Automatic Fault Location Identification and Isolation Method for Smart Distribution Network in Surabaya City

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Abstract - There are various types of fault that can occur in the distribution system network, so it is necessary to identify the location of the fault and isolate the fault in the area of the fault. The city of Surabaya is in preparation for the development of a smart city, so it is necessary to prepare a smart distribution system network system that can identify locations and isolate disturbed areas automatically. This paper describes the reconfiguration process to improve the value of losses in the system which results in a decrease in the value of total line losses after reconfiguration of 313.46 kW from 8 scenarios and includes the effect of adding solar energy to the existing network. The process of identifying the fault location and the isolation process on the Surabaya distribution system network in this paper uses the deep learning method. The fault location is determined based on the voltage and current profile of each bus in the system, while the isolation process is carried out by opening the switch closest to the fault area. In this process, deep learning can provide accurate fault location and isolation results for 6 fault tests.

I. Introduction

The distribution network is very vulnerable to disruption[1, 2]. 80% of network disruptions occur in the distribution network[2-4] plus at this time there are public electric vehicle charging stations and network integration with renewable energy so it is very important to maintain the performance and reliability of the distribution network system. Accurate identification of the location of the fault and the ability to isolate faults in the distribution automation system is a challenge and a very important role in improving the performance and reliability[2-4] of the distribution network.

The majority of fault location identification algorithms use radial networks[3-6] but along with the process of reconfiguring the distribution network topology slowly begins to change[3] thus making the process of identifying the location of the fault more difficult. Therefore we need an algorithm that is not only able to identify the location of the fault on the radial network but in the whole system.

From the research that has been done before, many methods have been used for the process of fault identification, such as the traveling-wave-based method[7-10], the voltage-sag method[11-14], the minimum reactance method[15, 16], the impedance-based method[17-22], and others[6, 23-26]. However, from several methods that have been worked on, there are shortcomings caused by the complexity of the current distribution system network. As the impedance-based method has drawbacks whose main point is the estimation of faults that are more than 1[1, 3, 5], the traveling-wave based method cannot be used with inhomogeneous feeders[1, 3, 5] and voltage-sag which must compare the identified faults with previous fault types to detect the point of interference [3].

In this paper, to identify the fault location is carried out using the Forward-Backward Sweep method to identify the characters that occur in the system when a fault occurs. Fault points that have occurred in the electrical network are also identified so that if the same fault occurs, the system is also able to identify it. To reduce fault at the same point and power outages, a reconfiguration process is needed so that the point that is experiencing interference can be isolated but still gets a power supply.
from another bus. The entry of renewable energy into the system is also the focus of identification on the distribution network to study the character of the impact on the system.

Identification of the character of the fault location and the isolation process that has been obtained will then be taught in deep learning. Deep learning is a promising algorithm[27-31] in a prediction function with large training data[27, 29-31] so that the identification process with more than 1 fault at different points and the isolation process decisions can be carried out quickly and precisely based on the characters that occur in the system who have been taught on deep learning.

2. Identification network and fault indicator

To know the condition of the existing network we need to identify it to solve any voltage problems and to reduce the system losses till can be minimize and solar energy penetration also consider. The fault indicator also very important to identify the location of fault and how it can be isolated. Detail description of identification network and fault indicator is described below.

2.1 Identify of existing system

Real plant system as shown in figure 1 in this paper is using 1 of the distribution networks in Surabaya city, Indonesia with 68 bus and 67 lines. Process identification aims to determine the voltage level on each bus and losses in existing conditions. The voltage drop on a certain bus is used as an indicator in the process of determining the network loop in the reconfiguration process.

2.2 Reconfiguration process

The aim of the process of reconfiguring the radial network is to reduce network losses[3, 32] with the losses equation[33] as shown in equation 1. The results from above process is to determine the loop or tie-switch to make new connection in order to improve voltage level on each bus. That process will change the topology network from figure 1 to figure 2 (as shown below). There are 2 grid tie as a new connection from bus 6 to 29 (line 68), from bus 17 to 54 (line 69) and 16 MW on-grid solar energy also be injected in bus 45.

\[
P_{\text{loss}} = \frac{i^2R}{1000} (kW)
\]  

(1)
With:

\[ P_{\text{loss}} \quad \text{= line losses (kW)} \]
\[ i \quad \text{= line current (Ampere)} \]
\[ R \quad \text{= line resistance (Ohm)} \]

2.3 Fault indicator to determine the location and the isolation

Fault indicator in this paper is indicated by voltage and current levels in every each bus. If there is a fault on one of the buses, voltage will drops and current will flows from up stream to down stream to the location which is faulted. The character from voltage drop and current flows in fault location can be identified and can be isolated. Isolated process that will do is to open the switch which the position in upside and downside the fault location.

2.4 Deep learning architecture

Deep learning structure is containing voltages and currents level in every each bus as the inputs and the output from this process are the fault location and the switch logic which connects the buses each other. From its structure the architecture of deep learning can be defined as shown in figure 3.
3. Automatic faulted location and isolation method

When fault occurs, the current will flow to the location which fault and the voltage will drop under the nominal. As shown in fig 4 as illustration of fault in bus number 17, it shown that how it can find the fault location by following the current flows as shown in a red line. From this indication, the decision can be performed by choosing where the switch should be open to isolate the fault as shown.

Figure 4. Fault location illustration with single fault

4. Simulation result

For evaluating the reconfiguration network system as shown in figure 2 will be compared by the 8 scenarios, they are the existing system, the loop 1 connection, the loop 2 connection, the loop 1 and 2 connection and also plus solar energy penetration which injected in bus 45. For the voltage comparison results in every each bus as shown in figure 5. As shown in the figure 5 after reconfiguration, loop 1 and 2 in service also solar energy penetration start to be injected to the system voltage profile start rise up close to voltage nominal which is 20 kV.

Figure 5. Voltage profile before and after reconfiguration
Losses values start to decrease after the system network is reconfigured. Decreasing value of total losses from existing network system to the minimum line losses results in about 313.46 kW with the detail values of total losses in every scenario as shown in table 1. Losses profiles in each line and scenario shown in figure 6. Loop 2 and Loop 1 2 all of them is penetrated by solar energy as shown in figure 6 looks likes the same have the lower losses but in total losses Loop 2 is better than Loop 1 2 as shown in Table 1.

Table 1. Total line losses profile in every scenario

| Total Losses (kW) | Total Losses (kW) System After Adding Solar Energy Penetration |
|-------------------|---------------------------------------------------------------|
| Existing (s1)     | Loop 1 (s2) | Loop 2 (s3) | Loop 2 (s4) | Loop 1 (s5) | Loop 1 (s6) | Loop 2 (s7) | Loop 1 (s8) |
| 532.34            | 494.2       | 495.26      | 459.13      | 205.7       | 204.47      | 218.69      | 218.87      |

**s1, s2,…,s8 = scenario 1, 2,…,8

Figure 6. Losses profiles in every each line

After evaluating the improvement from the reconfiguration network, the fault location identification and isolation using deep learning is evaluated too. The evaluation process is carried out by giving faults to several buses. Deep learning will identify faults by examining the input voltage and current profiles on each bus and making a decision on which bus is faulty and should be isolated. As shown in table 2 some identifying process was tested to find the fault location and the decision for the isolation. Fault condition was tested by two type, single and multiple. The identification process to find the fault location was shown a good identify and make a great decision to open the switch which connects to another bus.
Table 2. Fault location identification and isolation testing

| Bus Fault | Deep learning Output | Bus location | Open switch to isolate (Line) |
|-----------|-----------------------|--------------|-------------------------------|
| 6         | 6                     | 9, 10        |
| 17        | 17                    | 16, 17, 18, 69 |
| 31        | 31                    | 30, 31       |
| 17 & 31   | 17 & 31               | 16, 17, 18, 30, 31, 69 |
| 39 & 59   | 39 & 59               | 38, 39, 40, 45, 58, 59, 61 |
| 39 & 44   | 39 & 44               | 38, 40, 41, 42, 43 |

5. Conclusion

From the simulation results reconfiguration process make a great improve in voltage profiles and reduce the total line losses in significant of 313.46 kW which is shown in every scenario from before and after reconfiguration. Losses reduction from existing condition to scenario 2 until 8 are about 38.05 kW, 7.07 kW, 73.20 kW, 326.55 kW, 327.86 kW, 313.65 kW and 313.46 kW.

Fault location identification and isolation using deep learning contain minimum contrains, with voltage and current indicator in every each bus from input side and from the output side contains fault location and switch indicator. From 6 faults testing, deep learning shows good performance and can identify accurately the location of the fault and isolate it by opening a switch at the location fault both single and multiple faults.

6. References

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