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Combined fuzzy logic and genetic algorithm techniques—application to an electromagnetic field problem

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Abstract

The influence of a faulted electrical power transmission line on a buried pipeline is investigated. The induced electromagnetic field depends on several parameters, such as the position of the phase conductors, the currents flowing through conducting materials, and the earth resistivity. A fuzzy logic system was used to simulate the problem. It was trained using data derived from finite element method 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 electromagnetic fields compared to the time straining finite element method. In order to create the rule base for the fuzzy logic system a special incremental learning scheme is used during the training. The system is trained using genetic algorithms. Binary and real genetic encoding were implemented and compared. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Fuzzy logic; Genetic algorithms; Fuzzy modeling; Inductive interference

1. Introduction

The word fuzzy in its technical meaning appeared for the first time in the scientific community by Prof. Lotfi Zadeh [21]. Zadeh [21] laid the foundation for many applications of the fuzzy logic systems (FLS hereafter) in diverse areas like control systems, pattern recognition, forecasting, reliability engineering, signal processing, monitoring, and medical diagnosis that have appeared during the last few years. Fuzzy set theory as well as various applications are presented thoroughly in [22].

On the other hand, the underlying principles of genetic algorithms (GAs hereafter) were first published by Holland [7]. The mathematical framework was developed in the late 1960s and is presented by Holland's pioneering book "Adaptation in Natural and Artificial Systems", published in 1975 [8]. GAs have been also used in many diverse areas that require parameter training such as function optimization, image processing, system identifications, etc. A good reference

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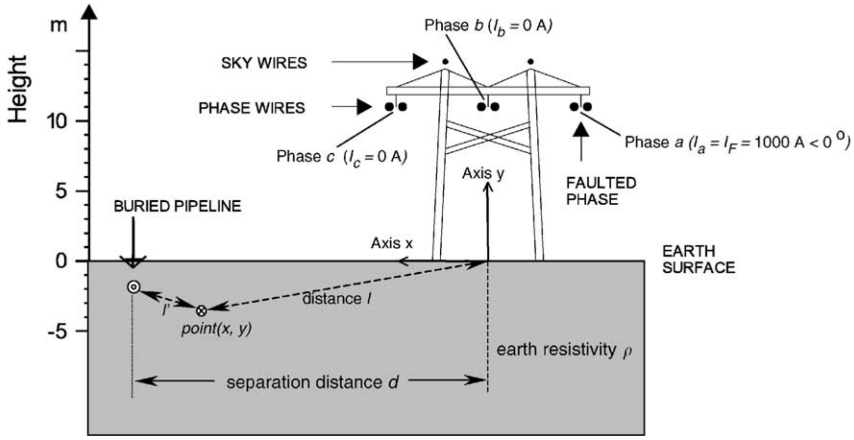

Fig. 1. Cross-section of the examined electromagnetic field problem.

on GAs and their implementation is the book of Goldberg [4].

The present paper presents a combination of fuzzy logic and genetic algorithm techniques for the creation of a system that calculates the electromagnetic field induced by a faulted transmission line to the surrounding area and the induced voltage on a nearby-buried pipeline. The inductive interference problem between a faulted overhead transmission line and a nearby-buried pipeline is of growing practical interest, due to 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 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 [15–17], 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 [18], resulting to a huge computational effort.

This paper suggests the following steps for reducing the computational effort: (a) the problem is solved for several sets of parameters using FEM 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 (evaluation set) the solution is found in negligible small computing time using the trained fuzzy rules.

The fuzzy logic system is trained using genetic algorithms; the result is called genetic fuzzy system. Genetic fuzzy systems (GFS) are already in use in the last years [1–3,5,6,9–12,14,19] and have led to standard coding schemes and genetic operators. Unlike FEM the GFS 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 given in [15–17]. The magnetic vector potential (MVP) is sought. Having the MVP, it is easy to calculate induced voltages across pipeline and earth, which is an important engineering task. The solution is governed by the diffusion equation

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

where μ is the permeability, A_z the phasor of vector potential, x, y are 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 the material properties (Fig. 1). In this paper we only consider as variables the point coordinates (x, y) where we calculate MVP, the separation 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.

3. The method

The MVP is found by solving the diffusion equation for several sets of parameters d, ρ using the finite elements procedure of [15–17]. The MVP at coordinates (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. Fuzzy rules are trained using genetic algorithms. The aim of the training is to minimize the average rms error between the real MVP values and the fuzzy system's outputs. The procedure is as described below.

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

The training patterns of the system consist of four inputs and one output. The inputs are

(a) the separation distance d between the overhead transmission line and the buried pipeline,
(b) the coordinate x,
(c) the coordinate y of a point in the cross-section of the TLS, and
(d) the soil resistivity ρ. The single output is the MVP $A(x, y)$ at point (x, y). The rules of each FLS consist of two premise inputs (variables): the separation distance and the soil resistivity, and two consequence inputs, which are the distance l of point (x, y) from the faulted line and the distance l' of point (x, y) from the buried pipeline.

The jth fuzzy rule (R^j) may be described as follows:

R^j: **IF** d and ρ belong to the jth membership functions μ_d^j and μ_ρ^j correspondingly (premise part of the jth rule)

THEN $A^j=\lambda_0^j+\lambda_l^j\frac{1}{l^2+c}+\lambda_{l'}^j\frac{1}{l'^2+c}$ (consequence part of the jth rule) (2)

where

$$l=\sqrt{x^2+y^2}, \qquad l'=\sqrt{(x-d)^2+(y-d_\mathrm{p})^2},$$
$$c=10^{-10}, \quad (3)$$

$j=(1,\ldots,m)$, m is the number of rules, c is a constant to prevent overflow in case the point is located on the pipeline or coordinates $(0,0)$, d, ρ are the premise input variables of the FLS, d_p is the depth at which the pipeline is buried, A^j is the MVP proposed by the jth rule and μ_d^j, μ_ρ^j are the membership functions that define the jth fuzzy rule. The parameters $\lambda_0^j, \lambda_l^j, \lambda_l^j$ are the consequence part coefficients 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 it is described below:

$$\mu_\varepsilon^j(\varepsilon)=\exp\left[-\frac{1}{2}\left(\frac{\varepsilon-\bar{\alpha}_\varepsilon^j}{\sigma_\varepsilon^j}\right)^2\right], \quad (4)$$

where "ε" stands for the premise input and takes the values d, ρ. In addition $\bar{\alpha}_d^j, \bar{\alpha}_\rho^j$ are the mean values and $\sigma_d^j, \sigma_\rho^j$ are the standard deviations of the membership functions (Fig. 2). Trapezoid and triangular membership functions have also been used, leading to a less accurate system.

In order to produce the actual output of the FLS, the weighted average interface [21], which is a commonly used method, 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

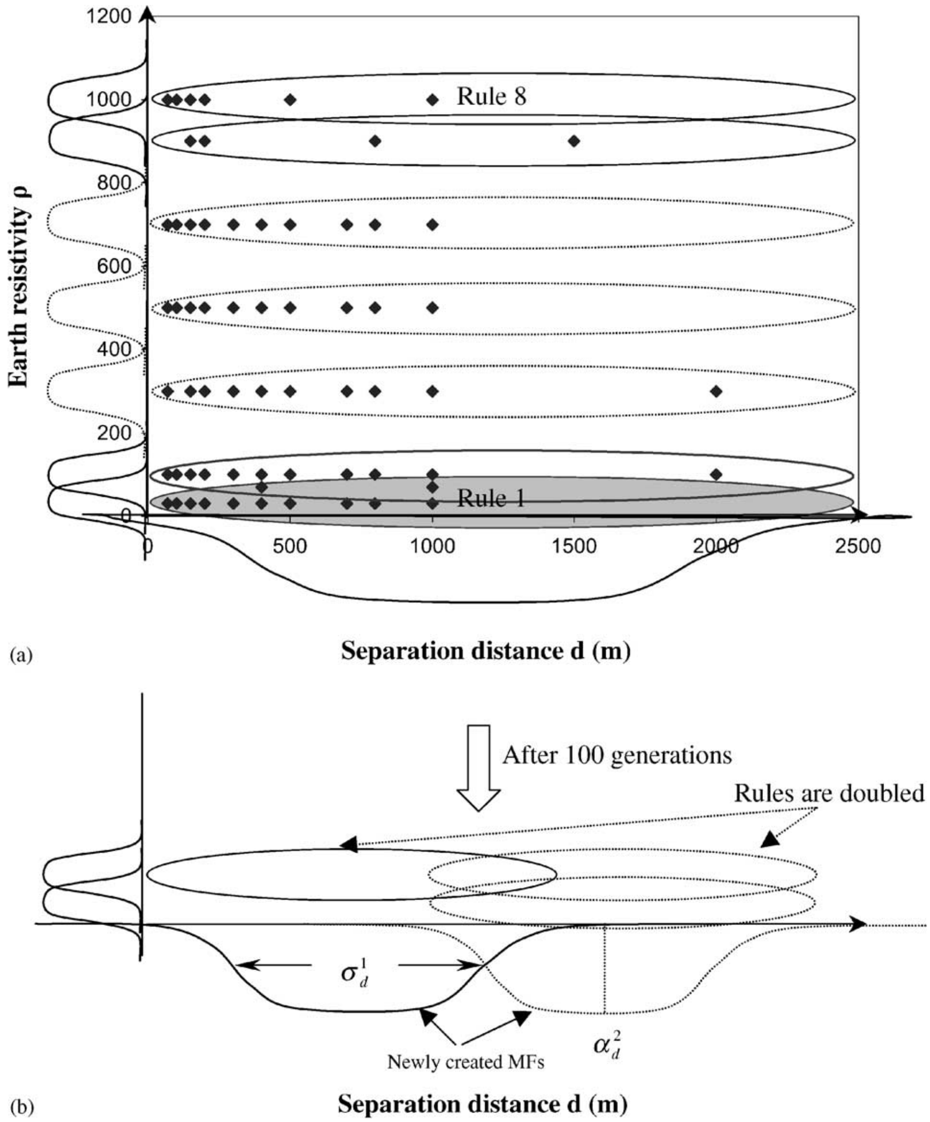

Fig. 2. Representation of the fuzzy search space and corresponding membership functions (MF). Further division of premise input d with the introduction of a new MF.

resistivity ρ, is given by

$$A(d,\rho) = \frac{\sum_{j=1}^{m} A^j \mu^j}{\sum_{j=1}^{m} \mu^j}, \tag{5}$$

where

$$\mu^j = \mu_d^j(d)\mu_\rho^j(\rho) \tag{6}$$

is the firing strength for rule R^j by the input vector (d,ρ), while A^j is the output of rule R^j as defined in (2).

If q is the number of training patterns in the training data set (TDS), the FLS is trained by introducing it with the set of q patterns $(d^p, x^p, y^p, \rho^p / A^p_{\text{FEM}}, p = 1,\ldots,q)$. The average rms error J_{av} of the FLS is defined by

$$J_{\text{av}} = \frac{1}{q}\sum_{p=1}^{q} J^p, \tag{7}$$

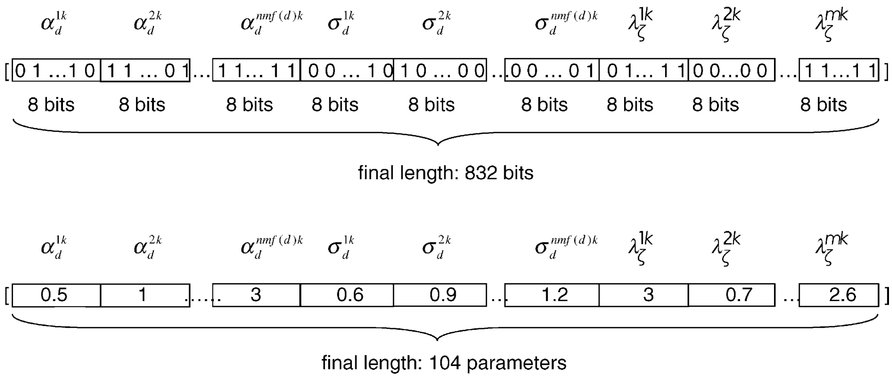

Fig. 3. String representing the kth fuzzy logic system of the GFS.

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

$$J^p = \tfrac{1}{2}|A^p_{\mathrm{FLS}}(d,x,y,\rho) - A^p_{\mathrm{FEM}}(d,x,y,\rho)|^2, \tag{8}$$

in which $A^p_{\mathrm{FLS}}(d,x,y,\rho)$ and $A^p_{\mathrm{FEM}}(d,x,y,\rho)$ are the calculated values of MVP for pattern p obtained from FLS and FEM, respectively. We define training to be the minimization of the average rms error, which means that the finally determined FLS corresponds to the highest accuracy in MVP calculation that could be obtained with this method.

3.1. GA for the training of the fuzzy parameters

3.1.1. Chromosome structure

The parameters of each FLS of the proposed GFS that have to be adjusted through the training procedure are the parameters of the membership functions $\bar{\alpha}_\varepsilon^{nmf(\varepsilon)}, \sigma_\varepsilon^{nmf(\varepsilon)}$ (for $\varepsilon = d, \rho$ and $nmf(\varepsilon)$ *is the number of membership functions used to partition each premise input* ε) and λ_ζ^j (for $\zeta = 0, l, l'$ and $j = 1,\dots,m$).

The GA that has been developed for the adjustment of the FLS parameters seeks the optimum FLS that presents the minimum rms error J_{av}. Every FLS of the GFS is represented by a vector of its parameters C^k, given by

$$C_k = (\alpha_\varepsilon^{nmf(\varepsilon)k}, \sigma_\varepsilon^{nmf(\varepsilon)k}, \lambda_\varepsilon^{jk}),$$
$$\varepsilon = d, \rho, \;\; \zeta = 0, l, l', \;\; j = 1,\dots,m, \tag{9}$$

where k ($k = 1,\dots,s$) is the index number of the FLS and s is the population size (i.e. the number of the FLS that constitute the GFS). In this paper s has been chosen equal to 50.

In the developed GFS two parameter-coding schemes were used, binary and real. In the binary coding, 8 bits resolution for every parameter was used. A vector of bits or real numbers (chromosome) is constructed, which embodies the FLS parameters (9). The vectors of the kth FLS for $m = 32$ rules are shown in Fig. 3.

3.1.2. Fitness function of the genetic algorithm

The fitness function of the kth FLS-chromosome has been selected to be

$$f_k = \frac{1}{J^k_{\mathrm{av}} + a} \quad (k = 1,\dots,l), \tag{10}$$

where J_{av} is given by (7) and $\alpha = 0.0001$ is a constant used to prevent overflow in case J_{av} becomes very small. The GA maximizes the fitness function f_k, leading to the minimization of J^k_{av}.

3.1.3. GA operators, rules optimization

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

3.1.3.1. 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 method of *Roulette wheel selection* [4].

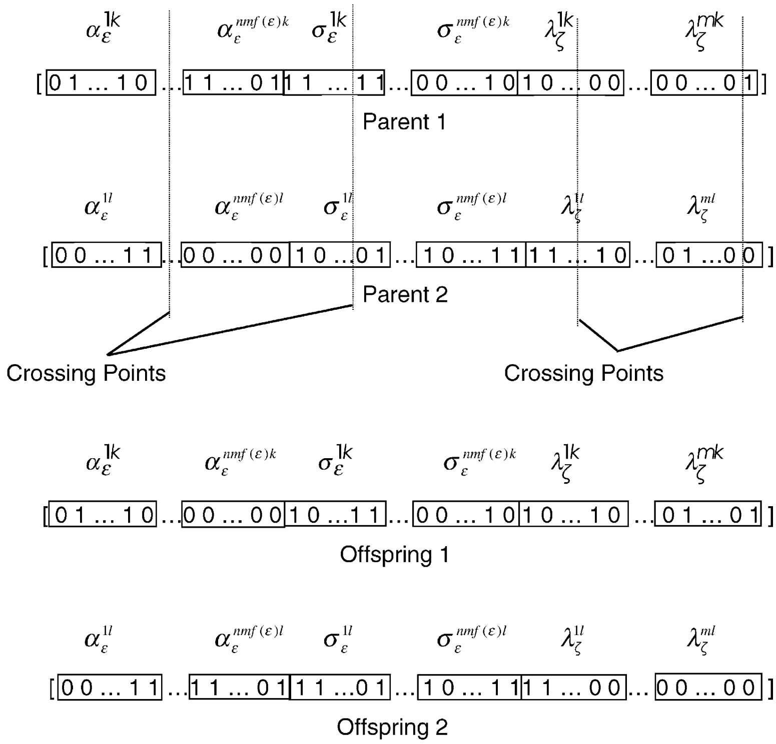

Fig. 4. Multi-point crossover operator.

3.1.3.2. 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 c*rossover* and m*utation* and are applied with varying probabilities. So, if a probability test is passed c*rossover* takes place. If the probability test fails, the produced children are identical replications of their parents.

In the binary GA a multi-point crossover operator has been used as shown in Fig. 4.

In the real GA the *Max–min-arithmetical crossover* operator was used [5]. If C_v^t and C_w^t are to be crossed four possible children are created:

$$\begin{aligned} &C_1^{t+1} = \alpha C_w^t + (1-\alpha)C_v^t,\\ &C_2^{t+1} = (1-\alpha)C_w^t + \alpha C_v^t,\\ &C_3^{t+1} \quad \text{with} \quad c_{3k}^{t+1} = \min\{c_k, c_k'\},\\ &C_4^{t+1} \quad \text{with} \quad c_{4k}^{t+1} = \max\{c_k, c_k'\}. \end{aligned} \tag{11}$$

Parameter α is a constant equal to 0.5 for our experiments. The two children who have the higher fitness are chosen to replace the parents in the new population.

3.1.3.3. Mutation. In the binary coding every bit of the offspring chromosomes undergoes a probability test and if it is passed, the mutation operator shown in Fig. 5 alters that bit. In the real coding the same probability test is performed with higher mutation probability and if passed Michalewicz's non-uniform mutation operator is applied [14]. This operator is described below:

If $C_v^t = (c_1, \ldots, c_k, \ldots, c_L)$ is an FLS-chromosome vector and c_k is an FLS parameter that is chosen to be mutated, the new parameter c_k^{mut} will be after mutation:

$$c_k^{\text{mut}} = \begin{cases} c_k + \Delta(t, c_{kr} - c_k) & \text{if } r = 0,\\ c_k - \Delta(t, c_k - c_{kl}) & \text{if } r = 1, \end{cases} \tag{12}$$

where L is the chromosome length, (c_{kl}, c_{kr}) the domain of parameter c_k $(k \in 1, \ldots, L), r$ a random bit, and function $\Delta(t, y)$ returns a value in the range $[0, y]$ such that the probability of the returning value being close to 0 increases with t:

$$\Delta(t, y) = y(1 - n^{(1-t/T)^b}),$$

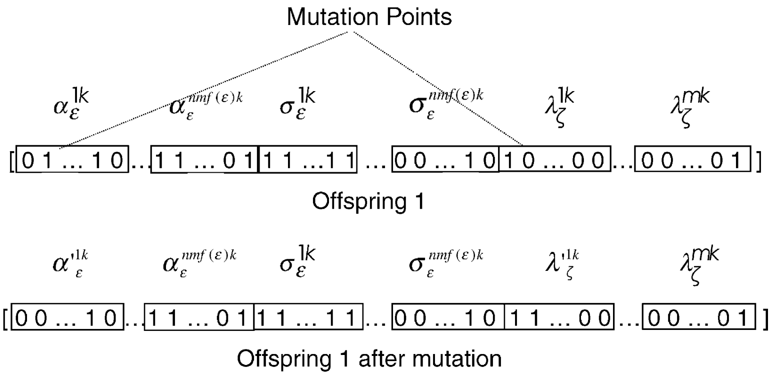

Fig. 5. Mutation operator.

where n is a random floating-point number in the interval $[0, 1]$, t the current generation, T the maximum number of generations, and b a parameter chosen by the user, which determines the degree of dependency with the number of generations. In that way the operator makes a uniform search at the beginning of the training and in later stages narrows the search around the local area of the parameter resembling a hill-climbing operator. For our experiments b was chosen equal to 5 [3].

3.1.3.4. Varying operator probabilities. It should be mentioned that chromosome selection method and crossover operator lead to population convergence, while mutation operator helps to maintain population diversity. If premature convergence or excessive diversity occurs, the training becomes inefficient. In this system crossover probability ranges from 40% to 90% per chromosome while mutation probability ranges from 0.04% to 0.24% per bit and 1% to 10% per real parameter. Premature convergence is monitored by extracting statistical information from the population. When premature convergence is observed, the crossover probability is lowered by 10% while mutation probability is increased by 0.004% per bit and 0.2% per real parameter. When excessive diversity occurs, the crossover probability is increased by 10% while mutation probability is lowered by 0.004% per bit and 0.2% per real parameter.

3.1.3.5. Elitism. The procedure for the two FLS-chromosomes described previously 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 population is copied to the next generation while the best FLS found in all the previous generations is stored, so that the probability of their destruction through a genetic operator is eliminated. According to the schemata theory [5] the new generation usually provides a better average fitness.

3.2. Fuzzy rule base incremental creation mechanism

The aim of a fuzzy logic system (or model) is the acquisition of a knowledge (rule) base that represents the input–output function of the real system or problem that we want to model. The objective of the learning process is to create and then fine tune the fuzzy sets and rules consisting the rule base so as to meet user specified performance criteria of the system, in our problem minimization of the error in MVP calculation. In this context the training/learning of the rule base can be considered as a parameter optimization problem. The parameters to be optimized are the centers and deviations of the fuzzy membership functions and the consequence part coefficients of each fuzzy rule. The encoding of these parameters lengthens a chromosome by 56 bits per rule (8 bits per parameter) in case of binary coding and by 7 real numbers in case of real coding. It is obvious that a complex fuzzy system with a large number of rules results in a huge chromosome and the finding of the optimal rules becomes a search for the “needle in the haystack”.

In case of two premise inputs the number of parameters remains tractable, but it grows rapidly with an

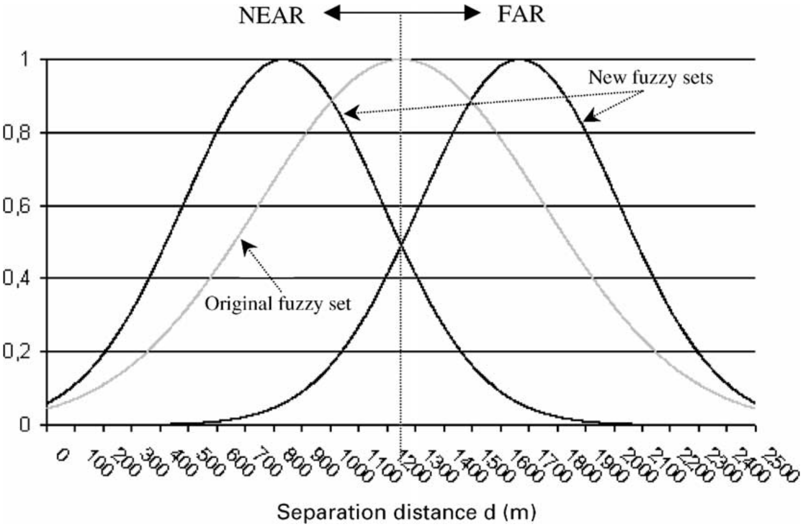

Fig. 6. Partitioning of the premise input d into two sub-domains linguistically expressed as "pipeline is near to the transmission line" and "pipeline is far from the transmission line".

increasing number of membership functions per premise input. The number of rules for each FLS of the proposed GFS is not constant but gradually increases in order to partition the overall optimization problem to smaller, more feasible steps. The creation of the rule base takes place in the following two steps:

1. The system scans the training database locating the number of n discrete values in the earth resistivity ρ premise input domain. The domain of the premise input "earth resistivity" is then partitioned with the introduction of n membership functions centered on these values:

$$\bar{\alpha}_\rho^q = \rho^q, \quad q = 1, \ldots, n,$$
$$\sigma_\rho^q = \frac{\rho_{\max} - \rho_{\min}}{n}. \tag{13}$$

This is possible because the "soil resistivity" variable takes only a few values, in our problem eight, so the system does not become very complex. These membership functions are centered on the patterns so they do not need training leading this way to a smaller chromosome.

2. Gradual partitioning of the "separation distance" premise input. Separation distance between the pipeline and the transmission line varies from 0 to more than 2 km so we cannot follow the technique we used for earth resistivity. Training begins with input d containing only one membership function, forming eight rules (Fig. 2(a)). That initial membership function must cover the entire range of the premise input for the following reason: Let us assume that the initial membership function covers only partially the premise space and the system encounters a pattern that is beyond the range on the membership function. Eq. (6) gives that the firing strength of every rule for this pattern will be zero. The weighted average (5) that produces the output of the system encounters a division by zero resulting in an overflow. Of course, this means that the calculated error (8) is infinite and there can be no continuance of the training since all the FLS individuals will have the same bad performance hence there can be no selection of the fittest.

The system optimizes the consequence part coefficients λ of the existing eight rules for 100 generations. If the desired accuracy is achieved (for our problem 2%) the training is complete. If not then the domain of the input d is partitioned into two sub-domains, using two, partially overlapping fuzzy sets with the result that the knowledge base now contains 16 rules (Fig. 2(b)). The parameters of the two new fuzzy sets that derive from the original fuzzy set are (Fig. 6):

$$a_{\text{new}}^1 = \frac{d_{\max} - d_{\min}}{3}, \tag{14a}$$

Table 1
Training data set used for the training of the two GFS. 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 pipeline itself. Output for the first GFS is the amplitude and for the second GFS the phase of the MVP as they were calculated with the FEM

ρ (Ω m)	d (m)	x (m)	y (m)	MVP(amplitude) (Wb/m)	MVP(phase) (deg)
30	70	70.00	−15.00	3.61E − 04	−22.80
30	70	81.66	−27.03	3.29E − 04	−25.57
30	100	100.00	−30.00	2.99E − 04	−31.23
30	800	770.00	−30.00	4.23E − 05	−82.64
30	800	785.00	0.00	4.27E − 05	−78.83
30	800	818.25	−13.50	3.88E − 05	−82.61
30	1000	1030.00	−15.00	2.48E − 05	−90.27
30	2000	1970.00	−22.50	4.76E − 06	−108.10
30	2000	2000.69	−8.61	4.65E − 06	−108.54
70	400	384.81	−7.82	1.72E − 04	−44.46
70	400	392.25	−25.56	1.67E − 04	−46.05
70	400	424.77	−6.93	1.58E − 04	−46.72
70	1000	970.00	−15.00	5.95E − 05	−73.04
70	1000	1007.50	0.00	5.68E − 05	−72.98
70	1000	1015.00	−30.00	5.47E − 05	−76.05
100	70	40.00	−30.00	5.09E − 04	−20.45
100	70	40.00	−15.00	5.38E − 04	−19.34
100	70	40.00	0.00	5.59E − 04	−18.53
100	100	92.25	−25.56	4.15E − 04	−23.98
100	800	770.00	0.00	1.04E − 04	−59.87
100	1000	980.55	−16.99	7.58E − 05	−67.10
100	1000	1015.00	−30.00	7.16E − 05	−69.22
100	1000	1022.50	0.00	7.23E − 05	−67.27
300	300	312.38	−8.10	3.17E − 04	−29.23
300	300	324.05	−23.53	3.10E − 04	−30.00
300	2000	2007.50	0.00	5.86E − 05	−72.55
500	200	215.00	−30.00	4.18E − 04	−23.83
500	300	281.66	−27.03	3.75E − 04	−25.93
500	300	290.36	−15.80	3.71E − 04	−26.01
500	300	322.50	0.00	3.55E − 04	−26.74
500	1000	1030.00	−15.00	1.70E − 04	−44.60
700	150	120.00	−15.00	5.46E − 04	−19.26
700	400	384.81	−7.82	3.52E − 04	−26.89
700	700	670.00	−22.50	2.60E − 04	−33.74
700	700	690.36	−15.80	2.56E − 04	−34.07
700	700	712.38	−8.10	2.51E − 04	−34.41
900	150	150.55	−16.99	5.30E − 04	−19.70
900	200	194.77	−6.93	4.88E − 04	−20.90
900	800	830.00	−30.00	2.46E − 04	−35.01
900	1500	1499.09	−17.48	1.56E − 04	−46.35
900	1500	1524.77	−6.93	1.54E − 04	−46.56
1000	70	54.81	−7.82	7.03E − 04	−15.94
1000	150	131.66	−27.03	5.58E − 04	−18.98
1000	500	524.05	−23.53	3.29E − 04	−28.27
1000	2000	2030.00	−15.00	1.22E − 04	−52.73

$$a_{\text{new}}^2 = \frac{2(d_{\max} - d_{\min})}{3}, \tag{14b}$$

$$\sigma_{\text{new}}^{1,2} = 0.6\sigma_{\text{old}}. \tag{14c}$$

The consequence part coefficients λ of the newly created rules (Fig. 2(b)) remain the same as the ones of the original rules. In that way, the behavior of the fuzzy system is not greatly disturbed by the fuzzy set's division. The partitioned premise input d can now be expressed by two linguistic variables: (1) the pipeline is near the faulted transmission line or (2) the pipeline is far from the faulted transmission line. This allows a more detailed modeling of the problem in the structure of the FLS. While before the partitioning the FLS could only be trained on the influence of the soil's resistivity on the MVP distribution, it can now produce different outputs depending on the distance between the pipeline and the transmission line. The knowledge that was acquired through the first step is now extended and not discarded since the new fuzzy rules inherit the input/output function (λ coefficients) of the original rules during initialization. During the training these coefficients will change so that they produce a more specialized output than the generic one of step 1.

The chromosome is expanded in order to include the parameters of the newly created rules ($\alpha_d^{\text{new}}, \sigma_d^{\text{new}}, \lambda_0^{j'}, \lambda_l^{j'}, \lambda_{l'}^{j'}$), for new $= 1,2$ and $j' = 1,\dots,16$. The new fuzzy sets can shift and dilate during training. In order to prevent complete overlapping, the overlapping between fuzzy sets of input d is restricted to a maximum of half the fuzzy set's standard deviation σ. Again training of the new parameters takes place for 200 generations and the performance is checked. A similar incremental building of the fuzzy rule base can be found in [9].

The gradual partitioning of the existing subdomains continues until the performance criterion is met or until a maximum number of fuzzy sets is reached. This number is chosen to be four (linguistically "very near", "near", "far", "very far") so that the system does not become too complex. If premise input d is partitioned in four parts the resulting fuzzy rules are 32.

As it was mentioned in Section 3.1.3.5 a part of the elitism operator is the storage of the best chromosome (FLS) that was found in all the previous generations. This ensures that the expansion of the chromosome and the addition of fuzzy rules will not ruin a possible better solution that appeared in a previous expansion step. Experiments though showed that the final FLSs are always more accurate than the simpler ones which is something that can be expected since the more rules the FLS has the more adapted to the patterns it is, which in turn leads to a smaller average error.

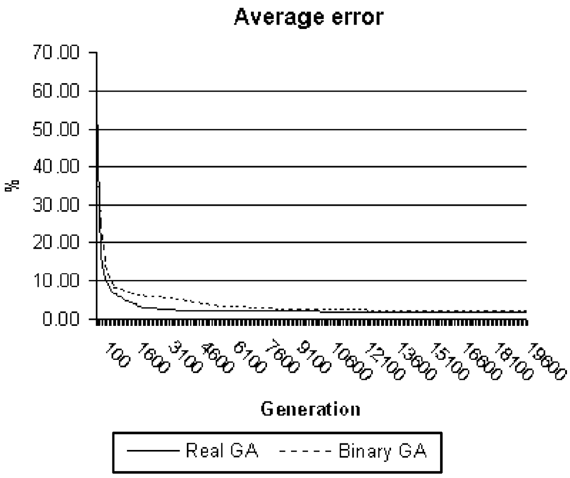

Fig. 7. Binary GA vs. real GA. Best out of 20 runs.

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 complex MVP nodal values, a GFS for MVP amplitude and a GFS for MVP 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 training data set (TDS) for the GFS has been calculated for the TLS shown in Fig. 1 for $I_F = 1000\,\text{A}$ and different sets of ρ and d using the FEM procedure described in detail in [15–17].

Various (x, y) points have been chosen in the earth around the pipeline neighborhood, as well as on 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

Table 2
MVP amplitude distribution in the earth around the pipeline neighborhood, including pipeline itself, for several new configuration cases of the examined electromagnetic field problem, obtained by the FEM and the best FLS of the GFS, respectively. The FLS calculation errors $= |[(A_{FEM} - A_{B\text{-}FLS})A_{FEM}] \cdot 100|$ are also reported

ρ (Ω m)	d (m)	x (m)	y (m)	A_{FEM} (Wb/m)	$A_{B\text{-}FLS}$ (Wb/m)	Error (%)
70	100	124.77	−6.93	3.47E − 04	3.47E − 04	0.04
70	150	120.00	0.00	3.50E − 04	3.56E − 04	1.55
70	150	162.38	−8.10	2.86E − 04	3.04E − 04	6.06
70	200	199.81	−1.75	2.55E − 04	2.73E − 04	6.77
70	200	200.00	−30.00	2.53E − 04	2.66E − 04	4.92
70	300	281.66	−27.03	2.15E − 04	2.16E − 04	0.35
70	300	299.81	−1.75	2.12E − 04	2.10E − 04	0.75
70	300	322.50	0.00	2.07E − 04	1.99E − 04	4.24
70	500	485.00	0.00	1.48E − 04	1.41E − 04	4.63
70	500	499.81	−1.75	1.46E − 04	1.36E − 04	7.66
70	700	699.09	−17.48	9.80E − 05	9.30E − 05	4.62
70	700	670.00	−15.00	9.90E − 05	9.80E − 05	0.38
70	800	799.81	−1.75	8.50E − 05	7.90E − 05	6.86
70	800	822.50	0.00	8.40E − 05	7.70E − 05	9.95
150	170	169.81	−1.75	3.46E − 04	3.61E − 04	4.02
150	170	169.09	−17.48	3.46E − 04	3.59E − 04	3.58
150	250	260.11	−21.49	2.85E − 04	2.89E − 04	1.49
150	250	274.05	−23.53	2.80E − 04	2.80E − 04	0.10
150	600	599.81	−1.75	1.58E − 04	1.64E − 04	3.58
150	600	600.00	−30.00	1.58E − 04	1.62E − 04	2.45
150	800	799.81	−1.75	1.19E − 04	1.24E − 04	4.25
150	800	790.36	−15.80	1.19E − 04	1.25E − 04	4.79
150	800	830.00	−15.00	1.18E − 04	1.19E − 04	0.97
150	900	900.00	−30.00	1.08E − 04	1.08E − 04	0.17
150	900	899.81	−1.75	1.08E − 04	1.09E − 04	1.06
150	900	892.50	0.00	1.08E − 04	1.10E − 04	1.81
150	1500	1500.69	−8.61	5.40E − 05	5.40E − 05	0.02
400	170	169.81	−1.75	4.43E − 04	4.43E − 04	0.01
400	250	231.66	−27.03	3.89E − 04	3.88E − 04	0.19
400	250	249.09	−17.48	3.83E − 04	3.77E − 04	1.47
400	600	599.81	−1.75	2.39E − 04	2.36E − 04	1.20
400	800	770.00	−30.00	1.96E − 04	1.96E − 04	0.00
400	800	824.77	−6.93	1.94E − 04	1.87E − 04	3.89
400	900	900.00	−30.00	1.82E − 04	1.73E − 04	5.32
400	1500	1524.05	−23.53	9.60E − 05	1.03E − 04	6.64
400	1800	1781.66	−27.03	8.40E − 05	8.40E − 05	0.01
400	1800	1792.50	0.00	8.40E − 05	8.40E − 05	0.01
600	170	169.81	−1.75	4.89E − 04	4.78E − 04	2.33
600	250	220.00	−30.00	4.20E − 04	4.30E − 04	2.27
600	250	249.81	−1.75	4.06E − 04	4.12E − 04	1.46
600	600	570.00	0.00	2.62E − 04	2.76E − 04	4.92
600	600	599.81	−1.75	2.60E − 04	2.67E − 04	2.78
600	800	784.81	−7.82	2.17E − 04	2.24E − 04	3.31
600	800	799.81	−1.75	2.16E − 04	2.22E − 04	2.74
600	900	884.81	−7.82	2.03E − 04	2.06E − 04	1.45
600	900	918.25	−13.50	2.02E − 04	2.00E − 04	1.00
600	1500	1507.50	0.00	1.30E − 04	1.29E − 04	0.72
600	1500	1499.81	−1.75	1.30E − 04	1.30E − 04	0.04
600	1800	1790.36	−15.80	1.06E − 04	1.07E − 04	0.55
600	1800	1799.81	−1.75	1.06E − 04	1.06E − 04	0.35
900	250	235.00	0.00	4.56E − 04	4.57E − 04	0.28
900	250	230.55	−16.99	4.59E − 04	4.59E − 04	0.08
900	900	870.00	−15.00	2.38E − 04	2.38E − 04	0.03
900	900	900.69	−8.61	2.37E − 04	2.33E − 04	1.74
900	1800	1792.50	0.00	1.32E − 04	1.32E − 04	0.05

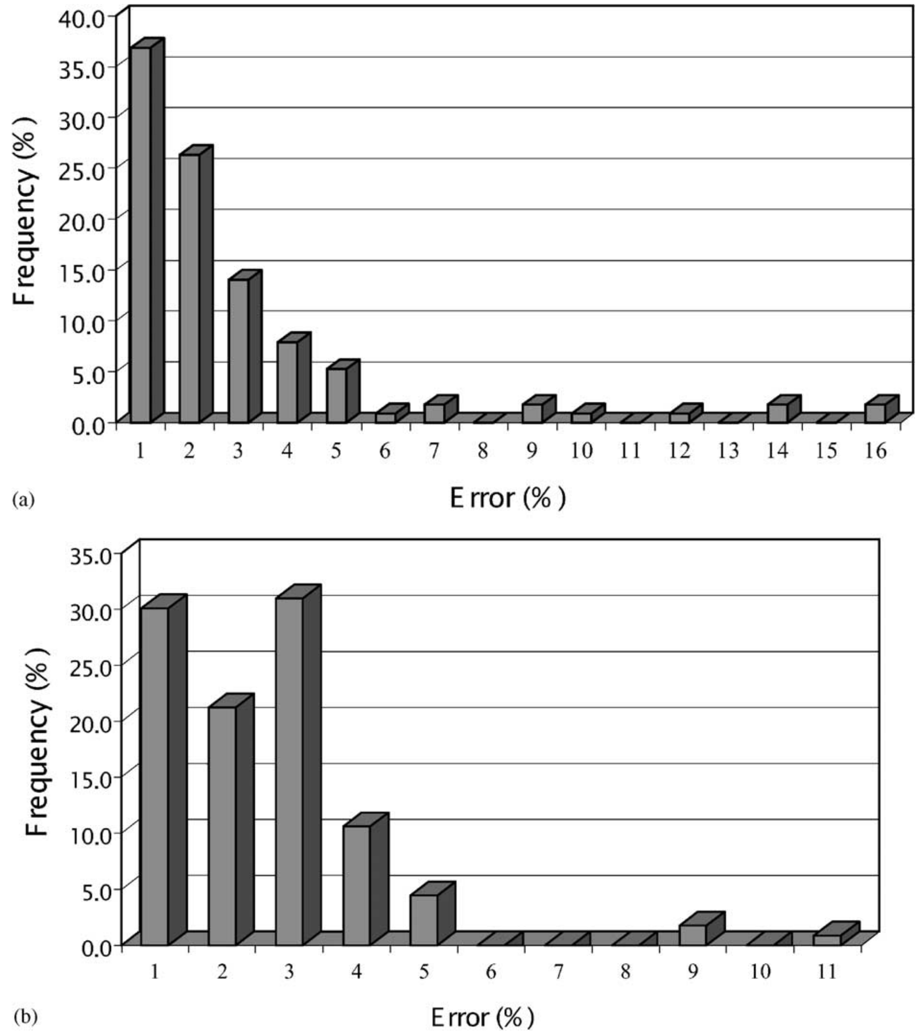

Fig. 8. Frequency distribution of the best fuzzy logic system errors, concerning (a) the amplitude, and (b) the phase of the magnetic vector potential distribution in the earth around the pipeline neighbourhood including pipeline itself.

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 to determine the MVP values in the earth around the pipeline neighborhood, including pipeline itself.

5. Performance analysis

Real-coded GA proved to be more efficient than the binary-coded one. While both implementations needed almost the same time to produce a generation, the real-coded GA required fewer generations in order to converge (Fig. 7). Someone would expect that real coding would be faster than binary since there is no need for breaking down the chromosomes and decoding the FLS parameters, but this advantage dis-

Table 3
Fuzzy rules' parameters of the best FLS of the GFS including the centers and standard deviations of the membership functions

Rule no.	α_d	σ_4	α_p	σ_p	λ_0	λ_l	$\lambda_{l'}$
1	200	247	30	100	0.000261	0	0
2	700	249	30	100	0	0	0.01955
3	1322	165	30	100	0.000018	12.02346	10.86999
4	1899	119	30	100	0.000298	10.43988	13.64614
5	200	247	70	100	0.00003	1.270772	0
6	700	249	70	100	0.00002	0.136852	0.039101
7	1322	165	70	100	0.000002	5.806452	0.273705
8	1899	119	70	100	0.000313	17.10655	6.549365
9	200	247	100	100	0.000187	3.460411	0
10	700	249	100	100	0.000116	17.49756	14.15445
11	1322	165	100	100	0.00004	6.529814	2.776149
12	1899	119	100	100	0.000504	7.781036	19.08113
13	200	247	300	150	0.000604	2.482893	0.078201
14	700	249	300	150	0.000192	11.12415	13.15738
15	1322	165	300	150	0.000124	19.98045	19.98045
16	1899	119	300	150	0.000062	2.776149	19.04203
17	200	247	500	150	0.000033	0.351906	0.938416
18	700	249	500	150	0.000126	3.773216	1.661779
19	1322	165	500	150	0.000015	4.496579	17.43891
20	1899	119	500	150	0.000076	6.744868	17.81036
21	200	247	700	150	0.000625	3.049853	0.097752
22	700	249	700	150	0.000187	19.98045	20
23	1322	165	700	150	0.00025	0.01955	7.44868
24	1899	119	700	150	0.000124	17.65396	9.442815
25	200	247	900	150	0.000064	2.502444	13.56794
26	700	249	900	150	0.000382	11.4565	0.449658
27	1322	165	900	150	0.000002	6.27566	0.54741
28	1899	119	900	150	0.000106	18.96383	17.43891
29	200	247	1000	100	0.000252	13.47019	1.505376
30	700	249	1000	100	0	1.642229	0.097752
31	1322	165	1000	100	0.000128	0.508309	17.1652
32	1899	119	1000	100	0.000155	0.195503	19.33529

appears due to the more complex crossover scheme that requires more computational effort. On the other hand, using floating-point numbers for the representation of the FLS parameters in the chromosome solves the problem of how many bits should be used to represent a parameter accurately in a binary GA. Fig. 7 is a representation of the training process of binary vs. real GA. The curves represent the best out of 20 runs.

After the training of the GFS down to an average training error of 1.8%, the performance of the best fuzzy logic system (B-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. The training of the GFS has produced a knowledge base consisting of $m = 32$ fuzzy rules.

Table 2 summarizes test results where MVP calculations by the B-FLS and FEM have been compared. Absolute errors have been computed as follows: $Error = |[(A_{\text{FEM}} - A_{\text{B-FLS}})/A_{\text{FEM}}] \cdot 100|$. 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 B-FLS is negligibly small (10^{-8} smaller) compared to the time needed for FEM calculations.

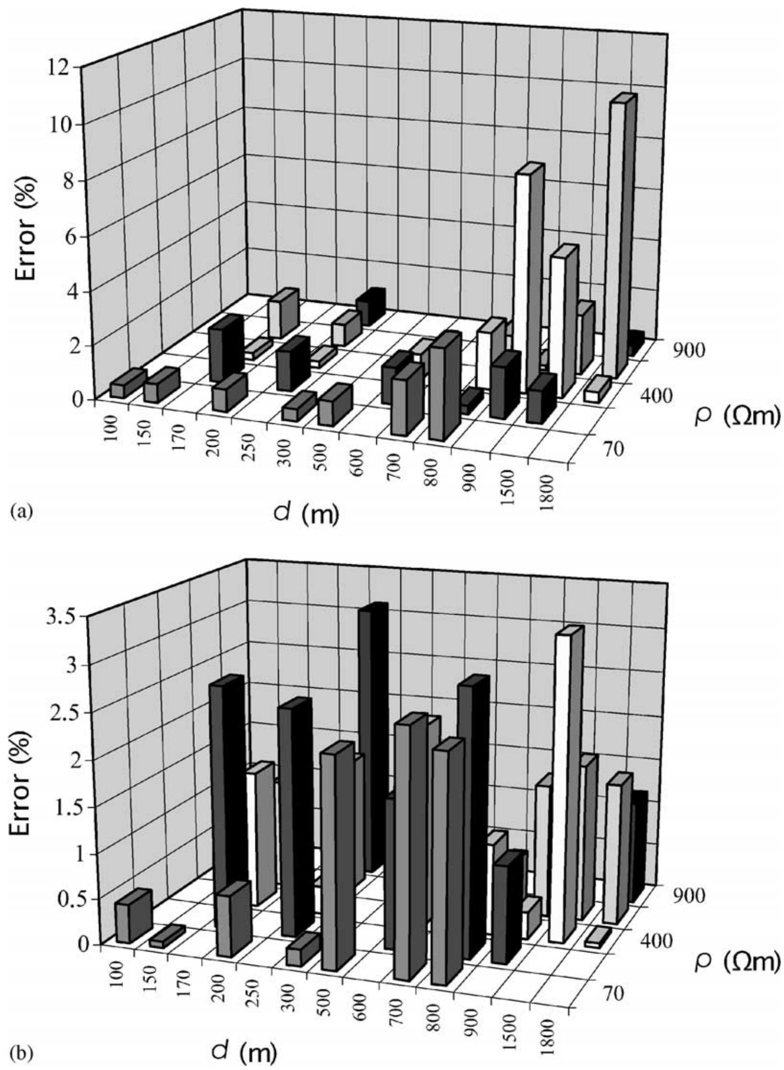

Fig. 9. Best fuzzy logic system errors, for various configurations of the examined electromagnetic field problem, concerning (a) the amplitude, and (b) the phase of pipeline surface magnetic vector potential.

Considering the range of parameters used the frequency distribution of the errors in MVP amplitude and phase are shown in Figs. 8(a) and (b). It can be seen that 77% of the errors in amplitude and 88% in phase are less than 3% (see Table 3).

Fig. 9 shows the errors for various parameter ρ, d configuration cases. From Table 2, and Figs. 8 and 9 it is evident that the B-FLS results are practically equal to those obtained by 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. 10 finally shows the voltage per km induced across pipeline and earth calculated with the proposed method.

6. Conclusions

The magnetic field and the voltage induced by a faulted transmission line on a buried pipeline have

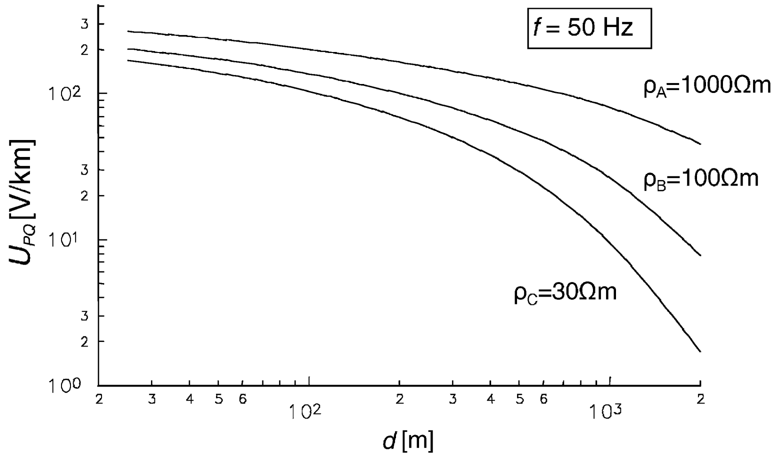

Fig. 10. Voltage per km induced across pipeline and earth as a function of distance d (cf. Fig. 1) for various soil resistivity values.

been calculated using finite element method and fuzzy techniques. The use of genetic algorithms in determining the optimal rules of fuzzy logic system has been efficient in providing accurate results. It is shown that an expert system can be built by which interference problems can easily and quickly be solved. The proposed expert system was capable of determining the induced voltage with an average error of less than 3%.

References

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

[2] O. Cordon, F. Herrera, A three-stage evolutionary process for learning descriptive and approximate fuzzy-logic-controller knowledge bases from examples, Internat. J. Approx. Reason. 17 (4) (1995) 369–407.

[3] O. Cordon, F. Herrera, Hybridizing genetic algorithms with sharing scheme and evolution strategies for designing approximate fuzzy rule-based systems, Fuzzy Sets and Systems 118 (2001) 235–255.

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

[5] F. Herrera, M. Lozano, J.L. Verdegay, Tuning fuzzy controllers by genetic algorithms, Internat. J. Approx. Reason. 12 (1995) 299–315.

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

[7] J.H. Holland, Outline for a logical theory of adaptive systems, J. ACM 3 (1962) 486–493.

[8] J.H. Holland, Adaptation in Natural and Artificial Systems, Mich. Univ. Press, Ann Arbor, MI, USA, 1975.

[9] F. Hoffmann, Incremental tuning of fuzzy controllers by means of an evolution strategy, GP'98 Conf., Madison, Wisconsin, 1998.

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

[11] H. Ishibuchi, K. Nozaki, N. Yamamoto, H. Tanaka, Selecting fuzzy if–then rules for classification problems using genetic algorithms, IEEE Trans. Fuzzy Systems 3 (3) (1995) 260–270.

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

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

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

[15] 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 Trans. Electrical Power (ETEP) 8 (3) (1998) 193–199.

[16] J. Satsios, D.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 Trans. Power Delivery 13 (3) (1998) 876–882.

[17] J. Satsios, D.P. Labridis, P.S. Dokopoulos, Inductive interference caused to telecommunication cables by nearby AC electric traction lines. Measurements and FEM calculations, IEEE Trans. Power Delivery 14 (2) (1999) 588–594.

[18] P. Silvester, R. Ferrari, Finite Elements for Electrical Engineers, Cambridge University Press, Cambridge, 1983.
[19] 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.
[20] T. Takagi, M. Sugeno, Fuzzy identification of systems and its applications to modeling and control, IEEE Trans. Systems Man Cybernet. SMC-15 (1985) 116–132.
[21] L.A. Zadeh, Outline of a new approach to the analysis of complex systems and decision processes, IEEE Trans. Systems Man Cybernet 1 (1973) 28–44.
[22] H.J. Zimmermann, Fuzzy Set Theory and its Applications, Kluwer, Boston, USA, 1996.