An Artificial Intelligence System for a Complex Electromagnetic Field Problem: Part I—Finite Element Calculations and Fuzzy Logic Development

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***Abstract*—Artificial intelligence (AI) has been used to determine the electromagnetic field in the complex problem of a faulted overhead transmission line above earth and a buried pipeline. A suitable AI system for scaling finite element electromagnetic field calculations has been developed. This system was trained by using finite element calculations for configurations, i.e., cases having different distances between the overhead transmission line and the buried pipeline as well as different earth resistivities. The AI system may be used to calculate the electromagnetic field in new cases differing significantly from the cases used for training.**

***Index Terms*—Finite element method, fuzzy logic, power transmission electromagnetic interference.**

I. Introduction

Finite element analysis arose essentially as a discipline for solving problems in structural engineering. It soon became clear, however, that the method had implications for beyond those originally considered and that it in fact presented a very general and powerful technique for the numerical solution of differential equations. The intense development of finite element analysis in the last decade showed that at the present time it is probably as important as the traditional engineering applications.

As in all other engineering fields, the use of finite element method (FEM) for the solution of Maxwell's differential equations describing an electromagnetic field problem, leads always to useful conclusions [1]–[4]. However, the original problem is always transformed to a numerical one, increasing the computing time with the number of the discretization nodes. A complex electromagnetic field problem, i.e., a problem consisting of a complicated geometry and many different materials, leads to a large computational effort. Therefore, a scaling method of the results from one configuration case to another may be of interest if it needs shorter computing time than an additional FEM calculation.

Fuzzy logic, which is a research area of artificial intelligence (AI), seems to be an efficient method to create systems capable of learning relationships and using this knowledge for further calculations. Fuzzy systems have been successfully applied in system control [5], system identification [6]–[7], optimal load flow [8], and short term load forecasting [9]. In [10] a fuzzy logic system (FLS) has been developed, capable of obtaining a solution of a simple problem involving FEM solutions only in a few cases and defining a scaling law for determining the missing cases with an acceptable error.

In the present work the method of [10] has been extended in order to solve more complex electromagnetic field problems, as in the case of an overhead transmission line above earth and a buried pipeline.

II. Finite Element Calculations

A finite element procedure has been used to determine the electromagnetic field in a typical transmission line system (TLS) shown in Figs. 1 and 2. FEM calculations have been made for different separation distances d between the overhead transmission line and the pipeline as well as for different earth resistivities ρ. FEM results have been used in order to initialize and train a FLS.

The TLS shown in Figs. 1 and 2 consists of a straight narrow corridor shared between one pipeline and one transmission line, indicated as "parallel exposure." A standard power frequency of 60.0 Hz has been used to simulate a phase a to ground fault at point B, which is assumed to be outside of the parallel exposure and far away from the buried pipeline as shown in Fig. 1(c). The earth current associated with this fault has a negligible action upon the buried pipeline. Therefore, in this case it may be reasonable to assume that only inductive interference, caused by the fault current flowing in the section where the TLS runs parallel to the buried pipeline [i.e., in the "parallel exposure" of Fig. 1(c)], exists. The TLS consists of an aluminum conductor steel reinforced (HAWK) two conductors bundle per phase [15]–[16]. Skywire conductors radius is 4 mm, pipeline inner radius is 0.195 m, its outer radius is 0.2 m, and coating thickness is 0.1 m. Finally, concerning the material properties, the soil is assumed to be homogeneous. Pipeline metal and skywires have a conductivity $\sigma_m = \sigma_s = 7.0\text{E}+06$ S/m and relative permeability $\mu_{rm} = \mu_{rs} = 250$, respectively.

End effects are neglected, leading to a two-dimensional (2-D) problem. This assumption is reasonable for the following reasons.

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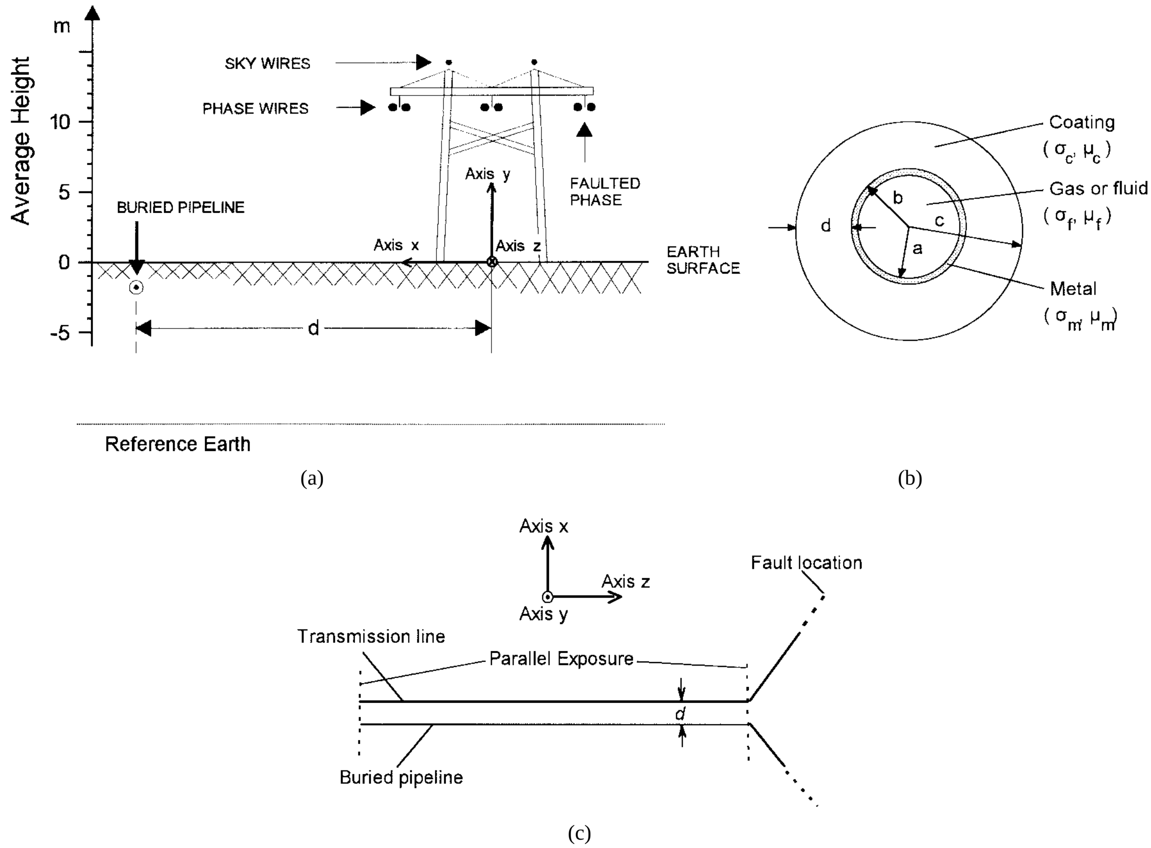

Fig. 1. (a) Cross section of the system under investigation, (b) detailed pipeline cross section, and (c) top view of the parallel exposure.

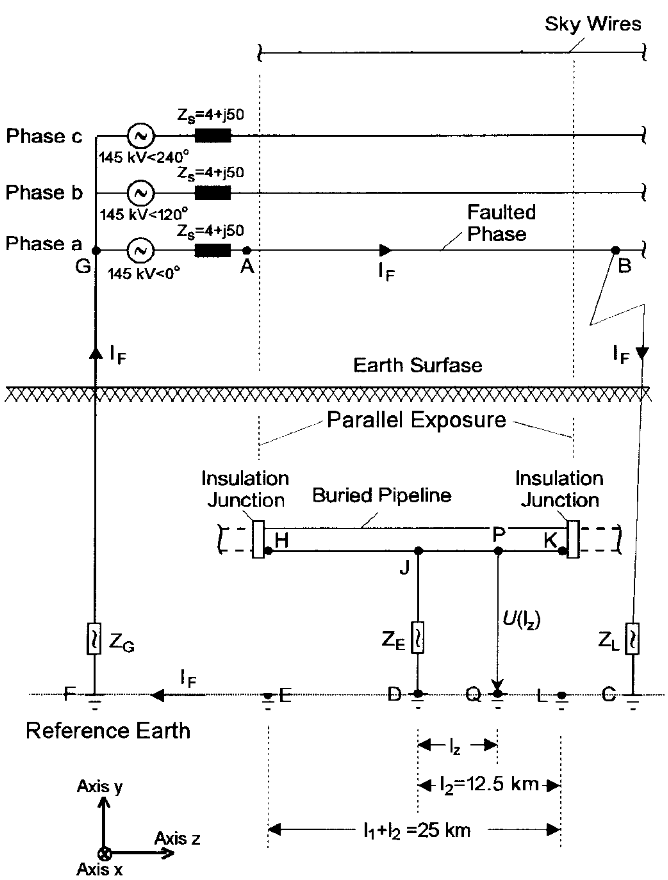

Fig. 2. Circuit diagram of the system under investigation.

- In the TLS examined in this paper, only the inductive interference, due to the magnetic field, exists.
- The parallel exposure is assumed to be equal to 25 km, leading to infinite length conductors.

Therefore, assuming the cross section shown in Fig. 1(a) lies on the x–y plane, the linear 2-D electromagnetic diffusion problem for the z-direction components of the magnetic vector potential (MVP) vector A_z and of the total current density vector J_z are described [11] by the system of (1a)–(1c)

$$\frac{1}{\mu_0\mu_r}\left[\frac{\partial^2 A_z}{\partial x^2}+\frac{\partial^2 A_z}{\partial y^2}\right]-j\omega\sigma A_z+J_{sz}=0 \tag{1a}$$

$$-j\omega\sigma A_z+J_{sz}=J_z \tag{1b}$$

$$\iint_{S_i} J_z\,ds=I_i \tag{1c}$$

where σ is the conductivity, ω is the angular frequency, μ_o and μ_r are the vacuum and relative permeabilities, respectively, J_{sz} is the source current density in the z direction, and I_i is the imposed current on conductor i of cross section S_i.

When applying FEM for the electromagnetic field calculation of a multiconductor system, a zero Dirichlet boundary ($A_z=0$) far away from the system enclosing all the currents, is assumed [11]. With maximum value $\rho = 1000\,\Omega\text{m}$ for the earth in the examined problem, the skin depth is about 2 km at 60 Hz. Consequently, the Dirichlet boundary inside the earth should be greater than 2 km in order to approximate accurately the earth current. The total solution domain for the examined problem is therefore a square with 10 km side.

The main driving parameter of the FEM problem examined is a fault current I_F flowing through the two conductors of phase a of the TLS. An open circuit (i.e., no load conditions) is assumed, for the other two unfaulted phases of the TLS. This condition is modeled in the FEM process by imposing zero currents on phases b and c ($I_b = I_c = 0$ A). The impedances Z_s and Z_G of Fig. 2 have actually no effect on the currents of these two phases, since no currents flow through phases b and c. Furthermore, from the pipeline configuration shown in Fig. 2, it is evident that the pipeline cannot carry any z-directed current. Therefore, a zero current has been also imposed on the pipeline in the FEM formulation. Finally, it should be mentioned that sky wires are assumed to be segmented [17], [18], in order to eliminate the losses associated with circulating currents magnetically induced to them. Therefore, these wires are treated as individual conductors with no current imposed to them. No current is also imposed for the earth, a conductive material with resistivity ρ. After the FEM solution of the system of (1a)–(1c) the total return current $(-I_F)$ will be distributed between sky wires and earth.

The finite element formulation of (1a)–(1c) leads [3]–[4] to a matrix equation, which is solved using the Crout variation of Gauss elimination. From the solution of this system, the values of the MVP in every node of the discretization domain, as well as the unknown source current densities, are calculated. Consequently, the eddy-current density J_{ez}^e of element e is obtained from the following [11]:

$$J_{ez}^e(x,y) = -j\omega\sigma A_z^e(x,y) \tag{2a}$$

and the total element current density J_z^e will be the sum of the conductor-i source current density J_{szi} and of the element-eddy current density J_{ez}^e given by (2a), i.e.,

$$J_z^e(x,y) = J_{ez}^e(x,y) + J_{szi}. \tag{2b}$$

Integration of (2b) over a conductor cross section will give the total current flowing through this conductor.

The solution domain is subdivided into first order triangular finite elements. A Delaunay based [12] adaptive mesh generation algorithm has been used for the original discretization. The continuity requirement of the flux density B on the interface between neighboring elements has been chosen [13] as the criterion for an iteratively adaptive mesh refinement. The Delaunay based original mesh of approximately 3000 elements, using the above criterion, led in almost all cases tested to a mesh of 19 000–21 000 elements. Relative element distribution in this mesh reveals the good behavior of the criterion chosen. A subsequent refinement is not necessary because, although it rises the number of triangles up to 50%, MVP results are hardly influenced.

Consider now the pipeline HK of Fig. 2 running parallel to the faulted phase a. The pipeline is grounded with a resistance Z_E at the point J, while junctions isolate the pipeline at both end-points H and K for cathodic protection purposes. The pipeline sections HJ and JK are long enough (12.5 km each) in order to allow the approximation of the problem by a 2-D analysis. Due to the symmetry of pipeline section HK across grounding point J, the 2-D FEM may be applied for both sections HJ and JK, with identical results.

The analysis that follows refers to pipeline section JK. If reference (remote) earth *CLQDEF* is supposed to be a conducting plane of infinite conductivity, then the voltage V_{PQ} across a point P of the pipeline section JK and remote earth Q may be determined by combining FEM calculations, and Faraday's law applied in the closed path $PQDJP$

$$\oint E\,\vec{dl} + \frac{\partial\Phi}{\partial t} = 0 \tag{3}$$

where Φ is the flux of the magnetic field through the closed path $PQDJP$. In a 2-D field, this flux in the plane (x,y) is given by

$$\Phi = A \cdot I_z \tag{4}$$

where A is the z component of the MVP and I_z is the distance of P from grounded point J. Writing (3) using phasors instead of time functions is obtained

$$V_{PQ} + V_{QD} + V_{DJ} + V_{JP} + j\omega\Phi = 0. \tag{5}$$

Finally the voltage V_{PQ} across the point P and remote earth Q is easily obtained as a linear function of its distance I_z from grounded point J

$$V_{PQ} = U(I_z) = jA\omega I_z \tag{6}$$

leading to a maximum value of this voltage across end point K and remote earth L as

$$V_{KL} = jA\omega I_z. \tag{7}$$

Due to the symmetry of pipeline HK across grounding point J, the same conclusions hold for section HJ.

III. Fuzzy Logic System Development

The main purpose of this paper is to develop and train a FLS in some configuration cases of the TLS shown in Figs. 1 and 2, with different separation distances d and different earth resistivities ρ. After the training, the MVP distribution may be calculated for every configuration case in a very short time, without an additional FEM calculation. Using pipeline's surface MVP values, derived via FLS and (6), pipeline induced voltages may also be calculated.

If a multi-input, single-output fuzzy system is considered, problem inputs are the separation distance d between the overhead transmission line and the buried pipeline, the coordinates x, y of a point, and the earth resistivity ρ from the space $U(d, x, y, \rho \in U)$, while the single output is the MVP in each point. Inputs have to be transformed to and from fuzzy variables in order to use fuzzy logic to solve our problem. So the basic configuration of the FLS used in this paper comprises four principal components: a *fuzzification interface*, a *fuzzy rule base*, a *fuzzy inference machine*, and a *defuzzification interface*.

The *fuzzification interface* performs a scale mapping that transfers the observed nonfuzzy input space $U \subseteq R^n$ to the fuzzy sets defined in U. Hence, the fuzzification interface provides a link between the nonfuzzy outside world and the fuzzy system framework. A fuzzy set [14] defined in U is characterized by a membership function μ. There are in general many fuzzy sets defined in U.

The *fuzzy rule base* is a set of m rules, in general linguistic or conditional statements, in the form of: "IF a set of conditions is satisfied, THEN a set of consequences are inferred."

The *fuzzy inference machine* is the decision making logic [6] which employs fuzzy rules from the fuzzy rule base to determine fuzzy outputs of a fuzzy system corresponding to its fuzzified inputs. In this paper, *fuzzy inference machine* of the form suggested in [6] are employed, where fuzzy sets are involved only in the premise part (IF part) of the rules while the consequent part (THEN part) is described by a nonfuzzy function of the input variables.

The jth rule, R^j in our case may be described as follows:

R^j: **IF** d and x and y and ρ belong to the $j\text{th}$ membership functions μ_d^j and μ_x^j and μ_y^j and μ_ρ^j correspondingly

THEN $$A^j = \lambda_0^j + \lambda_d^j d + \lambda_x^j x + \lambda_y^j y + \lambda_\rho^j \rho \quad (8)$$

where R^j $(j = 1, \cdots, m)$ are the fuzzy rules, d, x, y, ρ are the input variables to the fuzzy system, A^j is the MVP proposed by the jth rule, and $\mu_d^j, \mu_x^j, \mu_y^j, \mu_\rho^j$ are the membership functions which characterize the jth rule fuzzy sets defined in the space of the input variables of separation distance d, node's coordinates x, y,, and earth resistivity ρ. The parameters $\lambda_0^j, \lambda_d^j, \lambda_x^j, \lambda_y^j, \lambda_\rho^j$ are the factors of the consequent part of the jth rule. The membership functions in our case have been chosen as follows:

$$\mu_d^j(d) = \exp\left[-\frac{1}{2}\left(\frac{d - \overline{\alpha}_d^j}{\sigma_d^j}\right)^2\right] \quad (9a)$$

$$\mu_x^j(x) = \exp\left[-\frac{1}{2}\left(\frac{x - \overline{\alpha}_x^j}{\sigma_x^j}\right)^2\right] \quad (9b)$$

$$\mu_y^j(y) = \exp\left[-\frac{1}{2}\left(\frac{y - \overline{\alpha}_y^j}{\sigma_y^j}\right)^2\right] \quad (9c)$$

$$\mu_\rho^j(\rho) = \exp\left[-\frac{1}{2}\left(\frac{\rho - \overline{\alpha}_\rho^j}{\sigma_\rho^j}\right)^2\right] \quad (9d)$$

where $\overline{\alpha}_d^j, \overline{\alpha}_x^j, \overline{\alpha}_y^j, \overline{\alpha}_\rho^j$, and $\sigma_d^j, \sigma_x^j, \sigma_y^j, \sigma_\rho^j$ are the mean values and the standard deviations of the membership functions, respectively.

The *defuzzification interface* defuzzifies the fuzzy outputs of the fuzzy inference machine and generates a nonfuzzy output, which is the actual output of the fuzzy system. The weighted average defuzzification interface, which is [5] the most commonly used method, is also used here.

The single 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

$$A(d, x, y, \rho) = \frac{\sum_{j=1}^{m} A^j \mu^j}{\sum_{j=1}^{m} \mu^j} \quad (10)$$

where

$$\mu^j = \mu_d^j(d)\mu_x^j(x)\mu_y^j(y)\mu_\rho^j(\rho) \quad (11)$$

is the degree of fulfillment of rule R^j by the input vector (d, x, y, ρ) while A^j is defined in (8).

A. Gradient Training of the Fuzzy Logic System

FEM results of different configuration cases of the system shown in Figs. 1 and 2 for a fault current I_F of phase a equal to 1000 A are used to create a suitable training data base (TDB) for the FLS. The MVP of the steady state problem is expressed using complex phasors and therefore it consists of two parts, the amplitude and the phase. Since the FLS method has a single output, two different FLS's are required to calculate MVP nodal values. The first one must be trained in order to match the amplitude and the second one in order to match the phase. Therefore, the TDB must have two outputs, the MVP amplitude and the MVP phase, which are necessary for the amplitude and phase training, respectively. Using the TDB it is possible to construct the fuzzy rule base of each FLS. Fuzzy rule base parameters are determined by a training process, so that the output of each FLS adequately matches the FEM MVP results. These FLS's are capable, after suitable training, to calculate the MVP distribution in the whole solution area of the complex electromagnetic field problem of Figs. 1 and 2.

However, in this kind of electromagnetic field problems, attention is paid mainly to the voltages induced on the pipelines by the field. This will accordingly limit the range of the y coordinate. Therefore various different 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 TDB of Table I, separation distance d between the overhead transmission line and the buried pipeline varies between 70 and 2000 m, earth resistivity ρ varies between 30 and 1000 Ωm, coordinate x takes values between 40 and 2030 m, and finally coordinate y takes values between 0.0 and -30.0 m. This range of the input variables d, x, y, ρ in the TDB leads to a trained FLS capable to determine the MVP distribution in the earth around the pipeline neighborhood, including pipeline itself, for every new practical case having different separation distance d and different earth resistivity ρ. Both TDB outputs (MVP amplitude and MVP phase) will be normalized in the interval [0.0, 3.0] for an easier FLS training [5].

The parameters of the FLS to be adjusted through its training are $\overline{\alpha}_\varepsilon^j, \sigma_\varepsilon^j$ (for $\varepsilon = d, x, y, \rho$, and $j = 1, \cdots, m$) and λ_ζ^j (for $\zeta = 0, d, x, y, \rho$, and $j = 1, \cdots, m$). Let z denote the vector of the tuning parameters. Initially it is assumed that the number of rules m is fixed. If q is the number of training patterns of TDB shown in Table I, the FLS is trained by presenting it with the set of q input/desired output pairs $(d^p, x^p, y^p, \rho^p / A_{\text{FEM}}^p), p = 1, \cdots, \rho$. A gradient algorithm is then used to tune the FLS, so as to minimize its mean square error

$$J(z) = \frac{1}{q}\sum_{p=1}^{q} J^p \quad (12)$$

TABLE I
TRAINING DATA BASE USED FOR THE TRAINING OF THE TWO FLS'S. INPUT VARIABLES ARE THE SEPARATION DISTANCE d COORDINATES x AND y OF A POINT AND EARTH RESISTIVITY ρ. OUTPUT FOR THE FIRST FLS IS THE AMPLITUDE AND FOR THE SECOND FLS THE PHASE OF MVP $A_{\text{FEM}}(d, x, y, \rho)$

d	x	y	ρ	MVP(Amplitude)	MVP(Phase)
[m]	[m]	[m]	[Ωm]	[Wb/m]	Degrees
70	70,00	-15,00	30,00	3,61E-04	-22,80
70	81,66	-27,03	30,00	3,29E-04	-25,57
100	100,00	-30,00	30,00	2,99E-04	-31,23
800	770,00	-30,00	30,00	4,23E-05	-82,64
800	785,00	0,00	30,00	4,27E-05	-78,83
800	818,25	-13,50	30,00	3,88E-05	-82,61
1000	1030,00	-15,00	30,00	2,48E-05	-90,27
2000	1970,00	-22,50	30,00	4,76E-06	-108,10
2000	2020,69	-8,61	30,00	4,36E-06	-108,54
400	384,81	-7,82	70,00	1,72E-04	-44,46
400	392,25	-25,56	70,00	1,67E-04	-46,05
400	424,77	-6,93	70,00	1,58E-04	-46,72
1000	970,00	-15,00	70,00	5,95E-05	-73,04
1000	1007,50	0,00	70,00	5,68E-05	-72,98
1000	1015,00	-30,00	70,00	5,47E-05	-76,05
70	40,00	-30,00	100,00	5,09E-04	-20,45
70	40,00	-15,00	100,00	5,38E-04	-19,34
70	40,00	0,00	100,00	5,59E-04	-18,53
100	92,25	-25,56	100,00	4,15E-04	-23,98
800	770,00	0,00	100,00	1,04E-04	-59,87
1000	980,55	-16,99	100,00	7,58E-05	-67,10
1000	1015,00	-30,00	100,00	7,16E-05	-69,22
1000	1022,50	0,00	100,00	7,23E-05	-67,27
300	312,38	-8,10	300,00	3,17E-04	-29,23
300	324,05	-23,53	300,00	3,10E-04	-30,00
2000	2007,50	0,00	300,00	5,86E-05	-72,55
200	215,00	-30,00	500,00	4,18E-04	-23,83
300	281,66	-27,03	500,00	3,75E-04	-25,93
300	290,36	-15,80	500,00	3,71E-04	-26,01
300	322,50	0,00	500,00	3,55E-04	-26,74
1000	1030,00	-15,00	500,00	1,70E-04	-44,60
150	120,00	-15,00	700,00	5,46E-04	-19,26
400	384,81	-7,82	700,00	3,52E-04	-26,89
700	670,00	-22,50	700,00	2,60E-04	-33,74
700	690,36	-15,80	700,00	2,56E-04	-34,07
700	712,38	-8,10	700,00	2,51E-04	-34,41
150	150,55	-16,99	900,00	5,30E-04	-19,70
200	194,77	-6,93	900,00	4,88E-04	-20,90
800	830,00	-30,00	900,00	2,46E-04	-35,01
1500	1499,09	-17,48	900,00	1,56E-04	-46,35
1500	1524,77	-6,93	900,00	1,54E-04	-46,56
70	54,81	-7,82	1000,00	7,03E-04	-15,94
150	131,66	-27,03	1000,00	5,58E-04	-18,98
500	524,05	-23,53	1000,00	3,29E-04	-28,27
2000	2030,00	-15,00	1000,00	1,22E-04	-52,73

where the square error J^p of the input/desired output pair p is given by

$$J^p = \tfrac{1}{2}\left[A^p(d,x,y,\rho) - A^p_{\text{FEM}}(d,x,y,\rho)\right]^2 \tag{13}$$

in which $A^p(d,x,y,\rho)$ and $A^p_{\text{FEM}}(d,x,y,\rho)$ are the calculate values of MVP at the input/desired output pair p from FLS and FEM, respectively. Given an input/desired output pair $(d^p, x^p, y^p, \rho^p / A^p_{\text{FEM}})$, the gradients of J^p with respect to the system parameters are

$$\nabla_{\overline{\alpha}^j_\varepsilon} J^p = \frac{\mu^j}{\sum_{j=1}^{m}\mu^j}\left[A^p(d,x,y,\rho) - A^p_{\text{FEM}}(d,x,y,\rho)\right] \cdot \left[A^j - A^p(d,x,y,\rho)\right]\frac{\varepsilon^p - \overline{\alpha}^j_\varepsilon}{\sigma^{j^2}_\varepsilon} \tag{14a}$$

$$\nabla_{\sigma^j_\varepsilon} J^p = \frac{\mu^j}{\sum_{j=1}^{m}\mu^j}\left[A^p(d,x,y,\rho) - A^p_{\text{FEM}}(d,x,y,\rho)\right] \cdot \left[A^j - A^p(d,x,y,\rho)\right]\frac{\varepsilon^p - \overline{\alpha}^j_\varepsilon}{\sigma^{j^3}_\varepsilon} \tag{14b}$$

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

$$\nabla_{\lambda^j_\zeta} J^p = \frac{\mu^j}{\sum_{j=1}^{m}\mu^j}\left[A^p(d,x,y,\rho) - A^p_{\text{FEM}}(d,x,y,\rho)\right]\kappa^p \tag{14c}$$

where $\zeta = 0, d, x, y, \rho$ if $\kappa = 1, d, x, y, \rho,$ respectively.

The minimization of $J(z)$ in (12) through a gradient algorithm, leads to a learning rule which is expressed using z by the following:

$$z(v+1) = z(v) - n\nabla_z J \tag{15a}$$

$$\nabla_z J = \frac{1}{q}\sum_{p=1}^{q}\nabla_z J^p \tag{15b}$$

where n is an acceleration factor, v is the iteration index, and the gradient $\nabla_z J^p$ is computed using (14a)–(14c).

B. Initialization of the Fuzzy Logic System Rules

The number of rules m may be arbitrarily determined. This leads in general to a long training time and large training errors. To improve the training time and reduce these errors, m is determined sequentially. The training starts with a certain initialization of fuzzy rule base, beginning with a single rule $(m = 1)$. In the next step, a rule base adaptation procedure [9], [10] is used. The parameters of $m = 1$ fuzzy rule are initialized on the basis of the first input/desired output sample pair $(d^1, x^1, y^1, \rho^1 / A^1_{\text{FEM}})$ as follows:

$$\overline{\alpha}^1_\varepsilon = \varepsilon^1 \tag{16a}$$

$$\sigma^1_\varepsilon = \frac{1}{2m}[\max(\varepsilon^p) - \min(\varepsilon^p)] \ (\text{for } p = 1, \cdots, q) \tag{16b}$$

$$\lambda^1_0 = A^1_{\text{FEM}}, \quad \lambda^1_\varepsilon = 0 \tag{16c}$$

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

The choosing method for the parameters described in (16a)–(16c) performs the function of fuzzification, that converts input data into suitable membership values, which may be viewed as labels of fuzzy sets. The mean values of the membership functions are centered directly at point (d^1, x^1, y^1, ρ^1), while the standard deviations reflect the degree of fuzzification and they are selected in such a way that allows overlaps of membership functions $\mu^1_d, \mu^1_x, \mu^1_y, \mu^1_\rho$.

C. Rule Base Adaptation

This procedure starts with the initialization of the first $(m = 1)$ rule. The gradient training algorithm described by (14a)–(14c) is used to train the FLS based on input/desired output p pairs. When the procedure has reached m rules, an additional new training pattern $(d^p, x^p, y^p, \rho^p / A^p_{\text{FEM}})$ is considered.

The *firing strength* of the fuzzy rule base is expressed as

$$S_\mu(d^p, x^p, y^p, \rho^p) = \sum_{j=1}^{m} \mu^j \tag{17}$$

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

$$\overline{\alpha}_\varepsilon^{m+1} = \varepsilon^p \tag{18a}$$
$$\sigma_\varepsilon^{m+1} = \gamma(\varepsilon^p - \overline{\alpha}_\varepsilon^{\text{nearest}}) \tag{18b}$$
$$\lambda_0^{m+1} = A^p_{\text{FEM}}, \quad \lambda_\varepsilon^{m+1} = 0 \tag{18c}$$

where $\overline{\alpha}_\varepsilon^{\text{nearest}}$ is the mean value of an existing membership closest to the incoming pattern vector ε^p, γ is an overlapping factor (chosen equal to 1.5 from computer experiments), and $\varepsilon = d, x, y, \rho$. From (18c) it is evident that consequence parameters λ are normalized in interval [0.0, 3.0], since A_{FEM} values have already been normalized in this interval. This leads to a MVP A^j (8) proposed by the jth rule in the same interval.

The generation of new rules establishes the rule base adaptation mechanism, which is described by the following steps.

- The new pattern d^p, x^p, y^p, ρ^p is fed forward through the FLS and the corresponding firing strength $S_\mu(d^p, x^p, y^p, \rho^p)$ is computed.
- If $S_\mu(d^p, x^p, y^p, \rho^p) \geq \beta$ then the rule base is left unchanged and gradient training is performed in order to match the new sample pair.
- If $S_\mu(d^p, x^p, y^p, \rho^p) < \beta$ then a new fuzzy rule R^{m+1} is created, parameters according to (18a)–(18c) are selected, and gradiend training on the expanded fuzzy rule base is performed.

The overall FLS training procedure is described with the flow chart diagram of Fig. 3. The proposed training scheme offers the advantage of including only the necessary fuzzy rules within the premise space, leading to a minimum of FLS parameters for training. The FLS training has been executed using the above scheme and the TDB of Table I, with a mean absolute error E_{lim} of 1%. At the end of the procedure the FLS rule base contained 11 rules. The membership functions and the consequence factors obtained from the training of the FLS are reported in Part II of this paper.

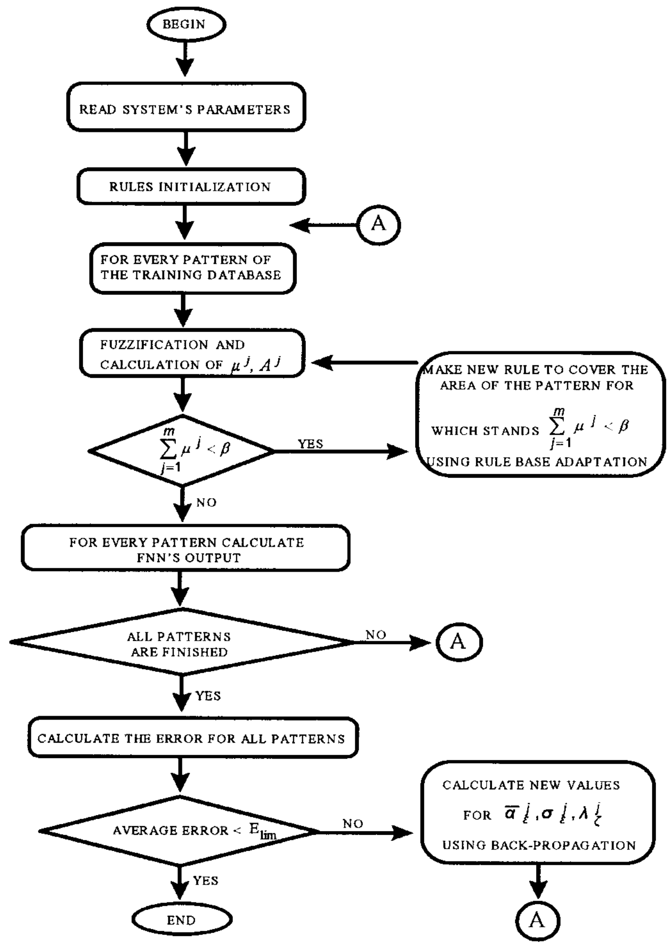

Fig. 3. Flow chart diagram of the FLS training procedure.

IV. Conclusions

A FLS has been developed in order to determine the electromagnetic field in a complex problem of an overhead transmission line above earth and a buried pipeline. This system is capable, after suitable training, to calculate the MVP distribution in the whole solution area of the above problem. Attention has been paid in this problem to the voltages induced on the pipeline by the electromagnetic field. Therefore, the TDB, derived by FEM calculations, has been limited geometrically in the earth around the pipeline, including pipeline itself.

The presented training scheme includes just the necessary fuzzy rules within the premise space, leading to a minimum of FLS trained parameters. The rule base adaptation procedure progressively generates new rules, expanding the existing fuzzy rule base.

Part II of this paper presents the calculation technique in order to compute the electromagnetic field of the above problem using the FLS trained parameters. Furthermore, Part II analyzes the test results of the FLS performance in a large number of different configuration cases of this complex electromagnetic field problem.

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