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Parameterization of Debye Model for Dielectrics Using Voltage Response Measurements and a Benchmark Problem

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Abstract

The Voltage Response measurement since its introduction in the 1960s has been used successfully for the diagnostics of electrical insulation. The method is based on two quantities of decay and return voltage slopes and can be used to study the conduction and polarization processes inside the insulation. Extended Voltage Response method, being an advanced version of the Voltage Response measurement helps in further studying the polarization process by using a large polarization spectrum and hence dielectric relaxation processes. These dielectric relaxation processes can be modeled by the Debye model. Since as most of the techniques used for diagnostic purpose does not give the information about the conduction and polarization processes separately, it is difficult to determine the *R-C* parameters of the Debye model. The Voltage Response technique is very useful in this regard because of the two voltage slopes. The paper shows a novel experimental benchmark for testing the function fitting methodologies of the Voltage Response methodologies, which helps in determining the *R-C* parameters. Moreover, the problem can be used for testing the novel genetic, evolutionary algorithms, where benchmarking is an actual challenge. The proposed nonlinear function fitting method uses the genetic algorithms via the Ārtap framework, which lets it possible to select the most accurate optimization algorithm from the provided list of the algorithms and achieve better fitting precision, faster calculation time or more powerful processing ability.

Keywords

Voltage Response (VR), Extended Voltage Response (EVR), Debye model, optimization, Ārtap framework, benchmark problem

1 Introduction

Aging of electrical insulating materials has been a topic of great interest for many years, which increased the importance of diagnostic techniques to determine the condition of electrical insulations [1, 2]. The measurement of the dielectric properties is a most important tool among the diagnostic techniques. The dielectric properties can be measured either using a time-domain method or frequency domain method [3]. Out of numerous time-domain techniques, measurement of return voltage is one such method, which was introduced in the 1960's by Endre Németh [4]. The concept behind the technique was to study the slow dielectric polarization processes inside the insulation material. Two techniques emerged from the voltage return method, Return Voltage Measurement (RVM) and Voltage Response (VR) method.

The non-destructive nature of the techniques gained the attention of the researcher for insulation diagnosis. Since then, the techniques have been used by many researchers for a wide range of electrical insulations to study the aging and the phenomenon of dielectric relaxation processes in the insulations [4–6]. Apart from its simplicity and robustness, the technique has a disadvantage of having a long measurement time [7]. In recent times, an extended version of the VR method Extended Voltage Response (EVR) method was introduced, which is useful to study in detail the polarization processes by measuring more than one return voltage slopes achieving a polarization spectrum [5–8].

It is well established that the dielectric can be modeled using the extended Debye circuit having *R* and *C* elements,

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which are used for model the conduction and polarization phenomenon of insulation (see Fig. 1). In this circuit model the R_0 represents the dc conductivity, the C_0 is the capacitiy of the electrode arrangement without dielectric. The R_{pi}—C_{pi} branches (Debye elements) represent the elementary polarisaion processes of the tested insulation. The determination of parameters of Debye branches can help to identify the characteristic ageing processes of insulations. Understanig the ageing phenomenon is essential for reliable life-time management of electrical equipment.

Besides the conventional iteration methods used to determine the parameters of extended Debye model, in this research work, a novel function fitting methodologies based on experimental benchmark problem solving is used [9–12]. A physical Debye circuit insulation models were used for experiments and the Voltage Responses of the models were measured. Then based on the Voltage Response measurement results of insulation models, a nonlinear function fitting method using genetic algorithms via the Ārtap framework is adopted. This helps in the selection of the most accurate optimization algorithm from the provided list of the algorithms [13, 14]. The results show that the technique was helpful in the computationally hard problem to calculate the *R* and *C* parameters of the Debye model due to its powerful processing ability and faster calculation speed. Moreover, this method finds the global optimum of the problem.

2 Extended Voltage Response measurements

The Extended Voltage Response is a developed method of Voltage Response measurement [4–6]. The measurement of Voltage Response is based on the measurement of decay and return voltages of a charged insulation. The test arrangement can be seen in Fig. 2 and the timing diagram of the measurement is in Fig. 3.

For charging, the SW1 is in "ON" position. The SW2 is used for discharging the charged insulation. During the measurement of Voltage Responses both switcheas are

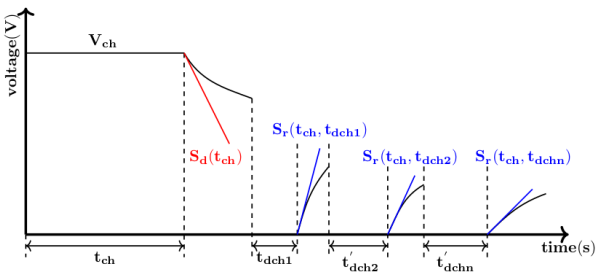

Fig. 1 *R-C* equivalent circuit of insulation based on extended Debye model

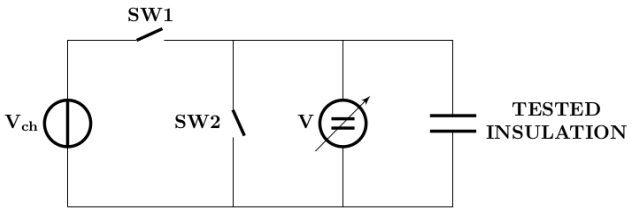

Fig. 2 Arragement of Voltage Response measurement

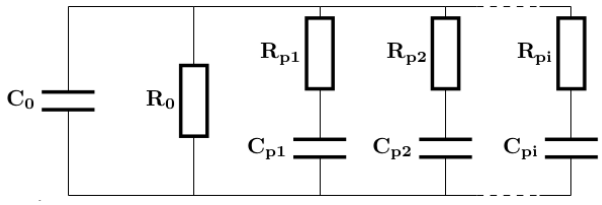

Fig. 3 The timing diagram of Extended Voltage Response measurement

in "OFF" position. The decay and return voltages are characterized by their intital slopes namely $S_d(t_{ch})$ and $S_r(t_{ch}, t_{dchn})$, repectively (see Fig. 3). Obviously these values are dependent on the charging (t_{ch}) af discharging times (t_{dchn}).

The values of Debye branches can be calculated by the initial slopes of return voltages. The voltage of a C_{pi} capacitor ($V_{C_{pi}}$) after tch charging and tdchn discharging times can be calculated by the multiplication of the exponential functions.

$$V_{C_{pi}} = V_{ch}\left(1 - e^{-t_{ch}/\tau}\right) \times e^{-t_{dch}/\tau} \tag{1}$$

Where V_{ch} is the charging voltage and $\tau = R_{pi}C_{pi}$. The slope of return voltage $S_{ri}(t_{ch}, t_{dchn})$ of one Debye element (i.e. one R_{pi}—C_{pi} branch) can be calculated by

$$S_{ri}\left(t_{ch}, t_{dchn}\right) = \frac{V_{ch}\left(1 - e^{-t_{ch}/\tau}\right) \times e^{-t_{dch}/\tau}}{R_{pi}C_0}. \tag{2}$$

If the equivalent circuit contains *N* Debye element, the total slope of return voltage can be cvalculated by using a superposition of return voltage slopes of each Debye element:

$$S_r\left(t_{ch}, t_{dchn}\right) = \sum_{i=1}^{N} S_{ri}\left(t_{ch}, t_{dchn}\right). \tag{3}$$

The determination of the values of Debye elements is based on the calculations above.

3 Nonlinear curve fitting with Ārtap

Curve fitting is a very general and important problem in science and industry. According to the type of the fitted function it can be categorized as a linear and non-linear optimization task. The literature contains a lot of different methods to solve this problem with the required accuracy [15–26].

Most of these measurements use the gradient-based solvers, the Gauss-Newton Algorithm or the Levenberg-Marquardt Algorithm, which use the fact that these problems can be expressed by the rules of the Quadratic Programming (QP) [27, 28].

These methods use the fact that after the measurements, we have *m* data points $t_i \in \mathbb{R}^n x \mathbb{R}$, where the least-squares fitting objective is

$$\min_{\beta} \sum_{i=1}^{m} \left(f\left(x_i;\beta\right) - y_i^2 \right) = r_1^2 + r_2^2 + \ldots + r_m^2, \tag{4}$$

where *f* is an instance of a convex function, $\beta \in \mathbb{R}^n$ is a vector, which contains the optimized parameters for the chosen function and *Y* is a vector, which represents the measured values. The vector of the residuals $\boldsymbol{r}(\beta)$ can be defined in the following way:

$$\boldsymbol{r}\left(\beta\right) = f\left(X;\beta\right) - Y, \tag{5}$$

where the task is to minimize the $\boldsymbol{r}(\beta)^T \boldsymbol{r}(\beta)$. Let the initial parameter is β_0, the value of the corresponding residual is $\boldsymbol{r}(\beta_0)$ and δ represent a small change in the input parameters, the new residual is

$$\boldsymbol{r}\left(\beta_0 + \delta\right) \approx \boldsymbol{r}\left(\beta_0\right) + \boldsymbol{J}\delta, \tag{6}$$

where $\boldsymbol{J}\left(\in \mathbb{R}^{mxn}\right)$ is the Jacobian of $f\left(\partial f / \partial \beta\right)$. From this, the problem can be expressed by its first order quadratic form in the following convex, quadratic form [26, 28]:

$$\min_{\delta} \delta^T \boldsymbol{J}^T \boldsymbol{J}\delta + 2\delta^T \boldsymbol{J}^T \boldsymbol{r} + \boldsymbol{r}^T \boldsymbol{r} \tag{7}$$

subject to

$$\delta \in \Delta, \tag{8}$$

where Δ is the trust region.

This task has a solution, when $\boldsymbol{r}(\beta)^T \boldsymbol{r}(\beta) = 0$. The optimal step of the solution can be calculated by Gauss-Newton methods, which finds the δ that minimizes the quadratic objective, but with no trust-region bounds:

$$\boldsymbol{J}^T \boldsymbol{J}\delta = -\boldsymbol{J}^T \boldsymbol{r}. \tag{9}$$

The Levenberg-Marquardt algorithms can be used to solve this problem with trust regions:

$$\boldsymbol{J}^T \boldsymbol{J} + \lambda \mathrm{diag}\left(\boldsymbol{J}^T \boldsymbol{J}\right)\delta = \boldsymbol{J}^T \boldsymbol{r}, \tag{10}$$

where λ controls the magnitude of the quadratic penalty on δ.

This methodology is widely used for linear and non-linear data-fitting. However, these algorithms are highly dependent on proper initial values, in the case of modeling engineering problems, correctly specifying the initial values is a hard task in the case of a practical problem [24]. Moreover, this approximated or interpolated functions have to be fitted on a noisy measurement data. One of the most widely used functions is the *b*-splines to describe a mathematical connection on the measured data [21]. Where the placement of the knots has to be optimized to minimize the error. This problem is a multi-modal and multi-variate nonlinear optimization problem with many local optima. Where the above mentioned gradient-based optimization methods can easily be trapped in a local optimum, because the optimization task cannot formulated as a convex optimization task. To overcome this problem there are many heuristics and metaheuristics developed for engineering applications. These methods are usually mixing some convex or mathematical optimization with a method of a branch and bound, genetic algorithms, neural networks or other meta-heuristics [17–20, 22–26, 29–34].

In this paper, a sum of exponentials has to be fitted. This task is highly non-linear, which complexity growth with the number of degrees of freedom (*n* is high). The size of the search space of the optimization task is large. Besides, the data is generally scattered and contains some noise from the measurement. A simple genetic algorithm-based fitting approach is used in this paper, via the Ārtap framework [9–12]. The main advantage of using this framework is the simplicity of the interface, which provides automatic parallelization and enables to exchange the applied genetic algorithm with another one. It is an important feature, because of the "no free lunch" theorem of optimization [34], which says that non-exists of an evolutionary methodology, which can overturn any other one. The pseudo-code of the NSGA-II algorithm is shown in Algorithm 1. NSGA-II is one of the most popularly used, a genetic algorithm-based, multi-objective optimization techniques [35–37]. Due to its three advantageous characteristics, which were outperformed the existing algorithms when it was published [38]. These properties are the elitism, the small computational complexity, which is almost $O(M\ N^2)$ and the explicit diversity preservation mechanism, which ensures good convergence and stability.

The object function can be defined in several ways, this type of optimization functions [19]:

- $F_{LS} = \sum_{i=1}^{n} \left(P_i - M_i\right)^2$
- $F_{ME} = \sum_{i=1}^{n} \left(P_i - M_i\right)^2 / n$

Algorithm 1 NSGA II [12, 38]

```
function NSGA II(n, g, f) → f means our unique function which calculates TOC and the key design-parameters for an individual
initialize parent population (P)
generate random population (R)
run f for every individual
Sorting, Assign Rank – Pareto dominance –
Generate Offsprings (O) – next generation
    Binary Tournament Selector
    Recombination and Mutation
        for i: = 1 to g do → g: max number of generations
        for on each P and O in a population do
            Sorting, Assign Rank – Pareto dominance –
            Generate sets of non-dominated vectors
            Loop – evaluates the user-defined
            f function – and add solutions to next-
            generation starting from the first front
            until n determine crowding distance
            between points on each front
end for
    Select individuals (elitist) with lower rank and are
    outside a crowding distance
    Generate Offsprings (O) – next generation
    Binary Tournament Selector
    Recombination and Mutation
    end for
end function
```

- $F_{RMSE} = \sqrt{\sum_{i=1}^{n}\left(P_i - M_i\right)^2 / n}$
- $F_{R^2} = 1 - \dfrac{\sum_{i=1}^{n}\left(P_i - M_i\right)^2}{\sum_{i=1}^{n}\left(P_i - A_i\right)^2}$
- $F_{MAPE} = \dfrac{\sum_{i=1}^{n}\left(A_i - P_i\right)/P_i}{n}$
- $F_A = n \times \log\left(\left(P_i - M_i\right)^2\right) + 2k$

where P_i, M_i and A_i are the predicted, measured and the averaged values, n denote the sample size and k is the number of the fittest parameters. There is some advice in the literature that if the parameters remain unchanged after the last 5 iterations, the iteration should be stopped [21, 24]. Algorithm 1 is used in this paper.

4 Results and discussion

To benchmark the measurement methodology, three measurements were made with three realized insulation model circuits. These models were made from precious resistors and capacitors, with $N = 1$, 2 and 3 branches, respectively. The values of the R and C parameters are shown in Table 1.

These values were measured by Agilent 4339B high resistance meter and Wayne Kerr 6430A component analyzer. Then, the Voltage Responses of model circuits were measured by the EVR equipment, which was developed at the Deapartment. The charging voltage and the charging time were 1000 V and 4000 s, respectively. Due to the measurement uncertainty, the Quadratic Programming based methodology provides different values for R_{pi}—C_{pi} elements of the Debye model. To prove the existence of one global optimum of the problem the ideal voltage slope parameters were calculated by analytical method based on Eqs. (1)–(3). These values provided a good benchmark to make the optimization on a data set without measurement error and uncertainties. The optimal parameters of the searched R and C values were calculated by two different methods. The first of them used the Ārtap and a built-in NSGA-II function. The used code and the project file can be downloaded from the project page of Ārtap, it is included in the package of [39]. The other calculation was made by the built-in optimizer of MATLAB, the GlobalSearch function [29]. This optimizer uses a Quadratic Programming solver, which starts from multiple points. The results of return voltage slopes are presented in Tables 2–4. Due to these properties, this metaheuristic solver is a very strong tool for this type of problem. The optimized parameters approximate well the original curvature. The fitted and the measured curves of slopes of return voltages as a function of shorting time are plotted in Fig. 4 in case of $N = 3$.

In the case of $N = 1$, both the NSGA-II and the GlobalSearch based calculations gave back the expected values with minimal calculation error. It can be seen that both solutions approximated well in the case of $N = 2$ branches. The calculated values of each R and C parameters by NSGA-II and the GlobalSearch are significantly different in the $N = 3$ case (case 3). This happened because

Table 1 The measured values of the R and C parameters.

Parameter	$N = 1$	$N = 2$	$N = 3$
R_0 [GΩ]	5.87	5.87	5.87
R_1 [GΩ]	2.1663	2.1663	2.1663
R_2 [GΩ]	-	1.7806	1.7806
R_3 [GΩ]	-	-	3.0078
C_0 [nF]	9.627	9.627	9.627
C_1 [nF]	19.589	10.236	10.236
C_2 [nF]	-	9.4081	9.4081
C_3 [nF]			46.2880

Table 2 The calculated voltage slopes based on analytical (*a*) and optimised values of *R C* parameters by GlobalSearch (*g*) and NSGA-II (*n*) in the case of $N = 1$

Shorting time *t* (sec)	Slopes of return voltages (V/s)		
	S_a	S_g	S_n
1	46.83347	46.83346	47.76
2	45.74274	45.74273	46.458
4	43.6369	43.6369	43.153
6	41.62801	41.628	41.717
8	39.7116	39.7116	39.697
10	37.88341	37.88341	37.662
15	33.67273	33.67274	33.207
20	29.93007	29.93008	29.496
30	23.64647	23.64648	23.241
50	14.75991	14.75992	14.522
75	8.188986	8.188999	8.029
100	4.543356	4.543365	4.479
150	1.398524	1.398528	1.429
200	0.43049	0.430492	0.454
300	0.04079	0.04079	0.073
500	0.000366	0.000366	0.001

Table 3 The calculated voltage slopes based on analytical (*a*) and optimised values of *R C* parameters by GlobalSearch (*g*) and NSGA-II (*n*) in the case of $N = 2$

Shorting time *t* (sec)	Slopes of return voltages (V/s)		
	S_a	S_g	S_n
1	100.7923	100.7923	98.786
2	95.58673	95.58672	94.485
4	85.98188	85.98188	84.833
6	77.35857	77.35858	75.677
8	69.6149	69.61492	68.024
10	62.65971	62.65974	60.888
15	48.20685	48.20688	46.472
20	37.13707	37.13709	35.956
30	22.12758	22.12759	21.456
50	7.979435	7.979439	7.912
75	2.29236	2.292368	2.318
100	0.676797	0.676805	0.72
150	0.062897	0.0629	0.069
200	0.006189	0.006189	0.014
300	6.49E-05	6.49E-05	0.026
500	7.75E-09	7.75E-09	0.001

of the optimized parameters are in the exponent of the objective function. Hence the objective function is relative flat consequently a small error in the precision of the parameter determination can produce a significantly high error. To present the problem difficulty the error function of objective function is calculated assuming the R_{pi} and

Table 4 The calculated voltage slopes based on analytical (*a*) and optimised values of *R C* parameters by GlobalSearch (*g*) and NSGA-II (*n*) in the case of $N = 3$

Shorting time *t* (sec)	Slopes of return voltages (V/s)		
	S_a	S_g	S_n
1	135.0715	135.0709	133.529
2	129.6215	129.6213	128.043
4	119.5329	119.5332	117.659
6	110.4325	110.433	108.684
8	102.2183	102.2187	100.426
10	94.79905	94.79937	92.752
15	79.21414	79.21396	76.645
20	67.05153	67.05094	65.032
30	49.96951	49.96882	48.625
50	32.09568	32.09618	31.257
75	22.44427	22.44511	21.111
100	17.51621	17.51614	16.426
150	11.8215	11.82052	11.051
200	8.217025	8.216676	7.65
300	4.003668	4.004454	3.718
500	0.951871	0.952578	0.89

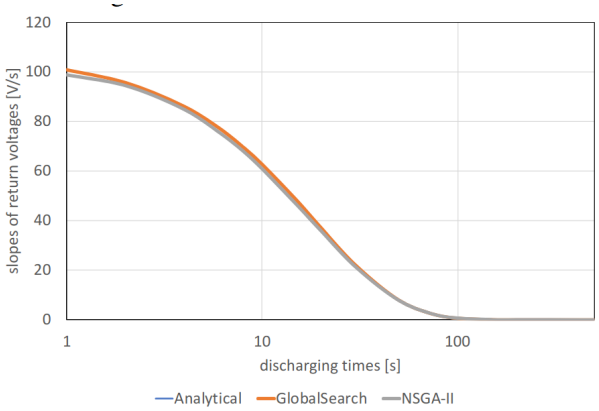

Fig. 4 The comparison of the model results and the fitted parameters in the case of $N = 3$.

C_{pi} values can be in range 1…30 GΩ and nF, repsctively (Fig. 5). The optimal values are represented by the darkest red region in the figure.

As the figures shows relative high variation in paremeters results in small change in error function therefore, the optimizated parameters of Debye elements are subject to high uncertainty.

The Quadratic Programming based methodology provides better results because it uses a Newton solver or a Levenberg-Marquardt based solver to find the exact function parameters. The solution of the NSGA-II based methodology can be improved similarly if a Newton-solver started from the found parameters and then they are refined similarly [23].

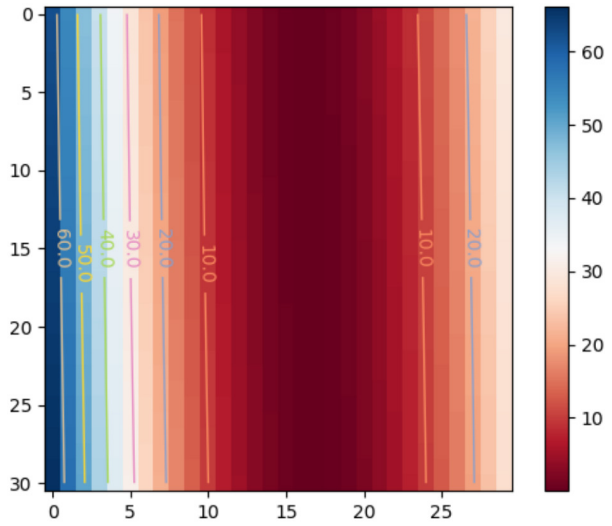

Fig. 5 The objective function error dependence on *R* and *C* parameters

5 Conclusion

The proposed paper has shown a novel experimental benchmark to determine the Debye representation of the insulating model. The parameterization is based on measurement results of Extended Voltage Response (EVR) on model dielectrics. As the results shows the proposed data and fitting problem can be used for testing the novel genetic, evolutionary algorithms, where benchmarking is an important and challenging problem. It can be seen from the results that this problem can be computationally hard and important to select a good metaheuristic solver to calculate the optimal *R* and *C* parameters of the Debye model.

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