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Report on network observability and risk assessment

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3. Version History

Version	Date	Modifications made by
0.01	2020.09.10	First draft
0.02	2020.10.13	TU/e internal review
0.03	2020.10.16	FlexiGrid internal review (1st)
0.04	2020.10.26	FlexiGrid internal review (2nd)
0.05	2021.11.25	Revision version

4. List of abbreviations

Abbreviation	Definition
ANN	Artificial neural networks
API	Application programming interface
ARMA	Auto regressive moving average
BFS	Backward-forward sweep
CP	Cumulative probability
CPD	Change point detection
DER	Distributed energy resources
DSO	Distribution system operator
DSSE	Distribution system state estimation
EV	Electric vehicle
FlexiGrid	Enabling flexibility for future distribution grids with high penetration of variable renewable penetration– FlexiGrid
GDPR	general data protection regulation
HP	Heat pump
IoT	Internet-of-thing
LF	Load forecasting
LMP	Locational marginal price
LV	Low voltage
MCS	Monte-Carlo simulations
MV	Medium voltage
NN	Neural network
NWPs	Numerical weather predictions
PDF	Probability distribution function
PEV	Plug-in electric vehicles
PF	Power factor
PMU	Phasor measurement units
PPF	Probabilistic power flow
RES	Renewable energy sources
SE	State estimation
WLS	Weighted least square

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7. Project overview

FlexiGrid is an innovation project funded by EU's largest research and innovation program, Horizon 2020.

The project will create an enabling architecture for small and medium Distribution System Operators (DSOs) to unlock flexibility resources. Through a cross-sectoral integration and optimization of resources, especially those arising from coupling between different energy sectors, as well as demand response using charging schemes for electric vehicles (EVs) or storage, DSOs will be able to meet the future capacity shortage with flexibility and updating old systems with smart technology.

In FlexiGrid, organizations from all over Europe cooperate to leverage digital and smart grid technologies at the grid edges. The project will deliver IoT platforms, peer-to-peer and peer-to-pool marketplaces, vehicle-to-grid, power-to-heat, and power-to-gas solutions, as well as innovative business models.

FlexiGrid will equip DSOs with advanced tools to enhance the observability and controllability of distribution networks while demonstrating both pool-based and peer-to-peer market mechanisms. Furthermore, implementing these market mechanisms in the project's demos will be facilitated by a flexible DSO-Customers coordination platform for efficient real-time trading of energy and grid services between market actors.

The overall objectives of FlexiGrid are:

• **To develop an integrated architecture** for flexibility measures and electricity grid services provided by electricity storage, vehicle charging, power-to-heat, demand response, and variable generation to enable additional decarbonization.

• **To define, test, deploy and demonstrate markets and market mechanisms** that incentivize flexibility, in particular for mitigating short-term and long-term congestions or other problems in the distribution network such as voltage issues

• **To drive cooperation** between DSOs, transmission system operators (TSOs), consumers and generators by defining market interactions, facilitating the integration of wholesale and retail markets and cross-sector interactions

• **To deploy smart grid technologies** to enable the architecture and markets, bringing actors together to participate as distributed energy sources, driving increased resilience of the electricity grid, increased system security, greater observability, higher automation and improved control of the grid

• **To enable future technical and commercial innovation** by identifying barriers to innovation, developing pathways to regulatory and policy reform, developing business models, and through strategic collaboration.

8. Consortium

1. Introduction

Due to the massive increase of distributed energy resources (DERs) into the distribution grid, Distribution System Operators (DSOs) are facing increased complexity in the distribution system. While flexibility is considered as an alternative and affordable solution, the procurement and dispatching process of flexibility urges for an improvement of monitoring capability from the DSOs. This deliverable D3.1 aims to contribute to improving the development of network observability and risk assessment. On the one hand, network observability will be enhanced by exploring measurement data and advanced data analytic models, i.e., using physics-aware neural network structure. This allows a fair allocation of computing resources to deploy effectively (distribution) state estimation algorithms. On the other hand, this deliverable will devise a set of advanced schemes to identify imminent risks in different levels of the distribution network. Risks will be identified for different time horizons, including the scheduling phase to real-time operation. Novel probabilistic methods and data-driven distributed algorithms will be employed to predict network security violations based on the dynamic price, weather conditions and the behaviour of the end-users.

The following Figure 1.1 presents the structure of the report as well as the interactions between the sections. In section 2, the requirements from the DSOs are discussed with an overview of the problems associated with an increasing penetration level of DERs. The state-of-the-art grid monitoring functionalities will be presented in section 3 to provide details of the techniques available in the literature. The development of advanced measurement infrastructure for the distribution system is discussed in sub-section 3.1. Then, in sub-section 3.2, the data collection, the importance of data and IoT for grid-edge, and the data integrity are discussed. A survey in the context of forecasting, state estimation (SE), and risk assessment technique will be presented in sub-section 3.3, 3.4 and 3.5, respectively, to provide details of the techniques available in the literature.

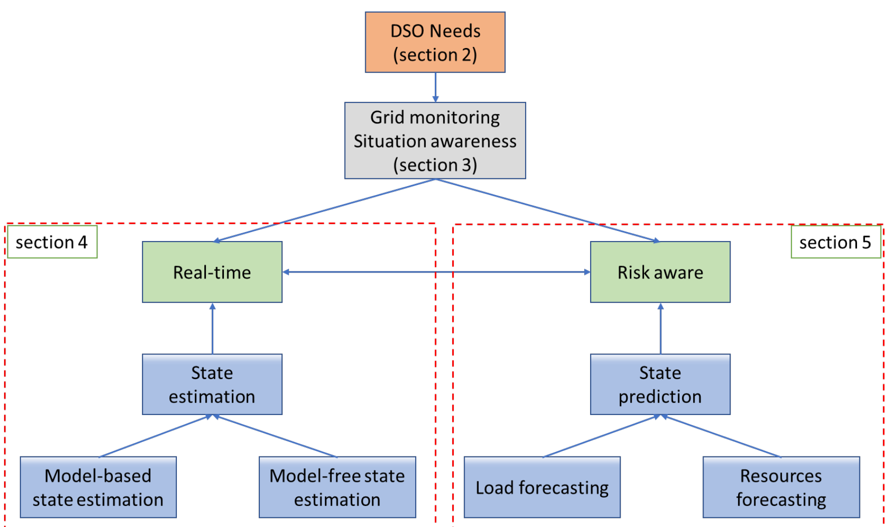

Figure 1.1: The overview of this deliverable.

In section 4, two different SE approaches, physics-based and data-driven, are developed to enhance grid monitoring capabilities. In section 5, the risk assessment topic is further consolidated with a congestion forecasting technique. The conclusion and discussion on the contributions together with the connection with other WPs are concluded in section 6.

1.1. Background

The main element of the emerging energy transition worldwide is the increase in renewable energy sources (RES), including especially solar PV and wind. However, these types of renewable energy are variable depending on the temperature, irradiation, and wind speed. Their integration into the traditional power systems could be a problem to the reliability, stability, and quality of power supply, e.g., power congestion or voltage stability. With the growth of DER, the flexibility from the customer's side becomes more and more important. This enables alternative options for the DSO to control and operate the distribution grids. While reinforcing the network is costly and time-consuming, the flexibility option could help the DSOs for the safe operation of their grid. However, trading energy without a good observability capability to reflect on actual states of the grid will result in an ineffective impact on resolving grid issues. It also hinders possibilities to maximize the utilization of existing assets and circumvent the need for extensive investment for network reinforcement.

DSOs need to build a future intelligent distribution system for monitoring and controlling the system. For instance, the recent H2020 project FLEXICIENCY [1] has proposed and deployed services in the retail electricity markets ranging from advanced monitoring to local energy control and flexibility services. It aims to realize high quality and high velocity near real-time information stream on customers' energy consumptions and prosumers' generation while providing accessibility to metering data. At the transmission level, the H2020 FutureFlow [2] project opens up possibilities for balancing and re-dispatching markets to new sources of flexibility and supporting such sources to act on such markets competitively. In particular, the H2020 Flex4Grid [3] project aims to create an open data and service framework for managing flexibility of prosumer demand and generation while utilizing cloud computing for power grid management. This approach would be relevant to facilitate the transition towards future intelligent distribution grids with DSO's role as a market facilitator.

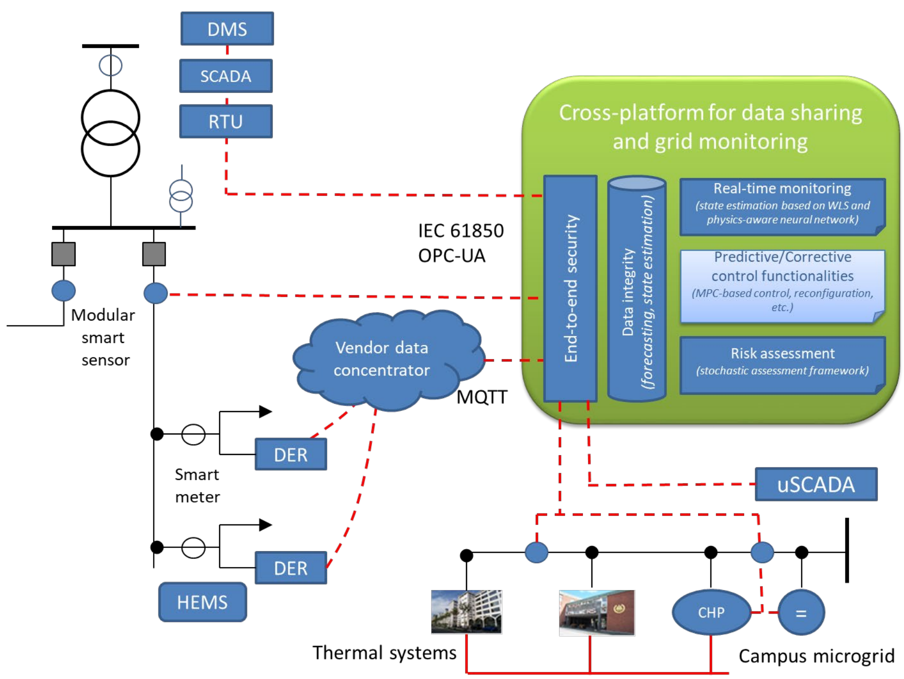

Figure 1.2: Cross-platform for data sharing and grid monitoring adopted from H2020 project UNITED-GRID.

Especially, a cross-platform for data sharing and grid monitoring from H2020 project UNITED-GRID is an important development to integrate data measurement gathered from both grid and DER's owners. FlexiGrid will adopt and strengthen this development with focuses on advanced physics-aware network structure for state estimation and integration of stochastic assessment framework for risk assessment. Figure 1.2 shows the principal of such a framework for data sharing, grid monitoring, and risk assessment. This enables control functionalities at the grid edges by leveraging the enriched energy data while addressing security and privacy issues thoroughly. The ultimate goal is to enable optimal solutions for operating different local demands and allocating flexibility when and where it is needed. The involvement of DERs' owners is important to provide relevant data as well as flexibility options, e.g., power curtailment or load shifting.

1.2. Report outline

The remainder of this report is structured as follows:

- Section 2: introduces the needs of DSOs.
- Section 3: presents the state of the art of different monitoring and risk assessment techniques.
- Section 4: focuses on the SE model.
- Section 5: explain a congestion forecasting technique for risk assessment purposes.
- Section 6: concludes and discusses future work.

2. DSO needs, requirements for flexibility

Due to the energy transition, the DSOs are facing many problems in their network. For instance, the natural growth in peak consumption is leading to constraints (voltage and current) on the electricity distribution system infrastructure. In addition, the inverse power from PV installation can cause the overloading of MV/LV transformers. Furthermore, with the large share of renewable energy resources, severe problems may occur by an unpredicted change of weather, such as network instability. This transition is also posing a serious threat to the security of supply and the affordability of energy bills.

The purpose of this section is to:

- Analyse the needs and requirements of DSOs
- Understand how DSOs can use smart systems (tools) to monitor the grid, analyse the state and improve the operation of their system

2.1. Challenges for DSOs

Table 2.1 shows the summary of the flexibility services procured by DSOs. It describes the DSOs' needs and which service could be used to cover that need.

Table 2.1: System flexibility services procured by DSOs

System needs	Potential service	Potential procurement mechanism	Involved stakeholders
Congestion management	Generation adjustment, peak shaving	Market	DSO
Voltage control	Reactive power provision, market procurement	Grid code	DSO
Maximizing DER connection and integration	Curtailment	Market, grid code	DSO
Investing efficiently in distribution grids	Peak shifting	Market, grid code	DSO

2.1.1. Congestion management

The integration of RES into the distribution networks could cause a problem, where the electricity supply exceeds the network capacity or when the power consumption is higher than the power supply (congestion problem). The challenge is maximizing the grid hosting capacity while keeping the security and quality of the electricity supply. Thus, congestion management is needed for network capacity planning. Flexibility is a good option to solve local grid constraints; flexibility could come from distributed generators or consumers. Thus, the network reinforcement can be postponed until the flexibility services become costlier than the network expansion. Congestion management can be set up for a real-time manner or a long-term perspective.

2.1.2. Voltage control

A grid code is the standard specification that defines the boundaries of the voltage, frequency, etc. DSOs need to follow this standard to operate the distribution network. However, with the rapid increase of renewable energy, more and more power is injected into their girds, causing voltage problems. By the coordinated control with the grid monitoring, the DSOs could use the DERs for voltage control and power losses management.

2.1.3. Maximizing DER connection and integration

Increasing the hosting capacity of the grid is necessary due to the increase in load consumption (EV, heat pump) and generation side (PV). In the distribution grid, rooftop solar is absolutely central to maximizing DER connection in the distribution system. However, it could cause a voltage rise in the radial distribution system. Thus, the term "curtailment" is used to solve this practical problem of voltage rise in the grid when the PV output capacity (supply) is higher than the load (demand). In order to maintain the power balance in the system, curtailment is a potential service.

2.1.4. Investing efficiently in distribution grids

These challenges mentioned above can be solved by reinforcing the distribution grid. However, it is a costly solution, and DSOs want to postpone it until other methods cannot ensure the safety operation in their grids [4]. Demand response or peak shaving is a technique used to change the load profile, shifting it from peak hours to off-peak hours. By this way, it helps DSOs avoid power congestion, voltage deviation or reduce network losses. Therefore, it could postpone the investment in grid expansion or reinforcement. In the end, DSOs can effectively invest in their system.

2.2. Needs and requirements

As shown in Figure 2.1 below, the scale of energy transition ahead is immense. Renewable generation is expected to meet 80% of Europe's future energy needs [5]. DSOs realize that the current model of *'connect and reinforce'* is not efficient for the future and that they will need to overcome the passive relationship between DSO and network customers.

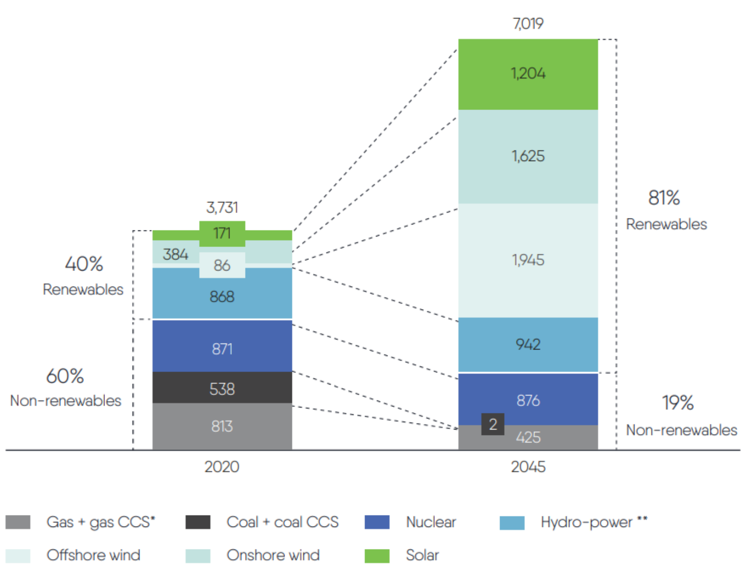

Figure 2.1: Electricity generation in the 95% EU economy decarbonisation scenario (Twh/year) [6].

As per the European Commission study, it is estimated that around €11 billion per year is needed to reinforce distribution grids [7]. Specifically, DSOs are looking at smart tools to:

- Monitor DERs across all voltage levels
- Create visible overpower flows, loads and connections at the local distribution level
- Enable the integration of flexible solutions across the network
- Develop platforms for procuring flexibility services to balance the local grid

The extent to which the above functions are required by DSOs varies on a regional or market basis. For example, DSOs are likely to be carrying out increased activities around service facilitation and system coordination and maybe less around restoration services. The underlying competencies required to deliver these six functions are evolving. DSOs need greater visibility, advanced monitoring and more control over the electricity flowing across their grids. Below in Table 2.2, the core functions currently performed by DSOs are presented, and subsection 2.2.1 will explain some of these use cases in detail.

Table 2.2: DSO core functions.

DSO Core Functions	Use Cases
Network operations	Asset management system
Investment planning (network development)	Visualization of investment work (modernization/reinforcement) planned on network
Maintenance of electricity infrastructure (protection arrangements and restoration)	Visualize live tenders for regions where DSO is seeking flexibility
Service facilitation (provision of network access services and other services for users)	Visualization of the hosting capacity of renewable energy resources (RES) on the distribution grid Geolocation current power outages or planned interruptions Geolocation an EV charging points
System coordination	Common access register for smart metering data and settlement system

2.2.1. Use cases visualization of DSO functions

In this section, we introduce several innovative use cases enabling proficiency within these DSO functions.

1. Visualization of the hosting capacity of renewable energy resources (RES) on distribution grid:
    - DSOs need to strengthen the business case when they request approval from the national regulation authority (NRA) on tariff rate justification. By showcasing a more transparent distribution grid network capacity to NRA as well as all the grid influencers— solar and wind developers, energy storage players, electric vehicle charging stations, etc. allow them to determine where it would be easier and more cost-effective to connect to the electricity distribution network and how it may affect their development plans and investment options.
    - As seen in Figure 2.2 below, the colours range from the dark blue areas, which have a hosting capacity value of DERs over 3.5MW, to the brown areas, which have a hosting capacity value of less than 0.5MW. The blue areas generally mean that a project should be good to go, and brown means that a project may not be feasible without major upgrades. With access to this data, a

project developer can prioritize a project where interconnection is most likely quick, easy, and inexpensive.

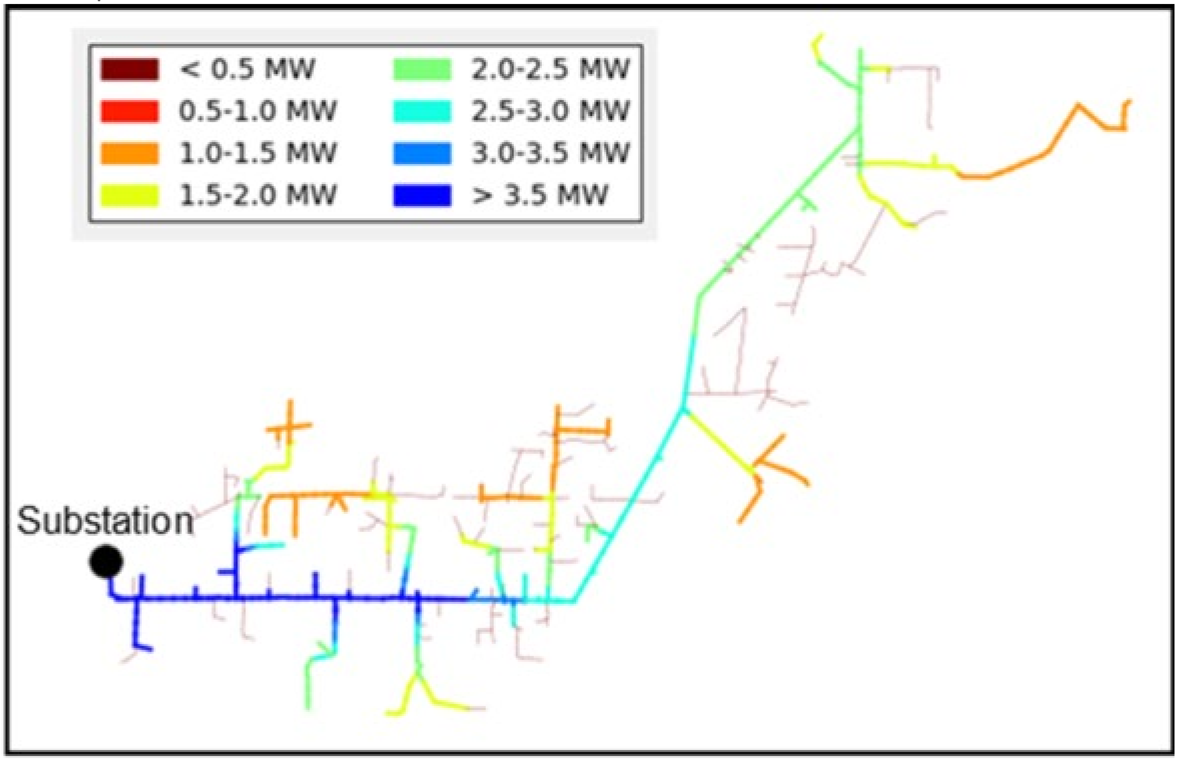

Figure 2.2: Example of visualization of hosting capacity.

- This kind of mapping also helps DSOs in understanding how the connection of a significant amount of solar PV capacity or EV stations in certain regions of the distribution network may cause violation of the voltage band or local congestions of network elements.
- In addition to the map shown above, spreadsheet analysis of data could be derived with a row for each different substation and feeder, which provides the maximum and minimum hosting capacity value at each location as well as the limiting factor for each.

2. Visualization of investment work (modernization/reinforcement) planned on network
   - By analysing various parts of the distribution system, DSOs can identify areas with ageing infrastructure, areas with overload in system components, areas with various system loading conditions, and areas with frequent power outages. Below in Figure 2.3, an example of an interactive investment map developed by the SP Energy Network in the U.K is shown.

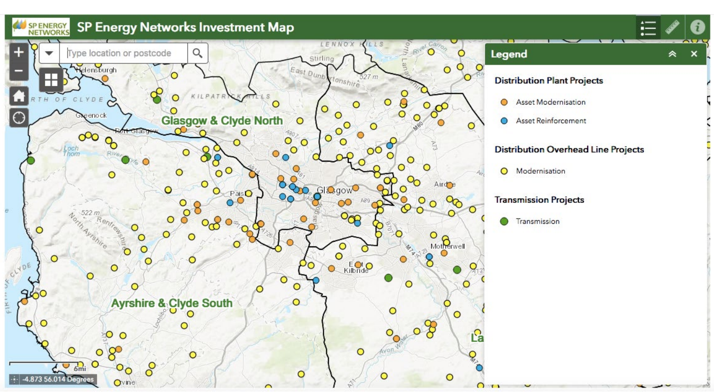

Figure 2.3: Interactive investment map in the UK [8].

3. Visualize live tenders for regions where DSO is seeking flexibility
   - The rapid growth of new hotspots for large scale solar and wind farms, EV charging, data centres, etc., is causing congestion-related issues such as feeder overload, constraints (voltage and current) on the infrastructure. For example, in Turkey (within the OEDAS DSO region), many PV installations are in long feeders and far from customers. At the same time, production is more than consumption in some MV feeders, so the voltage is increasing beyond acceptable limits representing congestion on the network.
   - Flexibility could be used in order to manage congestion, balance individual portfolios, control, and restore the voltage of the grid. In this project, flexibility is defined as a temporary increase or decrease in energy exchange with the network based on DSO's needs.
   - In Figure 2.4, an innovative mapping tool is developed by Western Power (DSO in the U.K) to display the current and potential future flexibility needs across the distribution network. For each region where a potential demand constraint has been identified by the DSO, a request for generation turn-up or demand turn down can be published. Here, flexibility (offered by distributed or industrial consumers) could be used in order to manage congestion, control, and restore the voltage of the grid.

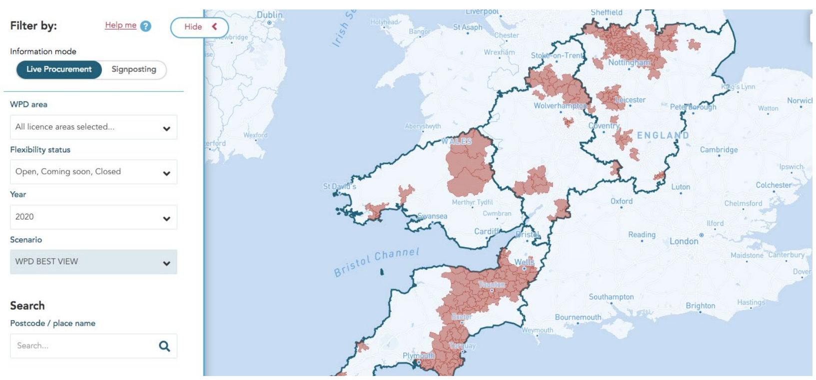

Figure 2.4: Current and potential future flexibility needs across distribution networks in the UK [9].

4. Geolocation current power outages or planned interruptions
   - DSOs have been mapping power outages or planned interruptions to provide proactive customer engagement. Just by entering your postal code, all planned outages and interruptions that could impact your building/apartment will appear on the map. Below is an example of a smart tool developed by ORES (DSO in Belgium).

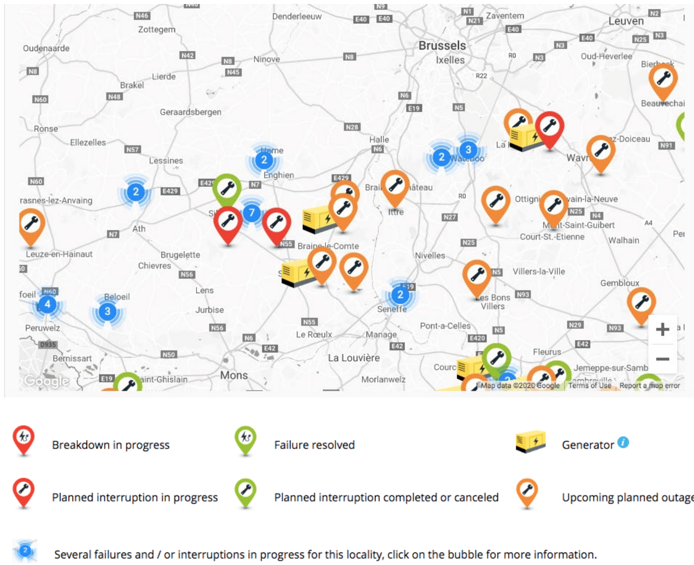

Figure 2.5: Smart tools developed by ORES (DSO in Belgium) [10].

5. Common access register for smart metering data and settlement system
    - Due to energy transition, ancillary service from TSO grid users is reducing, and TSO is looking to acquire more flexibility from DSO customers. DSO is looking forward to contributing as a neutral market facilitator of flexibility market products by measuring data, verifying contractual compliances, and processing (aggregation, baseline calculation) of data for settlement [11]. This is a challenging task since DSO also needs to maintain operational security and quality of supply for their network.

2.3. The remaining challenge for grid monitoring capability

2.3.1. System flexibility services procured by DSOs

As aforementioned, flexibility services seem to gain increased importance for distribution network operations. However, in the distribution level (medium or low voltage), the flexibility services provided by grid users or small DERs owners are still less predictable. The limited sensing in the distribution grid, the unpredictable and changing nature of renewable energy, the unknown user's behaviour, etc., are challenging the implementation of flexibility services.

This fact brings in the importance of grid monitoring in distribution grids. Hence, it is essential to implement SE and prediction into the distribution network, which can give the DSO valuable grid information in the nearly real-time or long-time prediction. So, DSOs will be able to define renewable energy production or electricity consumption together with grid state, and therefore, provide the system flexibility services (voltage control, congestion management).

2.3.2. Grid state estimation and prediction

One of the main contributions of this report is developing the SE for the distribution system. The traditional SE has been applied in the transmission system, playing an important role. For the distribution system, the SE and state prediction become more and more essential for the integration of renewable energy. State prediction is more about the forecasting of load consumption or power generation. Depending on the historical data or the physical data of the PV farm or wind farm, the power generation capacity can be estimated for different time horizons. At the same time, the load consumption of households is estimated depending on the customer's behaviour and historical data. This model can help the DSO, for example, with a day-ahead market or system planning. SE is mainly used for voltage magnitude or voltage angle estimation. SE model uses the grid or customer measurements as input, and the estimated state can be in real-time or nearly real-time. With the estimated state, the DSOs can determine the risk in the system or the current situation, hence having good decision making. Both SE and state prediction are crucial tools for grid monitoring and situation awareness.

3. The current state-of-the-art in grid monitoring functionalities

In this section, we will discuss in detail the current state-of-the-art in grid monitoring functionalities, as shown in Figure 3.1. The process from data processing, grid monitoring, and risk assessment will be addressed in the following subsections.

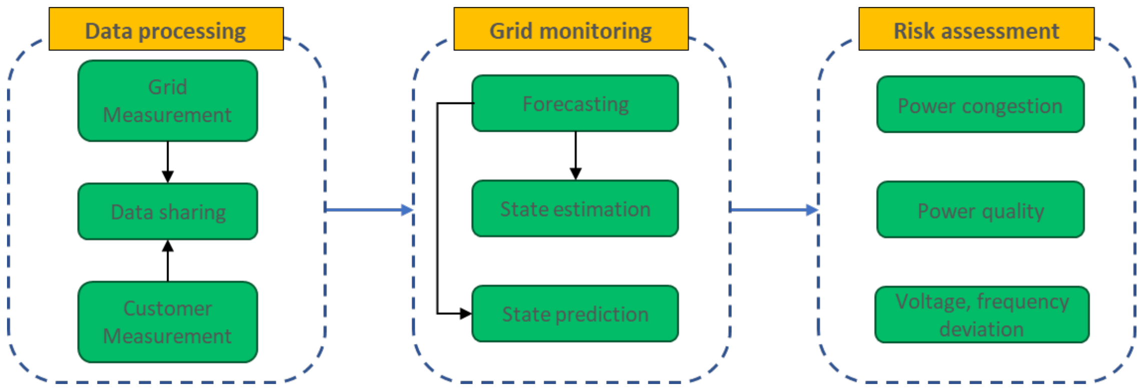

Figure 3.1: The overview of gird monitoring functionalities.

3.1. Development of advanced measurement infrastructure (AMI) for the distribution network

AMI meters measure and record data frequently (real-time, minute, hour, day, etc.). These data are used for various purposes (e.g., billing, forecasting). The AMI meters have two ways of communication capability (recording or transmitting data). To achieve the intelligent grid, the distribution system should be operated as an active grid. That means the grid must be monitored; the controller must control the systems smoothly. AMI plays an important role in the intelligent grid. Figure 3.2 shows some kinds of measurements in the distribution system and their application. As the first step, the data from grid measurements or customer measurements must be collected. Then, grid monitoring and risk assessment can be employed based on the collected data. This section will discuss the available data, data sharing, forecasting techniques, SE, and risk assessment in the distribution system.

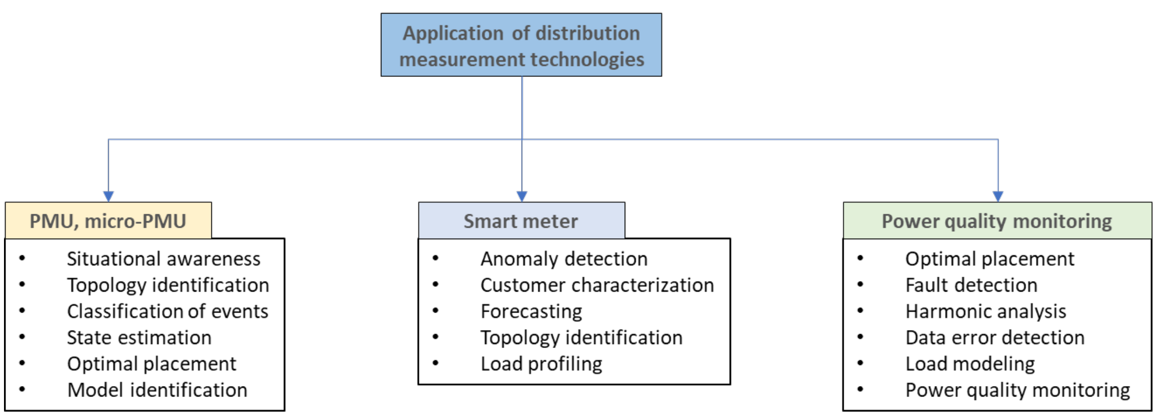

Figure 3.2: Application of distribution measurement technologies.

3.1.1. Customer measurements

Customer measurements are the measurements obtained from smart meters installed in customer households. These measurements have different time resolutions, and they can be either un-synchronized or synchronized. If the smart meter is synchronized, it will take measurements at the same moment. For example, if the time resolution is 15 minutes, measurements will be taken at 0, 15, 30, 45, and 60 minutes. In contrast, the un-synchronized measurements will be taken randomly within the time interval.

At the same time, with the rapid increase of EVs, the EV charging profiles could also be used as customer measurement data. Several studies have already analysed the impact of the uncoordinated charging of EVs in voltage profiles. So, residential smart meter data or EV charging profiles could be used as input for grid monitoring.

3.1.2. Grid measurements

The essential advanced measurement must come from the grid side. It could be power sensors, phasor measurement units (PMUs), micro phasor measurement units (μ-PMU), or substation meters, as shown in Table 3.1 below. These types of measurements are used to observe the behaviour of the grid, either in the steady-state or dynamic state. The accuracy of these devices highly depends on sampling and reporting rates.

Table 3.1: Comparison of advanced measurement devices in distribution networks [12].

Type	Reporting period:	System Observability	Measured Quantities	Sensor Accuracy
Power Sensors	1 sample each (2–4) s	Steady State	Voltage (RMS) Active Power, Reactive Power	$\pm$0.5%
Smart Meter	1 sample each 1–60 min	Load Profiles	Active Power, PF Reactive Power Frequency, Current, RMS Voltage and Power Quality data	Active Power: $\pm$1% Reactive power: $\pm$2%
μ-PMU	Up to 120 samples each second	Dynamic and Transient State	3 Ph-Voltage phasors 3 Ph-Current phasors Active Power Reactive Power Frequency, PF	Amplitude: $\pm$0.05% Angle: $\pm$0.01%
PMU	10–60 samples each second	Steady and Dynamic State	3 Ph-Voltage phasors 3 Ph-Current phasors Active Power Reactive Power Frequency, PF	Amplitude: $\pm$1% Angle: $\pm$1%
Substation Meters	1 sample each min	Dynamic State	Active and reactive power flow, complex current and complex voltage	$\pm$0.5%

3.2. Data sharing

3.2.1. *Digital transformation at the Grid-edge*

Regarding the grid monitoring functionalities such as SE and state prediction, measurement data play an important role. As aforementioned, limited sensing in the distribution system causes the unobservable distribution grid. However, refer to the "grid-edge", the new transition in the distribution system, which brings in the benefit from the internet-of-thing (IoT) cloud system into the traditional distribution system. The EVs, solar PVs, storage with their IoT platforms could provide an amount of system information, which could be used to enhance the grid monitoring capability.

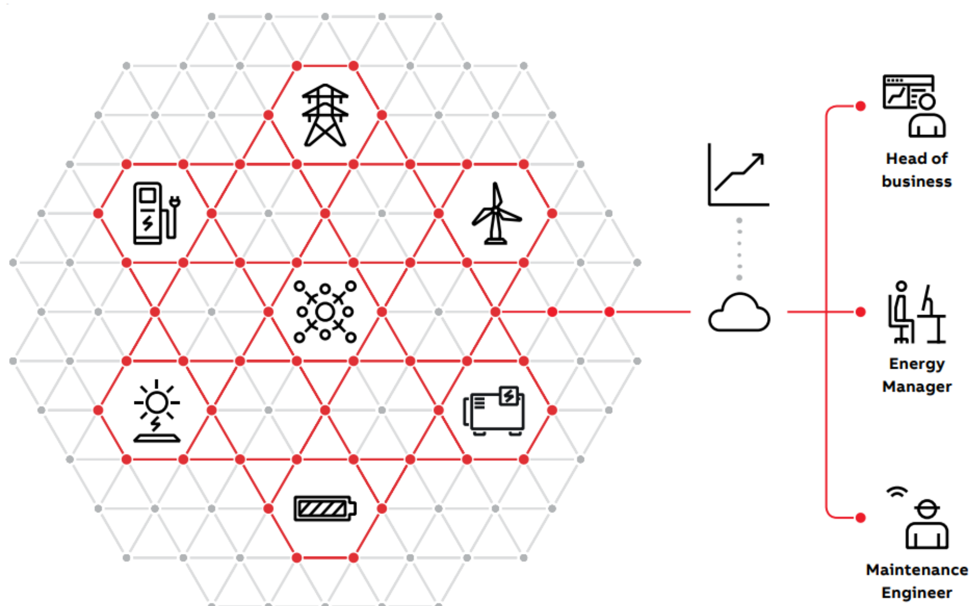

Figure 3.3. Example of ABB cloud-based digital platform [13].

Figure 3.3 shows an example of ABB could-based platform, where the measurement data from DER such as storage, PV, wind, a micro-grid is collected as cloud-based. Then, the DSOs will be able to operate, analyse, or maintain their grid. However, the challenge is how to handle the big data in this distribution system. Big data refers to the volume, velocity, and variety of the collected data, i.e., smart meter or other IoT devices.

- Volume is the amount of collected data. It can be too large to store and takes time to analyse using traditional technology. One of the solutions is to use local storage systems and then connect them with the ICT services.
- Velocity refers to the speed of the generated data. It could be 15, 30 minutes, an hour, or real-time, depending on the measurement devices. It is also a big challenge to collect and analyse the data in real-time, which comes from PMU or µ-PMU.
- Variety refers to the types of data, which could be voltage, current, power, charging profiles. In addition, it could have various kinds of data structures and time resolution.

Thus, there is a need for new technology to collect, handle, analyse, and share the data throughout the distribution grid.

- Data collection

In general, there are two kinds of data in power systems, including operational data and non-operational data. Operational data is the data related to network operation parameters (i.e., voltage magnitude, voltage angle, power flow, etc.). These data can be collected using advanced metering infrastructure (AMI), phase measurement unit (PMU), or supervisory control and data acquisition (SCADA) system. On the other hand, non-operation data is the data that helps network operators in network operation, management, and control. Non-operation data includes weather data, electricity market data, customer behaviour data, etc.

- Data handling, data analysis

With different data sources mentioned above, data handling and data analysis are the important processes to get useful information that can be used for system operation. Data handling is the process of gathering, recording, and presenting the data from the historical or real-time measurement data. First, some different issues such as bad data, missing data or errors in the measurement process need to be solved by either mode-based or data-driven based methods. After that, the data need to be analysed to predict or calculate the needed information. For example, the historical weather data is used to forecast further weather information (i.e., irradiance or wind speed), which is used to better estimate the power generation from renewable energy.

3.2.2. *Data integrity*

- Privacy

In the EU, the general data protection regulation (GDPR) was applied with specific rules on data protection [14]. GDPR also concerns the electricity sector. Personal data relates to a person (i.e., household data from the smart meter in the distribution grid). Smart meters are electronic devices that record the household consumption data and communicate with the utility operator for billing and monitoring purposes. While processing the data (i.e., collecting, storing, analysing, sharing, or erasing), the GDPR must be followed. The detailed physical infrastructure of a smart meter (e.g., in the Netherlands) is shown in Figure 3.4 below. It has four communication ports. Port P0 is used for installation and maintenance; port P1 is used for the communication with other devices installed in the customer's house; port P2 is used for connection with other local metering devices (i.e., smart gas/water meter); port P3 is used for the communication with the DSO, for sending their power consumption.

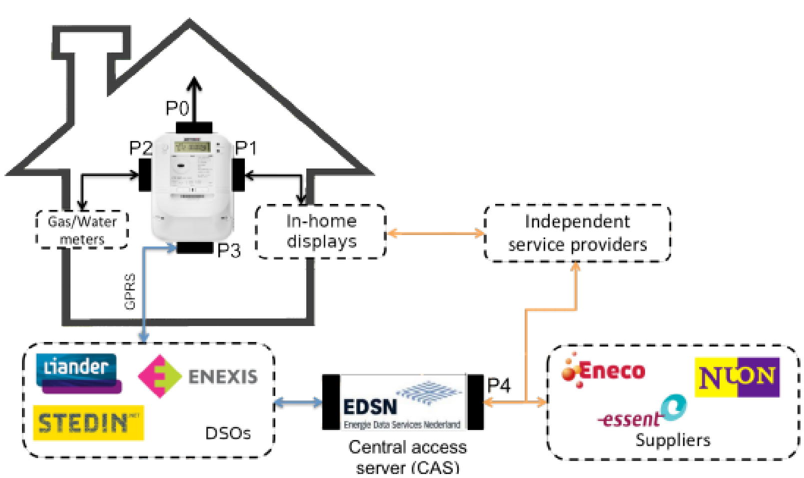

Figure 3.4: Standardized smart meter and surrounding infrastructure [15].

- Security

As in the traditional power system grid, the system is mostly a stand-alone system. However, with the increasing availability of ICT technology in the distribution grid, the grid gets more connected nowadays. However, a few smart meter data have leaked in the past years, which raises the question of system security. The security concept could be either from the DSO point of view or the customer perspective. From the DSO point of view, cybersecurity is not only deliberate attacks but also ICT errors or equipment failures. With the increase of connection points in the system, this problem becomes more and more challenging. In parallel, with sharing the power consumption data, a lot of private information about personal life may be disclosed.

- Transparency

For the distribution system operation, the accuracy of system modelling is highly important. However, it highly depends on the input of the available data. The stochastic model of renewable energy is built from historical data. Other necessary data for energy systems modelling is load estimation, electric price data, or generation capability. There is still the issue of grid data unavailability and lacking transparency of data. Thus, some power system operators in Europe partially released datasets of their networks [16], such as ENTSO-E [17], TenneT Germany [18], British National Grid [19].

3.2.3. Data exchange platforms

To overcome the above-mentioned issues, a data exchange platform needs to be developed, enabling system operators to use the available data effectively. Figure 3.5 depicts a data exchange platform, where different data inputs are collected and exchanged via a platform and then used by either TSOs, DSOs, end-users or third parties. The data exchange platform can be centralized or distributed, operated by the system operator or third party, who ensures data integrity and provides non-discriminatory data access. Several European countries are planning to use such data exchange platforms [20], which are summarized in Table 3.2.

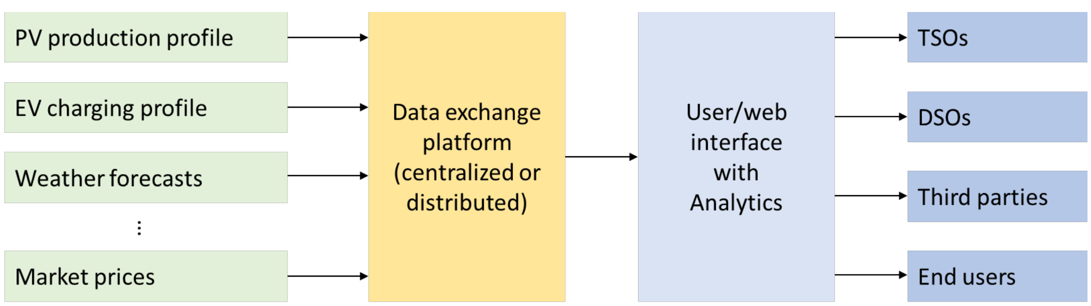

Figure 3.5: Concept of a data exchange platform.

Table 3.2: Status of data exchange platform implementation.

Country	Implementation status	Year
Sweden	Planned	2022
Finland	Planned	2021
Norway	Operational	2019
Belgium	Operational	2018
Denmark	Operational	2013

3.3. Forecasting techniques

Energy forecasting is a well-known technique used to predict the future of energy production and consumption. The rate of growth of energy is estimated at around 1.2% annually. Without the change of normal weather conditions, the peak load for winter periods (e.g. Pacific Northwest) is predicted to grow to 43,000 MW by 2030 [21]. So, energy forecast plays an essential role in distribution networks. In this section, the advantages and disadvantages of different forecast tools will be discussed.

With the integration of renewable energy, the distribution network is becoming more and more complex and unpredictable. So, various forecasting techniques are developed around the world to overcome this problem. Different models and approaches are selected depending on the objective of system reliability, efficiency, optimization, etc.

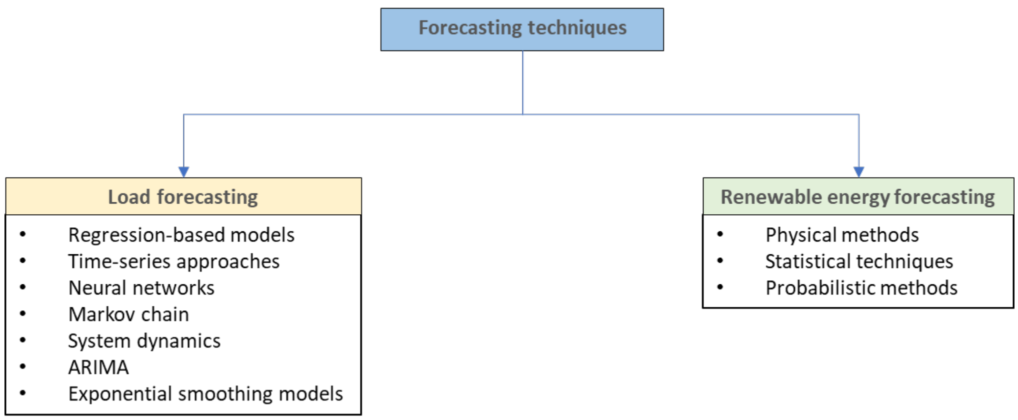

Figure 3.6: The most used forecasting techniques.

Forecasting errors could cause unbalanced supply-demand, which affects the safe operation, quality of the service or even lead to local or system power outages. Overestimation of power consumption may lead to unused capacity (wasting the resources). Especially, without or lack of distribution system data, the forecasting model could not give an accurate result. Thus, selecting the right models to predict future energy trends accurately is an essential step for DSOs.

3.3.1. Load forecasting

Load forecasting (LF) is used to predict future energy consumption based on historical data, weather data, and the capability of RES. It helps the DSOs to balance the demand and supply of energy. LF is widely used for the prediction of future load on a power system for a specific period. These predictions may be for a fraction of an hour for the operation process and maybe for 20–50 years for planning purposes. LF can be classified into three main areas [22], [23]:

- Short term LF is used to predict the load hourly for up to 1 week for daily running and cost minimization.
- Medium-term LF usually predicts load weekly, monthly, and yearly for efficient operational planning.
- Long term LF is used to estimate load up to 50 years ahead to facilitate expansion planning.

Demand forecasting is an essential parameter for the operation and planning of a power system and has a great saving potential for the utility provider. However, an error in the forecasting model could cause an increase in operational cost, so an accurate mathematical model is required, which forms the relationship between load and influential variables such as time, weather, and economic factor, etc. Forecasting models require estimation techniques to determine the model parameters. Numerous forecasting methods are proposed in the literature. The most used forecasting techniques are [24]–[30]:

- Regression-based models:

Problems exist in identifying the best model, which is due to the nonlinear correlation between electric loads and influencing factors. They are very popular due to their simplicity and generally good performance. Regression is used to estimate the relationship between different factors or predictors and the variable we want to predict. Linear regression assumes that these relationships are linear and try to find the optimal parameters (or weights) to minimize the prediction error. These models are used to correlate electric load and exogenous variables, i.e., maximum, and minimum temperature. Multiple regression models also exist to state the load as a function of exogenous factors.

- Time-series approaches

Estimate a future value given past values of a time series in the short term. It does not need additional time-series of the exogenous factors. A time-series operation performed at a minimal cost. A time-series method requires less historical data for operations. With the help of time-series statistical methods, we can evaluate the uncertainty of short-term load forecasting. However, the limitation of such methods is that they are time-consuming, they require a lot of human intervention, and they may become numerically unstable. The time-series method does not deeply study underlying patterns. With the time-series method, it is difficult to find and interpret the sources of errors. If past observations are very good indicators of future observations, the dependencies may render linear regression techniques an inappropriate forecasting tool.

- Neural Networks

A neural network is a series of algorithms that endeavours to recognize underlying relationships in a set of data through a process, creating an artificial neural network that, via an algorithm, allows the computer to learn by incorporating new data. Neural networks can handle missing and noisy data, a large number of parameters or variables, and can work with non-linearity models. The neural network also has the ability to provide solutions for forecasting problems with a very good predictive result while they exhibit continuous learning. However, the implementation is difficult, the need for more resources for computational work (for the training phase).

- Markov Chain

The stochastic process model with discreteness presents a quantitative analysis of the status of a system from one state to another. This method is also used to analyse the reliability of the power system, energy consumption. Furthermore, the combination of the electric load has provided strong theoretical support for the price and demand forecast, etc. This method is simple, has computational speed and stability. It comprises the forecast of the conditional and unconditional probability distribution.

- System Dynamics

System dynamics is an interdisciplinary approach that combines the feedback and control of information, the decision-making theory, and computer technology. It is especially suitable for simulating the behavioural characteristics of nonlinear, high order, and complex time-varying systems. This method can help in gaining insight and understanding in a messy situation by sketching increasingly sophisticated causal loop diagrams. However, defining each component or subsystem can be a very time-consuming job. Some issues that may arise are data availability, systems understanding, and systems uncertainties. A system dynamics diagram can become very complicated when actual situations with lots of variables are modelled. A system dynamics model can only run one version of a situation at a time, although it may capture a great deal of variety in the changing values of its variables.

- Autoregressive integrated moving average (ARIMA)

A time-series technique in which an own series history is used as an explanatory variable. Regression uses external factors as an explanatory variable for the dependent value. The method can capture the impact of weather on load. This method also provides a more straightforward model estimation and a more accessible interpretation of the model parameters. However, this is a univariate model. So, it cannot exploit the leading indicators or explanatory variables.

- Exponential Smoothing Models

The simplest exponential smoothing model puts exponentially decreasing weights on past observations. When the data contains a trend, a double exponential smoothing model is more suitable. This is done by having two exponential smoothing equations: the first on the overall data and the second on the trend. This method is easy to learn and apply. It gives more significance to recent observations. However, it produces forecasts that lag behind the actual trend. Sometimes this method neglects the ups and downs associated with a random variable. This method is not suitable for long-term forecasts because forecasts are not accurate when data with cylindrical or seasonal variations.

3.3.2. Renewable energy forecasting

RES (i.e., wind, solar) play an essential role in the power system [30]. At the same time, the uncertainties from these RES are a challenge for the power system, especially for the traditional passive distribution system [31]. The forecast of these RES is an essential topic as it has complete application in time-varying competitive energy markets, where the forecast accuracy plays a significant role concerning the economy and reliability of a renewable power plant [29], [32]. The prediction time horizon can be divided into four types: ultra-short-term, short-term, medium-term, and long-term prediction horizon [27]. The problem has been solved from various dimensions: physics (weather predictions), mathematics (probabilistic and statistical), machine learning, or the combination of these methods [31], [33], [34].

- Physical methods

In this subsection, we will discuss the physical forecasting models, which are based on numerical weather predictions (NWPs). These models use the physical data of wind (temperature, pressure, terrain, the layout of a wind farm, etc.) as the input information and forecast the future parameter using meteorological models [26], [35]. Beneficially, this method does not require the training phase via historical data. The result is suitable for the short-term prediction horizon. The challenge is the availability of the physical data and that it requires specialized equipment, making this method not applicable in many cases [24]. However, these methods are still developed and applied in the real system for wind and solar prediction [25], [36].

- Statistical techniques

Unlike physical methods, statistical methods are purely mathematical. The idea behind these methods is based on historical data; the model will recognize the data's relationship or pattern [37]. The time-series models such as curve fitting, autoregressive, moving average are mostly used. The periodic curve fitting technique for an appreciable forecast accuracy was presented in [38]. Another approach is an adaptive autoregressive model that pre-processes the data and updates the output using the cursive least squares curve fitting method. The most popular method for short term forecasting is ARMA (combining the autoregressive and moving average). In [28], the detailed analysis of four ARMA based models was given; these were used to predict wind speed and direction. A combination of wavelet theory and ARMA model is used to pre-process the wind speed in time-series, then for forecasting. The integration of the wavelet transform into the ARMA model is also used to improve the prediction accuracy of the model. Similarly, in [39], linear models making use of seasoning and diurnal historical trends are also implemented for wind speed and direction forecasting.

- Probabilistic methods

In these methods, solar irradiation and wind speed are expressed as a probability density function (PDF). The Weibull distribution was found as the best fit for the wind speed profiles [40], [41]. Several methods were proposed to improve the forecast accuracy by estimating the Weibull parameters. The most used method is maximum likelihood, modified maximum likelihood, graphical, and energy pattern factor [42]. Besides the wind profile, there are some different probabilistic methods that are used to predict the uncertainty, such as Quantile regression and kernel density estimation.

3.4. State estimation to enable flexibility procurement

The first research works on the distribution SE were carried out in [43]–[48]. The distribution system state estimation (DSSE) based on node voltage rectangular and polar are developed in [48], [49]. At the same time, the DSSE based on current rectangular and polar are presented in [50]. In [51], the performance of the branch current and node voltage state estimator is analysed. The accuracy of the two methods is reported as the same.

Most of the methods try to minimize the quadratic error. But, other methods like quadratic-constant, quadratic-linear, least measurement rejected, least median of square are applied to minimize the state error [52], [53]. For the non-normal distribution measurement errors, the probabilistic SE methods are used [45]. In this case, the PDF may be expressed based on equivalent Gaussian distributions [28], Beta distribution [45], [54], Gaussian mixture models [55], or via their own PDF [56]. Artificial Neural Network-based SE techniques are proposed in [57]–[59]. Fuzzy logic state estimation techniques are presented in [60], [61]. Furthermore, the weighted least square (WLS) method is well selected for the DSSE application. SE applied to the distribution system may conduct to the system with hundreds or thousands of state variables. In these cases, it might be useful to split the SE problems into several areas as is proposed in [62]–[64]. The application of model-based and data-driven SE will be discussed in detail in section 4.

3.5. State prediction for risk assessment

Risk assessment on distribution networks has gained much attention in recent years due to the energy transition that results in the high penetration of distributed resources and renewables in distribution grids. The uncertainties associated with renewable generation as well as with loads that are dependent on end-user's behaviour, such as EVs and heat pumps (HPs), have deteriorated the prognosis of the distribution level operation. Figure 3.7 shows some of the risk assessment methods and security indicators. New techniques are proposed to comprehensively determine the level of the potential risk that the operation of a given distribution grid faces considering multiple risk factors [65]. In [65], probabilistic models are established to determine the uncertainties, including temporal distributions of EVs and uncertainties of renewable energy, while a time-sequential security risk assessment method with several security indicators including overvoltage and undervoltage risk, line-congestion risk, and load-loss risk is established using probabilistic load flow and dynamical sensitivity weight analysis method.

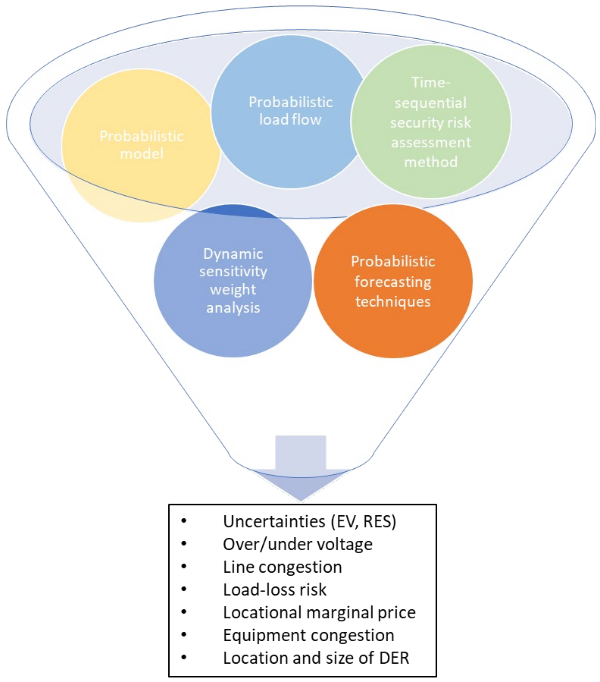

Figure 3.7: Some of risk assessment methods and security indicators.

Moreover, risk assessment methods based on probabilistic forecasting techniques can be used to forecast the locational marginal price (LMP) and the possible congestion of a given network. For example, in [66], a probabilistic forecasting technique is developed based on a formulation that partitions the uncertainty parameters into critical regions from which the conditional probability distribution of the real-time LMP and equipment congestion is obtained. The proposed method incorporates load and generation forecast, time-varying operation constraints, and contingency models [66]. To this extent, risk assessment techniques (i.e., congestion forecasting methods) can be utilized to forecast the changes of the LMPs in a network and, thus, determine the future energy price and define a suitable market strategy [67].

The traditional risk assessment determines whether the system is secure or not in the present state and lack identifying the risk level. Moreover, when assessing and managing the risk associated with the performance of the distribution network of renewable energy projects by means of probabilistic methods could lead to significant risk exposure. Such probabilistic methods include those employed in the calculation of classical availability/reliability related performance indicators (e.g., SAIDI and SAIFI). This situation may be crucial when predicting the availability of the distribution system associated with renewable generations, such as wind farms [68]. The results presented in [68] show that the risk assessment for distribution networks with significant renewable generation could be underestimated when probabilistic methods that are more suitable to larger-scale power systems are applied.

Moreover, in [69], a multi-stage overloading identification method for risk assessment in a smart distribution network with historical, real-time, and forecasting load data is proposed. The risk level is classified according to the overload risk identification rules based on the overload severity. The proposed method identifies the location of the risk and the risk level of the alert region, which can be used to evaluate the risk assessment of active protection in the self-healing process in a smart distribution network. Furthermore, in [70], an algorithm for evaluating the operational risk for distribution systems with PV substation is used to effectively calculate the distribution system's risk indices and help dispatchers determine the optimum control strategy that introduces the lowest risk to the distribution system. First, the operation risk assessment relationship between transmission and distribution level is analysed to clarify the aim of the assessment and the corresponding assessment indices. Then, the operation mode and the protection technique of the distribution network are determined to obtain the presumed fault set and derive the probability of occurrence for elements in the fault set.

Risk assessment methods can also be implemented to determine the suitable location and size of the distributed generation connected to a given network, either in the distribution or at the transmission level, to prevent the power lines' congestion [71]. Furthermore, risk assessment methods can be implemented for maintenance purposes and the inspection of the health of the equipment of a given distribution network. Due to the large number of items included in a typical distribution network, risk assessment methods can be implemented to improve the efficiency of the sample inspection while reducing the cost of the sample inspection [72]. In [72], a risk assessment method based on state evaluation of equipment gets the risk value of equipment by assets, assets loss degree and mean failure probability of equipment, and builds the risk grades standard of equipment to facilitate the inspection of the health of the equipment in a given distribution network (i.e., distribution transformers). The risk grades standard determines the sample inspection proportion and the test items, and a sample inspection strategy of distribution network equipment is introduced for multi-objective optimization based on risk grades assessment. This strategy brings the sample inspection work of equipment into the assets management system and makes the sample inspection work more reasonable and economical.

Furthermore, in [73], a method for state maintenance decision-making is developed, based on the evaluation of the real-time health status and the results of the risk assessment of the equipment of a distribution network. The real-time health index is evaluated based on the assessment of the equipment status, while the real-time failure rate is calculated following an exponential model. In addition, the average real-time failure rate of all equipment is calculated by the feeder partition method. The importance of the equipment is determined by the loss cost of failure assets, the equipment cost, and the environmental damage cost. Finally, the relative risk cost of each device is calculated based on the risk loss cost of each device. According to the indicator, the operation and maintenance mode and operation and maintenance sequence of different devices are determined, and a differentiated operation and maintenance strategy is formulated [73].

4. Physics-based and data-driven state estimation algorithms

This section defines the model formulations for the SE problem both in the concept of physics-based and data-driven. The traditional SE methods rely on the number of measurements and the quality of the measurement. The well-known method for model-based is the WLS method. In parallel, the data-driven methods could be a good solution for the distribution system, where a lack of real-time measurements is a big challenge.

4.1. Physics-based state estimation

SE as a data processing algorithm is an integral part of a power system's control and security analysis. SE filters redundant measurement data and other available information, thus providing high accuracy for system states. With a significant increase of distributed renewable energy in distribution networks, DSSE becomes essential. However, a lack of real-time measurements can cause an unobservable system that highly affects the accuracy of the DSSE. In this report, we investigate the impact of a new measurement device, named LV-sensor, on the accuracy of the DSSE. The change point detection technique (CPD) is used to calculate the measurement variance from the collected data. The WLS method is implemented for estimating the voltage magnitude and angle of a real distribution grid of a university campus. The results of the DSSE with the input variance using these LV-sensor can significantly increase the accuracy of the DSSE.

A lack of real-time measurements causes limited grid monitoring in the distribution networks, leading to limited application of SE in distribution grids [74]. Moreover, a massive integration of distributed energy resources into the distribution grid makes the DSSE more important than ever. To enable the DSSE, the grid must be observable.

Observability is the ability of the state estimator for solving the SE problem, providing accurate state variables. Moreover, observability highly depends on the number of measurements in the network. The network becomes observable when there are sufficient measurements to perform the system states [75], [76]. An unobservable system consists of observable areas and unobservable areas. In this case, historical data (or pseudo measurements) are used to solve the SE problem with unobservable areas. In [77], a statistical approach is used for the generation pseudo measurements, which are extracted from standard load profiles. It has been shown that generating pseudo measurements can improve the performance of SE. Another method is the Gaussian Mixture Models (GMM) [78], where the objective is to represent all the load probability functions through GMM as pseudo measurements. Recently, many works have considered the application of machine learning algorithms. The ANN-based approach is used in [79] for generating pseudo measurements, active and reactive power injection. A new estimation method based on a clustering algorithm is implemented to estimate pseudo load profiles [80]. In [81], a novel data-driven method is developed to determine the daily consumption of customers (pseudo load consumptions), which consists of three different machine learning models as the clustering algorithm, multi-time scale learning model and recursive Bayesian learning method.

In this section, we focus on analysing the applicability of devices for the DSSE. A low-voltage sensor (LV-sensor) device is used to provide advanced real-time measurements in the LV grid, thus improving the accuracy and observability of the DSSE [82]. The LV-sensor is capable of high-frequency sampling (typically 4kHz) and synchronizes each measurement sample with microsecond accuracy. In order to carry out the measurement's variance, i.e., the quality of real-time measurement data, a novel approach for calculating the covariance matrix based on online measurement without laboratory equipment is developed. The CPD method is implemented with the collected data from the Strijp-S substation in the Netherlands. Based on time-series data with the timestamp at the level of one-second resolution, the CPD detects any significant change of mean value, and the time-series data is divided into different stable sub-sections. Consequently, the variance is calculated for each time window. The well-known SE method [83], WLS, is used to perform the DSSE performance associated with the LV-sensors' variance. The real distribution grid of the Chalmers University campus in Sweden is used as a test case. The power flow results performed by MATPOWER [84] are compared with DSSE results.

4.1.1. Methodology

- CPD Method

The LV-sensors were used to measure the states of a substation in the Netherlands, which were developed in the UNITED-GRID project [85]. Considering only noise from measurements (the system is assumed to be static), the measurement function is as follows:

$$z(t) = x(t) + \varepsilon(t) \tag{4.1}$$

where z is a LV-sensor measurement, x is the system state, and ε is the LV-sensor noise. The noise is assumed as Gaussian random variable with zero mean and standard deviation σ. In theory, a set of measurements at time t from many "exactly same" LV-sensors installed at the Strijp-S substation is needed to estimate the system state.

However, this is not the case in the real system. Thus, using the maximum likelihood estimator of N measurements is a straightforward statistical method [86]. In this case, the mean and variance of the random variable Z considering N measurements are as follows:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} z_i \tag{4.2}$$

$$var\,(\mu) = \frac{1}{N}\sum_{i=1}^{N} (z_i - \mu)^2 \tag{4.3}$$

However, power systems always vary due to changes in operating conditions. Figure 4.1 shows time-series data of voltage magnitude collected by LV-sensor from the Strijp-S substation. The changing of voltage magnitude is caused by the load changing or the uncertainty from the unpredictable renewable energy resources. Thus, the equations (4.2) and (4.3) will no longer be applied directly for real-time stream data.

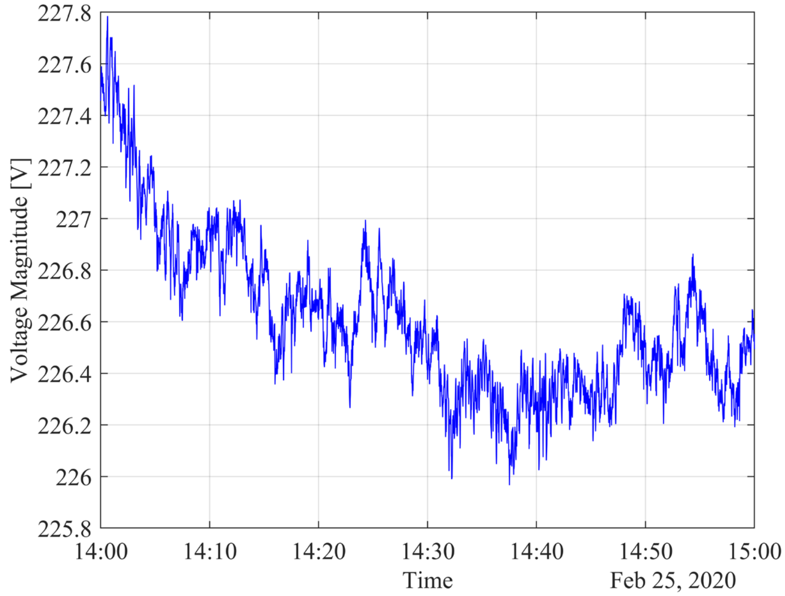

Figure 4.1: Time-series data of voltage magnitude collected by LV-sensor.

Considering a sub-section from the whole collected data, it consists of k samples as:

$$\begin{aligned} z_1 &= x_1 + \varepsilon_1 \\ z_2 &= x_1 + \Delta x_2 + \varepsilon_2 \\ z_3 &= x_1 + \Delta x_3 + \varepsilon_3 \\ &\ldots \\ z_k &= x_1 + \Delta x_k + \varepsilon_k \end{aligned} \tag{4.4}$$

where $z = [z_1, z_2, z_3 \ldots z_k]$ is a measurement series, x_1 is the system state at time t, the vector $\Delta x = [\Delta x_2, \Delta x_3 \ldots \Delta x_k]$ is the change of the system state compared to x_1. Vector Δx shows the changing system operation conditions. As aforementioned, it is unpredictable. One approach for solving this problem is the CPD method [14], a well-known method for analysing the time-series data. The idea behind the CPD method is to find abrupt changes in the signal, and different sub-sections are distinguished by change points. Thus, each sub-section consists of a set of k samples where the vector Δx is close to zero. This means in the time window of k samples, and the system is static. Hence, equations (4.2) and (4.3) are applied to calculate each sub-section mean and measurement variance.

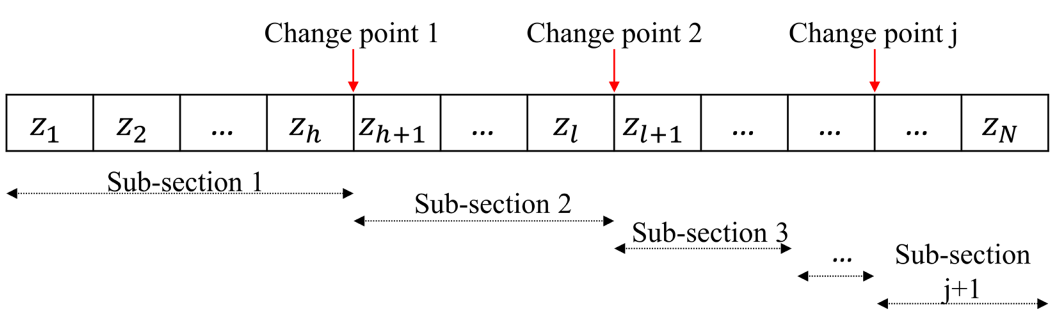

Figure 4.2: Time-series data and change points.

Figure 4.2 shows an example of the time-series data and change points. It consists of j change points, thus $(j+1)$ sub-sections are determined. Vector $K=[k_1,k_2,k_3...k_{j+1}]$ and, $\mu=[\mu_1,\mu_2,\mu_3...\mu_{j+1}]$ are the number of samples and mean value of each sub-section, respectively. The CPD method considers the total sum of square of sub-sections as cost function, the cost function J is as:

$$J=\sum_{i_1=1}^{j+1}\sum_{i_2=1}^{k_{i_1}}(x_{i_2}-\mu_{i_1})^2 \tag{4.5}$$

The objective is finding the j value for which the cost function returns as small as possible. However, this process is straightforward if the number of change points is known. Otherwise, adding change points always gives a smaller value of cost function J. In an extreme case, every sample data becomes a change point, resulting in zero sum of square. Generally, this is an overfitting problem. A factor β, named *threshold*, is added to equation (4.5) to solve the overfitting problem. Finally, the cost function is:

$$J'=\sum_{i_1=1}^{j+1}\sum_{i_2=1}^{k_{i_1}}(x_{i_2}-\mu_{i_1})^2+\ \beta j \tag{4.6}$$

- Weighted Least Square

The SE algorithm is a data processing given by a set of measurement which is used for estimating the system state. The measurement function is as follows:

$$z=h(x)+\ e \tag{4.7}$$

where, z is the measurement vector, $h(x)$ is the vector of function measurements of the state vector x, and e is the measurement error vector. The measurement errors are assumed to be independent zero mean Gaussian variables, and vector R is the covariance matrix of e. To solve the equation (4.7), the widely used WLS is implemented, and the objective is to minimize the sum of the square of the residuals.

$$J(x)=[z-h(x)]^TR^{-1}[z-h(x)] \tag{4.8}$$

Solving the first-order optimality condition of equation (4.8) equal to zero will give the x value, which satisfies the minimum value of objective function $J(x)$. It is given by:

$$g(x)=\frac{\partial J(x)}{\partial x}=-H^T(x)R^{-1}[z-h(x)]=0 \tag{4.9}$$

where:

$$H(x)=\frac{\partial h(x)}{\partial x} \tag{4.10}$$

However, the function $g(x)$ is nonlinear. Thus, the Gauss-Newton method is used to linearize the function, giving the result at the k_{th} iterative is as follows in equation (4.11). The iterative continues until the given convergence criterion is satisfied.

$$x^k=x^{k-1}+G\left(x^k\right)^{-1}H\left(x^k\right)^TR^{-1}[z-h(x)] \tag{4.11}$$

where $G(x)$ is the gain matrix.

$$G(x^k) = H(x^k)^T R^{-1} H(x^k) \tag{4.12}$$

The algorithm below summarizes the WLS algorithm used in this study.

Algorithm 1: Weighted Least Square Algorithm

Input: network parameters, measurement sets;

Initialization: $V_m = 1, V_\theta = 0, Iter. = 1, Tol. = 0$

While $Iter. < 10$ and $Tol. > 1e-4$ **do**

calculate measurement function $h(x)$;

calculate Jacobian matrix $H(x)$;

calculate gain matrix $G(x^k)$;

calculate $\Delta_V = G\left(x^k\right)^{-1} H\left(x^k\right)^T R^{-1}\left[z - h(x)\right]$;

update $V = V + \Delta_V$;

update $Iter. = Iter. + 1, Tol. = max(abs(\Delta_V))$;

end

Result: V_m, V_θ

4.1.2. Simulation results

This section presents the test case and simulation results in detail. First, the Chalmers University campus network is described. This is a typical university campus testbed that is investigated by Fossil Free Energy Districts (FED) project [87] and is widely used as a demonstration in different projects such as m2M-GRID [88] UNITED-GRID [85], and FlexiGrid. Second, the methodologies explained in subsection 4.1.1 are applied. Finally, the measurement variance of the LV-sensor is carried out by the CPD method. Thus, the DSSE is performed.

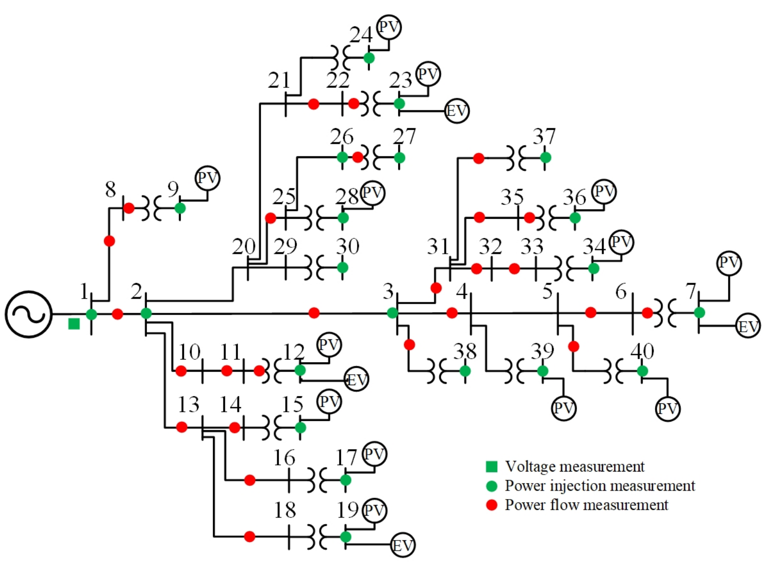

Figure 4.3: The distribution network of Chalmers University campus.

The Chalmers University campus network in Sweden is used as the test case to perform the DSSE. The modified electrical distribution system was presented in [89]. The system is radial and has 40 nodes, including medium voltage (MV) and low voltage (LV), 22 branches and 17 MV-LV transformers (10.5/0.4 kV). The single-line diagram of 10.5 kV Chalmers distribution system is shown in Figure 4.3 [90]. The network data is shown in Appendix A: The physical data of Chalmers University campus network”. Currently, the typical system demand varies between 3.5 and 5.5 MW for hourly consumption. The photovoltaic (PV) system is a combination of roof-tops and wall-mounted PV with 800 kW installed capacity by spring 2019. Moreover, the maximum generation of PVs system (roof-tops and wall-mounted) has been estimated to be between 9 MW and 10 MW, within the scope of the FED project.

- The variance of the LV-sensor

LV-sensors were installed at the Strijp-S substation in the Netherlands for testing and research purposes. Data collected over one week of data with the one-second resolution are used for this study. The data contain both magnitude and phase information. However, only collected data of voltage magnitude and active power are used in this deliverable. The objective is to calculate the variance. Figure 4.4 shows one hour of 50 Hz RMS voltage magnitude measurements reported by the LV-Sensor averaged per second. The reporting rate is one second, so there are 3600 measurements in total. The calculated variances based on the CPD method are conducted with the threshold value equal to one volt. As can be seen, by the results, there are 17 significant change points over one hour. The red lines are the mean value of each sub-section, where the system is nearly stable.

The calculated lengths for each sub-section are shown in Figure 4.5. There is several samples in each sub-section. There are two sub-sections where the lengths are higher than 500 samples, which means that the voltage magnitude is stable for a longer period. Thus, the given variances belonging to those sub-sections are more accurate than the others. The variance of the data collected by the LV-sensors are shown in Figure 4.6 and are calculated by equation (4.3) for each sub-section. As aforementioned, the higher number of samples in Figure 4.5 will give more accurate variance in Figure 4.6.

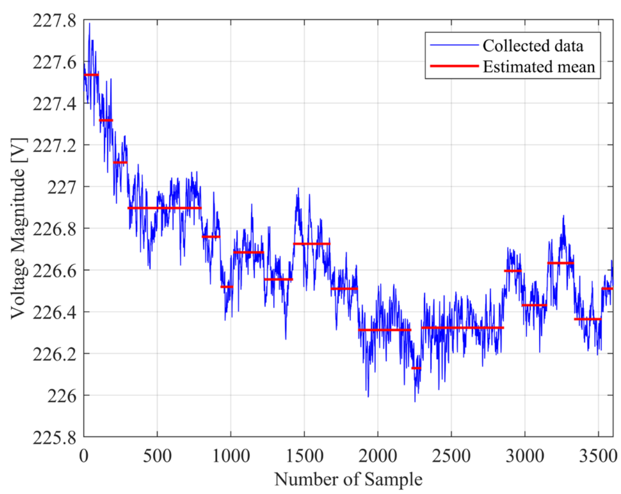

Figure 4.4: The 50 Hz RMS voltage magnitude averaged per second.

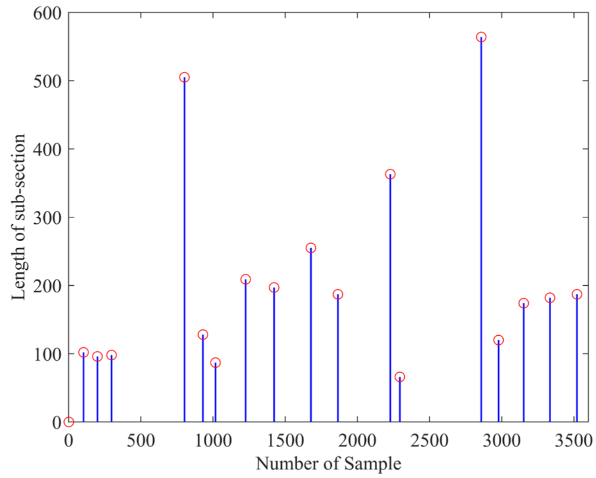

Figure 4.5: Calculated length of each sub-section over 1 hour.

It is important to note that the selection of different threshold values will affect the length of each sub-section. Therefore, it also affects the calculated variance.

Table 4.1: Variance of voltage magnitude with different threshold values.

Threshold	Length of longest sub-section	Variance (pu)
0.5	708 samples	8.74E-10
0.2	360 samples	5.72E-10
0.1	211 samples	2.45E-10
0.05	122 samples	1.84E-10

Table 4.2: Variance of active power with different threshold values.

Threshold	Length of longest sub-section	Variance (pu)
1500	78 samples	4.57E-10
1000	86 samples	4.57E-10
500	87 samples	4.57E-10
200	55 samples	1.54E-10

Table 4.1 shows the length of the longest sub-section and the corresponding variance with four different threshold values. As can be seen, the number of samples is reduced when decreasing the threshold values, thus giving smaller variances. However, the calculated variance is less reliable if the number of samples is small. There is a trade-off between the threshold value and the reliability of variance. Similarly, the variance of active power measurements is shown in Table 4.2. As a reference, the variances used for PMU are normally selected as 1E-8 pu and 4E-4 pu for voltage magnitude and active power, respectively [91]. Thus, the results show the accuracy of the LV-sensor compared with the existing PMU measurement device.

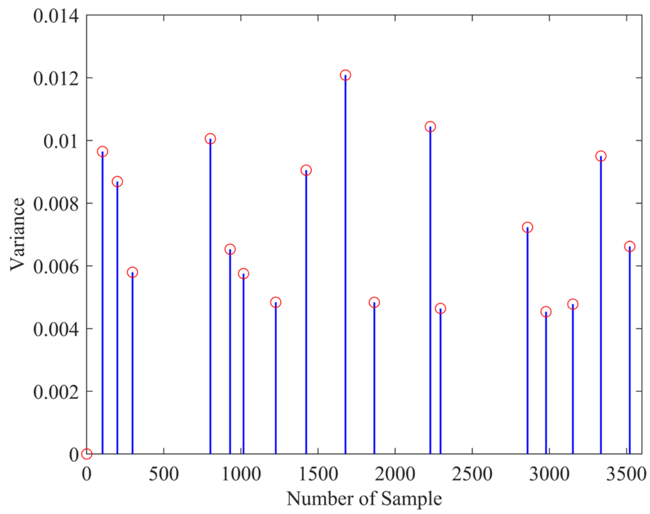

Figure 4.6: Variance of LV-sensor collected data over 1 hour.

- Distributed State Estimation

The calculated variances are implemented with the real distributed system, the Chalmers campus network. First, the network power flow based on MATPOWER is processed to obtain the true values of voltage magnitude, power injection, and power flow of the network. Then a Gaussian noise is added to the true values. Thus, there are considered as measurement values. The selected variance values for voltage magnitude and power (as the same for injection and flow) are 1.48E-10 pu and 1.54E-4 pu, respectively. These values are used for building the covariance matrix. The network is assumed to be a balanced system. Thus, the network can be solved as a single-phase estimator using the WLS method mentioned above. There are 95 measurements consisting of one voltage magnitude at the slack bus, 23 power injection measurement points, and 24 power flow measurement points (the power measurement is a pair of active and reactive measurements).

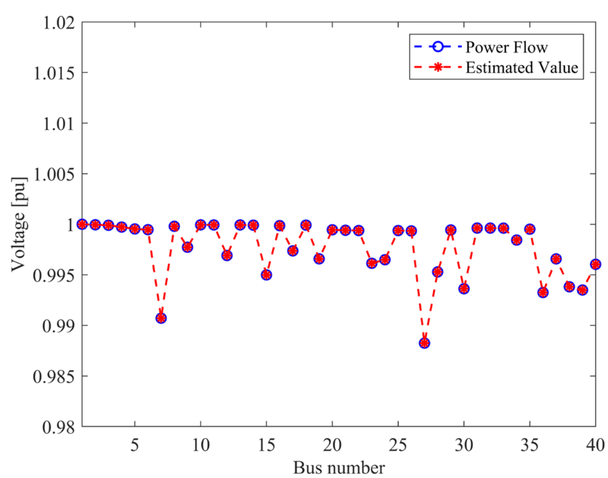

Figure 4.7: Estimated values and true values of voltage magnitude.

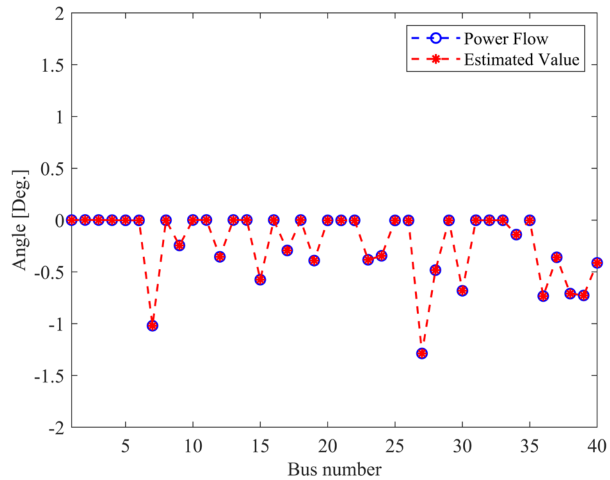

Figure 4.8: Estimated values and true values of voltage angle.

The simulation results of voltage magnitude and angle are shown in Figure 4.7 and Figure 4.8, respectively. The estimated values in red are compared to the true values (blue), which are based on the power flow equation. The results show the accuracy of estimation using the LV-sensors.

In this section, we analysed the performance of DSSE using a new LV-sensor. The variance of real-time measurement was calculated by using the CDP method. These are 1.48E-10 pu and 1.54E-4 pu for voltage and power measurement, respectively. The WLS was applied to estimate the voltage magnitude and angle of the Chalmers University campus. It is found that the estimated values are similar to the true values. The simulation results have shown the accuracy of DSSE by using the new sensor device. Moreover, we expect that this LV-sensor can be further applied as a PMU in the distribution network.

4.2. Data-driven state estimation

With the increase of abundant real-time and historical data, data-driven state estimation is the promising base technique in the DSSE. In data-driven techniques, the information is started at the input layer, then the information moves through several hidden layers and ends at the output layer. By training the model with the necessary amount of data, the model can learn the correlation between each layer (input, hidden, and output layer). This way, the DSSE model can be trained without the need for physical equations of the system.

4.2.1. Improvement physics-aware neural network

In this section, the physics-aware neural network model will be implemented. The context of a physics-aware neural network for DSSE is developed in [92]. The neural network model was built based on the physical connection of the power system network. However, there are still many unnecessary connections between hidden layers. The idea is to reduce the connections by zeroing out the weights of measurements that come from the outside of a partition.

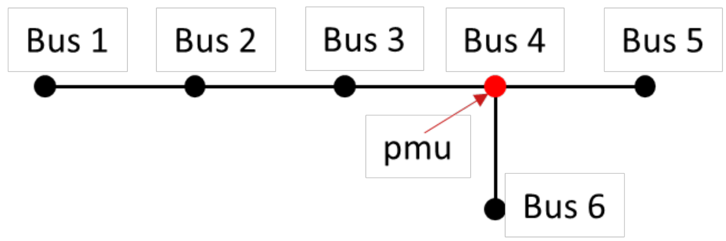

Figure 4.9: An example of 6-bus network.

Figure 4.9 shows an example of a 6-bus system, with a PMU installed at bus 4. The authors in [92] show the (approximate) partition of DSSE based on the position of PMU in the network. The SE at a particular bus can be estimated by the measurements at the partition where this bus is located. For example, by installing a PMU at bus 4, the system can be divided into three partitions:

Partition 1: bus 1, bus 2, bus 3, bus 4.

Partition 2: bus 4, bus 5.

Partition 3: bus 4, bus 6.

By counting the diameter of each partition, partition 1 has a diameter of 3. Similarly, partitions 2, and 3 have a set of the same diameter of 1. The partition value is the needed number of hidden layers for each partition. Thus, the grid needs three hidden layers for the physics-aware neural network. As mentioned before, partitions 2 and 3 need only one hidden layer for the neural network model. Figure 4.10 shows the weight matrix, hence, the connection between different layers. As we can see, graph 1 is the connection between the input layer and the first hidden layer. It is exactly the structure of the network admittance matrix. For graph 2, we kept the connections of the bus located in partition 1. However, in partitions 2, and 3, we zero out the connections between different buses in this partition, just kept the connection itself. To do so, we can build the physics-aware neural network model.

graph 1

1	1	0	0	0	0
1	1	1	0	0	0
0	1	1	1	0	0
0	0	1	1	1	1
0	0	0	1	1	0
0	0	0	1	0	1

graph 2

1	1	0	0	0	0
1	1	1	0	0	0
0	1	1	1	0	0
0	0	1	1	0	0
0	0	0	0	1	0
0	0	0	0	0	1

graph 3

1	1	0	0	0	0
1	1	1	0	0	0
0	1	1	1	0	0
0	0	1	1	0	0
0	0	0	0	1	0
0	0	0	0	0	1

graph 4

1	0	0	0	0	0
0	1	0	0	0	0
0	0	1	0	0	0
0	0	0	1	0	0
0	0	0	0	1	0
0	0	0	0	0	1

Figure 4.10: The graph of each connection between layers.

The graph of each connection between layers is shown in Figure 4.10. Then, it is implemented in a neural network model shown in Figure 4.11. As one can see, the traditional structure of the neural network model is modified based on the real connection and the PMU position in the distribution system. This proposed neural network model can reduce the training of the DSSE model. It can also be scaled up easily for a larger distribution system.

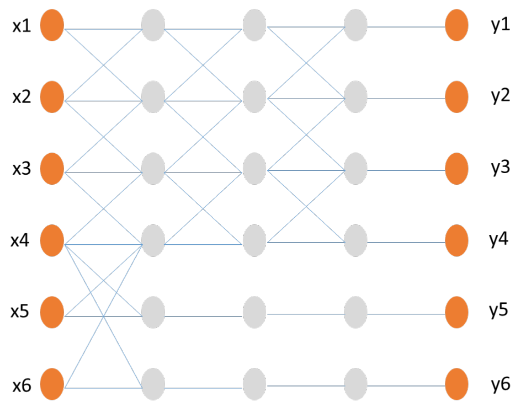

Figure 4.11: The neural network model for a 6-bus network.

4.2.2. Simulation results

In this subsection, the proposed neural network model is implemented in the modified IEEE 123 bus system. The IEEE 123 bus is a radial unbalanced distribution network. The network has single and two-phase loads; it also has different voltage levels. In this work, we consider the four switches as connection buses (i.e., the switches between 13-152, 18-135, 97-197, and 60-160, respectively). Furthermore, four voltage regulators have been excluded from the network. We evaluate the performance of the method with 2 PMUs installed at buses 1 and 60. As mentioned before, the network can be approximately partitioned into two partitions.

Following the design process of the proposed method, 14 hidden layers are needed for the first partition and ten hidden layers for the second partition. So, the whole system needs 14 hidden layers to train the DSSE model. In this work, the one-year time series of smart meter data is used for the simulation. First, the load flow calculation is set up for the network. Then, the well-known WLS method for DSSE based on node voltage [93] is implemented as the benchmark method. The model evaluation process is shown in Figure 4.12, where the basic parameter of the network is the input for the MATLAB model. Then the OpenDSS is used to solve the load flow of this unbalanced distribution system. The output of an API between MATLAB and OpenDSS is the pair of the input measurement (Z) and the voltage magnitude of the network (V_{tru}). The set of measurements Z is then used as input measurement for the WLS to estimate the voltage magnitude (V_{wls}). Then, the absolute error between V_{tru} and V_{wls} is calculated. The result is shown in Figure 4.13, where only the voltage magnitude of phase A is shown (there are many single-phase loads which are located at phase B or C). The results show the accuracy of the WLS method in the modified IEEE 123 network.

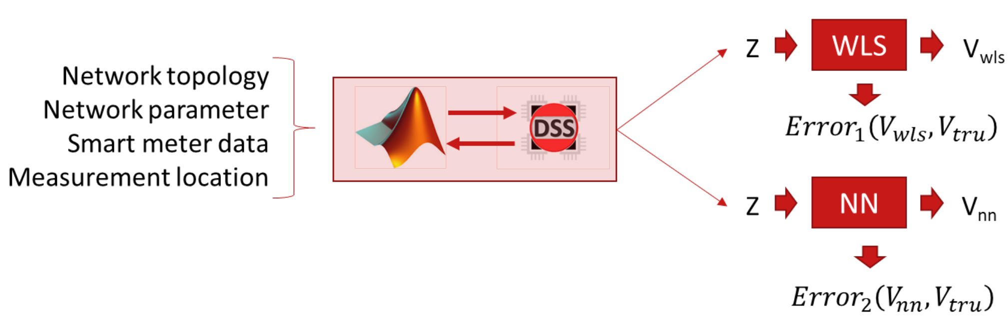

Figure 4.12: The model evaluation process.

By using the API between MATLAB and OpenDSS, we have the training pairs for the neural network model. The data set is created by the one-year data collected from the smart meter. Thus, the data are assumed to be a stochastic representation of the network. Then, the data are used to train the proposed neural network model. There are 35040 points of data; 90% of them are used for the training phase and 10% for the testing phase. The absolute error between the estimated voltage magnitude of the neural network model (V_{nn}) and V_{tru} is shown in Figure 4.14. As can be seen, the estimated voltage magnitude of phase A is almost similar to the true values; the maximum absolute error is around 1.5E-4. The results validate the robustness of the data-driven technique in the DSSE.

In this section, the new data-driven SE is developed for the distribution system. The simulation results corroborate the accuracy of the proposed method. Also, the method is easy to be applied and scaled up because it does not require any complex mathematical equations of the distribution system.

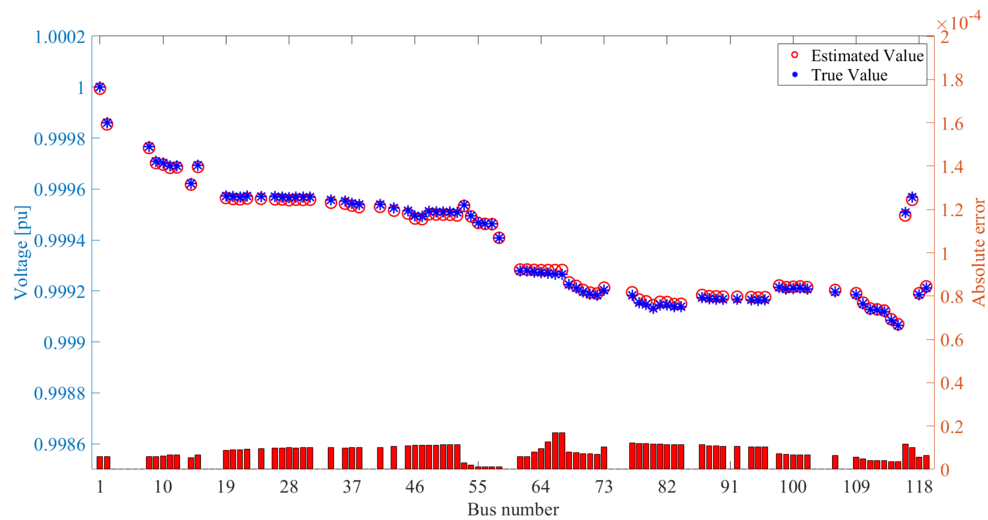

Figure 4.13: Estimated voltage magnitude at phase A of the WLS method.

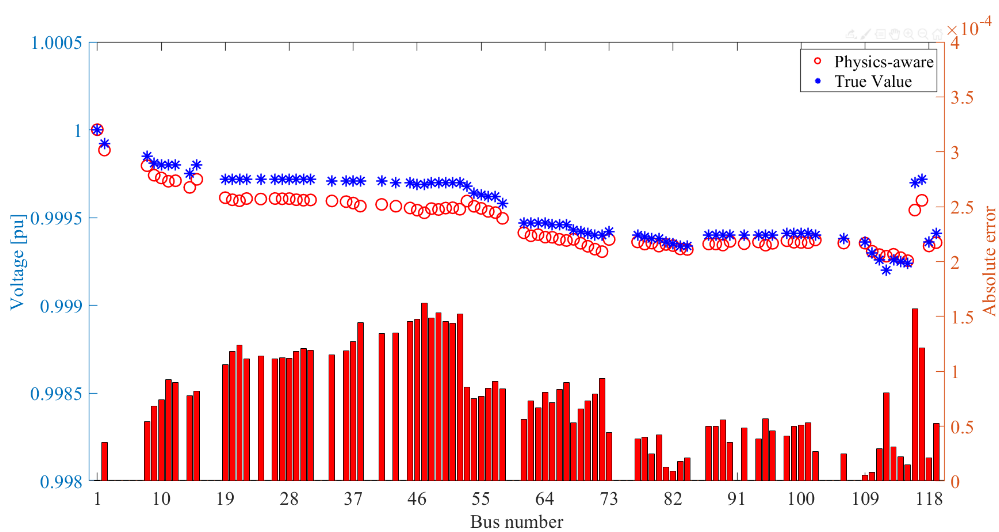

Figure 4.14: Estimated voltage magnitude at phase A of the NN method.

5. Risk assessment

The transition to active distribution grids and the need for better energy utilisation has led to the increased penetration of distributed energy resources (DERs) in distribution networks. Despite the advantages of this approach, significant issues regarding the stable and secure operation of distribution networks have emerged. Hence, adequate risk assessment techniques that will evaluate the possibility of undesired future operation of the grid have been developed, mostly for congestion and voltage deviation issues. This section presents an overview of distribution level risk assessment techniques and introduces the congestion forecasting tool that has been developed by Chalmers, as well as its future developments that will be implemented in FlexiGrid. The satisfying operation of the developed congestion forecasting tool will be demonstrated in WP5 on the Chalmers campus.

5.1. Congestion forecast in distribution networks

Despite the large range of implementation of risk assessment techniques in distribution systems, most of the research efforts focus on identifying the possible congestion in a distribution network, usually through congestion forecasting techniques, in order to determine suitable congestion management methods [94]–[96]. For this reason, international research has focused on identifying and forecasting the uncertainties that are associated with renewables and loads (especially user-dependent loads, e.g., EVs and HPs), emphasizing the uncertainties related to solar PV generation [97].

The probabilistic approach has been very useful in modelling such uncertainties. Hence, for the modelling of the generation and load uncertainties in distribution networks, several probabilistic-based methods have been proposed [98]. In [99], a probabilistic load model that can be included in probabilistic power flow (PPF) has been developed, while in [100], a probabilistic algorithm for power reserve evaluation with high PV penetration has been introduced. Moreover, in [101], a chronological probabilistic model is designed, while a polynomial chaos expansion method for the inclusion of non-Gaussian random variables and polynomial nonlinearities is developed in [102]. In [103], a probabilistic framework for the evaluation of the maximum integration limits for distributed generations with consideration of voltage constraints has been proposed. A simplified version of the backwards-forward sweep (BFS) method, which employs a Gaussian mixture distribution, is proposed to solve PPF more efficiently to be used for planning LV networks in [104]. Moreover, in [105], a probabilistic method is proposed based on quasi-static time-series analysis in combination with the golden section search algorithm to prevent reverse power flow in distribution systems due to PV integration. PV forecast is one of the most challenging uncertainties that a DSO faces. Hence, several approaches have focused on modelling the uncertainties associated with solar PV generation. In [106], a non-parametric kernel density estimation technique has been implemented in order to obtain the probability distribution of solar irradiance. Most of these research works have used a probabilistic framework for different applications, but still, a tool is missing which can help DSOs in understanding the current and future operating conditions of their systems while hosting a high percentage of PV and then help them in taking suitable action.

A computationally efficient tool for DSOs is proposed in [107] to assess the impact of uncertainties associated with distributed units. Another probabilistic method has also been proposed in [71] to detect and rank the congested lines for the grid operators. However, a well-developed visualization platform for network operating conditions is required for DSOs. In addition, regarding the requirements for operating PV inverters, an analysis of the impact of the different operating modes of the inverters could be highly interesting from the DSOs perspective.

In this section, the development and operation of a congestion forecasting tool based on PPF, considering uncertainties associated with PV and other conventional loads, is presented. The developed tool also considers the different operating modes of PV inverters, reflecting the requirements for connecting PVs to distribution systems. The most significant function of the proposed congestion forecasting tool is the visualization of the network congestion based on the cumulative probability of the proposed congestion indicators, including node voltage deviation, branch and transformer overload, both for the distribution system and its individual components. These indicators can help DSOs in analysing congestion in their network and then take appropriate measures to manage the possible network congestion. In addition, in section 5.4 the most important functions of the designed congestion forecasting tool that have been and will be developed further in the context of FlexiGrid will be presented.

5.2. Congestion forecasting tool for distribution systems

This section presents the developed congestion forecasting tool along with the details of the probabilistic power flow model that has been used. The functional diagram for the congestion forecasting tool is shown in Figure 5.1. The uncertainties associated with PV and conventional load are considered in the proposed tool. The probabilistic approach is employed through Monte-Carlo simulations (MCS), each of which leads to a power flow solution. With the obtained power flow solutions, the congestion forecast is evaluated through indices such as nodes voltage deviation, branches and transformers overloading**.**

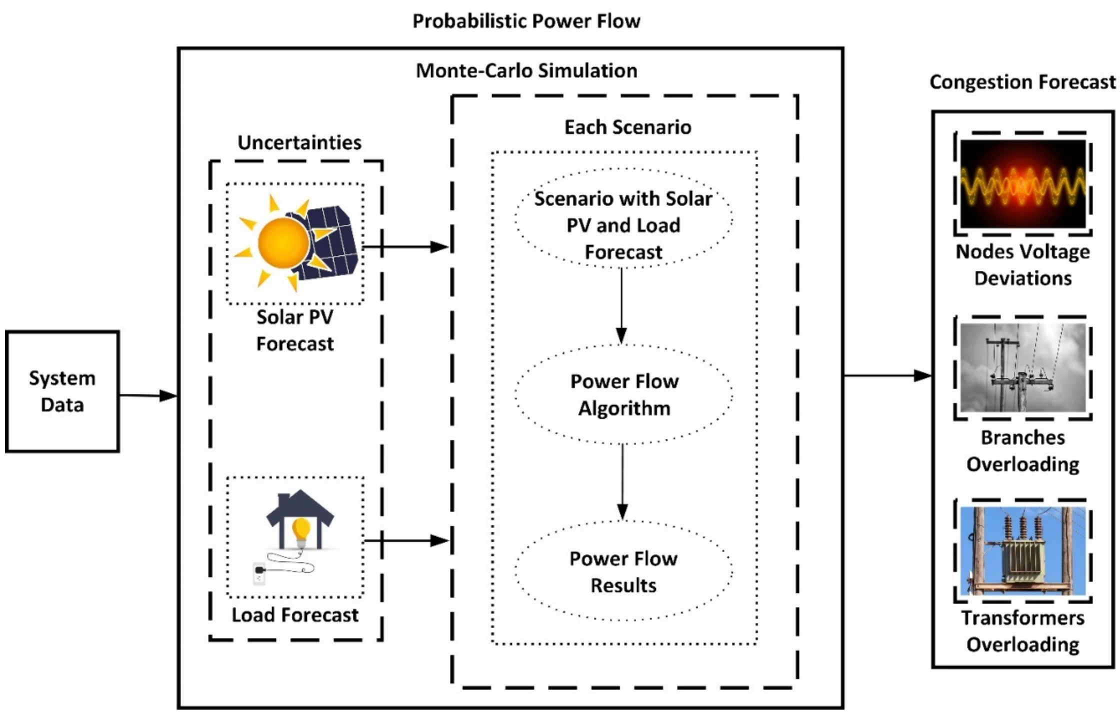

Figure 5.1: Functional diagram for the congestion forecasting tool.

5.2.1. Probabilistic Power Flow Method

The proposed tool uses MCS for PPF where a large number of scenarios are simulated based on the PDF of different variables (i.e., the different uncertainties). This work employs the BFS method for the power flow simulations. The details of the BFS method are presented as follows:

Backwards-Forward Sweep Method

The BFS method is suitable for highly radial distribution networks whose solution is obtained by iterative solution from two sets of recursive equations. The detailed procedures of BFS method without and with the consideration of P-V nodes in the system are as follows [108]:

1. ***Without P-V nodes***: Here, all the nodes except the slack node are modelled as P-Q nodes. To start, the voltage at the slack node is kept constant and a flat voltage start is assumed at all other nodes and then for the i^{th} iteration, the following iterative steps are performed:
   a) Calculate the current injection at node k, as:

$$C_k{}^{(i)} = \left[\frac{S_k}{V_k{}^{(i-1)}}\right]^* - Y_k V_k{}^{(i-1)} \quad \forall\, k = 1,2,\dots,n \tag{5.1}$$

   where, $V_k{}^{(i-1)}$ is the voltage at node k in $(i-1)^{\text{th}}$ iteration, while S_k and Y_k are the apparent power injection and sum of shunt elements admittances at node k.

   b) Calculate branch currents starting from the branch connected to the last node and then moving backward towards the branches connected to the slack node. Thus, the current in branch j, is calculated as:

$$I_j{}^{(i)} = C_N{}^{(i)} + \sum_{f=1}^{T} I_f{}^{(i)} \qquad \forall\, j = br,\dots,2,1 \tag{5.2}$$

   where, $C_N{}^{(i)}$ is the load current at node N and T is the total number of branches coming out from node N.

   c) Update the node voltages starting from the slack node and moving forward towards the last node. The voltage at node N is calculated using the updated voltage at node M and the updated current in branch j is calculated during backward sweep, as follows:

$$V_N{}^{(i)} = V_M{}^{(i)} - Z_j I_j{}^{(i)} \qquad \forall\, j = 1,2,\dots,br \tag{5.3}$$

   where, Z_j represents the impedance of a branch j.

These steps are performed iteratively until the convergence criteria is satisfied.

2. ***With P-V nodes***: Here, all the generator nodes are modelled as P-V nodes while the load nodes are modelled as P-Q nodes. A compensation method is used for the elimination of voltage mismatches from their specified values at P-V nodes. The basic idea is to compensate the node with a calculated amount of reactive power, so that the voltage mismatch becomes zero.

   Let us suppose that there are q P-V nodes in the network, then for α^{th} iteration, the procedure for the correction of voltage magnitude is as follows:

   a) Calculate the voltage magnitude mismatch for all P-V nodes:

$$\Delta V_k{}^{(\alpha)} = \left|V_k{}^{(sp)}\right| - \left|V_k{}^{(\alpha)}\right| \forall\, k = 1,2,\dots,q \tag{5.4}$$

   where, $V_k{}^{(sp)}$ is the specified voltage value at node k.

b) Calculate the reactive current injection as follows:

$$[I_Q]^{(\alpha)} = [Z]^{-1}[\Delta V]^{(\alpha)} \tag{5.5}$$

where, Z is the real and constant impedance matrix with size as the number of P-V nodes. The diagonal entries of Z are the sum of the absolute value of all branch impedances between the considered node and the slack node. For off-diagonal entries, they are the sum of the absolute value of all branch impedances which have the common path between the slack node and the considered nodes.

Thus, the injected reactive current at k^{th} node can be calculated as:

$$I_{kQ}{}^{(\alpha)} = j\left|I_{kQ}{}^{(\alpha)}\right| \tag{5.6}$$

c) Calculate the total reactive power requirement Q_{kR}, for all P-V nodes, as follows:

$$Q_{kR}{}^{(\alpha)} = Q_k{}^{(\alpha)} + Q_{kL} \tag{5.7}$$

$$Q_k{}^{(\alpha)} = \mathrm{Im}\left[V_k I'_{kQ}{}^{*}\right]^{(\alpha)} \quad \forall\, k = 1,2,\ldots,n \tag{5.8}$$

where, Q_{kL} is the reactive power load at node k and I'_{kQ} is the sum of the required reactive current injection and the load current injection is equal to the sum $\left(I_{kQ}{}^{(\alpha)} + I_{kL}\right)$.

d) Check for all nodes whether the calculated Q_{kR} $\left(= Q_{inj}\right)$ corresponding to P_{inj}, satisfies the constraint given by (5.9).

$$P_{inj}^2 + Q_{inj}^2 \leq S_{rated}^2 \tag{5.9}$$

If not, then a new value of P_{inj} and the corresponding value of Q_{inj} should be calculated. To do this more effectively, a curve-fitting method is used to express Q_{inj} as a function of P_{inj} (for a fixed system topology). Curve-fitting is a method for expressing a mathematical function which best fits to a series of data points. Here, P_{inj} and Q_{inj} are the data points. This method helps in avoiding the iterative process to find the new value of Q_{inj}.

These steps are performed iteratively until the voltage mismatches for all P-V nodes satisfy the convergence criteria.

5.2.2. Congestion Forecast

MCS are simulated to obtain the power flow solution using the above procedure. For simplicity, Gaussian PDF is used for generating samples of generation and load forecast to be used in MCS, as follows:

$$PDF = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{5.10}$$

where, μ and σ represent the mean and standard deviation, respectively.

Finally, with the results obtained from power flow solutions, the following indices are proposed to evaluate the congestion forecast:

1. ***Nodes Voltage Deviation***: It is the deviation of the node voltage from the specified values. Critical nodes are the ones where the deviation is more than a pre-specified value in at least an identified number of MCS simulations. For instance, if the deviation is more than 3% in at least 20% of MCS simulations, it is considered as a critical node.
2. ***Branch Overloading***: It is the measure of amount of the current flowing in the branches above their rated thermal capacity (I_c). Critical branches are the ones where the current flow is more than a pre-specified percentage in at least an identified number of MCS simulations.
3. **Transformer Overloading**: It is the measure of amount of the MVA power flow in the transformers above their rated MVA capacity (T_c). Critical transformers are the ones where the MVA power flow is more than a pre-specified percentage in at least an identified number of MCS simulations.

The congestion forecast algorithm is given as follows:

```
Algorithm: Congestion Forecast Algorithm

Data: V_k^sp, Z, Y, P_L^f, P_G^f, I_c, T_c, S_rated, ϵ
Result: V̄, Ī
Initialisation: Flat start for all V̄
for s = 1: S do
    i = 1;
    do
        Backward Sweep using (2) and (3)
        Forward Sweep using (4)
        For P − V Nodes:
        Calculate ΔV_k and Q_kR using (5.4), (5.6), (5.8)
        Incorporating Inverter Limits:
        for i = 1: k_1 do
            if (P_G^f)^2 + (Q_kR)^2 > (S_rated)^2 then
                Re-calculate P_G^f such that the constraint as
                mentioned in (1) is satisfied
        Iteration count: i = i + 1
    while |V̄^i − V̄^(i+1)|_k ≤ ϵ;
Evaluate Congestion:
Determine nodes voltage deviation (ΔV > |V_node − V_sp|), branch
overloading (I_branch > I_c) and transformer overloading (T_trans > T_c)
```

where, P_L^f and P_G^f are forecast value of load and PV, S is number of MCS and ϵ is tolerance limit.

5.3. Indicative results of the congestion forecasting tool on Chalmers campus

In this subsection some indicative results of the congestion forecasting tool implementation on Chalmers campus will be presented. Initially, the studied test cases will be explained and then the efficient application of the congestion forecasting tool will be validated through simulation results.

5.3.1. Chalmers campus test case

The proposed congestion forecasting tool is applied using the data of the modified electrical distribution system of the Chalmers campus in Sweden. The single-line diagram of 10.5 kV Chalmers distribution system is shown in Figure 5.2 [90], as explained in subsection 4.1.2.

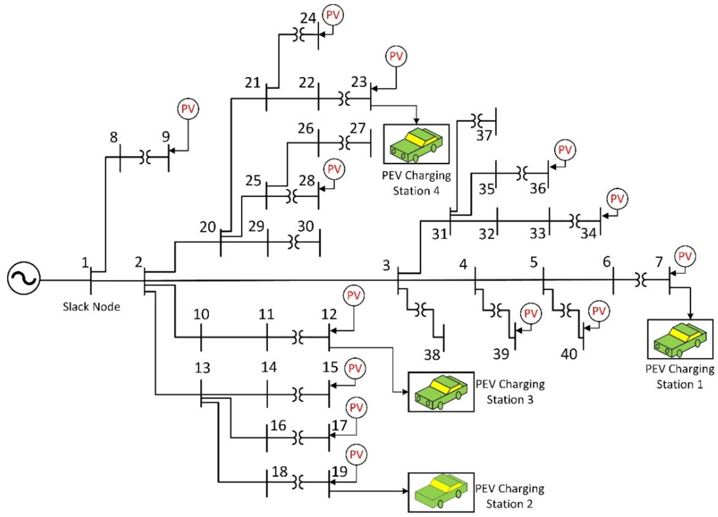

Figure 5.2: Single-line diagram of Chalmers 10.5 kV electrical distribution grid.

The congestion forecast analysis presents the congestion indicators for one snapshot while the number of MCS is taken as 10 000, and the convergence criterion ϵ is taken as 0.0001. For PV and load forecast scenarios, μ is taken as the forecast value of PV and load at one time instant, while σ is taken as 0.1. Additionally, the plug-in electric vehicles (PEV) which are present in Chalmers distribution system are considered here to present more realistic results. The charging power demand model for PEVs has been incorporated for the Chalmers network. The Chalmers distribution system presently has around 35 PEVs charging points at 32A/22kW and 16A/3.7kW level, located at two charging stations (nodes 7 and 19). The other two charging stations (nodes 12 and 23) are considered for future scenarios.

The location of the PV injection nodes and PEV charging stations are shown in Figure 5.2, while real recorded Chalmers load data are considered. The rated capacity of PV-inverter (S_{rated}) is taken as 120% of the maximum PV capacity, to be considered as defined in (5.9). The hourly load demand for Chalmers 10.5 kV electrical distribution grid for a typical day is shown in Figure 5.3.

In this work, the following two future scenarios are considered as presented in Table 5.2, where PV generation and load demand are the actual generation and demand for the network at that time instant. The load demand in scenario A is taken as 4.5 MW to consider the average hourly demand on a present typical day as shown in Figure 5.3, while it is taken as 8.8 MW in scenario B which considers the future average hourly load demand.

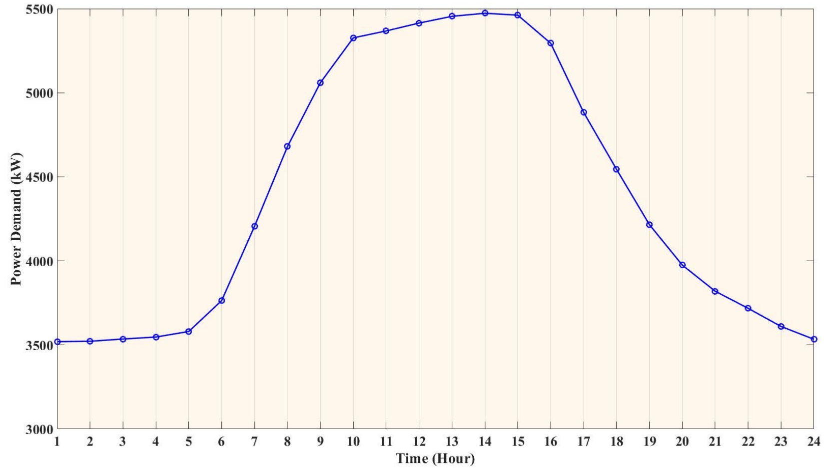

Figure 5.3: Hourly load demand for Chalmers 10.5 kV electrical distribution grid on a typical day.

Table 5.1. Future scenarios for Chalmers campus case study.

Scenarios	A	B
PV Generation (MW)	4	8
Number of PEV	150	300
Load Demand (MW)	4.5	8.8

The criteria used for the evaluation of the congestion indices are presented in Table 5.2. For instance, the criteria in the case of local production level are that all the nodes where the voltage is more than 1.03 p.u. (or the deviation is more than 3%) in at least 20% of MCS simulations are identified as critical nodes or the branches where the current is more than 100% of the rated capacity in at least 20% of MCS simulations are identified as critical branches. The selection of criteria for the evaluation of the congestion indices could be adjusted according to the DSO monitoring requirements and the proposed tool can easily adapt to these requirements.

Table 5.2. Criteria for evaluation of congestion indices for Chalmers case-study

Case	Local Production Level (For scenario A and B)	Operating Mode (constant-pf and -V)
Critical Nodes	1.03 pu, 20%	-
Critical Branches	100%, 20%	100%, 20%
Critical Transformers	100%, 20%	100%, 20%

5.3.2. Results on the impact of the local production level on Chalmers campus test case

To assess the impact of local production level, two different scenarios A and B, as mentioned in Table 5.1 and Table 5.2, are considered with constant-pf mode of operation. The same congestion indices evaluation criteria are used for visualizing the impact of local production level in the two scenarios. It can be seen in Figure 5.4 that the CP for having a voltage magnitude greater than 1.03 p.u. at all nodes has increased and similar results can be observed for the critical nodes. From Figure 5.5, the CP for branch currents to be more than 100% has increased approximately from 0.10 to 0.40. In addition, from Figure 5.6, the CP for transformer MVA loading to be more than 100% has increased approximately from 0.10 to 0.30.

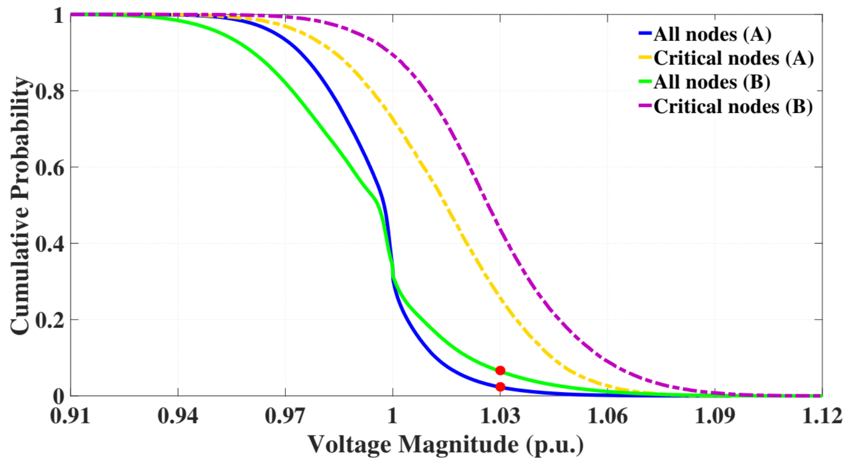

Figure 5.4: CP for nodes voltage deviation with constant-pf for scenario A and B.

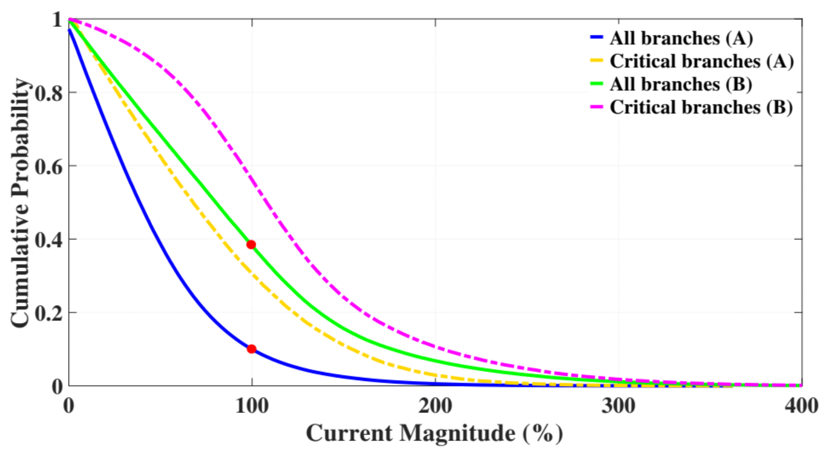

Figure 5.5: CP for branches overloading with constant-pf for scenario A and B.

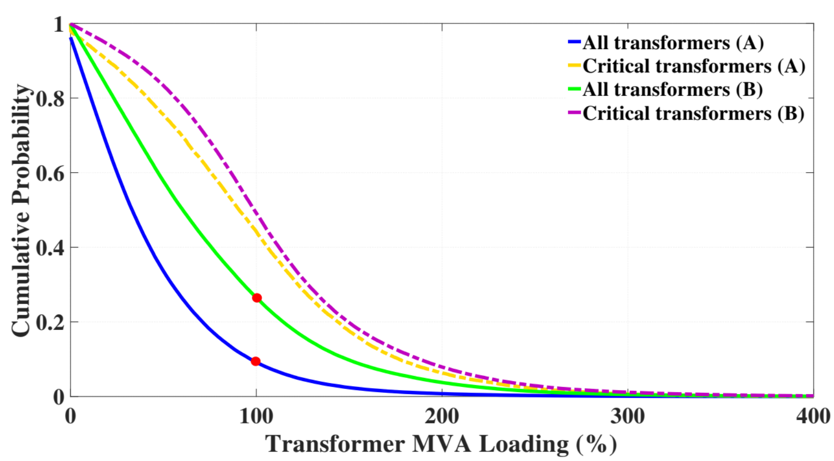

Figure 5.6: CP for transformers overloading with constant pf for scenario A and B.

Therefore, it is evident from the results that with increment of 100% in local generations, 100% in number of PEVs, and 95% in load demand (scenario A to B), the CP for congestion indices nodes voltage deviation has increased from 2% to 10%, branch overloading from 10% to 40% and transformer overloading from 10% to 30%. These increments are mainly because of higher current, active and reactive power flows, due to higher local production and demand. The nodes are subjected to more fluctuations which leads to higher CP for nodes voltage deviation. In addition, the CP for branch and transformer loadings have increased due to higher active and reactive power flow across them.

5.3.3. Results on the impact of the operating modes on Chalmers campus test case

To assess the impact of operating modes, scenario B, as mentioned in Table 5.1, is simulated under constant-pf and constant-V modes of operation. The evaluation criteria used for congestion indices are presented in Table 5.2.

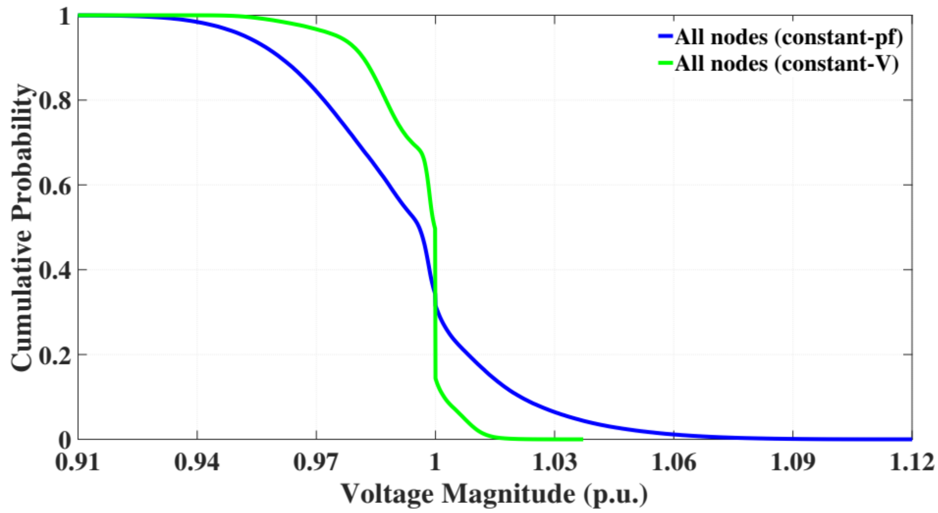

Figure 5.7: CP for nodes voltage deviation with constant-pf and -V modes for scenario B.

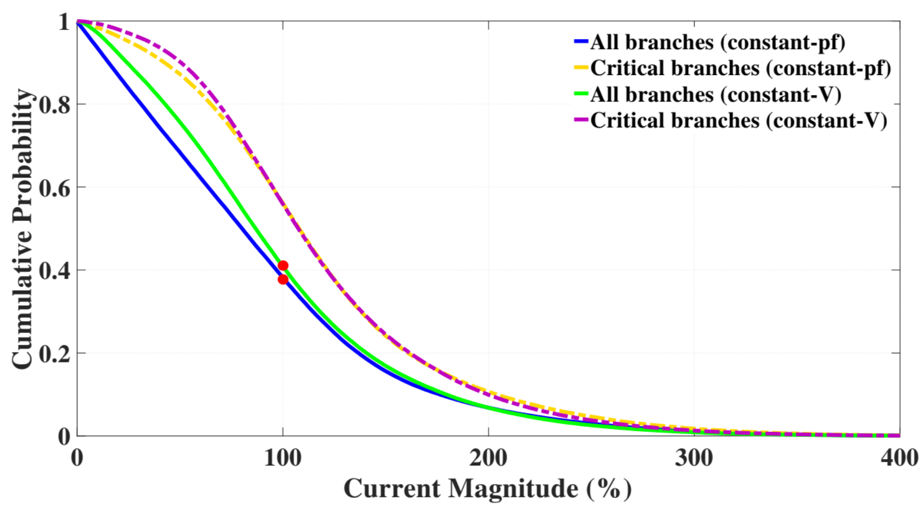

Figure 5.8: CP for branches overloading with constant-pf and -V modes for scenario B.

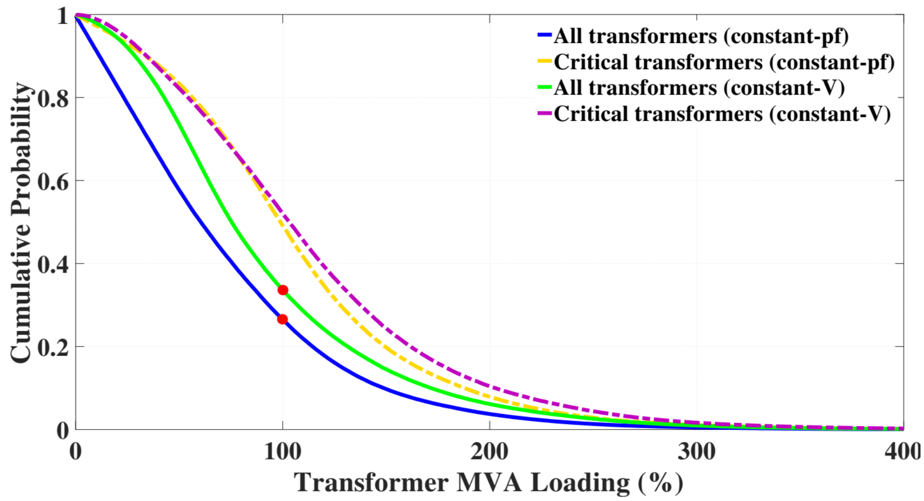

Figure 5.9: CP for transformers overloading with constant-pf and -V modes for scenario B.

It can be seen from Figure 5.7, that the CP for having a voltage magnitude greater than 1.03 p.u. at all nodes is almost 0 which is mainly due to the consideration of P-V nodes, where the node voltage remains fixed at specified values with reactive power compensation. Due to the small CP for voltage deviation, there are no critical nodes identified in constant-V mode. However, it can be seen from Figure 5.8, that the CP for branch currents to be more than 100% has slightly increased from 0.38 to 0.40. Moreover, from Figure 5.9, the CP for transformer MVA loading to be more than 100% has increased approximately from 0.28 to 0.36.

Therefore, it is evident from the results that in constant-V mode, the CP for nodes voltage deviation congestion index has decreased, branch overloading has increased approximately from 38% to 42% and transformer overloading from 28% to 36%. The reason for the decreased voltage deviation is due to the consideration of P-V nodes. In constant-V mode, the voltage is maintained at a specified value through reactive power compensation by injection of higher reactive current, which leads to higher current and MVA loading in associated branches and transformers.

5.4. Further developments of the congestion forecasting tool in FlexiGrid

The developed congestion forecasting tool will be further improved within the duration of the project. The envisioned future developments of the tool can be listed as follows:

- Congestion forecast over different forecasting horizons.
- Presentation of the congestion forecast results in a more interactive, visualised manner.
- Evaluation of the severity of congestion in the system components.
- Inclusion of load models in the load forecast to increase the congestion forecast accuracy.
- Provision of inputs to the market-based congestion management techniques for the evaluation of the amount of flexibility needed to relieve congestion.

6. Conclusions & Discussion about the limitation of the deliverable and further prospects

The work developed in the FlexiGrid project considers the flexibility option for medium and small DSOs. It allows a cross-sectoral integration to unlock flexibility resources, especially those existing in the coupling between different energy vectors as well as demand response using charging schemes of EVs or storage. This report focuses on the network observability problem and risk assessment in the distribution system. First, the DSOs need, and the requirement for flexibility context has been discussed to provide a good overview of the current situation of the distribution system. Then, the different techniques and functionalities of grid monitoring have been listed and discussed in detail.

Considering the main function of grid monitoring, the physics-based method has been developed for a real distribution system on the Chalmers University campus network. The simulation result shows a good estimation of the voltage magnitude and voltage angles. Thus, the method can be further tested on the Chalmers campus demonstration site. Due to the increasing amount of available data in the distribution system, a data-driven state estimation has also been developed—the method is based on the physical connection of the system to design the connection between layers. The method has been tested in the IEEE 123 bus system showing promising results.

Then, a congestion forecasting tool based on PPF, considering the uncertainties associated with PV and other conventional loads, has been presented. The most significant function of the proposed congestion forecasting tool is the visualization of the network congestion based on the cumulative probability of the proposed congestion indicators, including node voltage deviation as well as branch and transformer overload. These indicators can help DSOs in analysing congestion in their network and then take the appropriate measures to manage possible network congestion.

Besides the scientific contributions, the work carried out in this task will be further used as the input for other tasks and WPs. Task 3.2 aims to develop a model predictive control algorithm to reconfigure the network, where the estimated or predicted state from the SE or forecasting model is needed as the input for a model predictive control. The system condition that comes from the risk assessment model is one of the input signals for the control algorithm. For the flexibility service, how to quantify the available resources in the network is a remaining question, which will be addressed in Task 3.4. The developed model in this task could play an important role.

In the future, the field test conducted in WP5 (task 5.3) will evaluate the grid monitoring results in real-life conditions. In this task, the grid monitoring functionalities will be demonstrated. With the support from the IoT platform and the SCADA/DMS system, the real-time (or close to real-time) SE will be implemented for the real distribution network of the Chalmers University campus. Based on that, the network control, and the requested flexibility services (e.g., voltage control, power congestion, etc.) functions will be tested on-site.

7. Appendix A: The physical data of Chalmers University campus network

No.	From bus	To bus	R (pu)	X (pu)	B (pu)
1	1	2	1.45E-05	1.00E-06	1.70E-04
2	2	3	2.81E-05	1.90E-05	3.50E-04
3	3	4	2.55E-04	1.73E-04	3.10E-03
4	4	5	3.40E-04	2.30E-04	4.20E-03
5	5	6	1.87E-04	1.27E-04	2.30E-03
6	1	8	4.76E-04	3.23E-04	5.80E-03
7	2	10	1.72E-05	1.18E-05	2.10E-04
8	10	11	2.81E-05	1.90E-05	3.50E-04
9	2	13	2.27E-05	1.54E-05	2.80E-04
10	13	14	1.25E-04	8.44E-05	1.50E-03
11	13	16	3.75E-04	2.54E-04	4.60E-03
12	13	18	9.07E-05	6.17E-05	1.10E-03
13	2	20	3.12E-04	2.11E-04	3.80E-03
14	20	21	1.31E-04	5.80E-05	8.50E-04
15	21	22	1.87E-04	8.25E-05	1.20E-03
16	20	25	7.98E-05	5.35E-05	9.70E-04
17	25	26	8.53E-05	5.80E-05	1.00E-03
18	20	29	6.35E-05	3.08E-05	4.80E-04
19	3	31	4.54E-04	3.08E-04	5.50E-03
20	31	32	1.18E-05	8.20E-06	1.40E-04
21	32	33	3.63E-05	1.09E-05	1.20E-04
22	31	35	4.65E-04	3.16E-04	5.70E-03

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