Optimal Reconfiguration of Radial Distribution Network Considering Time Varying Load using Firefly Algorithm

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Abstract. Increase population growth, industrial growth and the economic growth of the Indonesian people is directly proportional to the level of need consumers of the need for electric power, this leads to the wider topology power grid of the plant, transmission system, medium voltage distribution system to low voltage distribution systems. At this time the distribution system is still often used is a radial distribution system, the impact of the use of the system radial distribution is an active power loss and high voltage drop, one of the solutions to solve this problem is to reconfigure the distribution network. Network reconfiguration is one way to optimize energy flow by opening and closing switches contained in the distribution network. The study using 2 scenarios in the reconfiguration process, the first scenario is fixed reconfiguration, determining the most optimal distribution network configuration based on peak load conditions, the second scenario is hourly reconfiguration, Hourly reconfiguration, determining the most optimal distribution network configuration with for each charge level, these two scenarios are expected to determine the most optimal radial distribution network configuration. The result of initial conditions simulating in the IEEE 33 bus in first scenario have power losses 202,66 kW, after fix reconfiguration obtained 139,53 kW. The result of initial conditions simulating in the IEEE 33 bus in second scenario have power losses 1665,8 kW, after fix reconfiguration obtained 745,78 kW.

Keywords: network reconfiguration, firefly algorithm, time varying load.

1 Introduction

The Distribution System is one of the systems in the electric power system that has an important role because it is directly related to electrical energy consumers, especially consumers of medium voltage and low voltage electrical energy [1]. With the increase in the number of consumers, it will increase the number of load points and load circuits, if the switching of the circuit is not carefully calculated, then the losses in the network will be even greater. On the other hand, the demand for load from each load point varies in each time, be it hourly, per day, or even certain conditions (seasonal). Thus the switching pattern settings need to be optimized both automatically and manually. Automatic settings are required for load switching settings at relatively short times (hourly or daily scales), while manual settings are for seasonal timescales.

Many algorithms have been carried out to reduce losses and service restoration through the reconfiguration of distribution nets. The reconfiguration approach can be classified into

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three main groups are heuristic, mathematical programming, and artificial intelligence (AI). The proposed heuristic distribution net reconfiguration approach according to Civanlar is a heuristic switch exchange algorithm to reduce feeder loss and introduces a simple formula for estimating changes in power losses when a group of loads is transferred from one feeder to another [2]. Baran and Wu present a heuristic reconfiguration methodology based on branch exchange methods to reduce power losses and load balancing purposes [3]. Nagata and Hasaki present a mathematical programming reconfiguration methodology for the improvement of the distribution system [4].

AI approaches using different types of metaheuristics have been proposed for the single-goal optimization of the problem of reconfiguration of distribution line. Nara in 1992 introduced GA for the reconfiguration of distribution nets to minimize power losses [5]. Zhu proposed a Binary Genetic Algorithm approach with an adaptive mutation process to solve the reconfiguration of the distribution net with the aim of minimal power loss [6]. Su presents a distribution net reconfiguration with Ant Colony Optimization (ACO) for power loss reduction [7]. Shariatkhah uses harmony search algorithms and dynamic programming to solve the reconfiguration of distribution feeders for minimum configuration of power loss [8]. Wu Chang Wu presents a distribution net reconfiguration using Binary Coding Particle Swarm Optimization to reduce power losses in the Distribution system [9]. Souza proposes an artificial intelligent Copt-aiNet and Opt-aiNet approach to minimize cost losses on distribution networks [10].

The problem of reconfiguring the distribution system has been carried out taking into account the demand for a constant load (steady state). Enrique Lopez in 2004 proposed an approach to reconfiguring the distribution net by considering the variation of the hourly load by dynamic programming methods to reduce energy losses on the distribution net [11], Zidan in 2008 proposed multi-objective reconfiguration taking into account load variations using the switching index method to minimize energy loss and increase the reliability index value in the Distribution net system [12]. Queiroz proposed an artificial intelligent method, the Adaptive Hybrid Genetic Algorithm, to reduce energy loss in the distribution net considering changes in load to time [13]. Finally in 2016 Souza proposed reconfiguring the distribution net using the Clonal Selection Algorithm and Opt-aiNet Algorihm methods to reduce daily cost losses on the distribution system [14] [15]. In this study, the reconfiguration on the distribution network used the Binary firefly algorithm method by considering the variation in load per time interval in one day. The purpose of this network reconfiguration is to obtain an optimal network reconfiguration each time interval with the least power loss.

2 Load Modeling

In this study the demand of distribution system is expected to follow different normalized daily load patterns (i.e., residential, commercial, industrial) with a peak load of 1 p.u, as shown in figure 1 [16]. The time varying load model is defined as a load model which is dependent on the time and voltage. Accordingly, the voltage dependent load model in [17] incorporates time varying loads at period t can be expressed as follows :

$$P_g(t) = P_{og}(t) \text{ x } V_g^{np}(t) \quad (1)$$

$$Q_g(t) = Q_{og}(t) \text{ x } V_g^{nq}(t) \quad (2)$$

Where Pg and Qg are, respectively, the active and reactive power injection at bus g, Pog dan Qog are, respectively , the active and reactive load at bus k at nominal voltage , Vg is the voltage at bus g, and n_p and n_q are respectively the active and reactive load voltage exponents as given in table 1 [17].

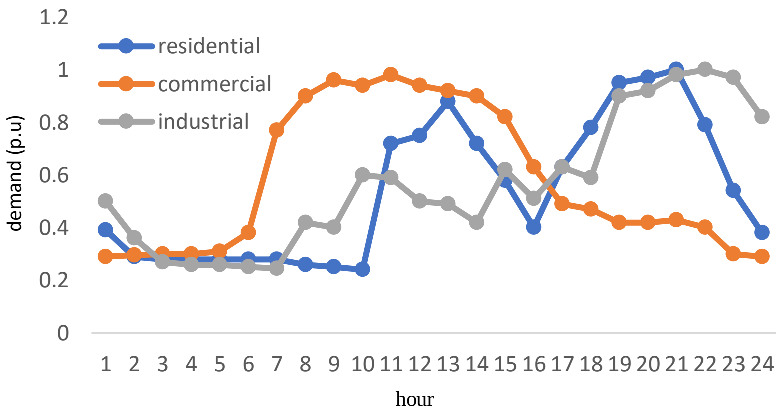

Fig 1. Normalized daily demand curve for various custumer

Table 1. Exponents for Voltage Dependent Loads and Load Type

Load Types	n_p	n_q
Constant	0	0
Commercial	1.51	3.40
Industrial	0.18	6.0
Residential	1.51	3.4

3 Firefly Algortihm

The binary firefly algorithm is a development of the firefly algorithm method [18]. The development carried out is input and output data in the form of binary data, namely "0" and "1". The output data in the Binary Firefly Algorithm is in the form of binary data so that additional functions are needed, namely the sigmoid function. Sigmoid functions such as equations (3)

$$S(x_i) = \frac{1}{1+\exp(-x_i)} \tag{3}$$

$$x_i = \begin{cases} 1, & if\ S(x_i) > r \\ 0, & - \end{cases} \tag{4}$$

Firefly algorithm is a metaheuristic algorithm inspired by the blinking behavior of fireflies [19]. The main purpose of the flashing behavior of fireflies is to attract other fireflies. The firefly algorithm was developed by Dr Xin-She Yang at cambridge university in 2007. Dr Xin-She Yang formulated the firefly algorithm as follows :

1. All fireflies are unisex so that one firefly will be attracted to another firefly.

2. The attractiveness of fireflies is comparable to the brightness level of fireflies. Fireflies with a lower brightness level will be attracted and move towards fireflies with a higher brightness level. The brightness level is affected by distance and light due to weather.
3. 3. The brightness or light intensity of fireflies is determined by the value of the goal function of a given problem. The light intensity is proportional to the value of the goal function for the optimization problem.

There are two things that are very important in the firefly algorithm, namely the intensity of light and the function of activity. The degree of activeness of fireflies is influenced by the level of light intensity. The activeness function is seen in the equation (5).

$$\beta(r) = \beta_0 * e(-\gamma r^m), \qquad (m \geq 1) \tag{5}$$

The distance between the fireflies i and j at locations x, xi and xj can be determined when laying the point where the fireflies are randomly distributed. The distance between fireflies can be formulated as follows:

$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{6}$$

Where the difference from the coordinates of the location of the firefly i to the firefly j is the distance between the two fireflies (rij).

The movement of fireflies i moving towards the best level of light intensity can be seen through the equation (7).

$$x_i baru = x_i + \beta_0 * e\left(-\gamma r_{ij}^2\right) * \left(x_i - x_j\right) + \propto * \left(rand - \tfrac{1}{2}\right) \tag{7}$$

Where the movement of fireflies (new xi) can be influenced by the initial position of the firefly (xi), the degree of activity (β), weather or environmental conditions (γ) and the distance between fireflies (xi-xj).

4 Case Study

In this study using IEEE 33 bus radial distribution network with two scenarios to obtain an optimal distribution network and the least power loss. IEEE 33 bus radial distribution network consists of one main feeder and three laterals. As shown in figure 2, this network mainly has: 33 busses, 32 sectionalizing switches switches ehich are closed in the normal state, 5 tie switch which are normally open. In this study two various scenarios tested on IEEE 33 bus radiol network system :

Scenario 1 : Fixed Reconfiguration
Scenario 2 : Hourly reconfiguration based on normalized daily demand curve for various custumer.

Taking into account the state of the system under normal operating conditions. Which represents the initial state of network. The IEEE 33 bus radial distribution network therefore has operating voltage 12.66 kV, atotal power load of 3715 kW, an initial real and reactive power losses of 202.67 kW and 135.14 kVAR.

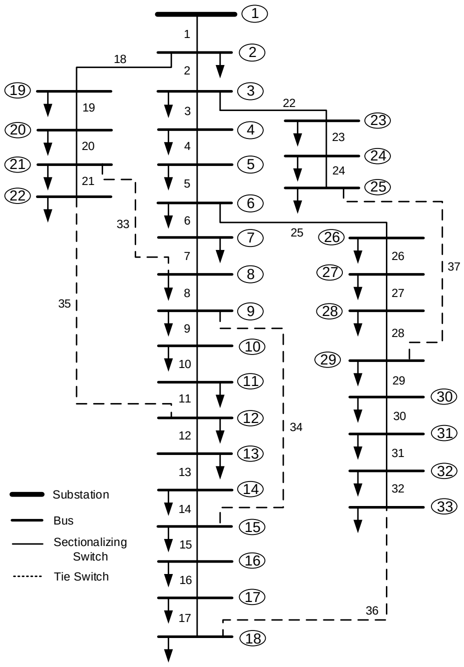

Fig 2. IEEE 33 Bus

4.1 Scenario 1 : Fixed Reconfiguration

reconfiguration of IEEE 33 bus using the firefly algorithm with scenario 1 results in a new distribution network configuration, n the initial condition, the open switches are switches 33, 34, 35, 36 and 37. After a network reconfiguration using the Binary Firefly Algorithm, a new combination of open switches was obtained. The combination of open switches is switches 7, 9, 14, 32 and 37. During the initial conditions in the IEEE 33 bus distribution system, there were 5 tie switches in an open state. After network reconfiguration, only 1 tie switch was obtained in an open state total power losses are reduced from 202.67 kW to 139.21 kW. So, the reduction rate after finding optimal network reconfiguration is equal to 31.31%

Table 2. Result of Fixed Reconfiguration

Reconfiguration conditions	Before Reconfiguration	After Reconfiguration	
		Literature	Proposed Algorithm
Open Swicthes	33, 34, 35, 36, 37	7, 9, 14, 25, 32	7, 9, 14, 32, 37
Real Power Loss (kW)	202.66	139.49	139.21
Percentage of loss reduction		31.17	31.31

Reconfiguration conditions	Before Reconfiguration	After Reconfiguration	
		Literature	Proposed Algorithm
Saving power (kW)		63.17	63.45

4.2 Scenario 2 : Hourly Reconfiguration

it is certain that one topology is very optimal for one time. For example, a configuration that is optimal for peak hours may no longer be optimal for off peak hours due to the change in behavior of loads on the nerwork. Network reconfiguration using firefly algorithm method in IEEE 33 bus radial distribution network for second scenario consists in applying the same reconfiguration technique studied in a fixed reconfiguration (scenario 1) but now over a whole load consumption time interval (daily load) and this frim normalized demand of load models.

the result of the hourly reconfiguration is shown in table 2 where in the last column shows the switching of switches from one load consumption to another point during 24 hours of the day. figure 6 shows the comparison of power losses before and after reconfiguration.

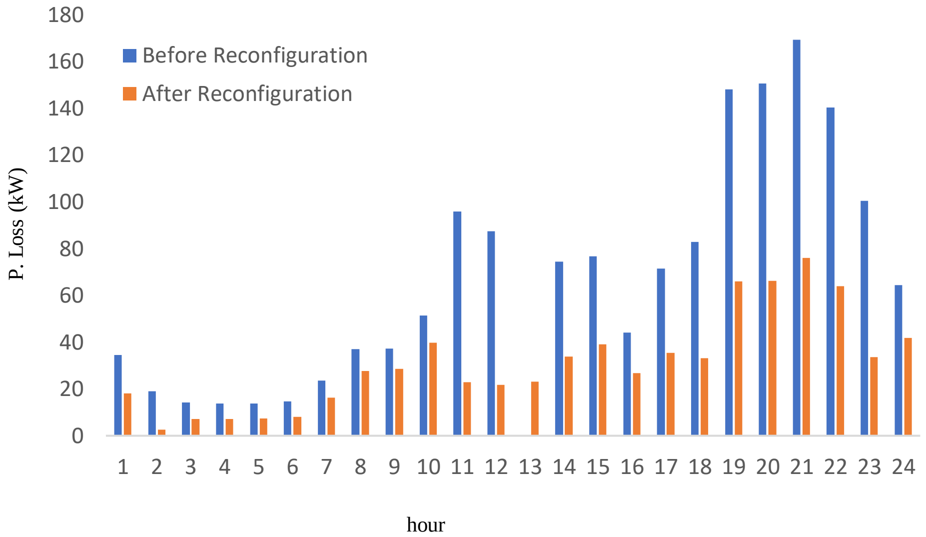

Fig 2. Hourly Variation of Power Losses

Table 3. Result of Hourly Reconfiguration

Hours	Before Reconfiguration		After Reconfiguration		Number of Switches Changes
	Switches	P. Loss (kW)	Switches	P. Loss (kW)	
01.00		34.43	7, 11, 14, 32,37	18.11	0
02.00		19.12	7, 9, 14, 32, 28	2.70	2

Hours	Before Reconfiguration		After Reconfiguration		Number of Switches Changes
	Switches	P. Loss (kW)	Switches	P. Loss (kW)	
03.00	33, 34, 35, 36, 37	14.16	2, 15, 33, 34, 37	7.04	5
04.00		13.71	7, 9, 14, 32, 37	7.15	0
05.00		13.87	7, 9, 14, 32, 37	7.28	0
06.00		14.60	7, 9, 14, 32, 37	8,01	0
07.00		23.62	7, 9, 14, 32, 37	16.35	0
08.00		36.98	7, 9, 14, 32, 37	27.67	0
09.00		37.25	7, 9, 14, 32, 37	28.54	0
10.00		51.35	7, 9, 14, 32, 37	39.85	0
11.00		95.91	7, 9, 14, 32, 28	22.84	1
12.00		87.45	7, 9, 14, 32, 28	21.67	1
13.00		101.29	7, 9, 14, 32, 28	23.04	1
14.00		74.30	7, 9, 14, 32, 37	33.74	1
15.00		76.75	6, 11, 14, 32, 37	39.11	2
16.00		43.97	7, 9, 14, 32, 37	26,73	2
17.00		71.50	7, 9, 14, 32, 37	35.35	0
18.00		82.74	7, 14, 32, 35, 37	33.21	2
19.00		148.08	7, 9, 14, 32, 37	65.90	1
20.00		150.53	7, 9, 14, 32, 37	66.29	0
21.00		169.32	7, 9, 14, 32, 37	75.95	0
22.00		140.21	6, 11, 14, 32, 37	63.99	2
23.00		100.29	4, 12, 22, 32, 33	33.57	1
24.00		64.37	7, 9, 14, 28, 32	41.69	1

5 Conclusion

the results of network reconfiguration on IEEE 33 bus using the firefly algorithm method in first scenario shown a reduction in power loss from 202.67 kW to 139.21 kW and network reconfiguration with second scenario reduction power losses from 1665,8 kW to 745,78 kW. switching switches from one point to another for 24 hours is not optimal, this is because the switch change process in the field requires costs and blackout time so that service continuity is disrupted.

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