Electric Field Optimization of High Voltage Electrode Based on Neural Network

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***Abstract* - For the insulation design of high voltage apparatus, electric field optimization technique becomes indispensable tool. We developed a highly efficient electric field optimization technique based on Neural Network under the personal computer. Once the Neural Network learns the relationship between inputs and outputs, the system easily allows to get a target solution. Principle of the developed optimization technique are described with the calculation example. Moreover, normalization of learning data is introduced and the applicability is expanded.**

I. INTRODUCTION

Recently, increase of electric power demand needs to introduce more reliable high voltage power apparatus, such as gas insulated switchgears (GIS) and transformers, with reducing the size and enhancing the space factor. Thus, the importance of insulation design is increasing more and more. For their insulation design, the electric field optimization technique is intensely required. The optimization technique makes the electric field distribution on the electrode surface not only as low as possible but also as uniform as possible. Although a number of electric field optimization techniques have been so far reported[1]-[8] all of the techniques have merits and demerits as well. For example, in that process, iterative calculation of electric field analysis and contour modification are needed.

Under the above background, we have been developing a new method for the electric field optimization method based on Neural Network (NN). Once NN learns, optimum solution satisfying desired specification can be found without iterative calculation, resulting in high speed method. Moreover, NN enables to be more intelligent by learning various optimization subjects.

In this paper, firstly, principle and fundamental processes of the electric field optimization method based on NN is described. Secondly, normalization method of learning data of NN is described. Introduction of this technique drastically expands the applicability and effectiveness of optimized contour.

PE-042-PWRS-0-12-1997 A paper recommended and approved by the IEEE Power System Engineering Committee of the IEEE Power Engineering Society for publication in the IEEE Transactions on Power Systems. Manuscript submitted April 1, 1996; made available for printing December 16, 1996.

II. ELECTRIC FIELD OPTIMIZATION BASED ON NEURAL NETWORK

A. *Basic structure of neural network*

When applying NN to electric field optimization problem, we introduce the Back Propagation method (BP)[9][10]. BP has been confirmed to be available in pattern recognition, optimization problem and so on. As shown in Figure 1, BP is the NN consisting of the multi layered structure with one input layer, one or more hidden layers and one output layer. Table 1 lists learning parameters used in BP. Firstly, one has to prepare an example of phenomenon to be learned as learning pattern for BP. The input and output of individual learning patterns are converted to input data and teach data respectively. Here, the input and teach data are called learning data. After the process of NN learning with the learning data, the NN enables to obtain the input-output relationship of the phenomenon.

Here, as an estimation of NN learning state at each learning process, let the average error E_{rr} be defined as the difference between teach data and output for all learning patterns as follows;

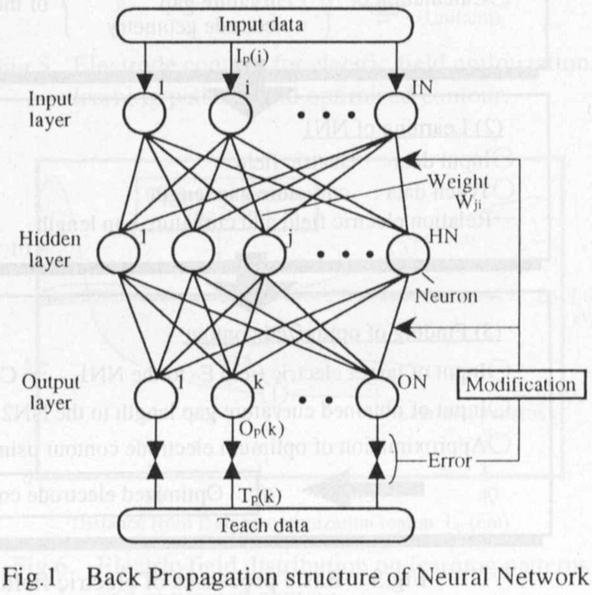

Fig.1 Back Propagation structure of Neural Network.

Table 1 Learning parameters

Mark	Learning parameter
PN	Total number of learning patterns
IN	Total neuron number of input layer
HN	Total neuron number of hidden layer
ON	Total neuron number of output layer
HL	Total layer number Hidden layer
p	Learning pattern number
i, j, k	Neuron number of input, hidden, output layer
$I_p(i)$	Learning pattern p input data of neuron i
$T_p(k)$	Learning pattern p teach data of neuron k
$O_p(k)$	Learning pattern p output signal of neuron k
W_{ji}	Weight between neuron i and neuron j

$$E_{rr} = \frac{\sum_{p=1}^{PN}\sum_{k=1}^{ON}\left|T_p(k) - O_p(k)\right|}{PN \times ON} \times 100\ (\%) \tag{1}$$

E_{rr} ($0<E_{rr}<100\%$) is referred to as "learning error" hereafter.

B. Processes of optimization

The electric field strength on a high voltage electrode surface has empirical relationship with the curvature and the gap length. However, except for an extremely simple electrode contour, it is difficult to determine quantitatively this relationship. Accordingly, we considered to introduce NN enabling to learn this relationship using a learning function. Then, a NN learns the relationship between the electric field and a set of curvature, and gap length. This NN is defined as NN1. However, our final aim is to obtain an optimized electrode contour. Hence, another NN should learn the relationship between a set of curvature, gap length and electrode contour. This NN is defined as NN2. After these NN learning, inputting the target electric field distribution into NN allows to output a curvature, gap length and electrode contour for the optimized electrode configuration. Figure 2 illustrates the outline of the developed optimization method in conformity with the conception described above.

Figure 3 depicts basic processes of the electric field optimization method based on NN. As seen in Fig.3, this optimization method can be classified into three main processes as follows.

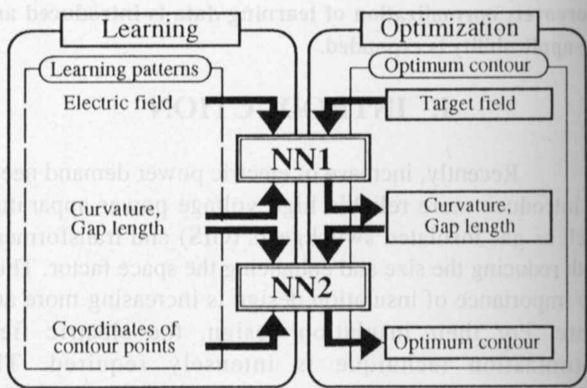

Fig.2 Outline for electric field optimization based on Neural Network.

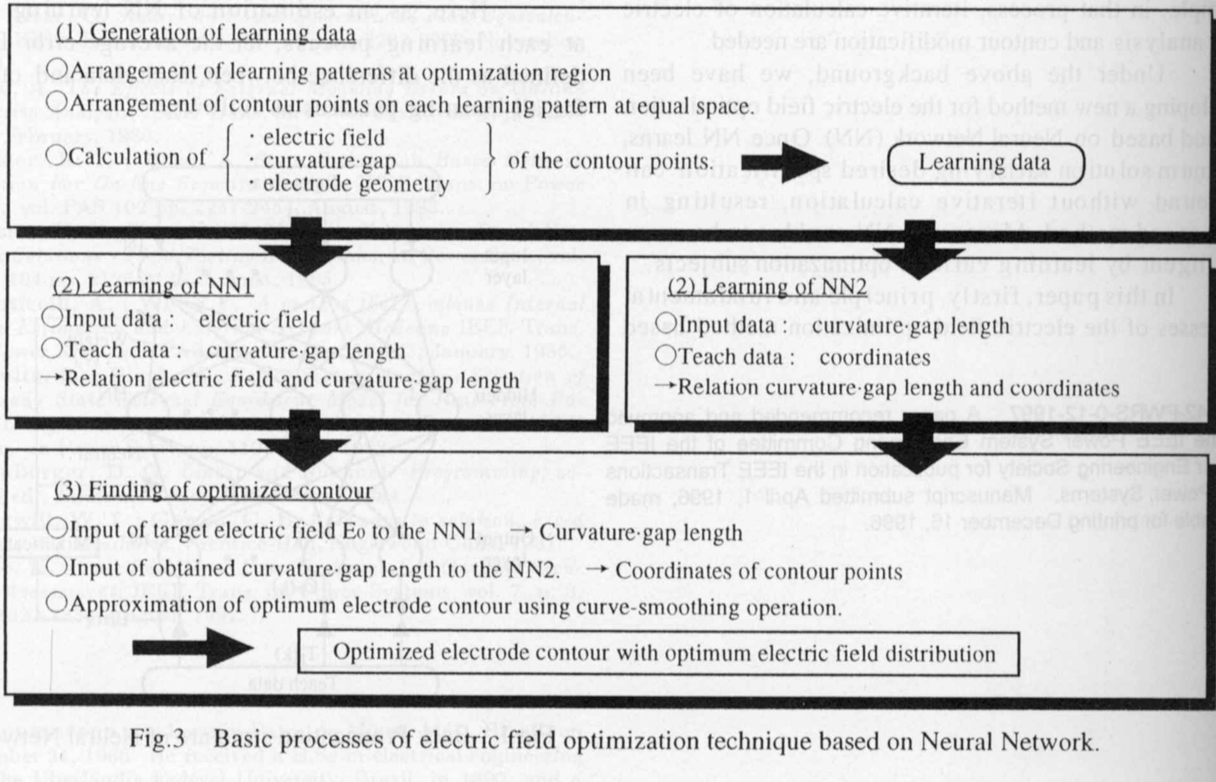

Fig.3 Basic processes of electric field optimization technique based on Neural Network.

(1) Generation of learning data

In this process, learning data to be learned by NN is generated. Firstl y, learning patterns with simple geometry such as an arc and straight line is arranged on the optimization area. In this case, differential coefficient on learning pattern has to be continuous, and learning patterns have to meet the symmetric axis at right angle. For example, we can suppose optimization region as shown in Figure 4, and then one of learning patterns presented in Fig.4 is considered.

A number of learning patterns like this are arranged. Next, equal number of contour points are arranged on each learning pattern at regular interval. For each of all contour points, field data E, curvature data C and A of vertical and cross section, gap length data G along the electric line of force, coordinates data (X,Y) are calculated and inputted into learning data. Figure 4 also illustrates concept of the arrangement of these data. Here, a set of data C,A and G are called "curvature·gap data".

(2) Learning of NN

Firstly, we prepare two kinds of NN (NN1, NN2). NN1 learns relationship between the electric field data and curvature·gap data, and NN2 learns the relationship between curvature·gap data and coordinates data. Once the learning process of NN1 progresses, the general relationship between the electric field and curvature·gap can be obtained effectively. Finally, it becomes unnecessary for NN1 to learn again. Since one needs to let only NN2 be learned, learning time can be decreased drastically.

(3) Finding of optimized contour

Inputting the target electric field distribution to NN1 allows to obtain curvature·gap data of the optimized contour. Next, inputting thus obtained curvature·gap data to NN2, one can readily obtain coordinates of the optimized contour points. Connecting all the obtained contour points with curve-smoothing operation gives an electric-field-optimized electrode contour.

Note that Charge Simulation Method (CSM)[11] is used in the field calculation process. A

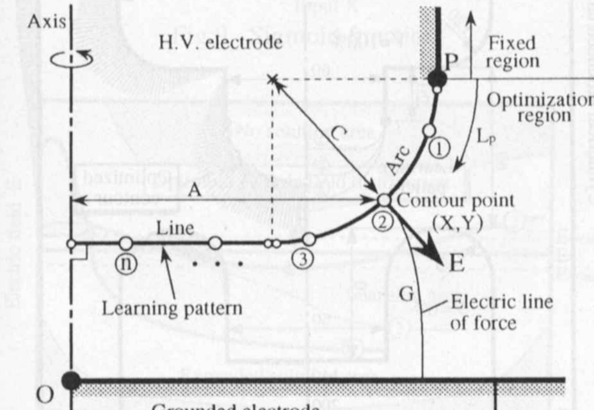

Fig.4 Learning pattern, contour points and learning data.

32 bit personal computer (CPU:80386) is used from user friendliness and economical view point.

C. *Calculation example*

Figure 5 illustrates one example of a typical electrode contour for electric field optimization. Electric field optimization calculation is performed for an end profile of high voltage rod electrode in the grounded cylinder, which given here simulates the end part of a high voltage conductor in GIS. In this figure, d denotes the distance between the side of the rod electrode and grounded cylinder. Thick solid lines represent fixed part, and the end of the high voltage electrode is the part to be optimized. Let us place three learning patterns ①~③ in the optimization area as shown in Fig.5.

Figure 6 depicts calculated electric field distribution for three different learning patterns when d=20cm. As seen in this figure, the electric field distribution on each learning patterns ①~③ is far from uniform one. In Fig.6, the region between the minimum and the maximum of the electric field distribution ①~③ is defined as a learning area. On the contrary, we can also define a learning area of contour as shown in Fig. 5.

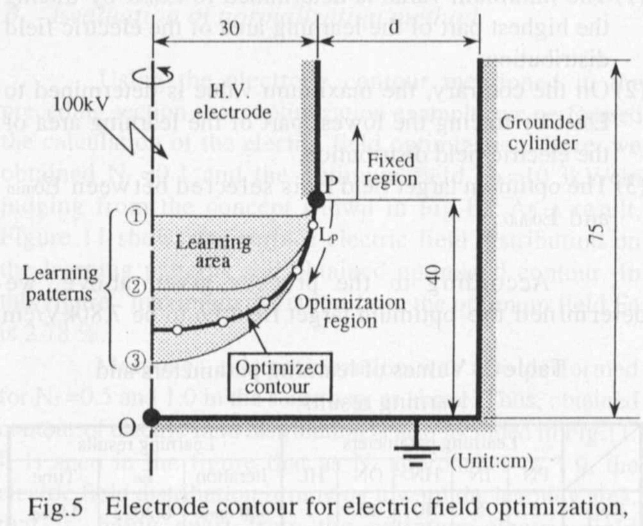

Fig.5 Electrode contour for electric field optimization, learning patterns and optimized contour.

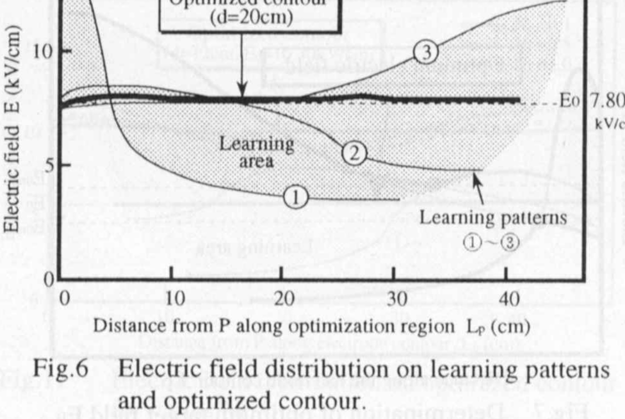

Fig.6 Electric field distribution on learning patterns and optimized contour.

It is noticed that five contour points are placed when the learning data is calculated. As a result, the NN produces 5 electric field data and 15 curvature-gap data and 10 coordinates data for a given learning pattern. We determined learning parameters based on these learning data. NN stops learning when the learning error E_{rr} is less than 1.0% of the initial value. Table 2 shows learning parameters and obtained results. It can be said from this result that the NN method has enough ability from practical application view point, like calculation accuracy and speed.

It is obvious that the optimized electric field distribution has uniform and the lowest electric field distribution along the electrode surface. Thus, it is possible to determine this uniform electric field value, referred to as "optimum field E_0". However it is very difficult to determine uniquely an optimum target field E_0 before hand, E_0 is generally determined based on trial and error. In this paper, we propose an algorithm to find out the optimum field E_0 automatically by judging from electric field distributions of learning patterns. We explain this algorithm by way of example shown in Figure 7 as follows;

(1) The minimum value is determined to E_{0max} by tracing the highest part of the learning area of the electric field distribution
(2) On the contrary, the maximum value is determined to E_{0min} by tracing the lowest part of the learning area of the electric field distribution.
(3) The optimum target field E_0 is selected between E_{0min} and E_{0max}.

According to the process given above, we determined the optimum target field E_0 to be 7.80kV/cm

Table 2 Values of learning parameters and learning results.

	Learning parameters					Learning results		
	PN	IN	HN	ON	HL	Iteration	E_{rr}	Time
NN1	5	40	15	1		460 times	0.2022	44 sec.
NN2	3	15	40	10	1	560 times	0.2231	48 sec.

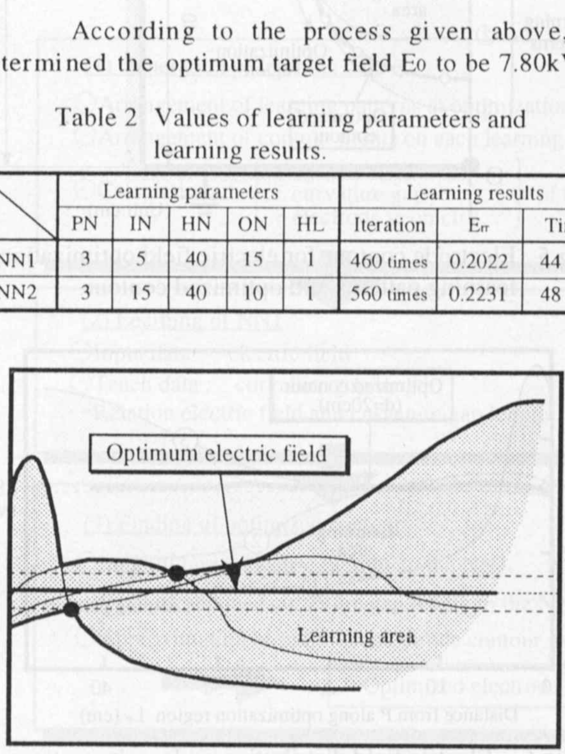

Fig.7 Determination of optimum target field E0.

in Fig.6, because E_{0max} and E_{0min} were 7.74kV/cm and 7.83kV/cm, respectively. Thus, obtained optimized contour and its electric field distribution have already shown in Fig.5 and Fig.6. The maximum deviation from the optimum field E_0 was estimated at 2.92%; sufficient accuracy is obtained.

Next, in the processes of optimization calculation, calculation time taken for each process and total processes are shown in Table 3. It is obvious in the table that it takes about 5 min. for optimization calculation from start to end; i.e. the optimization is performed within a practical and reasonable time using 32 bit personal computer. It is also found from the table that it takes about 80% of the total calculation time to make learning data and learn NN. Accordingly, once the NN learning is accomplished, it takes even shorter time to obtain the optimized contour. This point is the advantage of NN application to electric field optimization.

D. Application to practical apparatus

We applied this optimization method to practical apparatus to confirm the applicability of the NN method. The result is shown in Figure 8. This figure shows disconnector switch configuration of the high voltage power apparatus and we applied 500 charges to simulate the electrode contour by CSM. The left side of the rotational axis is the cross section of the optimization example with 3 learning patterns. The right side of the axis is the result of optimization calculation. It is clear that uniform field

Table 3 Calculation time of optimization processes.

Optimization process	Calculation time
(1) Generation of learning data	2min. 30sec.
(2) Learning of NN1, NN2	1min. 38sec.
(3) Finding of optimum contour	11sec.
Total processes	5min. 12sec.

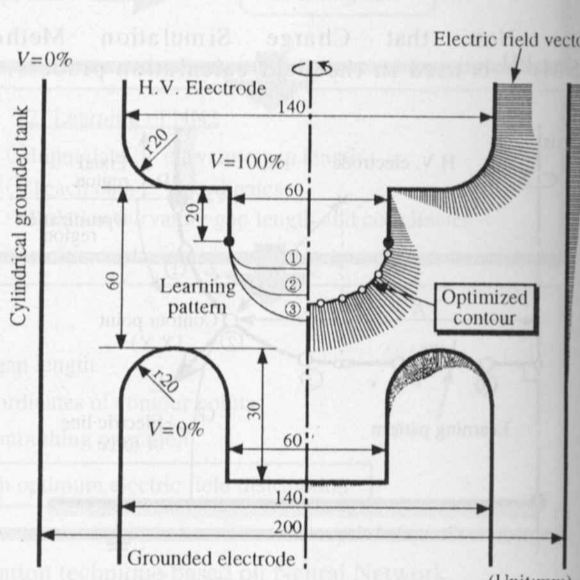

Fig.8 Disconnector switch

distribution is automatically obtained at the optimization region. The calculation time of the optimization is about 20 minutes. From the above results, it can be said that this optimization method has sufficient applicability.

III. EXPANSION OF SOLUTION AREA

A. *Normalization method*

A neuron constituting NN has multi inputs and one output. The state inside the neuron is given as the sum of weighted input signals from the other neurons. A sigmoid function shown in Figure 9 is generally used for input-output response function F(X) of the neuron. Sigmoid function is continuous and non-linear. Sigmoid function also has characteristics that the rate in change of F(X) is maximum for input signal X at near 0, and the output signal F(X) is limited from 0 to 1. In this optimization method, we used the sigmoid function as a response function F(X).

Input and teach data of NN are the electric field strength, electrode geometry and so on. Thus, these learning data need to be normalized so as to correspond to input and output characteristics of neuron.

Here, let us suppose the electrode contour and learning patterns given in Fig.5, with d=12cm as an optimization subject. Then, electric field distributions on learning patterns are obtained as shown in Figure 10. It is clear in this case that there exists learning patterns of electric field distribution where $E_{0max}<E_{0min}$ and thus no uniform electric field distribution exists within the learning area by the algorithm mentioned before. As a result, an optimized contour possibly would exist outside of the learning area in Fig.10. Hence, we propose a normalization method of learning data so as to avoid this problem.

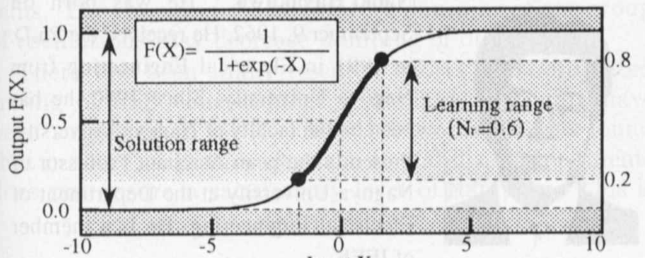

Fig.9 Sigmoid function.

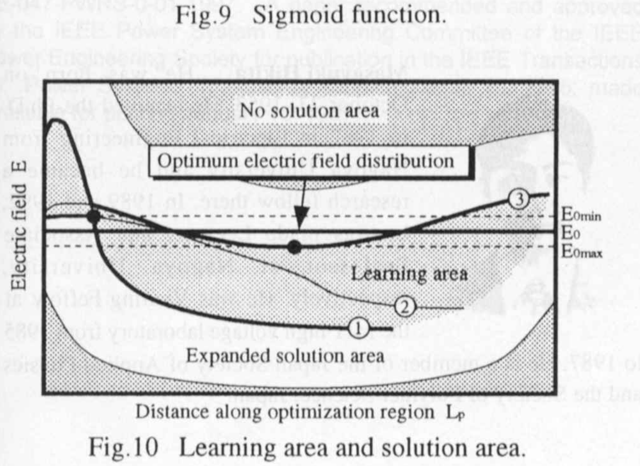

Fig.10 Learning area and solution area.

$$I_p^{nor}(i) = \frac{I_p(i) - I_{av}(i)}{\sigma(i)} \quad (2)$$

$$T_p^{nor}(k) = \frac{T_p(k) - T_{min}(k)}{T_{max}(k) - T_{min}(k)} \times N_r + \frac{1 - N_r}{2} \quad (3)$$

$$\left(\frac{1-N_r}{2} \le T_p^{nor} \le \frac{1+N_r}{2}\right)$$

where, $I_{av}(i)$ is the average of input data, $\sigma(i)$ is the standard deviation of input data, $T_{max}(k)$ is maximum teach data, $T_{min}(k)$ is minimum teach data, and N_r is normalization coefficient of teach data.

The range from the minimum to the maximum of the normalized teach data is referred to as "learning range". For example, when N_r=0.6, the learning range of each neuron covers 0.2 ~ 0.8 as shown in Fig.9. This learning range corresponds to the learning area given in Fig.10. This normalization method can expand the area of a possible optimized contour into the upper and lower sides of the learning area. Thus, the optimum electric field distribution can be determined, even when the optimized contour exists beyond the learning area. This concept is shown in Fig.10.

B. *Evaluation of normalization method*

Using the electrode contour mentioned in the preceding section as an optimization example, we performed the calculation of the electric field optimization. Here, we obtained N_r =0.1 and the optimum field E_0 =10.3kV/cm judging from the concept shown in Fig.10. As a result, Figure 11 shows the surface electric field distribution on the learning patterns and obtained optimized contour. In this figure, maximum deviation from the optimum field E_0 is 2.78 %.

Moreover, this optimization was also performed for N_r =0.5 and 1.0 in the same way as above. Thus, obtained contour of electric field distribution is also included in Fig.11. It is seen in the figure that as N_r approaches to 1.0, the electric field distribution is moving toward the learning area, that is, being apart from the optimum electric field distribution. On the other hand, when one takes N_r less than 0.1, obtained contour points varies more widely but the

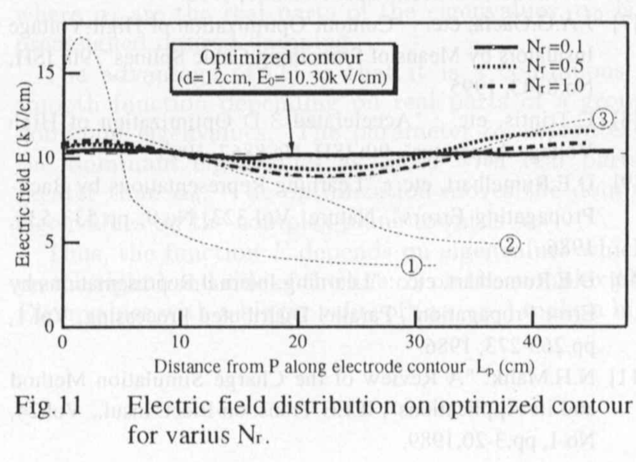

Fig.11 Electric field distribution on optimized contour for varius N_r.

error of the response of sigmoid function is enhanced. Then, the optimum value of N_r is considered to be existed between 0.1 and 1.0.

IV. CONCLUSION

In order to realize highly efficient electric field optimization calculation under personal computer, we introduced Neural Network(NN), that is available for optimization problem, with electric field analysis technique. In this paper, firstly, an algorithm of electric field optimization method using two kinds of NN is described.

Next, so as to evaluate availability of the method, as for an example of high voltage GIS conductor end, we calculated an optimum contour by electric field optimization method based on NN in this paper. As a result, optimized electrode contour with highly uniform electric field distribution could be obtained. Consequently, availability of this method is well proved. Moreover, it is confirmed that once NN has learned, optimized contour can be found with high speed on personal computer. From the above point, electric field optimization method based on NN has advantage in the calculation efficiency.

Next, normalization method of learning data used in learning process of NN is investigated. This normalization method allows us to expand the solution of optimized contour.

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