
Thesis report

Measurement strategy for state estimation of medium voltage grids with distributed generation

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Measurement strategy for state estimation of medium voltage grids with distributed generation

by

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Abstract

The world is going through an energy transition towards decentralized electricity generation like photovoltaic systems and new loads like electric vehicles, which contribute to the variability of the operation state of distribution systems. To ensure future operation under safe and efficient conditions, it becomes increasingly important to have precise knowledge of the state of the grid. For this, Distribution System State Estimation (DSSE) has extensively been discussed in the literature.

However, distribution networks at present are not only characterized by sparse measurement locations, which makes application of DSSE difficult due to un-observability, but also the anticipated highly stochastic load profiles will affect the accuracy of the system state estimate. Therefore, it is now necessary to assess how the DSSE accuracy is affected by different factors that result from continuous changes in the consumption pattern and measurement scheme. For this purpose, a measurement scheme is proposed in this thesis, that not only considers the meter placement, but also the required measurement intervals, to establish a minimum required accuracy level of the state estimator under stochastic conditions.

The work presented includes a sensitivity analysis of the Weighted Least Square (WLS) DSSE algorithm applied on a synthetic model of an existing 10kV distribution network in the Netherlands, with respect to the stochasticity of the load profiles applied. Then an algorithm is presented to determine the measurement configuration that satisfies a predefined maximum DSSE error. The effects of the following parameters on the state estimation accuracy are assessed:

- i. Percentage of pseudo measurements
- ii. Interval of measurements

The method first establishes the meter locations to achieve observability. Then, the algorithm uses the SE error resulting from Monte Carlo simulations to improve the accuracy. The measurement intervals are determined based on the analysis of sensitivity to the interval of measurements. This results in a measurement configuration that maintains the SE error within the acceptable range at every instant of time.

It is tested on the 10kV distribution network model, in the future scenario with high stochasticity in load profiles resulting from the projections of the energy transition for the year 2040. The results will show the effectiveness of the proposed algorithm for the determination of measurement scheme. This is important for the network operators who would use the results of the SE algorithm to make decisions on the grid operation.

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Chapter 1

Introduction

This chapter provides the introduction and background of the project. Through this chapter, the objective, methodology and contributions of the project are introduced.

Electricity grids are now under the challenge of being able to support increasing distributed generation in the distribution grid. According to DNV GL's Energy Transition Outlook 2018: Power Supply and Use report [1], due to the electrification of the energy needs in buildings, transportation and manufacturing sector, the share of electricity in energy use is expected to increase to 45% by the year 2050 [2]. The world trend of capacities of different energy supply sources seen over the past years and predicted until the year 2050 according to DNV GL's report is shown in 1.1.

World primary energy supply by source

Units: EJ/yr

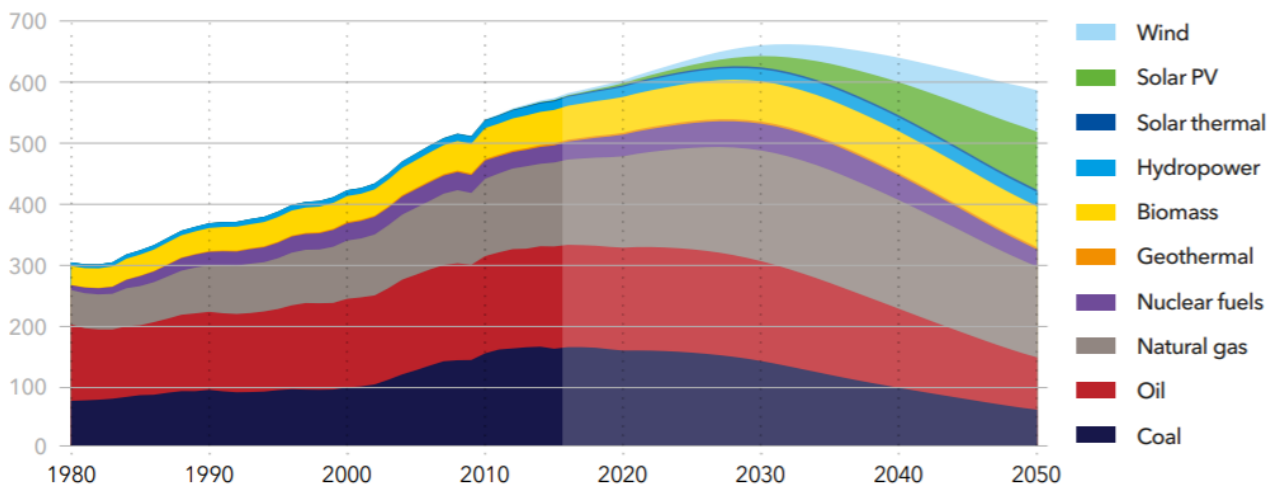


Figure 1.1: The trend of energy supply from various sources [1]

This trend can be attributed to the growing awareness among many homes and companies about energy and cost saving, and the environmental impact of the traditional electricity generation sources. The awareness is driven by international influences such as Kyoto protocol and Paris agreement along with other environmental concerns. The government in the Netherlands in fact wants to reduce the country's greenhouse gas emissions by 49% by the year 2030 compared to the emission levels in the year 1990 [3]. This provokes a vast expansion of the transmission and distribution grids [2]. The Medium Voltage (MV) grids are faced with high penetration of small distributed energy resources like roof-top Photo-Voltaic (PV) arrays and Combined Heat and Power units (CHP). Apart from this, in the Netherlands, electrification of heating and mobility is encouraged by the government ([4], [5]). This introduces new technologies like Heat Pumps (HPs) and Electric Vehicles (EVs). These distributed generation units and new technologies influence the power quality, protection, voltage profiles, etc [6]. So, more control actions at the MV grid level are required compared to the long-established passive distribution grid.

Before any control decision is made in any scenario, an accurate knowledge of the system state is crucial. In power systems, the system states are determined using State Estimation (SE) algorithms. SE algorithms calculate the most likely values of the variables that represent the system operating state. Stedin is a Distribution System Operator (DSO) in the Netherlands that has recognized the need for accurate knowledge of the system operating state and is now working to have SE for their networks.

1.1 Background

SE algorithms process inaccurate measurements to calculate the best estimate of the system state. It is well established in transmission systems, but not yet widely used in distribution systems [7]. The grid measurements are received by SCADA (Supervisory Control and Data Acquisition) system and have inaccuracies resulting from meter measurement errors, communication faults, etc.

A considerable factor that influences the accuracy of the SE is the input measurement variances [8]. MV networks typically have limited number of real measurements (from the meters in the grid). The variances of these measurements depend on the variances of the meters. Apart from these measurements, pseudo measurements are used to compensate for the lack of sufficient real measurements. These measurements are determined artificially and have high variances compared to the real measurements [9]. More grid measurements will then need to be included in addition to the existing real measurement set to improve the SE accuracy. But installation of new meters in the grid is expensive [10]. So, by using a strategy to determine the optimal number, locations and measurement intervals for the additional measurements, a required level accuracy of the SE algorithm can be achieved with minimum additional measurement units in the grid.

1.2 State of the art and scientific gap

Many algorithms for identifying the optimal measurement configuration for accurate SE have been proposed in literature over the past years. In [9], a robust meter placement algorithm is presented

to improve the SE accuracy. The algorithm determines the number of measurements and the locations of measurements in a sequential algorithm and considers the measurement uncertainties using Monte Carlo simulations. Non-heuristic approaches involving multi-objective optimization functions are also proposed, such as in [8]. Here, a multiobjective hybrid particle swarm optimization (PSO)–krill herd (KH) Pareto-based algorithm is proposed to optimize the number and location of the measurement devices considering the cost and percentage error as the optimization constraints. The error functions are modelled differently in each of the algorithms and they determine the outcome of the algorithms. For example, in [11], it is considered that using a uniform accuracy constraint for all estimated parameters may not be optimal. This results in a reduced number of required metering devices compared to other methods. Another cost effective method was published in [12], where it was proposed to place additional measurements at the nodes with existing measurements where measurement already exists. This way, the cost of Remote Transmission Units (RTUs) are reduced but it is possible to measure more variables.

The existing methods focus on determining the number and the locations of measurements to improve the SE accuracy. But when the SE accuracy profile over time, considered another aspect of input measurements that affects the SE accuracy is the measurement interval, as identified in [13]. In this project, a measurement configuration is proposed that heuristically assigns the measurement locations and using Monte Carlo simulations to allow for the random nature of the load profiles and measurement errors, the measurement intervals are determined such that the SE error meets the chosen threshold at every minute of the day.

1.3 Objective

The objective of the project is to identify a measurement configuration considering both the meter placement and the measurement intervals to achieve accurate state estimation of medium voltage grids with high distributed generation. The objective is realized through the solutions to the following research questions:

- i. *What modifications should be done to existing grid model to simulate future grid with increased distributed generation and new technologies?*

The addition of distributed generation and new technologies in the existing grid model (using offline simulation) should be done in such a way that it represents a relevant future grid for the Netherlands. Analysis of the state estimation can be done on this modified model. This will ensure that the results of the project will be directly applicable by Stedin. The presence of distributed generation and new technologies of electrical loads brings added uncertainty to the system because of their variability. The parameters of their model have to be selected such that this uncertainty can be reliably represented.

- ii. *Which is the SE algorithm that is suitable to be applied for Stedin's network?*

An SE algorithm should be selected that is suitable to be applied to the MV network model used in this project.

- iii. *How does the result of state estimation algorithm degrade with the influence of measurement parameters?*

The factors affecting the state estimation algorithm's accuracy should be analyzed since the future measurement profiles are likely to have more stochasticity and this can affect the performance of the SE algorithm.

- iv. *What is the suitable configuration of additional grid measurements for accurate state estimation?*

A strategy for identifying the locations of the additional grid measurements and the measurement intervals should be devised such that, with the least number of additional measurements, the SE algorithm's output is accurate in the presence of the new loads and distributed generation.

1.4 Research Approach and tools

For the purposes of this thesis, Python programming language was used, as its library pandapower has built-in power flow and state estimation functions. This simplifies the execution of power flow, state estimation and all further analysis. Further, it also allows the visualization of the results of power flow on the network map.

The research approach is summarized in the steps below:

- i. First, a state estimation method was chosen based on the suitability to Stedin's case. The chosen state estimation algorithm was applied on the network model (received in PowerFactory and read using Python) under study.
- ii. Load scenarios were created using an open source load profile generator available in python, developed by [14]. This was used to create load profiles of the system loads and then the load profiles were modelled using normal distribution fitting method to create the normal distribution profiles.
- iii. Measurement modelling was done by sampling from the normally distributed functions created from the load scenarios and adding Gaussian errors to represent meter inaccuracies.
- iv. The performance of the SE algorithm was evaluated with respect to two important parameters that affect the measurement variances. A sensitivity analysis which needs to be taken into account when deriving the new measurement configuration. Monte Carlo analysis was applied in these evaluations. For the Monte Carlo analysis, TU Delft's supercomputer was used in order to improve speed.
- v. The algorithm to determine the measurement configuration was developed using the supercomputer for Monte Carlo simulation steps.

1.5 Contributions

The most important contributions of this project, that are based on the scientific gap identified during the literature review, and the practical requirements for the Dutch Distribution System Operator (DSO) are summarized in the following paragraphs, in order for the importance of this study to become more clear:

- A sensitivity analysis was designed to evaluate the SE algorithm's performance with respect to two important parameters that affect the accuracy of the SE algorithm.
- Measurement configuration. Although there have been many meter placement methods existing in the literature, the measurement configuration introduced in this project takes into account not only the meter locations, but also the measurement interval, to improve the accuracy of the SE algorithm. The interval of measurement has not been used until now.
- For the sake of improving the speed of simulations using parallel computing, TU Delft's supercomputer was used. A brief user manual was prepared with the steps of using the supercomputer and running the code.

1.6 Stakeholders

This project is beneficial to Distribution System Operators. Distribution System Operators (DSOs) are responsible for ensuring the stable and reliable operation of the power system. Under a future scenario of increased distributed generation and new technologies in the MV grids, accurate state estimation is necessary to calculate the system state variables. Since the networks currently have limited number of meters present measuring at a certain fixed interval, this project aims to improve accuracy by introducing a new measurement configuration.

1.7 Thesis report outline

This thesis report is organised as follows:

Chapter 1 provides the introduction to the project. The background is provided and the research questions and research methodology are introduced. Through this chapter, the objective, methodology and contributions are introduced.

Chapter 2 describes the concept of SE algorithm for medium voltage networks. First, the practical scenario of medium voltage networks in the Netherlands is explained. Then, the choice of SE algorithm is presented. Then, the mathematical modelling of the SE algorithm is described.

Chapter 3 describes the network upon which the implementation of state estimation and further analysis is carried out. The load modelling used and the modelling of the future scenario is de-

scribed.

Chapter 4 explains the modelling of the measurements, and their variances. The result of the SE algorithm when applied on the grid model is shown. Then, the sensitivity analysis carried out to evaluate the SE algorithm's performance is presented. Some results are seen in this chapter.

Chapter 5 presents the algorithm developed to determine the measurement configuration. The steps of the algorithm, the measurement configuration and the resulting error profile are shown.

Chapter 6 has the most important conclusions obtained through this project and the the answers to the research questions presented in chapter 1.

Chapter 2

Overview of MV networks in the Netherlands and State estimation in MV networks

This chapter describes the the practical scenario of medium voltage networks in the Netherlands. The choice and mathematical modelling of SE algorithm for medium voltage networks is explained.

2.1 MV networks in the Netherlands

MV networks distribute electricity from a High Voltage (HV) connection point to commercial and residential consumers, who are the MV customers. In the Netherlands, there are many MV networks with different operating voltages, ranging from 6kV to 30kV [15]. These networks are usually meshed, to provide high availability and redundancy. The physical grid in the Netherlands consists almost entirely of underground cables. The networks transport electricity from a single HV/MV substation (primary substation) to hundreds of MV Points of Connections (PoCs). These PoCs are arranged in distribution rings, which can be operated as radial networks using Normally Open Points (NOPs). The NOPs are normally open circuit breakers that split up the distribution rings. This has the advantage that it makes the formerly ringed connections N-1 redundant. In case of faults, they can be rescheduled to have continuous availability. An example configuration of an MV is shown in the figure 2.1.

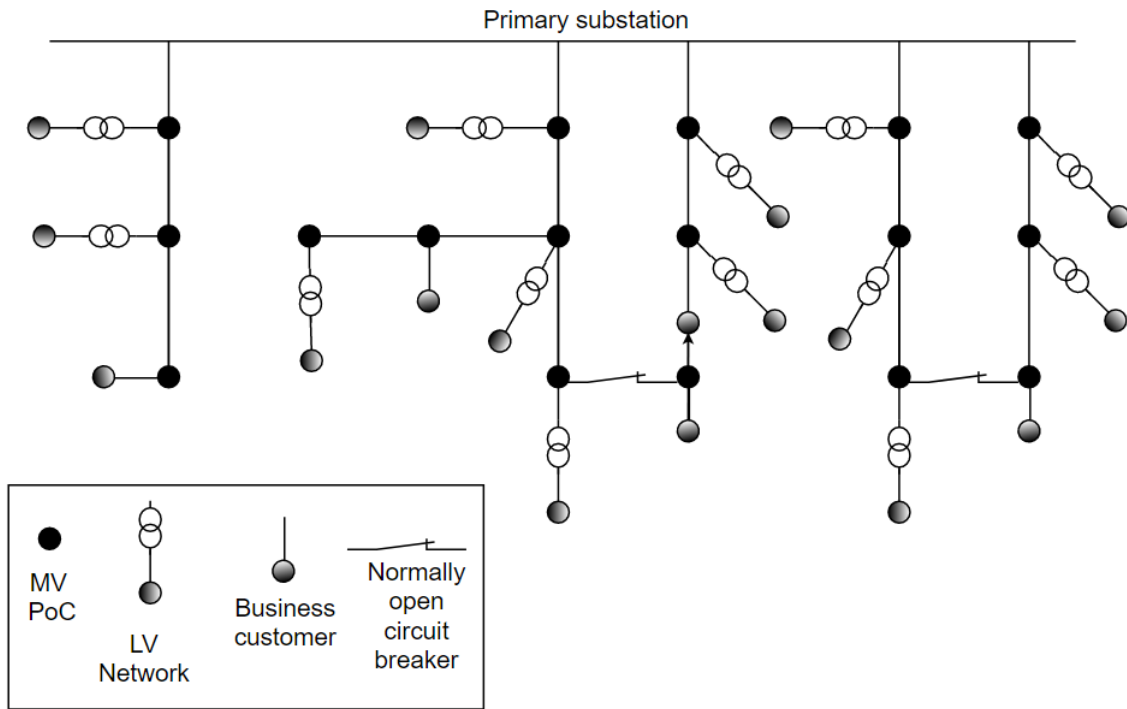


Figure 2.1: Example configuration of an MV network

2.1.1 MV connection types

MV customers are categorized by the requested capacity of the connection. Each of the connection types have a different tariff that is standardized. There can be two types of MV PoCs:

- Transformer stations that connect public Low Voltage (LV) networks to the MV distribution network.
- MV stations that feed an MV customer (Business customer). These stations do not have the need for a transformer.

2.1.2 MV network monitoring

Traditionally, MV network monitoring only includes Supervisory Control and Data Acquisition (SCADA) monitoring of the primary substation. The rest of the network usually is not metered for measurements.

The SCADA monitoring system has the following components:

- *Meters* The meters measure the bus voltages, branch powers, branch currents and bus power injections at predefined time intervals. They send the measurement data to the Remote Terminal Units (RTUs) at their location.

- *RTUs* RTUs are directly connected to the sensors/meters and receive the measured data from them. They are real-time field Programmable Logic Controllers (PLCs) and they convert the information received at the remote station into digital form ready for transmit to the central host.
- *Master Terminal Unit (MTU)* The MTU is the central host that communicates with all the RTUs in the network through reading/writing operations during scheduled scanning.
- *Communication System* The communication network is the integral part of SCADA system and is responsible for transferring data among MTU computer servers and the RTUs. The medium of communication can be telephone, radio, satellite, cable, etc. or a combination of any of them.
- *Operator Workstations* The computer stations consisting of HMI (Human Machine Interface) software are called the Operator Workstations. They are networked with a central host computer. They request and send data to host client computer in so as to monitor and control the network field parameters at the remote locations.

An overview of SCADA monitoring system is shown in the figure 2.2.

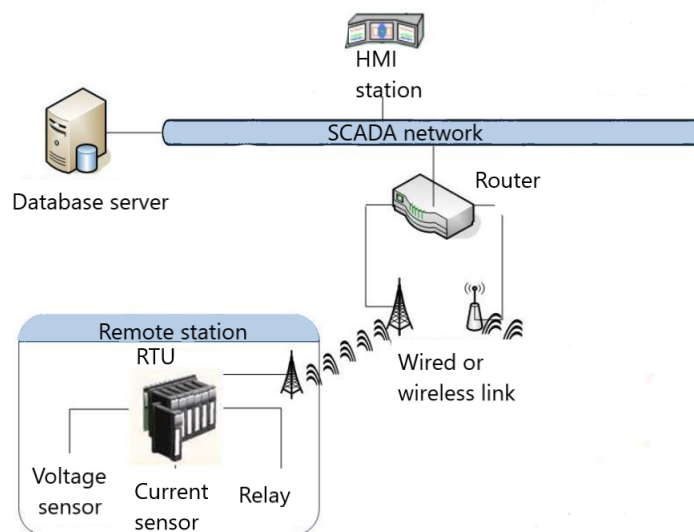


Figure 2.2: SCADA monitoring system overview. Modified from [16]

2.2 System states

The system states are the smallest subset of parameters which gives complete information about the operating condition of the network. For example, the parameters Voltage magnitudes and angles

at all nodes of the system $[V_i, \delta_i]$ give complete information about the state of the system. These parameters, along with the network parameters can be used to calculate all other parameters relating to the operation of the system. A few such equations are shown below:

- If the node voltages are known, power flows can be calculated using the relation

$$P_{ij} = V_i^2(g_{ij} + g_i^{sh}) - V_i V_j(g_{ij} \cos(\delta_i - \delta_j) + b_{ij} \sin(\delta_i - \delta_j)) \quad (2.1)$$

$$Q_{ij} = -V_i^2(b_{ij} + b_i^{sh}) - V_i V_j(g_{ij} \sin(\delta_i - \delta_j) - b_{ij} \cos(\delta_i - \delta_j)) \quad (2.2)$$

- If power flows are known, power injections at all buses can be calculated using the relation

$$P_i = \sum_{j=1}^C P_{ij} \quad (2.3)$$

$$Q_i = \sum_{j=1}^C Q_{ij} \quad (2.4)$$

Here, C is the number of nodes connected to a node i .

The parameters P_{ij} and Q_{ij} are the active and reactive power flows from node i to node j , V_i and V_j represent the voltage magnitudes at nodes i and j respectively, δ_i and δ_j represent the voltage angles at nodes i and j respectively, $g_{ij} + b_{ij}$ is the series admittance of the branch ij and $g_i + b_i$ is the shunt admittance connected at the i^{th} node.

2.3 Choice of Distribution System State Estimation (DSSE)

The grid-measurements in MV networks are received by the Distribution Management System (DMS) via SCADA system. These measurements, which are the meter readings from different locations of the grid, have inaccuracies due to meter errors. Power system state estimation is a method of calculating the system states by using measurements available from the grid and reducing the errors that are present in the measurements. This is an important tool used in Energy Management Systems (EMS).

The concept was introduced by Fred C. Schweppe J. Wildes in [17] and is popularly in use in transmission systems management. Distribution networks typically have very few grid-measurements compared to transmission systems. This presents the following issues:

- Redundancy cannot be achieved from the grid-measurements as was available in transmission systems.
- Pseudo-measurements are used in the input measurement set, which introduce high variances.

Due to these issues, transmission system state estimation techniques cannot be plainly applied to distribution networks. For state estimation in the distribution level, several DSSE techniques have been introduced and in the literature. The DSSE techniques are classified and analyzed comprehensively by Anggoro Primadianto and Chan-Nan Lu [7] as summarized below:

- i. *Weighted Least Square (WLS) based static DSSE*: WLS method is the most popular in use and in literature. The work presented in [18] shows that it is suitable to be applied on distribution networks. There are variations within this method based on choice of state variable to be calculated are studied. The state variable can be node voltage or branch current. There are several methods based on node voltage calculation (like in [19], [20], [21]) and branch current calculation (a few can be seen in [22], [23], [24]) exist and many comparison studies have been carried out between the two, as in [25], [26] and [27]. The comparison studies suggest that both methods produce similar accuracy, but when there are many voltage measurements involved, rectangular node voltage calculation method can be faster than rectangular branch current calculation based method[25].
- ii. *DSSE methods based on load adjustment*: Here, the measurement data are considered absolute and used as solution constraints in the algorithm. The current or power injection values are then adjusted to satisfy the constraints. Several techniques have been proposed such as those based on probabilistic power flow[28], iterative methods[29] and particle swarm techniques[30], etc.
- iii. *DSSE methods with improved robustness*: These methods attempt to improve robustness of the state estimation by suppressing bad data in the measurements, mainly by assigning lower weights to the measurements considered as bad data. Several techniques have been proposed which use different concepts like machine learning[31] and influence function concept from robust estimation theory [32].
- iv. *Dynamic or Forecast-aided DSSE methods*: These methods use the measurements along with a priori estimate to compute the state at the present time and predict an estimate at a future time. Several kalman filter based techniques exist which use different measurement functions and types of measurements (for example, as described in [33] and [34]).
- v. *Multi-area DSSE methods*: These methods are based on dividing the distribution grid into several areas based on topology, measurement areas, etc. and locally computing the states in each area. A common state estimation is then performed for the entire grid, using the estimates and border quantities from each of the areas as measurement data. Several techniques are presented in literature (for example, as described in [35]), but the practical implementation is problematic due to issues such as communication delays, limited real-time measurements, etc.

In this project, a static state estimation algorithm is used. For the choice of a state estimation algorithm, the following assumptions were followed:

- *State variables to be calculated*: In this project, node voltages are the system state considered.
- *No bad data assumed*: It is assumed that there is no bad data to be processed in the measurements. Due to the presence of a high percentage of pseudo measurements, there is expected to be high variances in the measurements as it is.

With these assumptions, WLS based node voltage estimator is selected for this project since it is suitable to be applied for MV networks.

2.4 Mathematical modeling of WLS SE algorithm

The WLS SE algorithm calculates the voltage magnitude and angle at a given time based on input measurements. A broad block diagram of the inputs and outputs are shown in figure 2.3 below:

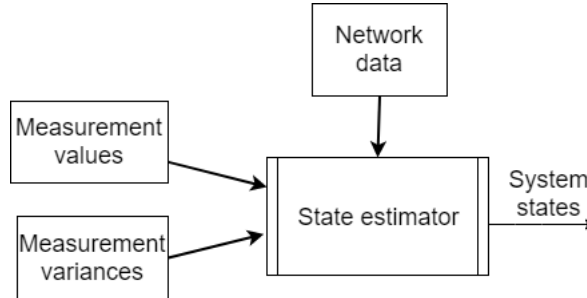


Figure 2.3: Overview of state estimation inputs and output

2.4.1 Network model

The underlying assumption is that the network is in steady state and is balanced. This means that all the branch power flows and loads are three phase and balanced, all the series and shunt devices are balanced three phase, and the lines are fully transposed. Under this assumption, a single phase positive sequence circuit model can be used to represent the network.

Line modeling

The lines are modelled as two port pi model of positive sequence equivalent circuit. Each line has a positive sequence series impedance with resistance R and reactance X and total line charging susceptance of B , as shown in figure 2.4 below:

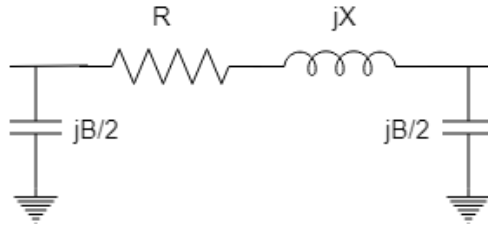


Figure 2.4: Line model

2.4.2 Shunt capacitor or reactor modeling

If there are any shunt capacitors or reactors present, they are modelled as susceptance per phase at the buses. A positive susceptance value represents a capacitor and a negative susceptance value represents a reactor. The network under consideration does not have any shunt capacitor or reactor.

2.4.3 Transformer

The 2-winding transformers are modelled as impedances in series with ideal transformers. The two terminals of the transformers j and i are called the impedance terminal and tap side terminal respectively as shown in figure 2.5 below:

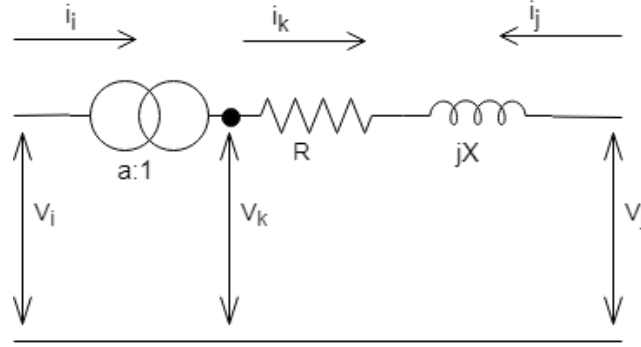


Figure 2.5: Transformer model

The nodal equations for the the equivalent 2-port circuit are derived as follows:

$$\begin{bmatrix} i_k \\ i_j \end{bmatrix} = \begin{bmatrix} y & -y \\ -y & y \end{bmatrix} \begin{bmatrix} v_k \\ v_j \end{bmatrix} \quad (2.5)$$

Here, i_k and i_j are current injections at nodes k and j respectively,

y is the admittance of branch k - j ,

v_k and v_j are the voltages at nodes k and j

The node k can be eliminated by using

$$i_k = a \cdot i_i v_k = v_i / a \quad (2.6)$$

Where, i_i is the current injection at node i and $a : 1$ is the transformer tap ratio. Substituting 2.6 in 2.5

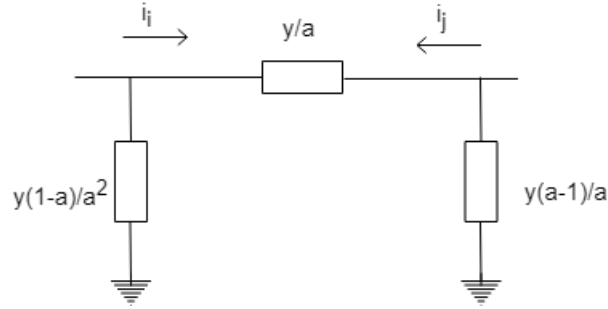
$$\begin{bmatrix} i_i \\ i_j \end{bmatrix} = \begin{bmatrix} y/a^2 & -y/a \\ -y/a & y \end{bmatrix} \begin{bmatrix} v_i \\ v_j \end{bmatrix} \quad (2.7)$$

The two 2-port circuit corresponding to 2.7 is shown in figure 2.6.

Loads and generation

The loads and generation at a node are modelled as complex power injections. The loads (consumption from households) are represented by negative power injections and the generations are represented by positive power injections.

Figure 2.6: Equivalent 2-port circuit model of transformer



2.4.4 Admittance matrix

The network admittance matrix is given by the matrix:

$$\begin{bmatrix} Y_{11} & \dots & Y_{1n} \\ \vdots & \ddots & \vdots \\ Y_{n1} & \dots & Y_{nn} \end{bmatrix} \quad (2.8)$$

Here, Y_{jk} is the admittance of branch $j - k$,

The matrix Y is a sparse matrix and in complex terms, can be written as the real part G and the imaginary part B .

2.4.5 Measurement values and variances

Three types of measurements can be used as inputs to the SE algorithm:

- i. Real measurements
- ii. Pseudo measurements
- iii. Virtual measurements

Real measurements are the measurements that are received from meters located in the network. The voltage magnitudes, angles (if available), branch currents and power flow values can be measured from the grid nodes and branches. These constitute real measurements. The variances of real measurements at the instant of measurement are dependent on the accuracy of measurement meters.

Pseudo measurements are the measurements that are computed for nodes without any telemetry. They are useful in MV networks to make the networks observable. They are bus active and reactive power injection values with high variances. They can be derived in different ways depending on the available information, as outlined below:

- The power injection values of the nodes can be derived from the historical data available corresponding to the nodes. The variances are dependent on the historical profiles as shown in [13].

- Load profile generation tools can be used in correspondence with known information about the consumers at the node to artificially generate realistic load profiles. These profiles can be used as power injection values. The profiles and variances can be modelled using suitable distributions as shown in [36].

An advantage of having pseudo measurements is that they can be used as back-up information in case of failures in the measurement or communication system.

Virtual measurements are deterministic measurements. These have the highest accuracy (least variance). They are zero injections used at buses with no loads. Noise components with very low variances are used with these measurements.

The three types of measurements, along with their noise components, are stochastic in nature and they are assumed to be normally distributed.

2.4.6 Mathematical modelling of measurement vector

The measurements available to the SE algorithm, represented here by the vector $\mathbf{z}$, are read by the SE algorithm in two parts: the measurement value and the measurement error. By using power system equations that relate the measurements received to the state variables, the following equation is obtained:

$$\mathbf{z} = \begin{bmatrix} z_1 \\ \vdots \\ z_m \end{bmatrix} = \begin{bmatrix} h_1(x_1 & \dots & x_n) \\ \vdots \\ h_m(x_1 & \dots & x_n) \end{bmatrix} + \begin{bmatrix} e_1 \\ \vdots \\ e_m \end{bmatrix} = \mathbf{h}(\mathbf{x}) + \mathbf{e} \quad (2.9)$$

Here,

$\mathbf{z}$ is the measurement vector,

$\mathbf{h}$ is the measurement function vector that relate the state variable vector $\mathbf{x}$ to the measurement value.

$\mathbf{e}$ is the measurement error. WLS algorithm works on the following assumptions:

- $\mathbf{e}$ is a Gaussian noise with zero mean. It is represented by:

$$\mathbf{e} = \mathbf{N}(0, \mathbf{R}_z) \quad (2.10)$$

- The measurement errors are independent.

$\mathbf{R}_z$ represents the measurement covariance matrix $\text{diag}(\sigma_{z1}^2, \sigma_{z2}^2 \dots \sigma_{zm}^2)$. Here σ_i is the i th measurement variance. If bus number 1 is considered as the slack bus, its bus angle is forced to zero. The state vector is, then, $\mathbf{x} = [\delta_2 \dots, \delta_n, V_1 \dots, V_n]$, where δ_i and V_i are the voltage angles magnitude at the i th bus respectively, for each of the n buses in the grid. m is the number of measurements. The SE algorithm utilizes the meter measurements taken from the grid and the network model in the form of the admittance matrix to calculate the most likely values of the state variables using an iterative process as explained in section 2.4.9.

Measurement functions

The typical measurements received from the power system are, bus voltage magnitudes, active and reactive power flows in the lines, active and reactive bus power injections, and current flow magnitudes in the lines. These measurements are then related to state variables (bus voltages and angles) using nonlinear functions, as shown in equations 2.11-2.15:

- *Power injections*: The active and reactive power injections at the i th bus are expressed as:

$$P_i = \Sigma P_{ij} = V_i \Sigma_{j \in C} V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (2.11)$$

$$Q_i = \Sigma Q_{ij} = V_i \Sigma_{j \in C} V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (2.12)$$

where C denotes the set of buses connected to the i th bus and $G_{ij} + jB_{ij}$ is the ij th element of the bus admittance matrix.

- *Power Flows*: For the two-port pi-model of a network branch $i - j$, the active and reactive power flows between the i th and the j th bus are expressed as:

$$P_{ij} = V_i^2 (g_{ij} + g_i^s h) - V_i V_j (g_{ij} \cos \delta_{ij} + b_{ij} \sin \delta_{ij}) \quad (2.13)$$

$$Q_{ij} = -V_i^2 (b_{ij} + b_i^s h) - V_i V_j (g_{ij} \sin \delta_{ij} - b_{ij} \cos \delta_{ij}) \quad (2.14)$$

Here, $g_{ij} + jb_{ij}$ is the series branch admittance of branch $i - j$ and $g_i^s h + jb_i^s h$ is the shunt branch admittance connected at bus i .

- *Branch Currents*: The current flow magnitude between the i th and the j th bus is expressed as:

$$I_{ij} = \sqrt{(V_i^2 + V_j^2 - 2V_i V_j \cos \delta_{ij})(g_{ij}^2 + b_{ij}^2)} \quad (2.15)$$

Measurement jacobian

The vector h relating the state variables to the conventional measurements is non-linear. The SE algorithm linearizes the vector around an operating condition. This is done by calculating the Jacobian matrix, which consists of 1st order derivatives of the measurement functions with respect to the state variables. It is represented by:

$$\mathbf{H} = \begin{bmatrix} \frac{\partial h_1(x)}{\partial \delta_2} \dots \frac{\partial h_1(x)}{\partial \delta_n} & \frac{\partial h_1(x)}{\partial V_1} \dots \frac{\partial h_1(x)}{\partial V_n} \\ \vdots & \\ \frac{\partial h_m(x)}{\partial \delta_2} \dots \frac{\partial h_m(x)}{\partial \delta_n} & \frac{\partial h_m(x)}{\partial V_1} \dots \frac{\partial h_m(x)}{\partial V_n} \end{bmatrix} \quad (2.16)$$

The Jacobian elements corresponding to each of the measurement functions are shown below:

- *Power Injections*:

$$\frac{\partial P_i}{\partial \delta_i} = \Sigma_{j=1}^n V_i V_j (-G_{ij} \sin \delta_{ij} + B_{ij} \cos \delta_{ij}) - V_j^2 B_{ii} \quad (2.17)$$

$$\frac{\partial P_i}{\partial \delta_j} = V_i V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (2.18)$$

$$\frac{\partial P_i}{\partial V_i} = \sum_{j=1}^n V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) + V_i^2 G_{ii} \quad (2.19)$$

$$\frac{\partial P_i}{\partial V_j} = V_i (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (2.20)$$

$$\frac{\partial Q_i}{\partial \delta_i} = \sum_{j=1}^n V_i V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) - V_j G_{ii} \quad (2.21)$$

$$\frac{\partial Q_i}{\partial \delta_j} = -V_i V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (2.22)$$

$$\frac{\partial Q_i}{\partial V_i} = \sum_{j=1}^n V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) - V_i B_{ii} \quad (2.23)$$

$$\frac{\partial Q_i}{\partial V_j} = V_i (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (2.24)$$

• *Power Flows:*

$$\frac{\partial P_{ij}}{\partial \delta_i} = V_i V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (2.25)$$

$$\frac{\partial P_{ij}}{\partial \delta_j} = -V_i V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (2.26)$$

$$\frac{\partial P_{ij}}{\partial V_i} = -V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) + 2V_p (g_{ij} + g_i^s h) \quad (2.27)$$

$$\frac{\partial P_{ij}}{\partial V_j} = -V_i (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (2.28)$$

$$\frac{\partial Q_{ij}}{\partial \delta_i} = -V_i V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (2.29)$$

$$\frac{\partial Q_{ij}}{\partial \delta_j} = V_i V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (2.30)$$

$$\frac{\partial Q_{ij}}{\partial V_i} = -V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) - 2V_p (b_{ij} + b_i^s h) \quad (2.31)$$

$$\frac{\partial Q_{ij}}{\partial V_j} = -V_i (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (2.32)$$

- *Line Current Magnitudes:*

$$\frac{\partial I_{ij}}{\partial \delta_i} = \frac{g_{ij}^2 + b_{ij}^2}{I_p q} V_i V_j \sin \delta_{ij} \quad (2.33)$$

$$\frac{\partial I_{ij}}{\partial \delta_j} = -\frac{g_{ij}^2 + b_{ij}^2}{I_p q} V_i V_j \sin \delta_{ij} \quad (2.34)$$

$$\frac{\partial I_{ij}}{\partial V_i} = \frac{g_{ij}^2 + b_{ij}^2}{I_p q} (V_i - V_j \cos \delta_{ij}) \quad (2.35)$$

$$\frac{\partial I_{ij}}{\partial V_j} = \frac{g_{ij}^2 + b_{ij}^2}{I_p q} (V_j - V_i \cos \delta_{ij}) \quad (2.36)$$

- *Power injections:*

$$\frac{\partial V_i}{\partial \delta_i} = 0 \quad (2.37)$$

$$\frac{\partial V_i}{\partial \delta_j} = 0 \quad (2.38)$$

$$\frac{\partial V_i}{\partial V_i} = 1 \quad (2.39)$$

$$\frac{\partial V_i}{\partial V_j} = 0 \quad (2.40)$$

2.4.7 WLS state estimation problem

The measurements used by the SE algorithm are noisy. This makes the measurement vector stochastic but the state vector is deterministic and there is no prior knowledge about it. For an unknown $\mathbf{x}$, a conditional probabilistic distribution function $f(\mathbf{z} | \mathbf{x})$ is considered. This function holds information about $\mathbf{x}$. The state vector $\mathbf{x}$ can be derived from f using the maximum likelihood criterion [37] as below:

Given measurement $\mathbf{z}$, the maximum-likelihood estimate $\hat{\mathbf{x}}$ is the value of $\mathbf{x}$ which maximizes $f(\mathbf{z} | \mathbf{x})$, the likelihood that $\mathbf{x}$ resulted in the observed $\mathbf{z}$.

$f(\mathbf{z} | \mathbf{x})$ is called a likelihood function. For convenience, the likelihood function is defined. Now, logarithm is a monotonically increasing function. This means that the maximisation of $f(\mathbf{z} | \mathbf{x})$ is equivalent to maximisation of log-likelihood $\ln(f(\mathbf{z} | \mathbf{x}))$. Here, the state estimation problem is defined as the minimisation of the negative log-likelihood function. This is stated as:

$$\text{Minimize } \mathbf{x} : \ln(f(\mathbf{z} | \mathbf{x})) \quad (2.41)$$

Considering $\mathbf{z}$ to be normally distributed as below,

$$f(\mathbf{z} | \mathbf{x}) = \frac{1}{\sqrt{(2\pi)^m \det \mathbf{R}_z}} \exp \frac{1}{2} (\mathbf{z} - \mathbf{h}(\mathbf{x}))^T \mathbf{R}_z^{-1} (\mathbf{z} - \mathbf{h}(\mathbf{x})) \quad (2.42)$$

Ignoring the constant terms (since they do not exist after taking derivatives), the minimisation problem becomes

$$\text{Minimize } x : J = \frac{1}{2}(\mathbf{z} - \mathbf{h}(\mathbf{x}))^T \mathbf{R}_z^{-1}(\mathbf{z} - \mathbf{h}(\mathbf{x})) \quad (2.43)$$

The WLS estimation of x is the solution to this minimization problem. The derivation of the solution is shown below.

2.4.8 Gauss-Newton method solution

To find the minimand $\hat{\mathbf{x}}$, Gauss-Newton method based approximations are applied to the first derivatives and second derivatives of J . The condition to satisfy at the first order derivative becomes,

$$\nabla J(\mathbf{x}) = -\mathbf{H}^T(\mathbf{x})\mathbf{R}_z^{-1}[\mathbf{z} - \mathbf{h}(\mathbf{x})] = 0 \quad (2.44)$$

Where $\mathbf{H} = \frac{\partial \mathbf{h}(\mathbf{x})}{\partial \mathbf{x}}$ and $\mathbf{H}^T(\mathbf{x})\mathbf{R}_z^{-1}\mathbf{H}(\mathbf{x})$ is the gain matrix $\mathbf{G}(\mathbf{x})$. It is a sparse matrix and if the system is fully observable, it is positive definite. The above expression can be expanded around state $\hat{\mathbf{x}}$, through Taylor expansion series as shown below,

$$\nabla J(\mathbf{x}) = \nabla J(\mathbf{x}_k) + \nabla^2 J(\mathbf{x}_k)(\mathbf{x} - \mathbf{x}_k) + \dots = 0 \quad (2.45)$$

Here, by substituting 2.44 in 2.45,

$$\nabla^2 J(\mathbf{x}_k) = \mathbf{H}^T(\mathbf{x}_k)\mathbf{R}_z^{-1}\mathbf{H}(\mathbf{x}_k) \quad (2.46)$$

Using 2.44 and 2.46 in 2.45 and neglecting the higher order terms, the iterates $\mathbf{x}_k$ can be calculated as,

$$\mathbf{x}_{k+1} = \mathbf{x}_k + (\mathbf{H}^T(\mathbf{x}_k)\mathbf{R}_z^{-1}\mathbf{H}(\mathbf{x}_k))^{-1}\mathbf{H}^T(\mathbf{x}_k)\mathbf{R}_z^{-1}[\mathbf{z} - \mathbf{h}(\mathbf{x}_k)] \quad (2.47)$$

This can be written as,

$$\mathbf{G}(\mathbf{x}_k)\Delta\mathbf{x}_{k+1} = \mathbf{H}^T(\mathbf{x}_k)\mathbf{R}_z^{-1}[\mathbf{z} - \mathbf{h}(\mathbf{x}_k)] \quad (2.48)$$

Where, $\Delta\mathbf{x}_{k+1} = \mathbf{x}_{k+1} - \mathbf{x}_k$

2.4.9 WLS state estimation algorithm

The algorithm involves iteratively solving the equation 2.48. At the start of the algorithm, an initial estimate of the state vector should be provided. A flat initialization is an option where all the bus voltages are initialized as 1 p.u and all bus angles are initialized as 0. The iterative algorithm is then carried out as follows:

- i. Setting the iteration index $k = 0$ and initializing the state vector.
- ii. Calculation of gain matrix. In this step, the computations that essentially take place are:
 - calculation of the measurement function $\mathbf{h}(\mathbf{x}_k)$.
 - Building the Jacobian $\mathbf{H}(\mathbf{x}_k)$

- iii. Calculation of the right hand side (RHS) of the equation 2.48.
- iv. Solve for $\Delta \mathbf{x}_{k+1}$.
- v. Convergence: is $\text{abs}(\Delta \mathbf{x}_{k+1}) < \text{tolerance } (\epsilon)$?
- vi. If no convergence, update $\mathbf{x}_{k+1}$ and go to step .

The state estimation algorithm is shown in the flowchart in figure 2.7

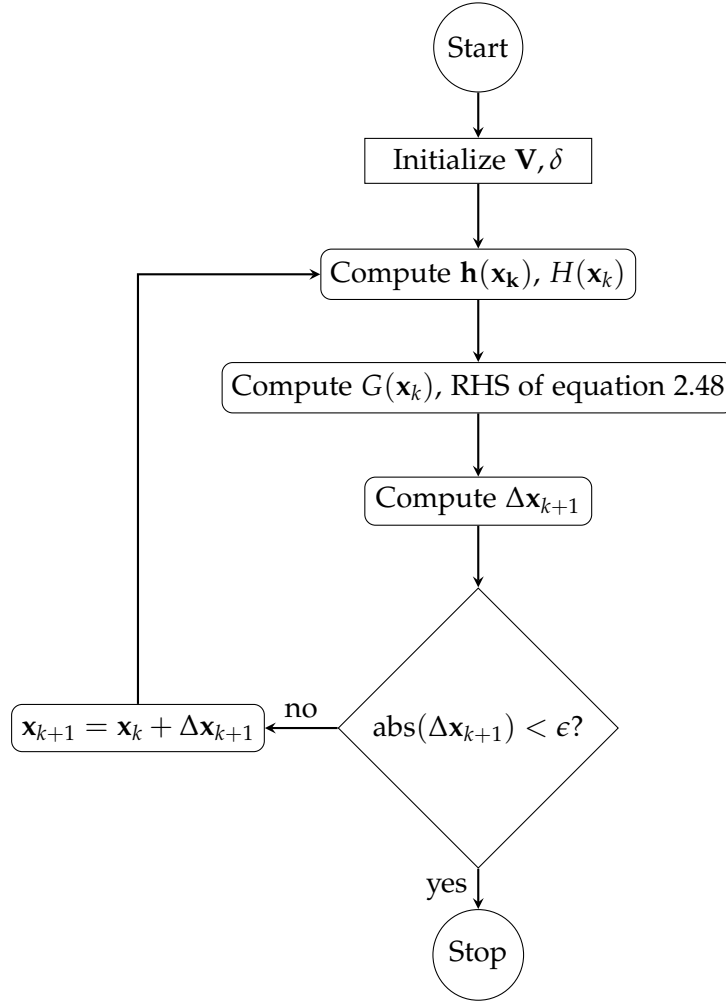


Figure 2.7: Computation steps of state estimation algorithm

2.5 Observability of a network

State estimation can only be carried out on a network if the network is fully observable. A network is said to be fully observable if the matrix $\mathbf{H}$ has full column rank, i.e., $\text{rank}[\mathbf{H}] = n$, where n is the

number of states to be calculated. A necessary condition for observability is that there should be at least $2n - 1$ independent measurements available from the network. If a network is unobservable, then it is made up of observable islands that are separated by unobservable branches. The identification of these unobservable branches is described in [38].

Chapter 3

Study system and measurement setup

This chapter describes the network upon which the implementation of state estimation and further analysis is carried out. The load modelling used and the modelling of the future scenario is described.

The SE algorithm described in the previous chapter is applied to the network described in this chapter. All further analysis/modifications described in the coming chapters are carried out on this network itself. A simulation model of a practical medium voltage network of an area in the Netherlands (MijdrecH) is downsized and anonymized in order to apply the WLS state estimation and perform analysis. The grid is owned by Stedin B.V., a Dutch distribution grid operator. The 10kV MV grid contains a 50/10kV primary substation. The 50kV node in this substation is used as the reference/slack node in the simulations. In reality, the topology of the MV network keeps changing due to grid maintenance, protection from faults, component failures and other dispatch decisions. But it is assumed in this project that the topology of this network is constant. The schematic view of the network is shown in figure 3.1

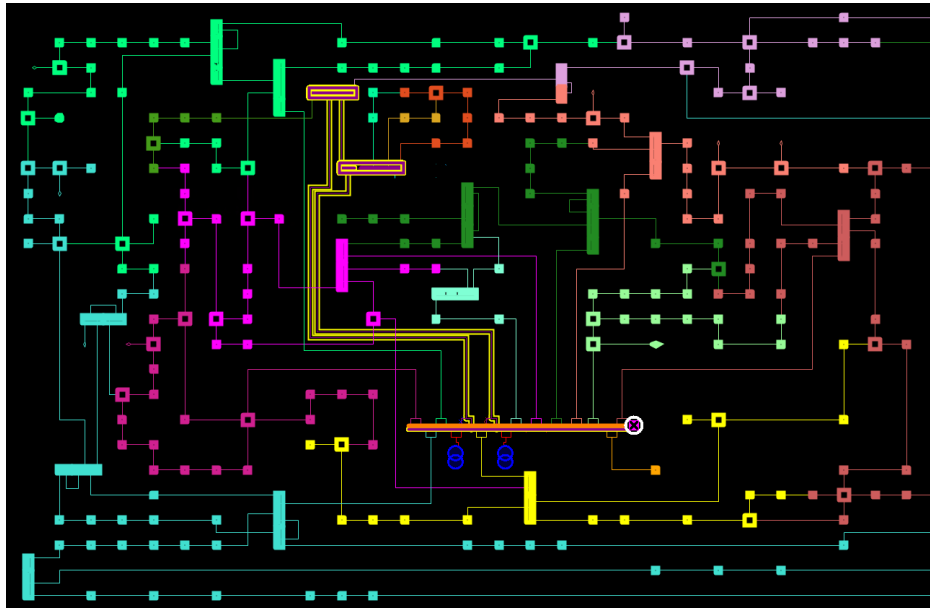


Figure 3.1: Network Schematic

Where,



is the primary substation with feeder connections going out.



is a 50kV/10kV transformer in the Primary substation



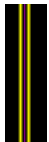
is a PoC



is a PoC with degree higher than 2



is a PoC which has more than one bus rail



is a looped feeder, which means that the feeder is energized by 2 sources.



is a business customer

3.1 Load and generation present in the network

There are 237 MV Point of Connections (PoCs), among which eight PoCs are connected to industrial loads (business customers) and no PoCs are connected with DGs. The others are connected to household/commercial loads. For each run of the SE algorithm, the loads are generated as described in section 3.2

3.2 Generating load profiles

At each PoC i where an LV network is connected, the load at the LV side of the MV/LV transformer is the summation of all the consumption in that LV network (the transformer losses are ignored). Here, an assumption is made that all the consumers in every LV network are residential customers. Supposing that at PoC i , there are n_i number of households. Then, to simulate the LV load profile ld_i at PoC i , n_i household profiles are generated and the summation of the n_i profiles gives the LV load ld_i . Both active profiles and reactive profiles are generated so that the LV load active part ld_{pi} and reactive part ld_{qi} are known. Each household active and reactive power profiles are generated using the open source load profile generator developed using a bottom-up approach in [14]. The process is briefly explained as follows:

- The flexible loads, Photovoltaic (PV) panels and/or batteries associated to the household are specified.
- Occupancy profile is obtained by simulating the individual inhabitant behaviour.
- Using the occupancy profile and device power ratings, device usage profiles are generated based on human interaction requirements of the devices.

The usage profiles of flexible devices are generated using the household configuration.

- By assigning power factors to each of the devices, the reactive power profiles are obtained.

The load profile generator uses the above steps to generate profiles for each household. Further, by taking input parameters such as:

- Total number of households to simulate (size of neighbourhood)
- Percentage of penetration of new technologies: Heat pump, Combined Heat and Power (CHP), Electric Vehicles (EVs) and PV.

The household profiles for a scenario with specific percentage of penetration of each type of the new load/generation devices are simulated.

The flowchart of the process can be seen in the figure 3.2

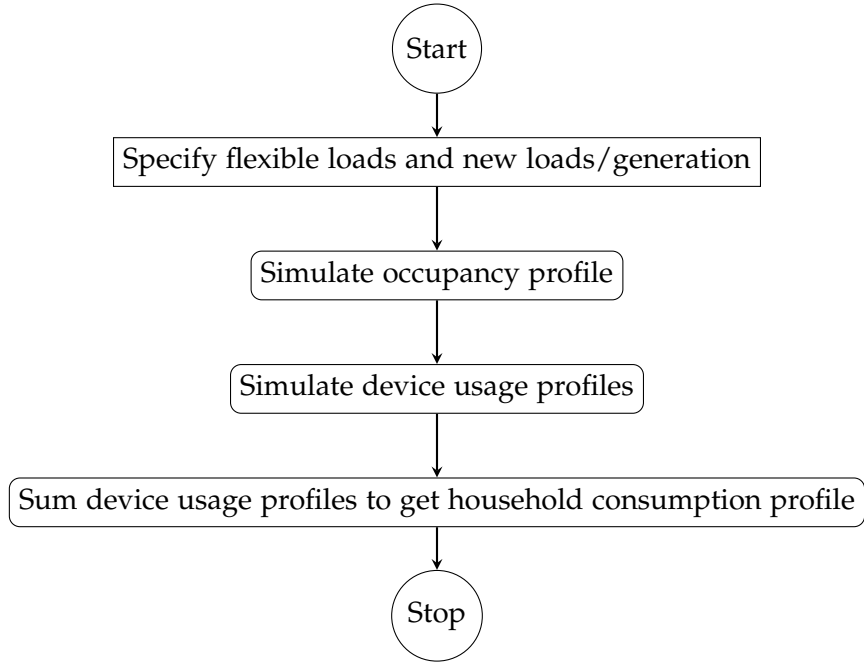


Figure 3.2: Computation steps of state estimation algorithm

Approximation applied: In this generator, 7 types of households are considered regarding the types of families (2 working parents and 2 children or a retired couple, etc.). To save time during the implementation of the simulations, for each node, 7 households were simulated, one of each type and scaled to represent the total number of households at that node. At each PoC i where a business customer is connected, a load with constant active power and reactive power are simulated.

3.3 New technologies load profiles

To include the emerging technologies that are likely to be part of the Netherlands, the study conducted in [39] was consulted. The work first identified the drivers that can influence the future demand and supply of energy. They are:

- i. Government policy: The focus on either a national or an international policy can affect the future energy dynamics.
- ii. Society: A society oriented towards economy or environmental consciousness.
- iii. Economic growth of the country.

Three future scenarios of the future energy supply were drafted, where each scenario shows the choices that are born out of the above drivers. Networking planning is done with the expected time-horizon of about 25 to 30 years. Since this study was conducted in the year 2011, the predicted scenarios are for the year 2040. The scenarios are shown in the table 3.1 below:

Scenario 1	Scenario 2	Scenario 3
· The policies do not change much · National policy · Focus is on saving energy · Not much new technology is included	· Global economy is the lead focus · High economic growth · To cope with economic growth, focus is on saving energy · Electrification of mobility and heating	· Policies focus on local and environmental enhancement · High economic growth · Focus is on saving energy and efficient technologies · Inclusion of many new technologies
The effect on electricity supply		
Mostly centralized generation	Relatively higher growth of centralized generation but PVs and CHPs also have some growth	High increase in distributed generation
The effect on electricity demand		
Demand growth around 0.5%, a few electric vehicles and heat pumps	Demand growth around 2%; comparatively high number of heat pumps and electric vehicles	Demand growth around 1%; comparatively high number of heat pumps and electric vehicles

Table 3.1: Possible future energy scenarios in the Netherlands

At present, the Netherlands is working towards the goal of reducing CO₂ emissions by 49% compared to the year 1990, by the year 2030 [40]. This has led to the trend of increased incentives for electrification of heating and transportation [4], [41]. Since this trend is most compatible with Scenario 2, this scenario is adopted for the project to show future generation. The penetration percentage of different generations according to [39] is then given by table 3.2:

Technology	
Photovoltaic Panels	
Penetration degree	0.1 m ₂
Efficiency	20%
Electric Vehicles	
Penetration degree	75%
Micro CHPs	
Penetration degree	3 - 6%
Electrical power	1kW
Thermal power	6kW
Heat Pumps	
Penetration degree	70%
Compressor power	0.6-0.9kW

Table 3.2: Scenario 2 specifications

The power capacity specifications of the PV generation and Electric vehicle consumption is included within the ALPG, modelled based on survey data [42] and load forecasting methods [43]. The heat pumps and CHPs are modelled as constant loads and generators respectively during the months of September to February. They are all modelled as direct current (DC) technologies. The generation profiles are modelled as negative load profiles. These are the specifications applied when generating the future load profiles as explained in 3.2.

The figure 3.3 shows the comparison of the present mean active power profile of an example MV node connected to an LV network vs the mean active power profile when Scenario 2 is applied. The dotted line represents that the curves are not continuous but have a resolution of 1-minute.

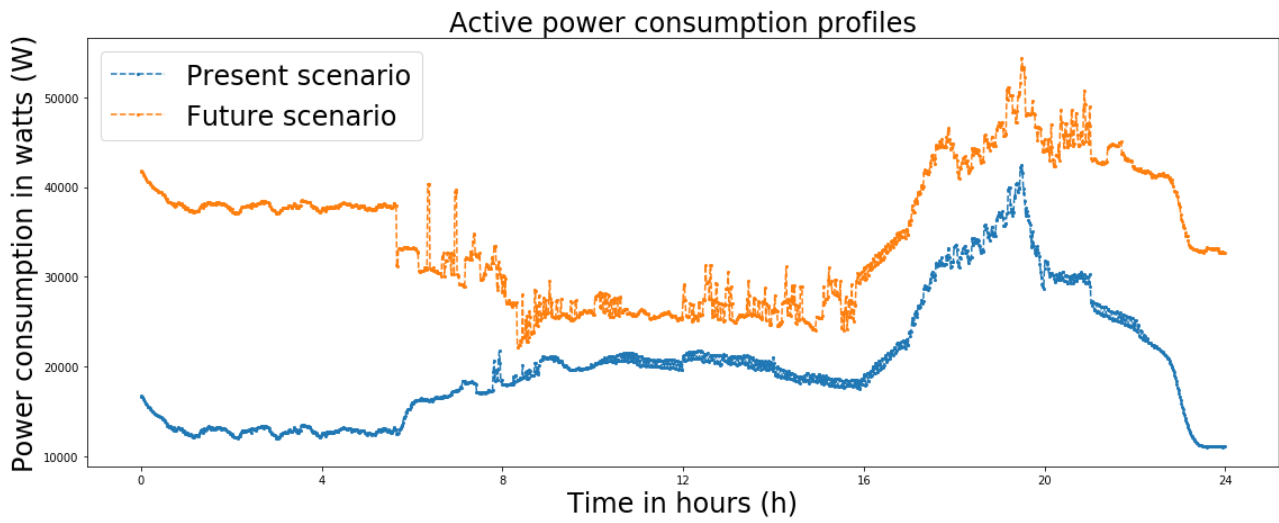


Figure 3.3: Comparison of active power profiles

The shape of the profile of Scenario 2 (with generation) looks different compared to the present consumption. This is because of the following reasons:

- The electrified heating increases the overall power consumption.
- The electric vehicles charging during the night raises the power consumption during those hours.
- The PV generation during the day reduces the power consumption during those hours.

Chapter 4

Measurement modelling and sensitivity analysis of the implemented SE algorithm

This chapter explains the modelling of the measurements, and their variances. The result of the SE algorithm when applied on the grid model and the sensitivity analysis carried out to evaluate the SE algorithm's performance is shown.

4.1 Creating loading scenario

All the load data in this project are generated artificially. In order to simulate the measurements, first load scenarios are generated. A load scenario is generated by creating load profiles at all the MV nodes connected to loads. The industrial loads are modelled as constant loads. The load profiles at the MV nodes connected to LV networks are generated using the artificial load profile generator (ALPG) as explained in chapter 3. A loading scenario is simulated as described in the sections below.

4.1.1 Load profile generation

Multiple load profiles of all the loads are generated as follows:

- First all the MV nodes that are connected to loads are identified.
- The industrial loads that are connected to MV nodes are modelled as constant impedances as shown below:

$$l_{Pj_i} = c_{Pi} \quad (4.1)$$

$$l_{Qj_i} = c_{Qi} \quad (4.2)$$

Where l_{Pj_i} is the active load and l_{Qj_i} is the reactive load at industrial load connected bus i for a load scenario j . The c_{Pi} and c_{Qi} are constant values representing the active and reactive power

values of the load at that node. Since the industrial loads are assumed to be fixed loads, their value does not change in different loading scenarios or with time.

- The LV networks that are connected to MV nodes comprise of a number of households. Each household in the LV networks are simulated using the ALPG. The ALPG generates statistical active and reactive load profiles for a household. The profiles generated represent the household loads for the duration of one day, at the resolution of 1-minute. By running the ALPG multiple times, multiple load profiles are generated statistically for each LV network. The ALPG considers 7 types of households in terms of the number and occupation of the people within the households. An approximation used to simulate the entire LV network load is that, for each LV network, 7 households are simulated using the ALPG (one of each type) and depending on the size of the LV network, the active/reactive power profile obtained from the sum of the 7 profiles is scaled up to obtain the load profile representing the LV network. Figure 4.1 shows an example of the present active power consumption profile of an MV node connected to an LV network.

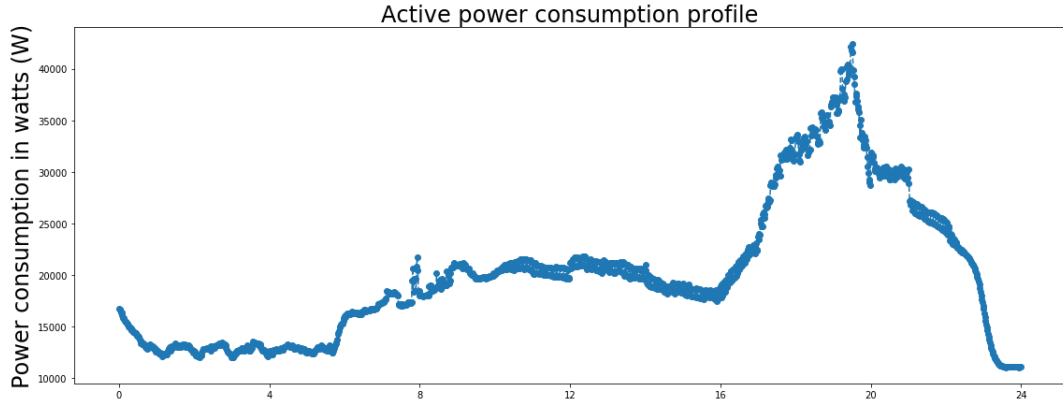


Figure 4.1: Total active power consumption profile of an LV network

4.1.2 Normal distribution fitting

For all the MV nodes connected to LV networks, The clusters of active and reactive load profiles created as explained in the above section are used to apply normal distribution fitting method. This creates a normally distributed function for each minute and for each MV node connected to connected to LV networks. Using these distributions, load scenarios can be generated. The following steps explain the process of creating the normally distributed function:

- For each LV network (at n th node out of a total of N MV nodes which are connected to LV networks), multiple profiles are generated and stored in **P** and **Q**. For M number of profiles

generated per load, the matrix $\mathbf{P}$ and matrix $\mathbf{Q}$ is shown.

$$\mathbf{P} = \begin{bmatrix} Pl_{d11} & \cdots & Pl_{d1M} \\ \vdots & & \\ Pl_{dN1} & \cdots & Pl_{dNM} \end{bmatrix} \quad (4.3)$$

$$\mathbf{Q} = \begin{bmatrix} Ql_{d11} & \cdots & Ql_{d1M} \\ \vdots & & \\ Ql_{dN1} & \cdots & Ql_{dNM} \end{bmatrix} \quad (4.4)$$

Where Pl_{dij} is the i th active power load profile and Ql_{dij} is the i th reactive power load profile for the j th node connected to an LV network.

- For the i th LV network, at every minute in time, a mean and a standard deviation is obtained from the cluster of profiles for both the active and reactive profiles. This is done using the pythonic function *scipy.stats.norm.fit*. This is a function from the *scipy* library and gives the normal distribution parameter estimates for generic data.
- These are stored in $\mathbf{F}_P$ and $\mathbf{F}_Q$.

$$f_{Pi} = N_{P_i}(\mu_{P_i}, \sigma_{P_i}) \quad (4.5)$$

$$f_{Qi} = N_{Q_i}(\mu_{Q_i}, \sigma_{Q_i}) \quad (4.6)$$

$$\mathbf{F}_P = \begin{bmatrix} f_{P1} \\ \vdots \\ f_{PN} \end{bmatrix} \quad \mathbf{F}_Q = \begin{bmatrix} f_{Q1} \\ \vdots \\ f_{QN} \end{bmatrix} \quad (4.7)$$

4.1.3 Random sampling to create load scenario

By random sampling from the normal distribution functions f_{Pi} and f_{Qi} at all the nodes with loads, a load scenario j is created, with l_{Pji} and l_{Qji} as the loads profiles of the i th (load connected) node. These form matrices $\mathbf{L}_{Pj}$ and $\mathbf{L}_{Qj}$.

$$\mathbf{L}_{Pj} = \begin{bmatrix} l_{Pj1} \\ \vdots \\ l_{PjN} \end{bmatrix} \quad \mathbf{L}_{Qj} = \begin{bmatrix} l_{Qj1} \\ \vdots \\ l_{QjN} \end{bmatrix} \quad (4.8)$$

where,

$$l_{Pji} = randnorm(f_{Pi}) \quad (4.9)$$

$$l_{Qji} = randnorm(f_{Qi}) \quad (4.10)$$

The function *randnorm* picks a random sample from the normally distributed function. This is done using the python function *numpy.random.normal* which is a function under the *numpy* library and draws random samples from a normal (Gaussian) distribution. Thus, the loading scenario is generated.

4.2 Creating the measurements from the loading scenario

State estimation algorithm requires the measurement values along with their corresponding measurement variances as inputs. The different types of measurements that can be used in state estimation are real measurements, pseudo measurements and virtual measurements. They are modelled as explained in the following sections.

4.2.1 True measurements

First, the loading scenario is simulated and using the power flow, the true measurements are formed as $\mathbf{P}_{injection} = -\mathbf{L}_{Pj}$ and $\mathbf{Q}_{injection} = -\mathbf{L}_{Qj}$. To obtain other true measurements for this loading scenario, power flow is run using the same network model and the loading scenario. From the result of the power flow at every minute, branch power flow values and bus voltage magnitudes in the entire network is obtained. The true system state profile is also obtained, which is $\mathbf{V}_{mag}$ and $\mathbf{V}_{ang}$.

The process is shown in flowchart 4.2.

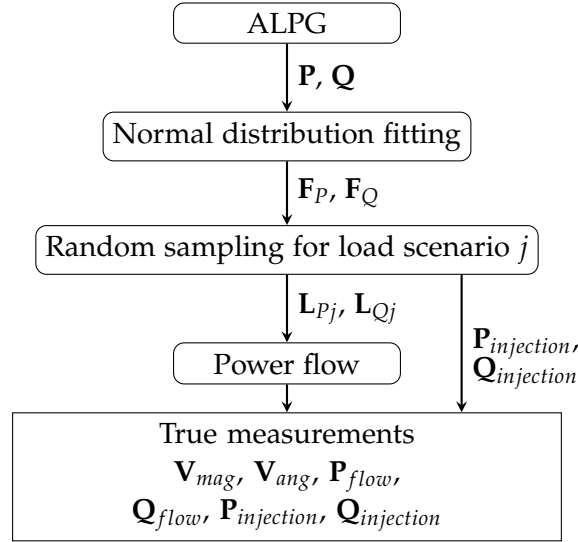


Figure 4.2: Flowchart to create load scenario and true measurements

4.2.2 Real measurements

Real measurements are the meter measurements from the different locations in the grid. At the instant of measurement, the variance of these measurements arise from the variance of the meters, which is assumed to be 10^{-5} [13]. The real measurements are simulated as follows:

$$z_i = z_{true-i} + randnorm(0, \sigma_i^2) \quad (4.11)$$

Here, z_i is the measurement at the i th node, z_{true-i} is the corresponding true measurement and σ_i^2 is the variance of the measurement. To simulate a measurement profile with a grid measurement

interval every k minutes, the measurement values and variances at the times of measurement are given by the meter measurement value and variance itself. At every minute between the times of measurement, the measurement value remains the same as the latest measured value and the variance depends on the change in actual value with respect to the latest measured value:

$$\sigma_{it}^2 = z_{i_{t1}} - z_{true-i_t} \quad (4.12)$$

where at the t th minute, the latest time of measurement is $t1$.

4.2.3 Pseudo measurements

At the load nodes with no meters, the power injection values are created using the profiles produced by ALPG. They have variances equal to the variances of normally distributed functions resulting from the profiles. They are simulated by sampling from the normal distribution functions shown in 4.5 and 4.6:

$$P_{inj-Pseudo} = -randnorm(f_{Pi}) \quad (4.13)$$

$$Q_{inj-Pseudo} = -randnorm(f_{Qi}) \quad (4.14)$$

4.2.4 Virtual measurements

At the nodes where there are no loads, the bus active and reactive power injection values are 0. These values can be considered the most accurate and the variance is assigned to be 10^{-8} .

4.2.5 Implementation of the WLS SE on the network

For the network model used, when the SE algorithm is executed using $\mathbf{P}_{injection}$ and $\mathbf{Q}_{injection}$ measurements at all the nodes and V_{mag} at the slack bus. The SE error in percentage is calculated as,

$$\text{error} = \frac{abs(\mathbf{Vse} - \mathbf{V})}{abs(\mathbf{Vse})} \cdot 100 \quad (4.15)$$

Where $\mathbf{Vse} = \mathbf{Vse}_{mag} + i \cdot \mathbf{Vse}_{ang}$ is the state vector calculated by the SE algorithm and $\mathbf{V} = \mathbf{V}_{mag} + i \cdot \mathbf{V}_{ang}$ is the is the state vector. The error at the buses is plotted in the figure 4.3

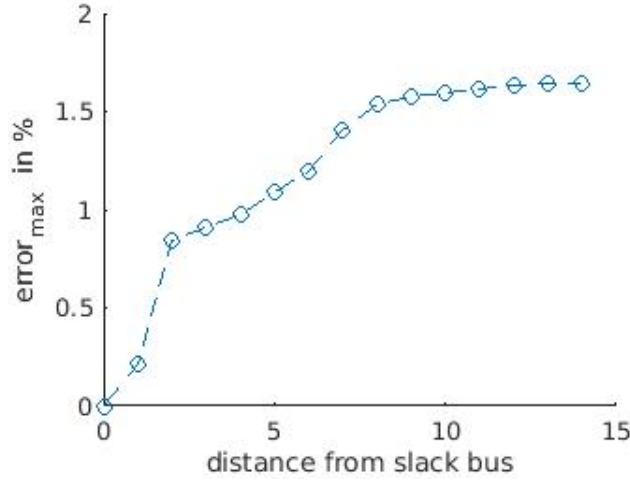


Figure 4.3: Effect of distance from slack bus

The figure is obtained running the SE algorithm explained in 2.7 and calculating the error using the equation 4.15. The maximum of all the errors at the nodes at a particular distance (number of hops) from the slack bus is plotted as $error_{max}$. This is done for all the distances in the network to obtain the figure. The performance of the SE algorithm decreases (error increases) as the distance between a bus and the slack bus increases. This is because an accurate voltage measurement is available for the slack bus. The error compounds at each hop away from the slack bus since the measurement functions actually use the states calculated at the connected buses and there are no more voltage references available. Having accurate voltage reference measurements at more nodes at different distances from the slack bus would reduce the error at the nodes farther away from the slack bus.

4.3 Sensitivity analysis of the SE algorithm

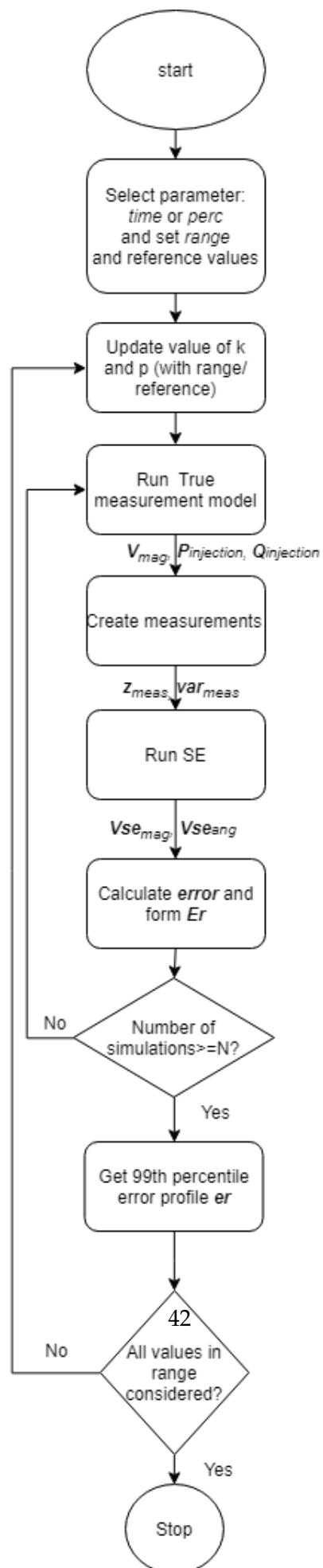
The variance of the input measurements have influence the SE algorithm's accuracy. Since the variance of the pseudo-measurements is considerably higher than the variances of the real measurements, the sensitivity of the SE algorithm to the percentage of pseudo-measurements in the input measurement set is analyzed. Another factor that affects the measurement variance is the measurement interval. A sensitivity analysis is performed by plotting the error profiles for increasing measurement intervals and the corresponding measurement variances.

The detailed steps to carry out both analyses is explained below:

- i. Start the analysis by selecting the parameter, *perc* (percentage of pseudo measurements) or *time* (measurement interval).
- ii. If the selected parameter is *perc*, the range of values against which the error profiles are calculated $range = [0, 25, 50, 75, 100]$ and reference value for *time* is $k = 5$. If the selected parameter is *time*, $range = [5, 15, 30]$ and reference value for *perc* is $p = 0$.

- iii. Run the True measurement model shown in 4.2 for every minute of the day.
- iv. Using the true measurements $\mathbf{V}_{mag}$, $\mathbf{P}_{injection}$ and $\mathbf{Q}_{injection}$, the real, virtual and pseudo measurements are created at every minute for grid-measurement intervals at every k minutes and p percentage of pseudo measurements assigned randomly in the network.
- v. Using the measurements $\mathbf{z}_{meas}$, i.e., $\mathbf{V}_{meas_{mag}}$, $\mathbf{P}_{meas_{injection}}$ and $\mathbf{Q}_{meas_{injection}}$ and virtual measurements, with their variances represented by $\mathbf{var}_{meas}$, run the SE algorithm model as explained in 2.7 at 1-minute intervals to get the resulting system states $\mathbf{Vse}_{mag}$, $\mathbf{Vse}_{ang}$
- vi. Calculation of percentage error as in equation 4.15. where, $\mathbf{Vse} = \mathbf{Vse}_{mag} + i \cdot \mathbf{Vse}_{ang}$ and $\mathbf{V} = \mathbf{V}_{mag} + i \cdot \mathbf{V}_{ang}$
 The error profile from each Monte Carlo (MC) simulation (with a total of N MC simulations) is stored in matrix $\mathbf{Er} = \begin{bmatrix} \mathbf{error}_{1_1} & \cdots & \mathbf{error}_{1_{1440}} \\ \vdots & & \\ \mathbf{error}_{N_1} & \cdots & \mathbf{error}_{N_{1440}} \end{bmatrix}$
- vii. Steps 3-6 are repeated N times (MC simulations) and then the 99th percentile error at every minute is calculated from $\mathbf{Er}$ to get the error profile $\mathbf{er}$. This eliminates the extreme values which can cause an over-determined system.
- viii. Steps 3-7 are repeated for each value in *range* to get error profiles for the range of parameter values.

The analyses are represented in the following flowchart:



4.4 Results of the analyses

After running the sensitivity analysis described above, the error profiles with increasing percentages of pseudo measurements are shown in this section.

The smart meter variances, in accordance with equation 4.12, depend on the meter variances at the time of measurement and increase as the number of minutes from the time of measurement increases. 100% pseudo measurements is applied by using pseudo measurements for 100% of the nodes connected to loads. Similarly, the 100% real measurements is applied by using real measurements for 100% of the nodes connected to loads. The measurements used in this section are $\mathbf{P}_{injection}$ and $\mathbf{Q}_{injection}$ measurements, with the power injection measurements composed of real and pseudo measurements as per the percentage at the nodes where real measurements are considered.

4.4.1 Percentage of pseudo-measurements

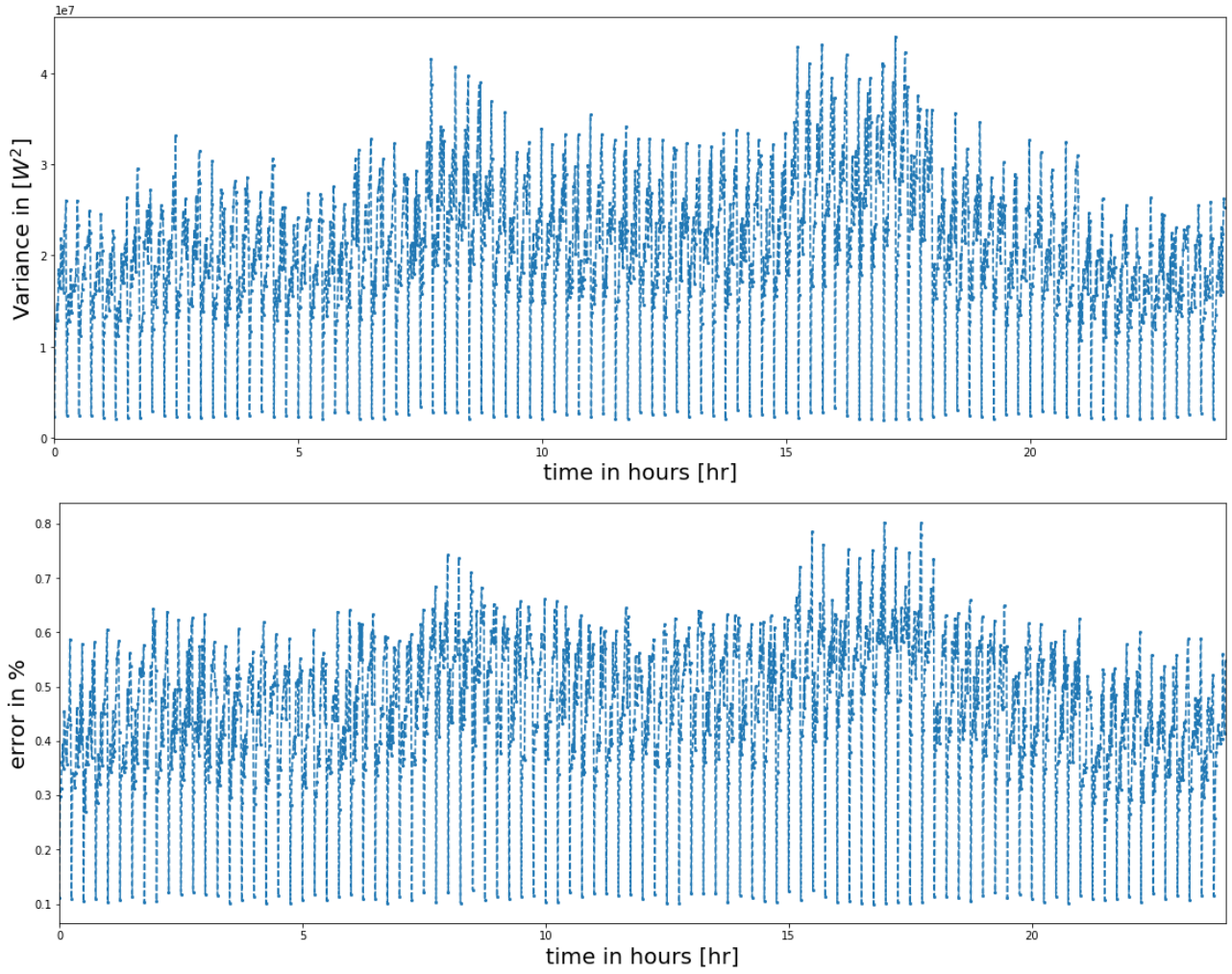


Figure 4.5: (a)The measurement variance profile for 0% pseudo measurements. (b) The SE error profile.

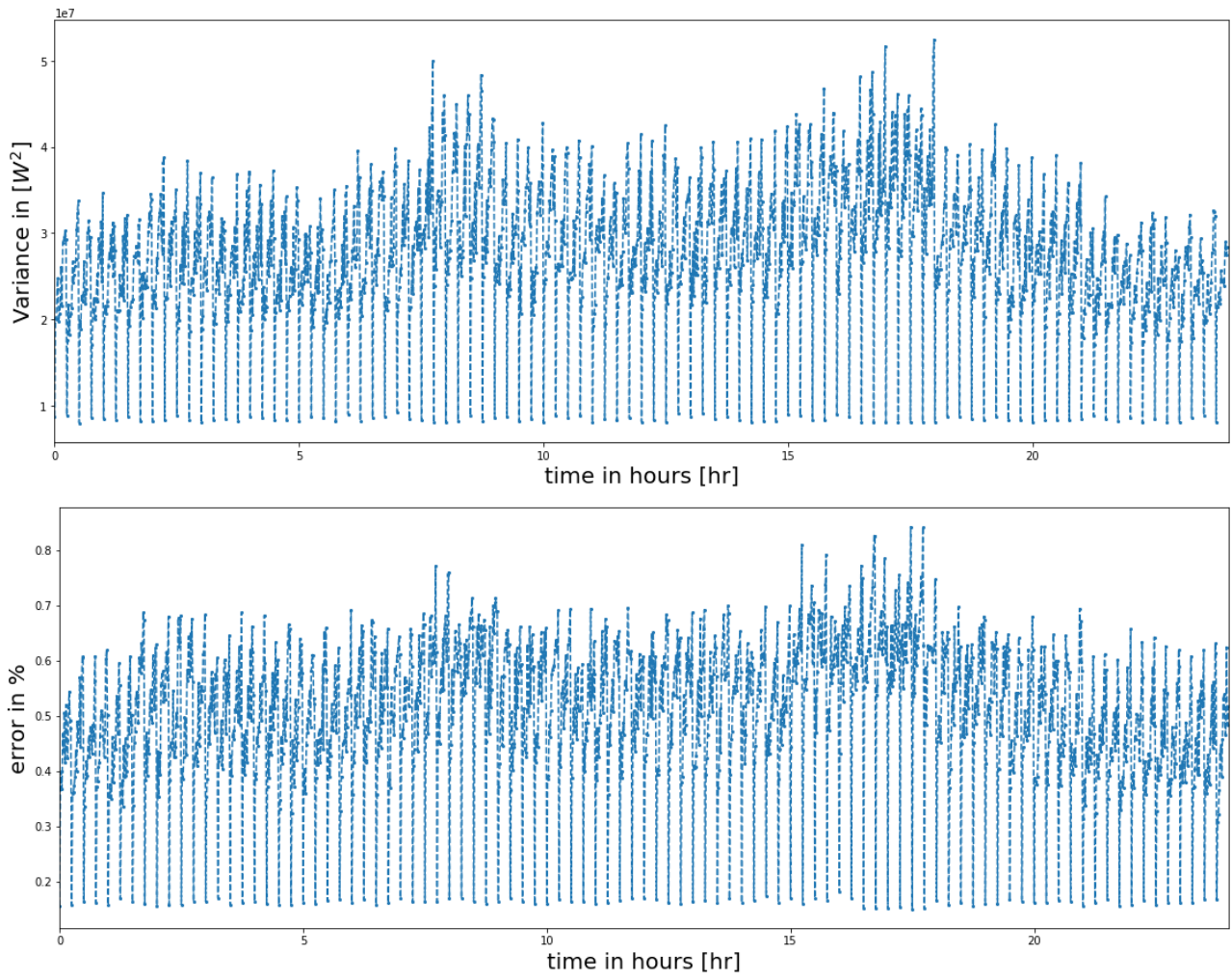


Figure 4.6: (a)The measurement variance profile for 25% pseudo measurements. (b) The SE error profile.

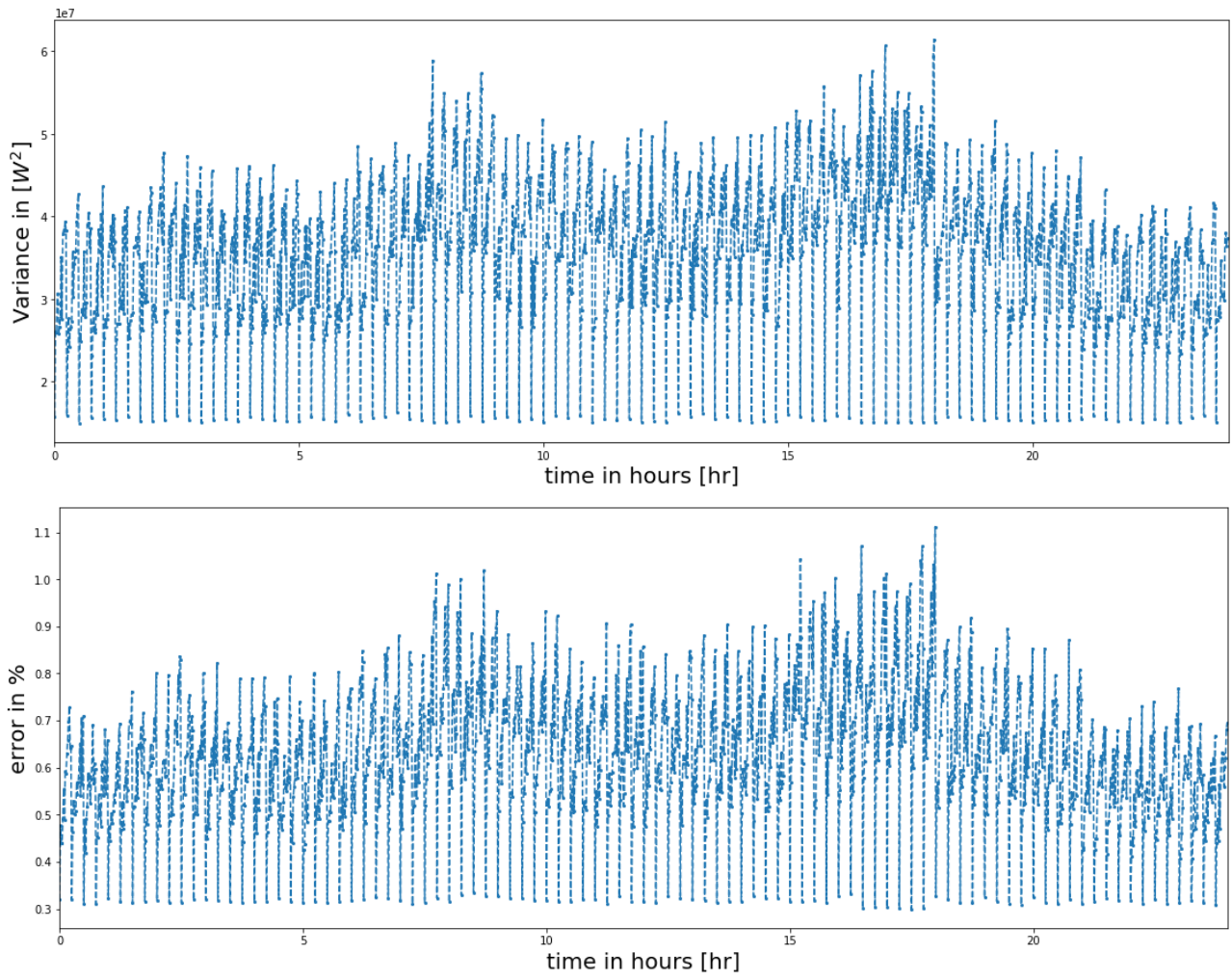


Figure 4.7: (a)The measurement variance profile for 50% pseudo measurements. (b) The SE error profile.

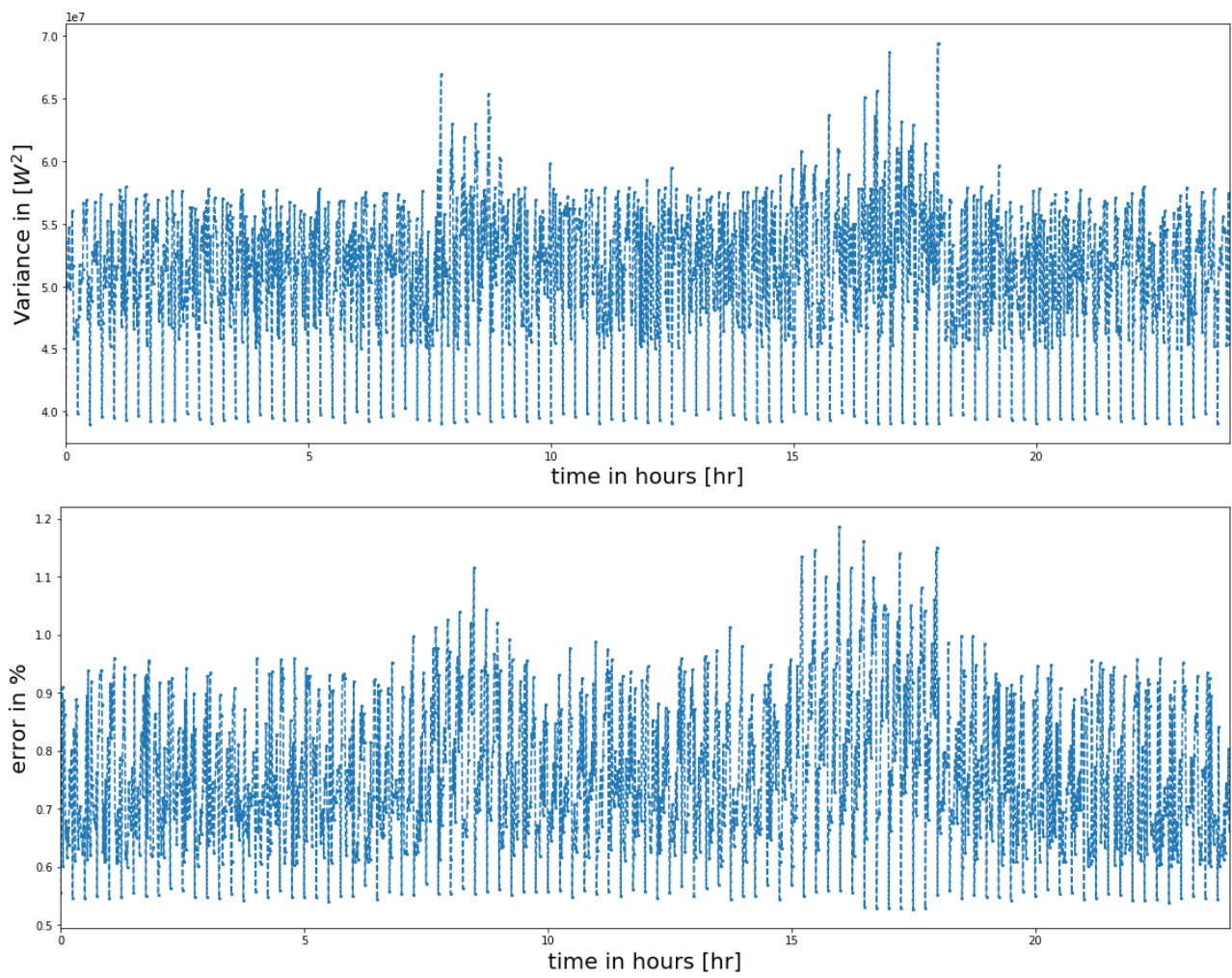


Figure 4.8: (a)The measurement variance profile for 75% pseudo measurements. (b) The SE error profile.

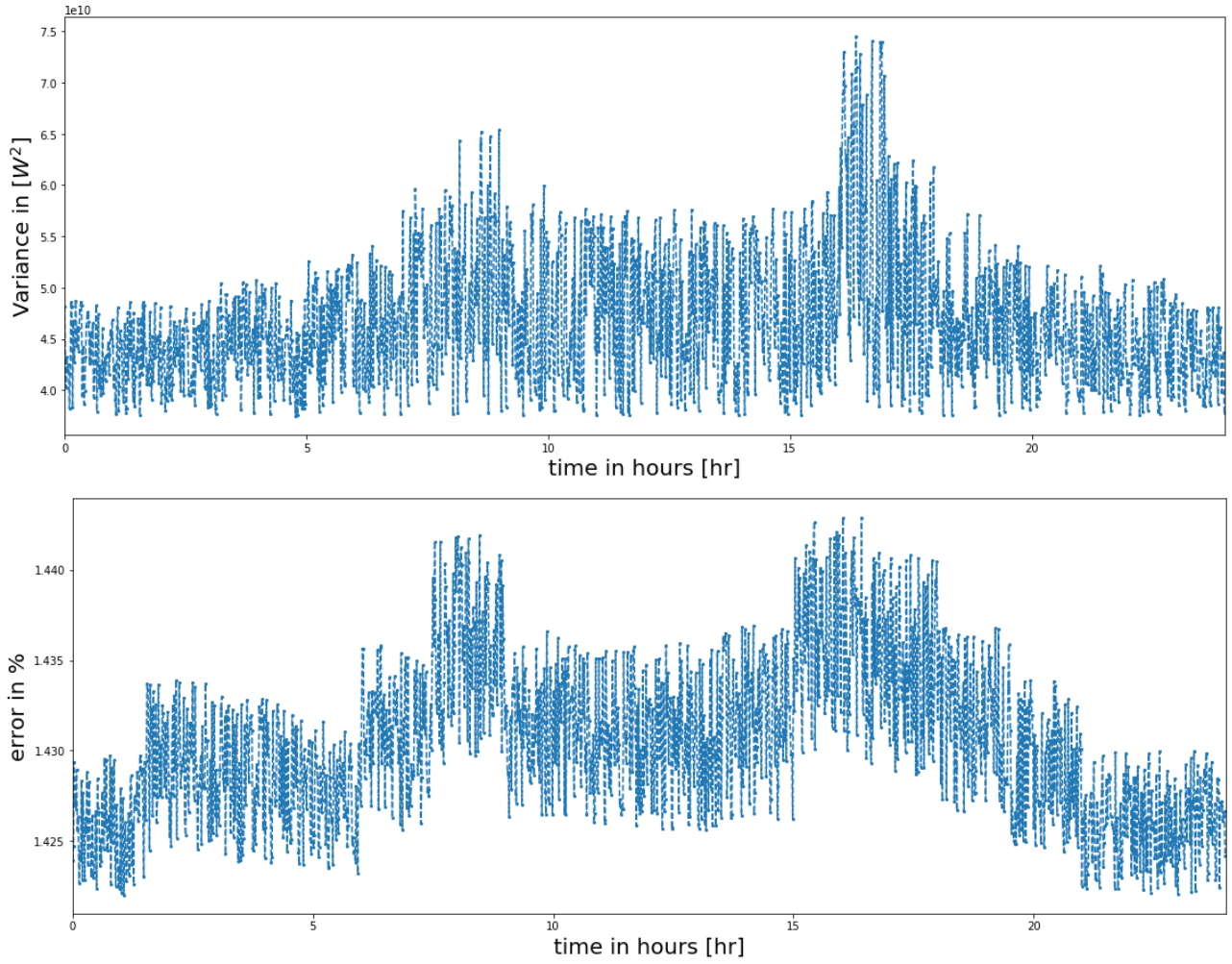


Figure 4.9: (a) The measurement variance profile for 100% pseudo measurements. (b) The SE error profile.

The figures above show the 1-minute resolution percentage error profiles and their corresponding measurement variance profiles. The error profiles are obtained by calculating the 99th percentile errors for every minute and the measurement variances are obtained by taking the mean of all power injection measurement variances in each iteration of the MC simulation and calculating the 99th percentile to get the corresponding measurement variances. It can be seen that as the percentage of pseudo-measurements increases, the values of variances increases. Further, at the time of measurement, the variance values increase with increasing values of pseudo measurements because less number of measurements are dependent on the meter accuracies. The corresponding error profiles show that the error increases for increasing percentage of pseudo measurements and at the instant of measurement, the drop in value decreases with increasing percentage of pseudo-measurements.

The maximum error from each percentage pseudo measurement is shown below:

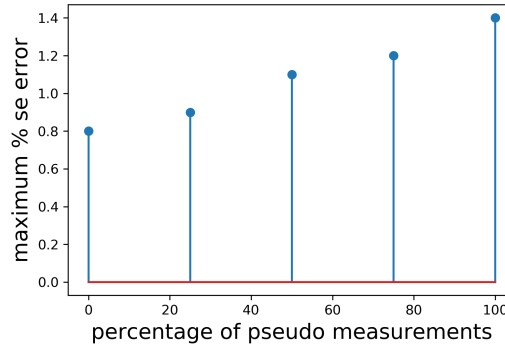


Figure 4.10: Maximum error for different percentages of pseudo measurements

The figure presents the maximum error values from the error profiles $\mathbf{er}$ of the different percentages of pseudo measurements. It can be seen that the maximum error increases with increasing percentage of pseudo measurements.

4.4.2 Measurement intervals

The figures show the 1-minute resolution percentage error profiles and their corresponding measurement variance profiles for different measurement intervals. The error profiles and measurement variances are obtained in the same manner as for the percentage of pseudo measurement analysis.

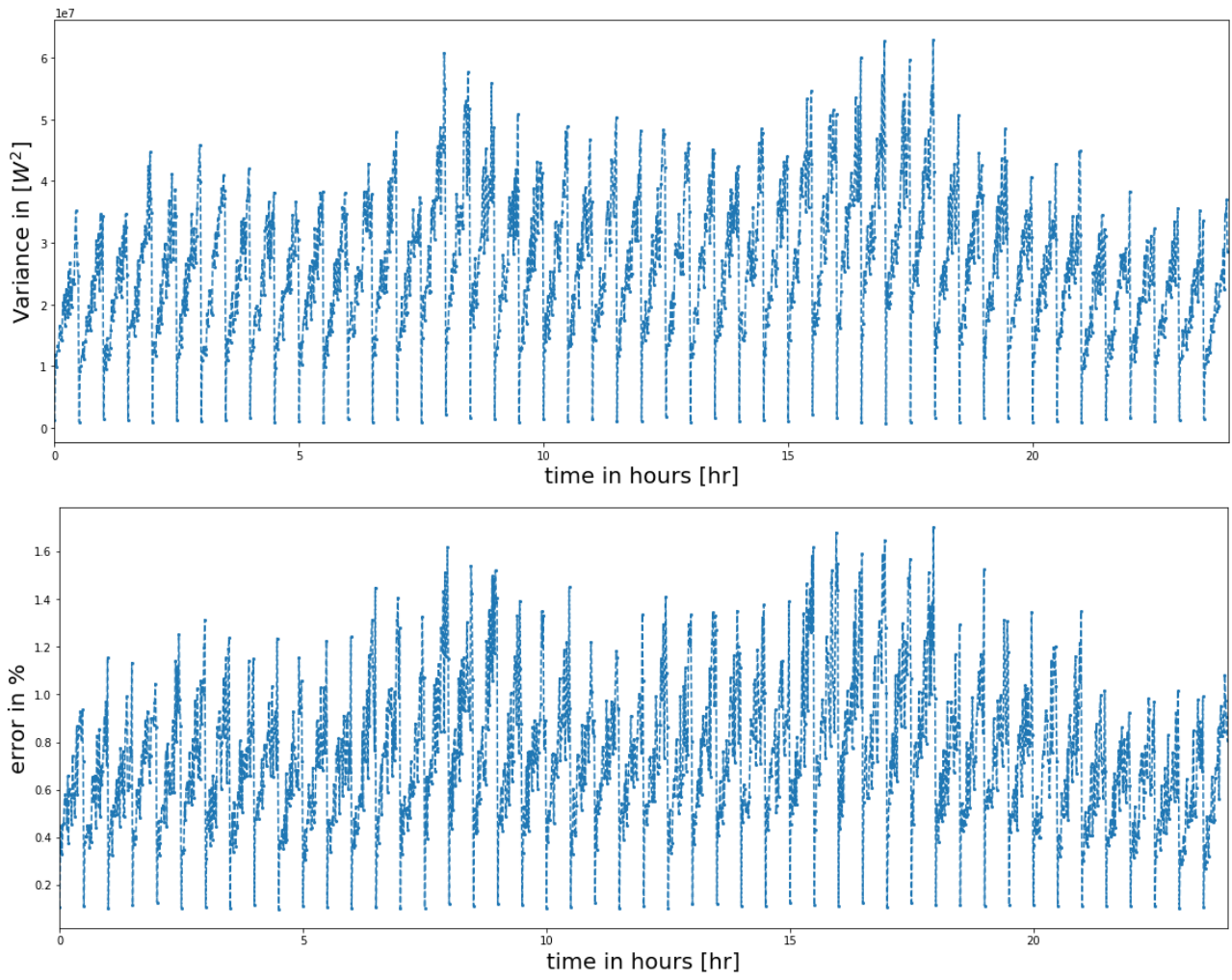


Figure 4.11: (a)The measurement variance profile for 30-minute measurement interval. (b) The SE error profile.

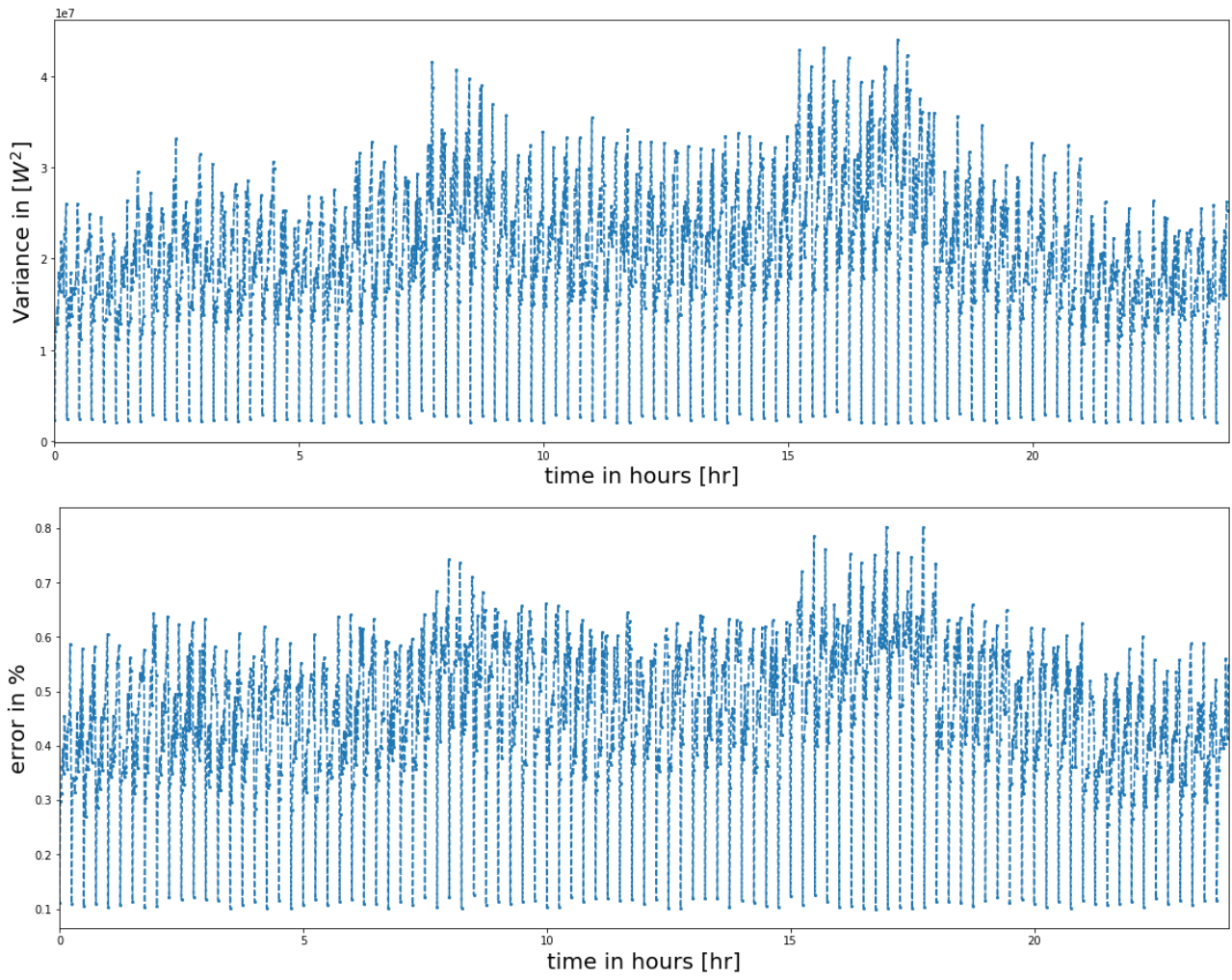


Figure 4.12: (a)The measurement variance profile for 15-minute measurement interval. (b) The SE error profile.

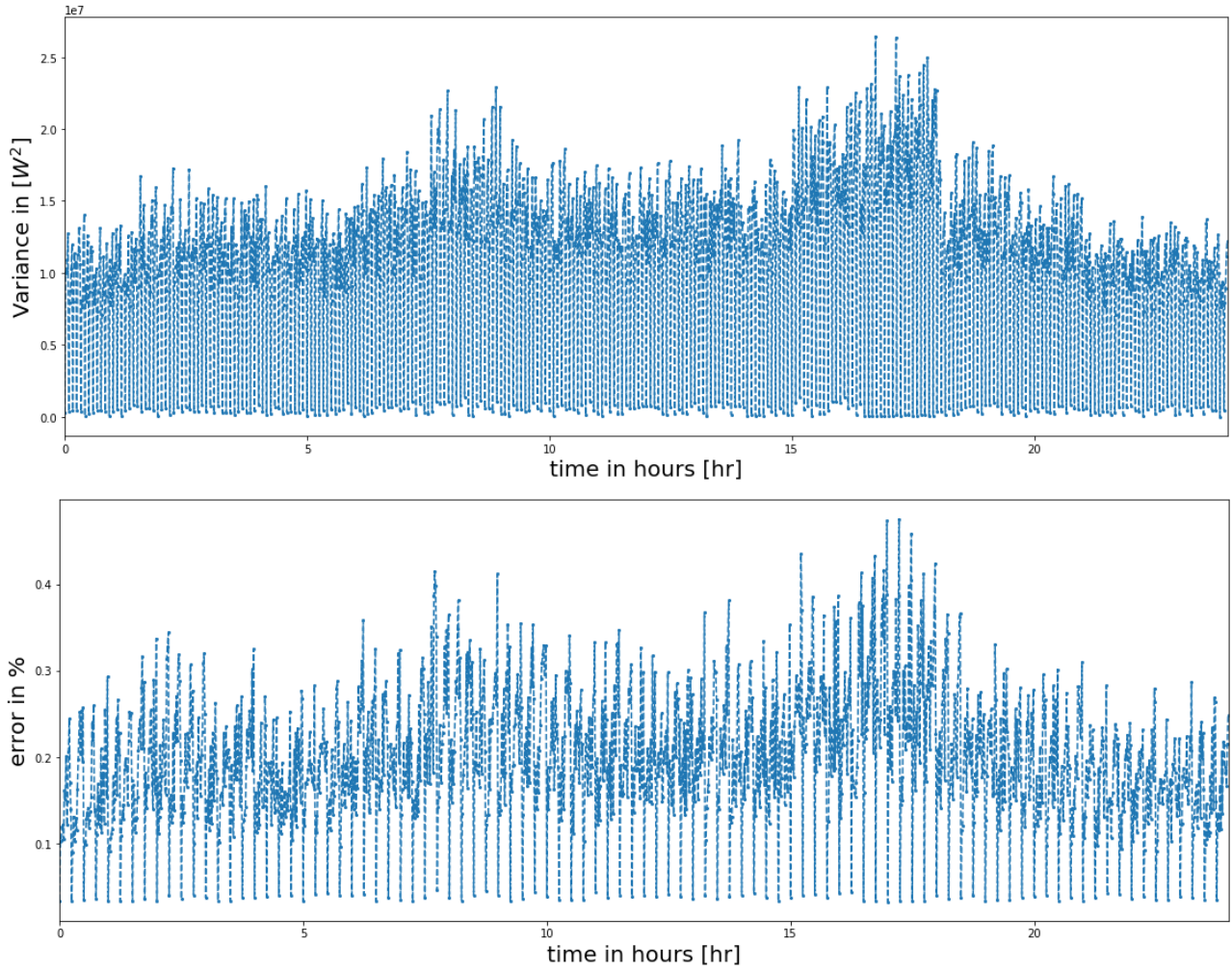


Figure 4.13: (a) The measurement variance profile for 5-minute measurement interval. (b) The SE error profile.

It can be seen that the values of variances increases with the number of minutes past the previous time of measurement. So, higher measurement variances are reached as the measurement interval increases. But at the time of measurement, the variance values are not affected because the number of measurements that are dependent on the meter accuracies do not vary. The corresponding error profiles show that higher error values are reached as the measurement interval increases but the error values at the time of measurement are not affected for the same type of measurements.

The maximum error from each time intervals of measurement is shown below:

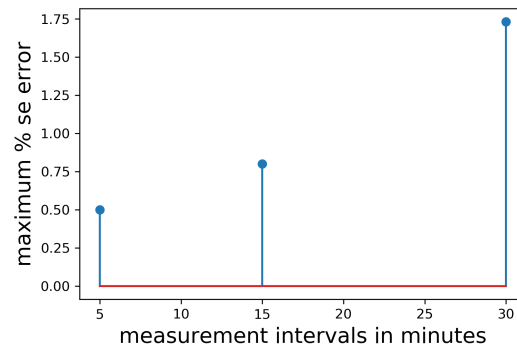


Figure 4.14: Maximum error for different time intervals of measurements

The figure presents the maximum error values from the error profiles **er** of the different measurement intervals. It can be seen that the maximum error increases with increasing measurement intervals.

Chapter 5

Measurement configuration

This chapter presents the algorithm developed to determine the measurement configuration. The steps of the algorithm, the measurement configuration and the resulting error profile are shown.

The objective of the project is to devise a measurement configuration for the grid-measurements such that the accuracy of the SE algorithm is acceptable at every instant of time. The measurement configuration consists of two parts:

- i. The locations of meters, which relates to the number of meters to be installed
- ii. The measurement intervals

In order to determine the suitable measurement configuration, an algorithm was developed that locates the additional grid nodes for the meter placement and the measurement intervals for all the measurements.

The algorithm has two parts:

- Determining the locations to place the meters
- Determining the measurement intervals

5.1 Locations of meters

To determine the locations of meters, first the grid nodes with existing meters are identified. Then, the grid nodes that are connected to a high number of branches are identified. These nodes are chosen for the installation of the new meters, as adopted in [21]. Since these nodes are connected to a high number of other nodes, they are more important for the grid operators to monitor. The minimum node degree that should be considered for this is deemed to be a user input to be decided by the operator. In the case presented in this chapter, a minimum degree of five is chosen. Once existing metered nodes and the important nodes are identified, a minimum number of nodes

are selected such that full observability is achieved from the meter measurements. Starting from the main substation and taking into account the previously identified nodes, the meters are placed at the MV node at every fourth hop from the previously identified MV node. At each node n , connected to nodes o and p , the active and reactive power flow measurements $\mathbf{P}_{flow}(no)$, $\mathbf{Q}_{flow}(no)$, $\mathbf{P}_{flow}(np)$, $\mathbf{Q}_{flow}(np)$ and voltage magnitudes $\mathbf{V}_{mag}(n)$ are metered. Apart from this, at the MV nodes at every second hop from the previously identified MV node, active and reactive power flow measurements $\mathbf{P}_{flow}(lm)$, $\mathbf{Q}_{flow}(lm)$ and voltage magnitudes $\mathbf{V}_{mag}(l)$ are metered using low cost meters at the node l at the LV side of the MV/LV transformer connected to MV node m . The variance of the meters is assumed to be $10e - 5$, as adopted for the meters installed by DSOs in [13]. This offers full observability of the grid from the least possible number of meters as there are exactly 8 measurements for every 4 nodes. The advantage of this meter placement is that there are no pseudo-measurements required. Further, at the node at the MV side of the transformer connected to l , since we know that the power injection values are zero, they are modelled as virtual measurements with high accuracy. This facilitates in reducing the overall variance of the input measurements and so improves the overall accuracy of the SE algorithm. This meter placement configuration is shown in the figure below:



Figure 5.1: Placement of meters: Metered MV nodes are represented in orange and metered LV nodes are represented in red

5.2 Measurement intervals

Once the locations are established, the first iteration starts with the measurement interval of 1-hour. In each iteration, a Monte Carlo simulation is performed as in the sensitivity analysis. From these Monte Carlo simulations, the 99th percentile error at every minute is selected to form the error profile. This eliminates the extreme values which can cause an over-determined system. Then, the error profile is compared with the user defined error threshold. This threshold can vary depending on the application that the DSO is considering. In the case presented in this chapter, a threshold of 1% is used. The end of every time-section where the error violates the error value threshold and error time threshold is chosen as a new measurement time. These iterations are repeated until the accuracy constraint is satisfied. This leads to a measurement configuration that has dynamic intervals throughout the day.

The configuration is built as shown in the figure 5.2:

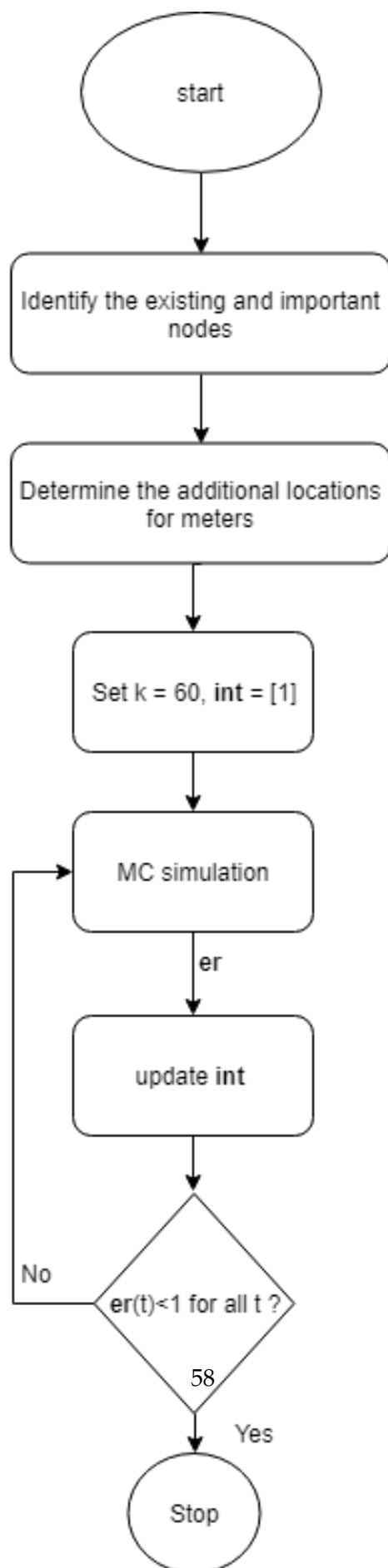


Figure 5.2: Measurement Configuration

The error profile after the first MC simulation, i.e., with 60-minute measurement interval is seen in figure 5.3 below.

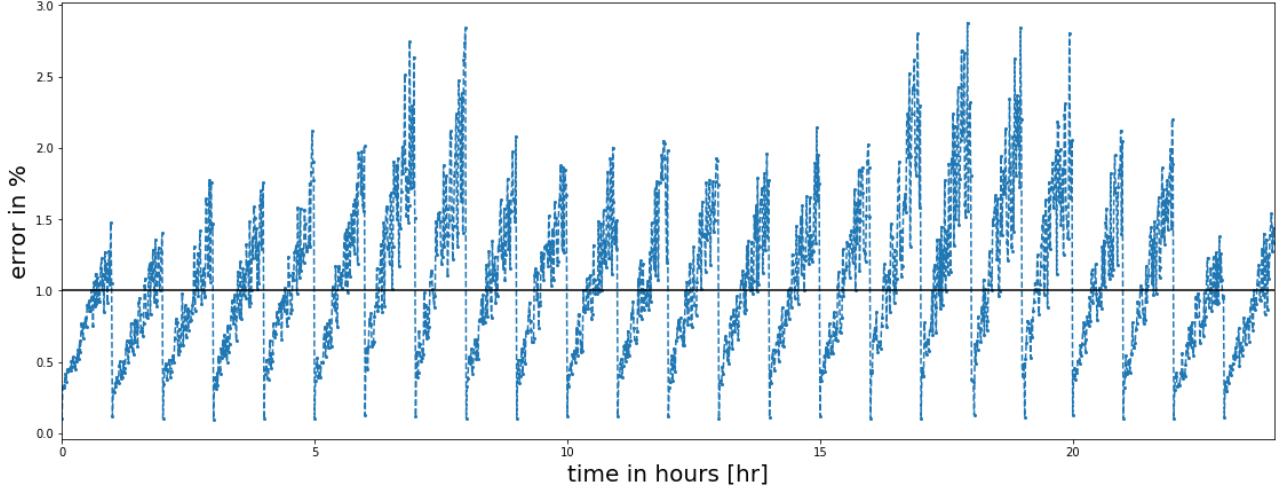


Figure 5.3: Error profile after the first MC simulation

This is the 99th percentile error profile $\mathbf{er}$ extracted calculated based on the matrix $\mathbf{Er}$ (as explained in the previous chapter). At the time of measurement, i.e., every every 1st minute of the hour, the measurement value is the meter measurement at that time and the variance of each measurements is the meter variance. But at all other time instants (minutes 2 to 60 of each hour), the measurement value is the same value as that of the previously measured time instant (every 1st minute of the hour). The variance increases as the number of minutes counting from the measured time instant after which the SE algorithm is executed increases. Since the error profile is dependent on the variance profile, as seen in the result of the sensitivity analysis with respect to measurement intervals (in the previous chapter), the error also increases as the number of minutes counting from the measured time instant after which the SE algorithm is executed increases.

Further, the error is higher during the hours of the day when the load profiles have higher variances.

After each MC simulation, the 99th percentile error profile is calculated and compared to the threshold and the algorithm runs until the error profile $\mathbf{er}$ is less than the threshold of 1% at every minute. This is shown in the figure 5.4.

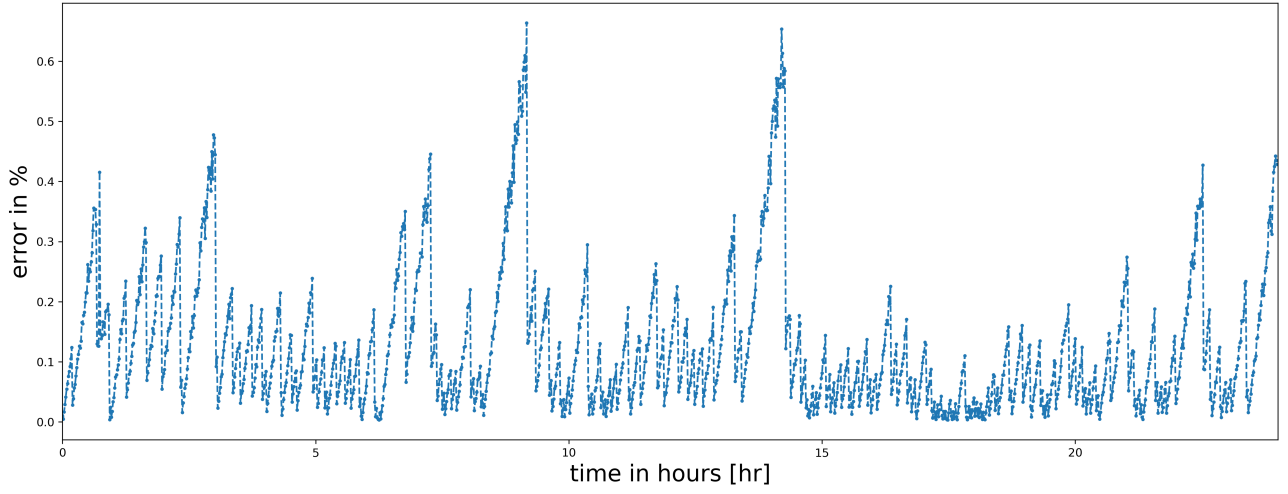


Figure 5.4: Final error profile e_r after the algorithm stops

The figure shows the 1-minute resolution percentage error profile with the new measurement configuration. It is evident that the error profile is below the threshold at every minute of the day. Once this is achieved, the algorithm stops and the measurement intervals that are updated can be seen in the figure 5.5.

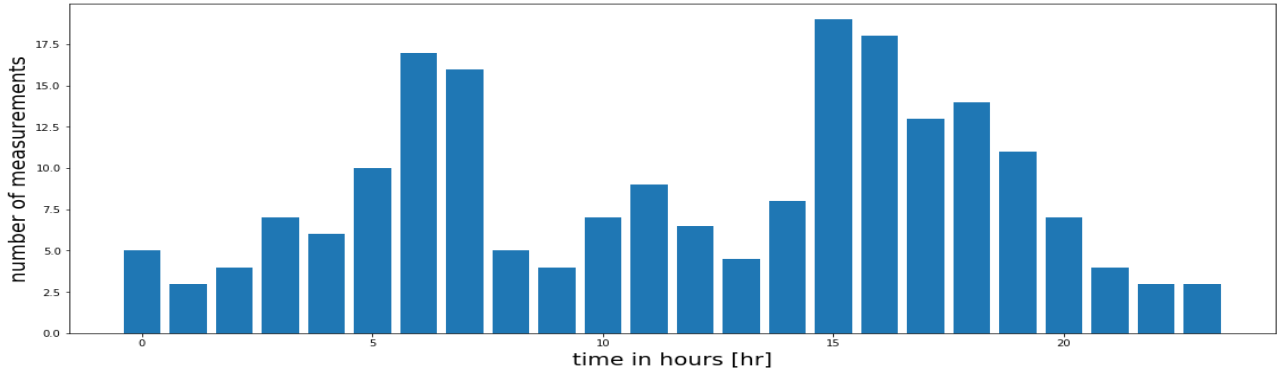


Figure 5.5: The number of measurements in each hour after the algorithm stops

It can be seen that the measurement intervals for every hour of the day are not fixed intervals but they are more concentrated around in the hours of the day corresponding to higher load variance compared to the hours corresponding to lower load variance.

In this way, a measurement configuration is determined with the meter placement locations and the measurement intervals as described above.

Chapter 6

Conclusions

This chapter has the most important conclusions obtained through this project and the the answers to the research questions presented in chapter 1.

In this project a WLS state estimation algorithm was applied to a reduced model of an MV network of 10kV. The performance of the SE algorithm was analyzed and a new measurement configuration was developed considers meter placement such that no pseudo measurements are needed. The intervals of measurement are identified hourly such that the error of the SE algorithm is below the chosen limit of 1% at all times.

Through this work, the following conclusions are drawn:

- *Load profile variance with new technologies:* The future scenario explored shows a different average load profile compared to the present case. Overall, the variance of the load profiles in the future is likely to be higher than the variance of the present load profiles due to the inclusion of new technologies, i.e., EVs, PVs, heat pumps and CHPs. Due to high penetration of EVs and PVs, compared to the present profiles, the load profiles have a very high variance during certain hours in the morning and in the evening. This is because the presence of the PVs reduces the consumption during the day and the EVs increase the consumption during the evenings and the night. This combined effect shows a higher variance during the transitional time.
- *State estimation algorithm performance in the network* It is seen that when the algorithm is applied to the network model, the accuracy of the state estimation algorithm is not the same at all the buses in the network. This is due to the availability of the voltage measurement that is most accurate at the slack bus. So, the state estimation algorithm result is most accurate at the slack bus. As the distance between the nodes slack bus (hence the most accurate measurement) increases, the error of the resulting state estimates increases. The accuracy at the farther nodes can be increased by introducing voltage measurements with higher accuracy at buses at a few different distances from the slack bus.
- *Performance evaluation of the state estimation algorithm* The state estimation algorithm's perfor-

mance is evaluated with respect to two parameters that introduce higher variance in the measurements. The parameters are, percentage of pseudo measurements in the grid and the measurement interval. It is seen that the higher the percentage of pseudo measurements in the grid, the higher the error. This is because pseudo measurements are characterized by higher variance compared to the real and virtual measurements.

The measurement interval affects the accuracy of the SE algorithm because, the variance of the measurements increases as the time instant from the time of measurement increases.

- *Measurement placement algorithm* A new algorithm is proposed to identify the locations for meter placement and the measurement intervals. The meter placement is chosen such that there is no need for pseudo measurements in the grid, hence reducing the measurement variance. The measurement intervals are dynamic throughout the day and the density of measurements ends up being higher during the high variance hours. This reduces the error of the state estimation algorithm such that the error is always under a chosen limit.

In this way, a state estimation algorithm is implemented and analyzed for an MV network and a measurement placement algorithm is developed to improve the accuracy the state estimation algorithm.

Through this project, the answers to the research questions posed in Chapter 1 are obtained and are explained below:

- i. *What modifications should be done to the existing grid model to simulate future grid with increased distributed generation and new technologies?*

In order to simulate the future grid, the likely future scenario for the year 2040 predicted in the research [39] is adopted. The technologies and demand growth is simulated as determined in that research. The technologies are simulated according to the penetration percentages in each of the existing LV networks in the network model. They are, PV generation, CHPs, heat pumps and electric vehicles. They are considered as DC technologies and generation is modelled as negative loads. Normal distribution fitting is used to represent the distribution of the final load profiles that include the technologies. This gives the normally distributed function of the profiles for each LV network for every minute and the loading scenarios can be sampled from these functions.

- ii. *Which is the SE algorithm that is suitable to be applied for Stedin's network?*

Static SE is considered and so, based on the popularity suitability as validated in research [18] to MV networks, the WLS SE algorithm is chosen.

- iii. *How does the result of state estimation algorithm degrade with the influence of measurement parameters?*

The SE algorithm depends on the variances of the measurements. When there are real measurements in the input measurement set, at the time of measurement, the error is lower and increases as the number of minutes from the previous time of measurement increases. The error values increase with the increasing percentage of pseudo-measurements in the measurement set and with the increasing measurement intervals.

iv. *What is the suitable configuration of additional grid measurements for accurate state estimation?*

The meter placement locations determined are as follows:

- The important medium voltage nodes that are connected to high number of nodes.
- Starting from the main substation and taking into account the previously established meters, at every fourth hop (of MV nodes) from the previous location.
- Low voltage node of the MV-LV transformer at every 2nd MV node from the previously established locations.

The measurements taken at the MV nodes are the voltage magnitude at the nodes and the branch power flows (Active and reactive) for each branch connected to the node. The measurements taken at the LV nodes are the voltage magnitude at the nodes and the branch power flows (Active and reactive) at the low voltage side of the transformer. The measurement interval resulting is not fixed, but have higher number of measurements during the hours of the day with higher measurement variance and lower number of measurements during the hours of the day with lower measurement variance. Such a configuration of the measurements has been determined using the algorithm presented in the chapter 5.

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Appendix A

A brief guide to using TU Delft's HPC cluster

HPC (High Performance Computing) is a cluster of Linux servers (computers) which offers a high processing power and memory. It is essentially a supercomputing service. It was useful for my thesis to Monte Carlo simulations. The main advantage of HPC was that it allowed me to run multiple scripts at once. Also, it was faster than my computer.

A.1 How to use the HPC cluster

- In order to use the cluster, access has to be requested from the ICT department, who manage the cluster. I contacted F.P.J. (Frans) Broos - Facultair ICT manager EWI, TBM, DEMO, CRE. Once access is given, TU Delft Net ID can be used for login.
- To connect from your computer to the server, SSH or Secure SHell network protocol is used. For windows, the software PuTTY can be installed in order to login and execute commands. The software FileZilla can be installed for file transfer between your computer and the server.
- A short overview of frequently used commands in the PuTTY environment:
 - `ls -l` : returns all files in specific folder
 - `cd <foldername>` : move to the specific folder
 - `cat <filename>` : opens filename
 - `dos2unix <jobname>` : converts job file format from dos2unix (this was needed for me because I was using Windows operating system).
 - `sbatch <jobname>` : submits the job to the queue. When the requested amount of resources become available, the job will run automatically. Every submitted job generates a job id

- seff <job id> : returns the status of the job, memory used, time used and efficiency information.
- Note that copy-paste happens with right mouse clicks, not with ctrl-c/ctrl-v
- After writing your Python code, transfer all the files needed to folders in your HPC working space using Filezilla.
- An HPC code (this is the job file) needs to be written that tells the cluster what resources and services are needed.
- Once the job starts running, a file called 'slurm-<job id>.out' is generated in the same folder where the job file is present. This file shows the printed outputs from the job and error messages. Alternatively, they can also be seen by typing 'cat slurm-<job id>.out'.
- If there are any generated output files from your python script, they can be seen in the same folder where the python script is present and can be transferred to your own PC.

A.2 Example of an HPC code

Following is an example of an HPC code. The comments are shown in italics.

```
#!/bin/sh This line is mandatory
```

```
#SBATCH -partition=general The default partition is the 'general' partition
```

```
#SBATCH -qos=short The default Quality of Service is the 'short' QoS (maximum run time: 4 hours)
```

```
#SBATCH -time=00:10:00 The maximum running time of the script.
```

```
#SBATCH -ntasks=2 The default number of parallel tasks per job is 1
```

```
#SBATCH -cpus-per-task=10 Request 1 CPU per active thread of your program (assumes 1 unless you specifically set this)
```

```
#SBATCH -mem-per-cpu=200 The default memory per node is 1024 megabytes (1GB) (for multiple tasks, specify -mem-per-cpu instead)
```

```
#SBATCH -mail-type=END Set mail type to 'END' to receive a mail when the job finishes (with usage statistics)
```

Your job commands go below here:

```
python3 $HOME/<folder name>/pythonscript1.py
```

```
python3 $HOME/<folder name>/pythonscript2.py
```

Appendix B

Load estimation procedure used at Stedin

Stedin uses the Distribution Management System (DMS) to monitor, analyze and remotely operate its networks. Performing the power flow calculation is one of its functions. But, since there is essentially no information available from the SCADA system about most of the network, the DMS performs load estimation to assign load values to the nodes, thus creating its own measurements. This enables it to run the power flow.

The DMS load estimation procedure is also called “Bus Load Allocation” (BLA). It allocates the active and reactive values of the complex loads at the nodes without telemetering and where loads exist. The BLA function ensures consistency between allocated and metered loads.

The load estimation method used is the Bus Load Allocation (BLA) method. This method essentially scales the loads so that they are consistent with the available real-time measurements.

The method uses real-time measurements from SCADA and predefined customer information to scale the loads. The value at a given time is obtained by multiplying the nominal load by a scaling factor. The scaling factor reflects the energy usage at a specific time. The allocation procedure requires minimum iterations in the power flow to maximize performance.

Load model data is used for load allocation. This takes into account factors like the type of the day, the time, feeder loads (actual or predicted), etc. The BLA function makes sure that the load model is consistent with metered flows, current breaker statuses, and metered loads along the distribution feeders.

The input data for the BLA procedure is taken from another function called the Network Topology Processor (NTP) and the distribution system model. The NTP determines the substation and feeder connectivity. The system model provides load data like the typical load shapes.

The BLA algorithm performs the following two major tasks:

- Forms measurement islands and performs measurement validation.
- Allocates loads

B.1 Forming Measurement Islands and Measurement Validation

Where analog measurement group is the set of analog measurements at one location in the network. This excludes the voltage measurements, which can be in a different location but with zero impedance between voltage measurement location and the flow measurement location.

A measurement island is a group of components bounded by one or more analog measurement groups. It is technically bounded by downstream measurement islands, reference bus interface objects, upstream measurement islands, or feeder and lateral ends. The non-telemetered loads inside of a measurement island are scaled up or down.

B.2 Load Allocation

After successfully forming a valid measurement island containing loads, the loads are scaled such that the total load values match the island net load. The net load is calculated from the effective active and reactive power, or apparent power measurement values.