Optimization of state-estimator-based operation framework including measurement placement for medium voltage distribution grid
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Optimization of State-Estimator-Based Operation Framework Including Measurement Placement for Medium Voltage Distribution Grid

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Abstract—To provide a guideline for grid operators to manage medium voltage distribution grids, this paper presents a probabilistic approach for measurement placement optimization and a state-estimator-based operation framework. The Monte Carlo method is used to optimize the measurement placement with minimum measured points, which support the observability of state estimator and satisfy the requirements for operation activities. The proposed framework covers several important factors from practical situations, including cost allocation of measurement systems, unavailability of measurement data, and small voltage deviation across medium voltage (MV) grids. Finally, a case study on a typical European distribution grid demonstrates the feasibility of the framework.

Index Terms—Central limit theorem, distribution management system (DMS), load estimation, measurement placement, Monte Carlo methods, state estimation.

I. INTRODUCTION

A S POWER systems continue to develop, the medium voltage (MV) and low voltage (LV) distribution grid will be operated autonomously. To achieve this, a distribution management system (DMS) is required. The heart of this system is a state estimator. Based on input measurement data and network parameters, the state estimator evaluates the condition of the grid with the highest probability, which can be further used for the operation activities. However, traditionally, the measurement data in MV grids are insufficient for the state estimator to achieve observability.

Installing more measurement devices will increase the investment of grid operators. Therefore, an optimization of measurement placement is essential. Li [1] discussed the impact of measurement placement and customer load estimation on the accuracy of state estimation results. Baran et al. [2] managed to solve the problem by differentiating the importance of state accuracies in individual locations. Installing meters should be prioritized to important places such as the main switch and fuse locations. Shafiu et al. [3] presented a heuristic approach to identify potential points or location of voltage measurements. Meters should first be installed at the points with a higher standard deviation of voltage magnitude estimation error. Singh et al. [4] adopted a probabilistic approach with bivariate Chebyshev’s bounds to determine the measurement placement. It has been proposed that the voltage meters should be installed on the bus with the largest ellipse area of the state error covariance matrix. The studies above aimed to minimize the total number of measured quantities in the MV grid, under the constraints that the estimation errors of node voltage magnitudes and angles should be limited.

Besides the real measurements, load estimation is needed as a pseudo measurement to achieve observability. Kersting and Phillips [5], Arritt [6], and others presented several load estimation methods and verified them with empirical data. It has been concluded that load allocation based on the energy bill has higher accuracy than that based on number of customers or transformer rating. Baran and McDermott [7] discussed the application of load estimation on a branch-current-based state estimation method. Besides that, evaluating the error range of load estimation is essential for the state estimation. To solve this problem, Singh et al. [8] adopted a Gaussian mixture model to integrate pseudo measurements into state estimation, while Manitats et al. [9] utilized artificial neural networks to generate pseudo measurements.

It has been proposed that some operation activities can be performed based on the results of state estimation. Deshmukh et al. [10] presented a control framework for voltage/VAR control based on a nonlinear state estimator. Unavailability of measurement data due to packet drops in the communication channel has been considered in the framework. Pazderin et al. [11], [12] solved the energy loss calculation problem based on state estimation approaches. The state estimation was adapted by using the weighted square sum of energy measurement relative errors.

Many aspects regarding the DMS development have been widely discussed by previous studies. However, distribution grid operators desire an integrated, practically feasible, and robust operation strategy for MV grids. To bridge this gap, this paper proposes a probabilistic approach to optimize the
measurement placement in MV grids. The resulted minimum necessary measurement scheme provides the observability of state estimator and satisfies the requirements for operation activities. In addition, an operation framework is designed based on the weighted least square (WLS) state estimator. This framework adapts several techniques for practical situations, including cost allocation of measurement systems, unavailability of measurement data, and small voltage deviation across MV grids.

Section II presents the proposed operation framework. The measurement systems are analyzed in Section III, while load estimation is discussed in Section IV. The WLS state estimator is briefly described in Section V, and three common operation activities are discussed in Section VI. Section VII gives a probabilistic approach to determine the minimum necessary measurement scheme. In Section VIII a case study demonstrates the feasibility of the framework.

II. OPERATION FRAMEWORK

A. Grid Structure and Operation Framework

The distribution grid is normally operated in a radial structure, for ease of control and protection [13]. And besides the main HV/MV transformers, MV/MV regulating transformers may be installed in the MV grid for voltage control.

The operation framework designed by the paper is shown in Fig. 1. The core of the framework is a state estimator. The input of the state estimator consists of network parameters and measurement data. Another important type of input is the load estimation, which acts as a pseudo measurement. The estimated state can further be used for the activities of normal operation, for example voltage regulation, loss estimation, and switching consequence assessment.

B. Network Parameters

The network parameters consist of the network topology status and component parameters. The network topology can be real-time updated because nowadays it is usually managed centrally. In addition, the accurate values of the positive/negative sequence parameters of the components are known.

Although there are considerable inaccuracies in zero sequence parameters, they are less relevant in normal operation due to the following two reasons: 1) the MV grid is fairly balanced; and 2) since most MV/LV transformers have delta-windings in the MV side, the zero sequence power flow in the LV grids cannot cross the MV/LV transformers and be present in the MV grid.

Therefore, it is unnecessary to consider the uncertainties of the network parameters, which are always assumed to be accurate. Without losing generality, this paper discusses balanced MV grids, while unbalanced MV grids (with negative sequence power flow) can be analyzed with similar methodology.

III. MEASUREMENTS

A. Structure and Cost Allocation of Measurement Units

Due to financial reasons it is too expensive to install measurement devices everywhere in MV grid. Therefore, the optimization of meter placement is essential. Before the optimization, the structure of measurement units is analyzed. Fig. 2 shows a simplified structure diagram of a measurement unit. A valid measurement unit consists of individual components and common components. Individual components are the current/voltage transformer and A/D converter for each measured quantity, while common components are the central processing unit (CPU) and communication channel.

The total investment of measurement system includes the cost of common components and individual components. Concerning the cost allocation of measurement units, usually the overall cost is dominated by the common components, i.e., purchasing and maintaining the common components is much more expensive than individual components.

Several studies [2]–[4] aimed to minimize the total number of measured quantities, i.e., the total number of measured voltages, currents, and powers. However, this might lead to a large number of geographically spread measured points, which will have overall high cost due to the necessity of common components for each measured point.

Instead, this paper proposes that the optimization should focus on minimizing the total number of measured points. Because each measured point requires a set of common components (the cost of which is the major expense), the minimal number of measured points implies the minimal cost. Moreover, if one point in the grid has been chosen for installing measurement devices, the cost of common components is already being spent. To maximize their usage, it is preferred to measure as many quantities as possible at this point.
Therefore, the paper suggests to install meters at all MV substations or MV regulating/switching substations, and MV points of connection (PoCs) can be categorized into MV substations (HV/MV substations and 2) active/reactive current at each feeder.

Fig. 4. Measurements in the field.

B. Measured Points at MV Substations and in the Field

The placement of meters in MV grid becomes then a matter of selecting the measured points. Generally the points can be categorized into MV substations (HV/MV substations or MV regulating/switching substations), and MV points of connection (PoCs) in the field.

The meters at MV substations are easy to install with relatively lower cost due to limited number of MV substations. Therefore, the paper suggests to install meters at all MV substations. As shown in Fig. 3, the following effective measured quantities are proposed: 1) voltage magnitude at each busbar; and 2) active/reactive current at each feeder.

For measurements in the field, it is too expensive to install meters at all MV PoCs. The approach to achieve the optimal selection of measured PoCs is given in Section VII. Principally, the paper suggests to install meters at all PoCs with large industrial loads or dispersed generations (DGs), due to their complex behavior. And at least one PoC with household loads and one PoC with commercial loads should have meters. The reason for this will be given in Section IV. If a certain PoC is chosen for installing measurement devices, as shown in Fig. 4, the following effective measured quantities are proposed: 1) voltage magnitude at the PoC; 2) active/reactive current to the LV grid or MV customer; and 3) active/reactive current at each connected MV branch.

C. Measurement Error

The measurement error of a measurement device is commonly assumed to be approximately normally distributed [4]. Its standard deviation $\delta$ can be calculated in (1), where $\Psi$ is the measuring range and $\tau$ is the maximum relative error

$$\delta = \frac{1}{3} \Psi \tau. \quad (1)$$

Obviously, the absolute error can be reduced by decreasing the measuring range, which can be done in a modern digital meter. The paper proposes to limit the range to cover the largest measured value with sufficient margin. The upper bounds of the measuring ranges are set for voltage $\Psi_U$, branch current $\Psi_{I,B}$, and PoC current $\Psi_{I,PoC}$

$$\Psi_U \leq 1.5 U_n, \quad \Psi_{I,B} \leq 1.5 I_{n,B}, \quad \Psi_{I,PoC} \leq \frac{2 S_{\text{max, PoC}}}{\sqrt{3} U_n} \quad (2)$$

where

$U_n$ nominal bus voltage;

$I_{n,B}$ nominal current of the branch;

$S_{\text{max, PoC}}$ maximum apparent power at the PoC.

D. Unavailability of Measurement Data

The measurement data are not always available to the state estimator. Every component in a measurement unit is subject to failure, which leads to data unavailability. For example, the data might be lost by packet drops in the communication channel [10]. Thus, this factor should be considered in the design of operation framework and meter placement.

For a measured point, two kinds of failure rates are defined: failure rate of common components $\rho_C$ and individual components $\rho_I$. If the common components of a measured quantity fail, all the data from that point are unavailable. However, if the individual components of a measured quantity fail, the data unavailability occurs only on that quantity, while the others can remain operational. Thus, the data unavailabilities of each measured quantity in the same unit are not independent events.

In particular, failure of voltage measurement will degrade the current measurements within the same unit to magnitude only, because they cannot be decomposed to active and reactive current without reference phase angle of voltage.

IV. LOAD ESTIMATION

To achieve the observability of the state estimator, it is necessary to estimate the loads at the unmeasured PoCs with household and commercial loads, and use them as pseudo measurements. Based on several methods proposed by previous studies [5]–[9], this section applies a relatively simpler approach with central limit theorem, which can facilitate its implementation for grid operators. The household loads are taken as an example in the analysis, while the commercial loads can be analyzed with similar approach.

A. Mathematical Modeling of Household Load Profile

This paper assumes that the total number of PoCs in the MV grid is $N_{PoC}$, and each PoC is numbered from 1 to $N_{PoC}$. Let $H$ be the set containing the numbers of all the PoCs connected with household loads, i.e., for any $i \in H$, PoC $i$ is connected with $n_i$ LV household customers in total.

$P_{i,j}(t)$ is defined as the active power curve of the $j$th customer in MV PoC $i$. The paper assumes that each $P_{i,j}(t)$ has the following form:

$$P_{i,j}(t) = \xi_{i,j} X_{i,j}(t). \quad (3)$$

Each $\xi_{i,j}$ in (3) is a user preference factor: some customers naturally use more electricity and others use less. Its mean should be 1, shown in (4), and $\lambda^2$ is the variance

$$E[\xi_{i,j}] = 1, \quad D[\xi_{i,j}] = \lambda^2. \quad (4)$$
Each $X_{ij}(t)$ in (3) is an independently identically distributed stochastic process, which represents the human behavior of the electricity usage. Its mean function $P_m(t)$ represents the average electricity consumption pattern in a certain region

$$P_m(t) = E[X_{ij}(t)].$$

The covariance function $K(t_1, t_2)$ is the covariance between the value of $X_{ij}(t)$ at two time points $t_1$ and $t_2$. For a mathematical approximation, some studies [14]–[16] suggested that it has the “squared exponential” form

$$K(t_1, t_2) = \sigma(t_1)\sigma(t_2)e^{-\frac{(t_1-t_2)^2}{2\tau^2}}.$$  

The time constant $\tau$ represents: “within how much time the user electricity usage is correlated.” Particularly, when $t_1 = t_2$, the $K(t_1, t_1) = \sigma^2(t_1)$ is the self-variance at time point $t_1$, and $\sigma(t)$ is the standard deviation.

The annual mean $\mu_m$ and maximum $\mu_{\text{max}}$ of $P_m(t)$ are defined in (7), while the annual maximum standard deviation $\sigma_{\text{max}}$ is defined in (8). At any given time point $t_0$, $P_t$ is defined as the total active power at PoC $i \in H$ when ignoring the loss in LV grid, shown in (9)

$$\begin{align*}
\mu_m &= \frac{1}{\text{year}} \int_{\text{year}} P_m(t)dt, \quad \mu_{\text{max}} = \max_{t \in \text{year}} \{P_m(t)\} \\
\sigma_{\text{max}} &= \max_{t \in \text{year}} \{\sigma(t)\} \\
P_t &= \sum_{j=1}^{n_t} P_{ij}(t_0).
\end{align*}$$

**B. Load Proportion Factor**

According to (3) and (5), for any $i_1, i_2 \in H$, the mathematical expectations of the real time active power $P_{i_1}$ and $P_{i_2}$ have the following relation:

$$\frac{E[P_{i_1}]}{E[P_{i_2}]} = \frac{\xi_{i_1}}{\xi_{i_2}} = \frac{\xi_i}{\xi_j} = \sum_{j=1}^{n_t} \xi_{i,j}$$

where $\xi_i$ is defined as load proportion factor.

The relation in (10) is the fundamental basis of the load estimation approach in this paper. The grid operators can use the real-time measurements at some of the household PoCs to estimate the power at the others. This is the reason why in Section III the paper proposes to measure at least one PoC connected with household load.

Unfortunately, the exact user preference factors and load proportion factors are unknown. This paper discusses two commonly used methods [5]–[7] to estimate them: 1) number of customers and 2) annual bill. The estimated relative load proportion factor $\hat{\Theta}_i$ is defined by each method.

1) Method 1: Estimation based on number of customers. Let PoC $x \in H$ have the most customers, and (11) defines $\hat{\Theta}_i$

$$\hat{\Theta}_i = \frac{n_i}{n_x}.$$  

2) Method 2: Estimation based on annual bill. The paper defines $C_i$ as the total annual consumption of all the customers at PoC $i$. Similarly, let PoC $x \in H$ have the largest total annual consumption, and (12) defines $\hat{\Theta}_i$

$$\hat{\Theta}_i = \frac{C_i}{C_x}.$$  

According to the definitions above, no matter which estimation method is used, the following statement is always true:

$$\hat{\Theta}_i \leq \hat{\Theta}_x = 1.$$  

**C. Load Measurements and Error**

Let $S \subset H$ be the set containing the numbers of the household PoCs where meters are installed. The active power is not directly measured, but calculated. The error of power calculation can be derived from the error of voltage and current measurements. Assume $\hat{U}_r$ and $\hat{I}_{r,a}$ are the measured values of voltage and active current at PoC $r \in S$, the active power $\hat{P}_r$ can be calculated by (14)

$$\hat{P}_r = \sqrt{3}\hat{U}_r\hat{I}_{r,a} = P_r + \zeta_r$$

where $P_r$ is the real value of the active power, and $\zeta_r$ is defined as the resulted error.

It can be assumed that $\zeta_r$ follows normal distribution with mean zero and variance $\delta_r^2$: almost all (99.7%) the $\zeta_r$ falls in the range of $\pm 3\delta_r$. According to (2) and (7), $\delta_r$ can be calculated by (15)

$$\delta_r = \frac{1}{3n_r\mu_{\text{max}}\tau_0}, \quad \tau_0 = 1.5\tau_U + 2\tau_I + 3\tau_U\tau_I$$

where

- $\tau_0$ the relative error of active power calculation;
- $\tau_U$ the relative error of voltage measurement;
- $\tau_I$ the relative error of current measurement.

**D. Active Load Estimation and Error**

For any $i \in H\setminus S$, i.e., an unmeasured PoC, the real time active power $\hat{P}_i$ is estimated based on the relative load proportion factor, as shown in (16), where $\Theta_i$ is the estimation coefficient. And the estimation error $\alpha_i$ is defined in (17)

$$\hat{P}_i = \Theta_i \sum_{r \in S} \hat{P}_r, \quad \Theta_i = \frac{\hat{\Theta}_i}{\sum_{r \in S} \hat{\Theta}_r}$$

$$\alpha_i = \hat{P}_i - P_i.$$  

Normally each PoC contains many LV household customers, which means each $P_i$ is the sum of a large number of independent random variables. Therefore, according to central limit theorem, for any $i \in H$, each $P_i$ approximately follows normal distribution. From (14) and (17) it can be concluded that $\alpha_i$ also follows normal distribution. Thus, the upper bound of $\alpha_i$ can be obtained by (18) at a confidence level of 0.997

$$|\alpha_i| \leq |E[\alpha_i]| + 3\sqrt{D[\alpha_i]}$$

where $E[\alpha_i]$ is the mean of $\alpha_i$, representing the system error, which is originated by estimating the load proportion factor.
And \( D[\alpha_i] \) is the variance of \( \alpha_i \), representing the random error, which is originated by the diversities of stochastic loads and measurement inaccuracies.

The upper bound of \( D[\alpha_i] \) can be derived by a number of variables defined in this section, as shown in (19)

\[
D[\alpha_i] \leq \sigma_{\text{max}}^2 \phi_d (\theta_i^2 N_S + n_i) + \sigma_i^2 \theta_i^2 N_{S,d}^2
\]

where

\[
N_S = \sum_{r \in S} n_r, \quad N_{S,d}^2 = \sum_{r \in S} n_r^2, \quad \phi_d = E[\xi_i^2].
\]

Similarly, the upper bound of \( E[\alpha_i] \) for both estimation methods can be obtained by (21) and (22), respectively Method 1

\[
|E[\alpha_i]| \leq 3 \lambda \mu_{\text{max}} \sqrt{n_i^2 + n_i}.
\]

Method 2

\[
|E[\alpha_i]| \leq \frac{3 \sigma_{\text{max}} \mu_{\text{max}} \Gamma_I}{\mu_m} \sqrt{\phi_d (\theta_i^2 N_S + n_i)}
\]

where

\[
\Gamma_I = \frac{1}{\text{year}} \sqrt{\int_0^{	ext{year}} \int_0^{	ext{year}} e^{-\frac{(t_2-t_1)^2}{2 \tau^2}} dt_1 dt_2.}
\]

To ensure the robustness of the algorithm, it is important to install meters at least at the PoC with the largest \( \theta_i \) (depending on the estimation method), i.e., \( x \in S \). According to (13) and (16), \( \theta_i \) is always smaller than 1. Therefore, the estimation error is limited by \( \theta_i \).

### E. Reactive Load Estimation and Error

Due to large number of household load types, sophisticated algorithms are needed to analyze the detailed characteristics of reactive power. However, statistical smart metering data on households suggest that the power factor is very close to 1, between 0.99 inductive and 0.97 capacitive [17]. Given the low proportion of reactive power, it is reasonable to sacrifice the accuracy of reactive power estimation for algorithm simplicity. This paper sets the real-time estimated reactive power to be 1. And the estimated reactive power is always zero

\[
\hat{Q}_i = 0.
\]

The estimation error on reactive power \( \gamma_i \) equals to the real active power \( Q_i \), shown in (25). Its upper bound can be calculated with the lowest power factor (0.97 capacitive) and the highest active power, shown in (26)

\[
|\gamma_i| = |\hat{Q}_i - Q_i| = |Q_i|
\]

\[
|Q_i| \leq \sqrt{1 - 0.97^2} P_{i,\text{max}} \approx 0.2506 n_i \mu_{\text{max}}.
\]

### V. State Estimator

#### A. Nonlinear Optimization

As the core of the operation framework, the state estimator evaluates the state of the grid based on network parameters, (pseudo) measurement data and topology status. In this paper, the widely used WLS state estimator is applied. Mathematically it can be expressed as the minimization of a weighted square sum of all deviations between calculated values and (pseudo) measured values

\[
f(v) = \sum_{i=1}^{N_M} w_i (C_i(v) - M_i)^2
\]

where

- \( v \) state vector;
- \( f(v) \) total deviation function;
- \( N_M \) total number of (pseudo) measurements;
- \( w_i \) weighting factor;
- \( C_i(v) \) calculated value from the estimated state vector;
- \( M_i \) (pseudo) measured value.

Each deviation is weighted by a weighting factor \( w_i \), which is inversely proportional to the square of the error range of the (pseudo) measurement, and the minimization of (27) is a nonlinear optimization. Its results include the estimated complex power flow \( \mathbf{S}_{\text{est}} \) and the complex voltage phasor \( \mathbf{U}_{\text{est}} \) at each PoC, defined in (28). These two vectors can be further used for the operation activities

\[
\mathbf{S}_{\text{est}} = [S_{i,\text{est}}], \quad \mathbf{U}_{\text{est}} = [U_{i,\text{est}}], \quad 1 \leq i \leq N_{\text{PoC}}
\]

where

- \( S_{i,\text{est}} = P_{i,\text{est}} + j Q_{i,\text{est}} \) estimated power flow at \( i \)th PoC;
- \( U_{i,\text{est}} \) estimated voltage phasor at \( i \)th PoC.

#### B. Failure of State Estimation

Due to measurement error or algorithm divergence, the state estimator may not give valid results. This paper considers the state estimation to be failed in two cases. First of all, the nonlinear optimization may fail to converge, and no optimal results can be obtained. Furthermore, even if the nonlinear optimization converges, it may give unrealistic results, because it is solved iteratively. The unrealistic results can be recognized by comparing the node voltage magnitudes and PoC power flows with their limit ranges. The limit ranges are determined according to the actual situations. This paper suggests the limit ranges for the MV grids with low DG penetration in LV level, as shown in Table I.

In these two cases above, the operation activities cannot be performed until the next successful state estimation. The interruption duration of the operation activities depends on the measurement timescale. The selection of measurement timescale has been discussed in detail in [18].

### VI. Operation Activities

The results of the state estimation can be further used for the operation activities in MV grid. Depending on the practical situation, the operation activities can differ from region

...
to region. This paper takes three common operation activities as examples: voltage regulation, switching consequence assessment, and loss estimation.

A. Voltage Regulation

The goal of voltage regulation in MV grid is to keep the real-time voltage level $U_i$ at each PoC as close to the reference voltage level $U_{i,ref}$ as possible. This can be achieved by optimizing the tap-positions $\kappa$ of HV/MV and MV/MV transformers, defined in (29).

With the estimated real-time power flow at each PoC, the optimization turns to be the minimization of the weighted average voltage quality deviation $\Delta U$, defined in (30), which is essentially an integer programming problem. As a result, the optimal tap positions $\kappa$ can be found

$$\kappa = [\kappa_j], \quad 1 \leq j \leq N_T$$

(29)

where $\kappa_j$ tap position at $j$th HV/MV or MV/MV transformer, which is an integer and within the range $\kappa_{j,min} \leq \kappa_j \leq \kappa_{j,max}$;

$N_T$ total number of HV/MV or MV/MV transformers

$$\Delta U(\kappa) = \min \sqrt{\sum_{i=1}^{N_{PoC}} \eta_i (U_i(S_{est}, \kappa) - U_{i,ref})^2}$$

(30)

where $\Delta U$ weighted average voltage quality deviation; $\eta_i$ importance factor, representing the voltage control priority; $U_i(S_{est}, \kappa)$ resulted voltage level at PoC $i$, with respect to the estimated power flow and tap positions.

The paper defines two indices to evaluate the performance of voltage regulation: $\epsilon_U$ is the probability that the estimated optimal transformer tap positions achieve the real optimal tap positions; $\Delta U_{diff,max}$ is the maximum difference on $\Delta U$ between the result with estimated and real optimal tap positions.

B. Switching Consequence Assessment

If a component in the grid is out of service, the topology of the grid will be changed to keep the power supply to customers: some disconnectors will be closed and some will be opened. A switching activity might have two consequences: 1) it changes the power flow, and some component in the grid might be overloaded and 2) in case of closing a disconnector, the voltage difference across the disconnector before closing might be too high, which would damage the disconnector during the switching transient. Therefore, a switching consequence assessment is necessary to determine whether a switching activity is safe. With the real-time power flow $S_{est}$, following calculations can be done before a switching activity.

1) Execute power flow calculation for the topology status at every stage of the switching activity. Check the potential overloading of all the components in the grid.

2) Before closing a disconnector, calculate the voltage different across the disconnector. Check if it is safe to close.

To evaluate the performance of the assessment, the rate of risky assessment $\epsilon_{swt,risk}$ is defined as the conditional probability of the estimated maximum loading being lower than 90%, given that the real maximum loading is higher than 95%. In contrast, $\epsilon_{swt,conv}$ is defined as the rate of conservative assessment. Additionally, $U_{swt,err,max}$ is defined as the maximum estimation error on voltage difference across the disconnector to be closed.

C. Loss Estimation

For grid operators an accurate estimation of the losses in MV grid is important. With estimated voltage phasor $U_{est}$, the real-time power loss across a certain branch can be calculated as in (31). The total real-time loss in the grid is the sum of the losses of all the branches. For the performance of loss estimation, $P_{loss,err,avg}$ and $P_{loss,err,max}$ are defined as the average and maximum error of loss estimation in percentage

$$P_{k,loss,est} = \frac{|U_{ik,est} - U_{i,k,est}|^2}{Z_k R_k}$$

(31)

where $P_{k,loss,est}$ estimated real-time power loss for $k$th branch; $i_k, j_k$ two node numbers $k$th branch is connected with; $Z_k, R_k$ impedance and resistance of $k$th branch.

VII. PROBABILISTIC APPROACH TO DETERMINE THE MEASUREMENT PLACEMENT IN THE FIELD

In Section III, an initial measurement scheme is proposed, including all MV substations, all PoCs with large industrial loads or DGs, and one PoC with household loads and one with commercial loads. Adding more measured points in the field can improve the performance of the state estimator and the operation activities, but the investment is also increased. This section presents a probabilistic approach to determine the minimum necessary measurement scheme, which consists of minimal number of measured points, and is sufficient to satisfy the requirements for operation performance.

A. Monte Carlo Simulation

This paper uses the Monte Carlo method to evaluate the performance and robustness of the designed operation framework.
with a certain measurement scheme. The following random factors are considered: 1) grid topology; 2) loads and generations; 3) measurement errors; and 4) unavailability of measurement data.

Based on the probability distribution of these random factors, a large number of cases are generated. The number of simulation cases depends on the variances of all the uncertainties in the grid [19]. For each simulation case, the state estimation is executed, and the operation activities are simulated. The results of all the simulation cases are aggregated, and the overall results can be obtained for a certain measurement scheme, which can be used to analyze the measurement placement.

B. Measurement Placement

When optimizing the measurement placement, many studies [2]–[4] focused on reducing the estimation errors of node voltage magnitudes and angles, and suggested to install meters at the point with the maximum error variance of node voltage. However, the operation activities depend more on the branch voltages (voltage differences between nodes), which are usually very small in MV grids. Due to cancellation effects, even tiny errors of node voltages can lead to large errors of the branch voltages, which will deteriorate the operation results. Thus, high estimation accuracy on node voltages does not necessarily guarantee adequate operation results.

Considering the issue above, this paper sets the constraints to be that the requirements for operation activities should be satisfied, and aims to minimize the total necessary number of measured PoCs. The error variance of branch voltage phasor is used as the primary criterion to select the PoCs. Another important type of estimation results is the complex power flow at each PoC, which is essential for switching consequence assessment. Thus, the error variance of complex power flow is used as the secondary criterion. The selection process for the measurement scheme is shown in Fig. 5.

First of all, for the robustness of the operation, it is necessary that the failure rate of state estimation is low enough. In the paper a threshold of 0.5% is chosen. If the failure rate exceeds 0.5%, meters are installed at the unmeasured PoC with the most abnormal results. The process continues until the failure rate drops below 0.5%.

The second step is to meet the operation requirements with more measured points. Among the PoCs connected by the branches with top five error variances of branch voltage phasors, meters are installed at the unmeasured PoC with the largest error variance of complex power flow. The process continues until the requirements for operation results are met.

VIII. CASE STUDY ON SAMPLE GRID

A. Grid Configurations and Requirements

A typical European distribution grid shown in Fig. 6 is studied. The sample grid is downsized and anonymized from a real MV grid OS Zaltbommel, owned by Alliander, a Dutch distribution grid operator which operates around 1/3 of the MV grids in the Netherlands.

The paper attempts to find the minimum measurement scheme. The MV grid contains a 150/10 kV substation, a 10 kV regulating substation and a 10 kV switching substation. There are 74 MV PoCs, among which six PoCs are connected to industrial loads. The others are connected to household/commercial loads. The number of customers at each household/commercial PoC varies from 100 to 400. Three PoCs are connected with DGs. The load estimation is based on annual bill. The other grid parameters [17] are as follows:

1) \( \mu_m = 0.464 \text{ kW} \), \( \mu_{\text{max}} = 1.19 \text{ kW} \);
2) \( T_H = 1 \text{ h} \) for household, \( T_C = 2 \text{ h} \) for commercial;
3) \( \sigma_{H,\text{max}} = 0.7 \text{ kW} \), \( \sigma_{C,\text{max}} = 1 \text{ kW} \);
4) \( \lambda = 0.5039 \), \( \phi_I = 1.2075 \);
5) \( \tau_I = \tau_U = 0.01 \);
6) \( \rho_{C,S} = 0.005 \) – common components in substations;
7) \( \rho_{C,F} = 0.01 \) – common components in the field;
8) \( \rho_I = 0.005 \) – individual components.

The following requirements are set for voltage regulation, switching consequence assessment and loss estimation:

1) \( \epsilon_U > 95\% \), \( \Delta U_{\text{diff, max}} < 0.005 \text{ V} \);
2) \( \epsilon_{\text{swt,risk}} < 0.5\% \), \( \epsilon_{\text{swt,conv}} < 1\% \), \( U_{\text{swt,err,max}} < 10 \text{ V} \);
3) \( P_{\text{loss,avg}} < 0.5\% \), \( P_{\text{loss,err,max}} < 2\% \).

B. Selection Process

According to the rules, three PoCs with large industrial loads and two PoCs with large DGs are measured. In addition,
PoC 61 and 54 are measured with the largest relative load proportion factor for household and commercial loads. Initially seven PoCs are measured: 9, 11, 34, 49, 52, 54, and 61.

Monte Carlo simulations are executed for 1000 cases, and the failure rate of state estimation is 3%. Fig. 7 shows the seven PoCs are measured: 9, 11, 34, 49, 52, 54, and 61. PoC 67, and the process continues. After adding meters on five PoCs, the operation results are as follows:

1) $\epsilon_U = 95.5\%, \Delta U_{\text{diff, max}} = 0.0035\text{kV}$;
2) $\epsilon_{\text{swt, risk}} = 0\%, \epsilon_{\text{swt, conv}} = 0\%, U_{\text{swt, err, max}} = 7.93\text{V}$;
3) $P_{\text{loss, err, avg}} = 0.498\%, P_{\text{loss, err, max}} = 1.86\%$.

The operation requirements are met, and the final minimum measurement scheme contains 15 PoCs. Considering measurement errors and failures, load estimation errors, and algorithm divergence, the paper manages to meet the operation requirements with measuring 20% of all the PoCs.

C. Comparison With Current Operation Strategy

To demonstrate the improvements that the proposed new framework may gain, the operation results are compared with those based on the currently used operation strategy in Alliander.

For voltage regulation, the tap positions of the transformers are controlled by the automatic voltage regulator with line drop compensation. Only the total transformer current is taken into account. Moreover, there is no coordination between the main transformer and the regulating transformers.

For switching consequence assessment, grid operators rely on different types of the disconnector symbols in the grid schematics. As shown in Fig. 6, a single sided flag indicates a disconnector from the same transformer and is safe to close, while a double sided flag indicates a disconnector from different transformers and is risky to close.

For loss estimation, the annual total loss is calculated by subtracting the total received energy by the total delivered energy. In this way, the real-time loss cannot be calculated.

With the same grid conditions, the operation activities are simulated with the strategy above. The relevant operation results are as follows:

1) $\epsilon_U = 12.3\%, \Delta U_{\text{diff, max}} = 0.149\text{kV}$;
2) $\epsilon_{\text{swt, risk}} = 50\%, \epsilon_{\text{swt, conv}} = 37.97\%$

voltage difference across the disconnector is unavailable;
3) real-time loss is unavailable.

In qualitative aspects, some operation activities, e.g., real-time load estimation, cannot be performed due to insufficient data. In quantitative aspects, there are indubitable significant improvements of the operation results for the proposed framework over the currently used strategy.

IX. CONCLUSION

This paper presents a probabilistic approach for measurement placement optimization in MV grids and an operation framework based on the WLS state estimator. Distribution grid operators can use the framework as a guideline to design their operation strategy, as this paper addresses several important issues from practical situations.

Considering the cost allocation of measurement units, it is preferred to minimize the total number of measured points, instead of the total number of measured quantities, because the cost of common components is significant. Meanwhile, the unavailability of measurement data is crucial for the actual operation of MV grids, and needs to be taken into account. Besides the real measurements, two load estimation methods
are presented, and their error ranges are analyzed based on central limit theorem.

The widely used WLS state estimator is applied in this paper. In addition, the failure of state estimation is defined to exclude unrealistic results. Three common operation activities are discussed: 1) voltage regulation; 2) switching consequence assessment; and 3) loss estimation. Depending on different circumstances, other activities could also be integrated.

Because the voltage differences between nodes in MV grids are fairly small, it is arguably less appropriate to use the estimation error of node voltage as the constraint and/or the selection criterion for measurement placement. Instead, this paper chooses the estimation error of branch voltage phasor and PoC complex power flow as the selection criteria to determine the minimum necessary measurement scheme, which could satisfy the requirements for operation activities.

A case study on a typical European distribution grid demonstrates the feasibility of the optimization framework. A minimum measurement scheme with 20% of all the PoCs is found, which satisfies the operation requirements. Moreover, the comparison with the currently used strategy indicates the qualitative and quantitative advantages of the proposed framework.

As the sponsor of this research, Alliander is currently carrying out several DMS-related pilot projects, and is interested in implementing the core concepts of this framework. In future research more complex aspects will be considered, such as harmonic distortions and phasor measurements.

REFERENCES


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