

Comparison of adaptive techniques for the prediction of the equivalent salt deposit density of medium voltage insulators

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Abstract: - One of the main reasons that flashover can occur in distribution lines is the sea salt contamination of medium voltage insulators. Equivalent salt deposit density (ESDD) expresses the contamination level of insulators and is used as the main criterion for scheduling the maintenance (washing) of insulators. In this paper two different adaptive techniques, a multi model partitioning filter (MMPF) and an artificial neural network (ANN), are developed and presented in order to predict the equivalent salt deposit density of medium voltage insulators. Real data are used for the MMPF modeling and the ANN training, as well as for the comparison of the produced by the two techniques ESDD results with actual measured ones. The proposed techniques can be very useful in the work of electrical maintenance engineers for estimating the insulator's contamination easily, accurately and at minimum cost resulting in a more effective maintenance scheduling.

Key-Words: - Artificial neural networks, Equivalent salt deposit density (ESDD), Extended Kalman filters, Medium voltage insulators, Multi model partitioning filter

1 Introduction

The sea salt contamination of insulators is one of the main reasons for flashovers in distribution lines that can cause outages and unscheduled power supply interruptions. Efficient insulator maintenance plans can control the contamination problem resulting in the elimination or even the absence of outages. The insulator maintenance is performed mainly with the insulator periodic washing or cleaning and rarely with the massive replacement of insulators. Generally the insulator maintenance is scheduled based on experience, measurements or even simple observations [1].

The contamination level of insulators is generally expressed by the equivalent salt deposit density (ESDD), and is taken into account in order to diagnose the sea salt pollution severity on insulators. Although the ESDD measurement is an expensive and time consuming process, its results is the main criterion for scheduling the maintenance (washing) of insulators that is why these measurements are still very popular and extensively used [2].

However the previous years, have been presented in the technical literature, alternative methods capable to assess the contamination of insulators. These methods are based on probabilistic assessments [3], multivariate models [4], leakage

current monitoring techniques [5], and artificial neural networks [1, 6, 7]. Finally sensors have been designed and used to measure the contamination level on the insulator surface [2].

In this paper two adaptive techniques were used in order to predict the equivalent salt deposit density of medium voltage insulators. The first one is based on a multi model partitioning filter (MMPF), while the second on a previous developed artificial neural network (ANN) [7]. Real data collected from Hellenic Public Power Corporation S.A. from 2004 to 2007 were used for the MMPF modeling, the ANN training, the ESDD prediction and the comparison with actual ESDD measurements.

Both techniques that have been proved capable to predict with accuracy the ESDD values, can be useful in the work of electrical maintenance engineers resulting in a more effective maintenance scheduling and consequently to less failures/outages offering with this way greater efficiency in the electrical networks.

2 Medium voltage insulators and ESDD measurements

Conductors of medium voltage distribution lines are generally suspended with the use of cap-and-pin or

suspension (disc) insulators. The insulators are made of either glass, porcelain or composite materials.

In coastline and island regions, where the salt sea contamination is intense the electric utilities' employees are washing the insulators at least twice during the summer period, while there are cases where the insulator washing can take place even every single week [1].

The pollution severity is quantified in terms of equivalent salt deposit density stated in units of mg/cm². ESDD is the equivalent amount of NaCl that would yield the same conductivity at complete dilution [8]. According to the literature, if the value of ESDD is equal or greater than 0.03-0.05 mg/cm², the insulators are washed [9, 10].

ESDD measurement activities were carried out by the personnel of Hellenic Public Power Corporation S.A. weekly in Elefsina, a coastal town in the periphery of Attica and in Chalkida, the capital of Evia Island, for a period of almost four years (2004-2007). Four samples of cap-and-pin porcelain insulators were utilized from each one of the two pre-mentioned areas. The samples were taken down weekly from the scaffold and the pollutants were removed by washing the insulators using paintbrush and distilled water. Every contaminated sample for each test was washed by immersing it in distilled water and the contamination value was measured by determining the conductivity or the rate of rise of the conductivity value for the polluted water after washing the insulator [9]. Using such procedure, ESDD value was determined.

3 Adaptive techniques

3.1 The MMPF method

The multi model partitioning filter (MMPF) was initially proposed and presented by Lainiotis in [11, 12] and since then it has been successfully applied in a numerous applications such as the modelling of the grounding resistance variation [13], order and parameter estimation of multivariate (MV) ARMA models [14], electric load modelling and forecasting [15, 16], network anomaly detection [17], multiple source detection [18], towed array shape estimation [19] and finally combined with evolutionary algorithms for data mining [20, 21].

In the current work the MMPF is applied in order to model and predict the sea salt contamination of medium voltage insulators, by implementing a bank of extended Kalman filters (EKF) with MV ARMA models.

The reason for applying EKFs is their ability handle data's non-linearities since the raw data used now is not subjected to any prior offline manipulation in order to remove weekly and annual seasonalities as was done in previous cases [16].

The method is analytically presented in [14] but a short description will be also presented here. Fig. 1 represents a block diagram of the first method proposed. A finite set of M models is designed, each matching one value of the parameter vector. Then a bank of EKF is applied, one for each model, which can be run in parallel. At each iteration the MMPF selects the model which corresponds to the maximum posteriori probability as the correct one. This probability tends to one, while the others tend to zero. The overall optimal estimate can be taken either to be the individual estimate of the elemental filter exhibiting the maximum posterior probability (MAP) or the weighted average of the estimates produced by each filter which the case used in this paper.

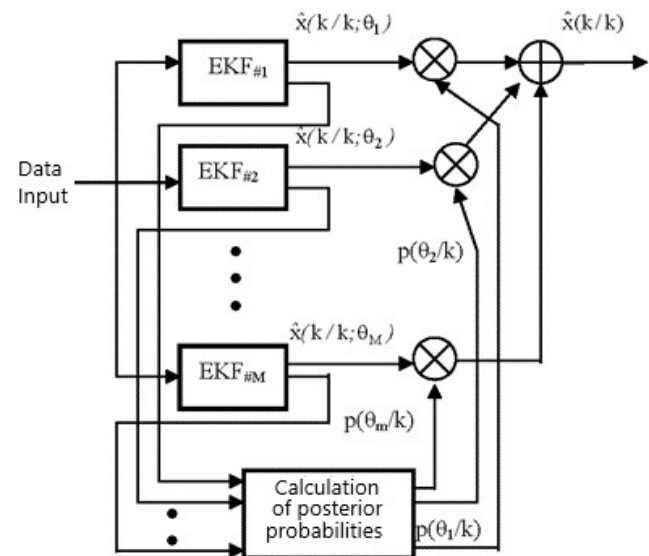


Figure 1: MMPF block diagram

The optimal Minimum Mean Square Error (MMSE) estimate of $x(k)$ is given by:

$$\hat{x}(k/k) = \sum_{i=1}^M \hat{x}(k/k; \theta) p(\theta/k) d\theta \tag{1}$$

The probabilities are calculated online in a recursive manner as follows:

$$p(\theta/k) = \frac{L(k/k; \theta)}{\sum_{i=1}^M L(k/k; \theta) p(\theta/k-1) d\theta} p(\theta/k-1) \tag{2}$$

where:

$$L(k/k;\theta) = \left| P_z(k/k-1;\theta) \right|^{1/2} \cdot \exp \left\{ -1/2 \left\| \hat{z}(k/k-1;\theta) \right\| \cdot P_z^{-1}(k/k-1;\theta) \right\} \quad (3)$$

and P_z^{-1} is given by the Kalman filter equations.

An important feature of the MMPF is that all the Kalman filters needed to implement can be independently realized. This enables us to implement them in parallel, thus saving us enormous computational time.

The method proposed will use different number of EKFs each time, namely $M=10$, $M=15$ and finally $M=20$.

The greater the number of the EKFs implemented the greater the accuracy of the prediction and also the bigger the computational load required. Since online rapid estimation is not necessary in this application the computational burden will be increased for the sake of a better output in terms of Absolute Percentage Error (APE).

The input to each MV ARMA that will be implemented within each EKF will be a row vector containing the values of wind velocity, temperature, month, humidity and rainfall. Each of these parameters are assumed to contribute by the same importance towards the final output.

3.2 The ANN method

The structure of the artificial neural network applied in this work is analytically presented in [7] and a schematic diagram of its architecture is depicted in Fig. 2.

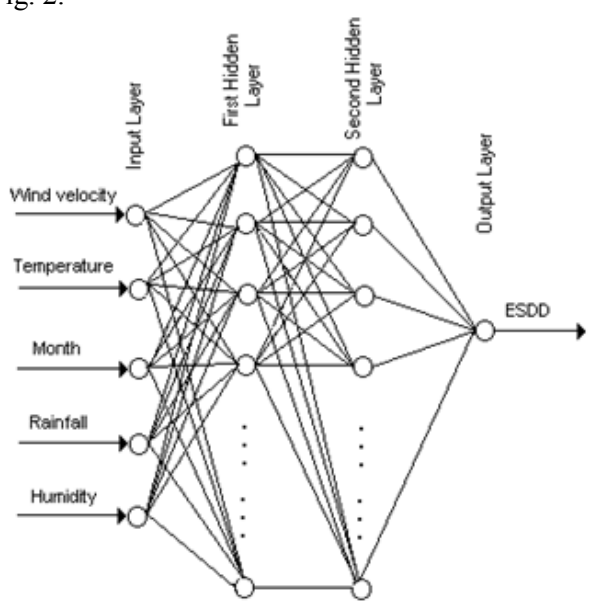


Fig. 2 The ANN model architecture for the ESDD value prediction on medium voltage insulators

Several different multilayer perceptron (MLP) models were designed and tested in order to identify the model with the best generalizing ability. These were combinations of four different learning algorithms, five different transfer functions and several different structures consisted of 1 to 4 hidden layers with 2 to 50 neurons in each hidden layer (Table 1).

Table 1 Designed MLP ANN models

Structure	Learning Algorithm	Transfer Function
- 1 to 4 hidden layers	- Gradient Descent - Quasi-Newton	- Hyperbolic Tangent Sigmoid
- 2 to 50 neurons in each hidden layer	- Levenberg-Marquardt - Random Order Incremental	- Logarithmic Sigmoid - Hard-Limit - Competitive - Linear

The selected ANN model had the following characteristics: three hidden layers, with eleven, twenty eight and eighteen neurons in each hidden layer respectively, random order incremental learning algorithm and logarithmic sigmoid transfer function.

4 Results

The available data covers a range of three years. The data of the first two years will be used to train the proposed methods. The prediction will be an average value of the ESDD for the 8 samples for the third year.

The comparison results between the performance of the MMPF in terms of actual values and absolute percentage error (APE) against ANN's are presented Figs 3 and 4.

Fig. 3 indicates that both adaptive techniques manage to accurately predict values close to the actual ones.

However a closer look in Fig. 4 indicates that the APE for the MMPF is significantly less than the ANN's in all 3 cases ($M=10$, $M=15$, $M=20$).

The range of the APE for the ANN is between 5 and 24. On the other hand the APE for the MMPF is not more than 10 in all 3 cases. Analytically for $M=10$ the APE lies between 5 and 9, for $M=15$ between 3 and 5 and for $M=20$ between 2 and 3.

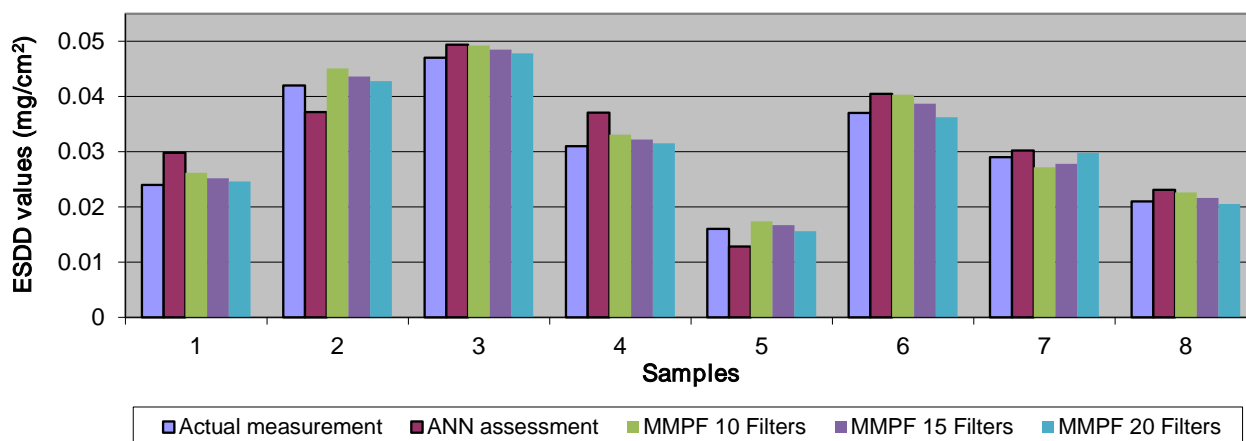


Fig. 3 Comparison of the predicted values with the actual values

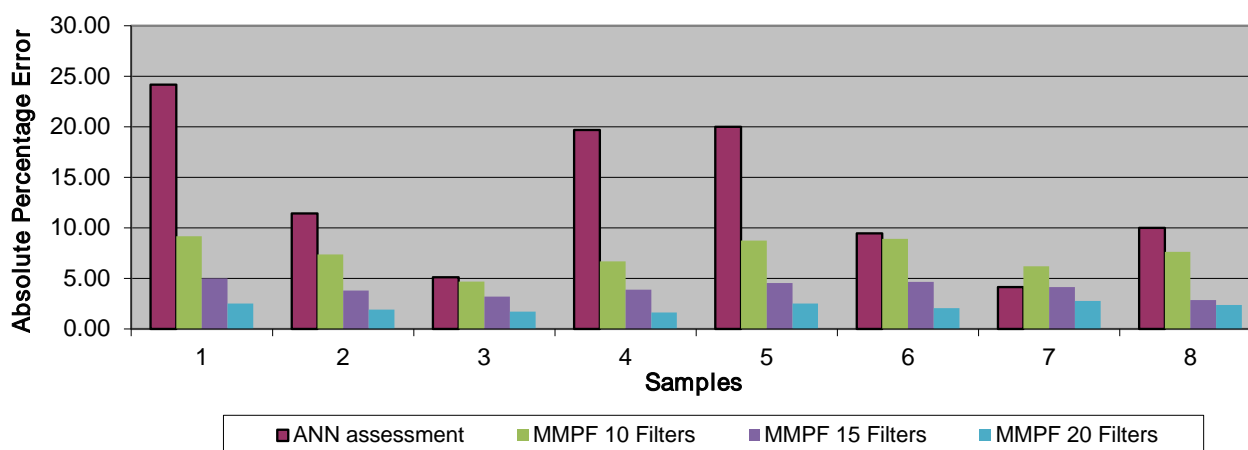


Fig. 4 Comparison of the absolute percentage errors

5 Conclusion

The paper presents two adaptive techniques, namely MMPF and ANN in order to model and predict the ESDD of medium voltage insulators placed in coastal regions. The data used was real and was collected from Hellenic Public Power Corporation S.A. from 2004 to 2007.

The results showed that both methods successfully tackled the problem, however the MMPF's performance is better in all its 3 different structures tried, since it presents the lowest absolute percentage error.

A useful comment is that by increasing the number of filters implemented by the MMPF the accuracy of the prediction increases significantly, with a cost on the computational burden, which however is not of great importance since on line estimation is not required in our case.

Both methods considered can be useful in the studies of electrical maintenance engineers since they can provide a deeper understanding and

knowledge about medium voltage insulators' contamination without cost and may lead to a more effective maintenance policy.

An interesting extension of this work is to reduce in half the number of the input data used to either train the ANN, or calculating the MMSE of MMPF and attempt to estimate the ESDD of the 8 samples for a period of the next 6 months, or less instead of the whole year.

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