

Novel Hybrid Fuzzy-Intelligent Water Drops Approach for Optimal Feeder Multi Objective Reconfiguration by Considering Multiple-Distributed Generation

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ABSTRACT

This paper presents a new hybrid method for optimal multi-objective reconfiguration in a distribution feeder in addition to determining the optimal size and location of multiple-Distributed Generation (DG). The purposes of this research are mitigation of losses, improving the voltage profile and equalizing the feeder load balancing in distribution systems. To reduce the search space, the improved analytical method has been employed to select the optimum candidate locations for multiple-DGs, and the intelligent water drops approach as a novel swarm intelligence based algorithm is used to simultaneously reconfigure and identify the optimal capacity for installation of DG units in the distribution network. In order to facilitate the algorithm for multi-objective search ability, the optimization problem is formulated for minimizing fuzzy performance indices. The proposed method is validated using the Tai-Power 11.4-kV distribution system as a real distribution network. The obtained results proved that this combined technique is more accurate and has the lowest fitness value as compared with other intelligent search algorithms. Also, the obtained results lead to the conclusion that multi-objective simultaneous placement of DGs along with reconfiguration can be more beneficial than separate single-objective optimization.

KEYWORDS: Multi objective reconfiguration, Intelligent water drops algorithm, Distribution system, Power loss, Load balancing, Voltage profile.

1. INTRODUCTION

Distribution system is an interface between consumers and transmission network. Due to the advantages such as lower short circuit current and easier protection coordination, they are generally utilized with radial configuration. On the other hand, this radial structure may lead to reduce the reliability of consumers feeding, increase the power losses and voltage drop at the load points. Electrical power distribution systems have two types of tie and sectionalizing switches, whose statuses determine the configuration of distribution network. By changing the switches states and transition of

sections between feeders during operation, the construction of distribution network will change [1]. Since network reconfiguration is a complex combinatorial, non-differentiable constrained optimization problem, many algorithms were proposed in the past. Many researches in the literature 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. After that, many algorithms have been developed for reconfiguration of distribution system with different aims. Goswami and Basu [3] presented a heuristic algorithm for

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reconfiguration, which is determined using a power flow program. The main advantages of this research are using a very fast power flow method and the independence of the final configurations upon the initial configuration of the feeders. Gomes *et al.* [4] reported a heuristic algorithm for the large distribution systems that begins in a meshed configuration with all switches closed. Several tests are performed using the procedure described in [4], and more efficient configurations are obtained when compared with the methods proposed in three classical papers. The obtained results proved that the proposed procedure [4] presents a very good compromise, as it tends to find a near-optimum or even the optimum solution without the risk of combinatorial explosion. A new path to node based modeling and its application to reconfiguration of distribution system has been proposed by Ramos *et al.* [5] in 2005. In this work, the authors suggested to employ a power flow method-based heuristic algorithm for determining the minimum loss configuration of radial distribution networks. Also, two different optimization algorithms-one resorting to a genetic algorithm and the other solving a conventional mixed-integer linear problem-are fully developed. 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 have suggested the operation cost reduction and it is based on the long term operation of the power system. An optimization technique to determine the network structure with minimum energy losses for a given period has proposed by Taleski and Rajicic [8]. In this research, a new method for checking system radiality which is based on upward-node expression is developed for solving the problem of restorative planning of power system. Kavousi-Fard and Niknam [9] solved the multi-objective distribution feeder reconfiguration problem from the reliability point of view. The investigated objective functions are: System Average Interruption Frequency Index (SAIFI), Average Energy Not Supplied (AENS), total active power losses and the total network cost. The obtained results show that neglecting the uncertainty

effect and so studying in a deterministic environment can deprive the operator from real optimal and dependable final solutions. In [10] multi objective reconfiguration of distribution network has solved using NSGA-II algorithm. It was shown that in addition to reduction of network losses, voltage regulation the load balancing on the system branches were also optimally improved.

Deregulation of electricity markets in many countries world-wide brings new perspectives for Distributed Generation (DG) of electrical energy using renewable energy sources with small capacity. Since the selection of optimal locations and sizes of DG units in distribution system, is also a complex combinatorial optimization problem, many methods have been proposed in this area in the recent past. Among recent works in this area, Ishak *et al.* [11] present a method to identify the optimal location and size of DGs based on the power stability index and Particle Swarm Optimization (PSO) algorithm. In this paper, the Maximum Power Stability Index (MPSI) is utilized as an objective function to determine the optimal DG locations. Next, a PSO-based model with randomized load is developed to optimize DG sizing in view of the system's real power losses. Doagu-mojarrad *et al.* propose an interactive fuzzy satisfying method, which is based on hybrid modified shuffled frog leaping algorithm to solve the problem of the Multi-objective optimal placement and sizing of DG units in the distribution network [12]. One of the advantages of this work is to account the technical, economical and environmental protection considerations.

Solving simultaneous reconfiguration and allocation of DGs problem together, despite the complexity has more advantages rather than separate solutions of them, and has been discussed recently in several studies. Tolabi *et al.* [13] used a method based on the combination of fuzzy sets and Bees Algorithm (BA) for simultaneous reconfiguration and optimal allocation of multiple-DG units in a distribution network. The proposed approach is tested on Taiwan power company system with three DGs. The obtained results are compared with GA, PSO and Harmony Search Algorithm (HSA) at nominal load and found better result than the above mentioned approaches because

of the lowest optimal fitness and more reliable convergence behavior.

In this paper, a novel Intelligent Water Drops (IWD) approach is used for both multi objective reconfiguration and optimal allocation of multiple-DG units in a distribution network. Also, a fuzzy logic technique is used to achieve a compromise between the objective functions. Along with the combination of fuzzy-IWD techniques, an effective approach is used in order to reduce the search space and simplify the selection of candidate buses for installation of DG units using IA method.

The main contribution of the paper is to solve the multi-objective problem using the combination of IWD algorithm and fuzzy approach in order to reduce of losses, improve the voltage profile and equalize the feeder load balancing in power distribution system.

The remainder of this paper is organized in the following manner: DG types are presented in section 2. Sec. 3 gives the problem formulation. Sec. 4 gives the idea about multi-objective function and constraints of the problem. Section 5 explains the IA method. Sec. 6 presents the optimization in fuzzy environment. Intelligent water drop approach is presented in Sec. 7. In Sec. 8, Fuzzy-IWD method is discussed. Results are presented in Sec. 9. A conclusion followed by references is presented in Sec. 10.

2. DG TYPES

Four different types of DGs are introduced as follows:

Type 1 DG: This type only injects the real power.

Type 2 DG: This type only injects the reactive power.

Type 3 DG: This type is capable of injecting both real power and reactive power.

Type 4 DG: This type is capable of injecting real power, but consuming reactive power [14].

3. PROBLEM FORMULATION

3.1. Power flow equations

The problem is formulated using the power flow equations. Power flows in a distribution system are computed by the following set of simplified recursive equations [15]:

$$P_{k+1} = P_k - P_{loss,k} - P_{Lk+1}$$

$$= P_k - \frac{R_k}{|V_k|^2} \{P_k^2 + (Q_k + Y_k |V_k|^2)^2\} - P_{Lk+1}, \quad (1)$$

$$Q_{k+1} = Q_k - Q_{loss,k} - Q_{Lk+1}$$

$$= Q_k - \frac{X_k}{|V_k|^2} \{P_k^2 + (Q_k + Y_k |V_k|^2)^2\} - Y_{k1} |V_k|^2 - Y_{k2} |V_{k+1}|^2 - Q_{Lk+1}$$

$$|V_{k+1}|^2 = |V_k|^2 + \frac{R_k^2 + X_k^2}{|V_k|^2} (P_k^2 + Q_k^2) - 2(R_k P_k + X_k Q_k)$$

$$= |V_k|^2 + \frac{R_k^2 + X_k^2}{|V_k|^2} (P_k^2 + (Q_k + Y_k |V_k|^2)^2)$$

$$- 2(R_k P_k + X_k (Q_k + Y_k |V_k|^2)). \quad (2)$$

where, P_k , Q_k are real and reactive power flowing out of bus k ; $P_{loss,k}$, $Q_{loss,k}$ are real and reactive power loss at bus k ; P_{Lk+1} , Q_{Lk+1} are real and reactive load power at bus $k+1$; R_k , X_k are resistance and reactance of the line section between buses k and $k+1$; Y_k , V_k are Shunt admittance and voltage amplitude at bus k .

The power loss when a DG is installed at an arbitrary is given by:

$$P_{DG,loss} = \frac{R_k}{V_k^2} (P_k^2 + Q_k^2)$$

$$+ \frac{R_k}{V_k^2} (P_G^2 + Q_G^2 - 2P_k P_G - 2Q_k Q_G) \left(\frac{G}{L}\right) \quad (3)$$

where, P_G , Q_G are real and reactive power supplied by DG; G and L are distance and length of the feeder from source to bus in Km.

4. MULTI OBJECTIVE FUNCTION AND CONSTRAINTS OF THE PROBLEM

The objective function $f(x)$ is a constrained optimization problem to find an optimal configuration of the distribution system and DG allocation. $f(x)$ is a multi objective function that consists of three goals: reducing the loss, increasing the load balancing, and improving the voltage that is formulated as follows:

$$\text{Min} F(X) = \min [P_{loss}, LBI, VPI] \quad (4)$$

The constraints of the problem are:

$$1: V_{k \min} \leq V_k' \leq V_{k \max}$$

$$2: |I_{k,k+1}| \leq |I_{k,k+1 \max}|$$

$$3: \sum_{k=1}^{nf} P_{Gk} \leq \sum_{k=1}^{nf} (P_k + P_{loss,k})$$

4: Radial structure of network should be maintained

5: 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 $k+1$.

n_f : Total number of lines sections in the system.

The first term of the objective function reflects real power losses that are defined by (5):

$$P_{loss} = \sum_{k=1}^{n_f} R_k \frac{P_k^2 + Q_k^2}{V_k^2} \quad (5)$$

The second term of the objective function is considered for the Load Balancing Index (LBI) of the lines in the feeder, which is given by:

$$LBI = \sum_{F_j} \left(\frac{I_{F_j}}{I_{F_{avg}}} \right)^2 \quad (6)$$

where, I_{F_j} is the current passing through line j and $I_{F_{avg}}$ is defined by (7):

$$I_{F_{avg}} = \frac{1}{n_f} \sum_{j=1}^{n_f} I_{F_j} \quad (7)$$

The decrease in this index implies increase of load balancing of lines in the distribution feeder.

The third term of the objective function reflects the improvement of the voltage profile, which is shown by Voltage Profile Index (VPI) in (8):

$$VPI = \sum_{k \in LB} |V_k - V_{ref,k}| \quad (8)$$

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 the profile of voltages in the distribution feeder buses.

5. REDUCE THE NUMBER OF SOLUTION SPACE

An effective method is used in order to simplify the selection of candidate buses for installation of DG units using Improved Analytical (IA) method. This method is chosen because it is effective as corroborated by Exhaustive Load Flow (ELF) and Loss Sensitivity Factor (LSF) solutions in terms of loss reduction and computational time [16]. It is based

on IA expressions to calculate the optimal size of different DG types and a methodology to identify the best location for DG allocation, which helps reduce the number of solution space. To reduce the search space in this paper, IA has been employed to select the candidate locations for multiple-DG [16] and the sizes of DG unit at candidate buses are calculated using fuzzy-IWD method. Because detailed description about multiple-DG placement using the AI method is presented in [16], only an overall view to this method is presented in this paper as follows:

First, a single DG is added to the system. After that, the load data are updated with the first DG placed and then another DG is added. Similarly, the algorithm continues to allocate other DG units until it does not satisfy at least one of the following constraints:

- The voltage at a particular bus is over the upper limit;
- The total size of DG units is over the total load plus loss;
- The maximum number of DG units is unavailable;
- The new iteration loss is greater than the previous iteration loss.

6. OPTIMIZATION IN FUZZY ENVIRONMENT

Since the different terms of the multi objective function are in various ranges, a fuzzy system [17] is used in order to compare these terms during reconfiguration and DG placement. In this plan each variable has a membership function (μ) that determines the rank and effectiveness of its variable. The membership values for each variable are between zero and unity in the fuzzy domain and may be different for each element. The membership function are presented by (9) and Fig. 1.

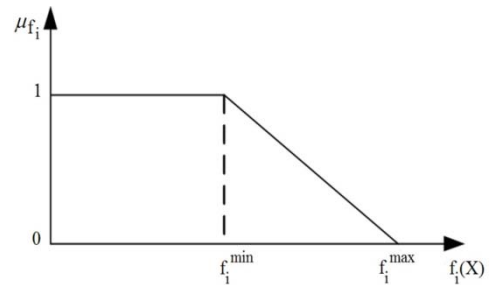


Fig. 1. Membership functions for three different terms of the objective function

$$\mu_{f_i}(X) = \begin{cases} 1, & f_i(X) \leq f_i^{\min} \\ \frac{f_i^{\max} - f_i(X)}{f_i^{\max} - f_i^{\min}}, & f_i^{\min} < f_i(X) < f_i^{\max} \\ 0, & f_i^{\max} \leq f_i(X) \end{cases} \quad (9)$$

where, f_i represents the i th term of the objective function ($i=1, 2, 3$), f_i^{\min} , and f_i^{\max} are the best and worst answers that observed in the single-objective optimization area for the i th term in the objective function, respectively.

By using of another advantage of fuzzy sets, three different objective functions are combined with each other in the form of a Fuzzy Interface System (FIS), so the multi-objective optimization problem will be converted into an optimized fuzzy single-objective function. To achieve this purpose, the value of each objective function, which is considered as an input in the FIS, is divided into several regions using fuzzy membership functions and the final objective function that wants to optimize it, is made through the appropriate rules [18].

Table 1 shows the fuzzy rules that were employed for reconfiguration process simultaneously allocation the optimum size for DGs. In these Table, B, A, G, VB, EB, VG, EG, and EX stand for bad, average, good, very bad, extremely bad, very good, extremely good, and excellent, respectively. In this system, the Mamdani's inference mechanism and the center of the area defuzzification method is used.

Table 1. Fuzzy rules when μ_{LBI} is **a.** bad, **b.** average, **c.** good.

		μ_{VPI}		
		G	A	B
a	G	G	B	EB
	A	A	VB	EB
	B	B	EB	EB

		μ_{VPI}		
		G	A	B
b	G	EG	A	VB
	A	VB	B	EB
	B	G	EB	EB

		μ_{VPI}		
		G	A	B
c	G	EX	A	VB
	A	EG	A	VB
	B	VG	VB	EB

7. INTELLIGENT WATER DROPS 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 [19]. Hosseini [20] presented the basics of the IWD algorithm, then applied it to solve different optimization problems. As described in [20], 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:

$$\Delta vel^{IWD} = \frac{a_v}{b_v + c_v [soil(i, j)]^2} \quad (10)$$

where, $soil(i, j)$ is the soil on the bed of the edge between two points i and j ; a_v , b_v and c_v are pre-defined positive parameters for the IWD algorithm. The relationship between velocity and the amount of soil of the edge is decided by a_v and c_v , meanwhile b_v is a small number used to prevent the singularity

problem. Equation (10) indicates that the rate of changing the velocity, Δvel^{IWD} is dependent on the soil of the edge, *i.e.*, 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:

$$vel_{t+1}^{IWD} = vel_t^{IWD} + \Delta vel_t^{IWD} \quad (11)$$

where, vel_t^{IWD} is the velocity of the IWD at time t .

The amount of soil removed from the bed of $edge(i, j)$ 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 (12):

$$\Delta soil(i, j) = \frac{a_s}{b_s + c_s [time(i, j; vel^{IWD})]^2} \quad (12)$$

where, a_s , b_s and c_s are pre-defined positive parameters for the IWD algorithm. a_s and c_s define the relationship between the amount of soil and the period of time IWD takes to move through the $edge(i, j)$, and b_s 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:

$$time(i, j; vel^{IWD}) = \frac{HUD(i, j)}{\max(\varepsilon_s, vel^{IWD})} \quad (13)$$

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 (12) and (13) 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.

$$soil(i, j)_{(t+1)} = (1 - \rho_n)(soil(i, j)_{(t)} - \rho_n \Delta soil(i, j)) \quad (14)$$

$$soil_{(t+1)}^{IWD} = soil_{(t)}^{IWD} + \Delta soil(i, j) \quad (15)$$

where ρ_n is the local soil updating parameter, which is chosen from $[0, 1]$, and $\Delta soil(i, j)$ is calculated in (12).

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.

$$p(i, j; IWD) = \frac{f(soil(i, j))}{\sum_{k \in v_c(IWD)} f(soil(i, k))} \quad (16)$$

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:

$$g(soil(i, j)) = \begin{cases} soil(i, j) & \text{if: } \min_{l \in v_c(IWD)} (soil(i, l)) \geq 0 \\ soil(i, j) - \min_{l \in v_c(IWD)} (soil(i, l)) & \text{otherwise} \end{cases} \quad (17)$$

The function $\min(\cdot)$ returns the minimum value of its arguments. A uniform random distribution is used to generate a random number which can be compared with this probability in order to decide which is the next location 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 $q(\cdot)$ 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:

$$T^{IB} = \arg \max_{\forall IWDs} q(T^{IWD}) \quad (18)$$

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

Equation (14) 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 (14) 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 (19) can be used to update the $soil(i, j)$ belonging to the current iteration best solution T^{IB} .

$$soil(i, j) = (1 + \rho_{IWD})soil(i, j) - \rho_{IWD} \frac{1}{N_{IB} - 1} soil_{IB}^{IWD}, \quad \forall (i, j) \in T^{IB} \quad (19)$$

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 (19) is the amount of soil that remains from the previous iteration. Meanwhile, the second term of the right-hand side of (19) 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:

$$T^{TB} = \begin{cases} T^{IB} & \text{if } q(T^{IB}) \geq q(T^{TB}) \\ T^{TB} & \text{otherwise} \end{cases} \quad (20)$$

By doing this, it is guaranteed that T^{TB} holds the best solution obtained so far by the IWD algorithm. The algorithm implementation details are specified in the following steps:

Step 1: Initialize soil updating parameters (as , bs and cs) and velocity updating parameters (av , bv , cv), 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 (16) 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 (11).

Step 7: For the IWD moving on the path from node i to j calculate the $\Delta soil(i, j)$ by using the (12) and (13).

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 (14) and (15).

Step 9: Find the iteration based best solution T^{IB} from all the solutions T^{IWD} found by the IWDs using (18).

Step 10: Update the soils on the paths that form the current iteration based best solution T^{IB} by (19).

Step 11: Update the total best solution T^{TB} by using (20).

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} .

8. EXPLANATION OF THE PROPOSED FUZZY-IWD METHOD

This section describes the application of proposed fuzzy-IWD in optimal network reconfiguration and multiple-DG allocation problems. Since both reconfiguration and DG(s) allocation problems are complex combinatorial optimization problems, to reduce the search space, first IA method has been employed to select the best candidate locations for DGs, then optimal configuration and optimal sizes of DG units at candidate buses are discovered using hybrid fuzzy-IWD technique with the objectives of mitigating power loss, improving voltage profile and equal load balancing of the lines.

To reconfigure and DG allocation in the distribution feeder using proposed method, optimal buses candidate for DGs installation are suggested using AI method (The sizes of DG units will vary in

discrete steps at suggested locations during optimization process). Thus, assuming to know the optimal location for DG(s) installation, in order to represent an optimal feeder topology, it is enough to know the positions of open (tie) switches and DG(s) sizes in the network. Accordingly, first solution vector using reconfiguration and DG installation without violating the constraints of problem is formed as follows:

$$IWD^1 = [proposedtieswitches^1, proposedDG(s)size^1]$$

where length of the first part of solution vector for reconfiguration problem (*proposedtieswitches*), is equal to the number of tie switches, and the length of second part for DGs size, (*proposedDGs size*) is equal to the number of DG units.

By updating IWD parameters, second, third, and ..., *i*th solution vector is generated with new proposed tie and new DG sizes at the same locations as follows:

$$IWD^i = \{proposedtieswitches^i, proposedDG(s)size^i\}$$

For each solution *i*, power flow program is carried out, the membership value for each objective and the fuzzified objective function are 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 Fig. 2.

Step 1) read data of distribution system (bus, load, branch, sectionalizing and tie switches numbers, DG types and numbers) and initialize the IWD parameters.

Step 2) give the best buses location for DG(s) using IA proposal.

Step 3) run the power flow program [15] based on equations (1-3), generate the solution vector as *IWD* for reconfiguration and determine DG sizes in the network without violating of five constraints that are presented in section 3.2.

Step 4) run the power flow program, calculate three terms of the objective function (P_{loss} , LBI , VPI) using (5-8), evaluate the membership value for each objective, compute $\mu_{P_{loss}}$, μ_{LBI} , and μ_{VPI} using (9). Compute fuzzified objective function value according to linguistic variable. Store the solution results.

Step 5) update the IWD algorithm parameters using (10-20). Go to step3 to generate a new solution using updated IWD parameters.

Step 6) if the fuzzified objective function value of the new solution is better than stored solution, update the *IWD* vector by storing solution=new solution.

Step 7) if $Itercount < Itermax$, $Itercount = Itercount + 1$ and go to step 5.

Step 8) Best solution=stored solution.

Step 9) defuzzification of best solution and print the result.

Step 10) stop.

9. 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 on a test system. Although the tool can handle four different DG types, only the results of applying three numbers of type 1 DG and three number of type 3 DG at the nominal load are presented.

In the simulation of network, six scenarios are considered to analyze the superiority of the proposed method for both type 1 and type 3 DGs as follow:

Scenario I: the base system without reconfiguration and DG;

Scenario II: the base system only with reconfiguration;

Scenario III: the base system only with DG type 1 allocation;

Scenario IV: the base system only with DG type 3 allocation;

Scenario V: the base system with simultaneous reconfiguration and DG type 1 allocation.

Scenario VI: the base system with simultaneous reconfiguration and DG type 3 allocation.

Using IA method the candidate bus locations to install the DGs are determined for scenarios III, IV, V, and VI. The limits of total DG unit sizes chosen for installation at candidate bus locations are 0 to 6 MVA.

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 $\epsilon_s = 0.001$.

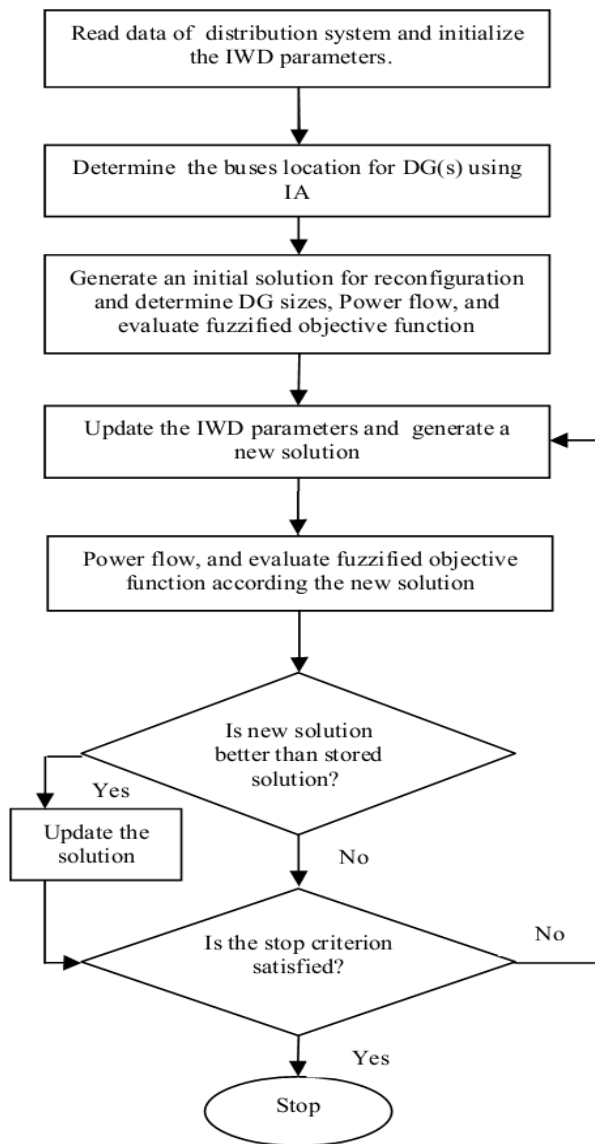


Fig. 2. Flow chart of the proposed method.

9.1 Test system

The test system is a real distribution network of the Taiwan power company. 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 obtained from [21]. 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 shown in Fig. 3.

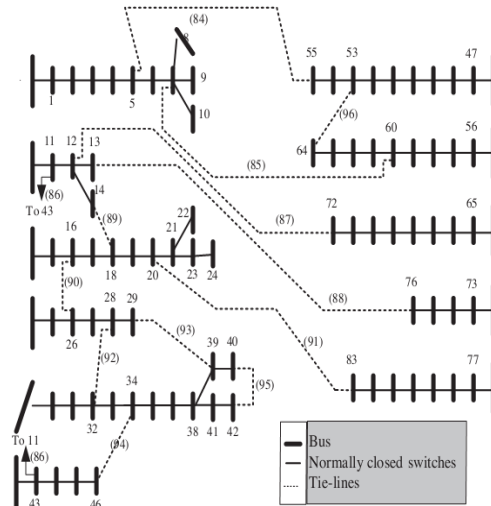


Fig. 3. Single line diagram of the Taiwan power company system.

9.2 Test result

The results of applying the proposed method on the test system are shown in Table 2 for all scenarios. It is observed from this Table that base case power loss in the system is 531.5 kW, which is reduced to 406.91, 326.43, 298.79, 210.62, and 197.23 kW using scenarios II, III, IV, V, and VI, respectively. VPI index is obtained 2.5, 2.35, 1.96, 1.83, 1.66, and 1.47 and LBI index is calculated 140.4, 117.01, 112.54, 114.89, 104.11, and 110.86 for scenarios I to VI, respectively. Also, Table 2 included the optimal locations and sizes for DG units. The total size of DG units is equal to 4.81, 4.83, 5.88, and 5.97 MVA for scenarios III to VI, respectively.

The percentage improvement in P_{loss} , VPI, and LBI as compared with the base system (scenario I) are presented in Table 3 for scenarios II to VI. As can be seen in this Table, the most improvements in loss reduction, and the voltage profile are 62.89% and 41.2%, respectively for scenario V (simultaneous reconfiguration and DG type 1 allocation). The maximum improvement in equal load balancing (LBI index) is 25.84% for scenario VI (simultaneous reconfiguration and DG type 3 allocation). These results prove that the superiority of the scenarios V and VI (proposed hybrid method) in comparison with others. Also, among all scenarios which DG is presented, it is seen that the presence of DG type 1 lead to more improvement in three indexes of P_{loss} and VPI in compared to DG type 3, while DG type 3 has led to more improvement in equal load balancing (LBI index) than DG type 1.

By investigating various scenarios involving reconfiguration, DG allocation, and hybrid of them, it is found that simultaneous multi-objective reconfiguration and placement of DG units is more beneficial than separate single-objective optimization. Scenario V (at nominal load) are simulated using GA [22], PSO [23], and HSA [24], Fuzzy-BA [13], and Honey Bee Mating Optimization (HBMO) and Shuffled Frog Leaping Algorithm (SFLA) (HBMO-SFLA) [25] to be compared with the results obtained by IWD and fuzzy-IWD (proposed method).

Table 2. Results of Taiwan power company

Scenario	Tie switches	Total DG sizes (MVA) @ buses	$P_{loss}(KW)$	VPI	LBI
Scenario I	84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96	-	531.50	2.5	140.4
Scenario II	7, 13, 34, 39, 41, 61, 84, 86, 87, 89, 90, 91, 92	-	406.91	2.35	117.01
Scenario III	7, 13, 34, 39, 41, 61, 84, 86, 87, 89, 90, 91, 92	4.81 @ 8, 42, 95	326.43	1.96	112.54
Scenario IV	7, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96	4.83 @ 26, 31, 80	298.79	1.83	114.89
Scenario V	7, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96	5.88 @ 17, 36, 50	210.62	1.66	104.11
Scenario VI	7, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96	5.97 @ 33, 59, 66	197.23	1.47	110.68

Table 3. Comparison of results for all tested scenarios

Improvements	Scenario II	Scenario III	Scenario IV	Scenario V	Scenario VI
P_{loss} (%)	23.44	38.58	43.78	60.37	62.89
VPI (%)	6.00	21.6	22.8	33.6	41.2
LBI (%)	16.65	19.84	18.16	25.84	21.16

Table 4. Comparison of simulation results for different methods

Method	Case	Scenario V
GA	Tie-switches	7, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96
	P_{loss}	370.09
	VPI	2.03
	LBI	129.8
	Total DG size (MVA) @ buses	4.76 @ 14, 43, 95
PSO	Tie-switches	7, 13, 34, 39, 41, 61, 84, 86, 87, 89, 90, 91, 92
	P_{loss}	323.98
	VPI	1.89
	LBI	112.41
	DG size (MVA) @ buses	4.93 @ 22, 43, 69
HSA	Tie-switches	7, 13, 34, 39, 41, 61, 84, 86, 87, 89, 90, 91, 92
	P_{loss}	341.60
	VPI	1.94
	LBI	118.23
	Total DG size (MVA) @ buses	4.79 @ 14, 43, 95
Fuzzy-BA	Tie-switches	7, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96
	P_{loss}	232.18
	VPI	1.71
	LBI	107.53
	Total DG size (MVA) @ buses	5.82 @ 10, 73, 84
HBMO-SFLA	Tie-switches	7, 13, 34, 39, 41, 61, 84, 86, 87, 89, 90, 91, 92
	P_{loss}	287.31
	VPI	1.73
	LBI	109.04
	Total DG size (MVA) @ buses	5.46 @ 2, 44, 78
IWD	Tie-switches	7, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96
	P_{loss}	294.55
	VPI	1.86
	LBI	110.57
	Total DG size (MVA) @ buses	5.12 @ 49, 52, 73
Fuzzy-IWD	Tie-switches	7, 13, 34, 39, 42, 55, 72, 86, 89, 90, 91, 92, 96
	P_{loss}	210.62
	VPI	1.66
	LBI	104.11
	Total DG size (MVA) @ buses	5.88 @ 17, 36, 50

From Table 4, it is observed that the performance of the fuzzy-IWD is better than GA, PSO, HSA in all terms of the loss reduction [26], voltage profile, and equal load balancing improvement for this scenario. In Figure 4, the obtained values for the optimal fitness of the different algorithms are

compared with together on Taiwan power company test system.

As it is shown in this figure, the fuzzy-IWD method has better performance than the others because of the lowest optimal fitness equal to 0.1306 in comparison with the fuzzy-BA (0.1352), HBMO-SFLA (0.1483), IWD (0.1527), PSO (0.1595), HSA (0.1874), and GA (0.2118) methods, which confirms the ability of the proposed method.

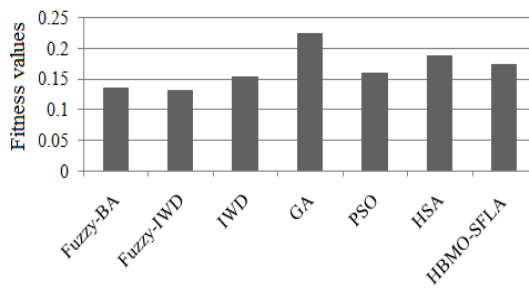


Fig. 4. Optimal fitness for different methods.

10. CONCLUSION

In this paper, a new hybrid method based on fuzzy-intelligent water drops approach has been proposed to simultaneous multi objective reconfiguration and installation of multiple DG units in order to loss reduction, improving the voltage profile, and equalizing the feeder load balancing in distribution system. To reduce the search space, the improved analytical method is employed to select the optimal candidate locations for multiple-DG. Six different scenarios have been tested on a Taiwan power company test system by considering three numbers of DG type 1 and DG type 3 to demonstrate the effectiveness of the proposed technique. From the simulation and analysis of the results, among the six scenarios, the scenario that includes simultaneous reconfiguration and DG type 1 allocation generated the best result in loss reduction (62.89%), and improving the voltage profile (41.2%) as compared with the base test system. The best result in equalizing the feeder load balancing has been obtained by the scenario that proposes simultaneous reconfiguration and DG type 3 allocation. This scenario led to load balancing improvement about 25.84 % as compared with the base case. By investigating all obtained results, it is proved that simultaneous reconfiguration and placement of

multiple DG units is more beneficial than separate single objective optimization.

The obtained results by applying the proposed hybrid method are compared with the obtained results based on another intelligent methods i.e. IWD, GA, PSO, HSA, fuzzy-BA, and HBMO-SFLA at nominal load for scenario V. The results of this comparison showed that performance of the proposed technique is better than others.

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