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A fuzzy logic system for calculation of the interference of overhead transmission lines on buried pipelines

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Abstract

The influence of a faulted electrical power transmission line on a buried pipeline is investigated. A calculation tool is suggested. Finite element solutions of field equations are used combined with artificial intelligence methods. The electromagnetic field depends on several parameters, such as the position of the phase conductors, the currents flowing through the conducting materials and the resistivity of the earth. A fuzzy logic system was used to simulate the problem. It was trained using data derived from finite element method (FEM) calculations for different configuration cases (training set) of the above electromagnetic field problem. After the training, the system was tested for several configuration cases, differing significantly from the training cases with satisfactory results. It is shown that the proposed method is very time efficient and accurate in calculating the electromagnetic fields compared to the time straining finite element method.

An important feature of the fuzzy logic system is that it consists of a varying rule base and is trained using genetic algorithms. In order to create the rule base for the fuzzy logic system a special operation is used at the beginning of the training. Afterwards, the training of the system is achieved with the use of a genetic algorithm (GA) that implements some special operators.

Keywords: Fuzzy logic systems; Genetic algorithms; Pattern recognition; Inductive interference

1. Introduction

The inductive interference problem between a faulted overhead transmission line and a pipeline buried nearby is of growing practical interest, due to the restrictions currently imposed on public utilities in the use of right-of-ways. These restrictions have resulted in situations in which overhead transmission lines, pipelines, railroads, telecommunication lines etc., have to be laid in straight narrow corridors for several kilometers. This policy minimizes the amount of land used but a faulted overhead transmission line in such a corridor causes significant interference to nearby parallel conductors.

The above mentioned interference is governed by Maxwell's electromagnetic field equations and depends upon several parameters such as the geometry, the boundaries and the electromagnetic properties of the materials. Recently a finite element method (FEM) approach has been proposed [1–3] in order to solve this problem in two dimensions. FEM is an accurate numerical method, but its main disadvantage is that the computing time may increase tremendously with the number of the finite elements [4], resulting in a huge computational effort.

The present paper suggests the following steps for reducing the computational effort: (a) the problem is solved for several sets of parameters and a database (training set) is built; (b) a fuzzy logic system is built and trained using the training set; and (c) for a new set of parameters the solution is found using fuzzy rules.

The fuzzy logic system is trained using genetic algorithms: the result is called a Genetic Fuzzy System.

Genetic fuzzy systems (GFS) are already in use over the last several years [5–12] and have led to standard coding schemes and genetic operators. This paper presents a new approach based on *genetically evolved* fuzzy

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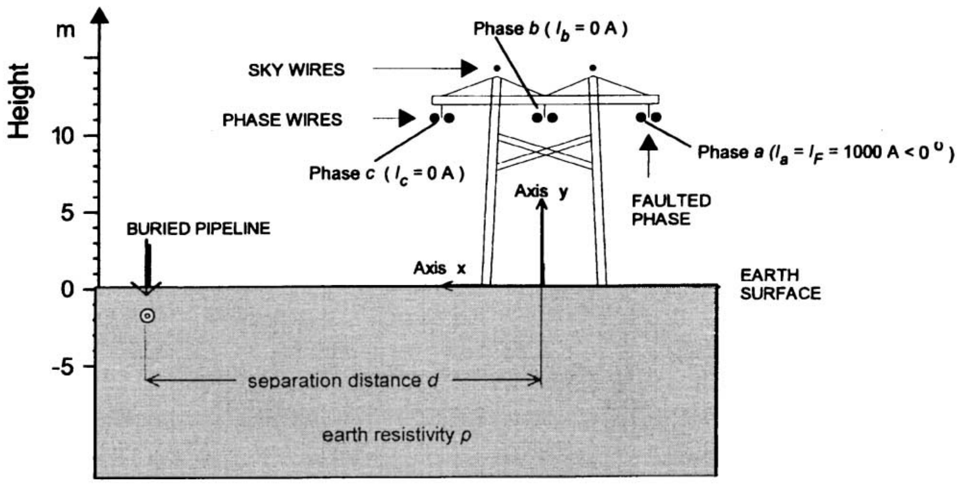


Fig. 1. Cross-section of the examined electromagnetic field problem.

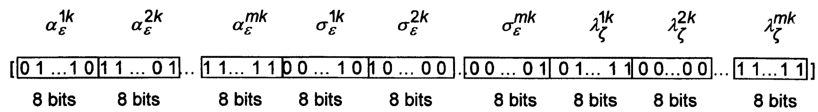


Fig. 2. String representing the kth Fuzzy Logic System of the developed Genetic Fuzzy System.

logic systems (FLS) to solve the problem of an overhead transmission line's electromagnetic field calculation in a fast and efficient way. Unlike FEM the system does not suffer in case the solution space is non-convex, and once it has been trained it can calculate the electromagnetic field in fractions of a second, which is very helpful, especially if the environmental parameters change rapidly.

2. Description of the problem

An overhead transmission line with a single phase fault runs in parallel with a buried pipeline (Fig. 1). More details about this configuration are in Refs. [1–3]. The Magnetic Vector Potential (MVP) is sought. Having the MVP, it is easy to calculate the induced voltages across the pipeline and the earth, which is one important engineering task [1–3]. The solution is governed by the diffusion equation:

$$\frac{1}{\mu}\left[\frac{\partial^2 A_z}{\partial x^2}+\frac{\partial^2 A_z}{\partial y^2}\right] \quad -\mathrm{j}\omega\sigma A_z + J_{sz} = 0 \qquad (1)$$

$$-\mathrm{j}\omega\sigma A_z + J_{sz} = J_z$$

where μ is the permeability, A_z the phasor of vector potential, x, y the point coordinates, σ the conductivity, ω the current frequency, and J_{sz} the current density. The solution depends on the boundary conditions, the geometry and material parameters, e.g. resistivity and distance d Fig. 1. In this paper we only consider as variables the point coordinates (x,y) where we calculate the MVP, the distance d and the soil resistivity ρ. Although there are many other parameters (variables) to consider, we restricted the variables in order to show in a simple way the effectiveness of the proposed method.

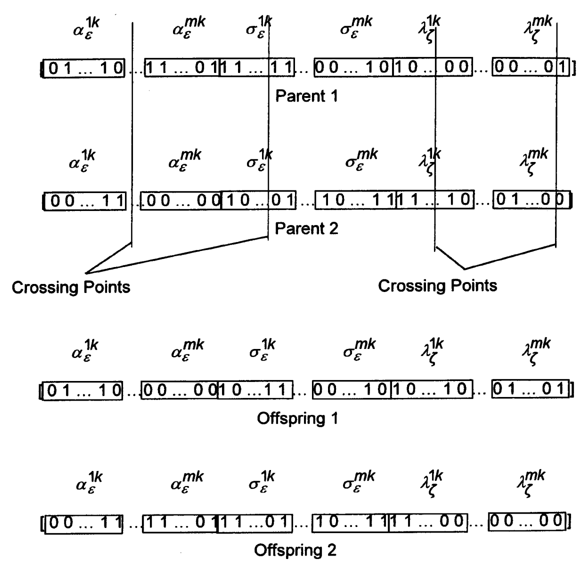


Fig. 3. Multi-point crossover operator.

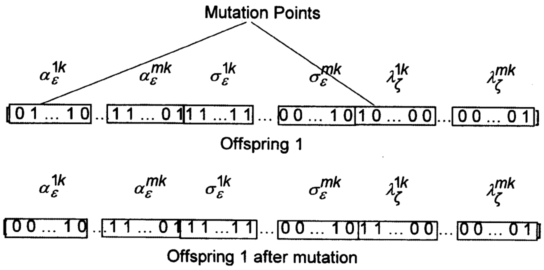


Fig. 4. Mutation operator.

3. The method

The MVP is found by solving the diffusion equation for several sets of the parameters d, ρ. Finite elements are used for the solution. The MVP at a coordinate (x,y) for other sets of parameters d, ρ is found by extrapolation of the known results in the space of the parameters. This extrapolation is made using fuzzy logic techniques [13,14]. Optimized fuzzy rules are found by using genetic algorithms. Optimal means minimizing least square errors in extrapolation. The number and parameters of the rules are optimized. The procedure is as described below.

A database is built, which contains the FEM solution for different sets of d, ρ at various points. This set of data is called the Training Data Set (TDS) and contains the training patterns of the fuzzy logic system (FLS) to be trained.

The training patterns for the system consist of four inputs and one output. The inputs are (a) the earth resistivity ρ; (b) the separation distance d between the overhead transmission line and the buried pipeline; (c) the coordinate x; and (d) the coordinate y of a point in the cross-section of the TLS. The single output is the MVP $A(x,y)$ at the point (x,y). The rules of each FLS are in the form suggested by Takagi–Sugeno [15] and the jth fuzzy rule (R^j) may be described as follows:

R^j: IF ρ, d, x, and y belong to the jth membership fun ctions μ_ρ^j, μ_d^j, μ_x^j and μ_y^j correspondingly (antecedent pa rt of the jth rule)

THEN $A^j = \lambda_0^j + \lambda_d^j d + \lambda_x^j x + \lambda_y^j y + \lambda_\rho^j \rho$ (consequent part of the jth rule) (2)

$j = (1 \ldots m)$, m is the number of rules, d, x, y, ρ are the input variables of the FLS, A^j is the MVP proposed by the jth rule and μ_d^j, μ_x^j, μ_y^j, μ_ρ^j are the membership functions that define the jth fuzzy rule. The parameters λ_0^j, λ_d^j, λ_x^j, λ_y^j, λ_ρ^j are the factors of the consequent part of the jth rule and define its output. The membership functions used in order to create the fuzzy inputs were chosen to be Gaussian as described below:

$$\mu_\varepsilon^j(\varepsilon) = \exp\left[-\frac{1}{2}\left(\frac{\varepsilon - \bar{\alpha}_\varepsilon^j}{\sigma_\varepsilon^j}\right)^2\right] \quad (3)$$

where ε stands for input and takes the values d, x, y, ρ. In addition, $\bar{\alpha}_d^j$, $\bar{\alpha}_x^j$, $\bar{\alpha}_y^j$, $\bar{\alpha}_\rho^j$ are the mean values and σ_d^j, σ_x^j, σ_y^j, σ_ρ^j are the standard deviations of the membership functions. Trapezoid and triangular membership functions have also been used, leading to a less accurate system.

In order to generate the actual output of the FLS, the weighted average *defuzzification interface* [16] has been selected. Therefore the output of the FLS defined above, i.e. the MVP in a point with coordinates x, y for separation distance d and earth resistivity ρ, is given by

$$A(d,x,y,\rho) = \frac{\sum_{j=1}^{m} A^j \mu^j}{\sum_{j=1}^{m} \mu^j} \quad (4)$$

where

$$\mu^j = \mu_d^j(d)\mu_x^j(x)\mu_y^j(y)\mu_\rho^j(\rho) \quad (5)$$

is called the degree of fulfillment for rule R^j by the input vector (d,x,y,ρ), while A^j is the output of rule R^j as defined in Eq. (2).

If q is the number of training patterns of the TDS derived by the FEM, every FLS is trained by 'feeding' it with the set of q patterns $(d^p,x^p,y^p,\rho^p/A_{FEM}^p,\ p = 1,\ldots,q)$. The mean square error J_m of each FLS is defined by

$$J_m = \frac{1}{q}\sum_{p=1}^{q} J^p \quad (6)$$

where the square error J^p of the FLS for pattern p is given by

$$J^p = \frac{1}{2}[A_{FLS}^p(d,x,y,p) - A_{FEM}^p(d,x,y,p)]^2 \quad (7)$$

in which $A_{FLS}^p(d,x,y,p)$ and $A_{FEM}^p(d,x,y,p)$ are the calculated values of the MVP at pattern p obtained from the FLS and the FEM, respectively. We arbitrarily define training to be the minimization of the mean square error, which means that the FLS finally determined corresponds to the smallest mean square error between the FLS output and the FEM calculation.

3.1. Fuzzy rule base creation mechanism

The number of rules of the FLS of the proposed GFS is not constant but gradually increases as follows. Training begins with one rule ($m = 1$). At the end of every training cycle, if the average error of the best FLS is larger than the training threshold $E_{\lim}$ a fuzzy rule creation mechanism is applied for the best FLS as follows:

The *firing strength* S [17] of the best fuzzy rule base for a training pattern p $(d^p,x^p,y^p,\rho^p/A_{\mathrm{FEM}}^p)$ is expressed as

$$S(d^p,x^p,y^p,\rho^p)=\sum_{j=1}^{m}\mu^j \quad (8)$$

while a threshold β is defined as the least acceptable firing strength of the best fuzzy rule base. If $S(d^p,x^p,y^p,\rho^p)<\beta$ then a new rule R^{m+1} is added to the best fuzzy rule base. If $\mu_\varepsilon^{m+1}(\bar{\alpha}_\varepsilon^{m+1},\sigma_\varepsilon^{m+1})$ represents the new membership in the εth premise input space, then the parameters of μ_ε^{m+1} are selected as:

$$\bar{\alpha}_\varepsilon^{m+1}=\varepsilon^p \quad (9a)$$

$$\sigma_\varepsilon^{m+1}=\gamma(\varepsilon^p-\bar{\alpha}_\varepsilon^{\text{nearest}}) \quad (9b)$$

$$\lambda_0^{m+1}=A^p_{\text{FEM}},\ \lambda_\varepsilon^{m+1}=0 \quad (9c)$$

where $\bar{\alpha}_\varepsilon^{\text{nearest}}$ is the mean value of an existing membership closest to the incoming pattern vector ε^p, y is an overlapping factor and $\varepsilon=d$, x, y, ρ. Overlapping factor γ was chosen equal to 1.5 after a number of trial computational tests, using as a criterion the genetic algorithm convergence time.

Table 1
Training data set used for the two GFS. The input variables are the earth resistivity ρ, the separation distance d and the coordinates x and y of points in the earth around the pipeline neighborhood, including the pipeline itself. The output for the first GFS is the amplitude, and for the second GFS the phase of the MVP, as calculated with the FEM

ρ (Ωm)	d (m)	x (m)	y (m)	MVP (amplitude) (10^{-04} Wb/m)	MVP (phase) (°)
30	70	70.00	−15.00	3.61	−22.80
30	70	81.66	−27.03	3.29	−25.57
30	100	100.00	−30.00	2.99	−31.23
30	800	770.00	−30.00	0.423	−82.64
30	800	785.00	0.00	0.427	−78.83
30	800	818.25	−13.50	0.388	−82.61
30	1000	1030.00	−15.00	0.248	−90.27
30	2000	1970.00	−22.50	0.0476	−108.10
30	2000	2000.69	−8.61	0.0465	−108.54
70	400	384.81	−7.82	1.72	−44.46
70	400	392.25	−25.65	1.67	−46.05
70	400	424.77	−6.93	1.58	−46.72
70	1000	970.00	−15.00	0.595	−73.04
70	1000	1007.50	0.00	0.568	−72.98
70	1000	1015.00	−30.00	0.547	−76.05
100	70	40.00	−30.00	5.09	−20.45
100	70	40.00	−15.00	5.38	−19.34
100	70	40.00	0.00	5.59	−18.53
100	100	92.25	−25.56	4.15	−23.98
100	800	770.00	0.00	1.04	−59.87
100	1000	980.55	−16.99	0.758	−67.10
100	1000	1015.00	−30.00	0.716	−69.22
100	1000	1022.50	0.00	0.723	−67.27
300	300	312.38	−8.10	3.17	−29.23
300	300	324.05	−23.53	3.10	−30.00
300	2000	2007.50	0.00	0.586	−72.55
500	200	215.00	−30.00	4.18	−23.83
500	300	281.66	−27.03	3.75	−25.93
500	300	290.36	−15.80	3.71	−26.01
500	300	322.50	0.00	3.55	−26.74
500	1000	1030.00	−15.00	1.70	−44.60
700	150	120.00	−15.00	5.46	−19.26
700	400	384.81	−7.82	3.52	−26.89
700	700	670.00	−22.50	2.60	−33.74
700	700	690.36	−15.80	2.56	−34.07
700	700	712.38	−8.10	2.51	−34.41
900	150	150.55	−16.99	5.30	−19.70
900	200	194.77	−6.93	4.88	−20.90
900	800	830.00	−30.00	2.46	−35.01
900	1500	1499.09	−17.48	1.56	−46.35
900	1500	1524.77	−6.93	1.54	−46.56
1000	70	54.81	−7.82	7.03	−15.94
1000	150	131.66	−27.03	5.58	−18.98
1000	500	524.05	−23.53	3.29	−28.27
1000	2000	2030.00	−15.00	1.22	−52.73

Table 2
MVP amplitude distribution in the earth around the pipeline neighborhood including the pipeline itself for several new configuration cases of the examined electromagnetic field problem obtained by the FEM and the optimum FLS of the GFS, respectively. [a]

ρ (Ωm)	d (m)	x (m)	y (m)	A_{FEM} (10^{-04} Wb/m)	$A_{O\text{-}FLS}$ (10^{-04} Wb/m)	Error (%)
70	70	88.25	−13.50	3.99	4.02	0.66
70	100	99.81	−1.75	3.84	3.86	0.47
70	100	124.77	−6.93	3.47	3.47	0.12
70	150	120.00	0.00	3.56	3.54	0.43
70	150	162.38	−8.10	3.04	3.03	0.53
70	200	199.81	−1.75	2.73	2.70	0.82
70	200	200.00	−30.00	2.66	2.59	2.63
70	300	281.66	−27.03	2.16	2.12	1.55
70	300	299.81	−1.75	2.10	2.11	0.44
70	300	322.50	0.00	1.99	2.00	0.62
70	500	485.00	0.00	1.41	1.40	0.41
70	500	499.81	−1.75	1.36	1.35	0.9
70	700	699.09	−17.48	0.933	0.895	4.1
70	700	670.00	−15.00	0.983	0.965	1.9
70	800	799.81	−1.75	0.794	0.768	3.28
70	800	822.50	0.00	0.767	0.733	4.4
70	2000	2010.11	−21.49	0.136	0.133	2.44
150	170	169.81	−1.75	3.61	3.68	2.03
150	170	169.08	−17.48	3.59	3.66	1.9
150	250	260.11	−21.49	2.89	3.00	3.98
150	250	274.05	−23.53	2.80	2.93	4.49
150	600	599.81	−1.75	1.64	1.66	1.38
150	600	600.00	−30.00	1.62	1.65	1.92
150	800	799.81	−1.75	1.24	1.25	0.31
150	800	790.36	−15.80	1.25	1.26	0.36
150	800	830.00	−15.00	1.19	1.18	0.7
150	900	900.00	−30.00	1.08	1.11	3.33
150	900	899.81	−1.75	1.09	1.11	1.88
150	900	892.50	0.00	1.10	1.12	1.95
150	1500	1500.69	−8.61	5.41	4.71	12.87
400	170	169.81	−1.75	4.43	4.42	0.27
400	250	231.66	−27.03	3.88	3.90	0.39
400	250	249.09	−17.48	3.77	3.80	0.8
400	600	599.81	−1.75	2.36	2.34	1
400	800	770.00	−30.00	1.96	1.94	1.17
400	800	824.77	−6.93	1.87	1.81	2.97
400	900	900.00	−30.00	1.73	1.64	4.84
400	900	930.00	−30.00	1.68	1.56	7.27
400	1500	1524.05	−23.53	1.03	9.49	7.46
400	1800	1781.66	−27.03	0.842	0.847	0.58
400	1800	2892.50	0.00	0.842	0.835	0.83
600	170	169.81	−1.75	4.78	4.85	1.5
600	250	220.00	−30.00	4.30	4.35	1.15
600	250	249.81	−1.75	4.12	4.16	0.86
600	600	570.00	0.00	2.76	2.75	0.4
600	600	599.81	−1.75	2.67	2.69	0.49
600	800	784.81	−7.82	2.24	2.27	1.17
600	800	799.81	−1.75	2.22	2.24	1.18
600	900	884.81	−7.82	2.06	2.06	0.32
600	900	918.25	−13.50	2.00	2.00	0.03
600	1500	1507.50	0.00	1.29	1.33	2.57
600	1500	1499.81	−1.75	1.30	1.33	2.28
600	1800	1790.36	−15.80	1.07	1.22	14.69
600	1800	1799.81	−1.75	1.06	1.22	14.34
900	250	235.00	0.00	4.57	4.45	2.61
900	250	230.55	−16.99	4.59	4.42	3.7
900	900	870.00	−15.00	2.38	2.32	2.81
900	900	900.69	−8.61	2.33	2.29	1.92
900	1800	1792.50	0.00	1.32	1.29	2.2

[a] The FLS calculation Errors $= |100(A_{FEM} - A_{O\text{-}FLS})/(A_{FEM})|$ are also reported.

The generation of new rules establishes the rule base creation mechanism, which is summarized by the following steps:

- A pattern (d^p, x^p, y^p, ρ^p) ($p=1\ldots$q) of the TDS is fed forward through the best FLS of the population and the corresponding firing strength $S(d^p, x^p, y^p, \rho^p)$ is computed.
- If $S(d^p, x^p, y^p, \rho^p) \geq \beta$ then the rule base of the best FLS is left unchanged.
- If $S(d^p, x^p, y^p, \rho^p) < \beta$ then a new fuzzy rule R^{m+1} is created, and parameters according to Eqs. (9a), (9b) and (9c), are selected.

The new fuzzy rule R^{m+1} is added to the rule bases of all the FLS and in this way all the chromosomes of the genetic algorithm are of the same length. From Eqs. (9a), (9b) and (9c), it can be shown that the new rules are centered on the patterns that are "covered" the least by the existing rules, thus showing the largest error during the training. As a result, after the addition of the new rule, the FLS will produce a null error for this pattern.

The rule base adaptation mechanism accelerates the training because it "injects" the GFS with new, valuable information and it leads toward areas of the search space where the optimum solution is more likely to be.

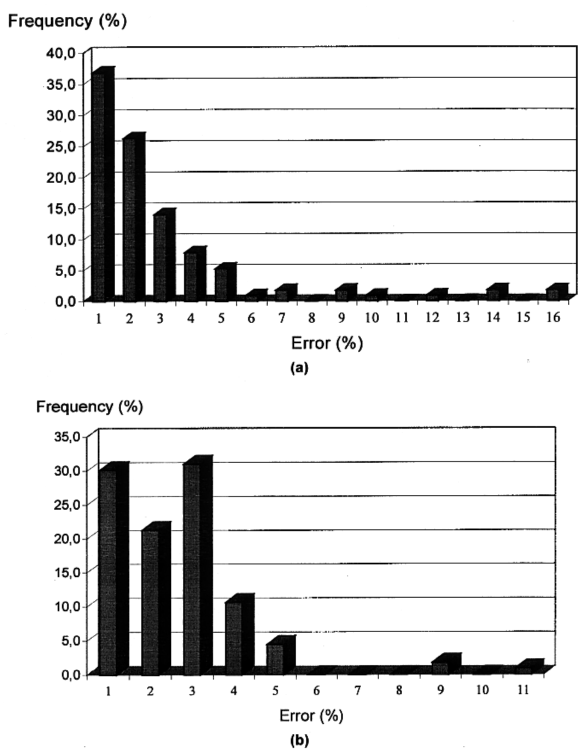


Fig. 5. Frequency distribution of the fuzzy logic system errors, concerning: (a) the amplitude and (b) the phase of the magnetic vector potential distribution in the earth around the pipeline neighborhood including the pipeline itself.

This method continues until no other rules are needed or until a heuristically-set maximum number of rules is reached. This number is defined by the user so that there is no overflow of new rules and the system does not become too complex to be trained in a logical amount of time. For our problem, the maximum number of fuzzy rules was set equal to 11.

3.2. Genetic algorithms for the training of the fuzzy parameters

3.2.1. Chromosome structure

The parameters to be adjusted through the training procedure are the parameters of the jth rule $\bar{\alpha}_{\varepsilon}^{j}$, σ_{ε}^{j} and λ_{ζ}^{j}.

The genetic algorithm (GA) that has been developed for the adjustment of the FLS parameters seeks the optimum FLS that has the minimum mean square error J_m. Every FLS of the GFS is represented by a vector of its parameters Z^k, given by:

$$Z^k = (\alpha_{\varepsilon}^{jk}, \sigma_{\varepsilon}^{jk}, \lambda_{\zeta}^{jk})$$

$$\text{(vector dimension is equal to } 13*m) \tag{10}$$

$$\varepsilon = d,\ x,\ y,\ \rho$$

$$\zeta = 0,\ d,\ x,\ y,\ \rho$$

$$j = 1,\ \ldots,\ m$$

where k ($k=1,\ldots,l$) is the index number of the FLS and l is the population size (i.e. the number of the FLS that constitute the GFS). In this paper l has been chosen equal to 50. The training begins with the initialization of one rule ($m=1$) for all the FLS. The initialization of the FLS parameters is accomplished using a random bit generator. In the developed GA, every parameter of each FLS has been coded in the binary form. This form uses eight bits for every parameter. The coding of every parameter takes place after normalization to the interval [0.0, 3.0] for $\alpha_{\varepsilon}^{jk}$, λ_{ζ}^{jk} and to the interval [0.1, 0.6] for $\sigma_{\varepsilon}^{jk}$.

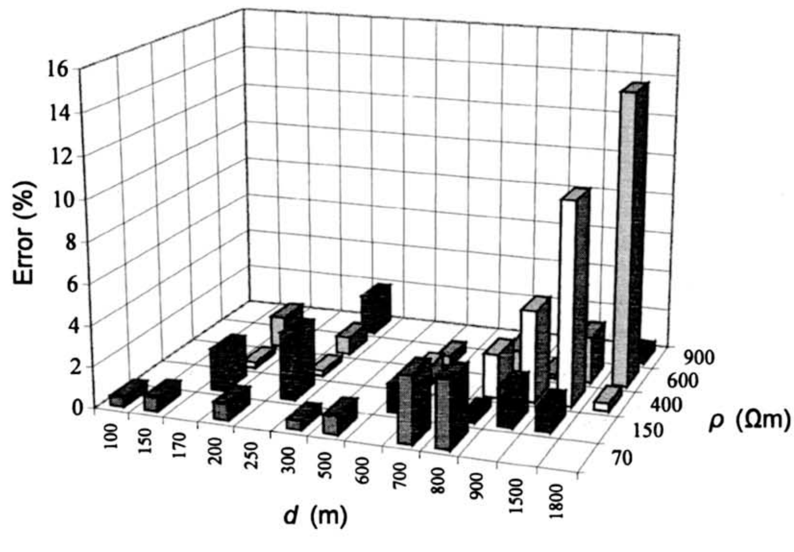
The normalization of the parameters is made in order to accelerate the training. After the coding a vector of bits (chromosome) is constructed for every FLS, which encloses the FLS parameters. The vector of the kth FLS is shown in Fig. 2.

3.2.2. Fitness function of the genetic algorithm

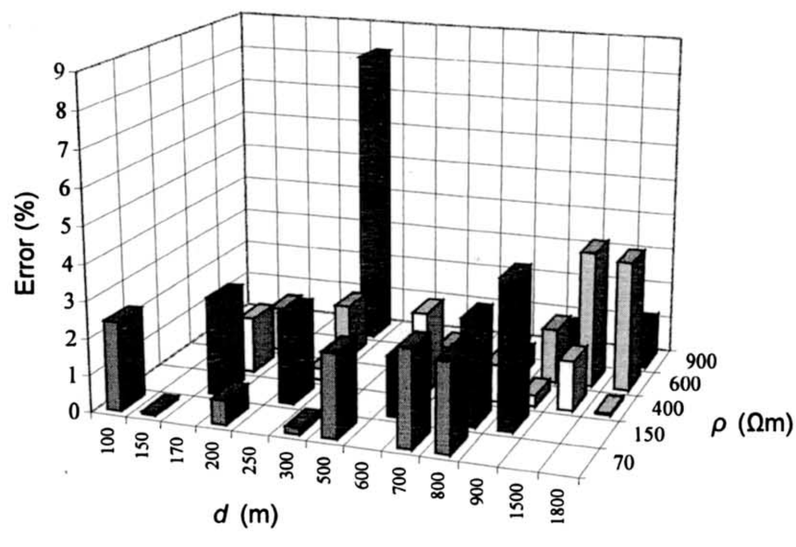
In our case the fitness function for the kth FLS-chromosome has been selected as

$$f_k = \frac{1}{J_m^k + a} \quad (k=1,\ldots,l) \tag{11}$$

where J_m is given by Eq. (6) and $\alpha = 0{,}0001$ is a constant used to prevent overflow in case J_m becomes very small. The GA maximizes the fitness function f_k, leading to the minimization of J_m^k.



(a)



(b)

Fig. 6. Fuzzy logic system errors, for various configuration of the examined electromagnetic field problem, concerning: (a) the amplitude and (b) the phase of pipeline surface magnetic vector potential.

3.3. GA operators, optimizing rules

The evolution, which leads from the initial population of the FLS to the best FLS, is described as follows.

3.3.1. Selection

After the evaluation of the initial randomly generated population, the GA begins the creation of the new FLS generation. FLS-chromosomes from the parent population are selected in pairs to replicate and form offspring FLS-chromosomes. The FLS-chromosome selection for reproduction is performed using the *Roulette wheel selection* method [18].

3.3.2. Crossover

When two chromosomes are selected, their vectors are combined in order to produce two new FLS using genetic operators. The main operators used are *crossover* and *mutation* and are applied with varying probabilities. So, if a probability test is passed crossover takes place. The crossover scheme used in this paper is a multi-point crossover operator as shown in

Fig. 3. If the probability test fails, the produced offspring are identical replications of their parents.

3.3.3. Mutation

Although crossover is the primary genetic operator, it cannot produce information that does not already exist within the population. Mutation satisfies this need by generating new information in the chromosome population. For every bit of the offspring chromosomes a probability test is performed and if it is passed, the mutation operator shown in Fig. 4 alters that bit.

3.3.4. Varying operator probabilities

It should be mentioned that the chromosome selection method and the crossover operator lead to population convergence, while the mutation operator helps to maintain population diversity. If premature convergence or excessive diversity occur, the training becomes inefficient. In this paper the crossover probability ranges from 0.4 to 0.9 per chromosome while mutation probability ranges from 0.004 to 0.024 per bit. Premature convergence is monitored by extracting statistical information from the population. When premature convergence is observed, the crossover probability is lowered by 0.1, while the mutation probability is increased by 0.004. When excessive diversity occurs, the crossover probability is increased by 0.1, while the mutation probability is lowered by 0.004.

3.4. Elitism

The previous procedure described for the two FLS-chromosomes is repeated until all the FLS of the parent generation are replaced by the FLS of the new generation. The best FLS of the parent generation and the best FLS found in all the previous generations are also copied to the next generation, so that the probability of their destruction through a genetic operator is eliminated. The new generation will provide a better average quality.

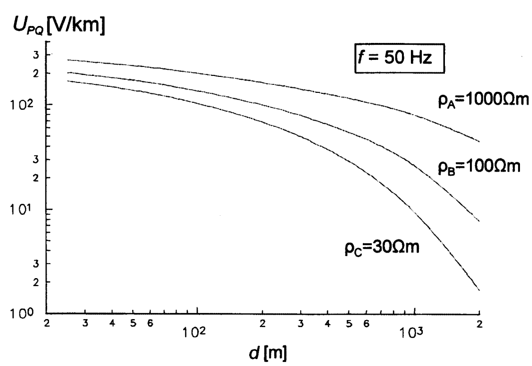


Fig. 7. Voltage per km induced across the pipeline and the earth as a function of distance d (cf. Fig. 1) for various earth resistivity values.

4. Creation of the training data set

The MVP is a phasor quantity and it is defined by its amplitude and its phase. Since the FLS of the developed GFS have a single output, two different GFS are required to calculate MVP nodal values, the GFS for the amplitude and the GFS for the phase. Therefore, the TDS must have two outputs, one for the amplitude and the other for the phase training, respectively. Using the optimum FLS, derived after training of the GFS, it is possible to calculate the MVP values in the area of the complex electromagnetic field problem of Fig. 1.

A TDS for the GFS has been calculated for the TLS in Fig. 1 for $I_F = 1000$ A and sets of ρ and d. The FEM procedure used is described in detail in Refs. [12–14].

Various (x,y) points have been chosen in the earth around the pipeline neighborhood, as well as in the pipeline itself. For each of those points, different separation distances d and earth resistivities ρ have been selected. As shown in the TDS of Table 1, the separation distance d between the overhead transmission line and the buried pipeline varies between 70 and 2000 m, the earth resistivity ρ varies between 30 and 1000 Ω m, coordinate x takes values between 40 and 2030 m, and finally coordinate y takes values between 0 and -30 m. This range of the input variables d, x, y, ρ in the TDS leads to a FLS, which is capable of determining the MVP values in the earth around the pipeline neighborhood, including the pipeline itself.

5. Performance analysis

After the training of the GFS down to an average training error of 1.8%, the performance of the optimum fuzzy logic system (O-FLS) has been tested in several new configuration cases of the examined electromagnetic field problem. These cases have various separation distances d between the overhead transmission line and the buried pipeline as well as various earth resistivities ρ and differ significantly from the cases used for training. Training the FLS has led to $m = 11$ rules.

Table 2 summarizes and compares the O-FLS and FEM test results. The absolute errors have been computed as: $\text{Error} = |(A_{\text{FEM}} - A_{\text{O-FLS}})/(A_{\text{FEM}})\cdot 100|$. The average error in amplitude calculation is 2.5%, and in phase calculation, 2.06%. For a new configuration case, the computing time using the O-FLS is negligibly small (10^{-8} smaller) compared with the time needed for the FEM calculations.

Considering the range of parameters used the frequency distribution of the errors in the MVP amplitude and phase are shown in Fig. 5a and b. It can be seen that 77% of the errors in amplitude and 88% in phase are less than 3%.

Fig. 6 shows the errors for various parameter ρ, d configuration cases. From Table 2 and Figs. 5 and 6 it is evident that the O-FLS results are practically equal to those obtained by the FEM. It should be mentioned that the MVP distribution is proportional to the fault current, so the presented results may be easily used for any given fault current I_F.

Fig. 7 shows the voltage per km induced across the pipeline and the earth calculated with the proposed method.

6. Conclusions

The magnetic field and the voltage induced by a transmission line and a buried pipeline have been calculated using the finite element method and fuzzy techniques. The use of genetic algorithms in determining the optimal rules of fuzzy logic system has shown advantages as compared to the back propagation method. It is shown that an expert system can be built by which interference problems can be easily and quickly solved. The expert system was capable of determining the induced Magnetic Vector Potential with an average error of less than 3%.

References

[1] K.J. Satsios, D.P. Labridis, P.S. Dokopoulos, Voltages and currents induced in a system consisting of a transmission line and a parallel pipeline, European Transactions on Electrical Power (ETEP) 8(3) (1998).

[2] K.J. Satsios, O.P. Labridis, P.S. Dokopoulos, Finite element computation of field and eddy currents of a system consisting of a power transmission line above conductors buried in nonhomogeneous earth, IEEE Transactions on Power Delivery 13(3) (1998).

[3] K.J. Satsios, D.P. Labridis, P.S. Dokopoulos, Inductive Interference caused to Telecommunication Cables by Nearby AC Electric Traction Lines. Measurements and FEM Calculations, PE-305-PWRD-O-06, 1998.

[4] P. Silvester, R. Ferrari, Finite Elements for Electrical Engineers, Cambridge University Press, Cambridge, 1983.

[5] C.L. Karr, Design of a cart-pole balancing fuzzy logic controller using a genetic algorithm, in: SPIE Conference on Applications of Artificial Intelligence, Bellingham, WA. 1991.

[6] J.C. Bezdek, R.J. Hathaway, Optimization of fuzzy clustering criteria using genetic algorithms, in: Proc. 1st IEEE Conference on Evolutionary Computation (EC-IEEE '94), vol. 2, 1994, pp. 589–594.

[7] Z. Michalewicz, Genetic Algorithms + Data Structures = Evolution Programs, Springer, New York, USA, 1996.

[8] H. Ishibuchi, K. Nozaki, N. Yamamoto, H. Tanaka, Selecting fuzzy If–Then rules for classification problems using genetic algorithms, IEEE Transactions on Fuzzy Systems 3 (3) (1995) 260–270.

[9] K. Shimojima, T. Fukuda, Y. Hasegawa, Self-tuning fuzzy modeling with adaptive membership function, rules, and hierarchical structure based on genetic algorithm, Fuzzy Sets and Systems 71 (3) (1995) 295–309.

[10] O. Cordon, F. Herrera, A three-stage evolutionary process for learning descriptive and approximate fuzzy-logic-controller knowledge bases from examples, International Journal of Approximate Reasoning 17 (4) (1995) 369–407.

[11] H. Ishibuchi, T. Nakashima, T. Murata, in: Genetic-algorithm-based approaches to the design of fuzzy systems for multi-dimensional pattern classification problems, in: Proc. of IEEE International Conference on Evolutionary Computation, Nagoya, Japan, 1996, pp. 229–234.

[12] F. Herrera, J.L. Verdegay (Eds.), Genetic Algorithms & Soft Computing, Springer, New York, USA, 1996.

[13] L.A. Zadeh, Outline of a new approach to the analysis of complex systems and secision processes, IEEE Transactions on Systems, Man and Cybernetics 1 (1973) 28–44.

[14] H.J. Zimmermann, Fuzzy Set Theory and its Applications, Kluwer, Boston, USA, 1996.

[15] T. Takagi, M. Sugeno, Fuzzy identification of systems and its applications to modeling and control, IEEE Transactions on Systems, Man and Cybernetics 15 (1985) 116–132.

[16] C.C. Lee, Fuzzy logic in control systems: fuzzy logic controller — Part I and II, IEEE Transactions on Systems, Man and Cybernetics 20 (2) (1990) 404–435.

[17] A.G. Bakirtzis, J.B. Theocharis, S.J. Kiartzis, K.J. Satsios, Short term load forecasting using fuzzy neural networks, IEEE Transactions on Power Systems 10 (3) (1995) 1518–1524.

[18] D.E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley, New York, USA, 1989.