Optimal Multi-Objective Reconfiguration in Distribution Systems Using the Novel Intelligent Water Drops Approach

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Received: December 2013 Revised: February 2014 Accepted: June 2014

ABSTARCT
This paper presents a new method for optimal multi-objective reconfiguration of distribution system based on the novel Intelligent Water Drops (IWD) algorithm in order to mitigation of losses, improving the voltage profile and equalizing the feeder load balancing. The proposed method is validated using the IEEE33-bus test system and a Tai-Power 11.4 KV distribution system as a real distribution network. Also to assess the performance of the proposed method at different load levels, the two test networks are simulated at three load levels: light, nominal, and heavy. The results show that multi objective reconfiguration using Intelligent Water Drops leads to improvement in all objectives at various load levels. The obtained results prove that the proposed technique can be more accurate than other well known methods such as Genetic Algorithm, Particle Swarm Optimization, and Harmony Search algorithm.

KEYWORDS: Multi Objective Reconfiguration, Intelligent Water Drops (IWD) Algorithm, Distribution System, Power Loss, Load Balancing, Voltage Profile.

1. INTRODUCTION

Distribution system is an interface between end users and transmission network which due to the advantages of lower short circuit current and easier protection coordination generally utilizes the radial configuration. On the other hand, the radial structure might reduce the reliability of end user feeding while increasing power losses and voltage drop at the load points. Electrical power distribution systems have two types of switches: tie and sectionalizing, which determine the configuration of distribution network. By changing the switches statue and transition of sections between feeders during operation, the construction of network distribution will change. This change is known as reconfiguration and is performed from time to time. The main objectives of reconfiguration of any distribution systems are [1]: loss reduction, increase stability, improving voltage profile, minimizing the times cutting off electrical current for services, increase reliability of network, and relieve overload in the network. However, due to dynamic nature of loads, total system load is more than its capacity which makes feeders unable to relieve loads hence voltage profile of the system will not increase to the required level. In order to meet required level of demand, DG units are integrated in distribution network to improve voltage profile, to provide reliable and uninterrupted power supply and also achieve economic benefits such as minimum power loss, energy efficiency and load leveling. Since network reconfiguration is a complex combinatorial, non-differentiable constrained optimization problem, it needs algorithms to resolve the reconfiguration. Many researches in literatures have presented several methods for the optimal reconfiguration of the distribution networks with different objectives. Reconfiguration of distribution network for loss reduction was first proposed by Merlin and Back [2] in 1975. They have used a branch and bound optimization method to determine the configuration that has the minimum total loss. In this method, all switches are first closed to establish a meshed configuration. The switches are then opened successively to achieve the radial configuration. Also, many algorithms have been developed for reconfiguration of distribution system with other objectives in mind. Goswami and Basu [3] presented a heuristic algorithm for reconfiguration which uses a power flow program. Gomes *et al*. [4] reported a heuristic algorithm for the large distribution systems that begins with meshed configuration and all switches closed. Switches will be opened one by one based on minimum system loss using power flow program. A new path to node based modeling and application to reconfiguration of distribution system has been proposed by Ramoset and Exposito [5] in 2005.

Schmidt *et al*. [6] have introduced a method for loss minimization based on the standard Newton technique. Zhou *et al*. [7] have presented two reconfiguration algorithms for service restoration and load balancing in distribution systems. They used combination of heuristic rules and fuzzy logics in optimization purposes to solve the reconfiguration problem. An optimization technique to determine the network structure with minimum energy losses for a given period has proposed by Taleski and Rajicic [8]. The application aspect of optimal distribution system reconfiguration was considered by Borozan and Rajakovic [9]. To determine the switching operation, an algorithm of network reconfiguration using voltage, ohmic, and decision indexes has been presented by Lin and Chin [10], Jeon [11], Augugliaro [12] and their colleagues used artificial-intelligence in a minimum loss reconfiguration. Nara *et al*. [13] have solved distribution reconfiguration problem for minimum loss using Genetic Algorithm (GA). A fuzzy multi-objective approach was offered by Das [14] to optimize distribution network configuration which four objectives load balancing among the feeders, real power loss, deviation of nodes voltage, and branch current constraint violation were modeled and results are encouraging, however, criteria for selecting a membership function for each objective are not provided. Rao *et al*. [15] proposed Harmony Search Algorithm (HSA) to solve the network reconfiguration problem to get optimal switching combinations simultaneously in the network to minimize real power losses in the distribution network. An approach for reconfiguration using combination of Imperialist Competitive Algorithm (ICA) and Graph theory was proposed by Bagheri Tolabi and Moradi [16]. The main objectives of the study are minimization of power losses and feeder load unbalancing. ICA is used for reconfiguration and Graph theory to check the radial structure and feeding all loads of distribution system.

In this paper, the novel Intelligent Water Drops (IWD) approach is used for multi objective reconfiguration in a distribution network in order to losses reduction, improving the voltage profile and equalizing the feeder load balancing. The remainder of this paper is organized in the following manner: Section 2 gives the problem formulation. Section 3 introduces the IWD approach and its overall progress. Section 4 explains the optimization procedure using the proposed IWD method. Section 5 presents the simulation and results and section 6 outlines conclusions.

2. FORMULATION PROBLEM

2.1. Power flow equations

Power flows in a distribution system are computed by the following set of simplified recursive equations [26] derived from the single line diagram shown in Figure 1(a):

$$
\begin{aligned}
P_{k+1} &= P_k - P_{loss,k} - P_{Lk+1} \\
&= P_k - \frac{R_k}{|V_k|^2}\left\{P_k^2 + (Q_k + Y_k |V_k|^2)^2\right\} - P_{Lk+1}, \\
Q_{k+1} &= Q_k - Q_{loss,k} - Q_{Lk+1} \\
&= Q_k - \frac{X_k}{|V_k|^2}\left\{P_k^2 + (Q_k + Y_{k1} |V_k|^2)^2\right\} - \\
&\quad Y_{k1}|V_k|^2 - Y_{k2}|V_{k+1}|^2 - Q_{Lk+1}
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
|V_{k+1}|^2 &= |V_k|^2 + \frac{R_k^2 + X_k^2}{|V_k|^2}(P_k^2 + Q_k^2) - \\
&\quad 2(R_k P_k + X_k Q_k) \\
&= |V_k|^2 + \frac{R_k^2 + X_k^2}{|V_k|^2}(P_k^2 + (Q_k^2 + Y_k |V_k|^2)^2) - \\
&\quad 2(R_k P_k + X_k (Q_k + Y_k |V_k|^2)).
\end{aligned} \tag{2}
$$

Where:

P_k : Real power flowing out of bus *k*,

Q_k : The reactive power flowing out of bus *k*,

$P_{loss,k}$: Real power loss at bus *k*,

$Q_{loss,k}$: Reactive power loss at bus *k*,

P_{Lk+1} : Real load power at bus at bus *k+1*,

P_{Lk+1} : Reactive load power at bus at bus *k+1*,

R_k : Resistance of the line section between buses *k* and *k+1*,

X_k : Reactance of the line section between buses *k* and *k+1*,

Y_k : Shunt admittance at any bus *k*,

V_k : Voltage amplitude at bus *k*.

2.2 Objective function and constraints of the problem

The objective function Fit(x) is a constrained optimization problem to find an optimal configuration for the distribution system. Fit(x) is a multi objective function that consists of three goals: reducing the loss, increasing the load balancing, and improving the voltage that is formulated s a following mathematics relation:

$$
\begin{aligned}
&MinFit(X) = \min\left[a_1.P_{loss} + a_2.LBI + a_3.VPI + C\right], \sum_{k=1}^{3} a_k = 1 \\
&C = D.Mesh(numbers) + E.Isolated(numbers)
\end{aligned} \tag{3}
$$

In the above equation, a_k is the weighting coefficient for each objective, *D* and *E* are the penalty coefficients for the wrong solutions that lead to form the meshes or isolated load in the system.

Mesh(numbers) is the number of generated meshes (rings) and *Isolated(numbers)* is the number of isolated loads in the system.
The constraints of the problem are:

$$1: V_{k\min} \le V'_k \le V_{k\max}$$

$$2: \left|I'_{k,k+1}\right| \le \left|I_{k,k+1\max}\right|$$

3: Radial structure of network should be maintained
4: All available nodes of considered distribution system should be fed.

Where:
V'_k : Voltage at bus *k* after reconfiguration.
$V_{k\max}$: Maximum bus voltage.
$V_{k\min}$: Minimum bus voltage.
$I'_{k,k+1}$: Current in line section between buses *k* and *k+1* after reconfiguration.
$I_{k,k+1\max}$: Maximum current limit of line section between buses *k* and *k+1*.
nf : Total number of lines sections in the system.

The first term of the objective function reflects real power losses that are defined by Eq. (4):

$$P_{loss} = \sum_{k=1}^{n_f} R_k \frac{P_k^2 + Q_k^2}{V_k^2} \tag{4}$$

The second term of the objective function is considered for the Load Balancing Index (LBI) of the lines in the feeder, which is shown in Eq. (5).

$$LBI = \sum_{F_j} \left(\frac{I_{Fj}}{I_{Favg}}\right)^2 \tag{5}$$

Where, I_{Fj} is the current passing through line *j* and I_{Favg} is defined by Eq. (6):

$$I_{Favg} = 1/n_f \sum_{j=1}^{n_f} I_{Fj} \tag{6}$$

The third term of the objective function reflects the improvement of the voltage profile, which is shown by Voltage Profile Index (VPI) in Eq. (7):

$$VPI = \sum_{k\in LB} \left|V_k - V_{ref,k}\right| \tag{7}$$

Where *LB* is the collection of the load buses and $V_{ref,k}$ is the nominal voltage at load bus *k*.
The decrease in this index implies improvement in voltages' profile in the distribution feeder buses.

3. INTELLIGENT WATER DROPS (IWD) APPROACH

IWD algorithm is inspired by the observation of natural water flow in the rivers formed by a swarm of water drops. The swarms of water drops find their own way to the lakes or oceans even though it has to overcome a number of obstacles in its path. Without the presence of these obstacles, the water drops tend to be pulled straight towards the destination by the gravitational force. However, being blocked by different kinds of obstacles and constraints, there exist lots of twists and turns in the real path of the river. The interesting point is that the path of the river, constructed by the flow of water drops, seems to be optimized in terms of distance from the source to the destination under the constraints of the environment. By mimicking the features of water drops and obstacles of the environment, the IWD algorithm uses a population of water drops to construct paths and obtain the optimal or near-optimal path among all these paths over time. The environment represents the optimization problem needed to be solved. A river of IWDs looks for an optimal route for the given problem [30]. Hosseini [31] presented the basics of the IWD algorithm, then applied it to solve different optimization problems. As described in [31], an IWD model is proposed with two important parameters:
The amount of soil it carries or its soil load, "$soil^{IWD}$"
The velocity at which it is moving, "vel^{IWD}".
The values of these two parameters may change as the IWD flows in its environment from the source to a destination. An IWD moves in discrete finite-length steps and updates its velocity by an amount Δvel^{IWD} when it changes the position from point *i* to point *j* as follows:

$$\Delta vel^{IWD} = \frac{a_v}{b_v + c_v[soil(i,j)]^2} \tag{8}$$

Where $soil(i,j)$ is the soil on the bed of the edge between two points *i* and *j*; *av*, *bv* and *cv* are pre-defined positive parameters for the IWD algorithm. The relationship between velocity and the amount of soil of the edge is decided by *av* and *cv*, meanwhile *bv* is a small number used to prevent the singularity problem. Equation (8) indicates that the rate of changing the velocity, Δvel^{IWD} is dependent on the soil of the edge, that is, edge with more soil provides more resistance to the water flow that results in a smaller increment in velocity and vice versa. Thus, the velocity at $time(t+1)$, vel_{t+1}^{IWD} is given by:

$$vel_{t+1}^{IWD} = vel_t^{IWD} + \Delta vel^{IWD} \tag{9}$$

Where vel_t^{IWD} is the velocity of the IWD at time *t*.

The amount of soil removed from the bed of $edg(i,j)$ is inversely proportional in a non-linear manner to the time needed for the IWD to move from point *i* to point *j* and can be calculated by using (10):

$$\Delta soil(i,j) = \frac{a_s}{b_s + c_s[time(i,j;vel^{IWD})]^2} \tag{10}$$

Where, *as*, *bs* and *cs* are pre-defined positive parameters for the IWD algorithm. *as* and *cs* define the relationship between the amount of soil and the period of time IWD takes to move through the $edg(i,j)$, and *bs* is a small number used to avoid the singularity problem. Meanwhile, the duration of time is calculated by the simple laws of physics for linear motion. The time spent by the IWD to move from point *i* to *j* with velocity vel^{IWD} is given by:

$$time(i,j;vel^{IWD}) = \frac{HUD(i,j)}{\max(\varepsilon_v; vel^{IWD})} \tag{11}$$

Where a local heuristic function $HUD(i,j)$ has to be defined for a given problem to measure the undesirability of an IWD to move from point i to point j, 1v is the threshold of velocity to avoid the negative value of vel^{IWD}. Equations (10) and (11) represent the assumption that the water drop which moves faster or spends less time to pass from point *i* to point *j* can gather more soil than the one which has a slower velocity. Once the IWD moves from point *i* to point *j*, the following formulae are used to calculate the updated soil of the edge and the soil load of the IWD, respectively.

$$soil(i,j)_{(t+1)} = (1-\rho_n)(soil(i,j)_{(t)} - \rho_n \Delta soil(i,j) \tag{12}$$

$$soil^{IWD}{}_{(t+1)} = soil^{IWD}{}_{(t)} + \Delta soil(i,j) \tag{13}$$

Where ρ_n is the local soil updating parameter, which is chosen from [0, 1], and $\Delta soil(i,j)$ is calculated in (10).

To present the behavior of an IWD that prefers the easier edge or the edge with less soil on their beds, the edge selection of an IWD is based on the probability, $P(i,j;IWD)$ defined as follows which is inversely proportional to the amount of soil on the available edges.

$$p(i,j;IWD) = \frac{f(soil(i,j))}{\sum_{k \notin v_c(IWD)} f(soil(i,k))} \tag{14}$$

Where $f(soil(i,k)) = 1 + \varepsilon_S + g(soil(i,j))$.

The constant ε_s is a small positive number to prevent singularity. The set $v_C(IWD)$ denotes the group of nodes that the IWD should not visit to satisfy the constraints of the problem. The function $g(soil(i,j))$ is used to shift $soil(i,j)$ of the edge connecting point *i* and point *j* towards a positive value and is described below:

$$g(soil(i,j)) = \begin{cases} soil(i,j) & if: \min_{l \notin v_C(IWD)} (soil(i,l)) \geq 0 \\ soil(i,j) - \min_{l \notin v_C(IWD)} (soil(i,l)) & otherwise \end{cases} \tag{15}$$

A uniform random distribution is used to generate a random number which can be compared with this probability in order to decide which location is the next that the IWD will move to.

For a given problem, an objective or quality function is needed to evaluate the fitness value of the solutions. A set of IWDs can be utilized and work together to find the optimal solution. The function $q(.)$ is denoted as the quality function and T^{IWD} is a solution founded by an IWD. When all the IWDs have constructed their solutions, one iteration can be considered complete. At the end of the iteration, the current iteration best solution T^{IB} is calculated by:

$$T^{IB} = \arg\max_{\forall IWDs} q(T^{IWD}) \tag{16}$$

Therefore, the iteration-best solution T^{IB} is the solution that has the highest quality over all solutions T^{IWD}.

Equation (12) updates the soil of each edge whenever an IWD traverses through a particular path based on the current amount of soil of the edge and the current velocity of the IWD. The soil is updated in (12) by using local information at each edge of the tree, and thus it may result in a local optimum. In order to increase the opportunities of finding the global optimum, the amount of soil on the edges of the current iteration best solution T^{IB} is updated according to the goodness of the solution after the iteration is complete and the overall knowledge of the solution is acquired. Equation (17) can be used to update the $soil(i,j)$ belonging to the current iteration best solution T^{IB}.

$$soil(i,j) = (1+\rho_{IWD})soil(i,j) - \rho_{IWD} \frac{1}{N_{IB}-1} soil_{IB}^{IWD}, \quad \forall (i,j) \in T^{IB} \tag{17}$$

where $soil_{IB}^{IWD}$ represents the soil of the current iteration best IWD when it reaches the destination, N_{IB} is the number of nodes in the solution T^{IB} and ρ_{IWD} is the global soil updating parameter which is chosen from [0, 1]. The first term on the right-hand side of (17) is the amount of soil that remains from the previous iteration. Meanwhile, the second term of the right-hand side of (17) represents the quality of the current solution, obtained by the IWD. This way of updating the soil assists the reinforcement of the best-iteration solutions gradually, and thus, the IWDs are guided to search near good solutions with the expectation of finding the global optimum.

At the end of each iteration of the algorithm, the total best solution T^{TB} is updated by the current iteration-best solution T^{IB} as follows:

$$T^{TB} = \begin{cases} T^{TB} & if \quad q(T^{TB}) \geq q(T^{IB}) \\ T^{IB} & otherwise \end{cases} \tag{18}$$

By doing this, it is guaranteed that T^{IB} holds the best solution obtained so far by the IWD algorithm.

The flowchart in Figure 1 shows the main process of the IWD algorithm. The algorithm implementation details are specified in the following steps:

Step 1: Initialize soil updating parameters (a_s, b_s and c_s), and velocity updating parameters (a_v, b_v, c_v), the quality of total best solution ($q(T^{IWD})$), the maximum number of iterations (MaxIter), the iteration count (Itercount), the local soil updating parameter (ρ_n), the global soil updating parameter (ρ_{IWD}), the initial soil on each path (Initsoil) and the initial velocity (Initvel).

Step 2: Every IWD has visited node of list $v_c(IWD)$, which is initially empty. The IWDs velocity is set to *Initvel* and the entire IWDs are set to have zero amount of soil.

Step 3: Spread the IWDs on the nodes of the graph and then update the visited nodes.

Step 4: Repeat Steps 5 to 8 for those IWDs with the partial solutions.

Step 5: For the IWD in node *i*, select the next node *j* by using the probability $P(i, j; IWD)$ presented in equation (14) such that doesn't violate any constraints of the problem and make certain it is not in the visited node list $v_c(IWD)$ and then add the recently visited node *j* to the list $v_c(IWD)$.

Step 6: For every IWD from node *i* to node *j*, updating its velocity $vel(t)$ to $vel(t+1)$) by equation (9).

Step 7: For the IWD moving on the path from node *i* to *j* calculate the $\Delta soil(i, j)$ by using the equations (10) and (12).

Step 8: Update $soil(i, j)$ of the path from node *i* to *j* traversed by that IWD, and also update the soil that IWD carries $soil^{IWD}$ by equations (12) and (13).

Step 9: Find the iteration based best solution T^{IB} from all the solutions T^{IWD} found by the IWDs using equation (16).

Step 10: Update the soils on the paths that form the current iteration based best solution T^{IB} by equation (17).

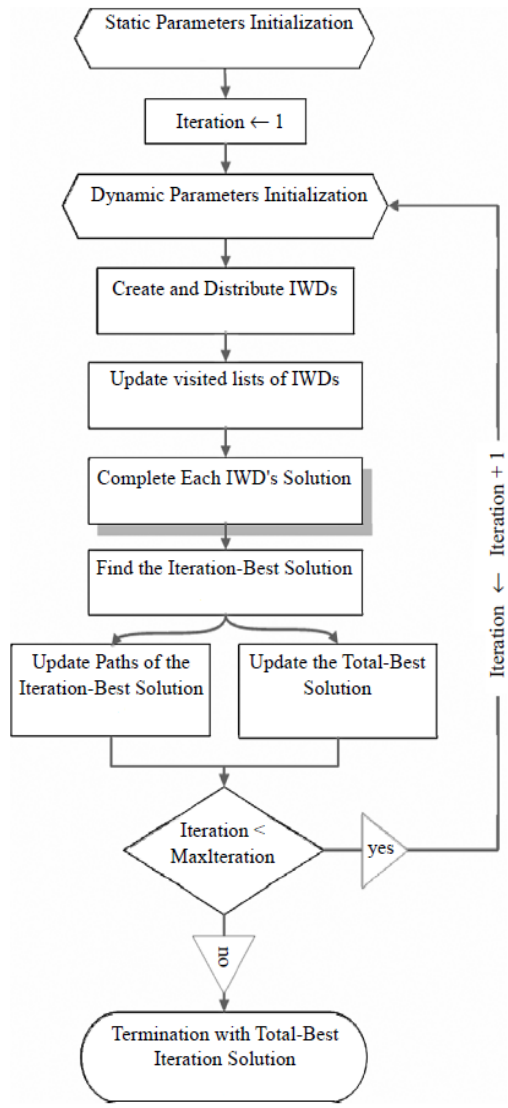


Fig. 1. The main process of the IWD algorithm

Step 11: Update the total best solution T^{TB} by using the equation (18).

Step 12: Increment the iteration number by one. Itercount = *Itercount* +1 and then, go to step 2 if *Itercount* < *Itermax* .

Step 13: The algorithm stops with the total-best solution T^{TB}.

4. EXPLANATION OF THE PROPOSED METHOD

This section describes application of proposed IWD method in optimal multi objective. In order to represent an optimal feeder topology, it is enough to know the positions of open (tie) switches in the new configuration of network. Accordingly without violating the constraints of problem, the first solution vector is formed as follows:

$$IWD^1 = [Tieswitches^1]$$

Where the solution vector (*Tieswitches*) is the proposed tie switches for new configuration, and the length of this vector is equal to the number of proposed tie switches.

By updating IWD parameters, second, third, and …, *i*th solution vector is generated as follows:

$$IWD^i = \{Tieswitches^i\}$$

For each solution *i*, power flow program is carried out, the value of objective function is evaluated and compared with the previous solution, and the better solution will be selected and replaced. This procedure is repeated until a termination criterion is satisfied.

The proposed method is described as following steps that is summarized as a flowchart in Figure 2:

Step 1) read data of distribution system (bus, load, branch, $V_{k\,\max}, V_{k\,\min}, I_{k,k+1\max}$, sectionalizing and tie switches numbers), penalty coefficients, and initialize the IWD parameters.

Step 2) run the power flow program [26] based on equations 1 and 2, generate the *IWD* solution vector without violating of constraints that mentioned in section 2.2.

Step 3) run the power flow program, calculate three terms of the objective function (P_{loss}, LBI, VPI) using equations (4-7).

Step 4) update the IWD algorithm parameters using equations (8-18). Go to step 2 to generate a new solution using updated IWD parameters.

Step 5) if the objective function value of new solution is better than stored solution, update the *IWD* vector by stored solution=new solution.

Step 6) if *Itercount* < *Itermax*, *Itercount* = *Itercount +1* and go to step 4.

Step 7) Best solution=stored solution.

Stop 8) Print the result and stop.

5. SIMULATION AND NUMERICAL RESULTS

Based on the proposed methodology, an analytical software tool has been developed in MATLAB environment. In order to investigate the effectiveness of the proposed method, the prepared program is applied to a test system.

In the simulation of network, two scenarios are considered to analyze the superiority of the proposed method as follow:

Scenario I: the base system without reconfiguration;

Scenario II: the base system with reconfiguration;

Both penalty coefficients *D* and *E* are selected as 0.04.

The selected IWD parameters for simulation are: *as*=1, *bs*=0.01, *cs*=1, *av*=1, *bv*=0.01, *cv*=1, $q(T^{IWD}) = -\infty$, *MaxIter*=300, *Itercount*=1, $\rho_n = 0.88$, $\rho_{IWD} = -0.85$, *Initsoil* = 1200, *Initvel*= 4, and ε_s =0.001.

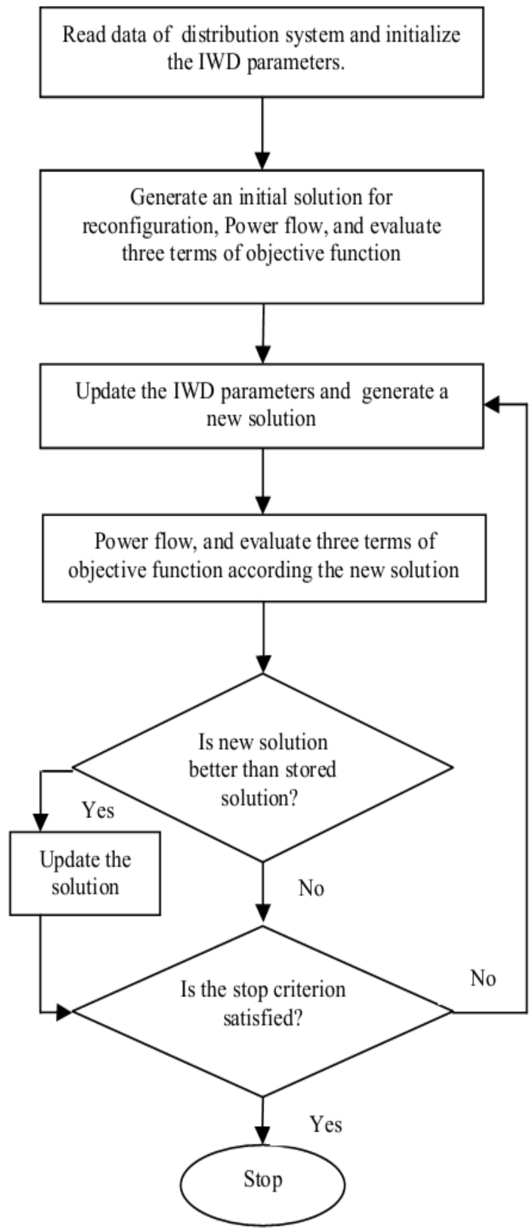


Fig. 2. Flow chart of the proposed method

5.1. Test systems and results

5.1.1. Test system 1

This test system is a 33-bus radial distribution system with a total load of 3.7 MW and 2.3 MVAr, 5 tie switches and 32 sectionalizing switches [16]. In the network, sectionalize switches (normally closed) are numbered from 1 to 32, and tie switches (normally open) are numbered from 33 to 37. The other information for this test system can be found in [16].The power flow calculation is performed using S_{base} =100 MVA and V_{base} = 12.66 kV. The single line diagram of the 33 bus test system is presented in Figure 3.

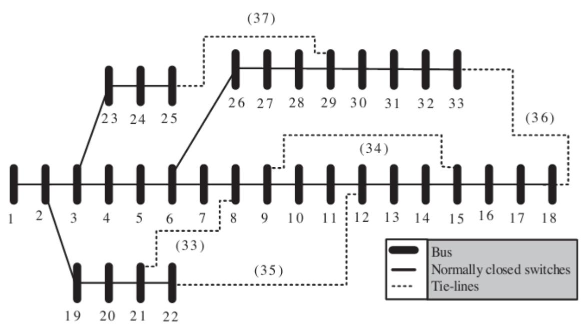


Fig. 3. Single line diagram of the 33 bus test system

The results of applying the proposed method on the test system 1 are shown in Table 1 for two scenarios. It is observed from this Table that base case power loss in the system is 202.5 kW which is reduced to 132.16 kW by conducting reconfiguration using proposed method. VPI index which is 1.7 for the base case has been decreased to 1.304 and LBI index which is 67.71 for the base case has been decreased to 48.33 by reconfiguration using proposed method. Also, as it can be seen in the Table 1, the worst voltage values are 0.9131p.u at bus 18 and 0.9471p.u at bus 32 for scenarios I and II respectively. Therefore by applying the reconfiguration using the proposed method the loss is reduced about 34.22%, voltage profile, load balancing, and worst voltage are improved about 23.29%, 28.62% and 3.72% respectively as compared with the base case.

Table 1. Results of 33 bus system

Scenario	Tie switches	P_{loss} (KW)	Loss reduction (%)	*VPI*	*VPI* improvement (%)	*LBI*	*LBI* improvement (%)	Worst voltage (p.u.) @ bus	Increment in worst voltage (%)
Scenario I	33,34, 35,36,37	202.5	-	1.7	-	67.71	-	0.9131 @ 18	-
Scenario II	33,21,14, 19,37	132.16	34.22	1.304	23.29	48.33	28.62	0.9471 @ 32	3.72

5.1.2. Test system 2

The second test system is a real distribution network from the Taiwan power company, which is shown in Figure. This practical 11.4-kV system is equipped with 83 sectionalizing switches and 13 tie switches. The total system load, which is considered as balanced and constant, is 28.35 kW and 20.7 kVAr. Other information can be derived from [33]. The power flow calculation is performed based on S_{base}=100 MVA and V_{base}= 11.4 kV. The single line diagram of the Tai-Power 11.4 kV distribution system is presented in Figure 4.

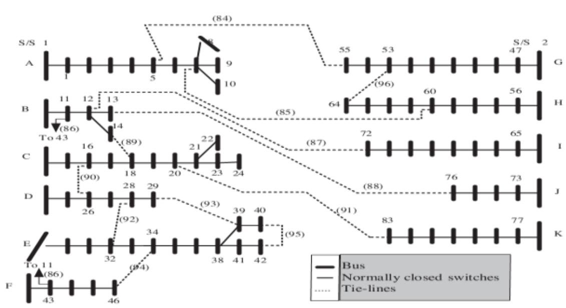


Fig. 4. Single line diagram of the Taiwan power company system

By applying the proposed method on the test system 2, it is observed that base case power loss in the system is 531 kW which is reduced to 387.2 kW through reconfiguration by using the proposed method. VPI index which is 2.5 for the base case has been decreased to 2.07 and LBI index which is 140.4 for the base case has been decreased to 112.61 by reconfiguration using proposed method. Also the worst voltage values are 0.92 p.u at bus 10 and 0.95 p.u at this bus for scenarios I and II respectively. Therefore by applying the reconfiguration using the proposed method the loss is reduced about 27.08%, voltage profile, load balancing, and worst voltage are improved about 17.2%, 19.79% and 3.26% respectively as compared with the base system (scenario I). The percentage improvement in P_{loss}, VPI ,and LBI, as compared with the base system (scenario I) are presented in Figure 5.

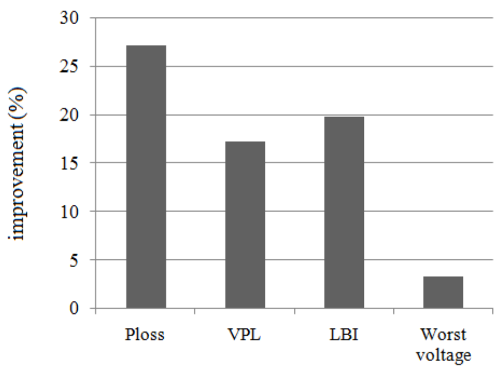


Fig. 5. Comparison of results in percent for Taiwan power company, **(a):** Loss reduction, **(b):** *VPI* improvement, **(c):** *LBI* improvement, and **(d):** worst voltage improvement

5.2. The results of different load levels

To assess the performance of the proposed IWD method at different load levels, the network is simulated at three load levels: 0.5 (light), 1.0 (nominal), and 1.6 (heavy) for scenarios I and II. The obtained results are presented in Table 2 for both test systems. As can be seen from this Table, for the test system 1, at light load, base case power loss (in kW) is 47.06 which is reduced to 35.17, using scenario II. At light load, base case *VPI* index is 1.15 which is improved to 1.14 using scenario II. Also at this load level, the base case *LBI* index is 50.78, that it is improved to 48.01, using II. At heavy load, base case power loss (in kW) is 574.36 which is reduced to 426.83, using scenario II. At heavy load, base case *VPI* index is 1.89 which is improved to 1.68using scenario II. Also the base case *LBI* index is 70.25, that it is improved to 63.43, using II at heavy load.

For the test system 2, at light load, base case power loss (in kW) is 123.77 which is reduced to 102.65, using scenario II. At light load, base case *VPI* index is 1.7 which is improved to 1.62 using scenario II. Also at this load level, the base case *LBI* index is 108, that it is improved to 101.07, using II. Similarly at heavy load, all three indexes of P_{loss}, *VPI*, and *LBI* have improved using scenario II in compared with the base case for the second test system.

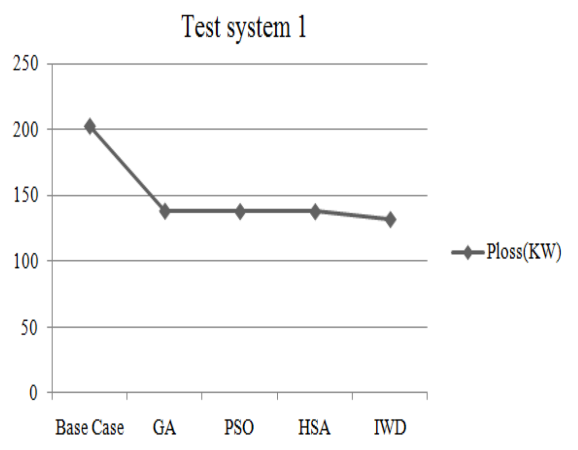
These results show that for all the three load levels, power loss reduction, voltage profile, and load balancing improvement using scenario II (proposed method) is highest, which confirms the satisfactory operation of the proposed method at different load levels.

Table 2. Obtained results based on various load levels

Test system	Scenario		Load level		
			Light (0.5)	Nominal (1)	Heavy (1.6)
1	Scenario I	Tie switches	33, 34, 35, 36, 37	33, 34, 35, 36, 37	33, 34, 35, 36, 37
		P_{loss} (KW)	47.06	202.50	574.36
		VPI	1.15	1.7	1.89
		LBI	50.78	67.71	70.25
	Scenario II	Tie switches	33,21,14,19,37	33,21,14,19,37	33,21,14,19,37
		P_{loss} (KW)	35.17	132.16	426.83
		VPI	1.14	1.304	1.68
		LBI	48.01	48.33	63.43
2	Scenario I	Tie switches	7, 13, 34, 39, 41, 61,	7, 13, 34, 39, 41, 61, 84, 86, 87,	7, 13, 34, 39, 41, 61, 84, 86, 87,
		Ploss (KW)	123.77	531	1508.73
		VPI	1.7	2.5	2.75
		LBI	108	140.4	184.26
	Scenario II	Tie switches	7, 13, 34, 39, 42, 55,	7, 13, 34, 39, 42, 55, 72, 86, 89,	7, 13, 34, 39, 42, 55, 72, 86, 89,
		Ploss (KW)	102.65	387.2	1248.4
		VPI	1.62	2.07	2.54
		LBI	101.07	112.61	153.24

5.3. Comparison of the simulation results by other meta-heuristic methods

Scenario II (multi-objective reconfiguration) is simulated using Genetic Algorithm (GA) [13], Particle Swarm Optimization (PSO) [32], and Harmonic Search Algorithm (HSA) [15] at nominal load, to compare with the results obtained by IWD (proposed method). From Table 3, it is observed that the performance of the IWD is better compared with GA, PSO, and HSA in all terms of the loss reduction, improving voltage profile, and equal load balancing. The measured P_{loss} of the base case as compared with, IWD, GA, PSO, and HSA are presented in Figure 6 for the both test systems. As can be seen in this Figure, for the both test systems, IWD has shown lower power losses in compared with other algorithms. For the other items such as LBI and VPI, as seen in the Table 3, better results has been delivered by the proposed method in compare with other algorithms.



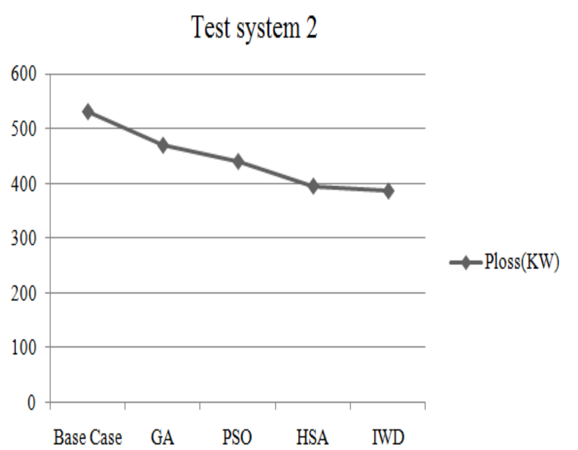


Fig. 6. The measured P_{loss} for base case and different methods

Table 3. Comparison of the simulation results

	Methods	Case	Scenario II
Test system 1	GA	Tie-switches	33,9,34,28,36
		P_{loss}	138.49
		VPI	1.597
		LBI	51.98
	PSO	Tie-switches	31,7,9, 14,37
		P_{loss}	138.12
		VPI	1.496
		LBI	51.87
	HSA	Tie-switches	7,14,9,32,37
		P_{loss}	138.06
		VPI	1.482
		LBI	51.74
	IWD	Tie-switches	33,21,14,19,37
		P_{loss}	132.16
		VPI	1.304
		LBI	48.33
	Methods	Case	Scenario II
Test system 2	GA	Tie-switches	, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96
		P_{loss}	470.09
		VPI	2.24
		LBI	137.36
	PSO	Tie-switches	7, 13, 34, 39, 41, 61, 84, 86, 87, 89, 90, 91, 92
		P_{loss}	440.7
		VPI	2.09
		LBI	135.16
	HSA	Tie-switches	7, 13, 34, 39, 41, 61, 84, 86, 87, 89, 90, 91, 92
		P_{loss}	396
		VPI	2.14
		LBI	123.76
	IWD	Tie-switches	7, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96
		P_{loss}	387.2
		VPI	2.07
		LBI	112.61

6. CONCLUSION

In this paper, a new method based on intelligent water drops approach has been proposed for multi-objective reconfiguration in order to loss reduction, improving the voltage profile, and equalizing the feeder load balancing in distribution system. The proposed method is validated using the IEEE 33-bus test system and a Tai-Power 11.4-kV distribution system as a real distribution network. By applying the reconfiguration using the proposed method on 33-bus test system, the loss is reduced about 34.22%, voltage profile, load balancing, and worst voltage are improved about 23.29%, 28.62% and 3.72% respectively as compared with the base case. In the case of Tai-Power distribution test system, the loss is reduced about 27.08%, voltage profile, load balancing, and worst voltage are improved about 17.2%, 19.79% and 3.26% respectively as compared with the base system. The proposed method is tested at three different load levels: light, nominal, and heavy. The results show that multi objective reconfiguration lead to improvement in all objectives at various load levels for both test systems. The obtained results are also compared with GA, PSO and HSA at nominal load. The computational results showed that performance of the IWD is better than GA, PSO, and HSA for reducing the loss, improving the voltage profile, and equalizing the feeder load balancing in distribution system.

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