ISSN 2321 – 2004

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 1, Issue 2, May 2013

Implementation and Validation of Different Reconfiguration Strategies Between HSA and PSO for Loss Reduction

Jamal Darusalam Giu[1], Ontoseno Penangsang[2], Rony Seto Wibowo[3]

Master Student, Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia [1]

Professor, Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia [2]

Associate Professor, Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia [3]

Abstract: In electric distribution system, the problem of finding the optimal configuration of radial network may be classified as the Travelling Salesman Problem. When a medium voltage system (20 kV) has a number of connected feeders whose circuit breakers (CBs) can be opened or closed, the combinatorial number of possible system configurations created by switching CBs become very large. In order to determine the minimum loss configuration of medium voltage system, a new computation algorithm is proposed. Harmony Search Algorithm (HSA) is proposed to solve the network re-configuration problem to get optimal switching combination in the network. The HSA is a recently developed algorithm which is conceptualized using the musical process of searching for a perfect state of harmony. It uses a stochastic random search instead of a gradient search which eliminates the need for derivative information. Simulations are carried out on 33-bus radial network of IEEE test system to validate the proposed algorithm. The results are compared with PSO (*Particle Swarm Optimization*) as a popular approaches available in the literature. It is observed that the proposed method performed well compared to the PSO in terms of the quality of solutions.

Keywords: TSP, HSA, optimal switching, loss reduction, electric distribution system, stochastic, PSO

I. INTRODUCTION

Power loss reduction is one of the main targets in a power company aimed for increasing profit margin. One of the practical solution in electric distribution system is reconfiguring the old structure of the feeders to a new one without exceed some electrical constraints. Power system operators have to determine the optimal system structure from the great number of possible system structures. For instance, the total number of possible system structure is the n^{th} power of 2, if the total number of the connected line or cables is n[1]. So, a system with 32-connected cables will results the total number of configuration candidates about 2^{32} (=4,294,967,296). Practically, they determine it using their experience and engineering knowledge. However it is not easy to verify objectively whether the system structure which they choose is optimal or not.

The distribution network reconfiguration problem may be classified as the Travelling Salesman Problem. Morton and Mareels [2] stated that the problem can be recast into a graph-theoretic frame-work, where the problem is to find a spanning tree in a graph with weighted nodes and branches, such that an objective function of the weights, obtained by reference to Ohm's and Kirchoff's Laws, is minimized. In fact, the network reconfiguration in electric distribution systems belongs to a complex combinatorial optimization problem where reconfiguration is realised by changing the status of sectionalizing and tie switches [3].

Several approaches to solve the problem based on heuristics and metaheuristics have been made. Heuristic methods include Switch Exchange Method by Civanlar et al. [4], Sequential Switch Opening Method by Shirmo-hammadi and Hong [5] and a Nonlinear Constructive Approach by McDermott et al. [6]. On the other hand, metaheuristic approaches have been developed since 1990 include Simulated Annealing by Chiang and Jean-Jumeau [7], Ant Colony Search Algorithm by Chang [8], Genetic Algorithms (GA) by Nara et al. [9], and the last but the most popular artificial intelligent approach, Particle Swarm Optimization (PSO). For example, [10]-[12] have applied PSO and its varian to a Distribution Network Reconfiguration (DNR) problem.

ISSN 2321 – 2004

IJIREEICE

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 1, Issue 2, May 2013

This paper presents a metaheuristic method based on Harmony Search to solve DNR problem. The proposed method is tested on 33-bus system which its complete data can be found in [13]. Simulation results are obtained to evaluate its effectiveness and robustness comparing with the PSO.

II. FORMULATION OF THE DISTRIBUTION NETWORK RECONFIGURATION PROBLEM FOR LOSS REDUCTION

The reconfiguration problem can be formulated as follows:

$$\min F = \sum_{j=1}^{N_R} R_j \left|I_j\right|^2 \quad \text{...(1)}$$

Subjected to the following constraints:

1. The bus voltage magnitude
   $V_{min} \le |V_i| \le V_{max}$; $\forall$ i $\in N_b$ ………………..……..(2)

2. The current limit of branches
   $|I_j| \le I_j$ max ; $\forall$ j $\in N_R$ ……………………..……...(3)

3. Radial Topology

Where, F is the objective function to be minimized corresponds to the total power loss in the system, R_j is the resistance of the branch j and I_j is the magnitude of the current flowing through the branch j, V_i is the voltage on bus i, V_{min} and V_{max} are minimum and maximum bus voltage limits respectively, I_j and I_{jmax} are current magnitude and maximum current limit of branch j respectively and N_b and N_R are the total number of buses and branches in the system respectively. The objective function is calculated starting from the solution of the power flow equations that can be solved using the BIBC–BCBV method [14]. This method has excellent convergence characteristics and is very robust and proved to be efficient for solving radial distribution networks.

To check the radiality constraints for a given configuration, a method based on the bus incidence matrix Â is used [15] in which a graph may be described in terms of a connection or incidence matrix. Particular interest is the branch to node incidence matrix Â, which has one row for each branch and one column for each node with a coefficient a_{ji} in row i and column j. The value of $a_{ji} = 0$ if branch j is not connected to node i, $a_{ji} = 1$ if branch j is directed away from node i and $a_{ji} = -1$ if branch j is directed towards node i. For a network calculation, a reference node must be chosen. The column corresponding to the reference node is omitted from Â and the resultant matrix is denoted by **A**. If the number of branches is equal to the number of nodes then, a square branch-to-node matrix is obtained. The determinant of **A** is then calculated. If *det*(**A**) is equal to 1 or −1, then the system is radial. Else if the *det*(**A**) is equal to zero, this means that either the system is not radial or group of loads are disconnected from service.

The HS algorithm is a new metaheuristic population search algorithm derived from the natural phenomena of musician's behavior when they "population members" collectively play their musical instruments "decision variables" to come up with a pleasing harmony "global optimal solution". This state is determined by an aesthetic standard "fitness function". When a musician is improvising, he has three possible choices; playing any famous tune exactly from his memory "Memory Consideration"; playing something similar to the aforementioned tune "pitch adjustment"; composing new or random notes from the pitch range "Random Selection". The Main Steps of HS are as follows:

A) Initialization

In this step, the optimization problem, algorithm parameters and harmony memory are defined. The optimization problem is specified as follows:

Minimize F(x) ………………………………………(4)

Where, $F(x)$ is an objective function, x is the set of each decision variable x_i, N is the number of decision variables, X_i is the set of the possible range of values for each decision variable. The HS algorithm parameters are also specified in this step. These are the Harmony Memory Size (HMS); Harmony Memory Considering rate (HMCR); Pitch Adjusting Rate (PAR) and the maximum number of improvisations (N_i). The harmony memory (HM) is a memory location where all the solution vectors (sets of decision variables) are stored. Here, (HMCR) and (PAR) are parameters that are used to improve the solution vector, which are defined in Step 2. The initial (HM) consists of a certain number of randomly generated solutions for the optimization problem under consideration without violating the constraints. For a problem of N variables, a (HM) with the size of (HMS) can be represented as follows:

$$\text{HM} = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_{N-1}^1 & x_N^1 & | & F_1 \\ x_1^2 & x_2^2 & \dots & x_{N-1}^2 & x_N^2 & | & F_2 \\ \vdots & \vdots & \dots & \vdots & \vdots & | & \vdots \\ x_1^{HMS} & x_2^{HMS} & \dots & x_{N-1}^{HMS} & x_N^{HMS} & | & F_{HMS} \end{bmatrix} \dots(5)$$

Where, $(x_1^i, x_2^i, \dots, x_N^i)$ represents a candidate solution for the optimization problem and F_1 is the value of the fitness function corresponding to the first solution vector. For the network reconfiguration problem, the solution vector is represented by the set of tie-switches in the radial configuration of the network [16]. The initial configuration of tie-switches for 33-bus test system which is shown in Fig. 1 can be represented as in (6).

Configuration = □ [33 34 35 36 37]………………(6)

ISSN 2321 – 2004

IJIREEICE

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 1, Issue 2, May 2013

Where, 33 is the tie-switch from loop 1, 35 is the tie-switch from loop 2, etc. The (HM) is sorted in ascending order with respect to the fitness function such that configuration with the least power loss (best configuration) is at the top and the one with the highest power loss (worst configuration) is at the bottom.

B) Improvise a New Harmony

A new harmony vector (x_1, x_2, …, x_N) is generated based on three main rules: (1) memory consideration (2) pitch adjustment and (3) random selection. Generating a new harmony is called 'improvisation'. Each component of the solution is chosen either from the harmony memory or by randomness depending on the value of the (HMCR), which varies between 0 and 1, and defined as the rate of choosing one value from the historical values stored in the (HM), while (1-HMCR) is the rate of randomly selecting one value from the possible range of values as follows:

$$
\begin{aligned}
&\mathit{if}\ (\text{rand}( ) < \text{HMCR})\\
&\quad x_i \leftarrow x_i \in \{x_i^1, x_i^2, ..., x_i^{\text{HMS}}\}\\
&\mathit{else}\\
&\quad x_i \leftarrow x_i \in X_i\\
&\mathit{end} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)
\end{aligned}
$$

Where, rand( ) is a uniformly distributed random number between 0 and 1 and X_i is the set of the possible range of values for each decision variable. Every variable x_i obtained by the memory consideration is examined to determine whether it should be pitch-adjusted. This operation uses the (PAR) parameter, which is the rate of pitch adjustment and the value (1-PAR) is the rate of doing nothing as follows:

$$
\begin{aligned}
&\mathit{if}\ (\text{rand}( ) < \text{PAR})\\
&\quad x_i \leftarrow x_i \pm \text{rand}( )*\text{BW}\\
&\mathit{else}\\
&\quad x_i \leftarrow x_i\\
&\mathit{end} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)
\end{aligned}
$$

Where, BW is an arbitrary distance bandwidth for the continuous design variable and rand( ) is uniform distribution between -1 and 1. If the problem is discrete in nature as the network reconfiguration problem, BW is taken as 1.

C) Update Harmony Memory

If the new harmony vector (x_1, x_2, …, x_N) is better than the worst harmony in the HM, judged in terms of the objective function value (yields to a better fitness than that of the worst member in the HM), the new harmony is included in the HM and the existing worst harmony is excluded from the HM. The HM is rearranged in ascending order according to the fitness function. Otherwise, the new harmony is discarded.

D) Check Stopping Criteria

If the stopping criterion (maximum number of improvisations) is satisfied, computation is terminated and finally the best one among the solution vectors stored in the HM is selected, which is the optimum solution of the problem. Otherwise, Steps 2 and 3 are repeated.

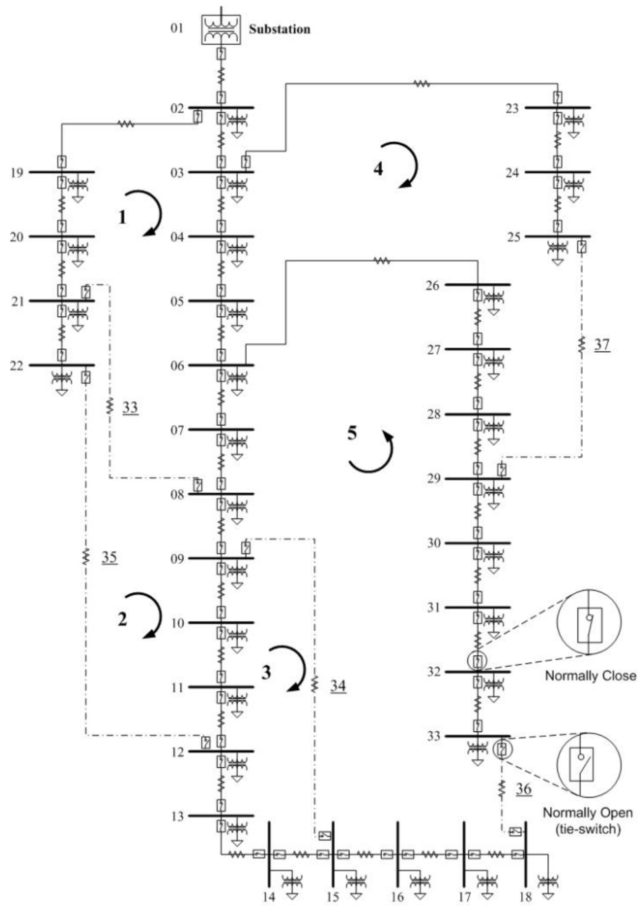

Fig. 1. The base configuration of 33-bus system

III. IMPLEMENTATION OF HSA FOR RECONFIGURATION PROBLEM

The system is a 33–bus, 12.66-kV, radial distribution system as shown in Fig. 1. It consists of five tie lines and 32 sectionalizing switches. The normally open switches are 33 to 37, and the normally closed switches are 1 to 32. The line and load data of the network are obtained from [13], and the total real and reactive power loads on the system are 3715 kW and 2300 kVAr, respectively. The initial power loss of this system is 201.588 kW. The lowest bus bar voltage is 0.9131 p.u., which occurs at node 18. The substation voltage is considered as 1 p.u. and all tie and sectionalizing switches are considered as candidate switches for reconfiguration problem. The algorithm was developed in MATLAB, and the simulations were done on a computer with Pentium Centrino Duo, 1.8 GHz, 1GB RAM.

The parameters of HSA used in the simulation of the network are shown in Table 1. The optimal configuration obtained by the proposed algorithm is 7, 35, 13, 28, 36, which has a real power loss of 120.39 kW. This amounts to a reduction of 40.28% in total power loss. The minimum node voltage of the system is improved to 0.943 p.u. (node 33) after reconfiguration. The node Voltages at each bus are shown in Table 2.

The voltage profiles of the system before and after reconfiguration are shown in Fig. 2. The minimum voltage in the system after reconfiguration is improved by 34.4%.

The real power flows in each branch before and after reconfiguration are shown in Fig. 3. From Fig. 3, it is observed that the power flow in each branch is reduced after reconfiguration. This shows that feeders are relieved from the overloading and makes it possible to load the feeders further.

The power loss in each branch before and after reconfiguration is shown in Fig. 4. It is observed that the losses in almost every branch is reduced, except at 8, 9, 20, 21, 24, 25, 26, 33 and 34, where the losses are increased because of shifting of loads onto these feeders.

To verify the performance of the proposed algorithm, this case was repeatedly solved 200 times. The best and the worst values among the best solutions as well as the average value and standard deviation (STD) for the best solutions of these 200 runs are listed in Table 3. A smaller standard deviation implies that most of the best solutions are close to the average. The best solutions for these 200 runs are compared with the best objective function values obtained by the PSO. The PSO got premature convergence so that their standard deviation is larger than that of the HSA method.

The convergence rate of the proposed HSA algorithm compared with that of the PSO method for 33-bus system is depicted in Fig. 5. It can be seen that although the PSO has a relatively fast convergence compared to the proposed method but the PSO usually being trapped in to the local optimum during iterations.

TABLE I
PARAMETERS OF THE HSA

HMS	10
HMCR	0.85
PAR	0.3
Number of iterations	250

TABLE II
NODE VOLTAGES OF 33-BUS SYSTEM (P.U.)

Before Reconfiguration				After Reconfiguration			
Bus	Voltage	Bus	Voltage	Bus	Voltage	Bus	Voltage
1	1.000	18	**0.9131**	1	1.000	18	0.9577
2	0.9970	19	0.9965	2	0.9971	19	0.9921
3	0.9829	20	0.9929	3	0.9868	20	0.9836
4	0.9755	21	0.9922	4	0.9850	21	0.9795
5	0.9681	22	0.9916	5	0.9835	22	0.9789
6	0.9497	23	0.9794	6	0.9804	23	0.9710
7	0.9462	24	0.9727	7	0.9797	24	0.9681
8	0.9413	25	0.9694	8	0.9717	25	0.9649
9	0.9351	26	0.9477	9	0.9657	26	0.9787
10	0.9293	27	0.9452	10	0.9653	27	0.9783
11	0.9284	28	0.9338	11	0.9649	28	0.9778
12	0.9269	29	0.9255	12	0.9632	29	0.9613
13	0.9208	30	0.9220	13	0.9628	30	0.9571
14	0.9185	31	0.9178	14	0.9596	31	0.9488
15	0.9171	32	0.9169	15	0.9605	32	0.9433
16	0.9157	33	0.9166	16	0.9592	33	**0.9430**
17	0.9137			17	0.9590		

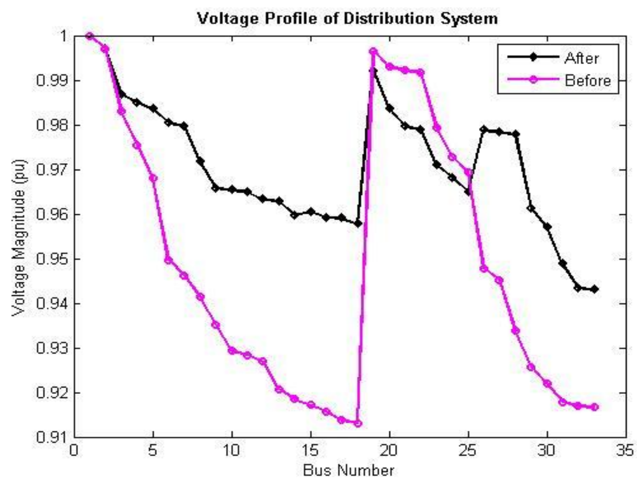

Fig. 2. Voltage profile of 33-bus radial system

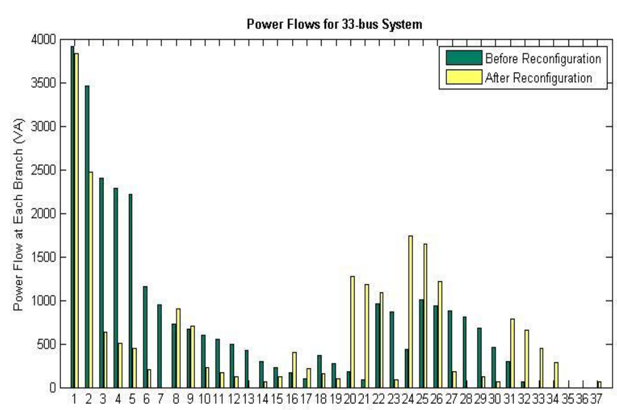

Fig. 3. Power flow in 33-bus system before and after reconfiguration

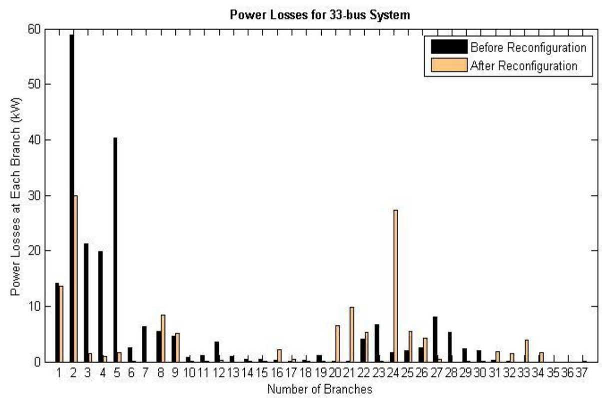

Fig. 4. Losses in 33-bus system before and after reconfiguration

TABLE III
COMPARISON RESULTS BETWEEN HSA VERSUS PSO

Item		Initial Configu-ration	Final Configuration PSO	Final Configuration Proposed Method HSA
Tie Switches		33,35,34, 37,36	07,35,12, 28,36	07,35,13, 28,36
Loss (kW) (For 200 Runs)	Best	201.59	120.85	120.39
	Worst		173.77	148.46
	Average		130.41	127.95
	STD		7.3	5.7
Average Loss Reduction (%)		--	35.30	36.53
Loss Reduction (Best value in %)		--	40.05	40.28
Minimum Voltage (p.u.)		0.9131	0.943	0.943
CPU Time (sec.)		--	5.8	2.7

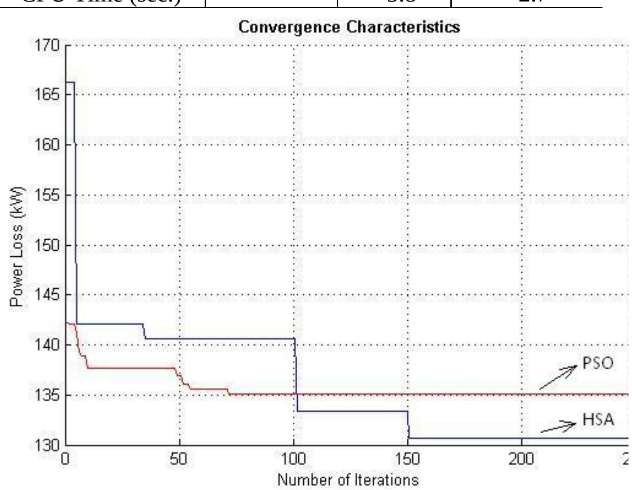

Fig. 5. Convergence characteristics of 33-bus system

TABLE IV
RESULTS BASED ON DIFFERENT PARAMETERS SETTING OF HSA FOR 33-BUS SYSTEM

Scenario	Parameter Setting HMCR	PAR	HMS	Power Loss (kW)
1	0.95	0.3	10	129.06
	0.70	0.3	10	124.44
	0.60	0.3	10	125.61
	0.30	0.3	10	135.93
2	**0.85**	**0.3**	**10**	**120.39**
	0.85	0.4	10	120.64
	0.85	0.5	10	120.73
	0.85	0.6	10	120.78
3	0.85	0.3	2	140.71
	0.85	0.3	15	130.29
	0.85	0.3	20	143.20
	0.85	0.3	30	145.00

Simulations are carried out for 250 iterations and optimum solution is obtained after 150 iterations. The average CPU time taken by the processor to carry out the simulations for 250 iterations is 2.7 second, which is less than the PSO.

To determine the impacts of different parameters of the HS algorithm on the solution quality and convergence behavior, an empirical study is performed. To show the effects of single parameter changes, 12 different cases are tested as shown in Table 4. Each case is tested over 200 runs in three scenarios, and maximum number of iterations is fixed to 250 for all runs. In scenario 1, 2, and 3, HMCR, PAR, and HMS are varied, respectively, and other two parameters are kept constant.

The total power loss for 33-bus distribution by varying the parameters are summarized in Table 4. The HMCR determines the rate of choosing one value from the historical values stored in the HM. The larger the HMCR, the less exploration is achieved; the algorithm further relies on stored values in HM, and this potentially leads to the algorithm getting stuck in a local optimum. On the other hand, choosing the HMCR too small decreases the algorithm efficiency, and the HS algorithm behaves like a pure random search, with less assistance from the historical memory. As shown in Table 4, large and small HMCR values lead to a decrease in the solution quality. Large and small HMS values decrease the efficiency of the harmony memory as seen in Table 4. For most problems, a HMS between N and 2N is reasonable. It is observed that the algorithm has small sensitivity to PAR values.

IV. CONCLUSION

In this paper, a recently developed metaheuristic HSA is successfully applied to optimize radial distribution systems with objective of reducing power losses. Simulations are carried on 33 buses and results are compared with a popular method available in the literature called Particle Swarm Optimization (PSO). Results show that the proposed algorithm can converge to optimum solution quickly with better accuracy compared to the PSO. Computational results of 33-bus system showed that proposed HSA method is better than PSO. It can be observed that 36.53% of average loss reduction is achieved by HSA comparing with 35.3% by the PSO as shown in Table 3. From Table 4, the results based on some different parameters setting for the HSA method show that the proposed method is effective in loss reduction for various parameters setting demonstrating a certain extent adaptive performance for the proposed method. The convergence rate curve confirms that the HSA method can more efficiently search the optimal or near-optimal solution for network reconfiguration problems without being trapped in to the local optimum. Moreover, it can be observed from results of 33-bus that the proposed method is the best in the solution as well as the CPU time.

This method is useful for analyzing existing systems, helps in planning a future system, online distribution automation system, and is especially suitable for a large-scale practical system. A real Indonesian power company (PT. PLN) distribution system will be used in the future study to verify the usefulness of the proposed algorithms. The distributed generators (DGs) impacts on reconfiguration problem also will be investigated when those connected to the grid.

ACKNOWLEDGMENT

The authors gratefully acknowledge the contributions of M. Syai'in and Y. Tonce to the program development. First author also acknowledge the financial support from Indonesian Government through Beasiswa Unggulan DIKTI.

REFERENCES

[1] Hayashi Y, Matsuki J,"Determination of Optimal System Configuration in Japanese Secondary Power System", IEEE Transaction on Power System, 2003; 18(1), pp. 394-399.

[2] Morton AB, and Mareels IMY, "An Efficient Brute-Force Solution to the Network Reconfiguration Problem", IEEE Transaction on Power Delivery, 2000; 15(3), pp. 996-1000.

[3] Ah King RTF, Radha B, and Rughooputh HCS, "A Real-Parameter Genetic Algorithm for Optimal Network Reconfiguration", Proceeding IEEE–ICIT, Maribor, Slovenia. 2003; pp. 54-59.

[4] Civanlar S, Grainger JJ, Yin H, and Lee SSH, "Distribution Feeder Reconfiguration for Loss Reduction", IEEE Transaction on Power Delivery, 1998; 3(3), pp. 1217-1223

[5] Shirmohammadi D, and Hong HW, "Reconfiguration of Electric Distribution for Resistive Line Loss Reduction", IEEE Transaction on Power Delivery, 1989; 4(2), pp. 1492-1498.

[6] Mc Dermott TE, Drezga L, and Broadwater RP, "A Heuristic Nonlinier Constructive Method for Distribution System Reconfiguration", IEEETransaction on Power Systems, 1989; 14(2), pp. 478-483.

[7] Chiang HD, and Jean-Jumeau R, "Optimal Network Reconfiguration in Distribution Systems: Part 1: A new formulation and a solution methodology", IEEE Transaction on Power Delivery, 1990; 2(4), pp. 1902-1909.

[8] Chang CF, "Reconfiguration and Capacitor Placement for Loss Reduction of Distribution Systems by Ant Colony Search Algorithm", IEEE Transaction on Power System, 2008; 23(4), pp. 1747-1755.

[9] Nara K, Shiose A, Kitagawa M, and Ishihara T, "Implementation of Genetic Algorithm for Distribution Systems Loss Minimum Re-configuration", IEEE Transaction on Power System, 1992; 7(3), pp. 1044-1051.

[10] Xu L, Lu L, and Liu J, "Modified Particle Swarm Optimization for Reconfiguration of Distribution Network", Automation of Electric Power Systems, 2006; 30, pp. 27-30.

[11] Xiaoling J, Jianguo Z, and Ying S, "Distribution network reconfiguration for load balancing using binary particle swarm optimization", Intl. Conf. on Power System Technology, November 2004.

[12] Cui-Ru W and Yun-E Z, "Distribution Network Reconfiguration Based on Modified Particle Swarm Optimization Algorithm", Intl. Conf. on Machine Learning and Cybernetics, Aug. 2006.

[13] M.E. Baran and F. Wu, "Network reconfiguration in distribution system for loss reduction and load balancing", IEEE Transaction on Power Delivery, 1989; 4(2), pp. 1401-1407.

[14] Jen-Hao T, "A Direct Approach for Distribution System Load Flow Solutions", IEEE Transaction on Power Delivery, 2003; 18(3), pp. 882-887.

[15] P. Wright, "On minimum spanning trees and determinants", Mathematics Magazine, 2000; Vol.73, pp.21-28.

[16] RS Rao, SVL Narasimham, MR Raju, and AS Rao, "Optimal Network Reconfiguration of Large-Scale Distribution System Using Harmony Search Algorithm", IEEE Transaction on Power Systems, 2011; 26(3), pp. 1080-1088.

BIOGRAPHY

Jamal Darusalam Giu, received his S.T. from Universitas Sam Ratulangi, Manado, Indonesia in 2010. Since 2011, he has been studying in Electrical Engineering, Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia as a master student. He is currently as prospective lecturer with the Universitas Negeri Gorontalo (UNG). His research interests include power system analysis, distribution automation, artificial intelligent and renewable energy.

Ontoseno Penangsang, received his Ir. from Institut Teknologi Sepuluh Nopember, M.Sc. and Ph.D. from University of Wisconsin, USA. He is a Professor of Electrical Engineering at Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia.]

Rony Seto Wibowo, received his S.T. from Institut Teknologi Sepuluh Nopember (ITS), M.T. from Institut Teknologi Bandung (ITB), and Dr.Eng. from University of Hiroshima, Japan. He is an Associate Professor of Electrical Engineering at Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia.