BPSO-Fuzzy Algorithm for Distribution System State Estimation under Unavailability of Measurements

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Abstract— This paper proposes a methodology for meter placement for state estimation in distribution networks. The proposed methodology considers that the meter placement is carried out including the unavailability of multifunctional meters. This formulation of the allocation problem prevents the accuracy of the state estimator from being degraded by failures in the meters. Consequently, more accurate estimates of power quality indexes associated with compliance voltage or voltage unbalance can be obtained. The meter placement was performed using a multi-objective formulation that maximizes the accuracy of the estimator and minimizes the number of meters installed in the distribution network. This optimization problem was solved using a fuzzy multi-objective optimization strategy combined with binary particle swarm optimization algorithm. In addition, the effect of the correlation between measurements was included. The results of the tests showed that the proposed methodology obtained good quality solutions to the meter placement problem under scenarios of unavailability of measurements.

Keywords— Particle Swarm Optimization, Fuzzy Multi-objective Optimization, State Estimator Accuracy, Unavailability of Measurements.

Resumo— Este artigo propõe uma metodologia de alocação de medidores para estimação de estado em redes de distribuição. A metodologia proposta considera que a alocação dos medidores é realizada incluindo-se a indisponibilidade de medidores multifuncionais. Esta formulação do problema de alocação evita que a precisão do estimador de estado seja degradada por falhas nos medidores. Consequentemente, estimativas mais precisas dos índices de qualidade de energia associados à conformidade de tensão ou desequilíbrio de tensão podem ser obtidas. A alocação dos medidores foi realizada usando-se uma formulação multiobjetivo que maximiza a precisão do estimador e minimiza o número de medidores instalados na rede de distribuição. Este problema de otimização foi resolvido usando-se uma estratégia de otimização multiobjetivo fuzzy combinada com um algoritmo de otimização por enxame de partículas na sua versão binária. Além disso, o efeito da correlação entre as medições foi incluído. Os resultados dos testes mostraram que a metodologia proposta obteve soluções de boa qualidade para o problema de alocação de medidores em cenários de indisponibilidade de medições.

Palavras-chave— Otimização por Enxame de Partículas, Otimização Multiobjetivo Fuzzy, Precisão do Estimador de Estado, Indisponibilidade das Medições.

1 Introduction

A smart grid (SG) requires new technical considerations, such as: stability, the dispatch of load and generation, the management of energy storage devices and the evaluation of the impact of the connection of electric vehicles in the distribution network. The main prerequisite for many of these new functions of the distribution management system (DMS) is the determination of the status of the electrical network (magnitude and angle of the nodal voltages) in real time from measuring devices installed along the network. In power system control centers, this task is performed using the state estimator (SE). The DMS collects measurements from a set of meters present on the network using various information and communication technologies. However, despite using advanced communication technologies, this data can be lost, corrupted or delayed due to intentional or involuntary failures. Involuntary communication failures include the total unavailability of the measuring device, failure in some measurement channels (partial unavailability), incorrect operation of the meter, human error, inadequate communication architecture, natural disasters, among others. On the other hand, intentional failures can be caused by situations of physical or cyber attacks, and so on. (Gu and Jirutitijaroen, 2015).

In addition to planning, the monitoring and adequate operation of a SG are essential to ensure a good quality service to the consumers and agents that compose it. Thus, it is necessary to know, with relative precision, the status of the distribution network. On the other hand, once a set of meters is present, the state estimator accuracy (SEA) can be greatly compromised in the event of any contingency in this measurement plan, whether intentional or involuntary. The meter placement considering the unavailability of measurements has been investigated in recent years. For example, Mosbah and El-Hawary (2017) proposed a method to improve the accuracy of a dynamic state estimator (DSE) at the transmission level using a multilayer perceptron artificial neural network as the load forecasting tool. The validation of the proposed technique is performed in scenarios containing errors in measurements and scenarios with communication failures. However, the proposed algorithm does not seek to improve SEA with the reduction of measurement devices.

A methodology for assessing DSE accuracy in situations where there are communication failures and measurement losses is proposed by Gu and Jirutitijaroen (2015). The approach combines the extended Kalman filter with the Kriging lead time model to predict loss of measurement data and thereby improve the accuracy of the filtered state. The results showed that the DSE is more accurate than the conventional estimator in several failure scenarios. However, as measurement errors increase, the conventional estimator becomes competitive with the DSE, especially with respect to the accuracy of the angle of the nodal voltages.

Raposo et al. (2019) propose a methodology for measurements placement in distribution networks when up to two multifunctional meters are unavailable. The meter placement was carried out using a multi-objective formulation that maximizes SEA while reducing the cost of installing meters in the network. The results obtained showed that the proposed methodology obtained good quality solutions to the meter placement problem (MPP) considering their failures.

Raposo et al. (2021) provide a technique that combines an analytical method of assessing SEA with Monte Carlo Simulation (MCS) to estimate the risks of violating SEA subject to failures of smart meters and multiple Data Aggregation Points (DAPs). The technique proposed by the authors produces highly accurate results and with low computational cost when compared to conventional MCS.

From the bibliographic review, it is observed that the existing methodologies obtain a robust allocation in the sense of maintaining observability and failures in the communication structure of the SE, and these methodologies are more used in the scope of transmission systems. Because of this, an acceptable compromise must be established between the objectives of allocating and reducing the cost of implementing a robust SE to the unavailability of meters for distribution networks. Thus, the main objective of this paper is to propose a multi-objective technique to meter placement in order to: (i) increase SEA, (ii) reduce installation costs and (iii) include meter failures. These objectives were achieved using an evolutionary strategy based on the Binary Particle Swarm Optimization (BPSO) and fuzzy set theory.

2 Formulation of the Meter Placement Problem

The computational cost to assess SEA under meter failure scenarios can be significantly reduced by replacing the conventional MCS with an analytical technique embedded in the MCS (Raposo et al., 2017). This analytical method is obtained from the first order optimality conditions of the objective function of the state estimation problem, defined in (1) and the first order Taylor expansion $h(\hat{x})$ around the true state vector (x^t) (Monticelli, 1999).

$$J(x) = \frac{1}{2}[z - h(x)]^T W_z [z - h(x)] \quad (1)$$

where: z is the measurement vector; $h(x)$ is the vector of non-linear equations that relate the measurements and state variables and W_z is the inverse of the covariance matrix associated with the measurements.

Consequently, there is the following linear relationship between $\hat{x}$ and e_z (Raposo et al., 2017):

$$\hat{x} = x^t + A \cdot e_z \quad (2)$$

where: $A = [H(x^t)^T W_z H(x^t)]^{-1} H(x^t) W_z$ and $H(x^t)$ is the Jacobian matrix associated with the vector $h(x^t)$, that is, $H(x^t) = \nabla h(x^t)$.

The equation (2) shows that the probability distribution of $\hat{x}$ can be obtained through a linear transformation of the random variables associated with the errors in the measurements. This procedure can also be applied when there is a correlation in measurement errors. Finally, the SEA can be calculated based on the probability distributions of the SE state variables (Raposo et al., 2019; Raposo et al., 2020).

One of the main objectives of MPP in distribution networks is to increase SEA. One way of assessing this accuracy is through the risk of errors between the estimated and true values of the state variables violating specified limits (Raposo et al., 2021). The probability of meeting specified limits for the relative error between the true and estimated values of the state variables can be defined as:

$$P_k = \Pr\left\{\left|\frac{\hat{V}_k - V_k^t}{V_k^t}\right| \le \epsilon_V, \left|\frac{\hat{\theta}_k - \theta_k^t}{\theta_k^t}\right| \le \epsilon_\theta\right\} \quad (3)$$

where: P_k is the probability that the nodal voltage in the k-th node does not violate a pre-established threshold; $k \in \Omega_B^*$; Ω_B^* is the set of system nodes without the slack (reference node); $\Pr\{x \le c_1, y \le c_2\}$ indicates the probability that the random variables x and y are less than or equal to c_1 and c_2, respectively; V_k^t and θ_k^t are the true values of the magnitude and angle for the voltage in the k-th node, respectively; $\hat{V}_k$ and $\hat{\theta}_k$ are the estimated values of the magnitude and angle for the voltage in the k-th node, respectively, and; ϵ_V and ϵ_θ are the specified limits for the relative erros in the magnitude and angle of the nodal voltages, respectively.

In order to increase SEA, the objective function associated with maximizing the minimum probability of violating relative errors is defined according to:

$$\begin{aligned} &max \quad F_1(X) \coloneqq P^{min} = \min_{k \in \Omega_B^*} P_k(X) \\ &s.\ t.: \quad P^{min} \ge \bar{P} \end{aligned} \quad (4)$$

where: P^{min} is the smallest value of $P_k(X)$ $\forall k \in \Omega_B^*$ associated with the measurement plane represented by the vector of decision variables X and $\bar{P}$ is the lower limit of P^{min}. The dimension of X is equal to the number of nodes in the network (N^{node}) with its elements given by: X_k = 1 (X_k = 0) if there is (if not) a meter installed in node k.

The maximization of (4) ensures that meters are allocated until the risk of violating the relative error limits is below an established threshold. However, the number of meters required to achieve a specified level of accuracy can become high. Because of this, utilities consider the costs of installing the meters in SEA-oriented planning.

In general, measurements are obtained using a multifunctional meter that collects analog signals from a set of current and potential transformers. These signals are processed and later transmitted to the DMS (Raposo et al., 2017; Raposo et al., 2020). In this paper, it is considered that a meter installed in a node of the distribution network is capable of measuring the magnitude of voltage and the active and reactive power flows of the branches connected to this node.

From these considerations, the second objective of the MPP is to ensure that (4) is satisfied with the minimum number of multifunctional meters. Thus, the objective function associated with the costs of measuring equipment is given by:

$$min \quad F_2(X) \coloneqq M = \sum_{k=1}^{N^{node}} X_k \tag{5}$$

where: M is the objective function corresponding to the number of multifunctional meters allocated in the network, calculated for a given measurement plan represented by the vector of decision variables X.

The P^{min} index defined in (4) considers that all M meters of the measurement plan are available. However, if the unavailability of the meters is considered and that these events are independent, then P^{min} will be equal to the expected value obtained from the failure states of the meters. The MCS can be used to estimate P^{min} under scenarios of meter failure states. Thus, in order to increase SEA, the objective function associated with the maximization of the minimum probability of violating the relative errors is defined considering the unavailability of the meters according to (6).

$$\begin{aligned} &max \quad F_3(X) \coloneqq \mathbb{E}\left[P^{min} \middle| m \leq M\right] = \frac{1}{NS}\sum_{j=1}^{NS} F_1^j(X) \\ &s.\ t.: \quad \mathbb{E}\left[P^{min} \middle| m \leq M\right] \geq \bar{P} \end{aligned} \tag{6}$$

where: NS is the number of Monte Carlo simulations and j is a failure scenario for m meters of the measurement plane.

3 Fuzzy Multi-objective Strategy for Analysis of the SEA under Unavailability of Measurements

Several problems present a large number of objectives to be optimized, which, in the great majority, are in conflict with each other. These problems are known as Multi-objective Optimization Problems (MOPs). The fuzzy set theory is one of the methods that can be used to solve MOPs. In this paper, a fuzzy system is used to obtain a solution that satisfies the objective (5) and (6) functions. However, these objective functions have different dimensions and units. Therefore, a fuzzy system was developed to combine the goals of the MPP in a single objective function through the definition of fuzzy membership functions.

The membership function indicates the degree of satisfaction of each objective function that makes up the MOP. It consists of an interval containing minimum and maximum values, together with a continuous monotonic function for the different objectives (Esmaeili et al., 2016). The membership functions for each optimized goal in this paper are described below.

The membership function associated with the cost of the measurement plan is defined according to (7).

$$\mu^M(X) = \frac{e^{-\frac{F_2(X)}{N^{node}}} - e^{-1}}{1 - e^{-1}} \tag{7}$$

With this definition, while $F_2(X) \to 0$, has been $\mu^M(X) \to 1$ and, as $1 \leq F_2(X) \leq N^{node}$, while $F_2(X) \to N^{node}$, $\mu^M(X) \to 0$.

The proposal for the membership function associated with SEA considering that all M meters are available is given by:

$$\mu^P(X) = \frac{1 - e^{F_1(X)}}{1 - e} \tag{8}$$

From this definition, the measurement plan that meets the criteria of high SEA and low cost of installation of the meters at the same time, considering the availability of the M meters, is obtained in accordance with (9) .

$$\begin{aligned} &max \quad F_4(X) \coloneqq \mu^{SEA}(X) = \sqrt{\mu^M(X) \cdot \mu^P(X)} \\ &s.\ t.: \quad P^{min} \geq \bar{P} \end{aligned} \tag{9}$$

The measurement plan with maximum $\mu^{SEA}(X)$ will represent the best solution X for the MPP under meter failure conditions.

The proposal for the membership function associated with SEA under meter failure scenarios is given by:

$$\mu_F^P(X) = \frac{1 - e^{F_3(X)}}{1 - e} \tag{10}$$

From this definition, the measurement plan that meets the criteria of high SEA and low cost of installation of the meters at the same time, considering the unavailability of the meters, is obtained in accordance with (11).

$$\begin{aligned} & max \quad F_5(X) := \mu_F^{SEA}(X) = \sqrt{\mu^M(X) \cdot \mu_F^P(X)} \\ & s.\ t.: \quad \mathbb{E}\left[P^{min} \middle| m \leq M\right] \geq \bar{P} \end{aligned} \tag{11}$$

The measurement plan with maximum $\mu_F^{SEA}(X)$ will represent the best solution X for the MPP under meter failure conditions.

4 BPSO Metaheuristic Applied to Meter Failure Scenarios

The proposed technique for maximizing (9) and (11) is based on BPSO. BPSO is an evolutionary metaheuristic for optimization problems in a discrete search space, whose domain contains finite variables (Kennedy and Eberhart, 1997). As in the particle swarm optimization, the BPSO is inspired by the social behavior of biological populations. The behavior of the swarm is influenced by the information contained in each individual (particle) belonging to it. The movement of individuals is determined by a vector called a velocity vector. Each particle updates its speed based on its current speed, the best position that has been explored and the best position explored by the swarm. The update of the speed of a particle is given by:

$$\begin{aligned} v_{*j}(t+1) \quad = \quad & c \cdot v_{*j}(t) + \\ & c_1 \cdot r_{*j}^{u1}(t) \cdot \left[\xi_{*j}^{best} - \xi_{*j}(t)\right] + \\ & c_2 \cdot r_{*j}^{u2}(t) \cdot \left[\bar{\xi}^{best} - \xi_{*j}(t)\right] \\ & \text{for } j = 1, \ldots, N^{part} \end{aligned} \tag{12}$$

where: $\xi_{*j}(t) = \left[\xi_{1j}(t) \quad \cdots \quad \xi_{N^{dim}j}(t)\right]^T$ and $v_{*j}(t) = \left[v_{1j}(t) \quad \cdots \quad v_{N^{dim}j}(t)\right]^T$ are the position and the speed vectors, respectively, of the particle j for the iteration t; $\xi_{ij}(t)$ and $v_{ij}(t)$ are, respectively, the position and the speed of the particle j in the dimension i for the iteration t; $N^{dim} = N^{node}$ is the number of the dimensions of the search space; ω is the inertia coefficient; c_1 and c_2 are positive constants for the acceleration used to weight the contributions of the cognitive and social factors, respectively; $r_{*j}^{u1}(t)$ and $r_{*j}^{u2}(t)$ are random numbers vectors with uniform distribution in the interval [0,1]; $\bar{\xi}^{best}$ is the best position found by the swarm; ξ_{*j}^{best} a is the best position found by particle j; N^{part} is the number of particles in the swarm.

In the BPSO, each particle has its position represented by binary values: zero or one. The basic algorithm is to look for the optimal solution within a multidimensional space in which each particle occupies a specific position with a speed that indicates its movement. The multidimensional space of the MPP is equivalent to the number of nodes in the distribution network, that is, N^{node}.

The update of the position of each particle j, in the dimension i, is obtained according to (13).

$$\xi_{ij}(t+1) = \begin{cases} 1, & \text{if } r_{ij}^{u3}(t) < \dfrac{1}{1 + e^{-v_{ij}(t)}} \\ 0, & \text{otherwise.} \end{cases} \tag{13}$$

where: $r_{ij}^{u3}(t)$ is the random number with uniform distribution in the interval [0,1].

The BPSO pseudocode used to solve (9) and (11) is illustrated in the Fig. 1.

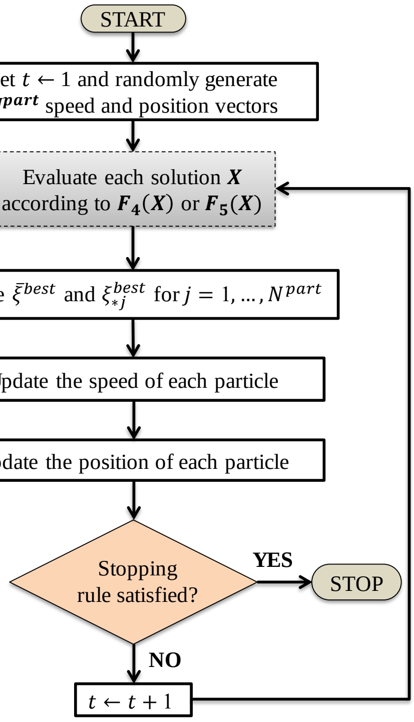

Fig. 1 BPSO flowchart applied to MPPs (9) and (11).

5 Results

5.1 Test System Characteristics and Case Studies Definitions

The proposed algorithm was tested in the 69 nodes distribution network (S69) (Savier and Das, 2007). The S69 has 73 branches, nominal voltage of 12.66 kV, has 3,8019 MW and 2,66941 MVAr of active and reactive installed power, respectively.

The simulations on the S69 were performed considering that: *NS* = 1000; the substation node, node #1, is the slack node; the specified relative erros in the magnitude and angle of the nodal voltages are, respectively, $\epsilon_V \leq 1\%$ and $\epsilon_\theta \leq 5\%$; $\bar{P} = 0.95$; a maximum error of 1% associated with real measurements and 50% associated with pseudo-measurements was considered and it was assumed that the correlation coefficient between measurements of active and reactive power is equal to 0.95. The BPSO used to evaluate (9) and (11) has the following parameters: $N^{part} = 40$; $\omega = 0.7$; $c_1 = c_2 = 2$, and; maximum number of generations equal to 1000.

The analysis of the proposed MPP algorithm considered four case studies:

Case #0 (base case): the measurement plan consists of a meter installed in the substation and pseudo-measurements.
Case #1: the BPSO algorithm is applied to case # 0 to maximize $F_4(X)$. This case is equivalent to conventional allocation in which all allocated meters are available.
Case #2: test of robustness to failures of the measurement plan obtained in case # 1 considering unavailability U of 5%, 10%, 15% and 20%.
Case #3: the BPSO algorithm is applied to case # 0 to maximize $F_5(X)$, that is, this case simultaneously reduces the number of meters while improving SEA under meter failure scenarios for U of 5%, 10%, 15% and 20%.

5.2 Case Studies Results

The S69 nodes illustrated in the heat maps are divided into three types: substation – defined by a blue rectangle; load nodes – defined by a magenta circle and null injection nodes – defined by a beige circle. For case # 0, only 8 nodes of the S69 present P_k above $\bar{P}$ = 0.95, illustrated in green in the heat map of the Fig. 2. This amount corresponds to only 11.60% of the total nodes in the system. With only one meter and pseudo-measurements, has been P^{min} = 0.0874. From Fig. 2, it can be noted that a large part of the system showed violations in P_k between 0.20 and 0.70. With major violations recorded between nodes #32 and #35.

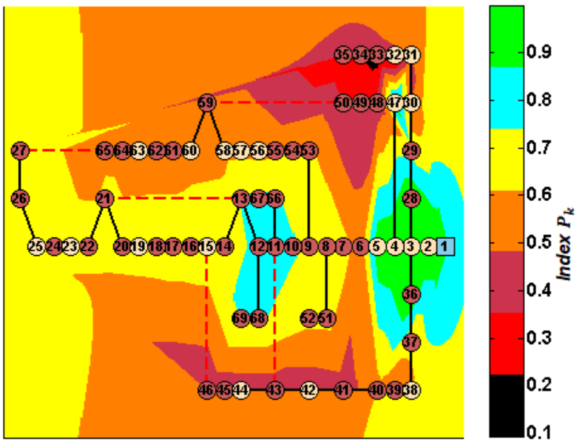

Fig. 2 Nodal probability for the case #0.

The application of the BPSO-Fuzzy algorithm to solve (9) obtained a measurement plan capable of meeting the SEA with significance level $\bar{P}$ using 6 meters installed on nodes #1, #4, #16, #28, #33, and #45, resulting in P^{min} = 0.9932. This result corresponds to case #1 and represents an improvement of around 91.2044% of the P^{min} value obtained from case #0. It can be seen, from Fig. 3, that few S69 nodes have P_k < 0.999 in contrast to case #0.

The results of case #2 for the values of the P^{min} index, defined in (6), associated with U = 5%, 10%, 15%, and 20% are 0.9067, 0.8456, 0.7643, and 0.7398, respectively. From these results it is possible to verify that the SEA is deteriorated due to meter failures. The Fig. 4 illustrates the nodal behavior of $\mathbb{E}[P^{min}|m \leq 6]$ considering several failure scenarios of the 6 meters present in the measurement plan generated in case #1 for U = 15% and 20%. In the upper part of Fig. 4 it is possible to verify that node #32 is the most compromised for U = 15%, resulting in $F_3(X)$ = 0.7643. In its lower part, it is possible to notice that node #32 is again the most compromised for U = 20%, resulting in $F_3(X)$ = 0.7398. The results of case #2 indicate that it is necessary to analyze the MPP considering contingencies in the measurement plan.

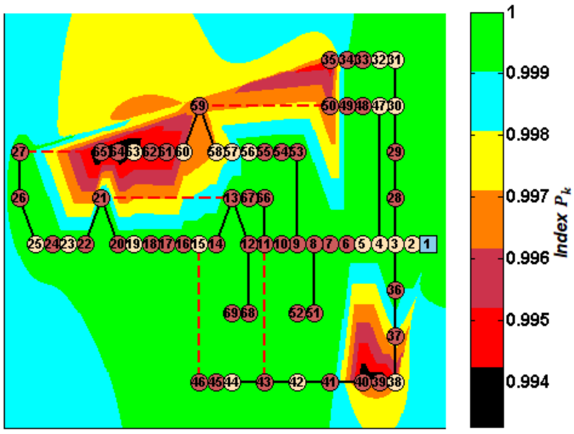

Fig. 3 Nodal probability for the case #1.

In order to mitigate the problems found in case #2, the BPSO-Fuzzy algorithm was applied to case #0 for different failure probabilities of the multifunctional meters. For case #3, considering U = 5%, the BPSO-Fuzzy algorithm added 9 meters to the measurement plan for case #0 at nodes #4, #7, #11, #12, #24, #29, #34, #42, and #65. With four additional meters in relation to case #1, there was an improvement of the order of 5.0627% in the index $\mathbb{E}[P^{min}|m \leq M]$ when compared to case #2. For U = 10%, the BPSO-Fuzzy algorithm obtained a measurement plan capable of meeting SEA with a significance level $\bar{P}$, using 17 meters installed at nodes #1, #3, #10, #21, #22, #25 , #28, #29, #33, #34, #44, #45, #49, #52, #56, #67, and #69. This result almost triples the cost of installing meters in relation to case #1, but there is an improvement of the order of 14.6133% in the $\mathbb{E}[P^{min}|m \leq M]$ index in relation to case # 2. For U = 15%, BPSO-Fuzzy added 5 meters to the measurement plan for case # 3 considering U = 10%. The nodes with installed meters are #1, #3, #17, #19, #20, #21, #22, #28, #29, #30, #33, #37, #40, #44, #45, #49, #48, #52, #60, #64, #65, and #69. Compared to case #2, there was an improvement in the $\mathbb{E}[P^{min}|m \leq M]$ index by around 24.0258%, but with an increase of over 266.67% in the cost of measuring equipment. Considering U = 20%, BPSO-Fuzzy added 20 meters to the measurement plan of case #0 at nodes #7, #8, #13, #18, #21, #28, #29, #30, #33, #34, #36, #44, #49, #50, #54, #56, #60, #64, #67, and #69, managing to improve the $\mathbb{E}[P^{min}|m \leq M]$ index by 28.1769% in relation to case # 2.

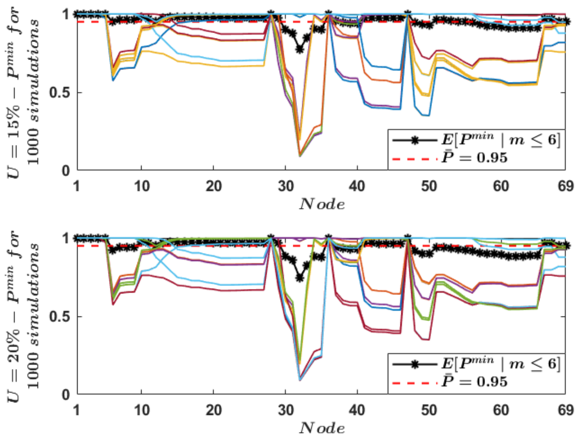

Fig. 4 Nodal probability for the case #2 with U = 15% and 20%.

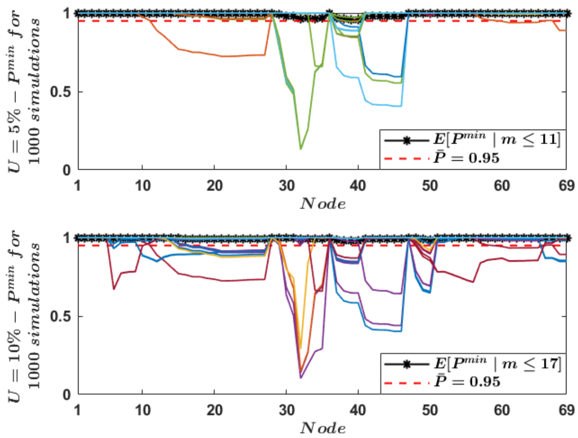

Fig. 5 Nodal probability for the case #3 with U = 5% and 10%.

The Fig. 5 illustrates the nodal behavior of $\mathbb{E}[P^{min}|m \leq M]$ considering several failure scenarios of the 11 and 17 meters in the measurement plans generated in case #3 for U = 5% and 10%, respectively. From Fig. 5, it can be seen that of the 1000 simulations carried out, few contribute to the deterioration of the SEA. Thus, it is possible to note that for both U = 5% and 10%, the expected value of the nodal precision index of the estimator is above the established threshold of 0.95.

6 Conclusions

This paper proposed a methodology to improve SEA in distribution networks. The proposed methodology considers that the meter placement is carried out simultaneously with the unavailability of multifunctional meters. The MPP was solved using a fuzzy multi-objective optimization strategy combined with BPSO. The tests on the S69 demonstrated that the allocation strategy considering the unavailability of the multifunctional meters proved to be efficient in relation to the improvement of SEA.

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