Journal of Engineering Science and Technology
Vol. 12, No. 1 (2017) 062 - 077

IMPROVED LS-SVM USING ACO TO ESTIMATE FLASHOVER VOLTAGE OF POLLUTED INSULATORS

SID AHMED BESSEDIK*, RABAH DJEKIDEL, AISSA AMEUR

Department of Electrical Engineering
University Ammar Telidji Laghouat , Algeria
*Corresponding Author: ahmed_7b@yahoo.fr

Abstract

The reliability of insulators under polluted environment is one of the guiding factors in the insulation coordination of high voltage transmission lines. In order to improve understanding of the flashover phenomenon in polluted insulators, several experimental studies and mathematical approaches have been made in last year's. In this paper, the critical flashover voltage behavior of polluted insulators has been calculated and a hybrid model between machine Learning (ML) and optimization technique has been proposed. For this purpose, firstly the ant colony optimization (ACO) technique is utilized to optimize the hyper-parameters needed in least squares support vector machines (LS-SVM). Then, a LS-SVM-ACO model is designed to establish a nonlinear model between the characteristics of the insulator and the critical flashover voltage. The data used to train the model and test its performance is derived from experimental measurements and a mathematical model. The results obtained from the proposed model are in good accord with other mathematical and experimental results of previous researchers.

Keywords: High voltage insulator, Flashover voltage, Least squares support vector machine, Ant colony optimization.

1. Introduction

The performances of insulators under polluted conditions constitute one of the guiding factors in the design and dimensioning of insulation in power transmission lines. Any failure in the satisfactory performance of high voltage insulators will result in considerable loss of capital, as there are numerous industries that depend upon the availability of an uninterrupted power supply. Outdoor insulators are being subjected to various operating conditions and environments.

Nomenclatures

A , n	Arc constants
C	Equivalent salt deposit density, mg/cm^2
d_{ij}	Desirability of edge (i, j)
D	Diameter of the insulator, cm
F	Form factor of the insulator
H	Height of the insulator, cm
K	Coefficient of the pollution layer resistance
L	Creepage distance, cm
N_{max}	Number of ants
R	Radius of the arc foot, cm
R^2	Coefficient of determination
$\Re^2$	Real numbers pairs
Uc	Critical flashover voltage, kV

Greek Symbols

α , β	Controlling parameters
α_i	Lagrange multipliers
γ	Regularization parameter
$\delta\tau_{ij}(t)$	Increment
λ	Evaporation constant
ζ_2	Decrease rate of the pheromones
ρ	Constant rate
σ_s	Surface conductivity, µS
σ^2	Squared variance (bandwidth)
$\tau(t)$	Pheromone concentration
ϕ	Non-linear mapping function
ω	Weight vector

Abbreviations

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Networks
DE	Differential Evolution
FL	Fuzzy Logic
FOV	Flashover Voltage
GA	Genetic Algorithms
IEC	International Electro-technical Commission
LS-SVM	Least Squares-Support Vector Machines
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
PSO	Particle Swarm Optimization
RBF	Radial Basis Function
RMSE	Root Mean Square Error
SVM	Support Vector Machines

Contamination on the surface of the insulators enhances the chances of flashover. Under dry conditions the contaminated surfaces do not conduct, and thus contamination is of little importance in dry periods.

In cases when there is light rain, fog or dew, the contamination on the surface dissolves. This promotes a conducting layer on the surface of the insulator and the line voltage initiates the leakage current. High current density near the electrodes results in the heating and drying of the pollution layer. An arc is initiated if the voltage stress across the dry band exceeds the withstand capability. The extension of the arc across the insulator ultimately results in flashover [1, 2]. Therefore it is important to monitor the insulator’s condition so as to ensure that maintenance takes place in due time.

For this purpose, Several researches concerning the insulators performance under pollution conditions have been conducted, in which mathematical or physical models have been used [3-10], experiments have been carried out have been developed [11-13].

In the last two decades, a variety of prediction models have been proposed for the estimation of the flashover voltage. Among of these approaches, Artificial Neural Networks (ANNs) [14-17], Fuzzy Logic (FL) [18], Adaptive Neuro-Fuzzy Inference System (ANFIS) [19-20] and Least Squares Support Vector Machines (LS-SVM) [21-23].

The LS-SVM algorithm provides a computational advantage over standard support vector machines (SVM) by converting quadratic optimization problem into a system of linear equations (linear programming). This method uses equality constraints instead of inequality constraints and adopts the least squares linear system as its loss function, which is computationally attractive [24]. However, it is very difficult to select appropriate LS-SVM parameters. The selection of LS-SVM parameters affects the regression accuracy of LS-SVM. To overcome this problem, numerous optimization techniques based on heuristic algorithms for LS-SVM parameters have been proposed such as genetic algorithms (GA), differential evolution (DE), particle swarm optimization algorithms (PSO), artificial bee colony (ABC) and other evolutionary algorithms [25-27].

The capability of LSSVM-GA, LSSVM-DA and LSSVM-ABC can be seen encouraging in solving several prediction problems in different fields [28-33]. Besides GA, DA, BA and ABC, the application of PSO in optimizing LS-SVM hyper-parameters is also encouraging in the literature [23, 34, 35]. In 2004, another optimization technique, called ant colony optimization (ACO) has been introduced and its performance is proven to be competitive to the other existing optimization approaches [36, 37].

In this paper, the LS-SVM optimized with ant colony optimization algorithm (ACO) is applied to estimate the critical flashover voltage of polluted insulators.

2. Data Selection and Mathematical Model

The LS-SVM model uses as input variables the characteristics of the insulator such as the diameter D (in cm), the height H (in cm), the creepage distance L (in cm), the form factor F of the insulator and the layer conductivity σ_s (in μS), and estimates the critical flashover voltage Uc (in kV).

The data used for the training and testing of the LS-SVM were selected from various sources. Some of them were acquired by experiments that were carried out in the High Voltage Laboratory of Public Power Corporation's Testing, Research and Standards Centre in Athens [38] according to the IEC standard 507:1991 [39]. Artificial pollution was applied on the insulators before conducting the test to determine the critical flashover voltage. As detailed in Ref. [7], the pollution was simulated according to the solid layer-cool fog method and the used contaminant was: 75 g/l kaolin clay, 675 g/l silica flour, NaCl as required, suspended in isopropyl alcohol. The salt deposit density on the insulator surface was used as an index for the pollution severity. Apart from this set of experimental measurements, other measurements were also used, from experiments performed by Zhicheng and Renyu [40] and Sundararajan et al. [41].

A mathematical model was also used to enrich the training data [7]. The equivalent circuit for the evaluation of the critical flashover voltage is comprised by a partial arc spanning over a dry zone in series with a resistance that represents the pollution layer, as shown in Fig. 1, where V_{arc} is the arcing voltage, R_p the resistance of the pollution layer and U a stable voltage supply source. In this model, the critical flashover voltage U_c is given by the following formula:

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

where L is the creepage distance of the insulator (in cm), D_{m} the maximum diameter of the insulator disc (in cm), F is the form factor. σ_s is the conductivity of the pollution layer (in Ω^{-1}), K is the coefficient of the pollution layer resistance, A and n are the arc constants.

The form factor of an insulator is determined from the insulator dimensions. For graphical estimation, the reciprocal value of the insulator circumference ($1/\rho$) is plotted against 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 [39].

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

The arc constants A and n have been calculated using a genetic algorithm approach [42] 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:

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

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:

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

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

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

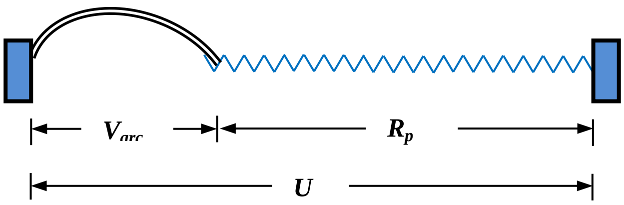


Fig. 1. Equivalent circuit of polluted insulator.

3. Flashover Voltage Estimation Using LSSVM-ACO

This section gives a brief description of LS-SVM and ACO followed by the proposed hybrid model.

3.1. Least square support vector machines

LS-SVM is a modification of SVM, adopts the least squares linear system as its loss function and therefore solves a set of linear equations. It is easier to use than standard SVM [43].

The formulation of LS-SVM is introduced as follows. Consider a given training set [24]:

$\{x_i, y_i\}\ \phi \in \Re^2$, $i=1,2,\ldots\ldots N$

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 minimize a cost function C containing a penalized 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

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

To solve this optimization problem, Lagrange function is constructed as:

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

where α_i are Lagrange multipliers.

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

$$w = \sum_{i=1}^{N} \alpha_i \phi(x_i) = \sum_{i=1}^{N} \gamma e_i \phi(x_i) \tag{10}$$

where a positive definite Kernel is used as follows:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j) \tag{11}$$

An important result of this approach is that the weights (w) can be written as linear combinations of the Lagrange multipliers with the corresponding data training (x_i). Putting the result of Eq. (10) into Eq. (6), the following result is obtained:

$$y = \sum_{i=1}^{N} \alpha_i \phi(x_i)^T \phi(x) + b \tag{12}$$

For a point y_i to be evaluated it is:

$$y_i = \sum_{i=1}^{N} \alpha_i \phi(x_i)^T \phi(x_j) + b \tag{13}$$

The vector follows from solving a set of linear equations:

$$A \begin{bmatrix} \alpha \\ b \end{bmatrix} = \begin{bmatrix} y \\ 0 \end{bmatrix} \tag{14}$$

where A is a square matrix given by:

$$A = \begin{bmatrix} K + \frac{1}{\gamma} & 1_N \\ 1_N^T & 0 \end{bmatrix} \tag{15}$$

where K denotes the kernel matrix with ijth element in Eq. (10) ; I denotes the NxN identity matrix; and $1_N = [1\ 1\ 1\ \ldots.\ 1]^T$.

Hence, the solution is given by:

$$\begin{bmatrix} \alpha \\ b \end{bmatrix} = A^{-1} \begin{bmatrix} y \\ 0 \end{bmatrix} \tag{16}$$

For LS-SVM, there are many kernel functions (linear, radial basis function (RBF), polynomial, sigmoid, etc. However, the most used kernel function is RBF:

$$K(x_i, x_j) = \exp\left(- \frac{\left\| x_i - x_j \right\|^2}{\sigma_{sv}{}^2} \right) \tag{17}$$

where σ^2 is the squared variance (bandwidth) of the Gaussian function.

From the training LS-SVM problem, one can see that there are two free parameters, viz. kernel width parameter Sigma σ^2 and regularization parameter γ, which may affect LS-SVM generalization performance.

It is well known that LS-SVM generalization performance depends on a good setting of regularization parameter γ and the kernel parameter σ^2 (case RBF kernel). In order to achieve the better generalization performance, it is necessary to select and optimize these parameters. In this paper, these parameters are automatically tuned using the ACO in the testing phase.

3.2. Ant colony optimization (ACO)

Ant colony algorithm (ACO) was introduced by Marco Dorigo in the early 1991 [36, 44]. It is a meta-heuristic inspired by the behavior of real ants in their search for the shortest path to food sources. Ants cooperate and communicate by depositing pheromones on their path which can be interpreted by other ants. The evaporation of pheromones and the random choice of paths allow the exploration of alternatives. The deposition of pheromones has to be configured so that a better path leads to a higher pheromone concentration which itself causes a higher probability, that this path is chosen by other ants. So, the overall process can be seen as a positive feedback loop.

At the beginning of the search process, a constant amount of pheromone is assigned to all arcs. When located at a node i an ant k uses the pheromone trail to compute the probability of choosing j as the next node:

$$p_{ij}^k = \frac{\tau_{ij}^{\alpha} d_{ij}^{\beta}}{\sum_{i,j=1}^{n} \tau_{ij}^{\alpha} d_{ij}^{\beta}} \tag{18}$$

where $\alpha > 0$ and $\beta > 0$ are the parameters controlling the relative importance of pheromone intensity and desirability respectively for each ant's decision. τ_{ij} is the concentration of pheromone associated with edge (i, j), and d_{ij} the desirability of edge (i, j). The pheromone concentration can change with time due to the evaporation of pheromone. Furthermore, the advantage of pheromone evaporation is that the system could avoid being trapped in local optima. If there is no evaporation, then the path randomly chosen by the first ants will become the preferred path as the attraction of other ants by their pheromone. For a constant rate ρ of pheromone decay or evaporation, the pheromone concentration usually varies with time exponentially as:

$$\tau(t) = \tau_0 e^{-\rho t} \tag{19}$$

where τ_0 is the initial concentration of pheromone and t is time. If $\rho t \ll 1$, then we have $\tau(t) = (1-\rho t)\tau_0$. For the unitary time increment $\Delta t = 1$, the evaporation can be approximated by $\tau^{t+1} \leftarrow (1-\rho)\,\tau^{t}$. Therefore, we have the simplified pheromone update formula as follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \delta\tau_{ij}(t) \tag{20}$$

where $\rho \in [0,1]$ is the rate of pheromone evaporation. The increment $\delta\tau_{ij}(t)$ is the amount of pheromone deposited at time t along course i to j when an ant travels distance L. Usually $\delta\tau_{ij}(t)\ \alpha 1/L$. The decision policy and the pheromone update rule used within ant system are given by Eq. (18) and Eq. (20), respectively, each ant adds pheromone to all selected edges and consequently the additional pheromone by each edge (*i*, *j*) is given by [36]:

$$\delta\tau_{ij}(t)=\sum_{k=1}^{m}\delta\tau_{ij}^{k}(t) \tag{21}$$

where *m* is the number of ants and $\delta\tau_{ij}^{k}(t)$ is the additional pheromone laid on edge (*i*, *j*) by the *k*th ant at the end of iteration *t*. The individual pheromone addition contributed by each ant is given by:

$$\delta\tau_{ij}^{k}(t)=\begin{cases}\dfrac{Q}{L_k(i,j)} & \textit{if kth ant use edg } (i,j) \\ & \textit{and } (i,j)\in \textit{globally best tour} \\ 0 & \textit{otherwise}\end{cases} \tag{22}$$

$\delta\tau_{ij}^{k}$ is used to reinforce the pheromone on the edges of the global best solution, *Q* is a problem parameter, $L_k(i, j)$ is the tour length of *k*th ant. From Eq. (22) it is clear that ants only add pheromone to the edges that they select and that solutions of better quality are rewarded with greater pheromone additions [45].

3.3. Parameters optimization of LS-SVM based on ACO algorithm

In optimizing the hyper-parameters of LS-SVM utilizing ACO, each ant is requested to represents a potential solution, viz. parameters combination. In this study, as RBF kernel is selected, the combination of parameters of interest are γ and σ^2. The proposed hybridization can be realized by embedding LS-SVM in ACO algorithm as fitness function evaluation.

The fitness function of each possible solution is evaluated using Root Mean Square Error (RMSE), the RMSE is given as:

$$RMSE=\sqrt{\frac{\sum_{i=1}^{N}(y_{tes,i}-y_{pre,i})^2}{N}} \tag{23}$$

where *N* is the number of data patterns in the data set, $y_{pre,i}$ indicates the predicted and $y_{tes,i}$ the testing value of one data point *i*. For the purpose of obtaining optimized hyper-parameters of LS-SVM, All of the values for each hyper-parameter (γ, σ^2) are placed in two different vectors. These vectors can be considered as paths between the nests. In the tour, the ant must visit two nests by choosing path between start and node.

The objective of ant colony algorithm is to find the best tour with the lowest fitness function among the two nests. The ants deposit pheromone to the beginning of each path. Then the pheromones were updated in two different ways:

3.3.1. Local pheromone updating

Each ant updates the pheromones deposited to the paths it followed after completing one tour:

$$\tau_{ij}(t) = \tau_{ij}(t-1) + \frac{\zeta_1 . a}{RMSE} \tag{24}$$

where $\tau_{ij}(t)$ is pheromone value between nest (i) and (j), a is the general pheromone updating coefficient, ζ_1 is the increase rate of the pheromones and *RMSE* is the fitness function for the tour travelled by the ant.

3.3.2. Global pheromone updating

The pheromones of the paths belonging to the best tour and worst tour of the ant colony are updated as given in the following equations:

$$\tau_{ij}^{best}(t) = \tau_{ij}^{best}(t) + \frac{a}{RMSE_{best}} \tag{25}$$

$$\tau_{ij}^{worst}(t) = \tau_{ij}^{worst}(t) - \frac{\zeta_2 . a}{RMSE_{worst}} \tag{26}$$

where ζ_2 is the decrease rate of the pheromones, τ^{best} and τ^{worst} are the pheromones of the paths followed by the ant in the tour with the lowest cost value ($RMSE_{best}$) and with the highest cost value ($RMSE_{worst}$) in one iteration, respectively [46].

The pheromones of the paths belonging to the best tour of the colony are increased considerably, whereas those of the paths belonging to the worst tour of the iteration are decreased. After each iteration some of the pheromones evaporate.

Pheromone evaporation allows the ant algorithm to forget its past history, so that ACO can direct its search towards new directions without being trapped in some local minima.

$$\tau_{ij}^{worst}(t) = \tau_{ij}^{\lambda}(t) + \left[\tau_{ij}^{best}(t) + \tau_{ij}^{worst}(t)\right] \tag{27}$$

where λ is the evaporation constant [46].

To validate the performance of the LSSVM-ACO three different type validation indexes were used, in this study. These were RMSE of Eq. (23), the coefficient of determination (R^2) and Mean Absolute Percentage Error (MAPE), the R^2 and MAPE are given in [23].

4. Results and Discussion

The parameters of ACO algorithm have been selected by a trial and error approach. Therefore, the parameters adopted for this study are: number of ants N_{max}=100, pheromone coefficient a=0.05, evaporation parameter λ=0.95, increase rate ζ_1=0.2, decrease rate ζ_2=0.3. The LS-SVM searching parameters are set as $\gamma = [2^3, 2^{23}]$ and $\sigma^2 = [2^{-8}, 2^5]$, respectively.

The simulation results in pairs of (γ, σ^2) values that finally converge to the optimum values γ = 2.2695e+006, σ^2 = 2.1277 as the number of generations increases (RMSE=0.01744) are shown in Figs. 2 and 3 respectively, where it becomes obvious that the algorithm converges rapidly to achieve these values.

According to Fig. 2, we notice that the results differ from generation to generation. The value of the performance criteria (RMSE) is quickly improved during first generations, and is reduced from 0.01748 to 0.01747 after 40 generations. It reaches its optimal value (RMSE = 0. 01744) after 45 generations only. Figure 3 shows the evolution of hyper-parameters of LS-SVM model justifies the role of ACO operators exploiting different points in the hyper-parameter search space.

The result of the training process of LS-SVM-ACO regression model is shown in Fig 4. Thus the comparison between the experimental data and the estimated values for the test set is shown in Fig. 5, in which 144 data were used to train the model and 24 were used to test it. We note a good adequacy of the approach to the measured data. Moreover, as illustrated in the same figure, the results show also that the LSSVM-ACO model is able to provide similar competitive results compared to LSSVM-PSO [23].

In addition, the validation indexes RMSE, MAPE and R^2 were compared with the previous results given in the literature, for two cases as given in Table 1, where case 1 contained 144 data for the training and 24 for the testing, while case 2 contained 148 to train the model and 20 to test its performance. From Table 1, the results show that LSSVM-ACO with RBF kernel predicts the flashover voltage of polluted insulators with higher accuracy than ANN, FL and the Classic LS-SVM-CL based on Grid Search [14, 18].

As given in Table 1, the proposed model have the minor RMSE for the test set than the LS-SVM-CL based on Grid Search and the previous results given in [19].

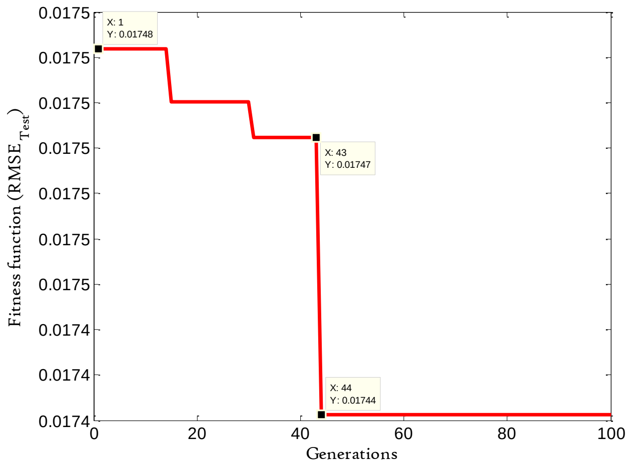
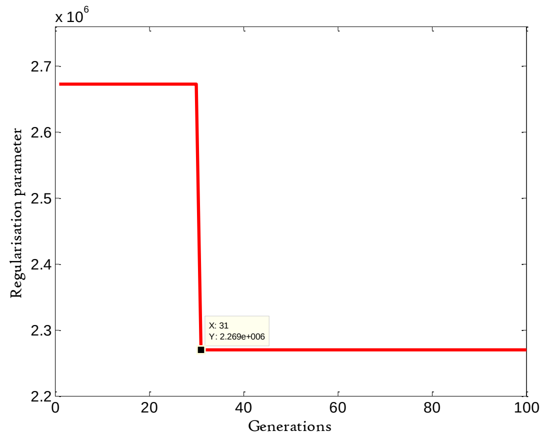
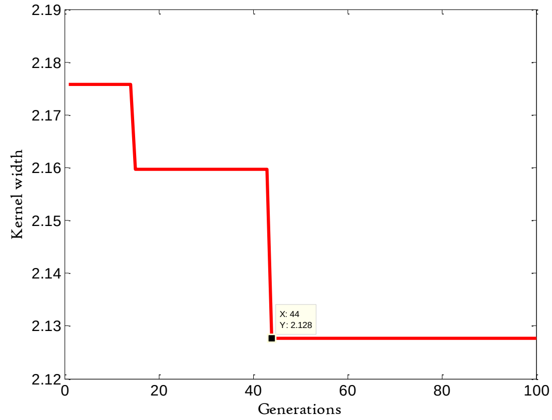


Fig. 2. Evolution of the fitness function (RMSE) vs. generations.



(a) Convergence of Regularization parameter γ.



(b) Convergence of RBF parameter σ^2.

Fig. 3. Evolution of hyper-parameters vs. generations.

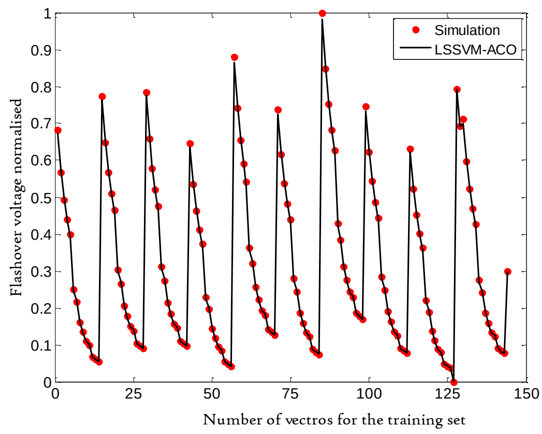


Fig. 4. Performance of LSSVM-ACO model for training.

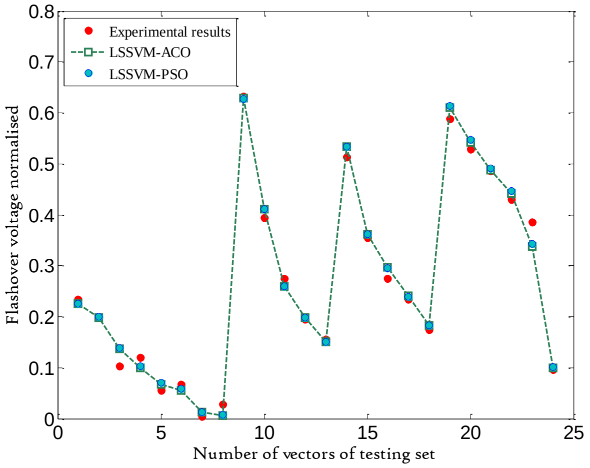


Fig. 5. Performance of LSSVM-ACO model for testing.

Table 1. Validation of the proposed approach.

	Methods	$RMSE_{TES}$	R_{TES}^2	$MAPE_{TEST}$
Case 1	LSSVM-ACO	0.0174	0.9910	1.1161
	LS-SVM-CL	0.0186	0.9896	1.1956
	ANN [14]	-	0.9853	3.8400
	FL [18]	-	0.9670	-
Case 2	LSSVM-ACO	0.0127	0.9971	0.8555
	LS-SVM-CL	0.0139	0.9966	0.9433
	ANFIS [19]	0.0473	0.9987	0.4597

5. Conclusions

In this paper an improved LS-SVM based on ACO algorithm has been successfully applied for the estimation of the flashover voltage on polluted insulators. The ACO algorithm is used to optimize parameters of LS-SVM in order to obtain a suitable LS-SVM model for the present problem.

The LSSVM-ACO with RBF kernel was trained to estimate the critical flashover voltage when some of geometric characteristics of the insulator are given. The presented results show that the proposed model is more successful in prediction of flashover voltages of polluted high voltage insulators.

Moreover, some statistical metrics were used to evaluate the estimating performance of the developed model, such as root mean square error (RMSE), coefficient of determination (R^2) and mean absolute percentage error (MAPE). The results show that LSSVM-ACO model could estimate the flashover voltage more accurate and precise than the previously proposed method (ANN, FL and LS-SVM-Cl).

References

1. Megriche, N.D.; and Beroual, A. (2000). Flashover dynamic model of polluted insulators under ac voltage. *IEEE Transaction on Dielectrics and Electrical Insulation*, 7(2), 283-289.
2. Chrzan, K.; Pohl, Z.; and Kowalak, T. (1989). Hygroscopic properties of pollutants on HV insulators. *IEEE Transactions on Electrical Insulation*, 24(1), 107-112
3. Rizk, F.A.M. (1981). Mathematical models for pollution flashover. *Electra*, 78, 71-103.
4. Zhicheng, G.; and Renyu Z. (1990). Calculation of DC and AC flashover voltage of polluted insulators. *IEEE Transactions on Electrical Insulation*, 25(4), 723-729.
5. Sundararajan, R.; and Gorur, R. S. (1993). Dynamic arc modeling of pollution flashover of insulators under dc voltge. *IEEE Transactions on Electrical Insulation*, 28(2), 209-218.
6. Megriche, N.D.; Beroual, A.; and Krahenruhl, L. (1997). A new proposal model for flashover of polluted insulators. *Journal of Physics D*: *Applied Physics*, 30(5), 889-894.
7. Topalis, F.V.; Gonos, I.F.; and Stathopoulos, I.A. (2001). Dielectric behaviour of polluted porcelain insulators. *IEE Proceedings Generation Transmission and Distribution*, 148(4), 269-274.
8. Hadi, H.; Flazi, S.; and Taieb, A. (2002). Modélisation dynamique du Contournement des isolateurs pollués des lignes aériennes en haute tension. *4'ème Conférence Internationale sur les Mathématiques Appliquées et les Sciences de l'Ingénieur CIMASI'02*, Casablanca, Maroc, 23-25.
9. Aydogmus, Z.; and Cebeci, M. (2004). A new flashover dynamic model of polluted HV insulator. *IEEE Transactions on Dielectrics and Electrical Insulation*, 11(4), 577-584.
10. Bessedik, S.A.; and Hadi, H. (2011). Dynamic arc model of the flashover of the polluted insulators. *Electrical Insulation and Dielectric Phenomena (CEIDP), Annual Report Conference on*. *IEEE*, Cancun, Mexico, 16-19.
11. Engelbrecht, C. S.; Hartings, R.; Tunell, H.; Engström, B.; Janssen, H.; and Hennings, R. (2003). Pollution tests for coastal conditions on an 800 Kv composite bushing. *IEEE Transactions on Power Delivery*, 18(3), 953-959
12. Boudissa, R.; Haddad, A.; Sahli, Z.; Mekhaldi, A.; and Baersch, R. (2005). Performance of outdoor insulators under non uniform pollution conditions. *14th International Symposium on High Voltage Engineering (ISH)*, Beijing, China, 25-29
13. Bessedik, S.A.; and Hadi, H. (2009). Etude expérimentale du modèle ouvert d'un isolateur réel haute tension. *4ème Conférence Internationale sur l'Electrotechnique ICEL'2009*, Oran, Algérie, 10-11.
14. Kontargyri, V. T.; Gialketsi, A. A.; Tsekouras, G. J.; Gonos, I. F.; and Stathopulos, I. A. (2007). Design of an artificial neural network for the estimation of the flashover voltage on insulators. *Electric Power Systems Research*, 77(12), 1532-1540.

15. Asimakopoulou, G. E.; Kontargyri ,V. T.; Tsekouras, G. J.; Asimakopoulou, F. E.; Gonos, I. F.; and Stathopulos, I. A. (2009). Artificial neural network optimisation methodology for the estimation of the flashover voltage on insulators. *IET Science, Measurement & Technology*, 3(1), 90-104.
16. Gençoglu, M. T.; and Cebeci, M. (2009). Investigation of pollution flashover on high voltage insulators using artificial neural network. *Expert Systems with Applications*, 36(4), 7338-7345.
17. Belkheiri, M.; Zegnini, B.; and Mahi, D. (2009). Modeling the critical flashover voltage of high voltage insulators using artificial intelligence. *Journal of Intelligent Computing and Applications JICA*, 2(2), 137-154.
18. Asimakopoulou, G. E.; Kontargyri, V. T.; Tsekouras, G. J.; Elias, C. N.; Asimakopoulou, F. E.; and Stathopu, los. I. A. (2001). A fuzzy logic optimisation methodology for the estimation of the critical flashover voltage on insulators. *Electric Power Systems Research*, 81(2), 580-588.
19. Erenturk, K. (2009). Adaptive-network-based fuzzy inference system application to estimate the flashover voltage on insulator. *Instrumentation Science & Technology*, 37(4), 446-461.
20. Bessedik, S. A.; and Hadi, H. (2013). Prediction of flashover voltage of insulators using adaptive-neuro-fuzzy inference system. *JEE Journal of Electric Engineering*, 13(3).
21. Gencoglu, M.; Uyar, M. T. (2009). Prediction of flashover voltage of insulators using least squares support vector machines. *Expert Systems with Applications*, 36 (7), 10789-10798.
22. Zegnini, B.; Mahdjoubi, A. H; and Belkheiri, M. (2011). A LS-SVM approach for predicting critical flashover voltage of polluted insulators. *Electrical Insulation and Dielectric Phenomena (CEIDP), Annual Report Conference on. IEEE,* Cancun, Mexico, 16-19.
23. Bessedik, S. A.; and Hadi, H. (2013). Prediction of flashover voltage of insulators using least squares support vector machine with particle swarm optimization, *Electric Power Systems Research*, 104, 87-92.
24. Suykens, J. A. K.; Van Gestel, T.; De Brabanter, J.; De Moor, B.; and Vandewalle, J. (2002). Least Squares support Vector Machines. *World Scientific*, Singapore.
25. Chen, X.; Wang, J.; Sun, D.; and Liang, J. (2008). Time series forecasting based on novel sup-port vector machine using artificial fish swarm algorithm, *4th International Conference on Natural Computation* (*ICNC*), Jinan, China, 18-20.
26. Sun, W.; Liu, M.; and Liang, d. Yi. (2015). Wind speed forecasting based on FEEMD and LSSVM optimized by the Bat Algorithm. *Energies*, 8(7), 6585-6607.
27. Mustaffa, Z.; Sulaiman, M.H.; and Kahar, M.N.M. (2015). LS-SVM hyper-parameters optimization based on GWO Algorithm for time series forecasting. *4th International Conference on Software Engineering and Computer Systems* (*ICSECS*), Kuantan, Malaysia, 19-21.
28. Zhou, H. R.; Zheng, P. E.; and Zhao, C. X. (2007). LS-SVM parameters selection based on genetic algorithm and its application in economic

forecasting. *Jisuanji Yingyong/Journal of Computer Applications*, 27(6), 1418-1419.

29. Xie, H. L.; Li, N.; Lu, F. C.; and Xie, Q. (2009). Application of LS-SVM by GA for dissolved gas concentration forecasting in power transformer oil, *Asia-Pacific Power and Energy Engineering Conference* (*APPEEC*), Wuhan, China, 28-31.
30. Xiaotian, Yan; Wu, Muqing; and Sun, Bing. (2009) .An adaptive LS-SVM based differential evolution algorithm. *International Conference on Signal Processing Systems, IEEE*. Singapore, 15-17.
31. Santos dos, G. S.; Luvizotto, L. G. J.; Mariani, V. C.; and Santos dos, C. L. (2012). Least squares support vector machines with tuning based on chaotic differential evolution approach applied to the identification of a thermal process. *Expert Systems with Applications*, 39 (5), 4805-4812.
32. Mustaffa, Z.; and Yusof, Y. (2008) .Optimizing LSSVM using ABC for non-volatile financial prediction. *Australian Journal of Basic and Applied Sciences*, 5, 549-556.
33. Mustaffa, Z.; Yusof, Y.; and Kamaruddin, S. S. (2014). Enhanced artificial bee colony for training least squares support vector machines in commodity price forecasting. *Journal of Computational Science*, 5(2), 196-205.
34. Guo, X. C.; Yang, J. H.; Wu, C. G.; Wang, C. Y.; and Liang, Y. C. (2008) .A novel LS-SVMs hyper-parameter selection based on particle swarm optimization. *Neurocomputing*, 71(16), 3211-3215.
35. Zhang, W.; Niu, P.; (2011). LS-SVM based on chaotic particle swarm optimization with simulated annealing and application. *2nd International Conference on Intelligent Control and Information Processing* (*ICICIP*), Harbin, China, 25-28.
36. Dorigo, M.; and Stützle, T. (2004) .*Ant Colony Optimization*. The MIT Press, London, England.
37. Xian, G. M.; and Xian, B. Z. (2012). A novel algorithm for predicting β-barrel outer membrane proteins using ACO-based hyper-parameter selection for LS-SVMs. *National Conference on Information Technology and Computer Science* (*CITCS*), Lanzhou, China, 16-18.
38. Ikonomou, K.; Katsibokis, G.; Panos, G.; Stathopoulos, I.A. (1987) .Cool fog tests on artificially polluted insulators. *5th International Symposium on High Voltage Engineering*, Braunschweig, Stadthalle, 24-28.
39. IEC 507. (1991) .*Artificial pollution tests on high-voltage insulators to be used on a.c. systems*.
40. Zhicheng, G.; and Renyu, Z. (1990) .Calculation of DC and AC flashover voltage of polluted insulators. *IEEE Transactions on Electrical Insulation*, 25(4), 723-729.
41. Sundararajan, R.; Sadhureddy, N.R.; and Gorur, R.S. (1995) .Computer-aided design of porcelain insulators under polluted conditions. *IEEE Transactions on Electrical Insulation*, 2(1), 21-127.
42. Gonos, I.F.; Topalis, F.V.; and Stathopoulos, I.A. (2002) .Genetic algorithm approach to the modelling of polluted insulators. *IEE Proceedings Generation Transmission and Distribution*, 149 (3), 373-376.

43. Vapnik, V.N. (1998) .*Statistical Learning Theory*, Wiley, New York, USA.
44. Dorigo, M.; Maniezzo, V.; and Colorni, A. (1991) .Positive feedback as a search strategy. *Dipartimento di Elettronica, Politecnico di Milano. Tech. Rep*, Italy.
45. Bououden, S.; Chadli, M.; and Karimi, H. R. (2015) .An ant colony optimization-based fuzzy predictive control approach for nonlinear processes. *Information Sciences*, 299(*C*), 143-158.
46. Varol, H.A.; and Bingul, Z. (2004) .A new PID tuning technique using Ant Algorithm. *American Control Conference*, Boston, Massachusetts.