

Biological dispersion in the time domain using finite element method software

Raul Guedert^{1,*}, Daniella L. L. S. Andrade¹, Guilherme B. Pintarelli², and Daniela O. H. Suzuki¹

¹Federal University of Santa Catarina, Institute of Biomedical Engineering, Florianopolis, 88040-900, Brazil

²Department of Control and Automation Engineering, Federal University of Santa Catarina, Blumenau, 89036-256, Brazil.

*raulguedert@gmail.com

SUPPLEMENTARY INFORMATION

The datasets generated and analysed during the current study are available in the figshare repository, www.doi.org/10.6084/m9.figshare.23895927.

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S.1 Conductivity and Relative Permittivity Derivation

Equation (S1) presents the Maxwell-Ampère law in the frequency domain.

$$\vec{J}(\omega) = \sigma_s \vec{E}(\omega) + j\omega \epsilon_0 \epsilon_r \vec{E}(\omega) + \vec{J}_e(\omega) \quad (\text{S1})$$

We can factor the electric field ($\vec{E}(\omega)$), which gives us.

$$\vec{J}(\omega) = j\omega \epsilon_0 \left(\overbrace{\frac{\sigma_s}{j\omega \epsilon_0} + \epsilon_r}^{\epsilon_r^*(\omega)} \right) \vec{E}(\omega) + \vec{J}_e(\omega) \quad (\text{S2})$$

The multipole Debye model is given in (S3).

$$\epsilon_r^*(\omega) = \frac{\sigma_s}{j\omega \epsilon_0} + \epsilon_\infty + \sum_{k=1}^N \frac{\Delta \epsilon_k}{1 + (j\omega \tau_k)} \quad (\text{S3})$$

The Debye model can be discriminated into real and imaginary parts according to the definitions in equation (S4).

$$\epsilon_r^*(\omega) = \epsilon'(\omega) - j\epsilon''(\omega) \quad (\text{S4})$$

where $\epsilon'(\omega)$ and $\epsilon''(\omega)$ are given by

$$\begin{aligned} \epsilon'(\omega) &= \Re(\epsilon_r^*(\omega)) \\ \epsilon''(\omega) &= -\Im(\epsilon_r^*(\omega)) \end{aligned} \quad (\text{S5})$$

Now we can substitute the relation of equation (S4) into the Maxwell-Ampère law represented in equation (S2), which gives us the following.

$$\vec{J}(\omega) = j\omega\epsilon_0 \left(\epsilon'(\omega) - j\epsilon''(\omega) \right) \vec{E}(\omega) + \vec{J}_e(\omega) \quad (\text{S6})$$

After some algebraic simplification, one finds the following.

$$\vec{J}(\omega) = \overbrace{\omega\epsilon_0\epsilon''(\omega)}^{\sigma(\omega)} \vec{E}(\omega) + j\omega\epsilon_0 \overbrace{\epsilon'(\omega)}^{\epsilon_r(\omega)} \vec{E}(\omega) + \vec{J}_e(\omega) \quad (\text{S7})$$

By comparing equations (S1) and (S7), we can determine conductivity and relative permittivity.

$$\sigma(\omega) = \omega\epsilon_0\epsilon''(\omega) = -\omega\epsilon_0\Im(\epsilon_r^*(\omega)) = \sigma_s + \omega^2\epsilon_0 \sum_{k=1}^N \tau_k \frac{\Delta\epsilon_k}{1 + (\omega\tau_k)^2} \quad (\text{S8})$$

$$\epsilon_r(\omega) = \epsilon'(\omega) = \Re(\epsilon_r^*(\omega)) = \epsilon_\infty + \sum_{k=1}^N \frac{\Delta\epsilon_k}{1 + (\omega\tau_k)^2} \quad (\text{S9})$$

The relation between conductance (G) and susceptance (B) with conductivity and relative permittivity is given by equations (S10) and (S11), respectively.

$$\sigma(\omega) = G(\omega) \frac{l}{S} \quad (\text{S10})$$

$$\epsilon_r(\omega) = \frac{B(\omega) l}{\omega\epsilon_0 S} \quad (\text{S11})$$

where l and S are the length and area of the sample, respectively.

By combining equations (S8) and (S9) with equations (S10) and (S11), one finds the following relation.

$$\Im(\epsilon_r^*(\omega)) = -\frac{\sigma(\omega)}{\omega\epsilon_0} = -\frac{G(\omega) l}{\omega\epsilon_0 S} \quad (\text{S12})$$

$$\Re(\epsilon_r^*(\omega)) = \epsilon_r(\omega) = \frac{B(\omega) l}{\omega\epsilon_0 S} \quad (\text{S13})$$

S.2 Experimental Setup

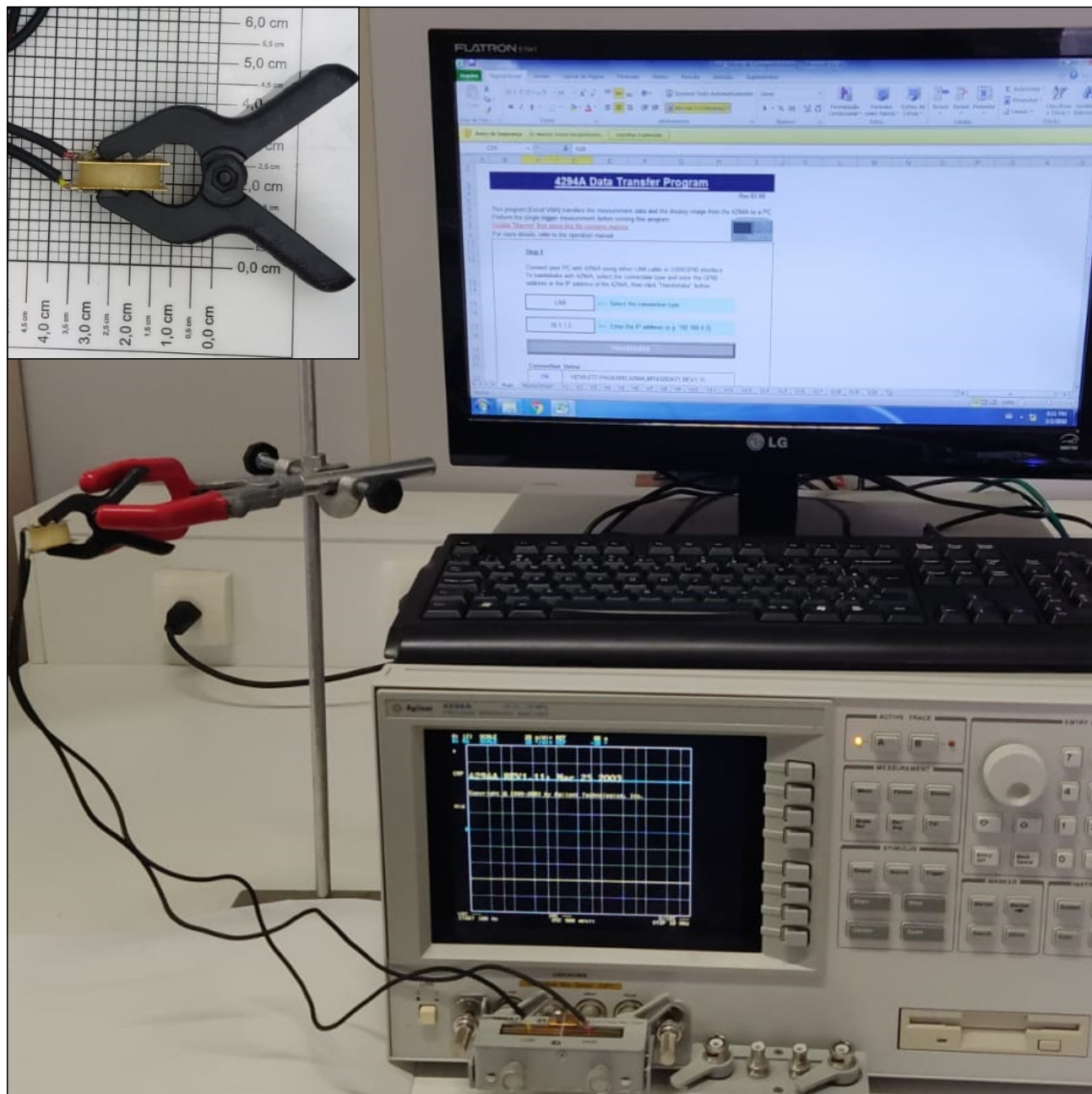


Figure S1. Experimental setup for the dielectric measurement of potato tuber samples. The electrodes can be seen in detail at the top left.

S.3 Biological Dispersion Parametrization Results

Parameter	N = 1	N = 2	N = 3	N = 4
CF Min Value	6.245×10^1	1.750	2.908×10^{-1}	5.174×10^{-2}
ϵ_∞	1.093×10^3	3.463×10^2	2.352×10^2	1.747×10^2
σ_s	3.015×10^{-2}	2.508×10^{-2}	2.208×10^{-2}	2.159×10^{-2}
$\Delta\epsilon_1$	5.041×10^2	1.104×10^6	1.753×10^6	2.251×10^6
τ_1 (s)	5.214×10^{-6}	1.932×10^{-3}	3.071×10^{-3}	3.783×10^{-3}
$\Delta\epsilon_2$		3.308×10^4	3.004×10^4	2.918×10^4
τ_2 (s)		4.181×10^{-7}	6.431×10^{-6}	2.309×10^{-5}
$\Delta\epsilon_3$			1.919×10^4	1.836×10^4
τ_3			2.530×10^{-7}	1.005×10^{-6}
$\Delta\epsilon_4$				1.053×10^4
τ_4 (s)				1.658×10^{-7}

Table S1. Parameterization of potato tissue dispersion with the multipole Debye model with 1, 2, 3, and 4 poles. CF Min Value is the minimum value reached by the cost function of the genetic algorithm after optimization.

Parameter	N = 5	N = 6	N = 7	N = 8
CF Min Value	2.287×10^{-2}	9.006×10^{-3}	5.583×10^{-3}	4.358×10^{-3}
ϵ_∞	1.765×10^2	1.621×10^2	1.495×10^2	1.354×10^2
σ_s	2.124×10^{-2}	2.087×10^{-2}	2.061×10^{-2}	2.074×10^{-2}
$\Delta\epsilon_1$	2.683×10^6	3.198×10^6	3.604×10^6	3.129×10^6
τ_1 (s)	4.407×10^{-3}	5.067×10^{-3}	5.543×10^{-3}	5.183×10^{-3}
$\Delta\epsilon_2$	2.458×10^4	3.321×10^4	1.863×10^4	2.983×10^5
τ_2 (s)	1.376×10^{-4}	3.563×10^{-4}	8.438×10^{-4}	7.310×10^{-3}
$\Delta\epsilon_3$	1.950×10^4	1.968×10^4	2.868×10^4	3.674×10^4
τ_3	1.097×10^{-5}	2.495×10^{-5}	3.763×10^{-4}	3.873×10^{-4}
$\Delta\epsilon_4$	1.654×10^4	1.048×10^4	1.993×10^4	2.116×10^4
τ_4 (s)	8.483×10^{-7}	3.775×10^{-6}	2.733×10^{-5}	2.340×10^{-5}
$\Delta\epsilon_5$	1.005×10^4	1.548×10^4	1.182×10^4	1.243×10^4
τ_5 (s)	1.636×10^{-7}	6.013×10^{-7}	3.684×10^{-6}	2.509×10^{-6}
$\Delta\epsilon_6$		7.628×10^3	1.649×10^4	1.607×10^4
τ_6 (s)		1.403×10^{-7}	5.100×10^{-7}	3.869×10^{-7}
$\Delta\epsilon_7$			5.830×10^3	6.852×10^2
τ_7 (s)			1.215×10^{-7}	1.205×10^{-7}
$\Delta\epsilon_8$				2.993×10^3
τ_8 (s)				9.330×10^{-8}

Table S2. Parameterization of potato tissue dispersion with the multipole Debye model with 5, 6, 7, and 8 poles. CF Min Value is the minimum value reached by the cost function of the genetic algorithm after optimization.

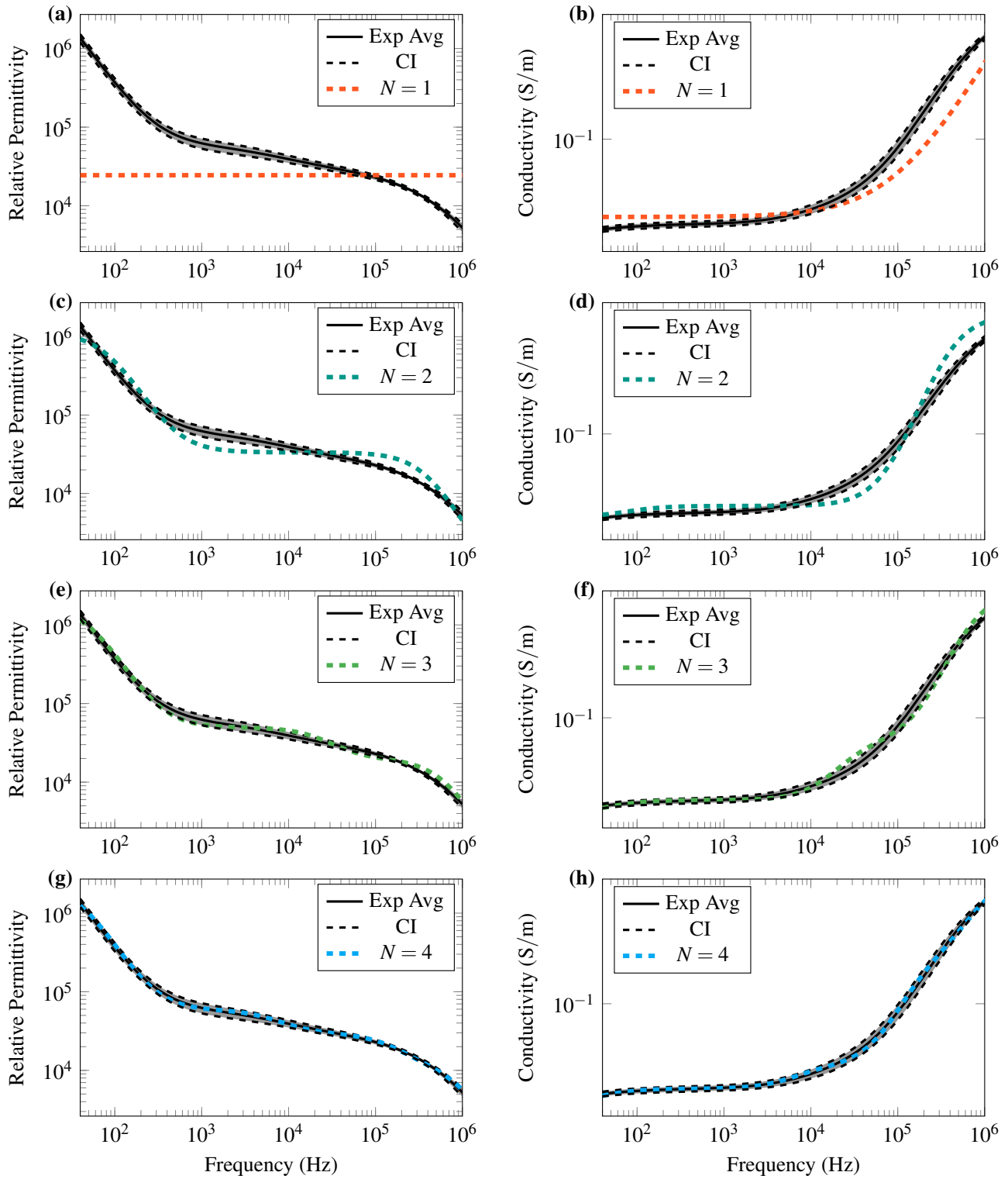


Figure S2. Experimental and parameterized results of (a, b, c, d) permittivity and (b, d, f, h) conductivity of potato tissue. Exp Avg is the experimental average, CI is the confidence interval (95%). N represents the number of Debye poles used to parameterize the experimental results. (a, b) 1 pole; (c, d) 2 poles; (e, f) 3 poles; (g, h) 4 poles.

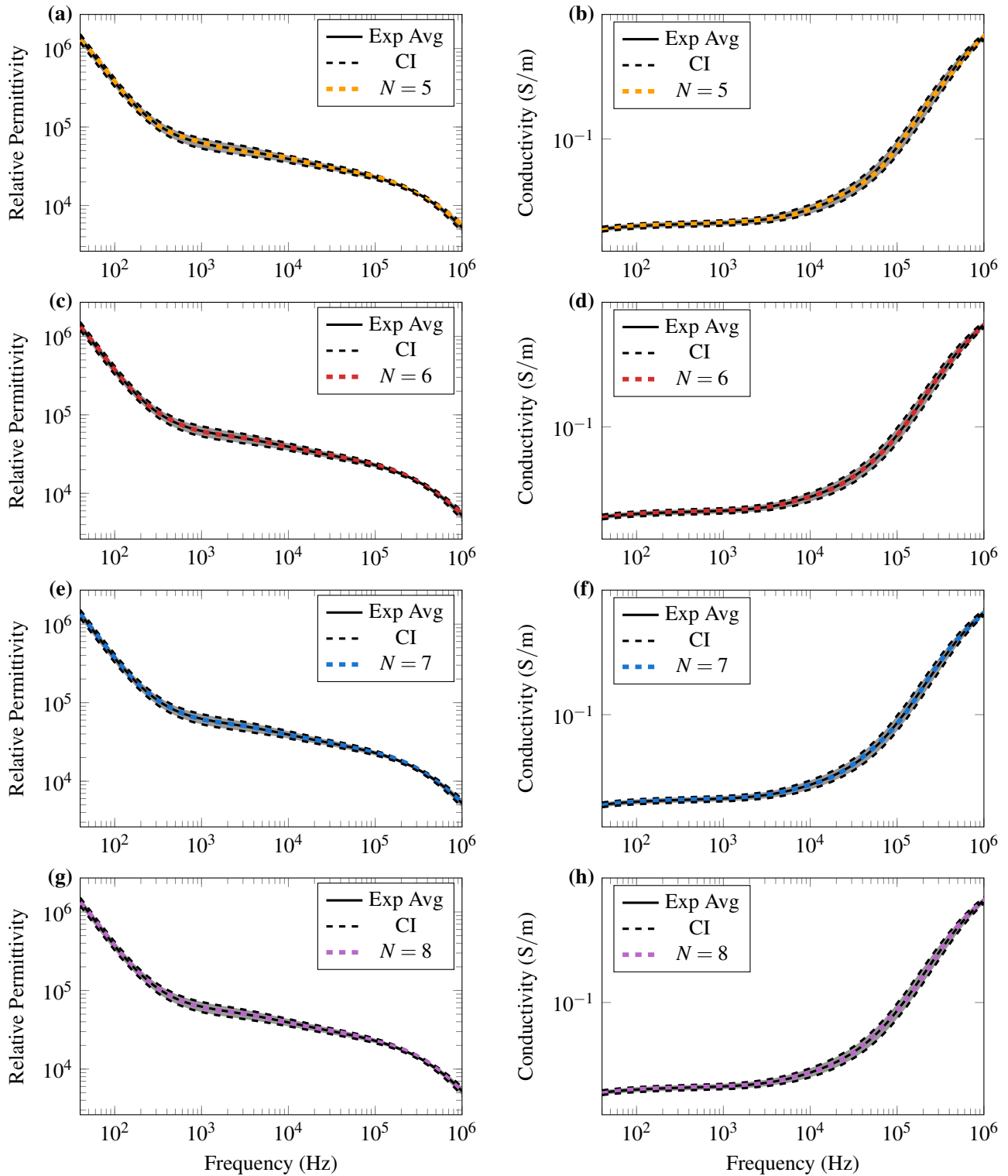


Figure S3. Experimental and parameterized results of (a, c, e, g) permittivity and (b, d, f, h) conductivity of potato tissue. Exp Avg is the experimental average, CI is the confidence interval (95%). N represents the number of Debye poles used to parameterize the experimental results. (a, b) 5 poles; (c, d) 6 poles; (e, f) 7 poles; (g, h) 8 poles.

S.4 Genetic Algorithm Code

```
1 % Experimental data load
2 experimental = readtable('directory_to_experimental_data');
3 experimental = table2array(experimental);
4
5 % -- Experimental data conditioning
6 frequency = experimental(:,1)';
7 experimental_cond = experimental(:,2)';
8 experimental_perm = experimental(:,3)';
9
10 %% Genetic Algorithm Code
11
12 % Number of poles of Debye dispersion
13 n_debye_poles = 6;
14
15 % Constant declaration
16 epsilon_0 = 8.854187817e-12;
17
18 % Frequency conversion
19 f = frequency;
20 w = 2*pi*f;
21
22 % Parameter Limits
23 delta_epsilon_upper_limit = 8;
24 delta_epsilon_lower_limit = -3;
25 tau_upper_limit = -1;
26 tau_lower_limit = -12;
27 epsilon_inf_upper_limit = 10; % Ideally inf, but 10 already works
28 epsilon_inf_lower_limit = 0;
29 sigma_s_upper_limit = 0;
30 sigma_s_lower_limit = -4;
31
32 % Multipole Debye dispersion model declaration
33 debye_func = @(epsilon_inf, sigma_s, delta_epsilon, tau)...
34     10^epsilon_inf + 10^sigma_s./(1j*w*epsilon_0) + ...
35     sum((10.^delta_epsilon)./(1 + (1j*w.*10.^tau)));
36
37 % Conversion of Experimental to Debye Real and Imaginary
38 experimental_real = experimental_perm;
39 experimental_imag = (-1)*experimental_cond./(epsilon_0*w);
40 experimental_func = experimental_real + 1i*experimental_imag;
41
42 % Number of variables of the Debye parameterization
43 n_variables = 2 + 2*n_debye_poles;
44
45 % Parameter limits vector initialization
46 lb = zeros(1, n_variables);
47 ub = zeros(1, n_variables,1);
48
49 % Parameter limits vectorization
50 % -- Lower limits
51 lb(1) = epsilon_inf_lower_limit;
52 lb(2) = sigma_s_lower_limit;
53 lb(3:(n_debye_poles + 2)) = delta_epsilon_lower_limit;
54 lb((n_debye_poles + 3):n_variables) = tau_lower_limit;
```

```

55 % -- Upper limits
56 ub(1) = epsilon_inf_upper_limit;
57 ub(2) = sigma_s_upper_limit;
58 ub(3:(n_debye_poles + 2)) = delta_epsilon_upper_limit;
59 ub((n_debye_poles + 3):n_variables) = tau_upper_limit;
60
61 % Genetic Algorithm declaration
62 ga_options_log = optimoptions('ga', ...
63     'PlotFcn', @gaplotbestf2, ...
64     'UseParallel', true, ...
65     'MaxGenerations', 2e3, ...
66     'MaxStallGenerations', 500, ...
67     'PopulationSize', 1e3, ...
68     'SelectionFcn', @selectiontournament, ...
69     'MutationFcn', @mutationadaptfeasible);
70
71 % Vectorization of parameterization variables
72 % -- The 'p' vector is used in the next functions. The vector contains the
73 % -- results of the parameters, which are organized according to the
74 % -- following structure
75 % -- p(1) = epsilon_inf
76 % -- p(2) = sigma_s
77 % -- p(3) = delta_epsilon_1
78 % -- p(4) = delta_epsilon_2
79 % -- ...
80 % -- p(n_debye_poles + 2) = delta_epsilon_n
81 % -- p(n_debye_poles + 3) = tau_1
82 % -- p(n_debye_poles + 4) = tau_2
83 % -- ...
84
85 % Auxiliary function to handle the p vector
86 debye_to_fit = @(p) debye_func(p(1), p(2), p(3:(n_debye_poles + 2))', ...
87     p((n_debye_poles + 3):n_variables)');
88
89 % Cost function declaration
90 log_cf = @(p) sum(...
91     (log10(real(experimental_func)) - log10(real(debye_to_fit(p)))).^2 + ...
92     (log10(imag(experimental_func)) - log10(imag(debye_to_fit(p)))).^2 ...
93 );
94
95 % Parameterization process
96 [sol_log, fval_log] = ...
97     ga(log_cf, n_variables, [], [], [], [], lb, ub, [], ga_options_log);
98
99 % Generate Plot to visual inspection
100 % -- Extracting conductivity and permittivity from the parameterized curve
101 cond_debye_solution = epsilon_0*(w).*imag(debye_to_fit(sol_log))*(-1);
102 perm_debye_solution = real(debye_to_fit(sol_log));
103 % -- Plot
104 figure(2);
105 subplot(2, 1, 1);
106 loglog(f, [experimental_perm; perm_debye_solution]);
107 subplot(2, 1, 2);
108 loglog(f, [experimental_cond; cond_debye_solution]);
109

```



```

110 % Print parameters
111 fprintf('%s\n',10^sol_log(1));
112 fprintf('%s\n',10^sol_log(2));
113 for i = 1:(n_debye_poles)
114     fprintf('%s\n',10^sol_log(2 + i));
115     fprintf('%s\n', 10^sol_log(n_debye_poles + 2 + i));
116 end
117
118 % Function to observe the CF during parametrization process
119 function state = gaplotbestf2(options,state,flag)
120 %GAPLOTBESTF Plots the best score and the mean score.
121 % STATE = GAPLOTBESTF(OPTIONS,STATE,FLAG) plots the best score as well
122 % as the mean of the scores.
123 %
124 % Example:
125 % Create an options structure that will use GAPLOTBESTF
126 % as the plot function
127 % options = optimoptions('ga','PlotFcn',@gaplotbestf);
128 % Copyright 2003-2016 The MathWorks, Inc.
129 state.Score = real(state.Score);
130 if size(state.Score,2) > 1
131     msg = getString(message('globaloptim:gaplotcommon:PlotFcnUnavailable','
gaplotbestf'));
132     title(msg,'interp','none');
133     return;
134 end
135 switch flag
136     case 'init'
137         figure(1);
138         hold on;
139         set(gca,'xlim',[0,options.MaxGenerations]);
140         xlabel('Generation','interp','none');
141         ylabel('Fitness value','interp','none');
142         plotBest = plot(state.Generation,min(state.Score),'.k');
143         set(plotBest,'Tag','gaplotbestf');
144         % plotMean = plot(state.Generation,meanf(state.Score),'.b');
145         % set(plotMean,'Tag','gaplotmean');
146         title('Best: ','interp','none')
147     case 'iter'
148         best = min(state.Score);
149         % m = meanf(state.Score);
150         plotBest = findobj(get(gca,'Children'),'Tag','gaplotbestf');
151         % plotMean = findobj(get(gca,'Children'),'Tag','gaplotmean');
152         newX = [get(plotBest,'Xdata') state.Generation];
153         newY = [get(plotBest,'Ydata') best];
154         set(plotBest,'Xdata',newX, 'Ydata',newY);
155         % newY = [get(plotMean,'Ydata') m];
156         % set(plotMean,'Xdata',newX, 'Ydata',newY);
157         set(get(gca,'Title'),'String',sprintf('Best: %g',best));
158     case 'done'
159         LegnD = legend('Best fitness');
160         set(LegnD,'FontSize',8);
161         hold off;
162 end
163 end

```