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A learning Automaton-Based Approach for Power loss Minimization and Voltage Profile Enhancement in large-Scale Distribution Systems

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Abstract

The reconfiguration problem consists of finding a new network topology with minimal power losses, while all the system constraints such as radial structure, lines power flow below capacity limits, node voltage magnitude within limits and all nodes connected are satisfied. This is a combinational optimization problem where the aim is to specify the final status of all switches (open/closed,) in a large-scale distribution system. Although there are a plenty of methods in the literature, but comprehensive analysis of bus and line failure has not been accomplished and just a limited version of failure has been studied. This paper presents a learning automaton-based algorithm for reconfiguration of large-scale distribution systems with assumption of probabilistic failure in both of the buses and lines. The main objective of the proposed algorithm is to minimize the power loss and voltage deviation, and also to maintain the distribution system in radial structure. To demonstrate the applicability of the proposed algorithm, it is tested on two standard IEEE sample systems and the obtained results are compared with other methods. Also, the numerical result indicates that the proposed method supplying power to the non-faulted areas with minimal power loss and maintains the radial structure of distribution system under abnormal conditions.

Keywords: network reconfiguration, radial distribution system, learning automata, power loss minimization, voltage profile enhancement, IEEE 33-bus distribution system.

1. Introduction

Distribution systems are developed to satisfy the customer demands in a reliable and more economical manner. During unexpected forced failure of buses and lines, the system operators require to reconfigure the system by checking the status of the different switches in order to improve the system efficiency.

Generally, distribution systems are reconfigured for loss minimization, load balancing and service restoration. In this sense, the better performance of distribution systems can be achieved by modifying the open/closed status of the different switches in order to transfer load between feeders. By balancing loads between feeders, the power losses are reduced and the voltage deviation is improved. Therefore, the distribution system reconfiguration (DSR) problem is the process of finding a new radial structure with minimal power losses, while all the system constraints are satisfied. This is a combinational optimization problem where the aim is to specify the final status of all switches in a large-scale distribution system [30, 32].

In last two decades, many researchers challenged with the DSR problem by the aim of power loss minimization and/or voltage profile improvement. Merlin et al. [1] used a branch and bound-type optimization technique to solve the DSR problem for loss reduction for the first time. The most important disadvantage of their method was its computation time. Shirmohammadi et al. [2] improved this method by opening the switches with the lowest current to find the optimal system configuration. Glamocamin et al. [3] and Sarfi et al. [4] used heuristic techniques, in order to solve the DSR problem. A heuristic nonlinear constructive method has been developed by McDermott et al. [5] for solving DSR problem. Ferdavani et al. [6] had solved the reconfiguration problem for loss reduction using minimum-current neighbour-chain updating methods. Khodr et al. [7] presented a new method for DSR problem for loss minimization and load balancing. Jazebi et al. [8] used differential evolution algorithm for solving the DSR problem to increase power quality issues such as voltage sags.

Later on, several optimization methods like fuzzy adaptation evolutionary programming[9,33], fuzzy mutated genetic algorithm [10], Refined Genetic Algorithm (RGA)[11], binary particle swarm optimization[12,31], plant growth simulation algorithm [13], Harmonic Search Algorithm (HSA)[14, 15] and rainfall optimization method [34,35] had been presented to solve the DSR problem with various objectives. In the many recent researches, discrete artificial bee colony [16,29] and particle swarm optimization [17] based approach had been proposed to solve the DSR problem. Torres et al. [18] proposed a new genetic algorithm based on the edge window decoder technique to solve the DSR problem. The main advantage of this method is ensuring the radial structure of distribution system and facilitates the use of efficient genetic operators.

Although all the above introduced researches are have gained promising results, but they also have some shortcoming such as computation time in reconfiguration large scale systems, convergence speed and are not implemented under abnormal condition of distribution system.

Sathish kumar et al. [19] assumed a variety of fault at a bus in solving the DSR problem. But the optimal solution gained was not satisfying the radial nature. [20] proposed a new Fireworks Algorithm for reconfiguration of the radial distribution system with aim to minimize the power loss and voltage deviation. Like [19] this research assumes a variety of fault at a bus and furthermore some failures in the lines.

Regarding the literature, just a few of the methods [19, 20] have analysed the DSR problem under abnormal conditions. That is, failures of lines and buses in the system have not been broadly analysed. Even in [19, 20], it is assumed that failure happens in some non-critical lines which are far from the source node.

In this paper, failure of busses and lines has been studied in a comprehensive manner under probabilistic nature which is the case in the real world. Based on such an assumption, all the lines and busses may be failed with equal probability. An algorithm based on learning automaton is proposed for solving the DSR problem. The main objective is to minimize the power loss and voltage deviation, while maintaining the radial nature of the distribution system. The novelty of this work lies in the implementation of learning automata-based algorithm for solving the combinational reconfiguration problem under critical failure conditions which according to the literature, has not been investigated by now. The proposed algorithm is simulated to solve two benchmark IEEE test systems, IEEE 33-Bus and IEEE 119-Bus, and the results obtained are compared with outstanding results which achieved by the state-of-the-art researches.

2. Problem Definition

In this paper, the DSR problem is solved to minimize the system power loss and voltage deviation while electrical constraints are met, that is the process of modifying the topological structures of distribution system by changing the open/closed status of switches so as to minimize total system real power loss and voltage deviation.

A set of feeder-line flow formulations is utilized. Considering the single-line diagram in Fig. 1, the following set of recursive equations is used to compute power flow [21]

$$P_{i+1} = P_i - P_{Li+1} - R_{i,i+1}[(P_i^2 + Q_i^2)/|V_i|^2] \quad (1)$$

$$Q_{i+1} = Q_i - Q_{Li+1} - X_{i,i+1}[(P_i^2 + Q_i^2)/|V_i|^2] \quad (2)$$

$$|V_{i+1}|^2 = |V_i|^2 - 2\left(R_{i,i+1}P_i + X_{i,i+1}Q_i\right) + ({R^2}_{i,i+1} + {X^2}_{i,i+1})[(P_i^2 + Q_i^2)/|V_i|^2] \quad (3)$$

In the above equations, P_i and Q_i are the real and reactive powers that flow out of bus i, and P_{Li} and Q_{Li} are the real and reactive load powers in bus i. The resistance and reactance of the line section between buses i and $i+1$ are represented by $R_{i,i+1}$ and $X_{i,i+1}$, respectively.

The power loss of the line section that connects buses i and $i+1$ is

$$P_{Loss}(i, i+1) = R_{i,i+1}[(P_i^2 + Q_i^2)/|V_i|^2] \quad (4)$$

$P_{F,loss}$ Is the power loss of the feeder and calculated by summing the losses of all line sections of the feeder, given by

$$P_{F,Loss} = \sum_{i=0}^{n-1} P_{Loss}(i, i+1)$$
$$P_{F,Loss} = \sum_{i=0}^{n-1} P_{Loss}(i, i+1) \quad (5)$$

$P_{T,loss}$ Is the total system power loss and calculated by summing the losses of all feeders in the system.

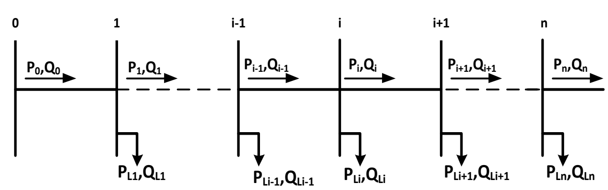

Fig. 1. Single-line diagram of a main feeder

One of the main advantages of the distribution system reconfiguration is the decline in voltage deviation. The voltage deviation index (ΔV_D) can be defined as

$$\Delta V_D = \max\left(\frac{V_{source} - V_k}{V_{source}}\right) \forall \quad k = 1,2,\dots,n \quad (6)$$

During network reconfiguration, the proposed algorithm will try to minimize the ΔV_D closer to zero.

The objective function of the DSR problem is given as

$$\text{Minimize } f = \min(\Delta P_{TL}^{R} + \Delta V_D) \tag{7}$$

Where ΔP_{TL}^{R} is taken as the ratio of total power loss before and after reconfiguration of the system.

Subjected to the voltage magnitude at each bus must be maintained within limits. The current in each line must satisfy the line's capacity. These constraints are represented in as follows:

$$V_{i,min} \leq |V_i| \leq V_{i,max} \tag{8}$$

$$|I_i| \leq I_{i,max} \tag{9}$$

In the above equations, $|V_i|$ is voltage magnitude of bus i. $V_{i,min}$ And $V_{i,max}$ are the minimum and maximum voltage limits of bus i. $|I_i|$ And $I_{i,max}$ are the current magnitude and maximum current limit of line i.

3. Learning Automata

Learning Automata are adaptive decision-making tools operating on unknown random environments. A Learning Automaton has a finite set of actions. Each action has a certain probability and is evaluated by the environment. The results of evaluation are sent to automaton as a negative or positive signal. Each action gets reward by this signal. The aim is to learn to select the optimal action (i.e., the action with the highest probability of being rewarded) via repeated interaction on the environment. If the learning algorithm of automata is chosen properly, then the iterative process of interacting on the environment can be lead to result in selection of the optimal action. Fig. 2 illustrates how a learning automaton works in feedback connection with a stochastic environment. Learning Automata can be classified into two main categories: fixed structure learning automata and variable structure learning automata [22]. In the rest of this section, the VSLA which will be used in this paper is explained.

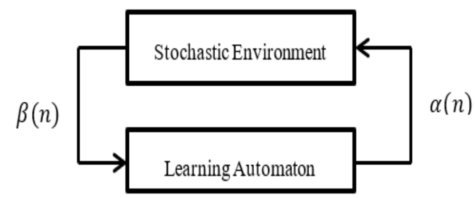

Fig. 2. The interaction between learning automata and environment

A VSLA is described as $< \alpha, \beta, p, T(\alpha,\beta,p) >$ where α is an action set with r actions, β is an environment response set and p is the probability vector containing r probabilities, each being the probability of performing every action in the current internal automaton state. The function of $T(\alpha,\beta,p)$ is the reinforcement algorithm, which update the action probability vector p regarding to the performed action and received response. If the response of the environment takes 0 (favorable response) or 1(unfavourable response) the environment model is P-model and if it takes more than two values in the interval$[0,1]$, the environment model is referred to as Q-model, and when the response of the environment is a continuous variable in the interval$[0,1]$, it is referred to as S-model. Let $\beta \epsilon [0,1]$, a general linear schema for updating action probabilities can be represented as follows. Assume action i be performed then:

$$p\_j\ (n+1) = p\_j\ (n) + \beta(n)[b/(r-1) - bp\_j\ (n)] - [1 - \beta(n)]ap\_j\ (n) \quad \forall j \quad j \neq i \tag{10}$$
$$p_i(n+1) = p_i(n) + \beta(n)[bp_i(n)] + [1-\beta(n)]a[1 - p_i(n)]$$

In Eq. (10) a and b are reward and penalty parameters. When $a = b$, the automaton is called L_{RP}. If $b = 0$ the automaton is called L_{RI} and if $0 < b << a < 1$, the automaton is called $L_{R\varepsilon P}$. For more Information about learning automata the reader can refer to[22].

4. Description of the Proposed Method

Generally, in solving the DSR problem the switch is chosen as the decision variable. It can be assigned either a value 0 or 1, meaning open switch or closed switch, respectively. But such manner will appear a lot of unfeasible solution in reconfiguration process. In a distribution system, the number of independent loops is the equal with the number of tie switches; the problem of network optimization is same as the problem of chosen a suitable tie switch for each loop so that the system power loss can be minimized. We propose a method to obtain an optimum configuration in distribution system using learning Automata. In the following subsections, we describe the proposed method.

4.1. Learning Automata Model

Fig. 3 shows the schematic of the learning automata model used for distribution systems reconfiguration. This model is constructed by associating every loop i in the distribution system with a variable structure learning automaton and represented by a 3-tuple$(\alpha(i), \beta(i), LA(i))$. Each action of $LA(i)$ is associated with a switch in loop i, and the number of its actions is equal with the number of switches in loop i.

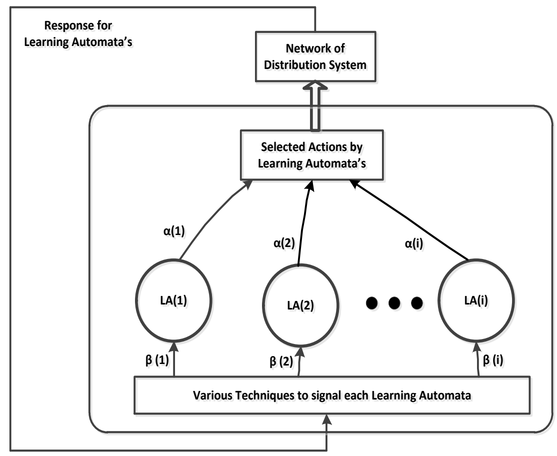

Fig. 3. Learning automata model for reconfiguration

To illustrate the proposed model, consider a 33-bus sample distribution system shown in Fig. 4, which consists of 32 sectionalizing switches and five tie switches. The sectionalizing switches are represented by straight lines and initial tie switches by dotted lines.

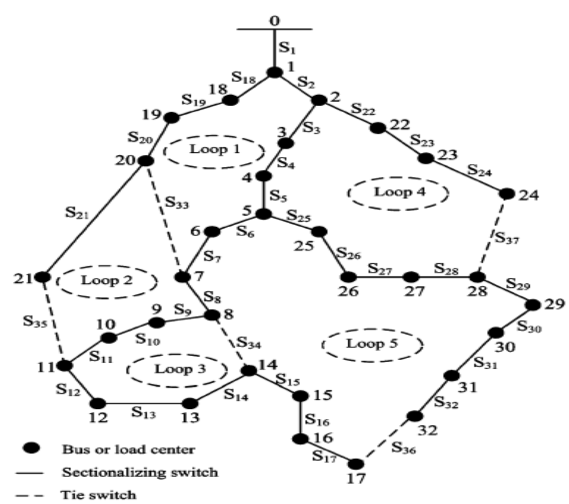

Fig. 4. The 33-bus sample system with loop numbers

The basic procedure for constructing learning automata model is as follows: 1) close all of the tie switches and determine the loops in system; 2) associate one learning automaton for each loop and determine its actions set. For example, we associate $LA(1)$ for loop 1 with action set $\{S_2, S_3, S_4, S_5, S_6, S_7, S_{18}, S_{19}, S_{20}, S_{33}\}$(assume $LA(1)$ selects action S_7 in configuration process, it means that the switch S_7 in loop 1 is opened). In the same way, we can also associate$LA(2)$,$LA(3)$,$LA(4)$ and $LA(5)$ for other loops. $\beta(i)\epsilon[0,1]$ And represents the environment response, where $\beta(i)$ closer to 0 represent that the action taken by the automaton of loop i is favorable to the system and closer to 1 represent an unfavorable response.

By chosen independent loops as decision variables, the dimension of decision variables is greatly decreased. It, however, cannot avoid the cases to appear unfeasible configuration in the iterative procedure. In our proposed method, to avoid the appearance of unfeasible configuration, we use the following case: Some switches, which belong to the same two or possibly more independent loops, are interrelated. In a feasible configuration, only one of the interrelated switches can be in open state; otherwise, there will appear isolated islands in the corresponding network. In Fig. 4, switches S_9, S_{10} *and* S_{11} belong to both loops 2 and 3, so they are interrelated. If the solution of $LA(2)$ is S_9, then the solution of $LA(3)$ cannot be the S_{10}, S_{11}. In our proposed method, to avoid the cases to appear unfeasible configuration, the interrelated switches only assigned to one of $LA(2)$ and $LA(3)$ in probabilistic manner.

$$\beta^n(i) = 1 - \left(f\left(P_{T,loss}^{n-1}, P_{T,loss}^{n}\right)\beta_L + f(\Delta V_D^{n-1}, \Delta V_D^{n})\beta_V\right) \quad (11)$$

$$where\ \beta_L + \beta_V = 1$$

At each iteration of the proposed method, the learning automata's selects a switch must be opened, and the new configuration is obtained. Then power loss and voltage deviation is calculated after executing a load flow run [23]. The constraints have been checked for radial characteristic, network connectivity, branch capacity, bus voltage and found within an acceptable tolerance. Fig.5 shows the general procedure of the proposed method.

4.2. Evaluating the response of environment

The goodness of an action chosen by an automaton determined with considering difference in power loss and voltage deviation index at each iteration with their values in the previous iteration. The environment interpreted as Q-model; therefore$\beta^n(i) \in [0,1]$. Power loss at iteration n may be greater, less than, or equal to its value at iteration $n-1$. Similarly, voltage deviation index at iteration n may be greater, less than, or equal to its value at iteration $n-1$. Therefore, regarding to power loss and the voltage deviation index in two consecutive iterations, nine states are possible and $\beta^n(i)$ is calculated by

Where β_L represents rewarding value as far as power loss is concerned, and β_V represents rewarding value as far as voltage deviation index is concerned. The greater the β_L the more impact of difference in power loss in evaluation of $\beta^n(i)$ will be. Similarly, the greater the β_V

the more impact of difference in voltage deviation index in evaluation of $\beta^{n}(i)$ will be. Function $f(a,b)$ determines the rewarding policy and defined as follow

$$f(a,b)=\begin{cases}0 & if\ a<b\\ 0.5 & if\ a==b\\ 1 & if\ a>b\end{cases} \tag{12}$$

In the proposed method, policy of rewarding is as follows: decrease in power loss and voltage deviation index is associated with full reward, no change in power loss and voltage deviation index is associated with half reward and increase in power loss and voltage deviation index is associated with no reward.

Learning Automata based Reconfiguration Algorithm

Begin

Close all tie switches and determine the loops in system.

Assign one Learning Automata for each loop, determine its actions set and initialize the its probability vector. //LA (1), LA (2), …, LA(i)

While no change in power loss is made for 100 consecutive iterations **do**

$n=n+1$ // n is the number of iterations

For each LA(i) do

LA(i). select Action ();

Execute load-flow run on new configuration, check the system constraint and calculate the parameters;

For each LA(i) do

Evaluate the response of environment (β(i)) according to Eq. (12);

Update probability vector of LA (i) according to the β(i) ;

End

Fig. 5: General procedure of proposed method

5. Test Results and Discussions

The computer program has been developed in MATLAB environment to evaluate the efficiency of the proposed method. A 33-bus sample system and a real large-scale system with 119 buses are tested using the proposed method. The learning automata model used in the experiments is L_{RI} with a=0.001 and $\beta_L=0.8$, $\beta_V=0.2$.

In the experiments, two various abnormal cases are also considered to evaluate the ability of the proposed method. The test system is reconfigured assuming a variety of fault at a bus (i.e., the reconfiguration process is done by separating the faulted bus). Also, the test system is reconfigured assuming a variety of fault at a line (i.e., the reconfiguration process is done by disconnecting the faulted lines). In this paper, failure of busses and lines has been studied in a comprehensive manner under probabilistic nature which is the case in the real world. Based on such an assumption, all the lines and busses may be failed with equal probability.

5.1. 33-bus distribution system

This is a 12.66 kV radial distribution system with 33 buses. The line and load data of this test system are taken from [21]. It consists of 32 sectionalizing switches and five tie switches. The normally open tie switches are $S_{31}-S_{37}$, and the normally closed sectionalize switches are S_1-S_{32}. The single line diagram of 33-bus system is shown in Fig. 4. The total real and reactive power loads of the system are 3.72MW and 2.3 MVAr, respectively. The total real and reactive power losses for the initial case calculate from power flow run are 202.67 kW and 135.14 kVAr, respectively. The minimum voltage magnitude of the system is 0.9131 occurs at bus 18.

The optimal configuration of 33-bus system obtained by the proposed method is 7, 9, 14, 37 and 32. The total power loss and minimum voltage magnitude of the system for the optimum case is139.5 kW and 0.9381p.u. It is observed that about 31.14% of total power loss has been reduced and also the minimum voltage magnitude has been improved from 0.9131 to 0.9381, after reconfiguration by learning automata.

In order to evaluate the efficiency of the proposed method, the simulated results are compared with the results of other methods like NSGA[27], HSA[14], FWA[20] and EWD-Reconfig[18] available in the literature. To avoid inessential inconsistency, the configuration obtained by other methods are executed by the developed power flow program and presented in Table 1. The results presented in Table 1 indicate that the proposed method has outperformed FWA and HSA in terms of power loss minimization.

Table 1 :result obtained for 33-bus distribution system

	Lines switched out	$P_{T,loss}$	ΔV_D	V_{worst}	% Loss reduced
Base Case	33,34,35,36,37	202.67	0.0869	0.9131	-
NSGA [27]	7,9,14,32,37	139.55	0.0622	0.9378	31.14
HSA [14]	7,14,10,36,37	146.63	0.0664	0.9336	27.65
EWD-Reconfig [18]	7,9,14,32,37	139.55	0.0622	0.9378	31.14
FWA [20]	7,14,9, 32,28	139.98	0.0587	0.9413	31
Proposed method	7,9,14,37, 32	139.55	0.0622	0.9378	31.14

The voltage profiles of the 33-bus system for initial case and optimum case obtained by the proposed learning automata-based method shown in Fig. 6. From the Fig. 6, it is observed that the voltage profile at all buses has been meliorated after reconfiguration.

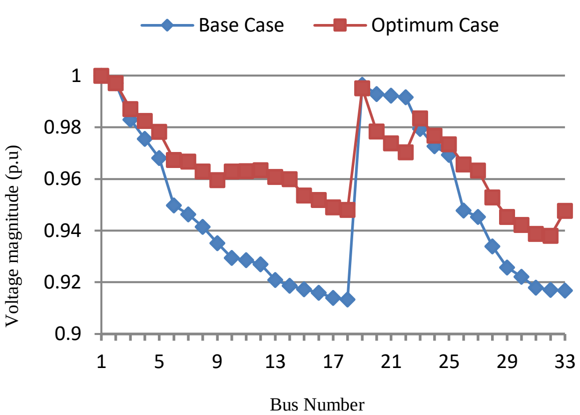

Fig. 6. Comparison of voltage magnitude of 33-bus system.

Fig.7 shows the power loss in each line of 33-bus system for initial case and optimum case obtained by the proposed method. From the Fig., it is observed that the losses in almost every line is degrade, except at some lines (18, 19, 20 and 21), where the losses are increased because of shifting of loads onto these buses.

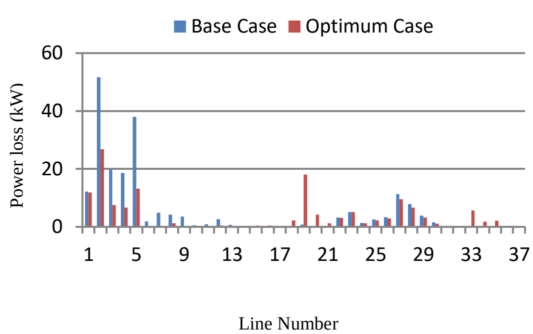

Fig. 7. Comparison of power loss at each line of 33-bus system.

In order to demonstrate the convergence of the learning automata model, the convergence characteristics of the proposed method for exploration the best solution are shown in Fig. 8. It is observed that only 2000 iteration is required, which takes less than 17 second.

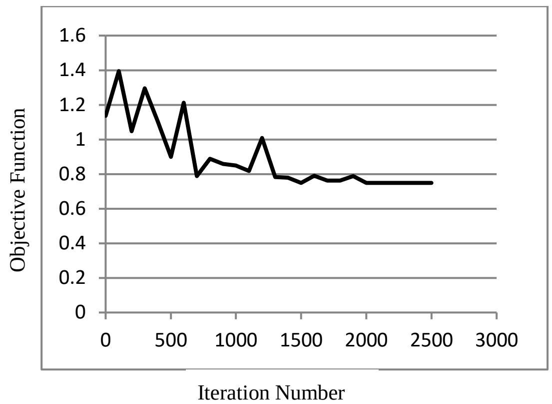

Fig. 8. Convergence characteristics of learning automata model for 33-bus system.

In order to analyse 33-bus distribution system under abnormal conditions, the failure rate of the buses and lines for this system is considered as 0.03. For cases which the buses are fail, the system is reconfigured by isolating the faulted bus, i.e., by disconnecting the lines connected that bus. In order to demonstrate the ability of the proposed method when some buses are failing, the simulated results for ten different cases are presented in Table 2. From Table 2, it is observed that the proposed method supplies power to the non-faulted areas and satisfies the radial structure of distribution system with minimal power loss.

Table 2: Experiment results of 33-bus system for different cases (faulted bus)

Item	Faulted bus	$P_{T,loss}$	% Loss reduced	V_{worst}	(node)	ΔV_D
Case1	13	130.971	26.19	0.938157	31	0.0625
Case2	9	135.758	29.51	0.938096	31	0.0626
Case3	23	157.474	33.56	0.925581	31	0.0796
Case4	3	165.226	54.03	0.936511	17	0.0680
Case5	6	126.778	12.49	0.94197	31	0.0588
Case6	21	147.096	26.81	0.938111	31	0.0649
Case7	31	116.423	31.94	0.947909	32	0.0554
Case8	27	137.603	19.34	0.941663	31	0.0585
Case9	25	145.673	17.44	0.938497	31	0.0616
Case10	29	120.475	34.18	0.920546	30	0.0830

Similarly, the simulated result for ten different cases (when some lines are failing) is presented in Table 3. From the table, it is observed that the proposed method supplies power to the non-faulted areas and satisfies the radial structure of distribution system with minimal power loss.

Table 3: Experiment results of 33-bus system for different cases (faulted lines)

Item	Faulted line	$P_{T,loss}$	% Loss reduced	V_{worst}	(node)	ΔV_D
Case1	6	142.587	19.67	0.939571	33	0.064
Case2	8,24	178.718	7.84	0.925693	32	0.0746
Case3	12	145.943	26.03	0.937822	33	0.0657
Case4	13,32	143.042	36.94	0.938046	32	0.0627
Case5	17	146.148	27.76	0.932795	18	0.0672
Case6	10,28	140.637	3.54	0.94138	32	0.0588
Case7	26	147.771	18.15	0.938206	32	0.0619
Case8	31	142.342	34.61	0.925276	32	0.0799
Case9	30	155.980	34.35	0.916681	31	0.0863
Case10	5	163.685	12.09	0.937697	18	0.0667

5.2. 119-bus distribution system

To verify the applicability of the proposed method in large-scale distribution systems, it is tested on this large scale, 11kV practical radial distribution system with 118 sectionalizing switches ($S_1 - S_{118}$) and fifteen tie switches ($S_{119} - S_{133}$). The initial configuration, line and load data of this system are taken from [28]. The total real and reactive power loads of the system are 22.7097MW and 17.0411MVAr, respectively. The total real and reactive power losses for the initial case calculated from power flow run are 1298.09 kW and 978.84kVAr, respectively. The minimum voltage magnitude of the system is 0.868893 p.u. occurs at bus 78.

The optimal configuration of 119-bus system obtained by the proposed method is 43,26,24,122,51,59,40,96,72,75,98,130,131,110,35. The total power loss and minimum voltage magnitude of the system for the optimum case is 854.06 kW and 0.935355p.u. It is observed that about 35% of total power loss has been reduced and also the minimum voltage magnitude has been improved to 0.935355p.u after reconfiguration by proposed method.

The simulated results of this system is also compared with the results of RGA[11], ITS [28], FWA [20] and HAS [14] available in the literature and presented in Table 4. From the table, it is very clear that the performance of proposed method is better than RGA, ITS and HSA methods. This indicates that the proposed method is capable for reconfiguration of large-scale distribution system.

Table 4: result obtained for 119-bus distribution system

	$P_{T,loss}$	ΔV_D	V_{worst}	% Loss reduced
Base Case	1298.08	0.131112	0.868893	-
RGA [11]	883.13	0.0679	0.9321	31.97
ITS [28]	865.86	0.0677	0.9323	33.30
HAS [14]	854.21	0.0677	0.9323	34.19
FWA [20]	854.06	0.0677	0.9323	34.21
Proposed method	854.06	0.0667	0.9355	34.21

In order to analyse 119-bus distribution system under abnormal conditions, the failure rate of the buses and lines for this system is considered as 0.01. To demonstrate the ability of the proposed method, when the buses are failing, the simulated results for ten different cases are presented in Table 5. From Table 5, it is observed that the proposed method supplies power to the non-faulted areas and satisfies the radial structure of distribution system with minimal power loss.

Table 5: Experiment results of 119-bus system for different cases (faulted buses)

Item	Faulted bus	$P_{T,loss}$	% Loss reduced	V_{worst}	(node)	ΔV_D
Case1	50	925.312	38.23	0.9132	51	0.0850
Case2	69	896.793	34.09	0.9327	112	0.0691
Case3	75	771.379	26.81	0.9327	112	0.0691
Case4	16	863.883	33.59	0.9327	112	0.0691
Case5	83	840.131	36.09	0.9325	112	0.0692
Case6	107	912.316	44.3	0.9213	108	0.0786
Case7	110	808.427	27.77	0.9329	112	0.0688
Case8	8	909.396	30.1	0.9322	51	0.0691
Case9	45	854.647	33.88	0.9327	112	0.0691
Case10	23	851.956	33.66	0.9327	112	0.0691

Similarly, the simulated result for ten different cases (when some lines are failing) is presented in Table 6. From the table, it is observed that the proposed method supplies power to the non-faulted areas and satisfies the radial structure of distribution system with minimal power loss.

Table 6: Experiment results of 119-bus system for different cases (faulted lines)

Item	Faulted line	$P_{T,loss}$	% Loss reduced	V_{worst}	(node)	ΔV_D
Case1	19	911.6	31	0.9327	112	0.0691
Case2	22,91	930.064	51	0.9161	96	0.0839
Case3	31	955.16	63.13	0.9302	32	0.0701
Case4	109	909.909	25.43	0.9126	112	0.0894
Case5	15,80,57	1015.74	39.22	0.9118	81	0.0904
Case6	71	862.998	30.94	0.9327	112	0.0691
Case7	41	891.72	36.16	0.9327	112	0.0691
Case8	34,106	937.832	55.48	0.9172	107	0.0827
Case9	52	861.035	32.08	0.9327	112	0.0691
Case10	96,25	889.3057	31.77	0.9327	112	0.0691

6. Conclusion

In this paper, an efficient approach that uses learning automata for solving the DSR problem presented. Moreover, failure of busses and lines studied in a comprehensive manner under probabilistic nature, which is the case in the real world. The radial structure of the system and suitable current flow direction through over all reconfiguration process maintained. The proposed method tested on 33-bus and 119-bus radial distribution systems. The computational results shows that the results obtained by proposed method are promising and found to be better than the other methods compared. In addition, the proposed method supplies power to the non-faulted areas and satisfies the radial structure under abnormal conditions. The proposed method is not only useful for operating an existing system but also for designing a future system, especially suitable for large-scale practical systems.

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