Digital measurement of lightning impulse parameters using curving fitting algorithms

DIGITAL MEASUREMENT OF LIGHTNING IMPULSE PARAMETERS USING CURVING FITTING ALGORITHMS

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ABSTRACT

This paper describes the application of curve fitting algorithms to aid the evaluation of lightning impulse parameters. A number of popular curve fitting algorithms have been evaluated and compared. Investigations using the genetic algorithm and other optimisation methods for the purpose of curve fitting have also been carried out and will be described.

1. INTRODUCTION

This study forms a part of an international collaborative project with KEMA, FFII-LCOE, Schering Institute (University of Hannover) and the National Grid Company. The aim of the project is to determine a set of parameters to characterise lightning impulses [1]. The project is funded by the European Community.

Today, lightning impulse (LI) waveforms are usually captured by high speed digital measurement systems. The captured wave sometimes appears to be discrete, especially when the sampling rate is not high enough or when some very high frequency components exist. This may affect the accuracy of the measurement. One of the possible solutions to overcome this problem is to apply a curve fitting algorithm to interpolate points in the waveform, so that the resulting curve will appear to be continuous and smooth. Another advantage of using this approach is the fact that the captured waveform can be represented by mathematical equations. As a result, the impulse wave can be analysed mathematically.

In Section 2, a general description of various curve fitting algorithms is given. The performance evaluation and comparison is also included. A more detailed description of using the genetic algorithm for the purpose of curve fitting is given in Section 3. Finally, a preliminary conclusion is given in Section 4.

2. CURVE FITTING ALGORITHMS

A large number of different curve fitting algorithms have been investigated and the following four algorithms are identified as being suitable for fitting LI waves :

- Polynomial curve fitting;
- Cubic Spline interpolation;
- Radial Basis Neural Network function approximation;
- Genetic Algorithm (GA) based curve fitting.

The test LI waves are generated by the IEC-TDG program [2] or captured by a practical digital measurement system.

Briefly, the polynomial curve fitting algorithm finds the coefficients of a polynomial series *p(x)* of degree *n* that fits the given data, *p(x(i))* to *y(i)*, in a least squares sense [3].

$$p(x) = p_1 x^n + p_2 x^{n-1} + \ldots + p_n x + p_{n+1}$$

The polynomial curve fitting algorithm has been successfully used to fit pure LI, however, it is unable to fit lightning impulse waves with oscillations.

The cubic spline interpolation applies piecewise polynomials to fit a curve[4]. It is capable of accurately and rapidly fitting both pure lightning impulse and lightning impulse with oscillations.

The radial basis neural network function approximation method applies a series of Gaussian functions to fit a curve[3]. A training procedure is required to find the best series of Gaussian functions. This method has been successfully applied to fit both pure lightning impulse and lightning impulse with oscillations. Generally, the time required to fit a curve is short and the quality of the fitting is accurate. The GA based curve fitting method is a searching algorithm inspired by the natural evolution process. It is employed to find the coefficients of a predefined objective function that fits the given data points. More detailed description of the GA technique is presented at Section 3. This approach has been successfully applied to fit both a pure lightning impulse and a lightning impulse with oscillations. The time required for the fitting is considerably long, but it is very accurate.

Table 1 summaries a general description and comparison of the four curve fitting methods. A simplified curve fitting example is shown in Figure 1. As can be seen, the fitted curve (grey curve) passes through all the given data points and appears to be significantly smoother.

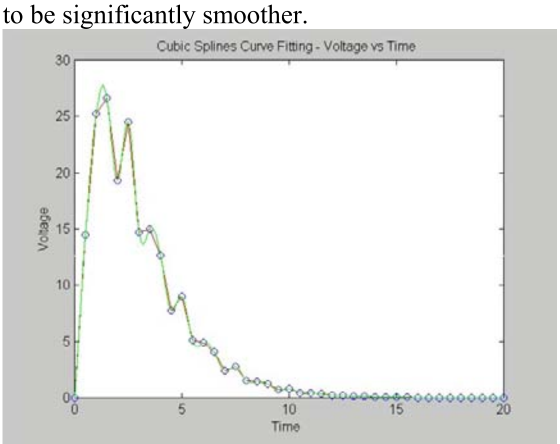

Figure 1: A simplied curve fitting example.

3. GA BASED CURVE FITTING METHOD

In Section 2, a brief description of the GA was introduced. The advantage of this approach is that the objective function can be customised in such a way as to match the given data. As a result, a digitised LI wave can be effectively represented by a relatively simple function, such as :

$$V = (A_1 e^{-\alpha_1 t} - A_2 e^{-\alpha_2 t}) + A_3(1 - e^{-\alpha_3 t})\cos(wt + \phi)\lambda(t_d)$$

where $\lambda(t_d)$ is a time delay function.

Thus, the LI parameters can be derived relatively easily from the equation. Because the objective function is changeable, it can also be employed to determine the mean curve of a LI with oscillations by fitting the given data into a double or quadruple exponential function. In the next paragraphs, a more detailed description of the GA covering its architecture and principle of operation is presented. GA is an effective global searching algorithm inspired by the natural genetic selection, in which new "creatures" are produced using components of the fittest individuals from previous generations (Darwin's theory of evolution). It has been widely and successfully applied in function optimisation and control applications. Specifically, a population of individuals, in this case potential solutions, compete with one another over successive generations, 'survival of the fittest'. After a number of generations, the best solutions survive and the less fit are gradually eliminated from the population. This enables exploitation of historical information to speculate on new search points. GA techniques use random choice as a tool to guide a highly exploitative search through a coding of a parameter space [5]. Compared to other traditional optimisation methods, the GA technique uses probabilistic transition rules rather than deterministic rules. It works with a coding of the parameter set rather than the parameters themselves and it searches from a population of points rather than a single point. The behaviour of the search mechanism relies only upon the fitness value derived from an evaluation function, and so that a derivative term or other auxiliary information is not required. This does not exhibit some fundamental limitations associated with other methods, such as continuity and existence of derivatives, that appear on many practical applications.

Item	Function Name	Performance	Description
1	Polynomial Curve Fitting	• It can fit pure LI but fails to fit LI with oscillations. • It can be used to find the mean curve of a LI with oscillation.	It applies a nth degree polynomial series to fit the curve.
2	Cubic Spline Interpolation	• It can fit both pure LI and LI with oscillations. • Fast and accurate.	It applies piecewise polynomials to fit the curve.
3	Radial Basis Neural Network Function Approximation	• It can fit both pure LI and LI with oscillations. • Fast and accurate.	It applies a series of Gaussian functions to fit the curve.
4	Genetic Algorithm based Curve Fitting	• It can fit both pure LI and LI with oscillations. • Slow, but accurate. • It can be used to find the mean curve of a LI with oscillation.	It finds the parameters of a predefined objective function that fits the given data points.

Table 1 : A summarised description of the four curve fitting algorithms.

The GA based searching mechanism consists of four main functional units, population pools, selection unit, reproduction unit, and evaluation unit. Figure 2 shows the block diagram of a GA based searching mechanism.

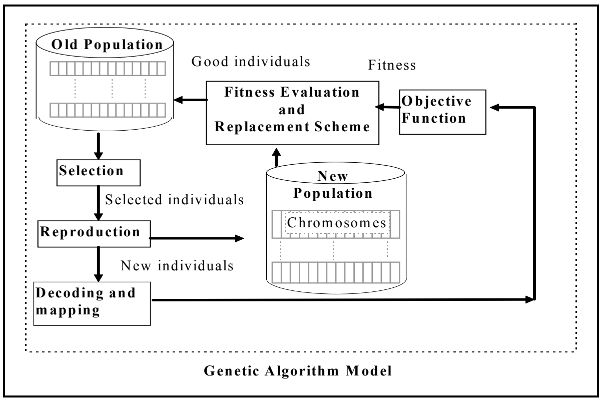

Figure 2 : : Block Diagram Of A GA Based Searching Mechanism.

A population pool contains a large number of individuals (solutions) which store the parameter values for the objective function. For the double exponential function example, the parameters for the objective function are A_1, A_2, α_1 and α_2.

$$y = A_1 e^{-\alpha_1 t} - A_2 e^{-\alpha_2 t}$$

The individuals in the original population are initialised by random numbers and their fitness values are evaluated by the evaluation function. Subsequently, the evaluation function calculates the fitness of an individual based on the differences between given digitised LI and the LI generated by the objective function. In this example, the least square error method is employed.

$$Fitness = \frac{F}{\sum \sqrt{\left[f(t) - O(t)\right]^2}}$$

where *F* is a multiplying factor, *f(t)* and *O(t)* are respectively the input digitised lightning impulse and the lightning impulse generated by the objective function.
The selection unit applies a random but biased manner to select individuals for producing new population of individuals for next generation. In this way, fit individuals have higher probability to be selected as parents. The selection method applied in this study is the biased roulette wheel selection approach, which has been widely used by many GA based applications.
After selecting individuals as parents, new child individuals can be reproduced by mixing and mutating the genes of the parents. The crossover and mutation operators have been successfully employed for this purpose.
When the reproduction process is finished, each of the individuals in the new population will be evaluated. Their fitness values are calculated by the evaluation function. The average fitness of the individuals in the new population is usually improved. The iterative generation process needs to be repeated until the solution is converged.
In order to evaluate the performance of the GA based curve fitting algorithm for finding the mean curve for a lightning impulse (LI), or switching impulse (SI), eight tests have been carried out, see Table 2. For each test, a digitised LI or SI was given and the GA based curve fitting algorithm was to find the appropriate parameter values for the double exponential function which closely matches the mean curve of the given LI or SI. The test data of the eight case studies (see Table 2) were generated by the IEC-TDG [2]. Case studies 1 to 3 concern smooth LI, smooth LI with long duration overshoot and smooth LI short duration overshoot respectively. Case studies 4 and 8 concern smooth switch impulse and noisy switch impulse respectively. Finally, case studies 5 to 7 concern noisy LI, noisy LI with long duration overshoot and noisy LI with short duration overshoot respectively. The results of the case studies are illustrated graphically in Figure 4 and Table 2.

CONCLUSIONS

Experiments undertaken to date indicate that digitised lightning impulse can be accurately represented by mathematical functions. The benefit of this approach is that the lightning impulse parameters can then be derived mathematically. This facilitates the automation of parameter evaluation when using computers. A number of curve fitting algorithms have been validated and evaluated, see Table 1. Generally, they all can be applied to fit a given digitised LI or the mean curve of a given LI. However, the mathematical functions applied to fit the curve are different. In some cases, it is very difficult to derive LI parameters from the given mathematical functions, for example, a series of complex Gaussian functions. As a result, the Genetic Algorithm was employed. The advantage of using GA is that the function employed to fit the curve can be customised. Users can apply their knowledge, or other background information, to design a simpler objective function. The preliminary results show that the GA based curve fitting algorithm can efficiently and accurately fit the mean curve of a given digitised impulse, see Figure 4. Investigation using an optimisation software package, Vensim, for the purpose of curve fitting has also been carried out. The results will be presented shortly in future more comprehensive publications.

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Case	Description	A_1	A_2	α_1	α_2
1	Smooth LI	1025243	749820	12979	3590463
2	LI with long duration of overshoot	1037226	645890	15202	2194034
3	LI with short duration of overshoot	1032295	626188	14500	3638646
4	Switch Impulse	1076340	382283	297	16146
5	Noisy LI	1024845	738643	12888	3495054
6	Noisy LI with long duration of overshoot	1042269	649852	15639	2206920
7	Noisy LI with short duration of overshoot	1030743	622700	14451	3483553
8	Noisy switch Impulse	1071077	382067	294	16563

Table 2 : Table 2 : Parameter values for the double exponential function that fit the given lightning impulse and switch impulse.

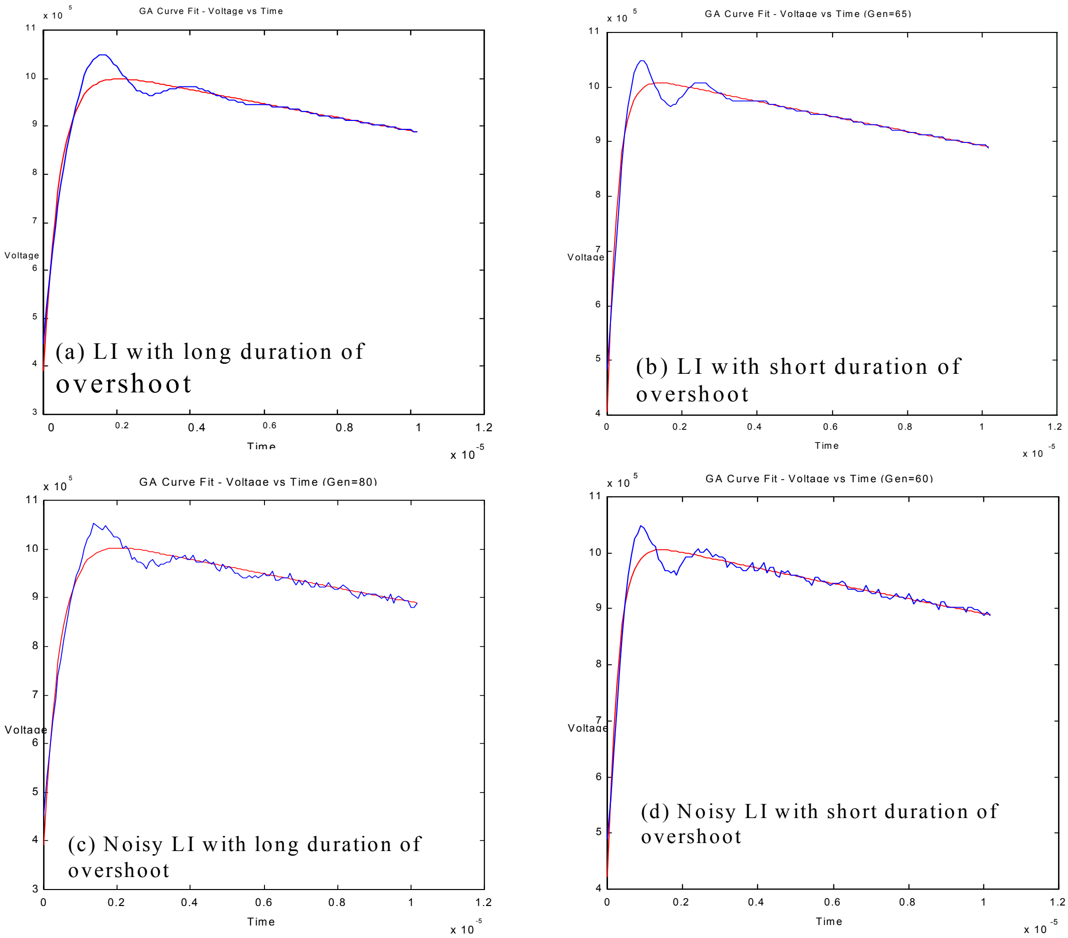

Figure 3 : Example curves produced by the GA based curve fitting Algorithm.