Meter Placement for State Estimation in distribution network

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Abstract

With the increasing environmental concerns, the world is moving towards rapid decarbonization, and to meet the growing energy demand, more renewable energy sources like solar, Wind are getting added to the existing Distribution grid. The addition of new loads like Electric vehicles (EV), Heat pumps, etc. is putting additional pressure on the grid leading to some technical problems. Due to this, it is important to have real-time monitoring of the system by the Distribution System Operators(DSO)s which can be obtained by performing the State Estimation. The Distribution System State Estimation along with the state estimator has been discussed in the literature.

However, the accuracy of the state estimation is highly affected by the absence of real measurements from the meter and the presence of high-variance pseudo measurements. But due to the cost factor, it is practically not possible to install meters at every node. To reduce the state estimation error, a new meter placement strategy has been proposed in this project with the help of open-source software called Power Grid Model, devolved by the Dutch DSO Alliander for performing steady state analysis of the network.

The work presented in this project includes a sensitivity analysis of the proposed meter placement algorithm which is applied to a test MV distribution network in the Netherlands for the different sample sizes of the load profile as well as the standard deviation of the pseudo measurements. The application of the meter placement algorithm results in a subsequent reduction of the state estimation error. To find a suitable number of meters that can be placed in the network, three-meter placement criteria have been proposed and applied to the test network.

The results show the effectiveness of the proposed meter placement algorithm for the determination of a suitable path as well as the number of meters that can be placed in the distribution network. This is important for the grid operators as it will help them to make decisions for the proper maintenance and operation of the grid.

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1

Introduction

Over a few decades, there is an incentivized rapid decarbonization of electric power generation due to increasing environmental concerns like climate change, high concentrations of greenhouse gas, etc. To reduce carbon emission, the penetration of Distributed Energy Resources(DER) has increased and will continue its growth in the coming years [3]. In the Netherlands, 84% of the electricity demand is fulfilled by utilizing natural gas and coal combustion while the remaining part of the demand is supplied by the solar PV, wind turbines, etc.

The excessive combustion of fossil fuels is increasing the CO_2 concentration in the atmosphere[4]. To address this issue, the Dutch government announced a paradigm shift: an initiative to integrate more renewable energy sources into the grid to meet the rising demand for energy. It has been expected that by 2050, over 85 percent of total energy will be generated using renewable energy sources such as solar, wind, and green hydrogen[5] as shown in the figure 1.1.

But this transition of energy demands expansion of the existing power grid as the integration of large projects requires additional networks[6]. Moreover, the addition of Heat Pumps(HPs) and Electric Vehicles are increasing the stress on the power system grids causing over-voltage problems, power quality issues, and power loss. Due to this, the Dutch Distribution System Operators(DSOs) are facing various challenges in maintaining the stability and reliability of the grid[7].

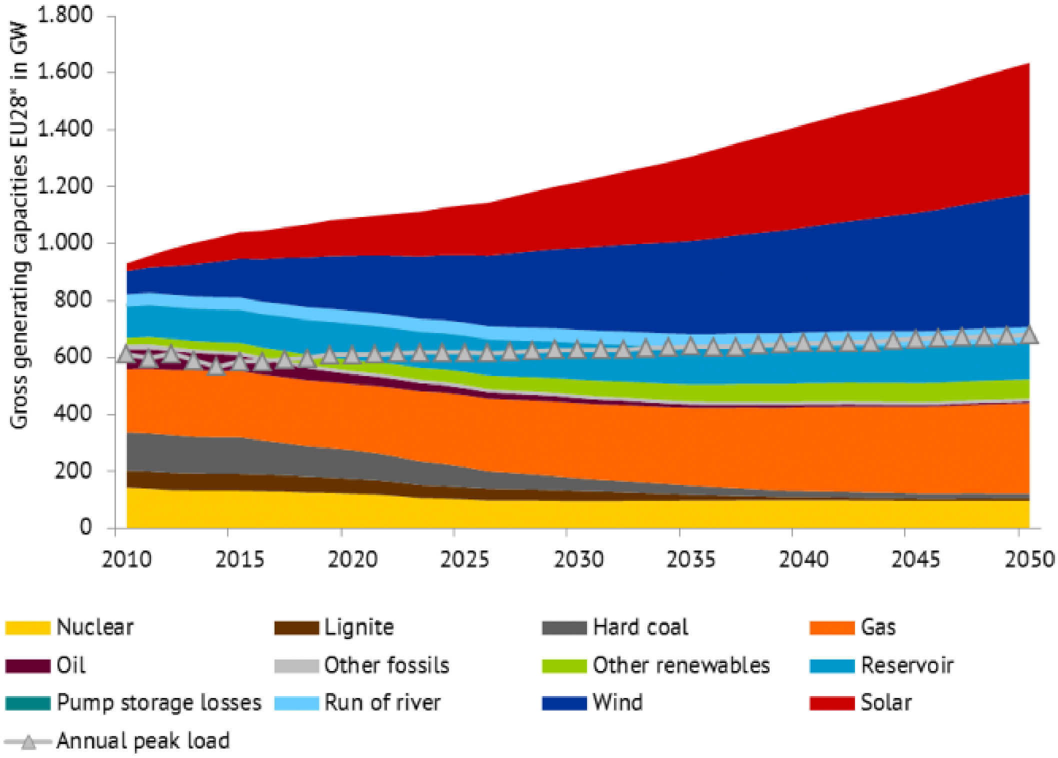

Figure 1.1: The Energy trend of Renewable Energy Sources[1]

1.1. Problem Definition

Future renewable energy integration in distribution systems is increasing with the growing demand for energy. A huge amount of PV, electric cars, Heat pumps, and penetration of RESs in the medium voltage grid, which is almost 40,000km long, is creating immense pressure on the grid leading to some technical problems like congestion, power loss, overvoltage, stability issues, etc. The main reason is the low inertia and the production of intermittent and variable power by the RES [8]. The congestion management of the network requires accurate ideas and awareness about the actual state of the network which can be obtained by State Estimation(SE).

State estimation is a digital processing scheme which is used for determining the real-time scenario of an electrical network by considering many central control and dispatch functions in a power system[9]. This is based on the mathematical relationships between the variables that represent the state of the system and the results of the system's measurements by removing inaccuracies and errors from measurement data. For a transmission system, it is quite easier to estimate the state compared to a distribution network. In a distribution system, the topology, operation, and number of measurement units are very limited compared to a transmission network where the real-time information of the line flows, voltage, etc. are readily available [10]. The EMS/supervisory control and data acquisition (SCADA) system is used to receive a standard set of measurements from the meters which are typically the bus voltage magnitude, branch flow, the angles of the network, etc. As compared to SCADA, Phasor Measurement Units (PMUs) are used intensively to get a synchronously controlled power system with high accuracy. They provide the measurements of the voltage phasors of a particular node and current phasors for all or some branches of the adjacent node with high accuracy[11]. Any inaccuracies in measured values can lead to measurement errors, resulting in incorrect estimation of the current state. So it is necessary to gather real-time measurements along with the pseudo-measurement at the substation.

Pseudo-measurements are the historical data of the loads which have high variance. Hence, the results of the state estimation will have low accuracy and cannot be used in the substation. It is thus important to include additional measuring units in the network for a higher accuracy [12]. But placing the meter at each and every node of a distribution network is practically impossible and also cost ineffective. So, it is important to use minimal measuring units in the network and get the maximum accuracy for the SE method with lesser error variance by employing a suitable meter placement strategy to obtain the optimal number, locations, and measurement intervals for the additional measurements.

1.2. Literature Review

In recent times, the pressure on the distribution network is increasing due to the expansion of the Distributed energy sources(DER) along with the volatility of the load. Because of this, it has undergone extensive infrastructural development to accommodate the new loads which are getting added. To maintain the operational efficiency of the network, efficient monitoring of the network is required. The precise knowledge of the states of the system can be obtained by using State estimation which is the heart of the Distributed Management System(DMS). However, obtaining higher accuracy in the SE is challenging due to the unavailability of the actual measurement of the network. In most cases, the observability of the system is achieved using pseudo measurements that have a high variance. In the transmission system, meters are placed to improve the observability of the network while in the distribution network, the network can be observable with the use of pseudo measurements, but the main goal is the reduce the error of the state estimation. The accuracy of the DSSE can be improved by placing meters in every node which is not an effective solution from an economic point of view. So it is important to investigate the way to achieve the optimal solution for the placement of the meters.

In the paper, [13], the meter placement has been formulated on the basis of optimal experimental approach(OED) using the M-optimality criteria which assures full observability and improved accuracy of SE. The main objective is to minimize the worst-case error variance occurring among all the states. A mixed integer semi-definite programming(MISDP) model is developed which optimally replaces the existing meters in the network with a more precise one. The concept of MISDP has also been used in the paper[14] to improve the DSE accuracy by minimizing the worst-case coordinate error variance of the estimated state by placing Distribution -level phasor measurement units(D-PMU) in the network. A circuit representation model based on the matrix formulation has been proposed in the paper [15] to represent the error of SE. The optimal meter placement has been converted from mixed integer nonlinear programming(MINLP) to a mixed integer linear programming(MILP) problem using the disjunctive model. The MILP formulation of [15] has been extended in this paper[16] so as to deal with the load volatility due to the Distributed Energy Resources(DER) in low observability of the distribution network. The impact of load volatility has been reduced by solving the meter placement problem by considering the uncertainty of multiple loads and different DER profile scenarios.

In another paper[17], to address the meter placement problem, the probabilistic method has been adopted based on Monte Carlo simulations. The relative errors in the voltage and angles have been reduced and kept below some predefined threshold, for 95% of the cases. Using the two-sided Chebyshev inequality, the meter placement problem is simplified by converting it into a probability-bound reduction problem. The proposed algorithm in [18] improves the method mentioned in the paper [17] by providing a smaller set of locations of the meters and also achieves the reduction of voltage and angle error with the same threshold value of 95%. Using stochastic optimization, the algorithm can solve the feasibility problem in the previous method and provide a solution with a possible improved probability threshold. Also, it considers the exact calculation of the relative error rather than the Chebychev approximation bounds. Furthermore, a probabilistic theory called the Ordinal Optimization(OO) used by this algorithm reduces computing work without compromising the effectiveness of the solution.

A stochastic meter placement algorithm has been developed in this paper [19] which mainly focuses on reducing the errors of the voltage magnitude while keeping the number of meters as minimum as possible. Other than the error reduction, the algorithm also focuses on improving the robustness of the state estimation. Here, the algorithm uses the scaling property of the singular values derived from a matrix's singular value decomposition to facilitate computation in a more efficient manner. The paper [20] focuses on placing the measurement units for increasing the observability of the Distribution Network and the

SE accuracy in the presence of DGs, Zero injection Buses(ZIBs), and tie-switches. An optimization problem has been formulated in order to minimize the marginal cost, which is solved using integer linear programming(ILP).

In this paper[21], a new method has been proposed that places the metering devices until it is possible to determine if the estimated parameters are within their constraints under normal operating conditions, or if a predefined minimum accuracy is achieved. The parameters which are within proximity or outside their constraints are monitored closely instead of those parameters which are not in proximity to their constraints. This method reduces the number of metering devices in the network while maintaining the SE accuracy.

In the previous methods, the author has considered comprehensive algorithms to address the meter placement problem. In this [22], the heuristic optimization technique is used for the optimal meter placement problem with the aim of obtaining a distribution system that is observable with established accuracy and minimum cost. A Distribution State Estimation algorithm is formulated where the input data are the pseudo measurements. But these measurements have errors which is giving an inaccurate SE. To overcome the change in load demand, uncertainty of the measurement devices, tolerances, etc, a Monte Carlo simulation is done. The author of [23] described a method of meter placement by sequentially eliminating the meters one after another until the constraint set for the quantity of interest is violated.

The existing methods focus on determining the optimal and sub-optimal placement of meters to improve the accuracy of SE when a fixed load profile or a Distributed Energy Resource(DER) is connected. But when the load profile changes randomly every time and also major loads are connected to the network, then it affects the placement of the meter thus affecting the SE accuracy. In this project, a heuristic meter placement algorithm is proposed which considers the effect of the load variability as well as the effect of the important load connected to a node and provides a suitable solution to the meter placement problem.

1.3. Objective

The Dutch DSO, Alliander is facing power quality and other grid-related issues due to the presence of limited measuring units in the medium voltage grid. The only measurement available for them is the current measurements which cannot provide the direction of power flow in the grid. So it is necessary to install enough measuring units in the network. But it's practically impossible to install them on every bus. So the objective of this project is to

investigate an approach for placing the meters in the existing grid considering the various placement locations. The placement of the meters should have the objective of minimizing the error variance of the neighboring nodal points.
As a part of the project, the questions that are needed to be answered are as follows:

- *How to place the meters in the existing Distribution Grid to reduce the error of the estimating state?*
- *What will be the nature of the error variance after performing State Estimation on the grid using a different number of load profiles?*
- *What will be a suitable location for placing the meter considering the deviation in the values obtained after performing the SE?*

1.4. Methodology

As a part of the project, Python programming language is used along with Alliander's in-house power system analysis algorithm called **Power Grid Model** which includes Linear Power Flow calculation and Linear Weighted Least Square(WLS) State Estimation.

- **Scope of the Thesis**

  The project's first and most important phase is to determine the research outcomes while keeping in mind the questions that will be investigated.

- **Literature Review**

  After determining the scope of the thesis, the Literature review is done to find the various meter placement strategies using the state estimation for the distribution network. This gives a clear idea of the concepts and helps to decide a possible solution for the problem.

- **Designing the Test bed**

  A certain grid is considered for the study and the corresponding equipment and topological information has been provided by Alliander. A time series data of the load profiles in the form of CSV of that area has been considered. To realize the data in a certain format, pivoting the received data frame has been done. Using the concept of Monte Carlo simulation, certain samples of load data have been extracted. These measurements are the real measurements of the network. Other than these, forecasted load profiles are considered which are the pseudo-measurements for each of the substations.

- **Implementation of the Algorithm**

  Power Grid Model which is the in-house algorithm of Alliander is used to perform the power flow analysis as well as the state estimation. The result of the load flow analysis provides the simulated state of the grid. The measurements obtained from the load flow analysis are further used for performing the State Estimation of the network by considering the sensors' error using Python scripting.

- **Sensitivity Analysis**

  The results obtained from the previous steps are further considered by creating various scenarios and the effects are studied to obtain a suitable result for the meter placement problem.

- **Conclusion**

  The obtained results are assessed in light of the stated study topics, and potential future directions are discussed.

1.5. Thesis Outline

Chapter 1 provides an introduction to the project. The background and the objective of the research have been described along with an approach to attain the desired result.

Chapter 2 describes the algorithm along with the mathematical formulation that has been used for the state estimator.

Chapter 3 describes the setup of the sample network along with different methodologies used for further analysis of the meter placement problem. The approach considered for determining the location of the meters in the network has also been explained in this chapter.

Chapter 4 discusses the various assumptions and considerations with a detailed analysis and explanation of the results of the different case studies along with the plots.

Chapter 5 has the important conclusions, limitations of the project, and recommendations for future research work.

2

State Estimation in the Distribution System

Energy demand is increasing due to rapid population growth, economic development, and technological innovation. The energy industry has seen massive growth in energy consumption since the early 1950s. This results in the current network being expanded, which increases its complexity. The idea of prosumers is emerging, where people are urged to install inexpensive renewable energy sources in their homes to meet the demand and reduce CO_2 emission. It can be concluded that the energy grid is getting vulnerable and need continuous observation and monitoring to keep it reliable. In addition to the High voltage (HV) Transmission grid, improvements must be made to the distribution network, which comprises the Medium voltage (MV) and Low voltage (LV) distribution grids as the new facilities and information directly influence them. So, the automatic operation of the LV and MV grid is required which can be achieved by improving the Distributed Management system **(DMS)** with digitalized grid schematic and advanced measurement infrastructure.

The DMS can be made more effective by improving the state estimator as it provides the steady state condition of the grid based on the available measurements. But in a distribution system, the amount of measuring units is less compared to the nodes. So it is neither practical nor economically justified to have a power system with measuring units/meters at each and every node. Thus, to have real-time monitoring of the system, Distribution System State Estimation **(DSSE)** is performed that yields a set of state variables to provide the state of the system. Moreover, due to the lack of real measurements in the system, pseudo-measurements are used which are necessary for the convergence of the SE algorithm [24]. But due to the high variance in the value of the pseudo-measurements, the accuracy of a few of the State Estimators like Weighted Least Square **(WLS)** is affected and can provide uncertainties in the DSSE calculation [25]. The potential applications of the DSSE in the control and management of a distribution network are shown in 2.1.

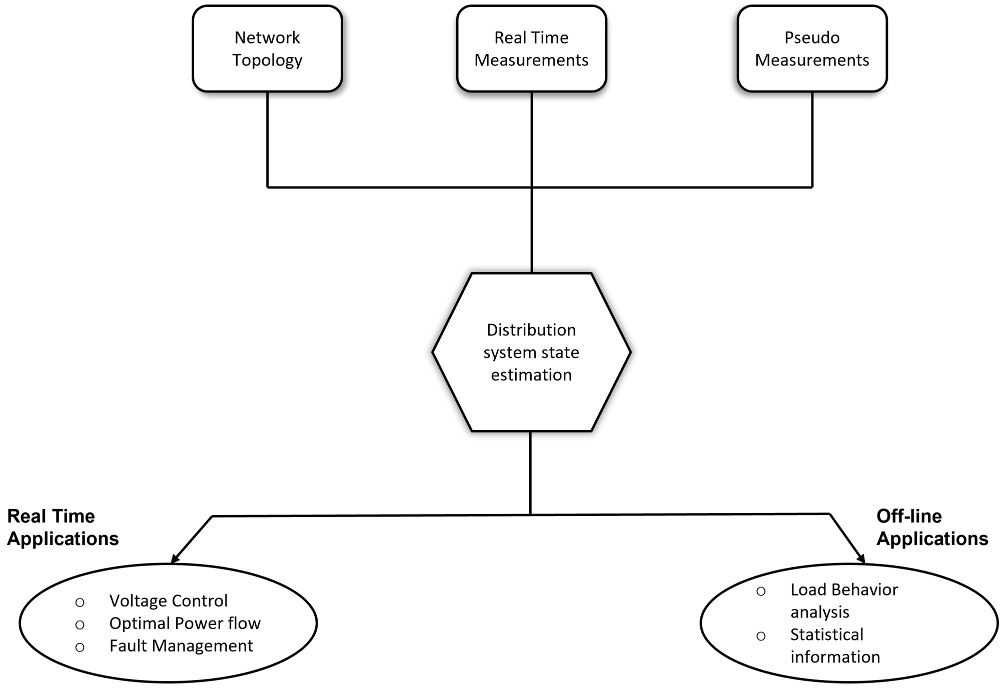

Figure 2.1: Application Of DSSE

In this Chapter, the factors affecting the Distribution System State Estimation (DSSE) is discussed followed by one of the commonly used DSSE algorithm - Weighted Least Square **(WLS)** method.

2.1. Distribution System State Estimation(DSSE)

SE was introduced by Fred Schweppe, who defined the vectors of voltage magnitude and phase angles at buses as the state of the network. For many years, SE has been applied in Transmission systems, but it's challenging to use the same concept on the Distribution Network [26]. A few of the reasons which affect the SE in the distribution system are explained below:

- ***Low X/R ratio*** **:** In the Distribution network, the ratio of *X/R* is quite low and sometimes becomes unity due to the physical characteristics of the lines. Due to this, the simplification of SE in the transmission system becomes impossible to apply in the distribution system [27].

- ***Unavailability of Measuring devices*** **:** The distribution system is highly unobservable compared to the transmission system as the number of measuring devices is very small compared to the huge size of the distribution network. For estimation, pseudo-measurements are used but due to the lack of redundancy, it compromises the robustness of the estimator [28].

- ***Unbalanced Operation* :** The distribution network is getting unbalanced due to the high penetration of Distributed generators(DGs) in the system. Due to this, there is a widespread of non-symmetrical loads. So the estimator for this network is developed based on the three-phase model as the single-phase equivalent scheme cannot be applied for system analysis.

- ***Radial and Weakly Meshed Topology* :** A typical distribution network follows a radial or a meshed topology and because of this, the branch current can be considered as a state variable. So there is a high possibility to formulate a linear state estimation problem based on the current magnitude and power measurements[29].

2.2. DSSE techniques

Based on the temporal evolution of the measurements, state variables, and the type of loads, the DSSE can be broadly classified into two categories - Static DSSE and Dynamic DSSE.

2.2.1. Static DSSE

A static state of a system can be defined by a set of phasors representing the magnitude of the voltage and angles at all the buses. In a static SE, the system's performance is monitored under normal conditions, when the system is in a quasi-steady state and responding to gradually changing network load and generation[30]. Different estimators such as Weighted Least Square (WLS), Weighted Least Absolute Value(WLAV), and Schweppe Huber Generalized M (SHGM), are used to reduce the residual vector which is the error vector. The WLS estimator reduces the weighted sum of the square of the residuals. A more detailed explanation is provided in the later part of the chapter. The WLAV method is considered to be more robust than the WLS method in terms of handling bad data. The estimator fails to handle the bad data when leverage measurements are present in the system. Because of their location, measurements that have a disproportionately large impact on state estimate are known as leverage measurements[31]. The vulnerability of the leverage measurement can be handled by using the Schweppe Huber Generalized M(SHGM) estimator.

2.2.2. Dynamic DSSE

With the increasing penetration of the DERs, complex load, and new demand response, the power system is getting dynamic in nature. For example, the intermittent changes in the

DERs will cause a sudden increase in the voltage phasor which will cause a change in the generator variables. Due to this, the concept used for Static SE (SSE) becomes questionable, as it is unable to capture these dynamics of the system. One of the reasons is the use of SCADA instead of PMU. As a result, it's important to reassess the SSE concepts by improving and enhancing the monitoring tools. [32].
To capture the dynamic nature and to get the status of the network, Dynamic State Estimation is introduced, a recursive estimation method, which considers the state of the network based on the time and tracks the system under normal operation. This technique is also called Forecasting-Aided SE (FASE) as this approach comes with a forecasting component by default, which can assist in providing the system with monitoring that is almost real-time. 2.2 shows the steps involved in the DSE method.

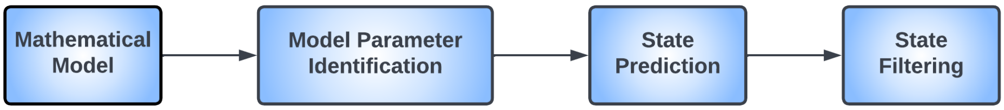

Figure 2.2: Steps involved in DSE [2]

As a part of this project, the Static SE has been assumed and chosen instead of the Dynamic SE. The state estimator used here is an in-house algorithm of Alliander, known as the **Power Grid Model**, which has been developed using the concept of the Linear WLS method. In the preceding sections, the Linear WLS method has been explained followed by the conventional method of SE i.e. Weighted Least Square(WLS) method.

2.3. Linear Weighted Least Square Estimator

SE techniques are used in the distribution system to have knowledge of the current state of the network based on a set of measurements. The measurements obtained from the grid have inaccuracies due to meter errors. SE can be expressed by the following measurement model:

$$\mathbf{z} = \mathbf{h}(\mathbf{x}) + \mathbf{e} \tag{2.1}$$

where
$\boldsymbol{z}$ is the vector of the available measurements(can be virtual, real and pseudo)
$\boldsymbol{h}$ is the vector of the different non-linear measurement functions like power, voltage, and current measurements
$\boldsymbol{x}$ is defined as the state variables vector of the system
$\boldsymbol{e}$ is the measurement error vector.

The measurement vector **z** is linearly related to the vector **X** representing the state variables $n = 2N - 1$, N representing the N-bus network. The relationship between the state variables and measurements can be represented by a linear equation:

$$\mathbf{z} = \mathbf{HX} + \mathbf{e} \tag{2.2}$$

2.3.1. Linearization of the Physical Measurements

In a Linear WLS, it is important that the measurements used are linear in nature which is only possible if all the measurements are from the PMUs. So the measurements which are traditionally obtained from the Relay, CT and PT, etc. are needed to be linearized before using them for the linear WLS. The possible measurements are the bus voltages, and shunt/branch power flows which have been explained in the following subsections.

Bus Voltage

The linear WLS requires the voltage phasor to incorporate the phase angle. The angle shift is assumed to be zero plus the intrinsic phase shift of transformers as there is a relatively small phase shift in the distribution grid. The voltage magnitude of the bus considering the voltage phasor is given below:

$$\underline{U}_i = U_i \cdot e^{j\theta_i} \tag{2.3}$$

where
i is referred to the bus.
θ_i is the intrinsic transformer phase shift between the reference bus and bus i.

Shunt/Branch Power Flow

Complex current phasors are needed for the linear WLS. To do this translation, the voltage at the terminal should also be measured; alternatively, a rough estimate can be made using the nominal voltage with zero angles. The current phasor equation with the measured voltage phasor is shown in the below equation:

$$\underline{I} = (\underline{S}/\underline{U})^* \tag{2.4}$$

where
$\underline{\text{U}}$ is either the measured voltage magnitude at the bus or assumed unity magnitude, with the intrinsic phase shift.

The above Equation 2.4 is applicable for Bus Power Injection where the nominal voltage with zero angles can be used as an estimation when the bus voltage is not measured.

2.3.2. Modelling of the measurement vectors

In a SE algorithm, the measurement vector **z** is expressed by the Equation 2.1. Given an M number of measurements in the grid, the measurement vector can be defined by :

$$\mathbf{z} = \begin{bmatrix} z_1 \\ \vdots \\ z_M \end{bmatrix} \tag{2.5}$$

The measurement error vector e is assumed to be a Gaussian noise with zero mean and is independent. It is represented by the following equation:

$$e = \boldsymbol{N}(0, \boldsymbol{R}_{\mathrm{z}}) \tag{2.6}$$

where $\boldsymbol{R}_{\mathrm{z}}$ represents the measurement covariance matrix as shown below:

$$\mathbf{R}_z = \operatorname{diag}\left(\sigma_1^2, \ldots, \sigma_M^2\right) \tag{2.7}$$

where σ_i is the standard deviation of the measurement error of the i-th measurement which is calculated to check the accuracy of the meter used.

2.3.3. Linear WLS state estimation problem

WLS State estimation algorithm uses the concept of Maximum Likelihood Function (MLE) which minimizes the likelihood by minimizing the objective function:

$$J(x) = \sum_{i=1}^{M} \frac{(z_i - h_i(x))^2}{R_{ii}} = [z - h(x)]^T R^{-1} [z - h(x)] \tag{2.8}$$

where R^{-1} is equivalent to the weighing factor matrix **W** as shown by the Equation 2.9.

$$\mathbf{W} = \boldsymbol{R}^{-1} = \begin{bmatrix} w_1 & 0 & \cdots & 0 \\ 0 & w_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_M \end{bmatrix} \tag{2.9}$$

In a linear WLS, the state variables and the measurements are related to each other linearly. A function **HX** is defined which represents the linear relation between the state variable to the real measurements as shown previously in section 3.1. The Equation 2.8 can be rewritten in the following form:

$$J(x) = [z - HX]^T W [z - HX] \tag{2.10}$$

where **F** is the $M \times B$ matrix representing the real measurements.

The analytical solution can be defined by a linear equation as shown below:

$$(H^T W H)X = G_l X = H^T W z \tag{2.11}$$

where $G_l = H^T$WH is the full gain matrix.

The above Equation 2.11 has few constraints due to which it is difficult to solve the equation. Firstly, due to the infinite weighing factor of the zero injection constraints, they are not strictly satisfied. Secondly, the matrix becomes less sparse than the node admittance matrix due to the injection of current/power measurements in the secondary neighbors of the gain matrix. To resolve this issues, **H**, **R**, **W** and **z** are divided into two categories:

$$\mathbf{H} = \begin{bmatrix} H_\mathrm{b} \\ H_\mathrm{c} \end{bmatrix}, \quad R = \begin{bmatrix} \boldsymbol{R}_\mathrm{b} & 0 \\ 0 & \boldsymbol{R}_\mathrm{c} \end{bmatrix}, \quad \mathbf{W} = \begin{bmatrix} \mathbf{W}_\mathrm{b} & 0 \\ 0 & \mathbf{W}_\mathrm{c} \end{bmatrix}, \quad \boldsymbol{z} = \begin{bmatrix} z_\mathrm{b} \\ z_\mathrm{c} \end{bmatrix} \tag{2.12}$$

where
H_b, R_b, W_b and z_b are the bus voltage and current/power measurements.
H_c, R_c, W_c and z_c are the bus injection voltage and current/power injection measurements.

The Equation 2.11 can be rewritten in the following augmented form:

$$\begin{bmatrix} \mathbf{H}_\mathrm{b}^T \mathbf{W}_\mathrm{b} \mathbf{H}_\mathrm{b} & \mathbf{H}_\mathrm{c}^T \\ \mathbf{H}_\mathrm{c} & -R_\mathrm{c} \end{bmatrix} \begin{bmatrix} \boldsymbol{U} \\ \Phi \end{bmatrix} = \begin{bmatrix} \mathbf{H}_\mathrm{b}^T \mathbf{W}_\mathrm{b} \boldsymbol{z}_\mathrm{b} \\ \boldsymbol{z}_\mathrm{c} \end{bmatrix} \tag{2.13}$$

where Φ is a $B \times 1$ vector of artificial unknowns:

$$\Phi = \begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \vdots \\ \varphi_{N_\mathrm{b}} \end{bmatrix} \tag{2.14}$$

2.4. Iterative Linear WLS

The iterative approach of the Linear WLS is done to remove the errors which get into the algorithm during the linearization of the physical measurements, described in section 2.3.1, due to the ignorance of the phase shifts of the bus voltages. Two steps are followed in this process which includes the initialization followed by the iteration process[33].

2.4.1. Initialization

Let $U^{(k)}$ be the column vector of the voltage phasor in the *k-th* iteration, s be the slack bus, connected to the external grid. $U^{(0)}$ is initialized in the following ways:

- For Bus i, with no voltage measurement, assign $U_i^0 = e^{j\theta_i}$, where θ_i is the intrinsic transformer phase shift between the reference bus s and bus i.

- For Bus i, with voltage measurement, assign $U_i^0 = U_{meas,i}e^{j\theta_i}$, where $U_{meas,i}$ is the measured voltage.

2.4.2. Iteration Process

In the *k-th* iteration step, the below steps are followed:

1. The voltage measurements are linearized, using the phase angle of the *k-1 th* iterated voltage i.e. $U_{meas,i} = U_{meas,i} \times U_i^{(k-1)} / |U_i^{(k-1)}|$.

2. Complex power flow measurements are linearized by using either linearized voltage measurement or the voltage phasor of the *k-1*th iteration value.

3. Using the pre-factorized matrix, a temporary voltage phasor $\widetilde{\boldsymbol{U}}^{(k)}$ is calculated.

4. The angle of the voltage phasor is normalized by considering the angle of the slack bus as Zero which is shown by the following equation: $U_i^{(k)} = \widetilde{U}_i^{(k)} \times |\widetilde{U}_s^{(k)}| / \widetilde{U}_s^{(k)}$

5. Stop the iteration if the maximum deviation between the $\boldsymbol{U}^{(k)}$ and $\boldsymbol{U}^{(k-1)}$ is smaller than the tolerance, or else, continue until the maximum iterations are reached.

2.5. Weighted Least Square Estimator

The Weighted Least Square method is used when there is heteroscedasticity in the errors, i.e. when the variance in the errors is non-constant. In a power system, the state estimator considers a set of redundant measurements along with the state variables obtained from certain assumptions and information[34]. The WLS estimator reduces the weighted sum of the squares of the measurement errors which is basically the difference between the actual and estimated state. The Equation 2.1 explains the measurement mode of a WLS State estimation.

2.5.1. State Variables

For a grid with **N**-buses, the column vector of the state variables could be defined as:

$$\boldsymbol{U} = \begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ U_N \end{bmatrix} \tag{2.15}$$

where U_i is the complex voltage phasor of i-th bus.

2.5.2. Branch Flow Equations

In Figure 2.3, the flow of current from one side of the branch to the other side has been shown by considering a transformer model. The two bus sides of the transformer are the tap side and the impedance side which have been denoted as i and j respectively. The

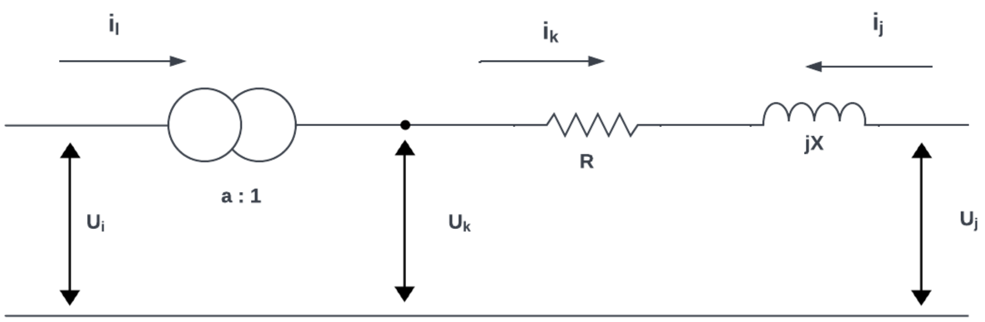

Figure 2.3: Model of a Transformer

current flowing through the branches is calculated using the branch admittance as shown below:

$$\begin{bmatrix} I_\mathrm{k} \\ I_\mathrm{j} \end{bmatrix} = \begin{bmatrix} Y_\mathrm{kk} & Y_\mathrm{kj} \\ Y_\mathrm{jk} & Y_\mathrm{jj} \end{bmatrix} \begin{bmatrix} U_\mathrm{k} \\ U_\mathrm{j} \end{bmatrix} \tag{2.16}$$

where

I_k and I_j are the current injections at k and j side of the branch
U_i and U_i are the voltage at the point k and j
Y_{kk}, Y_{jj}, Y_{jk} and Y_{kj} are the admittance of the branch k-j.

2.5.3. Shunt Injection Flow Equations

A network is considered where one side of the shunt is connected to a bus and the other side is grounded. Using the shunt admittance, the current flowing through the node can be calculated. The negative sign denotes the direction of the injection of current.

$$I_s = -Y_s U_s \tag{2.17}$$

where

I_s is the current flowing through the Shunt to the node

Y_s is the Shunt admittance

U_s is the voltage of the bus connected to the Shunt

2.5.4. Admittance Matrix

A $N_b \times N_b$ bus admittance matrix can be modeled using the concept of Kirchhoff's current law at each and every node. The matrix represents the relation between the injected current and the bus voltage as shown below:

$$\mathbf{Y}_\mathrm{n} = \begin{bmatrix} Y_{\mathrm{n},11} & Y_{\mathrm{n},12} & \cdots & Y_{\mathrm{n},1N_\mathrm{b}} \\ Y_{\mathrm{n},21} & Y_{\mathrm{n},22} & \cdots & Y_{\mathrm{n},2N_\mathrm{b}} \\ \vdots & \vdots & \ddots & \vdots \\ Y_{\mathrm{n},N_\mathrm{b}1} & Y_{\mathrm{n},N_\mathrm{b}2} & \cdots & Y_{\mathrm{n},N_\mathrm{b}N_\mathrm{b}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{Y}_{\mathrm{n},1} \\ \boldsymbol{Y}_{\mathrm{n},2} \\ \vdots \\ \boldsymbol{Y}_{\mathrm{n},N_\mathrm{b}} \end{bmatrix} \tag{2.18}$$

$$I = \begin{bmatrix} I_1 \\ I_2 \\ \vdots \\ I_\mathrm{b} \end{bmatrix} = \begin{bmatrix} Y_{\mathrm{n},11} & Y_{\mathrm{n},12} & \cdots & Y_{\mathrm{n},1N_\mathrm{b}} \\ Y_{\mathrm{n},21} & Y_{\mathrm{n},22} & \cdots & Y_{\mathrm{n},2N_\mathrm{b}} \\ \vdots & \vdots & \vdots & \vdots \\ Y_{\mathrm{n},N_\mathrm{b}1} & Y_{\mathrm{n},N_\mathrm{b}2} & \cdots & Y_{\mathrm{n},N_\mathrm{b}N_\mathrm{b}} \end{bmatrix} \begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ U_{\mathrm{n},N_\mathrm{b}} \end{bmatrix} = Y \cdot U \tag{2.19}$$

where **I** is the bus injection current.

Some of the properties of this matrix are as follows:

- It is a sparse matrix. Elements other than the diagonal elements and the off-diagonal elements where the buses are directly connected are zero.
- Structurally symmetric and complex.

2.5.5. Measurement Functions

In a SE, the estimator considers the active and reactive power in the lines, bus voltages, and line currents as the measurements in a power system. These measurements can be expressed using the state variables i.e. the bus voltage and the phase angles in a non-linear function. The active and reactive power injection in *i-th* bus is shown by the following equations:

$$P_i = |V_i| \sum_{j=1}^{N} \left|V_j\right| \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}\right)$$
$$Q_i = |V_i| \sum_{j=1}^{N} \left|V_j\right| \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}\right)$$

where G_{ij} and B_{ij} are the real and imaginary parts of the bus admittance matrix. The real and reactive power flow between the bus i and j are shown below:

$$P_{ij} = |V_i|^2 \left(g_{si} + g_{ij}\right) - |V_i| \left|V_j\right| \left(g_{ij} \cos\theta_{ij} + b_{ij} \sin\theta_j\right)$$
$$Q_{ij} = -|V_i|^2 \left(b_{si} + b_{ij}\right) - |V_i| \left|V_j\right| \left(g_{ij} \sin\theta_{ij} - b_{ij} \cos\theta_{ij}\right)$$

where
g_{ij} and b_{ij} are the real and imaginary parts of series branch admittance.
g_{si} and b_{si} are the real and imaginary parts of the shunt branch admittance.

These equations can be linearized by calculating the Jacobian matrix of the vector *h(x)*, which can be obtained by neglecting the second-order derivative of the measurement function with respect to the state variables, as shown below:

$$\mathrm{H} = \begin{bmatrix} \frac{\partial h_1(x)}{\partial \theta_2} \cdots & \frac{\partial h_1(x)}{\partial \theta_n} & \frac{\partial h_1(x)}{\partial V_1} \cdots & \frac{\partial h_1(x)}{\partial V_n} \\ \vdots & & & \\ \frac{\partial h_m(x)}{\partial \theta_2} \cdots & \frac{\partial h_m(x)}{\partial \theta_n} & \frac{\partial h_m(x)}{\partial V_1} \cdots & \frac{\partial h_m(x)}{\partial V_n} \end{bmatrix} \tag{2.20}$$

2.6. Observability of the network

State estimation can only be performed on a fully observable network. Due to the lack of real measurements in the system, pseudo-measurements are assigned based on the forecasted loads, generation schedules, etc. which play a critical role in making the system fully observable. For a system, to be observable, the Jacobian matrix **H** should have a full rank. Also, the number of independent measurements **m** should be greater or equal to the number of system states *n = 2N -1*.

3

Network setup and Measurement system

This chapter describes the different methodologies used in this project to find the sub-optimal path for the meter placement.

3.1. Power Grid Model

Power Grid Model is an open-source software developed by the Dutch DSO Alliander N.V for performing steady-state analysis of the distribution system. It is a Python-based library with a C++ core, which enables it to be cross-platform compatible and able to be used in larger computer systems. Other open-source libraries like panda power, and Matpower lack these capabilities. Even the DIgSILENT Powerfactory has restrictions when it comes to any custom modification and availability to users due to the lack of licenses. A comparison between the Power Grid model and panda power has shown a performance difference from 5x to 100x based on the type of calculation and the chosen network. The PGM has an argument called threading which can be used to perform parallel processing of the data. [35].

Power Grid model uses NumPy array format for inputting the grid data and converting it to a C++ data structure. The grid topology in C++ has been modeled using the boost library of C++. The PGM library doesn't store all the common parts of a network, instead, it has a base for implementing all the methodologies. For example, it stores the admittance matrix in the form of some linked elements rather than in a full matrix format. While performing a power flow analysis, the grid topology gets created from the lines and transformers, and from the buses which are denoted as edges and nodes respectively. The parameters for the line and transformers are inputted as physical quantities which in the later phase get converted into an admittance for the buses by linking it to the grid topology. This process saves storage space as well as computational complexities concerning the sparsity of matrices.

The PGM can perform symmetric as well as asymmetric power flow analysis and state estimation calculations on time series data or a single snapshot of the load data. For power flow analysis, the traditional Newton-Raphson algorithm or the linear method is used while the State Estimation has used the linear method with the Weighted Least Square Algorithm. In the linear method, all the loads have been modeled as a constant impedance instead of constant power to eliminate the iterative process and to improve the performance further. A typical network in the Power Grid Model **(PGM)** can be modeled using the following 14 components: Node, Line, Link, Transformer, Load (Symmetric and Asymmetric), Generator (Symmetric and Asymmetric), Source, Shunt. For State Estimation, symmetrical and asymmetrical voltage and power sensors are used.

Even though these functions have already been well implemented, their effectiveness for a large distribution network was insufficient. Alliander is driven to find a solution to the performance problem so that it can be applied to its business operations.

3.2. Power Flow Analysis

Power Flow analysis (PFA) is done to determine the steady-state operating characteristics of a network by calculating the voltage (magnitude and angle) of the nodes under certain loading criteria and network conditions. In the initial stage of the project, power flow analysis is required to determine the true state of the given network.

Figure 3.1, shows the steps followed before running the power flow which has been explained further. The *topology.json* and *equipment.json* files as well as the load profile will be the input parameters for the PFA which will be done using the PGM software.

Topology and Equipment

The two JSON files have to be converted into PGM format in the form of NumPy arrays. The conversion of the files from **CIM** format to **PGM** format has been done using a conversion tool of Alliander, called as CimPgmConverter from the 'Power Grid Model Conversions' library. The tool first loads the two .json files using 'CimDataLoader' and then converts the file into a NumPy array using CimPgmConverter, which can be further used as input to the PGM application.

Load

The data frame consisting of the yearly load profiles has to be pivoted to achieve the required PGM format. The pythonic function *pd.melt* is used to unpivot the data frame from wide to long based on the identifier variables. Later the function *pd.pivot_table* is used to get the final desired format of the data frame. Both the functions are from the *pandas* li-

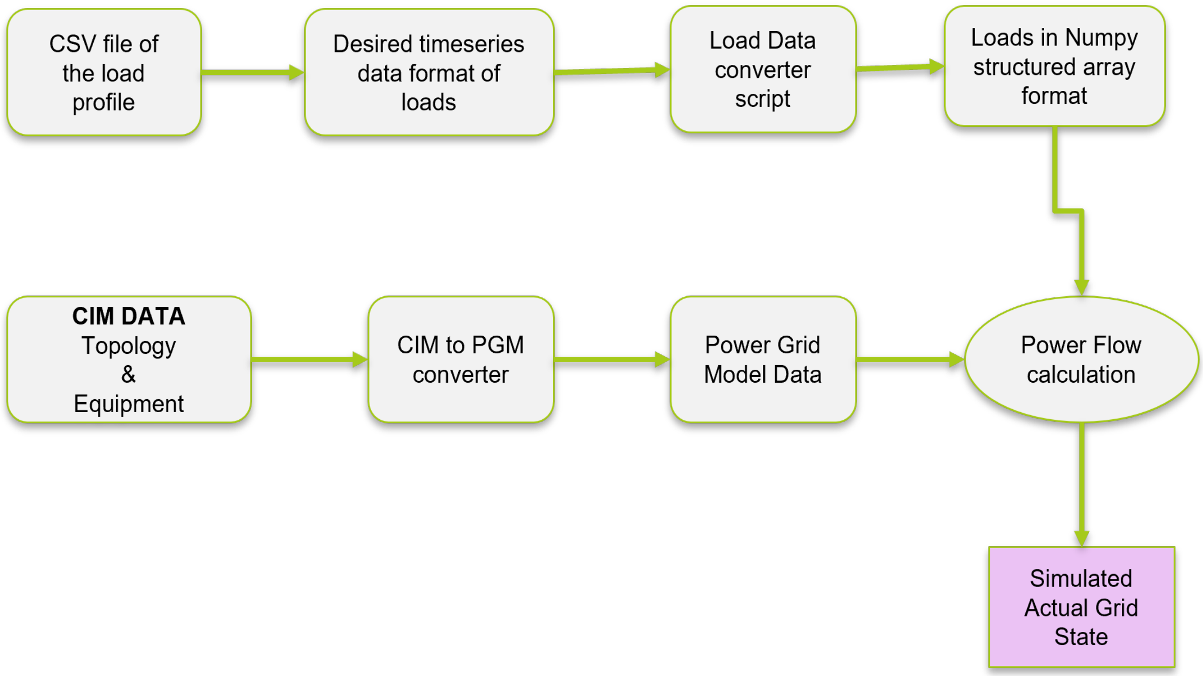

Figure 3.1: Steps for attaining the desired format for Power Flow Analysis

brary.

Before running the power flow analysis(PFA) using the PGM application, it's important to create a connection between the two files: topology, and equipment, so that the correct topology for the substation can be fetched based on the MSR ids. The term **MSR** is called ***middenspanningsruimte*** in Dutch which means secondary substation in English. Based on the MSR-id, the corresponding Id has been fetched from the equipment.json file which relates to the corresponding id value in the topology.json and fetches the correct topological information of the substation. The information of the nodes where the loads have to be connected has also been obtained by comparing the id from the topology.json with a lookup table which holds all the information of the nodes on which the assets/components of the network are connected. Accordingly, the load profiles for the MSR ids are connected to the corresponding nodes and have been added to the input file along with the equipment and topology details. This information serves as input for the Power Flow Analysis which has been done using the Power Grid Model Algorithm.

As described in the previous section 3.1, the PGM can perform Power flow analysis for a single snapshot of the load data and for a time series of data. A randomly selected load profile is used as an input for the 'Batch calculation' where the PGM algorithm runs the power flow for different values of the load while internally keeping the original model of the program constant. The output of the Power Flow Analysis provides the true state of the system by calculating the bus voltage (magnitude and the phase angle), active and reactive power (for both sides of the lines), line current, and the power of the slack bus. These network values are the true measurement values that have been used further in the State Estimation Algorithm.

3.2.1. Simulated Actual Measurement

For the Power Flow Analysis, a loading scenario is created by random sampling of the yearly load profiles. The result of the power flow provides information on the branch flow and bus voltage (magnitude and angle) of the entire network. The actual system state variables are also obtained from the power flow i.e voltage magnitude($\mathbf{V}_{mag,true}$) and phase angle($\mathbf{V}_{angle,true}$). The above process of creating the actual measurements is explained by a flowchart in figure 3.2.

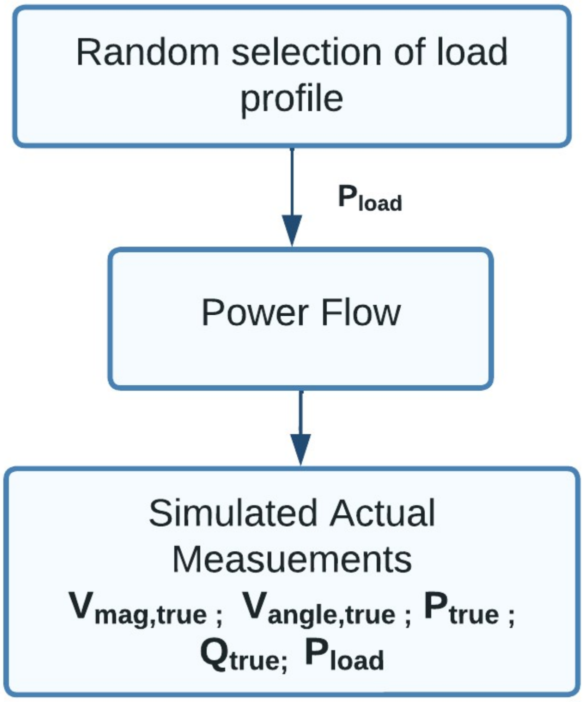

Figure 3.2: Flow chart for creating the simulated actual measurements

3.2.2. Simulated Real-Time Measurements

The measurements which can be obtained from the meters placed on the buses, lines, loads, and other components available on the electrical network are termed as Real measurements. The meter readings are telemetered as real-time measurements to the central control unit. But these meter readings are never perfect as they always contain small measurement errors due to meter inaccuracies, the effect of analog to digital conversion, communication errors due to packet loss, etc. The real measurement can be modeled by adding independent Gaussian distributed error to the actual measurement obtained from the power flow[36]. Let Z_{true} be the vector that denotes the actual measurement with no errors, then the real measurement can be denoted by the below equation:

$$\boldsymbol{Z_{real} = Z_{true} + N(0,\sigma)} \tag{3.1}$$

where $\boldsymbol{Z_{real}}$ is the real measurement vector and $\boldsymbol{\sigma}$ is the standard deviation of the measurement.

3.2.3. Simulated Pseudo Measurements

Not all buses have meters, which is why to have a functioning state estimator, pseudo-measurements need to be added. Pseudo-measurements are used in the state estimation to make the power system observable. When the real measurements are not available, based on historical data or short-term load forecasts, the pseudo-measurements are predicted to improve the measurement redundancy in a poorly monitored network. The pseudo measurements can be calculated based on either the scheduled generation at the generator buses or by forecasting the load at the load buses and thus have a quite high variance as compared to that of the real measurements. In this project, pseudo measurements are calculated by adding a Gaussian distributed error based on the standard deviation values of the forecasted load, to the actual measurement values from the power flow. The pseudo measurement $\boldsymbol{Z}_{pseudo}$ can be modeled as:

$$\boldsymbol{Z_{pseudo} = Z_{true} + N(0,\sigma_{forecast})} \tag{3.2}$$

where $\boldsymbol{Z_{pseudo}}$ is the pseudo measurement while $\boldsymbol{\sigma_{forecast}}$ is the standard deviation that has been determined from the forecasted data.

3.3. State Estimation

The output of the Power Flow Analysis provided the true state of the given network as described in the previous section section 3.2. The result is further used as input for performing the State estimation of the network. Two types of sensors are used as measuring units: voltage sensors and power sensors. The sensors are used as a way to provide measurement data available for the state estimation algorithm.

3.3.1. Voltage Sensor

Voltage sensors are typically used to measure AC/ DC voltage levels in a distribution network. It measures the magnitude of the voltage as well as the phase angle of the voltage at a particular node. The standard deviation of the voltage sensor is measured by considering the measurement features of a real meter which fulfills the IEC 61557-12 standards. The absolute error is calculated from the percentage error and the measuring range of the meter which is 280V by the following equation:

$$E_{abs} = E_{perc} * v \tag{3.3}$$

where v refers to the measuring range of the voltage sensor.
It is assumed that the measurement error follows a Gaussian distribution and considering the 99.73% of the confidence interval, the standard deviation is determined by the Equation 3.4.

$$\sigma = \frac{E_{abs}}{3} \tag{3.4}$$

3.3.2. Power Sensor

Power sensors are used to measure the active and reactive power flow through a terminal. It can be either a connection between a node and equipment or a node to a branch. The standard deviation for the power sensor is calculated by using the previously mentioned equations i.e Equation 3.3 and Equation 3.4. The only exception is in the value of the percentage error considered in this case.

As a part of the project, power sensors are connected to all the loads available and also to one of the lines in the given network. The input data for the power sensors have been modeled in the form of a NumPy array as it is the only format for the Power Grid Model algorithm. The variables **'p_measured'** and **'q_measured'** have been considered as the actual value of the active and reactive power respectively from the power flow output. Since the meters always have a certain error associated with them, so to consider that error in the calculation, artificial measurement errors are added to the power values. A detailed description of the process has been provided in subsection 3.2.2. Similarly, when a forecasted load is considered, due to the unavailability of the meters at that node, pseudo measurements are considered by adding an artificial forecasting error which is described in Equation 3.5. For the line, the required parameters are fetched from the output of the power flow analysis.

Along with the power sensors, voltage sensors are also added as it is important to incorporate the magnitude and angle of the voltage of the MV to LV node. Similar to the power sensor, in this case also, artificial measurement errors are added to get the real measurement of the network.

With all the available measurements, the PGM runs the state estimation using the "iterative linear" as the calculation method. The steps involved in the estimation of the state of the system have been described in the form of a flowchart as shown in figure 3.3. In the first step, real measurements are calculated by adding artificial measurement errors to the measurements obtained from the power flow. To obtain the pseudo measurements, in the second step, an artificial forecasted error has been added to the forecasted load values. The real and the pseudo measurements obtained from the two steps are used as input to the state estimator to compute the estimated state of the network. Similar to Power Flow, in the state estimation, the concept of "Batch Calculation" has been used where the state of the network has been predicted for a series of measurement values created from the time series of loading data.

3.3.3. Error calculation

For the network model, the state estimation is performed, by considering the real as well as pseudo measurement values. The error generated from the state estimation is calculated by comparing the state-estimated output from the true state of the network i.e the power flow results as described by the following equation:

$$\boldsymbol{E = (V_{se} - V_{pf})} \tag{3.5}$$

where $\boldsymbol{V_{se} = V_{mag,se} + iV_{ang,se}}$ and $\boldsymbol{V_{pf} = V_{mag,pf} + iV_{ang,pf}}$ are the complex value of the node voltages.

The error has been calculated for the loading scenarios for each node. Each MSR or substation has been considered here as a node. The complex value of the voltage has been averaged for each node and the error of the averaged value has been calculated using the Equation 3.5. The standard deviation of the errors for all the nodes has also been calculated using the formula as shown in the Equation 3.6 and has been used in the further step of the project.

$$\sigma_e = \sqrt{\frac{\sum_{n=1}^{N}(E^n - X_e)^2}{N-1}} \tag{3.6}$$

where X_e is the mean of the error :

$$X_e = \frac{\sum_{n=1}^{N} E^n}{N} \tag{3.7}$$

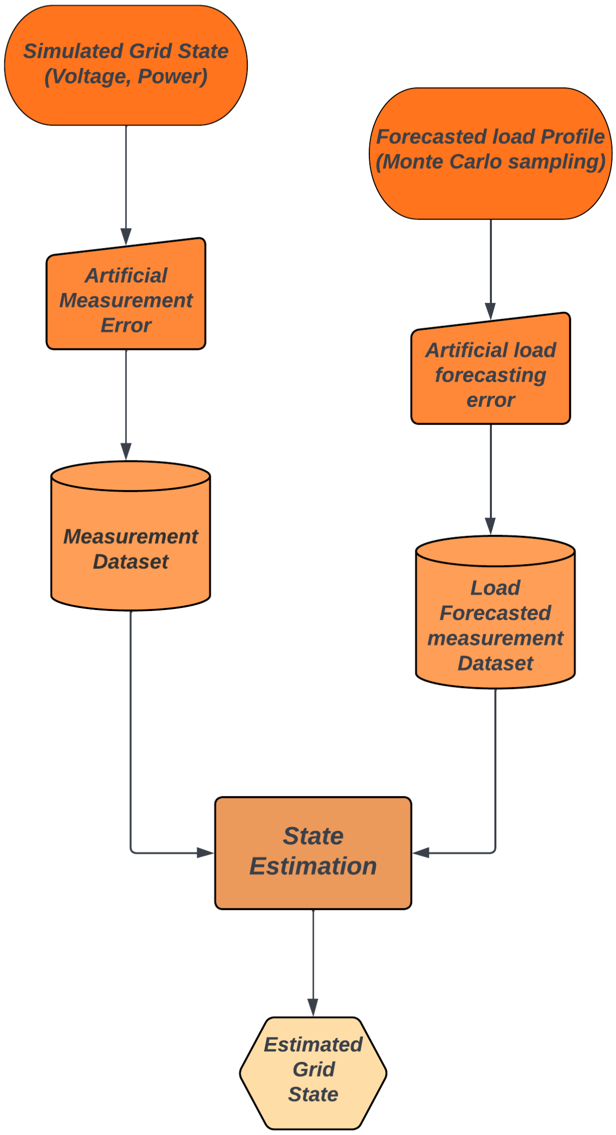

Figure 3.3: Flow chart for State Estimation

3.4. Meter Placement

In the distribution network, very little real-time information is available compared to its large number of nodes. The meters required for the State Estimation can be captured through different kinds of equipment such as smart meters(SM), Phasor Measurement Unit (PMU), power quality analyzers, etc. which has different installation cost and accuracy ranges[37]. Due to the scarcity of these measurement devices in the network, it becomes difficult to obtain an observable network. A large number of pseudo measurements are used, which are the forecasts derived from the historical data of the power generated or consumed at a particular node, to make the distribution network observable. But the pseudo measurements have high variance and due to this, the estimated state deviates from the actual state. If the error of the SE is too high, then additional real measurements should be considered by installing more meters in the network. But placing additional meters can also increase the investment needed. Therefore, it's important to compromise between accuracy, reliability, and cost.

Meter placement is a process that is done to determine the number, location, and type of meters that are required to be placed in the network so that it could reduce the error in the estimated state of the system. The placement of a meter in the network is a complex problem due to conflicting requirements between the performance of the SE and the cost of the meters. So it's important to find a solution to the placement issue. The solution can be optimal, feasible, heuristic, or sub-optimal. For a state-of-the-art SE model, it is difficult to precisely determine the effects of the measurements on the SE error. So the SE errors are mostly reduced by a heuristic or sub-optimal meter placement method. An optimal or an optimization approach provides the best solution to a problem by satisfying all the provided constraints whereas a solution is called feasible when the expected output for a particular problem is obtained. But the feasible solution might not provide an expected output when there is a change in the decision variable, while an optimization model can adapt to these changes easily due to its flexibility. The heuristic or sub-optimal approaches are practical ways of solving any problem faster and more efficient way which don't include accuracy, optimality, and precision. This approach is easy to implement but could not provide a viable solution that provides the best possible result. In an MV distribution network, the number of real measurements/meters is quite less, so it's important to place voltage sensors at the secondary substation to measure the voltage while the power sensors at the loads and line measure the branch power flows. There are many methods for meter placement that have been broadly described in the section 1.2 of chapter 1. But in this project, an incremental heuristic approach has been proposed to identify the suitable location for placing the next voltage measurement in the radial distribution network for the DSSE.

3.5. Heuristic Meter Placement

The performance of a State estimator can be improved by adding more measuring units in the network, but it will increase the investment. So to approach the meter placement problem, we proposed a statistical approach to determine the next possible location for placing the voltage measurement. The proposed method follows an incremental heuristic meter placement approach rather than a comprehensive one. In the previous studies[17, 38], the estimated error of the node magnitude and angle has been reduced individually and the meter placement is done based on the highest value of the standard deviation for both the voltage and angle. Utilizing the magnitude of the voltage alone is insufficient to determine the accuracy of the standard deviation and is not the best approach for the meter placement, since the magnitude of voltage doesn't determine the directionality of the phase. So to incorporate the effect of the phase direction, the voltage angle is considered. In this project, the limitation of the previous approaches has been overcome by adapting the complex value of the voltage instead of analyzing the magnitude and the angle of the voltage separately. The difference of the voltage phasor from both the power flow and the state estimation has been used to compute the standard deviation of the error.

The proposed meter placement identifies the next unmeasured point with the highest standard deviation value by a statistical method which is a modified version of the Weighted Arithmetic Mean (WAM). The WAM computes the average value by assigning weights to a set of observations to determine the relative importance of each observation. The WAM method is selected as it can help an individual in making decisions when certain factors are more significant than others. Moreover, the method has been useful for descriptive statistical analysis e.g. index number calculation. In our case, the concept of WAM is selected as the type of load connected to the nodes is different in terms of their effect on the whole network. So by assigning weights based on their importance, a sub-optimal solution can be determined. In [39], the WAM method is used to test the optimality of the Transportation problem by assigning weights to the cost matrix and thus finding the feasible solution to the problem.

The formula for the WAM is shown below:

$$\bar{x}_w = \frac{w_1 x_{1+} w_2 x_2 + w_3 x_3 + \ldots + w_n x_n}{w_1 + w_{2+} w_3 + \ldots + w_n} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \tag{3.8}$$

where $\sum_{i=1}^{n} w_i = 1$ and $w = (w_1, w_2, \ldots\ldots w_n) \in [0,1]^n$

In the proposed algorithm, for a certain node to be measured, its one-hop neighboring nodes are identified and weights are assigned to them. The highest weight has been assigned to the node to be measured (parent node), which is unity in this case. Since the neighboring nodes have equal contributions to the parent node, so the assigned weight of the parent node has been equally divided among the child nodes. The distribution of weights has been shown in figure 3.4 where the parent node and the corresponding neighboring nodes are colour coded as green and red respectively. If the node N_1 is the parent node with a weight unity, then its neighboring nodes i.e. nodes N_3, N_5, N_2 and N_5 will be assigned one-fourth of the weight of the node N_1. Similarly for node N_8, its neighboring nodes N_6 and N_{11} each will get half of the weight of the node to be measured i.e. N_8.

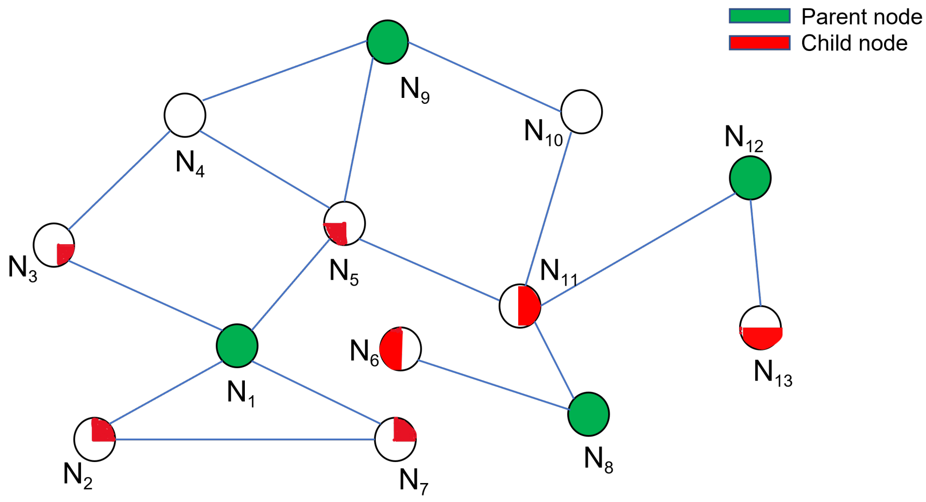

Figure 3.4: Weight distribution of a parent and child node indicated by green and red colour respectively

Consider **b** as the parent node/bus and ***i*** as the neighbors of the node $'b'$. Then the weighted average of the errors E_b for each of the nodes $'b'$ can be calculated by the following Equation 3.9:

$$E_b = \frac{\sum_{i\in\Omega_b} w_{bi}\sigma_{ib} + \sigma_B}{\sum_{i\in\Omega_b} w_{ib} + w_b} \tag{3.9}$$

where

w_b refers to the weight of the node to be measured (parent node).

w_{ib} is the weight assigned to the neighbors of the parent node $'b'$ i.e. the child nodes for $i = \Omega_b$, where Ω_b refers to to the set of neighboring nodes for the parent node $'b'$.

σ_b and σ_i are the standard deviation values of the error for the node to be measured and its neighboring nodes respectively.

The weighted average error for all the nodes is calculated and the values are ranked in ascending to descending order. The meter will be placed at the unmeasured node with the highest value of the weighted average error E_b.

If the errors of the parent nodes are considered as E_{bn}, where $n = (1, 2, ..., M)$, **M** being the number of meters, then the meter that will be placed in the unmeasured node can be mathematically described as follows:

$$b_n = max\{E_{b1}, E_{b2}......, E_{bM}\} \tag{3.10}$$

where b is the parent node where the meter will be placed.

A flowchart of the proposed incremental meter placement strategy has been shown in figure 3.5.

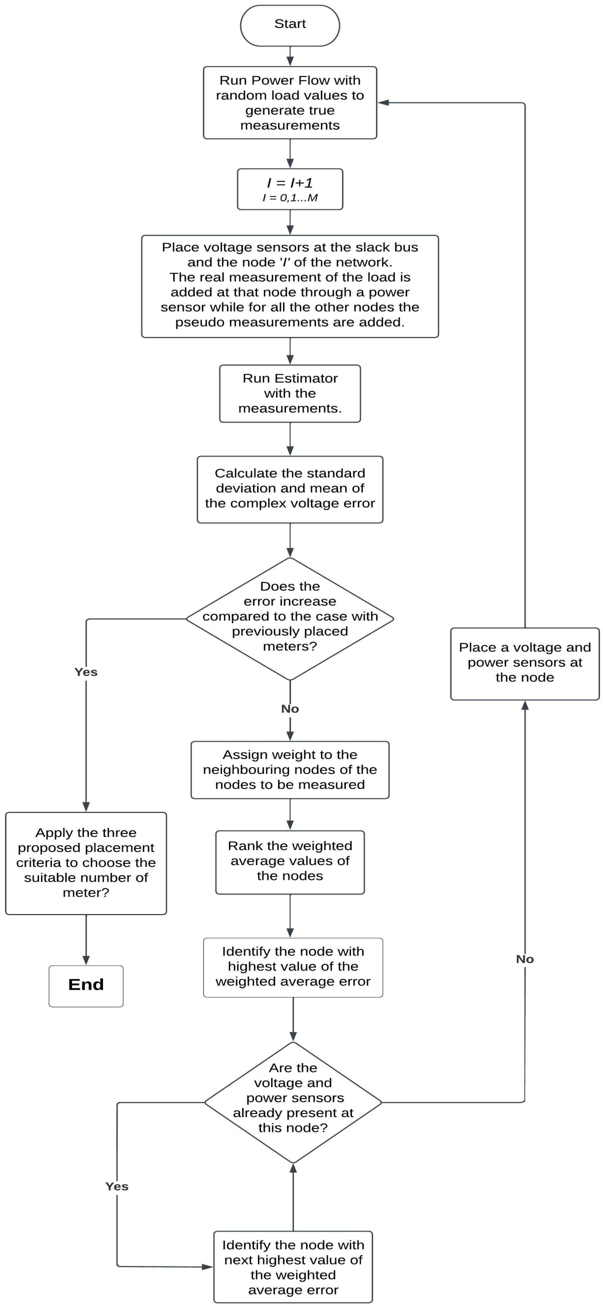

Figure 3.5: Flow chart for meter placement strategy

The steps shown in figure 3.5 for finding a sub-optimal path for the meter placement using the concept of the weighted average of the standard deviation of the error are described below:

***Step* 1:** A set of load values are selected by random sampling from the provided yearly load profiles for each of the nodes $'b'$. Power flow analysis has been done using the selected load profile to generate the actual measurements.

***Step* 2:** In the initial stage, the real measurement values have been added by placing a power sensor across a line and for a few loads. For the remaining loads, pseudo measurements have been added. A voltage sensor is placed at the starting node/substation $'b'$ closest to the slack bus. The real measurements of the meter and the pseudo measurements used in the simulation are computed by using the Equation 3.1 and Equation 3.2 respectively.

***Step* 3:** State Estimation is done based on available measurements which is the combination of both real and forecasted load(pseudo measurements) to estimate the state of the network.

***Step* 4:** The standard deviation σ_b, as well as the mean value of the error X_e for each node, are computed for each node using the formula as described in the Equation 3.6 and Equation 3.7 respectively.

***Step* 5:** Check if the total error σ of the nodes increases instead of decreasing compared to the case with the previously placed meter. If yes, then go to step 6, else go to step 7 and follow the succeeding steps for placing the next meter.

***Step* 6:** Apply the three proposed placement criteria to find the suitable number of meters that should be placed in the network.

***Step* 7:** The weighted average error of unmeasured nodes E_b has been calculated by assigning weights to the set of the neighboring nodes of node $'b'$ using the formula described in the Equation 3.9.

***Step* 8:** The weighted average errors of the nodes E_{b_n} are ranked in ascending to descending order.

***Step* 9:** The node with the highest value of the weighted average error E_{b_n} is identified.

***Step* 10:** The voltage sensor/meter is placed at the unmeasured node b with the highest value of the weighted average error E_{b_n}. In case, the weighted average error for an already measured node becomes higher, then the next unmeasured node will be considered for meter placement.

***Step* 11:** Change the ratio of real and pseudo measurements that have been assigned to the power and voltage sensors and repeat the steps from the beginning to find a sub-optimal meter placement path.

3.6. Proposed Placement Criteria

The standard deviation of the voltage error doesn't always decrease even when there are enough meters placed in the network due to the variation of the load profile. The measurements used for the State Estimation process often contain noisy data, resulting in inaccurate estimation of the system states, affecting the error's standard deviation and thus the meter placement. The load profiles used in this project were selected randomly from a normal distribution while performing the power flow and state estimation each time with newly added meters in the sample network.

To address the effect of noisy data, a few criteria have been considered based on which meters can be placed. They are as follows:

1. **Threshold on Error:** The standard deviation of the voltage error will tend to decrease with the increasing number of meters. But in reality, placing more meters in the network will increase the total investment cost. If $\mathbf{M}$ is the number of meters already placed in the network, then the total standard deviation of the errors for all the nodes can be denoted by $\boldsymbol{\epsilon}$. To find a suitable number of meters that can keep the investment cost low, a threshold value has been specified. The threshold value ($\boldsymbol{\gamma_1}$) is assumed and in reality, would be estimated based on costs for congestion management, installation of distributed generators, etc. Such a defined estimated $\boldsymbol{\gamma_1}$ would define the balance between the investment cost of meter placements and alternative approaches such as congestion management, installation of RESs, etc. After implementing the Heuristic Meter Placement(HMP) technique, for a set of measurements, if the standard deviation value of the error for a certain number of meters falls below the threshold, then it can be assumed that the network has enough meters as described by the Equation 3.12. Based on the criteria, the previously added meter can be removed to attain the maximum count of meters, acceptable for that network.

$$\epsilon(M) \leq \gamma_1 \tag{3.11}$$

2. **Number of placed meters:** Based on the criteria of threshold on error, the number of meters that can be placed in a given network can be determined. But there is a limitation in meter placement due to the high investment cost. Based on an accept-

able number of meters that are allowed to be placed on a network, a threshold value can be determined. For example, suppose the number of meters allowed to be placed in a network is 8(eight), then with the help of criteria 1, it can be checked that if the standard deviation of the error for the selected number of meters falls below the set value of threshold or not. If the number of meters is denoted by **M**, then the threshold value can be expressed by $\boldsymbol{\gamma_2}$. The criteria as mentioned earlier can be expressed by the following equation:

$$M \leq \gamma_2 \tag{3.12}$$

3. **Elbow Rule Optimality:** The concept of **Elbow-Rule** is one of the most popular ways of determining the number of clusters in a data set. The values for a certain variation of data are plotted against the number of clusters and the 'elbow of the curve' reflects the number of clusters that can be used[40]. The same concept is used in this project to find a sub-optimal number of meters by considering the two criteria i.e threshold of error and the number of placed meters. The **'Knee of the curve'** or **'Elbow of the curve'** is a point on the curve where the direction of the curve changes rapidly from large slopes to small slopes.

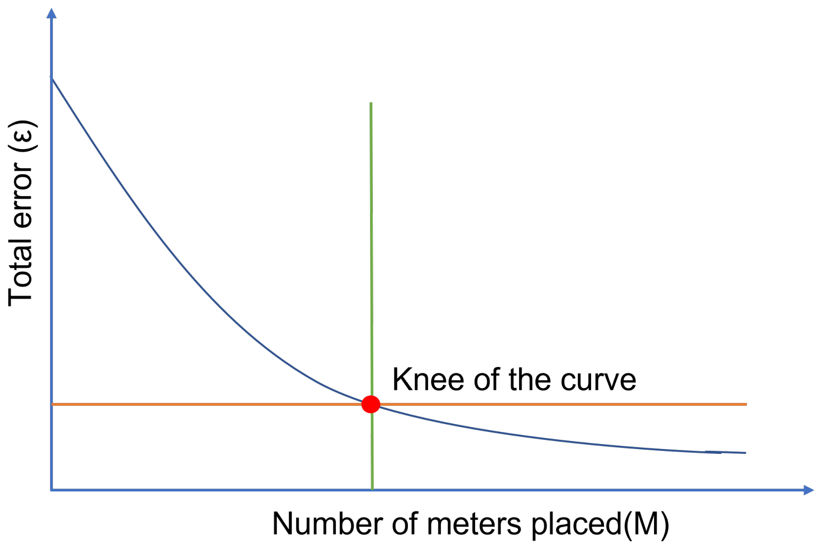

Figure 3.6: Elbow rule for optimality

As shown in figure 3.6, the red dot is the 'knee of the curve', while the orange line denotes the threshold for the reduction of the standard deviation of the error with the increasing number of meters and the green line denotes the threshold for the number of meters that are allowed to be placed in the network.

Consider **M** is the number of measurement units/meters that have been placed and $\boldsymbol{\epsilon(M)}$ denotes the total standard deviation of the error for all the node voltages, then in an ideal case

$$|\frac{\partial \epsilon(M)}{\partial M}| \rightarrow 0 \tag{3.13}$$

If a threshold is defined for the standard deviation of the error which is denoted as $\boldsymbol{\gamma}$, then the Equation 3.13 can be re-written as the below Equation 3.14:

$$|\frac{\partial \epsilon(M)}{\partial M}| \rightarrow \gamma_1 \tag{3.14}$$

4

Result and Analysis

The state estimation algorithm is described in the chapter 2. The implemented algorithm is tested in a case study with a practical MV network in an area in the Netherlands (Hoorn Holenweg) as shown in figure 4.2. In figure 4.2, the red dots refer to the MV substations while the blue ones are the joints connecting one substation to the other. This network is further considered for the placement of meters under different loading criteria which has been broadly discussed in the chapter 3. The radial network of Hoorn Helenweg is owned by the Dutch DSO Alliander and is a combination of 10kV/380V MV/LV substations. An external source is connected to the 5th secondary substation. As a part of this project, the network's topology is assumed to be constant. The physical representation of the network is shown below in figure 4.1

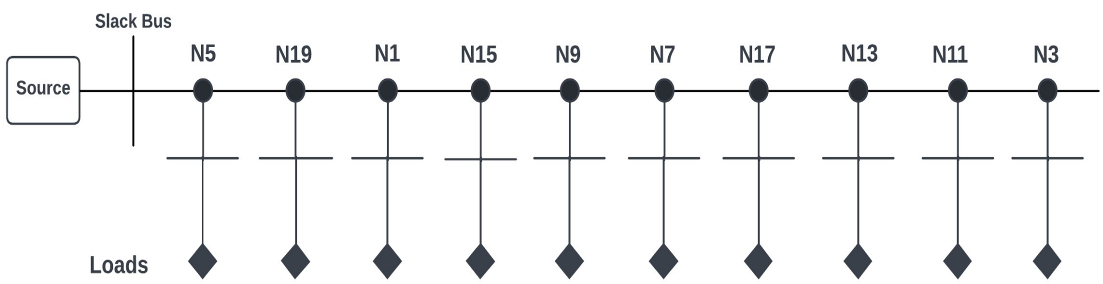

Figure 4.1: MV distribution network

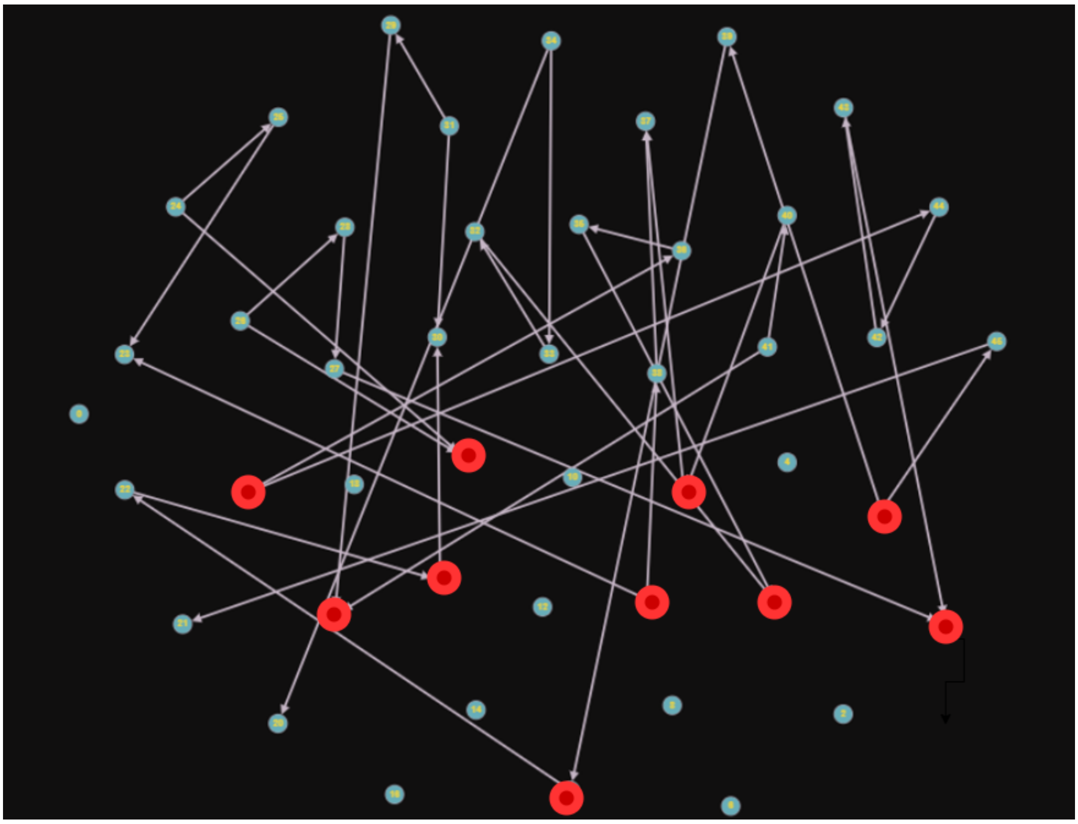

Figure 4.2: Distribution Network of Hoorn Holenweg

4.1. MV Distribution Grid

Alliander N.V is one of the largest Dutch DSOs to manage around 80,000km of MV and LV network, which is one-third (1/3) of the total dutch network in the Netherlands[41]. The sample network used in the project is anonymized from a real MV network of the Dutch DSO Alliander N.V. The information of the grid was provided in the form of two JSON files - *topology.json* and *equipment.json.* A set of 200 load profiles has been created for every 15 minutes duration for a year by Monte Carlo sampling of the data. A yearly profile of forecasted data has also been provided by Alliander for each of the ***middenspanningsruimte*** (MSR), also known as a secondary substation, along with the information on the standard deviation value for the pseudo-measurements which will be used for the meter placement problem. An in-house algorithm of Alliander, namely the Power Grid Model (PGM), has been used for performing the power flow analysis as well as the State Estimation on the given network. For using the PGM algorithm, few values have been set for the test. The error_tolerance value has been set as $1e^{-6}$, max_iterations as **20** and the system_frequency as 50Hz for the load flow and state estimation. But for the power flow, the calculation_type has been chosen as newton raphson while for the state estimation it is iterative linear. A detailed explanation of the PGM algorithm has been provided in the section 3.1 of chapter 3.

In this chapter, the analysis of the result after implementing the heuristic meter placement(HMP) strategy has been discussed. To study the efficacy of the meter placement strategy, various scenarios have been created in the form of case studies.

The standard deviation of the voltage error has been studied under different loading conditions. By randomly selecting the load profiles, power flow is done to obtain the actual measurement of the sample network. Random load profiles are considered to study the effect of changing load on the meter placement to find a statistically good result. The main objective of the HMP algorithm is to place meters based on the reduction of the standard deviation of the error. Few test cases are created to study the effect of random load profiles on the meter placement strategy. The following is the overview of four different case studies undertaken in this project:

- **Case 1:** This study investigates the impact of the meter placement strategy after performing the load flow and the state estimation by selecting a random sample of load profile.

- **Case 2:** This study investigates the effect of the increased number of random samples of load profile for the load flow and state estimation on the meter placement strategy.

- **Case 3:** This study investigates the effect on the meter placement when the standard deviation for the forecasted loads has been increased by a certain percentage.

- **Case 4:** This study investigates the three proposed placement criteria in section 3.6 which can be considered to find a suitable number as well as the location for the meter placement.

4.2. Case Study 1: Impact of Meter Placement

In this case study, a lower number of samples from the load profile has been selected to be added as input for the power flow analysis and later the state estimation. The sample size is kept in the range of 1000-1500. The difference between the power flow and the state estimation of the complex value has been computed to obtain the mean and the standard deviation of the error of the voltage phasor for each of the nodes. The meters are placed in the network based on the highest standard deviation value using the HMP algorithm. The effect on the standard deviation and mean of the errors due to the increasing number of meters are plotted in a graph as shown in the figures 4.3 and 4.4 respectively. The legend shows the nodes where the meters have been placed. The lines are plotted with different colours for presentation purposes.

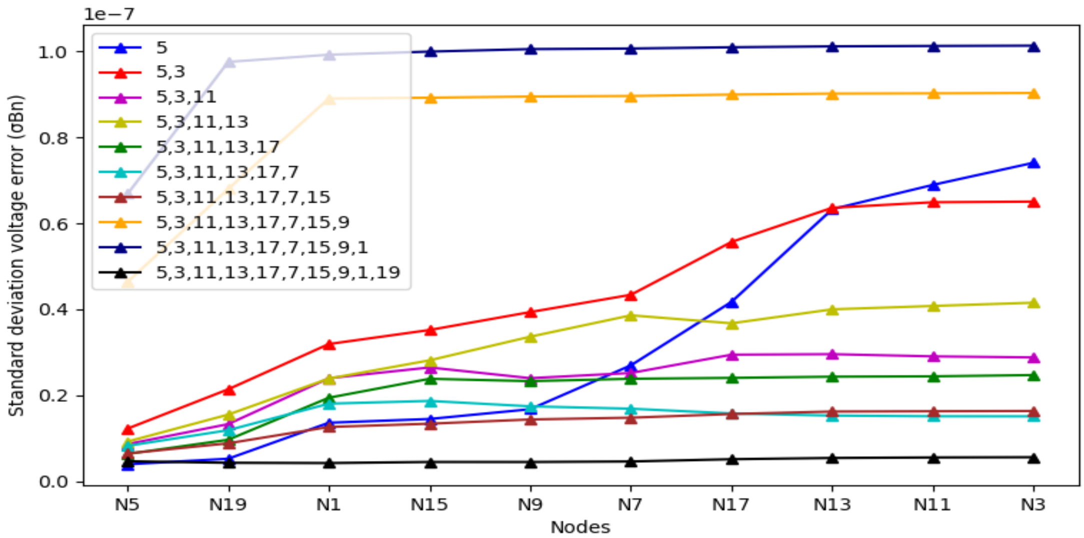

Figure 4.3: Standard deviation of the error for all the nodes for case 1

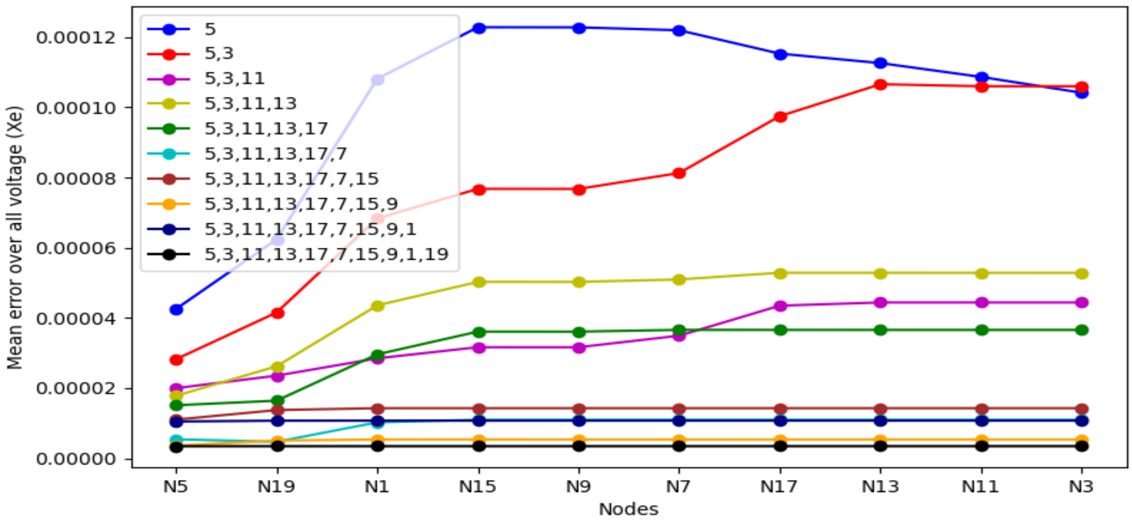

Figure 4.4: Mean value of the error for all the nodes for case 1

The main objective for placing the meters in the network is to reduce the standard deviation of error. As shown in figure 4.3, the standard deviation value increases when the 2nd meter is placed in the network. With the placement of the 3rd meter, the error value decreases.

When the 4th meter is placed, the standard deviation value of the error increases again but decreases with the subsequent placement of the 5th, 6th, and 7th meters. An increasing trend in the standard deviation of the error is again noticed when the 8th and 9th meter is placed. In these two cases, the error attains a value higher than the case with only one meter in the network. When all the meters are placed, the value of the standard deviation became the lowest of all the cases.
The result for the mean value of the voltage error deviates from the result obtained for the standard deviation of the error. As shown in figure 4.4, the mean value of the error decreases with the subsequent placement of the initial 3 meters. With the placement of the 4th meter, an increase in the error is noticed and the value decreases again with the placement of the 6th meter. An inconsistency of the decreasing trend of the error is noticed when the 7th and the 9th meter are placed. Comparing both the results of standard deviation and the mean of the error, it has been noticed that there is a huge variation in the result of the two graphs. With the HMP algorithm, a better result is obtained for the mean of the error but a huge deviation is observed in the standard deviation of the error. The reason is the random selection of the load profile, the forecasted data, and the artificial random error which is added due to the meter inaccuracies; and the lower number of samples of data from the load profile for the power flow, due to which it cannot produce statistically good representative. Because of the randomness in data, the graphs are simulated multiple times and the best result has been chosen for a better understanding of the process. To obtain a statistically good outcome, the number of samples for the load profiles should be increased as the more the number of samples, the more accurate the result becomes. To check the correctness of the statement, the sensitivity of the approach is analyzed with a larger dataset in the next section.

4.3. Case Study 2: Sensitivity to datasize

This case study investigates whether a low number of samples was the reason for poor meter placements in the previous study. The sample size used in this study is in the range of 8000-10000 which is quite higher compared to the sample size of 1000-1500 in the previous case study 1. The standard deviation, as well as the mean of the voltage errors, are shown in the figures 4.5 and 4.6

The results obtained from the previous case study have been improved in this scenario, by considering a higher number of samples from the load profile. As shown in figure 4.5, with the placement of meters in the network, the standard deviation of the error tends to decrease when more meters are placed. A small trend violation can be observed in the graph, for the case where 4 meters were placed. In this case, the error's standard deviation

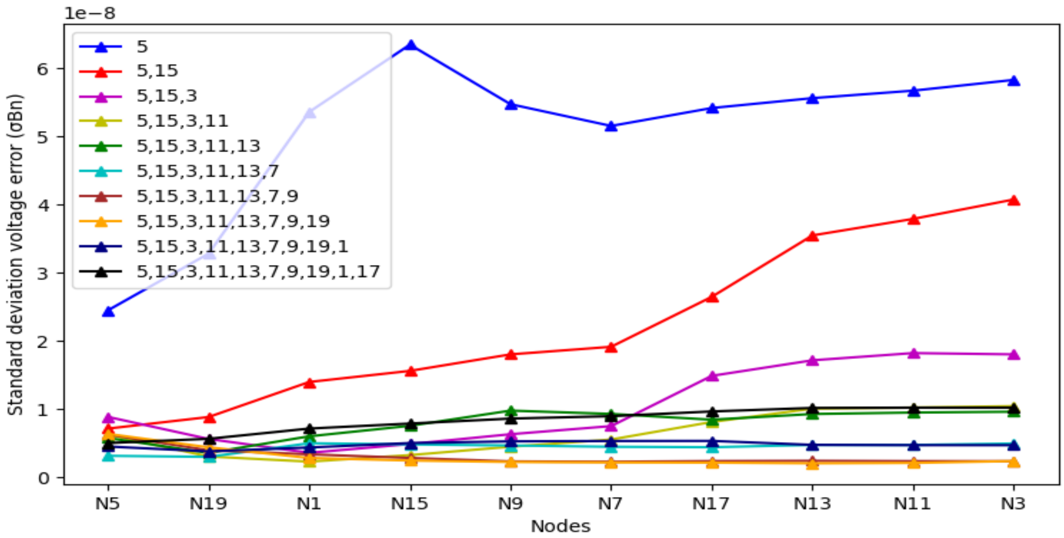

Figure 4.5: Standard deviation of the error for all the nodes for case 2

increases instead of decreases. From the 6th meter onward it follows a decreasing trend until the placement of the 9th meter. After that, it kept on increasing instead of placing meters at all the nodes. But overall, the standard deviation of the error decreased with the placement of the meter using the HMP algorithm. The reason for the increase in the value even with the placement of more meters is because of the random selection of the noisy load profile and the artificial random error which is getting added for the real and pseudo measurements. The mean value of the errors as shown in figure 4.6, decreases until the placement of the 5th meter. From the placement of the 6th meter till the 9th meter, a decreasing trend in the voltage error is observed. When the 10th meter is placed, there is a small increase in the error. The standard deviation and the mean value of the error showed a similar trend in the error reduction with the HMP algorithm. In this case, also, the best values for the graph have been selected for a better understanding of the process.

Comparing case study 1 with 1000-1500 samples and case study 2 with 8000-10000 samples, the sensitivity to the data size can be observed. In the previous case, the HMP approach could not provide a statistically good result while in this case, the decreasing trend of the standard deviation of the error with the subsequent meter placement has been observed. As shown in Table 4.1, the standard deviation of the error for a case where 8 meters are placed in the network, has a higher value when the small sample size is chosen, while for a higher sample size, the error has reduced considerably. This study shows the limitation of the HMP approach. Therefore, this approach should not be used with few samples. So it is recommended to consider a larger sample size which should be around 5-10 times the sample size of case study 1 for this particular network.

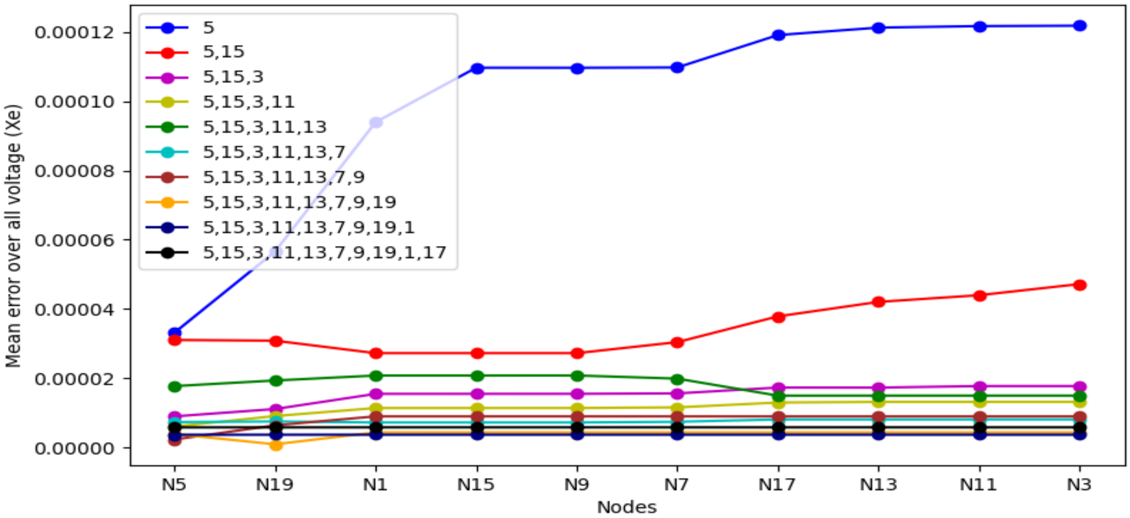

Figure 4.6: Mean value of the error for all the nodes for case 2

Table 4.1: Comparison of the standard deviation of the error for case study 1 and case study 2

Sensitivity to Smaller Datasize	**Sensitivity to Larger Datasize**
8.3243E-07	2.9541E-08

4.4. Case Study 3: Sensitivity to standard deviation of pseudo-measurements

This case study investigates the sensitivity to the measurement error of the pseudo measurements. The meter placement strategy has been applied to the sample network after increasing the standard deviation of the forecasted loads by 30%. The increased forecasted load will increase the variation of the pseudo measurements which will affect the standard deviation of the error and thus the meter placement. The state variables of the network have been estimated with the initial set of measurements, where the variation of the pseudo measurements is increased by 30% for the remaining nodes. The meters are placed based on the HMP strategy until it covers all the nodes.

In figure 4.7, initially, the standard deviation of the error is quite high. But with the placement of the next few meters, based on the HMP algorithm, the standard deviation value tends to decrease with the addition of actual measurements of the meters. The trend of the graph, after placing the 4th meter, increases with the further placement of the meters. With the increase of the real measurements in the network, the standard deviation decreases until the placement of the 8th meter and the 10th meter. An increase in the

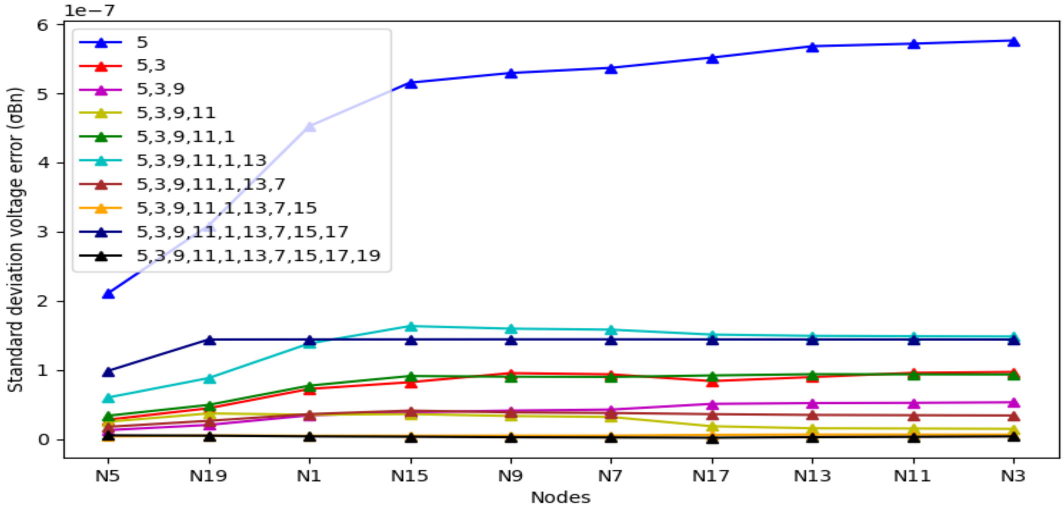

Figure 4.7: Standard deviation of the error for all the nodes for case 3

standard deviation is observed when the 9th meter is placed in the network. The deviation in the decreasing trend of the standard deviation is violated, compared to the previous case due to the random selection of the load profile and the high variation of the artificial forecasted error, which is getting added to calculate the pseudo measurement. Despite of mentioned factors of random load selection, the standard deviation of the error becomes negligible when all the meters were placed as there is no effect of pseudo measurement here. The same behavior of the graph has also been noticed for the mean of the voltage error for each node as shown in fig 4.8. The mean value of the error decreases until the placement of the 6th meter. For the 6th and the 7th meter, the error value increases further with the placement of the 8th meter. Similar to the standard deviation, the mean value of the error also increases with the placement of the 9th meter in the network.

A comparison has been drawn between case study 2 and case study 3 to understand the effectiveness of the HMP approach. The Table 4.2 shows that for a case where 6 meters are placed, the standard deviation value increased in case 3 while it reduced in case 2. From this case study, we can say that, if the artificial forecasted error value increases due to the increase of the standard deviation of the pseudo measurements, a deviation in the decreasing trend of the error will be affected. The standard deviation or the mean of the error will increase even when enough meters are placed. This shows the limitation of the HMP approach and is recommended to consider a pseudo measurement with less variance/standard deviation value.

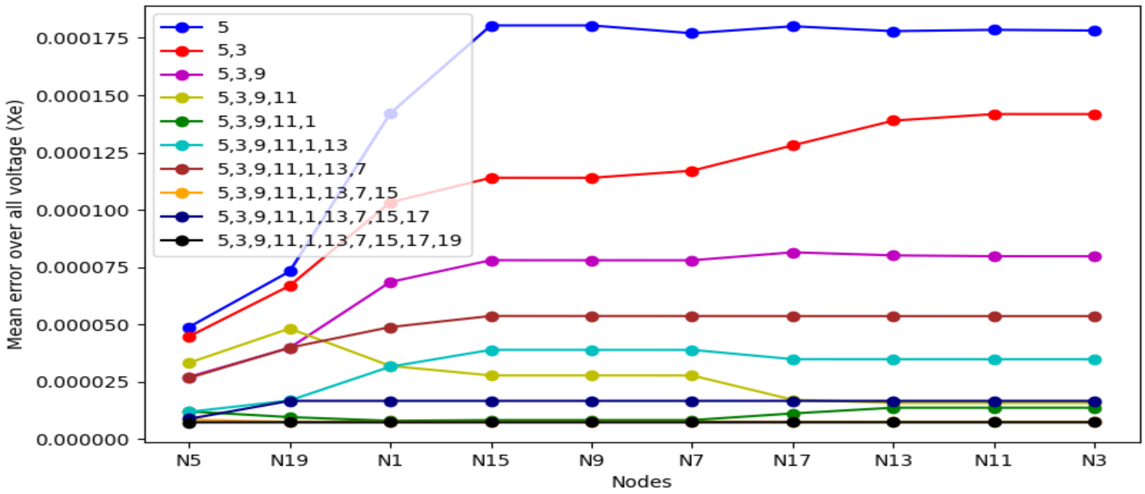

Figure 4.8: Mean value of the error for all the nodes for case 3

Table 4.2: Comparison of the standard deviation of the error for case study 2 and case study 3

Low Standard Deviation	High Standard Deviation
4.4326E-08	1.3631E-06

4.5. Case Study 4: Criterion Analysis

This case study investigates the three criteria which have been introduced in the section 3.6 of chapter 3 for determining a suitable number of meters that can be placed in the network. The threshold values have been assumed in this project due to the unavailability of the correct information. The standard deviation of the error for all the nodes is summed up to find the total value of the standard deviation of the error (σ). As shown in figure 4.9, The total standard deviation of the error is plotted against the number of meters placed for the case study2. It can be observed that the error curve changes its slope when there are 4 meters placed. Even if we use the criteria of *Threshold of error*, then the number of meters that can be chosen will be 4, 6,7,8,9. But considering the investment cost, either 4 or 6 meters can be chosen. Since the difference between the error is not that high, so 4 meters can be placed in the network which can be determined effectively by the third criterion i.e *Elbow Rule*.

Similarly, the proposed meter placement criteria have been applied for case study 3 to find a suitable number of meters that will be sufficient to keep the standard deviation of the error in the lowest range. In this case, as shown in figure 4.10, *Elbow-Rule* is applied in the network which is denoted by the blue and yellow line, and it has been observed that the number of meters that can be placed in the network is 2. But this criteria is not providing a suitable solution as the error is still on the higher side compared to the other meters. The

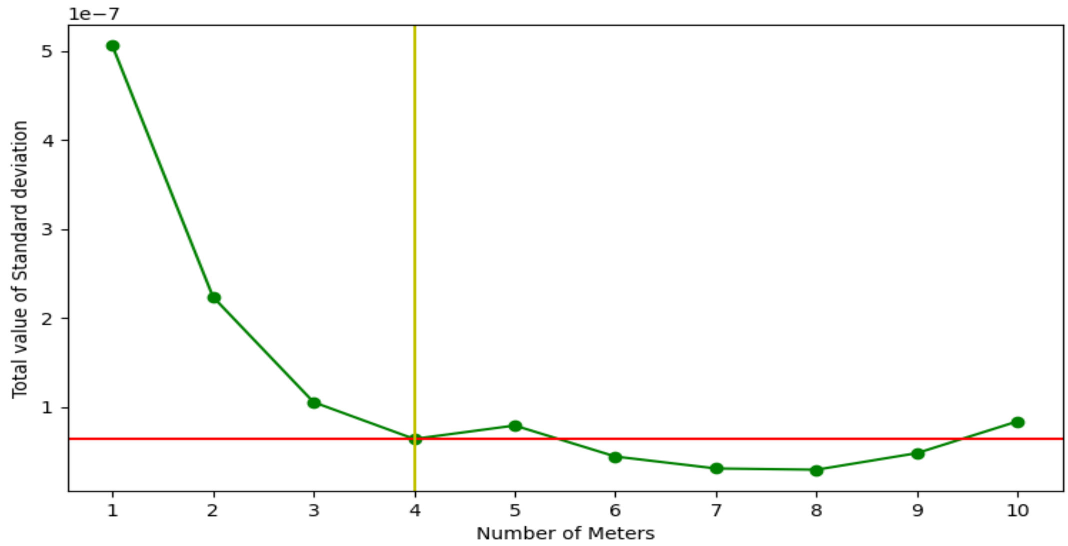

Figure 4.9: Elbow rule optimality for Case with larger sample size

criteria of *Threshold of Error* and *Number of placed meters* is applied which is denoted by the red line. It can be observed that a suitable solution of the number of meters can be obtained which will be either 4 or 8. But because the number of meters should be less due to the cost factor, 4 meters will be placed in the network.

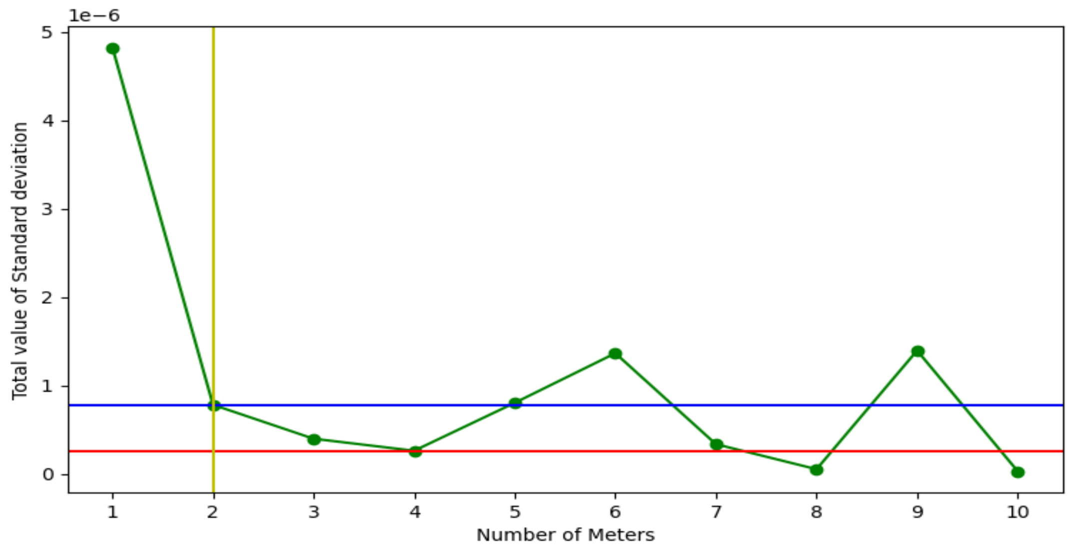

Figure 4.10: Elbow rule optimality with increased variation in the forecasted load

5

Conclusion

This chapter summarizes the project and answers the research questions by concluding the results obtained after performing the State Estimation. A few recommendations for future work have also been discussed at the end of the chapter.

5.1. Summary

In this project, an in-house algorithm of Alliander, the Power Grid Model has been used to perform the Power flow analysis and the State estimation. The Power flow has been done using the Newton-Raphson method while for the State estimation iterative linear WLS method has been used which has been described broadly in chapter 2. The mean and the standard deviation of the error have been calculated by finding the difference in the voltage of the output of the load flow from the estimated state. For the proposed meter placement in the sample network, a heuristic meter placement strategy has been introduced, described in section 3.5 of chapter 3, for finding the next suitable location for the meter placement based on the standard deviation value of the error. In chapter 4, the HMP strategy has been implemented on the network with smaller and larger data sizes and the increased standard deviation of the pseudo measurements, to study the sensitivity of the proposed algorithm. The findings of the different case studies have been discussed in the previous chapter.

5.2. Research Questions

- **How to place the meters in the existing Distribution Grid to reduce the error of the estimating state?**

For the meter placement, various methods have been discussed in the literature review section of chapter 1. In this project, instead of a comprehensive method, a heuristic method has been proposed to find the sub-optimal path for the future placement of the meters. The concept of Weighted Arithmetic Mean(WAM) has been used where the node to the measured has been assigned the highest weight i.e unity while its neighboring nodes connected to the parent node have been assigned half of the weight. The standard deviation of the error for all the unmeasured nodes is calculated using the concept of the weighted average of the error. The meter will be placed on the node with the highest value of the standard deviation, to reduce the overall error of the network.

- **What will be the nature of the error variance or the standard deviation after performing State Estimation on the grid using a different number of load profiles?**

  The meters are placed in the network to improve the accuracy of the SE by reducing the standard deviation of error. When a smaller data size is considered for the meter placement, inconsistency has been noticed in error values. For more number of meter, the standard deviation value increases for cases instead of decreasing. In the second case, a larger data size of the load profile is considered and the HMP algorithm is used to place the meters. The standard deviation of the error decreases with the subsequent placement of the meter. A slight violation in the decreasing trend is observed when the 5th, 9th, and 10th meters are placed. The reason for this deviation is the random selection of the noisy load profile and the measurement error which is getting added each time while performing the load flow and the state estimation. So it has been observed that, with a smaller data size of the load profile, the standard deviation of the error doesn't decrease in most of the cases even when enough meters are present in the network. Hence we can conclude that larger data sizes should always be considered for the reduction of the error variance with the HMP strategy.

- **What will be a suitable location for placing the meter considering the deviation in the values obtained after performing the SE?**

  An initial measurement has been considered on the slack bus and the node nearest to the slack bus as it is important to have a measuring unit at the beginning of the feeder. This is because the slack bus provides the reference value for the voltage magnitude and phase angle which is important for the power flow analysis. With the initial set of measurements, the proposed HMP algorithm places meters considering the standard deviation representing the deviation of the values in the SE. Applying the meter placement criteria as the stopping criteria for the proposed meter placement, the result was that for Case Study 2, 4 meters will be placed at nodes 5, 15, 3, and 11. The suitable number of meters has been identified using the third criterion i.e. Elbow-Rule. Similarly, for case study 3, 4 meters will be placed which has been identified using the first and the second criteria i.e. Threshold on Error and Number of placed meters at nodes 5, 3, 9, and 11.

5.3. Limitations

In chapter 4, the HMP method has been applied to the network under different situations. In the first case, the size of the random samples for the load profile is considered less, typically in the range of 1000-1500. Load flow and State estimation have been done by taking the random sample of load flow as an input. The meters are placed in the network starting from 2 to 10. In the second case, the sample sizes are increased more, typically in the range of 8000-10000 samples, to decrease the variability of the sampling distribution and to obtain statistically more correct results. The same process as that of the first case has been applied to place all the meters in the network. Comparing both results, it has been observed that, with a lower number of samples the standard deviation of the error doesn't always decrease. So it can be concluded that with a lesser sample size, the HMP algorithm doesn't provide a statistically good result which is one of the limitations.

Moreover, due to the random selection of the load profile, some variation has been observed where with more measured nodes the standard deviation of the error increases instead of decreasing. Due to this variation, the best values are selected from the randomly simulated cases for illustration purposes. In the third case, the standard deviation of the pseudo measurements is increased by 30% to observe the effect of the variation on the placement of the meter. It has been observed that during the presence of more pseudo measurements with high variability, the standard deviation of the error didn't follow the expected trend of getting reduced, instead, it tends to increase. The violation of the expected trend of reduction of the error in the third case is another limitation of the HMP approach.

5.4. Recommendations for the future work

Based on the results and the limitations, a few future recommendations have been suggested for expanding the scope of the proposed algorithm.

- The heuristic method that has been proposed in the project could not provide an optimal solution to the meter placement especially when the load profile and the measurement errors are added randomly each time. To overcome this, a proper optimization approach could be investigated to find an optimal solution to the placement problem.

- The concept of assigning weights to the neighboring nodes has been proposed to give the importance of the node in the calculation for finding the standard deviation of the error. But in this project, the network obtained from Alliander doesn't have any information regarding which node has an industrial load or RES connected to it to understand its importance. In future work, if the information regarding the nature of the load connected to the node is available, then instead of assigning the same weight to the neighboring nodes, unequal assignment of weights could be done. This would have an impact on the weighted average error calculation, and a better estimation of the location of meter placement can be obtained.
- The load profile used in this project is noisy data due to which there was a deviation in the trend of the standard deviation of the error with the placement of each meter. If a lower variance in the load values is considered then it is possible to obtain a result close to an optimal solution.
- For a smaller network, the Brute-Force method can be implemented to identify the optimal set of meters for individual small areas. Brute Force is an exhaustive search process that systematically enumerates all the possible combinations for a suitable solution.
- The meter placement approach is implemented on a radial distribution network. For future work, the effect of the approach on a meshed network can be studied to verify the effectiveness of this algorithm.

Bibliography

[1] E. B. G. . Co.KG, “Eu energy outlook 2050 – how will europe evolve over the next 30 years?” *https://blog.energybrainpool.com/en/eu-energy-outlook-2050-how-will-europe-evolve-over-the-next-30-years-2/*, 2022.

[2] F. Ahmad, A. Rasool, E. Ozsoy, R. Sekar, A. Sabanovic, and M. Elitaş, “Distribution system state estimation-a step towards smart grid,” *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 2659–2671, 2018.

[3] H. B. Puttgen, P. R. Macgregor, and F. C. Lambert, “Distributed generation: Semantic hype or the dawn of a new era?” *IEEE power and energy magazine*, vol. 1, no. 1, pp. 22–29, 2003.

[4] R. P. van Leeuwen, J. De Wit, and G. J. M. Smit, “Review of urban energy transition in the netherlands and the role of smart energy management,” *Energy conversion and management*, vol. 150, pp. 941–948, 2017.

[5] N. E. F. Bloomberg, “New energy outlook 2021-executive summary,” *Available from:< a href=" https://about. bnef. com/new-energy-outlook/" target="_blank"> https://about. bnef. com/new-energy-outlook/</a*, 2021.

[6] H. Kim, S. Park, and J. Lee, “Is renewable energy acceptable with power grid expansion? a quantitative study of south korea’s renewable energy acceptance,” *Renewable and Sustainable Energy Reviews*, vol. 139, p. 110584, 2021.

[7] E. J. Coster, J. M. Myrzik, B. Kruimer, and W. L. Kling, “Integration issues of distributed generation in distribution grids,” *Proceedings of the IEEE*, vol. 99, no. 1, pp. 28–39, 2010.

[8] J. V. Paatero and P. D. Lund, “Effects of large-scale photovoltaic power integration on electricity distribution networks,” *Renewable Energy*, vol. 32, no. 2, pp. 216–234, 2007.

[9] R. E. Larson, W. F. Tinney, and J. Peschon, “State estimation in power systems part i: Theory and feasibility,” *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-89, no. 3, pp. 345–352, 1970.

[10] R. Singh, B. Pal, and R. Jabr, "Choice of estimator for distribution system state estimation," *IET generation, transmission & distribution*, vol. 3, no. 7, p. 666, 2009.

[11] S. Skok, I. Ivankovic, and Z. Cerina, "Hybrid state estimation model based on pmu and scada measurements," *IFAC-PapersOnLine*, vol. 49, no. 27, pp. 390–394, 2016.

[12] Y. Yao, X. Liu, and Z. Li, "Robust measurement placement for distribution system state estimation," *IEEE Transactions on Sustainable Energy*, vol. 10, no. 1, pp. 364–374, 2017.

[13] T. C. Xygkis and G. N. Korres, "Optimized measurement allocation for power distribution systems using mixed integer sdp," *IEEE Transactions on Instrumentation and measurement*, vol. 66, no. 11, pp. 2967–2976, 2017.

[14] ——, "Optimizing d-pmu deployment for distribution system state estimation," in *2022 International Conference on Smart Grid Synchronized Measurements and Analytics (SGSMA)*. IEEE, 2022, pp. 1–8.

[15] X. Chen, J. Lin, C. Wan, Y. Song, S. You, Y. Zong, W. Guo, and Y. Li, "Optimal meter placement for distribution network state estimation: A circuit representation based milp approach," *IEEE Transactions on Power Systems*, vol. 31, no. 6, pp. 4357–4370, 2016.

[16] D. M. Ferreira, P. M. Carvalho, and L. A. Ferreira, "Optimal meter placement in low observability distribution networks with der," *Electric Power Systems Research*, vol. 189, p. 106707, 2020.

[17] R. Singh, B. C. Pal, and R. B. Vinter, "Measurement placement in distribution system state estimation," *IEEE Transactions on Power Systems*, vol. 24, no. 2, pp. 668–675, 2009.

[18] R. Singh, B. C. Pal, R. A. Jabr, and R. B. Vinter, "Meter placement for distribution system state estimation: An ordinal optimization approach," *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2328–2335, 2011.

[19] N. Nusrat, M. Irving, and G. Taylor, "Novel meter placement algorithm for enhanced accuracy of distribution system state estimation," in *2012 IEEE Power and Energy Society General Meeting*. IEEE, 2012, pp. 1–8.

[20] K. Chauhan and R. Sodhi, "Placement of distribution-level phasor measurements for topological observability and monitoring of active distribution networks," *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 6, pp. 3451–3460, 2019.

[21] B. Brinkmann, R. Scott, K. Bicevskis, and M. Negnevitsky, "A practical approach to meter placement in distribution networks," in *2017 IEEE Manchester PowerTech*. IEEE, 2017, pp. 1–6.

[22] C. Muscas, F. Pilo, G. Pisano, and S. Sulis, "Optimal allocation of multichannel measurement devices for distribution state estimation," *IEEE Transactions on Instrumentation and Measurement*, vol. 58, no. 6, pp. 1929–1937, 2008.

[23] H. Koglin, "Optimal measuring system for state estimation," in *Proc. PSCC*, 1975.

[24] H. Wang and N. N. Schulz, "A revised branch current-based distribution system state estimation algorithm and meter placement impact," *IEEE Transactions on Power Systems*, vol. 19, no. 1, pp. 207–213, 2004.

[25] A. Angioni, T. Schlösser, F. Ponci, and A. Monti, "Impact of pseudo-measurements from new power profiles on state estimation in low-voltage grids," *IEEE Transactions on Instrumentation and Measurement*, vol. 65, no. 1, pp. 70–77, 2015.

[26] S. Radhoush, M. Bahramipanah, H. Nehrir, and Z. Shahooei, "A review on state estimation techniques in active distribution networks: Existing practices and their challenges," *Sustainability*, vol. 14, no. 5, p. 2520, 2022.

[27] F. F. Wu, "Power system state estimation: a survey," *International Journal of Electrical Power & Energy Systems*, vol. 12, no. 2, pp. 80–87, 1990.

[28] M. E. Baran and A. W. Kelley, "A branch-current-based state estimation method for distribution systems," *IEEE transactions on power systems*, vol. 10, no. 1, pp. 483–491, 1995.

[29] M. Gholami, A. Abbaspour, M. Moeini-Aghtaie, M. Fotuhi-Firuzabad, and M. Lehtonen, "Detecting the location of short-circuit faults in active distribution network using pmu-based state estimation," *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1396–1406, 2019.

[30] A. Gomez-Exposito, A. J. Conejo, and C. Cañizares, *Electric energy systems: analysis and operation*. CRC press, 2018.

[31] C. Rakpenthai, S. Uatrongjit, I. Ngamroo, and N. R. Watson, "Weighted least absolute value power system state estimation using rectangular coordinates and equivalent measurement functions," *IEEJ transactions on electrical and electronic engineering*, vol. 6, no. 6, pp. 534–539, 2011.

[32] A. Abur and A. G. Exposito, *Power system state estimation: theory and implementation.* CRC press, 2004.

[33] T. Xiang and W. v. Westering, "State estimation alliander," *Technical Document of Alliander (Internal)*, pp. 1–15, 2021.

[34] N. V G and L. T M, "Smart grid state estimation by weighted least square estimation," *International Journal of Engineering and Advanced Technology (IJEAT)*, vol. 5, no. 6, pp. 20–25, 2016.

[35] Alliander N.V, "Power grid model benchmark," 2022, https://github.com/alliander-opensource/power-grid-model-benchmark, Last accessed on 2022-08-26.

[36] E. Caro, A. J. Conejo, and R. Minguez, "Power system state estimation considering measurement dependencies," *IEEE Transactions on Power Systems*, vol. 24, no. 4, pp. 1875–1885, 2009.

[37] M. Pau, P. A. Pegoraro, A. Monti, C. Muscas, F. Ponci, and S. Sulis, "Impact of current and power measurements on distribution system state estimation uncertainty," *IEEE Transactions on Instrumentation and Measurement*, vol. 68, no. 10, pp. 3992–4002, 2019.

[38] A. Shafiu, N. Jenkins, and G. Strbac, "Measurement location for state estimation of distribution networks with generation," *IEE Proceedings-Generation, Transmission and Distribution*, vol. 152, no. 2, pp. 240–246, 2005.

[39] M. M. Gothi, R. G. Patel, and B. S. Patel, "A concept of an optimal solution of the transportation problem using the weighted arithmetic mean," *Adv. Math. Sci. J*, vol. 10, no. 3, pp. 1707–1720, 2021.

[40] C. Yuan and H. Yang, "Research on k-value selection method of k-means clustering algorithm," *J*, vol. 2, no. 2, pp. 226–235, 2019.

[41] W. van Westering, B. Droste, and H. Hellendoorn, in *Proceedings CIRED 2019 Conference.* CIRED, 2019, cIRED 2019: 25th International Conference on Electricity Distribution, CIRED 2019 ; Conference date: 03-06-2019 Through 06-06-2019.