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Comparative Evaluation of the Models for Predicting the Rela-Tionship Between Electrical and Chemical Properties of Engine Lubricants: An Exact Monitoring Approach

Mohammad-Reza Pourramezan [1], Abbas Rohani [1,*] and Mohammad Hossein Abbaspour-Fard [1]

[1] Department of Biosystems Engineering, Faculty of Agriculture, Ferdowsi University of Mashhad, Mashhad, Iran

* Correspondence: Tel: +985138805819; fax: +985138804686, DOI: 0000-0002-4494-7058, Email Address: arohani@um.ac.ir

Abstract: Condition monitoring is a primary principle for predictive maintenance. In this regard, several techniques have been employed, each of which has its strengths and weaknesses. In this work, the relationships between the electrical (ε', ε'', tan δ) and chemical (Fe, Pb, Cu, Cr, Al, Si, Zn) properties of engine lubricants were investigated using soft computing models. The models' performance was evaluated considering some criteria, including RMSE and MAPE. The RBF model was determined as the best one to predict chemical properties (Fe, Pb, Cu, Cr, Al, Si, Zn) through electrical indexes (ε', ε'', tan δ). The RBF's parameters (e.g., hidden size and training algorithm) were then optimized for optimum performance. For instance, in the RBF model implemented to predict Al, the best hidden size and training algorithmic were 15 and 'trainlm', respectively. Finally, by sensitivity analysis it was observed that eliminating any of the inputs does not improve the performance of the RBF model performance. In general, the results of the current research showed that the electrical properties (e.g., ε', ε'', tan δ) have the capability of estimating the contaminants in the lubricants which can improve the existing monitoring methods.

Keywords: Soft computing models; Monitoring engine lubricant condition; Dielectric; Chemical properties

1. Introduction

Nowadays, high-reliable mechanical systems are expected[1]. Condition monitoring is known as a fundamental program for maintaining and assuring the safety, permanence, and performance of a machine [2, 3]. Lubricant in a machine acts almost the same as blood in a living organism[4]. In other words, lubricants are responsible for many tasks like reducing friction and wear, transferring heat and energy, and reducing noise [5]. However, the primary function of a lubricant is to reduce the tribological operation problems relevant to friction and wear [6]. From maintenance point of view, oil analysis is an effective technique to evaluating the operational condition of mechanical systems [7]. The evolution of maintenance strategies over time is presented in **Figure1**. Currently, there are several different methods for evaluating lubricating oil, which include [8]:

Physical and chemical methods, such as chromatography.

Spectral analysis techniques, mainly infrared absorption spectroscopy (IAS) and Raman spectroscopy.

Electrical diagnosis methods, including return voltage measurement and frequency-domain spectroscopy.

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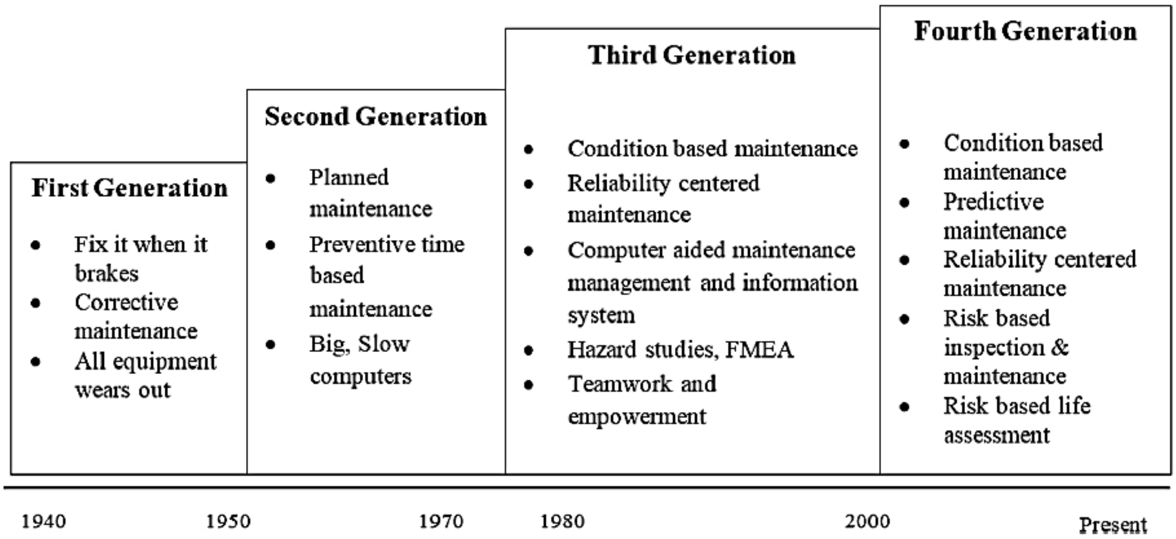

Figure 1. Development of maintenance strategies [9].

The timeline for changing and testing lubricants is a controversial issue. Although the laboratory methods can report the exact results, however they cannot determine timely maintenance [10, 11]. Having this, the electrical techniques are promising methods since they provide in-situ measurement and allow easy to use and cost-effective [12, 13]. On the other hand, the soft computing methods have been employed to analyze without experts [11, 14, 15].

Several research works on the issue of lubricant condition monitoring can be found in the literature, which are reviewed hereinafter, some of them have concentrated on modeling and using soft computing [11, 16-19]. Research was recently accomplished and applied a preliminary test on engine lubricant spectral analysis based on K-nearest neighbor (KNN) and Radial Basis Function (RBF). By doing that, twelve indexes were reduced to seven indexes including iron, chromium, lead, copper, aluminum, nickel, and TDPQ. They reported that RBF-ANN modeling was able to provide detection for all three sizes of the training set with accuracy of approximately 99.85%[11]. In another study, to identify and predict external wear failure the Recursive Feature Elimination (RFE) method was used to reduce the independent variables. They could achieve the accuracy of 94.20%. They also observed that iron, aluminum, and lead were more important in assessing wear condition [18].

Dielectric or Impedance Spectroscopy (IS) is another way of measuring the electrical indexes of various materials (concrete, paper, liquids, biofuels, etc.) as an effective, economical, and non-destructive method [20]. One research has assumed a method for locomotive system maintenance. Actually, this study has studied the relationship between dielectric properties and metallic and non-metallic particles. Artificial neural networks have been employed to determine the relationship between the dielectric constant and oil impurities, and also the dielectric loss factor and oil impurities. In the modeling process, the oil impurities (chemical properties) have been considered inputs, and dielectric properties as outputs. The highest regression values (R) have been obtained for the dielectric constant (0.8513) and the dielectric loss factor (0.8015) at 7.4 GHz[11].

In this study, the primary purpose was to compare soft computing models employed to predict the chemical properties (Fe, Pb, Cu, Cr, Al, Si, Zn) of lubricants through their electrical properties (ε', ε'', tan δ). The dataset was obtained from two sources: data extruded from other papers and data experimented in this study. More detailed information was given in section.2. The result of this work will make to develop monitoring condition engine lubricant and promote online and portable methods for sensing and detecting faults in engine health. The research process and results are as follows.

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2. Materials and Methods

2.1. Data set

The required data set was supplied from two sources. Some of them (33 records) were extracted from previous research [10] and the rest (16 records) were provided by an Iranian company (Tirage). These records are mainly the chemical properties (Fe, Pb, Cu, Cr, Al, Si, Zn) of the lubricants. While, their electrical factors (ε', ε", tan δ) were measured through this work. The procedure of data collection is depicted in **Figure2**. The additional information is provided in sections 2.1.1 and 2.1.2. To remove the effect of amplitude of changes in the values, normalization was accomplished in the range of -1 to 1 as follow [21, 22]:

$$E_n = 1 + \frac{2(E - E_{min})}{(E_{max} - E_{min})} \quad (1)$$

where, $E = [E_1, E_2, \ldots, E_n]$ represents the principal value of the index vector. E_n represents the normalized value of the index vector. E_{max} and E_{min} represent the maximum and minimum values of the index.

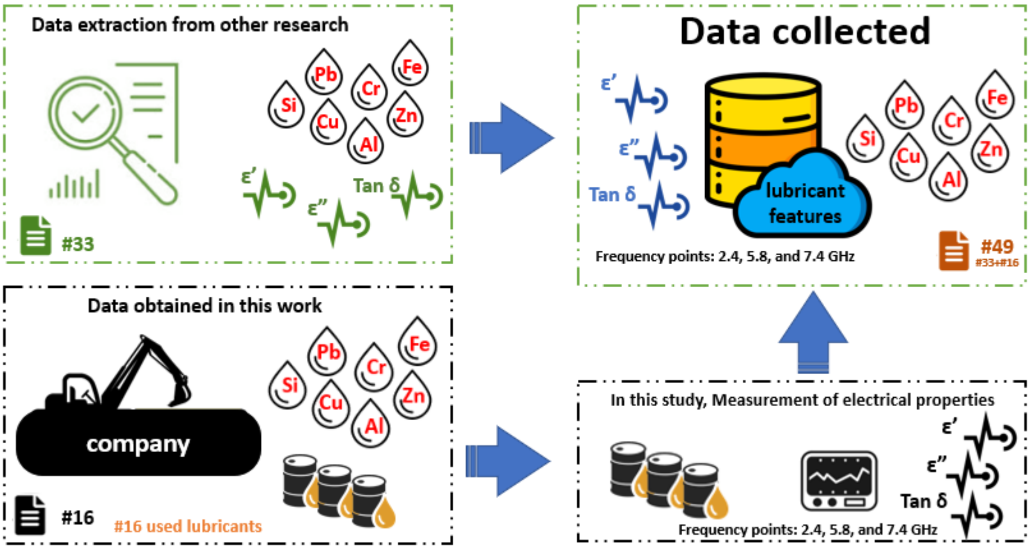

Figure 2. The schematic view of dataset preparation from sources.

2.1.1. Extracted datasets

As mentioned, the 33 records were extracted from a published work. These data included the chemical (Fe, Pb, Cu, Cr, Al, Si, Zn) and electrical properties (ε', ε", tan δ) of the second-hand lubricant [10]. Also, the 16 records were provided by an Iranian local company called Tirage. The lubricant samples had been picked up from engines and were shared by Tirage, along with their chemical properties (**Table 1**). Therefore, their electrical properties (ε', ε", tan δ) were measured in this work and reported in section 2.1.2.

Table 1. Spectral analysis results for the samples provided by Tirage company (Unit: ppm).

Sample No.	Fe	Pb	Cu	Cr	Al	Si	Zn
1	11.05	2.83	0.98	1.26	3.62	8.79	1319
2	9.94	0	0.97	0.46	1.61	17.77	1362
3	30.25	0	1.64	5.33	10.18	9.23	1359
4	81.17	0	2.59	7.46	34.59	36.21	1493
5	13.19	1.8	0.59	1.8	1.09	7.14	1281
6	24.65	0	1.25	1.55	5.05	9.89	1398
7	9.24	0	0.92	0.11	1	6.11	1362
8	15.46	0	1.75	0	0.38	4.01	1360

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9	39	4.42	7.78	6.52	10.93	16.29	1297
10	39.76	3.2	1.4	2.2	3.77	15.44	1657
11	34.69	0.18	1.23	7.2	13.45	16.55	1264
12	39.67	3.91	2.31	6.48	12.45	16.33	1342
13	86.06	1.17	2.76	3.69	10.95	40.05	1445
14	21.73	3.22	7.23	0.91	5.31	7.27	1317
15	8.17	1.79	3.23	0.04	0	7.22	803
16	49.75	3.51	4.11	4.15	5.07	13.65	1327

2.1.2. Experimental datasets

The 16 lubricant samples that had been extracted from engines were provided by Tirage Company (Table 1). Their chemical properties including Fe, Pb, Cu, Cr, Al, Si, and Zn contents were provided by the company, however their electrical properties (e.g., ε', ε", tan δ) are not specified. Therefore, the electrical properties (ε', ε", tan δ) were measured through current research by a Vector Network Analyzer (VNA) (R&S ZVL 13, made in USA). This device can analyze microwave absorbing properties in the frequency range of 9 kHz–13.6 GHz with ±0.2 dB accuracy. The lubricant sample of 50 ml was poured into a beaker, and a coaxial dielectric probe was inserted inside the oil sample, as seen in **Figure3**. The measurements were performed at 2.4, 5.8, and 7.4 GHz frequencies in triplicate, under similar conditions for all samples. The results of measurements are reported in **Table 2**.

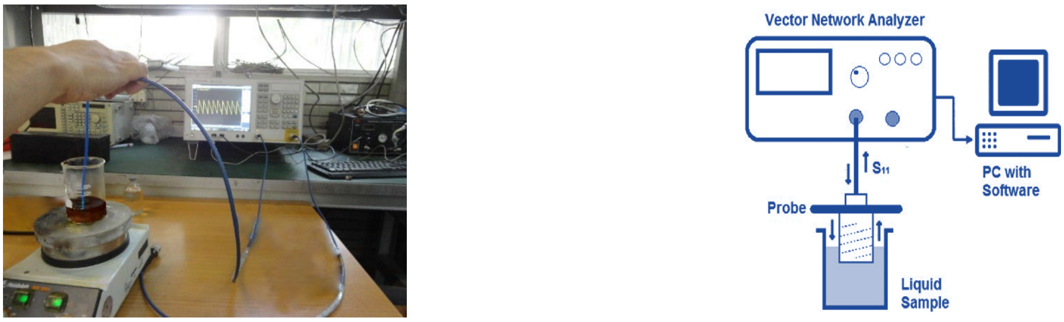

Figure 3. The experimental setup and its schematic view for measuring dielectric properties of lubricants.

Table 2. Dielectric properties measurement results for samples provide by Tirage Company.

Sample No.	2.40 GHz			5.80 GHz			7.40 GHz		
	ε'	ε"	tan δ	ε'	ε"	tan δ	ε'	ε"	tan δ
1	2.62	0.15	0.058	2.94	0.13	0.044	2.55	0.23	0.090
2	2.68	0.12	0.045	2.99	0.10	0.033	2.60	0.18	0.069
3	2.45	0.09	0.037	2.79	0.07	0.025	2.40	0.17	0.071
4	2.55	0.05	0.020	2.86	0.05	0.017	2.47	0.12	0.049
5	2.60	0.13	0.051	2.91	0.12	0.041	2.52	0.21	0.083
6	2.58	0.13	0.051	2.90	0.11	0.038	2.50	0.20	0.080
7	2.60	0.17	0.066	2.93	0.14	0.048	2.52	0.26	0.103
8	2.54	0.20	0.079	2.85	0.19	0.067	2.43	0.30	0.123
9	2.53	0.08	0.032	2.83	0.06	0.021	2.45	0.15	0.061
10	2.52	0.06	0.025	2.81	0.05	0.018	2.43	0.13	0.053
11	2.55	0.09	0.036	2.88	0.07	0.024	2.50	0.14	0.056
12	2.50	0.07	0.029	2.79	0.05	0.018	2.42	0.14	0.058
13	2.41	0.05	0.021	2.70	0.04	0.015	2.34	0.10	0.043
14	2.66	0.11	0.042	2.97	0.10	0.034	2.58	0.16	0.062
15	2.60	0.13	0.051	2.93	0.12	0.041	2.53	0.21	0.083
16	2.50	0.07	0.029	2.81	0.06	0.021	2.42	0.13	0.054

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2.2. Soft computing methods

2.2.1. Fundamentals and theories

Soft computing models make the possibility of doing maintenance without experts. In this article, some models were designed to meet the objectives of performing maintenance and are explained below. MLP is the most commonly used type of neural network in most academic research[23, 24]. In MLP, the summation functions (**Eq. 2-4**) is used to obtain the output of hidden neurons[25].

$$z_j = \sum_{i=1}^{n_0} W_{ij}E_i + b_j \tag{2}$$

$$y_j = f(z_j) = \frac{1}{1+e^{-z_j}} \tag{3}$$

$$p_k = \sum_{j=1}^{n_1} W_{jk}y_j + b_k \tag{4}$$

where, z_j is the input of the j^th^ neuron in the hidden layer, b_j is the bias of j^th^ neuron in the hidden layer, W_{ij} is the weight value between the i^th^ input neuron and the j^th^ neuron in the hidden layer, $f(z_j)$ is the activation function, y_j is the outputs of j^th^ neuron, p_k is the output of the neurons in the k^th^ output, W_{jk} is the weight value between the neuron in the j^th^ hidden layer and the neuron in the k^th^ output layer, and n_1 is the number of neurons in the hidden layers. MLP commonly uses the backpropagation algorithm to find its parameters.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) applies as a machine learning technique that integrates the adaptive neural network (ANN) rules and fuzzy logic (FL) theories inside an adaptive network framework to form a logical relationship between inputs and outputs[26, 27]. ANFIS is a five-layered structure consisting of the fuzzy layer, product layer, normalized layer, de-fuzzy layer, and the total output layer [28].

RBF network acts as a feed-forward neural network with one hidden layer of RBF units and a linear output layer [29, 30]. The output is given as [31]:

$$p_i = b_i + \sum_{j=1}^{N} W_{ij}\exp(-\frac{E-\mu^2}{2\sigma_j^2}) \tag{5}$$

where, p_i is the output, b_i is the bias terms, N is the number of basic functions, W_{ij} is the weight between hidden and output layers, E is the input data vector, μ is the center of RBF unit, and σ represents the spread of the Gaussian basis function.

Support Vector Machine (SVM) was first developed by Vladimir Vapnik and further employed by others for various applications [e.g. 32]. The SVM is based on statistical learning and the estimation function of y(i) was provided as [33-35]:

$$f(E) = W\varphi(E) + b \tag{6}$$

where, $\varphi(E)$ defines a nonlinear mapping of E, W is a weight vector, and b represents the bias factor.

Gaussian Process Regression (GPR) is a nonparametric Bayesian approach to regression. This method has been employed in various scientific fields [36]. GPR is providing a reliable response for the input data [37]. In Gaussian process regression, it is supposed that the output can be calculated as [38, 39]:

$$p_i = f(E_i) + \varepsilon_i \quad , \quad \varepsilon_i \sim \mathcal{N}(0, \sigma_{noise}^2) \in \mathcal{R} \tag{7}$$

where, σ_{noise}^2 is the equal noise variance for E_i of all samples.

The current study is focused on the soft computing approaches, however the theoretical principles of these methods are not addressed, as they can be found elsewhere in the literature. Comparing the performance of several different soft computing models as an intelligent way to improve the maintenance and monitoring of engine lubricantion conditions based on their electrical properties (ε', ε'', tan δ).

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2.2.2. Application

Considering the aforementioned section, the soft computing models were employed and their performance were comparatively evaluated to provide an innovative way for engine lubricant monitoring condition through their electrical properties (ε', ε", tan δ). In this regard, practical steps were performed to implement their algorithm (soft computing algorithms) in the MATLAB software. The inputs of models are the electrical properties (ε', ε", tan δ) of lubricants and the outputs of models are the chemical properties (Fe, Pb, Cu, Cr, Al, Si, Zn) of lubricants. The models were trained using 80% of the total data, while the rest is used for testing and validation. The optimizing indexes for the selected model were reported. The most common way to adjust model indexes is to experiment or trial and error [23].

2.3. Performance criteria

Performance criteria must be used to evaluate the predictive accuracy of models. It will help to improve and choose the optimal model. The Mean Absolute Percentage Error (MAPE) (Eq.8) and Root Means Square Error (RMSE) (Eq.10) were used as metrics in assessing and comparing [40-45].

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_{pi} - y_{ei})^2}{n}} \tag{8}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_{pi} - y_{ei}|}{y_{pi}} \tag{9}$$

where, y_{ei} is the i[th] component of the desired (actual) output for the j[th] pattern, and y_{pi} is the component of the predicted (fitted) output produced by the network for the i[th] pattern. The "n" is the number of lubricant samples.

3. Results and discussion

3.1. Preliminary Statistical analysis

Correlation is a statistical measure of how two or more variables change in connection with each other. On the other hand, it expresses the extent to which two variables are linearly related. Consequently, its results make it possible to select the best modeling method. In other words, some of the statistical models such as Multiple Linear Regression (MLR) are not appropriate when the correlation indicates a weak relation. In addition, it shows that it is a complex and non-linear issue. The closer the correlation to one, the better relation between the two variables. Also, the sign of correlation indicates a direct or inverse relationship. In this study, the best correlation observed between Zn and tan δ, and with inverse relationship. However, the least correlation achieved between Fe and ε', and with inverse relationship. All correlations are illustrated in **Table 3**.

Table 3. Result of correlations between variable 1 (chemical properties) and variable 2 (electrical properties).

Var. 1	Var. 2	Corr.	Var. 1	Var. 2	Corr.	Var. 1	Var. 2	Corr.	Var. 1	Var. 2	Corr.
	ε'	-0.13^{ns}		ε'	0.45^{**}		ε'	-0.23^{***}		ε'	-0.54^{**}
Fe	ε''	-0.20^{***}	*Cu*	ε''	0.53^{**}	*Al*	ε''	-0.49^{**}	Zn	ε"	-0.77^{**}
	$\tan\delta$	-0.22^{***}		$\tan\delta$	0.53^{**}		$\tan\delta$	-0.56^{**}		tan δ	-0.79^{**}
	ε'	0.41^{**}		ε'	0.45^{**}		ε'	-0.14^{ns}			
Pb	ε''	0.48^{**}	*Cr*	ε''	0.45^{**}	*Si*	ε''	-0.42^{**}			
	$\tan\delta$	0.48^{**}		$\tan\delta$	0.41^{**}		$\tan\delta$	-0.50^{**}			

3.2. Performance evaluation of models

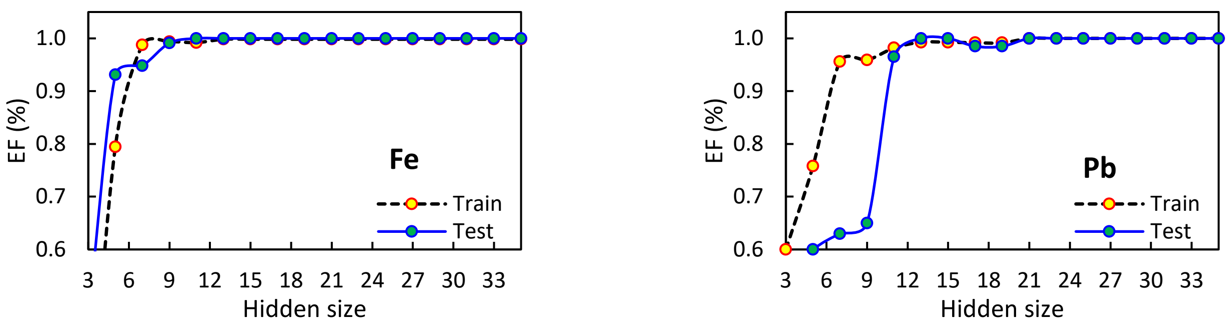
Table 4 shows the statistical analysis of the models. Comparison and judgment are possible considering the values of RMSE and MAPE. The closer the RMSE and MAPE, to zero, the better model performance. It can be seen that the smallest value of MAPE and RMSE was obtained for all variables in RBF at 7.40 GHz. For instance, RMSE and MAPE were respectively equal to 0.4 and 0.7 for Si in RBF at 7.40 GHz

Table 4. Comparing the performance of models by RMSE and MAPE.

Frequency		2.4 GHz					5.80 GHz					7.40 GHz				
ML model		[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Fe	RMSE	2.4	11.0	2.4	16.8	23.4	1.4	23.9	1.5	19.7	17.3	**0.9**	15.5	0.9	14.3	16.5
	MAPE	3.7	33.8	3.8	48.5	51.9	2.8	69.5	2.6	34.5	43.5	**0.9**	47.3	1.1	40.3	36.2
Pb	RMSE	1.4	5.4	2.2	3.8	15.6	1.0	4.9	1.0	5.3	6.5	**0.3**	3.3	0.3	5.5	7.5
	MAPE	-	-	-	-	-	-	-	-	-	-	**-**	-	-	-	-
Cu	RMSE	4.4	22.4	5.0	16.4	19.0	3.9	18.7	3.9	18.6	53.2	**2.2**	13.2	2.2	18.5	21.3
	MAPE	10.3	70.0	10.2	70.7	68.3	7.9	40.3	9.3	93.4	87.2	**1.3**	11.0	2.4	96.8	72.3
Cr	RMSE	4.0	13.3	4.3	12.7	15.7	3.9	13.2	8.1	12.7	15.5	**0.2**	13.2	3.5	11.3	16.2
	MAPE	-	-	-	-	-	-	-	-	-	-	**-**	-	-	-	-
Al	RMSE	0.7	0.7	0.8	0.7	0.9	0.2	0.7	0.3	0.7	3.5	**0.1**	0.7	0.1	0.7	0.9
	MAPE	-	-	-	-	-	-	-	-	-	-	**-**	-	-	-	-
Si	RMSE	0.7	3.4	2.2	2.5	4.3	0.6	2.9	0.8	3.1	3.5	**0.4**	2.2	0.5	2.9	3.3
	MAPE	4.3	38.4	8.9	28.1	48.2	1.7	28.2	1.9	33.0	36.1	**0.7**	25.7	1.1	24.4	34.2
Zn	RMSE	10.3	20.7	80.3	29.2	39.1	6.5	41.9	53.8	28.0	28.3	**1.0**	6.7	2.2	28.6	35.3
	MAPE	16.4	32.0	70.7	35.3	48.3	9.0	80.9	74.9	75.2	65.4	**1.4**	25.4	2.3	73.1	65.4

3.2.1. Adjusting RBF parameters

As mentioned earlier, this work is aimed to compare soft computing models performance in predicting the chemical properties (Fe, Pb, Cu, Cr, Al, Si, Zn) of lubricants based on their electrical properties (ε', ε", tan δ). Considering the statistical results of the models, the RBF exhibited the best performance. So, in this section, RBF parameters are discussed to promote its performance. **Figure4** shows the RBF efficiency (EF) in different hidden sizes for various chemical properties (Fe, Pb, Cu, Cr, Al, Si, Zn) at train and test steps. For example, if the hidden size is set to 12, the efficiency is the highest with no notable difference between the efficiency at train and test steps in "*Fe*" prediction. **Figure5** illustrates the RBF efficiency (EF) when employing different training algorithms for various chemical properties (Fe, Pb, Cu, Cr, Al, Si, Zn) at train and test steps. The "*Trainlm*" provided approximately the best RBF efficiency to predict all chemical properties (Fe, Pb, Cu, Cr, Al, Si, Zn) at train and test steps. **Figure 6** plotted the coefficient of determination (R^2) between the actual and predicted values of the spectral analysis indices of the lubricant. The coefficient is reported separately for the testing and training stages. It is seen that the slope of the regression line between the actual and predicted values in the RBF model is close to one and the intercept is very close to zero. Thus, the RBF model could predict the values of most spectral analysis indices of engine lubricant by a coefficient of 0.99.



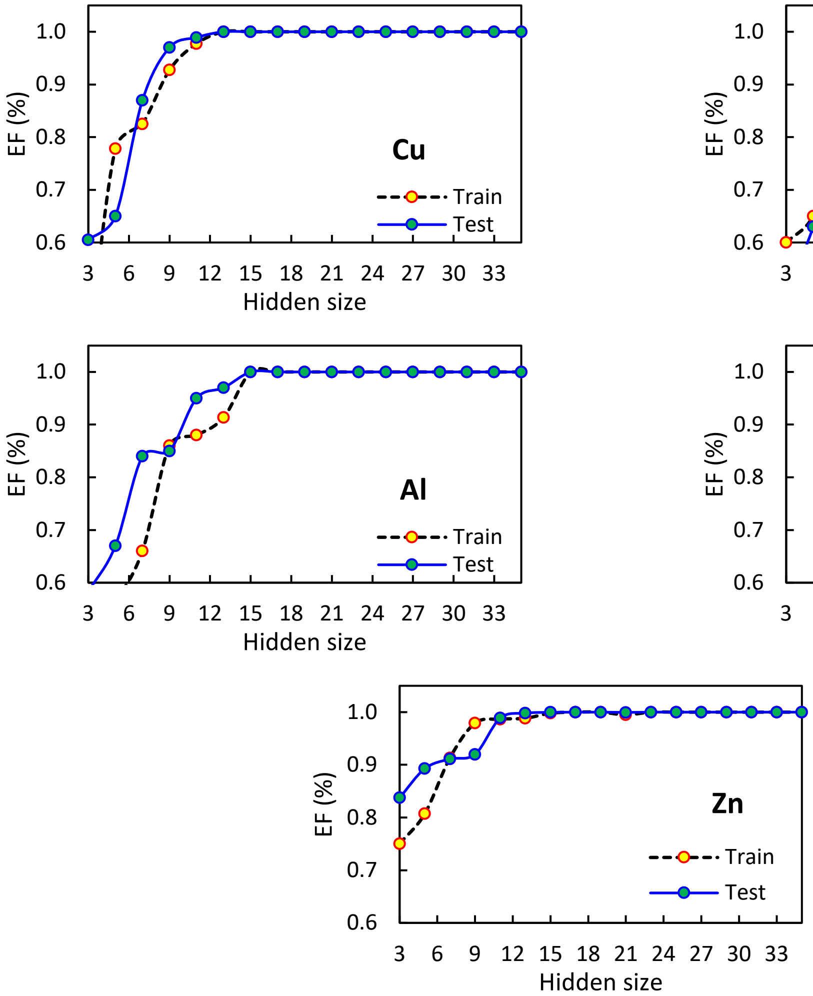
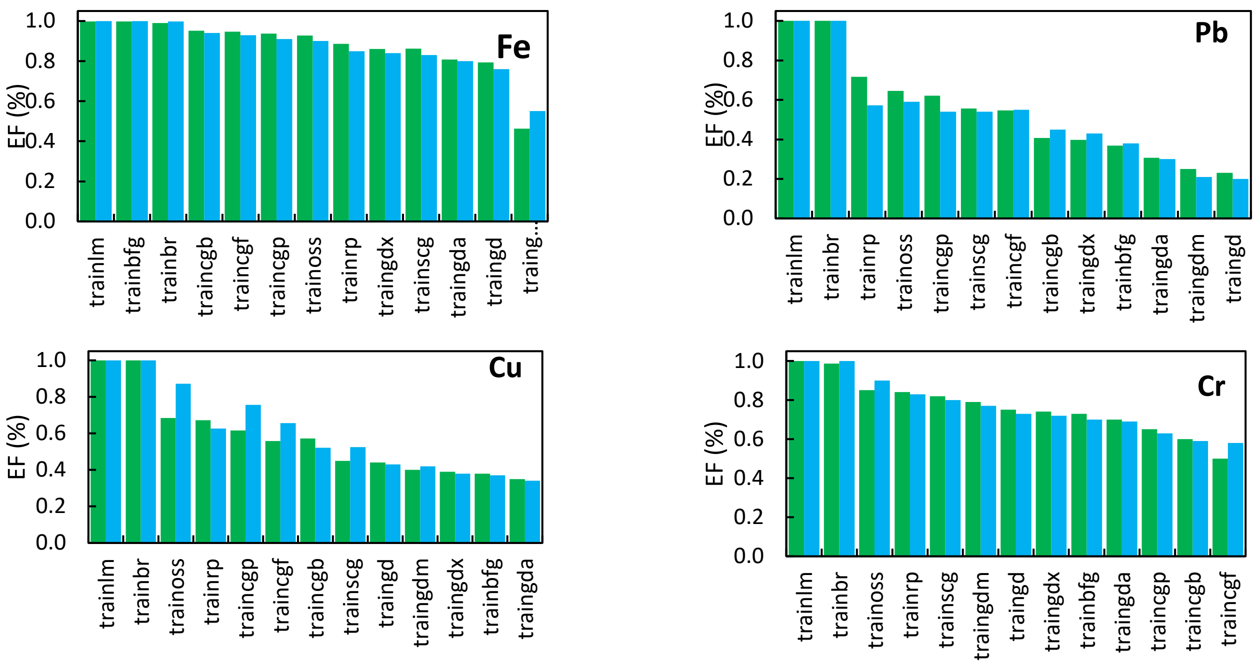


Figure 4. Result of RBF efficiency in different hidden sizes for various chemical properties.



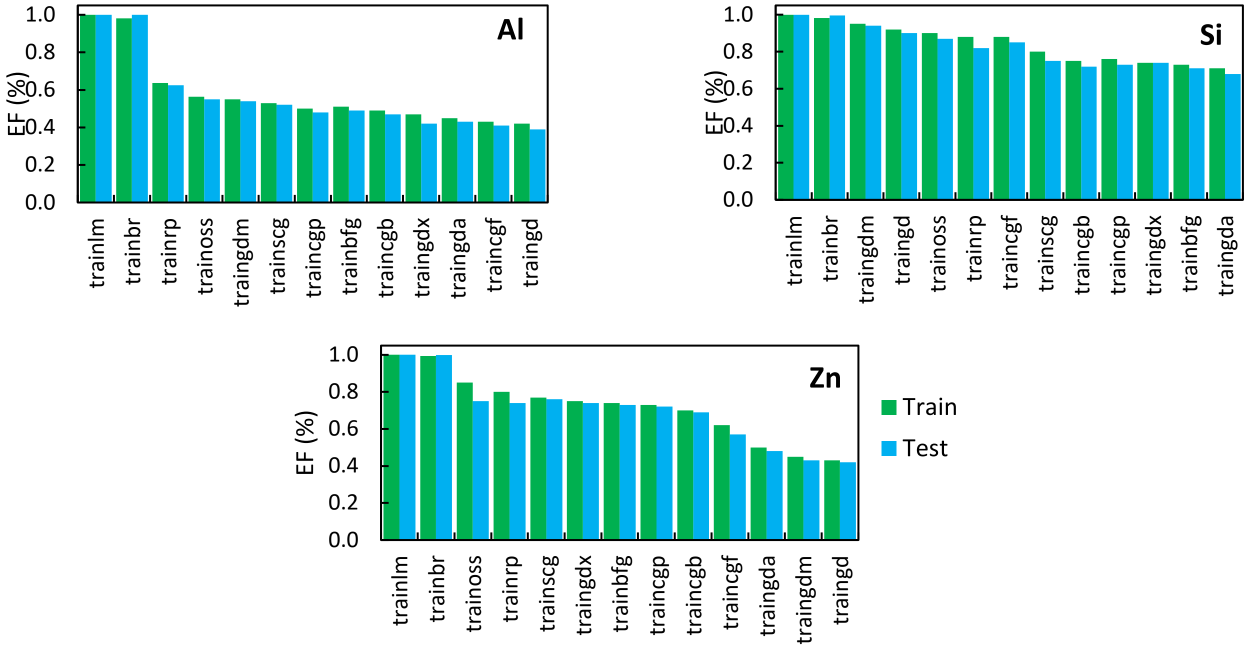
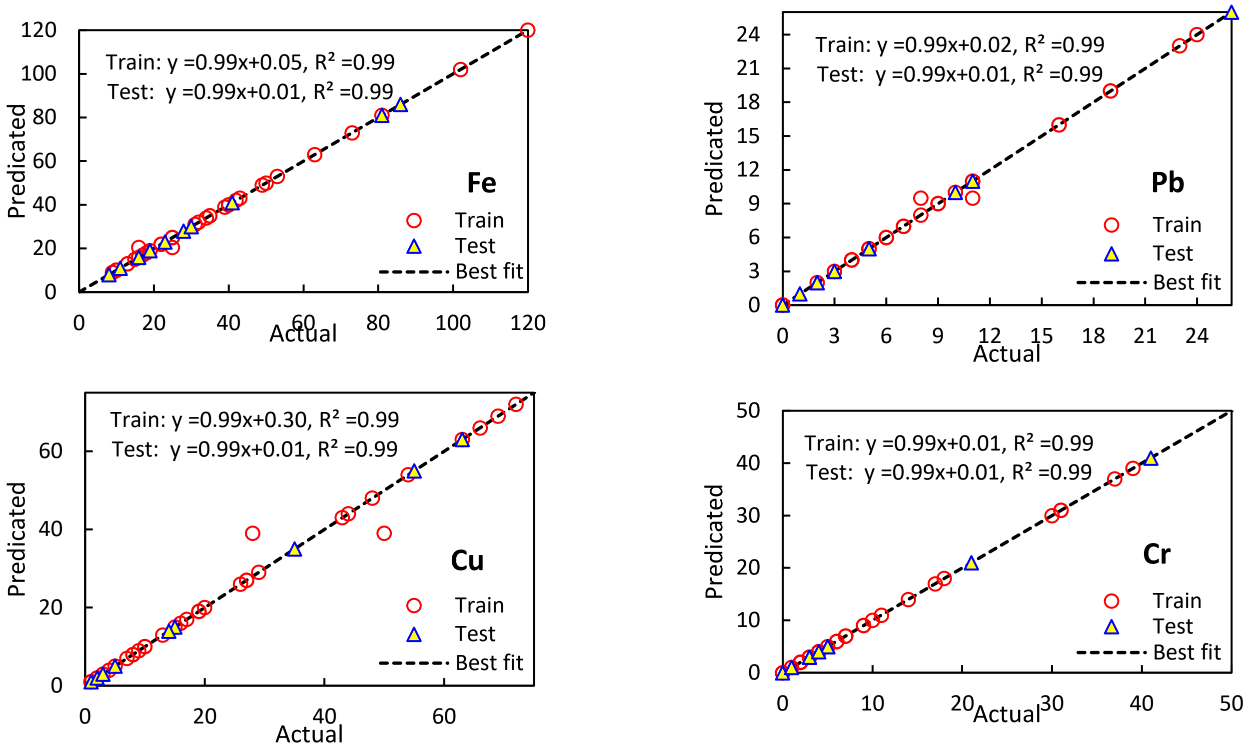


Figure 5. Result of RBF efficiency in different train algorithms for various chemical properties.



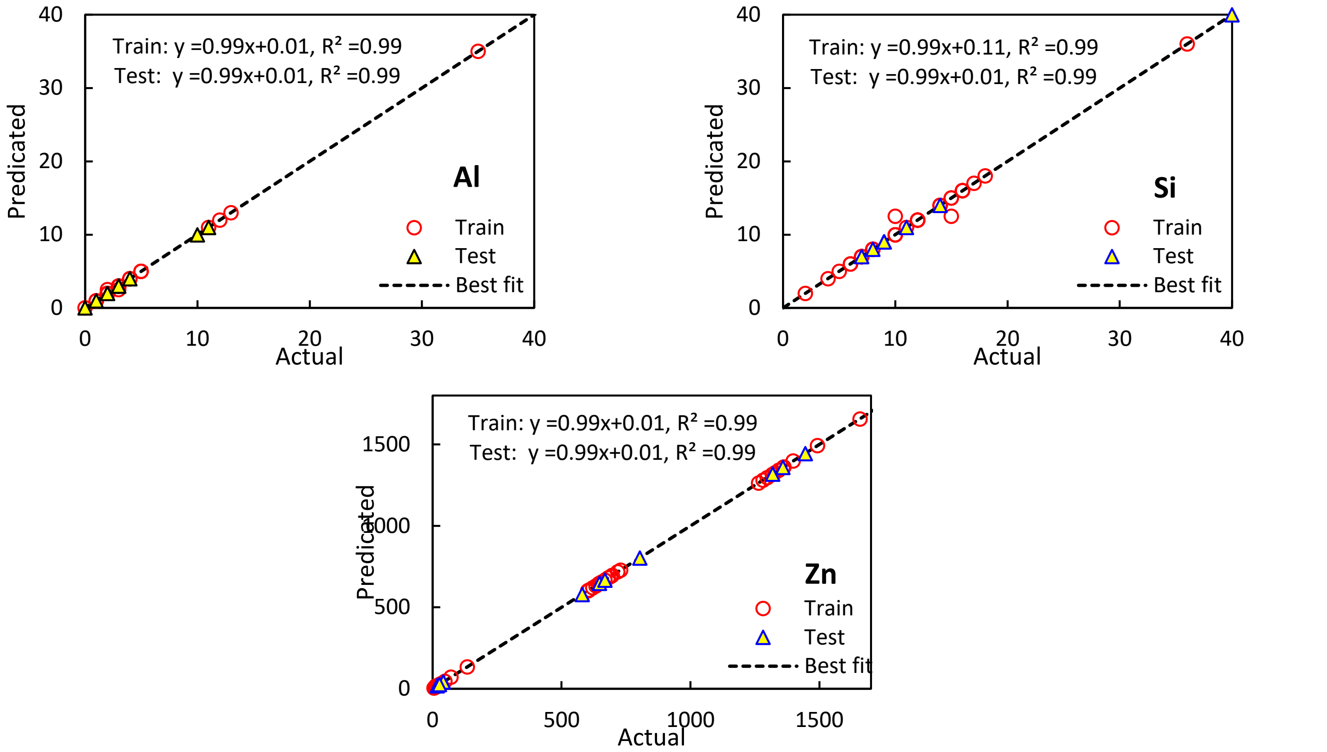
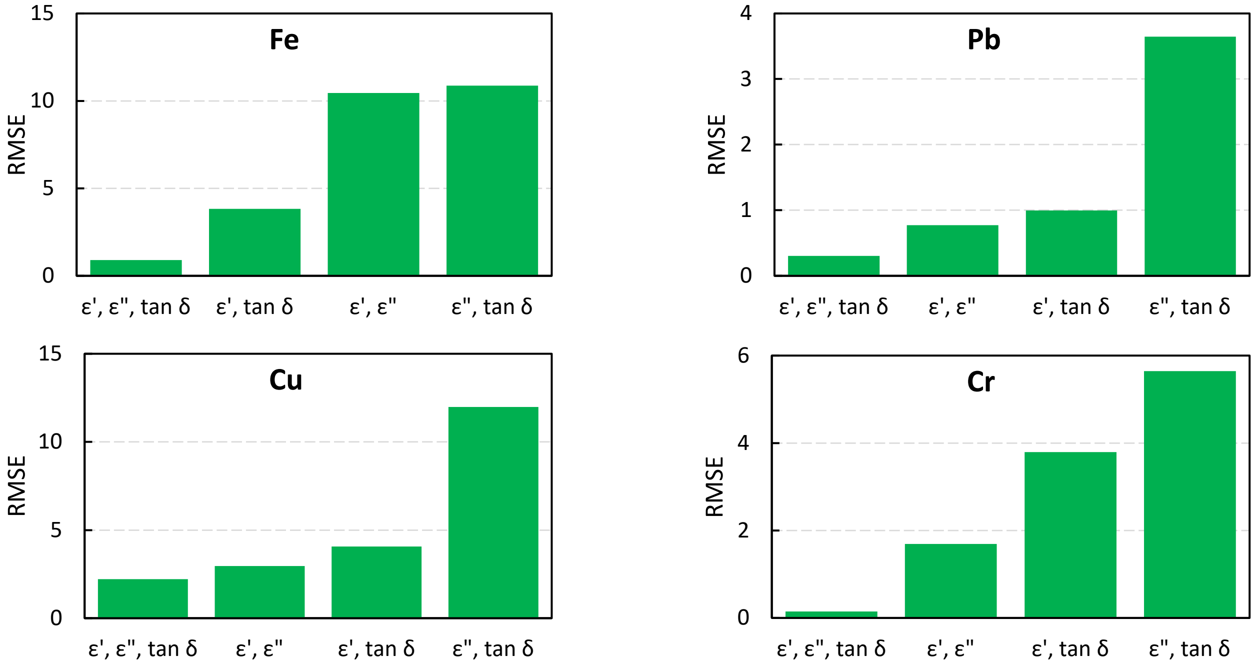


Figure 6. Actual and predicted values of the chemical properties in two steps (training and testing).

3.2.2. Sensitivity analysis

The ability of soft computing models to predict the chemical properties (Fe, Pb, Cu, Cr, Al, Si, Zn) of lubricants through electrical properties (ε', ε", tan δ) was investigated step by step as follow.



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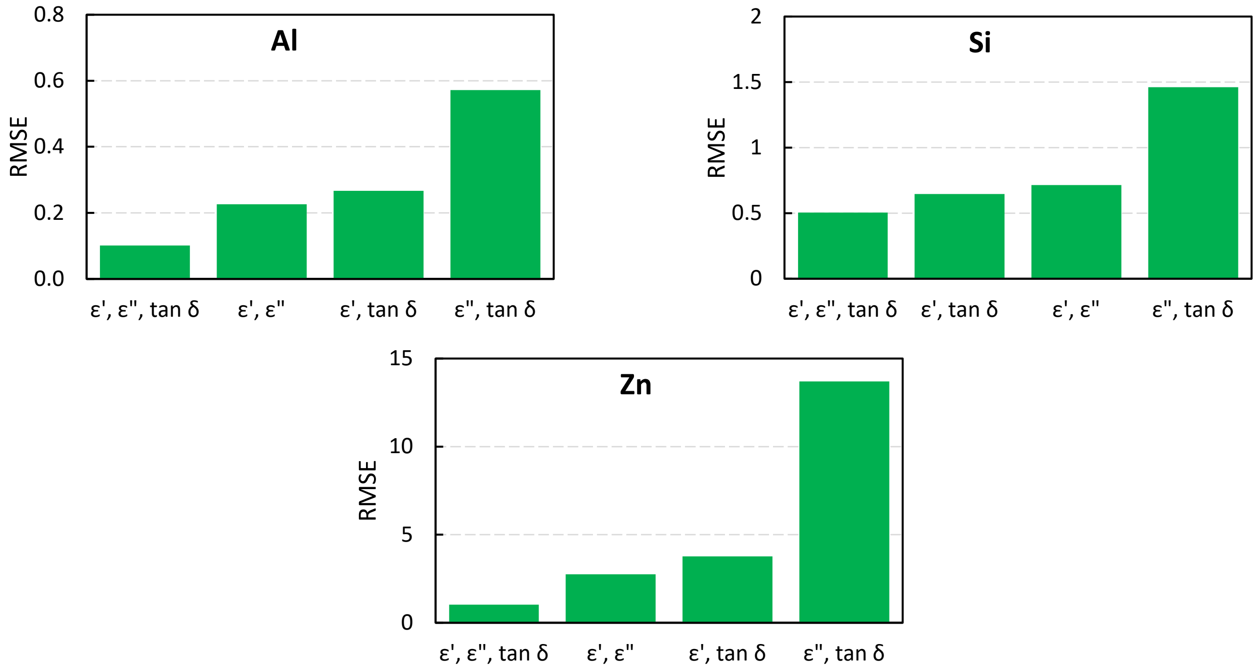

Figure 7. Result of sensitivity analysis to prioritize RBF inputs for various chemical properties.

In section 3.2, the performance of the models was evaluated, and the appropriate model (RBF) was reported. In section 3.2.1, RBF parameters were set, and then sensitivity analysis was performed as an essential part to have a comprehensive study. In this section, the results of the sensitivity analysis are presented which are illustrated in **Figure7**. The sensitivity analysis prioritizes the model inputs. For instance, if ε' is removed from inputs, the RMSE is greatly increased in all terms. Since decreasing RMSE indicates that the model is more suitable, this means that ε' is detected as a more effective input. In general, removing any of the inputs cannot improve the RMSE, so it is not recommended to remove any of the inputs.

4. Conclusion

This study focused on comparing the performance of soft computing models to predict the chemical properties (Fe, Pb, Cu, Cr, Al, Si, Zn) of engine lubricants through their electrical properties (ε', ε", tan δ). This can help to promote predictive maintenance. It is also an efficient method to promote academic efforts in terms of saving time, energy, and financial costs. In this work, the data was gained from two sources, consisting of data extracted from a published work and the data experimented during the current research. Subsequently, the RMSE and MAPE of the model's performance were obtained for several frequency points. The RBF was the best model in predicting chemical properties (Fe, Pb, Cu, Cr, Al, Si, Zn) via electrical properties (ε', ε", tan δ) at 7.4 GHz frequency. The RBF parameters were then adjusted and optimized. For instance, in the RBF implemented to predict Al, the best hidden size and train algorithmic were 15 and *'trainlm'*, respectively. Finally, sensitivity analysis was implemented to prioritize the RBF inputs for each chemical property (Fe, Pb, Cu, Cr, Al, Si, Zn). The results showed that removing any of the inputs worsened the RMSE. In other words, none of the electrical attributes (ε', ε", tan δ) are recommended to be removed. It is concluded that soft computing models can promote condition monitoring of the lubricants through electrical properties (ε', ε", tan δ).

Abbreviations

ANN	Artificial neural network	MLP	Multilayer perceptron
ANFIS	Adaptive neuro-fuzzy inference system	MLR	Multiple Linear Regression
FL	Fuzzy logic	RFE	Recursive feature elimination
GPR	Gaussian process regression	RBF	Radial basic function
IAS	Infrared absorption spectroscopy	RMSE	Root means square error
IS	Impedance spectroscopy	SVM	Support vector machine
KNN	K-nearest neighbor	TDPQ	Time depending on the particle quantifier
MAPE	Mean absolute percentage error	VNA	Vector Network Analyzer

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