A Meter Placement Strategy for Distribution Grids Based on Cost–Benefit Analysis

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***Abstract*— Distribution system operators are progressively expanding the measurement infrastructure in their grids to enhance the real-time monitoring capabilities. Meter placement algorithms allow identifying the best type and location for new measurements, thus being a key tool in support of meter installation decisions and planning. Existing meter placement solutions aim at reducing the monitoring uncertainties below an arbitrary accuracy threshold, but typically they are not explicitly linked to some tangible benefits achievable by the grid operator via the measurement infrastructure upgrade. This article aims at filling this gap by presenting an overall meter placement strategy that takes into account how the monitoring uncertainties translate into costs for avoiding contingencies and then drives the meter placement process according to the economic benefit resulting from the reduction of those uncertainties. An exemplary implementation is presented to describe the underlying concepts and the role and functionalities of the different software components involved in the meter placement cost–benefit analysis. Simulations performed on a sample grid show the application of the proposed meter placement strategy in a realistic scenario and highlight how this may be used to determine not only type and location of the new meters but also the number of measurements that makes sense to install according to cost–benefit criteria.**

***Index Terms*— Cost–benefit analysis, distribution grids, global sensitivity analysis (GSA), meter placement, state estimation, uncertainty, voltage control.**

I. Introduction

DISTRIBUTION grids are rapidly evolving into highly complex systems due to, among other reasons, the growing penetration of small-scale generation based on renewable sources, the ongoing electrification of the heating and mobility sector, and the interconnection of power electronics-based components to the grid. As a result of this transition, the operation of distribution systems is facing new challenges and is pushed closer to its boundaries, which calls for the adoption of advanced management and control to guarantee system reliability and security. In turn, the effective deployment of smart control applications strictly depends on the availability of an accurate monitoring of the system and on the associated capability to closely track the real-time operating conditions of the grid. As a consequence, having an accurate monitoring of the distribution grid is one of the key factors to enable the transition toward the so-called smart grid.

State estimation techniques focus on the processing of measurement data considering their uncertainty characteristics and are the basis behind the tools adopted for the monitoring of electrical grids [1]. In the past years, several approaches have been proposed to deal with the problem of distribution system state estimation (DSSE). These approaches offer possible solutions to different challenges associated with the monitoring of distribution grids, such as, multiphase modeling of unbalanced grids [2], [3], [4], efficient implementation for large networks [5], [6], [7], integration of heterogeneous and asynchronous measurements [8], [9], and modeling of non-Gaussian uncertainties [10], [11], [12]. Among them, the most important issue for the practical implementation of DSSE is, however, the scarcity of measurement devices available in the field. Several solutions have been identified to deal with the minimal amount of real-time measurements, such as augmentation of the measurement set through pseudo-measurements derived from statistical information of power generation and consumption [13], [14], or use of artificial neural networks to run the DSSE in unobservable scenarios [15]. Nonetheless, it is commonly recognized that strengthening the measurement infrastructure through the progressive deployment of additional meters is an impelling requirement for distribution system operators (DSOs).

To this purpose, meter placement solutions are proposed in the literature, which help identifying the best measurement installation plan in terms of type and location of the meters. While in transmission systems different objectives may exist, at distribution level the main target is usually to enhance the accuracy of the DSSE results. In [16], it was proposed to incrementally place voltage measurements in the nodes with the worst accuracy of the voltage magnitude estimation. This method was extended in [17] to improve also the accuracy of voltage angle estimations through the installation of power measurements. In [18], the placement of load power measurements was proposed to achieve a target uncertainty in

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the power flow estimation. In [19], recommendations were provided on critical points of the network where the placement of measurements should be prioritized. More sophisticated options exploring the solution space via heuristic methods are presented in [20], where a genetic algorithm is used, and in [21] and [22], which adopt dynamic programming. Rigorous optimization models can also be formulated when using the weighted least squares (WLS) method as core algorithm for the DSSE, as shown in [23], which presents a mixed-integer linear programming solution, and in [24] and [25], which propose semi-definite programming formulations derived from the use of the Fisher information matrix. More recently, [26] proposed an alternative meter placement approach based on global sensitivity analysis (GSA), which allows avoiding the use of complex optimization routines and flexibly integrating the effects of various uncertainty sources.

The above methods offer valid solutions to the meter placement problem, but they all aim at bringing the uncertainty of the DSSE results below a threshold that is arbitrarily chosen. A still-open question is therefore which target makes sense to pursue from a technical or economical perspective for the DSOs. This article makes a step forward in this direction, defining an overall meter placement strategy where a cost–benefit analysis (CBA) subtends the meter placement process and drives the decision on whether additional meters are needed or not. The cost–benefit evaluation relies on the quantification of how the monitoring uncertainties can translate into actual costs for the DSOs. To this purpose, the proposed CBA-based meter placement strategy involves an uncertainty-inclusive voltage control application, which uses the output uncertainties of the DSSE to define voltage safety margins. In this scenario, the monitoring uncertainties directly affect the amount of power flexibility needed to keep the voltage within the accepted boundaries, hence translating into measurable costs. Through this approach, the cost savings achievable by reinforcing the measurement infrastructure can then be compared with the costs associated with the measurement installations and it is possible to infer how many meters are beneficial to install from an economic perspective.

Overall, this article brings the following novel contributions.

1) It extends the GSA-based incremental placement procedure presented in [26] by showing how to integrate multiple operating conditions of the grid.
2) It analyses how measurement uncertainties propagate over the monitoring and control chain and how they eventually affect the operation of the voltage control application.
3) It shows how the monitoring uncertainties would translate into economic costs associated with the redispatch power required to keep the voltage within the allowed limits.
4) It presents a comprehensive CBA-based meter placement strategy, where the meter placement decisions are ultimately taken on the basis of a cost–benefit evaluation, thus considering the concrete benefits arising for the DSOs.
5) Leveraging on the previous points, it proposes an innovative approach to identify the measurement requirements and define the measurement infrastructure needed for future smart grids.

The remainder of this article is organized as follows. Section II provides the overview of the software modules needed to implement the conceived CBA-based meter placement strategy. Section III presents cost considerations and the overall CBA framework used for the meter placement and the analysis of how monitoring uncertainties eventually translate into costs. Section IV shows the simulations performed to demonstrate the proposed idea and discusses the obtained results. Finally, Section V provides the final remarks and concludes the article.

II. Software Components for the CBA

The proposed CBA-based meter placement strategy builds upon the use of three main components to perform the CBA, namely, a DSSE, a meter placement routine, and a voltage control algorithm. The algorithms used in the article for these three modules are shortly described hereafter. However, it should be noted that the CBA-based meter placement strategy presented in Section III is not bounded to the use of these specific algorithms. Indeed, the presented algorithms may be replaced with other ones, provided that their inputs and outputs fulfill the following basic requirements.

1) State estimation: the adopted algorithm must be able to integrate any type of measurement in input and provide not only the estimated voltages but also information on the associated uncertainty as output.
2) Meter placement: the incremental placement procedure should aim at reducing the DSSE uncertainty and provide the indication of both type and location of the next best meter to be installed as output.
3) Voltage control: the used algorithm must consider the uncertainties of the voltage estimates given by the DSSE and provide the set points of active and reactive power adjustment requested to the flexibility sources as output.

A. WLS DSSE

The first module of the CBA-based meter placement strategy is the DSSE, i.e., the mathematical process used to estimate the operating conditions of the distribution grid from the measurements gathered from the field. While different approaches exist to perform DSSE, the WLS method is still the most common one, due to its accuracy performance as well as its simplicity and explainability. Consider the measurement model

$$\mathbf{z} = \mathbf{h}(\mathbf{x}) + \mathbf{e} \tag{1}$$

where $\mathbf{z}$ is the vector of input measurements (which may include voltage, power, and current measurements, coming from conventional meters or last generation phasor measurement units), $\mathbf{x}$ is the vector of the state variables used to represent the electric grid operating conditions, $\mathbf{h}(\mathbf{x})$ is the vector of measurement functions expressing the measurements in terms of the state variables, and $\mathbf{e}$ is the vector of measurement errors. The goal of the WLS method is to minimize the following objective function:

$$\min\left\{[\mathbf{z} - \mathbf{h}(\mathbf{x})]^{\mathrm{T}}\mathbf{W}[\mathbf{z} - \mathbf{h}(\mathbf{x})]\right\} \tag{2}$$

where $^{\mathrm{T}}$ indicates the transpose operator and $\mathbf{W}$ is a weighting matrix equal to the inverse of the measurement error covariance matrix.

Due to the nonlinearity of the measurement functions $\mathbf{h}(\mathbf{x})$, the solution of (2) is typically found through the iterative Gauss–Newton approach, where the estimated state vector is updated by means of the following equation system:

$$\mathbf{G} \cdot \Delta\mathbf{x} = \mathbf{H}^{\mathrm{T}}\mathbf{W}[\mathbf{z} - \mathbf{h}(\mathbf{x})] \tag{3}$$

where $\mathbf{G} = \mathbf{H}^{\mathrm{T}}\mathbf{W}\mathbf{H}$ is a gain matrix, $\mathbf{H}$ is the Jacobian of the measurement functions $\mathbf{h}(\mathbf{x})$, and $\Delta\mathbf{x} = \mathbf{x}_k - \mathbf{x}_{k-1}$ is the updating vector of the state variables at iteration k. The iterative procedure continues until the largest term (in absolute value) of $\Delta\mathbf{x}$ is lower than a chosen threshold.

From a meter placement perspective, it is important to highlight that the estimated values will be still affected by uncertainties, due to the propagation of the uncertainties from the measurements to the DSSE results. In the WLS, the covariance matrix of the estimated state variables can be found through the inverse of the gain matrix $\mathbf{G}$.

In the proposed CBA-based meter placement strategy, DSSE solutions different from the WLS could also be implemented. The only requirement existing for the DSSE algorithm is to be capable of providing the estimated voltages together with a reliable indication of their associated uncertainty as output.

B. Meter Placement via GSA

The second module of the CBA-based meter placement strategy is a placement procedure, whose goal is to indicate the next best meter that can be added to the existing measurement configuration. In this article, a GSA-based procedure derived from the incremental meter placement algorithm presented in [26] is used. This algorithm builds upon the variance-based sensitivity analysis (VBSA) theory [27] to identify the best location and type of meter (e.g., voltage, power, or current) to be considered for upgrading the measurement infrastructure.

Consider a generic model $\mathbf{y} = \mathbf{f}(\mathbf{u})$, where $\mathbf{y}$ is the vector of the N model outputs $\{y_n\}_{n\in\{1,\ldots,N\}}$ and $\mathbf{u}$ is the vector of the d model inputs $\{u_i\}_{i\in\{1,\ldots,d\}}$. In a meter placement perspective, the DSSE module can be seen as the model $\mathbf{f}(\cdot)$: the voltage estimates represent the outputs $\mathbf{y}$, whereas measurements, pseudo-measurements, and other possible uncertainty sources (e.g., network parameters) constitute the inputs $\mathbf{u}$. The VBSA apportions the variability of each output to its uncertain inputs, based on the normalized equation of the decomposition of the variance $\mathrm{Var}(y_n)$ of the output y_n [27]

$$1 = \sum_i S_i^{(n)} + \sum_i \sum_{i<j} S_{ij}^{(n)} + \cdots + S_{1\ldots d}^{(n)} \tag{4}$$

where $S_i^{(n)}$ is the first-order Sobol' sensitivity index (SI), which quantifies the individual effect of the input u_i on $\mathrm{Var}(y_n)$, $S_{ij}^{(n)}$ is the second-order Sobol' SI, which quantifies the interactive effect of the inputs u_i and u_j on $\mathrm{Var}(y_n)$, and so on up to the dth-order Sobol' index $S_{1\ldots d}^{(n)}$. The first- and second-order Sobol' SIs are formally defined as follows:

$$S_i^{(n)} = \frac{\mathrm{Var}_{u_i}\left(\mathbb{E}_{\mathbf{u}_{\sim i}}\left[y_n | u_i\right]\right)}{\mathrm{Var}(y_n)} \tag{5}$$

$$S_{ij}^{(n)} = \frac{\mathrm{Var}_{u_i,u_j}\left(\mathbb{E}_{\mathbf{u}_{\sim ij}}\left[y_n | u_i, u_j\right]\right)}{\mathrm{Var}(y_n)} - S_i^{(n)} - S_j^{(n)} \tag{6}$$

where $\mathbb{E}$ indicates the expected value, the subscripts of $\mathbb{E}$ and Var define the inputs over which the operators are taken, and $\mathbf{u}_{\sim i}$ and $\mathbf{u}_{\sim ij}$ indicate the removal of the input u_i and the inputs' pair $\{u_i, u_j\}$ from $\mathbf{u}$, respectively. Similar definitions hold for higher-order Sobol' SIs [27].

In addition to Sobol' SIs, it is possible to define the total effect SI of the input u_i as follows:

$$T_i^{(n)} = S_i^{(n)} + \sum_{j=1, j\neq i}^{d} S_{ij}^{(n)} +, \ldots, + S_{1,\ldots,d}^{(n)} = \frac{\mathbb{E}_{\mathbf{u}_{\sim i}}\left(\mathrm{Var}_{u_i}(y_n | \mathbf{u}_{\sim i})\right)}{\mathrm{Var}(y_n)} \tag{7}$$

which quantifies the amount of $\mathrm{Var}(y_n)$ due to all the contributions of u_i, including its interactive effects with other inputs of $\mathbf{u}_{\sim i}$. For example, if $d = 3$, $T_2^{(n)} = S_2^{(n)} + S_{12}^{(n)} + S_{23}^{(n)} + S_{123}^{(n)}$. Using the VBSA for the meter placement, the total effect SIs quantify the overall effect that each of the uncertainty sources has on the final uncertainties of the state estimates, to ultimately identify those having the highest impact on the progressive reduction of the state estimates' variability.

A stepwise description of the adopted GSA-based incremental placement procedure is given in Algorithm 1. After computing the reference operating conditions for the considered scenario(s), a crucial step is the definition of the input vector $\mathbf{u}$ (step 2). Here, it should be noted that the input vector has to include not only the measurements already existing in the grid but also those that could be potentially installed, which are subject to the meter placement selection and integrated as pseudo-measurements. As presented in [26], this is needed to ensure that their potential impact on the DSSE results' accuracy may be evaluated through the VBSA. Moreover, all the inputs have to be described with their associated probability density function (pdf). For the already existing measurements, their pdf should reflect the uncertainty characteristics of the measurement device and the used sensors. For the pseudo-measurements used to represent the installable meters, a higher uncertainty should be instead considered and chosen as a tradeoff between the need to avoid affecting the DSSE results and the necessity to have the effects of the installable meter visible from the VBSA. The defined pdfs are considered in step 3 for the random extraction of measurement samples, which are used as input in step 4 to run the DSSE $N_{\mathbf{u}}$ times. The voltage magnitude estimation results obtained from the DSSE runs are then used in step 5 for the computation of the total effect SIs. As discussed in [26], $T_i^{(n)}$ indexes of each element in $\mathbf{u}$ provide node-level sensitivity information in a meter placement perspective, namely, each $T_i^{(n)}$ indicates the impact of the ith measurement on the voltage magnitude estimation of the nth node. To derive a grid-level criterion for the meter placement, $T_i^{(n)}$ indexes for the estimated voltage magnitude of the nth node are hence aggregated over all the grid nodes to yield specific ranking scores $\mathbf{m}$ for each element in $\mathbf{u}$ according to a given ranking metric. In [26], it was shown that different user-defined metrics can be potentially conceived, which may also depend on the specific target pursued via the meter placement (e.g., reduction of the peak uncertainties, or of the average one).

Algorithm 1 GSA-Based Incremental Placement Procedure

1: Run a load flow for the considered scenario(s) to obtain the reference operating conditions of the grid.
2: Define the input $\mathbf{u}$, which includes both the already existing measurements and those that may be potentially added, and assign the associated uncertainties.
3: Extract $N_{\mathbf{u}}$ different samples of the inputs in $\mathbf{u}$ from the space spanned by their pdfs.
4: Run the DSSE for the $N_{\mathbf{u}}$ extracted samples of $\mathbf{u}$ to obtain the corresponding voltage estimates $\hat{V}$ at all the nodes.
5: Perform the VBSA and compute the T_is of all the elements in $\mathbf{u}$ for each of the voltage estimates in $\hat{V}$.
6: Compute the ranking scores $\mathbf{m}$ for each element of the input vector $\mathbf{u}$ according to the chosen ranking metric.
7: Sort the elements of $\mathbf{u}$ in descendent order according to the obtained values of the ranking scores.
8: Select the first element of $\mathbf{u}$ that does not belong to the set of already existing measurements as the best next meter to install in the grid.

In this article, the metric considered to score the effect of the ith installable meter on the DSSE accuracy is defined as follows:

$$m_i = \sum_{n=1}^{N_{\text{bus}}} T_i^{(n)} \cdot \Sigma^2_{\hat{V}_n} \tag{8}$$

where N_{bus} is the number of nodes in the grid and $\Sigma_{\hat{V}_n}$ is the expanded uncertainty (with coverage factor equal to 3) of the voltage magnitude estimation at node n. The goal of such a ranking metric is to prioritize the installation of meters having a larger impact (quantified by $T_i^{(n)}$) on improving the voltage estimation $\hat{V}_n$ at the nodes with higher uncertainties. Unlike [26], where only one single operating condition is considered for (8), this metric can be further extended to encompass different operating conditions potentially occurring in the grid. In this case, indicating with τ the total number of operating conditions relevant for the meter placement, the metric in (8) can be expanded as follows:

$$m_i = \sum_{t}^{\tau} \beta_t \cdot \left[\sum_{n=1}^{N_{\text{bus}}} T_{i,t}^{(n)} \cdot \Sigma^2_{\hat{V}_{n,t}} \right] \tag{9}$$

where the terms $T_{i,t}^{(n)}$ and $\Sigma^2_{\hat{V}_{n,t}}$ have been adapted to include their dependency from the particular operating condition t and β_ts are coefficients introduced to give the flexibility to weigh the τ operating conditions differently (e.g., according to their frequency of occurrence). In the proposed incremental placement procedure, eventually, the installable meter with the highest score for the defined ranking metric will be the one selected as the next best measurement installation.

In the proposed CBA-based meter placement strategy, alternative meter placement procedures may be adopted instead of the one just presented. No stringent requirements exist neither for the type of measurements to include (both those already existing and those potentially integrated in the grid) nor for the targets or metrics used for the placement. The only requirement is related to the desired output, which must be the indication of the type and location of the next best measurement to be installed in the grid.

C. Uncertainty-Inclusive Voltage Control

The third module of the CBA-based meter placement strategy is a voltage control algorithm.

In particular, the goal of the control algorithm presented here is to tune the active and reactive power of the controllable sources available in the grid to keep the voltage magnitude profile within the accepted limits. This is done via an optimization model, whose formulation is derived from the control algorithm of [28].

The optimization model builds upon the following relationship, which approximates the effects of active and reactive power changes on the voltage profile of the grid

$$\mathbf{V}_c = \mathbf{V}_u + \mathbf{R}\Delta\mathbf{P} + \mathbf{X}\Delta\mathbf{Q} \tag{10}$$

where $\mathbf{V}_u$ and $\mathbf{V}_c$ are the vectors of voltage magnitudes before and after the application of the control actions, respectively, $\Delta\mathbf{P}$ and $\Delta\mathbf{Q}$ are the vectors of active and reactive power injection changes requested by the control algorithm, respectively, and $\mathbf{R}$ and $\mathbf{X}$ are the real and imaginary parts of the impedance matrix $\mathbf{Z}$ of the grid. Henceforth, powers are considered as positive when injected in the grid (generation) and as negative when absorbed (loads). It is worth noting that (10) may look incorrect from a dimensional point of view. The reason for this is that such relationship is derived under the assumption that in first approximation, voltage magnitudes can be considered equal to 1 pu. With such an assumption, the quadratic relationship between voltages and powers can be linearized, thus leading to (10). More details on the derivation of the so-called linearized branch-flow model behind (10) can be found in [29].

The goal of the optimization model is to minimize the following objective function:

$$\min\left\{ \sum_{i\in\Gamma} w_{P,i}\left[\Delta\mathbf{P}_i^{\mathrm{T}} \cdot \mathbf{R} \cdot \Delta\mathbf{P}_i\right] + w_{Q,i}\left[\Delta\mathbf{Q}_i^{\mathrm{T}} \cdot \mathbf{X} \cdot \Delta\mathbf{Q}_i\right] \right\}. \tag{11}$$

In (11), the aim is to minimize the flexibility contributions (namely, the power changes) requested to the controllable sources. To this purpose, the impedance terms $\mathbf{R}$ and $\mathbf{X}$ are used to consider the effects that different nodes may have on the overall change in the voltage profile. Moreover, in the adopted formulation, the sources of power flexibility are differentiated depending on their nature (e.g., storage systems, loads, PV plants) and included in different clusters within the set Γ. Each cluster i can be weighted differently with the weights $w_{P,i}$ and $w_{Q,i}$ (for the active and reactive power, respectively) to foster (or disadvantage) the use of specific flexibility sources. As an example, through these weights, it would be possible to assign higher priority to the charging of storage systems rather than to the curtailment of the active power from renewable energy sources.

The optimization model also needs to integrate different sets of constraints. The first set of constraints is related to the final goal of the control algorithm, namely, keeping the voltage within the allowed upper and lower boundaries. This constraint is formally expressed through the following relationships:

$$\Delta \mathbf{V}(t) \leq \mathbf{1}V_{\max} - \Sigma_{\hat{V}(t)} - \hat{\mathbf{V}}(t) + \Delta \mathbf{V}(t-1) \tag{12}$$

$$\Delta \mathbf{V}(t) \geq \mathbf{1}V_{\min} + \Sigma_{\hat{V}(t)} - \hat{\mathbf{V}}(t) + \Delta \mathbf{V}(t-1). \tag{13}$$

In (12) and (13), $V_{\max}$ and $V_{\min}$ are the limits for the maximum and minimum voltages allowed in the grid (given as scalar values), respectively, $\mathbf{1}$ is a column vector of ones, $\hat{\mathbf{V}}$ is the vector of voltage magnitude estimations, $\Sigma_{\hat{V}}$ is the vector of the associated estimation uncertainties, and $\Delta\mathbf{V}$ is the vector of voltage magnitude deviations determined by the activation of the power flexibilities according to

$$\Delta \mathbf{V} = \sum_{i \in \Gamma} [\mathbf{R}\Delta\mathbf{P}_i + \mathbf{X}\Delta\mathbf{Q}_i]. \tag{14}$$

Having a closer look at the voltage constraints in (12) and (13), it is possible to note that the proposed formulation provides an uncertainty-inclusive voltage control, in that the voltage limits are always adjusted considering the uncertainty of the voltage estimates. This ensures that the uncertainties are duly taken into account and that the voltage limits are always respected regardless of the possible errors present in the voltage estimates [30]. Moreover, a term related to the voltage deviation applied at the previous time step $t-1$ is also included in the constraint. This allows keeping memory of the previous actions and making sure that the control action is maintained until needed, without being relaxed due to the improved conditions seen by the state estimator.

The additional set of constraints needed for the optimization model concerns the physical limits or the power flexibility offered by each controllable source. These are expressed via the following relationships:

$$-P_{k,i}^{\text{abs}}(t) \leq \Delta P_{k,i} \leq P_{k,i}^{\text{inj}}(t) \quad \forall k = 1, \ldots, N; \forall i \in \Gamma \tag{15}$$

$$-Q_{k,i}^{\text{abs}}(t) \leq \Delta Q_{k,i} \leq Q_{k,i}^{\text{inj}}(t) \quad \forall k = 1, \ldots, N; \forall i \in \Gamma. \tag{16}$$

Overall, the formulation of the voltage control used in this article can be hence summarized as follows:

$$\begin{aligned} &\underset{\Delta\mathbf{P},\Delta\mathbf{Q}}{\text{minimize}} \quad (11) \\ &\text{subject to} \quad (12), (13), (15), (16). \end{aligned} \tag{17}$$

Different voltage control formulations could be potentially applied in the CBA-based meter placement strategy presented in Section III. The requirements for the control application are to integrate the voltage estimates together with the associated uncertainties, as given by the DSSE module, and to provide the set points of required active and reactive power adjustment for the flexibility sources in the grid as output.

III. CBA-Based Meter Placement Procedure

The CBA-based meter placement procedure builds upon the analysis of: 1) the redispatch costs required to keep the voltage within the allowed boundaries and 2) the costs associated with the deployment of the (new) meters. The aim is to minimize the overall costs, which has to be achieved considering that:

1) the redispatch costs decrease for an increasing number of meters, as an effect of the reduced monitoring uncertainties (see Section III-A);
2) the costs for the monitoring infrastructure clearly increase with the placement of additional meters, due to the involved installation and operational costs.

Hereafter, Section III-A will discuss the redispatch costs and how these are affected by the monitoring uncertainties, Section III-B will focus on the costs for the measurement infrastructure, and Section III-C will present the logic to minimize the overall costs and decide the meter placement.

A. Cost of Monitoring Uncertainties

A first category of costs for the CBA is given by the costs C_{RD} associated with the redispatch actions, namely, those costs to be paid for the active and reactive power changes requested by the grid operator to the flexibility sources for keeping the voltage within the allowed boundaries. It should be noted that in general, other options may also be available to the DSO for controlling the voltage (e.g., switching capacitor banks, regulating the tap changers of substation transformers). When these options exist and have priority over the use of power flexibility, they should be taken into account. Redispatch measures would then be adopted only to solve the potentially still remaining voltage issues. The costs associated with the use of resources owned by the DSO (like tap change transformers) are disregarded in the cost analysis, as they are assumed to have no or little impact from a cost perspective. Hereafter, the redispatch costs are assumed to be proportional to the amount of power variation asked to the flexible resources. The total costs computed over the time horizon considered for the CBA can then be expressed as follows:

$$C_{\text{RD}} = \sum_{t=1}^{T_{\text{steps}}} \sum_{n=1}^{N_{\text{bus}}} C_{P_t} \Delta P_{n,t} \Delta t + C_{Q_t} \Delta Q_{n,t} \Delta t \tag{18}$$

where C_{P_t} and C_{Q_t} are the unitary costs at time t associated with the active and reactive power changes, respectively (e.g., expressed in €/MWh and €/Mvarh), $\Delta P_{n,t}$ and $\Delta Q_{n,t}$ are active and reactive power changes requested for the time step t to the flexible resources connected at bus n, respectively, Δt is the length of the time step used in the analysis (e.g., 15 min), and T_{steps} is the total number of time steps included in the overall time horizon T considered for the CBA.

In (18), the underlying assumption is that the costs for the offered flexibility are the same for all the resources in the grid. In principle, it is possible to integrate in the CBA also more complex cost models, for example, differentiating the costs of the flexibility offered by each resource according to a market-based scenario. In this case, also the used voltage control algorithm may need to be adapted accordingly, as in a market-based scenario the DSO may want to pursue an optimal control not from a strictly technical perspective (as done in the algorithm in Section II-C) but rather from an economic point of view. Furthermore, for doing this, a prediction of the individual costs for each flexibility resource should be created, as the meter placement and the proposed CBA are planning tools intended to work with forecast/planning data.

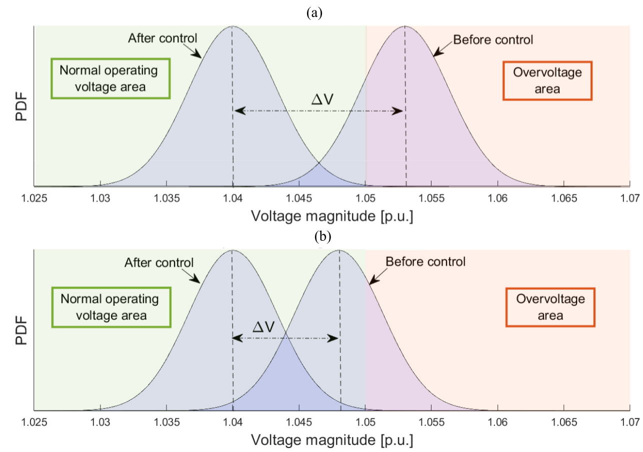

Fig. 1. Illustration of the impact of monitoring uncertainties on the voltage control and the associated redispatch costs. (a) Estimated voltage beyond allowed limits. (b) Estimated voltage within allowed limits.

Regardless of the used model, for the CBA purposes, it is important to note that the redispatch costs decrease for an increasing number of meters deployed in the grid due to the improvements achievable in terms of voltage estimation accuracy. Fig. 1 allows observing more closely the reasons behind this and how the monitoring uncertainties affect the redispatch costs. In the figure, the vertical dashed lines represent estimated voltages, whereas the Gaussian curve centered around them represents the estimation uncertainty (here assumed equal to 1%), namely, the interval where the true voltage could lie. In particular, here and in the rest of the article, "uncertainty" refers to the expanded uncertainty with a coverage factor equal to 3, which corresponds to a level of confidence of around 99.7% that the true value lies within the indicated uncertainty limit. The overvoltage boundary is chosen to be 1.05 pu. Two relevant cases are discussed next.

In Fig. 1(a), the estimated voltage exceeds the allowed boundaries. As it can be expected, the voltage control should intervene here to bring the voltage back into the allowed limits. The monitoring uncertainty brings two main degradation effects. The first one is that to ensure that the true voltage after the control is not beyond the boundaries, a larger voltage variation ΔV has to be applied. In fact, considering that the true voltage can be anywhere within the uncertainty interval, a larger shift has to be applied to the Gaussian curve to bring it (or, more precisely, to bring the portion of the Gaussian curve between $\pm 3\sigma$, where σ is its standard deviation) into the normal operating voltage area. It is easy to infer that the same voltage estimation, but with a smaller uncertainty (namely, with a narrower Gaussian curve), would instead require a smaller voltage deviation ΔV, which automatically means less power changes requested to the flexibility sources [see (10)]. A second degradation effect is that there could be a number of cases where the voltage control is applied even if not necessary. From Fig. 1(a), in fact, it can be observed that even if the estimate is beyond the limits, its uncertainty encloses cases where the true voltage lies in the normal operation area. Statistically, there will be thus cases where the voltage control is applied (and power flexibility requested) even if this was actually not needed. Lower estimation uncertainties would clearly reduce the number of cases where this can happen.

In Fig. 1(b), the estimated voltage does not exceed the limits. Such scenario is presented to highlight that the voltage control still needs to intervene also in this case, if the interval of the estimation uncertainty crosses the overvoltage limits (hence, if the true voltage could be beyond the boundaries). The same degradation effects brought by the monitoring uncertainties for the scenario in Fig. 1(a) occur also here: a larger voltage deviation is needed to shift the Gaussian curve (its $\pm 3\sigma$ portion) into the normal operating area and, statistically, the voltage control will be performed also in many cases where the true voltage does not actually exceed the overvoltage limit.

Overall, it is possible to derive that the smaller the monitoring uncertainties, the smaller the described degradation effects, and, accordingly, the smaller the amount of power flexibility necessary to control the voltage. As a consequence, an improvement of the monitoring accuracy through an incremental placement of meters eventually brings a corresponding decrease in the redispatch costs.

B. Cost of the Measurement Infrastructure

The cost C_M of each meter placement can be divided into associated capital and operational expenditures (CAPEX and OPEX, respectively). The CAPEX includes the costs of sensors, measurement devices, possible additional hardware needed (e.g., modems), and the costs for the installation of both the measurement equipment and the ICT infrastructure. When considering the amortization of these costs over a given time period, the CAPEX can be eventually expressed into equivalent costs over time (e.g., €/year). The OPEX includes instead those costs related to the operation of the measurement infrastructure. These comprise, among others, possible communication and data transfer costs, the replacement of faulty units, and the maintenance of the hardware and software components of the measurement infrastructure. From this point of view, it is also worth noting that different communication solutions (e.g., PLC, 4G, or 5G) may imply a different share of CAPEX and OPEX. These costs are typically expressed as costs over time.

Even if it concerns the scenario of end-user smart meters, [31] provides a quite comprehensive overview of the different types of costs possibly involved in the installation of the metering infrastructure. In the proposed CBA, more or less detailed models can be considered (e.g., including also inflation rates). A detailed definition of all the involved costs and of the cost model is out of the scope of this article. For the purposes of the proposed CBA, the existing requirement is to dispose of a realistic estimation of the costs over time involved in the deployment of each additional meter as input to the CBA.

C. CBA-Based Meter Placement

The proposed CBA aims at comparing the costs associated with the installation of new meters to the benefits resulting in terms of reduction in the redispatch costs. For doing this, the algorithms presented in Section II are linked together and used sequentially to allow the estimation of the redispatch costs.

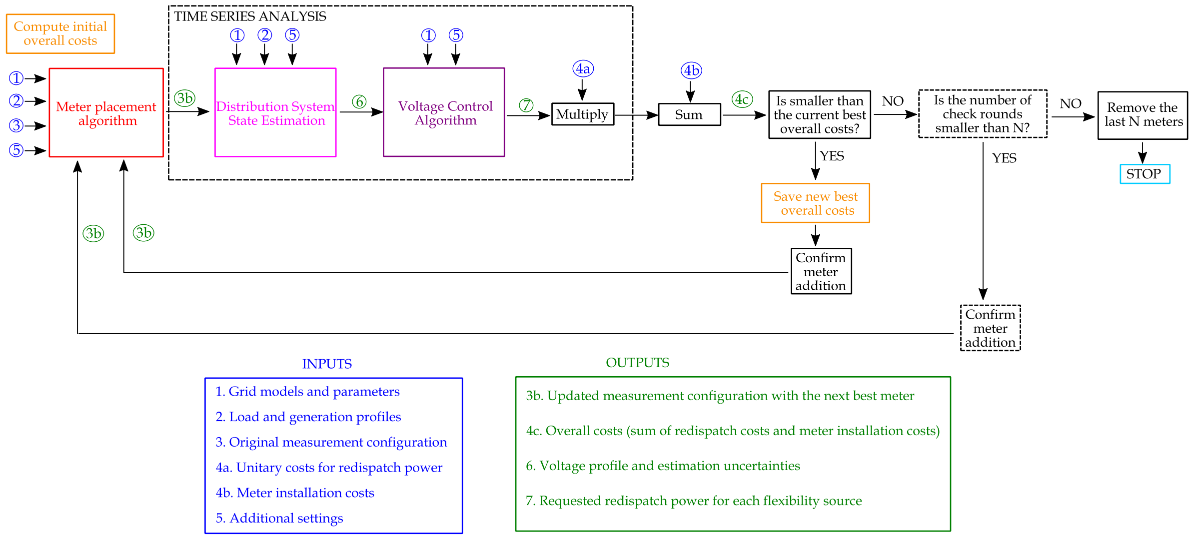

Fig. 2. Overall flowchart of the proposed CBA-based meter placement strategy.

The overall framework and logic of the CBA is depicted in Fig. 2. The main inputs required for the analysis are: 1) the model and parameters of the grid; 2) the future (expected) load and generation data in the form of time series; 3) the information about the starting measurement configuration (namely, the meters already available in the grid); and 4) the unitary costs (C_P and C_Q) for the redispatch power and those associated with the meter installation (C_M). Additional settings necessary for the CBA are the boundaries for the voltage magnitude, the considered accuracy of the meters, and the limits of active and reactive power flexibility for the flexible resources in the grid. A meaningful time horizon for the CBA has also to be selected. This can be a multiannual time window, which would make sense if the load and generation data are expected to evolve over time and if also variable costs are considered (e.g., due to inflation rates). Within the considered time horizon, load and generation data have to be defined with a given time resolution (e.g., hourly data) to capture the seasonality and daily variations. In this regard, the higher the granularity, the better the accuracy of the analysis.

The CBA-based meter placement is an iterative procedure, where at each round the convenience (from a cost perspective) of placing an additional meter is evaluated. At each round, the first step is to identify the best next meter to be installed in the grid via a meter placement algorithm. In this article, the GSA-based procedure presented in Section II-B is used, which provides the advantages to be not too computationally demanding and to flexibly integrate the effects of various uncertainty sources [26]. The output of this first step is the knowledge of the next meter that would be beneficial to install in the grid. The new measurement configuration with the identified additional meter is then provided as input to the time series analysis block containing the SE and voltage control algorithms. Here, a time series analysis is performed over all the time steps of the considered time horizon. At each time step, the load and generation data are used to create the "true" reference operating conditions of the grid, whereas the input measurement configuration is considered to randomly extract measurements (affected by errors according to the uncertainty of the meters) for each meter in the grid. The created measurements are then used as input to the SE process, which provides the uncertainty with which the operating conditions would be estimated as output. This information is used by the voltage control algorithm, which derives the possible needs for redispatch measures. Combining the power change requested by the voltage control with the costs of the flexibility, it is possible to compute, for each time step, the resulting redispatch costs. By summing them over all the time steps, the total redispatch costs for the time horizon of the CBA can be eventually obtained. The sum of redispatch costs and the costs for installing the meters being added with the CBA-based meter placement procedure gives the overall costs. These costs should be compared with the lowest overall costs temporarily obtained during the iterative procedure (in the first round, the comparison is against the redispatch costs resulting when no meters are added to the starting measurement configuration). If the obtained overall costs are lower than the current best ones, the installation of the new meter is convenient and should be considered for meter placement. The lowest overall cost is then updated for the following round, where the process is repeated again to assess whether installing one more meter is economically convenient. When the overall costs obtained with the new meter are larger than the available best ones, a further check routine can be optionally activated, whose scope is to avoid stopping in a local minimum. This is motivated by the fact that there might be cases where installing one more meter is not economically convenient, but installing two (or more) meters leads again to a decrease in the overall costs and possibly to a new best. The reasons behind this possible behavior are multiple. In the first place, the adopted GSA-based meter placement procedure cannot guarantee that local minima are avoided due to its incremental nature. Furthermore, the considered scenario and the nonlinearities of the underlying models can determine results that do not follow a monotonic trend. Just as an example, when using complex cost models with flexibilities

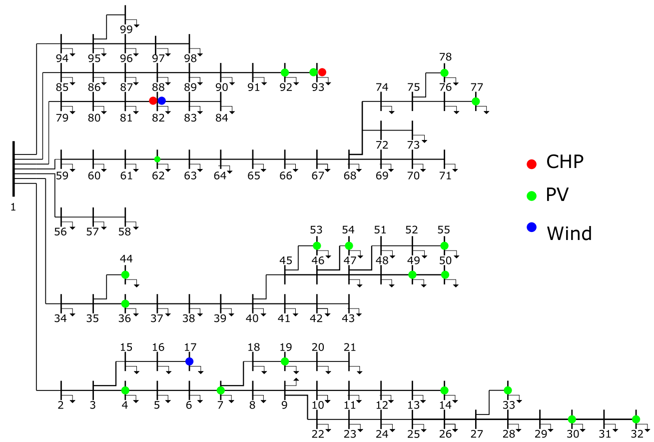

Fig. 3. Single line diagram of the ATLANTIDE test distribution system.

offered at different prices, it may happen that below a certain threshold of monitoring uncertainty it is possible to avoid the use of expensive resources, which may lead to a sudden decrease in the overall costs. The check routine allows hence assessing whether configurations with up to N meters more than those giving the best overall costs would lead to a new minimum. If yes, all the meters leading to the new minimum should be considered for the meter placement and the iterative procedure continues. If, after doing the check of N more meters, a new best result is not found, the overall procedure is then stopped, and only those meters that led to the best overall costs are considered for meter placement. It is worth noting that due to the incremental nature of the proposed approach, it cannot be guaranteed that the found solution is a global optimum, i.e., different meter placement configurations may possibly exist, which provide better results. However, the proposed solution should still allow to find a near-optimal solution while taking into account the resulting cost–benefit ratio for the DSO.

IV. Tests and Results

A. Simulation Setup and Scenarios

To illustrate the CBA-based meter placement strategy, the industrial network from the ATLANTIDE project [32] is used. The network is a 99-node seven-feeder distribution grid hosting several distributed generators, including three wind, 22 PV, and three CHP plants, with a mix of industrial, commercial, and residential loads (see Fig. 3). It is given with 15-min resolution profiles of consumption and production over multiple years. The CBA presented in the following is performed considering a time horizon of one year. To test the placement strategy and the underlying algorithms under stressed conditions, the consumption and generation profiles of 2030 have been chosen, which represent the worst case scenario in terms of over- and undervoltages. Fig. 4 shows the corresponding voltage profile of the grid for the time steps with the largest over- and undervoltage when no voltage control is applied. The lower and upper boundaries of voltage magnitude considered for the tests are 0.95 and 1.05 pu, respectively.

The default measurement configuration considered as starting point for the CBA is composed of only a voltage

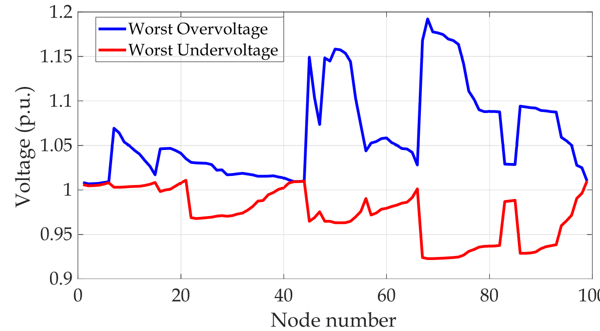

Fig. 4. Voltage magnitude profiles at the time steps in 2030 where the worst overvoltage and undervoltage occur (blue and red lines, respectively).

measurement (with 1% uncertainty) at the main substation (bus 1) and of pseudo-measurements of power injection at all the nodes of the grid with 50% uncertainty. The installable meters can provide voltage magnitude measurements with 1% uncertainty, and active and reactive power measurements (either of the node injection or of the branch flows) with 2% uncertainty. The active and reactive power measurements are typically provided by the same device and are hence considered jointly.

Concerning the costs, a price of 100 €/MWh has been considered for the redispatch costs associated with active power regulation requests [33]. Reactive power flexibility provision has been assumed instead to be cheaper, with a unitary cost of 20 €/Mvarh. The available flexibility in the grid is given by the distributed generation, whose reactive power can be regulated (within certain limits) and the active power curtailed in case of overvoltages, and by storage systems (installed at the PV nodes) which can be used to absorb part of the PV generation or to inject power, e.g., during time periods with high loading conditions leading to undervoltages. For the sake of simplicity, the same price of power flexibility is considered for all the flexible resources and time steps. Moreover, no detailed modeling of the storage system and its energy management system has been implemented. These assumptions, although simplistic, have been adopted because they concern modeling details beyond the desired goal of the simulations, which is to show the operation and the concepts behind the proposed meter placement strategy. Finally, regarding the costs of the meters, the total investment associated with the installation of a meter is assumed equal to 40 k€ (same order of magnitude as in [34]), with an amortization over 15 years.

B. Impact of the Monitoring Uncertainties

The first series of tests has been performed to demonstrate the degrading effects of the voltage estimation uncertainty on the redispatch costs. To clearly track the impact of different uncertainty levels, in these tests the voltage control has been run using the true voltage states and increasing levels of voltage uncertainty (0%, 0.5%, 1%, and 2%) for all the nodes as inputs. Hence, the tests and results shown here do not consider yet any meter placement procedure. Their aim is to validate the analysis done in Section III-A and show how

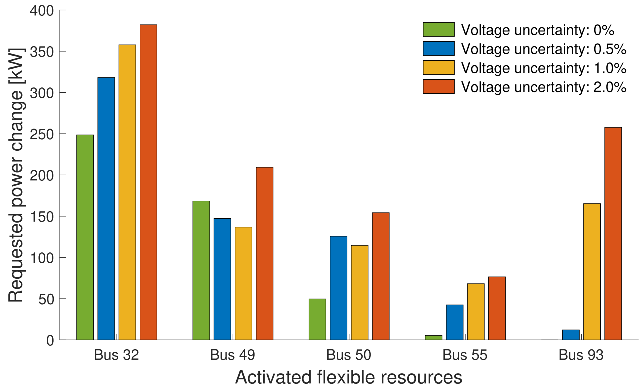

Fig. 5. Redispatch power requested at different buses with varying levels of voltage uncertainty (time step: 12:00 of 1st July).

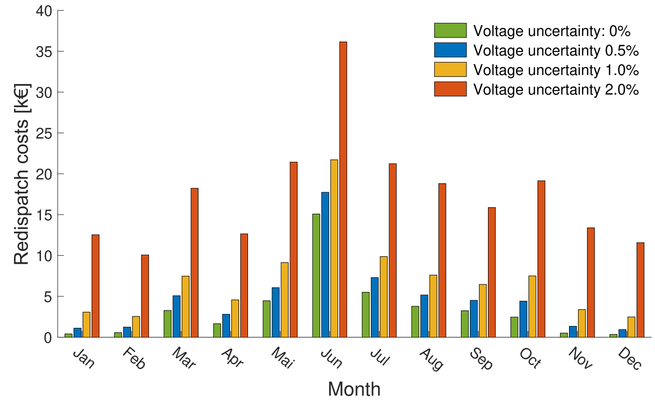

Fig. 6. Summary of the monthly redispatch costs with varying levels of voltage uncertainty.

the monitoring uncertainties affect the control performance resulting into higher redispatch costs for the DSO.

Fig. 5 shows the results for a particular time step of the simulation (1st July, 12:00) with some strong overvoltages due to the high generation of the PV plants. It is possible to observe that the flexible resources being asked to contribute to the overvoltage mitigation are those at the end of the feeder, since these are in general those that contribute more strongly to the final voltage profile of the grid. As expected, higher levels of uncertainty determine an increase in the requested redispatch power. A different trend seems to exist for bus 49, but it should be noted that the smaller demand at this node (for increasing levels of uncertainty) is widely compensated by the higher requests at the other nodes of the same feeder (buses 50 and 55). A particular scenario can also be observed for bus 93. In fact, it is possible to note that when no uncertainty is considered, no redispatch power is requested. This reflects the fact that its feeder does not suffer of any overvoltage. However, when taking into account the uncertainty in the knowledge of the voltages, the existing uncertainty interval does not allow to exclude the case that the true voltage is beyond the overvoltage threshold. Consequently, this determines a request of redispatch power to shift the Gaussian curve (its $\pm 3\sigma$ portion) within the boundaries [this scenario is similar to the one discussed in Section III-A and depicted in Fig. 1(b)]. This case is hence a clear example of a scenario where redispatch power is demanded even if actually not needed (since an overvoltage does not actually exist in that feeder).

Fig. 6 provides an overview of the resulting redispatch costs for the time series simulation over the entire year. The redispatch costs tend to increase in the summer months due to the higher levels of PV generation, and in particular in June, where the grid profiles have quite large peaks of generation (resulting in strong overvoltages). Once more, it is possible to observe that increasing levels of uncertainty lead to a growth of the redispatch costs. Moreover, it can be noted that the increase in the costs is not linear. This is clearly visible when looking at the steep increase existing when moving from 1% to 2% voltage uncertainty. Along the entire year, the scenario with 0.5% uncertainty brings a 40% increase in the redispatch costs, whereas the scenarios with 1% and 2% uncertainty determine costs that are more than 2 and 5 times larger, respectively, than the ideal scenario with no uncertainties.

TABLE I
RECOMMENDED BEST METERS FROM THE GSA METER PLACEMENT ALGORITHM

Round	Type	Location	Feeder
1	Voltage	Bus 32	7
2	Voltage	Bus 84	3
3	Voltage	Bus 50	6
4	Power	Line 62-63	4
5	Voltage	Bus 93	2
6	Voltage	Bus 14	7
7	Power	Line 35-44	6
8	Voltage	Bus 75	4
9	Power	Line 1-85	2
10	Voltage	Bus 55	6

C. Meter Placement Results

This section focuses on the results of the CBA-based meter placement strategy. To analyze the behavior of the CBA, results have been created for ten rounds of the procedure. Table I shows the best meters to be installed at each round according to the results given by the GSA-based placement algorithm. The GSA has been run considering the effects of two different time steps, namely, those having the worst over- and undervoltages. To set the two coefficients β_t of (9), each of the time steps of the year has been associated with one of those under- or overvoltage profiles according to the highest similarity of the voltage magnitude (measured in terms of smallest Euclidean distance). The values of the two coefficients are then decided depending on the number of time steps being associated with the over- or undervoltage case, respectively. Looking at the results, the GSA recommends placing the meters alternatively in feeders that exhibit large voltage deviations (i.e., feeders 2, 3, 4, 6, and 7). In general, voltage meters are placed close to the end of the feeders, whereas power meters are placed either at the beginning of the feeders or close to nodes with large power injections from distributed generators. The selection of the type of meter (here either voltage or power) is an outcome of the GSA, which identifies the most effective combination of type and location

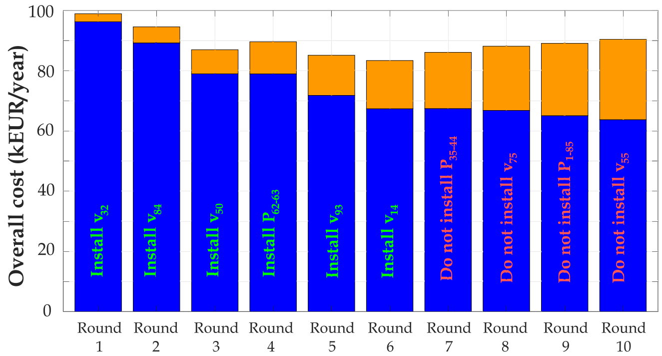

Fig. 7. Overall cost for consecutive meter placement rounds, split between redispatch costs (blue) and meter installation costs (orange).

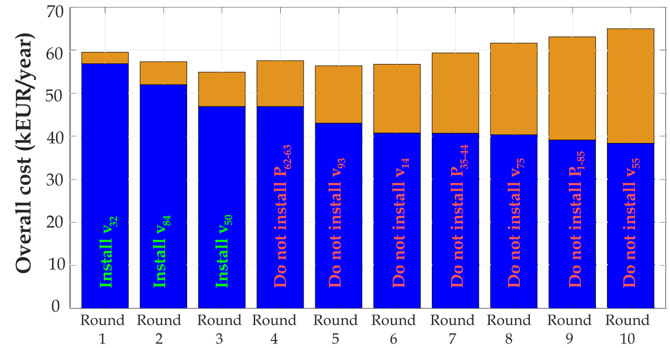

Fig. 8. Overall cost for consecutive meter placement rounds with halved price of active and reactive power flexibility.

of the meter to reduce the uncertainty of the voltage estimation in the DSSE, according to the metric defined in Section II-B.

The results of the CBA are shown in Fig. 7. Blue bars refer to the cost for the redispatch power and orange bars indicate the (incremental) costs of the installed meters. Looking at the total costs, after a constant decrease for the first three meters (rounds 1–3), the installation of P_{62-63} (round 4) leads to a slight increase in the total costs. The trend, however, returns to decrease if two more meters are installed (rounds 5 and 6). After round 6, the redispatch costs decrease only slightly and, therefore, the total costs start to monotonically increase due to the impact of the meter installation costs. These results show the importance of having a check routine as the one described in Section III-C. In fact, if the procedure stops at the first occurrence of a total cost increase, then it would not be possible to reach the minimum overall costs, which, in the considered scenario, are indeed found at round 6.

For the sake of comparison, Fig. 8 shows the results for the same scenario but when considering a halved price for the active and reactive power flexibility (active power: 50 €/MWh; reactive power: 10 €/Mvarh). In this case, the redispatch costs obviously exhibit the same trend but they are halved, which leads the cost of the metering installation to have a relatively larger impact. Consequently, it is reasonable to expect that the installation of multiple meters is disincentivised, as confirmed by the results, according to which the lowest overall costs are already found at round 3. In this case, therefore, the installation of the voltage meters at buses 32, 84, and 50 would be the best solution from an economic perspective for the DSO. Installing more meters would still lead to further enhancements of the monitoring accuracy and to a reduction of the redispatch needs, but those improvements do not determine a benefit large enough to justify the deployment of more meters.

Overall, the test cases presented in this section highlight the main concepts behind the design of the proposed CBA-based procedure. In these scenarios, having the check of the total costs for one more meter (after finding a cost that is not the best one) would eventually allow finding the minimum. In other scenarios, and in particular if more complex models (e.g., for the costs) are used, using only a single check round may not suffice and it may be advisable to foresee a check over more meters. This would obviously determine an increase in the computation time to find the final meter placement recommendation, but considering that this is a planning task executed off-line, in most of the cases it can be considered as an acceptable tradeoff.

V. Conclusion

This article presented an overall meter placement strategy that allows identifying the reinforcement needs for the measurement infrastructure based on a cost–benefit analysis. In particular, the focus is on the redispatch costs that can be avoided, thanks to the improvement of the monitoring accuracy. Performed analyses and test results prove that the monitoring uncertainties bring detrimental effects on the operation of control algorithms, which eventually translate into larger redispatch costs for maintaining the operation of the system within the allowed boundaries. The placement of additional meters allows reducing such costs, but at the same time leads to increasing costs for the installation and operation of the measurement infrastructure. The proposed framework allows identifying a tradeoff among these costs, and thus to find the number, type and location of the meters that are convenient to install from an economic perspective. Performed simulations showed the operation of the proposed framework in a test scenario, using exemplary cost models and algorithms for meter placement, state estimation, and voltage control. The devised framework is, however, flexible and can accommodate different cost models and versions of the underlying algorithms, hence offering the possibility to easily adapt to possibly different DSO or simulation requirements.

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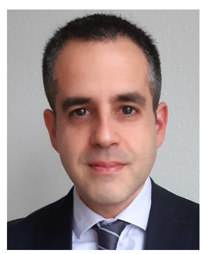

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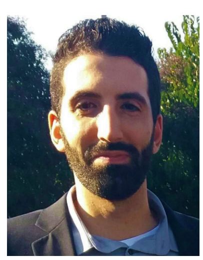
Dr. Pau is an Associate Editor of IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT.



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