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Prediction of flashover voltage of insulators using least squares support vector machine with particle swarm optimisation

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ABSTRACT

This paper describes the application of least squares support vector machine combined with particle swarm optimisation (LS-SVM-PSO) model to estimate the critical Flashover Voltage (FOV) on polluted insulators. The characteristics of the insulator: the diameter, the height, the creepage distance, the form factor and the equivalent salt deposit density were used as input variables for the LS-SVM-PSO model, and critical flashover voltage was estimated. In order to train the LS-SVM and to test its performance, the data sets are derived from experimental results obtained from the literature and a mathematical model. First, the LS-SVM regression model, with Radial Basis Function (RBF) kernel, is established. Then a global optimiser, PSO is employed to optimise the hyper-parameters needed in LS-SVM regression. Afterward, a LS-SVM-PSO model is designed to establish a nonlinear model between the above mentioned characteristics and the critical flashover voltage. Satisfactory and more accurate results are obtained by using LS-SVM-PSO to estimate the critical flashover voltage for the considered conditions compared with the previous works.

1. Introduction

The reliability of the power system mainly depends on the environmental and weather conditions which cause flashover on polluted insulators leading to system outages. A major problem of insulation systems is the accumulation of airborne pollutants due to natural, industrial or even mixed pollution, during the dry weather period and their subsequent wetting, mainly by high humidity. At the coastal areas the high voltage insulators are affected by salt particles that settle on the insulators surfaces. These particles are not dangerous in its dry condition but with high environmental humidity or drizzle rain conditions the salt can absorb the water and form a thin film with high conductivity. This layer gives an ideal path for the leakage current to pass through between the high voltage side and the ground side. The conductivity of this layer depends on the type of salts which this layer consists of [1,2]. High failure rate of polluted insulator due to the flashover has been found near the coastal areas [3]. This problem was the motivation for the installation of a test station performs laboratory tests on artificially polluted insulators.

Several researches concerning the insulators performance under pollution conditions have been conducted, in which mathematical or physical models have been used [4–7]. Experiments have been conducted [8–10]. And simulation programmes have been developed [11,12].

A variety of prediction models have been proposed in the literature. Artificial Neural Networks (ANNs) models are developed for the qualitative control of the insulators by determining important parameters (such as leakage current or the critical flashover voltage) [13–16], an Adaptive Neuro-Fuzzy Inference System (ANFIS) [17], and Fuzzy Logic (FL) model [18] have been applied in order to estimate the critical flashover voltage on polluted insulators.

Recently, SVM has been used as a popular algorithm developed from the machine learning community [19]. Due to its advantages and remarkable generalisation performance (i.e. error rates on test sets) over other methods, SVM has attracted attention and gained extensive applications. As simplification of traditional SVM, Suykens and Vandewalle have proposed the use of the least squares support vector machines LS-SVM [20], LS-SVM encompasses similar advantages as SVM, but its additional advantage is that it requires solving a set of only linear equations (linear programming), which is much easier and computationally more simple. The SVMs and LS-SVMs are called uniformly as SVMs for the convenient narration. The parameters in regularisation item and kernel function are called hyper-parameters in SVMs, which plays an important role to the algorithm performance. Iterative gradient-based algorithms rely on smoothed approximations of a function. So, it does not ensure that the search direction points exactly to an optimum of the generalisation performance measure which is often

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discontinuous [21]. Grid Search (GS) [22,23] is one of the conventional approaches to deal with discontinuous problems. However, it needs an exhaustive search over the space of hyper-parameters, which must be time consuming. This procedure needs to locate the interval of feasible solution and a suitable sampling step. Moreover, when there are more than two hyper-parameters, the manual model selection may become intractable.

PSO is a stochastic global optimisation technique proposed by Kennedy and Eberhart in 1995 [24,25]. Compared to Genetic Algorithms (GAs) and Evolutionary Algorithms (EAs), the advantages of PSO are that PSO possesses the capability to escape from local optima, it is easy to be implemented and has fewer parameters to be adjusted. The PSO has been found to be robust and fast in solving non-linear, non-differentiable and multi-modal problems [26]. In this paper, a LS-SVM regression with PSO based model is proposed to estimate the critical flashover voltage of polluted insulators.

2. Experimental measurements and data collection

The data used for training and testing the method was collected from both experiments [27–30] and an application of a mathematical model for calculating flashover voltage. As detailed in [14]. The experiments were carried out in an insulator test station, installed in the High Voltage Laboratory of Public Power Corporation's Testing, Research and Standards Center in Athens [27] and according to the IEC norm [31]. Apart from this set of experimental measurements, measurements from similar experiments performed by Zhicheng and Renyu [28] and Sundararajan et al. [29] were also used.

The mathematical model for the evaluation of the flashover process of a polluted insulator consists of a partial arc spanning over a dry zone and the resistance of the pollution layer in series. The critical voltage U_c (in V), which is the applied voltage across the insulator when the partial arc is developed into a complete flashover, is given by the following formula [30]:

$$U_C = \frac{A}{n+1}(L + \pi D_m FKn)(\pi D_m \sigma_S A)^{-n/(n+1)} \tag{1}$$

where L is the creepage distance of the insulator (in cm), D_m the maximum diameter of the insulator disc (in cm) and F is the form factor. The form factor of an insulator is determined from the insulator dimensions. For graphical estimation, the reciprocal value of the insulator circumference ($1/p$) is plotted versus the partial creepage distance l counted from the end of the insulator up to the point reckoned. The form factor is given by the area under this curve and calculated according to the formula [31]:

$$F = \int_0^L \frac{dl}{p(l)} \tag{2}$$

The arc constants A and n have been calculated using a genetic algorithm model [32] and their values are $A = 124.8$ and $n = 0.409$. The surface conductivity σ_s (in Ω^{-1}) is given by the following type:

$$\sigma_S = (369.05C + 0.42) \times 10^{-6} \tag{3}$$

where C is the equivalent salt deposit density in mg/cm^2. The coefficient of the pollution layer resistance K in case of cap-and-pin insulators is given by:

$$K = 1 + \frac{n+1}{2\pi Fn} \ln\left(\frac{L}{2\pi RF}\right) \tag{4}$$

where R is the radius of the arc foot (in cm) and is given by

$$R = 0.469(\pi A D_m \sigma_s)^{1/(2(n+1))} \tag{5}$$

The above mathematical model is a result of experiments in specific insulators types and specific pollutants in their surface.

3. Least Squares Support Vector Machine (LS-SVM)

SVMs have often been found to provide better prediction results than other widely used machine learning tools, such as the neural networks [33]. This novel approach motivated by statistical learning theory led to a class of algorithms characterised by the use of non-linear kernels, high generalisation ability and the sparseness of the solution. Unlike the classical neural networks approach the SVM formulation of the learning problem leads to Quadratic Programming (QP) with linear constraint. However, the size of matrix involved in the QP problem is directly proportional to the number of training points. Hence, to reduce the complexity of optimisation processes, a modified version, called LS-SVM is proposed by taking with equality instead of inequality constraints to obtain a linear set of equations instead of a QP problem in the dual space [20]. Instead of solving a QP problem as in SVM, LS-SVM can obtain the solutions of a set of linear equations. The formulation of LS-SVM is introduced as follows. Consider a given training set $\{x_i, y_i\}\ \phi \in R^2$, $i = 1,2,\ldots,N$ with input data x_i, and output data y_i. The following regression model can be constructed by using non-linear mapping function ϕ (.):

$$y = w^T \phi(x) + b \tag{6}$$

where w is the weight vector and b is the bias term. As in SVM, it is necessary to minimise a cost function C containing a penalised regression error, as follows:

$$\min\ C(w, e) = \frac{1}{2} w^T w + \frac{1}{2}\gamma \sum_{i=1}^{N} e_i^2 \tag{7}$$

subject to equality constraints

$$y = w^T \phi(x_i) + b + e_i, \quad i = 1, 2, \ldots, N \tag{8}$$

The first part of this cost function is a weight decay which is used to regularise weight sizes and penalise large weights. Due to this regularisation, the weights converge to similar value. Large weights deteriorate the generalisation ability of the LS-SVM because they can cause excessive variance. The second part of (7) is the regression error for all training data. The parameter C, which has to be optimised by the user, gives the relative weight of this part as compared to the first part. The restriction supplied by (8) gives the definition of the regression error. To solve this optimisation problem, Lagrange function is constructed as:

$$L(w, b, e, \alpha) = \frac{1}{2}\|w\|^2 + \gamma \sum_{i=1}^{N} e_i^2 - \sum_{i=1}^{N} \alpha_i \{w^T \phi(x_i) + b + e_i - y_i\} \tag{9}$$

where α_i are Lagrange multipliers.

The solution of (9) can be obtained by partially differentiating with respect to w, b, e_i and α_i:

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \to w = \displaystyle\sum_{i=1}^{N} \alpha_i \phi(x_i) \\ \dfrac{\partial L}{\partial b} = 0 \to \displaystyle\sum_{i=1}^{N} \alpha_i = 0 \\ \dfrac{\partial L}{\partial e_i} = 0 \to \alpha_i = \gamma e_i \quad i = 1, 2, \ldots, N \\ \dfrac{\partial L}{\partial \alpha_i} = 0 \to w^T \phi(x_i) + b + e_i - y_i = \gamma e_i \quad i = 1, 2, \ldots, N \end{cases} \tag{10}$$

then

$$w = \sum_{i=1}^{N} \alpha_i \phi(x_i) = \sum_{i=1}^{N} \gamma e_i \phi(x_i) \tag{11}$$