International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol.10, No.2, 2023, pp.62-70.

ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

Reliability Enhancement on Distribution System Using Modified Multi-Objective Particle Swarm Optimization Technique

K.S. Chandragupta Mauryan [a], R. Purrnimaa Shiva Sakthi [b], K. Rajesh Babu [c]

[a] *Professor, Department of Electrical and Electronics Engineering, Guru Nanak Institution Technical Campus, Hyderabad, Telangana State, India.*
[b] *Assistant Professor, Department of Electrical and Electronics Engineering, Hindusthan College of Engineering and Technology, Coimbatore, Tamil Nadu State, India.*
[c] *Assistant Professor, Department of Electrical and Electronics Engineering, Guru Nanak Institution Technical Campus, Hyderabad, Telangana State, India.*

Abstract

This research paper introduces an innovative approach for optimizing the placement of fault indicators (FIs) within electric distribution systems. The primary focus is on addressing how the presence of existing protection and control devices affects the time it takes to restore service to customers in the event of a fault. Unlike conventional FI placement methods, this extended approach considers the uncertainties associated with automatic switching and introduces a novel technical objective function known as the Customers' Average Restoration Time Index (CARTI). To tackle the complex task of multi-objective optimization, a solution approach has been devised, with the goal of simultaneously minimizing both economic and technical objectives. This methodology harnesses a Multi-Objective Particle Swarm Optimization (MOPSO) algorithm and incorporates a Modified Particle Swarm Optimization technique to select the most suitable solution from the set of Pareto optimal solutions generated. The proposed method's effectiveness is demonstrated through its application in two scenarios: firstly, in the context of bus number four within the Roy Billinton test system (RBTS4), and secondly, in a practical real-life distribution network. The study assesses technical objectives, specifically the System Average Interruption Duration Index (SAIDI) and CARTI, providing insights into the method's practical utility and its capacity to enhance FI placement for improved distribution system performance.

Index Terms: Distribution System, Fault Indicator Placement, Optimization Techniques for Reliability, Multi-objective Particle Swarm Optimization (MOPSO), Power System Planning and Optimization, Reliability Evaluation.

DOI:10.9756/IAJSE/V10I2/IAJSE1009
Received:15 April 2023/Accepted: 26 May 2023/Published: 10 June 2023

Introduction

Distribution Automation Systems (DASs) play a pivotal role in enhancing the efficiency and reliability of distribution networks, as outlined in [3] - [5]. Within this framework, the Outage Management System (OMS) is dedicated to overseeing the Fault Location, Isolation, and Service Restoration (FLISR) process during contingencies. To achieve this, the network is equipped with an array of control and protective devices, accompanied by relevant measurements [6], [7]. When a fault occurs, FLISR initiates control sequences to restore power to customers who can be brought back online, taking into account the switch locations. Initially, protective relays detect the fault. Subsequently, the circuit breaker opens and de-energizes the faulty feeder. Consequently, all downstream customers experience an outage due to the fault. The control sequence is successfully completed once the fault's location is identified and isolated, enabling the restoration of power to those customers who can be restored.

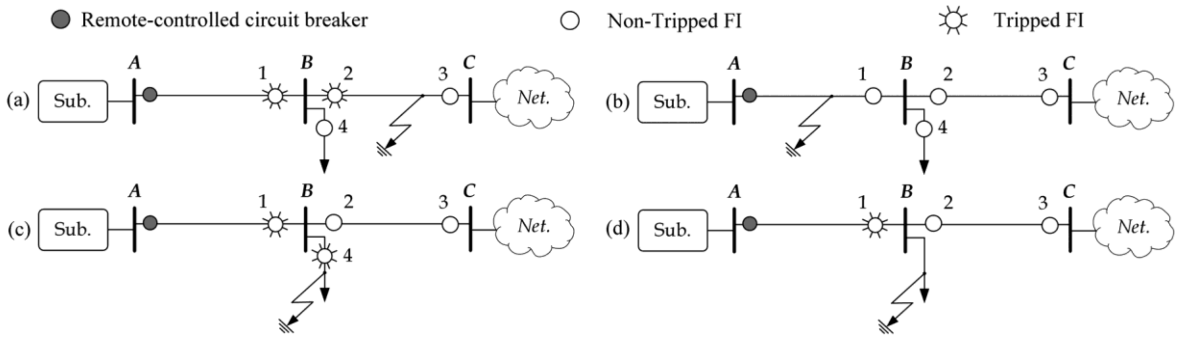

Fig. 1: Illustrative Network Reinforced by FIs and their Response to the Occurred Faults

The effectiveness of supplying power to both restorable and non-restorable customers is significantly impacted by the time it takes to locate faults. As a result, various approaches have been developed to expedite the fault location process [7]. In distribution operations, it has been observed empirically that fault location typically accounts for approximately 25% of the total service restoration time, particularly for manually restorable customers. In Figure 1, we see a sample network that has been reinforced with multiple Fault Indicators (FIs). As depicted in Figure 1(a), when a fault occurs between buses, the 1st and 2nd FIs have tripped.

This means that the repairing/switching crew is accurately informed about the location of the faulted zone because the 2nd FI has tripped, while the 3rd one has not. Consequently, the patrol's search distance to locate the faulted zone is reduced by nearly 66%. Based on the above scenario, it becomes evident that expanding the deployment of FIs throughout the distribution network is a viable solution to minimize fault detection and restoration time, ultimately leading to improved reliability. In Figure 1, we can observe an illustrative network that has been reinforced with Fault Indicators (FIs) and how they respond to various fault occurrences. (i) When a fault occurs in the upstream zones of a bus, the fault location is detected by checking the responses of the 2nd and 3rd FIs, as shown in Figure 1(a). (ii) On the other hand, when a fault takes place downstream of a bus, a remote-controlled circuit breaker (RCCB) trips, but the FIs remain untripped. In this scenario, the faulted zone is identified based on the data received from the 1st FI and the RCCB, as depicted in Figure 1(b). (iii) Figures 1(c) and (d) demonstrate that when a fault occurs in the lateral of a bus, it is indicated by the responses of the 1st and 2nd FIs.

The primary objectives of such optimization problems are to determine the optimal number of FIs and their precise locations while adhering to technical constraints and minimizing costs. Mathematical models and algorithms have been developed to address these challenges, as documented in the literature. One notable approach involves the creation of a reliability model for FIs, which assesses the impact of varying numbers of FIs on reliability indices. However, it's important to note that these models typically do not consider economic factors. In a separate study [11], an economic-based approach to FIs placement is explored, employing a binary shuffled frog leaping algorithm within a real-life distribution network.

In an effort to determine the optimal positions of Fault Indicators (FIs) in an actual distribution network, a Particle Swarm Optimization (PSO) based algorithm has been employed. It's noteworthy that, in the studied network, a mid-point recloser is already in place, but the existing switches have not been taken into consideration to solve the FI placement problem in the existing literature. To effectively showcase the efficacy of the proposed approach, restoration times for each load point in Figure 3 have been calculated and compared. It's worth noting that the method proposed in this paper relies on conditional probabilities of switching, which is distinct from the approach relying on a fixed time for average fault detection duration. The restoration times for load points are visualized in Figure 4 as a means of illustrating the benefits of the proposed approach. This research represents a significant advancement in optimizing FI placement, taking into account various factors including existing devices, control sequences, and economic considerations, ultimately leading to improved efficiency and reliability in distribution networks.

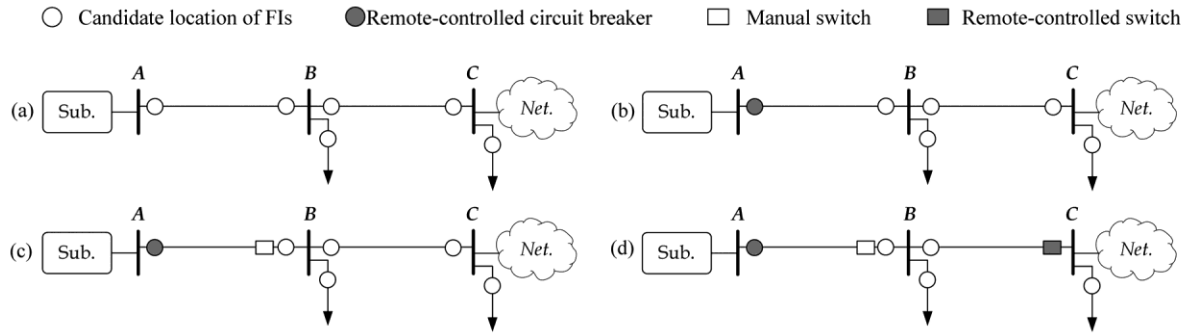

Fig. 2: Candidate Locations Among a Simple Network with Respect to the Installation Rules

Problem Formulation

The objective of the optimal Fault Indicator (FI) placement problem is to identify a set of FI locations that simultaneously minimize specific objective functions, following the installation rules proposed in references [10] and [15]. These rules are designed to guide the selection of suitable FI locations based on practical considerations within the distribution network:

- Candidate Locations: Feasible candidate locations for FI installation include the starting point of each lateral, as well as both upstream and downstream positions of buses situated along the main feeder. However, it's important to note that normally open tie nodes are excluded from this set of candidate locations (as shown in Figure 2(a)).
- Consideration of Protective Devices: Remote-controlled switches (RCSs) and the Remote-Controlled Circuit Breakers (RCCBs) are equipped with fault detection capabilities and communication interfaces. Therefore, it is neither necessary nor cost-effective to install FIs in areas where these devices are present (as depicted in Figures 2(b) - (d)).

As illustrated in Figure 2(a), the first installation rule results in a comprehensive set of candidate locations adhering to the network's topology. The second rule, as evident in Figures 2(b) and 2(d), further refines the candidate locations in response to the presence of RCS and RCCB devices. Notably, manual switches have no impact on the selection of possible candidate locations, as shown in Figure 2(c).

To formulate the economic aspects of FI deployment as a mixed-integer nonlinear programming problem. This mathematical model, represented by equations and constraints, addresses the optimization of FI placement while considering investment and maintenance costs for FIs, as well as the aggregated costs related to customer interruptions within the specified planning horizon. This method enables a systematic and informed decision-making process to strike a balance between cost-effectiveness and improved reliability in the distribution network through (1) - (4):

$$Min\, F_1 = ECOST + FIC \tag{1}$$

$$ECOST = \sum_{i=1}^{n_y} \left[PW^i \cdot \sum_{j \in \Omega^{LP}} \sum_{z \in \Omega^{LT}} \sum_{k \in \{\Omega^l \cup \Omega^t \cup \Omega^b\}} \left[L_{ij}^z \cdot \lambda_k \cdot C_z^O(r_{jk}) \right] \right] \tag{2}$$

$$FIC = \sum_{i \in \Omega^C} \psi_i \cdot \left[C_i^{FI} + \sum_{j=1}^{n_y} PW^j \cdot C_{ij}^m \right] \frac{C_z^O}{PW} \tag{3}$$

$$PW = \frac{1 + \alpha_{inf}}{1 + \alpha_{int}} \tag{4}$$

The economic objective function of this problem is expressed in equation (1). In this equation, the first term represents the expected outage cost to customers over the planning horizon, which is modeled to consider various contingencies. Equation (2) calculates the annual expected outage costs incurred by customers at each load point, taking into account different types of customer service priorities by applying weighting coefficients. To account for the time value of money, equation (4) is used to calculate the present value of the costs in (2). The second term in equation (1) addresses the total investment and maintenance costs associated with Fault Indicators (FIs) and is calculated using equation (3). In this section, the paper's main contributions are explored through numerical studies in two scenarios:

First Scenario: This scenario examines the capabilities of the proposed method while considering standard economic functions. It also investigates the impact of existing control devices on the optimal locations for FIs.

Second Scenario: This scenario illustrates the effects of employing a multi-objective approach to the FI placement problem. Various combinations of objective functions, denoted as F1, F2, etc., are assumed. The results obtained are compared to those from the first scenario to assess the advantages of the multi-objective approach.

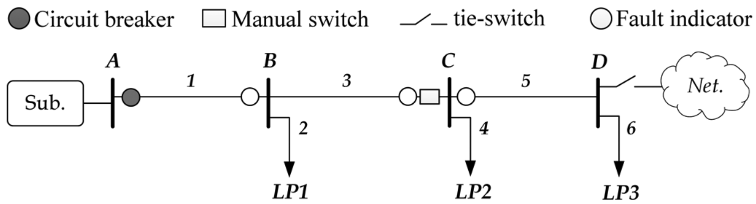

Fig. 3: Simple Network to Illustrate the Restoration Times

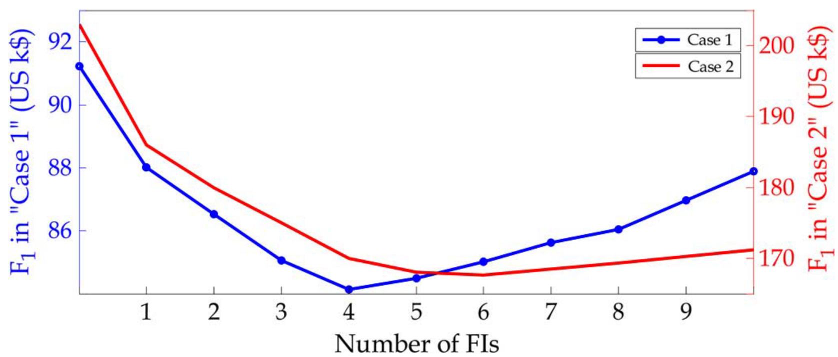

Fig. 4: Restoration Times of Each Load Points Containing FI Obtained for Two Different Cases

Solution Algorithm

Incorporating fuzzy set theory, the paper emphasizes the importance of normalizing each objective function to attain a linear membership function during the minimization process. The optimization procedure in this paper is executed through a combination of Particle Swarm Optimization (PSO) and Multi-Objective Particle Swarm Optimization (MOPSO). This approach is effective for both single and multi-objective optimization tasks, showcasing its versatility and applicability in various optimization scenarios [24], [25]. In this algorithm, the particles, symbolizing potential solutions, navigate through the problem space in search of the optimal solution [26]. A general multi-objective problem is typically formulated as outlined in the paper [27], taking into account multiple objectives and their respective constraints. To select the best compromise solution from the set of solutions generated by the algorithm, the approach considers the results associated with the maximum normalized membership value [30]. In this algorithm, the particles which represent possible solutions fly through the problem space to find the best solution [26]. A general multi-objective problem can be formulated as follows [27]. In order to select the best compromising solution, the result associated with the maximum normalized membership value is employed [30].

The MOPSO algorithm is conducted based on a set of principles, and random initialization is applied to the problem. Throughout a series of iterations, the velocity of particles and their positions are adjusted according to the algorithm's rules. In this process, all non-dominated solutions, which are solutions that are not inferior to any other solution in all objectives, are archived. The developed method follows a systematic sequence of steps for solving optimization problems. Here's an outline of the process:

Step 1: Begin by gathering technical and economic information.

Step 2: Create a set of candidate locations for optimization.

Step 3: Generate and update particle positions and velocities.

Step 4: Evaluate the objective functions to assess solution performance.

Step 5: Search for non-dominated solutions, which are solutions not inferior to others in all objectives.

Step 6: Identify both local and global best solutions for each particle.

Step 7: Repeat Steps 3 through 6 iteratively until specific stopping criteria are met. These criteria often include a maximum number of iterations or convergence thresholds.

Step 8: At the end of the optimization process, select the best compromising solution that optimally balances multiple objectives and criteria.

This systematic approach enables the method to efficiently explore, evaluate, and select solutions that meet both technical and economic requirements, making it a powerful tool for addressing complex optimization problems.

Experimental Results

To tackle the challenge of Fault Indicator (FI) placement using the proposed method, a user-friendly software application has been developed. This software empowers users to input both technical and economic data, as well as generate a GIS-compatible map. Through this intuitive interface, users can easily visualize the outcomes of FI placement. Table 2 provides a comparison of reliability indices for the RBTS4 network, both before and after the distribution of FIs, in two distinct scenarios labeled as "Case 1" and "Case 2." It's worth noting that the reliability indices of the pre-existing networks in these two cases differ, based on whether the available control devices are taken into account or not. This approach not only simplifies the FI deployment process but also allows users to assess the impact of FIs on network reliability through a user-friendly software environment.

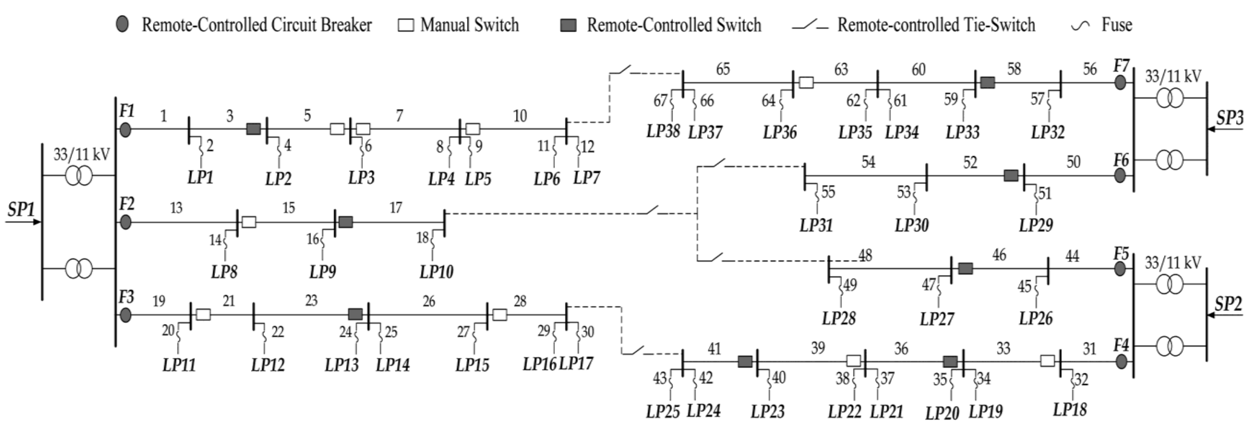

Fig. 5: Single-line Diagram of RBTS4

To assess the performance of the proposed approach, we apply it to bus number four within the Roy Billinton test system (RBTS4) under various scenarios. RBTS4 comprises three supply points (substations), seven feeders, 38 load points, and a total of 4,779 customers, as depicted in Figure 5. These customers belong to five distinct categories, encompassing residential, commercial, industrial, public, and critical customer types. It is assumed that the probability of successful operation of RCSs, fuses, RTUs, control center, communication interface and feeder protection relays are 0.985, 0.90, 0.98, 0.98, 0.996, and 0.995, respectively. Moreover, the auto-switching time and manual switching times are set equal to 30 s and 1 h, respectively. Total installation costs of a remote access FI are assumed US$ 1000 [15]. The analysis encompasses a planning horizon of 10 years, with consideration for an inflation rate of 6% and an interest rate of 7%. The computer employed for conducting simulations boasts technical specifications that include a Centrino 1.8GHz CPU and 1 GB of RAM.

Table 1: Feeder Type, Length and Section Number

Feeder type (bus-2)	Feeder length (Km)	Feeder section number
1	0.65	2 6 10 14 17 21 25 28 30 34
2	0.75	1 4 7 9 12 16 19 22 24 27 29 32 35
3	0.80	3 5 8 11 13 15 18 20 23 26 31 33 36

To effectively demonstrate the impact of existing control devices on the placement of Fault Indicators (FIs), we have derived an economic objective function associated with the installation of varying numbers of FIs in the third feeder of RBTS4. This objective function is visually represented in Figure 6. In the optimal FI placement for "Case 1," the chosen locations are 21U, 26D, 27D, and 28U, where "U" and "D" respectively denote "Upstream" and "Downstream" positions along a line section. Notably, the optimal FI arrangement for "Case 2" incorporates 23U and 25D in addition to those of "Case 1".

Table 2: Location for Fault Indicator

LINE	UPSTREAM / DOWNSTREAM
1	2D
2	1U
3	1U
4	1U
5	1U
6	1U
7	2D
8	1U
9	1U
10	2D

Table 2 shows that the optimal FI deployment of “Case 1” results in almost 15% reduction in both $SAIDI$ and CAIDI. The decrease in $ECOST$is about 12% during the planning horizon, which not only compensates the investment and maintenance costs, but also brings almost US k$ 62 benefits. In addition, trajectory of the best solution for each algorithm is shown in Fig. 7. As shown in this figure, both methods could find the best solution; however, the PSO converges at the 852nd generation while MMOPSO converges at the 945th generation. It might be helpful to mention that the maximum investment cost is set according to the total installation cost associated to “Case 1” of Table 1. Obtained results of this test reveal that the proposed FI locations are changed by almost 60% in comparison to those reported inTable 1. Moreover, reliability indices are significantly altered, as shown in Table 3.

Table 3: Cost of Interruption for Different Customers

Time (hrs) x Cost ($)	Residential	Industrial	Commercial
0.33	0.22	400	1721.04
1	1.27	1182.61	3323.21
2	5.34	2087.45	4808.70
4	14.02	4352.91	8496.43
8	29.83	7806.86	14820.69
24	135.72	17138.70	24707.79

It can be seen in Table VI that minimizing $SAIDI$consequences higher reliability level as regards planning profit is de- creased about 63%. Thus, although optimal FI placement by minimizing $SAIDI$results higher reliability level, it is not as economical as the obtained layout reaches by minimizing the cost function.

Table 4: Line Data and the Load Point Location of Various Lines

Line Number	Load Point	Line Length (Km)
1	1	0.75
2	1	0.60
3	1	0.80
4	2	0.75
5	2	0.80
6	3	0.60
7	3	0.75
8	4	0.80
9	5	0.75
10	5	0.60
11	6	0.80

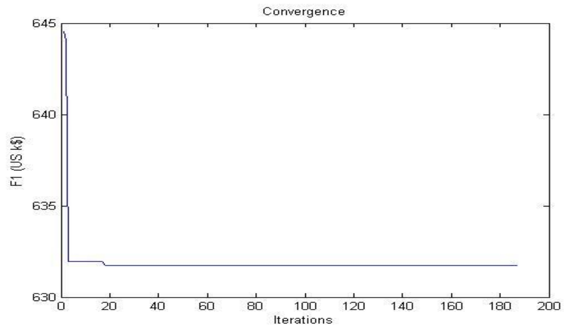

Fig. 6: Pareto-optimal set of Solutions While Minimizing F1

In this scenario, a multi-objective optimization-based approach is applied to the FI problem to simultaneously minimize the cost function represented in (1) as well as the technical objectives formulated. the proposed solution approach could find a proper compromised result for the FI problem in case of minimizing F1 and F2. The obtained results shown in Table 4, the objectives and seem to have high homogeneity which may harm the multi-objective solution method. Hence, in order to efficiently investigate the effects of the multi-objective approach on FI placement, the problem is solved by minimizing and; the obtained Pareto-optimal set of solutions is depicted in Fig. 6. The results show that the distribution utilities may consider multi-objective FI placement while planning their networks according to the customer's choices on reliability.

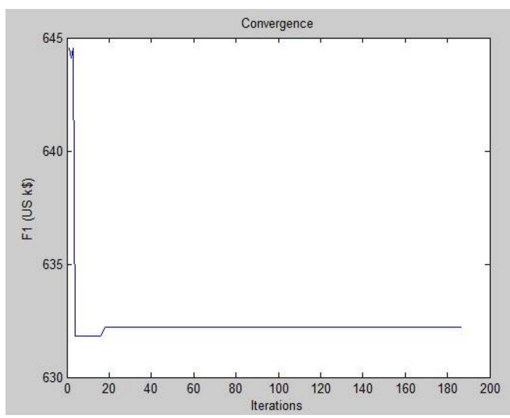

Fig. 7: Pareto-optimal Set of Solutions While Minimizing F1 and F2

Based on the proposed installation rules and considering communication constraint of a real-life distribution network, such as communication range, there are 1330 candidate location to install FIs. The three mentioned configurations and the multi-objective approach is applied to thiscase, to simultaneously minimize F1, F2, and F3., the reliability indices associated to the "Existing system" in "CaseI" and "Case II" are not the same, which is due to the feeder reconfigurations applied to "Case II". The algorithm proposes 124 FIs for "Case II", comparing to the 117 FIs proposed for"Case I". The results of minimizing the set of three objectives reveal that the proposed FI locations for "Case II" are changed by almost 24% in comparison to those of "Case I". Therefore, ECOST associated to optimal arrangements of FIs for "Case II" is decreased less than it is decreased in "Case I". The obtained results associated to "Case II" are more realistic in comparison to those of "Case I", since the distribution systems topology is changed during operation practice. Hereupon, the best layout of FIs may be achieved by simultaneously minimizingF1, F2and F3 considering the possible network topologies.

Conclusions

This research approached the Fault Indicator (FI) placement problem with a multi-objective strategy, employing an algorithm based on Multi-Objective Particle Swarm Optimization (MOPSO). The traditional formulation of the FI placement problem was expanded to account for the presence of protection and control devices and their impact on operational uncertainties during contingencies. Additionally, a new technical objective called the Customers' Average

Restoration Time Index (CARTI) was introduced. The investigation assessed how the existing control and protection devices influenced the FI placement problem across various scenarios. It also explored the potential ramifications of changes in distribution network topology on the FI placement problem. Subsequently, the proposed methodology was put into practice on both a standard test system (RBTS4) and a real-world distribution network, considering multiple scenarios. The results and discussions presented in the paper underscore the efficacy of this approach as a framework for optimizing FI deployment in practical networks, particularly in scenarios involving contingencies.

Future research opportunities include investigating the impact of redundant FIs and determining the optimal FI layout while considering constraints imposed by information technology infrastructure. Furthermore, exploring the FI placement problem in the presence of Distributed Generators (DGs) under both online and offline DG operations, as well as considering uni/bi-directional FIs, represents promising areas for further exploration.

References

Billinton, R., & Allan, R.N. (1996). Reliability of power systems. In *Second Edition*. Plenum Press.

Shahsavari, A., Mazhari, S.M., Fereidunian, A., & Lesani, H. (2014). Fault indicator deployment in distribution systems considering available control and protection devices: a multi-objective formulation approach. *IEEE Transactions on Power Systems*, *29*(5), 2359-2369.

Mazhari, S.M., Monsef, H., Lesani, H., & Fereidunian, A. (2013). A multi-objective PMU placement method considering measurement redundancy and observability value under contingencies. *IEEE Transactions on Power Systems*, *28*(3), 2136-2146.

Chen, C.S., Lin, C.H., Chuang, H.J., Li, C.S., Huang, M.Y., & Huang, C.W. (2006). Optimal placement of line switches for distribution automation systems using immune algorithm. *IEEE Transactions on Power Systems, 21*(3), 1209-1217.

Jinsong, L., Dong, L., Wangshui, L., & Zhibin, L. (2010). Study on Simulation and Testing of FLISR. *In CICED IEEE Proceedings*, 1-7.

Kazemi, S. (2011). Reliability Evaluation of Smart Distribution Grids (Ph. D. Dissertation), Depts. *Elec. Eng., Sharif University of Technology and Aalto University*.

Momoh, J.A. (2017). *Electric power distribution, automation, protection, and control*. CRC press.

Falaghi, H., Haghifam, M.R., & Tabrizi, M.O. (2005). Fault indicators effects on distribution reliability indices. *In CIRED IET 18th International Conference and Exhibition on Electricity Distribution*, 1-4.

Kimiyaghalam, A., Ashouri, A., & Beykverdi, M. (2012). Application of IBSFLA and BSFLA approaches for locating of fault indicators in distribution networks. *In IEEE Proceedings of 17th Conference on Electrical Power Distribution*, 1-7.

Dashti, R., & Sadeh, J. (2011). Fault indicator allocation in power distribution network for improving reliability and fault section estimation. *In IEEE International Conference on Advanced Power System Automation and Protection*, *2*, 1406-1411.

Hendi, R.B., Seyed-Sheneva, S.J., & Gandomkar, M. (2012). Electrical distribution system reliability improvement by optimal placement of fault indicators using immune algorithm. *International Journal of Engineering Research and Applications (IJERA)*, *2*(2), 1383-1390.

Usida, W.F., Coury, D.V., Flauzino, R.A., & da Silva, I.N. (2012). Efficient placement of fault indicators in an actual distribution system using evolutionary computing. *IEEE Transactions on Power Systems*, *27*(4), 1841-1849.

Ho, C.Y., Lee, T.E., & Lin, C.H. (2010). Optimal placement of fault indicators using the immune algorithm. *IEEE Transactions on Power Systems*, *26*(1), 38-45.

Cong, D.P., Raison, B., Rognon, J.P., Bonnoit, S., & Manjal, B. (2005). Optimization of fault indicators placement with dispersed generation insertion. *In IEEE Power Engineering Society General Meeting*, 355-362.

Cong, D.P., Raison, B., & Rognon, J.P. (2006). Optimal placement of fault indicators in distribution network. *IREE International Review of Electrical Engineering*.

Tang, Y., Wang, H.F., Aggarwal, R.K., & Johns, A.T. (2000). Fault indicators in transmission and distribution systems. *In IEEE DRPT. International Conference on Electric Utility Deregulation and Restructuring and Power Technologies. Proceedings (Cat. No. 00EX382)*, 238-243.

Krajnak, D.J. (2000). Faulted circuit indicators and system reliability. *In IEEE Rural Electric Power Conference. Papers Presented at the 44th Annual Conference (Cat. No. 00CH37071)*, A4-1.

Luan, S.W., Teng, J.H., Chen, C.S., & Liu, Y.H. (2011). Development of an intelligent fault indicator for smart grids. In *international conference on information and electronics engineering, Bangkok Thailand*.

Newnan, D.G., Eschenbach, T.G., & Lavelle, J.P. (2004). *Engineering economic analysis*, 1. Oxford University Press.

Fereidunian, A., Lucas, C., Lesani, H., Rahmani, R., & Wymore, A.W. (2010). A policy-driven method for IT infrastructure selection in power distribution automation system. *International Review of Electrical Engineering*, *5*(2), 671-682.

Sahoo, N.C., Ganguly, S., & Das, D. (2012). Multi-objective planning of electrical distribution systems incorporating sectionalizing switches and tie-lines using particle swarm optimization. *Swarm and Evolutionary Computation*, *3*, 15-32.

Bui, L.T., & Alam, S. (2008). An introduction to multi-objective optimization. In *Multi-objective optimization in computational intelligence: Theory and practice*, 1-19. IGI Global.

Coello, C.A.C., Pulido, G.T., & Lechuga, M.S. (2004). Handling multiple objectives with particle swarm optimization. *IEEE Transactions on evolutionary computation*, *8*(3), 256-279.

Abido, M.A. (2009). Multiobjective particle swarm optimization for environmental/economic dispatch problem. *Electric Power Systems Research*, *79*(7), 1105-1113.

Caramia, M., & Dell'Olmo, P. (2008). *Multi-objective management in freight logistics* (pp. 59-63). London: Springer.

Sayyaadi, H., Babaie, M., & Farmani, M.R. (2011). Implementing of the multi-objective particle swarm optimizer and fuzzy decision-maker in exergetic, exergoeconomic and environmental optimization of a benchmark cogeneration system. *Energy*, *36*(8), 4777-4789.

Zangeneh, A., Jadid, S., & Rahimi-Kian, A. (2011). A fuzzy environmental-technical-economic model for distributed generation planning. *Energy*, *36*(5), 3437-3445.

Rezagholizadeh, M., Fereidunian, A., Dehghan, B., Moshiri, B., & Lesani, H. (2011). Multi criteria decision making (MCDM): A modified partial order theory (POT) approach. *In IEEE 3rd International Conference on Advanced Computer Control*, 650-655.

Allan, R.N., Billinton, R., Sjarief, I., Goel, L., & So, K.S. (1991). A reliability test system for educational purposes-basic distribution system data and results. *IEEE Transactions on Power systems*, *6*(2), 813-820.

Billinton, R., & Jonnavithula, S. (1996). Optimal switching device placement in radial distribution systems. *IEEE transactions on power delivery*, *11*(3), 1646-1651.

Mazhari, S.M., Monsef, H., & Romero, R. (2013). A hybrid heuristic and evolutionary algorithm for distribution substation planning. *IEEE Systems Journal*, *9*(4), 1396-1408.