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Lifetime estimation of DC XLPE cable insulation using BPNN-IPM improved with various schemes and optimization methods

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ABSTRACT

The world's need for green energy is something that cannot be postponed any longer, where the transmission-distribution process requires power distribution in DC voltage. However, currently, the majority use AC voltage, so limited experience and lack of data regarding electrical cable aging under high voltage (HVDC) and their reliability are problems that must be resolved. Crosslinked polyethylene (XLPE) constitutes many insulation cables used today, so estimating the lifetime of DC XLPE cable insulation is urgent research, even though various model-optimization improvements are needed to obtain accurate results. This research begins with pre-processing for the input and output data. These results were then analyzed using two improved model schemes to accommodate the addition of variable space charge and thickness: backpropagation neural network (BPNN) and hybrid BPNN with inverse power model (BPNN-IPM). The learning process uses gradient descent (GD), genetic algorithm (GA), and Levenberg-Marquardt (LM) optimization methods. Finally, the proposed method was verified using experimental data from previous research. The results show that the hybrid BPNN-IPM with LM optimization method is the most accurate: training root mean square error (RMSE) achieved 0 days, and testing RMSE achieved 0.83 days. These results show that the method BPNN-IPM-LM used is most accurate in estimating the lifetime of DC XLPE insulation.

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1. INTRODUCTION

Insulation is an important element so that electric power systems can operate well and reliably, especially at high voltage (HV) [1], [2], where insulators make the biggest contribution to system failure in HV equipment [3]. In HV transmission lines, cable insulator failure detection is an important task [4]. The material commonly used as cable insulation is crosslinked polyethylene (XLPE) [5]–[7]. Although XLPE polymer insulation materials have been very successfully used for power transmission in extruded underground HVAC cables for a long time [8], nowadays, HVDC has experienced significant developments compared to HVAC [9], [10]. This is because HVDC can increase transmission capacity and distance [11], is cheaper for longer lines, reduces losses on transmission lines, and most importantly, is more environmentally friendly [12]–[14], so it is hoped that it can reduce global warming, climate change, problems environment in addition to addressing interconnection problems [15]–[17]. Apart from that, applying HVDC to XLPE extruded electrical cables has another advantage, namely a longer service life compared to HVAC. So, using it for transmission and distribution lines is a consideration to support a net zero emissions target by 2050 more reliable [18]–[24]. Especially during the current industrial revolution 4.0, namely, reliability has a new paradigm called asset management (AM) [25] where AM is very dependent on equipment age [26]–[32], so research into DC XLPE cable insulation lifetime modelling is an urgent that cannot be postponed again.

In lifetime modeling for DC cable insulation, there are influencing factors, namely TEAMS stresses (thermal, electrical, ambient/environment, mechanic, space charge) [33]–[42]. Several studies have been carried out on the influence of these factors on the lifetime of DC XLPE insulation, for example, electric stress [43], thermal stress [27], [44], thermal and electric stresses [45], electric, mechanical and thermal [46]. The main problem in this research is the available models can only estimate cable remaining useful lifetime (RUL) based on some of the factors that cause insulation failure [44], [47]. Aside from that few HVDC connections are installed, limited experience with how cables age electrically under HVDC, and a lack of data on ageing and reliability [48].

Previous research [49] used BPNN to obtain modified inverse power model (IPM) model parameters to accommodate space charge and thickness using the Levenberg-Marquardt (LM) optimization method, and research [50] used the gradient descent optimization method. This research will be carried out using data referring to [49], [50]. The contributions of this paper are: i) improvement scheme for the backpropagation neural network (BPNN) and hybrid BPNN-IPM models so that the best model scheme is obtained; ii) each model scheme improvement is optimized using gradient descent (GD), genetic algorithm (GA) and LM methods to obtain a improved formulation; and iii) the improvement model is applied with variations in input-output data normalization to obtain the best DC XLPE cable insulation lifetime estimation. Section 2 discusses the data and method for lifetime DC cable insulation. Section 3 discusses the results and discussion obtained, starting from simulation to comparison of previous research. Section 4 contains conclusions about the research conducted and suggestions for improvement in subsequent research. The method proposed with these thirty-six schemes has been verified, and it is hoped that accurate and efficient results will be obtained for estimating DC cable lifetime insulation.

2. METHOD

A BPNN is a development of the perceptron, which is widely used to model problems with tabular data. This research uses BPNN to estimate the lifetime of DC XLPE cable insulation. The application of BPNN is carried out using a hybrid BPNN-IPM method or just BPNN, which can be seen in Figure 1.

Figure 1 explains the scheme in this research: the input data is normalized so that there are three different treatments, and the output data is transformed so that there are two different treatments. Then, there are two model schemes, namely the BPNN-IPM and BPNN hybrid models, after which the model is optimized using three optimization methods: GD, GA, and LM. As a result, there are thirty-six simulations in this research, so it is hoped that an accurate and efficient model will be obtained to estimate the lifetime of DC XLPE cable insulation. The steps taken in this research are: i) presentation of data; ii) normalization; iii) proposed hybrid BPNN-IPM and BPNN models; iv) parameter model formulation estimation; v) simulation; and vi) comparison of previous research.

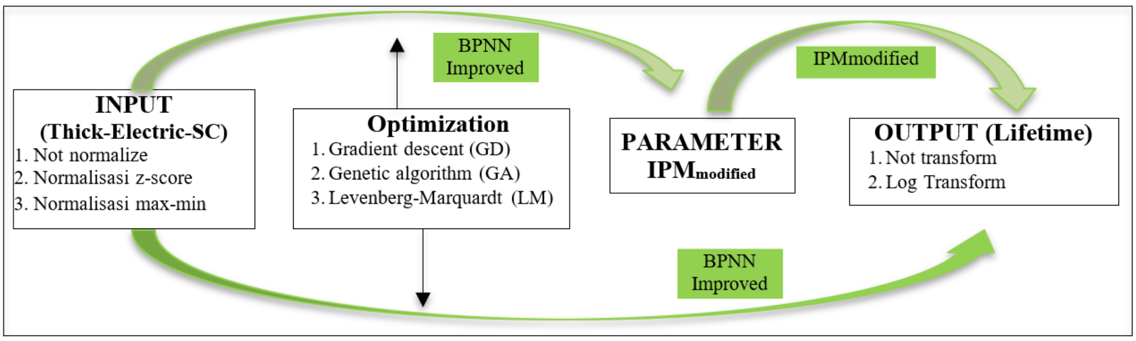

Figure 1. Research design for lifetime DC XLPE cable insulation with various schemes

2.1. Presentation of data

In this research, DC cable insulation lifetime estimation data in the form of an accelerated lifetime test (ALT) was carried out using research data [49] as follows. With d representing the XLPE thickness, E_a is the electric field, and k_{max}, k_{mean}, Q, and b represent the space charge parameters. Based on this data, analysis was then carried out to obtain model improvement parameters (α, β), which were the main problem and the focus of this research to accommodate space charge, and thickness. In previous research, the estimation of (α, β) used the BPNN-IPM model and the LM optimization method. This research was carried out using a variety of model schemes, optimization methods and pre-processing. After that, the estimated lifetime from experiments T (last column of Table 1) and simulations can be easily obtained using (6).

Table 1. Data for DC XLPE cable insulation lifetime measurements

$d\ (\mu m)$	$E_a\ (kV/mm)$	k_{max}	k_{mean}	$Q\ (C/m^3)$	b	α	β	T
60	80	1.453	1.431	56.95	1.307	1.092	1.178	2.677
60	100	1.540	1.511	74.09	1.307	1.092	1.178	0.543
60	120	1.883	1.770	113.00	1.307	1.092	1.178	0.076
60	140	1.623	1.594	124.26	1.307	1.092	1.178	0.057
60	160	1.690	1.664	133.16	1.307	1.092	1.178	0.021
70	80	1.288	1.248	45.15	1.392	1.210	1.327	14.94
70	100	1.506	1.463	67.06	1.392	1.210	1.327	1.252
70	120	1.604	1.565	86.46	1.392	1.210	1.327	0.248
70	140	1.480	1.468	100.30	1.392	1.210	1.327	0.138
70	160	1.345	1.332	121.19	1.392	1.210	1.327	0.109
80	80	1.293	1.259	50.38	1.135	1.326	1.472	36.22
80	100	1.262	1.224	57.59	1.135	1.326	1.472	8.903
80	120	1.306	1.283	70.76	1.135	1.326	1.472	1.709
80	140	1.305	1.284	91.37	1.135	1.326	1.472	0.560
80	160	1.248	1.230	108.06	1.135	1.326	1.472	0.292

2.2. Normalization

This research has data from experimental results of input X and output T [49]. Apart from these two data being used in the simulation of the training-testing process, normalization and transformation are also used. This needs to be done so that the data has different ranges to ensure consistency and quality. There are two normalization techniques for input data used, namely z-score normalization:

$$X_{zs} = \frac{X-\mu(X)}{\sigma(X)} \tag{1}$$

and min-max normalization:

$$X_{mm} = \frac{X-min(X)}{max(X)-min(X)} \tag{2}$$

then, because the modified IPM is in the form of an exponential function, the output transformation is carried out with its inverse function, namely the logarithmic function, as follows:

$$T_{tl} = log(T) \tag{3}$$

so, in this research, three input data will be simulated, namely $X^* = (X, X_{zs}, X_{mm})$ and two output data, namely $T^\# = (T, T_{tl})$.

2.3. Proposed hybrid BPNN-IPM and BPNN models

The conventional IPM is a phenomenological lifetime that connects electric stress and DC cable lifetime. This model has the (4):

$$L = CE^{-n} \tag{4}$$

with E is the electric field strength in kV/mm, L is the failure time or life in seconds, C is a constant representing the cumulative electrical damage required for material failure, and n is the voltage tolerance index representing the degree of electric influence [44], [47].

Ma *et al.* [49] carried out improvements to IPM to accommodate not only electric stress but also space charge on the lifetime of DC XLPE insulation with the (5):

$$L = C_r^{\alpha}.E_r^{-\beta n_r} \tag{5}$$

with L, C_r, E_r, n_r as in (1). The main problem in improving this model is estimating parameters (α, β). In research [49], parameters (α, β) were estimated with BPNN optimized with the LM method in one simulation. In this research, parameters (α, β) were estimated using BPNN, then optimized using GD, GA, and LM methods, variations in data normalization, and other modelling schemes. The BPNN-IPM architecture can be seen in Figure 2.

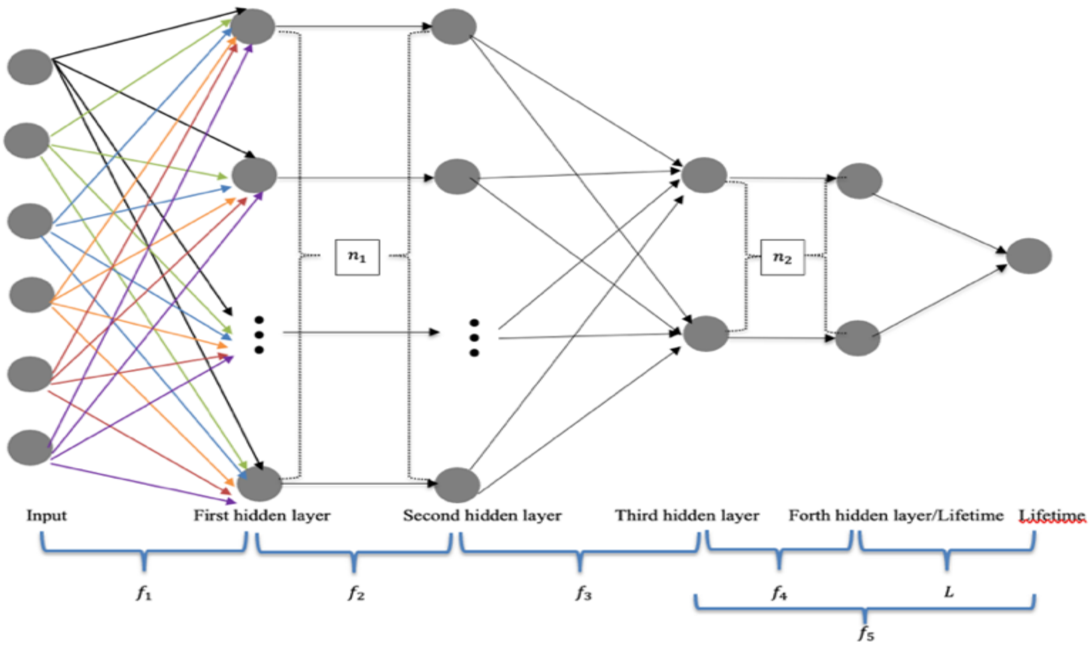

Figure 2. Architecture BPNN-IPM and BPNN for the lifetime of DC XLPE cable insulation

In Figure 2 (this scheme), the input is XLPE thickness, electric field, and space charge data, and the output is parameters (α, β) or DC XLPE cable insulation lifetime. From input to output, it passes through three to four hidden layers. The connectivity corresponding to Figure 2 can be seen in Table 2.

Table 2. Connected function of model for lifetime DC XLPE cable insulation model

Connected function	Scheme	
	BPNN-IPM	BPNN
$z_{in} = f_1 = f_1(X^*, b1, v)$	$b1 + X\,v$	$b1 + X\,v$
$z = f_2 = f_2(z_{in})$	$\frac{1}{(1+exp(-z_{in}))}$	$\frac{1}{(1+exp(-z_{in}))}$
$y_{in} = f_3 = f_3(z, b2, w)$	$b2 + z\,w$	$b2 + z\,w$
$(\alpha, \beta) = f_4 = f_4(y_{in})$	y_{in}	-
$T^* = L = L(\alpha, \beta, C, E, n)$	$C^{\alpha}.E^{-\beta n}$	-
$T^* = f_5 = f_5(y_{in})$	-	y_{in}
n_1	4	4
n_2	2	1

With X^* input and $T^{\#}$ lifetime data [49], as explained in subsection 2.2. So, the objective function for BPNN-IPM and BPNN in this research model is as (6):

$$T^* = \begin{cases} L\ o\ f_4\ o\ f_3\ o\ f_2\ o\ f_1 & for\ BPNN-IPM \\ f_5\ o\ f_3\ o\ f_2\ o\ f_1 & for\ BPNN \end{cases} \tag{6}$$

The parameters in this model are $b1, v, b2, w$ for the BPNN scheme and plus (α, β) for the BPNN-IPM scheme.

2.4. Parameter model estimation

Based on the objective function in (6), optimization was then carried out using the GD, GA, and LM methods and obtained a improved formulation of model parameters in Table 2. T^* is the objective model function in (6), with model construction referring to Table 2. The objective function optimized using the GD method is formed based on the difference between the model and experimental data, namely the sum of the squared errors as (7):

$$\xi = \frac{1}{2}\sum_{j\in C} e_j^2(n) \tag{7}$$

with $e_j(n) = T_j^{\#}(n) - T_j^*(n)$. Based on [51], [52], the GD method works by deriving the (7) for each parameter $w, b2, v, b1$ equal to 0 which corresponds to Table 2.

A GA is a heuristic approach whose way of working imitates the way genes work and has stages [53], [54]: (i) initialization; (ii) individual evaluation; (iii) linear fitness ranking; (iv) roulette wheel, (v) crossover, and (vi) mutation. All these stages are standardized processes except for the individual evaluation stage. At this stage, adapt to the objective function according to Table 2. Based on [53], [55], stages (1)-(6) of the GA guarantee the convergence of the GA method for BPNN and BPNN-IPM, namely that the results obtained in the model increasingly reduce the difference between experiment and model along with increasing iterations.

Based on [56], [57], updating the parameters of the Lavenberg-Marquardt (LM) method using the objective function in (6) as follows:

$$parameter(n+1) = parameter(n) - (J^T J\ + \lambda I)^{-1}\left(J^T(y - y_{model})\right) \tag{8}$$

with Jacobi matrix $J = \left(-\frac{\partial T^*}{\partial b_1}, -\frac{\partial T^*}{\partial v}, -\frac{\partial T^*}{\partial b_2}, -\frac{\partial T^*}{\partial w}\right)$ and λ is a scalar. Based on [56], [58], to minimize the error between experimental data and the model and guarantee convergence. then updating the parameters will guarantee the convergence of the LM optimization method for BPNN and BPNN-IPM. Namely, the difference between the experimental and model results gets smaller as the iterations increase. This entire process is summarized in Table 3. Table 3 explains the improved formulation for each optimization method with various schemes. Next will discuss the simulation results using the improved formulation in Table 3 to estimate parameters (α, β) and the lifetime of the DC XLPE cable insulation.

Table 3. Parameter formulation of BPNN and BPNN-IPM improved for lifetime DC XLPE insulation

Optimization	Scheme	Formulation
Gradient descent [51], [52], [59], [60]	BPNN-IPM and BPNN	$w_{ji}(n+1) = w_{ji}(n) - \alpha e_j(n+1)\, z$, $b2_i(n+1) = b2_i(n) - \alpha e_j(n+1)$, $v_j(n+1) = v_j(n) - \alpha e_j(n+1)\left(\frac{1}{(1+exp(-z_{in}))}\frac{exp(-z_{in})}{(1+exp(-z_{in}))}\right)X$, $b1_j(n+1) = b1_j(n) - \alpha e_j(n+1)\left(\frac{1}{(1+exp(-z_{in}))}\frac{exp(-z_{in})}{(1+exp(-z_{in}))}\right)$, with α is a scalar (learning rate).
GA [53]-[55]	BPNN-IPM and BPNN	$f = f_4\ o\ f_3\ o\ f_2\ o\ f_1$, with $z_{in} = f_1(X, b1, v) = b1 + X\, v$, $z = f_2(z_{in}) = \frac{1}{(1+exp(-z_{in}))}$, $y_{in} = f_3(z, b2, w) = b2 + z\, w$, $f_4(y_{in}) = y_{in}$.
LM [56]-[58]	BPNN-IPM and BPNN	$[b_1, v, b_2, w]' = [b_1, v, b_2, w]' - (J_C^T J_C + \lambda I)^{-1}\left(J_C^T(y - y_{model})\right)$, with J is Jacobi matrix and λ is scalar.

3. RESULTS AND DISCUSSION

3.1. Simulation

The BPNN and BPNN-IPM parameters obtained use some of the data in Table 1 and the formulation in Table 3. They are then evaluated using all the data (training-testing) to determine the accuracy of the improvement method used. The parameters obtained using BPNN-IPM are then used to estimate the lifetime of DC XLPE cable insulation, while BPNN directly obtains the lifetime of DC XLPE cable insulation using Matlab. The results obtained are then tabulated for accuracy with various treatments according to Figure 1 and learning process using improved formulation in Table 3 which implies to thirty-six simulation treatments total in this research. The thirty-six simulation results are discussed in Table 4.

Table 4. Performance simulation results of BPNN-IPM with NT output for lifetime DC XLPE cable: (a) GD parameter estimation, (b) GD lifetime estimation, (c) GA parameter estimation, (d) GA lifetime estimation, (e) LM parameter estimation, and (f) LM lifetime estimation

(a)

Training			Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime(s)	Amount of data	RMSE-day (NN/ZS/MM)
3	0.128/10^{-6}/10^{-4}	0.0079	12	0.128/0.176/0.048
6	0.118/10^{-4}/0.008	0.0074	9	0.118/0.044/0.011
9	0.178/0.010/0.006	0.0126	6	0.178/0.023/0.007
12	0.136/0.005/0.004	0.0145	3	0.136/0.014/0.004
15	0.186/0.005/0.006	0.018	0	-/-/-
Average	0.158/0.005/0.0053	0.0139	Average	0.1358/0.0896/0.0243

(b)

Training		Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Amoun of data	RMSE-day (NN/ZS/MM)
3	8.32/0.001/0.04	12	3.08/1.44/2.57
6	7.05/0.64/8.95	9	2.39/0.28/1.4
9	4.472/1.74/0.58	6	11.1/1.181/1.43
12	3.87/1.22/1.121	3	7.15/2.8/0.42
15	8.6/1.14/0.55	0	-/-/-
Average	6.287/1.138/1.794	Average	4.884/1.176/1.776

(c)

Training			Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime(s)	Amount of data	RMSE-day (NN/ZS/MM)
3	0.057/0.032/0.013	3.54	12	0.120/0.181/0.168
6	0.066/0.04/0.032	3.65	9	0.15/0.1/0.086
9	0.098/0.041/0.031	3.74	6	0.11/0.047/0.063
12	0.073/0.045/0.033	3.85	3	0.068/0.044/0.033
15	0.07/0.044/0.038	3.94	0	-/-/-
Average	0.075/0.0423/0.0328	3.81	Average	0.122/0.116/0.109

(d)

Training		Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Amount of data	RMSE-day (NN/ZS/MM)
3	49.446/17.07/3.89	12	2.44/7417.22/1.41
6	51.80/56.54/10.16	9	26.95/12.14/23.92
9	83.91/37.97/3.64	6	3.133/4.07/2.33
12	150.13/4.16/10.03	3	40.1/5.08/0.9
15	9.68/33.93/77.38	0	-/-/-
Average	70.24/28.68/30.81	Average	13.697/2971/8.296

(e)

Training			Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime(s)	Amount of data	RMSE-day (NN/ZS/MM)
3	0.108/0/10^{-17}	0.0098	12	0.108/0.096/0.054
6	0.108/10^{-17}/10^{-17}	0.011	9	0.108/0.017/0.021
9	0.108/10^{-17}/10^{-16}	0.0123	6	0.108/0.004/0.002
12	0.108/10^{-17}/10^{-17}	0.0183	3	0.108/10^{-16}/10^{-16}
15	0.108/10^{-5}/10^{-17}	0.025	0	-/-/-
Average	0.108/$\mathbf{10^{-6}}$/$\mathbf{10^{-17}}$	0.0178	Average	0.108/0.044/0.028

(f)

Training		Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Amount of data	RMSE-day (NN/ZS/MM)
3	12.88/0/10^{-14}	12	1.44/2.353/1.43
6	9.11/10^{-16}/10^{-13}	9	1.63/0.30/0.38
9	7.44/10^{-15}/10^{-14}	6	2/0.14/0.72
12	6.6/10^{-14}/10^{-16}	3	0.141/10^{-13}/10^{-13}
15	5.90/10^{-3}/10^{-14}	0	-/-/-
Average	7.288/$\mathbf{10^{-4}}$/$\mathbf{10^{-14}}$	Average	1.479/1.059/0.83

Tables 4 and 5 discusses the simulation performance of BPNN-IPM and BPNN with NT output using three optimization methods to estimate the lifetime of DC XLPE cable. The results obtained were carried out by treating variations in the amount of training and testing data by utilizing fifteen available data, which then calculated the average. Next, Tables 6 and 7 is presented in Appendix. Tables 6 and 7 discusses the simulation performance of BPNN-IPM and BPNN with LT output using three optimization methods to estimate the lifetime of DC XLPE cable. The results obtained were carried out by treating variations in the amount of training and testing data by utilizing fifteen available data, which then calculated the average. This simulation is also accompanied by learning process can be seen in Figure 3.

Table 5. Performance simulation results of BPNN with NT output for lifetime DC XLPE cable: (a) GD method, (b) GA method, and (c) LM method

(a)

Training			Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime(s)	Amount of data	RMSE-day (NN/ZS/MM)
3	37.17/10^{-4}/17.2	0.00412	12	44.17/18.52/16.29
6	10.24/11.32/10.19	0.00534	9	7.37/4.72/7.33
9	29.31/11.14/11.27	0.01111	6	28.05/5.73/5.94
12	17.2/8.49/11.1	0.0115	3	16.41/5.95/8.1
15	9.59/8.89/8.3	0.0134	0	-/-/-
Average	17.488/8.965/10.49	0.0091	Average	27.13/10.56/10.71

(b)

Training			Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime(s)	Amount of data	RMSE-day (NN/ZS/MM)
3	18.14/18.26/18.65	3.028	12	3.52/3.84/4.05
6	13/13/13.289	3.176	9	4.21/4.29/4.75
9	10.63/10.67/10.95	3.187	6	4.98/4.96/5.46
12	9.39/9.31/9.58	3.306	3	6.26/6.47/7.11
15	8.86/8.89/9.17	3.383	0	-/-/-
Average	10.53/10.53/10.82	3.216	Average	4.293/4.462/4.848

(c)

Training			Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime(s)	Amount of data	RMSE-day (NN/ZS/MM)
3	16.45/10^{-15}/10^{-15}	0.0083	12	11.96/19.63/17.85
6	13.15/10^{-16}/10^{-16}	0.0066	9	6.41/18.67/6.95
9	11.18/10^{-15}/0.03	0.0104	6	5.7/4.04/3.49
12	9.9/10^{-15}/0.003	0.0122	3	6.96/6.02/5.13
15	9.38/0.03/10^{-16}	0.0127	0	-/-/-
Average	10.85/0.01/0.0068	0.01	Average	8.543/14.86/10.436

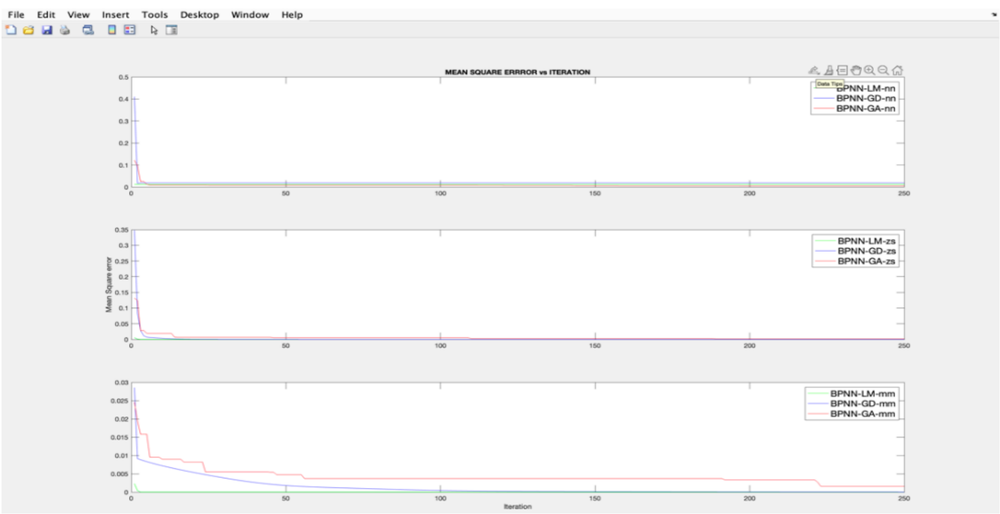

Figure 3. Sampel learning process for BPNN-IPM or BPNN schemes

Figure 3 explains that increasing iterations decreases the mean square error (MSE) both the BPNN and BPNN-IPM model parameters with experimental data. This figure shows the learning process converges and validates the improved formulation in Table 3 and Figure 3. The output obtained from these results will be recapitulated in the next sub-discussion.

3.2. Recapitulation of simulation

Evaluation of model improvement results needs to be carried out so that the results' performance is known. Parameter accuracy is obtained for the BPNN-IPM scheme, which is then used to estimate the lifetime of the DC XLPE cable insulation. Evaluation of the results obtained for all schemes and optimization methods can be seen in Table 8 which discusses RMSE in days and average runtime in seconds with evaluation based on training and testing data. The following is presented in Table 8.

Table 8. RMSE recapitulation of model simulation for lifetime DC XLPE cable insulation (days)

Model-Optimization	Output														
	Output not log-transform							Output log-transform							
	Training				Testing			Training				Testing			
	Input normalize			Average runtime(s)	Input normalize			Input normalize			Average runtime(s)	Input normalize			
	NN	ZS	MM		NN	ZS	MM	NN	ZS	MM		NN	ZS	MM	
BPNN-IPM-GD	6.28	1.14	1.79	0.0139	4.88	1.18	1.77	6.33	5.15	5.11	0.017	4.73	65.41	5.39	
BPNN-IPM-GA	70.24	28.68	30.81	3.81	13.7	2971	8.29	86.46	646.4	30.36	3.8	2.06	4070	6.18	
BPNN-IPM-LM	7.28	10^{-4}	10^{-14}	0.0177	1.48	1.06	**0.83**	7.35	10^{-16}	**0**	0.019	1.49	2.52	0.96	
BPNN-GD	17.48	8.96	10.48	0.009	27.13	10.56	10.7	102	0.3	0.2	0,01	513	5.78	3.29	
BPNN-GA	10.52	10.53	10.82	3.21	4.29	4.46	4.85	9.75	10.29	11.07	3.2	3.19	4.12	5.05	
BPNN-LM	10.85	0.01	0.007	0.01	8.543	14.86	10.4	11.82	10^{-16}	10^{-15}	0.008	5.58	8.87	4.95	

Table 8 recapitulates the simulation performance of BPNN-IPM and BPNN with NT and LT output using three optimization methods to estimate the lifetime of DC XLPE cable insulation. The data presented is average data for both training and testing so that it can represent the thirty-six treatments carried out. The table shows that the BPNN-IPM-GD simulation obtained the majority of RMSE between 1 day and 10 days, while BPNN-GD RMSE partly decreased and partly increased but with a faster runtime of 38.51%. As for BPNN-IPM-GA, the RMSE was still quite large, but there was quite a significant decrease in RMSE and runtime using BPNN-GA. Finally, the BPNN-IPM-LM method obtains the smallest RMSE with normalized MM input compared to all other methods, while the BPNN-LM method only reduces runtime, but the RMSE is greater. So, the BPNN-IPM-LM hybrid method with MM normalized input pre-processing is the most accurate method with two output pre-processing, namely LT for training with an RMSE of 0-day and NT for testing with an RMSE of 0.83-day.

3.3. Comparison of previous research

Previous research [49] used BPNN to obtain modified IPM model parameters to accommodate space charge and thickness using the LM optimization method, and research [50] used the gradient descent optimization method. In these two studies, only one variation of the method scheme was used and only parameter estimation was carried out. Meanwhile, this research uses thirty-six variations of method schemes and not only estimates parameters but also estimates the lifetime of DC XLPE cable, which was not done in previous research. Thirty-six variations of simulations were carried out in this research, the scheme of which can be seen in Figure 1 and a summary of the results can be seen in Table 8. The large number of variations carried out provides the advantage of obtaining an optimal scheme in order to obtain the smallest error. The error in estimating model parameters in research [47] was estimated at 1% and in research [48] an error of 3.0152% was obtained, whereas in this study it almost reached 0. In addition, in this study, in estimating the lifetime of DC XLPE cable, RMSE was 0-day for training and 0.83-day for testing. This result is certainly very good because in previous research lifetime estimates like this were carried out.

4. CONCLUSION

In this article, DC XLPE cable insulation lifetime improvements are carried out using thirty-six treatment variations to overcome the problem of adding thickness and space charge variables to obtain the best method. Then, the initial step taken was to create a improved formulation and based on this improved formulation, a simulation was carried out. These results indicate that of these thirty-six simulations, the BPNN-IPM hybrid method with input pre-processing min-max normalization and the LM optimization method is the best simulation treatments. The most accurate method with two pre-process outputs is log-transform output for training with an RMSE of 0-day and not log-transform output for testing with an RMSE of 0.83-day. These results show that the accuracy obtained is very good with the RMSE lifetime of DC XLPE cable insulation below one day. Further development of this research still needs to be carried out with potential improvements, namely the addition of DC XLPE cable lifetime insulation data so that the results obtained can be tested in real case. Apart from that, developing the best simulation treatment, especially improving the LM optimization method, also needs to be carried out. In this research, the LM used is a standard LM (multiple data output) so that it can be improved to become a multivariate data output. Although it is rare, the Hessian matrix approximation using the LM method still occurs ill-conditioning, so improvement in multivariate analysis is needed to overcome this problem. Apart from that, the combination of the GA-LM optimization method has the potential to be carried out in future research to avoid obtaining parameters with global minimum errors.

APPENDIX

Table 6. Performance simulation results of BPNN-IPM with LT output for lifetime DC XLPE cable: (a) GD parameter estimation, (b) GD lifetime estimation, (c) GA parameter estimation, (d) GA lifetime estimation, (e) LM lifetime estimation, and (f) LM lifetime estimation

(a)

	Training			Testing
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime(s)	Amount of data	RMSE-day (NN/ZS/MM)
3	$0.122/10^{-8}/10^{-5}$	0.0057	12	0.122/0.062/0.064
6	0.116/0.007/0.02	0.0092	9	0.116/0.117/0.048
9	0.176/0.021/0.029	0.013	6	0.176/0.049/0.046
12	0.135/0.007/0.018	0.017	3	0.135/0.014/0.041
15	0.186/0.007/0.024	0.024	0	-/-/-
Average	**0.157/0.0093/0.0213**	**0.01674**	Average	**0.132/0.071/0.053**

(b)

	Training		Testing
Amount of data	RMSE-day (NN/ZS/MM)	Amount of data	RMSE-day (NN/ZS/MM)
3	$8.66/10^{-6}/0.003$	12	2.85/51.9/7.43
6	7.14/2.89/6.95	9	2.32/2.75/0.79
9	4.43/17.77/8.75	6	10.98/218.91/3.87
12	3.9/1.97/0.87	3	7.02/0.42/14.12
15	8.62/2.059/6.62	0	-/-/-
Average	**6.328/5.151/5.115**	Average	**4.734/65.41/5.395**

(c)

	Training			Testing
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime(s)	Amount of data	RMSE-day (NN/ZS/MM)
3	0.063/0.033/0.034	3.54	12	0.127/0.064/0.145
6	0.058/0.042/0.036	3.64	9	0.11/0.082/0.085
9	0.052/0.040/0.039	3.73	6	0.074/0.074/0.056
12	0.069/0.034/0.05	3.83	3	0.057/0.032/0.037
15	0.087/0.088/0.033	3.95	0	-/-/-
Average	**0.07/0.054/0.039**	**3.805**	Average	**0.104/0.068/0.098**

(d)

	Training		Testing
Amount of data	RMSE-day (NN/ZS/MM)	Amount of data	RMSE-day (NN/ZS/MM)
3	20/19.802/18.36	12	1.91/4.03/1.18
6	10.21/13.5/11.76	9	2.06/5.02/5.1
9	7.96/142.66/35.76	6	2.7/20333.62/18.1
12	4.54/5.23/6.92	3	1.34/5.18/5.526
15	242.91/1840.07/55.72	0	-/-/-
Average	**86.47/646.4/30.36**	Average	**2.06/4070/6.18**

(e)

Training			Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime(s)	Amount of data	RMSE-day (NN/ZS/MM)
3	0.108/0/0	0.0154	12	0.108/0.089/0.059
6	0.108/0/0	0.0135	9	0.108/0.101/0.019
9	0.108/0/0	0.0181	6	0.108/0.01/10^{-4}
12	0.108/0/0	0.0194	3	0.108/0.006/10^{-16}
15	0.108/10^{-17}/0	0.0233	0	-/-/-
Average	**0.108/10^{-18}/0**	**0.0194**	Average	**0.108/0.068/0.029**

(f)

Training		Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Amount of data	RMSE-day (NN/ZS/MM)
3	12.98/0/0	12	1.45/3.65/1.96
6	9.19/0/0	9	1.64/2.81/0.275
9	7.5/0/0	6	2.01/0.64/0.48
12	6.65/0/0	3	0.151/0.88/10^{-14}
15	5.95/10^{-15}/0	0	-/-/-
Average	**7.347/10^{-16}/0**	Average	**1.49/2.52/0.96**

Table 7. Performance simulation results of BPNN with LT output for lifetime DC XLPE cable: (a) GD method (b) GA method, and (c) LM method

(a)

Training			Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime (s)	Amount of data	RMSE-day (NN/ZS/MM)
3	1255.94/10^{-7}/10^{-9}	0.00415	12	1266.45/9.6/4.93
6	14.84/10^{-6}/0.005	0.00716	9	5.82/3.61/2.705
9	11.37/10^{-4}/0.052	0.00985	6	5.92/3.14/1.92
12	39.36/0.036/0.18	0.01277	3	37.9/2.279/1.27
15	10.41/0.88/0.44	0.0164	0	-/-/-
Average	**101.9/0.303/0.206**	**0.01**	Average	**513.3/5.779/3.29**

(b)

Training			Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime (s)	Amount of data	RMSE-day (NN/ZS/MM)
3	16.6/14.91/16.1	3.026	12	2.32/3.4/3.8
6	8.1/12.37/13.59	3.11	9	2.32/3.76/4.88
9	10.33/10.41/11.46	3.193	6	4.89/4.77/6.43
12	8.91/9.39/9.96	3.28	3	5.9/6.8/7.83
15	9.37/9.185/9.72	3.382	0	-/-/-
Average	**9.75/10.29/11.07**	**3.198**	Average	**3.192/4.12/5.05**

(c)

Training			Testing	
Amount of data	RMSE-day (NN/ZS/MM)	Average runtime(s)	Amount of data	RMSE-day (NN/ZS/MM)
3	19.68/10^{-15}/10^{-15}	0.0056	12	4.47/7.88/7.86
6	14.39/10^{-16}/10^{-16}	0.0065	9	5.36/8.63/2.11
9	11.91/10^{-16}/10^{-16}	0.0083	6	6.79/14.01/4.12
12	10.57/10^{-15}/10^{-15}	0.0093	3	8.26/3.31/3.46
15	10.16/10^{-16}/10^{-14}	0.0106	0	-/-/-
Average	**11.818/10^{-16}/10^{-15}**	**0.008**	Average	**5.58/8.87/4.947**

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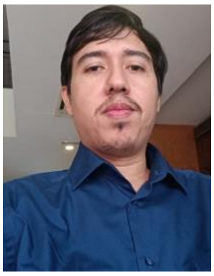

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