THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

On Possibilities of Using Smart Meters for Compulsory Load Shedding Supported by Load Forecasting

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Alhamdulillah!

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Abstract

The smart meter rollout is progressing in several parts of the world with early adoption in some parts, e.g., Europe. Remote ON/OFF control switch of the smart meter allows distribution system operators to switch the smart meter of any customer remotely. This thesis investigated the possibility of using ON/OFF control switch of the smart meters for compulsory load shedding supported by load forecasting.

Acute situations, e.g., critical power shortage could require today compulsory load shedding as a last resort if the power reserve becomes insufficient. The compulsory load shedding is typically done from medium voltage substation level, and in that case, all customers including emergency service providers located under the affected substation would lose power. By using the remote ON/OFF control switch, it is possible to exclude the vulnerable groups of customers such as elderly and also socially critical customers such as clinics, pharmacies, and fire stations.

Three field tests have been performed on small-scale load shedding using the smart meters. The results have shown that the smart meters' switching has no or negligible impact on the power quality at the low voltage level of the grid. Moreover, existing challenges in the present smart metering system, e.g., the reliability of confirmation report on smart meters' switch status, are identified. Thus, demands that need to be put on the future smart metering system are identified.

This thesis developed large-scale smart meters' switching model based on the field tests' results. Moreover, load forecasting models are developed using Artificial Neural Network method to forecast load at the individual customer level and also at low aggregation levels, e.g., low voltage substation level.

The results from aggregated load forecasting models, e.g., at an hour with high load condition, have shown that the total load in, e.g., a 10kV residential grid can be estimated with an error of around ± 3% by using up to previous day's hourly smart meter data as input predictor. Moreover, the results from a simulated example of selecting low voltage areas for load shedding have shown that, compared to load estimation from average load values, aggregated load forecasting models could help to save around 25% of number of customers from unnecessary load shedding.

The simulation results on voltage calculation at each of the low voltage substation during and after the load shedding show that the voltage calculation using individual customers' forecasted load values gives a negligible error (around ± 0.001 per unit), compared to voltage calculation using actual load values.

The smart meters can be used for the compulsory load shedding for excluding prioritized customers. However, assurance of accurate status update report of smart meters' switch and consideration of delays in smart meters' disconnection are required to perform compulsory load shedding within the allowable time. Moreover, the assurance of either more extended battery backup time for smart meters and meter data collection units, or quick communication network buildup capability, are recommended to enable rapid reconnection of smart meters if power system fails after compulsory load shedding.

Index Terms: Electrical distribution system, Load forecasting, Compulsory load shedding, Power quality, Remote switching, Smart meter.

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Gothenburg, Sweden
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List of Abbreviations

ANN	Artificial Neural Network
AMI	Advanced Metering Infrastructure
AMR	Automatic Meter Reading
AMM	Automatic Meter Management
CBA	Cost Benefit Analysis
CLS	Compulsory Load Shedding
CS	Central System
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
EC	European Commission
ECD	Energy Consumption Data
Ei	Swedish Energy Market Inspectorate
EM	Extra Meter
EMC	Electro-Magnetic Compatibility
EN	European Standard
ERGEG	European Regulators' Group for Electricity and Gas
EU	European Union
GENAB	Gothenburg Energy Network Company
GSM	Global System for Mobile communications
GPRS	General Packet Radio Service
HAN	Home Area Network
HEMS	Home Energy Management System
IEC	International Electro-technical Commission
LAL	Low Aggregation Level
LF	Load Forecasting
LMA	Levenberg-Marquardt Algorithm
LV	Low Voltage
MAPE	Mean Absolute Percentage Error
MCU	Meter data Collection Unit
MG	Micro-Grid
MLP	Multi-Layer Perceptron
MSE	Mean Square Error
MV	Medium Voltage
PEV	Plug-in Electric Vehicle

POC	Point of Connection
PM	Preventive Maintenance
PQ	Power Quality
PQM	Power Quality Meter
PLC	Power Line Communication
Plt	Long-term Flicker severity
Pst	Short-term Flicker severity
RMS	Root Mean Square
SG	Smart Grid
SM	Smart Meter
SMS	Smart Metering System
SMCG	Smart Meters Co-ordination Group
SMsD	Disconnection of Smart Meters
SMsR	Reconnection of Smart Meters
TSO	Transmission System Operator
THD	Total Harmonic Distortion

Contents

Chapter 1
Introduction

This chapter provides an overview of the background and motivations of the thesis. The potential application of smart meters for compulsory load shedding and the possible use of smart meter data for load forecasting at low aggregation level are discussed. The main contributions of the thesis and the list of resulting scientific publications are provided.

1.1 Background and Motivation

Smart metering is becoming a central part of distribution grid management, e.g., maintaining acceptable voltage levels with the help of voltage monitoring down to customer level. The Smart Metering System (SMS) will be able to provide a number of new functionalities if they have the right specifications. Many Distribution System Operators (DSOs), e.g., in Sweden, who installed Smart Meters (SMs) around ten years ago, are in the process of preparing for the next generation of SMs. According to [1], the average asset life of SM mentioned is around 15 years. Many of the existing SMs are therefore expected to have reached their useful economic lives within the next few years. Moreover, the Swedish Energy Markets Inspectorate (Ei) set a deadline to meet the proposed requirements by 1st January 2025 [2].The electric power system is also expected to undergo some changes, both in electricity production, e.g., higher share of intermittent generation (photovoltaics panels and wind farms) by 2030 and consumption, e.g., higher share of electric vehicles. Also, there has been a rapid technological development in the field of smart metering and Smart Grids (SGs) which has led to increased functionalities as well as new uses of SMs. It is therefore important that the DSOs need to know which specifications for the next generation of SMs they should have. This thesis attempts to address this need by the DSOs.

The SMs can provide not only Energy Consumption Data (ECD) and voltage data from the customer level but also functionalities such as on-demand reading, remote switching, as well as remote SM management. The historical data from the SM can be used for the DSOs' short-term planning, e.g., anticipating network congestion as well as, long-term planning, e.g., anticipating load growth. This thesis attempts to develop Load Forecasting (LF) models using SMs data to support the operation of distribution system. However, the load types, generations, customers' behaviours, etc., are changing rapidly with time, and therefore the functionalities of the SMs also need to be adjusted to provide best possible services to the customers and to increase the efficiency and reliability of the distribution system operation.

1.2 Investigated Potential Applications of Smart Meters (SMs)

The potential application of SMs for Compulsory Load Shedding (CLS) and the possible use of SM data for developing LF models are discussed in this section.

1.2.1 Potential Application of Smart Meters for Compulsory Load Shedding (CLS)

In many European countries, new units of wind power and solar power are installed and connected to the grid to meet the target set by the European Union (EU), to produce 20% of EU energy from renewable energy sources [3]. Therefore, the share of fluctuating infeed of the total electricity generation is substantial in many European countries today, due to fluctuating nature of wind power and solar power. The load is also predicted to fluctuate more in the future, due to the charging of electric vehicles and more electronic loads. These changes in the grid pose new challenges for the Transmission System Operators (TSO) [4]. In general, four operational states of the power system are used to describe the operational condition of the power system, i.e., Normal, Alert, Disturbed and Emergency states. Figure 1.1 shows the typical operational states of a power system [5]. It is noted here that the network collapse is not specified in Figure 1.1.

Normal state refers to a state when all consumption requirements are being met; frequency, voltage, and transmission lie within their limits; and also reserve requirements are being met. The difference between the normal state and the alert state is that the reserve requirements are not fulfilled and hence the faults in network components or in production components will lead to disturbed state or emergency state. From the alert state, the normal state can be achieved in 15 minutes. The difference between the alert state and the disturbed state is that the frequency, voltage, and transmission are not within acceptable limits, and also the normal state cannot be achieved in 15 minutes. When a system is operating at disturbed state, an additional fault could lead the system from disturbed state to emergency state. The emergency state refers to an operational state when the CLS has been applied and that production shedding and network divisions may occur. Dimensioning fault refers to the faults which entail the greatest impact on the power system due to the loss of individual principal components such as a line, a bus bar, a transformer, a production unit, etc. Faults in the power system are called serious disturbance when the fault is too large, e.g., a combination of two faults caused by the same event or multiple faults. Restoration refers to the transition between operational states due to control actions.

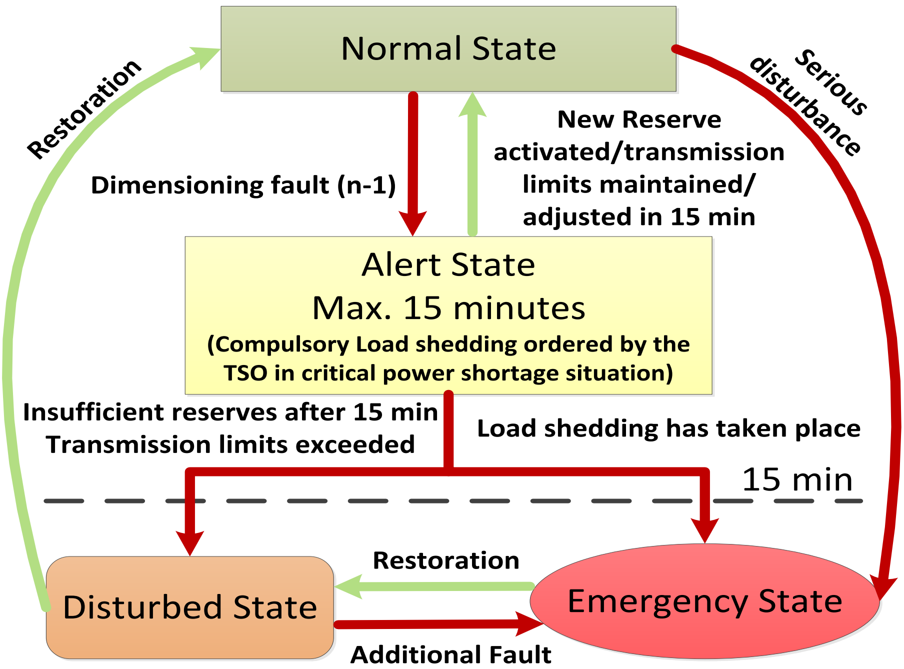

Figure 1.1: Operational states of a power system (network collapse is not specified in the figure) [5]

Among the four operational states, the CLS could be ordered to perform manually under the alert state if necessary. The CLS can be useful to maintain the system security so that dimensioning fault does not lead to extensive follow-on disturbances. The primary goal of the CLS is to prevent a possible collapse in a part or the entire synchronized system and faster return to a normal state of electricity supply. The secondary goal of the CLS is to minimize the amount of additional load shedding to save the entire system [6].

Load shedding can be done manually and automatically. During exceptionally high consumption period, e.g., due to very cold weather, acute situations could require manual load shedding. Examples of acute situations are critical power shortages or power shortages resulting from disturbances in power systems, or bottleneck situations, i.e., a capacity limitation on the transmission network. The CLS which is manual is carried out as a last resort when other measures are insufficient, i.e., insufficient manual active reserve [5],[6]. Automatic load shedding takes place when time does not allow to perform manual load shedding since the frequency of the network drops rapidly, e.g., due to a fault that requires several large production units to be disconnected. In Sweden, automatic load shedding is triggered when the frequency drops below 48.8 Hz. However, electric boilers and heat pumps, with a minimum of 5 MW power, are disconnected at 49.4 Hz [7].

The CLS is typically ordered during critical power shortage and during regional power shortages caused by bottlenecks or grid disturbances [6]. Critical power shortage refers to the hour of operation when consumption has to be reduced or disconnected. Preparations for manual load shedding will be ordered in the deficit areas when a critical power shortage is approaching, and the load shedding needs to be done within 15 minutes. Similarly, preparations for manual load shedding within 15 minutes will be ordered due to regional power shortages caused by bottlenecks or grid disturbances.

According to [8], each TSO shall be entitled to define an amount of load to be manually disconnected based on the frequency condition, when necessary to prevent any propagation or worsening of an emergency situation. The TSO shall notify DSOs of the amount of load to be disconnected from their distribution systems. Each DSO shall disconnect the notified amount of load, within the specified time.

Today, the CLS would be done from the Medium Voltage (MV) substation level, and in that case, all customers under the affected substation would lose power. This type of load shedding could disconnect power supply to the emergency service providers located in the affected area. However, it is crucial for a society to exclude emergency service providers such as clinics from load shedding.

The SMs are typically equipped with a remotely accessible switch which gives a unique opportunity to select individual customers for switching. Therefore, with the SMs, it is possible to perform the CLS at the customers' level by excluding customers on a pre-defined prioritized list. A list of prioritized customers is needed to be prepared beforehand by the authorities, e.g., county administrative boards and municipalities together with DSOs which can be used in critical situations to exclude the vulnerable customers such as elderly and also the critical customers such as clinics, pharmacy and fire stations. Moreover, this process can help to keep the communication network of the SMs alive, which is crucial to check grid's condition remotely at local level and also to reconnect the SMs after the critical situation is over.

Pre-selection of load shedding could be made to ensure emergency services always available. Each customer can be predefined by a different priority value. From the pre-prepared prioritized customers' group, the DSOs can select which group(s) of customers need to be disconnected based on the load shedding request from the TSO. The SMs also allow the DSOs to perform gradual load shedding rather than instant load shedding which is the case for feeder disconnection from MV levels. The reconnection of each customer can also be predefined by the DSO. When the critical situation is over, the disconnected customers can be gradually reconnected to the grid using the SMs.

This thesis investigated the use of the SMs for the CLS. Large-scale load shedding scenarios are simulated with the developed models that are based on the field tests' results on small-scale load shedding. Small-scale field tests refer to the tests performed on 12, 37 and 86 customers, and large-scale load shedding scenario refers to the model developed considering 2000 residential customers.

1.2.2 Possible Use of Smart Meter Data for Load Forecasting (LF) at Low Aggregation Level

The development of the SMs has resulted in a vast increase in the data volume as well as types of data measured and collected. The SM data can help to increase the accuracy of many applications, e.g., distribution system state estimation, load modelling, and overloading detection of grid's component. Unlike traditional aggregated system-level LF, the availability of SM data introduces a fresh perspective to the way LF can be made [9],[10]. The SM data can help to forecast load at lower aggregation level, ranging from substation level, feeder level, or even down to the individual customer level [11],[12], [13], which used to be difficult before the deployment of the SMs. The LF utilizing SM data is, however, still limited due to the lack of previous household level SM data [14],[15] since the SM rollout is not in progress in all countries yet. Moreover, there are some countries that are deploying the SMs, have not completed the rollout in the whole country yet.

According to the literature on LF at LALs, more frequent ECD, e.g., 5 to 10 mins data can help to get more accurate load forecast compared to the one with less frequent data, e.g., hourly data. However, typically hourly or half-hourly ECD is available from the SMs since frequent data requires additional cost for additional storage capacity and data communication capability. Hence, it could be a challenge to get more frequent data for developing LF models.

Forecasting the distribution-level load, e.g., Low Voltage (LV) substation level is much more difficult than forecasting a system-level load [16]. However, the problem of LF at the low aggregate level, e.g., at LV substation level or feeder level has been studied in some literature, but very few studies have been conducted regarding individual customer's consumption prediction [17],[18].

1.2.2.1 Potential Application of LF

In case of using the SMs for CLS, the forecasted load at the hour of operation could support the CLS which is the primary focus of this thesis. Aggregated LF models at LV substation level could help the DSOs to more accurately estimate the loads in selected areas for the CLS. Therefore, the DSOs can minimize the unnecessary load shedding while fulfilling the load shedding request from the TSO.

Moreover, as a spin-off, this thesis investigated the LF over a short time horizon, e.g., few minutes to hour-ahead. According to the studied literature, the forecasted load over a short time horizon can benefit the utility service providers, e.g., aggregators, customers, as well as the system as a whole in the following ways:

- Improve scheduling and dispatching of storage devices to reduce peak load demands [19].
- Help the utility get early warnings about, e.g., i) how the load demand is changing; ii) how often grid constraints (e.g., cable overloading) are violated; iii) which practical solutions are available to solve the problems [20].
- Improve control actions such as switching on/off the Demand Response (DR) appliances to balance the electricity supply and demand. Home Energy Management Systems (HEMS) can also be optimized by scheduling household smart device based on the

forecasted load [21]. The utility service providers who wish to apply real-time load shifting could also benefit from the LF at the individual level [22].

- Help to minimize imbalance costs to energy retailers. The LF at individual level could also help the customers to plan accordingly in case of real-time and dynamic pricing [17].

The LF over a short time horizon can also help the customers with prepaid electricity programs which have become more popular in recent years in several countries (e.g., Bangladesh, India, and Tanzania). The customers under these programs need to pay for energy usage in advance, having a deposit account and getting the daily energy usage cost debited from the account [23],[27]. Moreover, the LF can provide the customers an estimation of when their credit is going to finish.

1.2.2.2 Method Chosen for LF based on Literature

The possibility of improving the LF by using the statistical relations between ECD series is addressed in [24] both at the household level and also at the district scales, i.e., hundreds of houses. The paper showed that energy consumption is highly correlated to the energy consumption of up to three hours previously in the case of one hour-ahead prediction.

A hybrid method which is a combination of Artificial Neural Network (ANN), fuzzy logic, Auto-Regressive Integrated Moving Average and wavelet neural networks is examined in [25] for day-ahead load forecast using SM data for a small community, i.e., 90 houses and 230 houses. The paper showed that ANN performs very well in estimating the load peaks, fuzzy logic performs well during night time close to the morning time peak, where the user behaviour tends to be more routinized, and the wavelet neural networks help in eliminating the noise of individual behaviour in the cluster.

Extensive error analyses are performed in [21] on the ANN model to investigate the suitability of the model for day-ahead prediction. The paper showed that ANN method is suitable for forecasts of residential loads.

The paper [13] showed that at the local level, e.g., LV feeders, the correlations between load demand and the influencing variables become much weaker and hence significant decrease in LF accuracy is observed with a move towards lower levels of load demand aggregation. A sensor-based approach is discussed in [26] to forecast multi-family building’s energy consumption, using support vector regression technique. The paper showed that most effective models could be built with hourly consumption data.

The use of ANN for the load forecasts at MV/LV substations is addressed in [28] with a focus on the methodology of ANN model design. The paper showed that the ANN-based models outperform the time series models and also showed that the ANN models are very efficient in mapping complex relationships between inputs and outputs.

This thesis chose ANN method for load forecast since the method is shown to be effective and efficient to forecast load at Low Aggregation Level (LAL) using SM data.

1.3 Regulations on the SMs' Functional Requirements

Different national and international authorities proposed functional requirements of SMs to cope with future grid conditions, e.g., enabling local generation and DR, home energy management, etc. The proposed functionalities are discussed and mapped in Section 3.5.

1.3.1 European Guidelines and Proposals on Functional Requirements

In February 2011, the European Regulators' Group for Electricity and Gas (ERGEG) provided a set of sixteen requirements as guidelines of good practice on regulatory aspects of smart metering for electricity [3], where three of the guidelines are regarding the rollout of SMs. In December 2012, CEN/CENELEC/ETSI Smart Meters Co-ordination Group (SMCG) had proposed a set of 6 functionalities relevant for communications under the mandate M/441 [29].

In [30], the European Commission (EC) defined a SMS in terms of 13 key functionalities and using a questionnaire asked the EU member states whether these functionalities have been considered or not. Based on the results, the EC has included ten common minimum functional requirements for electricity SMS in Recommendation 2012/148/EU [31]. The ten minimum functionalities are also discussed in a report EC published in 2016 [32], under a cyber-security and privacy perspective of the functionalities.

On November 2016, the EC published proposals which are called "Clean energy for all Europeans," and it includes a proposal for a new electricity market directive in 2016 requiring the features of SMs [33]. Moreover, there is an extensive effort in Europe to develop standards for the SMs. E.g., European Smart Grid Task Force Expert Group 1 published a report in August 2016 describing how the EU Member States and regulators can ensure the interoperability between different parts of the SG and SMs. The interoperability is needed to promote demand flexibility [34].

1.3.2 Sweden's Proposals on Functional Requirements

The Swedish Energy Markets Inspectorate (Ei) first proposed functional requirements for future electricity meter in 2015, where Ei proposed eight functional requirements [35]. The Ei's proposal on minimum functionalities promotes reliable and efficient grid management, greater integration of local-generation, and wider opportunity for demand flexibility and also easier access for the LV customers to be active in the market. However, the Ei has excluded one of the eight functional requirements in the draft proposal that the Ei recently has made for constitutional amendments required to regulate functional requirements for electricity meters [2]. The function of alarm at a neutral error has been removed due to the lack of a standardized method to measure this fault and also due to the uncertainties present in the measurement methods used today.

The seven minimum functional requirements proposed by Ei covers all LV (< 1 kV) customers. The customers with a fuse rating of up to 63A, and with direct measurements, are proposed to meet the requirements by 1st of January 2025, e.g., household customers. There are over five million SMs in this category in Sweden.

The LV customers with 1) fuse rating of above 63A (direct measurements or measurements with only current transformer) and 2) with a fuse rating of up to 63A (measurements with only current transformer), are proposed to meet the requirements by 1st of January 2030. The examples of these type of customers are property owners, apartment blocks, or smaller industries. The DSOs should also meet the requirements for these customers from 1st of January 2025 if customers request it. There are around 0.12 million SMs in this category in Sweden. However, the customers of this second category do not need to meet the requirement of being able to connect or disconnect the SMs remotely.

1.3.3 Identified Gaps in Proposed Functionalities

The reports mentioned above proposed few functional requirements, e.g., frequent readings from the SMs mentioned in [31], without explicitly specifying any time resolution. The requirement of the SM data granularity can vary depending on the application of the data, e.g., LF, load scheduling, etc. The accuracies of load forecasts can be improved by using the latest energy consumption value from the SMs and hence this type of application could require very frequent readings, e.g., every hour. The time resolution at which the data needs to be recorded is also not mentioned explicitly in [31]. However, in [2], third-party permissions to the proposed near real-time SM data are suggested to be supported for different energy-saving applications.

Moreover, the reports on the functional requirements from EC addressed about the recording of ECD by only mentioning that it needs to be frequent enough to allow the information to be used for grid planning. However, how frequent the data need to be saved can depend on the application, e.g., LF to support the CLS or distribution system congestion prediction.

Also, the reports from EC and Ei addressed about the possibility of critical grid condition handling using SMs' ON/OFF control switch but detail requirements on this functionality is not addressed, e.g., requirements on SMs' switching time, and the necessity of reliable reports on SMs' switch status, etc.

Furthermore, the functionality regarding Power Quality (PQ) indices e.g., flicker, individual harmonics, and transient measurements are not explicitly addressed in the reports although the importance of the PQ monitoring is indicated to be increasing in future [30].

1.4 Objectives of the Thesis

To address the challenges (which will be described in more details in Chapter 2) in using the present SMs for the CLS, the difficulties in forecasting loads at LAL, and the limitations in getting the high granularity SM data as well as the latest SM data for the LF, the objectives of the thesis are to:

1) **Identify** the challenges and opportunities of using present SMS for compulsory large-scale load shedding considering the possible impacts of SMs' switching on the voltage quality.
2) **Propose** a method of CLS based on aggregated load forecasting at the hour of load shedding to reduce unnecessary amount of load shedding.
3) **Determine** the smart meter data granularity and data availability requirement for load forecasting to support CLS.

4) **Propose** functional requirements for future SMS to enable the use of SMs for CLS based on the performance of the present SMS, simulation results on load shedding, and requirements from authorities.

1.5 Main Contributions of the Thesis

The following contributions have been made in the thesis:

1) Three field tests performed on the SMs' switching for three small groups of residential customers. The impacts of the SMs' switching on the PQ, e.g., transients are analyzed from the tests' results. The results show no impact on PQ due to SMs' disconnection other than some transient events during SMs' reconnection which are negligible.

2) The possibilities and the challenges in using the SMs of the present SMS for large-scale CLS are identified, which can be used to propose functional requirements for the future SMS.

3) The SMs' switching model is developed, based on the results of the field tests, to simulate large-scale CLS with the SMs.

4) Aggregated LF models are developed at LV substation levels of a 10kV residential grid to investigate the support of forecasted aggregated loads in selecting groups of customers for the CLS. The benefit of using forecasted load values during the CLS is shown by comparing the results obtained by using forecasted load values with the results obtained by using estimated load values from average or maximum daily load profile.

5) Individual LF models are developed for the two thousand customers in the investigated 10kV residential grid to study the support of forecasted individual loads in estimating the change in load at each load bus during and after the load shedding. The voltages at each load bus are then calculated using the change in load values in the load flow model. The accuracy of voltage calculation is verified by comparing voltage calculation from forecasted load value, with voltage calculation from actual load value.

6) The possibility of using the typical hourly SM data for LF model development and using the historical SM data up to previous 24 hours as input predictor are studied considering the CLS application. The options are found as good enough to support the CLS.

7) Recommendations are made on the functionality requirements of future SMS considering the application of SMs for the CLS, and accuracy improvement of LF at LAL.

1.6 Thesis Outline

With the introduction of the thesis already given in this chapter, the rest of the thesis is organized as follows:

- **Chapter 2** presents the conceptual framework, which lays the foundation for the work in the thesis.
- **Chapter 3** provides an introduction to a SMS for electricity, and the functionalities of a SMS focusing on the SMs' remote ON/OFF control.
- **Chapter 4** describes the field tests performed on multiple SMs' switching in a real electrical distribution network.
- **Chapter 5** presents the results of the field tests concerning the performance of the existing SMS and the impacts of SMs' switching on the PQ.
- **Chapter 6** provides results and analysis on factors influencing the accuracy of LF models, developed using ANN method.
- **Chapter 7** presents the developed model for load shedding with SMs' switching (the switching model) which is integrated in a multi-time-steps load flow simulation model. The description of a real 10 kV residential distribution system which is used in a case study with the integrated model is provided. Moreover, the chapter presents the simulation results of the large-scale SMs' switching model with variations in the number of SMs per Meter data Collection Unit (MCU) and the SMs' switching time.
- **Chapter 8** presents and discusses the results of compulsory load shedding scenarios supported by load forecasting. The benefits of using pre-developed aggregated load forecasting models to minimize the unnecessary load shedding are demonstrated. The use of pre-developed individual load forecasting models to calculate, using the load flow model, the voltage values of the prioritized customers which remain connected after the compulsory load shedding are demonstrated.
- **Chapter 9** presents the main conclusions of the thesis and proposes potential ideas for future work.

1.7 List of Publications

The following papers have been published/submitted as the results from the thesis:

I. **Yasir Arafat,** Lina Bertling Tjernberg, Per-Anders Gustafsson, "Remote switching of multiple smart meters and steps to check the effect on the grid's power quality," in *T&D Conference and Exposition, 2014 IEEE/PES,* 14-17 Apr. 2014.

II. **Yasir Arafat,** Lina Bertling Tjernberg, Per-Anders Gustafsson, "Experience from Real Tests on Multiple Smart Meter Switching," in *Innovative Smart Grid Technologies Europe (ISGT EUROPE), 2014 5th IEEE/PES,* 12-15 Oct. 2014.

III. **Yasir Arafat,** Lina Bertling Tjernberg, Per-Anders Gustafsson, "Possibilities of demand side management with Smart Meters," in *CIRED 2015, 23rd International Conference and Exhibition on* electricity distribution, Lyon, 15-18 Jun. 2015.

IV. **Yasir Arafat,** Lina Bertling Tjernberg, Per-Anders Gustafsson, "Field test on multiple Smart Meters switching to study the effect on power quality at customers level," in PowerTech, *2015 IEEE/PES, Eindhoven,* 29 June-02 Jul. 2015.

V. **Yasir Arafat,** Lina Bertling Tjernberg, Per-Anders Gustafsson, "On possibilities of using smart meters for emergency grid management- Analysing the effect on power quality," in *2015 IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA), Bangkok,* Nov. 2015.

VI. **Yasir Arafat**, Jimmy Ehnberg, Le Anh Tuan, "Customer-Utility Interface for 2030," Technical Report, Chalmers University of Technology, Gothenburg, Sweden, May 2015.

VII. **Yasir Arafat**, Jimmy Ehnberg, Le Anh Tuan, Ola Carlson, "ANN-based Residential Load Forecasting at Low Aggregation Level: Factors Influencing Accuracies," Submitted to International Journal of Electrical Power and Energy Systems.

VIII. **Yasir Arafat**, Le Anh Tuan, Jimmy Ehnberg, Ola Carlson, "Residential Load Forecasting at Individual Customer Level Using ANNs: Effects of Data Granularity," Submitted to IET Journal of Generation, Transmission and Distribution.

The paper listed below is not related to the work:

I. **Yasir Arafat,** Lina Bertling Tjernberg, Stephan Mangold, "Feasibility study on low voltage DC systems using smart meter data," in *CIRED 2013, 22nd International Conference and Exhibition on* electricity distribution, Stockholm, 10-13 June 2013.

Chapter 2
Conceptual Framework

This chapter presents the conceptual framework, which lays the foundation of the work in the thesis. This framework constitutes the potential use of smart meters for compulsory load shedding, use of smart meter data for load forecasting, relating load forecasting with compulsory load shedding, and identification of functional requirements for the future smart metering system.

2.1 Use of SMs for Compulsory Load Shedding (CLS)

The ten common minimum functionalities proposed by EC, include the essential elements that a SMS should have to benefit all stakeholders, i.e., the customer, the metering, and the DSO. The minimum functionalities include several aspects such as enabling smart metering in a secured and safe environment, commercial aspects of supply/load demand and the integration of distributed generation. One functionality requirement among the ten common minimum functional requirements is that the SM should allow remote ON/OFF control of the supply and/or power flow limitation. This functionality relates to both the demand side and the supply side. It can speed up processes such as when customers are moving home, the old supply can be disconnected, and the new supply can be enabled quickly and simply. Moreover, it can be used for handling technical grid emergencies.

Most of the DSOs in Europe have installed remote ON/OFF control in the SM [36],[37]. The DSOs can switch the SM of any customer remotely when needed. Some DSOs in Sweden, e.g., Gothenburg Energy Network Company (GENAB) who have installed remote ON/OFF control are currently applying this technique for customers typically one by one when customers are changing addresses or when contracts are terminated or have defaulted on their payments. The ON/OFF control functionality of the SMs could be used to disconnect/connect selected customers at the LV level of the distribution system, thereby opening up new possibilities to balance electricity consumption and production in critical situations. The LV distribution system is the part of the electrical grid from the last substation to the customers. In Sweden, a three-phase connection with a voltage of 0.4 kV is usual in this part of the grid where most of the customers are residential, service and small industrial sectors.

2.1.1 Research Gaps in CLS using SMs

Large-scale load shedding using SMs' switching technique is a new concept in the field of CLS. How the technology has been functioning in practice has, however, not been fully investigated about multiple SMs' switching. This thesis addresses the following challenges and gains the knowledge on how the SMs are to be used for the CLS at the customers' level. The following research ideas with regards to using the SMs for the CLS have been identified:

- Understanding on impacts of simultaneous multiple SMs' switching on the PQ, e.g., voltage transient due to current transient. Knowledge on the propagation of voltage transient created due to a SMs' switching and the impact of that voltage transient on the neighbors' PQ, and also on the PQ at the LV substation level.
- Knowledge of how the existing SMS works concerning small-scale simultaneous SMs' switching. Understanding of the possibilities and limitations of the existing SMS regarding large-scale CLS.
- Perception on the total load shedding time using the present SMs for large scale load shedding.
- Knowledge of the functional requirements that need to be put on the future SMS which will be capable of performing large-scale CLS.

2.1.2 Method used to meet the Research Gaps in CLS

In this thesis, under voltage situation is considered as a critical grid situation and the load shedding is considered to be the only remaining solution to save the grid from the total collapse. The identified challenges on CLS are addressed, and the following contributions have been made:

- The PQ indices are monitored and recorded in the installed five PQ meters during each of the field test which were located at the selected four customers' site and also at the LV substation.
- On-demand readings are collected from the selected SMs before, during and after the load shedding. The readings are compared with the PQ meter data to study e.g., the communication delays, recoded PQ events in the PQ meters, etc.
- Real time status update of the SMs' switch are collected during each of the test which shows the switching success or failure for the selected SMs. The switching performance of the present SMS is investigated and challenges are identified concerning the load shedding with the SMs.

- Total load shedding time is calculated by using the actual SMs' switching time obtained from the field tests. The ways of load shedding time reduction are studied by simulating load shedding using shorter SMs' switching times than the actual SMs' switching time. Also total load shedding time is simulated by varying the number of SMs per MCU and along with the shorter switching time.
- The regulations concerning the use of SMs for the CLS are studied, and the demands are identified that need to be put on the future SMS to perform the large-scale CLS with the SMs.

2.2 Load Forecasting (LF) using Smart Meter Data

In the field of electrical LF, most of the research has been done on large-scale systems. Previous studies have shown that high precision, with Mean Absolute Percentage Error (MAPE) as low as around 2%, can be achieved on large-scale LF, e.g., at national and municipal level [38],[39],[40],[41]. However, load forecast at a local level, e.g., transformer level or feeder level recently emerged as a research interest [9],[10],[11],[12].

2.2.1 Challenges and Applications of LF at a Local Level

2.2.1.1 Challenges of LF at a Local Level

Latest developments in the electrical grids have introduced recent concepts in the field of electric power engineering such as SG, Demand Side Management (DSM), Micro-Grid (MG), and large-scale integration of distributed energy resources. These concepts and availability of SM data have led to significant interest in applying LF at a local and disaggregated level [24].

Typically, LF for a large area is comparatively easy because the fluctuations and the noise in the individual houses may cancel out each other while taking the sum, and at the same time provide little chaotic curves in which trend and seasonality are easily identifiable [20],[42]. The LF is particularly more challenging if it is to be done at LAL, e.g., LV substation level than at high aggregation level, e.g., MV substation level or municipality level. Because, the load demands at LAL are more volatile [20],[43]. The LF for individual customers is known to be a much more difficult problem and has been shown to be prone to large errors [17]. It is difficult because of several factors, e.g., hourly energy consumption of individual customers is relatively smaller than the aggregated load at LAL, highly variable and deeply irregular as a result of natural human behaviour.

2.2.1.2 LF at Local Level to Support Compulsory Load Shedding

The LF at local level i.e., at LV substation level and individual customer level can be used to support the CLS. Today, the SMs can be used to perform the CLS by excluding the selected customers. However, the CLS would be done without approximately knowing the actual load at the time of disconnections and also the amount of load successfully disconnected. The LF for the pre-selected groups, e.g., residential customers with certain priority level could be helpful to determine approximately how many individual customers' load need to be shed to fulfill the load shedding request from the TSO. The forecasted load values at the hour of load shedding can then be helpful to minimize unnecessary load shedding during the CLS. Because, instead of using estimated load values which requires high error margins, the DSOs could use much lower error margin while using forecasted load values. Moreover, the DSOs could fulfill the load shedding request more precisely than performing the load shedding without the LF.

2.2.2 Research Gaps in LF

Research gaps on LF using the SMs' data can be divided according to those of LF at the individual customer level and those of LF at LAL, e.g., LV substation level.

<u>LF at Individual Customer Level:</u>

For LF at the individual customer level, it is essential to investigate how often the ECD need to be measured and recorded by the SMs due to the followings:

- Lowering data granularity requires additional communication costs to handle the increased amount of data during collection.
- Lowering data granularity would require additional costs of operation and maintenance. For storing more frequent data, the SMs must have sufficient storage capacity and increased data capacity is also needed for communication servers, databases, etc.
- Capabilities of the communications networks and the Central System (CS) need to be increased as well.

LF at Low Aggregation Level:

The following research questions with regards to LF at LAL have been identified and addressed in the thesis:

- How is the accuracy level of LF dependent on types of residential customers, e.g., Villa or Apartment customers, for different load aggregation levels?
- Which level of load aggregation level can be considered as the minimum aggregation level based on the accuracy requirement for different types of applications considering different types of residential customers?
- How significant the influence of latest ECD over different time periods on the accuracies of LF, concerning the CLS?
- Can the aggregated LF models developed with hourly ECD support the CLS application?

2.2.3 Method used to meet the Research Gaps in LF

This thesis addresses the identified challenges on LF at the individual customer level and following method has been used to meet the research gaps:

- The individual LF models are initially developed for 200 residential customers where half are Villas and half are Apartments, and the models are trained with hourly SM data. Also, individual LF models are developed for four individual residential customers, which are trained with different lower granularity data, e.g., 6-min data. The impacts of the customer types and the data granularity on the accuracy of the forecasted load are analyzed.
- The impacts of the previous ECD over different time periods on the accuracies of forecasted loads are studied by using both the hourly ECD and the 6-min ECD.
- Impacts of data granularity on the accuracy of the forecasted loads are also analyzed for two forecast time-horizons, i.e., 30-min ahead and 1-hour-ahead, using data with different granularity, e.g., 6-min to 1-hour.
- Forecasted individual customer's load values are used to calculate the voltage values during and after the load shedding and verified the voltage calculation using actual load values.

Moreover, the identified challenges on LF at LAL are addressed, and the following method has been used to meet the research gaps:

- Initially, aggregated LF models are developed by aggregating the load of three different types of residential customers and also aggregating the loads at three LV substation levels. The accuracies of the forecasted loads are studied by using real data from the 717 SMs of residential customers in Gothenburg, Sweden.
- Loads of Villa customers and Apartment customers have been aggregated at different levels, i.e., two customers to 350 customers and the impacts of aggregation levels on the load forecast accuracies have been evaluated.
- Previous ECD over different time periods have been used to analyze their impacts on the accuracies of the LF at LV substation levels.
- Aggregated hourly ECD are used to develop aggregated LF models at LV substation level of the 10kV residential grid. The forecasted load values from the models are used in the load shedding simulation to analyze the possibility of using the LF models developed hourly SM data to support the CLS.

2.3 Developed Models to Support CLS

Field tests' results have been used to develop the models for load shedding using the SMs. The preparation steps for the field tests on small-scale SMs' switching and the outcomes from the field tests are shown in Figure 2.1.

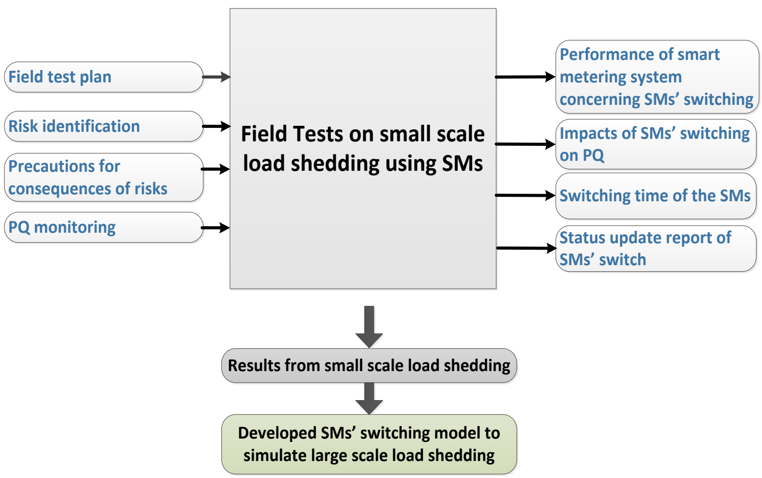

Figure 2.1: SMs' switching model developed using field tests' results

In this thesis, models have been developed considering three aspects: 1) minimizing unnecessary load shedding, 2) estimating load shedding time to compare time with the allowed load shedding time and 3) calculating expected supply voltage levels to the remaining customers after the load shedding.

Figure 2.2 shows the conceptual framework for the CLS. The DSOs would need to have some pre-prepared load shedding plans for the predefined prioritized customers' lists to exclude the prioritized customers from the CLS. However, the load shedding with the SMs can be done more efficiently by having few pre-prepared models, e.g., aggregated LF models at LV substation level for non-prioritized customers, individual LF models for all non-prioritized customers in the selected areas, SMs' switching model and load flow model. The inputs to the models and the outputs from the models are shown in Figure 2.2.

The outputs from a model which are used as input to the other model are shown with similar color, i.e., blue or green. Moreover, Figure 2.2 shows how each of the model(s) can allow additional benefits to the DSOs concerning efficient load shedding, e.g., pre-prepared aggregated LF models can be used to minimize unnecessary load shedding.

Aggregated LF Models at LV Substation Level:

Aggregated LF models are developed at each of the LV substation level of the investigated 10kV residential grid. 26 aggregated LF models are developed since there are 26 load buses. The models are developed using ANN method, and each model is trained by using one-year's hourly aggregated ECD of the respective customers under each load bus. The aggregated LF models can forecast load for a particular hour which represents the estimated load for each load bus at the load shedding hour.

LF Models at Individual Customer Level:

In addition to the developed aggregated LF models at LV substation level, individual LF models are also developed using ANN method for each of the two thousand customers in the investigated 10kV residential grid. The individual LF models are trained with one-year's hourly ECD. The estimated individual load of all selected customers can be obtained from the pre-prepared LF models at the individual customer level.

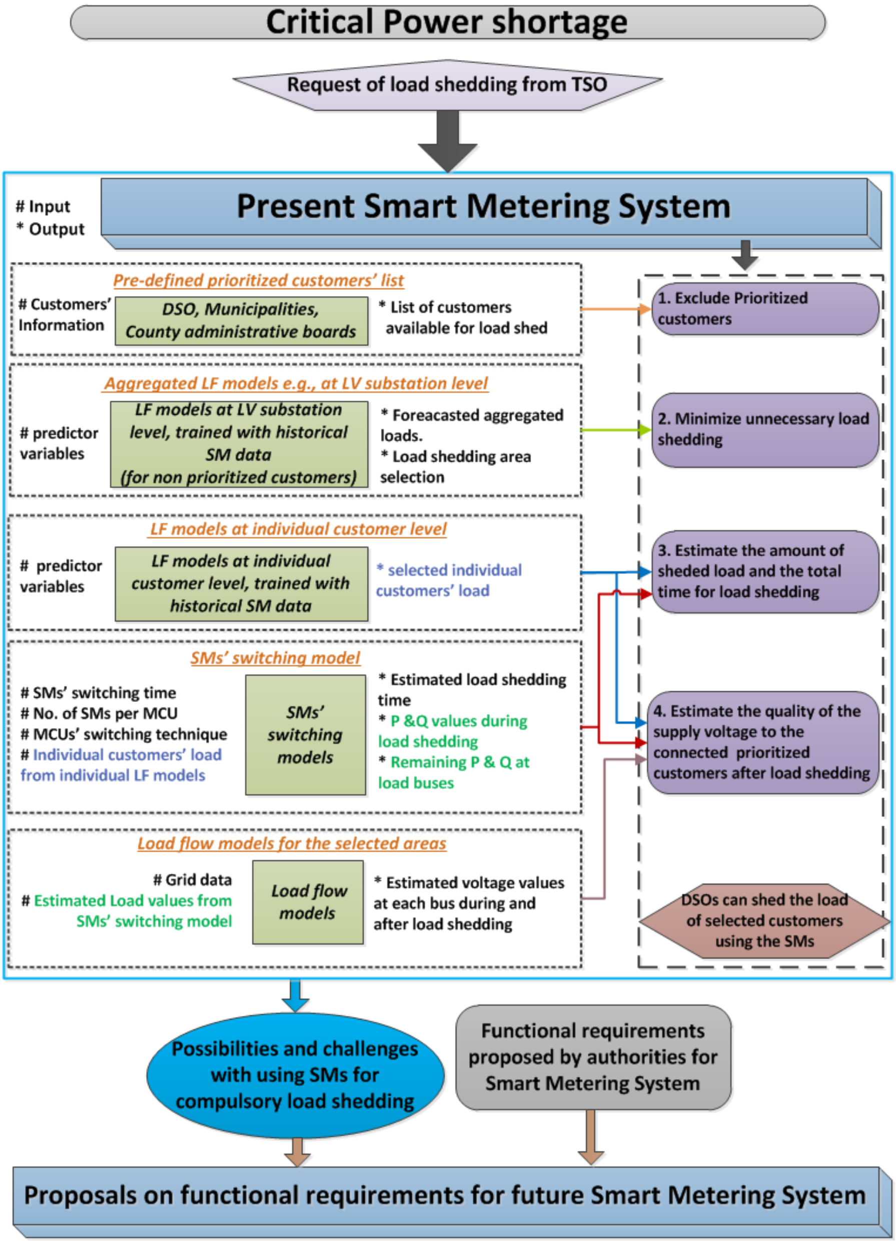

Figure 2.2: Block diagram of the conceptual framework

Smart Meters’ Switching Model:

The SMs’ switching model is developed based on the existing SMS’ switching performance obtained from the field tests. The SMS configuration, i.e., the number of SMs per MCU, and also the real switching time of the SMs are considered in the model. The forecasted load values of individual customers can be used in the SMs’ switching model to run the CLS scenario for the selected customers. The SMs’ switching model can then estimate the SM’s disconnection moments for all individual customers. The model can also estimate the amount of load disconnected at every second (sec) of the load shedding period while considering the parallel operation of all MCUs and the series operation of individual MCU. The SMs’ switching model can estimate aggregated disconnected load values from each load bus over the total load shedding period with one sec interval. Moreover, the model estimates the remaining aggregated load values, i.e., for the excluded customers on each load bus. Moreover, the switching model can help the DSOs to get an estimated total load shedding time for the selected customers and compare it with the allowed time for load shedding by the TSO.

Multi-Time-Steps Load Flow Simulation Model:

The SMs’ switching model is integrated in a multi-time-steps load flow simulation model of the investigated 10kV residential grid where real grid data are considered. The output from the SMs’ switching model, i.e., the aggregated load values at each load bus with one sec interval and for the total load shedding period, can be used as an input to the pre-prepared load flow model. The load flow model provides the voltage profile for each load bus for the load shedding period and also the voltage values after the load shedding. The DSOs can use the calculated voltage values at each load bus to check if the excluded customers are supplied with acceptable voltage values or not. Moreover, the voltage profile for each load bus can help the DSOs to take necessary actions if needed after checking the level of the supply voltage to the remaining connected customers.

Finally, as shown in Figure 2.2, functional requirements are proposed for the future SMS concerning the CLS. The proposals are based on the lessons learned from the analysis of the models’ results, and also the functional requirements proposed by authorities for SMS.

Chapter 3
Smart Metering System

This chapter provides an introduction to the smart metering system for electricity discussed in this thesis. The functional requirements of the smart metering system proposed by different national and international authorities are discussed in this chapter. Moreover, potential future applications of remote ON/OFF control switch in the SM are discussed. Cyber security issues related to remote ON/OFF control, and the current situation of the worldwide rollout of the SMs are also presented. Finally, recognized standards on power quality measurements are summarized.

3.1 Overview of the Smart Metering System

3.1.1 What is a Smart Metering System

The Smart Metering System (SMS) is an actual application of the SMs on a larger scale, i.e., the application of a general principle on a system rather than on an individual appliance. In the history of metering technology spanning more than hundred years, SMS represents the third stage in a chain of developments which are described below [44]:

In the first stage, the traditional electromechanical meters were developed in the late Nineteenth century, which have a spinning disc and a mechanical counter display. This type of meters operates by counting the number of revolutions of a metal disc that rotates at speed proportional to the power drawn through the main fuse box.

The substitution of electromechanical meters with solid-state electronic meters happened in the second stage of the meter evolution, making it possible to measure energy using highly integrated components. These devices digitize the instantaneous voltage and current by using analog to digital converter. The energy data is displayed on a liquid-crystal display. Once meter data is available in electronic form, it becomes feasible to add communications to the meter, allowing the meter to use Automatic Meter Reading (AMR) to access data remotely via the one-way communication link. This remote data access capability helps eliminate estimated bills for energy consumption and the need for a meter reader to visit individual premises which are required for traditional electricity meter readings.

The SMS, the third stage in the meter evolution, broadens the scope of AMR beyond just meter readings with additional features enabled by two-way data communication. A smart metering solution delivers a range of applications using an infrastructure comprising networked meters, communication networks and data collection and management systems, which is called Advanced Metering Infrastructure (AMI). An overview of a SMS, i.e., AMI can be represented as shown in Figure 3.1. An AMI can take real-time or near-real-time measurements, provide outage notification and basic PQ monitoring, and also can support in-home energy applications. It allows data exchange between the SM and the Central System (CS) of DSO, while also allowing customers to have timely and easily accessible information about their usage. The system with AMI can also manage the configuration of all units in the system, which function is referred as Automatic Meter Management (AMM). Moreover, the AMM function can provide the basis for meter data management, event and fault management, operation and maintenance.

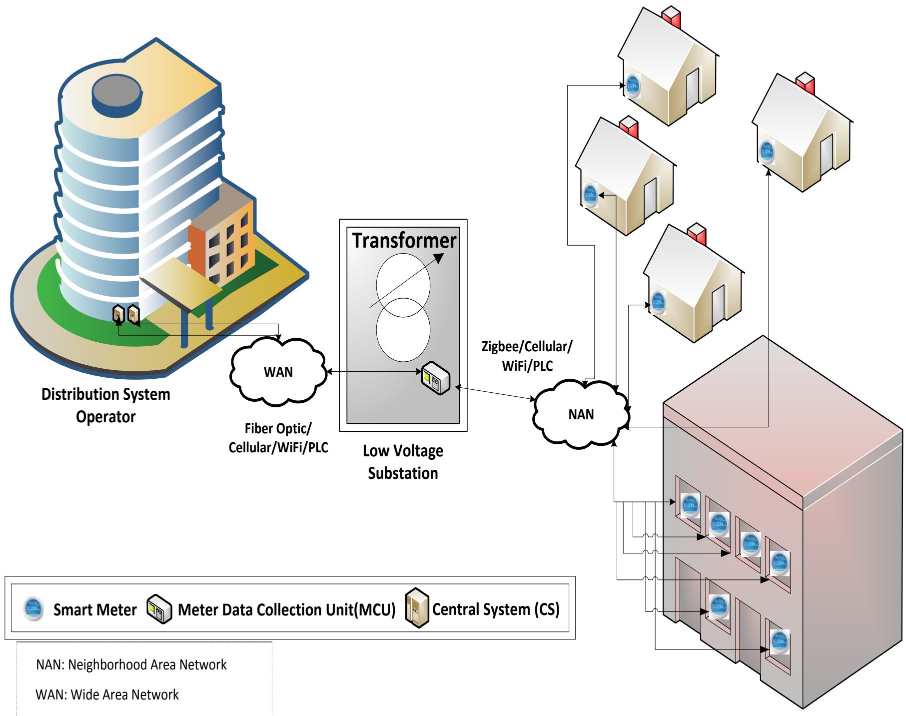

Figure 3.1: An overview of the smart metering system, i.e., AMI

3.1.2 Components of a Smart Metering System

A SMS generally contains four main components, i.e., SMs, terminals, Meter-data Collection Units (MCUs) and a CS. The functions of each component are given below:

Smart Meter: The SM is a remotely readable energy meter with two-way communication capability which measures the consumptions of electric energy of a household or an industry in real-time or near-real-time and securely sends the measured data to the DSO [45],[46]. The SM is electrically fed and composed of electronic controllers with a digital display. Some SMs allow the ECD to be displayed on a device within the home. It has an interface allowing data to be transmitted from the meter terminal to the MCU or directly to the CS. The main functions of the SMs are to measure, display and record actual data of electricity consumption. Most of the SMs can also record the energy that the customer feeds back into the distribution grid from own generation sources, such as wind turbines and solar panels. In addition to these, most of the SMs can provide the opportunity for remote connection and disconnection of the customer's power supply. Moreover, alarm functions can be implemented which will send an alarm to the CS automatically if someone tries to manipulate the meter. Furthermore, some of the SMs can receive information remotely, e.g., tariff information or transfer from the credit to the prepayment mode.

Terminal: The terminal is the unit which maintains communication between the SM and the MCU. It collects the data, e.g., the ECD from the meter and sends it to the MCU or directly to the CS. How often the data is transmitted depends on the configuration set by DSOs. Usually, the terminal is integrated into the meter, and the DSO can communicate with it. Several techniques are used for communication between the SM, the MCU, and the CS. The choice of technique depends on the area, number of customers and the available communication infrastructure. The data can be transmitted by using Power Line Communication (PLC), Radio link and/or Global System for Mobile communications (GSM)/General Packet Radio Service (GPRS). The data is collected from the meter in accordance with the internal schedule set by the administrator of the SMS.

Meter data Collection Unit: The MCU is the unit which supervises and maintains communication with all meter terminals assigned to it. The MCU collects the data from several meter terminals and stores it temporarily. The CS finally collects the data from MCU regularly after a certain time interval. The MCUs are usually placed on the LV side of a substation to make a communication path between the SMs and the CS. The MCUs maintain local communication with the SMs, and if a meter cannot be reached within a particular time, it reports to the CS. The MCUs can support various MCU management functions such as firmware download, control, setup and information view.

Central System: The CS acts as a brain where it is decided what to do and at which time. The CS receives commands from a user at the DSO through the web user-interface and sends the commands to the SMs via MCU and returns the result to the user. By using the software, the CS can control and configure different units in the system. The CS mostly communicates with the MCU. The data processed in the CS are the basis for invoice management and statistics which is regularly provided to customers via the web-based customer portal.

3.1.3 Applications of Smart Metering System

The SMS has been shown to provide benefits to both customers and the DSOs, e.g., the SMS can provide electricity customers a chance to get better customer service and also can provide the DSOs an opportunity to analyze the time-varying characteristics of the electricity consumption of individual customer. The SMS can also help in different grid applications, e.g., DR, to reduce the peak load. Moreover, the SMS can provide new customer offerings such as time-of-use billing and prepayment. The smart metering technology is helping the DSOs to address modern energy challenges such as optimized grid planning and operation.

However, the applications of the SMS depend on the available functionalities in the SMS, and the available functionalities in SMS can vary from country to country and even from one DSO to another DSO within the same country. The applications of the SMS can be categorized according to who is getting benefit from the application, e.g., end-users or energy industry [47],[48], [49],[50].

3.1.3.1 Benefits for End-Users

Better bill information: SMS provides actual and more accurate ECD to the customers and timely billing based on actual consumption data.

Smart homes: Smart home refers to a home which has automation system to control different home appliances, lighting, ventilation system, etc. according to customer’s preferences, outdoor climate, and other parameters. Now a day, remote control of appliances, heating and alarm systems become more common. The customers can control the individual appliances in response to information obtained from the SM.

Alarm Services: The communication system of the SMS can be used to provide some additional services such as fire alarms, burglar alarms, panic alarms or other safety-related alarms.

Prepaid service: The SM may introduce more cost efficient and customer friendly prepaid service compared to traditional prepaid meters due to the advantage of a communication system with SM.

Customer usage feedback: The customer will be provided with the information of their usage, and thus the customer would be in the position to reduce its energy consumption or to shift its energy use. The customer can get supplementary information or guideline on how to make energy-savings by using their usage pattern.

3.1.3.2 Benefits for Distribution System Operator

Status of electrical distribution grid: By taking measurements at the customer point of connection the loading and the losses of the distribution grid can be known more accurately. It can help the DSOs to take actions to prevent overloading of transformers and lines.

Power Quality monitoring: PQ involves the voltage quality of the distribution grid and the current quality of the loads. Most of the voltage quality problems originate from the customers. The SM can keep the record of power supply interruption and voltage dips to help the DSOs to understand where investments are most needed.

Customer Service: SMS can increase the service quality of the customer call center due to the availability of real-time power consumption data. Remote connection and disconnection of the customer are also possible with the SM. The DSOs can switch any SM remotely according to the necessity of the customers, e.g., while changing addresses.

Load analysis and forecasting: ECD can be used for load analysis. By combining some information with the load profile, the total energy use and peak load demand can be estimated and forecasted. This information is useful for retail suppliers and for the DSO to make a plan for operating the power distribution grid.

Demand Response: The DR largely refers to customers' "response" to price information by adjusting their load demand. The SMS can enable the DR by allowing real-time pricing which can be, e.g., an hourly rate applied to energy consumption, to the customers through, e.g., a customer interface.

Integration of renewables: The ability of the SM to measure power flow in both directions, i.e., generation and consumption can facilitate the installation of renewable generation, e.g., photovoltaic installations.

Management of smart meter: The information of the SM such as a database of the vendor, type of the meter, configuration settings, working life, a record of scheduled or urgent visit of safety and security checks can help the management process of the SM and the customer record.

Load control: Some DSOs can control the load of the customer by using the interface of the SM. However, the load can be controlled in different ways such as remote connection and disconnection of the total load which is a common practice. Some SMs can also allow remote connection and disconnections of the partial load or remotely limiting the maximum allowed capacity for a metering point, which are not common practice.

Illegal customer detection: Some SMs can detect any illegal attempt to open the meter box or to modify the connections to the meter or reprogram the meter software. The SM can send signals of any illegal attempt to the CS promptly.

3.1.4 Data from Smart Metering System

Data collected regularly: The MCUs collect hourly ECD from the SMs and send the collected data to the CS on a regular basis. The SMs send various types of data, e.g., hourly ECD, last metering time, meter information, sensor information, total energy consumption of the customer from the beginning. Moreover, the SMs also send the voltages of the time instants when MCUs asked for meter data.

On-demand data: It is also possible to get on-demand readings from the SMs. With the on-demand readings, the CS can get instantaneous voltages and currents of three-phases, active and reactive cumulative ECD and information of meter along with other information such as last power outage date, SM's switch status.

Data on Power quality events: Some SMs can send event report automatically to the CS. It can detect different PQ problems according to the configuration, e.g., power supply interruption. The SMs can also send the time instants and the duration of the events.

Data triggering an alarm: Some SMs can send an alarm in real-time to the CS for a power outage, tamper detection, low battery, etc. The software in the SMS can filter the alarms to analyze the severity of the cause of alarm and helps to take necessary steps rapidly and efficiently.

3.2 Communication Technologies in Smart Metering System

Several techniques are used for data transmission between the SMs and the CS. Different factors impact the choice of communication technology such as the number of customers within the area, telecommunication network coverage of the area and the availability of internet connection. However, research is required towards robust, low power and low-cost communication medium that can adapt to multiple environments [51].

Currently used communication technologies for the SMS can be distinguished as wired communication medium such as PLC and a wireless communication medium such as GPRS and ZigBee. Some of the most common communication technologies are given below:

3.2.1 Power Line Communication

The dominant technology in wired smart metering communication is PLC which is also known as Power line Carrier. PLC has evolved since 1980 [51]. The PLC technology uses the existing electrical power cable network with a frequency range of 24 kHz to 500 kHz, and the data rate is up to 9.6 kbps. It provides a convenient and economical solution which is suitable for densely populated areas. This technology has the main limitation that the low range signal deteriorates with distance and beyond a certain distance such as some few hundred meters, the signal is completely lost. PLC technology is thus used to establish communication between a set of SMs and the nearby MCU. Then the data are encoded by the MCU in digital format and sent to the CS by using the GPRS network.

Due to the most cost-effective way for two-way communication, PLC technique has gained higher interest in data communication of SM. However, the power line is full of various types of noises [52].

Significant attenuation of signal can occur in power line due to various interferences from the noise. Power line noises can be created from a normal operation such as noises by partial discharges on insulators and apparatus. It may also come from switching operation such as isolator switch, circuit breaker, and faults. Moreover, noise can be created from the interference of external sources. The noise which comes from switching operations usually has a high amplitude of noise, and in most of the case, it causes a short interruption in signal transmission [52].

All of the different smart energy devices inside and outside homes, e.g., distributed consumer electronics, sensing and monitoring devices, etc. need to be reliably connected all the time in any environmental condition and resilient to interference. The required data throughput for these purposes is low, and the data packet size is less than 64 bytes. Based on it, the narrowband PLC is the most preferred choice because it has low power consumption, low cost, higher scalability, and flexibility. Moreover, it can be implemented in a full programmable fashion economically [53].

3.2.2 ZigBee Radio

Different radio-based communication solutions exist in the world. ZigBee communication system is discussed here since this is what the studied system uses. ZigBee is a suite of high-level communication protocol specifications based on the IEEE 802.15.4-2003 standard [54]. ZigBee uses the frequency band of 2400 MHz to 2483.5 MHz for the globally open standard. The higher frequency of 2.4 GHz means that the data rate should be up to 250 kbps compared to 1 Mbps data rate of Bluetooth. The technology is intended to be simpler and less expensive than other wireless solutions based on radio technology, e.g., Bluetooth. ZigBee is used at radio-frequency applications that require a low data rate, long battery life, and secure networking. This standard has been developed to meet the growing demand to enable wireless networking between numerous low power devices. Devices in the ZigBee network could include light switches with lamps, in-home displays, and customers' electronics equipment. It also offers many potential applications such as Home Area Network (HAN), heating control, home security, industrial, and building automation. The high spreading factor of IEEE 802.15.4 at 2.4 GHz and the sixteen available channels can empirically deliver a disturbance-free network, even on a citywide network.

The ZigBee network is self-healing, which indicates route rediscovery if messages fail. The signal passes by another node if one node is not working. In the ZigBee network, each meter thus becomes a repeater, and the network becomes stronger. The nodes may act as an independent router. Since the numbers of neighbors are not fixed, it is easy to connect and disconnect new nodes. It occurs automatically in a spontaneous network. Moreover, the ZigBee network can also be easily expanded as new homes are built, or new services need to be added.

ZigBee is suitable for home automation since the reach of the ZigBee signal is stated to be below 250 m with free sight line. However, a reach of more than 2,000 m with free sight line can be attained [55]. Moreover, the average power consumption of ZigBee is very low since the wake-up time to be in active mode is 15ms or less. The MCU has a power usage of only 3 W to 4 W, which is not much more than SM consumption. Moreover, the SM does not initiate transmission by itself except for alerts/alarm but answers when data is requested from the CS. Finally, it is advantageous and cost-effective for the DSOs since the DSOs own the infrastructure and are independent of other actors.

3.2.3 GPRS

GPRS is a packet-based wireless communication service that provides data rates from 56 Kbps up to 114 Kbps. The GPRS is based on GSM communication. It provides moderate-speed data transfer, by using unused Time Division Multiple Access (TDMA) channels in, for example, the GSM system [56]. In theory, GPRS packet-based services cost users less than circuit-switched services since packets are needed basis rather than dedicated to only one user at a time. The GPRS also complements Bluetooth, a standard for replacing wired connections between devices with wireless radio connections.

The GPRS technique can be used to build a communication network of the SMS. The GPRS technique is used in the investigated system of this thesis for communication between the MCUs and the CS. Investment and operation cost of this technique is high. Service level is fast, but there is a possibility of missing values. It has possibilities to add more service but with a high expense.

3.2.4 Comparison between Communication Technologies

Each communication technology has advantages and also disadvantages. Table 3.1 presents a comparison between these three communication technologies mentioned above.

Table 3.1 Comparison of three communication technologies

	PLC	**GPRS**	**Zigbee Radio**
Investment Cost	Low	High	High
Operational Cost	High	High	Low
Service level (data transfer)	Slow/missing values	Fast/missing values	Fast/secure operation
Added service	Hard	Possible but expensive	Easy

3.3 Remote ON/OFF Control of the SMs

3.3.1 What is Remote ON/OFF Control

The SMs can be equipped with an additional remotely accessible switch to allow the DSO to control customer power supply and the switch is referred as remote ON/OFF control switch or remote connect/disconnect switch. Among the ten minimum functionalities recommended by the EC, there was a high consensus on the provision that the SM should allow remote ON/OFF control of the supply [31]. In a power failure scenario, the SM will start functioning automatically after the power supply is back since the switch was ON. However, the switch of the SM needs to be remotely reconnected if it is disconnected remotely. Some SMs, however, allow physical reconnection using an optical eye if the remote reconnection command does not function properly. Moreover, the communication signal strength needs to be sufficient to execute SM switching.

3.3.2 Potential Future Applications of Remote ON/OFF Control

Several goals can be achieved by using the remote ON/OFF control switch of the SM. Some potential applications of remote ON/OFF control switch provided below:

3.3.2.1 Demand Side Management during Over Load Condition

One of the main issues that are discussed nowadays regarding the electrical grid infrastructure is the problem with congestion during peak electricity demand periods. The DSM can be necessary to keep the balance between the load demand and supply [57]. The DSM refers to actions from the demand-side in such a way that the electricity demand is adapted to the electricity production and the available electricity in the grid. The DSM aims to reducing electricity demand and avoiding load peaks during congestion in the grid. The benefit for a DSO to control the energy use is to be better able to handle congestion situations and decrease the risk of blackouts. The distribution grid generally holds overcapacity to handle peak demand situations. Since the power reserve that can be started on short notice and agreements might be phased out in future, the implementation of the SG and DSM are expected to provide flexibility which will contribute to reducing the need for the generation capacity reserve. The key to making the DSM more effective and the grid smarter is to fully and dynamically integrate customer's loads, and information about their usage into the operation of the grid. The SMs can help in achieving this target by providing hourly electricity consumption data.

According to [58], there are two ways of controlling the customer energy use: direct and indirect. Direct control of the energy use indicates that a contract is made with customers where the customers give permission for direct control over the power output. The controlling authority could be, e.g., the DSO or the electricity supplier. The indirect control means giving incentives to the customers based on different types of contracts that will motivate the customers to adapt their electricity use. In this case, no certainty of the customer reaction is given, but with experience, the supplier and grid owner could predict the reactions. The SMS can be used for direct control of demand side in the grid based on a contract with the customers. Moreover, using SM switching technique for DSM may help the DSO to exclude emergency service providers and prioritized customers from a power outage.

Disconnecting selected customers during over-load condition can help to reduce overloading of the electricity distribution lines. The DSOs can decide which customers to disconnect and at which overloading level. All disconnection levels need to be remotely configured within the SMS software, and each customer can be predefined by a priority value. This action might allow differentiated and gradual step-wise load shedding for more balanced load management. The reconnection of each customer can also be predefined by the DSO. When the overload condition is over, customers will also be gradually reconnected to the grid. The switching functionality of the SMs can help the DSOs to perform gradual and selective load shedding on the customer level without the need to disconnect all customers within a substation area.

3.3.2.2 Power to Prioritized Customers during Maintenance Work

The DSO might need to perform maintenance work on the grid to clear faults, conduct network reinforcement or upgrade the grid. The maintenance work can either be Preventive Maintenance (PM) or corrective maintenance. The PM work is usually planned, e.g., to adjust voltage level at LV substation and scheduled before while the corrective maintenance work is carried out after failure detection to restore an asset to an operation condition. When a DSO performs maintenance work, e.g., PM work in an area, most of the time the DSO needs to disconnect power from the substation with the consequence that all customers under that substation lose power supply, including prioritized customers. Sometimes, it can be possible to supply the customers of the impacted area from a nearby substation if the total load falls within the capacity of that substation. But for some area, the total load might exceed the capacity of other substation. In that case, remote switching technique of the SMs can be used to disconnect some customers until the capacity of the other substation is matched. The rest of the customers can then be supplied from a nearby substation while doing maintenance work at the main local substation. In this way, the essential service providers and the prioritized customers can have power supply during the PM or corrective maintenance work when the DSO needs to shut down the power from the substation.

3.3.2.3 Outage Planning during Natural Disasters

Natural disasters might damage electric power system components, causing widespread outages over an extended period of restoration, resulting in the overloading of distribution lines. The remote SM switching technique can be used to provide power supply to essential service providers during disasters. This technique can either be used to shed some loads for reduction of line overloading or can be used to continue power supply to the prioritized customers from an active substation. This practice may help the DSO to handle the critical conditions during natural disasters, and also to ensure continuous power supply to the prioritized customers.

3.3.3 Cyber security Issues Related to ON/OFF Control Switch of Smart Meter

The remotely accessible ON/OFF control switch of the SMs is valuable for DSOs, but researchers have raised concerns about possible abuse by malicious attackers which could lead to blackouts or affect the stability of the electrical grid, e.g., by disturbing the system frequency.

The remote connect/disconnect capability of the SMs has caught the attention of the security community in recent years [59],[60],[61]. Because the remote ON/OFF control switches of the SMs can either be used as planned or misused by an adversary. The DSOs have not had to face this kind of security problem before. By using the remote switch, the adversary can tamper with the frequency of the electrical grid which could cause a widespread blackout or could potentially harm the electrical grid.

An oversight may lead to no change of the default settings [60]. Security measures such as data encryption and intrusion detection systems offer some level of protection for AMI systems. However, these security measures provide little help if an attacker is able to compromise the system and issue a malicious disconnect commands to millions of SMs [62].

Related work on cyber security issues of SM can be found in some articles. For example, problems related to the communication module with interception and injection of false messages is discussed in [63]. It also presents a scenario showing how the injection of false malicious data lets the adversary gain different benefits from the system. Moreover, a methodology to extract and reverse engineer the firmware from a SM to obtain valuable information such as passwords and communication encryption keys is described in [64]. Furthermore, weakness of the communication channel between the SMs and the CS has been shown in [65]. In [66],[67] the model and the functionalities of intrusion detection systems are covered for AMI system.

A successful attack would have severe economic and political consequences. Significant research efforts can be seen in securing the SG mainly focused on the Supervisory Control And Data Acquisition (SCADA) systems and the transmission grid. However, attacks originating from the distribution side can also have significant effects on the grid. More research is recommended in this new research area.

3.4 Smart Meter Rollout

The SM rollout is progressing in several parts of the world with early adoption in some parts, e.g., in Europe. The DSOs worldwide are deploying SMs as the first step of moving toward the SGs, enabling two-way power and information flows. According to [69], by the end of 1st quarter of 2017, China accounted for 68.3% of tracked global installations while North America and Western Europe followed at 12.9% and 12.5%, respectively. The rest of Asia Pacific accounted for around 4.8% while the remaining regions at only 1.4% of tracked SM installations.

The Electricity Directive in the Third Energy Package, Directive 2009/72/EC1, triggered the installation of the SMs in the EU countries and it is foreseen that at least 80% of the electricity customers will adopt this technology by 2020. The rollout is subject to a cost-benefit assessment of long-term cost and benefits to the market and the individual customers or which form of intelligent metering is economically reasonable and cost-effective [36]. Over the past years, almost all European countries have performed Cost Benefit Analysis (CBA) of smart metering, and the majority of the cases have resulted in a recommendation to go ahead with a rollout [36],[70]. Some examples of SM rollout progress in the several parts of the world are given below:

Smart Meters in Europe:

The EC adopted an energy and climate change package in 2007. The objectives on the initiative state that by 2020, greenhouse gas emissions must be reduced by 20%, there must be a 20% of renewable energy sources in the EU energy mix, and EU primary energy use must be reduced by 20% [71]. Local electricity supply management is expected to play a crucial role in reaching the ambitious 2020 targets and can be enabled and enhanced by SMS which can increase customer awareness and participation. Due to the EU policy recommendations regarding energy, the EU member states committed to rolling out close to 200 million SMs for electricity, and it is expected that by 2020, 72% of the European customers will have a SM for electricity [72]. According to [72], 80 million SMs have been installed in the 28 EU countries and Norway by the end of November 2016. SMS rollout in Europe keeps steady progress forward, but the pace of SMS deployment has been different from one country to the other.

In Europe, five EU member states have already completed the full rollout of the SMs by the end of 2017. Italy and Sweden are the first countries to complete a near full rollout of the SMs [73],[72], while several European countries prepare the take-off. During 2001 to 2011, Italy completed a close to full rollout, installing around 36 million SMs [74]. In the years 2003 to 2009, Sweden completed a full rollout, installing 5.2 million SMs. The SMS coverage of Finland was 100% by the end of 2013 which indicates 3.3 million SMs installation throughout the country. Malta has also completed a full rollout of 260 thousand SMs by 2014. Estonia and Spain have joined the pioneers Sweden, Finland and Malta where Estonia completed 100% rollout by 2017 and Spain will complete 100% rollout by 2018. Most of the countries in Europe have already mandated the SM rollout with a specified timetable. There are different deadlines in each country from 2017 to 2020. For example, France will install 35 million SMs by 2020 and the UK will install 56 million by 2020.

According to [73],[72], 16 EU member states (Austria, Denmark, Estonia, Finland, France, Greece, Ireland, Italy, Luxemburg, Malta, Netherlands, Poland, Romania, Spain, Sweden and the UK) have decided to complete large-scale rollout of SMs by 2020 or earlier, except for Poland and Romania which planned to complete the rollout by 2022. However, eight member states (Belgium, Croatia, the Czech Republic, Germany, Latvia, Lithuania, Portugal, and Slovakia) got negative or inconclusive outcomes of CBA for a large-scale rollout of SMs and hence faced delays in SMs' rollout. The remaining four member states (Bulgaria, Cyprus, Hungary, and Slovenia) have not made the plan for large-scale SMs' rollout available yet. Norway, which is not among the EU member states, planned to complete 100% rollout SMs by the beginning of 2019.

The Swedish Parliament approved monthly reading of all electricity meters from 1 July 2009, supported by the findings of the Swedish Energy Agency that more frequent meter reading would generate economic net benefit. Since July 2009 monthly meter reading is required for customers with a fuse of less than 63A and hourly metering should be performed for larger customers [75]. From 1st October 2012, a new regulation was introduced, that allowed the customers to require hourly metering of their electricity consumption if they had an hourly energy contract with their retailer [76].

Smart Meters in America:

According to [77], in the United States, 70 million SMs have been installed by the year 2016, and the deployments of the SMs are projected to be 90 million by 2020. However, according to [78], the United States has seen a slowdown in the activity of the SMs' project since 2013, following the conclusion of the SG Investment Grant Program which contributed to an influx of SM installations across the United States. Most of the states in the United States are still at the beginning phase of the SMs' deployment [77]. In Canada, the rollout of SMs across all provinces is near completion where Ontario was one of the first provinces to complete the rollout of SMs. The majority of Canadian households have SMs installed. However, nationwide deployments of the SMs have slowed down in 2013 since the deployment was near conclusion and the deployment is predicted to remain at around 1 million units per year through 2018 [79]. However, the provinces of Ontario and British Columbia have introduced mandatory requirements for SMs for all customers. In Latin America, Brazil and Mexico are leading the region in SM rollout which accounts for more than 60% of the region's total electricity meters [80]. Mexico's state-run utility aims to install over 30 million SMs by 2025. Among other countries, significant activity has been noted in Barbados, Brazil, Costa Rica, Ecuador, Jamaica, and Puerto Rico.

Smart Meters in Asia:

In Asia, some of the East Asian countries are leading the rollout of SM. Large-scale rollouts of SM continue across China and Japan where the utilities of these countries pushing toward near nationwide coverage. Japan already has the world's most advanced grid monitoring systems. In Japan, ten utilities planned to deploy around 80 million SMs by 2024 [69]. South Korea has adopted a national plan for the construction of a SG by 2020. China remains the leading global SM market with more than 408 million SMs installed which accounts for 68.3% of tracked global installation until March 2017. China's two utilities are set to conclude their massive rollouts by the end of 2017 [69].

Smart Meters in Middle East and Africa:

The deployment of the SMs in the Middle East and Africa is still in its early stages. In the Middle East, countries, e.g., Kuwait, Lebanon, and the United Arab Emirates have all announced large-scale projects on SMs' deployment. Qatar has completed the first phase of SMs' deployment in 2016 by replacing all analog meters in the Doha area by the SMs. Saudi Arabia planned for a massive rollout of SMs starting from 2017 and expected to finish the rollout by the end of 2021 [81]. The Middle East SMs' market is forecasted to reach 16.1 million units by 2022 where 86% of homes and businesses in the region are expected to have SMs by the same year [82].

In Africa, more high-level activity is emerging from countries, e.g., Egypt, Nigeria, and South Africa [69]. Moreover, small-scale projects on SMs' deployment exist in countries, e.g., Algeria, Kenya, Tunisia, and Zimbabwe.

3.5 Mapping of Functional Requirements and Guidelines Proposed by Different Authorities

Different national and international authorities, e.g., EC, ERGEG, SMCG, Ei, etc. proposed functional requirements and guidelines for SMS as presented in Appendix A. Three reports from EC [30], [31], and [32], which are named as EC11, EC12 and EC16 in the mapping, discussed functional requirements for the SMS. Moreover, a report from EC on a new electricity market directive, named as ECM16 also discussed the functional requirements of the SMs to enable the new market [33].

This thesis attempts to map the functionalities and guidelines proposed by EC with the ones proposed by SMCG, ERGEG, and Ei. However, it is noted that there are interrelations between different functional requirements and their applications. Therefore, mapping of functionalities with their applications could be tricky. E.g., the functionality called 'two-way communication' is needed for functionality 'support advanced tariff,' 'provide import/export metering,' 'frequent reading to operators,' and 'update firmware,' etc. The functionalities are divided into five parts following the EC11 report, where the divisions are made based on the stakeholders of the functionalities, e.g., customers, and DSOs, and also based on different aspects of the functionalities such as the commercial and security aspects. The applications of different functionalities which are described in slightly different ways in different reports are addressed in this section. It is noted here that same functionality could be used for customers and also for the DSOs. E.g., the interval data of active energy import/export could help to increase the customer's ability to participate in the market while the data gives tariffing and billing support for the energy suppliers. Moreover, the interval data can support grid planning for the DSOs.

3.5.1 Mapping of Functionalities for Customers

The functionalities for customers and their applications are mapped in Table 3.2. The table shows that all the authorities support the functionality of the SMs to provide readings from the SM to the customer's in-house device, i.e., customer interface. However, only Ei has explicitly mentioned about the type of data to be transferred to the customer interface and also the interval of the data to be transferred from the SM. Other information such as tariff, warnings on low credit for prepaid customers, etc. are not explicitly mentioned or proposed in the reports except in the questionnaire of EC11.

Table 3.2 Functionalities for customers and their applications

Functionalities For Customers	Applications	EC 11	EC 12	EC 16	SM CG	ER GEG	Ei	EC M16
Readings from the meter to the customer	SM-HAN or a user accessible communications port/interface, by which this data is transmitted to in-house devices 'which would enable energy management solutions in 'real-time,' such as home automation, and different DR schemes'	√	√		√	√	√	√
	Accurate, user-friendly and timely readings		√					
	Or remotely through different channels (web portal, mobile applications, paper communications, file downloads or sending).			√	√	√		√
	Capable of measuring phase voltages, phase currents, active and reactive power both import/export on each phase						√	
	Capable of measuring and recording the total active energy for both import/export.						√	√
	An update rate of every 15 minutes is needed at least.		√					
	To record transferred active energy (both way) data per hour and capable of recording data with 15-minute interval if needed.						√	
	Increase the customers ' ability to participate in the markets.						√	
A standardized customer interface	A standardized interface which provides visualized individual consumption data to the consumer.		√	√	√	√	√	√
	Activation and de-activation of the interface on customers' request.						√	√
Frequent readings to achieve energy savings	The information flow to the customer is fast enough to allow the customer to react to excessive loads	√					√	
	Customers need to see the information responding to their action		√					
	To allow the customers to react to price signals and adapt consumption			√		√	√	
	Data on phase voltages, phase currents, active and reactive power, and active energy both import/export need to be displayed at least once per ten seconds.						√	
Readings in a form easily understood by the untrained consumer, enabling final customers to control their energy consumption better	Readily available easily understandable data	√	√			√		√
	High consumption warning	√						
	Information on impending tariff changes, where the Time-of-Use tariff is in use	√						
	Information on outstanding available credit, for Pre-payment systems	√						
	The accrued cost in the current billing period, for credit customers	√				√		
	Information on the present status of SMs' switch	√						
	The effect of continued consumption at the present level, for impending power limitation	√						
	Showing the impact of his behaviour on energy consumption, and on derived values like money and CO2 emission			√				

3.5.2 Mapping of Functionalities for Commercial Aspects of Energy Supply

The functionalities for commercial aspects of energy supply, and their applications are mapped in Table 3.3. The table shows that most of the authorities proposed the functionality to support the advanced tariff system, remote ON/OFF control of the supply. However, the functionality to support energy supply by pre-payment and remote power flow limitation are not proposed by the Ei. The functional requirement of the remote ON/OFF control switch for CLS are not mentioned in the reports although the possibility of the using the switch is mentioned in the reports from the Ei and the EC. It is noted here that few cells of the table are merged to represent that the authority mentioned about all applications in respective cells of Applications column.

Table 3.3 Functionalities for commercial aspects of energy supply, and applications

Functionalities for commercial aspects of energy supply	**Applications**	**EC 11**	**EC 12**	**EC 16**	**SM CG**	**ER GEG**	**Ei**	**EC M16**
Supports advanced tariff systems	Data storage capacity within the Smart Meter System to allow effective comparison of consumption profiles	√		√			√	
	Storage of, e.g., Peak Demands with date/time of occurrence	√						
	Support for time-of-use, block and demand based tariffs	√	√			√		
	Support for remote control of tariffs; switching times, unit costs, etc	√	√			√		
	Provision of active tariff information to the customer.	√	√					
	Set billing parameters, e.g., payment mode, tariff scheme, thresholds and response action, data sets				√			
	To make offers to the customer that better reflect actual consumption/injection divided into different time periods.					√		
Supports energy supply by pre-payment and on credit	Ability to switch between Credit & Pre-payment; and back	√						
	Credit top-up for pre-payment meters			√	√			
	Pre-payment with remote top-up			√				
Remote ON/OFF control of the supply	Speeds up processes such as when moving home or non-payment;	√		√	√	√	√	
	Protection of vulnerable customers	√						
	Needed for handling technical grid emergencies.	√	√				√	
Remote flow or power limitation	The net benefit to the customer of the application of power limitation;	√				√		
	Protection of vulnerable customers by allowing grading in the limitations.	√	√					
	The supply of energy can be limited if the consumer does not pay the bill (the possibility of using essential devices)			√	√	√		
	Allows the formulation of individually designed contract enhancements					√		

3.5.3 Mapping of Functionalities for Grid and Grid Operators

The functionalities for grid and grid operators, and their applications are mapped in Table 3.4. The table shows that all authorities support the functionality of two-way communication, remote readings of meter registers by third parties and the DSOs, remote meter management, e.g., upgrading firmware. However, monitoring PQ with the SM is not proposed in most of the reports.

Table 3.4 Functionalities for grid and grid operators, and their applications

Functionalities for grid & grid operators	Applications	EC 11	EC 12	EC 16	SM CG	ER GEG	Ei	EC M16
Remote reading of meter registers by meter operators	Both on-demand readings, e.g., when a consumer moves out or when he changes supplier and scheduled readings which are sent periodically to the meter operator.	√	√	√	√			
	Information on, e.g., interval readings or peak demands by the supplier to the customer	√						
	Data storage within the meter to retrieve data on past consumption	√	√			√	√	
	Correct billing, both on a regular basis or on-demand (on the change of occupier or energy supplier)	√				√		
	Alarms, which are sent unscheduled when e.g., power failure or a fraud attempt occurs.			√	√	√		
	Retrieve AMI component information & check device availability				√			
Recording power interruption	Able to record data on power interruption by recording the start and the end time of each power outages in one or more phases that are longer than three minutes.						√	
	Strengthens the role of the customer in getting the interrupt compensation payment.						√	
Remote reading of meter registers by third parties	Provide readings directly to any third party designated by the consumer	√	√		√			
	Allow customers to grant access to third parties to their data through the entitled data management entity (Meter Operator or another party), for example for consumption analysis and comparison of suppliers.			√		√		
	If a service provider is in charge of information on the customer's voltage quality, the customer should know that this data exists and also receive information on explicit data which could be subject to a reasonable fee					√		√
	Alarm in case of exceptional energy consumption					√		
	Phase voltages, phase currents, active and reactive power, and active energy both import/export, and also power interruption data						√	
Two-way communication between the meter and external networks for maintenance and control of the meter	Ability to remotely upgrade the firmware	√	√	√	√	√	√	
	Monitoring of the status of the meter with the ability to provide warnings of actual or impending problems	√						
	Time synchronization of meter's internal clock	√		√	√			
	Update of new tariff details, including changes in cost and/or switching times and the calendar.	√		√				
	Adding and removing communication links to other meters			√	√			
	Emergency or Demand Response signals sent by TSO, DSO or third parties			√			√	
	Configure meter events and actions; Manage events				√			
	Configure AMI device, e.g., configuring, parameterizing, adjusting the Smart Meter				√			
Monitoring of Power Quality	Provision of a warning to the customer if voltage quality falls to such a level that equipment could be damaged.	√						
	Provision of warning to the supplier, e.g., excessive harmonic currents	√						
	Logging of power quality issues, e.g., interruptions	√						
Readings frequently enough to allow the information to be used for grid planning	Depending on whether grid control is being considered at a micro (e.g., local) level or a macro (e.g., sub-station) level	√	√			√		
	Readings obtained from a subset of customers can be used to generate load profiles, which are commonly used for tariff design and system operation planning			√				√

The questionnaire that was included in the report EC11 showed that some EU member states commented to the questionnaire mentioning that their already installed SMs are monitoring PQ, e.g., supply failures, harmonic distortion and voltage sag/swell. The frequency of getting the SM readings to the CS to allow the information to be used for different applications, e.g., grid planning, LF, etc. are not explicitly mentioned in the reports.

3.5.4 Mapping of Functionalities Required to Allow Distributed Generation

The functionalities to allow distributed generation, and their applications are mapped in Table 3.5. The table shows that almost all the reports proposed the functionality to measure the import/export, i.e., two-way power flow & reactive metering.

Table 3.5 Functionalities to allow distributed generation, and their applications

Functionalities to allow distributed generation	**Applications**	**EC 11**	**EC 12**	**EC 16**	**SM CG**	**ER GEG**	**Ei**	**EC M16**
Provides Import / Export & Reactive Metering [promote micro (or distributed) generation]	Provision of 4 quadrant measurement of active energy (kWh) — import & export;	√		√		√	√	
	In a 4 quadrant kWh meter, differentiation between net energy and generated energy;	√						
	Provision of 2 quadrant measurement of reactive energy (kvarh) — import/export or inductive/reactive;	√						
	Provision of 4 quadrant measurement of reactive energy (kvarh) — import/export and inductive/reactive;	√						
	Communication of high reactive energy to relevant actors.	√						
	The function should be installed by default and activated/disabled in accordance with the wishes and needs of the consumer		√					
	Rapid and detailed feedback on customer’s energy consumption.							
	Measurements support grid planning for the grid operator							
	Tariffing and billing support for an energy supplier							

3.5.5 Mapping of Functionalities for Security and Privacy

The functionalities to allow distributed generation, and their applications are mapped in Table 3.6. The table shows that most of the reports proposed to provide secure data communication where the reports from the EC proposed fraud prevention and detection functionality also. The report from the Ei discussed the security and privacy issues related to each functionality proposed by Ei.

Table 3.6 Functionalities to allow distributed generation, and their applications

Functionalities for security and privacy	Applications	EC 11	EC 12	EC 16	SM CG	ER GEG	Ei	EC M16
Provide secure data communications	High levels of security are essential for all communications between the meter and the operator	√	√		√			√
	Applies to direct communications with the meter	√	√					
	Applies to any messages passed via the meter to or from any appliances or controls on the consumer's premises	√	√					
	Privacy consideration may apply a restricting collection of specific data sets, or restraining the granularity of certain data sets.			√				
Fraud prevention and detection	Relates to the supply side: security and safety in the case of access	√	√					√
	Physical measures like tamper evident seals and plausibility checks.			√				
	Real-time alarm, for example, if the meter case is opened or if unusual operating conditions like a very strong magnetic field are detected			√				

3.6 Summary of Functionalities Proposed in Considered Reports

From the discussion in Section 3.5, it is clear that there are some functionalities which are proposed by Ei but not recommended by EC, e.g., recording power interruption data that are longer than three minutes. Moreover, regarding the data to the customers, the Ei has specified that some data needs to be collected via the customer interface at least once per 10 seconds. The data can include, e.g., root mean square (rms) voltage, rms current, active and reactive power for both import and export for each phase and also the reading of the total active energy for both import and export. Similarly, there are some functionalities which were recommended by EC but not proposed by Ei, e.g., support for advanced tariff system and limitation of power flow to the customer.

This section summarized all the functionalities proposed in the considered reports. The mapping of functional requirements and guidelines proposed by different authorities showed that most the functionalities are common among the proposals. However, there are some functionalities that are proposed in one or more reports but not in all the reports. Table 3.7 shows the summary of all the functionalities indicated in the reports.

Table 3.7 Summary of all the functionalities indicated in the reports

Functionalities	**EC 11**	**EC 12**	**EC 16**	**SM CG**	**ER GEG**	**Ei**	**EC M16**
Functionalities for customers							
Readings from the meter to the customer	√	√	√	√	√	√	√
Capable of measuring phase voltages, phase currents, active and reactive power for both import/export on each phase						√	
A standardized customer interface		√		√	√	√	√
Frequent readings to achieve energy-savings	√	√			√	√	
Readings in a form easily understood by the customers	√	√	√		√		√
High consumption warning	√						
Support demand response signal	√	√			√	√	
Functionalities for grid & grid operators							
Remote reading of meter registers by meter operators	√	√	√	√	√	√	
Recording power interruption						√	
Remote reading of meter registers by third parties	√	√	√	√	√	√	√
Two-way communication between the meter and external networks for maintenance and control of the meter	√	√	√	√	√	√	
Monitoring of Power Quality	√						
Readings frequently enough to allow the information to be used for grid planning	√	√	√		√	√	
Alarm in case of exceptional energy consumption					√		
Alarms, which are sent unscheduled when, e.g., power failure occurs.			√	√	√		
Functionalities for commercial aspects of energy supply							
Supports advanced tariff systems	√	√	√	√	√	√	√
Supports energy supply by pre-payment and on credit	√		√	√			
Remote ON/OFF control of the supply	√	√	√	√	√	√	
Remote flow or power limitation	√	√	√	√	√		
Functionalities to allow distributed generation							
Provides Import / Export & Reactive Metering	√	√	√		√	√	√
Functionalities for security and privacy							
Provide secure data communications	√	√	√	√			√
Fraud prevention and detection e.g.,, e.g., Alarm when a fraud attempt occurs.	√	√	√				√

3.7 Identification of New Functionalities from the Proposals

The functionalities that are available in the present SMS, e.g., in Gothenburg, Sweden, are studied based on the available information from online documents. Functionalities that are not included yet or included but not in use or may be partially included in the present SMS are presented in Table 3.8. However, the functionalities for recording interruptions, and sending alarms when a power failure occurs, are not included in Table 3.8 since the function is already included in the SMs by many DSOs [1]. The EC discussed the functionality of logging interruptions as an example of PQ monitoring [30], although the functionality is not recommended by the EC in [31]. However, it is proposed as functionality by the Ei.

Table 3.8 Summary of functionalities that are not available to all yet

Functionalities	**EC 11**	**EC 12**	**EC 16**	**SM CG**	**ER GEG**	**Ei**	**EC M16**
Functionalities for customers							
Readings from the meter to the customer	√	√	√	√	√	√	√
Capable of measuring phase voltages, phase currents, active and reactive power for both import/export on each phase						√	
A standardized customer interface		√	√	√	√	√	√
Frequent readings to achieve energy-savings	√	√	√		√	√	
Readings in a form easily understood by the customers	√	√	√		√		√
High consumption warning	√						
Support demand response signal	√	√			√	√	
Functionalities for grid & grid operators							
Remote reading of meter registers by third parties	√	√	√	√	√	√	√
Monitoring of Power Quality	√						
Alarm in case of exceptional energy consumption					√		
Functionalities for commercial aspects of energy supply							
Supports advanced tariff systems	√	√	√	√	√	√	√
Supports energy supply by pre-payment and on credit	√		√	√			
Remote ON/OFF control of the supply	√	√	√	√	√	√	
Remote flow or power limitation	√	√	√	√	√		
Functionalities to allow distributed generation							
Provides Import / Export & Reactive Metering	√	√	√		√	√	√

3.8 Conclusions

Large-scale SM rollout is currently underway in different subcontinents, while new rollout will continue among later adaptors, e.g., in Europe and USA. The market for the SM remains strong and growing more than a decade after the early first generation models of the SM. The countries who adopted the SM in the last decade, e.g., Italy and Sweden, are making preparations for a second wave of rollouts since the technical lifespan of SMs and communications equipment is considered to be ten to fifteen years. These indicate that the global penetration of SM is expected to increase in the coming years.

To meet the future demands of digitalization in the energy industry, the second generation of SMs would include few new functionalities, if the functionalities are not already available in the first generation of SMs. One of the functionalities would be lower data resolution, i.e., 10 or 15-minutes data resolution, which is typically one-hour resolution. Moreover, it would include easy access to near real-time data for the customers, e.g., through a customer interface. Among other things, it would include two-way power flow measurement capability of the SM to support the integration of renewable micro-generation.

The functional requirements proposed by different authorities show that the customers would be able to get near real-time data from the SM through the customer interface of the future SMS. Among other things, the future SMS could also encourage more customers to have a renewable micro-generation, e.g., rooftop solar panels.

Based on the studied proposals from different authorities and the results from this thesis, functional requirements are proposed in Chapter 9 to facilitate the CLS with support from the LF models.

Chapter 4
Field Tests on Small-scale Smart Meters Switching

This chapter describes the field tests on multiple SMs switching in a real electrical distribution network. The tests have been performed to investigate the performance of the present smart metering system concerning multiple smart meters switching, and also to study the impact of smart meters' switching on the PQ. The chapter begins with an introduction to the investigated smart metering system, and test locations selection and PQ measurement methods. These are then followed by the test procedure, a review of the risk identification, and the test scenarios.

4.1 Investigated Smart Metering System and the Test Locations

The communication technologies associated with the investigated SMS are discussed in this section. Moreover, a summary is provided on the selected areas for the field tests.

4.1.1 Communication Technology and Functionalities

GENAB, a DSO in Western Sweden, has installed approximately 265,000 SMs with remote ON/OFF control switch in Gothenburg city of around 500,000 citizens and the SMs have been in operation since 2009 [55]. GENAB is one of the few companies in Sweden which have installed remote ON/OFF control switches in the SMs. A city-wide wireless meshed network with AMM system is created. The SM is integrated with a ZigBee system on chips and networking software is used to create a wireless meshed network so that the SMs can communicate with each other and route data reliably. The SMs communicate through ZigBee with approximately 8,000 MCUs or concentrators. The ZigBee network is built up as a self-configuring mesh. Only 20 repeaters had been installed because of the advantage of the mesh network [55]. GPRS or optical fiber is used to connect the MCUs to the CS. Figure 4.1 shows the communication structure used in the investigated SMS. The SMs not only send data to the CS but also receive a command from the CS via the MCUs.

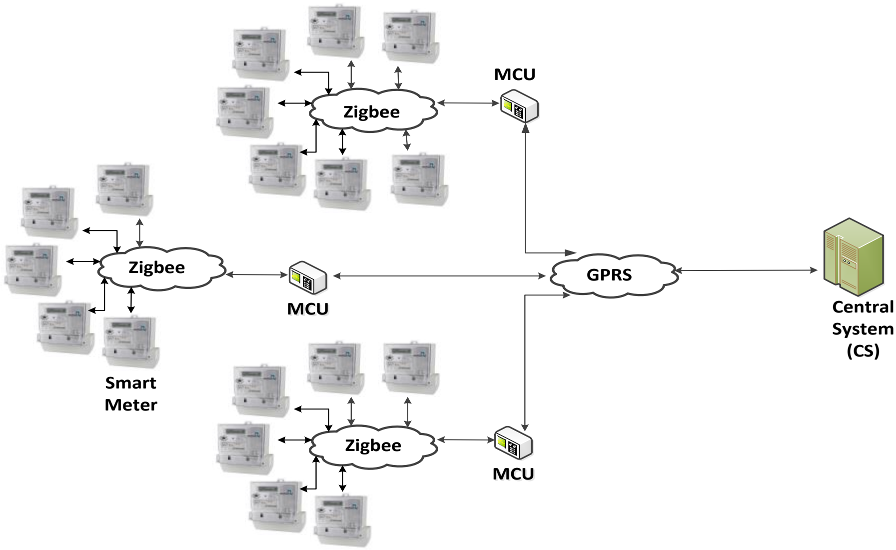

Figure 4.1: Two-way communication structure of GENAB's smart metering system

The investigated SMS provides several functionalities which are already in use, e.g., hourly readings, on-demand readings, i.e., at any time, remote connect/disconnect, power-failure alarm in real-time, monitoring of power usage and voltage levels, and also other advanced functionalities. Remote connect/disconnect was the first so-called AMM functionality put to use. Hourly readings are collected daily from the SMs. On-demand readings are mainly used in the customer contact center for discussions with customers. Moreover, real-time alarms for power failures are reported to the CS continuously. The SMS also supports GENAB with many other benefits, such as improved customer service and dialogue, improved monitoring of the low-voltage grid, improved quality of data for grid planning as well as opportunities for new customer services.

4.1.2 Area Selection for Multiple SMs Switching Tests

The aims of the field tests on small scale load shedding using the SMs are to investigate the followings:

- The impacts of multiple SMs' switching on the PQ at the end customers level and also at the LV substation level.
- The ability of the investigated SMS for doing multiple SMs' switching.
- The performance of the SMS during SMs' switching.

The tests were performed during the planned outage work of the DSO to avoid extra power outage of the customers. Adjusting the voltage level at the substation was the main purpose of planned outage during each test. Three areas have been selected for the tests within Gothenburg city where GENAB had planned to conduct PM work by interrupting the power supply to the customers.

4.2 Test Approach and Plan

The DSOs conduct regular PM work on the distribution grid. For PM activities, the DSOs make a planned outage plan for different areas. All customers that will be impacted by the PM work get information about expected downtime, at least one week before the PM work.

Test approach:

The DSOs generally start PM work by first disconnecting the power supply of the selected area from the LV substation. The power supply to the customers is usually switched back immediately after completion of the intended task. The timeline of multiple SMs' switching tests is shown in Figure 4.2.

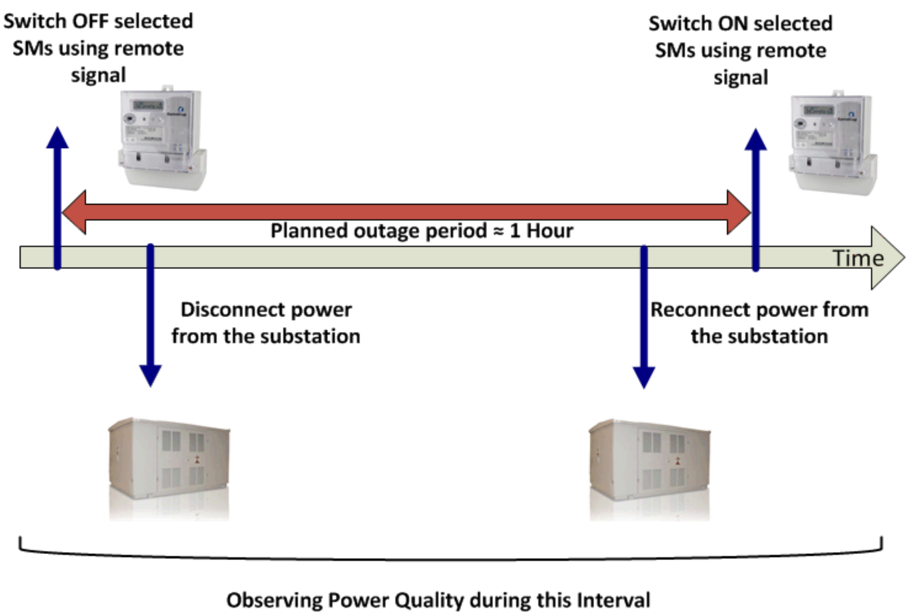

Figure 4.2: Timeline of multiple SMs' switching tests

A new additional approach was taken for disconnecting and reconnecting the customers as follows:

Step 1: The customers in the selected area were first remotely disconnected by switching their SMs. In the first two tests, all SMs in the test area were remotely disconnected, but in Test 3, almost half of the SMs were remotely disconnected while another half of the customers had a power supply until disconnection made from the substation.

Step 2: The power supply of the whole area was disconnected from the substation.

Step 3: The breaker of the substation was reconnected again after completing the PM work.

Step 4: Finally, the selected SMs were reconnected remotely.

Test plan:

An individual test plan was made for each test before conducting the field test. The test plans, e.g., steps of the tests, selecting customers for load shedding, etc., were made after having group discussions within GENAB with people having expertise on the power system, measurement system, and the SMS. The data of the PQ measurements were recorded from few minutes, e.g., 10 minutes before the beginning of the test period and it was done due to data storage capacity limitation of the Power Quality Meters (PQMs). Moreover, several people from GENAB were at the test locations during the tests with necessary preparations to handle any urgent situations, e.g., SM replacement if needed. The tests were performed by following few common steps as shown in Figure 4.3.

- First of all, the communication signal strengths of the selected area were checked for both the ZigBee network and also the GPRS network.
- The PQMs were made ready with full memory capability to store the data of all assigned parameters with a specified data interval for the test periods.
- The clocks of the PQMs were synchronized with the clock in the CS of GENAB to compare the time instants of measurements later in the analysis.
- Real-time measurements of voltages and currents were taken from the SMs remotely few minutes before sending a command to switch the SMs.
- After that, a command was sent to all the selected SMs via MCUs to disconnect the SMs.
- The disconnect command was sent from the CS when the planned outage period started.

- The customer service department of GENAB was immediately informed about the successful disconnections of the SMs.

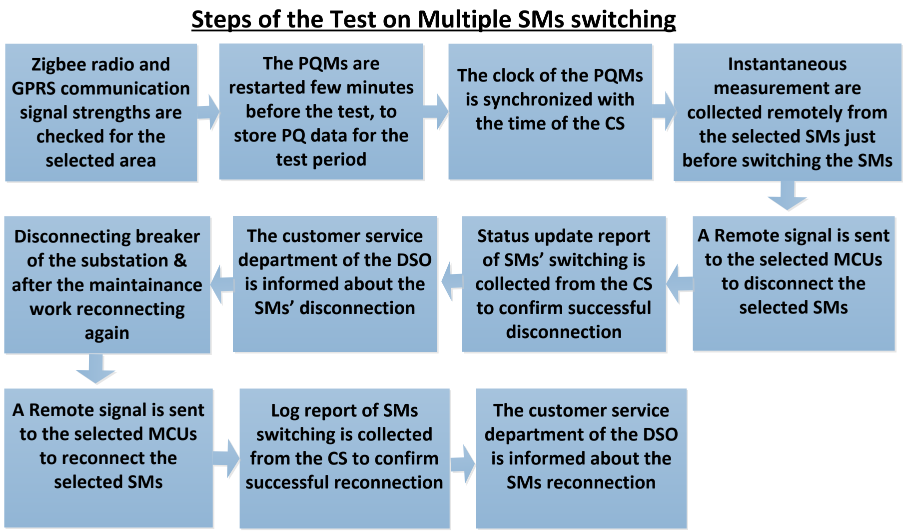

Figure 4.3: Block diagram of the test steps on multiple SMs' switching

- The power supply of the selected area was disconnected from the substation to use the tap-changer to step up or step down the voltage level. The power supply of the area was reconnected again from the substation after adjusting the voltage level. The voltage level was decreased by 6V, i.e., one step in the tap changer, during Test 1 and test2, and increased by 6V during Test 3.
- At this stage, real-time one-demand readings were collected again from the SMs to make sure that all the SMs are back into function state and contribute to the system availability.
- Finally, a new reconnect command signal was sent from CS to reconnect all the selected SMs.
- The customer service department of GENAB was again informed about the successful reconnections of the SMs.

The status update reports of SMs disconnection and reconnection and also the data from the PQMs were collected for PQ analysis. The status update report contains the SMs' real-time status update which the selected SMs typically send to the CS to confirm the execution of the SMs' switching command. The overall process of the SMs' switching was completed within the one hour planned outage period for the first two tests. However, switching during Test 3 took longer than the planned time due to communication problems and because of that few SMs were not reachable to reconnect.

4.3 Risk Identification of Multiple SMs' Switching Test

This thesis identified risks associated with field test before conducting the field tests on the real customers. Figure 4.4 shows the various aspects considered for the risk identification.

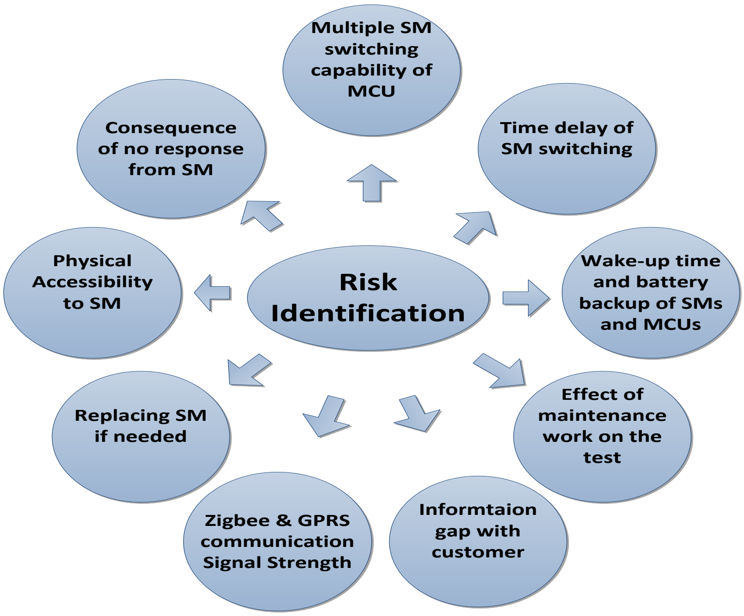

Figure 4.4: Risk identification of the test on multiple SMs' switching

Different time factors were taken into account for the risk identification, e.g., the time required to switch a SM remotely, battery backup time of the SM and the MCU, communication delay and the time necessary to replace a SM if something happens during the test.

Moreover, expected effects on PQ were discussed within the project group to select which parameters need to be recorded in the PQMs. Furthermore, the ability of the existing MCUs for multiple SMs' switching was checked. It is found that the investigated MCUs can execute multiple SMs' switching but switches one SM at a time.

The possible effects of planned outage work on the test result, e.g., the effect of substation switching on the test result are also investigated. The effect of the PM work on the test result was not expected since the DSO planned to adjust only the voltage level during the PM work.

Moreover, the location of each SM was checked to ensure easy physical accessibility to every SM if something happens. Because, any SM might need replacement with a new SM if there is no ZigBee communication. Possible risks associated with the weak signal of the ZigBee and GPRS communication network were also investigated.

Finally, various customer related issues were considered during the risk identification, e.g., conveying the message clearly to the customers about the test on PQ while installing the PQMs at their premises. Measures were also taken to avoid customer's confusion about the power interruption by updating the customer service department of the DSO time to time during the tests.

Moreover, possible consequences associated with the identified risks were also investigated to take necessary precautions for minimizing the consequences as shown in Table 4.1.

Table 4.1 Possible risks, associated consequences, and precautions for the tests

Possible Risks	Possible Consequences	Precaution
Zigbee signal strength may be weak during the test.	SM will not be reachable from CS during the test.	Zigbee signal strength needs to be checked before sending the remote signal to the SM.
GPRS signal strength may be weak during the test.	SM will not be reachable from CS during the test.	GPRS signal strength needs to be checked before sending the remote signal to the SM.
Problem in executing command by MCU.	SM will not be reachable from CS without changing the mother MCU ID for those SMs.	Other MCU can be used to send command to the SM. Need to have a decision about which MCU needs to be used.
MCU may lose power and battery backup may not be sufficient enough.	Consequence will not be serious because MCU will store its data in the memory before it dies.	No precaution is required as the MCU starts very quickly and data will be available fast. It will not hamper the test result.
SM may not respond to the remote signal of switching OFF the breaker.	The SM needs to be disconnected manually or will be disconnected when the substation power is switched OFF.	No precaution is required as the SM will not be required to switch ON using remote signal.
SM may not respond to remote signal of switching ON the breaker.	The SM needs to be replaced with a new SM which is already switched ON and the customer will not get power until the meter replaced with a new one.	New SM and persons from service department should be available during the test to replace the SM as soon as possible.
Duration of load shedding may be longer than scheduled due to any problem.	Customers may make phone calls to the customer service center and service people may misunderstand the situation if they are not well informed about the test.	Customer center and operation department needs to be well informed and updated about the test.
Customers may get annoyed if power is unavailable for longer than expected.	The customer may file a complaint to GEAB and may claim for compensation.	Steps need to be taken to ensure that customers are well informed about the situation and to ensure the power back as soon as possible.
Newly replaced SM may take long time (around two hours) to be available in the CS.	It will not be possible to send remote signal to the newly replaced SM until it is available in the CS. Information will come to the system when it is available and will have no effect on the test.	No precaution is required as the newly replaced SM is already switched ON from the beginning and the data will be stored in SM.
Customer may not be at home when it is necessary for GEAB to replace the SM due to any fault.	This will make delay to replace a non-functioning SM by the service person and the customer will be out of power during that period which is unexpected for the customer.	The SMs those are not accessible to the service person in absence of customer need to be excluded from remote switching.

Low Medium High   Low Medium High

Table 4.1 shows the level of risks and also the severity of the possible consequences. Different colors are used to indicate low, medium, and high probability of the risks and also different colors are used to indicate the low, medium and high level of consequences.

4.4 Field Tests

An overview of the three test scenarios and the time periods of the SMs' disconnections (SMsD) and also the time period of the SMs' reconnections (SMsR) are presented in this section. The number of customers affected by the tests has been increased from Test 1 to Test 3. Table 4.2 shows a summary of the three selected test areas:

Table 4.2: Summary of the three test areas

	Area Type	Voltage level	Trans-former ratings	No. of customers	Customers selected for SM switching test	No. of MCUs for the area
Test 1	Residential	10/0.4 kV	500 kVA	13	12	1
Test 2	Residential	10/0.4 kV	800 kVA	37	37	4
Test 3	Residential	10/0.4 kV	800 kVA	177	86	3

4.4.1 Test 1

Test 1 was carried out during the summer period when the load is typically low, and the temperature is high. In the test area, 13 residential customers were connected to a 500 kVA transformer as shown in Figure 4.5.

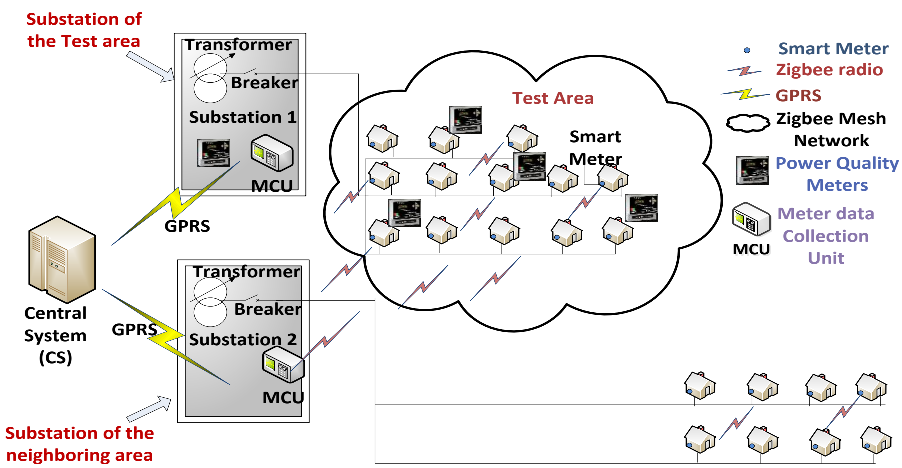

Figure 4.5: Test 1 Scenario of remote SM switching

The fuse ratings of the customers were between 16A to 35A except for one customer who had a fuse of 50A rating. All customers in the area had a three-phase connection which is a general standard in Sweden. One SM was not easily accessible in the absence of the customer, and thereby excluded from SMs' switching test as a precaution. Other 12 SMs in the area were switched during the test, and the PQ was monitored during the disconnection and the reconnection of the SMs. All selected 12 SMs of the area were communicating with one MCU which was located at a substation located near the test area named as Substation 2 as shown in Figure 4.5.

Timeline of Test 1:

The time periods for the SMsD and the SMsR and also the time instants of the substation switching are presented in Figure 4.6. As seen here, the disconnection process of 12 selected SMs required 96 seconds while the reconnection process of the SMs required 127 seconds which was expected for the SMs' switching.

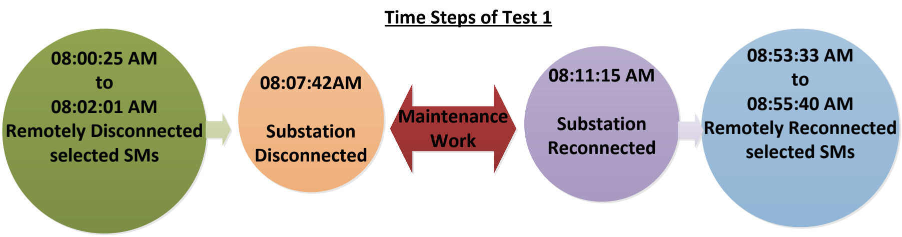

Figure 4.6: Time instants of SMs' switching during Test 1

4.4.2 Test 2

Test 2 was carried out in an area during the autumn period where 37 residential customers were connected to a transformer of 800 kVA rating. The fuse ratings of the customers were between 16A to 35A. All customers of this area also had a three-phase power supply. Four customers were selected to install the PQMs after studying their energy consumption history and fuse rating. Because, high current flow through the PQM gives better PQ measurement compared to low current flow through the PQM. The PQ was not measured at the remaining 33 customers by the PQMs. These 33 SMs and also the four selected SMs with the four PQMs were switched during the test. The PQ was monitored during the test period of the SMs' switching. The MCUs are usually located at the substations, but it can also be located in the cable box as shown in Figure 4.7. The figure also shows that four MCUs were communicating with the selected 37 SMs of the test area. Different MCU was communicating with different SMs and also the number of SMs under each MCU was different during the test.

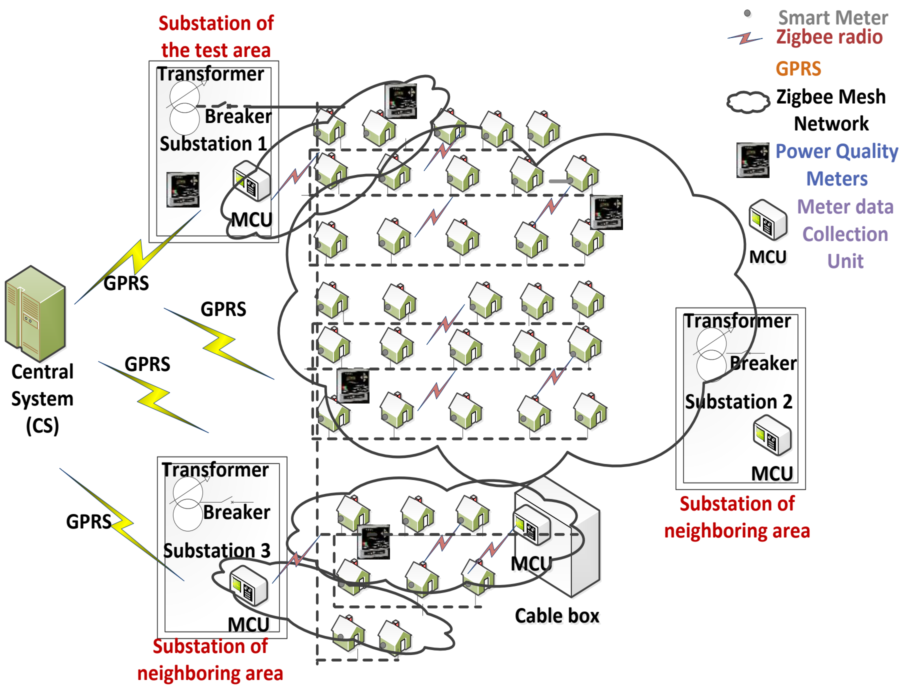

Figure 4.7: Test 2 Scenario of remote SM switching

Timeline of Test 2:

The timeline for Test 2 is presented in Figure 4.8. As seen here, the disconnection process of 37 selected SMs required 224 seconds while the reconnection process of the SMs required 225 seconds.

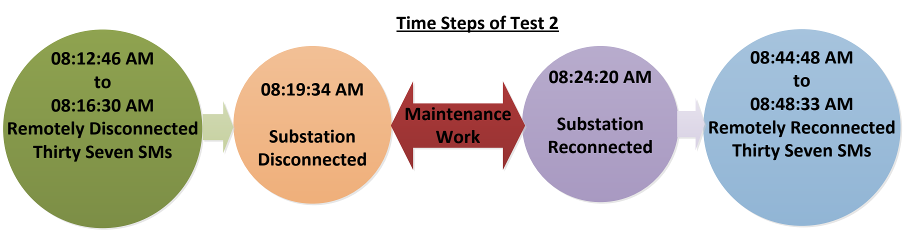

Figure 4.8: Time instants of SMs' switching during Test 2

4.4.3 Test 3

Test 3 was conducted in a residential area where 177 customers were connected to a transformer of 800 kVA rating. In the test area, some of the SMs were located outside which are easily accessible. However, some of the SMs were located inside the apartments which are not easily accessible in case of urgent replacement of SM. Total 88 customers were selected from the test area for the SMs' switching test after checking easy physical accessibly to the SMs. The reason was to make sure that the DSO can replace any faulted SMs if necessary. Because, some SMs might take a longer time to re-establish the communication network due to any problem in the communication network. All selected customers had three-phase connections except for one customer who had single phase connection. The fuse ratings of the customers were below 63A.

The plan of Test 3 was to switch two customers (one near and one far from the substation) out of four customers where PQMs were installed. The remaining two customers with PQMs (one near and one far from the substation) were not switched remotely to investigate the impact of multiple SMs' switching on these two customers. Moreover, one PQM was also installed at the substation of the selected area to record the PQ data.

The test was performed during the planned outage period. First, the selected SMs (86 customers out of 88 customers which were selected from total 177 customers) were tried to disconnect them remotely. The remaining 91 customers in the area had a power supply at this point in time. Then, the power supply of the selected area was completely interrupted from the substation of that area for the PM work and reconnected again after the work. The reason for planned PM work was to step up the voltage of the transformer by using the tap-changer. The breaker of the substation was reconnected after stepping up the voltage. At this stage, the excluded ninety-one customers immediately got power supply back. However, the 86 remotely switched customers did not have power supply back to their appliances at this point in time. Finally, the SMs of the selected customers were reconnected remotely to return the power supply to the customer's load. Figure 4.9 shows the scenario of Test 3.

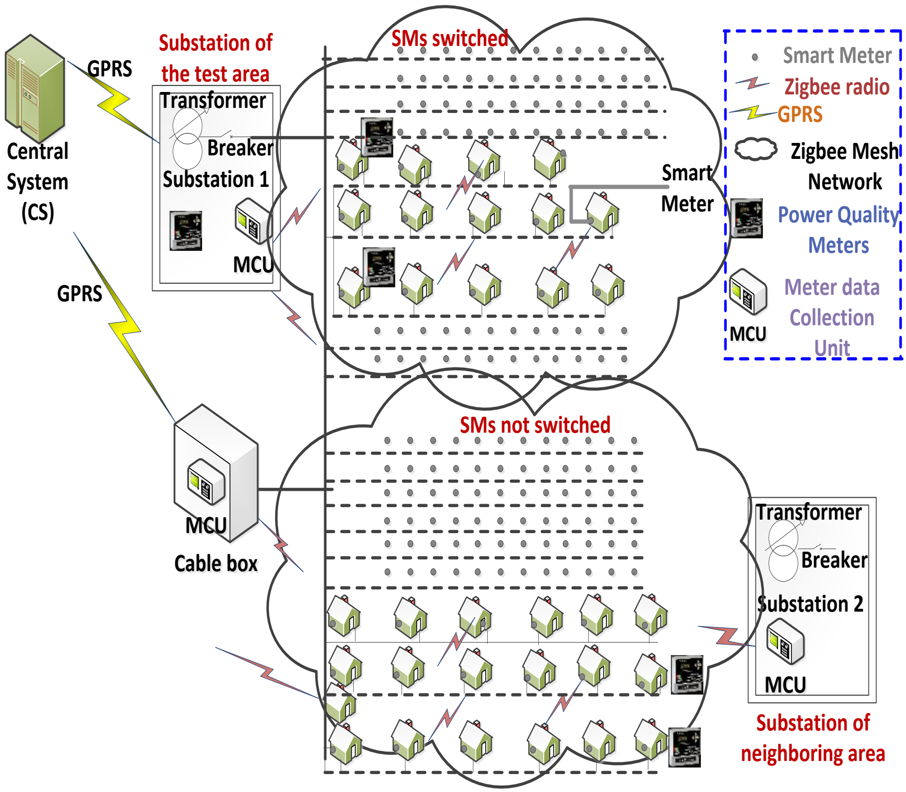

Figure 4.9: Test 3 Scenario of multiple SMs' switching

Timeline of Test 3:

The timeline for Test 3 are presented in Figure 4.10 (a). As seen here, the disconnection process of 84 selected SMs required three hundred thirty seconds. It is noted here that the status update report showed that 6 SMs were failed to disconnect, but after checking the on-demand reading two SMs were found with actual failure. On the other hand, the reconnection of the SMs required a longer time than the test period. Because, some of the SMs took a long time to join the ZigBee network. Several attempts were needed to reconnect most of the SMs. Each disconnect/reconnect command from the CS for a list of SMs is referred as an attempt. An MCU tries to switch the SMs on the list but one by one. However, after going through the complete list once, the MCU keeps trying the failed SMs according to the SMs' serial in the list until the SMs are successfully switched or the past command is replaced with a new command. Due to the error in the status update report, each failed SMs was checked by requesting on-demand readings, and the SMs that were actually connected were removed from the list. The new list of the actually failed SMs was then sent to the MCUs to try the SMs in the list, which is referred here as a next attempt. Figure 4.10 (b) shows the reconnection attempts and the success in reconnection at each attempt.

In the first attempt of reconnection, forty-six SMs were reconnected after trying the initial list of SMs for eighteen minutes and eight seconds. In the next attempt that lasted for eleven minutes and fifty seconds, five SMs were reconnected. During the third attempt which had a duration of twenty-eight minutes and thirty-eight seconds, the MCUs were not successful to connect any SM of the remaining 35 SMs. However, the fourth attempt was successful in connecting 25 SMs, and the duration of the attempt was twenty-seven minutes and sixteen seconds. Finally, during the last attempt of the test that lasted for next fifty-seven minutes, only one SM was successfully connected. Therefore, nine SMs could not be reconnected remotely which were reconnected manually by using the optical eye. The optical eye can be used to reconnect SM manually if the SM does not respond to the remote signal. However, this technique can be applied to a particular type of SM because other types of SMs do not support optical eye technique for manual reconnection of SM. If any SM, which does not support the optical eye solution, fails to respond to the remote switching signal, replacing the SM would be a solution for these types of SMs.

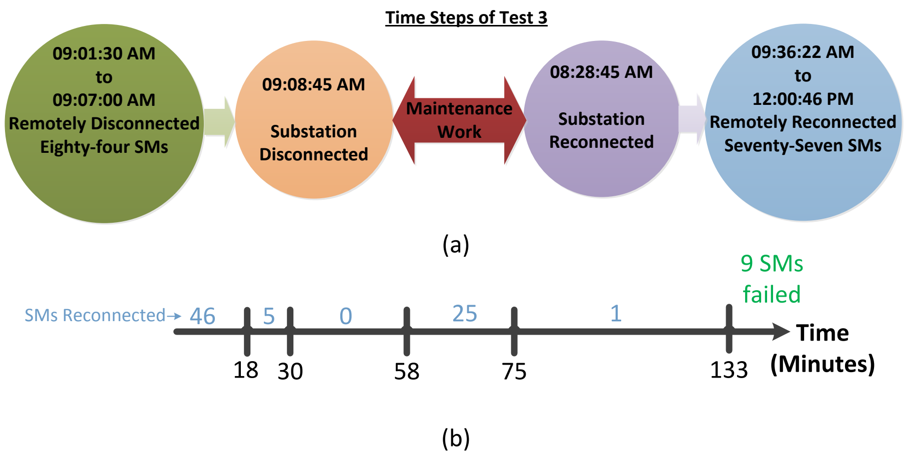

Figure 4.10: (a) Time instants of SMs' switching during Test 3, (b) SMs' Reconnection attempts showing success and failure

4.5 Status Update of the SMs' Switch during the Tests

A command with a list of selected SMs to be disconnected or reconnected was sent remotely from the CS to the selected MCUs during the tests. The MCUs were sending back the status update of the SMs' switching to the CS in real-time while executing the SMs' switching. The status update report showed the time instants when the MCUs started disconnecting or reconnecting SMs and also the confirmation of disconnections and reconnections of the SMs. Moreover, the report shows the time instants of switching attempt and failure feedback for the SMs that failed to follow the command. The status update reports were collected from the CS during each test to identify the time required to disconnect/reconnect each SM and also to analyze the test data. The MCUs start disconnecting or reconnecting SMs one by one and try all SMs once in the first attempt. In the second attempt, the MCUs try the failed SMs to switch again and again until it becomes successful to switch or until the switching command is canceled. The status update report also helps to identify after how many attempts the failed SMs successfully got connected.

4.6 Power Quality Standards for Monitoring and Measurement

The definition of the PQ is addressed in Appendix B, and the standards for monitoring and measurement of PQ are addressed in this section.

The standard defines what is meant by good PQ and what demands the customers can put on the DSOs. A number of different norms and regulations have been introduced to give guidance for defining good PQ. The international standards on PQ can be found in the International Electro-technical Commission (IEC) documents on Electro-Magnetic Compatibility (EMC). There is a common European standard (EN) for voltage quality, EN 50160 [68]. According to an investigation by Council of European Energy Regulators, many European countries have adopted or acknowledged all or some parts of the standard. Also, the IEEE has published a significant number of standard documents on PQ, e.g., IEEE 1159 [83] for monitoring PQ.

Several countries have written their own PQ documents, especially on harmonic distortion, e.g., Sweden has adopted their own PQ standard, EIFS 2013:1 (Swedish regulation) [84]. The new standard EIFS 2013:1, established by the Ei is somewhat similar to EN 50160 and an important step towards SG.

Monitoring of voltages and currents provides the DSOs information about the performance of their grid, both for the system as a whole and also for individual locations and customers [85]. Measuring PQ at the end customer is important but even more important is to measure in the grid to discover potential issues at an early stage. The change in the types of loads connected to the power system puts additional pressure on DSOs to monitor and record various aspects of grid performance.

There are some guidelines for PQ monitoring, e.g., CIGRE/CIRED JWG C4.112 [85]. The guideline provides information about measurement locations, processing, and presentation of measured data. Moreover, types of monitoring, e.g., continuous or short-term, monitoring location, monitored parameters, sampling rate, averaging window are mentioned in the guideline. There is also a measurement standard (IEC 61000-4-30) which divides the measurement instruments into different classes (A/B). The class A means that the measurement instrument can be used as a reference instrument [86] and the class B means that the readings from the measurement instrument would be useful but not necessarily comparable. In field tests, the PQMs of class A standard are used to measure the PQ in accordance with the applicable norms.

4.7 Power Quality Measurements during SMs' Switching

The SMs can be configured to measure a limited set of voltage quality indices, e.g., the supply voltage variations. However, PQMs were used in parallel with the SMs to measure different PQ parameters. The test results presented are from portable PQMs which were used for temporary and short-term PQ monitoring at the customer site and also at the substation. The PQMs stayed at the test location during the test period and captured a sample of measurements.

The PQ measurements carried out in accordance with Class A of IEC 61000-4-30 [86]. Flagging was used according to the standard to prevent double counting. The phase to neutral voltage was measured to evaluate the voltage quality. Typically, PQ indices such as flicker, transients and total harmonic distortion are not monitored at LV customer level. Hence, to increase the general knowledge on PQ indices at LV customer level, it was decided together with the DSO to monitor all the PQ indices that the chosen PQMs are capable of monitoring [87]. The monitored PQ indices which are given below, are also covered in the analysis of Chapter 5:

- Supply voltage variations;
- Flicker;
- Voltage unbalance, Ub (%);
- Total Harmonic Distortion (THD) (%);
- Voltage sag;
- Voltage swell;
- Transient

Among the monitored PQ indices, transient events were expected during the reconnection of the SMs. Moreover, small variation was expected in THD (%), flicker, and Ub (%), due to switching of the SMs. The PQMs measured and recorded the PQ data during the field tests. The data were recorded during the SMs' switching period and also during normal operating condition. The PQ data recorded during the SMs' switching period is compared with the PQ data recorded during normal operation in Chapter 5.

4.7.1 Selection of Power Quality Monitoring Locations

In LV grids, it is recommended to perform PQ measurements at the point of connection of a selection of customers [88]. In this thesis, during all the three tests, four LV customer locations were selected among all customers in the area.

In Test 1, the distances from the substation to the nearest and the farthest customers with PQMs were 98 meters and 447 meters respectively. In Test 2, the distances from the substation to the nearest and the farthest customers with PQMs were 77 meters and 209 meters respectively. For the tests, four customers were selected for PQMs installation based on their energy consumption history, but the customers' distances from the substation were not considered. The customers with higher energy consumptions were chosen to get best measurement results from the PQMs.

However, in Test 3, an additional criterion was added in the selection of measurement locations. The distance between the end customers and the LV substation was also considered during monitoring locations selection to see the variations of impact at different locations. Two measurement locations were selected which are the closest to the substation, while the other two locations were selected locations which are far from the substation. In Test 3, the distances from the substation to the nearest and the farthest customers with PQMs were 60 meters and 505 meters respectively.

The LV substations of the selected areas were also a PQ monitoring location during each test. The PQ was monitored to investigate the impact of multiple SMs' switching both at the end customers level as well as at the substation level. Table 4.3 shows the number of PQMs installed during each test and also the locations of the PQMs. Moreover, Table 4.3 shows if the SMs of the customers with PQMs were switched or not during the tests. As seen here, the SMs associated with the four PQMs were switched during the first two tests while two SMs among the four SMs associated with the PQMs were excluded from remote switching during Test 3.

Table 4.3: Number of PQMs installed during each test and locations of the PQMs

	No. of PQMs used in the Test	PQM at the LV substation	PQMs at LV customers level	Customers having PQMs switched	Customers having PQMs not switched
Test 1	5	1	4	4	0
Test 2	5	1	4	4	0
Test 3	5	1	4	2	2

4.7.2 Parameters Recorded during the Tests

Different parameters were measured and recorded in the PQMs, e.g., average voltages, currents, and powers. The maximum and minimum values of different parameters were also monitored in addition to parameter averages over a certain period, e.g., one minute. A short time window was used to monitor the PQ during the tests. In the first two tests, all parameters were recorded with one-sec interval except for the short-term flicker, and the U_b (%) values which were recorded with ten-minute and one-minute time window respectively (according to the standard settings of the PQMs for these parameters). However, for Test 3, one-sec time window was used for all parameters to collect as much data as possible.

Table 4.4 shows the time window used in PQMs for different parameters during the three tests.

Table 4.4: Time window used for different parameters measurement

Parameters	Time Window for Test 1	Time Window for Test 2	Time Window for Test 3
Average Phase to neutral voltages	1 sec	1 sec	1 sec
Average phase currents	1 sec	1 sec	1 sec
Average powers	1 sec	1 sec	1 sec
Average values of power factor	1 sec	1 sec	1 sec
Short-term flicker	10 min	10 min	1 sec
Voltage Unbalance U_b (%)	1 min	1 min	1 sec
Total Harmonic Distortions (THD) (%)	1 sec	1 sec	1 sec

4.7.3 Event Triggering

The PQMs can trigger events. Waveform data was triggered when the PQMs detected events such as voltage sag/swell, and transients.

Table 4.5: Threshold limits used to record the PQ events during the tests; ΔUstat: Change in steady state voltage level, and ΔUmax: Maximum voltage change

	Voltage Sag/swell (%)	**Slow voltage variation (%)**	**Rapid voltage change**	**Transients (%)**
Test 1	± 10	± 10	3% for ΔUstat and 5% for ΔUmax	± 50
Test 2	± 10	± 10	3% for ΔUstat and 5% for ΔUmax	± 25
Test 3	± 10	± 10	3% for ΔUstat and 5% for ΔUmax	± 25

The triggering limits used for PQ events were in accordance with Class A of IEC 61000-4-30. There is no standardized method for the detection of transients, neither transient overvoltage nor transient overcurrent [88]. A limit of ± 50% of the nominal value is used as a normal practice for triggering transient events in Sweden, and this limit was used during Test 1. However, during Test 2 and Test 3, a lower limit was used for triggering transient events, which was ± 25% of nominal value. The reason was to capture possible small transient effects during multiple SMs' switching. The limit used for triggering voltage sag/swell event was ± 10% of the nominal voltage. The limits used during the tests are shown in Table 4.5.

4.7.4 Data Sampling

The PQMs recorded average values of different parameters such as phase voltages and currents with one-sec data interval for the whole test period. Waveform data was recorded for the triggered PQ events, e.g., transient events at 12.8 kHz sampling frequency. The PQMs recorded waveform data for a number of cycles before and after the events were triggered, e.g., waveform data of ten cycles for a transient event; two cycles before and eight cycles after the event triggered.

4.7.5 Reference Voltage

The reference voltage used to relate the size of voltage-quality disturbances to, is in accordance with EN 50160 [68]. The reference voltage was equal to the nominal voltage, in this case, 230 V phase-to-neutral voltages.

4.8 Conclusions

The field tests aimed to investigate the impacts of SMs' switching on the PQ at LV level, and to identify the challenges in execution of large-scale SMs' switching by investigating the performance of the SMS. The plan for the field tests has been designed with planned outage work of the DSO to avoid extra power outage of the customers. The PQ monitoring locations have been selected based on 1) energy consumptions, since best measurement results can be achieved from the PQMs higher energy consumptions and 2) the distance between the end customers and the LV substation, to see the variations of impact at different locations.

The PQ indices such as supply voltage variations, flicker, voltage unbalance (%), total harmonic distortion (%), voltage sag/swell, and transient have been measured with the PQMs and analyzed.

The settings used to trigger PQ events are in some cases changed from the standard settings because of shorter observation period during the field tests, compared to the typical PQ observation period. Moreover, the intention was to record as much data as possible within the limit of available memory in the PQMs. However, the results and the analysis presented in Chapter 5 are carried out based on the standards.

The status update reports are important as they are used to get the number of SMs that are disconnected or reconnected, and the number of SMs that failed to do so. The identified errors in the status update report during the field tests are presented in Chapter 5. The functional requirements for getting reliable status update report during CLS is addressed in Chapter 9.

Chapter 5
Field Test Results and Analysis

This chapter presents the results of the field tests which were described in Chapter 4. The data received from the PQMs, and the switching data from the CS during the tests have been compiled and presented. The switching technique of the investigated smart metering system is also studied in this chapter. The data from the PQMs are used to study the voltage variations and PQ events for the period during the SMs switching. The results from PQ events are presented and discussed.

5.1 Field Test Results

Five PQMs recorded the average phase voltages and phase currents with one-sec time window during each of the three tests. The phase voltages and currents were measured at the customer level and also at the substation level. In this section, average voltage variations are shown by comparing the average voltage values of each phase before the SMs' switching over one minute with the average voltage values of each phase after the SMs' switching over one minute. The variation in voltage is shown both at the customer level and the substation level for the three tests. It is noted here that the voltage variations that can be caused by other events in the upstream grid were not monitored during the field tests, and thereby upstream effects are unknown. Moreover, information was not available on customers' home appliances.

5.1.1 Field Test Results on Voltage Variations

5.1.1.1 Voltage Variations during Test 1

The number of customers was 13 during Test 1, and the transformer rating of the test area was 500 kVA. The voltage variations at the substation level and also at the customer level were not significant since the number of customers in the area was very low, and hence their total load demand, compared to the capacity of their respective transformer. Therefore, small load variation was expected to create small voltage variation as the voltage drop over the transformers is lower due to low impedance of the transformer. Figure 5.1 shows the one line diagram of Test 1 area indicating PQMs' location.

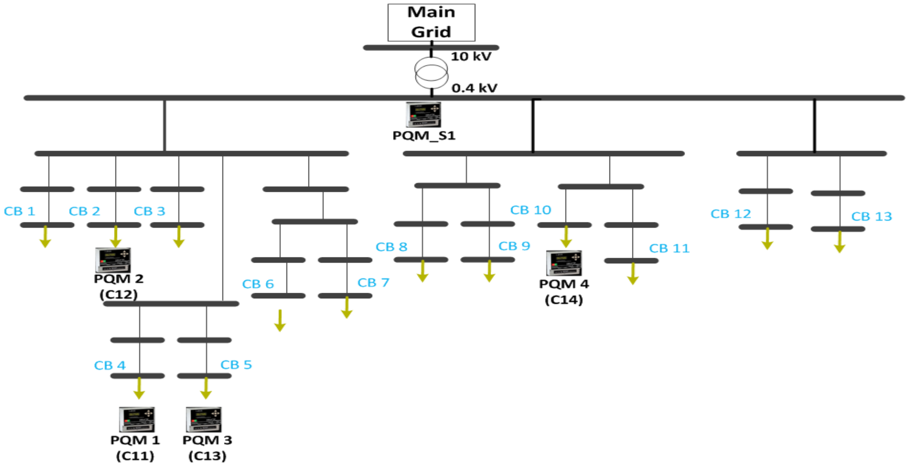

Figure 5.1 One line diagram showing the location of the PQMs during Test 1

The average changes in phase voltages during SMsD of Test 1 are shown in Table 5.1, which shows the phase voltages at the beginning of the SMsD period and also at the end of the SMsD period. Moreover, Table 5.1 shows the differences in voltage changes for SMsD. The locations of the PQMs at the four customer levels are denoted as C11, C12, C13 and C14, where the first digit after 'C' represents the test number and the second digit represents the customer number. Moreover, the location of the PQM at the substation of Test 1 is denoted as S1. The voltages at the three different phases are denoted as Ph1, Ph2, and Ph3.

Table 5.1: Change in phase voltages during SMsD of Test 1

PQM location	**Before SMsD**			**After SMsD**			**Change in voltage for SMsD**		
	Ph1 (V)	**Ph2 (V)**	**Ph3 (V)**	**Ph1 (V)**	**Ph2 (V)**	**Ph3 (V)**	**Ph1 (V)**	**Ph2 (V)**	**Ph3 (V)**
Sub-Station, S1	235.7	235.6	236.8	235.9	235.6	236.9	0.2	0	0.1
C11	235.6	235.3	236.8	236.1	235.8	237.0	0.5	0.5	0.2
C12	235.8	235.5	236.7	236.1	235.8	237.0	0.3	0.3	0.3
C13	234.9	234.5	236.2	236.0	235.7	236.9	1.1	1.2	0.7
C14	234.6	235.9	236.9	235.9	236.2	236.4	1.3	0.3	0.5

The voltage at the substation was reduced by operating the tap changer of the transformer according to the plan of PM work. For this reason, the voltage values are seen decreased before the SMsR. Table 5.2 shows the average change in phase voltages for SMsR, the phase voltages before and after the SMsR period, and also the changes in voltage for SMsR concerning Test 1. It can be seen here that phase 1 voltage of the customer C14 decreased by 8.6 V. From the measurements of phase currents, it is found that the customer was taking almost 30 A current on that phase after reconnection of the associated SM. The voltage increase that was observed on different phases are probably due to unbalance in the connected three-phase loads.

Table 5.2: Change in phase voltages during SMsR of Test 1

PQM location	Before SMsR			After SMsR			Change in voltage for SMsR		
	Ph1 (V)	Ph2 (V)	Ph3 (V)	Ph1 (V)	Ph2 (V)	Ph3 (V)	Ph1 (V)	Ph2 (V)	Ph3 (V)
Sub-Station, S1	230.5	230.3	231.4	230.1	230.1	231.1	-0.4	-0.2	-0.3
C11	230.8	230.6	231.6	229.5	228.9	230.9	-1.3	-1.7	-0.7
C12	230.8	230.5	231.6	228.1	230.6	229.5	-2.7	0.1	-2.1
C13	230.7	230.5	231.5	228.2	227.9	229.7	-2.5	-2.6	-1.8
C14	230.8	230.5	231.6	222.2	231.6	231.5	-8.6	1.1	-0.1

5.1.1.2 Voltage Variations during Test 2

The number of customers during Test 2 was higher than the number of customers during Test 1. However, the power rating of the transformer was also higher in Test 2 compared to the transformer of Test 1. For this reason, the expectation of significant voltage change was low during Test 2. The one line diagram of Test 2 is shown in Figure 5.2 indicating the PQMs' location.

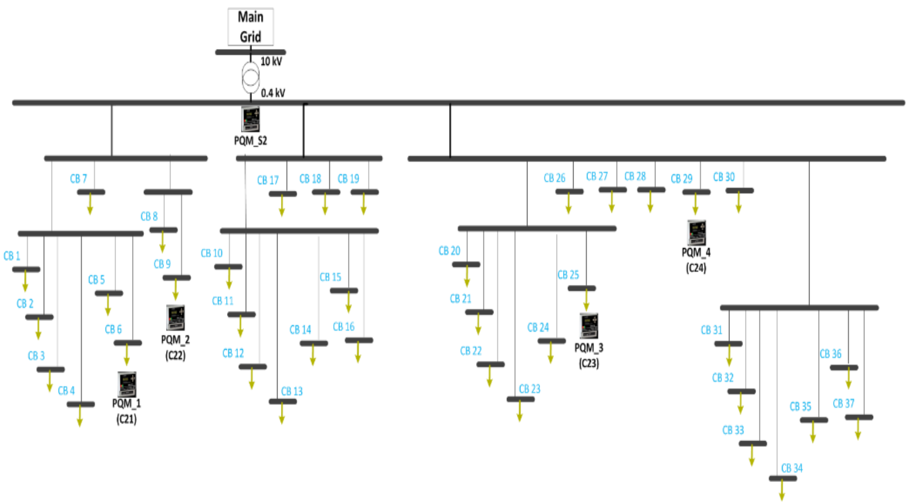

Figure 5.2 One line diagram showing the location of the PQMs during Test 2

The average changes in voltages for SMsD of Test 2 are shown in Table 5.3. The table shows the voltages at the beginning of SMsD and also the voltages at the end of SMsD. Moreover, the changes in voltages due to SMsD are shown in the table. The locations of the PQMs at the four customer levels are denoted at C21, C22, C23, and C24, where the first digit after 'C' represents the test number and the second digit represents the customer number. The location of the PQM at the substation of Test 2 is denoted as S2.

Table 5.3: Change in phase voltages during SMsD of Test 2

PQM location	**Before SMsD**			**After SMsD**			**Change in voltage for SMsD**		
	Ph1 (V)	**Ph2 (V)**	**Ph3 (V)**	**Ph1 (V)**	**Ph2 (V)**	**Ph3 (V)**	**Ph1 (V)**	**Ph2 (V)**	**Ph3 (V)**
Sub-Station, S2	238.8	238.4	240.3	239.5	239.3	240.8	0.7	0.9	0.5
C21	238.5	238.4	240.3	239.5	239.2	240.7	1.0	0.8	0.4
C22	238.3	240.1	238.7	239.4	240.9	239.6	1.1	0.8	0.9
C23	238.2	238.3	240.0	239.9	239.4	240.9	1.7	1.1	0.9
C24	239.3	237.9	240.0	239.6	239.4	240.8	0.3	1.5	0.8

The voltage at the substation was stepped down by using the tap changer of the transformer according to the plan of PM work. For this reason, the voltage values before the SMsR are seen generally decreased compared to the voltage values after the SMsD. The voltage increase at the substation level is due to upstream action in the network such as tap change operation in the MV transformer or the load variations.

Table 5.4 shows the average changes in phase voltages during SMsR, the phase voltages before and after the SMsR period, and also the changes in voltage for SMsR concerning Test 2. It can be seen here that the voltage at the substation increased after completing the SMsR. However, by analyzing the voltage data at the substation, it is found that the voltage had been fluctuating during the period of SMsR. The reason for the fluctuation could be that the voltage change at the upstream grid influenced the voltage at the substation of the test area. The fluctuation of the voltage at the substation was observed similarly in all three-phases throughout the SMsR period.

Moreover, the voltages at C24 are seen to be increased on phase 1 and phase 3. By analyzing the voltage data at C24 for the whole SMsR period, it was found that C24 was connected almost at the last moment of the SMsR period, and the voltages on each phase were decreased after the load reconnection. However, since the voltages at C24 fluctuated similarly as the voltage fluctuation of the substation, the voltages were found higher just before reconnection of the SM. For this reason, the change in the voltages at the C24 was found positive, i.e., increased although the voltage decreased due to the connection of loads. The voltage increase at the substation level is probably due to upstream action in the network such as tap change operation in the MV transformer.

Table 5.4: Change in phase voltages during SMsR of Test 2

PQM location	**Before SMsR**			**After SMsR**			**Change in voltage for SMsR**		
	Ph1 (V)	**Ph2 (V)**	**Ph3 (V)**	**Ph1 (V)**	**Ph2 (V)**	**Ph3 (V)**	**Ph1 (V)**	**Ph2 (V)**	**Ph3 (V)**
Sub-Station, S2	231.0	230.8	232.2	231.7	230.9	233.0	0.7	0.1	0.8
C21	231.3	230.7	232.3	230.1	229.3	231.3	-1.2	-1.4	-1.0
C22	231.0	232.5	231.4	229.5	231.4	230.1	-1.5	-1.1	-1.3
C23	231.5	230.9	232.4	230.5	230.0	231.2	-1.0	-0.9	-1.2
C24	231.0	230.7	232.1	232.0	230.4	232.6	1.0	-0.3	0.5

5.1.1.3 Voltage Variations during Test 3

The voltage variations for the SMs' switching during Test 3 are shown in Table 5.5. The number of customers in the area of Test 3 was much higher compared to the first two tests. Almost 50% of the SMs were switched during the test, and the number of switched customers is still much higher than the customers switched in the first two tests. The power rating of the transformer of this area was however 800 kVA, which is similar to the transformer rating of Test 2. Table 5.5 shows the phase voltages at the beginning of the SMsD period and also at the end of the SMsD period, and also the changes in voltages for the SMsD. It is seen that the phase voltages of the substation increased by around 1 V after the SMsD. By analyzing the voltage measurements during the SMsD period, it is seen that the voltages at the four customer level were varied following the variation of the substation voltage and also with the changes in the load current of the respective customer.

Moreover, at some customer level, the phase 3 voltages are seen to be higher than the phase 3 voltage of the substation. The reason is that as the load currents on phase 3 of the customers were very low, the capacitive effect of the underground cable was dominant which caused the increase in voltage on the other end of the underground cable. However, the voltage variations were found within the acceptable limit.

Table 5.5: Change in phase voltages during SMsD of Test 3

PQM location	Before SMsD			After SMsD			Change in voltage for SMsD		
	Ph1 (V)	Ph2 (V)	Ph3 (V)	Ph1 (V)	Ph2 (V)	Ph3 (V)	Ph1 (V)	Ph2 (V)	Ph3 (V)
Sub-Station, S3	235.0	233.3	233.7	235.8	234.5	234.4	0.8	1.2	0.7
C31	231.7	231.9	235.2	234.3	234.2	235.6	2.6	2.3	0.4
C32	228.3	229.3	232.2	232.2	232.8	234.6	3.9	3.5	2.4
C33	231.9	232.7	234.7	233.9	234.1	235.5	2	1.4	0.8
C34	228.5	226.5	234.1	231.4	233.1	234.3	2.9	6.6	0.2

Unlike the first two test, the voltage at the substation was not reduced by operating the tap changer during Test 3. Table 5.6 shows the changes in phase voltages during SMsR, the phase voltages before and after the SMsR period, and also the changes in voltage for SMsR concerning Test 3. The voltage values shown here are one-sec average value. It is seen here that the voltage variations at the four customer level and also at the substation level were also within the acceptable limit for the SMsR. The increase in phase voltages at some customer levels is probably due to unbalance in the connected three-phase loads.

Table 5.6: Change in phase voltages during SMsR of Test 3

PQM location	Before SMsR			After SMsR			Change in voltage for SMsR		
	Ph1 (V)	Ph2 (V)	Ph3 (V)	Ph1 (V)	Ph2 (V)	Ph3 (V)	Ph1 (V)	Ph2 (V)	Ph3 (V)
Sub-Station, S3	236.7	235.7	235.1	236.0	235.1	234.7	-0.7	-0.6	-0.4
C31	235.6	234.9	236.5	235.2	234.9	236.1	-0.4	0	-0.4
C32	232.3	234.0	234.8	232.4	233.4	235.0	0.1	-0.6	0.2
C33	234.9	234.6	236.4	234.3	234.1	236.6	-0.6	-0.5	0.2
C34	226.8	235.4	235.6	229.6	231.6	233.4	2.8	-3.8	-2.2

5.1.2 Power Quality Events Recorded during SMs' Switching

The PQMs recorded waveform data for the triggered PQ events. All PQ events recorded in the PQM were not related to the SMs' switching, e.g., long interrupt events were recorded when the substation was disconnected for PM work, and the events are marked with green color. The events that were recorded during the SMs' switching are marked with red color. Moreover, some events were recorded during the substation power disconnection in addition to long interrupt events and those events are marked with blue color. Table 5.7 shows numbers of different PQ events recorded during the test period of Test 1.

Table 5.7: PQ events recorded during Test 1

PQM location	Long Interrupt	Voltage Sag	Voltage Swell	Transient
Substation, S1	***1***	***0***	***0***	***0***
C11	***1***	***0***	***0***	***0***
C12	***1***	***0***	***0***	***0***
C13	***1***	***0***	***0***	***0***
C14	***1***	***0***	***0***	***0***

Table 5.8 shows numbers of PQ events recorded during the test period of Test 2. The PQMs recorded one long interrupt event which was recorded for the disconnection of the substation. It is seen here that one transient event were recorded at C22 and one transient event was recorded at C24 during the SMs' switching. However, four more transient events were recorded in these two PQMs which is not shown in the table where each PQM recorded two transient events which were later identified as measurement noise. Finally, two transient events were found as related to the SMs' switching, and the events were recorded during the reconnection of the two SMs which were located at customer site C22 and C24.

Table 5.8: PQ events recorded during Test 2

PQM location	Long Interrupt	Voltage Sag	Voltage Swell	Transient
Substation, S2	***1***	***0***	***0***	***0***
C21	***1***	***0***	***0***	***0***
C22	***1***	***0***	***0***	***1***
C23	***1***	***0***	***0***	***0***
C24	***1***	***0***	***0***	***1***

Table 5.9 shows numbers of PQ events recorded during the test period of Test 3. It is seen here that five transient events were recorded during the period of SMs' switching at three customers' location, the C32, C33, and C34. However, each of the five transient events at C32 and C34 was related to each other and caused by the reconnection of five SMs on the same feeder.

Table 5.9: PQ events recorded during Test 3

PQM location	Long Interrupt	Voltage Sag	Voltage Swell	Transient
Substation, S3	***1***	***0***	***0***	***0***
C31	***1***	***0***	***0***	***0***
C32	***1***	***0***	***0***	***5***
C33	***1***	***0***	***0***	***1+5***
C34	***1***	***0***	***0***	***1+5***

5.1.3 Error in the SMs' Status Update Reports

This section analyzed the status update reports of the SMs' disconnection and reconnection which were collected from the CS and identified the actual instants of each SM switching. Since the MCUs send the real-time status of SMs' switching to the CS, it is important that the report should be reliable. Otherwise, wrong information might lead to taking unnecessary actions by the DSO, e.g., replacing the SM, which is reported as failed to reconnect. Some errors are found in the status update report of each test, e.g., the wrong update about successful disconnect/connect of the SMs, showing different update for the same SM at different attempts of the same switching signal, multiple status updates for same SM.

During the tests, the reports were showing that some of the SMs were failed to disconnect or reconnect. However, after investigating each failed SM individually, some of the SMs were found to be actually disconnected or reconnected. Each failed SM was investigated by asking real-time data from the SMs. It was seen that some of the SMs were showing real-time voltages and currents, which indicates an error in the report. Moreover, it was observed in the status update report of Test 3 that some of the SMs which were successfully connected in the first attempt, are shown as failed in the second attempt of reconnection. The percentage of this type of error in the status update report of Test 3 was 27.6%.

Furthermore, in the status update report of Test 2 only it was observed that two SMs were tried to reconnect two times and reported as connected both times. It is seen that same SM received reconnect command from two MCUs. This kind of error could lead to confusion in the data analysis. Percentage of this kind of error in Test 2 was 5.4%. Moreover, it was observed that same SM received reconnect signals from two MCUs, and both MCUs reported failure to reconnect almost at the same time.

Table 5.10 shows a summary of the percentage of error in the status update reports considering only one type of error where a SM which was actually disconnected/connected but the report shows that SM was failed to disconnect/reconnect.

Table 5.10: Percentage of error found in the Status update report

	Test 1	**Test 2**	**Test 3**
Error (%) in SMs' status update during SMsD	8.3	18.9	2.3
Error (%) in SMs' status update during SMsR	8.3	21.6	4.7

By comparing the SMs' actual switching instants from the installed PQMs with the reported switching time in the status update report, it is found that the communication between the SM to the CS takes average 4 sec to report the switching of a SM. However, 11 sec delay was also observed in two reported cases which could also be a type of error in the status update report.

5.1.4 Comparison of SMs' Switching Time

The time required to disconnect and reconnect the SMs, are obtained from the status update reports. Most of the SMs were disconnected at first disconnection attempt, but few of them were disconnected after multiple attempts. Similarly, most of the SMs were reconnected at first reconnection attempt, but few of them were reconnected after multiple attempts. However, in Test 3 reconnection of the SMs were mostly unsuccessful in the first attempt. Because the SMs took time to get connected to the ZigBee network, and during that time period, the SMs were not available for communication.

Moreover, there is one kind of SM which requires two steps to connect the SM. First, it needs to activate the switch, and after that, it connects the switch in the next step. This specific type of SM takes more time to reconnect compared to the reconnection time required for other types of SMs. However, the disconnection process needs only one step for all types of SMs.

Table 5.11 shows the number of SMs which are reported as successfully disconnected and reconnected in the status update report. Since there were errors in the reported numbers, therefore, the actual number of SMs that were successfully disconnected and reconnected are also shown in the Table. Moreover, the average time required to disconnect and reconnect the SMs are shown. From the status update report, only the reported successful SMs' switching times are considered for SMs' average switching time calculation. It is noted here that all the selected SMs in the first two tests were switched successfully, i.e., the reported failures in switching were just errors in the status update report. However, in Test 3, two SMs and nine SMs were actually failed to disconnect and reconnect respectively. It is seen here during Test 3, on an average, the SMs took longer reconnection time. The reason is that out of 77 successfully reconnected SMs there were 57 SMs which requires two steps for reconnection. During the first two tests, there was only one SM of this kind.

Table 5.11: Time (sec) required for disconnecting and reconnecting SMs

	Number of disconnected SM		**Average time required for SM disconnection (sec)**	**Number of reconnected SM**		**Average Time required for SM reconnection (sec)**
	Reported	**Actual**		**Reported**	**Actual**	
Test 1	11	12	8.0	11	12	10.5
Test 2	30	37	7.2	29	37	07.2
Test 3	80	84	7.6	73	77	14.2

5.1.5 Switching Technique of the MCUs

In Test 1, there was only one MCU, and the MCU switched all SMs one by one. However, in Test 2 and Test 3, there were four and three MCUs respectively. During Test 2, the number of SMs under each of the four MCUs was 27 SMs, 5 SMs, 2 SMs and 3 SMs respectively. During Test 3, the number of SMs under each of three MCUs were found as 41 SMs, 44 SMs, and 1 SM respectively.

All MCUs start switching the selected SMs in parallel, after receiving switching command from the CS. Moreover, the MCUs send the confirmation report to the CS in parallel. It is also seen that the MCUs start executing the next switching almost instantly after completing the previous switching. Table 5.12 shows an example of parallel switching performance of multiple MCUs, and also individual MCU's performance on multiple SMs switching from Test 2. However, for MCU 1, switching executions are shown only the first ten SMs out of twenty-seven SMs.

Table 5.12: Switching techniques of MCUs from Test 2; where SM_S, SM_C, and T are starting, confirmation and required time (sec) of reconnections respectively.

Sl.	MCU 1			MCU 2		
	SM_S	**SM_C**	**T**	**SM_S**	**SM_C**	**T**
1	08:44:54.913	08:45:05.372	**10s**	08:44:56.319	08:45:06.858	**10s**
2	08:45:05.373	08:45:13.280	**8s**	08:45:06.858	08:45:17.299	**11s**
3	08:45:13.280	08:45:20.990	**7s**	08:45:17.299	08:45:25.286	**8s**
4	08:45:20.991	08:45:28.682	**8s**	08:45:25.286	08:45:33.097	**8s**
5	08:45:28.682	08:45:36.231	**8s**	08:45:33.097	08:45:40.905	**7s**
6	08:45:36.232	08:45:43.880	**7s**			
7	08:45:43.881	08:45:51.650	**8s**			
8	08:45:51.651	08:45:59.599	**8s**			
9	08:45:59.599	08:46:07.588	8s			
10	08:46:07.589	08:46:15.339	**8s**			
Sl.	**MCU 3**			**MCU 4**		
	SM_S	**SM_C**	**T**	**SM_S**	**SM_C**	**T**
1	08:44:56.124	08:45:03.984	**7s**	08:44:56.147	08:45:06.704	**10s**
2	08:45:03.985	08:45:11.804	**8s**	08:45:06.704	08:45:14.465	**8s**
3				08:45:14.465	08:45:22.226	**8s**

Figure 5.3 shows the time required to disconnect and reconnect 85 SMs under two MCUs during Test 3. The MCU1 and the MCU2 attempted to switch 41 SMs and 44 SMs respectively. As seen in (a), the MCU1 reported successful disconnection of 37 SMs and failure for 4 SMs, while the MCU2 reported successful disconnection of 42 SMs and failure for 2 SMs. Moreover, it is seen here that the required disconnection times of the SMs are quite equal.

As discussed in Section 4.4.3, reconnection of the 85 SMs required much longer time and several attempts with many tries. Among hundreds of tries, only successful reports of reconnections and last reports of failure are considered to get an overview of time required for the SMs' reconnection. As seen in (b), in general, successful reconnection of the SMs required two types of durations where one duration is almost double of the other. This is because there were SMs from two brands and the SMs from one of the brands require two steps, i.e., activate the switch and then reconnect. Therefore, to reconnect that type of SM requires almost double time. It is also seen that reconnection of a SM can take up to one minute. Moreover, it is seen in (b) that the MCU1 reported successful reconnection of 38 SMs and failure for 3 SMs, while the MCU2 reported successful reconnection of 34 SMs and failure for 10 SMs.

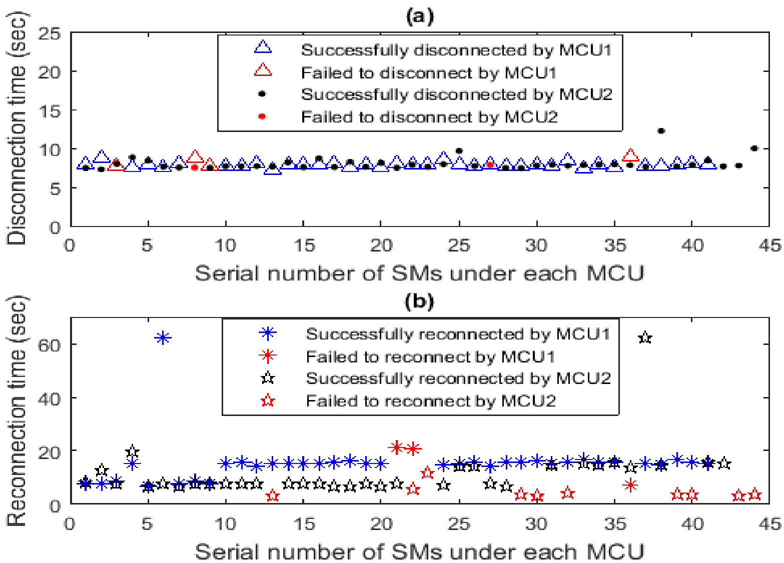

Figure 5.3 Time required to get status updates of the SMs' switch

5.2 Analysis of Field Test Results based on Power Quality Standards

5.2.1 Analysis of Voltage Quality

In the regulations, limits are given for the voltage-quality variations such as unbalance, THD and voltage fluctuations [88], [89].

5.2.1.1 Voltage Unbalance

The five PQMs that were used during each of the tests recorded the Ub (%) data. The Ub (%) data at the customer level were recorded in the four PQMs with ten-minute data interval during Test 1 and Test 2. However, the Ub (%) data at the substation level was recorded with one-minute data interval during the first two tests to get more data at the substation level. According to EN 50160, for the voltage quality to be considered sufficient, all ten-minute values of the Ub (%) are required to be less than 2% for all voltage levels. Table 5.13 shows the maximum values of Ub (%) during the switching period of the SMs and also during the normal power supply condition to compare the values of Ub (%). As seen here, all ten-minute values of the Ub (%) during the SMs' switching period both at the substation level and at the customer level are clearly below 2% for the first two tests.

Table 5.13: Maximum values of Ub (%) during the first two Tests

	Test 1					Test 2				
Location of PQMs	***C11***	***C12***	***C13***	***C14***	***S1***	***C21***	***C22***	***C23***	***C24***	***S2***
Max Ub% during Switching	0.38	0.35	0.37	0.59	0.34	0.43	0.43	0.44	0.43	0.44
Max Ub% in normal operating condition	0.38	0.37	0.38	0.54	0.38	0.43	0.44	0.46	0.43	0.41

During Test 3, the Ub (%) values were recorded in the five PQMs with one-sec data interval. Table 5.14 shows the maximum Ub (%) values at the selected customers and substation level during Test 3. As seen here, the Ub (%) values were less than 1% during the SMsD and the SMsR. By comparing the Ub (%) values during SMs' switching with the Ub (%) values during normal operating condition from all three tests, it can be said that the Ub (%) was not affected significantly by SMs' switching.

Table 5.14: Maximum values of Ub (%) during Test 3

	Test 3				
Location of PQMs	***C31***	***C32***	***C33***	***C34***	***S3***
Max Ub (%) during SMs' switching	0.70	0.61	0.56	0.83	0.47
Max Ub (%) in normal operating condition	0.77	0.67	0.60	0.86	0.53

Figure 5.4 combined the comparison between maximum values of Ub (%) during the SMs' switching period and the normal operating condition.

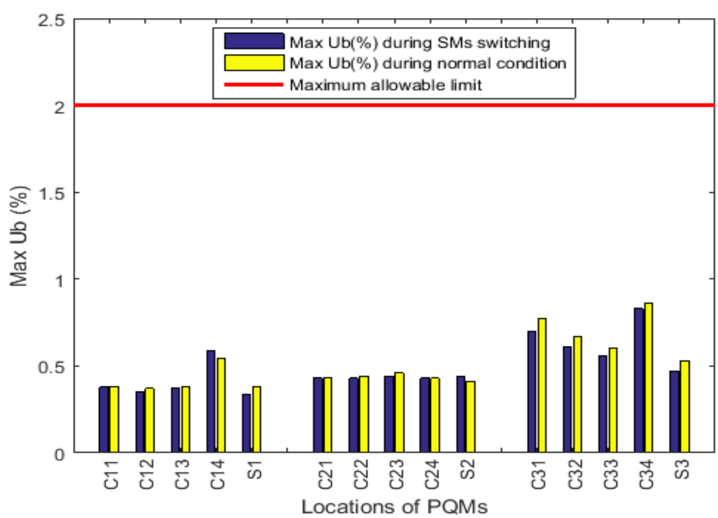

Figure 5.4: Maximum value of Ub (%) during the tests

5.2.1.2 Flicker

The EN 50160 gives an indication only for the Long-term Flicker severity (Plt) parameter which is evaluated over a period of two hours. According to EN 50160, 95% of the Plt values should be below 1.0 in one week measurement period. However, the standard IEC 61000-3-3 [90] requires the Pst index ≤ 1.0 and the Plt index ≤ 0.65. During the first two tests, the Short-term Flicker severity (Pst) values were evaluated over a ten minutes period of time which is the standard time period for Pst evaluation. Table 5.15 shows the maximum values of Pst among the Pst values recorded in the PQMs during the SMs' switching of the first two tests. Table 5.15 also shows the maximum values of Pst among the Pst values recorded in the PQMs during normal operation of the first two tests. As seen here, the maximum values of ten-minute Pst values are below 1.0 both at the customer level and also at the substation level. By comparing the Pst values during the SMs' switching with the Pst values during normal power supply period, it can be said that the flicker level did not get additional impact due to multiple SMs' switching.

Table 5.15: Maximum values of Pst during the first two tests

	Test 1					**Test 2**				
Location of PQMs	*C11*	*C12*	*C13*	*C14*	*S1*	*C21*	*C22*	*C23*	*C24*	*S2*
Max Pst during Switching	0.27	0.16	0.18	0.62	0.13	0.13	0.15	0.16	0.09	0.08
Max Pst in normal operating condition	0.16	0.14	0.16	0.36	0.16	0.10	0.10	0.19	0.10	0.10

The Pst values were recorded with one-sec evaluation period during Test 3 to monitor the frequency of voltage fluctuation due to the SMs' switching over a short period. Table 5.16 shows the maximum values among the one-sec Pst values recorded during the SMs' switching period and also during the normal operating condition of Test 3. The table also shows how many times one-sec Pst values reached values higher than 1.0 during the SMs' switching period and also during normal operating condition. As seen here, few one-sec Pst values with values higher than 1.0 were observed at some customer level during SMs' switching. However, the calculated ten-minute average values of Pst from the one-sec interval Pst values showed that all Pst values were below the limit of 1.0. However, the ten-min average Pst values are not shown in the table. Similarly, one-sec Pst values with values higher than 1.0 were also observed at some customer level and the substation level during the normal operating condition. The calculated ten-minute average values of Pst during normal operating condition also shows that all Pst values were below 1.0. By comparing the Pst values of Test 3 during the SMs' switching period and the normal operating condition, it can be said that flicker level was not impacted due to multiple SMs' switching.

Table 5.16: Maximum values of Pst during Test 3

	Test 3				
Location of PQMs	***C31***	***C32***	***C33***	***C34***	***S3***
Max Pst during Switching	1.11	1.74	0.74	3.87	0.37
Number of times one-sec Pst values reached higher than 1.0 during SMs' switching	6	4	0	7	0
Max Pst in operating condition	2.25	0.85	1.69	3.78	2.28
Number of times one-sec Pst values reached higher than 1.0 during normal operation	136	0	4	6	7

Figure 5.5 shows the comparison between maximum values of one-sec short-term severity, Pst during the SMs' switching period and the normal operating condition.

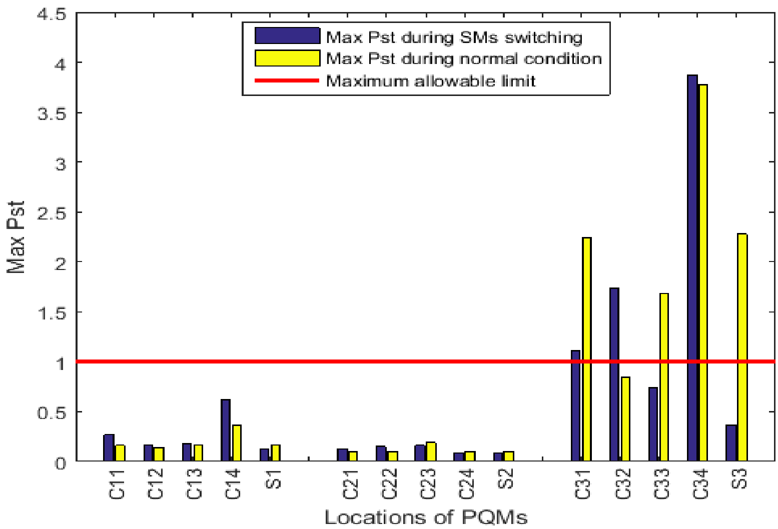

Figure 5.5: Maximum value of Flicker effect during the tests

5.2.1.3 Total Harmonics Distortion

The PQMs measured the individual harmonic contents and expressed the output with reference to the fundamental component of the voltage, indicating the THD factor in percent. The THD (%) values were recorded with one-sec data interval during the three tests. According to EN 50160, the THD values in percent should be less than 8% on a LV grid [91]. Figure 5.6 shows the comparison between maximum values of THD (%) during the SMs' switching period and the normal operating condition for the three tests.

As seen here, the THD (%) values were much lower than the limit of 8% during the SMs' switching period and also during the normal operating condition. By comparing the THD (%) values during the SMs' switching period with the THD (%) values during the normal operating condition, it can be said that the SMs' switching did not affect the THD (%) at LV level. The THD (%) was expected to be low since the field tests had been performed on working days and during office hours when most people are not at home. Hence, the loads that contribute to the THD (%), e.g., power electronic loads, were expected to be small in numbers during the tests.

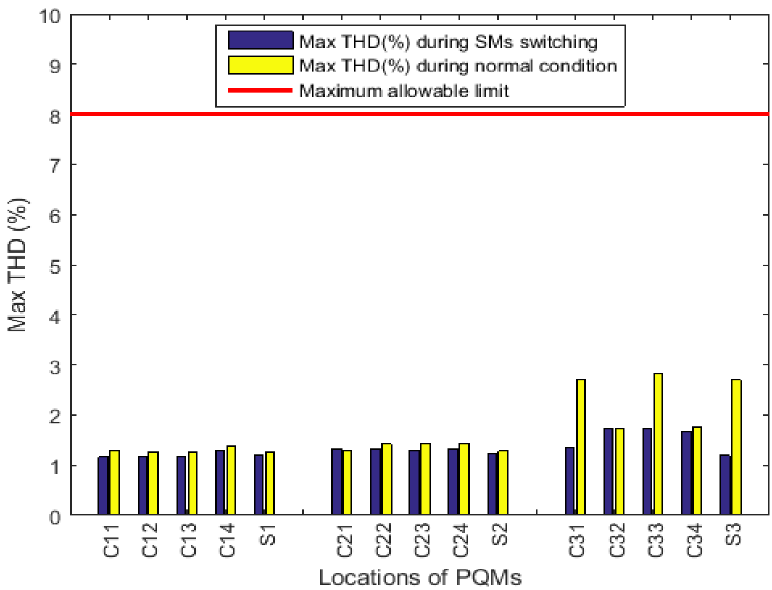

Figure 5.6: Maximum value of THD (%) during all tests

5.2.2 Analysis of Power Quality Events

The characteristic of an event can be determined by using triggering method when an event is detected [89],[92]. The voltage quality is regulated based on the defined limits for voltage quality events such as voltage sag, voltage swells, and rapid voltage changes [86]. The PQMs were configured to trigger the following events.

5.2.2.1 Voltage Sag

The voltage sag is defined as an event during which the one cycle rms voltage suddenly drops below 90% of the nominal voltage, followed by a return to a value higher than 90% of nominal value, in a time varying from 10 ms to 60 s [93]. The PQMs were set to trigger the voltage sag event based on the EN 50160 standard. The results from the three tests show that not a single voltage sag event was recorded in the PQMs during the multiple SMs' switching.

5.2.2.2 Voltage Swell

The voltage swell is defined as an event during which the one cycle rms voltage suddenly exceeds 110% of the nominal voltage, followed by a return to a value lower than 110% of nominal value, in a time varying from 10 ms to 60 s. The PQMs were set to trigger the voltage swell event based on the EN 50160 standard. The results from the three tests show that not a single voltage swell event was recorded in the PQMs during the multiple SMs' switching.

5.2.2.3 Rapid Voltage Changes

A rapid voltage change is defined as a change in rms voltage per sec faster than 5% of the reference voltage [94]. The test results show that there was no rapid voltage change event recorded in the PQMs during the SMs' switching.

5.2.2.4 Voltage Transients

Voltage transients are also referred as voltage surges or voltage spikes or voltage impulses. A voltage transient shows up as brief and fast-rising voltage excursions on the sine wave. They typically last for a few microseconds to several milliseconds. The spikes in voltage may vary in duration and magnitude.

a) <u>Voltage Transients due to Downstream Current Transients</u>

During Test 2, two transient events were recorded in two PQMs among the four PQMs. These two PQMs were installed at the two selected customers' site. The transient events were recorded at the moment of the reconnections of the SMs associated with these two PQMs.

Figure 5.7 shows a voltage transient event recorded at a customer level during Test 2. Figure 5.7 also shows the waveforms of the phase currents during the transient event. As seen here, the voltage and the current are in opposite phase which indicates that this a downstream event. The voltage transient event was recorded on phase 2 due to the current transient event on that phase while SM reconnection took place at the customer premise. The voltage on phase 2 suddenly dropped from 314 V to 237 V which represents a drop of 77 V, and the voltage dropped in 0.4 milliseconds. The voltage drop was 33.5% of the nominal voltage. The switching transient could be due to energizing of capacitor [95].

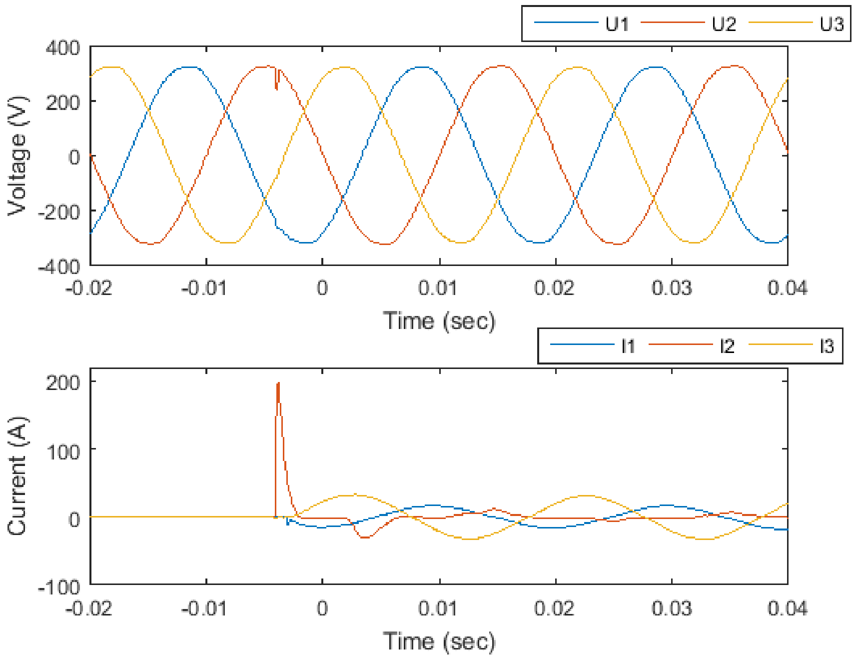

Figure 5.7: Currents and voltages of a voltage transient event recorded at customer C22 during Test 2

Figure 5.8 shows a voltage transient event recorded at another customer level during Test 2. Similar to the transient event shown in Figure 5.7, this transient event was also recorded at the moment of the reconnections of the SMs associated with the PQMs. However, as seen in Figure 5.8, the voltage transient event was recorded on phase 1 and phase 2 due to corresponding current transients on phase 1 and phase 2. The voltage on phase 1 suddenly dropped from 313 V to 253 V which represents a drop of 60 V, and the voltage dropped in 0.08 milliseconds. Again the phase 1 voltage increased from 253 V to 353 V in 0.32 milliseconds which represents a rise of 100 V. The voltage decrease was 26.1% of the nominal voltage, and voltage increase was 43.5% of the nominal voltage respectively. Moreover, the voltage on phase 2 dropped from 230 V to 122 V which is 47% of the nominal value taking around the same time as phase 1.

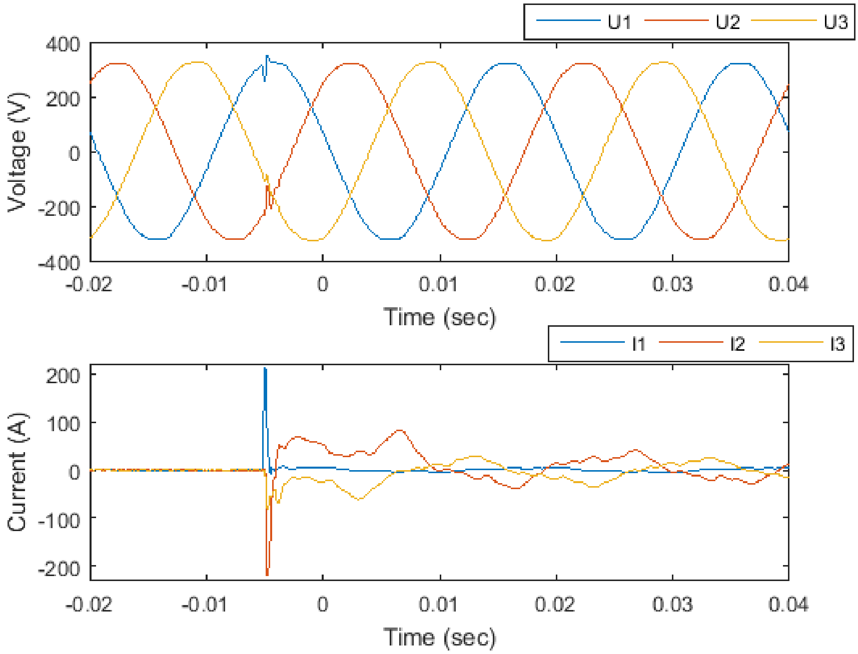

Figure 5.8: Currents and voltages of a voltage transient event recorded at customer C24 during Test 2

b) Voltage Transients due to Upstream Current Transients

The results from Test 3 show that fifteen transient events were recorded in the PQMs during the SMs' switching. The events were recorded at the customer level. The two SMs associated with two PQMs at customer C33 and C34 were not switched during Test 3 and these two PQMs recorded ten transient events during the SMs' switching. The test results also show that among the other two PQMs who's associated SMs were switched, the PQM that was located at C32 recorded five transient events. It is noted here that the SM associated with the PQM that was located at C31, could not be reconnected within the planned test period due to communication problem and hence the SM's reconnection moment could not be monitored.

The transient events recorded in Test 3 have similarities in their nature, e.g., all events were recorded at the moment of another SM reconnection during Test 3. By comparing the SMs' switching status update report and the moments of recorded transient events, it is seen that the transient events were recorded when SMs were reconnected. The reason could be that when a SM was reconnected, the current transient was created which caused a voltage transient and this voltage transient was propagated to the PQM which was monitoring the PQ at a customer site. Similarly, other transient events may also have been recorded when another SM was reconnected, and a load of that customer created current transient and thereby resulting voltage transients. The customers C32 and C34 are located far from the substation and close to each other. The test results from the PQMs of C32 and C34 show that when the PQM at C34 recorded a voltage transient event, the PQM at C32 also recorded a voltage transient event at an approximately same time.

Table 5.17 shows the time instants when the transient events were recorded in the PQMs of C32 and C34. One-sec time differences are seen here which could be because of time synchronization error in the clock of the PQMs.

Table 5.17: Time instants of transient events recorded at C32 and C34 during Test 3

PQ event (Voltage transient)	**C32 (Associated SM was reconnected at 09:44:31) Moment of Transient recorded**	**C34 (Associated SM was always ON) Moment of Transient recorded**	**Duration of the transient (duration of distortion due to transient) ms**	**Percentage of voltage change from the nominal value (%)**
Transient 1	09:36:27	09:36:26	0.23 (0.7)	60
Transient 2	09:38:53	09:38:52	0.08 (1.0)	55
Transient 3	09:41:36	09:41:35	0.16 (0.7)	44
Transient 4	09:41:43	09:41:42	0.08 (1.2)	34
Transient 5	09:49:14	09:49:13	0.16 (0.4)	38

The PQM located at the customer C33 also recorded five voltage transient events during the SMs' switching. The customer C33 was located close to the substation and was not on the same feeder as of C32 and C34. The PQM at C33 recorded voltage transients when some of the SMs on the same feeder were reconnected. The resultant voltage transients due to the current transients then propagated to the PQM at C33. Table 5.18 shows the time instants of voltage transients recorded in the PQM at C33 and also the time instants of the reconnection of the relevant SMs. As mentioned in Section 5.1.3, average 4 sec communication delay was observed between the actual switching and the confirmation of switching in the status update report, which can also take 11 sec as seen for transient 4. These time instants from the PQMs and the status update report clearly shows a relation between the recorded voltage transients at C33 and the reconnection of the SMs on the same feeder.

Table 5.18: The time instants of transient events recorded in PQM3 during Test 3.

PQ event (Voltage transient)	**C33 (Associated SM was always ON) Moment of Transient recorded**	**Time instants of relevant SM's reconnection from the status update report**	**Duration of the transient (duration of distortion due to transient) ms**	**Percentage of voltage change from the nominal value (%)**
Transient 1	09:43:47	09:43:50	0.08 (1.9)	31
Transient 2	09:45:03	09:45:07	0.16 (0.8)	43
Transient 3	09:45:18	09:45:21	0.16 (1.1)	55
Transient 4	09:45:34	09:45:45	0.16 (0.8)	35
Transient 5	09:48:38	09:48:42	0.16 (1.6)	54

As seen from Table 5.17 and Table 5.18, during Test 3 four voltage transients would have been recorded in the PQMs if the standard ± 50% transient limit was used as it is practiced for voltage transient measurement. The tables also show that the durations of the voltage transients were between 0.08 ms to 0.23 ms.

Figure 5.9 shows one of the two similar voltage transients recorded in the PQMs at C32 and C34 almost at the same time, and the current distortions created by the voltage distortion. The current distortions at C32 and C34 are not seen at exactly same instants in Figure 5.9 which could be because of the time delay between the PQMs' clocks. Loads of the associated customers were operating in normal mode before the transient event was recorded. As seen here, the change in current is in phase with the change in voltage. Hence, it can be said that the voltage transient is due to an upstream action, e.g., reconnection of another SM on the same feeder. The current transient is due to the voltage transient. The distortion in the currents indicates the presence of electronic loads [95]. According to [96], the transient events with short durations such as 0.08 ms to 0.23 ms and deviations of less than 60% of the nominal value will not damage the sensitive loads of the customers.

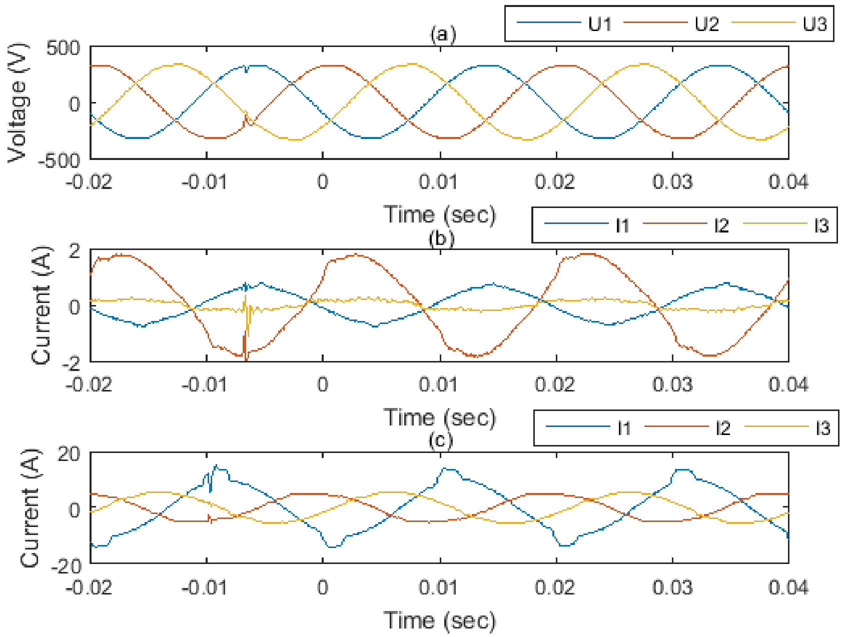

Figure 5.9: Currents and voltages of a voltage transient event during Test 3. (a) Voltage at C32 and C34, (b) Current at C32, (c) Current at C34

According to [95], it is expected to have such kind of transient events during reconnections of the SMs because many electronic equipment have a capacitor over the terminals on the grid side which is often part of the electromagnetic compatibility filter. These type of transient events occur mainly due to the energizing of the capacitor during supply voltage connection to the devices. The PQ analysis of the field tests' results indicates that during the CLS, loads of the excluded prioritized customers could experience either negligibly small impact on PQ or no impact due to the use of SMs.

5.3 Conclusions

The analysis of the voltage variations shows that nothing but expected voltage variations are recorded during the field tests. The recorded PQ events show that no PQ events other than 12 transient events are relevant to SMs' switching. All the transient events are related to the reconnections of the SMs which could be due to, e.g., switching of electronic equipment. Only four out of 12 transient events exceeded the standard limit of ± 50% but not above ± 60% which is shown in the literature as not harmful to the sensitive equipment of the customers due to its presence for the very short duration.

The types of errors in the status update report and the percentage of error in reporting failed SMs are presented in this chapter. The errors in status update report obtained from the small-scale load shedding test indicate the consequence it could have if large-scale CLS is planned to be performed using the existing SMS.

The problems with reconnecting some of the SMs after the tests are presented in the thesis which happened due to the problem in communication network and finally required field visits to restart 9 SMs that could not be reached after trying continuously for more than 2 hours. Moreover, 25 SMs were reconnected after almost 1 hour which is a very long delay than expectations. Hence, the importance of having extended battery support for SMs and the MCUs are identified which is included as a functional requirement for future SMS in Chapter 9.

Moreover, the switching procedure of MCUs has been learned from the field tests' results, which was not known before since the switching of the SMs has not been done before with respect to multiple SMs switching. This knowledge on MCUs has been used while developing the SMs' switching model which is described in Chapter 7.

Chapter 6
Load Forecasting Using Smart Meter Data

This chapter presents the load forecasting models based on Artificial Neural Network (ANN) method using smart meter data. Moreover, the chapter provides the results and analysis on load forecasting using hourly SM data and six-minute interval data. The ANN method is used for load forecasting at low aggregation level, e.g., at low voltage transformer level, and also at the individual customer level. The impact of different factors on the accuracy of the LF are presented and analyzed.

6.1 Acceptable Level of LF Accuracy to Support CLS

According to current practice of the CLS, all customers under selected MV substation(s) are supposed to lose power. The use of SMs could help to exclude prioritized customers from the CLS, and the LF with high accuracy could support the DSOs to fulfill the load shedding request by the TSO more precisely. The amount of load in the residential areas could be estimated by looking at the feeders' currents of the MV transformers supplying the areas. However, in case of CLS with SM, it would not be possible to know the amount of load from non-prioritized customers in different residential areas at the moment of load shedding. The ANN models can be developed for aggregated non-prioritized customers in different residential areas by aggregating their load at each LV substation level. The ANN models that are pre-trained with the historical SM data can then be used to get an idea about their load at the time of load shedding request. How many customers from how many LV substations need to be shed can be estimated by summing up the amount of loads available to shed from each LV substation until the demand of load shedding requested by the TSO is fulfilled. The LF can help the DSOs to gain a better knowledge on the condition of the distribution grid after load shedding. The required level of MAPE which can be accepted for the CLS has been discussed with an expert group in GENAB. It has been suggested that the maximum 5% to 10% MAPE at LAL is acceptable for the CLS application. The analysis on the MAPE of the aggregated LF models which are aimed to support the CLS will be presented in Chapter 8.

6.2 LF Model using Artificial Neural Network (ANN)

6.2.1 Artificial Neural Network

Supervised Learning is one of the classes of Machine Learning. Artificial Neural Network (ANN) is one of the methods of Supervised Learning. The ANNs act via an interconnected group of artificial neurons for processing information. The word network refers to the interconnections between the neurons in the different layers of each system. The main aim of using ANNs is to find a function to infer the mapping between the input and the output using a given set of data. One of the main advantages of ANNs is their ability to be used as an arbitrary function approximation mechanism that learns from observed data. A simple neuron of a typical ANN can be represented as shown in Figure 6.1.

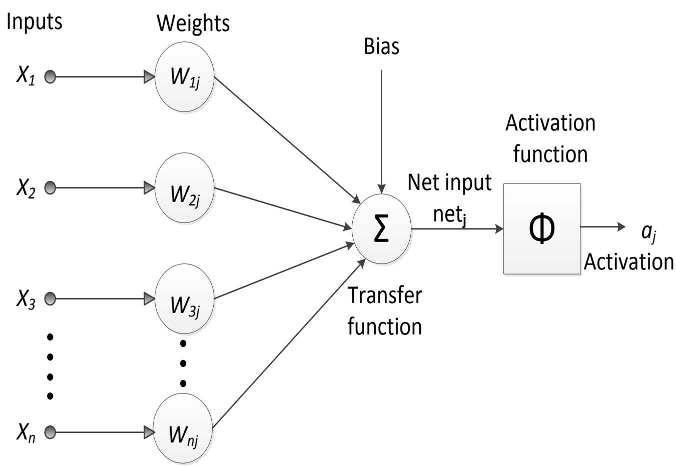

Figure 6.1: A simple neuron of a typical ANN

The number of inputs to the neuron is x_n and w_{ij} indicates the weights associated with each input. The transfer function sums up the weighted inputs and the bias. The activation function calculates the output of the neuron.

According to [97], ANN is widely used for various forecasting applications, since it can model nonlinearity. The LF models that are based on ANN are well summarized in [98]. The use of ANNs has been a widely studied technique for electric LF [10],[28]. The ANNs have been proven to be a reliable method for electricity LF in the past [99],[100],[101]. According to [102], the ANN models are used by many DSOs in practice. This thesis chose ANN method for load forecast since the method is shown to be effective and efficient to forecast load at LAL, which is discussed in Section 1.2.2. Moreover, the ANNs are data-driven methods and are therefore well-suited for use with SM data [103].

There has been no consensus on the most appropriate ANN model in LF applications. However, feed-forward Multi-Layer Perceptron (MLP) with one or more hidden layer has been widely used [104] with satisfactory results regarding accuracy [98],[105],[106].

A typical ANN consists of a number of inputs, outputs, and hidden intermediate layer(s), where an attempt to match the computed outputs with the corresponding outputs is performed [103]. A set of given inputs and corresponding outputs is initially given for training. Under supervised learning, the actual numerical weights assigned to input elements are determined by matching historical data, e.g., time and weather, to corresponding outputs, e.g., historical electric loads.

This supervised learning is also referred to as a training session. The training of the neurons using a set of training data involves a choice of the learning algorithm. The most popular learning algorithm in the ANN architecture for electric LF is the back-propagation algorithm [107].

6.2.2 The ANN Model for LF

The ANNs are used to provide nonlinear functions that can map historical load values and exogenous variables at a given time to a future value of the load. The ANN used for function fitting is a multilayer feedforward network with the tan-sigmoid activation function in the hidden layer and linear activation function in the output layer. One of the more popular activation functions for back-propagation ANN is the sigmoid [108]. According to [109], it has been found reasonable to use the tan-sigmoid function as activation function of hidden neurons. A linear activation function in the output layer is necessary so that the neuron does not generate a limited output interval. The activation functions calculate a layer's output from its net input. Initially, a two-layer feedforward network with ten neurons in the hidden layer is created to start the LF. The first layer is the hidden layer and the second layer is the output layer. One hidden layer is chosen for the ANN since one hidden layer is enough to approximate any continuous functions [98],[109]. There is one input vector to the network, which contains six or seven predictor elements. The number of neurons in the output layer is set to one. There is no standard solution for the question of how many neurons that should be used [109]. A workable number of hidden neurons to use in the hidden layer of the ANNs was selected by a trial and error procedure. A few alternative numbers were chosen for the hidden neurons, and the best number of neurons was achieved by running simulations for each alternative numbers. The number of neurons that gave the best performance was selected for the ANNs.

The multilayer feed-forward networks are then trained for the function approximation, i.e., non-linear regression. The batch training is applied to the ANNs, i.e., by applying all inputs in the dataset, e.g., training set, to the network before the weights are updated. The weights are then updated only once in each iteration. The Mean Square Error (MSE) between the network outputs and the target outputs is used as the performance function or cost function during the training of the ANNs. The gradient of the network performance is calculated with respect to the network weights using the back-propagation algorithm. The algorithm updates the network weights and biases in the direction in which the performance function decreases most rapidly. The training process stops when the magnitude of the gradient becomes less than 1e-5. In the ANN models, Levenberg-Marquardt Algorithm (LMA) is used as a back-propagation algorithm since the LMA can train an ANN 10–100 times faster than the usual back-propagation algorithms [107]. The LMA is a numerical solution for minimizing a cost function. It is a method that iteratively updates the weight and the bias values in the network until a local minimum is reached [97].

The ANNs have parameters ($IW_{j,i}$, LW_j, $b^{(1)}$, $b^{(2)}$), where the matrix input weights, $IW_{j,i}$ denotes the weights that connect the neuron j to the input i. The layer weight vector LW_j includes the weights associated with the connections between the output neuron and the neurons j in the hidden layer. The final parameters are the bias vectors, $b^{(1)}$ connected to the hidden layer and $b^{(2)}$ connected to the output layer. The overall model of an ANN used can be formulated as in (6.1):

$$y_{w,b}(p) = \sum_{j=1}^{10} LW_j \,\mathrm{tansig}\left(\sum_{i=1}^{7} IW_{j,i} p_i + b^{(1)}\right) + b^{(2)} \qquad (6.1)$$

Figure 6.2 shows the mapping between the input and the output of an ANN with ten neurons in the hidden layer.

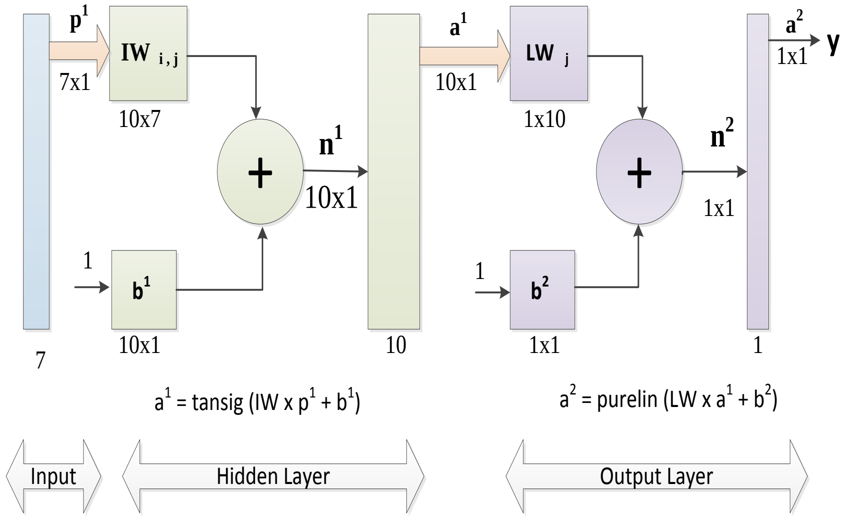

Figure 6.2: An overall model of an ANN with seven input predictors, one hidden layer and ten neurons in the hidden layer

6.2.3 Forecast Accuracy Evaluation

The performance of an ANN depends on the selection of the input predictor variables or predictors, the volume of historical data used for the training of the neurons and the number of trained neurons. The predictors can be classified as weather factors, time factors, and historical data. For LF, it is vital that these three factors are optimized to reduce forecasting errors [21].

The accuracy of the forecast model is often evaluated by calculating the so-called forecast error. This error is the difference between the actual or measured value and the predicted or forecasted value. There are many methods proposed and used for comparing the accuracy of time-series forecast methods. These accuracy evaluation methods give indications of how close forecasts or predictions are to the real outcome.

The MAPE is one of the most widely used measures of forecast accuracy, because of its advantages of scale-independency and interpretability. Moreover, the use of MAPE is recommended in most textbooks on forecasting, e.g., in [110],[111]. The MAPE is based on a percentage (or relative) of the mean errors. It is often used in a situation where one is more interested in relative error [21]. The MAPE is adopted in this thesis to measure the accuracy of the LF models for aggregated customers and also for individual customers. The MAPE is calculated as given in (6.2).

$$MAPE = \frac{100\%}{m} \sum_{n=1}^{m} \left| \frac{Actual\ load - Forecasted\ load}{Actual\ load} \right| \quad (6.2)$$

Where, m is the maximum number of data points.

6.2.4 Input Predictor Variables

The selection of input variables, which are also known as predictors, is vital for the accuracy of the models for LF. It is a known factor that the weather conditions influence the load. Researchers have shown that forecasted weather parameters are the most essential factors in short-term load forecasts [112]. Time factors also influence the load significantly. There are important differences in load between weekdays and weekends. Moreover, the load on different weekdays can also behave differently. For example, Mondays and Fridays being adjacent to weekends may have structurally different loads than Tuesday through Thursday. Furthermore, loads of holidays are more difficult to forecast than on non-holidays because of their relatively infrequent occurrence. In this thesis, the ANNs are developed using seven input predictor variables while keeping the number of neurons in the hidden layer and the volume of historical data constant. These variables have been selected studying common practices in the literatures and also by investigating the performance of ANNs using different predictor variables. Same predictor variables are used for LF at LAL level and at also individual level. The same predictor variables that are used as inputs to the ANNs can be categorized into three types of variables:

1) **Historical data**
   a) The previous day, same hour load (kWh)
   b) The previous week, same day, same hour load (kWh)
   c) The average load of the previous certain time period (kWh)
2) **Time factors**
   d) Hour of the day (1-24)
   e) Day of the week (1-7)
   f) Working day or not (1 or 0)
3) **Weather factor**
   g) Air temperature (^{o}C)

6.3 LF at Low Aggregation Level using ANN: A Case Study

6.3.1 Input Data: Hourly Energy Consumptions

The dataset used in this case study contains real hourly energy consumption records from the SMs of 717 residential customers in Gothenburg. The meters have been put in operation since 2009. The SM readings used have been recorded from 1st January 2014 to 31st December 2014. The residential customers have two types of heating system, electrical heating, and district heating. District heating refers to a system which is built for distributing heat generated in a centralized location for residential and commercial heating requirements such as space heating and water heating. There are three groups of customers in this dataset: 400 Apartments with district heating, i.e., no electric heating, 33 Villas with electric heating and 284 Villas with district heating. These 717 customers were connected to three LV substations and the number of the customers under the three substations named as A, B and C were 51, 296 and 370, respectively.

The dataset is divided into three subsets: a training set (70%), a validation set (15%) and a test set (15%) to use in the ANNs. The training set is used for computing the gradient and updating the network weights and biases. The error on the validation set is monitored during the training process. The network weights and biases are saved at the minimum of the validation set error. The mapping between the past load values and the exogenous variables is expected to generalize to the data of the test set that has not been used for designing the model. Before the input is applied to the network, the data is normalized so that all inputs fall in the range $[-1, 1]$.

6.3.2 LF for Aggregated Customers

The ECD in the dataset is recorded at hourly intervals. It gives 24 data points per day. Equation (6.3) shows the simple relation between the number of days (d), the number of time intervals in a day (t) and the number of data points (n) for each customer.

$$n = t * d \tag{6.3}$$

The time series vector that represents the hourly energy consumption of customer i for the n data points is shown in (6.4).

$$E_i = \{E_i^1, E_i^2, E_i^3, \ldots\ldots, E_i^n\} \tag{6.4}$$

where, E_i denotes the vector of all ECD for customer i.

The aggregated load of a certain number of customers at each time interval

t of a day is the sum of energy consumption of the aggregated customers at each particular time interval t, which is shown in (6.5).

$$E_{total}^{t} = \sum_{i=1}^{A} E_i^t \tag{6.5}$$

where, A is the number of aggregated customers.

The time series vector of total aggregated ECD can be represented as shown in (6.6).

$$E_{total,A} = \{E_{total,A}^{1}, E_{total,A}^{2}, \ldots, E_{total,A}^{n}\} \tag{6.6}$$

The purpose of the developed ANNs is to forecast aggregated ECD for a certain time horizon. In this thesis, the performance of the ANNs is tested by using the test dataset as described in Section 6.3.1. The forecast of energy consumption is a vector with m elements for the m time intervals and is shown in (6.7).

$$\hat{E}_{total,A} = \{\hat{E}_{total,A}^{1}, \hat{E}_{total,A}^{2}, \ldots, \hat{E}_{total,A}^{m}\} \tag{6.7}$$

where, m is the number of time intervals.

6.3.3 Case Study: Results and Discussions on Aggregated LF

In this section, the accuracies of the LF models for residential customers at LALs, are presented by showing the MAPE. The MAPE of the ANNs is shown here for hour-ahead LF using seven predictors, and also for hour-ahead LF using six predictors. Moreover, the factors influencing the MAPE are presented and discussed.

6.3.3.1 Influence of Input Predictors on MAPE

The influence of the input predictor variables on the accuracy of the ANN models has been investigated. Table 6.1 shows the influence of predictors on MAPE for different aggregations. The tick mark (**√**) shows when each of the seven input predictors, e.g., ‘Day of the week’ is considered as an input to the model. The input predictors have been reduced one by one using “educated” guesses, after checking the highest influence to lowest influence of the input predictors on MAPE.

It is found that hourly values have a powerful influence on the MAPE since most of the people have routine behaviours such as eating breakfast in the morning or turning off lights before going to work. It can be said that loads associated with routine actions are usually strongly correlated to time, such as seasons and working hours and the dominant factor in energy consumption compared to random actions such as turning on a light or making a cup of coffee.

The substations are denoted as S_A, S_B, and S_C, and the number of customers are denoted as suffix with C. The Villa customers and the Apartment customers are denoted with V and A respectively where the number of customers is denoted as suffix with V and A. The customers with electric heating and without electric heating are denoted by EH and NEH respectively.

Table 6.1 Influence of input predictors on MAPE

Input Predictors	**Considered as the input of ANN (√)**						
Hour	√	√	√	√	√	√	√
Temperature	√	√	√	√	√	√	
Day of week	√	√	√	√	√		
Working day	√	√	√	√			
Prev. day same hour load	√	√	√				
Prev. week same day same hour load	√	√					
Prev. hour's average load	√						
MAPE (%) for (SA-C51)	6.14	7.83	9.23	10.15	10.50	11.72	50.19
MAPE (%) for (SB-C296)	2.20	3.33	4.07	4.55	6.21	17.34	18.65
MAPE (%) for (SC-C370)	2.77	3.48	3.67	5.26	5.57	7.21	10.57
MAPE (%) for (V33-EH)	7.08	8.88	9.16	11.13	11.68	12.74	51.57
MAPE (%) for (V284-NEH)	2.06	2.79	3.70	4.17	5.85	14.79	16.79
MAPE (%) for (A400-NEH)	3.62	4.97	6.30	7.95	8.23	9.47	14.86
MAPE (%) for (C717)	1.84	2.68	3.05	4.11	5.21	12.56	15.94

From Table 6.1, it can be seen that the temperature value predictor also has a powerful correlation with the load since the use of some high power consuming appliances, e.g., electric heater, depends on the weather. Moreover, the day of the week predictor has a strong correlation with the load, e.g., daily load profiles of weekdays are different from the daily load profiles of the weekends. Other four predictors help to increase the accuracy of the models, i.e., decreasing the MAPE.

6.3.3.2 Impact of Changing the Number of Neurons in Hidden Layer of the ANNs

The performance of the ANNs has been investigated by changing the number of neurons using trial-and-error approach. The result from this analysis is used for selecting the number of neurons for the base case of the ANNs. Moreover, previous hour's average load is used as one of the input predictor variables of the ANNs, since it is observed that it can help to learn the variations in load demand better compared to using an average load over previous 2-hours to previous 24-hours as shown in Subsection 6.3.3.3.

The selection of the number of neurons in the hidden layer to be trained need to be carefully chosen. This is because too many neurons make the network overspecialized, leading to loss of generalizing capability and too little neurons makes it difficult for the network to learn the behaviour of the series. Moreover, more neurons require more computation, but they allow the network to solve more complicated problems. The number of neurons in each ANN models has been varied until the MAPE of the ANN models started increasing with the variation in the number of neurons. The impact of the number of neurons on the MAPE of the ANNs is shown in Figure 6.3. As can be seen, the ANNs with 40 to 50 neurons give better accuracy on forecasted load. The load demand is volatile and noisy at LAL and typically consists of many different types of behaviour, e.g., frequent but irregular peaks. Hence, around 40 neurons in the hidden layer could be useful for such complicated problems.

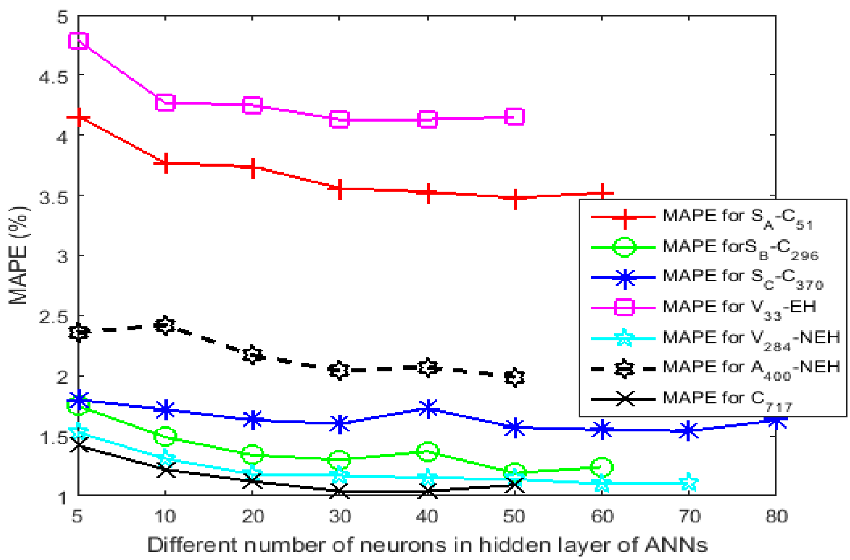

Figure 6.3: Impact of number of neurons in the hidden layer on the MAPE

6.3.3.3 Influence of Using Average Load over Previous Different Time Periods as a Predictor of ANNs

The influence of using average load over previous time periods as one of the input predictor variables on MAPE, which has been investigated by using the average load over the previous period of 1-hour, 2-hours, 3-hours and 4-hours and 24-hours as one of the input predictors in the ANNs, is shown in Figure 6.4. It can be seen that lowest MAPEs can be obtained if previous 1-

hour's average load is used as one of the input predictor variables since this predictor can help to capture the irregular variations in the load. It can help to forecast load more accurately for the coming hour or hours.

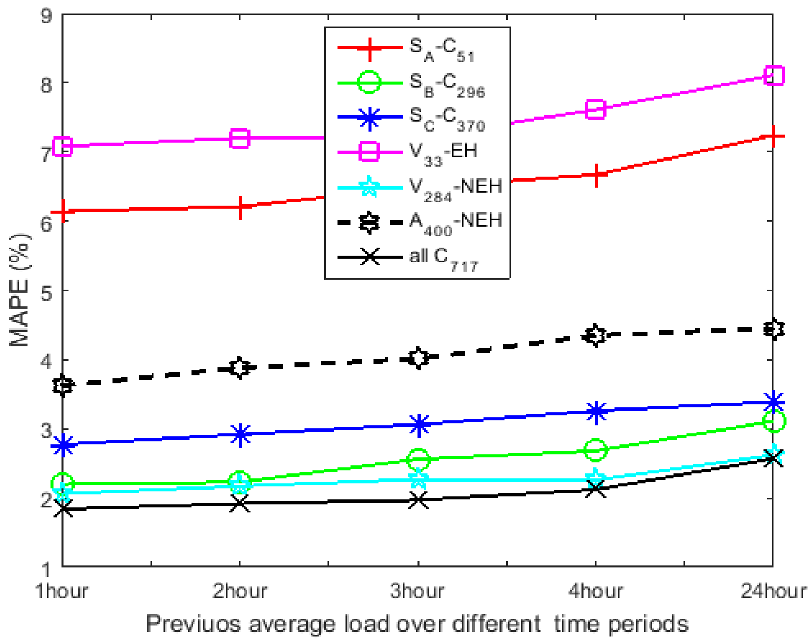

Figure 6.4: Influence of using average load over previous different time periods as a predictor of ANNs on the MAPE

6.3.3.4 Influence of Aggregation Level on MAPE

The number of aggregated customers influences the accuracy of LF. However, the influence decreases with the increase of a number of aggregated customers. The influence of aggregated customers has been investigated by creating the ANNs for different levels of aggregated customers. The numbers of aggregated customers are 2, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 120, 140, 160, 180, 200, 230 and 260 for customers with Villa. However, the number of Apartment customers is higher than Villa customers. Thus, in addition to the mentioned numbers of the aggregated customers, three more aggregation levels with 290, 320 and 350 customers are created for Apartment customers. It can be noted that the single customer with Apartment and also the single customer with Villa are chosen randomly and hence, the MAPE for a single customer could vary significantly depending on the type and habits of the selected customer.

Figure 6.5, shows the influence of the number of aggregated customers on the MAPE. It can be seen here that an aggregation level of around 50 customers gives significantly better MAPE for residential customers with Villa and the MAPE does not decrease significantly after that aggregation level. Similarly, for Apartment customers, an aggregation level of around 70 customers give significantly better MAPE, and the MAPE does not decrease significantly after that aggregation level. This is because, the fluctuations and the noise in the individual houses may cancel each other out while taking the sum.

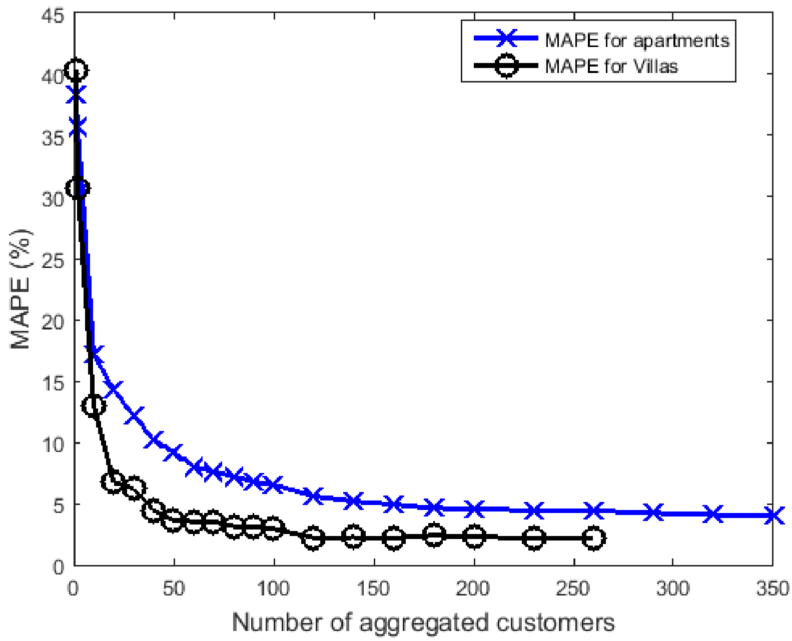

Figure 6.5: Influence of aggregation level on MAPE

6.3.3.5 Influence of Data Volume on MAPE

The data volume used in the base models of the three substations contains one-year data. This section investigated the performance of the ANNs by changing the volume of data used to train and validate the ANNs of the three substations. The volumes of the data are categorized as three months' data, six months' data, nine months' data and twelve months' data which are denoted by 3M, 6M, 9M, and 12M, respectively. Moreover, the three months data are divided into four parts, i.e., first quarter to fourth quarter. Similarly, six months data are divided into two parts, i.e., first six months and second six months. However, in case of nine months' data volume, the data for first nine months was arbitrarily selected. Figure 6.6, shows the influence of data volume on the MAPE of the ANNs which is discussed below:

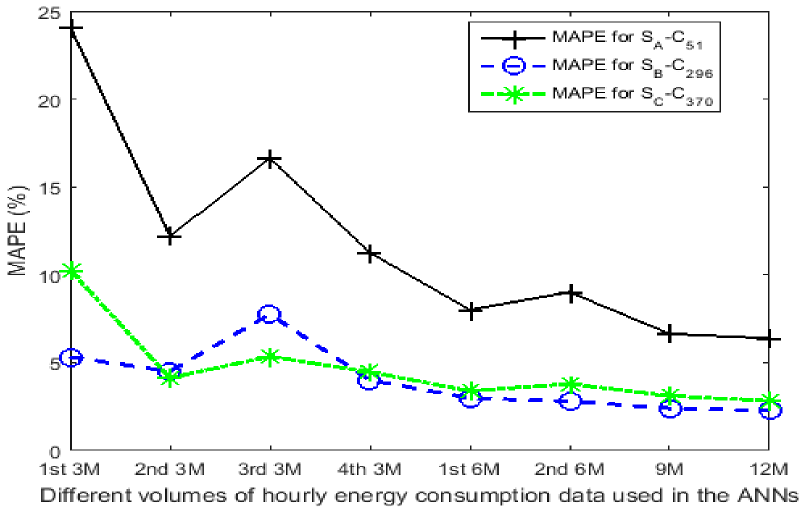

Figure 6.6: Influence of data volume on the MAPE

- **Twelve months' data:** The ANNs trained with twelve months' data provide less MAPE compared to the ANNs trained with three months', six months' and nine months' data. However, the ANNs trained with the nine months' data predict the load with the MAPE which is almost equal to the MAPE from the ANNs trained with twelve months' data. This is due to that the nine months' data covers most of the same general information covered by the yearly data, i.e., all days of a year, different holidays and also the temperature variations in different seasons of the year.
- **Six months' data:** The results have shown that the ANNs trained with either the first six months' data or second six months' data provide almost similar MAPE which could be because the dataset covers a nearly whole range of weather condition.
- **Three months' data**: The ANNs trained by the data of first and third quarter, provide higher MAPE. The reason is that the models are trained either with the data when the weather in Sweden is typically very cold or comparatively warm. Hence, the models predict the loads with a higher error for other weather conditions. However, the ANNs trained by the data of second and fourth quarter, provide comparatively less error in the prediction. Since the weather during these two quarters varies between

cold and warm, the models tend to learn the variations in the consumptions with the variation of temperature.

6.3.3.6 MAPE of the ANN Models

The accuracy of the forecasted load is evaluated by calculating the MAPE. Table 6.2 shows the values of the MAPE for different hour-ahead LF models with 7-input predictor variables. The previous hour's average load has been used as one of the 7-input predictor variables. The models have been retrained several times, and the number of neurons has been changed to get as lowest MAPE values as possible. The obtained lowest MAPE are presented in Table 6.2. The ANNs are developed using 40 neurons in the hidden layer.

Table 6.2 shows that the load prediction for the Villa customers can be more accurate than the load prediction for the Apartment customers with the similar heating system. The study on the daily load profiles of the investigated customers from the SM data reveals that Villa customers have regularity in daily load pattern compared to daily load patterns of the Apartment customers. This could be the reason for higher forecasting accuracies for Villa customers.

Table 6.2 MAPE for different hour-ahead LF models using seven predictors

ANN Models for aggregated loads	**MAPE (%)**
Substation A with 51 customers (S_A-C_{51})	6.09
Substation B with 296 customers (S_B-C_{296})	1.99
Substation C with 370 customers (S_C-C_{370})	2.79
33 Villas with electric heating (V_{33}-EH)	7.08
284 Villas without electric heating (V_{284}-NEH)	1.96
400 Apartments without electric heating (A_{400}-NEH)	3.75
Monitored all 717 customers (C_{717})	1.74

Moreover, the performance of the ANNs for hour-ahead LF has been investigated by using six input predictors, i.e., excluding the average load over a previous certain period from the input predictor variables. The MAPEs for different LF models with different aggregation levels are shown in Table 6.3. The models have been re-trained several times, and the number of neurons has been changed to get as lowest MAPE values as possible. Table 6.3 shows that the MAPE of a hour-ahead forecasted load using six predictors can be around 1% higher than the MAPE of hour-ahead forecasted load using seven predictors.

Table 6.3 MAPE for different hour-ahead LF models using six predictors

ANN Models for aggregated loads	MAPE (%)
Substation A with 51 customers (S_A-C_{51})	7.92
Substation B with 296 customers (S_B-C_{296})	2.94
Substation C with 370 customers (S_C-C_{370})	3.46
33 Villas with electric heating (V_{33}-EH)	8.79
284 Villas without electric heating (V_{284}-NEH)	2.66
400 Apartments without electric heating (A_{400}-NEH)	4.94
Monitored all 717 customers	2.42

6.4 LF for Individual Customer Using ANN: A Case Study

6.4.1 Input Data: 6-Minute to 1-Hour Interval

- **1-hour data:** The hourly dataset used for LF at the individual customer level contains real hourly energy consumption records from the SMs of residential customers as mentioned in Section 6.3.1. Data from two groups of residential customers are used to train the ANNs: 100 Apartments with district heating (i.e., without electric heating) and 100 Villas with district heating (i.e., without electric heating). Different types of residential customers are selected to investigate the impact of customer type on the accuracy of the forecast.
- **6-minute data:** The 6-min interval dataset used in this thesis is collected from 4 individual customers for four months. The customers are equipped with additional meters which are named here as Extra Meter (EM). The SMs are typically equipped with LEDs which flash and the rate of flashing is proportional to the amount of power passing through the meter. The frequency of pulses indicates the power demand and the number of pulses indicates energy metered. The EMs store 6-min intervals ECD by using pulses from the SMs. The 6-min intervals data of the four customers are converted to data with different granularity, i.e., 10-min, 12-min, 15-min, 30-min and 60-min intervals data to investigate the impact of data granularity on the accuracy of the load forecast. Each 6-min data is divided into six equal sections of one-minute data to get the contribution of each 6-min data over a specific time interval, e.g., 10-min or 15-min. The data with new intervals, e.g., 10-min intervals are created by considering the share of each 6-min data over a 10-min period. For example, first 6-min data and second 6-min data have three-fifth and two-fifth contributions respectively in creating the first 10-min interval data. The dataset is divided into three subsets as mentioned in Section 6.3.1.

6.4.2 Description of Study Cases

The influence of data granularity on the accuracy of LF at the individual customer level is presented and discussed in three categories as shown in Figure 6.7. There cases have been investigated and are described below:

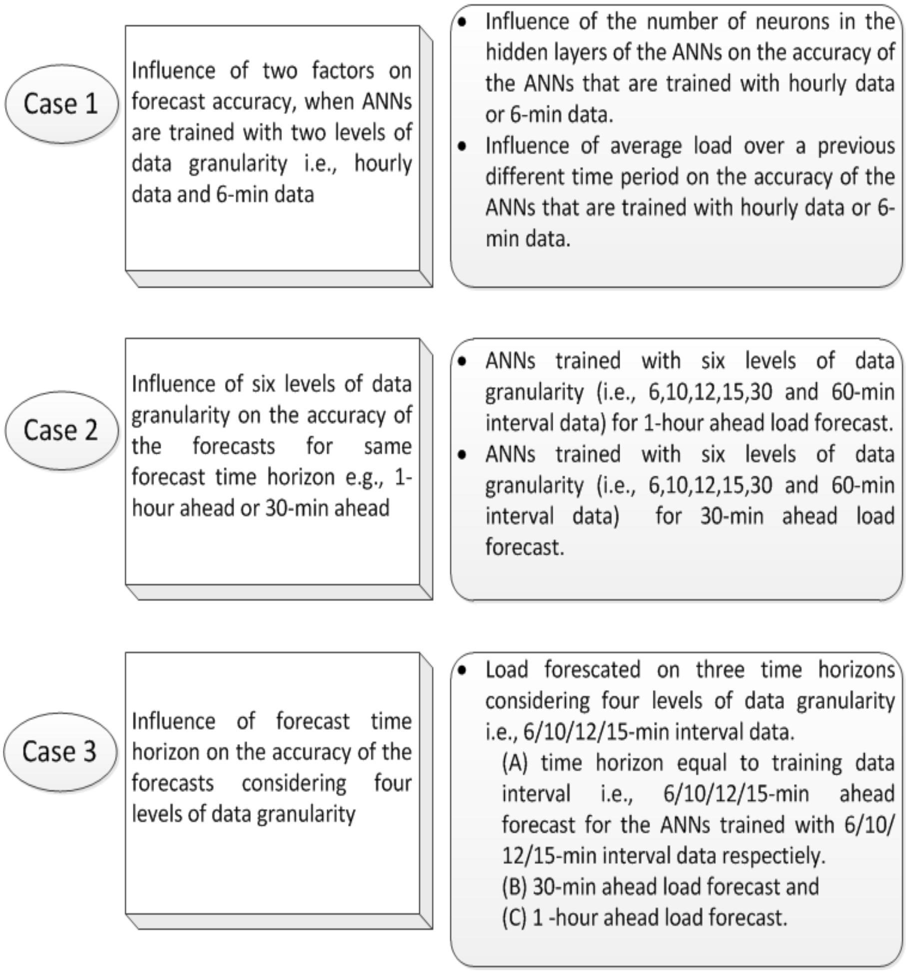

Figure 6.7: Cases under study

Case 1: The ANNs are trained with typical SM data with 1-hour interval and additionally collected low interval (6-min) data from EM. The difference in the influence of two factors, i.e., number of neurons and average load over previous different time period, on the accuracy are analyzed for the ANNs trained with two level data granularity, i.e., hourly data and 6-min data.

Case 2: The 6-min data is converted to higher granularity data for five new levels. The impact of data granularity on the accuracy of forecasts are analyzed considering same time horizon for load forecast, i.e., 30-min ahead or 1-hour-ahead. Six levels of data granularity, i.e., ECD with 6, 10, 12, 15, 30 and 60-min interval, are used to train the ANNs.

Case 3: The relation between forecast time horizon and data granularity is analyzed by forecasting load on three time horizons considering four levels of data granularity, i.e., 6, 10 12 and 15 min interval data. A) Load forecast on a time horizon equal to the time interval of the data used to train the ANNs, e.g., 6-min ahead load forecast by the ANNs trained with 6-min interval data. B) 30-min ahead load forecast and C) 60-min ahead load forecast.

Hourly ECD from the SMs to forecast load at the individual level has been used. 100 individual Villa customers and 100 individual Apartment customers were randomly chosen for the analysis on Case 1 mentioned above. Moreover, 6-min interval data from four individual customers are used for the analysis on Case 1. The data with different higher granularities, which are converted from 6-min data of the four individual customers, are used for the analysis of Case 2 and Case 3 mentioned above.

Among the four customers with EM, two customers are living in the Villas which are denoted as CUST 1 and CUST 2. The other two customers are living in the Apartments which are denoted as CUST 3 and CUST 4. The customer CUST 1 has a solar panel on the rooftop and also a Plug-in Electric Vehicle (PEV). Hence, the load profile of the customer CUST 1 is irregular where the customer CUST 2 has comparatively regular load profile.

6.4.3 Results and Discussions on Individual LF

6.4.3.1 Influence of Number of Neurons on Forecast Accuracies for ANNs Trained with Hourly SM Data and 6-min EM Data

The influence of a number of neurons in the hidden layer of the ANNs on the forecast accuracy is analyzed in this subsection by considering the ANNs trained by hourly SM data first and then the ANNs trained by 6-min interval EM data. The analysis was done on the selection of the number of neurons to be used in the hidden layer of the ANNs.

Hourly SM Data:

(a) For Apartment Customers

Too few neurons can lead to under-fitting, and too many neurons can contribute to over-fitting. More neurons require more computation but they allow the network to solve more complicated problems. The number of neurons in each ANN models is varied until the MAPE of the ANN models started increasing. The result from this analysis is used for selecting the number of neurons for the base case of the ANNs. The impact of the number of neurons on the MAPE of the ANNs is shown in Figure 6.8 for 100 individual customers living in Apartments.

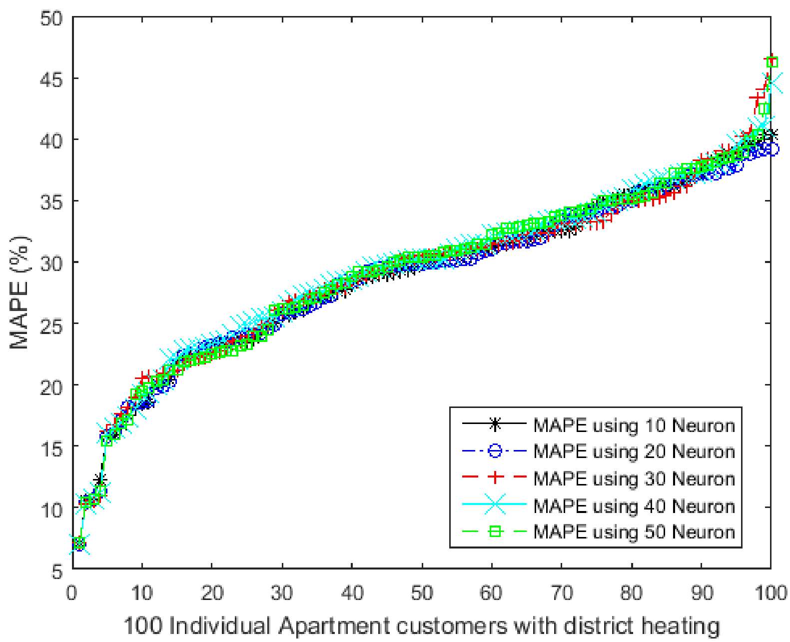

Figure 6.8: Impact of changing the number of neurons on MAPE for 100 individual customers in Apartments. (Note: MAPE values are presented in ascending order)

It can be seen from Figure 6.8 that the number of neurons may not influence the MAPE significantly. However, it is seen here that 20 neurons in the hidden layer give a better result for the cases when MAPE is higher. Since more neurons require higher computational time hence 20 neurons in the hidden layer could be recommended for LF at the individual customer level.

(b) For Villa Customers

The impact of the number of neurons on the MAPE of the ANNs for 100 individual customers living in Villas is shown in Figure 6.9. As can be seen, the variation of MAPE for the Villa customers is much lower than the variation of MAPE for Apartment customers. Moreover, it is seen here that around 40 to 50 neurons in the hidden layer can help to decrease the MAPE by 1% to 4% for the ANNs where the MAPE is higher than 10%. However, as can be seen in Figure 6.9, the MAPE does not decrease significantly for most of the customers when compared the MAPE values for 20 neurons and 50 neurons. Hence, 20 neurons in the hidden layer could be recommended for LF at the individual customer level for Villa customers as well.

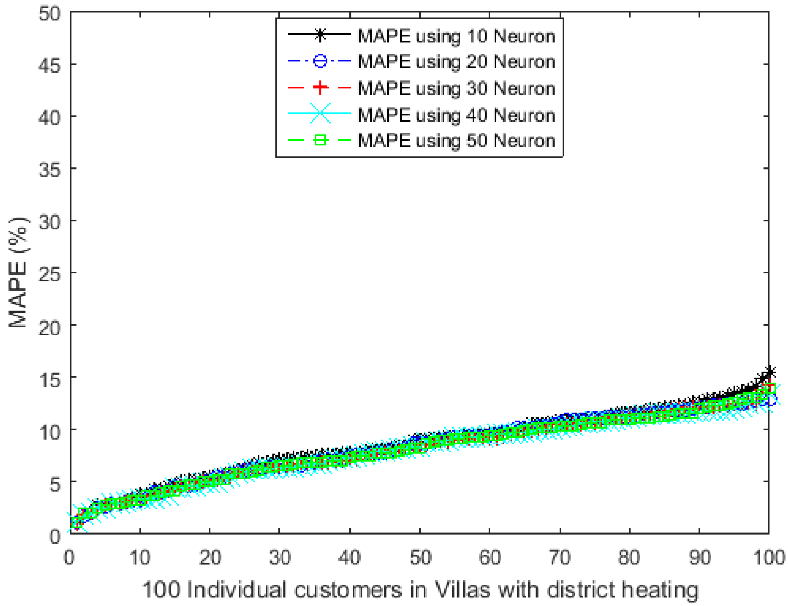

Figure 6.9: Impact of changing the number of neurons on MAPE for 100 individual customers in Villas (Note: MAPE values are presented in ascending order)

6-Min EM Data:

The number of neurons in the hidden layer of the ANNs may not have a significant impact on the MAPE of the ANNs trained with hourly data. As seen above, the higher number of neurons may not help to improve the accuracy of the ANNs that are trained by hourly SM data. This section investigated if the higher number of neurons can help to improve the accuracy of the ANNs that are trained by 6-min data. Figure 6.10, shows the values of

MAPE for a different number of neurons in the hidden layer.

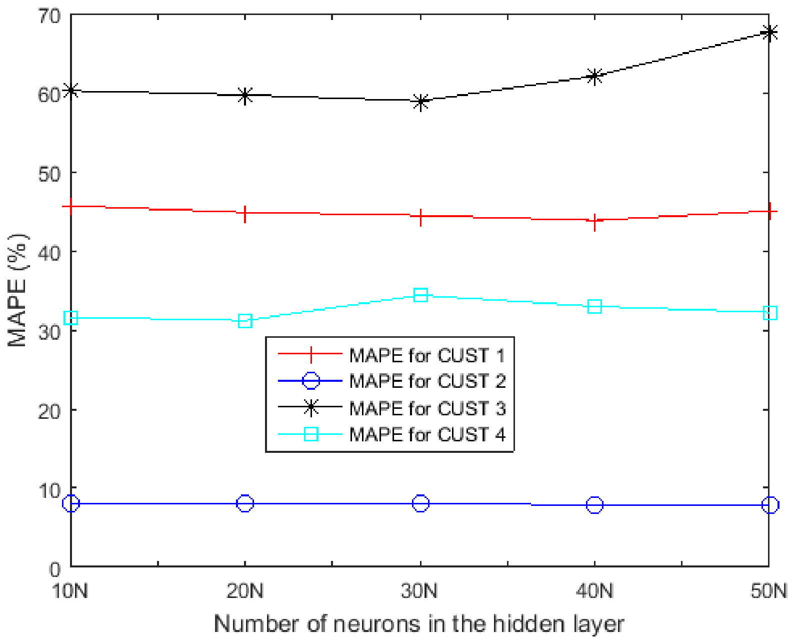

Figure 6.10: Impact of the changing the number of neurons in the hidden layer of the ANNs- 6 Min Data

It can be seen from Figure 6.10 that the number of neurons may not impact the MAPE of the ANNs significantly. The result shows that the MAPE of the Villa customers CUST 1 and CUST 2 are not impacted by the number of neurons. However, the MAPE of the Apartment customers CUST 3 and CUST 4 showed a tendency to increase with the increase of number of neurons. The reason could be that the ANNs of the Apartment customers become incapable of capturing highly variable nature of the loads since the ANNs have a tendency to contribute to over-fitting with the increase of the number of neurons. Since the load pattern of individual customers is in general highly variable hence 20 neurons in the hidden layer could be a better choice to avoid over-fitting and at the same time having better capabilities of solving complex LF problems at the individual customer level than with ten neurons.

6.4.3.2 Influence of Average Load over Previous Different Time Periods on Forecast Accuracies for ANNs Trained with Hourly SM Data and 6-min EM Data

The influence of average load over previous different time periods on the forecast accuracy is described in this subsection by considering the ANNs trained by hourly SM data first and then the ANNs trained by 6-min interval EM data.

Hourly SM Data:

The analysis was done on the selection of the time scale for the input predictor 1c - the previous load over a certain time period (as presented in Section 6.2.4.) considering hourly SM data of the customers living in Apartments and Villas.

(a) For Apartment Customers

The hourly ECD from the SMs were used to train the ANNs for 100 individual Apartment customers. The accuracy of the forecasted load is evaluated by calculating the MAPE. The models are trained using 7-input predictor variables. For 1-hour-ahead LF, the predictor 1c can influence the accuracy of the forecasted load. The influence of this predictor is investigated by changing the time scale for this predictor, e.g., previous 1-hour or previous 2-hours or previous 24-hours average load. The number of neurons in the hidden layer of the ANNs was chosen as 20 for this investigation for the reason shown in Subsection 6.4.3.1.

Figure 6.11 shows the MAPEs of hour-ahead LF models with 7-input predictor variables and 20 neurons in the hidden layer. The results are shown for 100 individual customers who are living in Apartments with district heating, considering the average loads over previous 1-hour or 2-hours or 24-hours. The values of the MAPE are shown by sorting the values from lowest to highest values.

It can be seen from Figure 6.11 that the MAPE from the ANNs of the 100 customers varied between around 8% to around 60%. However, the MAPE can be higher than 60%, depending on the irregularities in energy consumption behaviour of a customer. To the best knowledge of the authors, there exists no standard limit on the maximum acceptable limit of MAPE for LF at the individual level. Figure 6.11 shows that only 10% of the ANNs of the investigated customers produce MAPE less than 20%. This poor accuracy level indicates the difficulty in forecasting load at the individual customer level for Apartment customers, and also suggests that the forecast results are prone to errors.

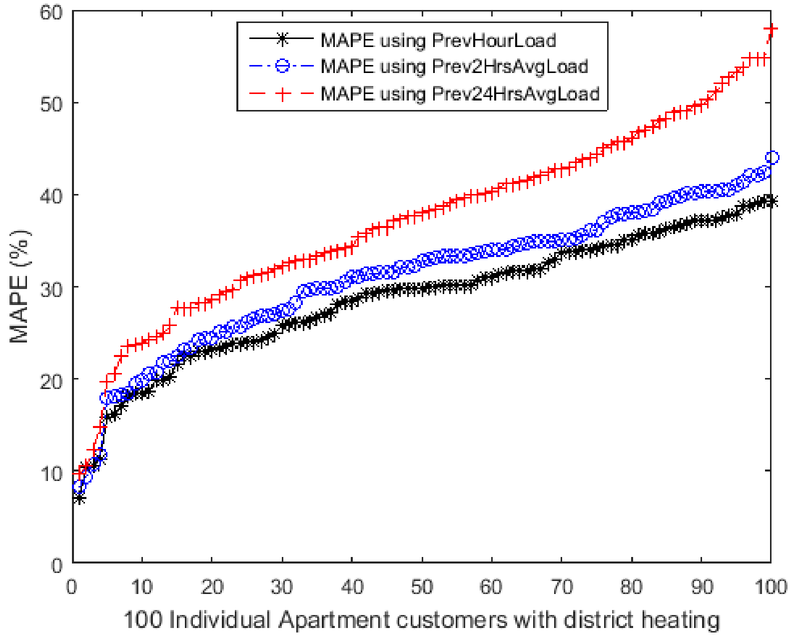

Figure 6.11: Impacts of using average load over previous different time intervals on MAPE for 100 customers in Apartments (Note: MAPE values are presented in ascending order)

By inspecting the daily energy consumption behaviour of investigated customers, it is found that the daily load profile of the customers living in Apartments are highly variable and irregular. The energy consumption of the customers fluctuates heavily even in consecutive hours or on successive days from any regular pattern. Due to this, the following results are observed:

The customers with the following characteristics could have MAPE less than 10%: i) regular load pattern; ii) stayed in the Apartments throughout the year; iii) having with almost similar daily load peak; iv) daily peak occurs almost at around same time. The MAPE values of the ANNs for some customers with similar regular behaviour are higher than 10% because the customers were not at home (i.e., very low energy consumption) for some days or weeks during the year.

The ANNs of the customers having regular load pattern but irregular peak values could give the MAPE from 20% to 30%. On the other hand, the ANNs of the customers having irregular load pattern and irregular peak values could give the MAPE above 30%. For the first one, the errors in the load forecast could come mainly from the deviation in peak prediction. However, for the latter one, the errors could come both from the deviation in peak prediction and also from irregularities in daily load pattern.

Some customers were not at home for a few days with some intervals throughout the year, and the ANNs of this type of customers could produce an even higher error in the forecast.

However, as can be seen in Figure 6.11, using previous 1-hour load as one of the seven input predictors would help to improve the accuracy of the forecast results. The reason could be that ECD over the previous 1-hour helps to reduce the errors that come with irregular load pattern and peak occurrences, due to the knowledge of the latest available energy consumption information.

(b) For Villa Customers

LF models were also developed for 100 individual customers who are living in Villas with district heating. The impact of customer types on the accuracy of the ANNs is studied. The hourly ECD from the SMs were used to train the ANNs of 100 Villa customers. Figure 6.12 shows the MAPEs of hour-ahead LF models with 7-input predictor variables and 20 neurons in the hidden layer. The MAPE values with an average load the over previous 1-hour, 2-hours, and 24-hours for 100 customers are presented in Figure 6.12, where the values of MAPE are shown by sorting the values from lowest to highest values.

As can be seen, the MAPE from the ANNs of the 100 Villa customers varied between approximately 2% to 20% which is considerably better than the MAPE of the 100 Apartment customers. However, it is noted here that the MAPE can be higher than 20%, depending on the irregularities in energy consumption behaviour of a customer. Figure 6.12 shows that around 40% to 60% of the ANNs for investigated customers provide MAPE less than 10% which indicates a higher level of regularity in the energy consumption behaviour of the customers living in the Villas as compared to that of customers living in Apartments.

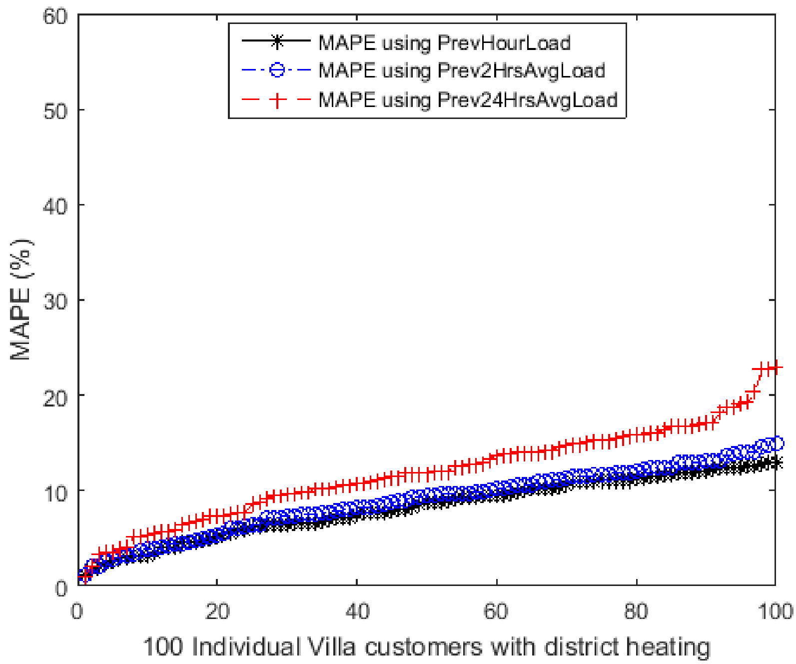

Figure 6.12: Impact of using average load over previous different time intervals on MAPE for 100 customers in Villas (Note: MAPE values are presented in ascending order)

By inspecting the daily energy consumption behaviour of investigated customers, it is found that the daily load profile of the customers living in Villas are comparatively less variable and less irregular. Due to this, the following results are observed:

The customers with the following characteristics could have MAPE less than 10%: i) regular load pattern; ii) stayed in the Villas throughout the year; iii) having with almost similar daily load peak and iv) the daily peak occurred almost at around same time.

The MAPE is found to be higher than 10% due to following behaviours of the customers i) irregular peak values; ii) daily peaks are sometimes much higher than the regular peaks; iii) the loads during weekdays are sometimes similar to the loads during weekends; iv) customers do not stay in the Villas during some weekends or take vacations several times in a year; etc.

It can be seen from Figure 6.12, that using previous 1-hour load as the time scale for the predictor 1c, can help to improve the accuracy of the forecast.

The reason could be that ECD over the previous 1-hour helps to reduce the errors that come with irregular load pattern and peak occurrences, due to the knowledge of the latest available energy consumption information. Hence, the previous 1-hour average load has been selected as the predictor 1c for later analysis.

From Figure 6.11 and Figure 6.12, it can be observed that the load forecast for the Villa customers can be more accurate than the load forecast for the Apartment customers with the similar heating system. The studied load profiles of the customers reveal that the probability of getting regular load pattern is higher for Villa customers than for the Apartment customers. This regularity is the reason for higher forecasting accuracy for Villa customers.

6-Min EM Data:

The influence of using average load over previous different time periods and the number of neurons in the hidden layer has been investigated where 6-min intervals data has been used to train the ANNs of the customers. The ANNs of the four customers that are trained with 6-min intervals data can be used for LF over a short time horizon, e.g., 6-min ahead. The influence of using average load over previous different time periods on MAPE has been investigated by using the average load over the previous period of 6-min, 12-min, 18-min, 30-min and 1-hour. The influence on the MAPE is shown in Figure 6.13.

As can be seen, using previous 6-min average load as the time scale for the predictor variable 1c, can improve the accuracy of the LF models compared to using average load over previous 1- hour. However, Figure 6.13 shows that the previous 6-min average load may not help to decrease the MAPE for the customer CUST 2 who has comparatively regular load pattern most of the time. The reason could be that the previous 6-min data helps to identify the random behaviour of the customers and hence the model could predict the load for the next 6-min more accurately for the customers who have comparatively irregular load patterns. Since the load pattern of individual customers is in general highly variable hence 6-min average load could be a better choice to use as the time scale for the predictor 1c.

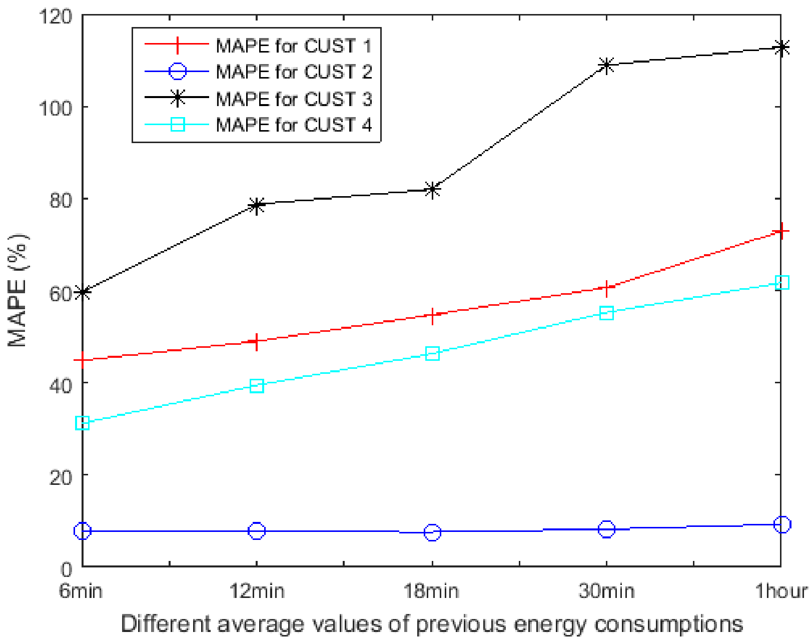

Figure 6.13: Impact of using average load over previous different time intervals on MAPE for four customers- 6-min data

6.4.3.3 Impact of Data Granularity on Forecast Accuracy for Same Forecast Time Horizon

In this section, the impact of data granularity on the MAPE is investigated. Figure 6.14 presents the MAPE of the ANNs for different data granularity, i.e., 6-min, 10-min, 12-min, 15-min, 30-min and 60-min intervals data. It can be seen in Figure 6.14 and Figure 6.15 that 1-hour-ahead and 30-min ahead LF for Villas may not be impacted significantly due to differences in the training data granularity. However, 1-hour-ahead and 30-min ahead LF for Apartments may be impacted significantly, where the data with lower granularity can help to improve the accuracy of the ANNs.

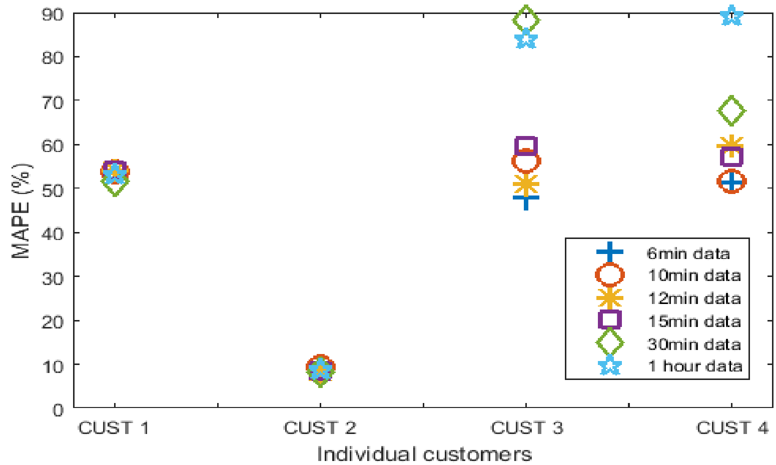

Figure 6.14: 1-hour-ahead load forecast with ANNs of the four customers that are trained with different data granularity

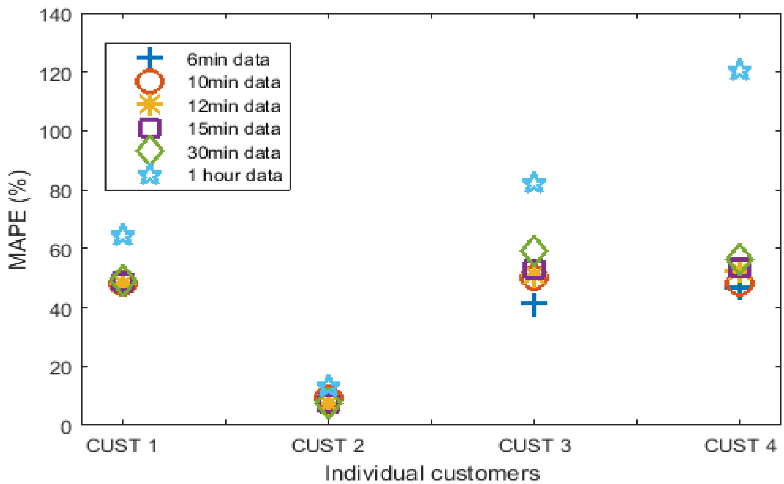

Figure 6.15: 30-min ahead load forecast with ANNs of the four customers that are trained with different data granularity

It is expected that data with low granularity may help the ANNs to better learn the highly variable nature of the energy consumption of the Apartment customers. It is also likely that the ANNs trained with hourly data may not be able to learn the correlation between the load with time within each hour intervals.

6.4.3.4 Relation between Forecast Time Horizon and Data Granularity

This section also investigated how MAPE is impacted with the time horizon of load forecast using the ANNs trained with different data granularity, e.g., how ANN of customer CUST 1 which is trained with 6-min data, performs for 6-min ahead, 30-min ahead and hour-ahead load forecast. The investigation is conducted using the data with a granularity of 6-min, 10-min, 12-min and 15-min. The forecast time horizons, i.e., ahead of time are denoted as 1-hour, 30-min and sampling time ahead, ST. The term, sampling time ahead is used to refer the forecast time horizon which is equal to the intervals of the training data, e.g., 6-min ahead LF and 10-min ahead LF using the ANNs trained with 6-min data and 10-min data respectively.

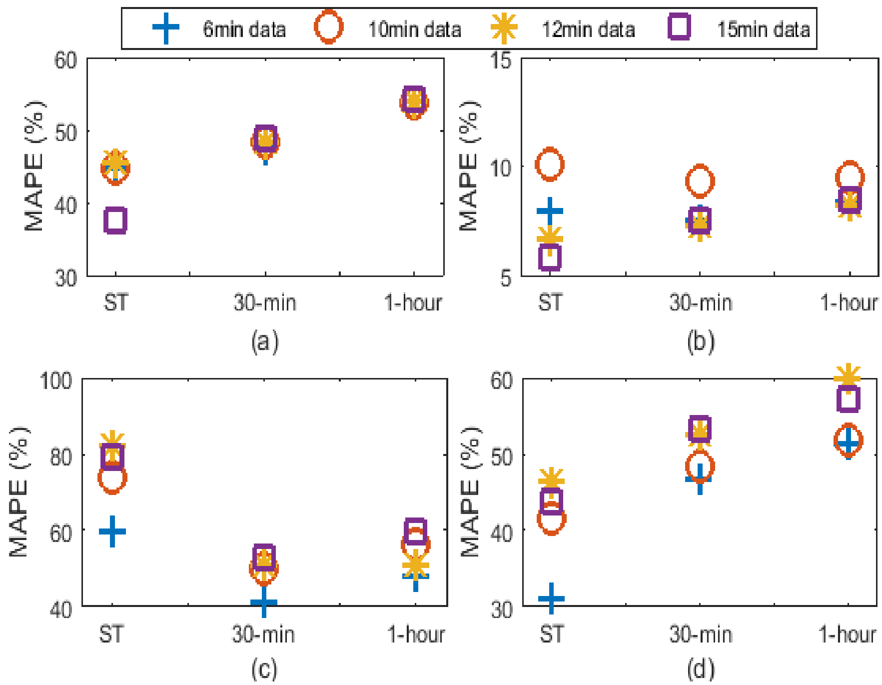

Figure 6.16: Impact of data granularity on load forecast (a) for CUST 1, (b) for CUST 2, (c) for CUST 3 and (d) for CUST 4. (Note: Difference in scale on Y-axis)

Figure 6.16 shows the impact of forecast time horizons with respect to training data granularity for the customers CUST 1, CUST 2, CUST 3 and CUST 4. As can be seen, for the Villa customers, the MAPE values may not be impacted significantly by the training data granularity when the forecast time horizon is 30-min ahead or 1-hour-ahead, except for the 10 min data of the customer CUST 2 where the MAPE is higher. However, the results show that 15-min ahead load forecast using the ANNs trained with 15 min data provides less MAPE. On the other hand, it can be seen that for the Apartment customers, the MAPE values may be impacted significantly by the training data granularity if forecast horizon is 30-min ahead or 1-hour-ahead, where 6-min data can help to decrease the MAPE of the ANN. However, for the sampling time ahead LF, the results show that 6-min ahead load forecast using the ANNs trained with 6-min data provides less MAPE. In general, it is observed from the results that to forecast load with different time horizons, 15-min data could be a good choice for Villa customers, and 6-min data could be a good choice for Apartment customers.

6.5 Conclusions

The following can be concluded regarding the influence of number of aggregated customers on the accuracy of load forecast at LAL:

- The accuracy at LAL increases with the increase in the number of aggregated customers.
- An MAPE of around 5% can be obtained by aggregating loads of around 50 Villa customers or around 100 Apartment customers.

The following can be concluded regarding the influence of different input predictors, number of neurons on the accuracy of the LF at LAL:

- 40 neurons in the hidden layer could be helpful for improving the accuracy of the forecast. Therefore, the aggregated LF models that have been discussed in Chapter 8, have been developed using 40 neurons.
- Average load over the previous hour could be used as one of the input predictors to improve the accuracy of the forecast. Therefore, the aggregated LF models that have been discussed in Chapter 8, have been developed and tested using the average load over the previous hour.

The following can be concluded regarding the influence of data granularity on the accuracy of load forecast at the individual customer level:

- The accuracy can be improved with the decrease of the interval of ECD.
- The impact of the number of neurons in the hidden layer on the accuracy could be negligible.
- By using previous hour's load value, the accuracy of the forecast can be increased. These results have been considered for recommending functional requirements in Chapter 9.

Chapter 7
Large-scale Smart Meters Switching: Modelling and Application

This chapter presents the developed model for load shedding with SMs' switching (the switching model). The disconnection method of the SMs used in the model is based on results from the field tests. The switching model is integrated in a multi-time-steps load flow simulation model (the integrated model). The integrated model can be used to simulate the SMs switching and evaluate their effects on the load flow results. The description of a real 10 kV residential distribution system which is used in a case study with the integrated model is provided in this chapter. Moreover, the simulation results on large-scale SMs switching are provided in this chapter. The effect of the number of SMs per MCU on the load shedding time is presented by considering four different scenarios based on the number of SMs per MCU. Moreover, simulation results are obtained for these scenarios where faster SMs' switching time than the normal switching time is considered to find out the estimated load shedding time for the same number of SMs.

7.1 The SMs Switching Model

7.1.1 Modelling of Load Shedding Using SMs

The SMs switching model is developed to simulate the large-scale load shedding with the SMs based on the field tests' results on the small-scale load shedding using the SMs. One of the aims of the model is to simulate the change in load values due to SMs' disconnection during the load shedding period. In the model, the MCUs' disconnection method of the SMs, variations in the disconnection time of the SMs, and also the forecasted load values of individual customer at the load shedding hour are considered. Moreover, the model gives the estimated value of the remaining connected load at each load bus, i.e., for the excluded customers at each load bus from the load shedding.

7.1.1.1 SMs' Disconnection Time from a Field Test

The field tests on small-scale SMs' switching showed that the switching time required to disconnect individual SMs is not the same. The SMs' actual switching time obtained during Test 3 is shown in Table 7.1. The table shows that the typical time for switching a SM is around 7 seconds to 8 seconds. All measured SMs' disconnection times are around this time with ± 1 sec deviations except for one SM which took around 12 sec. Since the ZigBee communication network of the investigated SMS is developed as a tree network, therefore each switching signal requires multiple hops to reach the target SM.

The number of hops required to reach each of the SM is different, and it depends on the configuration of the mesh network. Moreover, the ZigBee communication network works as a self-healing meshed network which indicates the number of hops required to reach a specific SM can vary at any time.

Table 7.1 Time required to disconnect 80 SMs in parallel during Test 3

	Disconnection time of SMs under MCU1				**Disconnection time of SMs under MCU2**		
Sl.		Sl.		Sl.		Sl.	
1	7.85	20	7.55	1	7.44	22	7.86
2	8.64	21	7.95	2	7.26	23	7.58
3	7.62	22	7.88	3	7.98	24	7.94
4	7.55	23	7.82	4	8.83	25	9.64
5	7.81	24	8.6	5	8.39	26	7.68
6	7.5	25	7.88	6	7.59	27	7.84
7	8.02	26	7.6	7	7.51	28	7.44
8	8.78	27	7.84	8	7.5	29	7.42
9	7.59	28	7.6	9	7.46	30	7.76
10	7.61	29	7.6	10	7.66	31	7.86
11	7.65	30	7.92	11	7.64	32	7.72
12	7.98	31	7.6	12	7.68	33	7.82
13	7.2	32	8.37	13	7.6	34	7.88
14	7.82	33	7.38	14	8.14	35	7.92
15	7.82	34	7.92	15	7.54	36	7.8
16	7.87	35	7.56	16	8.68	37	7.58
17	7.95	36	8.94	17	7.56	38	12.22
18	7.42	37	7.66	18	8.24	39	7.62
19	7.79	38	7.62	19	7.58	40	7.84
				20	8.09	41	8.42
				21	7.47	42	7.64

Table 7.1 shows the time required to disconnect each of the 80 SMs, which were successfully disconnected by the three MCUs during Test 3. There were 41 and 44 SMs under two MCUs and one SM under 1 MCU. According to the SMs' status update report, these three MCUs successfully disconnected 37 SMs, 42 SMs, and 1 SM respectively. Table 7.1 shows required disconnection time for all 80 SMs, where the single SM's disconnection time, i.e., 7.62 s, is merged with the 37 SMs' disconnection time under the MCU1.

In can be seen from Table 7.1 that disconnection of the SMs varies from one SM to another. Moreover, it can be seen that when two MCUs disconnected the SMs in parallel, both MCUs did not switch their first SMs at the same instant i.e., the time delay in disconnecting their first SMs were not equal. However, the time delays in disconnecting the SMs can coincide for some of the MCUs during large-scale load shedding. The time after which each of the SM under MCU1 and the MCU2 has been disconnected, can be calculated by taking cumulative sums of the SMs' disconnections' time starting from the moment disconnections' signal has been sent from the CS. By calculating the cumulative sum, it can be found that the MCU1 disconnected its second SM at 14.7th sec, and the MCU2 disconnected its second SM at 16.49th sec. The duration of switching the second SMs of both MCUs is calculated from the moments the disconnection command was sent from the CS until the moments when the second SMs are disconnected by the respective MCUs. This indicates that when many MCUs disconnect SMs in parallel, the number of SMs switched at a moment may not be equal to the number of MCUs disconnecting the SMs in parallel.

7.1.1.2 Block Diagram of the Large-Scale Smart Meters' Switching Model

SMs' switching model has been developed by using the actual disconnection time of 121 SMs, obtained from the three field tests. The actual disconnection time of the SMs is repeatedly used to create SMs' disconnection time for all the 2000 customers considered in the simulation. All the SMs in the SMs' switching model are then allocated with a disconnection time serially from repeated actual disconnection time of the SMs. Moreover, power consumption value of each customer has been allocated with each SM where the power consumption value could be historical values or forecasted values from each of individual LF models.

Figure 7.1 shows the block diagram of the SMs' switching model. The SMs' switching model has been developed considering the SMs of the customers in a 10kV residential grid.

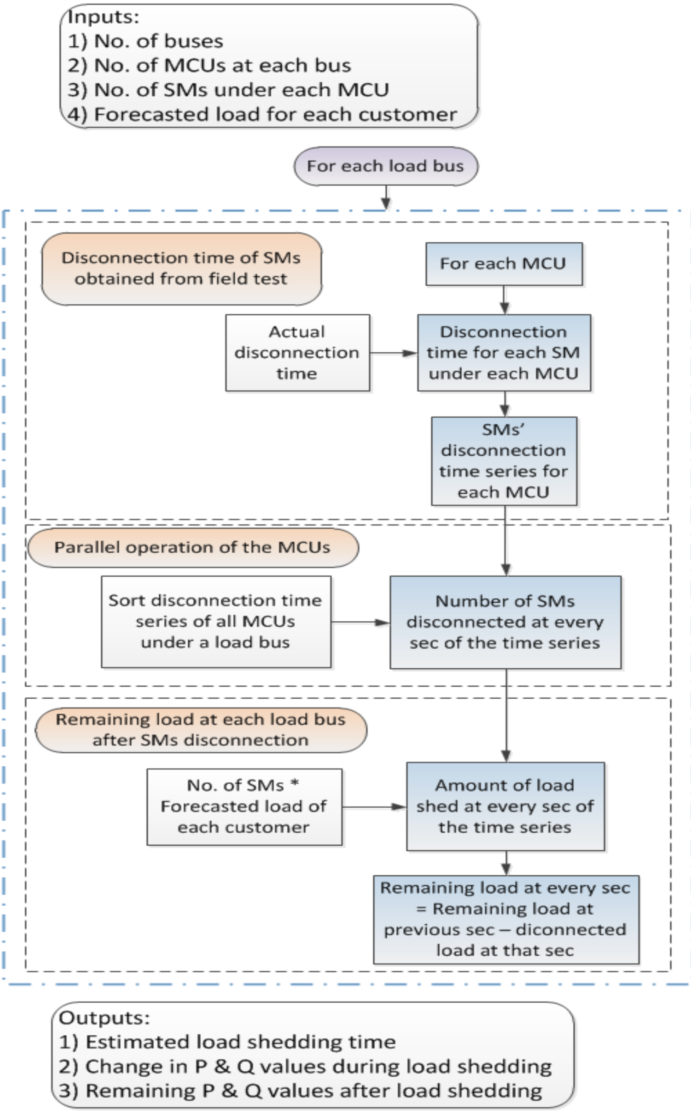

Figure 7.1: Block diagram of the Smart Meters' switching model

In the model, the number of buses in the 10kV residential grid is known. The number of MCUs at each bus is estimated according to the number of customers at each bus where 50 SMs per MCU is considered as a limit while allocating the number of SMs per MCU. Each SM under each MCU is then allocated with a unique SMs' disconnection time based on the actual disconnection time. As a result, all SMs under each bus have been allocated with a unique disconnection time. Therefore, the model uses actual disconnection time of the SMs when simulating the SMs' disconnection by the MCUs. As a result, the model can estimate total load shedding time for different numbers of SMs' disconnection.

It can also be seen from Figure 7.1 that the final outcome of the SMs' switching model is the remaining load at each of the load bus after disconnection of the SMs. The model gives the values of the remaining load for the total load shedding period with an interval of one sec. For each bus, the remaining load at each of the load bus is calculated by subtracting the disconnected load at a sec from the remaining load on that bus at previous sec.

7.2 Integrating the SM Switching Model in Multi-Time-Steps Load Flow Model

Power system simulation package MATPOWER [113] has been used to solve the power flow after modifications based on the need for this thesis. The Newton-Raphson algorithm is used for solving power flow equations. The net injected active or reactive power at any bus at a particular time is the summation of active or reactive power demand of all customers under that bus whose SMs' switch status is ON, which is given by (7.1), (7.2). The standard power flow equations are given by (7.3) and (7.4) [114].

$$P_{i,t} = P_{G\ i,t} - P_{D\ i,t} = \sum_{k=1}^{NCi} P_{D\ \mathrm{k},t} \ * Sw_{k,t} \tag{7.1}$$

$$Q_{i,t} = Q_{G\ i,t} - Q_{D\ i,t} = \sum_{j=1}^{NCi} Q_{D\ k,t} \ * Sw_{k,t} \tag{7.2}$$

$$P_{i,t} = \sum_{j=1}^{n} |V_{i,t}|\,|V_{j,t}||Y_{\mathrm{ij}}|\cos(\theta_{ij} + \delta_{j,t} - \delta_{i,t}) \tag{7.3}$$

$$Q_{i,t} = -\sum_{j=1}^{n} |V_{i,t}|\,|V_{j,t}||Y_{\mathrm{ij}}|\sin(\theta_{ij} + \delta_{j,t} - \delta_{i,t}) \tag{7.4}$$

where, i is the bus index, n is the number of buses, t is the time (second) index, k is the customer index, NC_i is the total number of customers at bus i, $P_{i,t}$ is the net injected active power at bus i at time t, $P_{G\ i,t}$ is the active power generation at bus i at time t, $P_{D\ i,t}$ is the active power demand at bus i at time t, $Q_{i,t}$ is the net injected reactive power at bus i at time t, $Q_{G\ i,t}$ is the reactive power generation at bus i at time t, $Q_{D\,i,t}$ is the reactive power demand at bus i at time t, $P_{D\,k,t}$ is the active power demand of customer k at time t, $Q_{D\,k,t}$ is the reactive power demand of customer k at time t, $V_{i,t}$ is the voltage magnitude at bus i at time t, θ_{ij} is the angle associated with the element of the admittance matrix Y_{ij}, $\delta_{i,t}$ is the angle associated with $V_{i,t}$, and $Sw_{k,t}$ is the SM's switch status of customer k in bus i at time t where zero would represent that the customer is disconnected, and one would represent that the customer is still connected. The SMs' switching model simulates the parallel operation of the MCUs where each MCU disconnects its associated customers' SMs one by one. In this way, the switching model determines the switch position $Sw_{k,t}$ of each of the selected customer at a given time of the load shedding period.

7.3 Description of the Case Study Using a Real Distribution System

A case study has been carried out using a real 10 kV distribution system by using the models presented earlier. The aim of the case study is to analyze the impact of load shedding on the voltage values at the LV substation levels. In this part, the description of the simulated distribution system and considered grid condition are given, while the results are presented in Chapter 8. Moreover, SMs' switching scenarios are simulated for the SMs considered for all the customers in the simulated distribution system. The factors influencing the total load shedding time are presented in Section 7.4.

7.3.1 Description of the Simulated Systems

The investigated distribution grid is a 31-bus system with the data provided by GENAB where 26 buses are load bus, i.e., PQ bus, one slack bus and four buses are without any load as shown in Figure 7.2. The 10kV residential distribution system is of the radial configuration with three main feeders named as Feeder A, Feeder B, and Feeder C. It can be seen from Figure 7.2 that the Bus 8 of Feeder A and the Bus 21 of Feeder B can be connected when it is necessary, e.g., during maintenance work. Similarly, the Bus 17 of Feeder B and the Bus 30 of Feeder C can be connected when it is necessary. These two lines between the feeders are shown in Figure 7.2 with orange color dotted lines.

The real power and reactive power values at each of the load buses are the aggregated loads from the customers under each load bus. Power factor is considered as 0.95 lagging which is the value obtained from the field tests as average power factor.

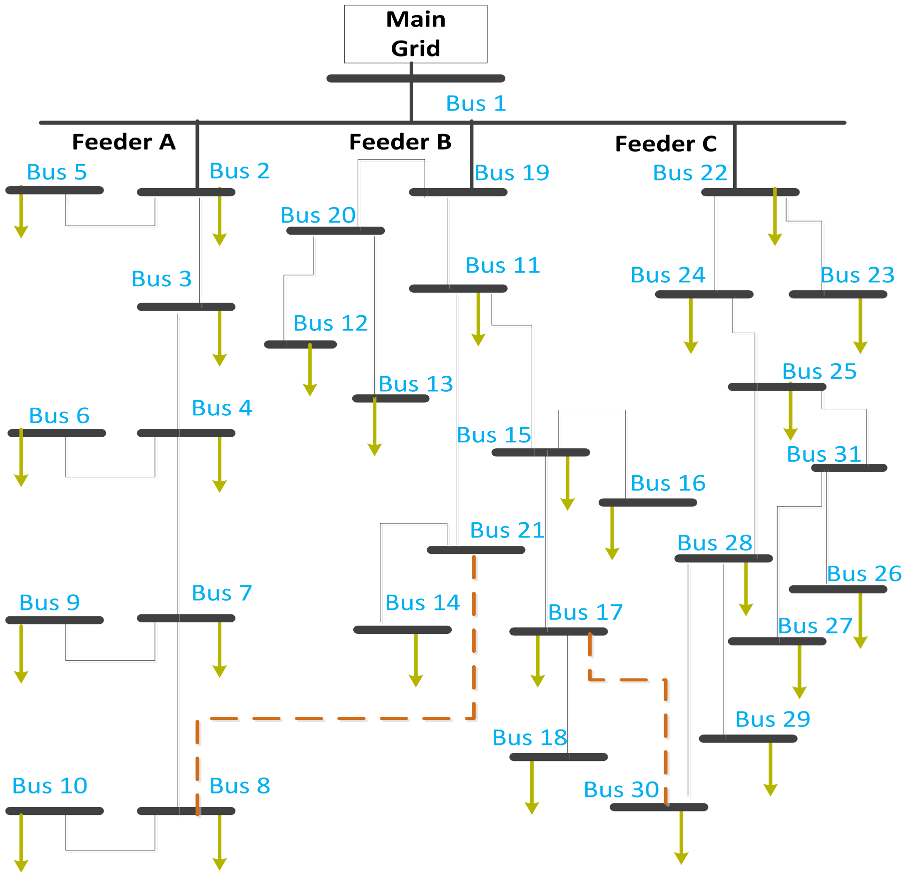

Figure 7.2: One line diagram of investigated 10kV residential distribution grid

Table 7.2 shows the number of SMs considered at each bus which is equal to the number of customers at each bus. The SMs' number are represented by zero for the buses that are without any load.

Table 7.2 The number of SMs i.e., number of customers at each bus

Bus No.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
SMs	0	65	109	118	63	20	144	95	13	65	62	92	50	52	92	105
Bus No.	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	
SMs	52	111	0	0	0	131	72	79	20	65	126	72	94	33	0	

7.3.2 Description of Simulation Scenario

A critical situation is created by assuming certain grid condition and also the parameters. The pre-critical distribution grid is assumed to be operating in the N-1 contingency condition where the branch between the bus 1 and the bus 2 is assumed to be disconnected for maintenance work. The loads on feeder A is then supplied through the feeder B by connecting the branch between the bus 8 and the bus 21.

One-sec interval values of the real and reactive power that are obtained from the SMs' switching model for the load shedding period considering maximum 50 SMs per MCU, are used in the simulation scenario to analyze the voltage levels during and after the load shedding. The simulation results are presented in Chapter 8.

7.3.3 Applications of Switching Model and Integrated Models

The SMs' switching model is used to simulate load shedding scenarios considering the forecasted load values of individual customers and the SMs' disconnection time. The integrated model is used to calculate voltage at LV substation level.

SMs' Switching Model for Load Shedding Scenarios

The SMs' switching model is used to simulate load shedding scenarios using SMs, and the results from the simulation are presented in Section 7.4 where the effect of changing the number of SMs per MCU and the SMs' disconnection on the total load shedding time is studied.

Moreover, the SMs' switching model will be used to estimate the change in load due to load shedding during the load shedding period, and also the remaining load at each bus after the load shedding considering the forecasted load values from the individual LF model. The simulation results on load change, and the remaining load is used in the integrated model.

A simulated large-scale SMs' disconnection scenario using the actual disconnection time of the SMs is shown in Figure 7.3. Each load bus is considered to have one MCU which is considered to be communicating with all the SMs under that load bus. As seen here, total SMs' disconnection can take around 20 minutes, i.e., around 1200 seconds to disconnect all the SMs in the considered distribution system. However, more than 90% of the SMs would be disconnected by around 14 minutes, i.e., after around 840 seconds (time to disconnect around 100 SMs) since all the MCUs at all the load buses would operate in parallel where only 7 out of 26 MCUs would have more than 100 SMs.

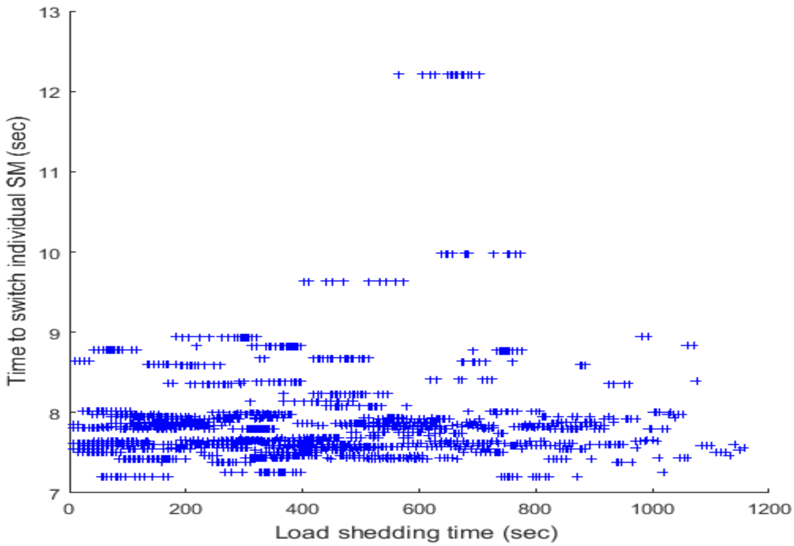

Figure 7.3: A scenario of large-scale SMs' disconnection i.e., 2000 SMs

Integrated Model for Voltage Calculation

The integrated model will be used in Chapter 8 where the CLS are simulated by excluding prioritized customers. The integrated model will show the impact of load shedding on the voltage values at the LV substation levels.

7.4 Factors Influencing the Load Shedding Time

The number of SMs per MCU varies in an actual SMS. This section analyzed the effect of the number of SMs per MCU and the disconnection time on the overall load shedding period. Four scenarios are created for load shedding simulation with the SMs by varying the number of SMs per MCU as follows:

- **Scenario 1**: All the SMs under a load bus in a 10 kV residential distribution system are communicating with one MCU. This means that the number of MCU in the investigated distribution grid is equal to the number of load buses i.e., 26 MCUs.
- **Scenario 2:** Maximum 50 SMs per MCU is considered i.e., bus 7 which has 144 SMs would require three MCUs, and the number of SMs under the three MCUs is considered to be 50, 50 and 44 SMs respectively. The

total number of MCUs in the in Scenario 2 is 53 as compared to 26 MCUs in Scenario 1.

- **Scenario 3:** Max 40 SMs per MCU is considered in this scenario. It is noted here that the average number of SMs per MCU in the investigated GENAB's distribution system is 40. In this scenario, bus 7 would require four MCUs, and the number of SMs under the four MCUs is considered to be 40, 40, 40 and 24 SMs respectively. The total number of MCUs in Scenario 3 is 62 as compared to 26 MCUs in Scenario 1.
- **Scenario 4:** Maximum 30 SMs per MCU is considered. In this scenario, bus 7 would require five MCUs, and the number of SMs under the five MCUs is considered to be 30, 30, 30, 30 and 24 SMs respectively. The number of MCUs in Scenario 4 is 81 as compared to 26 MCUs in Scenario 1.

7.4.1 Simulation Results on Load Shedding Time for Each Bus Considering Actual Disconnection Time of SMs

Table 7.3 shows the total load shedding time i.e., maximum length of time taken by MCU(s) of the respective load bus to disconnect all the SMs under that bus. The load shedding times are presented for each bus considering the actual disconnection of the SMs in the considered four scenarios. The scenario numbers are denoted by Sc_x, where x is the scenario number.

Table 7.3 Maximum length of time that MCU(s) can take to disconnect all the respective SMs under at each load bus in the four scenarios

Bus No.		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
No. of SMs		0	65	109	118	63	20	144	95	13	65	62	92	50	52	92	105
Time (sec)	Sc_1	0	525	880	950	510	159	1164	764	106	522	494	741	401	417	751	850
	Sc_2	0	397	402	397	391	161	401	405	104	397	398	398	402	414	397	402
	Sc_3	0	317	320	322	318	159	320	327	104	320	325	323	325	322	323	323
	Sc_4	0	242	244	243	242	160	241	241	107	243	241	242	244	241	243	244

Bus No.		**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**
No. of SMs		52	111	0	0	0	131	72	79	20	65	126	72	94	33	0
Time (sec)	Sc_1	411	891	0	0	0	1050	571	637	160	519	1020	572	764	264	0
	Sc_2	410	397	0	0	0	401	396	400	157	400	402	405	397	266	0
	Sc_3	325	323	0	0	0	323	314	323	161	324	323	319	324	262	0
	Sc_4	243	242	0	0	0	242	244	245	157	242	243	243	245	266	0

7.4.2 Simulation Results on Load Shedding Time for Each Bus Considering Faster Disconnection Time of SMs

Shorter SMs' disconnection times than the actual SMs' disconnection times are also considered in the simulation of the four load shedding scenarios, which is named as faster SMs' switching. As seen in Figure 7.3, the SMs' actual disconnection times are above seven sec. Hence, in this section the faster SMs' switching simulation results are shown by decreasing the SMs' actual disconnection time from one sec to seven sec with a step of one sec. In the simulation, up to seven faster SMs' switching is considered assuming that in the future, it might be possible to disconnect a SM almost instantly. Figure 7.4 shows the reduction in load shedding time that can be achieved by making the faster disconnection of the SMs.

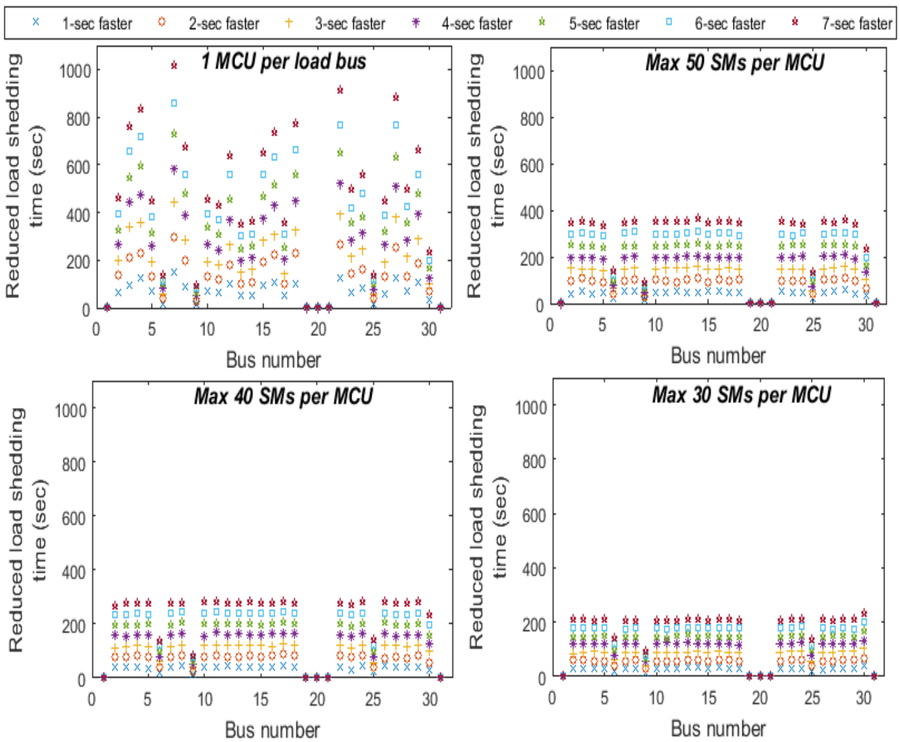

Figure 7.4 Reduction in load shedding time that can be achieved by making the faster disconnection of the SMs in the four scenarios

It is noted here that the reduced load shedding times that are shown in Figure 7.4 are obtained by subtracting the load shedding time using the faster disconnection from the load shedding time obtained using the actual disconnection time of the SMs. The reduction that can be achieved by performing faster disconnection of SMs are shown for each of the bus in the 10 kV distribution system using seven kinds of faster SMs switching. Moreover, the simulation results are shown for the four considered scenarios to compare the reduction in load shedding time for different switching strategies. The comparisons of the load shedding time are given below:

Scenario 1 (1 MCU per Load Bus):

Considering SM's disconnection can be one sec faster, it can be seen from Figure 7.4 that the load shedding time of the MCU at bus 7 which has the maximum number of SMs can be reduced by 2.5 minutes which is around 19.5 minutes when actual disconnection times are considered. And, if 7-sec faster disconnection is considered, it can be seen that the load shedding time for the bus 7 can be reduced by around 17 minutes, i.e., the SMs at the bus 7 can be disconnected within around 2.5 minutes.

Scenario 2 (Max 50 SMs per MCU):

The SMs' switching model considering max 50 SMs per MCU has shown that all loads in the investigated 10kV grid can be disconnected in around 7 minutes if normal load shedding time is considered. It can be seen from Figure 7.4 that 1-sec faster disconnection can save around 50 seconds from the overall load shedding time. Moreover, Figure 7.4 shows that the 7-sec faster disconnection can save around 5.5 minutes from the overall load shedding time, i.e., all loads in the 10kV grid can be disconnected in around 1.5 minutes.

Scenario 3 (Max 40 SMs per MCU):

The SMs' switching model considering max 40 SMs per MCU has shown that all loads in the investigated 10kV grid can be disconnected in around 5.5 minutes if the normal SM's disconnection time is considered. It can also be seen from Figure 7.4 that 1-sec faster disconnection can save around 40 seconds from the overall load shedding time. Moreover, Figure 7.4 shows that the 7-sec faster disconnection can save around 4.5 minutes from the overall load shedding time, i.e., all loads in the 10kV grid can be disconnected in around 1 minute.

Scenario 4 (Max 30 SMs per MCU):

The SMs' switching model considering max 30 SMs per MCU has shown that all loads in the investigated 10kV grid can be disconnected in around 4 minutes if actual disconnection times are considered. As seen in Figure 7.4, the load shedding time for the bus 30 seems to be considerably higher than load shedding time for the other buses and the reason is that all 33 customers on this bus are considered to be communicating with one MCU. Moreover, it is seen that 1-sec faster disconnection can save around 30 seconds from the overall load shedding time. Also, Figure 7.4 shows that the 7-sec faster disconnection can save around 3.5 minutes from the overall load shedding time, i.e., all loads in the 10kV grid can be disconnected in around 0.5 minute.

7.5 Comparison of Total Load Shedding Time

The simulation results on the total load shedding time are compared for the four scenarios mentioned in Section 7.4. Figure 7.5 shows the simulation results on the time required to shed all loads in the 10kV system for different scenarios considering from 1-sec to 7-sec faster SMs' disconnection times. The total load shedding times which are presented for all four scenarios, are expressed in Figure 7.5a as a percentage of base load shedding time, and in Figure 7.5b as time in seconds. The total load shedding time which is obtained by using the actual disconnection times of the SMs is considered as the base load shedding time which is 1164 sec, and used as y axis limit in (b) and is shown as 100% in (a).

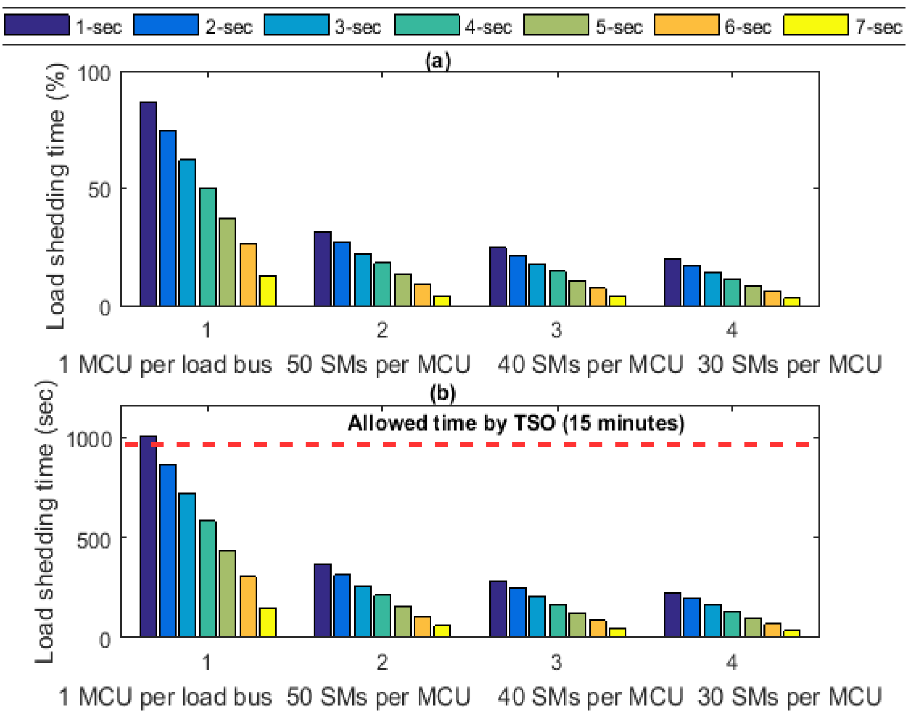

Figure 7.5: Comparison of total load shedding time obtained using actual, and 1-sec to 7sec faster switching which is shown in (a) % of actual switching time; (b) in sec

From Figure 7.5 it can be seen that the total load shedding time can be reduced by more than 60% of the base load shedding time, i.e., around 12 minutes reduction by keeping the number of SMs per MCU to 50 or lower while considering the typical disconnection time of the SMs. Another way to reduce the load shedding time is to reduce the disconnection time of the SMs. Figure 7.5 shows that while considering up to 144 SMs under a MCU, 5-sec faster disconnection time than the typical disconnection time of around 8 sec would give a load shedding time of around 7 minutes which is close to the load shedding time for having 50 SMs per MCU.

Figure 7.5 also shows that by reducing the maximum number of SMs per MCU, e.g., 30 SMs, the total load shedding can be achieved in around 4 minutes. However, extra investment cost would be required to keep the maximum number of SMs per MCU to a lower value. The number of SMs per MCU in the investigated SMS shows that 78% of the MCUs has 50 SMs per MCU. Hence, it can be said that if 50 SMs per MCU is considered as a maximum limit, CLS can be done in 6 minutes with the typical SMs' disconnection time which is lower than the allowed load shedding time of 15 minutes by the TSO. However, 15 minutes is the maximum allowed time, and the load shedding process may require additional time for planning, e.g., forecasting loads for different areas, selecting groups of customers for load shedding, and additional load shedding, if needed to take care of the amount of loads failed to disconnect. However, pre-planned load shedding strategies for different amounts of load shedding with the SMs, and automated process of load shedding area selection based on the forecasted aggregated load values would help to minimize the planning time and thereby allow to maximize the use of allowed load shedding time.

7.6 Conclusions

According to present practice, allowable 15-minute time would be enough for CLS since the load would be disconnected by disconnecting the feeders remotely and a large amount of load would be disconnected almost instantly, which is not the case when using the SMs for CLS. Large-scale load shedding using the SMs could take time longer than allowed 15 minutes. Hence, the total load shedding time needs to be reduced. The simulation results show that the load shedding time can be reduced by keeping the maximum number of SMs per MCU up to a limit, which in this study case is 50 SMs/MCU if SM's disconnection time cannot be reduced. Another way of reducing total shedding time is by making each MCU capable of switching multiple SMs at a time, or reducing the SM's disconnection time.

Chapter 8
Compulsory Load Shedding Supported by Load Forecasting

This chapter presents and discusses the results of compulsory load shedding scenarios supported by load forecasting. The benefits of using pre-developed aggregated load forecasting models to minimize the unnecessary load shedding are demonstrated. This chapter also illustrates the use of pre-developed individual load forecasting models to calculate, using the load flow model, the voltage values of the prioritized customers which remain connected after the compulsory load shedding.

8.1 CLS Supported by Aggregated LF

8.1.1 Description of Simulation Cases

This thesis developed aggregated LF at the LV substation levels for the 10kV residential grid described in Section 7.3.1. The investigated residential distribution grid is a 31-bus system where 26 buses are load bus, i.e., PQ bus, one slack bus and four buses are without any load. Hence, 26 aggregated LF models are developed for the 26 load buses. The number of customers under each load bus is given in Section 7.3.1. The real ECD, i.e., SM data of individual customers for one-year is used for the analysis. The models are developed using ANN method, and the ECD which are aggregated at each load bus level are used to develop the LF models. The historical ECD of all the individual customers under the respective load buses are used to create the aggregated ECD.

8.1.2 Input Predictors for Aggregated LF

Seven input predictors are used in total as described in Section 6.2.4. The input predictors together with the aggregated ECD are used to train and validate the ANNs. The number of neurons used in the hidden layer of the ANNs is 40, as it is found to provide best accuracies for the investigated data with respect to aggregated LF, as shown in Section 6.3.3.2.

The developed aggregated LF models are then used to forecast the aggregated load at each LV substation level, i.e., load bus level in the investigated residential grid. Among the seven input predictors, only the average load over a certain previous period can be varied and hence created different sets of input predictors by varying the period of this predictor. Four different types of input predictors' sets are used to forecast the aggregated load to analyze the impact of these different sets on the forecast accuracy. The input predictors' sets are: 1) Six predictors, i.e., not requiring recent energy consumption values of last few hours; 2) Seven predictors, where one of the predictors is previous 24 hour's average aggregated value (7 Pred 24H); 3) Seven predictors, where one of the predictors is previous 2 hour's average aggregated value (7 Pred 2H); 4) Seven predictors, where one of the predictors is previous hour's aggregated value (7 Pred 1H).

8.1.3 Load Shedding Instants for Aggregated LF

This chapter simulated a total of 24 load shedding events where each of the events is associated with a specific time instant. The time instants are chosen to cover one week-day from each of the four seasons and every fourth hour (i.e., 02:00, 06:00, 10:00, 14:00, 18:00 and 22:00) is chosen to represent the load variation in different times of the day. The dates that are chosen for each season are:

1. 30th January [Winter]: When maximum load occurred in the investigated system.
2. 15th April [Spring]: Mid of the season.
3. 18th August [Summer]: When minimum load occurred in the investigated system.
4. 15th October [Autumn]: Mid of the season.

8.1.4 Actual Total Load at the Considered Load Shedding Instants

Figure 8.1 shows the total actual load in the investigated residential grid, i.e., the sum of the actual loads on each of the 26 load buses. The total load is shown for all the 24 load shedding instants. It can be seen from Figure 8.1 that the peak load occurs during the period from 10:00 to 14:00 for all four dates considered for four seasons.

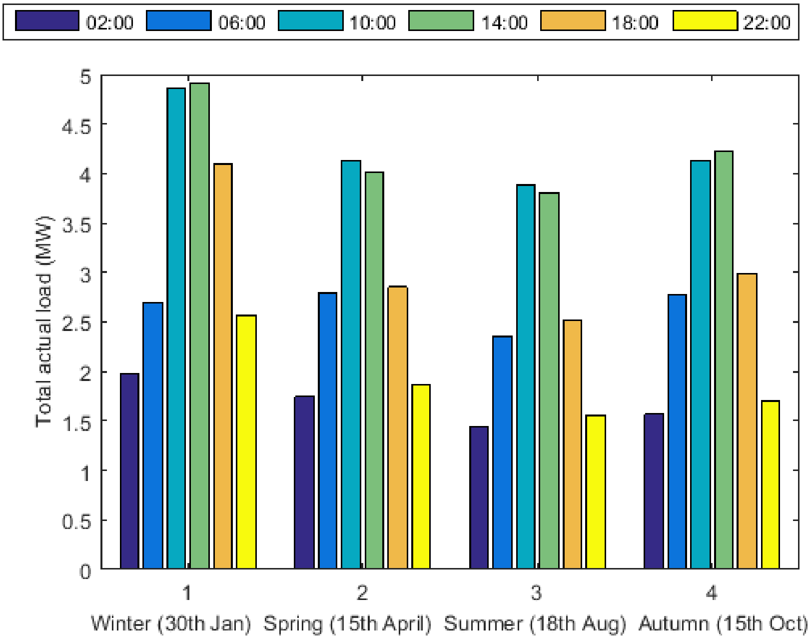

Figure 8.1: Actual total load at the considered load shedding instants

8.2 Simulation Results on Aggregated LF

8.2.1 Error in Forecasted Aggregated Load with Six Input Predictors

Figure 8.2 shows the error in total load forecast for all load shedding instants. The errors are obtained by deducting total forecasted load from the total actual load. The total forecasted load at a particular time is obtained by taking the sum of all load forecasted by each of the 26 aggregated LF models for that particular time. The error is positive when the actual load is higher than the forecasted load, i.e., under forecasted and vice versa. It can be seen from Figure 8.2 that chance of getting over forecast or under forecast is almost 50%. In general, the absolute errors in load forecast during high load hours, e.g., between 06:00 to 18:00, are higher than the errors in load forecast during low load hours. During high load hours, the absolute error in forecasted total load is found to be around 130 kW while in two instants of autumn the errors are found to be around 200 kW. The reason for the under forecasted load in autumn could be the rapid temperature variation during this period, e.g., the temperature on the considered day of 15th October was around 8 degree Celsius while the temperature on the same weekday of the previous week was around 13 degree Celsius in the investigated area. There is a correlation between the temperature and the load and load of the previous week same hour has a correlation with the forecast since previous week's same day and same hour values are used as one of the input predictors. Sometimes, lower temperature of about 8 degree Celsius could trigger some customers to turn their electric heaters if the district heating is not turned on which is not exceptional in the investigated region. This could be the reason of a higher error in forecasted total load for the particular hours of considered date in autumn.

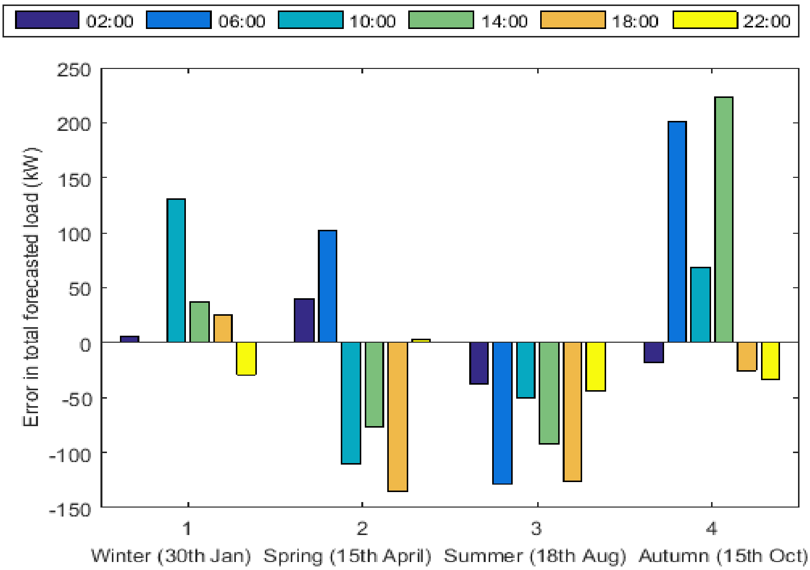

Figure 8.2: Error in forecasted aggregated load (kW) with six input predictors

The error in the total load forecast which is shown in Figure 8.3 is not high in terms of the percentage of the total actual load. It can be seen that the errors in the forecasted total load vary between 0.2% to around 7%. However, during the considered winter day when the max load occurred, the error in the forecasted total load is found to be between 0.1% to around 2.5%.

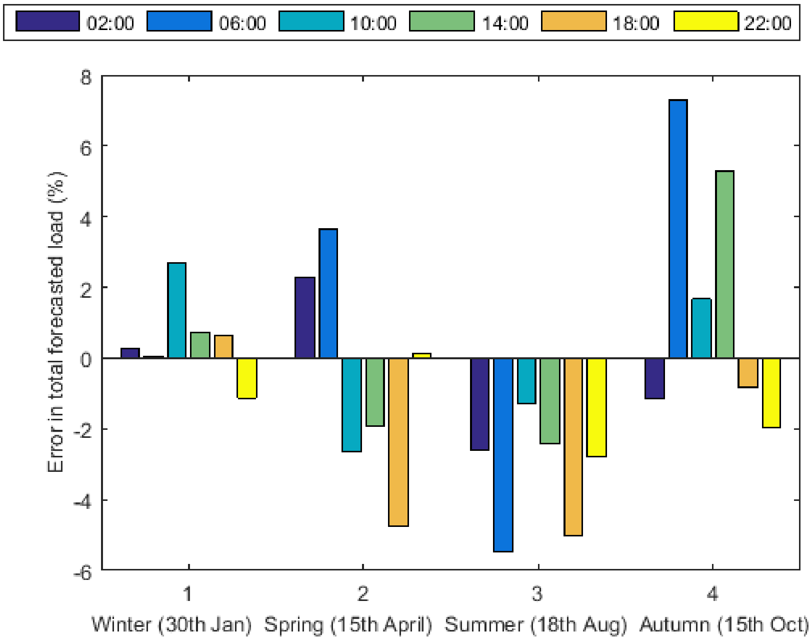

Figure 8.3: Error in forecasted aggregated load (%) with six input predictors

8.2.2 MAPE of the Aggregated LF Models with Six Input Predictors

Since the percentage error of each of the 26 forecasted values could be either positive or negative, hence MAPE is calculated by taking an average of the absolute percentage error obtained from all 26 forecasted load values. Figure 8.4 shows the MAPE for all twenty 24 load shedding instants. It can be seen that the MAPE varies between 4% to 10% for the aggregated LF models, where the loads are predicted by using 6 input predictors. As maximum MAPE of 5% to 10% has been suggested as acceptable for the CLS application by the expert group in GENAB, the forecasted aggregated load values with six predictors can therefore be considered as acceptable.

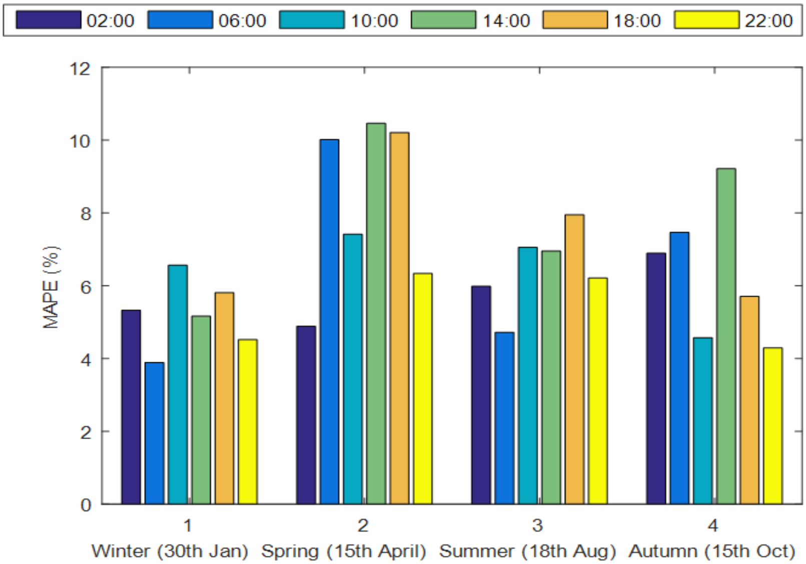

Figure 8.4: MAPE of the aggregated load forecasting models

8.2.3 Error in Forecasted Aggregated Load with Seven Input Predictors

The aggregated LF models are also used to forecast aggregated loads using the seven input predictors where previous hour's aggregated load values are considered for respective load shedding events. The previous hour's aggregated load values are used as one of the input predictors to know the significance of the impact of this predictor on the accuracies of the forecasts since the previous hour's load value is found to have more influence on accuracy.

Figure 8.5 shows (a) MAPE; (b) error in forecasted total aggregated load in the residential grid (kW); (c) error in forecasted total aggregated load (%); (d) the total actual load in the residential grid; for all 24 load shedding instants. It can be noted that the MAPE values obtained considering all the twenty-six forecasted loads at each load bus, are found to be approximately 1% to 3% lower (i.e., better forecast) than the MAPE values obtained for six predictors. Moreover, the percentage of error in total forecasted load of the grid is also around 1% to 2% lower in general as compared to that of the case of six predictors. It can be said that investment cost that would be required to get the latest SM data which is required for the 7th predictor, the accuracy improvement is not quite significant when aggregated LF is considered for CLS application.

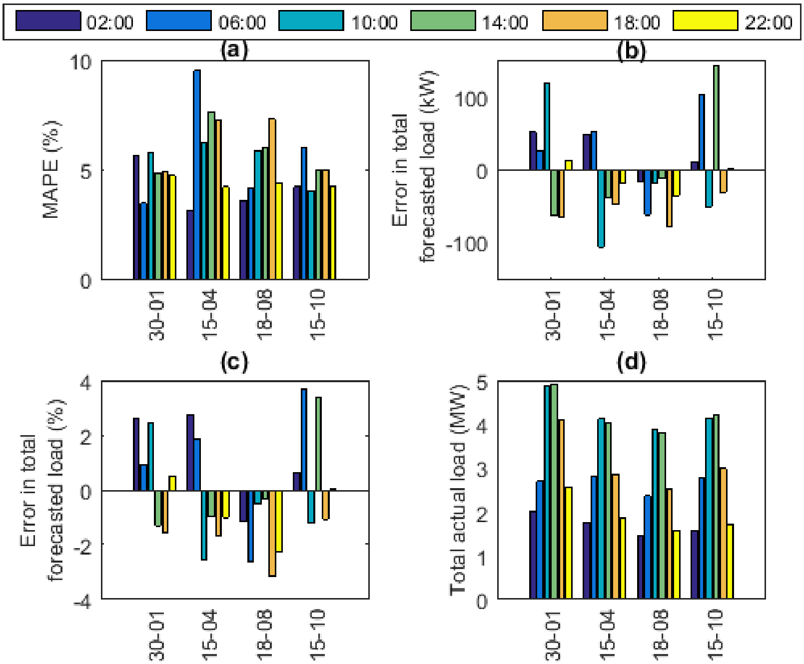

Figure 8.5: Error in forecasted aggregated load with seven input predictors

8.2.4 Comparison of MAPE for Different Sets of Input Predictors

The MAPEs of the forecasts are compared for the four different sets of input predictors mentioned in Section 8.1.2, and for each of the 24 load shedding instants. Figure 8.6 shows the comparison between MAPEs. It can be seen that the MAPE for different sets of input predictors varied between around 0.5% to around 4% considering all 24 load shedding instants. However, in most of the observed load shedding instants, the MAPE for different sets of input predictors varied between around 0.5% to around 1.5%. Hence, it can be said that aggregated LF can be done using six input predictors to estimate the amount of load at each load buses at the hour of critical power shortage. This load estimation can help the DSOs to select the load buses to shed the requested amount of load more accurately as well as to minimize the amount of unnecessary load shedding. Moreover, the results show that higher forecast accuracies can be obtained by using either the previous hour's aggregated value or previous two hour's aggregated average value as one of the seven input predictors.

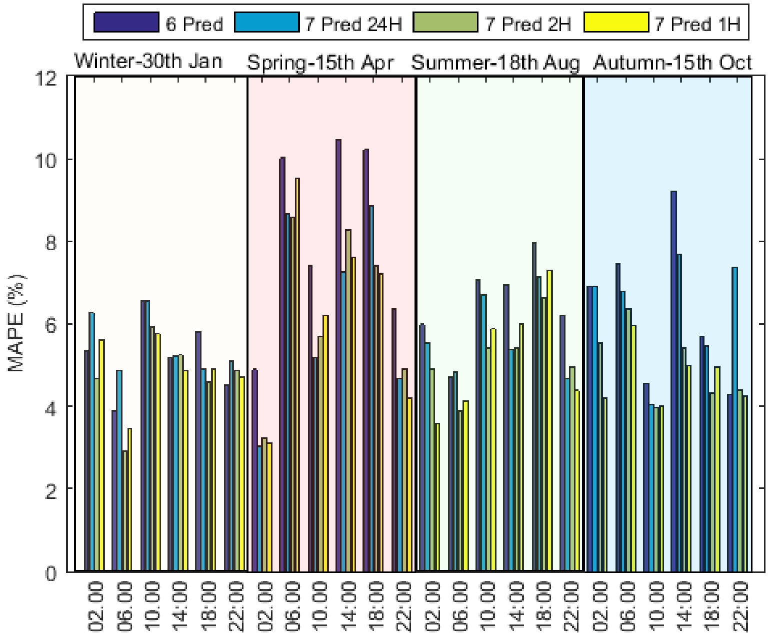

Figure 8.6: Comparison of MAPE for different sets of input predictors

8.2.5 Comparison of Forecasted Load Values for Different Sets of Input Predictors with Actual Load Values

The total forecasted loads using different sets of input predictors are compared with the total actual load for each of the 24 load shedding instants as shown in Figure 8.7. It can be seen that the difference between the actual load and the forecasted loads with different sets of input predictors are not very significant. Hence, it can be said that aggregated load forecast can be performed using six input predictors to estimate the amount of loads on each bus. Therefore, it reduces the necessity of getting latest previous few hours' ECD from the SMs.

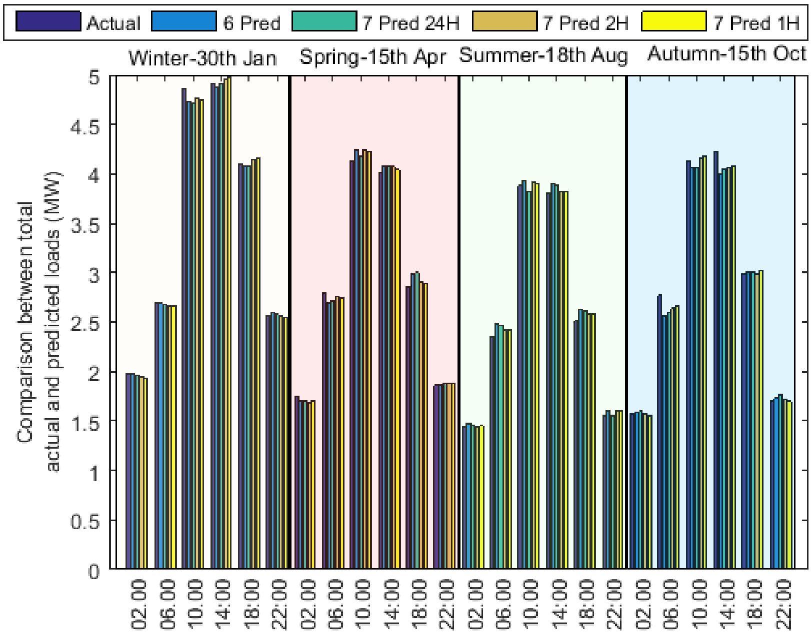

Figure 8.7: Comparison of Forecasted Load Values for Different Sets of Input Predictors with Actual load values

8.3 Comparison between Forecasted Load and Probable Estimation

8.3.1 Seasonal Load Profile

The CLS can be requested during a critical power shortage situation and hence the maximum load value for each hour calculated from hourly load values over a year can be considered to assume load at a certain hour. Moreover, the DSOs typically have peak current values at LV substation levels over a year or a season which the DSOs can use to assume load. However, the CLS might also become necessary during off-peak hours due to any natural disasters. Hence, the average load value for each hour calculated from hourly load values over a year can also be considered to assume load at a certain hour. In this chapter, it is assumed that the DSOs have seasonal and yearly load profiles both for the maximum and the average load values over every hour in a day.

A daily load profile was created for an aggregated load of the investigated 10kV residential grid to compare the forecasted load values with the estimated load values. It is noted here that the daily load profile for the whole investigated grid is obtained from the daily load profile values calculated for each of the 26 load buses in the investigated grid. The load profiles are created using the historical aggregated total load values of one year for each of the 24 hours in a day. Four seasonal daily load profiles are also created considering only the aggregated total load values of the respective four seasons. Two considerations are made to create the daily load profiles: 1) The maximum value of total load, e.g., max total load at 02:00 among all values at this hour in a year or season; 2) The average value of total load, e.g., average total load at 02:00 among all values at this hour in a year or season. Figure 8.8 shows the daily load profiles considering load values of a year and also for four seasons, where (a) is for hourly maximum load and (b) is for the hourly average load. The seasonal load profiles are used in Section 8.3.2 and Section 8.3.3 to estimate load values more accurately by considering seasonal impacts on load profiles. However, yearly load profile is considered in Section 8.3.4, since maximum or average load values are typically measured at LV substation level over a period of one year.

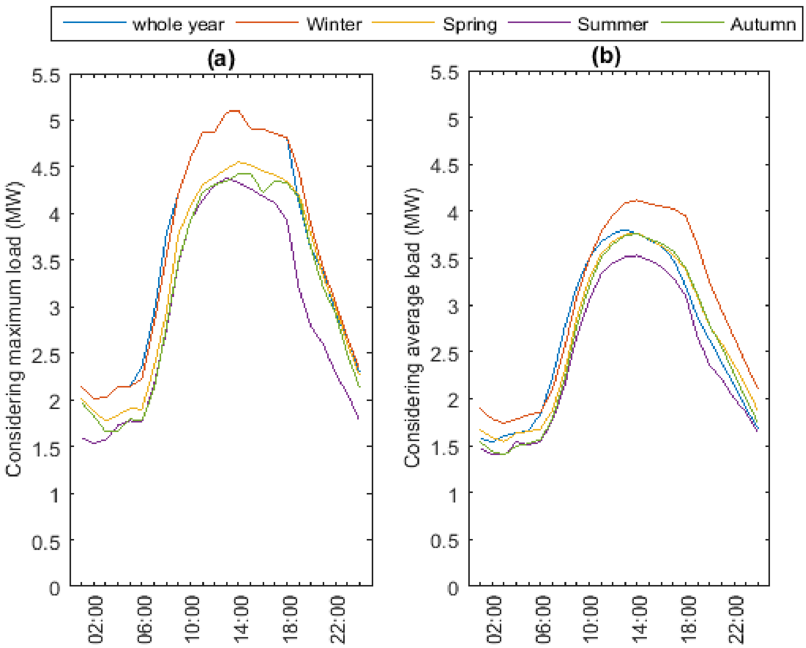

Figure 8.8: Seasonal load profile (a) considering maximum load and (b) considering average load

Table 8.1 shows the maximum and average load values over a year and four seasons for the considered six hours of a day.

Table 8.1 Maximum and average load values over a year and four seasons

Load values	Period	Hour					
		02:00	06:00	10:00	14:00	18:00	22:00
Maximum Load (MW)	1 Year	2.01	2.36	4.59	5.10	4.81	2.93
	Winter	2.01	2.23	4.59	5.10	4.81	3.06
	Spring	1.89	1.90	4.07	4.55	4.34	3.00
	Summer	1.54	1.76	3.92	4.33	3.93	2.29
	Autumn	1.83	1.78	3.92	4.42	4.33	2.93
Average Load (MW)	1 Year	1.54	1.84	3.50	3.76	3.20	2.15
	Winter	1.78	1.86	3.48	4.11	3.95	2.66
	Spring	1.59	1.68	3.27	3.77	3.38	2.37
	Summer	1.41	1.54	3.04	3.53	3.10	2.01
	Autumn	1.44	1.56	3.20	3.76	3.40	2.27

8.3.2 Load shedding under Load Assumptions and Load Forecasts

The forecasted total load value at a particular hour is then compared with the load values of that hour according to the two types of daily load profile. Figure 8.9 shows the comparison between differences in load assumptions (a) from maximum daily load profile, (b) from average daily load profile and (c) difference in load forecasts with six predictors. The differences are calculated by subtracting the assumed load values or forecasted load values from the actual load values. Hence, the difference is positive when assumption or forecasted value is less than actual and vice versa. It can be seen from Figure 8.9 that the errors in the total forecasted loads with 6 input predictors are much lower than the errors in the assumed load based on the created daily load profiles for the four seasons.

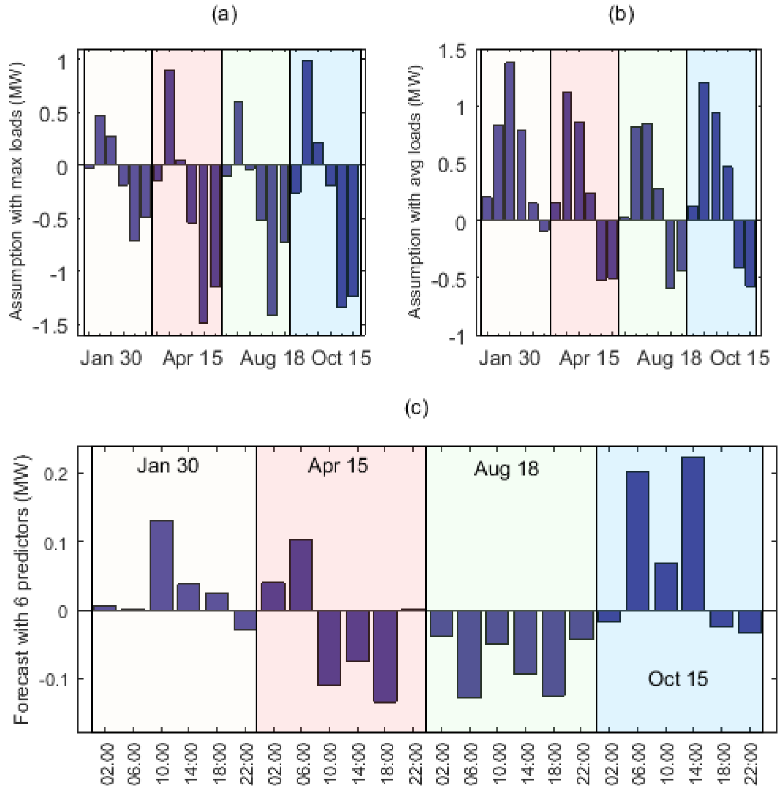

Figure 8.9: Comparison between differences in load assumptions (a) from maximum daily load profile, (b) from average daily load profile and (c) difference in load forecasts with six predictors

The difference between the errors in assumed load in (a) and forecasted load in (c), is found to be as high as 1.35 MW. This maximum difference is obtained on 18th August at 18:00, when the seasonal daily load profile is considered for load assumption. Moreover, the difference between the errors in assumed load in (b) and forecasted load in (c), is found to be as high as 1.25 MW. This maximum difference is obtained on 30th January at 10:00, when seasonal daily load profile is considered for load assumption. Hence, the results indicate that aggregated load forecast with 6 predictors can help the DSOs to estimate the load values more accurately than load estimation.

Moreover, the load assumptions from maximum load profile and average load profile are compared with the forecasted load both with the six input predictors and the seven input predictors including the previous hour's load.

Figure 8.10 shows the combined comparisons between the differences in load assumptions and load forecasts compared with the actual load, where (a) considered the load assumptions based on the created daily load profile for maximum load and (b) considered the load assumptions based on the created daily load profile for average load. The results show that using load forecast models gives much better ideas about load values compared to assuming load either from maximum load profile or average load profile. Moreover, it can be seen from Figure 8.10 that using six predictors for load forecast could be acceptable with respect to LF for a particular hour.

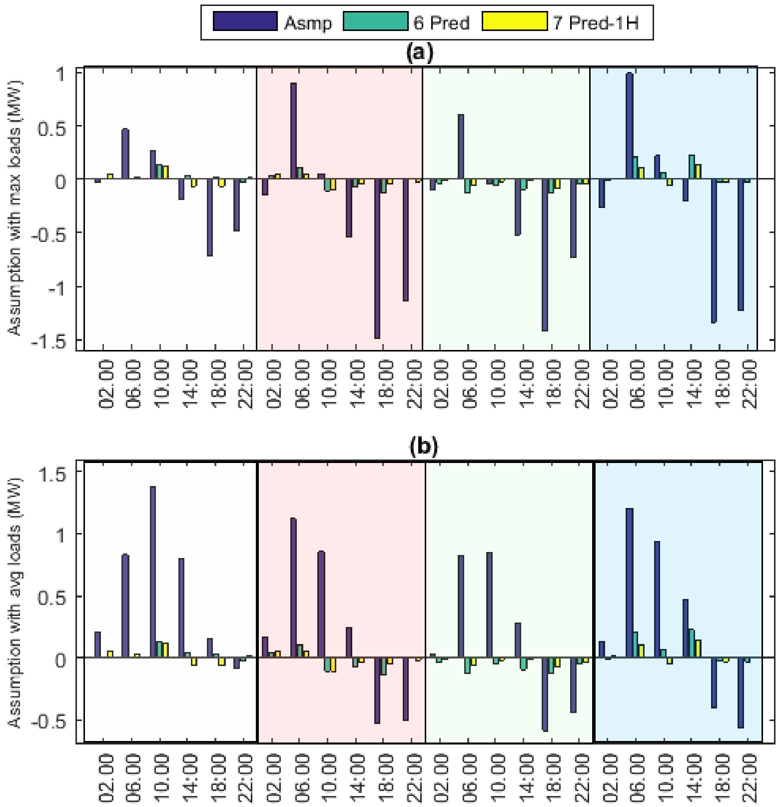

Figure 8.10: Comparison between (a) differences in load assumptions from maximum daily load profile and load forecasts with six and seven predictors and, (b) differences in load assumptions from average daily load profile and load forecasts with six and seven predictors

8.3.3 Area Selections for Load Shedding under Load Assumptions and Load Forecasts

A load shedding scenario is simulated to show the differences in the selection of load shedding areas using i) estimated load from the average load profile; ii) estimated load from the maximum load profile; and iii) the forecasted load using ANN with six input predictors. The area selection for load shedding has been evaluated for the load shedding scenario: The TSO requested a DSO to shed 2.5MW of load on 30th of January at 18:00 within 15 minutes. It is assumed that the DSO would disconnect the requested amount of load from the investigated 10kV residential grid consisting of 26 load buses. At each of the load bus, it is assumed that 80% of the customers are non-prioritized customers, i.e., the load of these customers can be disconnected in a critical situation, while 20% of the customers are considered as prioritized customers, i.e., the loads of these customers will be excluded from load shedding.

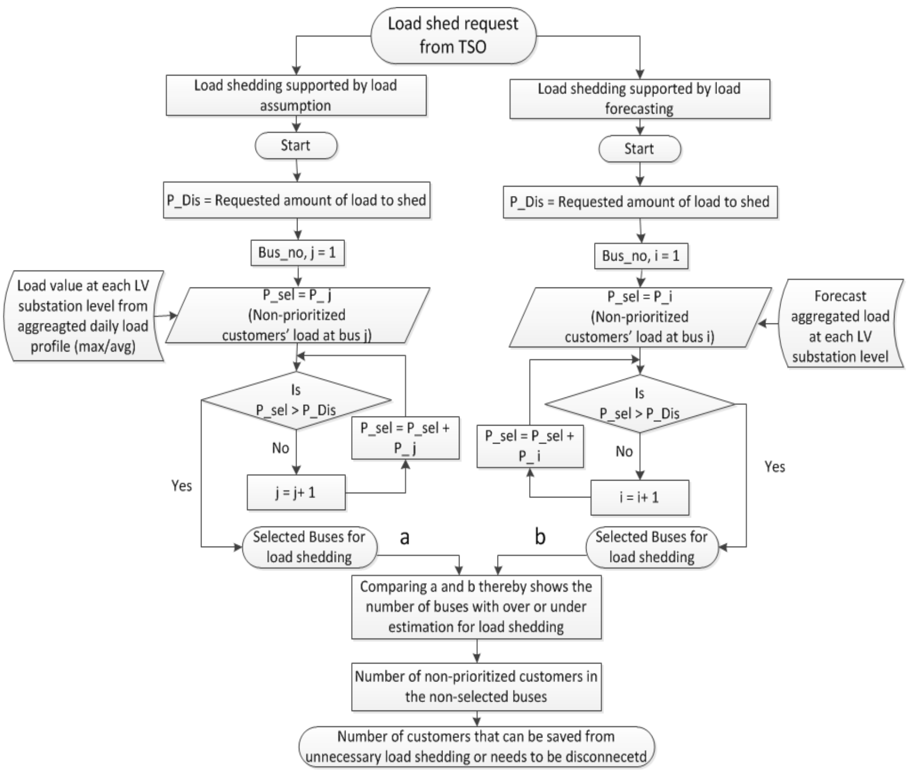

Figure 8.11: Block diagram for the comparison between load shedding by load assumption and by support from LF

Figure 8.11 shows the steps to be done for comparison between the load shedding by load assumption, i.e., estimated load from the maximum or average load profile, and the load shedding supported by LF. In the block diagram, the requested amount of load to disconnect is denoted by P_dis, and the amount of load from the selected areas for load shedding is denoted by P_sel. In Step 1, the requested amount of load is taken as input. In Step 2, the forecasted (at the hour of load shedding) or estimated aggregated load values for the non-prioritized customers at each of the load bus are taken as input. In Step 3, cumulative sum of the load values, i.e., from the first load bus is calculated to determine the number of buses that fulfils the requested amount of load. In Step 4, the selected number of buses are compared to get the number of buses with over or under estimation for load shedding. Finally, the number of customers that can be saved from unnecessary load shedding or the number of customers that need to be disconnected to fulfill the load shed request more precisely are determined.

Figure 8.12 shows the comparisons between the total estimated load from average load profile, estimated load from maximum load profile, total actual load and total forecasted load under each of the load bus, where all customers' load under the respective buses are considered. As can be seen in Figure 8.12, the values of the forecasted loads at most of the load buses are much closer to the values of the actual loads compared to the estimated loads on each bus.

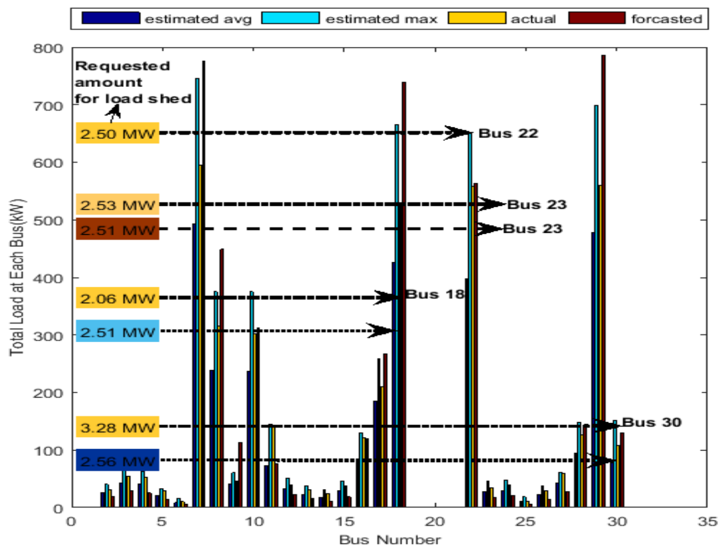

Figure 8.12: Comparison between selection of areas with and without load forecasting. Load shedding request: 2.5MW, on 30th of January at 18:00.

The customers under each LV substation is referred here as customers of an area. The DSO can select areas for load shedding in order to minimize unnecessary load shedding while fulfilling the load shedding request by the TSO. To select the areas for load shedding for example with estimate load values, the estimated load values from non-prioritized customers are summed up cumulatively. The cumulative sum is calculated from the first load bus to the last load bus in the system. Similarly, the cumulative sum is calculated for the examples with the actual load and the forecasted load.

It can be seen from Figure 8.12 that if estimated load values from average load profile are used to select areas for load shedding, non-prioritized customers' loads from the first load bus to the Bus 30 need to be disconnected which in total amounts for 2.56 MW according to the estimations. The actual load of non-prioritized customers on these buses is 3.28 MW which shows that in this example 0.78 MW load would be disconnected unnecessarily. However, since this is an estimation, to be on the safe side more load might also be disconnected depending on the safety margin considered by the DSO.

If estimated load values from maximum load profile are used to select areas for load shedding, then non-prioritized customers' loads from the first load bus to the Bus 18 need to be disconnected which in total amounts for 2.51 MW according to the estimations. The actual load of non-prioritized customers on these buses is 2.06 MW which shows that in this example 0.44 MW load would be short from the requested load shedding.

Figure 8.12 also shows that if forecasted load values with six predictors are used to select areas for load shedding, then non-prioritized customers' loads from the first load bus to the Bus 23 need to be disconnected which in total amounts for 2.51 MW according to the forecasts. It can be seen from Figure 8.12 that the non-prioritized customers' actual loads from the first load bus to the Bus 22 amounts for 2.50 MW and the load 2.53 MW up to bus 23. Hence, the total load up to the Bus 23 is under forecasted by 0.03 MW. The results show that by using forecasted load values, loads of the non-prioritized customers at the Bus 24, 25, 26, 27, 28, 29 and 30 can be excluded from load shedding which would otherwise be disconnected when using the estimated load values from average load profile. The number of customers associated with these buses is 489. This clearly demonstrates the advantage, i.e., avoid unnecessary load shedding, of using LF in CLS.

8.3.4 Safety Margins Against Errors in Load Assumptions and Load Forecasts

The errors in the forecasted load values using six predictors, and the estimated load values using maximum, and also using average load values, are calculated in percentage concerning the actual load values for all the 24 load shedding instants. Average load and maximum load over a year are used to estimate the load values assuming that only yearly average and maximum load values are available at the LV substation level. The errors are calculated to determine approximate safety margins that need to be used while using forecasted or any of the two types of estimated values in selecting areas for CLS. Figure 8.13 shows the error values in percentage for all the 24 load shedding instants considered over a year. It can be seen from Figure 8.13 that adding 5% load value with the forecasted load values could be enough to compensate for the errors in the forecasted load. The forecasted values can be over forecasted or under forecasted, therefore adding load values with the forecasted load values would help to perform CLS safely. Similarly, estimated values using yearly average load profile could give an over-estimation or an under-estimation, but the errors in the estimation could be as high as 30%, e.g., during high load periods. The estimated values using yearly maximum load profile which mainly gives an over-estimation could give errors as high as 80%, e.g., during the low load period. Therefore, it can be said that the error margin can be kept quite low by using aggregated LF models which helps to minimize unnecessary load shedding during the CLS.

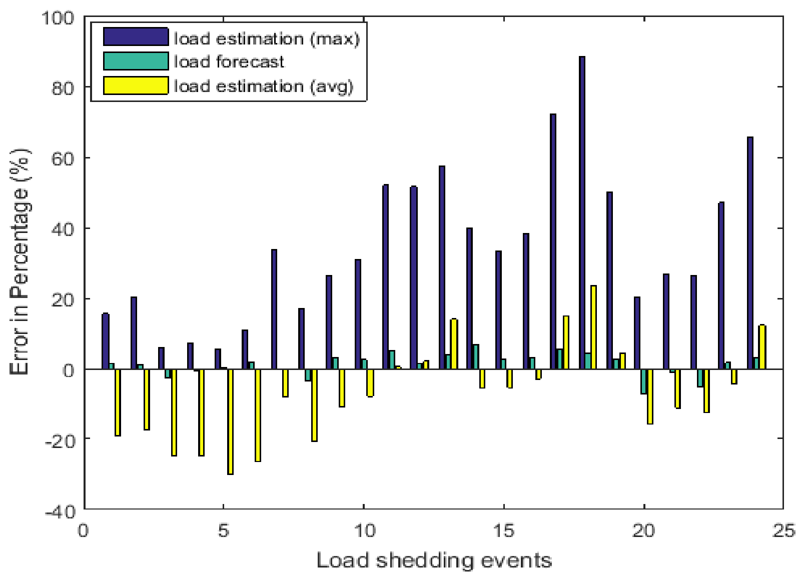

Figure 8.13: Comparison between errors (%) from forecasted and estimated loads

8.4 Individual LF Model to Calculate Voltage Level for the Excluded Customers from Load Shedding

8.4.1 Individual LF Applied to CLS

The main motivation for using the SMs for the CLS is to exclude the prioritized customers which is not the case in the present practice of CLS where all customers lose power. Hence, it is desirable to maintain at least minimum acceptable level of the voltage supply at excluded customers from the CLS.

The information about power consumption at the individual customer level can be used to simulate load shedding with the SMs. However, in the existing SMS, it is not possible to get real-time power consumption data from a large number of SMs within few minutes when TSO requested for CLS manually. Therefore, to apply individual LF in CLS, the following steps are needed:

Step-1: The individual LF model is developed for each customer in the considered 10 kV residential grid to estimate the load of the individual customers at an hour of interest. The models are developed using ANN method where hourly ECD of one year is used to train each model of the individual customer. The forecasted load for each customer is then used in the developed SMs' switching model.

Step-2: The SMs' switching model is developed considering a smart metering network for all the customers in the residential grid. The maximum number of SMs per MCU is assumed to be 50. The real SMs' switching times obtained from the field tests are distributed to each of the two thousand SMs considered in the switching model. Hence, each SM is associated with a fixed disconnection time where the disconnection time typically varies from one SM to another SM.

Step-3: The SMs' switching model associates each customer with the forecasted load for that customer. The switching model traces the amount of load disconnected when a customer is disconnected. The switching model also calculates the total amount of load disconnected at a particular sec by tracing the number of customers disconnected at that sec and the disconnected customers' associated loads. The load of each customer is assumed to be constant for the load shedding period.

Step-4: Load flow model: The SMs' switching models output, e.g., changes in load values at each load bus for every sec of the load shedding period and remaining load values at each load bus is used in the load flow simulation model as described in Section 7.3.1. In [115], the voltage threshold limit for under voltage load shedding scheme is considered to be around 0.93

to 0.95 pu at the transmission level. The corresponding voltage at the MV/LV grid can be considered lower than 0.95 pu. Hence, 0.92 pu is considered as the threshold voltage at the main substation bus during a critical grid situation when the CLS needs to be initiated. It should be noted that this voltage threshold value at the main substation can be different in different grid conditions.

The impact of using load values from individual forecasting models on the bus voltage calculation after the load shedding is analyzed. The calculated voltages at each load bus during and after the load shedding using forecasted individual customer's load value are compared with the calculated voltages at each load bus during and after the load shedding using individual customer's actual load value.

8.4.2 MAPE in the Forecasted Load by Individual LF Models

The MAPE for a particular load shedding instant is obtained by calculating the mean of the errors in individual forecasted load values of the considered individual customers in the residential grid. The MAPE values are calculated for each of the 24 load shedding instants and compared the MAPE values obtained for using six input predictors and seven input predictors with previous hour's value. Previous hour's value is considered for the predictor which is average load over the previous certain period because in general, previous hour's value is found to have the most influence on the accuracy as shown in Section 6.4.3.2.

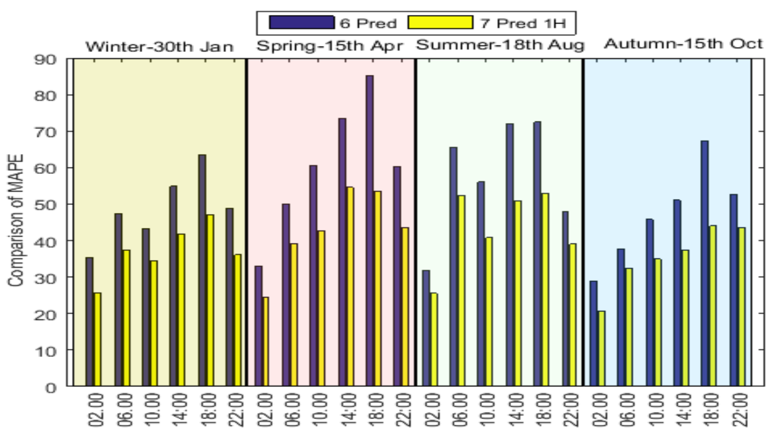

Figure 8.14: Comparison of MAPE in the forecasted load by individual load forecasting models

Figure 8.14 shows the comparison of MAPE values. It can be seen that the MAPEs for individual forecasted load values are quite high as expected due to the random nature of electrical energy usage of individual customers. The results show that the MAPE values could be improved by around 15% to 30% by using seven input predictors instead of six predictors to forecast load.

8.4.3 Comparison of Voltages on Each Bus with and without Load Forecast

The simulation results on voltage values on each of the 31 buses are compared considering individual customers for the cases 1) forecasted load values with six predictors; 2) forecasted load values with seven predictors (7 Pred 1H); 3) real load values. Two load shedding instants among the investigated 24 load shedding events are selected for the comparison. The selected load shedding instants are: 1) when the voltage deviation was high, i.e., the 4th load shedding instant (30th January, 14:00) with highest load condition; 2) when the voltage deviation was low, i.e., the 13th load shedding instant (18th August, 02:00) with lowest load condition. Figure 8.15 shows simulation results of the initial voltage, i.e., before load shedding and final voltage, i.e., after shedding 80% customers' loads at each load bus.

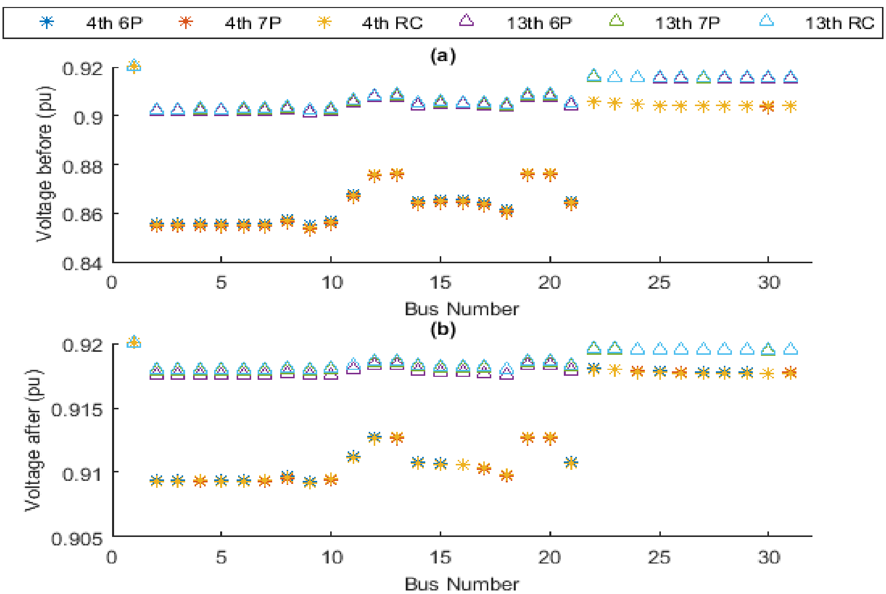

Figure 8.15: Comparison of voltages on each bus before and after load shedding, using forecasted load values (6P & 7P) and historical real energy consumption value

The voltage values for the 4th load shedding instant using forecasted load values with six and seven predictors are shown as 4th 6P and 4th 7P respectively while the 4th RC is used to denote the use of historical real energy consumption values in a simulation. Similarly, the voltage values for 13th load shedding instants are denoted. Figure 8.15 shows that the errors in the forecasted individual load values have a negligible impact on the voltage value calculation at each load bus. Hence, it can be said that the forecasted individual customers' load values using six input predictors can be used to estimate the voltage level at the excluded customers after the CLS.

Figure 8.16 shows the voltage deviation on each bus due to 80% customers' load shedding at each load bus. It can be seen that comparatively high voltage deviation occurred during the 4th load shedding instant since the load was high and comparatively low voltage deviation occurred during the 13th load shedding instant since the load was low.

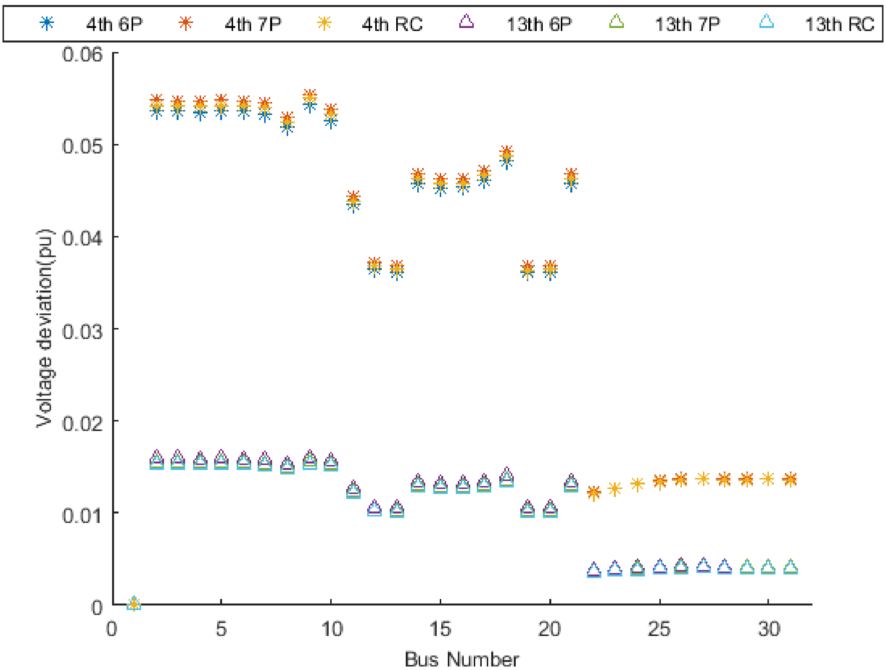

Figure 8.16: Comparison of voltage deviations on each bus, using forecasted load values (6P & 7P) and the historical real energy consumption value

8.4.4 Comparison of Voltage at the Furthest Bus with and without Load Forecast during Load Shedding

As described in Section 7.3.2, the furthest bus which would have the lowest voltage is Bus 5 for the considered grid topology in the investigated residential grid. The voltage variation in the furthest bus due to load shedding is shown in Figure 8.17 considering the two load shedding instants, i.e., 4th and the 13th. The voltage variation is shown with one sec interval for the whole load shedding period which is 344 sec for the considered SMS with 50 SMs per MCU. The voltage values are compared for individual load values with and without load forecast.

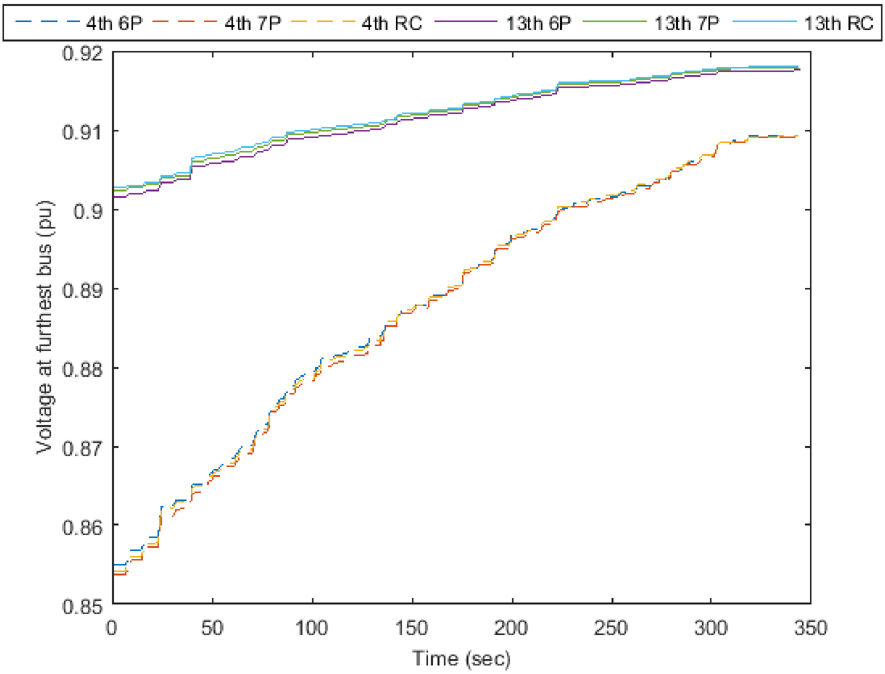

Figure 8.17: Comparison of Voltage at the Furthest Bus with and without Load Forecast during Load Shedding

It can be seen from Figure 8.17 that the impact of errors in the forecasted individual load on the customers' voltage is comparatively larger before load shedding, i.e., when the load at each load bus is high, and vice versa. However, the visible higher impact before the load shedding is around 0.001 per unit, which is negligible. Hence, it can be said that forecasted individual load values using six predictors can be used for voltage calculation at the furthest bus.

8.5 Conclusions

The results from the developed aggregated LF models show that the use of aggregated LF models at LV substation level would be helpful to select areas for load shedding more accurately than simple load estimation based on average load values or maximum load values. Although the forecasted load values could be higher or lower than the actual values, the simulation results show that significant improvement can be achieved by using LF models with 6 predictors compared to a simple load estimation. The use of aggregated LF models thus can help the DSOs to avoid unnecessary load shedding or to avoid under load shedding. Moreover, by using the aggregated LF models, the DSOs could keep the error margin quite low to avoid under load shedding compared the margin that the DSOs would need to consider in case of simple load estimation.

The MAPE values of aggregated LF models show that adding 5% to 10% load with the forecasted load would help to perform the load shedding fulfilling the request from the TSO. However, the results on estimated load show that significantly higher percentage of the load may need to be added or subtracted from the estimated load in case of estimating load using average and maximum load profile respectively. This is due to the chance of getting a higher error in load estimation depending on the day and hour of the CLS.

The use of forecasted loads of individual customer in load flow study shows that individual LF model can be used to estimate the voltage level after the load shedding. The results show that the voltage at the LV substation level can be calculated with an error on around 0.001 pu when up to previous day's energy consumption value is used to forecast load at the individual customer level.

Chapter 9
Conclusions and Future Works

This chapter presents the main conclusions of this thesis and ideas for future works.

9.1 Conclusions

Unlike the current practice for the manual CLS from MV substation level, the SMS gives the unique opportunity to select customers individually and thereby provides the way of excluding prioritized customers from the CLS. The exclusion of socially important prioritized customers from the CLS will give benefit to the society. Moreover, the SMS can allow to perform the CLS within allocated time of 15 minutes, and thereby can help relieve the system in critical power shortage situations, which would benefit the DSOs, the TSOs, and the society. The main conclusions from the field tests performed in this work, and the simulation results on load shedding supported by LF, are provided below:

The field tests' results on small-scale load shedding using the SMs have shown that during reconnection of the SMs, current transients could be created due to the energizing of the capacitors that exist in many electronic equipment over the terminals on the grid side. Only four out of a total of twelve recorded transient events exceeded the standard limit of ± 50% but not above ± 60%. However, the duration of the current transients which created voltage transients are very short, e.g., ranging from 0.08 ms to 0.23 ms, and according to the literature, this type of very short duration transients are less harmful to the sensitive equipment of the customers. Moreover, the voltage transients that were recorded at few customers' sites due to upstream action, i.e., reconnection of the neighbor's SM, created negligible current transients with similar duration and much smaller amplitude. Also, the series operation of each MCU and parallel operation of all MCUs can help to get "distributed" transients over the load reconnection period compared to today's instantaneous load reconnection technique from MV substation. Hence, it can be concluded that the SMS could be used for the CLS without creating any significant impact on the voltage quality of the customers.

The performance of the existing SMS has shown that on average the SMs take around 8 seconds to disconnect and around 10 seconds to reconnect individual SM. However, the reconnection process of the SMs could take few minutes to hours if the power system fails after remotely disconnecting the

SMs since the self-healing ZigBee communication network need to build up the network again from scratch. More extended battery support of the SMs and the MCUs could help to keep the communication system alive even if the power system fails after remote disconnection of the SMs, and thereby can enable faster reconnection of the SMs. Since remotely disconnected SMs need to be reconnected either remotely or using optical eye solution through field visits, more extended battery support could also help to avoid those types of SMs' replacement which do not support optical eye solution.

The errors in the SMs' status update report which were found to be around 10% on average, could create the confusion on how much of load is actually shed and how many of SMs actually failed to do so. Since the individual verification process of the failed reported SMs requires around six seconds, a reliable status update report would, therefore, be necessary to perform a large-scale load shedding without getting confused by the errors in the status update report.

Unlike the CLS by disconnecting the MV feeders where the aggregated load values are known (measured) in near real-time, in case of the CLS with excluding prioritized customers, the load from the selected customers on each feeder would be difficult to know. The simulation results on using aggregated LF models at LV substation level have shown that by using forecasted aggregated load values, the DSOs could select areas for load shedding more precisely while fulfilling the load shedding request from the TSO more accurately than the load shedding without LF. The simulation results have shown that the total load in, e.g., a 10kV residential grid can be forecasted with an error of around ± 3% by using up to previous day's hourly SM data in the pre-developed aggregated LF models. Moreover, during maximum load hour, the use of aggregated LF models could save around 25% of number of customers from unnecessary load shedding, as compared with the load shedding scenario considering average load values from the daily load profile.

Since the CLS using the SMS would allow prioritized customers to remain connected to the grid, the quality of the voltage to the excluded customers need to be checked to determine if further steps are necessary. This work used up to previous day's hourly SM data in the individual LF models to forecast load at load shedding hour. The forecasted load values are used to calculate the voltage change during and after the load shedding. The simulation results have shown that the voltage calculation at each of the LV substation gives a negligible error (around 0.001 per unit), when calculated voltages using forecasted individual customers' load values are compared to the voltages calculated using individual customer's actual load values.

Considering the application of SMs for the CLS, and accuracy improvement of LF at LAL, the following recommendations can be made on the functionality requirements of future SMS:

1. Considering the maximum disconnection time of the present SMs, the number of SMs per MCU should be limited to 75 to ensure the CLS within allowed 15 minutes. However, the total load shedding time can also be reduced by allowing multiple SMs switching capability for each MCU, or by decreasing the switching delay.
2. Assurance of accurate update report from the SMs on the status of the remote ON/OFF control switch during the CLS.
3. The SM data with one-hour interval could be used to develop LF models to support the CLS. However, the SM data with lower granularity can be used to increase the accuracy of the forecast for other applications, such as network congestion identification where higher level of accuracy can be required.
4. Frequent readings from the SMs to the CS, e.g., every hour can help to improve the load forecast accuracy at LAL and the individual customer level. However, the typical SM readings that come to the CS two times a day can be used to forecast load to support the CLS.
5. Extended battery backup time of the SMs would be recommended to keep the communication system alive for faster reconnection, in case the power system fails after the CLS using the SMs. An alternative could be to enable the communication network to start from a saved network information rather than from scratch as it is done today.

9.2 Future Works

The following suggestions could be considered for future work:

- This thesis did not consider the types of customers to prioritize them for load shedding. If the types of the customers were known, e.g., residential customers, small and/or medium business, etc., this information could be used for prioritizing the customers with different priority levels. In future, customers' types could be used to propose different load shedding strategies considering customers' priority levels.
- The uncertainty or the error in the status update report from the SMs could be considered in the SMs' switching model to reflect the impact of the error in performing the load shedding using the SMs. Moreover, a simulation model can be developed for the

communication network of the SMS to evaluate the inter-dependency between the electrical network and the communication network.

- The optimal load shedding model could be developed to study the load shedding with SMs considering various objectives and constraints, e.g., minimizing the sum of disconnected loads and also keeping the voltage levels at each load bus within the acceptable limit, and/or minimizing the sum of the disconnected residential customers. Moreover, instead of full load disconnection of each customer, optimal load shedding can be studied considering potential option of partial load disconnection from each customer to allow the basic power supply need of the customers.
- The LF models have been used to support the CLS. The models have been developed using available historical hourly ECD. It would be interesting to further investigate the impacts of using more frequent data, e.g., 10-min interval data, on the performance of the LF models. Moreover, the accuracy of LF can be studied for the houses with solar panels, PEV and battery storage, by using the SM data.
- This thesis used ANN method to forecast loads at LAL and individual level. It could be interesting to compare the results with the forecasted load values using other methods, e.g., fuzzy logic, Auto-Regressive Integrated Moving Average, support vector regression technique, deep learning method, etc.
- This thesis showed that the accuracy of the forecasted load at any load shedding hour could be improved by using previous hour's ECD as one of the input predictors. In the future, the necessity of the frequent SM readings, e.g., every hour, and lower SM data granularity, e.g., 15 minutes interval, can be studied for LF accuracy improvement, and also other applications, e.g., network congestion identification, demand response, load scheduling, etc.
- The literature study performed in this thesis has indicated the necessity of having PQ measurement capability in the future SMS. However, more investigation is needed to identify the necessary parameters to be recorded in the SMs. Future studies could be made on the data granularity requirement for each parameter, duration and sampling frequency to record data of triggered PQ events, efficient method of extracting the useful message from the data, and also on the method of saving the PQ data which would require less memory capability, etc.

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Appendix A
Smart Meters' Functional Requirements Proposed by Different Authorities

For SMs, functional requirements have been proposed by different national and international authorities to cope with upcoming grid condition, e.g., enabling local micro generation and also future SG applications, e.g., demand response, HEMS, etc. The proposed functional requirements are presented and discussed in this section.

A.1 Functional Requirements Proposed by Ei

The seven minimum functionalities proposed by Ei are presented in Table A.0.1 [2]. The proposal included two new functionalities which is not common in the existing SMS, e.g., in Sweden. One functionality is the ability for extended measurement data, i.e., supplying customers with near real-time data, e.g., every 10 seconds. Another functionality is to supply the customers near real-time data from the SM and other information such as electricity price or DR signal from DSOs or any third party.

Table A.0.1 Functional requirements proposed by Ei

Sl.	Functional requirements by Ei
1	The electricity meter should be capable of measuring phase voltages, phase currents, active and reactive power both import/export on each phase, and should also be capable to measuring and recording the total active energy for both import/export.
2	Electricity meters should be equipped with a customer interface supported by an open standard that enables the customer to access the measured data in close real-time.
3	Electricity meters should support remote readings of measurement data and data on power interruption.

4	Electricity meters should record the amount of energy transferred every 1 hour and also should be able to record values every 15 minutes if needed.
5	Electricity meters should be able to record data on power interruption by recording the start and the end time of each power outages in one or more phases that are longer than three minutes.
6	It should be possible for the electricity companies to upgrade firmware and change settings in the electricity meter remotely.
7	It should be possible for the electricity grid companies to be able to power-on and power-off electrical installations via the electricity meter remotely.

A.2 Functional Requirements Proposed by EC

The minimum functional requirements proposed by EC are presented in [30]. The functionalities that were present in EC's definition of a SMS in [30] but were not included in the proposal of minimum functional requirements for SMS in [31], are marked by underlining the words in Table A.0.2. The functionalities that are included in the proposed ten minimum functionalities are 1) ability to send SM readings to the customer interface 2) support for pre-payment system and 3) ability of the SM to monitor PQ.

Table A.0.2 Functional requirements proposed by EC

Sl.	Functional requirements by EC
1	Provides readings from the meter to the customer and to equipment that he may have installed and any third party designated by the customer.
2	Updates these readings frequently enough to allow the information to be used to achieve energy-savings
3	Provides Import / Export & Reactive Metering.
4	Supports advanced tariff systems
5	Allows remote reading of meter registers by Meter Operators and by third parties
6	Allows readings to be taken frequently enough to allow the information to be used for network planning
7	Provides two-way communication between the smart metering system and external networks for maintenance and control of the metering system.

8	Allows remote ON/OFF control of the supply and/or flow or power limitation.
9	Provides Secure Data Communications
10	Fraud prevention and detection.
11	Provides the readings in a form easily understood by the untrained consumer, and with calculations enabling final customers to better control their energy consumption.
12	Supports energy supply by pre-payment and on credit
13	Provides for the monitoring of Power Quality

A.3 ERGEG's Guidelines of Good Practice on Regulatory Aspects of Smart Metering

The guidelines proposed by European Regulators' Group for Electricity and Gas (ERGEG) on regulatory aspects of SMS are presented in Table A.0.3. The ten functionalities proposed by EC, however, did not mention explicitly about three of the guidelines from ERGEG which are marked by a star (*) sign in Table A.0.3. The ERGEG suggested that when a service provider is in charge of any information, e.g., on the customer's voltage quality, the customer should be able to know that this data exists, and should be able to receive information on the explicit data with a reasonable fee. Moreover, ERGEG suggested that if a customer wishes to reduce or increase power capacity, he/she can contact the relevant market actor and the market actor will remotely perform this service. This service can also be used in case of non-payment by customers, to reduce power capacity of customers to a minimum level instead of deactivating electricity supply, leaving to the customer the possibility of using essential devices. In addition, ERGEG suggested that if a customer chooses to receive immediate information on exceptional energy consumption at his/her connection point and thus act upon it, service provider need to be able to communicate this to the customer by having an alarm service in the SMS, could be subject to a fee.

Table A.0.3 Guidelines from smart metering system proposed by ERGEG

Sl.	Guidelines proposed by ERGEG
1*	Customer control of metering data
2	Information on actual consumption and cost, on a monthly basis, free of charge

3	Access to information on consumption and cost data on customer demand
4	Easier to switch supplier, move or change contract
5	Bills based on actual consumption
6	Offers reflecting actual consumption patterns
7*	Remote power capacity reduction/increase
8	Remote activation and de-activation of supply
9	All customers should be equipped with a metering device capable of measuring consumption and injection
10	Alert in case of non-notified interruption
11*	Alert in case of exceptional energy consumption
12	Interface with the home
13	Software to be upgraded remotely

A.4 Functionalities Proposed by SM Coordination Group, M/441

The European Standardization Organizations (ESOs), CEN, CENELEC and ETSI decided to combine their expertise and resources by establishing the Smart Meters Coordination Group (SM-CG) in response to Mandate M/441. The functionalities proposed by SM-CG under the mandate M/441 is presented in Table A.0.4 [29]. The functionalities are relevant to communications of the SMS.

Table A.0.4 Functionalities proposed by SMCG in M/441

Sl.	**Functionalities proposed by SMCG in M/441**
1	Remote reading of metrological register(s) and provision to designated market organizations.
2	Two-way communication between the metering system and designated market organization(s)
3	To support advanced tariffing and payment systems
4	To allow remote disablement and enablement of supply and flow / power limitation
5	To provide secure communication enabling the smart meter to export metrological data for display and potential analysis to the end consumer or a third party designated by the end consumer
6	To provide information via web portal/gateway to an in-home/building display or auxiliary equipment

A.5 Functionalities Proposed EC for a New Electricity Market Directive

The EC’s proposal for a new electricity market directive, published in 2016, requires some features of the SMs [33]. According to the EC's proposal, the introduction of the SMs should be carried out in accordance with principles which are presented in Table A.0.5.

Table A.0.5 Proposal by EC for a new electricity market directive requiring features of the SMs

Sl.	Proposal by EC for a new electricity market directive requiring features of the SMs
1	Measure the actual electricity consumption and make the information readily available and visualized to the customers in near real-time and with no additional cost.
2	Ensure safety of the smart metering system and also ensure privacy and data protection of customers in accordance with EU’s respective legislations.
3	On customers’ request, make their consumption and injection information available to them, in an easy to understand format via a local standard customer interface and/or remote access.
4	Provide appropriate advice and information in connection with the installation of the electricity meter, electricity meter's full potential and on the collection and processing of personal data.
5	The smart meter should enable measurement and settlement with the time resolution same as the imbalance period on the national market.

Appendix B
Possibilities of Power Quality Monitoring using SMs

The impact of SMs' switching on the PQ are monitored during the field tests both at the LV substation level and also at the selected individual customers' level. The PQMs are used to monitor the PQ by recording the PQ related parameters and also the events when an event was triggered based on the preset trigger values for the events. However, the use of additional PQMs appeared to be an expensive solution with respect to monitoring the PQ. Inclusion of PQ measurement capability therefore could be a cheaper solution to monitor the PQ at the customers' level. Hence, this thesis performed literature study on the importance of functional requirements for PQ measurement with the SMs. The study included the aspects of PQ problems from DSOs point of view, expected intensity of PQ problems in future, sources and the impacts of the PQ problems in the distribution system, PQ measurements capabilities of SMs in the market and also the challenges and importance of PQ measurement with the SMs. The literature study on the PQ measurement with the SMs indicated the importance and possibilities of PQ measurement with the SMs which however needs further study for proper specification on the parameters need to be recorded with respect to data sampling, storage, communication, etc.

B.1 What is Power Quality?

PQ is often defined as the electrical grid's ability to supply a clean and stable power flow and determines the fitness of electric power to customers' devices. The aim of the electric power system is to generate electrical energy and deliver this energy to the customer equipment at an acceptable voltage. With an ideal power system, each customer should perceive the electricity supply as an ideal voltage source with zero impedance. In this case, the voltage should be constant whatever the current is. However, the reality is not ideal. The electric power system connects many customers. Different customers have different patterns of current variation, fluctuation, and distortion, thus polluting the voltage for other customers in different ways. Moreover, different customers have different demands on voltage magnitude, frequency, waveform, etc.

PQ is the combination of voltage quality and current quality [116]. Voltage quality concerns the deviation between reality and ideal. The ideal voltage is a single frequency sine wave of constant amplitude and frequency. Similarly, current quality concerns the deviation of the current from the ideal where an ideal current is a single-frequency sine wave of constant amplitude and frequency, with the additional requirement that the current sine wave is in phase with the voltage sine wave.

PQ disturbances, e.g., deviations of voltage and/or current from the ideal can be classified as two types variations and events. The classification is based on the measurement procedure of the characteristic of voltage or current.

The term ‘Variations’ refers to the small deviations of voltage or current characteristics from its nominal or ideal value. For example, the variation of root mean square (rms) value of voltage from their nominal values, or the harmonic distortion of voltage and current. Variations are disturbances in the electric power system that can be measured at any moment in time.

The term ‘Events’ refers to the larger deviations of voltage or current characteristics from its nominal value that only occur occasionally, e.g., voltage interruptions or transients. The events are disturbances in the electric power system that start and end with a threshold crossing. The events require waiting for a voltage or current characteristic to exceed a predefined threshold level.

A greater part of all electrical equipment used today is built up of power electronics that create disturbances on the electrical grid. The introduction of increasing amount of electronics appliances means that the electrical grid is affected by new types of disturbances from connected loads, e.g., harmonic related problems, transients, and flicker. Moreover, single phase loads and loads with higher starting currents are becoming more common in contributing disturbances such as unbalance and voltage dips.

Poor PQ increases loss in the electrical grid, which in turn leads to higher costs for the transmission and distribution system operators. Furthermore, the collaborative effects of these different types of loads can manifest themselves in different ways, e.g., cables and transformers overheating and light bulbs having shorter lives.

Flicker is an example of PQ problem, which is the effect produced on the visual human perception by a changing emission of light by lamps subjected to fluctuations of their supply voltage. The severity of the disturbance is described by two parameters, the short-term flicker severity (Pst) evaluated over a short period of time i.e., 10 minutes, and the long-term flicker severity (Plt) evaluated over a long period of time i.e., 2 hours respectively.

Voltage transient is another example of PQ problem. The electronic appliances used at homes and offices are designed to operate at a specified nominal voltage. Most equipment is designed to handle minor variations in their standard nominal operating voltage. However, if the transient is repetitive, the continual stressing may weaken sensitive electronics over time. A future transient with a low peak voltage event that would otherwise be safe could cause complete failure of a weakened component if circuit components become progressively weaker. Repeated small voltage transients may shorten the life of today's computerized appliances and electronics.

B.2 Power Quality Monitoring at Customer Level

In [30], the EC discussed about the provision of having functionality for PQ monitoring, e.g., to send warning to the customers if voltage quality fall to such a low level that equipment could be damaged. Factors affecting voltage quality include voltage sags & surges, high harmonic content, etc. Moreover, there can be a provision of warning to the authorities, e.g., to DSOs about excessive harmonic currents. Logging of power outages in excess of a defined time are also addressed as PQ issues. In the survey report by EC, seven out of eleven countries who responded in 2011, answered that they were monitoring some aspects of PQ or have the ability to do so. The report has indicated that with the growth of distributed generation, there will be greater need for PQ monitoring at the SMs' level. In [1], the Ei has also indicated that the importance of PQ monitoring is expected to increase not only as a result of increase in local generation of electricity, increase in the number of the sensitive equipment used by customers but also that the proportion of devices that affect the voltage, are increasing at the customer premises, e.g., LED lights and dimmers.

B.3 Power Quality Problems from DSOs Point of View

The DSOs are responsible to provide a voltage supply at the customer's Point of Connection (POC) that must fulfill the voltage quality requirements of the standards, e.g., EN 50160, IEEE 1159, etc. to guarantee the customers' equipment protection and safety. Non-conformance of the supply voltage has a high societal cost as it impacts the lifetime, efficiency, and performance of customers' loads. However, it is becoming difficult for the DSOs to maintain high voltage quality at customers' POC due to a large amount of PQ emissions from the customers' sides [117]. In the electricity grid, among various PQ problems, mainly harmonics often interact adversely with the grid components and cause inconveniences to the DSOs. However, currently it is not feasible to impose penalties to the harmonic producing LV customers because of the lack of proper PQ measurements. The PQ in the LV grid and customer premises, especially homes, is largely unmonitored and is not well understood. Specific monitoring typically takes place only after customer complaints have been laid or abnormalities noticed. The DSOs often suffer inconveniences due to inaccurate operation of protective devices and also failure or decreased life time of grid components such as transformers, cables, etc. The harmonic currents generated from the customer's installations are often the main reasons for these type of problems. Typically, a transformer is expected to have a lifetime of at least 30-40 years but early aging caused by increased harmonic pollutions in the grid could require early transformer replacement, e.g., 10 years earlier [117]. The effects of harmonics are not immediately visible and therefor stays hidden most of the time. In the electricity business, the light flicker problem can cause bad reputation of the DSOs, and also can cause extra cost for the DSOs due to the costly field inspection which is required for taking necessary action after customer complaints.

B.4 Importance of PQ Measurements at Individual Customer Level

Customer complaints on PQ related disturbances, e.g., harmonics, voltage dips and flicker are increasing with time. Modern customers use large number power electronic based devices that are quite sensitive to PQ disturbances. The power electronics based devices produce current harmonics which in combination with the grid's impedance at a customer's POC influence the grid's voltage quality. High grid impedance along with the grid current can contribute to harmonic voltages, high frequency noise, and high flicker severity. It is the polluting loads of the customers that often interact adversely with the grid components and contributes to the distortion of the supply voltage. The connected devices generate different harmonic currents with distorted supply voltage than that generated at sinusoidal voltage condition. Continuous monitoring of the PQ aspects in the distribution system will give an insight to the existing performance level in comparison to the limits of the applicable PQ standards. Moreover, improved monitoring gives the DSOs the proof of PQ that can be delivered to residential customers, e.g., through customer interface. The SMs can serve as indicators of possible PQ disturbances in the distribution system and also can help in localizing the sources of disturbances.

B.5 Impacts of PQ Problems in Distribution System

The voltage flicker problem can cause severe headache, epilepsy, reduced concentration level and also other vision related illness to the customers. Poor PQ can lead to abnormal operation of a device, and can also damage the device partially or completely. The PQ problems can cause additional heating, abnormal operation and early aging of the customers' devices. The non-sinusoidal current also causes additional losses and overloading to various grid components, e.g., cables and transformers. The presence of harmonic currents causes an additional power flow in the grid thus contributes to a lower power factor of the grid and increase the demand of total active power and apparent power in the grid. The presence of harmonic currents increases the core losses and copper losses in a transformer [117]. The load losses of a transformer increase sharply at high harmonic frequencies. The eddy current losses are of large concern when harmonic current is present in the grid since the losses increase approximately with the square of frequency. Moreover, the harmonic currents creates additional ohmic losses in the line and neutral conductors of a cable which contributes to overheating of neutral wires of the LV feeders at which many single-phase polluting loads are connected. The harmonic voltage caused by harmonic currents increases the dielectric stresses on the cables and can shorten their useful lifetime. The skin effect increases the effective resistance of the conductor and eddy current losses, mainly at high frequencies, which further increases the cable's operating temperature.

B.6 Sources of PQ Problems in Distribution System

The PQ problems can be caused by natural phenomena or human errors, e.g., storm, lightning, digging of cable, etc. It can also be caused by the customer's own disturbing equipment/s or neighboring customers' variable load demands, e.g., motor loads. According to the national PQM survey results in the MV and LV grids of Netherlands for years 2005-2008, PQ problems are local issues rather than a grid-wide global problem in most of the situations [118]. The local problems occur mainly due to the operation of customers' devices. The light flicker problem is mainly generated from various disturbing loads in the LV grid, e.g., elevators, air conditioners, welding device, etc. The harmonics problems can be caused by the power electronic domestic appliances, e.g., compact fluorescent lamps, televisions, microwave ovens, personal computers, HVAC, dishwashers, dryers, etc., the business and office equipment, e.g., workstations, personal computers, copiers, printers, lighting, etc., and the industrial equipment, e.g., programmable logic controllers, automation and data processors, variable speed drives VSD, soft starters,

inverters, etc. Many of these devices are sensitive to PQ disturbances. Moreover, magnetic core reactors, transformers and induction motors produce non-linear currents due to the saturation behaviour of their magnetic cores. The power electronics based power flow controllers also cause current waveform distortions in the grid. The non-linear loads containing power electronics converters, e.g., with six pulse and twelve pulse rectifiers can cause harmonic pollutions in the grid during their switching processes. In a grid with a MV/LV transformer of Δ/Y configuration, triple-n harmonic currents circulate in the closed delta winding and therefore only the 'non triple-n' harmonics pass to the upstream grid. With the increased use of high demanding load such as heat pumps, air conditioners, PEV at the household installation, the long term flicker value, Plt at a POC can increase in the future [118]. The time varying distributed generations can increase PQ problems, e.g., over-voltage, harmonics, etc. and cause instability in the grid. It was observed that the installations with many solar panels can cause high 15th harmonic voltages in the grid [118], the neighborhood with many wind turbines can increase lower order harmonic voltages in the grid and the industries with variable speed drives and converter loads also contribute to lower orders harmonic voltages in the grid.
The Governments in many countries also promoting the use of more energy efficient devices to reduce overall electricity consumption in the society which cause an increased use of power electronic based nonlinear devices and increase the PQ related problems.

B.7 What PQ Aspects to Monitor?

There are yet no clear recommendations or proposals from international authorities on what PQ aspects could be or need to be monitored by the SMs, except a proposal from Ei to record the interruptions that are longer 3 minutes. The DSOs participated in the survey suggested some PQ aspects to monitor, e.g., power interruptions, real/reactive import and export, peak voltages, rms voltage, over/under voltage, voltage sags & swells, voltage distortion, etc. [30]. According to [119], power interruptions, and voltage sags & swells are the higher requirement of DSOs with respect to PQ measurements with the SM, while flicker, individual harmonics, and transient measurements are some of the least.

B.8 PQ Measurement Capabilities of SMs in the Market

Most of the currently available SMs in the market, have the capability of measuring some PQ parameters, e.g., power interruptions, over voltages/voltage swells, under voltages/voltage dips, and also can measure: voltage, current, frequency, voltage harmonics and current harmonics, e.g., THD and individual harmonics [120],[121]. In [122], test results on the PQ measurement capabilities of SMs are presented which shows that the SMs can measure parameters relevant of PQ analysis, e.g., registration of power interruptions, voltage variations, voltage dips and lowest functional voltages. It is underlined in [123] that most of existing SMs can make valuable data available for voltage quality assessment, and also provide waveform measurements with reporting rate of 1 frame/s which represents the so called real-time values of voltage (rms), current (rms), frequency, active and reactive power. The SM used in [121], can compute harmonics using A/D converter with 16 samples per channel per period (50Hz).

B.9 Use of SMs to Monitor PQ

By using the capabilities of modern SMs, grid PQ monitoring can be improved while keeping costs low. Moreover, PQ monitoring would allow residential customers to monitor their own PQ which offers greater potential for early problem identification and PM. In addition, it could enable the DSOs to better optimize the voltage delivered, which may lead to a reduction of the power consumed by the constant impedance load. Based on local voltage deviation detections, the SMs can trigger events to alert the local DSO. The events could either trigger a request to automatically increase the sampling rate in the affected area, or be forwarded to a DSO for manual decision making. According to [123], voltage characteristics with high reporting rates can be efficiently used in deriving information on quality of the electricity supplied by the DSOs. However, if the PQ variables are measured, the meters must also have sufficient storage capability. It is not only the capabilities of the SMs themselves which must be considered, but also the capabilities of the communications networks and the CS. There is a lack of clarity over what data and in what format, timeframe, and level of aggregation would be useful. There is also a lack of clarity over exactly how the data could be utilized to improve the electricity grid operation and business.

The challenges of implementing PQ measurements in distribution applications include the following:

- Increased cost of SMs with PQ measurement capabilities.
- Capability of present communication infrastructure to support for transmission of large data packets, particularly for real-time applications.
- Data integration, long-term storage, and sharing.

Possible benefits (beneficiary):

- o Customers can monitor their own PQ which offers greater potential for early problem identification and PM.(customer)
- o With more PQ monitoring capability, the DSO is more informed about the actual PQ in their grid and can easily identify any source of problems (e.g., harmonics, flickers, etc.) which can save a lot of work (and cost) to identify otherwise. (DSO)
- o Better PQ in the system can reduce the losses in the system as well as potential faults and mal-functions of equipment in the system (power electronic converters, relays) which can be caused by, e.g., harmonics.(DSO)

Recommendations:

- This thesis proposes to include PQ monitoring functionalities covering as much PQ indices as possible in addition to the already available PQ monitoring capability in some of the existing SMs. However, research is needed to find e.g., optimal data sampling rate, and to identify important PQ indices for storing and also the most efficient way of communication.
- To increase the PQ compatibility in the most cost efficient way there is a need either to reduce the number of PQ monitoring locations or the data need to be processed in more efficient way to reduce the size of the stored data. One way could be to store and send text based data on PQ events.
- There is a need for common standard from respective authorities specifying the duration for which the data need to be stored in SMs, e.g., for three months [30], and how the data will be accessed and by whom.