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EMF Estimation of Over Head Transmission Line Using CS Algorithm with Aid of NFC

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Abstract: In this paper, the cuckoo search (CS) algorithm - neuro fuzzy controller (NFC) technique is proposed for estimating the electric and magnetic field (EMF) of over head transmission line (OHTL). In the proposed method, the CS algorithm is used to optimize the conductor spacing (arrangements) and to minimize the EMF. From the optimized arrangement of the conductors, the EMF of the transmission lines is evaluated and formed as the datasets. Then the optimized data set values are applied to the input of the NFC. Subsequently, the coordinates are given to the input of the NFC which predicts their corresponding EMF data. The proposed method is implemented in the MATLAB working platform. For testing the performance of the proposed estimation methods, two overhead transmission line models with 110 kV and 400 kV respectively are considered. In order to verify the effectiveness of the proposed method this is compared with the CS algorithm-ANN controller.

Keywords: EMF, CS algorithm, NFC, transmission lines, conductor and coordinates

1. Introduction

The magnetic fields provoked in the vicinity of open air type substations are of great anxiety for possible health effects to people working inside these substations, or people leaving close by [1]. The only manner to be safest from the electric and magnetic fields publicity generated in open air type substations is to at least make certain that one is pictured to electric and magnetic fields inside the existing safety guideline limits [2]. Newly, environmental exposure to synthetic EMFs has been gradually increasing as the growing demand for electricity, and ever advancing technologies and varies in social behaviour have formed more and more artificial sources [3] [4]. To the improvement of transmission lines in operation range, which produce very strongly electric field in their near locality [5]. Consequently, it is significant to address the issue of environmental conditions in and around the overhead transmission line [6] [7].

Various concerns are there regarding possible biological effects of low-frequency electric and magnetic fields [11]. The calculation of the electric and magnetic field values within a substation is a hard task [8]. Owing to the difficulty arrangements of geometry of the bus bars, power transformers, insulators, voltage and current measurement transformers and increase of connected power lines within the covered space [9] [11]. As a result, it is needed to apply a dimensional based coordinate approach to the computation and study of the electromagnetic field [10]. Artificial intelligence techniques have been effectively used to an estimate the overhead transmission line electromagnetic field during latest years [14]. Fuzzy logic is applied for magnetic field estimations at transformer substations [12]. In fuzzy logic, the overhead line condition index, which symbolizes the numerical expression of the degree of its condition aggravation and the basis for the choice of the maintenance actions to be taken [15].

For the adjustment of the fuzzy parameters the genetic algorithm has been proposed [16] [17]. Artificial neural networks are addressed in order to give precise solutions to high voltage transmission line problems [18]. ANFIS and RBF network have been effectively employed to a

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number of engineering problems during latest years [19]. The architecture and learning procedure of fuzzy interference system executed in the framework of adaptive networks. One of ANFIS functions is modelling difficult nonlinear functions by a set of fuzzy rules. Neural network and fuzzy logic system are common approximations. The RBF neural network as well has the ability of common approximation [20]. These artificial intelligence techniques are effectively used for electromagnetic fields estimation around an overhead power transmission line [13]. In this paper, CS algorithm with aid of NFC is proposed to estimate the EMF of transmission line and also find the optimal arrangement of conductors. The detailed description of the proposed technique is presented in Section 3. Prior to that, the recent research works are presented in Section 2. The experimental results and discussion are given in Section 4. Finally, the Section 5 concludes the paper.

2. Recent Research Works: A Brief Review

In literature different research works are already presented which based on electric and magnetic field estimation in overhead transmission line by AI techniques, noncontact technology and etc. In this segment, a generic reassess performed.

Jasna Radulovic *et al*. [21] have distressed the chance that the revelation to very low frequency electromagnetic fields from power lines may have dangerous effects on human and living organisms. They have been offered approach based on the employ of both feed forward neural network (FNN) and adaptive network based fuzzy inference system (ANFIS) to calculate approximately electric and magnetic fields around an overhead power transmission lines. Using the results obtained from the earlier research an FNN and ANFIS is employed to reproduce this problem that was coached. It was demonstrated that suggested approach makes certain satisfactory precision and could be a competent tool and constructive substitute for such examinations.

A calculation of the 3-D magnetic and electric fields in terms of the influence of a steel tower has been offered by Zemljaric. B *et al*. [22]. The method joins the magnetic and electric quasi-static field calculation approach through the suitable electric circuit model and equations. By means of this approach the electric field potentials of the tower elements are not equal to zero and the involvement of the induced electric field was taken into report. The potentials mainly rely on the value of the current running through the tower elements from the top to the ground. The electric field values for dissimilar climbing routes on the tower were computed and compared with reference values in order to forecast an optimal climbing route on the tower.

Jasna Radulovic *et al*. [23] have explained in detail the design of radial basis neural network models in order to assess magnetic field of power transmission lines. The network was coached by gradient descent algorithm. The results attained according to the suggested NRBF method were very near to those computed by means of Charge simulation method, which obviously implies that the suggested method makes certain acceptable precision and pleasing convergence. The benefit of the employ of NRBF in relation to conventional methods for computation of magnetic fields of power lines is that neural network was necessary to be coached only once. NRBF could be employed to find out the magnetic field distribution after the achievement of training in a novel geometry varying from the geometries applied for training. Maximal absolute fault is less than 4% when NRBF was employed. These developed NRBF model makes it feasible to find out the magnetic fields easier, while offering significant diminution of analysis time.

A noncontact technology of operation state monitoring has been suggested by Xu Sun *et al*. [24] based on magnetic field sensing for high voltage transmission lines, which could at the same time calculate both electrical and spatial parameters in real time. This technology was obtained from research on the magnetic field distribution at the ground level when the transmission lines function in different states, together with sagging, galloping, and current imbalance. Two distinctive models of high-voltage three phase transmission lines were reproduced, and the resulting magnetic fields were worked out. The association among the magnetic field variations and the operation states were examined. Based on such correlation, a source reconstruction method was proposed to renovate the spatial and electrical parameters from the magnetic field derived by the overhead transmission lines. The reconstruction effects for the 500-kV and 220-kV transmission lines validate the possibility and practicality of this noncontact transmission line monitoring technology based on magnetic field sensing.

F. Munoz *et al*. [25] have conversed the application of particular Artificial Intelligence techniques offers a competent solution to the problem of characterizing the magnetic field of a high voltage overhead transmission line, and is a substitute to the expensive procedure of direct measurements, which needs equipment and time, to the employ of complex numerical methods of a very precise scope, or of simply gaining a theoretical value calculated by means of analytical procedures which give up the quality of the solution in support of making simpler the computations. They offered an execution which based on a hybrid algorithm in which the best solutions presented by a metaheuristics define the initial simplex for the application of the Nelder–Mead Method, which as a local search method allows a calculation-intensive search. In order to authenticate the quality of the results produced by this hybrid implementation, the estimates attained were compared with measured values and with values attained using analytical procedures.

The reassess of the current research works demonstrates that, the extra high voltage transmission line produces very low frequency electric and magnetic fields. Different human health hazards are related with this low frequency fields as the low frequency field's prediction participates an important role. Many methods have been suggested for categorizing the frequency of the signal such as Maxwell's equation, analytical method, empirical method and etc. For calculating the magnetic field Maxwell's equation permits only very easy geometries to direct integration. The benefits of analytical method regarding other techniques which presented information on the subject of the parameters so as to have an outcome on the magnetic field produced by overhead lines and tolerate examining original configurations in a simpler approach. In investigative methods, the computed magnetic field value is just appropriate at large distances from the line assessed to the distances among conductors. As a result, this method is appropriate only for electrical lines with multilateral regularity, apart from for in the smallest amount configuration. The process of Empirical method is based on the features measurement of high voltage transmission line under electromagnetic environment. However, the effect of this procedure is high-priced for both time and equipment. Hence by the difference of electrical and environmental conditions the measurement is affected. To conquer problem related with characterization over head line signal in the magnetic environment, the artificial intelligence technique is applied. In the paper, an optimization algorithm based artificial intelligence technique is applied for estimating the EMF generated by overhead transmission line. The detailed explanation is described in the following section.

3. EMF Calculation of Over Head Transmission Line

The magnetic field around a three-phase line can be computed by superimposing the individual contribution of the current of each phase conductor and taking into consideration the return currents through the earth. The magnetic field intensity at the point 'j' is achieved by taking into account the contribution of all 'N' conductors, presuming parallel lines over a flat earth [26]. A line conductor is located at (x_i, y_i) with electric current of Ii. The geometry is taken into consideration to estimate the magnetic field at (x_j, y_j) because of the fact that the phase conductor takes the complicated images. The magnetic field is estimated by means of the formula as per Equation 1.

$$H_e^j = \sum_i^N \left(\frac{I_i}{r_{ij} 6.28} \right) u_{ij} + \sum_i^N \left(\frac{-I_i}{r_{ij}^{'} 6.28} \right) \left(\left(1 + \frac{16}{3 \left(\gamma r^{'} \right)^4} \right) \right) u_{ij}^{'} \tag{1}$$

Note that r_{ij} represents the distance between line conductor and field point, while $r_{ij}^{'}$ indicates the distance between the complex image of line conductor, through earth, and the field point.

$$\gamma = \sqrt{j\omega\mu(\sigma + j\omega\varepsilon)} \tag{2}$$

$$u_{ij} = \left(\frac{y_i - y}{r_{ij}} \right) u_x - \left(\frac{x_i - x}{r_{ij}} \right) u_y \tag{3}$$

$$u_{ij}^{'} = \left(\frac{y_j + y_i + \left(\frac{2}{\gamma} \right)}{r_{ij}^{'}} \right) u_x - \left(\frac{x_i - x_j}{r_{ij}^{'}} \right) u_y \tag{4}$$

In the above equation, $\sigma,\ \varepsilon,\ \mu$ represent the conductivity, permittivity, and permeability of the earth. The phase current, and unit vectors are symbolized as $I_i,\ u_x,\ u_y$. By means of the above-mentioned equation, the magnetic field is computed. For the purpose of evaluation of the electric field, the following equation is employed.

$$E_e^j = \left(\frac{CV}{4\pi\varepsilon_0} \right) \left[\frac{2(y-h)u_y + 2(x-x_0)u_x}{(y-h)^2 + (x-x_0)^2} - \frac{2(y+h)u_y + 2(x-x_0)u_x}{(y+h)^2 + (x-x_0)^2} \right] \tag{5}$$

$$C = \frac{1}{18 \ln(GMD / r)} \tag{6}$$

$$GMD = \left(D_{AB} D_{BC} D_{AC} \right)^{\frac{1}{3}} \tag{7}$$

Where r denotes the conductor radius and GMD represents the geometric mean distance. Thereafter, the electric field of the communication line is estimated.

A. EMF Estimation of transmission line using proposed method

In this paper, an innovative method is used to estimate the EMF of the OHTL systems. The proposed method is the CS algorithm with aid of NFC. Here, the CS algorithm is used to optimize the conductor spacing and minimize the EMF. Initially, the x and y co-ordinates, conductor size, voltage, current etc. are given as the inputs of the proposed method. Then the EMF is evaluated according to their optimal conductor arrangements. Subsequently, the optimized datasets are formed by using the CS algorithm and are given as the input to the NFC.

The NFC controller is used to predict the corresponding EMF data for the given input. The detailed explanation of the proposed CS algorithm combined with the NFC technique is described in the following section 3.1. The block diagram of the proposed technique is illustrated in Figure 1.

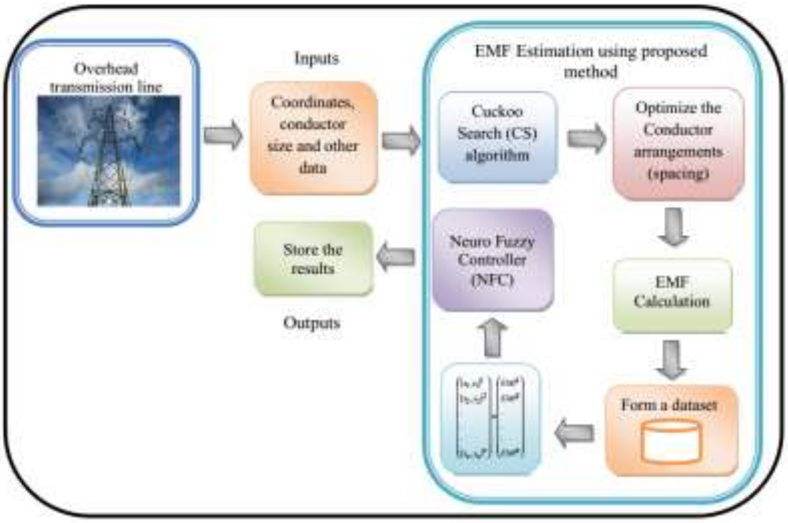


Figure 1. EMF estimation of OHTL using proposed method

A.1. Optimal conductor arrangements and EMF dataset generation using CS algorithm

Cuckoo search technique, in essence, is a meta-heuristic method enthused by the breeding trend of the cuckoos and is easy to implement. In the cuckoo search, there is a host of nests. Each and every egg accounts for a solution and the egg of a Cuckoo specifies a new solution. The new and better solution displaces the worst solution in the nest [27]. Now, the cuckoo search technique is employed for reducing the EMF of the transmission line system to optimize the conductor arrangements. The inputs of CS algorithm are represented by the x and y co-ordinates, voltage, current, conductor size etc. The fitness function is estimated for ach iteration. The EMF data represents the output of the innovative technique, An extensive account of the novel method is elegantly explained hereunder.

Step 1: Define the Objective function

In this section, the objective function is considered as an optimization problem. Here, the optimization problem is defined as follows:

$$O_f = \min(EM_F) \tag{8}$$

Where, $\min(EM_F) = \min(H_e^j, E_e^j)$. The objective function (O_f) has to be minimized by arranging the conductor in an optimal way in the search space of its limits.

Step 2: Describe the Initialization Process

In this section, the host nests are randomly initiated. Here, the nest is an array of size ‘n’.

$$N_k = \{n_1, n_2, \ldots\ldots\ldots n_n\} \tag{9}$$

$$C_k = \{c_1, c_2, \ldots\ldots\ldots c_n\}$$

Here, N_k and C_k are denoted as the x and y coordinates respectively. Then each nest n_n is a solution vector to the optimization problem. It can hold n number of variables, which are optimized so as to minimize the objective function.

Step 3: Establish the new cuckoo generation

A cuckoo randomly generates new solutions by using the Levy function and determines the quality of solutions. The Levy function ($Levy(\lambda)$) is represented as follows:

$$N_K^{t+1} = N_k^t + \alpha \oplus Levy(\lambda) \tag{10}$$

The Cuckoo is evaluated using the objective function to determine the quality of the solutions.

Step 4: Compute the Fitness for all inputs

Here, the fitness function (FF) of all the inputs are evaluated by using the following formula,

$$(FF) = \min(EM_F) \tag{11}$$

Where, the electric and magnetic field depend on the conductor arrangements and the x & y co-ordinates. If the fitness function is minimized then the current solution is saved as an optimal solution. Otherwise, the previous solution is kept as the best solution.

Step 5: Discard the worst nest

In this part, the worst nests are discarded based on their probability p_a values and the new ones are built using the equation (1). Subsequently, the best solutions are ranked based on their quality. Then the present best solutions are identified as the optimal solutions.

Step 6: Terminate the process

This process is repeated until the termination iteration is reached. The output is categorized according to their inputs and the corresponding output is noted. The output of the Cuckoo search algorithm is furnished as follows:

$$\begin{pmatrix} (x_1, y_1)^1 \\ (x_2, y_2)^2 \\ . \\ . \\ . \\ (x_n, y_n)^n \end{pmatrix} = \begin{pmatrix} EMF^1 \\ EMF^2 \\ . \\ . \\ . \\ EMF^n \end{pmatrix} \tag{12}$$

From the output of the CS algorithm, the conductor arrangement is optimized and the optimal set of the minimum EMF of the transmission line system is evaluated. The Flow chart of the CS algorithm is illustrated in Figure 2.

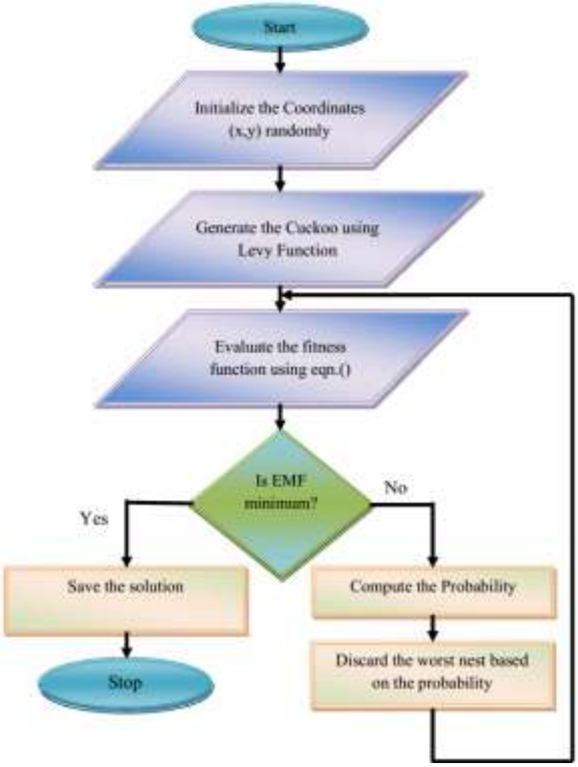


Figure 2. Flow chart of proposed CS algorithm

A.2. Neuro fuzzy controller (NFC)

Neuro fuzzy is associated with the domain of the artificial intelligence, which represents the integration of the artificial neural networks and the fuzzy logic [28]. The neural network is employed to build up the training dataset and testing for the input data applied. The innovative feed forward type neural network is employed in this regard. Normally, the neural network is home to three specific layers such as the (i) Input layer, (ii) Hidden layer and the (iii) Output layer. In the document, the optimized datasets are furnished as input to the NFC. It possesses two input layers such as the x and y coordinates a number of hidden layers and a single output i.e., the optimized electric and magnetic field (EMF) data. The function of NFC is concisely offered in the ensuing Section 3.1.2.

- *Neural network*

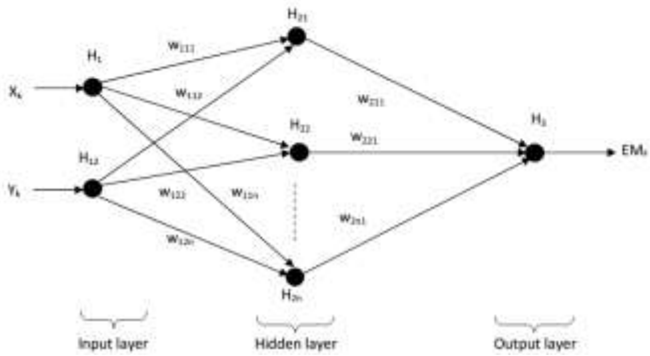


Figure 3. Structure of Neural network

Here, two inputs are furnished as the input to the network and a single output is offered. The neural network procedure is carried out in the hidden layer. The structure of the neural network is exhibited in Figure 3.

In Figure 3, the hidden layer is given as $H_{21}, H_{22}, \ldots H_{2N}$ and the neuron weight is labelled as W. The input layer to hidden neuron weight is represented by W_1 and the hidden layer to output layer weight is W_2. The proposed neural network training and weight adjustment are carried out by means of the Back Propagation (BP) process. The detailed working procedure of neural network is explained below:

Step 1: Initialize all the datasets such as the input, output and weight of the neuron. Here the inputs of the network are represented x and y coordinates. The optimized EMF signifies the output of the network.

Step 2: Evaluate the BP error of the input dataset.

$$E_1 = EMF^N{}_T - EMF^N{}_{out} \tag{13}$$

Where, $EMF^N{}_T$ represents the target output EMF, $EMF^N{}_{out}$ the real output EMF.

Step 3: Calculate the network output using the following relation.

$$EMF^N{}_{out} = \sum_{n=1}^{N} W_{2n1} EMF^N(n) \tag{14}$$

Where,

$$EMF^N(n) = [1 + e^{(-W_{1n}X(n) - W_{2n}Y)}]^{-1} \tag{15}$$

Both the equations given above represent the output layer and hidden layer activation function respectively.

Step 4: Find the new weights of all the neurons.

$$W_{new} = W_{old} + \Delta W \tag{16}$$

Where, ΔW represents the alteration in weight, which may be calculated by the following relation, $\Delta W = \gamma V_{cv}{}^N E_1$ γ represents the learning rate which is in the range of 0.2 to 0.5.

Step 5: The procedure will be repeated from step 2, till the E_1 gets reduced to the minimum value.

$$10E_1 < 1 \tag{7}$$

After the process is finished, the network is well trained and generates the optimal EMF (EMF^N). After the training procedure comes to an end, the fuzzy rules are created, which comprises three specific phases such as the fuzzification, decision making and defuzzification, which are employed to generate the optimal EMF (EMF^N). The fuzzy rules creation is detailed in the ensuing Section 3.1.2.2.

- Development of training dataset using fuzzy rules

The functioning of the controller is invariably dependent on the fuzzy rules. Now, the fuzzy rules are created by employing the Genfis2. The fuzzy controller comprises three phases which are detailed below:

a. Fuzzification
b. Decision making
c. Defuzzification

In the course of the fuzzification procedure, the crisp values are transformed into fuzzy value. The output is forwarded to the decision making block, which comprise of a group of regulations. By effectively employing the fuzzy rules the decision for the suitable output is produced, which is furnished to the defuzzification procedure. Defuzzification represents the inverse procedure of the fuzzification.

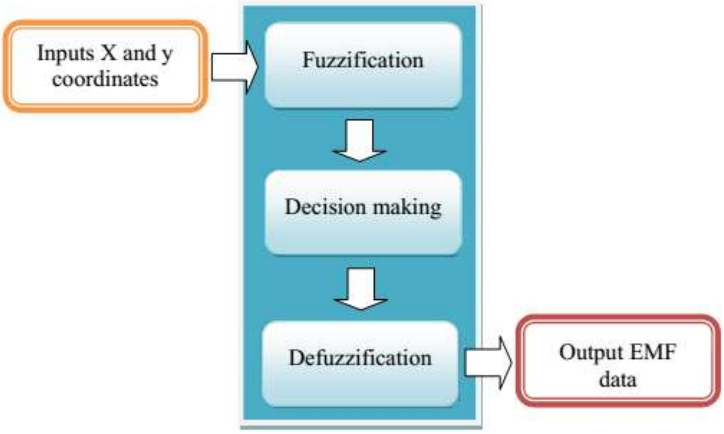


Figure 4. Fuzzy logic controller

These are in the rule base, which rules are tabulated in the following Table.1.

Table 1. Fuzzy Rules

y \ x	NB	NS	ZE	PS	PB
NB	ZE	NS	NB	PB	PB
NS	ZE	NS	NB	PB	PB
ZE	NS	NB	ZE	PS	PB
PS	NB	PB	NS	PS	PS
PB	NB	PB	NS	PS	PS

The Table shown above illustrates the fuzzy rules, which are capable of developing the EMF. The proposed system is discussed with the NFC, by performing on the MATAB platform. The outcomes of the proposed system together with details are furnished in the ensuing Section 4.

4. Results and discussion

The proposed method is implemented in MATLAB working platform. Here, the CS algorithm and the NFC are used for estimating the electric & magnetic field of the transmission line. The x and y coordinates are given to the input of CS algorithm and the EMF is estimated. Subsequently, the optimized datasets are given as input to the NF controller. In order to verify the effectiveness and robustness of the proposed method, it is compared with the CS algorithm-NN techniques. Here, the 400kV and 110kV transmission lines data [21] [23] are used to estimate the EMF. The implementation parameters of the proposed method are given in Table 2.

Table 2. Implementation parameters

Description	Values
Conductor radius	15 mm
Current	50 A
permeability	1
conductivity	0.01
permittivity	3

A. Performance analysis of 400kV OHTL

Here, the magnetic field values for several new geometries are estimated and formed as a data set for training the neural network. Then the electric field of the transmission line values are evaluated for several new geometries. By applying the proposed method, the magnetic field dataset of 400kV transmission line is estimated and it is applied for training the NN which is tabulated in Table 4. And also, the electric field of 400kV transmission line data set is examined and tabulated in Table 5. Prior to that, the experimental results are evaluated by using the formula and are tabulated in Table 3. Similarly, the magnetic and electric field dataset for 110kV transmission line is determined using the proposed method and tabulated in Tables 6 and 7. Similarly, the electric and magnetic field values are determined by using the CS algorithm- NN controller.

Table 3. Training data sets for magnetic and electric field

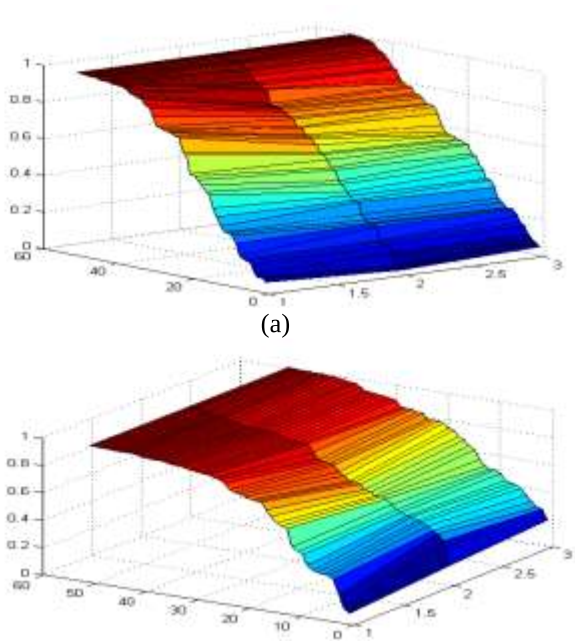
x	Magnetic field			Electric field		
y	0	2	5	0	2	5
0	0.176051	0.877975	0.790776	0.975875	0.945632	0.894799
1	0.079679	0.996605	0.986747	0.988294	0.595727	0.410902
2	0.155611	0.643388	0.268714	0.494047	0.907412	0.823737
3	0.982771	0.027791	0.323179	0.306694	0.81117	0.41857
4	0.063984	0.282935	0.409614	0.996551	0.960034	0.747199
5	0.941139	0.494852	0.950255	0.076406	0.996258	0.985401
6	0.290498	0.997869	0.106145	0.903384	0.562984	0.552139

7	0.525132	0.919423	0.080968	0.92107	0.917502	0.845556
8	0.682114	0.575742	0.227229	0.807989	0.872616	0.497713
9	0.994606	0.108595	0.904407	0.987458	0.135439	0.775396
10	0.66697	0.997503	0.981246	0.792188	0.914662	0.826793
11	0.990318	0.149705	0.193985	0.949355	0.477385	0.309858
12	0.787536	0.374738	0.605206	0.111116	0.557374	0.96387
13	0.757792	0.979148	0.149491	0.997436	0.486735	0.619204
14	0.894403	0.440025	0.531612	0.654395	0.86632	0.901596
15	0.149373	0.652855	0.745344	0.992848	0.761951	0.682737
16	0.977421	0.24295	0.99905	0.952554	0.917323	0.699777
17	0.924271	0.757036	0.069857	0.826193	0.872025	0.99552
18	0.99796	0.786246	0.705224	0.637367	0.740822	0.784396
19	0.774564	0.03401	0.483698	0.738361	0.927111	0.905192
20	0.9956	0.612996	0.254182	0.928919	0.315062	0.842084
21	0.925713	0.729098	0.987965	0.45132	0.930967	0.791761
22	0.93888	0.392145	0.226845	0.327452	0.918183	0.642574
23	0.973896	0.687925	0.81236	0.380416	0.753364	0.922696
24	0.318727	0.350766	0.35802	0.345369	0.405938	0.512698
25	0.838107	0.859851	0.939482	0.931357	0.881294	0.274842
26	0.773461	0.691476	0.662089	0.204938	0.982926	0.786779
27	0.971154	0.347338	0.560459	0.787863	0.865527	0.476231
28	0.57176	0.038161	0.573791	0.999679	0.966412	0.494106
29	0.791531	0.160156	0.783029	0.969707	0.63156	0.996559
30	0.290132	0.656576	0.779058	0.326591	0.433398	0.998374
31	0.75535	0.992678	0.860443	0.879794	0.973652	0.94581
32	0.884595	0.243494	0.529639	0.626537	0.674123	0.915845
33	0.281584	0.769707	0.560112	0.468655	0.900272	0.345528
34	0.960061	0.430719	0.697965	0.909305	0.999511	0.989999
35	0.991292	0.973248	0.863319	0.989599	0.42909	0.976614
36	0.095918	0.861121	0.994715	0.97512	0.746695	0.98764
37	0.980517	0.974404	0.748794	0.991926	0.642458	0.990431
38	0.41029	0.165633	0.545766	0.96091	0.910554	0.8872
39	0.982462	0.777069	0.431248	0.93828	0.640141	0.190038
40	0.988562	0.233165	0.542845	0.996382	0.584642	0.999036
41	0.166611	0.942065	0.733387	0.992331	0.699243	0.911028
42	0.775952	0.259098	0.157517	0.971612	0.995509	0.965895
43	0.079015	0.542845	0.996826	0.787967	0.960885	0.993103
44	0.560378	0.571564	0.707404	0.922549	0.454656	0.427784
45	0.542845	0.735723	0.999274	0.816712	0.455433	0.392755
46	0.968192	0.887957	0.049425	0.692679	0.361059	0.739193
47	0.47736	0.506866	0.928585	0.970138	0.518676	0.842479
48	0.24193	0.978044	0.364647	0.83949	0.891734	0.261852

49	0.36348	0.951917	0.473625	0.337767	0.379851	0.99947
50	0.490466	0.781581	0.227775	0.956565	0.563254	0.980543

Table 4. Testing data sets for magnetic field (400kV OHTL)

x	y	He	He (CS-NN)	He (proposed method)
0	5	0.790776	0.30324	0.749885
2	2	0.643388	0.730791	0.689639
5	2	0.49484852	0.692206	0.561518
13	0	0.757792	0.713019	0.722503
14	2	0.440025	0.552434	0.607727
16	0	0.977421	0.746597	0.730118
17	5	0.069857	0.642169	0.601908
20	0	0.9956	0.761714	0.927319
22	0	0.93888	0.760479	0.864049
23	0	0.973896	0.758175	0.821831
27	2	0.341338	0.719527	0.471032
33	0	0.281584	0.729675	0.813204
40	2	0.233165	0.732004	0.540464
46	5	0.887957	0.788332	0.535828
49	0	0.36348	0.558246	0.465347
50	2	0.781581	0.853539	0.818384



(a)

(b)

Figure 5. Analysis of (a) Magnetic field and (b) Electric field distribution in surrounding of 400 kV power transmission line

Tables 2 and 3 represent the magnetic field data for the training and testing of the neural network. Here, the x and y coordinates and their corresponding EMF data are 80% trained and 20% tested. Then the performance of the proposed method is determined and compared with the existing method. The performances of magnetic and electric fields are illustrated in the Figure 5.

Similarly, the absolute and relative error of the electric field is calculated. The performance of the absolute and relative error values are evaluated by using the proposed and existing methods, which are illustrated in Figures 6 and 7.

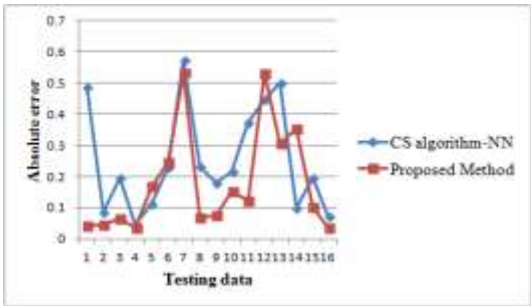
Table 5. Testing data sets for electric field (400kV OHTL)

x	y	Ee	Ee (CS-NN)	Ee (proposed method)
0	5	0.894799	0.737746	0.786864
2	2	0.907412	0.917799	0.738793
5	2	0.996258	0.84324	0.77354
13	0	0.997436	0.788316	0.720248
14	2	0.86632	0.630977	0.705231
16	0	0.952554	0.745242	0.694367
17	5	0.99552	0.808164	0.767581
20	0	0.928919	0.692387	0.618246
22	0	0.327452	0.699699	0.538451
23	0	0.380416	0.716428	0.528423
27	2	0.865527	0.598921	0.70372
33	0	0.468655	0.802203	0.739323
40	2	0.584642	0.638523	0.76525
46	5	0.361059	0.589273	0.53724
49	0	0.337767	0.950802	0.853199
50	2	0.563254	0.625189	0.507234

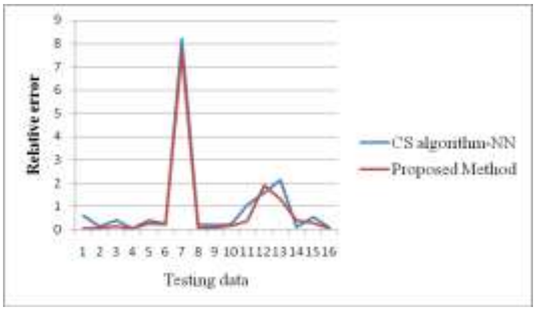
Also, the absolute and relative error performance of the proposed method is evaluated. Similarly, the corresponding error values are calculated by using the existing method. The absolute value of the absolute error has been computed as per the following equation:

$$Absolute\ error = \left| H_e - H_e^{CS-NFC} \right| \tag{17}$$

$$\mathrm{Re}lative\ error = \left| \frac{H_e - H_e^{CS-NFC}}{H_e} \right| \tag{18}$$

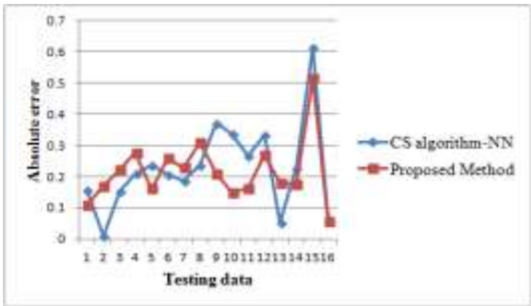


(a)

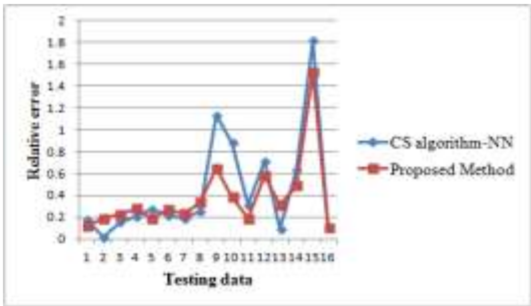


(b)

Figure 6. Comparison analysis of (a) absolute error and (b) relative error



(a)



(b)

Figure 7. Comparison analysis of (a) absolute error and (b) relative error

B. Performance analysis of 110kV OHTL

Table 6. Training data sets for magnetic field

x	Magnetic field			Electric field		
y	0	2	5	0	2	5
0	0.156659	0.540718	0.680792	0.968401	0.765946	0.896318
1	0.075306	0.910585	0.915871	0.899372	0.970569	0.95971
2	0.832005	0.110672	0.047686	0.825399	0.626363	0.836841
3	0.1711	0.138034	0.898131	0.958403	0.960523	0.301752
4	0.699274	0.008757	0.483611	0.935258	0.840954	0.542465
5	0.656374	0.980125	0.991636	0.551327	0.936239	0.584069
6	0.934452	0.390335	0.348992	0.998471	0.326468	0.756595
7	0.960608	0.201321	0.081413	0.678436	0.94012	0.927438
8	0.994902	0.928847	0.742023	0.859355	0.48609	0.838213
9	0.349416	0.661595	0.784857	0.972387	0.979741	0.311088
10	0.940644	0.907431	0.431502	0.917884	0.72304	0.334725
11	0.676737	0.91173	0.632703	0.859552	0.416283	0.982556
12	0.173855	0.98662	0.984216	0.882455	0.895777	0.857537
13	0.23628	0.98216	0.746811	0.948523	0.702253	0.909711
14	0.67769	0.98067	0.560449	0.428774	0.980583	0.892104
15	0.922323	0.285407	0.888201	0.614223	0.990567	0.981231
16	0.13197	0.353394	0.308504	0.981171	0.40977	0.98075
17	0.858765	0.734205	0.139543	0.901637	0.749911	0.936567
18	0.978306	0.937751	0.095483	0.893269	0.903388	0.833691
19	0.522104	0.754865	0.653823	0.960398	0.785075	0.450306
20	0.59909	0.547994	0.719087	0.85948	0.513877	0.48225
21	0.034842	0.821421	0.818369	0.90422	0.927915	0.876003
22	0.843923	0.96067	0.461749	0.963881	0.328237	0.844463
23	0.638644	0.415375	0.098925	0.962259	0.935285	0.447114
24	0.960856	0.914799	0.901413	0.794028	0.985514	0.867843
25	0.925466	0.958192	0.606373	0.940252	0.934111	0.205787
26	0.999468	0.806971	0.9972	0.498365	0.935895	0.433524
27	0.441978	0.670574	0.016995	0.160743	0.945823	0.51683
28	0.790808	0.573207	0.729877	0.976389	0.581496	0.71045
29	0.513427	0.83523	0.710855	0.864404	0.457556	0.995759
30	0.989671	0.311045	0.905415	0.90395	0.202445	0.226913
31	0.856419	0.433348	0.931232	0.980199	0.996932	0.212785

32	0.005381	0.670057	0.264093	0.884975	0.587797	0.661596
33	0.363745	0.007915	0.798633	0.974247	0.22636	0.972224
34	0.096152	0.615228	0.217905	0.910246	0.378433	0.994777
35	0.532371	0.206332	0.307541	0.889468	0.438639	0.988436
36	0.993853	0.33871	0.17304	0.833497	0.616671	0.99832
37	0.386475	0.73087	0.998458	0.988228	0.152464	0.922792
38	0.581466	0.867274	0.428122	0.715737	0.560512	0.817602
39	0.333348	0.976748	0.909318	0.323896	0.593916	0.183138
40	0.876189	0.810738	0.056271	0.694105	0.960633	0.94951
41	0.296649	0.88492	0.035896	0.898011	0.395502	0.150418
42	0.744469	0.944458	0.846754	0.976149	0.938289	0.921875
43	0.950693	0.542845	0.134706	0.827293	0.861363	0.885615
44	0.684222	0.432843	0.703281	0.807887	0.963487	0.904422
45	0.265877	0.638113	0.627033	0.555306	0.64623	0.23932
46	0.383741	0.774615	0.232844	0.95515	0.989927	0.667583
47	0.807276	0.942794	0.368375	0.985203	0.906295	0.202853
48	0.50645	0.969056	0.746163	0.744025	0.638388	0.961279
49	0.006548	0.989587	0.555021	0.960507	0.93212	0.966959
50	0.158204	0.140217	0.74727	0.939494	0.821832	0.977984

Table 7. Testing data sets for magnetic field (110kV OHTL)

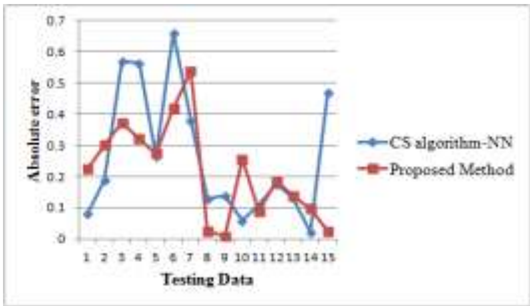
x	y	He	He (CS-NN)	He (proposed method)
0	5	0.680792	0.596972	0.907385
2	2	0.110672	0.301365	0.411713
5	2	0.980125	0.410075	0.607799
13	0	0.23628	0.801731	0.55679
14	2	0.98067	0.713082	0.706235
16	0	0.13197	0.791938	0.550705
17	5	0.139543	0.520015	0.677181
20	0	0.59909	0.730082	0.573192
22	0	0.843923	0.704044	0.834652
23	0	0.638644	0.69793	0.895444
27	2	0.670574	0.561553	0.582789
33	0	0.363745	0.54131	0.550163
40	2	0.810738	0.677061	0.949398
46	2	0.774615	0.751552	0.678015
49	0	0.006548	0.477473	0.030879
50	2	0.140217	0.838409	0.23785

Here, the magnetic field values for several new geometries are estimated and formed as a data set for training the neural network. Then the electric field of the transmission line values are evaluated for several new geometries. By applying the proposed method, the magnetic field dataset of 110kV transmission line is estimated and is applied for training the NN which is tabulated in Table 4. And also, the electric field is examined and tabulated in Table 5. Similarly, the electric and magnetic field values are determined by using the CS algorithm- NN controller.

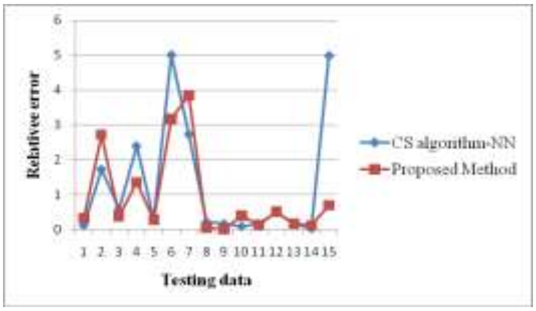
Table 8. Testing data sets for electric field (110kV OHTL)

x	y	Ee	Ee (CS-NN)	Ee (proposed method)
0	5	0.896318	0.701468	0.878384
2	2	0.626363	0.821291	0.786044
5	2	0.936239	0.769309	0.844694
13	0	0.948523	0.716992	0.755737
14	2	0.980583	0.749322	0.800426
16	0	0.981171	0.720208	0.760828
17	5	0.936567	0.781834	0.794069
20	0	0.85948	0.748284	0.87633
22	0	0.963881	0.764822	0.849627
23	0	0.962259	0.773075	0.88784
27	2	0.945823	0.66013	0.637044
33	0	0.974247	0.800511	0.780812
40	2	0.960633	0.61742	0.642404
46	2	0.989927	0.822026	0.838124
49	0	0.960507	0.919525	0.957955
50	2	0.821832	0.888833	0.87204

From the above illustration, the traditional method has the relative error for the magnetic field at about 0.35. Whereas for the proposed method the relative error for the magnetic field is about 0.05. However, from the above Figure it is clear that the relative power error of the proposed method is very much lower than that of the traditional method. Therefore, the magnetic field is highly minimized using the proposed method when compared to the existing methods. Similarly, the electric field is highly minimized using the proposed method vis-a-vis the existing methods.

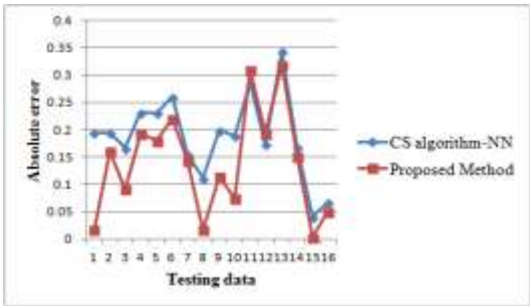


(a)

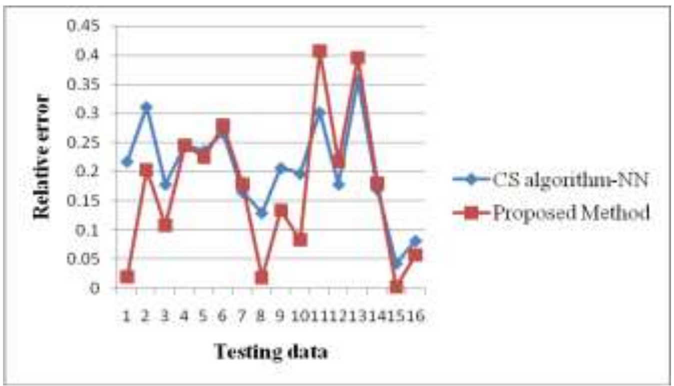


(b)

Figure 8. Comparison analysis of (a) absolute error and (b) relative error in magnetic field



(a)



(b)

Figure 9. Comparison analysis of (a) absolute error and (b) relative error in electric field

5. Conclusion

In the paper, a CS-NFC technique is proposed for estimating the electric and magnetic field of the transmission line. The proposed method is implemented in the Matlab platform. In order to obtain the minimal EMF, the arrangements of the conductor should be optimized. Initially, the x and y coordinates are given as input to the proposed method and the corresponding EMF is evaluated by using the proposed method. Then the performance of the proposed method is evaluated and analyzed with the existing methods. From the analysis, it is observed that the results of the transmission line can ensure the minimal EMF by optimizing the conductor arrangements. Therefore, by the optimal arrangement of the conductors by using proposed method, the minimal EMF is achieved when compared to the other technique. In addition, the error measurement confirms the effectiveness of the proposed method.

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