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OPTIMIZATION OF LEARNING ALGORITHMS IN THE PREDICTION OF PITTING CORROSION

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Abstract

This work is part of a scientific research program whose objective is to prevent pitting corrosion of an open cooling circuit of a nuclear installation. Various corrosion inhibitors have been studied. The performances of pitting corrosion inhibition were discussed and compared on the basis of several criteria. The experimental data were collected in a large table and subjected to algorithms in order to construct models for predicting corrosion inhibition performance. We used four algorithms: Genetic Algorithm-Artificial Neural Network (GA-ANN); Least Squares-Support Vector Machine (LS-SVM), K Nearest Neighbors (KNN) and Regression Tree (RT). We optimized the data fraction reserved for learning and we sought to optimize the parameters specific to each algorithm. The efficiency of pitting inhibition increases in the following order: HCO_3^- < $H_2PO_4^-$ < CO_3^{2-} < HPO_4^{-2} < PO_4^{3-} < SiO_3^{2-} < MoO_4^{2-} < WO_4^{2-}. Our results showed that the order of performance of the algorithms is: RT < KNN < LS-SVM < GA-ANN.

Keywords: Genetic Algorithm-Artificial Neural Network (GA-ANN), Least squares support vector machine (LS-SVM), Regression tree (RT), K Nearest neighbor (KNN), Pitting potential (Epit), Inorganic inhibitors.

1. Introduction

The Pitting corrosion is considered as one of the most harmful types of corrosion [1]; it can lead to catastrophic consequences following a metal perforation [2]. Predicting this kind of corrosion is difficult because a pit can occur at any point

Abbreviations

City	Cityblock distance
Corr	Correlation distance
Epit	Pitting potential
Epit-cal	Pitting potential calculated
Epit-exp	Pitting potential experimental
Eucl	Euclidean distance
GA-ANN	Genetic Algorithm-Artificial Neural Network
Gam	Gamma
Gen	Generation
Hamm	Hamming distance
H. Lay	Hidden Layers
KNN	K Nearest Neighbor
LS-SVM	Least Squares Support Vector Machine
Maha	Mahalanobis distance
Pop	Population
RT	Regression Tree (RT)
Rtest	Correlation coefficient of test phase
Rtrain	Correlation coefficient of training phase
SCE	Saturated calomel electrode
Sig2	Sigma squared
Spea	Spearman distance

on a metal surface. With its microscopic dimension it can evolve quickly without being detected [3]. Curative actions are useless in this case and only preventive approaches can be considered. Chemical inhibitors are usually the most appropriate way to prevent pitting corrosion [4, 5]. A number of studies have been carried out with inorganic inhibitors [6-8] the choice for selecting the best inhibitor must be based on a set of desired characteristics including inhibition efficiency [9]. In past studies we were interested in efficient stable cheap and environmentally friendly chemicals [1]. The performance of an inhibitor is deduced from electrochemical studies which are commonly based on pitting potential (Epit) measurements [10].

As pitting corrosion remains stochastic phenomena [11] caused by a multitude of parameters [12], it is impossible to predict the performance of an inhibitor based only on the knowledge of the physicochemical parameters of the metal and its environment. This explains the interest of several studies in using machine learning algorithms in the process of estimating of the performance of pitting corrosion inhibitors.

This work is part of a program whose aim is to prevent pitting corrosion of an open cooling circuit in a nuclear installation. In the laboratory investigations, we carried out Epit measurements for different concentrations of various inhibitors. An Epit value was measured for various experimental situation described by various physicochemical parameters. Then a number of algorithms have been applied in order to investigate the possibility of predicting Epit values from the knowledge of the physicochemical parameters.

In the present paper, we consider four algorithms. We applied a combination of genetic algorithm with artificial neural networks designed by GA-ANN. GA is an

important tool for optimizing functions. It based on the evolutionary process of biological organisms in nature. An Artificial Neural Network (ANN) is a mathematical model that is inspired by the behavior of biological nervous system. ANN has three layers in its structure, input layer, hidden layer and output layer. The algorithm has been used with success in concrete corrosion [13]. We also applied Least Square Support Vector Machine designated by LS-SVM, which has been developed, by Suykens and Vandewalle [14] for reducing the SVM model complexity. LSSVM obtain the solution by solving a linear set of equations, instead of solving a quadratic programming problem for classical SVM. The algorithm has been successfully used recently to predict corrosion pits on pipes [15].

The other two algorithms used in this study are the RT and the KNN. Breiman has developed RT. The RT is composed of leaf nodes and branch nodes, which a branch node is called a parent node. The parent node represents a choice between two alternatives, and the leaf node represents a solution. It has been used to investigate corrosion behavior of steels in concrete [16]. Fix and Hodges introduced the KNN. The classification accuracy of KNN depends on the way that distances between nearest neighbors are computed and the choice of the neighborhood size. Even though, KNN has been used in many fields; there are few studies relating to corrosion [17].

In this work, we discuss and compare the efficiency of a number of pitting corrosion inhibitors. We show that it is impossible to estimate the corrosiveness of a medium from its physicochemical parameters. We consider the option of applying corrosion prediction algorithms and then optimizing their use.

2. Experimental

All electrochemical experiments have been conducted on a carbon steel containing 0.18 % carbon. More than 400 experiments have been conducted. For each one we prepare a solution containing NaCl, Chloride is considered responsible for pitting corrosion [18]. In the solution, we add a specific quantity of an inorganic chemical considered as the corrosion inhibitor. Eight chemicals have been independently considered: Na_2WO_4, Na_2MoO_4, $NaHCO_3$, Na_2CO_3, Na_3PO_4, Na_2HPO_4, NaH_2PO_4 and Na_2SiO_3. In Addition to the inhibitor, we dissolve some quantity of the oxidant KIO_3. We reported on a previous work that this oxidant could improve the efficiency of some corrosion inhibitors [1]. Overall, the reagent concentrations were fixed in accordance with Table 1.

Table 1. Reactants concentrations used to prepare the solutions.

	Molar Concentration			
Pitting Element (NaCl)	$3\ 10^{-4}$	10^{-3}	$5\ 10^{-3}$	10^{-2}
Each Inhibitors (Na_2WO_4, Na_2MoO_4, $NaHCO_3$, Na_2CO_3, Na_3PO_4, Na_2HPO_4, NaH_2PO_4, Na_2SiO_3)	0	10^{-3}	$5\ 10^{-3}$	10^{-2}
Oxydant (KIO_3)	0	10^{-3}	$5\ 10^{-3}$	10^{-2}

For each prepared solution, the pH and the ionic conductivity are recorded. The electrochemical experiments were performed in an aerated three electrodes

cell as it is described in [5]. With each experiment, a voltammogram is obtained by sweeping the potential from -0.8 to 1 V/SCE at a scan rate of 1 mV/s. At the end of the experiment, the pitting potential Epit value is determined from the voltammogram. This value corresponds to the potential at which we observe a sharp increase in the current [19]. Each electrochemical experiment was repeated at least twice in order to ensure reproducibility and accuracy of the results. At the end of the electrochemical experiments, we prepared a data table (419 rows x 13 columns). Each row corresponds to an experiment. The two first columns correspond to the ionic conductivity of the solution and its pH, Column 3 and 4 correspond to NaCl and KIO_3 concentrations. Columns 5 to 12 correspond respectively to the concentrations of Na_3PO_4, Na_2HPO_4, NaH_2PO_4, Na_2CO_3, $NaHCO_3$, Na_2MoO_4, Na_2WO_4, and Na_2SiO_3. In one experiment, we cannot use more than one inhibitor. The last column (13) is reserved to the experimentally obtained pitting potential Epit-exp value.

The four prediction algorithms were then applied on the experimental data using Matlab. To use GA-ANN, LS-SVM, KNN and RT we call respectively "gabpnet", "simlssvm", "classificationknn" and "regressiontree".

The aim of the modelling is to predict the pitting potential Epit-cal. To do this an algorithm considers the first 12 columns of the experimental table as input data. The performance of the algorithm is estimated by a correlation coefficient *R* which measures the gap between Epit-cal and Epit-exp. As the processing is based on learning and test phases the experimental table is divided into two parts. Each algorithm exploits one part for the learning phase and the other for the test phase. One of the objectives of this work is to assess the percentage of experiments used for each phase. Each algorithm is estimated by its learning capacity indicated by the correlation coefficient Rtrain and also by its generalization capacity indicated by the correlation coefficient Rtest.

3. Results and Discussion

The electrochemical data considered in this work are the fruit of a long work whose results have been presented in various papers [1,5,10]. The Table 2 below summarizes relevant findings and conclusions. All inhibitors are known to be stable. This stability is required for a cooling circuit open to the atmosphere and whose water is in a continuous circulation. All reagents are also non-toxic so that the circuit can be drained periodically without any particular precaution.

However, the inhibitors showed different effects on pH. It can be seen that trisodium phosphate and silicates clearly increase the pH. From a practical point of view, increasing the pH always reinforces the passive film, which protects the metal. This results in a better resistance to pitting corrosion [20]. However, increasing the pH can lead to the formation of scale deposits. For installations with heat exchangers, this may have undesired thermal consequences. A good inhibitor in a cooling circuit should be able to reduce corrosion without causing scale deposition.

Ionic conductivity also promotes the mobility of ions and increases the corrosivity of the aqueous medium. It is therefore not desirable for an inhibitor to increase this parameter, as is the case for trisodium phosphates. Carbonates and

bicarbonates are not very efficient; they increase both pH and the ionic conductivity. Finally, we found that the efficiency of tungstates and molybdates could be improved in the presence of small amounts of oxidants. Tungstates and molybdates also provided good results in terms of its inhibition efficiency in other comparative study between inorganic inhibitors [21]. According to the analysis of the results, the efficiency of pitting inhibition increases in the order: HCO_3^- < $H_2PO_4^-$ < CO_3^{2-} < HPO_4^{2-}< PO_4^{3-}< SiO_3^{2-}< MoO_4^{2-}< WO_4^{2-}.

Table 2. Comparison of the effectiveness between various studied inhibitors.

Inhibitor	Stability	Non-toxicity	Effect on pH	Conductivity µS/cm for [0,01]	Effect on Epit	Synergy with oxidant
WO_4^{2-}	☑	☑	Medium	2096	strong	☑
MoO_4^{2-}	☑	☑	Medium	1910	strong	☑
SiO_3^-	☑	☑	Strong	1386	medium	☒
PO_4^{3-}	☑	☑	Strong	3890	medium	☒
HPO_4^{2-}	☑	☑	medium	2030	weak	☒
$H_2PO_4^-$	☑	☑	weak	787	negligible	☒
CO_3^{2-}	☑	☑	strong	2140	weak	☒
HCO_3^-	☑	☑	medium	943	negligible	☒

Once the experimental table was completed and the results discussed, we have been interested in pitting potential prediction based on the knowledge of the properties of the solution. All the algorithms considered require a learning phase followed by a test phase. The amount of data reserved for the learning phase affects both the learning quality as well as the generalization capacity of the algorithm.

The qualification of an algorithm is based both on the estimation of the correlation coefficient R, which in the ideal case is equal to 1, and also on the capacity of generalization of the algorithm with respect to its learning ability that can be estimated by |Rtrain - Rtest|.

Fig. 1(a) to (d) illustrate the ability to learn and the capacity to generalize for the four algorithms according to the percentage of experimental data allocated to the training phase. These capacities are indicated by the value of the correlation coefficient R. The data table has been split in three ways: (training/testing) 50% (1/2); 67% (2/3); 90% (9/10).

The first observation that emerges from these figures is that KNN algorithm presents moderate learning and generalisation capacities, even if the algorithm seems to be optimised by the fact that Rtest approach Rtrain. The two correlation coefficients increase with the amount of learning data. It should also be noted that in no case Rtest exceeds Rtrain. This is particularly visible for GA-ANN and LS-SVM. This makes it possible to assert that all these algorithms are capable of predicting only within the limits of their learning ability. The optimization of the data proportion reserved for learning must therefore be based on the reduction of the difference between Rtest and Rtrain and not on an independent improvement of Rtest. From this position, it appears that GA-ANN and LS-SVM are the most interesting algorithms. Moreover, 2/3 of the experimental data are sufficient to train optimally these algorithms. If there is a need to improve testing,

consideration should be given to increasing the number of experiments rather than the ratio of data to be reserved for learning.

Each algorithm performs specific procedures built on parameters. Some of them are configurable under Matlab. Training an artificial neural network using a genetic algorithm can be controlled by parameters specific to genetic algorithms and others to artificial neural networks.

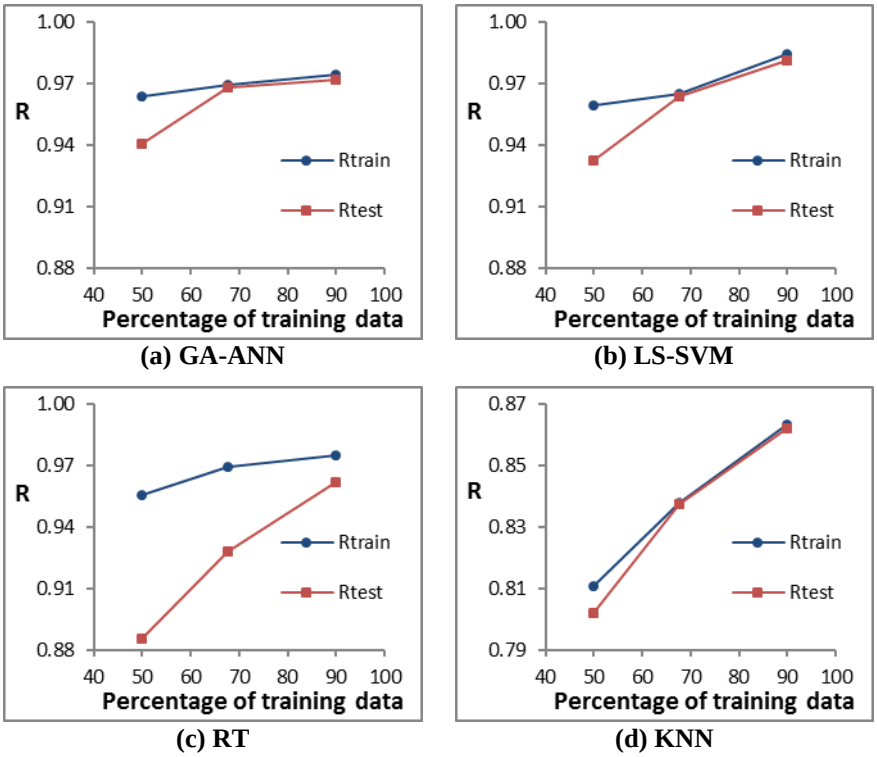


Fig. 1. The effect of different percentage of training data on R of each model: (a) GA-ANN, (b) LS-SVM, (c) RT, (d) KNN.

The influence of the number of the population, the number of generations and also the number of hidden layers of the neural network are studied next. Each parameter is studied separately and the performance is assessed by *R*.

From Fig. 22(a), it appears clearly that the R improves when increasing the number of generation. However, after 90 generations, we can assume that Rtest is close enough to Rtrain. A similar observation can be made by varying the number of population as seen in Fig. 2(b); for a value equal to 30 Rtest coincides with Rtrain. A parameter is considered optimized when the indicator of the generalization capacity Rtest approximates that of its learning. The other optimization parameter of the GA-ANN algorithm was the number of hidden layers of the associated neural network. The number of hidden layers was varied from 1 to 24 by keeping the number of neurons per hidden layer constant at 10. The effect of the number of hidden layers on R is illustrated in Fig. 2(c).

R reaches its maximum for a number of hidden layers equal to 12. The evolution of R beyond this number shows that the learning and generalization capacities are reduced.

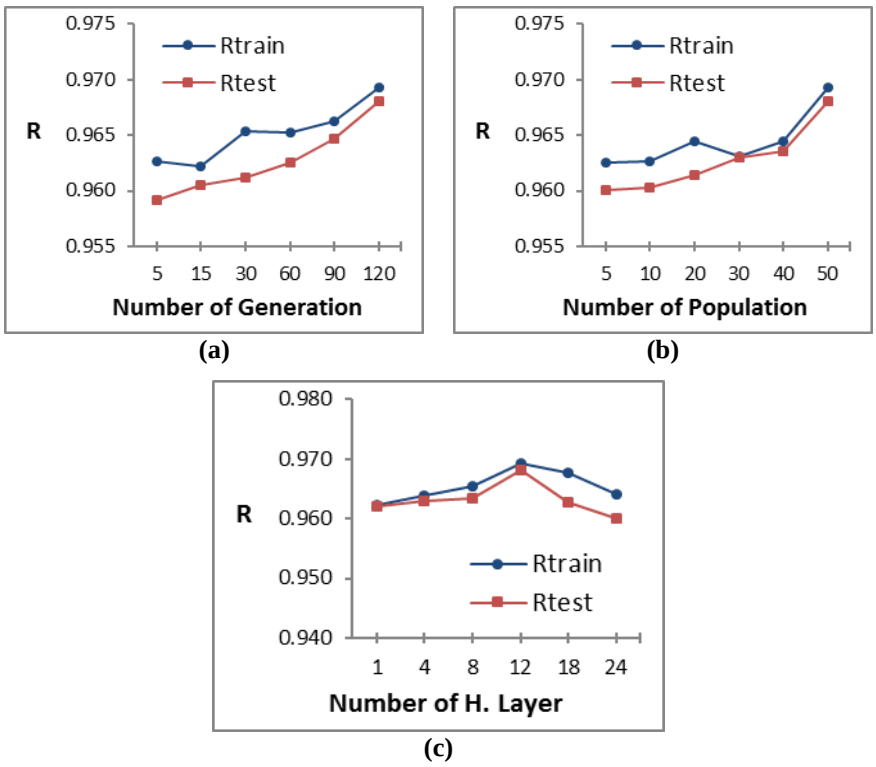


Fig. 2. The effect of variation the (a) number of Generation, (b) population and (c) hidden layer on R.

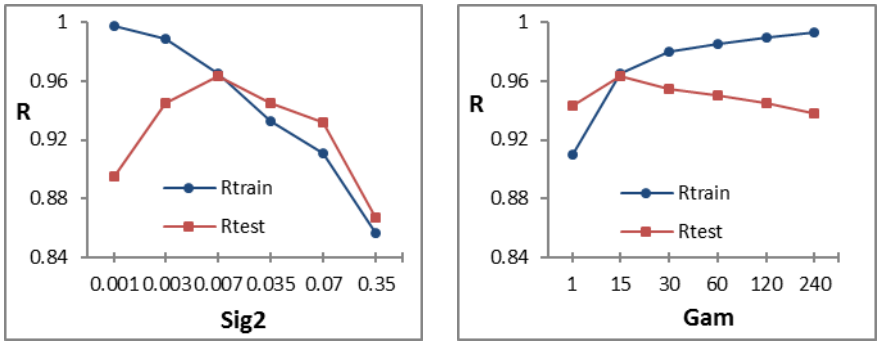
The results of Fig. 2 show that the optimization of an algorithm does not require the limitless increase of the correlation coefficient R, but rather an ability to generalize limited by the ability to learn.

This result is also confirmed by the application of LS-SVM algorithm. Fig. **3**(a) and (b) have been obtained following the use of this algorithm.

Two parameters have been considered: the bandwidth of kernel function Sig2 ($\sigma 2$) and the regularisation parameter Gam (γ). Sig2 represents the variance of the Gaussian kernel function. Gam determines the trade-off cost between minimizing the training error and minimizing the models complexity [22]. From Fig. 3(a) and (b), it can be seen that the learning quality decreases as Sig2 increases whereas it improves with the increase of the Gam parameter. Obviously, studying the variation of a parameter requires keeping the other constant. To obtain Fig. 3(a) Gam was kept at 15. To get Fig. 3(b) Sig2 was kept at 0,007.

The choice of these values was not fortuitous. Indeed, it is precisely these two values that allow Rtest to approach Rtrain. It is for these values that the

generalization capacity of the algorithm approximates its learning ability. In addition, it is precisely for these two values that Rtest reaches a maximum value.

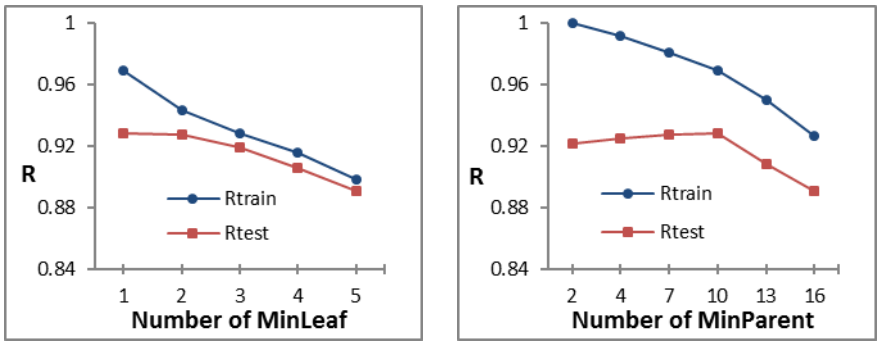


(a) **(b)**

Fig. 3. The effect of (a) Sig2 and (b) Gam on R.

A similar study was conducted with the regression tree algorithm. Results are shown on Fig. 4. The search for optimization focused on two parameters: MinLeaf and MinParent. MinLeaf represents the minimum number of observations per tree leaf. MinParent is the number k such that impure nodes must have k or more observations to be split.

From **Error! Reference source not found.**(a), it appears that the increase of MinLeaf continuously reduces Rtrain and Rtest. This study was conducted by keeping MinParent at its default value of 10. By keeping MinLeaf at its default value of 1 and by varying MinParent from 1 to 16, it can be seen on **Error! Reference source not found.**(b) that the learning ability Rtrain is at its maximum for MinParent equal to 1. However, Rtrain decreases as MinParent increases. However, the generalization capacity Rtest reaches a maximum for MinParent equal to 10, which is the default value of the parameter.



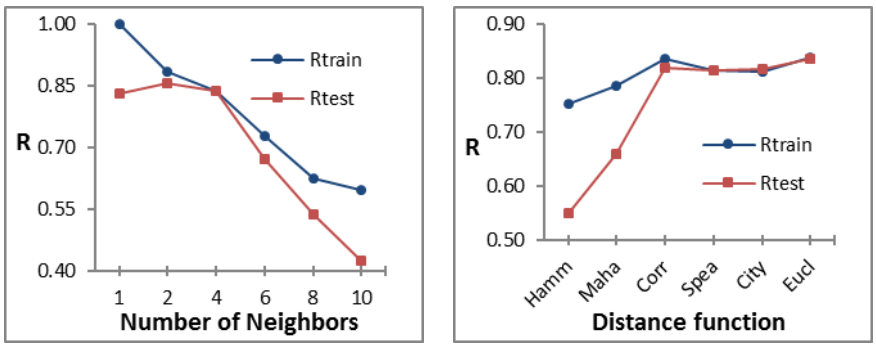
(a) **(b)**

Fig. 4. The effect of MinLeaf (a) and MinParent (b) on R.

Based on these results we decided to keep both MinLeaf and MinParent parameters at their default values for all pitting potential prediction studies.

Under Matlab KNN algorithm can be controlled, among other things, by the number k of the nearest neighbours and also by the distance measurement function.

Fig. **5**(a) illustrates the evolution of Rtrain and Rtest with the number of neighbours. The estimation of the distance by the Euclidean calculation seems to be the most appropriate. In fact, the 'Distance' property for the 'ClassificationKNN' class is set to 'Euclidean' by default.



(a) **(b)**

Fig. 5. The effect of (a) the number of neighbors and (b) the kind of the distance function on R.

The Euclidean function was chosen to estimate the distance to neighbours. If Rtrain decreases continuously with the number of neighbours, Rtest passes through a maximum at 4 and decrease for a larger number of neighbours. In fact, for the kind of data we have, it is unnecessary to set an important value for k. It is not recommended in cases where experimental data is subject to significant noise [23]. This corresponds exactly to the nature of our experimental data. We have indeed in an earlier publication underlined the imprecise character in picking Epit from voltammograms [10].

Fig. **5**(b) shows the performance of the distance estimation functions. The calculations were carried out by fixing the number of neighbours at 4. The estimation of the distance by the Euclidean calculation seems to be the most appropriate. In fact, the 'Distance' property for the 'ClassificationKNN' class is set to 'Euclidean' by default.

The results of the optimization study are summarized in Fig. 6 where the values of Rtrain and Rtest for the four algorithms are shown. The optimal values of the studied parameters were selected for each algorithm as detailed above. Indeed, it is by making sure that the algorithms are adjusted optimally that the comparison between them becomes appropriate.

Whether we consider Rtest as a performance indicator or even its proximity to Rtrain, it is clear that GA-ANN and LS-SVM remain the best algorithms. These two algorithms possess the best capacities of generalization and this capacity is limited by their ability of learning. Results from the recently study also showed GA-ANN is better than LS-SVM in forecasting solar irradiance [24]. If we

consider the correlation coefficient as a whole, it might be suggested that RT exhibits a high Rtrain value. However, this remains a situation of over-learning insofar as Rtest remain low. KNN is a moderate tool. It provides moderate learning and generalisation capacities.

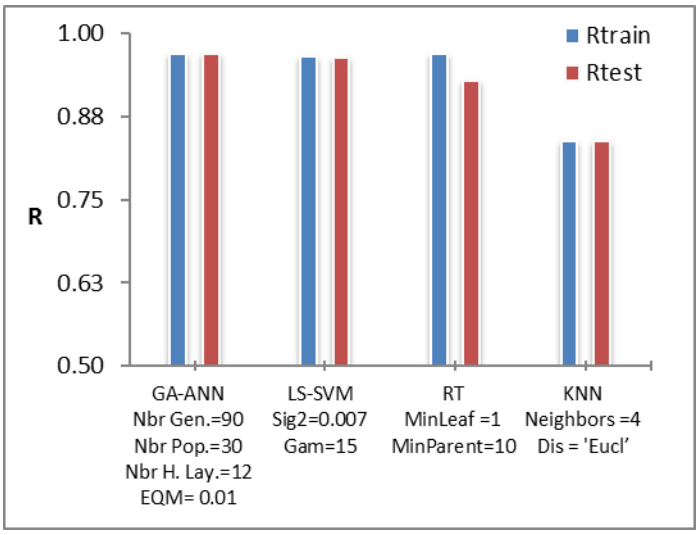


Fig. 6. Comparison between the algorithms in their optimal state.

Finally, it is interesting to note that generally the optimal values of the parameters to which we have arrived are all close to the default values set by the algorithms in Matlab.

4. Conclusion

This work was carried out in two steps: a comparative study of pitting corrosion inhibitors and a comparative study of algorithms for the prediction of pitting potential.

Electrochemical studies show that tungstate, and to a lesser extent molybdate, have the best advantages for the prevention of pitting corrosion. This is due to their effect on the pitting potential and also to the synergy; they have in the presence of oxidants. Using these inhibitors is required to avoid serious pollution to the groundwater after the periodic water draining. From the electrochemical study, we can deduce this order of performance: HCO_3^- < $H_2PO_4^-$ < CO_3^{2-} < HPO_4^{-2} < PO_4^{3-} < SiO_3^{2-} < MoO_4^{2-} < WO_4^{2-}.

Modelling studies confirm that the performance of an algorithm depends on the optimization of its parameters. However, we found that these performance values are fairly close to the default values. The performance of an algorithm was estimated by its ability to generalize with respect to its ability to learn: implicitly appreciated by the difference (Rtest - Rtrain). From the overall results it appears that, the order of performance of the algorithms is: RT < KNN < LS-SVM < GA-ANN.

References

1. Boucherit, M. N.; Amzert S.; Arbaoui, F.; Hannini, S.; Hammache, A. (2008). Pitting corrosion in presence of inhibitors and oxidants. *Anti-Corrosion Methods and Materials*, 55(3), 155-122.
2. Burstein, T.; Liu, C.; Souto, R.M.; Vines, S.P. Origins of pitting corrosion. (2004). *Corrosion Engineering Science and Technology*, 39 (1), 25-30.
3. Li, H.B.; Jiang, Z.H.; Cao, Y.; Zhang, Z.R. (2009). Fabrication of high nitrogen austenitic stainless steels with excellent mechanical and pitting corrosion properties. *International Journal of Minerals Metallurgy and Materials*, 16(4), 387-392.
4. Benabdellah, M.; Dafali, A.; Hammouti, B.; Aounti, A.; Rhomari, M.; Raada, A.; Senhaji, O.; Robin, J.J. (2007). The role of phosphonate derivatives on the corrosion inhibition of steel in HCl media. *Chemical Engineering Communications*, 194(10-12), 1328-1341.
5. Boucherit, M. N.; Amzert, S.; Arbaoui, F.; Sari, A.; Tebib, D. (2006). Study of the evolution of a semi-open cooling circuit. *Anti-corrosion methods and materials*, 53(4), 212-217.
6. Chen, J.R.; Chao, H.Y. (1991). Studies on carbon steel corrosion in molybdate and silicate solutions as corrosion inhibitors. *Surface Science*, 247(2), 352-359.
7. Cheng, Y.F.; Wilmott, M.; Luo, J.L. (1999). The role of chloride ions in pitting of carbon steel studied by the statistical analysis of electrochemical noise. *Applied Surface Science*, 152(3-4), 161-168.
8. Li, S.; Ni, L.; Sung, C.; Wang, L. (2004). Influence of organic matter on orthophosphate corrosion inhibition for copper pipe in soft water. *Corrosion Science*, 46(1), 137-145.
9. Yurt, A.; Balaban, A.; Kandemir, S.U.; Bereket, G.; Erk, B. (2004). Investigation on some Schiff bases as HCl corrosion inhibitors for carbon steel. *Materials Chemistry and Physics*, 85(2-3), 420-426.
10. Boucherit, M. N.; Tebbib, D. (2005). A study of carbon steels in basic pitting environment. *Anti-Corrosion Methods and Materials*, 52(6), 365-370.
11. Velázquez, J.C.; Van Der Weide, J.A.M.; Hernández, E.; Hernández, H. H. (2014). Statistical Modelling of Pitting Corrosion: Extrapolation of the Maximum Pit Depth-Growth. *International Journal of Electrochemical Science*, 9(8), 4129-4143.
12. Franke, G. S. (1998). Pitting corrosion of metals A review of the critical factors. *Journal of the Electrochemical Society*, 145(6), 2186-2197.
13. Firouzia, A.; Rahaib, A. (2012). An integrated ANN-GA for reliability based inspection of concrete bridge decks considering extent of corrosion-induced cracks and life cycle costs. *Scientia Iranica*, 19(4), 974-981.
14. Suykens, J. A. K.; Vandewalle, J. (2000). Recurrent Least Squares Support Vector Machines. *IEEE transactions on circuits and systems-i: fundamental theory and applications*, 47(7), 1109-1114.

15. Ji, J.; Zhang, C.; Kodikara, J.; Yang, SQ. (2015). Prediction of stress concentration factor of corrosion pits on buried pipes by least squares support vector machine. *Engineering Failure Analysis*, 55,131-138.
16. Kainuma, S.; Hosomi, N. (2006). Numerical simulation of time-dependent corroded surface of structural steel members in boundary with concrete. *Doboku Gakkai Ronbunshuu A*, 62(2), 440-453.
17. Jiménez-Come, M. J.; Turias, I. J.; Ruiz-Aguilar, J. J.; Trujillo, F. J. (2015). Characterization of pitting corrosion of stainless steel using artificial neural networks. *Materials and Corrosion*, 66(10), 1084-1091.
18. Siti, F.A.R.; Mohammad, I.; Norhazilan, MD. N.; Hazri, B. (2012). Embedded capacitor sensor for monitoring corrosion of reinforcement in concrete. *Journal of Engineering Science and Technology*, 7(2), 209-218.
19. Chen, Y.Y.; Hong, U.T.; Shih, H.C.; Yeh, J.W.; Duval, T. (2005). Electrochemical kinetics of the high entropy alloys in aqueous environments A comparison with type 304 stainless steel. *Corrosion Science*, 47(11), 2679-2699.
20. Bird, H.E.H.; Pearson, B.R.; Brook, P.A. (1988). The breakdown of passive films on iron. *Corrosion science*, 28(1), 81-86.
21. Yuming, T.; Guodong, Z.; Yu, Z. (2012). The inhibition effects of several inhibitors on rebar in acidified concrete pore solution. *Construction and Building Materials*, 28(1), 327-332.
22. Kumar, S.; Gurusamy, S. K.; Subathra, B.; Srinivasan, S. (2015). An approach for Short-Term Load Forecasting Using RBFNN in the Smart Grid. *International Journal of Control Theory and Applications*, 8(5), 2169-2177.
23. Medjahed, S. A.; Tamazouzt, A. S.; Benyettou, A. (2013). Breast cancer diagnosis by using k-nearest neighbor with different distances and classification rules. *International Journal of Computer Applications*, 62(1),1-5.
24. Bao, A.; Fei, S.; Zhong, M. (2016). Short-term solar irradiance forecasting using neural network and genetic algorithm. *Proceedings of 2016 Chinese Intelligent Systems Conference*, Singapore, Malaysia, 619-627.