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Fault Section Estimation by Neural Networks and Genetic Algorithm

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***Abstract*: -- Fault section estimation plays a significant role in the process of restoring the power system to its normal state in minimum time. In this paper, an approach involving artificial neural networks and the genetic algorithm has been used for performing fault section estimation. We have presented a procedure to formulate objective function using neural networks and continuous genetic algorithm. This objective function is then minimized with the help of continuous genetic algorithm and fault section is identified. To validate the efficient performance of the approach, different systems were used for testing the method and it provides accurate results in all cases. One illustration is described in detail. It is seen that solution can be found out effectively in the situation of multiple faults and malfunctioning of protective devices.**

***Keywords:* - Fault section estimation; objective function; genetic algorithm.**

I. INTRODUCTION

Electrical power systems consist of large generating stations, transformers, high voltage lines, etc. Some abnormal activities can occur at particular instances where a large amount of current might flow through the normal load or a part of circuit may be interrupted. In such situations it is highly desirable to minimize damage to equipment's and interruptions to service. Power system should be restored expeditiously to augment service reliability. Protective devices are used to cause the prompt removal from service any equipment that suffers a fault. The relaying equipment aided by the circuit breakers are capable of disconnecting the faulty elements. Disturbance is limited to a small area due to removal of the faulty element [1]. While estimating the fault section, the inputs from protective devices are used to identify the fault components in the power system. However multiple faults or failure of protective devices pose greater difficulty in the process of identification [2]. Various methods have been employed to solve fault section estimation problems such as cause-effect networks [3], expert systems [4], petri nets [5], artificial neural networks [6], genetic algorithm [7], particle swarm optimization [8] and evolutionary programming [9]. An expert system emulates the decision making ability of human expert. Though the model-based system is easy to maintain, the inference process is time consuming [6].

In general regression neural networks learning occurs in a single step and the net can generalize as soon as examples are stored [10]. In evolutionary programming (EP), the objective function formulated is of high order.

This paper is based on the application of ANN and continuous genetic algorithm for predicting the fault section.

The basic measures involved in evaluating the correct fault section include:

(a) Formulating target functions in terms of inputs from relays and circuit breakers, through which objective function can be formulated

(b) Identifying the section at which fault occurs with the help of inputs from protective devices and formulated objective function.

Building blocks of artificial neural networks are simple computational devices that are highly interconnected and the connections between neurons determine the function of the network. ANN's can be trained by the known instances of the particular problem. The objective function is formulated using the inputs and outputs from the training set.

The genetic algorithm is a search technique which conforms to the fundamentals of genetics. In genetic algorithm there is evolution of candidates under specific rules that aid in achieving maximum "fitness" [11]. This optimization assists in predicting the section at which fault occurs with the help of target functions formulated using ANN.

II. FAULT SECTION ESTIMATION

For any distribution system, provision of uninterruptible power and reliable service, the system should be restored in minimum time after occurrence of fault. To estimate the fault section accurately in least possible time, forms the primary step of restoration process. However, the task of finding the location of fault section has many difficulties. During instances of malfunctioning of primary relays, back up protective devices play a significant role in fault clearance. This results in larger disconnected area and it is difficult to analyze the situation. Occurrence of multiple faults makes the situation very complex. Following assumptions are made before dealing with FSE problem:

(1) Relays and circuit breakers are in the final states. Binary values are used to represent the on-off states.
(2) In a protection zone relays do not operate in the absence of a fault. Also breaker does not open by itself without a tripping signal from a corresponding relay.
(3) There is a possibility of malfunctioning of protective devices which should be identified.

III. HEBB RULE

Neural networks comprise of synthetic networks that emulate the biological nervous system found in living beings. The input patterns can be mapped to outputs using neural networks. This confirms its ability of mapping. They are able to provide solutions even for untrained cases and generalize the results depending on historical data. When the inputs are incomplete neural networks are able to provide accurate solutions. Supervised learning provides an opportunity to alter parameters of network through the produced error, which enhances its implementation capability. Neurons perform as summing and nonlinear mapping junctions. After appropriate training, the network can be effectively used in solving cases that are not included in training set.
Using the Hebb's rule, weight matrix can be evaluated as

$$W_m = TP^T \tag{1}$$

where T is the target matrix and P is the pattern matrix.

In case of non-orthogonal patterns, the rule creates errors. This problem can be addressed by using pseudo inverse rule. It can be evaluated as

$$P^+ = (P^T P)^{-1} P^T \tag{2}$$

Using the pseudo inverse, weight matrix is evaluated as

$$W_m = TP^+ \tag{3}$$

The matrix thus obtained is used to formulate the target equations.
Each target function (T_i) is written as

$$T_i = \sum_{j=1}^{l} (W_{ij} I_j) \tag{4}$$

IV. THE CONTINUOUS GENETIC ALGORITHM

Genetic algorithm is based on the process of modeling genetic recombination and natural selection. It deals with continuous variables which are used to minimize the fitness function. It terminates by testing for convergence. The continuous genetic algorithm is very similar to binary genetic algorithm. The primary difference is the fact that floating point numbers instead of bits of zeroes and ones as in binary GA. Representation to machine precision, less storage requirement and faster evaluation of cost function are some of the advantages that continuous GA has over binary GA [12].

The continuous GA is also called a real-valued GA. The flowchart in the figure provides an overview of continuous GA.

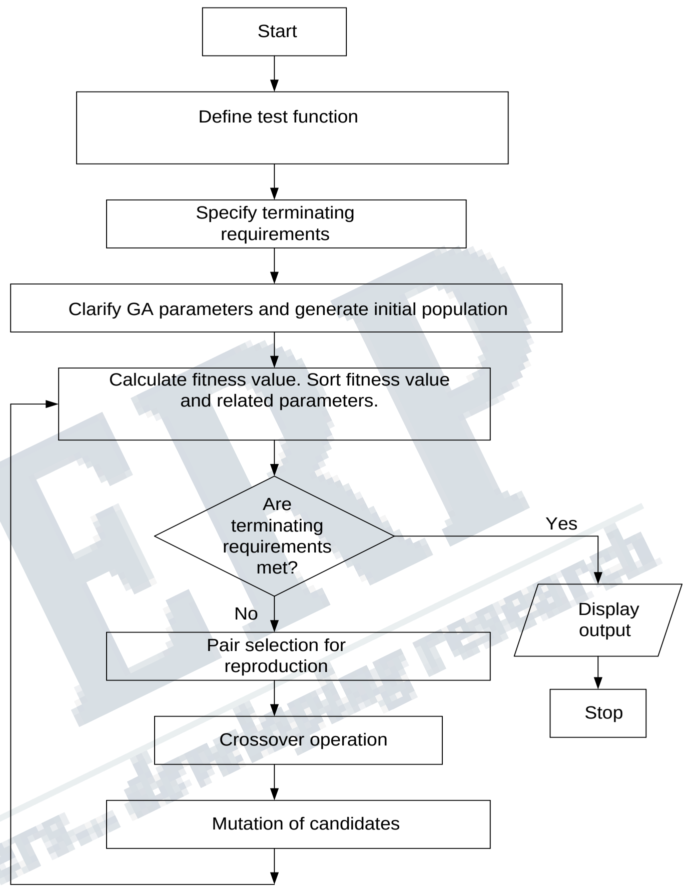

Fig. 1 Flow chart for genetic algorithm

To begin the GA, initial population of chromosomes is defined. After this, it decided which of the initial chromosomes will survive depending on the fitness value and produce off springs. This process of selection of individuals based on fitness is known as "reproduction". The individuals with highest fitness are selected for reproduction. After this, crossover operation is performed. New information is not added due to crossover operation and each value is carried forward to next generation. Lastly mutation is applied. In mutation, a variable is replaced by continuous random variable. Mutation plays an important role in delaying convergence so that global minima can be obtained.
It is formulated as

$$F = \sum_{i=1}^{k} [(T_i - S_i)^2] \tag{5}$$

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Here k represents total sections in the considered system. Using equation (4) target function values T_i can be calculated. S_i values are obtained from the chromosomes of initial population.

V. RESULTS

A simple distribution system, shown in Fig. 2 is taken which consists of seven protected sections: three buses, one transformer and three feeders.

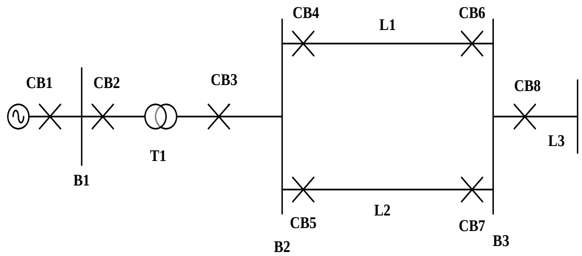

Fig. 2 The sample system

A seven section system is used to test the ANN and continuous genetic algorithm based method. It comprises of 3 busbars, 1 transformer and 3 lines. The circuit breakers are numbers CB1 to CB8. Table I gives details of the relays used. Since there are 7 sections, we use 18 patterns (2*7+4) for training. Each pattern has 22 inputs. The pattern matrix of order 22 x 18 and target matrix of order 7 x 18 are formed. Weight matrix obtained by using Hebb's rule is of order 7 x 22. The target functions for buses B1 and B2 are as follows:

$$T_1 = 0.2678*(r(1)+r(10)) + 0.0203*(r(2)+r(3)+r(11)+ r(12)) - 0.1695*(r(4)+r(13)) - 0.068*(r(5)-r(20)) - 0.0339*(r(6)-r(18)) + 0.0542*r(8) + 0.5356*r(15) + 0.1966*r(16) - 0.0271*(r(17)+r(19)+r(21))$$

$$T_2 = 0.0203*(r(1)+r(10)) + 0.4161*(r(2)+r(11)) - 0.0839* (r(3)+r(12)) - 0.0508*(r(4)+r(13)) - 0.4720*r(5) + 0.1398*r(6) - 0.2237*r(8) + 0.0407*r(15) - 0.0610*r(16) + 0.119*(r(17)+r(19)+r(21)) + 0.3602*r(18) + 0.0068*r(20)$$

Similarly target function values can be obtained for remaining sections.

Different cases depicting varied situations have been tested. Here fault at one section, multiple sections with/without failure of protective devices have been considered. Some patterns used for testing were not included in the training set. After evaluating the values of target functions, a fitness function is formulated. This is then minimized using continuous genetic algorithm. All sections having S_i values > 0.5 are considered. Different cases have been tested, out of which five cases have been illustrated and the results are discussed in brief. The status of protective devices in these cases is presented in Table I.

(a) Fault on one section

Here relay T1p has actuated and tripping signal is given to circuit breakers CB2 and B3. For testing, one of the patterns from the training set was used which is represented in binary form as [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0]. The fitness function obtained was minimized using genetic algorithm. It is observed that only section 4 has final value 1 (>0.5) which indicates that it the desired section.

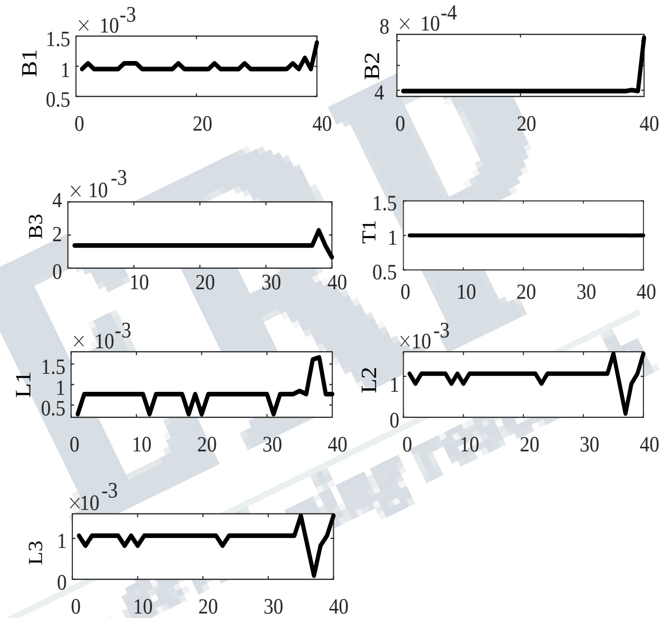

Fig. 3 Best individuals using continuous genetic algorithm

(b) Faults on two or more sections

There is no failure of protective device. The relays actuated are L1ps, L1pr, L2ps and L2pr. The breakers that have tripped are CB4, CB5, CB6 and CB7. This pattern was not used for training. After minimizing the fitness function using genetic algorithm, it is observed that only sections L1 and L2 have values greater than the limit on chromosome.

TABLE I
OPERATED DEVICES IN VARIOUS SITUATIONS

Example	Operated Relays	Operated Breakers
a	T1p	CB2, CB3
b	L1ps, L1pr, L2ps, L2pr	CB4, CB5, CB6,CB7
c	L1pr, Y56	CB3, CB6
d	L1ps, L2ps, L3p	CB4, CB5
e	L1ps, L2ps, L3p, Y56	CB3, CB5

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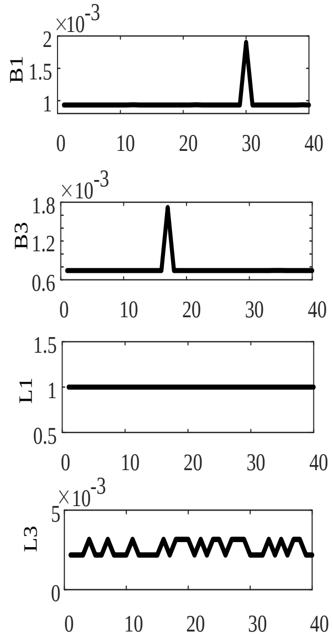

Fig. 4 Best individuals using continuous genetic algorithm

(c) Fault on one section with malfunctioning of protective device

There is malfunctioning of L1ps. Thus Y56 has actuated and tripped the breaker CB3. Relay L1pr at the receiving end of the feeder is actuated and the breaker CB6 operates. This pattern was not used for training. After minimization it is observed that only section L1 has final value greater than the limit on chromosome.

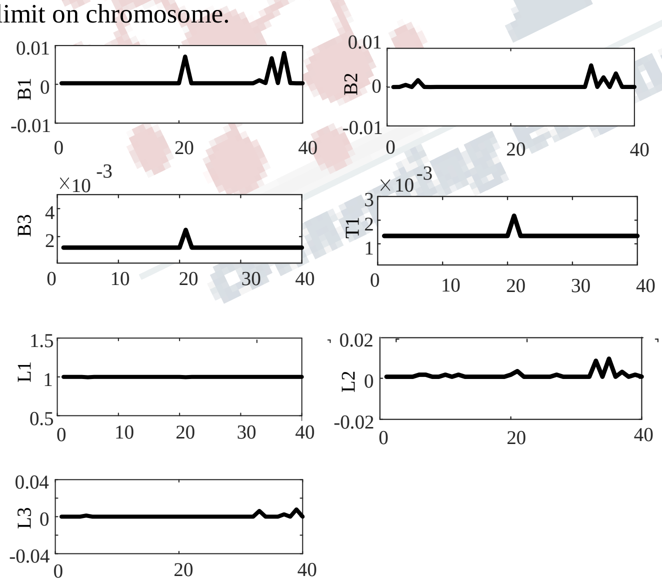

Fig. 5 Best individuals using continuous genetic algorithm

(d) Fault on one section with malfunctioning of protective device circuit breaker:

Here malfunctioning of CB8 is considered. L1ps operates and trips the breaker CB4. Primary relay L2ps is actuated and the breaker CB5 operates. Failure of breaker CB8 caused L1ps and L2ps to actuate. This pattern was used for training. Fitness function obtained for the above pattern is minimized using genetic algorithm. It is observed that only L1 and L3 have final values greater than the limit on chromosome. Though the fault sections obtained in this case are sections L1 and L3, the correct fault section i.e. L3 is not missed.

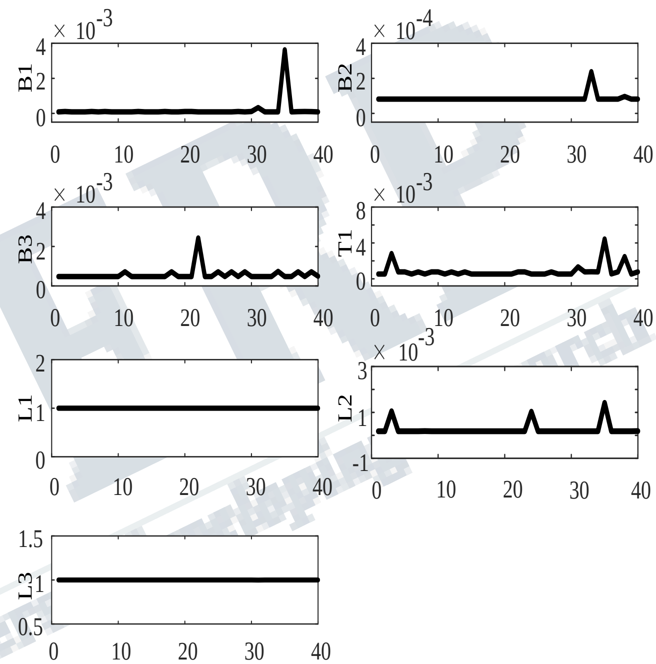

Fig. 6 Best individuals using continuous genetic algorithm

(e) Faults on two or more sections and malfunctioning of protective devices

Here malfunctioning of L1pr, CB4 and CB5 is considered. Due to failure of CB6, L1ps and L2ps are actuated. However, breaker CB4 failed to trip and back up K56 operates thereby tripping the breaker CB3. L2ps operates the breaker CB5. This pattern was not used for training. Here, L1 and L3 have values greater than the limit on chromosome.

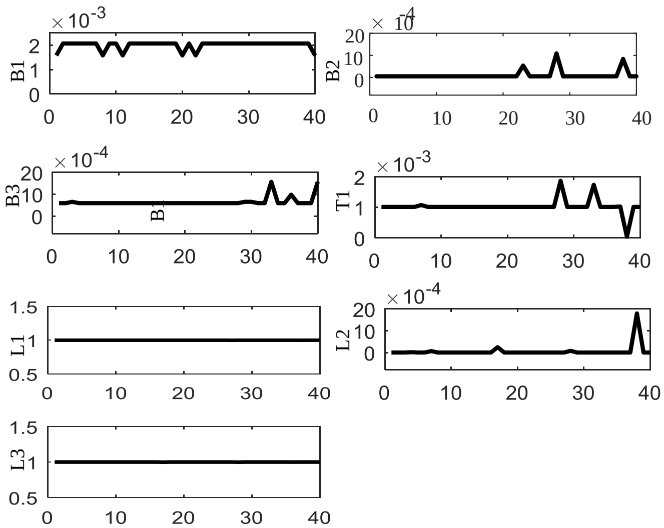

Fig. 7 Best individuals using continuous genetic algorithm

VI. CONCLUSION

Fault section should be predicted in minimum time to restore power. Genetic algorithm is used to find the fault section with the help of objective function which is formulated using the inputs from protective devices. Fitness function is formulated with the help of Hebb's learning rule. Results obtained imply that the system works suitably under different situations. Each fault section represents a variable. It is possible to construct the system based on available information from protective devices and the associated fault sections.

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