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Multiobjective Optimization of Maintenance Applied in Electric Power Distribution Systems

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HIGHLIGHTS

- Reliability-centered maintenance model for power distribution systems is presented.
- Fuzzy inference and integer nonlinear multiobjective programming is applied.
- A meta-heuristic called Lichtenberg's algorithm is used.
- The results can assist maintenance teams in decision making.

Abstract: Power distribution utilities effort to ensure the quality of energy to their consumers and the reliability of their power distribution system. It is necessary that maintenance activities are planned with the aim of maintaining or improving reliability indicators in supply to consumers. In this paper, a computational model based on integer nonlinear multiobjective programming is presented to improve the maintenance of equipment in the power distribution system. Since it is a reliability-centered approach, a probabilistic failure model is first used to obtain equipment reliability values at each time point through fuzzy inference. Three objective functions are optimized: i) minimizing maintenance cost, ii) minimizing failure frequency, and iii) maximizing equipment reliability. The optimization problem is also formed by three sets of constraints: i) individual and collective continuity indicators; ii) task execution time; and iii) maintenance limit for each type of equipment. Lichtenberg's algorithm is used to solve the model. A case study is performed for a feeder section consisting of twenty-eight distribution equipment. The results obtained using the Pareto constraints show scenarios that can help maintenance teams to make decisions and develop the preventive maintenance planning. Adding constraints on the duration and frequency of collective interruptions indicators improves the power quality of the distribution system; however, it requires an increase in investment by 36%.

Keywords: Continuity Indicators; Fuzzy Inference; Lichtenberg Algorithm; Multiobjective Programming; Power Distribution Systems; Reliability-Centered Maintenance.

INTRODUCTION

The challenge of the power distribution system is to provide consumers with high quality and continuous electricity at the prices set by ANEEL (National Electric Energy Agency). Interruptions and failures in the system cause financial and social costs, such as: revenue loss due to unsold energy, payment of fines, damaged equipment, loss of customer revenue, loss of material and damage to the image of the utility [1]. Therefore, in order to ensure better control over the quality of electricity supply to the population, utilities must meet with a series of requirements to guarantee the quality of electricity supply to consumers, highlighting the frequency and continuity of interruption, as well as the time to restore power supply. According to ANEEL, the interruption of the power supply is a temporary shutdown for the preservation and maintenance of the network and in cases of fortuitous events or force majeure [2]. To monitor the power supply, the regulator in Brazil uses collective continuity indicators (DEC and FEC) and individual continuity indicators (DIC and FIC). These data provide information on the quality of the energy supplied by the utility.

The quality of electrical energy is linked to the reliability and continuity of supply and can be affected by climatic factors, system failures, preventive maintenance, among other factors. Endrenyi and coauthors [3] state that maintenance has a direct impact on reliability and that there must be a balance in interventions in the system. If maintenance is done minimally, the system may have low performance and the number of failures may increase. If it is done frequently, reliability improves, but maintenance costs increase. Some mathematical models have been developed to assist in maintenance planning.

Reis [4] presents a mathematical model and an optimization methodology to find the best repair strategies. In the study, two application models are used to find planning actions that minimize the use of resources for preventive and corrective maintenance while guaranteeing a desired reliability level for the system. The optimization models GRASP (greedy randomized adaptive search procedure) and GA (genetic algorithm) are implemented from the point of view of reliability of distribution system. The author reports that the GA method proved to be more efficient GRASP model. The use of this technique can assist in planning the maintenance of the power distribution system, as it identifies at which intervals interventions should occur.

With the help of an optimization methodology through Mixed Integer Linear Programming (MILP) models, Martin [5] developed a strategy to optimize maintenance in electricity distribution networks. He used different maintenance levels for equipment and maintenance scheduling cycles. The model used considers the sum of the total maintenance costs as an objective function, taking into account an interest rate. The studies carried out indicated that the methodology is successful, even if used in distribution networks with radial operation.

Pereira [6] determines a maintenance schedule based on Markov chain and using penalties associated with the unavailability of the power supply. He uses a database of protection devices over eleven years to determine the probability of failure of the system. Thus, it is possible to determine the maintenance interval necessary to minimize the penalties payable by a power distribution utility and avoid unplanned shutdowns. However, the operation of the system becomes complex due to the uncertainties in the power demand of the problem and the large number of components.

Neto [7] proposed a strategy to solve the problem of transmission system maintenance planning based on the relationship between reliability and cost. The modelling applied consists of minimizing maintenance costs and failure risk (based on Markov chains) to produce a feasible schedule (taking into account systemic constraints) with logistic optimization. The solution technique used is Simulated Annealing. As the object of the study, a system with 13 equipment for power transmission activity was determined. The results obtained showed that the proposed methodology presented significant relative improvement, demonstrating its feasibility of application to real problems.

However, a different approach model based on reliability, also called RCM (Reliability Centered Maintenance), is presented by Piasson [8] and Rodriguez [9]. The authors used a multiobjective metaheuristic with a trade-off between the reliability of the system and the cost of preventive maintenance of the equipment. The reliability of the individual installations was modeled using fuzzy inference and failure probability. This first approach provides data for the application of the NSGA-II algorithm (Non-dominated Sorting Genetic Algorithm). Rodriguez explains that by applying this strategy, it is possible to define the optimal Pareto curve of the two functions in question, which (respecting the operational constraints) gives a logical sequence of maintenance tasks for the system under study. The maintenance task schedules obtained by this technique ensure to supply the energy for the system without failures and prevent possible penalties by the regulator based on the indicators.

Similar to Neto [7], Carnero and coauthors [10] apply the Markov chain process to a single objective model. In summary, the model solves problems in sustaining energy supply in healthcare organizations where energy supply is critical. Thus, the MACBETH approach (Measuring Attractiveness by a Categorical Based

Evaluation Technique) leads to a combination of measures that make the maintenance of distribution more reliable. The application of the proposed technique in a power distribution system for a hospital area resulted in a 20% cost reduction and an increase in system reliability by 0.15%.

Using the Lagrange multipliers, Moradi and coauthors [11] present techniques for identifying critical components in a microgrid and their failure rates. The proposed model was implemented in a part of the distribution network in Tehran, the capital of the Islamic Republic of Iran. The results proved the effectiveness of the model by lowering the values of the SAIFI (System Average Interruption Frequency Index) reliability indices. Afzali and coauthors [12] proposed (Weighted Importance), i.e., a reliability index of weighted importance for the assets of the distribution. This model is applied to two levels of a feeder. At the first level, the feeders of a substation are prioritized for reliability measures. At the second level, the components of a base case feeder are prioritized for measures. The authors conclude that the higher the value of the WI index, the lower the reliability of the system, and consequently the greater the need for maintenance at these points.

Ferreira [13] addresses in his paper the implementation of a risk matrix to identify defective assets using data provided by power distribution utility. He also notes that with this technique it is possible to identify the points that require more preventive intervention, which leads to a reduction in losses for utilities. Thus, carrying out these maintenance practices makes distribution more assertive, both in planning and in carrying out maintenance on electricity network that can prevent future defects. All these practices lead to a reduction in financial compensation for customers.

To provide electric power with a high level of reliability, Yari and coauthors [14] use Big Data to determine the actual failure rate of equipment and the average repair time applying stochastic optimization. The developers propose a practical model for maintenance scheduling considering the economic risk function and budget constraints based on the cost of preventive maintenance and the value of the lost. The authors note that using the NSGA-II algorithm for a multiobjective model proved to be efficient and it was possible to achieve significant improvements in reliability indices.

Similarly, Kong and coauthors [15] propose data analysis through Big Data and power supply uncertainties. The approach uses the Improved Elman Neural Network (IENN) method, and the authors note that this technique makes it possible to simplify the calculations and insert uncertainty factors into the distribution network model, bringing the study closer to reality. They report that the application of neural networks proves to be effective, but that different topologies of distribution networks may affect the effectiveness of the method.

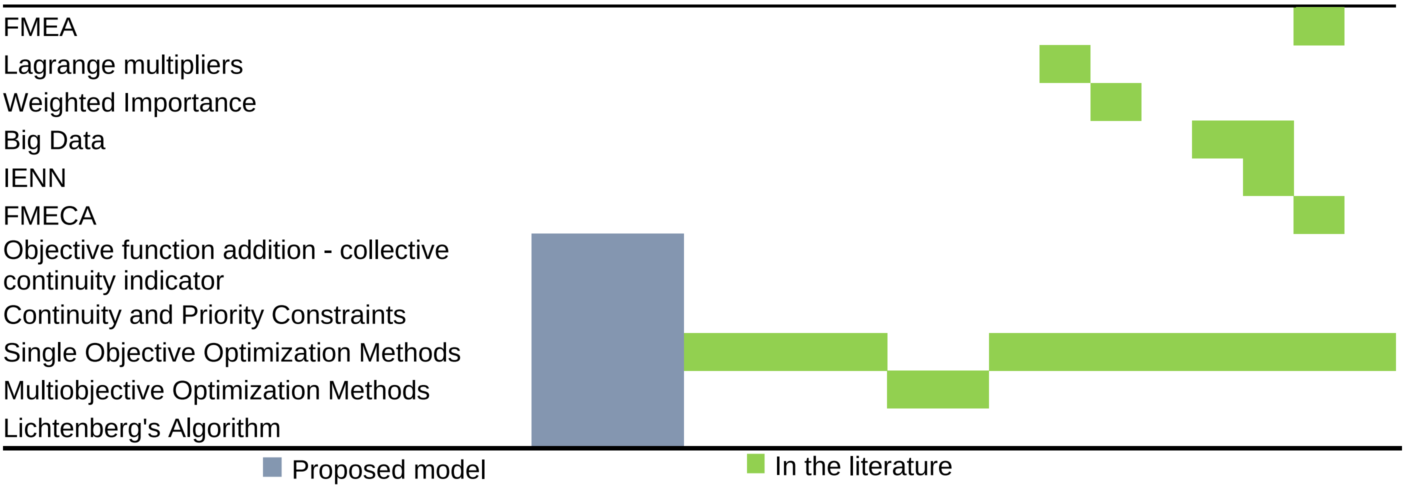
Catelani and coauthors [16] use the data-driven system in the context of reliability-centered maintenance. The study optimizes a maintenance plan for wind turbines and helps in decision making and cost reduction. The authors explain that the use of FMECA (Failure Modes, Effects and Criticality Analysis) facilitates generator maintenance by assigning only one maintenance task to each scenario. In this study, only 5% of maintenance was corrective.

In his study, Neto [17] uses real data from a substation to develop strategies for performing maintenance tasks. Through cost and reliability relationships, the application of heuristic combination with dynamic programming, a feasible system maintenance schedule is developed. The author shows that the implemented algorithm allows the selection of the most cost-effective preventive maintenance schedules with little computational effort. Neto states that the results obtained in the simulations performed show the impact of the methodology on reducing costs in all maintenance activities. Table 1 shows a comparison of the presented tools for maintenance of power system distribution asset for different cases.

Table 1. Comparison of works presented in the literature review

Technique Used	Proposed Model	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]
Mixed Integer Linear Programming	■		■												
Markov model				■				■							
Simulated Annealing					■										
Fuzzy Inference & NSGAII	■					■	■					■			
Risk Matrix											■				
GRASP		■													
GA - Genetic Algorithms	■	■													
Dynamic Programming															■
MACBETH								■							

Cont. Table 1



According to Pomalis and coauthors [18], the quality of electrical energy is a set of characteristics of the electrical energy delivered by the utilities to the consumer and which is directly linked to the individual and collective continuity indicators applied by the utilities. Degradation of DEC values may be linked to adverse weather conditions, access to the location and problems with energy protection equipment. The FEC may be related to the lack of maintenance and improvements, as well as the growth of vegetation around the network.

Complex problem involves multiple objectives and there are heuristic and mathematics methods to solve multiobjective problems [19]; however, not many studies applied multiobjective formulation in optimization of maintenance. Collective and individual continuity indicators are very important for Brazilian power distribution utilities and ANEEL may totally or partially suspend the activities of utilities when they violate the limits of established quality indicators. However, only Piasson [8] and Rodriguez [9] applied DIC and FIC constraints. In the literature review, no use of DEC and FEC was found and only two objectives are formulated.

Since the objective of a power distribution utilities is to deliver energy with quality and within reasonable limits, corrective, preventive and predictive maintenance is necessary for the system to be reliable and to avoid penalties due to the unavailability of service. In order to avoid unnecessary expenses for maintenance and consequently improve the continuity indicators, it is necessary to optimize the intervention process in order to “make the most of” the benefits of the installed equipment. Therefore, this paper proposes the implementation of an optimization method that can be applied in the optimal reliability-centered maintenance planning of the power distribution systems. Such a technique can help to find a trade-off between the cost and reliability of electricity network maintenance and help utilities repair teams in their decision making. By targeting these resources, power distribution utilities can reduce their costs and effectively improve indicators.

Therefore, this paper presents a computational model based on multiobjective integer nonlinear programming to improve asset maintenance in the power distribution system. Since it is a reliability-centered approach, a probabilistic failure model using fuzzy inference (Mamdani) is first used to obtain the equipment reliability values at each instant of time. The model is built with the objective of optimizing three objective functions: i) minimizing maintenance cost, ii) minimizing failure frequency, and iii) maximizing equipment reliability. The optimization problem is also formed by three sets of constraints, namely: i) individual and collective continuity indicators (DIC, FIC, DEC, FEC), ii) time to perform tasks, and iii) maintenance limits for each type of equipment. A meta-heuristic called Lichtenberg's algorithm is used to solve this model. To validate the model, a case study is conducted over a twenty-four-month period for a feeder section consisting of twenty-eight distribution equipment.

The paper is organized into four sections. Section 2 explains the materials, methods, and modeling of the problem. Section 3 is dedicated to the presentation of the results obtained in the application of the developed method. Section 4 concludes the paper with its main highlights.

MATERIAL AND METHODS

MOLA (Multi-objective Lichtenberg Algorithm) takes a similar approach to NSGA-II. The approximation through non-dominated form genetic algorithms (NSGA-II) is often used to solve optimizations with two objective functions. Also, the algorithm MOLA defined by Pereira and coauthors [20] uses metaheuristics to solve multiobjective problems with two or more functions. They demonstrate that the algorithm's search technique uses Lichtenberg figures resembling lightning bolts in clouds to create its search space. The authors claim that the algorithm is promising in solving multiobjective problems and is superior to traditional algorithms such as NSGA-II, MOPSO (Multi-objective Particle Swarm Optimization), MOGOA (Multi-objective Grasshopper Optimization Algorithm), MOEA/D (Multi-objective Evolutionary Algorithm based on decomposition) and MGWO (Multi-objective Gray Wolf Optimizer) because it has meaningful values for convergence and speed.

The algorithm first consists of creating a Lichtenberg Figure (LF) that is fixed in the search space, and points of its structure are used as candidates for checking the objective functions (Table 2). The algorithm consists of releasing particles randomly in the matrix. If they reach LF, which was only one particle in the center to begin with, they have a probability S of fixation, also called the coefficient of adhesion. If the value found reaches a radius greater than R_c, it is discarded, and the random mode starts again. This continues until all particles found in the N_p input are contained in the LF or until it reaches its build limit (Table 3).

Table 2. MOLA's main algorithm

Algorithm 1: Main
Define objective functions and search space – J_i upper and lower limits
Set the number of iterations and population – N_{iter}, Pop (common for all optimizers)
Set LF refinement and switch parameters - Ref, M (MOLA routine parameters)
Define LF parameters - R_c, N_p, S
if $M = 0$, load LF, **end if**
if $M = 1$, create LF, **end if**
while $(iter < N_{iter})$ **Do**
if $M = 2$, create LF, **end if**
$X_{trigger}$ = space center search (first LF trigger point)
if $ref = 0$
Applies to random scaling and rotation
Initialize the random population over the LF, $X_i(i = 1,2, \dots, Pop)$
copy the LF to create the second LF from the same *LF (Local)
Same random scaling and rotation applies to both
The random global population is initialized through the LF $Xglobal_i(i = 1,2, \dots, 0.4 * Pop)$
Initialize the random local population through the LF $Xlocal_j(j = 1,2, \dots, 0.6 * Pop)$
$X_i = Xglobal_i + Xlocal_j$
end if
Calculate J_i for each one X_i of the problem
Find the dominated and non-dominated solutions analyzed in J_i
Builds the current Pareto frontier with non-dominated solutions
Saves non-dominated solutions across iterations
$X_{trigger} = X_{ND}$
$Iter = iter + 1$
End while
return Pareto border

Table 3. Algorithm for creating Lichtenberg Figures - MOLA

Algorithm 2: Creation of LF
An array R_c is created – size zero
A unit particle is placed at the center
while $(\boldsymbol{i} < \boldsymbol{N_p})$ **do**
Randomly place a unit particle in the array
if the plotted unit particle t is close to another unit particle
if $rand < S$
This new unit particle is placed in the matrix
$\boldsymbol{i} = \boldsymbol{i} + \mathbf{1}$
If not
The plotted unit particle is eliminated
end if
end if
if the agglomerate of unit particles reaches R_c
The simulation is finished
end if
end while
$X =$ coordinates of all unit particles of cartesian space in the size of the search space

Problem modeling

The aim of this paper is proposed an optimization of maintenance in a section of an electricity distribution network, using the Reliability-centered Maintenance (RCM) method to model uncertainties and minimize the cost of violating continuity indicators. Most real-world problems field of optimization multiple goals that must be achieved simultaneously. They are usually in conflict with each other, that is, there is no single solution that optimizes all objectives simultaneously [19]. Piasson [8] and Rodriguez [9] used the RCM method, the failure rate of equipment, to model system uncertainties. With the values of the continuity and historical unavailability indicators of the distribution assets, it is possible to project the failure rate of each equipment over the time horizon. The proposed optimization model differs from Piasson by using an algorithm with the possibility of using two or more objective functions.

Decision variables

For each unit, maintenance can be performed with different levels of intervention. There are therefore two possibilities that can be performed in this model. The first is to use only binary variables. In this case, a variable would have to create for each level and, subsequently, a constraint to not allow more than one level of maintenance to be carried out at the same time. The second would be to use only one variable, but with all levels of maintenance. For this modelling, the second option was chosen because it is easier to implement and contains a smaller number of variables and constraints. Therefore, the optimization variables alternate between m0 and m3 and denote the presence or absence of maintenance at the respective time. Each of the integer variables represents a level of maintenance to be performed.

For a set E of equipment and such that each equipment e has the possibility to perform maintenance tasks m in the period of time t and in the planning horizon PH. Each type of maintenance on equipment represents an integer variable in Eq. (1), where:

- "m0" perform no maintenance;
- "m1" soft maintenance;
- "m2" intermediate maintenance;
- "m3" hard maintenance.

$$x_{(e,m)}^{t} = \{m = m0, m1, m2, m3\}\ , \qquad \forall\ e \in E \tag{1}$$

During the planning horizon, whether or not the maintenance is carried out impacts the reliability index. This value is updated at each point in time by the failure rate multiplier.

Objective functions

The first objective function (Eq. 2) represents the cost of maintenance tasks. It represents the value of each repair, which varies according to the intensity of maintenance in each equipment. The function also has an associated interest rate so that the value is updated with each month that passes in the simulation.

$$f_1 = \sum_{t=1}^{PH} \sum_{e=1}^{E} C\left[x_{(e,m)}^t\right] \left(\frac{1}{1+r}\right)^t \tag{2}$$

where:

t	time (month)
PH	planning horizon
e	type of equipment installed in the system
E	system equipment set
$C\left[x_{(e,m)}^t\right]$	variable maintenance cost depending on to the level of maintenance ($)
$x_{(e,m)}^t$	integer decision variable that defines the level of equipment maintenance and time (*t*)
r	interest rate (%)

The second objective function (Eq. 3) deals with the reliability of the equipment. It is represented in terms of unreliability, which is the opposite of reliability, decreasing the value over time. It is also related to with the power demand of each radial section of the feeder with which the unreliability is associated.

$$f_2 = \frac{1}{PH} \sum_{t=1}^{PH} \left[\frac{\sum_{s=1}^{S}(1 - R_s(t))P_s}{\sum_{s=1}^{S} P_s}\right] \tag{3}$$

where:

S	number of customers per section
R_s	reliability of customer service
P_s	active power per feeder section (W)

The calculation of the reliability of the section R_s is previously done by fuzzy inference and is updated at each iteration of the algorithm routine. In this way, an attempt is made to approximate the wear and tear and natural ageing of the equipment over the planning horizon.

Since it is feasible to use a system with more than one objective function, it was decided to use the energy interruption frequency equivalent (FEC) as the objective function. Thus, the third objective function (Eq. 4) can assume values of minimum and maximum and improve the solutions arranged in the search space.

$$f_3 = \sum_{t=1}^{PH} FEC_{\text{monthly}}(t) \tag{4}$$

Interruption accumulation is defined as the ratio between the number of supply interruptions and the number of consumers affected. This search helps to identify points where the number of affected consumers is more frequent.

Constraints

Duration and Frequency of Individual Interruption per Consumer Unit

In the constraints of the problem, there are individual continuity indicators in Eq. (5-10). These provide information on the duration and frequency of the power interruption for each individual consumer. FIC is the frequency of individual interruption per consumer Unit and DIC is the duration of individual interruption per consumer unit. The indicators limits are defined and monitored by ANEEL: monthly, quarterly, and annually.

$$DIC_{\text{monthly}}(t) \leq DIC_{\text{monthly}}^{max} \tag{5}$$

$$DIC_{\text{quarterly}}(t) \leq DIC_{\text{quarterly}}^{max} \tag{6}$$

$$DIC_{annual}(t) \le DIC_{annual}^{max} \tag{7}$$

$$FIC_{\text{monthly}}(t) \le FIC_{\text{monthly}}^{max} \tag{8}$$

$$FIC_{\text{quarterly}}(t) \le FIC_{\text{quarterly}}^{max} \tag{9}$$

$$FIC_{annual}(t) \le FIC_{annual}^{max} \tag{10}$$

In addition to Piasson and Rodriguez, some changes were made to the formulation of the original problem and the collective continuity indicators (FEC and DEC) were added to complement the continuity indicators. FEC is energy interruption frequency equivalent and DEC is the interruption duration equivalent per consumer Unit.

$$DEC_{\text{monthly}}(t) \le DEC_{\text{monthly}}^{max} \tag{11}$$

$$FEC_{\text{monthly}}(t) \le FEC_{\text{monthly}}^{max} \tag{12}$$

It was then necessary to add customers (*Cc*) to the model to simulate the insertion of these indicators and give fidelity to the proposed model.

$$DEC\,(t) = \frac{\sum_{i=1}^{Cc} DIC_{\text{monthly}}(t)}{Cc} \tag{13}$$

$$FEC\,(t) = \frac{\sum_{i=1}^{Cc} FIC_{\text{monthly}}(t)}{Cc} \tag{14}$$

With equations (15-20) we have the description of the continuity indicators used in the constraints. Equations (15-16) define how the monthly indicator values are calculated, depending on the integer variable, the reliability of the section and the average operating time. The following equations (17-20) show the approximation used by Piasson and coauthors [21] for monthly and annual reference values, using a proportionality relationship.

where:

$$DIC_{monthly}(t) \le AET\left[x_{(e,m)}^{t}\right] + [1 - R_s]MERT \tag{15}$$

$$FIC_{monthly}(t) \le x_{(e,m)}^{t} + [1 - R_s] \tag{16}$$

$$DIC_{quarterly}(t) \approx \frac{1}{k_{quarterly}DIC} \sum_{t=1+3(m-1)}^{3m} DIC_{monthly}(t) \tag{17}$$

$$FIC_{quarterly}(t) \approx \frac{1}{k_{quarterly}FIC} \sum_{t=1+3(m-1)}^{3m} FIC_{monthly}(t) \tag{18}$$

$$DIC_{annual}(t) \approx \frac{1}{k_{annual}DIC} \sum_{t=1+12(a-1)}^{3a} DIC_{monthly}(t) \tag{19}$$

$$FIC_{annual}(t) \approx \frac{1}{k_{annual}FIC} \sum_{t=1+12(a-1)}^{3a} FIC_{monthly}(t) \tag{20}$$

Mean emergency response time (MERT)

According to ANEEL, the MERT represents the average value corresponding to the execution time of the maintenance of a given group of consumption units from preparation to execution [22]. For this model, the implementation as [9] addressed in his study was used. It highlights the constraint as the sum of the execution times at each level of maintenance and for each type of equipment. These indicators are used to check the response time to emergencies related to the group of consumption units. The recorded values are expressed in minutes and are calculated monthly by the power distribution utilities.

- Average Preparation Time (APT);
- Average Travel Time (ATT);
- Average Execution Time (AET);
- Average Time to Fault Location (ATL).

$$MERT = AET + ATT + APT + ATL \tag{21}$$

The maximum values for performing maintenance are set by the regulator and are presented in eq. (22).

$$\sum_{e=1}^{E} APT\left[x_{(e,m)}^{t}\right] + ATT\left[x_{(e,m)}^{t}\right] + AET\left[x_{(e,m)}^{t}\right] \leq T_{feasible} \tag{22}$$

where:

$APT\left[x_{(e,m)}^{t}\right]$	average preparation time of the team for the maintenance (min.);
$ATT\left[x_{(e,m)}^{t}\right]$	average travel time of the team to perform the maintenance (min.);
$AET\left[x_{(e,m)}^{t}\right]$	average execution time of maintenance (min.);
T_{feasible}	available time of the maintenance team (min.).

Depreciation of equipment assets

Asset depreciation aims to allocate maintenance needs during the useful life of the equipment. Therefore, the aging of each equipment is presented in eq. (23).

$$T_e + t - T_{l_e} \geq 0 \tag{23}$$

where:

T_e	equipment life cycle (in years);
T_{l_e}	equipment life upgrade rate *e* (in years).

One time maintenance

Finally, to ensure that only one maintenance is performed per time period will be performed, constraint (24) is inserted.

$$\sum_{t=1}^{PH} x_{(e,m)}^{t} \leq 0 \tag{24}$$

The update of the failure rate is done by eq. (25) every month (*t*). When equipment is repaired, there is a reduction in the occurrence of failures. The reliability calculation according to eq. (26) is done using the exponential model of the Poisson distribution, a characteristic curve for the useful life of the equipment. Finally, eq. (27) defines the product of the reliability of all feeders.

$$\lambda_e^{t_{initial}} = \delta_e^m \lambda_e^{typical} \tag{25}$$

$$R_{s_{consi}}(t) = R(t) = \exp(-\lambda t) \tag{26}$$

$$R_s(t) = \prod_{i=1}^{n} R_{consi_i}(t) \tag{27}$$

Consumer supply priority constraint

Another change made to the constraints is the addition of a priority for section two (Figure 1). This addition is intended to simulate the priority of consumers that depend on uninterrupted power supply, such as hospitals, supermarkets, and priority group A consumers. The selected equipment $e = \{e_i : e_f\}$, are part of the main supply at the substation output. For this reason, the constraint acts only on the first five equipment that form the main supply node, and with a minimum reliability ($R(t)$) value for this section of 0.8, according to eq. (28).

$$f_{(t)} = \sum_{e=1}^{5} R(t) > 0{,}8 \tag{28}$$

Proposed model

The case study has 28 operating devices: 3 circuit breakers (DJ), 8 primary network cables (LN), 1 capacitor bank (CP), 4 voltage regulators (RT), 9 distribution transformers (TR) and 3 protection switch and/or maneuvers (CS).

The adopted radial model (Figure 1) represents a feeder fragment that is widely used in distribution systems because of its low cost and also because of the ease of protection coordination. In the event of a failure in the main feeder sections (01 and 02), the supply to the remaining loads may be affected. In this way, the effect of the priority constraint (eq. 28) added to the main branch can be verified.

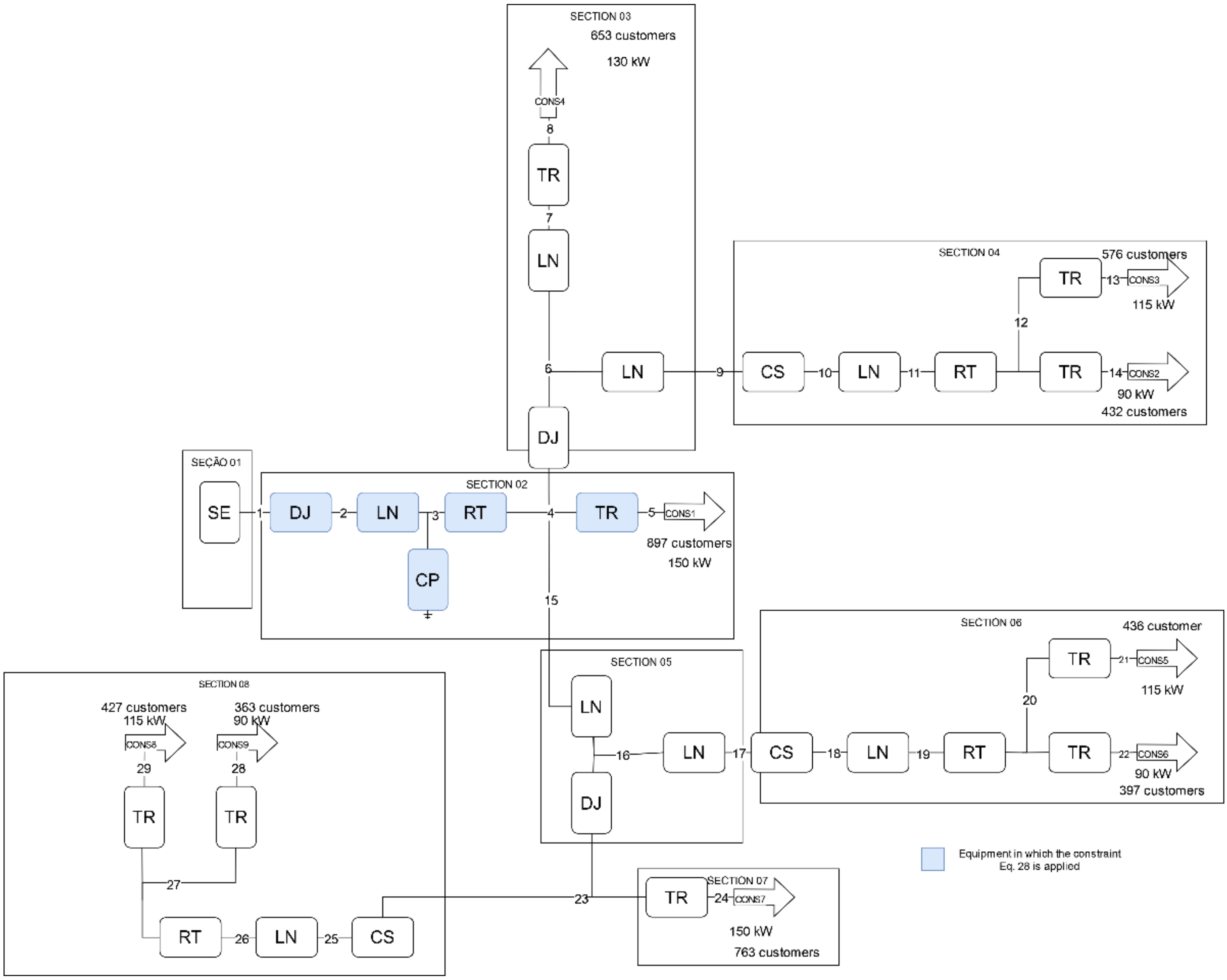


Figure 1. Feeder Section 28 equipment.

To develop fuzzy inference and the Lichtenberg algorithm, it is necessary to input the initial values of the equipment behavior. Each maintenance performed has a level of intensity and provides a repair cost. The equipment maintenance cost and the initial values of failure rates were obtained through historical data from utilities. The failure rate parameter multiplier refers to the update of the occurrence of an outage. Every time a failure occurs, the equipment updates this value through an associated multiplication constant, which will provide an increase or decrease in the failure rate (eq. 25). Table 4 presents data proposed by [8,9].

Table 4. Maintenance parameters.

Equipment	Maintenance cost (R$)				Failure rate parameter multiplier				Failure rate (failures/year)
	m_0	m_1	m_2	m_3	m_0	m_1	m_2	m_3	
TR	0	120	550	2500	1.04	0.8	0.5	0.01	0.2723
CP	0	350	1000	-	1.04	0.8	0.08	1.04	0.2723
RT	0	150	650	1200	1.03	0.8	0.5	0.01	0.4312
LN	0	80	170	-	1.04	0.8	0.08	1.04	0.4312
CS	0	30	70	-	1.01	0.8	0.01	1.01	0.2723
DJ	0	150	800	2000	1.04	0.8	0.5	0.01	0.4312

Legend: DJ – Circuit breakers; LN – primary network cables; CP – capacitor bank; RT – voltage regulators; TR – distribution transformers; CS – protection and/or maneuvering key.

Through eq. (21), the regulatory agency monitors exceeded values. Table 5 presents the maintenance execution time [8,9].

Table 5. Maintenance execution time (min.).

Equipment	AET				ATT				APT				ATL
	m_0	m_1	m_2	m_3	m_0	m_1	m_2	m_3	m_0	m_1	m_2	m_3	
TR	0	120	150	180	0	60	80	100	0	20	30	60	30
CP	0	30	60	0	0	60	100	0	0	20	30	0	30
RT	0	120	150	180	0	60	80	100	0	20	30	60	30
LN	0	30	120	0	0	60	100	0	0	20	30	0	30
CS	0	30	60	0	0	60	100	0	0	20	30	0	30
DJ	0	60	120	0	0	60	100	0	0	20	30	0	30

RESULTS AND DISCUSSION

This section presents the results obtained in the implementation of the computational model to optimize the preventive maintenance of an electrical power distribution system for a small feeder. A planning horizon of 24 months was used for all scenarios.

Initial example results

The test was performed using the Multi-Objective Lichtenberg Algorithm V2.0 (MOLA) solver, developed by [20], in MATLAB and available in the MathWorks community. The change in Piasson's model (2014) is due to the insertion of the collective indicators DEC and FEC (Figure 2), which makes the problem more constrained. Moreover, the reliability of the system improves by inserting the continuity constraint (eq. 28) in the main distribution branch.

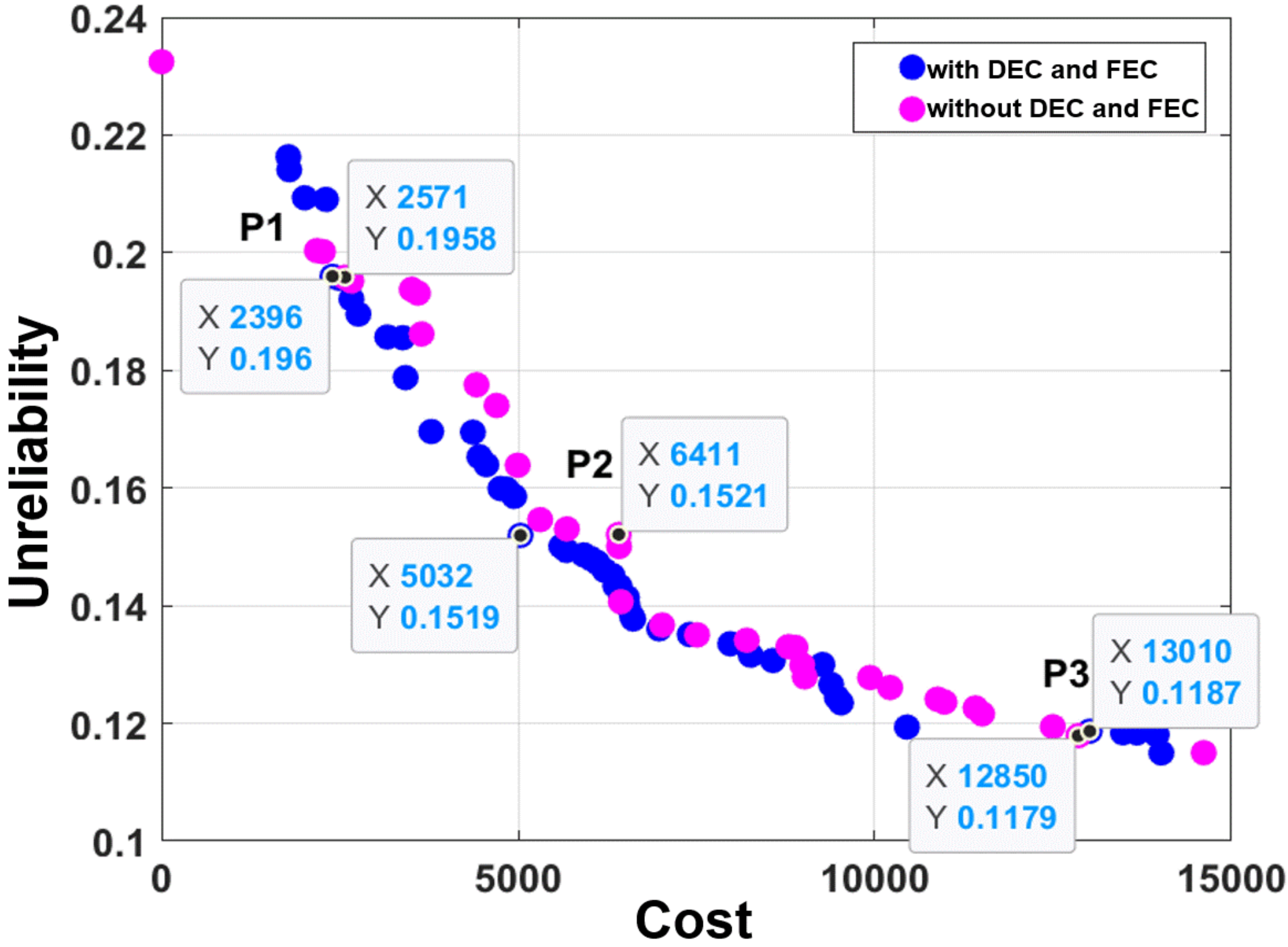


Figure 2. Pareto Frontier – Cost vs. Unreliability – with addition DEC and FEC.

In this example, the magenta Pareto curve is slightly higher than the blue curve, which is due to the introduction of constraints on collective indicators that were not included in the original proposal. This is because the increase in constraints due to the addition of indicators means that the manifold has greater maintenance requirements to maintain the same level of system reliability. The collective continuity indicators DEC and FEC are of paramount importance because they not only ensure the quality of continuity of energy supply to consumers, but also consumer perceptions of the service provided. The inclusion of constraints in the problem is intended to improve the model and bring it closer to the requirements of the regulator ANEEL.

Results for final modeling

In this section of the paper, the results of applying the Lichtenberg algorithm to the asset maintenance model in the electric power distribution system were shown. By using three objective functions, it was possible to present several interpretations of possible results. However, it is important to point out that the presented evaluation does not provide a single result, and it is up to the manager to choose one.

The first result diagram of the optimization is the Pareto frontier between the first two objective functions, cost, and reliability (Figure 3). This figure shows possible maintenance scenarios, where increasing the investment in equipment directly leads to an improvement in reliability values, which was already expected. However, higher investments do not always lead to a viable scenario for maintenance team decision making.

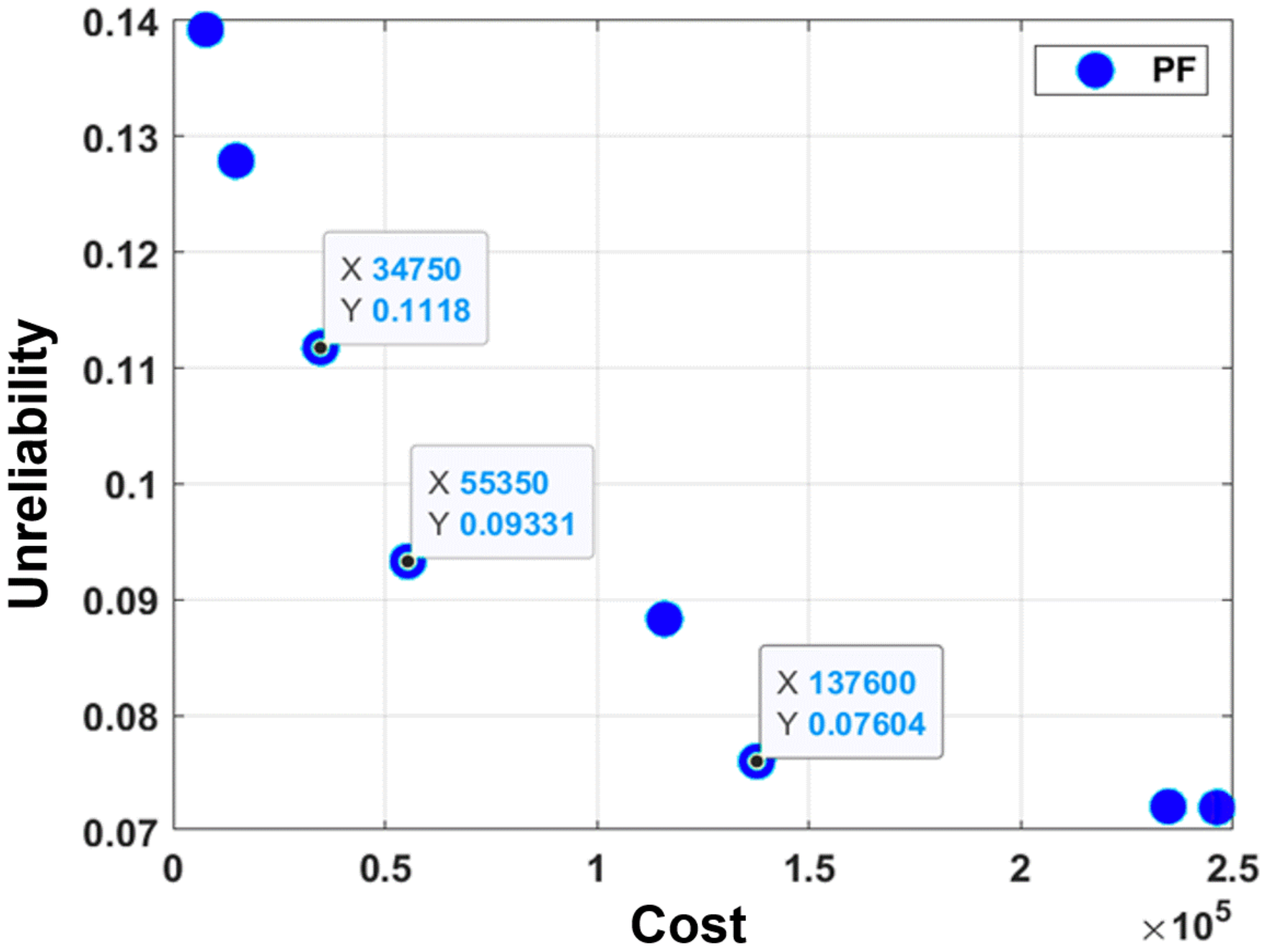


Figure 3. Pareto Frontier – Cost vs. Unreliability

It is verified that the insertion of constraints and the objective function forces the algorithm to improve the possible output responses of the graph. If we compare the values produced by the two curves (Figure 2 and Figure 3) (adding the consumer priority constraint and FEC as the third objective function), the cost increases from R$13,010.00 to R$34,750.00, an increase of 267.10% to maintain the same system reliability, 0.1187. This confirms the idea that the increase in constraints in this model signals the need to intensify system maintenance. The priority constraint causes the levels of unreliability in sections 01 and 02 to have values above 0.8 and as result more preventive maintenance is needed. Another point to consider is the increase in equipment and consumers between the two examples. Even if the reliability values do not improve, the comparison shows that the model becomes more realistic and approaches the specifications of ANEEL.

For each approach, three solutions were chosen (P4, P5 and P6), as follows: Point P4 represents lower investment and low reliability; P5 is an intermediate solution that ensure reliability without increasing costs too much; P6 represents maximizing investment. The points were chosen with the aim of maintaining the same level of reliability in both cases to allow comparison of the addition of the function (eq. 4) as the objective and the insertion of the constraint (eq. 28). Figure 4 shows a significant increase in maintenance cost between the three points.

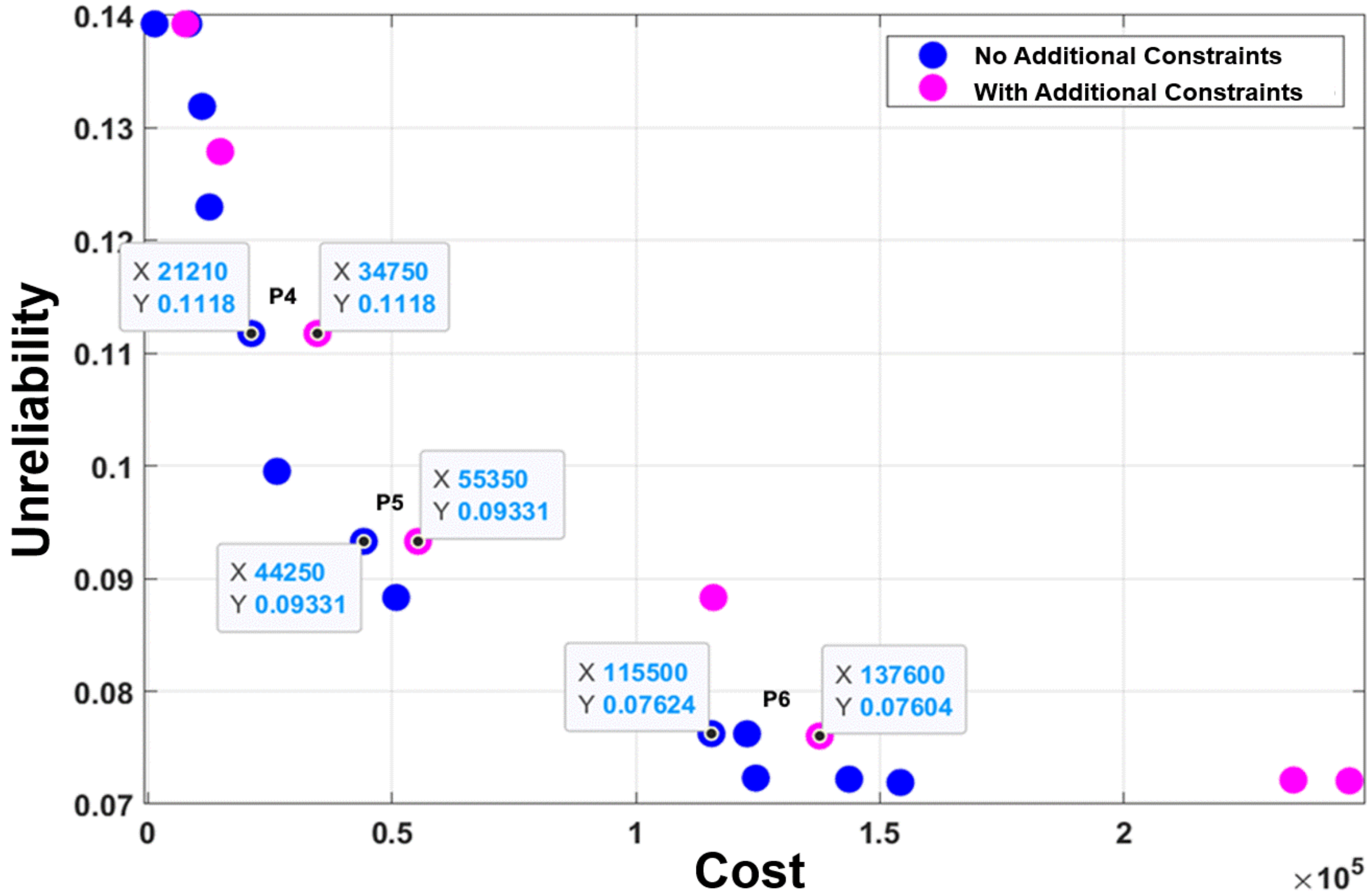


Figure 4. Pareto Frontier – Cost vs. unreliability

Table 6 summarizes the points chosen in Figure 4 and compares the unreliability of the system, the maintenance cost, and the number of interventions in the two models.

The addition of the objective function (eq. 4) and the priority constraint (eq. 28) change the investments in the selected points: in P4 there was a 63.84% variation in cost when the level of maintenance was increased by 115 units; in P5 there was an increase of 25.08% in cost and 62.98% in the level of maintenance; P6 had the highest cost, the scenario with additional constraints and without additional constraints had the same number of maintenance and the cost increased by 19.13%, this means that there was a change in the maintenance level. The additional costs recorded in Figure 4 can also be associated with the use of a third objective function. The interpretation of the algorithm in the addition of the constraint (eq. 4) adds higher levels of maintenance to aim for continuity of the system and reduce the time between maintenance. When the system uses a higher level of maintenance, the failure rate and the probability of a new failure decrease.

Table 6. Comparative table of results.

Points	Unreliability	Cost (R$)	Quantity of Maintenance	
P4	0.1118	21,210.00	74	
P5	0.09331	44,250.00	262	without (eq. 28)
P6	0.07624	115,500.00	672	
P4’	0.1118	34,750.00	189	
P5’	0.09331	55,350.00	427	with (eq. 4) and (eq. 28)
P6’	0.07604	137,600.00	672	

Figure 5 shows the unreliability and registered interruptions by section. The third objective function is the cumulative FEC, which is the sum of the individual power interruptions. The increase in these interruptions causes the algorithm to make more interventions in the system, which improves the reliability of the system. Figure 5 shows that the unreliability decreases only because the interruptions increase and consequently more maintenance is required. By adding the indicator FEC as an objective function, the number of possible solutions in the search space has improved, i.e., the function can reach maximum and minimum values, unlike when it was only used as a constraint.

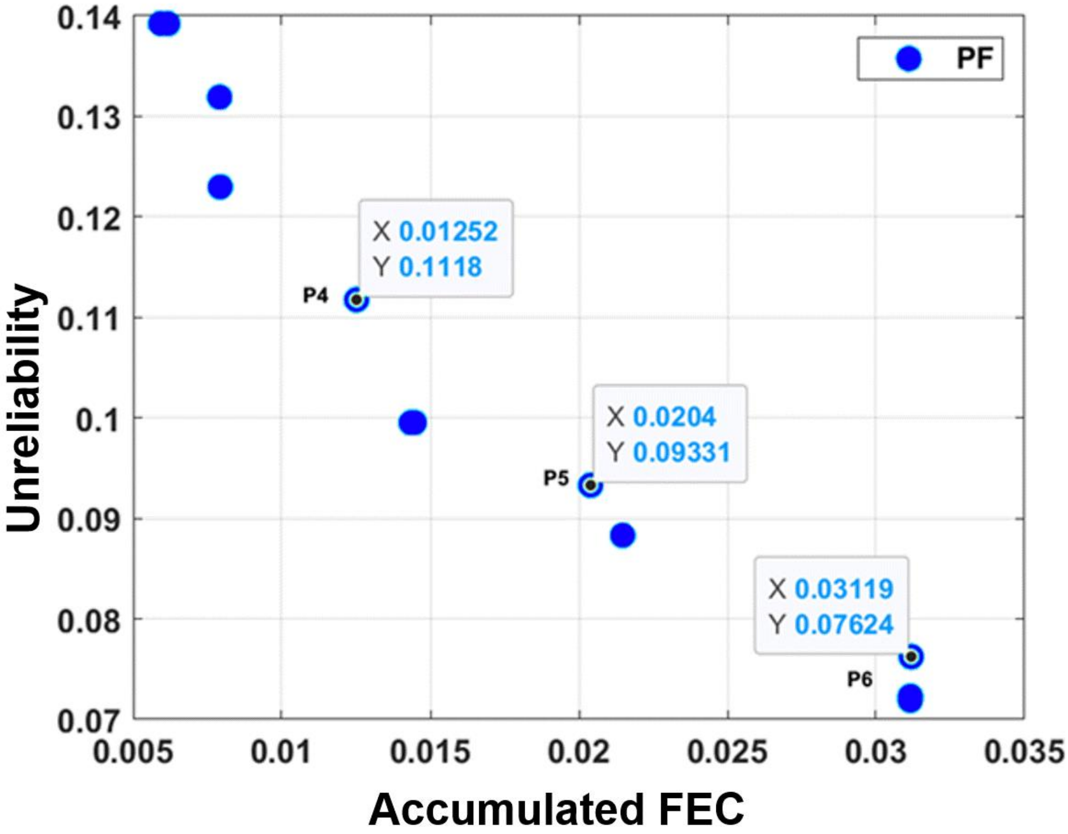


Figure 5. Pareto Frontier Unreliability x Accumulated FEC

From this perspective, the heuristic interprets the need to maintain the reliability level and intensify the maintenance of the system. The extreme solution with more maintenance is not always a viable model for the maintenance team. For this reason, the proposed model provides support for decision making for each scenario.

CONCLUSION

The concern with the interruption in the supply and improving energy quality through assertive maintenance have become the goal of the power distribution utilities. For this reason, heuristic methods are increasingly used to solve problems that would not be possible with mathematical optimization methods. In this context, the Lichtenberg algorithm proves to be an efficient alternative to obtain solutions in multiobjective modeling with the possibility of two or more objective functions.

Nevertheless, based on the results, it was found that the constraints on the indicators required by the agency in the distribution procedures are indeed necessary. The introduction of new constraints in the proposed model resulted in need to intensify maintenance by 72.79% on average, which led to a 34.69% increase in the average total value of repairs. This shows the importance of investing in maintenance not only on the part of the utility, but also to agency control through continuity indicators. When the continuity constraint was introduced, simulating possible priority energy consumers, more investments had to be triggered to maintain the reliability level.

Therefore, the proposed model was generally found to be suitable for the optimization of reliability-centered maintenance plans applied to electric power distribution. In addition, it is important to point out that the use of the Pareto curve as a result shows a set of solutions that are not dominated by the three objective functions, which, in turn do not represent a final answer, but a set of solutions that, depending on the strategy, can help managers make decisions about the best relationship between reliability and cost.

Moreover, among the challenges found in the development of this work, the historical values of failure rates and maintenance in power distribution utilities. Due to the unavailability of some information from these entities, there is some difficulty in optimizing the model and the accuracy of the maintenance carried out in recent years, and thus in planning better interventions in the system.

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