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Adaptive fault diagnosis of large interconnected power networks using genetic algorithms

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Abstract

One of the most important requirements of a power network is to provide reliable supply of power. Power system components such as buses, lines and transformers which are distributed geographically over a wide area are prone to faults because of environmental conditions, overvoltages and insulation failure. Modern power networks are becoming larger in size owing to the interconnection with neighbouring power systems. The satisfactory operation of such large interconnected power networks requires a fast and accurate fault diagnosis in the network. The breakthrough in information processing technology has led to the development of newer tools that are capable of solving complex problems. This paper reviews various techniques that have been tried on the fault diagnosis of electrical power systems and proposes a new method based on Genetic algorithms for adaptive fault diagnosis of large interconnected power systems.

Keywords: Power systems, fault diagnosis, expert systems, ANN and genetic algorithms

1. Introduction

Electric power systems comprise of a number of components such as buses, transformers and lines etc., which are distributed over a wide geographical area. The main objective of any power network is to provide a good quality of power without interruption. However faults are inevitable in the system because of

- Over voltages due to lightning and switching.
- Environmental conditions such as humidity, rain and pollution.
- Aging of equipments.
- Insulation failure at high stress regions.

Steady state operation of the power system is severely disturbed upon the occurrence of a fault. Faults are to be identified, by the operator very quickly based on signals derived from circuit breakers (CBs) and relays and have to be isolated. Modern power systems are very large in size because of interconnections with neighbouring power systems. Hence fast and reliable fault diagnosis is very much essential in the present day power systems.

Fault diagnosis is defined as the process of identifying, the faulted components such as buses, lines and transformers and their location upon the occurrence of a fault. Fault diagnosis may be classified as

- Fault diagnosis which is local to the power station or substation.

- Fault diagnosis which is global. i.e., the faulted components in the entire network is identified .

The fault at a point in the system causes a sequence of events i.e., tripping of relays followed by the tripping of breakers. The stream of signals from the circuit breakers and relays appear in the form of alarms at the control centres. The operator at the control centre has to diagnose these alarms in order to take any corrective action. Any wrong diagnosis will complicate the problem causing not only damage to the equipment but also power interruption over large areas. Present day control centres are equipped with Energy Management Systems (EMS) and Supervisory Control and Data Acquisition Systems (SCADA). The primary task of such systems is to identify the fault and its location before initiating any action. The diagnostic system faces challenges especially when

- alarms themselves are corrupted.
- simultaneous and multiple faults occur.
- When the system is largely interconnected and high speed diagnosis is required.

Traditional approach to fault diagnosis consists of interpretation of alarm arrival patterns by the skilled operator in the control centre. However when the number of alarms are large, interpretation of alarms will be difficult for the operator and hence this method fails for a large integrated network. Expert Systems (ES) nicely fit into the framework of fault diagnosis because it retains the same structure of traditional approach except that the operator is replaced by the computer. Although ESs have demonstrated higher level of performance than conventional approaches, they still have certain drawbacks such as knowledge acquisition and upgradation whenever the topology of the system changes. Artificial Neural Networks (ANN) are new computational paradigms which are capable of solving complex problems. Fault diagnosis of power systems is viewed as pattern classification problem using ANNs. The performance of ANNs mainly depends upon the size of the training set. It has been shown that for better performance a large number of training patterns are necessary. For a large power system generation of such a large training set requires good simulation tools and often this take a long time. Genetic algorithms (GA) are also new computational models which have been successfully applied to many optimization problems. GAs initially consist of a finite number of strings which represents a partial solution to the problem. The algorithm continues to evolve better solutions over generations with the aid of genetic operators. The fault diagnosis problem here is modified to fit the structure of GAs. Fault diagnosis is adaptive in the sense that the system upon getting the alarm signals from the SCADA continuously changes its solutions through the structured application of genetic operators until an optimal solution is obtained. In Section 2, we discuss the different methods of diagnosing power system faults. Section 3 introduces the Genetic Algorithms and our approach to the fault diagnosis of power systems. In Section 4, we discuss an example to illustrate the proposed approach.

2. Methods of fault diagnosis

Power system fault diagnosis can be accomplished using the following methods.

- Conventional approaches
- Expert systems
- Artificial neural networks

2.1. *Conventional approaches*

In the earlier approaches a table was prepared in advance which contains information such as operating relay, tripped CB, fault location and fault type. This table was scanned to pick up the fault location and type based on the CB and relay signal arrival patterns[1]. This type of diagnostic system works well for small systems. For large systems a large number of alarms arrive at the control centre and hence manual interpretation of them is difficult. This calls for automating the diagnostic systems.

2.2. *Expert systems for fault diagnosis*

The developments in artificial intelligence has opened up newer avenues for diagnostic problem solving[2]. Expert systems were found to be highly suited to this kind of application because the knowledge of the system can be easily transformed in to "IF .... THEN " type of constructs. Even though expert systems have achieved better performance they still have the following drawbacks.

- Collection of huge amount of system dependent data.
- Handling corrupted and missing signals.
- Inability to handle simultaneous and multiple faults.

2.3. *Artificial neural networks for fault diagnosis*

Artificial Neural Networks are new computational tools capable of solving complex problems. The ANNs are to be trained before it can be used for any application. Basically ANNs consist of a number of neurons that are connected together according to some pattern of connectivity. For example in some models the output of neurons from one layer is allowed to activate neurons in the next adjacent layer. However in some other models the signals are allowed to activate neurons in the same layer. In general a typical ANN can be represented as shown in Fig. 1. The neural networks must have a mechanism for learning. There are two types of learning

- Supervised learning
- Unsupervised learning

Supervised learning needs both the input and the desired output of the network while unsupervised learning uses only the input patterns. Both learning algorithms basically adjust the weights associated with the various interconnections and thus lead to the modification of the strengths.

The high speed processing and generalizing capability of the ANNs helped researchers generate pioneering work in the area of fault diagnosis of electric power systems[3,4]. Most of the papers have used model power systems and have employed traditional Back

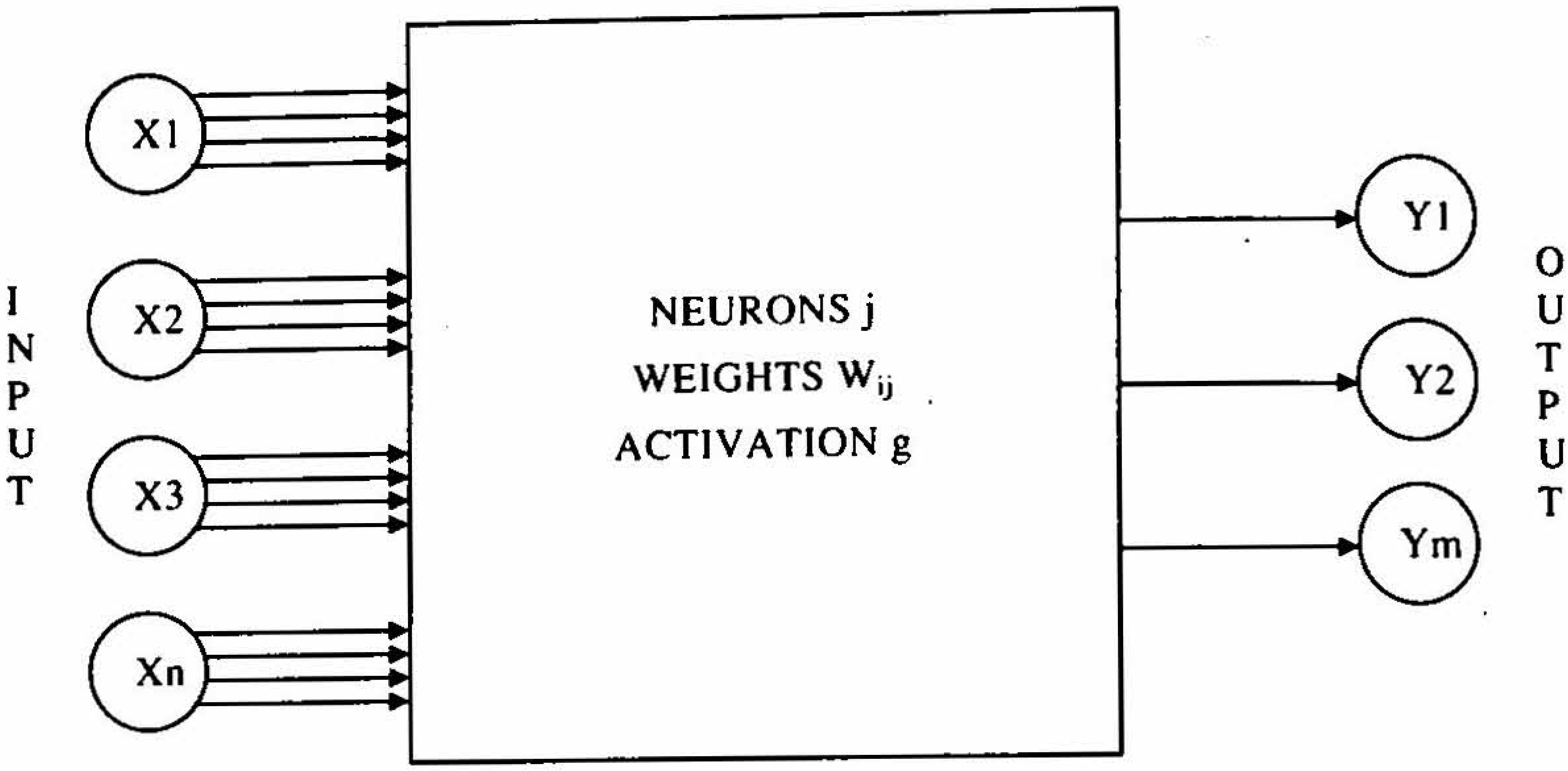

FIG. 1. General neural network architecture.

Propagation (BP) algorithms[5-9]. Only a few authors have proposed a modular neural network approach for the fault diagnosis of the power networks[10,11]. Kwang-Ho Kim *et al*[10] proposed a three-level hierarchical ANN for fault diagnosis of power systems. Hong-Tzer Yang et al[11] have proposed a new neural network approach to on line fault section estimation. They also propose a three level hierarchically organised ANNs. The first layer has several ANNs which are trained independently for different fault conditions such as

- fault at a point in the system but main relay operates.
- fault at a point in the system but only back up relay operates.
- fault at a point in the system but only remote relay operates etc....

Each ANN outputs a fault section code. The second layer also consists of ANNs which are trained independently in producing template patterns for every input fault section code. Thus the second layer produces the template symptom vector which is fed into the third layer of ANN. This layer produces correct diagnosis of the system. This model incorporates automatic training of new patterns.

A new concept for fault location is reported by E.Handschin et al[12]. They classify the entire power system into three classes such as bus coupler, power lines and transformer. An ANN was used for each of the classes to find which of the devices connected to it is at fault.

K. Bieler *et al*[13] have reported the evaluation of different AI methods for fault diagnosis especially from the point of view of uncertainties and inconsistent information. They propose Kohonens feature map and hidden Markov model for fault diagnosis.

In general fault diagnosis of large interconnected power networks at the control centre is highly complex. One of the problems with ANNs is the requirement of massive training data which is to be obtained through simulation. For large systems it is not trivial. Hence there is a need for a new method for the fault diagnosis of large power systems. Recently Genetic algorithms have emerged as new tools for solving complex problems. In the next section we propose a new method based on Genetic algorithms for adaptive fault diagnosis of large interconnected power systems.

3. Genetic algorithms

Genetic algorithms are heuristic search routines that are guided by a model of Darwin's theory of natural selection or the survival of the fittest. Here the fittest means the most highly ranked solution in a large solution space. The basic idea behind the genetic search strategy is to generate solutions that converge on the global maximum. GAs show some important characteristics that allow them to behave differently from traditional methods.

- GAs search for a function optimum starting from not a single one but a population of points of the function domain, this suggest that GAs are global search methods and that they can infact climb many peaks in parallel, reducing the possibility of finding a local minima, which is one of the drawbacks of traditional methods.
- GAs use information from the objective function not needing any information about the derivatives or any other auxiliary information.
- GAs use probabilistic transition rules during iteration and not deterministic ones.

The basic paradigm of a genetic algorithm is shown in Fig. 2. Genetic algorithms maintain a population of knowledge structures representing a candidate solution to a given problem. The initial population can be initialized using whatever knowledge is available on possible solutions. In the absence of such knowledge the initial population should represent a random sample of the search space. Each member of the population is evaluated and assigned a measure of its fitness as a solution. When each structure in the population has been evaluated, a new population of structures is formed in two steps. First, structures in the current population are selected for replication based on their relative fitness. High performance structures may be selected several times for replication, while poorly performing structures might not be chosen at all. In the absence of any other mechanisms , the resulting selective pressure would cause the best performing structure to occupy a larger and larger population of the knowledge base over time. Next, the selected structures are altered using genetic operators to form a new set of structures for evaluation. The primary genetic operator is the crossover operator, which combines two parent structures to form two similar offsprings. There are many possible crossover operators such as single point crossover, two point crossover, etc. For example, if the parents are represented by two strings $(a_1\ a_2\ a_3\ a_4\ a_5)$ and $(b_1\ b_2\ b_3\ b_4\ b_5)$ then crossover may produce the offsprings $(a_1\ a_2\ b_3\ b_4\ b_5)$ and $(b_1\ b_2\ a_3\ a_4\ a_5)$. A mutation operator alters one or more bits of the selected structures and provides a way to introduce new information into the knowledge base. The resulting offsprings are then inserted back into the population replacing older members. This procedure is repeated until an optimal solution is found. For more details refer Goldberg[19] and Davis[20].

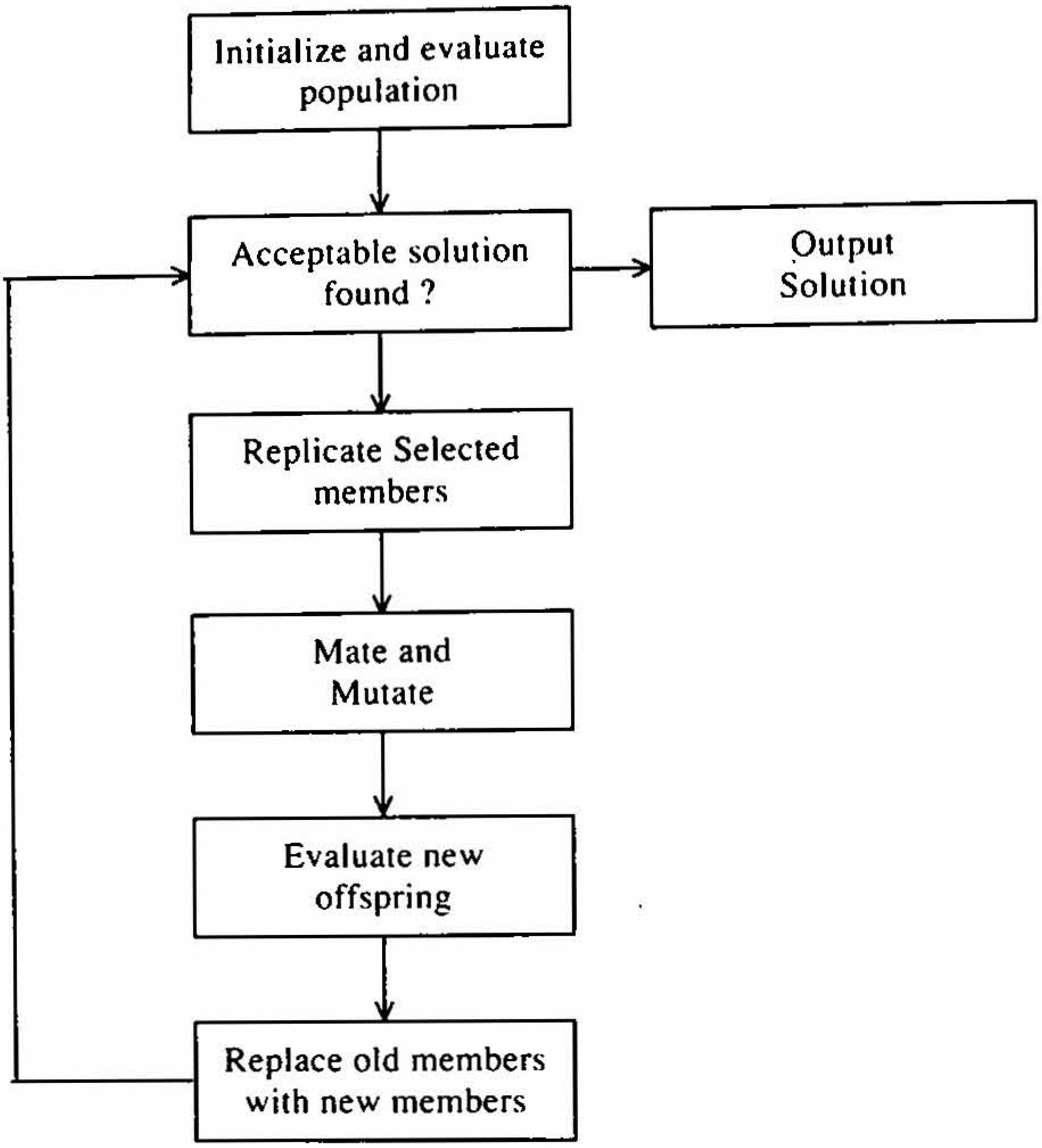

FIG. 2. Paradigm of a Genetic Algorithm.

3.1. *Adaptive fault diagnosis of interconnected power systems using genetic algorithms*

Genetic algorithms (GA) find optimal solutions in complex landscapes using directed random search. They have been used for solving optimization problems and also as classifier systems[14]. Peng and Reggia[15] suggested a Probablistic Causal Model (PCM) for diagnostic problem solving. Potter W.D et al[16–18] have developed a diagnostic system based on the Genetic algorithms. Their diagnostic system identifies multiple faults in communication networks. In our approach we use the same probabilistic causal model as suggested by Peng and Reggia[15] for diagnosing faults in power networks. Any large power system is composed of many subsystems which are generally identified as regional control centres. In our approach we derive the status of relays and circuit breakers of each subsystem as an unsigned binary string having a positional semantic *i.e.*, a '1' represents either opening of a CB or triggering of a relay and a '0' represents normal condition. This constitutes the symptom vector for each subsystem. These symptom vectors are obtained at regular intervals of time. Since our objective is to find the global status of the network we have implemented on a parallel machine. The GA running on different

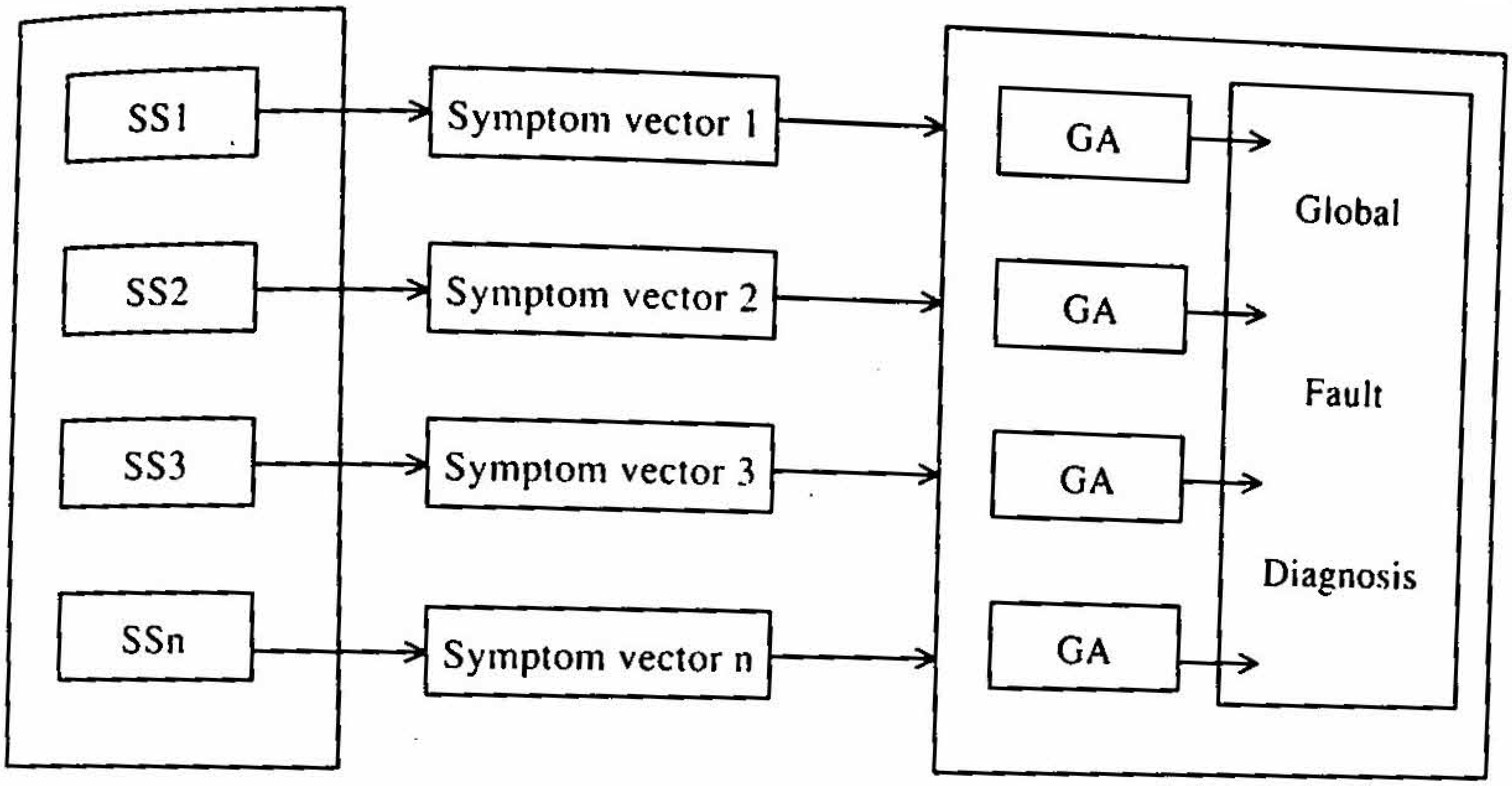

FIG. 3. The diagnostic system.

processors can take the symptom vectors of various subsystems in parallel and output the fault code. The fault code of each subsystem is then analysed to indicate the global status of the entire power network. The diagnostic system is shown in Fig. 3. The standard genetic algorithm has the following components.

- A population of binary strings.
- A fitness function.
- A selection mechanism.
- Genetic operators.

The population in our case are binary strings where each bit in the string identifies a particular component being faulted or not. Fig. 5 shows the binary string and the structure of the alarm pattern is shown in Fig. 6. where each bit has a value '1' if the component it is representing is faulted, otherwise a value of '0'. So the strings in the population represent the status of the components in the subsystem. We can use the seeding policy to pick up one solution that is close to the observed symptom vectors. Remaining members of the population are generated randomly.

The PCM model is used to compute the fitness function of each chromosome. The fitness function measures the likelihood of a component being faulted. The fitness function is given by

$$L\left(DI, M^{+}\right) = L_1 L_2 L_3 \tag{1}$$

$$L_1 = \prod_{m_i \in M^{+}} \left(1 - \prod_{d_j \in DI} \left(1 - c_{ij}\right) \right) \tag{2}$$

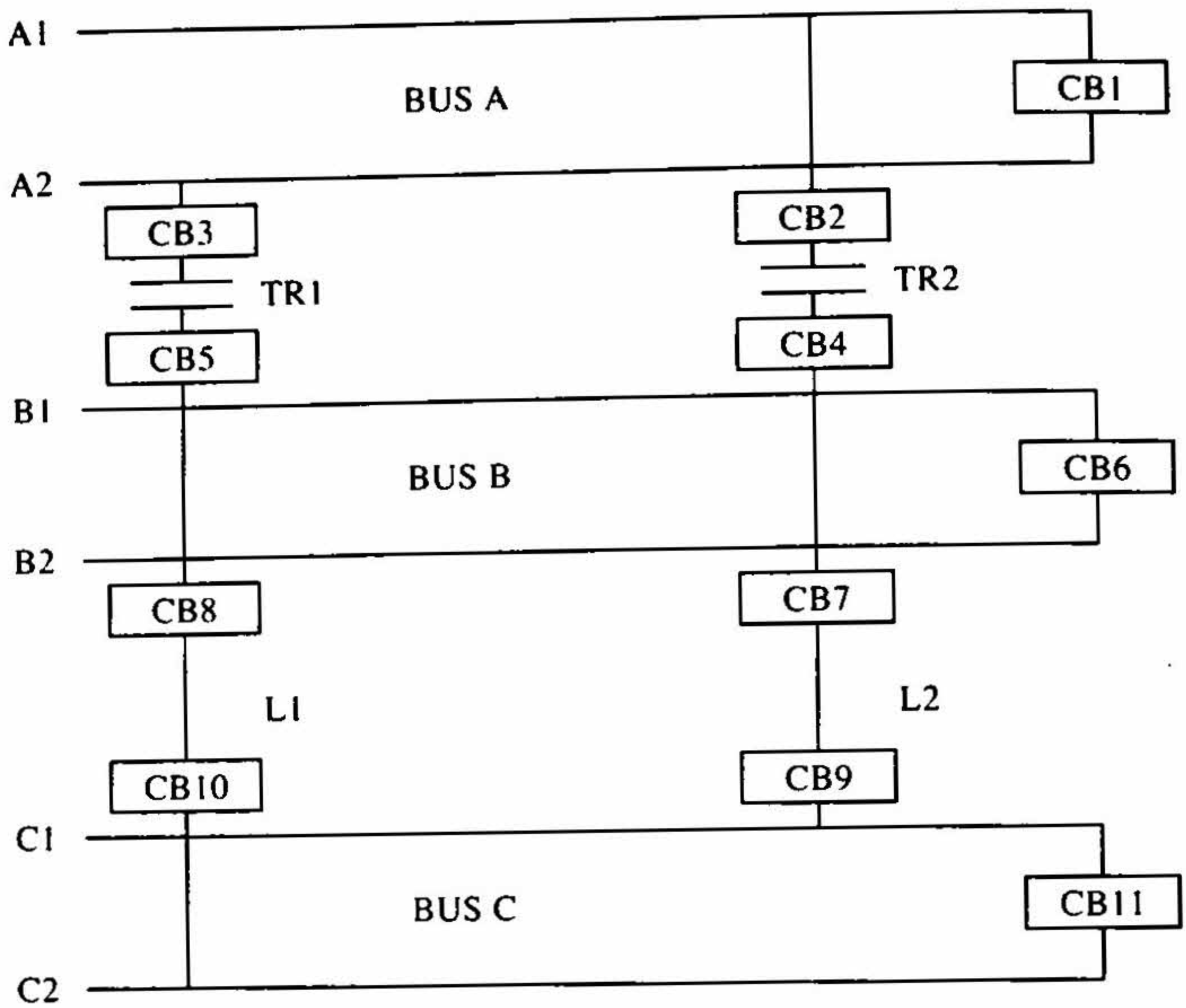

FIG. 4. Model power system.

$$L_2 = \prod_{d_i \in DI} \prod_{m_i \in M^-} \left(1 - C_{ij}\right) \tag{3}$$

$$L_3 = \prod_{d_i \in DI} \left(\frac{P_j}{1 - P_j}\right) \tag{4}$$

Where

DI is a set of faulted components.

d_j is jth component in DI.

M^+ is the set of available symptom vectors.

M^- is the set of unavailable symptom vectors.

C_{ij} is a fixed causal strength.

P_j is the apriori probability that the component j is being faulted.

The tendency matrix C comprises of elements C_{ij} which represents a causal relation between the faulted component d_j and symptom vectors m_i. The elements of the tendency matrix are filled in advance based on the heuristics that govern the possibility of a component being faulted and its observed symptom vectors. The values in the tendency ma-

CB 1	CB 2	CB 3	CB 4	CB 5	CB 6	CB 7	CB 8	CB 9	CB10	CB11	A_1M	A_2M	B_1M	B_2M

C1M	C2M	T1 M	T1 B	T1 R	T2 M	T2 B	T2 R	L1B M	L1B B	L1B R	L1C M	L1C B

L1C R	L2B M	L2B B	L2B R	L2C M	L2C B	L2C R

FIG. 5. Structure of the alarm string.

trix are fixed. The value of the fitness function thus depends upon the observed signals from relays and CBs and the elements of the tendency matrix. Chromosomes with higher fitness values are copied into a mating pool. Crossover is performed on the selected chromosomes. A Mutation is applied depending upon its probability and eventually old chromosomes are replaced by the newly created chromosomes. This process is repeated until the terminating condition is satisfied.

4. Illustration

In order to illustrate the proposed technique we consider a small subsystem shown in Fig. 4. It consists of 6 bus sections, 2 transformers and 2 transmission lines. The protective system consists of 11 circuit breakers and 24 relays. Thus the alarms for this system can be considered as an unsigned binary string of dimension 35 where each bit in the string has a positional semantic with a value 0 or a 1. The chromosomes or structures represent the status of the components of the power system. Thus each chromosome has a length of 10 where each bit has a position semantic and has either a 0 or a 1 in its place. Here a 1 indicates that the particular component is faulted and a 0 indicates normal status. For the model power system 50 alarm patterns are generated each of which indicates a particular fault in the system. We have used these alarm patterns for evaluating the performance of the diagnostic system. It has been found that the GA at convergence produces correct solutions. A typical snap shot of a GA run for a fault at bus section A2 is shown in the table. The parameters of the simulation are, Cross over rate = 0.65, Mutation rate = 0.0005. It can be seen that the Genetic Algorithm correctly identifies the faulted component.

5. Conclusion

In this paper we have reviewed the different techniques that have been used for fault diagnosis of an electrical power system. For larger systems the performance of the expert systems deteriorates and changes in the system cause significant changes in the expert knowledge which will have to be updated again and again. ANNs require training of massive data. A Genetic Algorithm based fault diagnosis technique that can be easily

A1	A2	B1	B2	C1	C2	T1	T2	L1	L2

FIG. 6. Structure of the chromosome.

ALARM PATTERN 1010000000001000000000000000000000			
DIAGNOSIS: FAULT AT BUS SECTION A2			
	GEN #1	GEN #10	GEN #22
1	1101010000	0000100000	0000000010
2	1100010001	0001100100	0100000000
3	1100000011	0000110000	0100000000
4	1100101110	0001110010	0100000000
5	1000100011	0001110000	0101000000
6	0111100110	0100100000	0100000000
7	0101100001	0000100000	0100000000
8	1111000100	0000100010	0100000000
9	0001110000	0000100000	0100010000
10	0011011001	0001100000	0100000000
11	0000111100	0000100000	0100000000
12	0000001000	0000100000	0100000000
13	1001100111	0000100000	0100000000
14	1110010010	0001101000	0100000000
15	0010001101	0000110000	0100000001
16	1001001110	0000100000	0000000101
17	1001110111	0100010000	0100000000
18	1100001000	0000100000	0100000000
19	0111001011	0000101011	0100000000
20	0100110110	0000100000	0101001000
21	1011001110	1100100000	0100000000
22	1010101000	1000100000	0100001000
23	0011010000	0000101000	0100000000
24	1001001101	1000101100	0100000000
25	1100101010	0000100000	0100000000

FIG. 7. Snapshot of the diagnostic system for fault on Bus section A2.

extended to large interconnected power networks is proposed in this paper. The result obtained on the model power system shows that an elegant way of fault diagnosis is possible with Genetic algorithm. The probability of getting accurate solutions increases with better understanding of the causal relationship between the alarms and the corresponding faults. One of the distinguishing features of the proposed diagnostic system is that, when a new alarm pattern arrives during a GA run, it can be easily incorporated in the next immediate generation of the GA run. Thus it is possible to obtain most recent status of the network with this system. The performance analysis of the diagnostic system on:

- Different ranking strategies
- Variations in the numerical values of the tendency matrix
- Different crossover and mutation rates
- Large string lengths

is under progress.

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