# Probabilistic Techno-Economic Optimization in Medium Voltage Distribution Networks with Fault Passage Indicators and Fault Locators 

Predrag Mršić, Đorđe Lekić, Bojan Erceg, Čedomir Zeljković, Petar Matić, Siniša Zubić, and Przemyslaw Balcerek


#### Abstract

Fault passage indicators (FPIs) and fault locators (FLs) are employed in modern distribution networks in order to enhance the process of fault localization, thus resulting in reduction of interruption time and improving the reliability of power supply. In this paper, a novel probabilistic techno-economic optimization method is proposed for determining the number and positions of FPIs that lead to maximum reduction of interruption time and investment costs in medium voltage (MV) distribution networks with and without FLs. The proposed method is based on a probabilistic non-sequential Monte Carlo simulation model of the real network, which is a proper compromise between complicated sequential simulation models and too simplified analytical models. The main goal of the method is to obtain maximum improvement of the network reliability indices while using the minimum number of FPIs. The method is tested on a combined urban/rural MV distribution network in Bosnia and Herzegovina and results are thoroughly discussed.


Index Terms-Distribution network, fault locators, fault passage indicators, non-sequential Monte Carlo simulation.

## Original Research Paper

DOI: 10.7251/ELS1822080M

## I. Introduction

Occurrences of faults in the power distribution system are unavoidable due to many reasons [1]. Short circuit faults lead to interruptions in the power supply, decreasing thereby reliability offered to the customers. Each outage results in financial costs to distribution companies due to undelivered energy and penalties for energy not supplied [2]-[4]. On the other hand, quality regulation schemes adopted in many countries provide incentives to distribution system operators (DSOs) for establishing satisfactory levels of reliability indices [5]-[7]. Thus, one of the main tasks of the DSO is to improve the system reliability.

[^0]An efficient measure for increasing the reliability of the distribution system is to reduce the interruption time by performing faster fault localization [1]. As a cost-effective solution, fault locators (FLs) and fault passage indicators (FPIs) are employed in modern distribution networks [8]-[12]. FLs determine the distance to the fault based on the faulty line impedance, which is derived from voltage and current measured at the supply point during the fault. FLs are reasonably accurate for faults adjacent to the beginning of the line and/or for low impedance faults, while their accuracy significantly decreases in cases of remote and high impedance faults [8]. Another drawback of the FLs is that they cannot unambiguously determine the faulty branch in networks containing branches [8]. FPIs determine the location of the fault by detecting the passage of fault current through a section of a feeder on which they are installed. The fault is located in the area between the last indicator that detected the passage of fault current and the first following that did not.

Commonly, one FL is placed in the substation at the supply point of the network, while several FPIs can be placed at suitable locations in the distribution network. Because of significant costs related to the installation of FPIs, their exact number and positions for a given network must be determined in order to achieve a satisfactory ratio between installation costs and increased reliability [13]-[21].

Based on the research conducted in [21]-[24], the main goal of this paper is to propose a probabilistic techno-economic analysis for determining optimal number and positions of FPIs which will yield the maximum reduction of interruption time and costs both for networks with and without FLs. In order to take all influential factors into consideration, a comprehensive assessment methodology is developed and a simulation approach based on the probabilistic principle is employed.

The methodology is presented in Section II, where the optimization process is divided in two parts - technical and economic. Existence of the optimum, dimensionality problems and convergence of the technical optimization are addressed in detail and verified through results obtained on a real test network. Economic optimization, which is further explained, is based on achieving the techno-economic balance between benefits arisen from improved reliability and installation costs of FPIs. At the end of Section II, a comprehensive optimization algorithm is presented, followed by a thorough analysis of
mathematical models used on each step of the algorithm. As many inputs are uncertain and behave according to the laws of probability theory, the Monte Carlo simulation technique is employed. In Section III, the final results of the probabilistic optimization are displayed in form of cumulative probability density functions (CDFs) for one real combined urban/rural medium voltage (MV) distribution network in Bosnia and Herzegovina. Conclusions are given in Section IV.

## II. Methodology

In this section, a methodology for determining the number and positions of FPIs in MV distribution network is proposed and discussed. According to our literature review, there are two approaches to determine optimal locations and number of FPIs. The first approach includes direct optimization methods. The most common direct approach is finding the positions of FPIs by minimizing the sum of total interruption costs and the costs of investment and installation. Since the interruption costs are in a complex relation with the locations of FPIs, the minimum of the objective function is not easily achievable. The authors in [13] employed a mixed integer linear programming (MILP) formulation. By considering not only FPIs but also the other remotely controlled switching equipment, the number of independent variables included in the problem formulation is greater than 30. The approach in [14] is similar though with a simpler objective function. Instead of using the MILP technique for optimization, the authors employed the immune algorithm. The authors in [15] showed the application of the genetic algorithm (GA) for various types of technical and economic objective functions. Another application of GA in combined techno-economic optimization can be found in [16]. The second approach is based on the indirect principle. An auxiliary objective function is created which is much simpler for optimization, while the obtained results are still located in the vicinity of the optimal solution. Under the indirect approach, the authors use rather heuristic methods to find locations in the network which are good candidates for installing the FPIs. The cost effectiveness of the method is tested and verified afterwards. One of the first ideas for indirect approach is the fuzzy method [17], [18]. Instead of computing precise positions appropriate for installation of FPIs, the method provides the results in a form of a chart which shows the installation potential for each bus along the main feeder, which represents distance from the network substation to the farthest network bus [19]. Another step forward is made in [19], where a simple auxiliary function is proposed and GA is employed for its minimization.

In this paper, the indirect approach is utilized because of its simplicity and acceptable accuracy in practical applications. The methodology consists of technical and economic optimization and is sketched in Fig. 1. The technical optimization is performed first, where a given number of FPIs is properly distributed across the network. After the technical optimization, the economic optimization is performed, with potential FPI locations and their number as an input. The output of economic optimization is selection of the best set of FPIs (number and locations) which will provide the greatest profit.


Fig. 1. The optimization process consisted of two main components.

## A. Technical Optimization

The technical part of the optimization contains an algorithm which suggests potential locations for a given number of FPIs. The initial idea for technical optimization, which is based on the indirect principle, was introduced in [19]. In order to perform a fast, yet acceptably accurate, search optimization process, a simplified auxiliary objective function is formed which is in correlation with the target reliability indices. It is recognized that load, number of customers and distances between FPIs are the most important inputs for this optimization function. The following two principles are introduced:

- A feeder bus is a good candidate to install an FPI if the load and the number of customers located downstream from that feeder bus are high.
- The considered bus becomes a less favorable candidate for FPI installation if another FPI has already been installed in its vicinity.

Moreover, the technical and economic indices could be further improved if a couple of additional principles are also taken into account [21]:

- Impact of lateral branches should be included in the fault search priority.
- Failure rate is not constant along the main feeder.

The mentioned four principles are incorporated in the objective function:

$$
\begin{equation*}
f_{o b j}=\int_{0}^{x_{\max }}\left[\alpha_{1} l(x)+\alpha_{2} c(x)\right] d(x) f(x) d x \tag{1}
\end{equation*}
$$

In (1), the first principle is modeled by $\alpha_{1} l(x)+\alpha_{2} c(x)$, where $l(x)$ represents the normalized load, and $c(x)$ represents the normalized number of customers in terms of location on the main feeder. The constants $\alpha_{1}$ and $\alpha_{2}$ are the weighting coefficients for the load and number of customers, respectively. The second and third principles are taken into account by the distance $d(x)$. This distance represents relative distance from the location of the fault to the nearest device able to indicate that fault and the impact of lateral branches to the expected time to find a fault. Finally, the fourth principle means that the failure rate changes along the main feeder. The failure rates are not the same in urban and rural areas. In addition, the failure rates of the laterals are greater than the failure rate of the main feeder. The failure rate function which combines impacts of both main feeder and its laterals is designated with $f(x)$. A graphic illustration of (1), calculated for the test network (see Appendix), is presented in Fig. 2. In order to find the best solution, the locations of the FPIs are varied along the main feeder until the area under the curve is minimized.


Fig. 2. Example of the objective function computed for the test network with one FPI. The FPI is located 5 km downstream along main feeder.

## 1) Existence of the optimum

For a small number of FPIs and an acceptable (small) search step, the objective function (1) can be minimized by employing a simple, yet time consuming, brute force search method. In this method, the value of the objective function (1) is calculated for all possible locations of FPIs and for several numbers of FPIs in a given distribution network. The combination that yields the minimum value of the objective function (1) is declared the optimal solution. For example, by moving one FPI along the main feeder of the test network (see Appendix) one obtains the diagram in Fig. 3. It can be seen that the objective function for this case reaches its minimum when the FPI is located 7908 m away from the network substation. Therefore, if one FPI is to be installed in this test network, it should be placed 7908 m away from the network substation along the main feeder.

If there are more than two FPIs, then it is not possible to construct a graphical interpretation of the objective function vs. FPI locations. However, in order to demonstrate the problems which arise when minimizing the objective function for cases with more than two FPIs, a special diagram in Fig. 4 is constructed. This diagram shows the objective function vs. positions of two FPIs for the case when eight FPIs are used, whereas six of them have fixed positions. For the area shown in Fig. 4 the objective function has a total of four extremes, of which three are local extremes. The existence of local extremes can lead to the result where the optimization algorithm converges to the local rather than to the global extreme. Thus, one should be careful when using evolutionary algorithms for finding the optimal number of FPIs.


Fig. 3. Objective function vs. FPI location for the case when one FPI is located at the main feeder of the test network.


Fig. 4. Objective function vs. FPI location for the case when eight FPIs are located at the main feeder of the test network (positions of six FPIs are fixed).
2) Dimensionality problem of brute force search method

As was mentioned before, the brute force search method is applicable only for a small number of FPIs in a given distribution network. The reason behind this is the rapid increase in the number of combinations of FPI locations followed by the increase in the number of installed FPIs. In order to demonstrate this, let us consider the test network in which the length of the main feeder is 20100 m . If the resolution for FPI locations along the main feeder is chosen to be 50 m , then there would be 402 possible FPI locations. If one FPI is to be installed in this network, one would have to search for the optimum location among these 402 possible locations, i.e. there would be a total of 402 combinations. If $N$ FPIs are to be installed, then the number of total combinations would be:
$N_{\text {com }}=\binom{402}{N}=\frac{402!}{(402-N)!N!}$.
The increase of the number of combinations with the increase of the number of FPIs and search resolution is shown in Fig. 5. By observing Fig. 5, it can be concluded that number of combinations rapidly increases with the increase in the number of FPIs. It is clear that for a large number of FPIs or in the case of a small search step, the objective function cannot be efficiently minimized in this manner.


Fig. 5. Number of combinations vs. searching resolution and number of FPIs.

## 3) Pattern Search method

One of the fast and efficient methods for minimization of the objective function is the Pattern Search (PS) algorithm. Initial research on the applicability of the PS method to the problem of optimal location of FPIs was presented in [21]. In this paper, the method is further improved in terms of setting the initial guess, increasing the stability of convergence and applicability to the problem defined in the probabilistic form.

The idea of PS is about a half century old [25]. The method has been tested and developed over the years so far and it has been applied to many scientific disciplines. There are also applications of PS algorithm to the problems of electric power engineering [26]. The main advantage of the method is that PS does not require a gradient of the objective function. It is therefore applicable for minimization of various noncontinuous and non-differentiable functions.

In order to apply the PS method for minimizing the objective function (1) a few modifications have to be made. First of all, the FPIs can be located only on the main feeder, which means that the FPI location can move along one axis of the mesh only. Second of all, if the basic PS principle is to be used, the optimum location of all or some of the FPIs could be placed to fall beyond the main feeder, due to doubling of the mesh step. By introducing constraints in the minimization of objective function (1), modified PS methods are obtained.

The first method (PS1) is similar to the original PS method [26]. Starting from the initial guess of the optimal point, the step of the mesh is doubled or divided by two depending on the location for which the value of (1) is minimal. The initial mesh step for this method is 1 m . By applying this method, it can easily happen that the optimum FPI location falls beyond the main feeder. If so, following rules are applied:

- If the obtained optimal location, measured as the distance from the network substation to the FPI along the main feeder, is less than zero, the FPI is set to location zero at the beginning of the main feeder.
- If the obtained optimal location is larger than the length of the main feeder, the FPI is moved to the end of the main feeder.

In the second method (PS2) the step of the mesh is never doubled but only divided by two if certain conditions are met [21]. In this manner, one avoids the situation where optimal FPI locations fall beyond the main feeder. The initial mesh step for this method is selected to obtain fast search for optimal FPI locations between two initial FPI locations. A good empirical value is $L_{\mathrm{MF}} /(5 N)$, where $L_{\mathrm{MF}}$ is the length of the main feeder and $N$ is the total number of FPIs.

The third method (PS3) is proposed in this paper and is based on the sequential principle where in each step the PS mesh for one FPI is observed. If it turns out that the locations of FPIs are optimal for a given mesh step, the mesh step is divided by two. As in the s method the initial mesh step is chosen in a way that enables fast search for optimal FPI locations between two initial FPI locations. The optimization process is continued until a specified accuracy is achieved or until the maximum allowable number of iterations is reached.

## 4) Initialization and convergence analysis of PS

So far we have defined three methods obtained by the modification of the original PS method. From these definitions it can be concluded that different optimization methods in general require different total number of iterations for convergence. In order to compare convergence speed of these methods, the iteration step must be strictly defined. In the following analysis, one iteration step of the optimization method is defined as a set of operations needed to calculate the value of the objective function (1) for one particular combination of FPI locations. The initial guess of FPI locations greatly affects the convergence speed and the accuracy of the obtained solution. In order to formulate recommendations for the selection of initial FPI locations, the influence of the initial guess on the number of iterations and solution accuracy is analyzed for several cases.

A series of simulations was conducted for different initial locations and different number of FPIs. For a particular number of FPIs, the value of the objective function (1) was calculated for all solutions with different initial guesses. The solutions for which the value of the objective function (1) was minimal were declared as global minima for that particular number of FPIs, while the other solutions were declared as local minima. The results of these simulations will serve as the basis for deriving a new method for the selection of initial FPI locations.

Before the convergence analysis, we will explain the meaning of used symbols. A circle indicates that the method converges towards the global minimum, while a triangle indicates that the method converges towards a local minimum.

If the FPIs are initially equally distributed along the main feeder:

$$
\begin{equation*}
x_{\mathrm{FPI}}(j)=\frac{j}{i+1} L_{\mathrm{MF}}, \quad j=1, \ldots i \quad i=1,2 \ldots N \tag{3}
\end{equation*}
$$

results shown in Fig. 6 are obtained. In this case, the first method (PS1) converges towards the global minimum when the total number of FPIs is lower than four. The second and third method (PS2 and PS3) converge towards the global minimum when the total number of FPIs is equal to one or three. Thus, selecting the initial locations of FPIs in this manner gives poor optimization results, especially when the number of FPIs increases.


Fig. 6. Number of iterations vs. number of FPIs for the case when all FPIs are initially equally distributed along the main feeder.

In the second case, FPIs are initially equally distributed along the first half of the main feeder. For this case the results are shown in Fig. 7. All methods, except PS3 for three FPIs, converge to the global minimum when the total number of FPIs is lower than six.

In the third case, FPIs are initially equally distributed along the first $70 \%$ of the main feeder. The first method (PS1) converges towards the global minimum when the total number of FPIs is lower than four and equal to six, seven, eight and nine. The second method (PS2) converges towards the global minimum when the total number of FPIs is lower than four and equal seven, nine and ten, while the third method (PS3) converges to the global minimum when the total number of FPIs is lower than four and higher than six. For this case the results are shown in Fig. 8.

From these results, we conclude that, for a given distribution network, optimal selection of initial FPI locations depends on the total number of FPIs. The authors did not notice any regularity in convergence that could be applied to an arbitrary number of FPIs. The convergence to the global optimum is also highly dependent on the topology of the particular distribution network.

## 5) Results of the technical part of the optimization

According to the optimization principle depicted in Fig. 1, the technical component of the optimization method provides the suggested positions of FPIs along the main feeder, for an initially given number of indicators. The procedure is repeated for all numbers of FPIs which can result in reasonable benefit to cost ratio.


Fig. 7. Number of iterations vs. number of FPIs for the case when the all FPIs are initially equally distributed along the first half of the main feeder.


Fig. 8. Number of iterations vs. number of FPIs for the case when the all FPIs are initially equally distributed along the first $70 \%$ of the main feeder.

It is believed that it is sufficient to test cases containing up to 10 FPIs, since the benefit of improved reliability does not uniformly follow the FPI installation costs, but significantly decreases the speed of its growth as the number of indicators increases. The results of the technical part of the optimization can concisely be shown in one chart, as represented by Fig. 9. The most profitable case from this finite set of options will be declared to be the optimum solution, which will be selected in the economic part of the optimization.


Fig. 9. The suggestion for optimal placement of the FPIs.

## B. Economic Optimization

In the economic part of the optimization, the economically best solution of previously determined total FPI numbers and locations will be selected. The optimum number of FPIs is the one that yields the maximum difference between the incentive, i.e. reward or penalty, according to achieved values of reliability indices due to optimum placement of FPIs, and the total cost of installed FPIs. The objective function for the economic optimization can be formulated as [24]:

$$
\begin{equation*}
Y_{\mathrm{FPI}}(N)=B_{\mathrm{FPI}}(N)-N \cdot F P I_{\text {cost }}, \tag{4}
\end{equation*}
$$

where $Y_{\text {FPI }}(N)$ is the annual financial profit of the distribution company when $N$ FPIs are installed, $B_{\text {FPI }}(N)$ is some kind of benefit of improved reliability, expressed as either avoided penalty, gained incentive or just decreased raw costs of not supplied energy (in countries without developed regulation in the area of system reliability) for the case when $N$ FPIs are installed, and $F P I_{\text {cost }}$ is the annual cost per installed FPI. The optimal number of FPIs in a specific distribution network is found as the number $N_{\text {opt }}$ that yields the maximum value of (4), which is shown in Fig. 10.

The reliability indices in a specific distribution network improve with the increase in the number of installed FPIs. This increase is not linear, which means that for each distribution network there is a number of FPIs beyond which the improvement of the reliability indices, and the corresponding benefit $B_{\text {FPI }}(N)$, is insignificant (solid line in Fig. 10). The investment and maintenance costs of FPIs increase with the number of installed FPIs, whereas this increase is linear (dotted line in Fig. 10). For a particular number of FPIs, all the benefit, due to increased reliability, is cancelled out by the total investment costs (point B in Fig. 10).


Fig. 10. The principle of finding the optimum number of FPIs [24].
The optimal number of FPIs for a given distribution network is therefore determined as the option that gives the maximum value of profit (point A on dashed line in Fig. 10).

The annual costs per FPI depend on the price of the FPI itself and on the price of additional equipment, the cost of installation and maintenance, as well as the lifetime. These costs are derived from following expression [15]:

$$
\begin{equation*}
F P I_{\text {cost }}=\frac{F P I_{\text {price }}+F P I_{\text {inst }}}{F P I_{\text {age }}}+F P I_{\text {maint }} \tag{5}
\end{equation*}
$$

where $F P I_{\text {price }}$ is the price, $F P I_{\text {inst }}$ is the installation cost, $F P I_{\text {age }}$ is the lifetime and $F P I_{\text {maint }}$ is the maintenance cost of one FPI. The maintenance costs primarily contain the costs for maintenance and rental of communication channels, while the installation cost is primarily related to the additional equipment needed for installation and deployment of FPIs, as well as for the purchase of certain software and other necessary equipment.

The cost of the FL is considered to be negligible in this analysis. This is done because the FL is a standard piece of equipment which is already embedded in protective relays at the moment they are shipped and it is not billed separately.

Benefits $B_{\text {FPI }}(N)$ may significantly vary from country to country so they should be analyzed in more detail. Norway was one of the first countries which introduced a penalty scheme for operation at poor reliability. The penalties introduced in 2001 were based on not supplied energy. Regulated penalty prices are determined as 38 NOK (cca \$2) per kWh for commercial/industrial customers interrupted for all sustained interruptions (longer than 5 minutes) and 4.2 NOK (cca \$0.2) per kWh interrupted for residential customers [27]. According to a principle applied in Sweden [5], Germany or Spain [7], $B_{\text {FPI }}(N)$ is calculated based on customer interruption costs and the performance using the System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) compared to some defined baseline [27].

The optimal positions of FPIs do not affect the value of SAIFI, but they affect the value of SAIDI, which means that the incentive $B_{\mathrm{FPI}}(N)$ can be calculated as [27]:

$$
\begin{equation*}
B_{\mathrm{FPI}}(N)=\sum_{i=1}^{5} \sum_{j=1}^{2}\left[\operatorname{SAIDI}_{\mathrm{b}, i j}-\operatorname{SAIDI}_{i j}(N)\right] \cdot c_{i j} \cdot P_{\mathrm{av}, i} \tag{6}
\end{equation*}
$$

where $i$ represents the index of five different customer groups (industry, residential, agriculture, public and commercial services), $j$ represents the index of two different categories of interruption (planned and unplanned), $S A I D I_{\mathrm{b}, i j}$ is the defined baseline value of SAIDI for $i$-th customer group and $j$-th category of interruption, $\operatorname{SAIDI}_{i j}(N)$ is the achieved value of SAIDI for $i$-th customer group and $j$-th category of interruption due to optimal placement of $N$ FPIs, $c_{i j}$ is a cost parameter given in $€ / \mathrm{kWh}$ and $P_{\mathrm{av}, i}$ is the average yearly power usage for $i$-th customer group.

## C. Simulation Algorithm

The main steps of the proposed simulation algorithm are listed in the following procedure [23], [24]:

1) Preparing the Network Data: Prepare the common input data such as distribution network topology, failure rates, customer power demands, number of simulated years etc.
2) Generating the Artificial Set of Faults: Determine the set of random faults for each simulated year, respecting their conditional probability distributions in terms of hour, weekday and month of occurrence, as well as their yearly variation.
3) Simulating the Customer Loads: Simulate the customer loads at the instants of faults, which are needed for calculating Energy Not Supplied (ENS).
4) Simulating a Decision of the FL: Simulate decisions made by the FLs, which are influenced both by their performance and the characteristics of the fault.
5) Computing the Time Needed to Find a Fault: Compute the time taken by the repair crew to find the fault (support provided by the FPIs is taken into account).
6) Evaluating the Reliability Indices: Evaluate the reliability indices such as SAIDI and ENS.
7) Presenting the results: Present the results and make conclusions.

A detailed explanation of each step of the simulation algorithm is given in the following text.

## 1) Preparing the Network Data

Information about the distribution network topology is stored in a matrix form. The matrix contains data about the number of buses, number, length and failure rates of power lines, number and power demands of customers, and location of disconnectors, reclosers, fuses and FPIs. In this analysis, disconnectors, reclosers, fuses and FPIs are considered to be $100 \%$ reliable, which means that their failure rate is equal to zero or that their failure rates are included in failure rates of power lines. Furthermore, distributed generation is neglected.

## 2) Generating the Artificial Set of Faults

The methodology for generating random faults is inspired by the research published in [28]. The main idea is to draw random numbers to reproduce a time-dependent failure rate pattern similar to the observed pattern recorded in failure statistics. This pattern includes all types of faults, caused by the weather or by technical and human aspects. Fault causes and mechanisms are not modeled explicitly and the observed pattern is assumed to be representative for the analysis period ahead. As the first step, the number of faults in a simulated year should be determined. For that purpose, a random number is drawn from the Poisson probability distribution. The Poisson probability distribution is a discrete probability distribution that expresses the probability of a given number of events occurring in a fixed interval of time and/or space if these events occur with a known constant rate and independently of the time since the last event [23].

For the chosen number of faults per year, the timing of these faults is determined. It is widely known that instants of fault occurrence are not uniformly distributed in time. There are many reasons for this. For example, construction works will cause faults to occur more frequently during the first shift ( $9 \mathrm{AM}-5 \mathrm{PM}$ ) in working days than during the nights or weekends. Another example is summer thunderstorms which cause faults more frequently during summer months than in other seasons. Therefore, failure probability distribution should be determined from recorded instants of occurrence of faults in a given time interval (in a month or in a day/time in a week). The examples of hourly, daily and monthly failure probability distributions are given in Fig. 11 to 13, which are determined from recorded instants of fault occurrence in a test network (see Appendix). Faults which are generated for Monte Carlo simulation should follow the given probability distributions.

An example for drawing numbers which will represent a month in which fault occurs is given in Fig. 14. The input discrete failure probability distribution function by months (data in Fig. 13) is transformed into the cumulative distribution function (Fig. 14). Then, a random number from the uniform distribution $U[0,1]$ is drawn (in our example, the number is $0.65)$. The month in which the fault occurs is determined from the point where the line of constant value 0.65 intersects the cumulative distribution function (CDF), which is the eight month in the example (August). Since the probability for all numbers from 0 to 1 is the same, it can be concluded that numbers of months that have a larger increment of the CDF will be generated more frequently. In other words, months in which failures are more frequent will be selected more often.

Four types of faults are considered: Phase-to-ground fault (L-G), Double-phase-to-ground fault (L-L-G), Double-phase fault (L-L) and Three-phase fault (L-L-L). Similarly as for determining instants of failure occurrence, statistics of fault types is used as input function. A usual probability distribution per fault type is shown in Fig. 15, but there also are some specific networks when probability distribution differs from the most common cases. For instance, in networks where phase conductors touch each other more frequently, $68 \%$ of failures are of double-phase fault type [29].


Fig. 11. Probability of faults per hour of day.


Fig. 12. Probability of faults per day of week.


Fig. 13. Probability of faults per month [23].


Fig. 14. The principle of drawing a random month of a fault occurrence.


Fig. 15. Typical probability distribution per fault type [23].

The failure rates change along the main feeder as we move from urban to rural areas. Additionally, the failure rates of the lateral branches are greater than the failure rate of the main feeder. The faulted line is chosen by intersecting the CDF curve of branch failure rates with a line of constant value drawn from the uniform distribution. When the faulted line is chosen, the fault location along the line is picked by drawing a random number, again from the uniform distribution.

Fault impedance is simulated by the Weibull probability density function [8]. For inter-phase faults, fault impedance is small and in general does not exceed $0.5 \Omega$. They may, however, become much higher during ground faults, because tower footing resistance may be as high as $10 \Omega$. If there is a flashover of an insulator, the connection of towers with ground wires makes the resulting fault impedance smaller. In practice, it seldom exceeds $3 \Omega$. For some ground faults the fault impedances may become much higher, which happens in cases of fallen trees, or if a broken conductor lies on the highresistive soil [8].

## 3) Simulating the Customer Loads

Just as the probability of fault occurrence varies with time, the customer load is also dependent on the hour of day, day of week and month of year [30]. Based on long-term measurements, it is possible to determine the usual patterns of expected customer load in terms of hour, day and month. Expected load of the customer connected at some bus $i$, at the instant of fault occurred in hour $h$, day $d$ and month $m$, is computed by the following expression [23]:

$$
\begin{equation*}
P_{e}(h, d, m)=P_{h} \cdot P_{d} \cdot P_{m} \cdot P_{i} \tag{7}
\end{equation*}
$$

where $P_{h}$ is the average relative load during the hour $h$, independent of weekday and month (presented in Fig. 16), $P_{d}$ is the average load in day $d$, independent of month (presented in Fig. 17), $P_{m}$ is the average load in month $m$ (as illustrated in Fig. 18), and $P_{i}$ is the annual peak load for the customer connected at bus $i$ (given as a part of common input data, explained in the first step of the simulation algorithm). The actual simulated load is then sampled from the normal distribution using the following equation [23]:

$$
\begin{equation*}
P_{\text {simulated }}=P_{e}+\sigma \cdot P_{e} \cdot N(0,1), \tag{8}
\end{equation*}
$$

where $\sigma$ is relative average standard deviation of the customer load and $N(0,1)$ is a random number drawn from the standard normal distribution, having zero mean value and unity standard deviation.

## 4) Simulating a Decision of the FL

The starting point for developing this model are the empirical findings which state that $1 \%$ (of the main feeder length) fault location error can be achieved for phase-to-phase faults $\left(R_{\text {fault }}=15 \Omega\right)$, while the errors for solid earth faults $\left(R_{\text {fault }}=0 \Omega\right)$ are $10-15 \%$. The error is given as a fraction of the main feeder length. Fault location error $e$, according to appropriate IEEE standard [31], is defined as follows:
$e=(I R-D F) / L_{\mathrm{MF}}$,


Fig. 16. Hourly load as a percentage of daily peak load.


Fig. 17. Daily load as a percentage of weekly peak load.


Fig. 18. Monthly load as a percentage of annual peak load.
where $I R$ is the instrument reading and $D F$ is the exact distance to the fault. Therefore, a simulated instrument reading would be:
$I R=D F+e \cdot L_{\mathrm{MF}}$.
It will be assumed that the error magnitudes are normally distributed and that their values are always negative, according to testing reports published in [8]. In order to respect the assumption that the expected value of the error should be $1 \%$ for phase-to-phase faults and $15 \%$ for earth faults, the simulated errors will be computed as follows [23]:
$e=-\mid$ Expected error $\cdot \sqrt{\pi / 2} \cdot N(0,1) \mid$.

## 5) Computing the Time Needed to Find a Fault

When calculating the time needed for fault localization, three scenarios should be considered:

- Scenario 1: Sole application of the FL (denoted as FL),
- Scenario 2: Sole application of FPIs (denoted as FPI),
- Scenario 3: Combined application of both technologies (denoted as FL + FPI).

For the first scenario, the idea is to calculate the time needed for the maintenance crew to find the fault by searching along the lines which are located in the vicinity of the location to which the FL is pointing. This vicinity is defined by the fault location error of the FL, as illustrated in Fig. 19a. According to (11), this error is negative, meaning that the crew should only inspect lines located at distances which are larger than the FL reading. If the network contains many branches and there are multiple potential fault locations, the search is performed by a pre-established priority order.

In the second scenario, the crew should search only the network area between the tripped and untripped FPI (Fig. 19b). The search is started from the tripped FPI and finished when the fault is localized. As for the previous scenario, the priority order is respected. A constant speed of moving along the lines is assumed.

In the third scenario, when both FLs and FPIs are used, the potential area on which the fault might have occurred is found as the intersection of the FL and FPI readings (Fig. 19c). Four possible cases of FPI and FL disposition during the fault are presented in Fig. 20. For the cases shown in Fig. 20a and Fig. 20d, the FPI doesn't influence the fault localization time, while for cases shown in Fig. 20b and Fig. 20c, the presence of FPI decreases the time needed to find the fault.

The overall time taken by the crew to realize the fault occurrence, to prepare the necessary tools and spare parts and to start the search process is considered to be constant and is added afterwards.

## 6) Evaluating the Reliability Indices

The most frequently used reliability indices are [32], [33]:

- average number of interruptions per customer per year,
- average interruption duration per customer per year,
- energy not supplied.

The average number of interruptions per customer per year (SAIFI - System Average Interruption Frequency Index) is defined as:

SAIFI $=\frac{\text { Total number of customer interruptions }}{\text { Total number of customers served }}$,
while the average interruption duration per customer per year (SAIDI - System Average Interruption Duration Index) is defined as:

SAIDI $=\frac{\text { Sum of all customer interruption durations }}{\text { Total number of customers served }}$.
Energy Not Supplied (ENS) is defined as the sum of the products of all customer interruption durations and their power demands:

$$
\begin{equation*}
E N S=\sum_{i} \text { Interruption duration }(i) \times \text { Power demand }(i) . \tag{14}
\end{equation*}
$$

In this paper, the presence of FLs and/or FPIs affects the value of SAIDI and ENS only, while SAIFI remains the same, regardless of the analyzed scenario.


Fig. 19. Illustration of fault detection in a simple radial distribution system with a) one FL, b) two FPIs, and c) two FPIs and one FL. The red flag represents a tripped FPI, the green flag represents an untripped FPI, the blue square represents the FL installed in the substation, while the blue cross represents the FL reading.

a)

b)

c)

d)

Fig. 20. Illustration of fault detection in a simple radial distribution system with one FPI and one FL in the case when a) the tripped FPI is located in front of the FL reading, b) the tripped FPI is located beyond the FL reading, inside the FL error area, c) the untripped FPI is located beyond the FL reading, inside the FL error area and d) the untripped FPI is located beyond the FL reading, outside the FL error area.

## 7) Presenting the results

The main outputs of the presented methodology are the reliability indices displayed in function of the number of installed FPIs, and cumulative probability density functions (CDFs) for objective function (4). As described above, three scenarios are compared: sole usage of one FL, sole usage of FPIs, and combined usage of both the FL and FPIs.

## III. Application to Real-Life Test Network

In this Section the methodology proposed in the previous Section is applied to a representative real-life test network in Bosnia and Herzegovina (see Appendix). The results are obtained using the non-sequential Monte Carlo simulation method. Contingencies, that are determined before the simulation begins, are randomly selected from a pool of possible contingencies based on their probabilities of occurrence. The selected contingencies are then simulated in any order, assuming that all contingencies are mutually exclusive [34], [35]. As a consequence of the non-sequential approach, the actualization of costs is not considered.

## A. Base case results

The inputs to the simulation algorithm are given in Table I and include target (baseline) value of SAIDI required by the distribution system regulator, cost parameter $c_{i j}$, average number of faults per year and time horizon (number of simulated years). Cost-benefit analysis is based on the approach explained in Section II, where the annual benefit is defined according to (4). The key economic benefit is modeled by cost parameter $c_{i j}$ which makes the worth of reliability proportional to the difference between target and real SAIDI. The solution with the largest benefit is declared as "the optimal" for the given set of inputs, and contains "optimal number" and "optimal locations" of FPIs. By analyzing the final results, which are in the form of CDFs, the investor can select a proper solution from several cases: possibility of high profit, risk of possible loss, or a stable solution not having high possibility nor for extra high profit, nor for significant loss.

Fig. 21 shows main results of the proposed methodology for the base case. In this case, the installation options with 1,2 or 3 FPIs represent the best achievable solutions, being very similar to each other. As seen from Fig. 21, the lines for 1 and 2 FPIs are more on the right-hand side with larger values of CDF. Therefore, 1 or 2 FPIs can be selected by risk taking investors which could achieve larger profits in some particular cases. On the other hand, risk averse investors would select 3 FPIs, which would provide a solid benefit with a lower risk of possible losses. Fig. 22 shows average SAIDI (expected value) as a function of the number of FPIs added in the network together with the FL. From Fig. 22, it can be concluded that for the case with no fault locating equipment installed (nor FL, nor FPI), SAIDI is 77.9 (value for zero FPIs on red FPI curve), while for the case with one FL only, SAIDI is decreased to 25.6 (blue FL curve).

TABLE I
The Values Of The Key Variables

| THE VALUES OF THE KEY VARIABLES |  |  |  |
| :--- | :---: | :---: | :---: |
| Input variable | Value |  |  |
|  | Min. | Base | Max. |
| Cost parameter $c_{i j}(€ / \mathrm{kWh})$ | 0.25 | 0.50 | 1.00 |
| Average number of faults per year | 5 | 10 | 20 |
| Target SAIDI (hours/customer/year) | 20 | 35 | 50 |
| Number of simulated years |  | 10000 |  |
| FPI price $(€)$ | 1000 |  |  |
| FPI installation cost $(€)$ |  | 2500 |  |
| FPI lifetime $($ years $)$ |  | 15 |  |
| FPI maintenance cost $(€ /$ year $)$ |  | 500 |  |



Fig. 21. CDF computed for profit, particularly for each investment solution from 1 to 10 FPIs for base values of key parameters.


Fig. 22. Average SAIDI as a function of the number of FPIs for base values of key parameters.

For the case with both the FL and FPIs, decrease of SAIDI is the largest and it depends on the number of installed FPIs (FL + FPI curve). The curve starts at point $(0 ; 25.6)$ at which the FL and zero FPIs are installed and stays below the FL and FPI curves regardless of the number of installed FPIs, which means that lowest values of SAIDI can be obtained if both the FL and FPIs are used.

## B. Sensitivity Analysis

In order to analyze sensitivity of the proposed methodology to the variations of input variables, the key parameters are varied according to Table I. On the basis of this sensitivity analysis, proper planning actions for different scenarios can be undertaken in order to improve the network reliability.

Results of simulation for the case when the cost parameter is decreased from 0.5 to $0.25 € / \mathrm{kWh}$ are given in Fig. 23. Since the reliability incentives are halved here, the profit earned from the installation of FPIs is decreased for any number of FPIs in the given range. In comparison with the base case results, shown in Fig. 21, the CDF curves are therefore shifted to the left. In this case, the installation option with one FPI represents the best achievable solution. Simulation results for the case when the cost parameter is increased from 0.5 to $1.0 € / \mathrm{kWh}$ are given in Fig. 24. As opposed to results shown in Fig. 23, the reliability incentive is increased and all the CDF curves are pushed to the right. In this case, the installation of a greater number of FPIs becomes more profitable. The optimal number of FPIs for this scenario is 3 .

Simulation results for the scenario where the number of faults per year is decreased from 10 to 5 are shown in Fig. 25. The lower failure rate reflects to the appropriate lower SAIDI, so the target level set for this reliability index is more easily achievable. The probability distributions of profit are acceptable for each considered number of FPIs, as can be seen in Fig. 25. However, the installation of one FPI represents the most profitable option. The simulation results for the scenario where the number of faults per year is increased from 10 to 20 are shown in Fig. 26. In this case, the distribution system regulator should adjust the target SAIDI to a value which would be more appropriate for the given network.

The simulation results for the scenario where the target SAIDI is decreased from 35 to 20 are shown in Fig. 27. In this scenario, due to significantly decreased value of required SAIDI, the profit is dominantly negative for any number of FPIs. Even with negative profit, the most adequate number of FPIs is 1,2 or 3 . Finally, the simulation results for the scenario where the target SAIDI is increased from 35 to 50 are shown in Fig. 28. In this scenario profit is always positive, and the optimal number of FPIs is 1,2 or 3 .

## IV. Conclusion

The subject of this paper is a techno-economic analysis which determines the optimal number and positions of fault passage indicators (FPIs) for maximum reduction of interruption time and costs in radial distribution networks, both with and without fault locators (FLs) installed at the supply point.


Fig. 23. CDF computed for profit, particularly for each investment solution from 1 to 10 FPIs for decreased cost parameter.


Fig. 24. CDF computed for profit, particularly for each investment solution from 1 to 10 FPIs for increased cost parameter.


Fig. 25. CDF computed for profit, particularly for each investment solution from 1 to 10 FPIs for decreased number of faults per year.


Fig. 26. CDF computed for profit, particularly for each investment solution from 1 to 10 FPIs for increased number of faults per year.


Fig. 27. CDF computed for profit, particularly for each investment solution from 1 to 10 FPIs for decreased value of target SAIDI.


Fig. 28. CDF computed for profit, particularly for each investment solution from 1 to 10 FPIs for increased value of target SAIDI.

The developed optimization methodology is verified by several sets of simulations on a representative distribution network. The proposed method is suitable for application in suburban and rural networks which have high fault probabilities. In those networks the consumers are distributed over a large area having relatively low power consumption and priority, so it is not acceptable to invest in expensive automation equipment such as reclosers. In these networks, proper installation of FPIs can decrease the interruption time and improve network reliability quantified by indices SAIDI and ENS. On the other hand, if the proposed methodology would be applied in networks with a large number of ultra priority users and/or if the penalties for undelivered energy would be very high, it would result in the proposition of a large number of FPIs. However, those FPIs would only shorten the time of finding a fault location but would not reduce the number of power interruptions. For those networks the proposed methodology should be adjusted to include the installation of automated switching equipment as well.

## References

[1] J. Northcote-Green and R. G. Wilson, Control and Automation of Electric Power Distribution Systems, CRC Press, Taylor \& Francis Group, 2007.
[2] G. Kjöle and H. Vefsnmo, "Customer Interruption Costs in Quality of Supply Regulation: Methods for Cost Estimation and Data Challenges," in 23rd International Conference on Electricity Distribution, Lyon, France, pp. 1-5, 15-18 June 2015.
[3] I. Losa and O. Bertoldi, "Regulation of Continuity of Supply in the Electricity Sector and Cost of Energy not Supplied," in 2009 International Energy Workshop, Venice, pp. 1-10, 2009.
[4] K. Samdal, G. H. Kjölle, B. Singh and O. Kvitastein, "Interruption Costs and Consumer Valuation of Reliability of Service in a Liberalised Power Market," in 9th International Conference on Probabilistic Methods Applied to Power Systems, KTH, Stockholm, Sweden, pp. 1-7, June 11-15, 2006.
[5] E. Grahn, L. Ström, K. Alvehag, C. J. Wallnerström, L. W. Öhling and T. Johansson, "Incentivizing Continuity of Supply in Sweden," in European Energy Market (EEM), 2016 13th International Conference on the, Porto, Portugal, pp. 1-5, 6-9 June 2016.
[6] K. Alvehag and K. Awodele, "Impact of Reward and Penalty Scheme on the Incentives for Distribution System Reliability," IEEE Trans. Power Syst., vol. 29, no. 1, pp. 386-394, 2014.
[7] C. Fernandesa, A. Candelab and T. Gómez, "An Approach to Calibrate Incentives for Continuity of Supply in the Spanish Electricity Distribution System," Electric Power Systems Research, vol. 82, pp. 81-87, 2012.
[8] M. Saha, J. Izykowski and E. Rosolowski, Fault Location on Power Networks, Dordrecht, Heidelberg, New York: Springer, 2010.
[9] E. Vidyasagar, P. V. N. Prasad, and A. Fatima, "Reliability Improvement of a Radial Feeder Using Multiple Fault Passage Indicators," Energy Procedia, vol. 14, pp. 223-228, 2012.
[10] H. Falaghi, M. -R. Haghifam, and M. R. Osouli Tabrizi, "Fault Indicators Effects on Distribution Reliability Indices," in CIRED 2005-18th International Conference and Exhibition on Electricity Distribution, Turin, pp. 1-4, June 2005.
[11] D. J. Krajnak, "Faulted Circuit Indicators and System Reliability," IEEE Rural Electric Power Conference, Kentucky, USA, pp. 1-4, May 2000.
[12] F. M. Angerer, "New developments in Faulted Circuit Indicators Help Utilities Reduce Cost and Improve Service," IEEE Rural Electric Power Conference, Charleston, South Carolina, USA, pp. 1-3, April 2008.
[13] Ž. Popović, S. Knežević, and B. Brbaklić, "Optimal Number, Type and Location of Remotely Controlled and Supervised Devices in Distribution Networks," in IEEE PowerTech, Eindhoven, pp. 1-6, June-July 2015.
[14] C. Y. Ho, T. E. Lee, and C. H. Lin, "Optimal Placement of Fault Indicators Using the Immune Algorithm," IEEE Trans. Power Syst., vol. 26, pp. 38-45, February 2011.
[15] D-P. Cong, B. Raison, J-P. Rognon, S. Bonnoit, and B. Manjal, "Optimization of Fault Indicators Placement with Dispersed Generation Inser-
tion," IEEE Power Engineering Society General Meeting, vol. 1, pp. 355-362, June 2005.
[16] R. Dashti and J. Sadeh, "Fault Indicator Allocation in Power Distribution Network for Improving Reliability and Fault Section Estimation," International Conference on Advanced System Automation and Protection, pp. 1406-1411, October 2011.
[17] D. M. B. S. de Souza, A. F. de Assis, I. N. da Silva, and W. F. Usida, "Efficient Fuzzy Approach for Allocating Fault Indicators in Power Distribution Lines," IEEE Transmission and Distribution Conference and Exposition: Latin America, pp. 1-6, August 2008.
[18] D. M. B. S. de Souza, I. N. da Silva, V. Ziolkowski and R. A. Flauzino, "Efficient Allocation of Fault Indicators in Distribution Circuits Using Fuzzy Logic," IEEE Power \& Energy Society General Meeting, pp. 1-6, Calgary, Alberta Canada, July 2009.
[19] W. F. Usida, D. V. Coury, R. A. Flauzino and I. N. da Silva, "Efficient Placement of Fault Indicators in an Actual Distribution System Using Evolutionary Computing," IEEE Trans. Power Syst., vol. 27, no. 4, pp. 1841-1849, November 2014.
[20] A. Shahsavari, S. M. Mazhari, A. Fereiduisn, and H. Lesani, "Fault Indicator Deployment in Distribution Systems Considering Available Control and Protect Devices: A Multi-Objective Formulation Approach," IEEE Trans. Power Syst., vol. 29, pp. 2359-2369, September 2014.
[21] Č. Zeljković and P. Mršić, "Fast and Efficient Placement of Fault Indicators Based on the Pattern Search Algorithm," in Power Electronics (Ee), 2017 International Symposium on, Novi Sad, Serbia, pp. 1-5, 19-21 Oct. 2017.
[22] Đ. Lekić, P. Mršić, B. Erceg and Č. Zeljković, "Three Phase Line Model for Laboratory Testing of Fault Passage Indicators," in The 10th Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion - Med Power 2016, Belgrade, Serbia, pp. 1-8, 6-9 Nov. 2016.
[23] Č. Zeljković, P. Mršić, Đ. Lekić, B. Erceg, P. Matić, S. Zubić, and P. Balcerek, "Performance Assessment of Fault Locators and Fault Passage Indicators in Distribution Networks by the Non-Sequential Monte Carlo Simulation," in 2018 International Symposium on Industrial Electronics (INDEL), Banja Luka, Bosnia and Herzegovina, pp. 1-7, 1-3 Nov. 2018.
[24] P. Mršić, Č. Zeljković, Đ. Lekić, B. Erceg, P. Matić, S. Zubić, and P. Balcerek, "Minimization of Power Interruption Time in MV Distribution Networks with Fault Locators Based on Optimal Placement of Fault Passage Indicators," in 2018 International Symposium on Industrial Electronics (INDEL), Banja Luka, Bosnia and Herzegovina, pp. 1-7, 1-3 Nov. 2018.
[25] R. Hooke and T. A. Jeeves, "Direct search solution of numerical and statistical problems," Journal of the Association for Computing Machin$\operatorname{ery}$ (ACM), vol. 8, no. 2, pp. 212-229, 1961.
[26] A. K. Al-Othman and K. M. El-Naggar, "Application of pattern search method to power system security constrained economic dispatch with non-smooth cost function," Electric Power Systems Research, vol. 78, no. 4, pp. 667-675, April 2008.
[27] Electricity Working Group, Quality of Supply Task Force, "Third Benchmarking Report on Quality of Electricity Supply 2005," Council of European Energy Regulators, Bruxelles, 2005.
[28] G. H. Kjölle and A. T. Holen, "Reliability and interruption cost prediction using time-dependent failure rates and interruption costs," Quality and Reliability Engineering International, vol. 14, no. 3, pp. 159-165, 1998.
[29] V. Vega-Garcia, J. C. Cebrian and N.Kagan, "Evaluation of probability functions related to short circuit random variables using power quality meters," in 2010 IEEE/PES Transmission and Distribution Conference and Exposition, Latin America, pp. 712-718, Nov. 8, 2010.
[30] I.-S.Bae, J.O.Kim, J.-C.Kim and C.Singh, "Optimal operating strategy for distributed generation considering hourly reliability worth," IEEE Trans. Power Syst., vol. 19, pp. 287-292, February 2004.
[31] IEEE Std C37.114, IEEE Guide for Determining Fault Location on AC Transmission and Distribution Lines, June 2005.
[32] E. Fumagalli, L. Lo Schiavo and F. Delestre, Service Quality Regulation in Electricity Distribution and Retail, Springer-Verlag Berlin, 2007.
[33] T. A. Short, Electric Power Distribution Handbook, Taylor \& Francis Group, 2014.
[34] R. Billinton and W. Li, Reliability assessment of electric power systems using Monte Carlo methods, Springer Science+Business Media, LLC, New York, 1994.
[35] R. E. Brown, Electric Power Distribution Reliability, CRC Press, Taylor \& Francis Group, Boca Raton, FL, 2009.

## APPENDIX

The test network used in simulations is given below. The distances between adjacent system bus bars are indicated in meters on power lines connecting them, while the total number and annual peak load of customers are indicated by two numbers at the bus bar to which the load is connected. The failure rate of power lines in suburban area is $0.21 / \mathrm{km} / \mathrm{year}$, while the failure rate in rural area is $0.31 / \mathrm{km} /$ year.


Fig. 29. Test network [24].


[^0]:    Manuscript received 26 October 2018. Accepted for publication 17 December 2018.
    P. Mršić, Đ. Lekić, B. Erceg, Č. Zeljković, and P. Matić are with the Faculty of Electrical Engineering, University of Banja Luka, Banja Luka, Republika Srpska, Bosnia and Herzegovina $(+387(51) 221-868$; fax: +387(51)221-820; e-mail: predrag.mrsic@etf.unibl.org).
    S. Zubić is with ABB AB , Grid Automation Products, Västerås, Sweden (e-mail: sinisa.zubic@se.abb.com).
    P. Balcerek is with ABB Corporate Research Center, Krakow, Poland (email: przemyslaw.balcerek@pl.abb.com).

