using the VAR model.

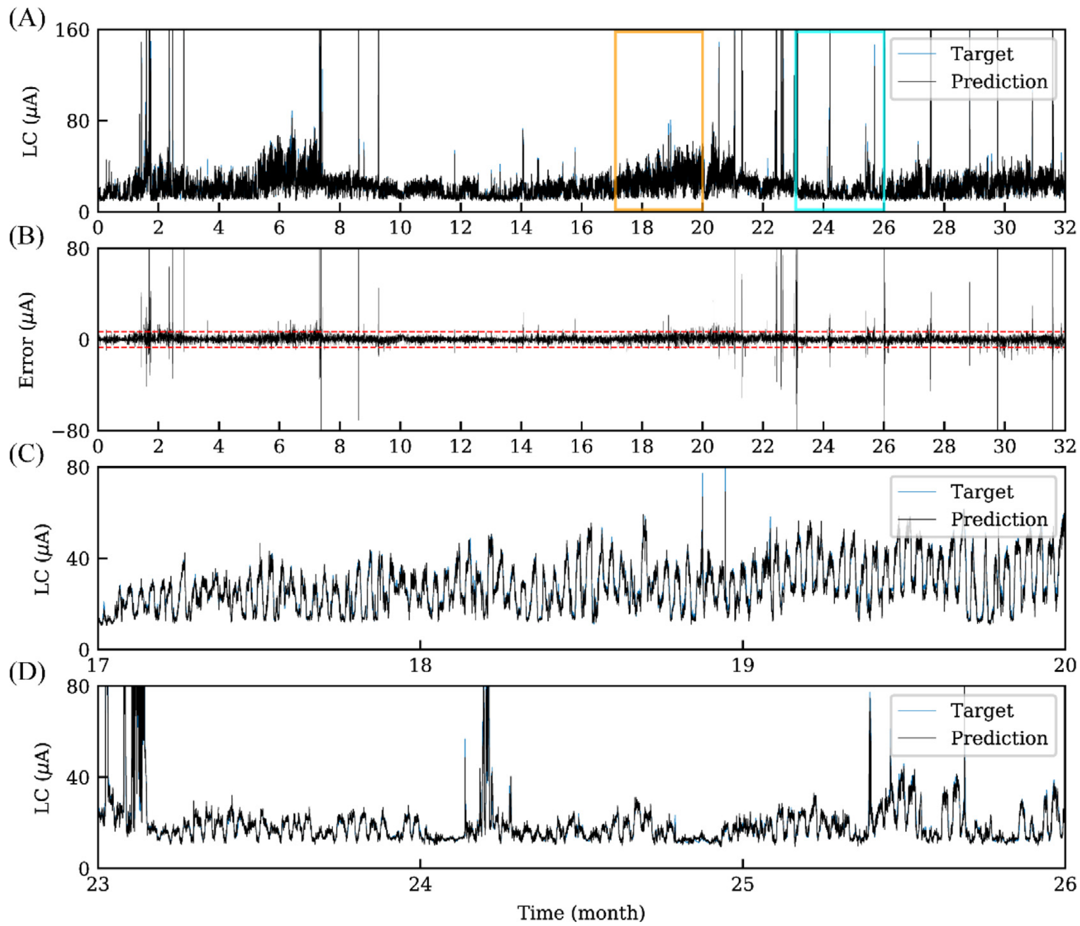

Fig. 5. (A) Time evolution of raw leakage current recorded on silicone composite insulator n°7 and its prediction by the 1D-CNN model using the last 21 samples of environmental data as input features. (B) Prediction error. Red horizontal line indicates the thresholds of 6.9 μA, which consisted of the percentile 99% of absolute prediction error. (C) Detail of temporal evolution of leakage current prediction for months 17–20, which is the orange rectangle in trace (A). (D) Detail of temporal evolution of leakage current prediction for month 23–26, which is the cyan rectangle in trace (A).

4.2. Influence of insulator type on leakage current prediction

Regardless of the regression technique, we found a certain difference in the predictability of the leakage current from the environmental data. Porcelain insulators 1 and 2 with an RTV coating showed similar performances and usually gave better results than insulator 3 (porcelain without coating) and 6 (porcelain with RTV coating), and this in turn performed better than insulators 4 and 5 (porcelain with RTV coating). Insulator 7 (silicone composite), in which the lowest leakage current was recorded, obtained the worst leakage current prediction performance. The worse predictability of silicone composite insulators could be mainly due to their increased accumulation of pollution deposits and their complex wetting process. Previous studies determined that porcelain insulators have a better self-wash ability during heavy rains than silicone insulators (Chrzan and Zipp, 2020), obtaining three times lower ESDD values (Chrzan, 2010; Naito et al., 2020). The pollution deposits on silicone insulator surfaces also cause hydrophobicity degradation (Arshad et al., 2016; Kumagai and Yoshimura, 2004). In fact, silicone insulators showed a longer absorption time and a lower temperature influence on the moisture absorption process than porcelain (Zhang et al., 2013). Sunlight ultraviolet radiation and heat exposure also play an important role in the degradation of the silicone insulator surface (Arshad et al., 2016), which can vary the wetting process over time. By contrast, despite the fact that insulator 3 with no coating presented the highest leakage current, the wetting process of this type of insulator seems to be less complex, since water deposition on the surface was uniform, forming a water film due to the hydrophilicity of the material. In addition, porcelain insulators were not influenced by ultraviolet sunlight radiation and heat exposure (Gençoğlu, 2007), so that the influence of environmental data on the leakage current is relatively less complex. As for RTV coated porcelain insulators, their wetting process may be highly dependent on the surface treatment, which determines the repellence of pollution deposits and the hydrophobicity of the surface.

4.3. Leakage current prediction using environmental data

In this work, we implemented and compared 3 regression techniques for ILC prediction: MVR, SVR and 1D-CNN. We found that MVR fitted relatively well for short-term recordings of each week (results not shown). However, the regression coefficients of the model showed significant fluctuation and had to be dynamically adjusted with the measured data every short period of time, which is in agreement with other authors (Vosloo and Holtzhausen, 2002; Zhao et al., 2011). For long-term recordings, the MVR technique performed rather poorly, with an average R^2~0.40, which was considerably lower than the results obtained by other authors who obtained an R^2 above 0.60 for short-term recordings (Ahmad et al., 2003; Castillo-Sierra et al., 2018; Vosloo and Holtzhausen, 2002; Zhao et al., 2011). These results suggest that the interaction of the different environmental variables and the leakage current were dynamic with large fluctuations over time, giving rise to a much more complex data structure than a linear relationship, so that the MVR technique obtained a relatively poor performance.

Thanks to the non-linear transformation using the radial basis function kernel, SVR models performed significantly better than MVR. We believe that the ANN would have obtained similar results. Our result was much lower than that obtained by Bahramiazar and Oskuoee for short term recordings (R^2 of 0.98) (Bahramiazar and Oskuoee, 2014). The mean absolute error normalized with respect to the leakage current itself was of the order of 18% (our result not shown), which was higher than the 9.11% obtained by Kazemi et al. over a record of 60 days (Kazemi et al., 2008). Again, we believe that the poorer performance of our SVR model was due to its greater data structure complexity when using a long-term recording, and our result more closely reflects the model's generalizability. Short-term recordings tend to overestimate model performance since they do not have representative data that reflects the underlying leakage current mechanism. Indeed, Gao et al. suggested the difficulty of developing a valid global model for large and small leakage currents (Gao et al., 2018a). It should be noted that using the last 21 samples as input features of the SVR model did not improve the performance of the test dataset, suggesting that it is necessary to pre-process the last 21 samples of the environmental data to extract the relevant information to predict leakage current.

We found that 1D-CNN using current samples as input features obtained similar results to SVR. In this specific case, since it was restricted to using kernel size K = 1, the inception architecture could not extract information on different time scales and therefore did not provide any advantage over SVR. We believe that standard convolution layers with deeper architecture would obtain similar results when using only current sample as input features. By contrast, when using the last 21 samples as input features, 1D-CNN performed significantly better than SVR and MVR, which was equally valid for the different insulator types: porcelain with or without coatings or composite silicone. Our results revealed the importance of extracting both local and regional information through the inception architecture (Szegedy et al., 2015). The inception architecture was used to extract both local ($K = 1$) and regional ($K = 3\ y\ K = 5$) information to determine the interaction of the environmental data between K time instants (Szegedy et al., 2015). The combination of local and regional information on the same feature map can determine their underlying relationship. The successive application of inception architecture makes it possible to extract information from increasingly larger regions, where the extracted features can be hierarchically and progressively more complex (Szegedy et al., 2015). Inception architecture convolution layers can automatically capture the dynamic interaction between environmental data and leakage current without human interaction or expert knowledge (Li et al., 2020), achieving an average R^2 of 0.94 ± 0.03 for a test dataset.

The performance of our 1D-CNN model using the last 21 samples was much better than the different leakage current prediction models developed in the literature (Ahmad et al., 2003; Castillo-Sierra et al., 2018; Cho and Lin, 2015; Gao et al., 2018a; Kazemi et al., 2008; Pinotti and Meyer, 2017; Vosloo and Holtzhausen, 2002; Zhao et al., 2011). Compared with the leakage current prediction method proposed by De Santos and Sanz Bobi, which achieved an R^2 above 0.85 for uncovered, half-silicone covered and fully-silicone covered insulators, our model offered a similar performance (De Santos and Sanz Bobi, 2020). However, our technique also has a number of advantages: first, De Santos and Sanz Bobi estimated the cumulative pollution index taking into account both the pollution index with the additional measure of directional dust deposition and the washing coefficient, ESDD measurement being necessary together with the leakage current. As the mathematical model parameters must be experimentally configured for each electrical insulator in-situ, they are not easily adaptable to other substations since the underlying mechanism between these factors does not necessarily respond to the same mathematical model. Furthermore, the reference insulators for measuring ESDD were not energized, which was not an accurate ESDD measure of the electrical insulators in which they were used to record the leakage current, since pollution does not deposit in the same way on energized and non-energized insulators (Vosloo, 2002). Our 1D-CNN model using the last 21 samples is not only accurate in predicting leakage current in different types of electrical insulator, but can also be implemented in real-time applications on mobile devices (Abdeljaber et al., 2017; Avci et al., 2018; Kiranyaz et al., 2019) thanks to its lower computational cost. In addition, we believe that our method can also be easily adapted for predicting insulator flashover, which still remains a challenge in the scientific-technical community (Arshad et al., 2020; Narmadhai and Jeyakumar, 2011; Salem et al., 2021; Samakosh and Mirzaie, 2020; Zhu et al., 2021). Also, long-term recording has representative data of the underlying mechanism between the different environmental data and the leakage current of the in-situ installation, including seasonal fluctuations and therefore our model has high leakage current generalizability of the same insulators in the same substation at a later time. Thanks to the self-learning ability of CNN to learn the relevant features, the model is easily adaptable to other electrical insulators and/or other substations. Starting from a trained CNN model, transfer learning can also be used to develop the leakage current prediction models of other electrical insulators and/or substations by transferring knowledge contained in a different but related source domain (our model) to the domain of interest (other insulators and/ or substations) (Zhuang et al., 2019). Transfer learning requires far fewer samples for its training (Zhuang et al., 2019).

4.4. Limitation and future works

Despite the promising results, this work is not without its limitations. First, since we used recordings conducted on new insulators during the first two years, which have been shown to have an average useful life of around 24 years (Amin and Amin, 2014; Ghosh and Khastgir, 2018), insulator aging was not considered in our model. Even so, we believe that our model can be implemented in practice to improve electrical insulator maintenance. It could be used to anticipate the negative consequences of the weather and/or pollution deposits in the short and medium term, when the effect of aging on the leakage current is irrelevant, potentially constituting a new engineering tool for designing a strategic preventive maintenance plan for high voltage electrical insulators. It can also be used to determine the discrepancy between the predicted leakage current and the data measured in situ. A large discrepancy between these may indicate some anomalies: abnormally high pollution deposits, insulator aging and/or presence of surface damage, in which case an installation stop can be programmed for cleaning. Increasing the frequency of installation stops would be related to the material's aging effect, suggesting its replacement. As simultaneous recording of the insulator surface temperature by cameras may help to identify surface damage (Darwison et al., 2019), it would thus be useful to include a thermal camera to measure insulator surface temperature in future applications. Our model also tends to underestimate leakage current peaks due to rain or other phenomena. We believe that a more accurate leakage current prediction model can be obtained by including additional information, such as precipitation (Ahmad et al., 2000; Cho and Lin, 2015; Gao et al., 2018a; Pinotti and Meyer, 2017), ultraviolet radiation (Abdullah et al., 2020; Amin et al., 2009; Bahramiazar and Oskuoee, 2014; Vosloo and Holtzhausen, 2002), environmental pressure (Abdullah et al., 2020), images of spark discharge (Thanh et al., 2021), insulator creepage distance (Abdullah et al., 2020) and insulator surface temperature by thermal cameras (Darwison et al., 2019), among others. Regardless of this, to the authors' knowledge, this is the first time that an accurate leakage current prediction model has been successfully achieved using only 4 environmental data items for 30-month long-term recordings during normal insulator operation. The method can also be easily transferred to other insulators and/or other substations.

5. Conclusions

The experimental results showed that the last 21 samples of environmental data contained relevant information for predicting ILC, although including their past raw information does not necessarily improve prediction performance. The pre-processing of input features was an indispensable step in capturing the data's temporal structure to describe the complex underlying dynamic mechanism between the environmental data and ILC. This was achieved by simultaneously extracting increasingly larger local and regional information through the successive application of the inception architecture.

The 1D-CNN model based on inception architecture using the last 21 samples of environmental data as input features performed much better than SVR and MVR, achieving an average R^2 of 0.94 ± 0.03 and NRMSE of 1.71 ± 1.22%. Our model could be used for precise prediction of leakage current on porcelain insulators with or without coating and silicone composite insulators during normal operations in which the wetting of surface pollution deposits is much more complex. Our results pave the way for developing an on-line early-warning system to anticipate negative weather consequences and/or pollution deposits. This system will potentially constitute an engineering tool for designing an effective strategy for preventive maintenance of high-voltage electrical insulators and minimizing contamination flashover, responsible for unexpected power outages, thus increasing power grid reliability and resilience.

CRediT authorship contribution statement

Jose-M. Bueno-Barrachina: Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Yiyao Ye-Lin:** Conceptualization, Formal analysis, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Felix Nieto-del-Amor:** Methodology, Software, Validation, Visualization. **Vicente Fuster-Roig:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yiyao Ye Lin reports administrative support was provided by Spanish Ministry of Economy and Competitiveness.

Data availability

The data that has been used is confidential.

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References

Abdel-Hamid, O., Mohamed, A.R., Jiang, H., Deng, L., Penn, G., Yu, D., 2014. Convolutional neural networks for speech recognition. IEEE Trans. Audio Speech Lang. Process. 22, 1533–1545. http://dx.doi.org/10.1109/TASLP.2014.2339736.

Abdeljaber, O., Avci, O., Kiranyaz, S., Gabbouj, M., Inman, D.J., 2017. Real-time vibration-based structural damage detection using one-dimensional convolutional neural networks. J. Sound Vib. 388, 154–170. http://dx.doi.org/10.1016/J.JSV.2016.10.043.

Abdullah, F.S.B., Piah, M.A.M., Othman, N.A., Din, A., 2020. Prediction of surface leakage current of overhead insulators under environmental and electrical stresses. Bull. Electr. Eng. Inform. 9, 1747–1754. http://dx.doi.org/10.11591/EEI.V9I5.2182.

Ahmad, A.S., Ahmad, H., Salam, M.A., Tamsir, T., Buntat, Z., Mustafa, M.W., 2000. Prediction of salt contamination on high voltage insulators in rainy season using regression technique. In: IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON 3. http://dx.doi.org/10.1109/TENCON.2000.892247.

Ahmad, A.S., Ghosh, P.S., Aljunid, S.A.K., Ahmad, S., 2003. Estimation of leakage current level on the transformer bushing using regression technique. In: Proceedings of the 7th International Conference on Properties and Applications of Dielectric Materials (Cat. No. 03CH37417). IEEE, pp. 1174–1177. http://dx.doi.org/10.1109/ICPADM.2003.1218633.

Ahmed, R., Kim, T., Lee, Y.J., Jeon, S., Yi, J., Choi, I.H., Son, J.A., Koo, J. Bin, 2020. Online condition monitoring and leakage current effect based on local area environment. Trans. Electr. Electron. Mater. http://dx.doi.org/10.1007/s42341-020-00184-1.

Alaskar, H., 2018. Convolutional neural network application in biomedical signals. J. Comput. Sci. Inf. Technol. 6, http://dx.doi.org/10.15640/JCSIT.V6N2A5.

Alston, L.L., Zoledziowski, S., 1963. Growth of discharges on polluted insulation. Proc. Inst. Electr. Eng. 110, 1260–1266. http://dx.doi.org/10.1049/piee.1963.0176.

Amin, M., Amin, S., 2014. Aging research on sir and tpe insulators (an overview). Rev. Adv. Mater. Sci. 36, 29–39.

Amin, M., Amin, S., Ali, M., 2009. Monitoring of leakage current for composite insulators and electrical devices. Rev. Adv. Mater. Sci. 21, 75–89.

Amin, M., Salman, M., 2006. Aging of polymeric insulators (an overview). Rev. Adv. Mater. Sci. 13, 93–116.

Araya, J., Montaña, J., Schurch, R., 2021. Electric field distribution and leakage currents in glass insulator under different altitudes and pollutions conditions using FEM simulations. IEEE Lat. Am. Trans. 19, 1278–1285.

Arora, S., Bhaskara, A., Ge, R., Ma, T., 2013. Provable bounds for learning some deep representations. In: 31st Int. Conf. Mach. Learn. ICML 2014, Vol. 1. pp. 883–891.

Arshad, Ahmad, J., Tahir, A., Stewart, B.G., Nekahi, A., 2020. Forecasting flashover parameters of polymeric insulators under contaminated conditions using the machine learning technique. Energies 13, 3889. http://dx.doi.org/10.3390/EN13153889.

Arshad, Nekahi, A., McMeekin, S., Farzaneh, M., 2016. Flashover characteristics of silicone rubber sheets under various environmental conditions. Energies http://dx.doi.org/10.3390/en9090683.

Aschwanden, M.J., Shimizu, T., Wang, X., Hong, X., Wang, H., Hao, W.-.al., Zeng, H., Chen, X., Huzaimah Kamal Hamadi, S., Isa, M., Nizam Md Arshad, S., Othman, M., 2020. Review on RTV silicone rubber coatings insulator for transmission lines. IOP Conf. Ser. Mater. Sci. Eng. 864, 012188. http://dx.doi.org/10.1088/1757-899X/864/1/012188.

Avci, O., Abdeljaber, O., Kiranyaz, S., Hussein, M., Inman, D.J., 2018. Wireless and real-time structural damage detection: A novel decentralized method for wireless sensor networks. J. Sound Vib. 424, 158–172. http://dx.doi.org/10.1016/J.JSV.2018.03.008.

Avci, O., Abdeljaber, O., Kiranyaz, S., Inman, D., 2017. Structural damage detection in real time: Implementation of 1D convolutional neural networks for SHM applications. In: Conf. Proc. Soc. Exp. Mech. Ser.. pp. 49–54. http://dx.doi.org/10.1007/978-3-319-54109-9_6.

Bahramiazar, A., Oskuoee, M., 2014. Experimental study of the artificial neural network solutions for insulators leakage current modeling in a power network. Int. J. Electr. Energy 2, http://dx.doi.org/10.12720/ijoee.2.4.331-336.

Barnett, L., Seth, A.K., 2014. The MVGC multivariate Granger causality toolbox: A new approach to granger-causal inference. J. Neurosci. Methods 223, 50–68. http://dx.doi.org/10.1016/J.JNEUMETH.2013.10.018.

Bora, M.B., Daimary, D., Amitab, K., Kandar, D., 2020. Handwritten character recognition from images using CNN-ECOC. Procedia Comput. Sci. 167, 2403–2409. http://dx.doi.org/10.1016/J.PROCS.2020.03.293.

Bueno-Barrachina, J.M., Canas-Penuelas, C.S., Ye-Lin, Y., Fuster-Roig, V., 2021. Novel technique for estimating pollution-associated leakage current in high-voltage insulators based on adaptive filtering in long-term recording. Meas. Sci. Technol. 32, http://dx.doi.org/10.1088/1361-6501/ABEA3D.

Castillo Sierra, R., Oviedo-Trespalacios, O., Candelo, J.E., Soto, J.D., 2015. The influence of atmospheric conditions on the leakage current of ceramic insulators on the Colombian caribbean coast. Environ. Sci. Pollut. Res. Int. 22, 2526–2536. http://dx.doi.org/10.1007/S11356-014-3729-3.

Castillo-Sierra, R., Oviedo-Trespalacios, O., Candelo, J.E., Soto-Ortiz, J.D., 2018. Modeling leakage current of ceramic insulators subject to high pollution levels for improving maintenance activities. DYNA 85, 364–371. http://dx.doi.org/10.15446/DYNA.V85N204.61445.

Cho, M.-Y., Lin, P.-S., 2015. Using support vector machine for classifying insulator leakage current. Int. J. Electr. Comput. Sci. IJECS-IJENS 15, 30–39.

Chrzan, K.L., 2010. Leakage currents on naturally contaminated porcelain and silicone insulators. IEEE Trans. Power Deliv. 25, 904–910. http://dx.doi.org/10.1109/TPWRD.2009.2034665.

Chrzan, K.L., Zipp, M., 2020. Anomalous leakage currents on silicone rubber hollow insulators. Prz. Elektrotech. 96, 91–93. http://dx.doi.org/10.15199/48.2020.10.15.

CIGRE, 2008. CIGRE WG C4.303 Outdoor Insulation in Polluted Conditions: Guidelines for Selection and Dimensioning - Part 1: General Principles and the A.C. Case.

Dai, H., Mei, H., Liming, W., Zhicheng, G., 2011. Preliminary research of temperature effect on surface leakage current of insulators. In: XVII International Symposium on High Voltage Engineering. Hannover, Germany, pp. 1–5.

Darwison, Arief, S., Abral, H., Hazmi, A., Ahmad, M.H., Waldi, E.P., Fernandez, R., 2019. A leakage current estimation based on thermal image of polymer insulator. Indones. J. Electr. Eng. Comput. Sci. 16, 1096–1106. http://dx.doi.org/10.11591/IJEECS.V16.I3.PP1096-1106.

De Santos, H., Sanz Bobi, M.A., 2020. A cumulative pollution index for the estimation of the leakage current on insulator strings. IEEE Trans. Power Deliv. 35, 2438–2446. http://dx.doi.org/10.1109/TPWRD.2020.2968556.

Gao, S., Jia, Y., Bi, X., Cao, B., Li, X., Yang, D., Wang, L., 2018a. Prediction method of leakage current of insulators on the transmission line based on BP neural network. In: Proc. 2018 IEEE 2nd Int. Electr. Energy Conf. CIEEC 2018. pp. 569–572. http://dx.doi.org/10.1109/CIEEC.2018.8745839.

Gao, C., Liu, Y., Gao, S., Cao, B., Yang, D., Wang, L., 2018b. Research on the relationship between leakage current of on-site insulators and environmental factors. In: Proc. 2018 IEEE 2nd Int. Electr. Energy Conf. CIEEC 2018. pp. 589–592. http://dx.doi.org/10.1109/CIEEC.2018.8745724.

Gençoğlu, M.T., 2007. The comparison of ceramic and non-ceramic insulators. Eng. Sci. 2, 274–294. http://dx.doi.org/10.12739/nwsaes.v2i4.5000067211.

Gençoğlu, M.T., Cebeci, M., 2008. The pollution flashover on high voltage insulators. Electr. Power Syst. Res. 78, 1914–1921. http://dx.doi.org/10.1016/j.epsr.2008.03.019.

Ghiasi, Z., Faghihi, F., Shayegani-Akmal, A.A., 2022. Artificial neural network approach for prediction of leakage current of polymeric insulator under non-uniform fan-shaped contamination. Electr. Power Syst. Res. 209, 107920. http://dx.doi.org/10.1016/J.EPSR.2022.107920.

Ghosh, D., Khastgir, D., 2018. Degradation and stability of polymeric high-voltage insulators and prediction of their service life through environmental and accelerated aging processes. ACS Omega 3, 11317–11330. http://dx.doi.org/10.1021/acsomega.8b01560.

Gu, C., Lu, G., Yi, M., Li, J., 2016. Study on artificial contamination test of typical transmission line insulators. In: Proc. 5th IEEE Int. Conf. Electr. Util. Deregulation, Restruct. Power Technol. DRPT 2015. pp. 1624–1627. http://dx.doi.org/10.1109/DRPT.2015.7432502.

Hussain, M.M., Farokhi, S., McMeekin, S.G., Farzaneh, M., 2017. Mechanism of saline deposition and surface flashover on outdoor insulators near coastal areas part II: Impact of various environment stresses. IEEE Trans. Dielectr. Electr. Insul. 24, 1068–1076. http://dx.doi.org/10.1109/TDEI.2017.006386.

Ince, T., Kiranyaz, S., Eren, L., Askar, M., Gabbouj, M., 2016. Real-time motor fault detection by 1-D convolutional neural networks. IEEE Trans. Ind. Electron. 63, 7067–7075. http://dx.doi.org/10.1109/TIE.2016.2582729.

Jahromi, A.N., El-Hag, A.H., Jayaram, S.H., Cherney, E.A., Sanaye-Pasand, M., Mohseni, H., 2006. A neural network based method for leakage current prediction of polymeric insulators. IEEE Trans. Power Deliv. 21, 506–507. http://dx.doi.org/10.1109/TPWRD.2005.858805.

Jamaludin, F.A., Abidin Ab-Kadir, M.Z., Izadi, M., Azis, N., Jasni, J., Abd-Rahman, M.S., 2017. Effects of RTV coating on the electrical performance of polymer insulator under lightning impulse voltage condition. PLoS One 12, http://dx.doi.org/10.1371/JOURNAL.PONE.0187892.

Kazemi, A., Hassanzadeh, M.T., Gholami, A., 2008. Artificial neural network for insulator leakage currents prediction from environmental data. In: PECon 2008-2008 IEEE 2nd Int. Power Energy Conf.. pp. 13–17. http://dx.doi.org/10.1109/PECON.2008.4762434.

Khafaf, N. Al, El-Hag, A., 2018. Bayesian regularization of neural network to predict leakage current in a salt fog environment. IEEE Trans. Dielectr. Electr. Insul. 25, 686–693. http://dx.doi.org/10.1109/TDEI.2017.006936.

Kim, J.H., Song, W.C., Lee, J.H., Park, Y.K., Cho, H.G., Yoo, Y.S., Yang, K.J., 2001. Leakage current monitoring and outdoor degradation of silicone rubber. IEEE Trans. Dielectr. Electr. Insul. http://dx.doi.org/10.1109/94.971471.

Kingma, D.P., Ba, J.L., 2014. Adam: A method for stochastic optimization. In: 3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc.

Kiranyaz, S., Avci, O., Abdeljaber, O., Ince, T., Gabbouj, M., Inman, D.J., 2021. 1D convolutional neural networks and applications: A survey. Mech. Syst. Signal Process. 151, 107398. http://dx.doi.org/10.1016/J.YMSSP.2020.107398.

Kiranyaz, S., Gastli, A., Ben-Brahim, L., Al-Emadi, N., Gabbouj, M., 2019. Real-time fault detection and identification for MMC using 1-D convolutional neural networks. IEEE Trans. Ind. Electron. 66, 8760–8771. http://dx.doi.org/10.1109/TIE.2018.2833045.

Kiranyaz, S., Ince, T., Gabbouj, M., 2016. Real-time patient-specific ECG classification by 1-D convolutional neural networks. IEEE Trans. Biomed. Eng. 63, 664–675. http://dx.doi.org/10.1109/TBME.2015.2468589.

Krizhevsky, A., Sutskever, I., Hinton, G.E., 2012. ImageNet classification with deep convolutional neural networks. Adv. Neural Inf. Process. Syst. 25.

Kumagai, S., Yoshimura, N., 2004. Leakage current characterization for estimating the conditions of ceramic and polymeric insulating surfaces. IEEE Trans. Dielectr. Electr. Insul. 11, 681–690. http://dx.doi.org/10.1109/TDEI.2004.1324357.

Li, Z., Liu, F., Yang, W., Peng, S., Zhou, J., 2020. A survey of convolutional neural networks: Analysis, applications, and prospects. IEEE Trans. Neural Netw. Learn. Syst. 1–21. http://dx.doi.org/10.1109/tnnls.2021.3084827.

Li, J., Sima, W., Sun, C., Sebo, S.A., 2010. Use of leakage currents of insulators to determine the stage characteristics of the flashover process and contamination level prediction. IEEE Trans. Dielectr. Electr. Insul. 17, 490–501. http://dx.doi.org/10.1109/TDEI.2010.5448105.

Lin, M., Chen, Q., Yan, S., 2013. Network in network. In: 2nd Int. Conf. Learn. Represent. ICLR 2014 - Conf. Track Proc.

Lu, P., Song, B., Xu, L., 2020. Human face recognition based on convolutional neural network and augmented dataset. http://mc.manuscriptcentral.com/tssc 9, 29–37. http://dx.doi.org/10.1080/21642583.2020.1836526.

Matsuoka, R., Naito, K., Irie, T., Kondo, K., 2002. Evaluation methods of polymer insulators under contaminated conditions. In: IEEE/PES Transmission and Distribution Conference and Exhibition. IEEE, pp. 2197–2202. http://dx.doi.org/10.1109/TDC.2002.1177804.

Naito, K., Matsuoka, R., Irie, T., Kondo, K., 2020. Test methods and results for recent outdoor insulation in Japan. IEEE Trans. Dielectr. Electr. Insul. 6, 732–743. http://dx.doi.org/10.1109/TDEI.1999.9286747.

Narmadhai, N., Jeyakumar, A.E., 2011. Analysis of leakage current to predict insulator flashover using artificial neural network. J. Comput. Sci. 7, 167–172. http://dx.doi.org/10.3844/JCSSP.2011.167.172.

Pinotti, M.A., Meyer, L.H., 2017. Mathematical model for prediction of the leakage current on distribution insulators of 25 kV class. In: 2017 IEEE Electr. Insul. Conf. EIC 2017. pp. 256–260. http://dx.doi.org/10.1109/EIC.2017.8004689.

Rahal, A., Huraux, C., 1979. Flashover mechanism of high voltage insulators. IEEE Trans. Power Appar. Syst. PAS-98, 2223–2231. http://dx.doi.org/10.1109/TPAS.1979.319421.

Ramos, N.G., Campillo, R.M.T., Naito, K., 1993. A study on the characteristics of various conductive contaminants accumulated on high voltage insulators. IEEE Trans. Power Deliv. 8, 1842–1850. http://dx.doi.org/10.1109/61.248293.

Rodriguez, A., Nour, H., Wang, F., Dale, S.J., 1985. Effect of insulator surface temperature on the flashover voltage of outdoor insulators. In: Proc. Electr. Insul. Conf.. pp. 56–61. http://dx.doi.org/10.1109/EIC.1985.7458580.

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A.C., Fei-Fei, L., 2015. ImageNet large scale visual recognition challenge. Int. J. Comput. Vis. 115, 211–252. http://dx.doi.org/10.1007/s11263-015-0816-y.

Salam, M.A., Ang, S.P., Ong, B.T., Malik, O.A., Voon, W., Alinurrezan, M., 2013. Measurement of pollution level of 66 kv transmission line insulators. In: Annu. Rep. - Conf. Electr. Insul. Dielectr. Phenomena, CEIDP. pp. 1124–1127. http://dx.doi.org/10.1109/CEIDP.2013.6748144.

Salem, A., Abd-Rahman, R., Ghanem, W., Al-Gailani, S., Al-Ameri, S., 2021. Prediction flashover voltage on polluted porcelain insulator using ANN. Comput. Mater. Contin. 68 (3755), http://dx.doi.org/10.32604/CMC.2021.016988.

Samakosh, J.D., Mirzaie, M., 2020. Experimental-based models for predicting the flashover voltage of polluted sir insulators using leakage current characteristics. IET Sci. Meas. Technol. 14, 943–952. http://dx.doi.org/10.1049/IET-SMT.2020.0021.

Schindelholz, E., Kelly, R.G., 2012. Wetting phenomena and time of wetness in atmospheric corrosion: A review. Corros. Rev. 30, 135–170. http://dx.doi.org/10.1515/corrrev-2012-0015.

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., Rabinovich, A., 2015. Going deeper with convolutions. In: Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. 07-12-June-2015. pp. 1–9. http://dx.doi.org/10.1109/CVPR.2015.7298594.

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., Wojna, Z., 2016. Rethinking the inception architecture for computer vision. In: Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. 2016-December. pp. 2818–2826. http://dx.doi.org/10.1109/CVPR.2016.308.

Thanh, P.N., Cho, M.Y., Da, T.N., 2021. Insulator leakage current prediction using surface spark discharge data and particle swarm optimization based neural network. Electr. Power Syst. Res. 191, 106888. http://dx.doi.org/10.1016/J.EPSR.2020.106888.

Venkataraman, S., Gorur, R.S., Mishra, A.P., 2008. Impact of weathering on flashover performance of nonceramic insulators. IEEE Trans. Dielectr. Electr. Insul. 15, 1073–1080. http://dx.doi.org/10.1109/TDEI.2008.4591230.

Vosloo, W.L., 2002. A Comparison of the Performance of High-Voltage Insulator Materials in a Severely Polluted Coastal Environment. Stellenbosch University, Stellenbosch.

Vosloo, W.L., Holtzhausen, J.P., 2002. The prediction of insulator leakage currents from environmental data. In: IEEE AFRICON Conf. 2. pp. 603–608. http://dx.doi.org/10.1109/AFRCON.2002.1159978.

Waluyo, Fauziah, D., Khaidir, I.M., 2021. The evaluation of daily comparative leakage currents on porcelain and silicone rubber insulators under natural environmental conditions. IEEE Access 9, 27451–27466. http://dx.doi.org/10.1109/ACCESS.2021.3057626.

Wang, L., Cao, B., Guan, Z., Wang, K., 2017. Influence of temperature difference on wetting characteristics of insulators. IEEE Trans. Dielectr. Electr. Insul. 24, 3622–3629. http://dx.doi.org/10.1109/TDEI.2017.006813.

Wang, Wei, Yang, Y., Wang, X., Wang, Weizheng, Li, J., 2019. Development of convolutional neural network and its application in image classification: a survey. 58, 040901. http://dx.doi.org/10.1117/1.OE.58.4.040901.

Wang, X., Zhao, J., Li, Q., Fang, N., Wang, P., Ding, L., Li, S., 2020. A hybrid model for prediction in asphalt pavement performance based on support vector machine and grey relation analysis. J. Adv. Transp. 2020, http://dx.doi.org/10.1155/2020/7534970.

Xia, Y., Jiang, X., Sun, C., Dong, B., 2012. A method to estimate leakage current of polluted insulators. Prz. Elektrotech. 88, 161–164.

Yu, Y., Wang, C., Gu, X., Li, J., 2018. A novel deep learning-based method for damage identification of smart building structures. 18, 143–163. http://dx.doi.org/10.1177/1475921718804132.

Zhang, S., 2021. Language processing model construction and simulation based on hybrid CNN and LSTM. Comput. Intell. Neurosci. 2021, http://dx.doi.org/10.1155/2021/2578422.

Zhang, Z., Jiang, X., Huang, H., Sun, C., Hu, J., Gao, D.W., 2013. Study on the wetting process and its influencing factors of pollution deposited on different insulators based on leakage current. IEEE Trans. Power Deliv. 28, 678–685. http://dx.doi.org/10.1109/TPWRD.2012.2226758.

Zhao, L., Jiang, J., Duan, S., Fang, C., Wang, J., Wang, K., Cao, P., Zhou, J., 2011. The prediction of post insulators leakage current from environmental data. In: 2011 Int. Conf. Electr. Control Eng. ICECE 2011 - Proc.. pp. 5103–5106. http://dx.doi.org/10.1109/ICECENG.2011.6057235.

Zhi-yi, S., 2003. To intensify basic external insulation level of power system-fundamental way for prevention of large-scale pollution flashover. Electr. Power.

Zhu, Y., Zhou, R., Zhang, Y., Dong, X., Huang, X., 2021. Review on flashover risk prediction method of iced insulator based on icing monitoring technology. Cold Reg. Sci. & Technol. 185, 103252. http://dx.doi.org/10.1016/J.COLDREGIONS.2021.103252.

Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., Xiong, H., He, Q., 2019. A comprehensive survey on transfer learning. Proc. IEEE 109, 43–76. http://dx.doi.org/10.1109/JPROC.2020.3004555.