Load and Flexibility Models for Distribution Grid Management

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Load and Flexibility Models for Distribution Grid Management

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by the Department of Energy Technology

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This present report combined with the above listed scientific papers has been submitted for assessment in partial fulfillment of the PhD degree. The scientific papers are not included in this version due to copyright issues. Detailed publication information is provided above and the interested reader is referred to the original published papers. As part of the assessment, co-author statements have been made available to the assessment committee and are also available at the Faculty of Engineering and Science, Aalborg University.

Abstract

Recent trends in power systems have favored the electrification of residential heating and transportation by means of modern partially flexible loads. Furthermore, environmental concerns have promoted the notion of distributed generation, thus increasing its penetration in low voltage distribution grids. These technological advancements have changed the nature of conventional demand and supply; nonetheless, the grid has remained the same on the grounds that network modifications are considerably more complex and expensive than individual load/generation changes.

It is evident, that by radically changing the energy flow in low voltage distribution grids, several grid complications are bound to emerge like, for instance, capacity adequacy limitations, power quality issues, reverse power flows etc. One of the Distribution System Operator options to manage these complications is to proceed to advanced metering and control infrastructure investments. These investments will transform distribution networks into "smarter" grids, which will facilitate flexible load/generation control in return for financial and reliability benefits to electricity consumers.

The theoretical idea of modernising the grid so as to cope with load and generation changes is indeed innovative; nevertheless, its implementation is, up to day, impaired by many practical difficulties. In this Ph.D. study, four of these issues are detected, elaborated and consequently solved by dedicated grid and/or load models. These issues involve lack of generic load forecasts, need for flexible load/generation estimation techniques from smart meter measurements, deficiencies in online load distribution observability, and, finally, energy market compatible control algorithms which treat consumer flexibility in a fair manner. These modules will aid the Distribution System Operator in understanding the grid's load distribution, forecast it, identify any upcoming problems, estimate the available flexibility to alleviate them, and, eventually, schedule this flexibility accordingly.

Regarding the first topic, that is to say load forecasting, a simple, generic, and automated load forecasting technique based on machine learning principles is proposed. Unlike other benchmark forecasting models, this non-parametric approach does not introduce any assumptions regarding the system model and is solely based on past observations. Thus, this method is to a great extent flexible, albeit strongly history dependent.

As far as the flexibility estimation is concerned, a new philosophy is introduced. Contrary to contemporary practices, this philosophy is compatible with the low data recording and transmitting rates which smart meters are operated with. Although demonstrated for the Heat Pump case, the methodology is applicable to any flexible device as long as it has an impactive power pattern.

One other issue which modern distribution grids frequently encounter, is the lack of thorough online monitoring. Though smart meters might be installed, relevant smart meter data are usually collected with substantial delay from the moment of their recording. To compensate for this situation, a power meter allocation methodology is presented. This methodology, which is applicable to low voltage distribution grids, aims at allocating a few extra power meters as a trade-off for a reasonable online load distribution approximation. Since it results in grouping grid areas hierarchically, the applicability of the methodology in formulating aggregated flexibility offers by Aggregators is demonstrated.

As for the scheduling, a two-step control mechanism, which aims at alleviating grid congestions, is proposed. In the first step, a central controller manages flexibility proactively, whereas, in the second step, a decentralised control scheme deals with flexibility reactively. Both controllers are designed in such a way that compatibility with contemporary markets is assured, while special focus is given to the fair activation of consumer flexibility. Finally, possible interactions between the entities handling the technical and the economic aspects of flexibility in a market environment are discussed.

Dansk Resumé

De seneste trends i elforsyningssystemet vil imødekomme elektrificering of opvarmningen på landet samt transportsektoren i form af moderne delvist fleksible laster. Endvidere har bekymringerne for miljøet promoveret distribuerede og vedvarende forsyninger og derved forøget deres tilslutning til lavspændingsnettet. Disse teknologiske forbedringer har ændret det konventionelle forbrug samt forsyningen, uagtet at el-nettet er forblevet som det var, da modificeringer af nettet er mere komplekse og dyre end individuelle ændringer i laster of forsyninger.

Det er klart, ved radikalt at ændre energibelastningen i lavspændingsnettet vil der opstå forskellige net komplikationer som f.eks. kapacitetsproblemer, spændingskvalitets forhold, og returstrømme. En af måderne forsyningsselskaberne kan imødekomme disse komplikationer på er at investere i og overgå til avancerede måle og styringsinfrastrukturer. Disse investeringer vil transformere distributionsnettet til et "smartere" net, som kan give bedre faciliteter til de fleksible laster og forsyninger mod finansielle og pålidelighedsfordele for el-kunderne.

Den teoretiske ide for moderniseringen af el-nettet for at kunne klare last og forsyningsændringerne er innovativ; men implementeringen er ind til nu svækket af mange praktiske vanskeligheder. I dette Ph.D studium er der fundet fire forhold, der er uddybet og derefter løst via dedikerede net og/eller last modeller. Disse forhold involverer mangel på generiske lastprognoser, et behov for fleksible last/forsynings estimeringsteknikker baseret på smart meter målinger, mangler vedrørende observerbarheden af lastfordelingen, og endelig kompatible styringsalgoritmer i forhold til elmarkedet, som anvender kundernes fleksibilitet på en fair måde. Disse moduler vil hjælpe forsyningsselskaberne med at forstå nettets lastfordeling, lave prognoser for det, og identificere kommende problemer, estimere fleksibiliteten fra kunderne og anvende den eventuelt ved at tidssætte hvornår fleksibiliteten skal anvendes.

Vedrørende det første emne omkring lastprognoser, er der opbygget en simpel, generisk og automatisk teknik baseret på maskinlæringsprincipper. I modsæt-

ning til andre benchmarkings modeller introducerer denne ikke-parametriske metode ikke nogle tilnærmelse vedrørende systemmodellen og er alene baseret på tidligere observationer. Derfor er denne metode meget fleksibel men med en stærkt historisk afhængighed.

Med hensyn til fleksibilitetsestimeringen er der introduceret en ny filosofi. I modsætning til moderne praksis, er denne filosofi kompatibel med den lave dataopsamling og transmissionshastighed som de smart el-målere opereres med. Metoden er vist for et scenarie med varmepumper, men kan anvendes for alle fleksible enheder så længe deres forbrug kan påvirke elsystemet.

Et andet aspekt, som det moderne distributionssystem ofte ser, er manglen på online målinger. Selvom der er installeret smart meters hentes data fra disse typisk med en væsentlig forsinkelse fra hvornår de er målt. For at kompensere for denne situation, er der her præsenteret en metode til at fastslå, hvor der skal opsættes online dataopsamlingsenheder. Denne metode, som er udviklet til lavspændingsnettet, har til formål at placere nogle få ekstra målere til at fastlægge en fornuftig lastfordelings approksimation. Da det resulterer i at nettet grupperes i nogle hierarkiske områder, er anvendelsen demonstreret ved at metoden bestemmer en aggregeret fleksibilitet, som kan anvendes af forskellige energihandlere.

Med hensyn til tidsfastsættelsen er der foreslået en to-trins styringsfunktion, som har til hensigt at modvirke overbelastningerne i nettet. I første trin styrer en central enhed fleksibiliteten proaktivt, hvorefter det andet trin, som er decentralt, behandler fleksibiliteten reaktivt. Begge styringer er designet på en sådan måde, at kompatibilitet med de respektive markeder er sikret samtidig med, at der er givet fokus på at de enkelte kunder bliver aktiveret på en fair måde. Endeligt diskuteres mulige interaktioner mellem aktører der behandler de tekniske og økonomiske aspekter for fleksibiliteten i et markedsperspektiv.

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Acronyms

ANN	Artificial Neural Network
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
BRP	Balance Responsible Party
CVPP	Commercial Virtual Power Plant
DBI	Davies Bouldin Indicator
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
ECDF	Empirical Cumulative Distribution Function
ER	Electricity Retailer
EV	Electric Vehicle
GENCO	Generation Company
HP	Heat Pump
MA	Moving Average
MADP	Mean Average Deviation Percentage
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression
NILM	Non-Intrusive Load Monitoring
PDF	Probability Density Function
POC	Point of Connection
PQ	Power Quality
PV	Photovoltaic
QQ	Quantile-Quantile
SARIMA	Seasonal Autoregressive Integrated Moving Average
SE	State Estimation
SG	Smart Grid
SLR	Single Linear Regression
TSO	Transmission System Operator
TVPP	Technical Virtual Power Plant

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Chapter 1

Prologue

This chapter is dedicated to present the usual power system structure, operation, and planning. Recent trends affecting those topics are highlighted and the applicability of potential remedies is discussed.

1.1 Power System Structure

An electric power system is a network comprising many components, connected to generate, transmit, and, finally, deliver electricity to various electrical appliances. In practice, these three objectives do also segment contemporary power systems to the generation, transmission, and distribution sector each consisting of respective entities, namely:

- Generation Companies (GENCOs)
- Transmission System Operator[1] (TSO)
- Distribution System Operators (DSOs)
- Electricity Retailers (ERs)

As the name implies, GENCOs are responsible for generating electricity. Their facilities usually comprise large power plants. On the other hand, the TSO is in possession of the electrical transmission grid which is responsible for transmitting the bulk electrical power within the grid's technical capabilities. Ensuring the demand-to-supply balance reactively, by initiating ancillary services when this balance is not met, is also part of the TSO's responsibilities. Similarly, the DSO is in charge of reliably delivering electricity via the lower power-rated

[1] Equivalently, two similar entities, namely the Independent System Operator and the Regional Transmission Organization, are frequently encountered in the U.S.

distribution grid. Finally, ERs aim at selling electricity to consumers. DSOs and ERs are closely related and can frequently refer to the same entity.

1.2 Power System Operation

One of the most important features of electricity is that, unlike other forms of energy, storing it is an expensive and troublesome option. As such, traditionally, GENCOs and ERs have been dynamically interacting to cope with imbalances between electricity demand and supply. In monopoly systems, these players along with TSOs and DSOs have been operated by one -usually governmental- institution. During operation, variations in demand have resulted in respective variations in generation to keep the power equilibrium. Antithetically, in deregulated environments, GENCOs and ERs have been interacting through market mechanisms to sustain the power balance. Thus, these parties have also been addressed as Balance Responsible Parties (BRPs).

As outlined previously, since electricity storage is inefficient, keeping the power balance is essential. This is further highlighted by the fact that, traditionally, electricity demand and, to a lesser extent, supply have been subject to uncertainty variations. Variations in demand stem from the unpredictable use of electricity by consumers, while uncertainty in supply is usually linked to volatility of renewable energy resources or to technical failure of equipment; be it of GENCOs, TSOs or DSOs. To this end, the electricity market has been built to accommodate these variations in the short term; the day ahead load has been traded within spot markets, which also cater for the operational restrictions of large power plants, the less unpredictable intra-day load has been bargained in balancing markets, while real-time imbalances have reactively been settled via regulating markets [1]. As for variations in the long run, long term purchase contracts between BRPs have been established. Moreover, regarding the grid capacity, TSOs and DSOs have catered for the slowly but evergrowing demand in the planning stage of their networks.

1.3 Recent Trends in Power Systems

Recent technological advancements tend to change the traditional nature of generation and demand. On the one hand, higher penetration of renewable energy offers efficient and environmental friendly, yet rather uncontrollable and intermittent, electric power. Relevant technologies enable the distribution of generation even to individual consumers, thus evolving them to prosumers, i.e. consumers and concurrently producers. Additionally, they tend to substitute conventional coal power plants, which provided supply inertia. On the other hand, the electrification of transportation and heating with partially controllable loads steps up the electricity demand considerably. This whole framework endangers the presented traditional grid operation and planning procedures.

1.4 Power System Planning

Taking into account the upcoming complications in the nature of demand and generation, DSOs -and to a lesser extent TSOs- are likely to face capacity adequacy problems. Further considering the inherent flexibility of future residential loads, a decision has to be made by the grid operator in order to fortify the reliable operation of the grid. Two broadly accepted solutions are reinforcing the grid or implementing Demand Side Management (DSM).

1.4.1 Grid Reinforcement

The reasoning behind the first option, namely grid reinforcement, is straightforward to comprehend. The most impactive upcoming loads in the grid are the ones associated with electrifying the heating, e.g. Heat Pumps (HPs), and transportation, e.g. Electric Vehicles (EVs). Hence, once the DSO has assured sufficient capacity for their accommodation, no further problems are to be expected. Moreover, considering that planning is a long term routine for the DSO, lacking the experience of this task will not be an issue. *Then, since grid reinforcement is so elementar to apply, why does the DSO have a dilemma?*

The answer to this question is fairly simple to presume: costs. Investing in grid reinforcement is in most cases not financially the best option. Especially for utilities which have recently upgraded their grid capacity without considering the impact of HPs and EVs, grid reinforcement is not a viable solution. Additionally, upgrading the distribution grid requires considerable time. Another arising matter is that, although the DSO has the know-how of planning grid reinforcements, any decisions for system changes should accommodate a long term grid operation. As such, relevant planning requires exhaustive research, that is to say considerable time, effort and most importantly data availability. Nevertheless, the required data are not always available, while their accuracy and consistency is oftentimes doubtful.

1.4.2 Demand Side Management

An alternative remedy for the rapidly changing conditions, is a notion which researchers came up in the early and mid-90's, known as Demand Side Management [2]-[8]. This notion actually consists of 2 topics, namely:

1. **Energy Efficiency:**
   Energy efficiency refers to the permanent consumption reduction of power hungry devices such as water heaters, commercial or residential refrigeration systems, washing machines etc. without altering their efficacy [9].

2. **Demand Response:**
   Demand Response (DR) concerns any intentional adjustments to consumption patterns of electricity prosumers, which intend to modify the timing, power, and/or total energy consumption over a time period [10]. It is usually driven by financial and/or reliability incentives. A special case of DR is the Dynamic Demand concept which, unlike other DR mechanisms, operates in short time frames, i.e. seconds. It aims at controlling intermittent loads by switching them on or off according to the electrical frequency [11], [12].

Schematically, DSM can be presented as in Fig. 1.1. As can be observed from this figure, DSM aims at altering the load shape of prosumers; be it by generating or by consuming more power[2].

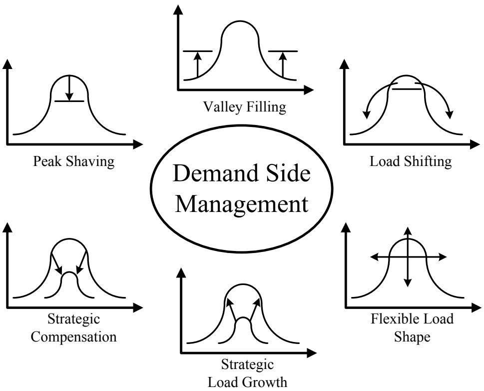

Figure 1.1: Typical Demand Side Management Objectives [9].

1.4.3 Demand Side Management and the Smart Grid

DSM mechanisms are beneficial since they proactively and/or reactively reshape the consumption/generation pattern of prosumers, especially through DR. This change is oftentimes referred to as “flexibility” and is the core of distribution system load management. Flexibility is not a newly introduced term in power system studies. It has frequently been used for describing the capability of generation to follow demand at the transmission level [13]-[17].

[2]For DR, increasing generation is equivalent to reducing consumption and vice versa.

Nevertheless, in the DSM context, flexibility refers to the opposite action, namely demand meeting generation. This action is essential to mitigate the volatility of intermittent renewable energy resources and ensure a reliable and efficient operation of the grid. A key factor about flexibility is that since it is distributed along individual prosumers, it can be activated so as to resolve grid constraint problems at either local or global level.

Implementing DSM and exploiting flexibility requires investments in advanced metering, communication, data storage, and control infrastructure. These investments will vastly broaden the grid's capabilities bringing it to a whole new level. The distribution grid will overall evolve to a "smarter" network, also known as Smart Grid (SG). Transforming conventional distribution grids to SGs offers various advantages which do not restrict to technical aspects alone:

- **Grid Operation:**
  In a SG, the risk of grid stressing due to high coincident demand decreases by implementing DR; hence, the power quality of the network increases, while the probability of forced outages diminishes. Other DR applications include loss minimization, peak load shaving, and voltage support. Apart from the DR objectives, many other attributes are jointly enhanced such as the data collection potential and the load distribution observability. Technically, a SG is beneficial in improving the utilisation of existing capacity, preventing grid limit violations, creating archives of detailed historical consumption data, and, consequently, detecting any erroneous input. In particular, the first two points are frequently associated with the term Technical Virtual Power Plant (TVPP); an entity which modifies the demand/supply within its territory, either day-ahead or intra-day, so as to ensure an efficient, stable, and reliable operation of the grid [18].

- **Grid Planning:**
  Since SGs improve the capacity utilisation through DR, costly grid reinforcements can be considerably postponed. Moreover, by establishing a SG, the data availability will greatly increase, thereby simplifying grid reinforcement planning at a later stage. Furthermore, due to DR the extent of future reinforcement will be reduced [19]. Besides saving cost, time, and effort for upcoming grid capacity upgrades, the benefits of SG investments are somewhat independent from these upgrades. This means that future grid reinforcement can rely on data provision and control strategies provided by the SG infrastructure; however, it will not necessarily lead to upgrading the SG infrastructure itself.

- **Electricity Prices:**
  DR averts the need to use costly-to-run power plants during periods of otherwise high demand. As such, lower wholesale market prices are achieved. This is principally illustrated in Fig 1.2. From this figure, it can also be understood, that DR mitigates the supplier's ability to ex-

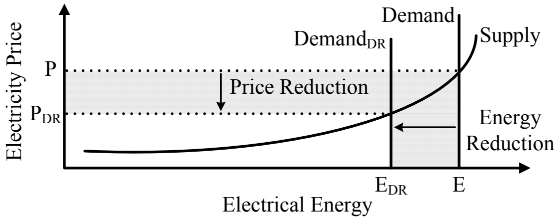

Figure 1.2: Schematic function of DR in wholesale markets [19].

ercise market power by intentionally raising the power price far beyond production costs in periods of otherwise high consumption [19]. Additionally, more benefits can be harvested by the introduction of flexibility markets. These markets will further deregulate the electricity commerce, increase competition, and thus lower the price of the traded commodity, namely flexible electricity consumption/production. Eventually, this price reduction will be depicted in electricity invoices; an outcome which will be welcomed by electricity consumers.

- **Pronsumer Benefits:**
  Apart from the reduction of electricity prices and the system's reliability improvement, prosumers of a SG will be able to enjoy further appealing features. For instance, they will be able to select their electricity provision contract among a variety of suppliers. Hence, environmentally sensitive prosumers might decide to purchase electricity solely from renewable energy resource suppliers. Moreover, the type of contract will also vary according to the flexibility provision of the prosumer. Lastly, and maybe more significantly, prosumers will get acquainted with electricity as a commodity and eventually cultivate environmental consciousness.

Overall, the SG bids advantageous attributes to grid operation, grid planning, market operation, and prosumers at the same time.

1.4.4 Smart Grid Implications

Similar to reinfocring the grid, SGs are no panacea. They suffers from many drawbacks, the most common being:

- **Metering Investment:**
  This investment refers to the installation of Advanced Metering Infrastructure, particularly smart meters. Smart meters are measurement devices installed at the prosumer level, which are primarily responsible for collecting consumption/generation data up to the device level in various temporal resolutions. Usually, the capabilities of these meters extend to

many more features such as measurement of additional local electrical quantities (e.g. voltage), two-way communication potential, and facilitation of appliance control [9].

- **Communication Infrastructure Investment:**
  This investment relates to technologies and physical devices employed to transmit data from smart meters to a central entity and vice versa. These data may refer to recorded smart meter data or other signals, e.g. control actions. Machine-to-Machine communication, Digital Subscriber Line, Optic Fibers, Power Line Carrier and other technologies are frequently considered for this kind of applications [20]-[22].

- **Data Storage Investment:**
  Obviously, the aforementioned framework would not be operational without data storage facilities. This investment is not negligible owing to the huge amount of recorded data, i.e. the "Big Data" problem [23].

It is apparent that relying on a SG has its own investment costs. Additionally, the SG implementation is far more complicated than grid reinforcement. Fundamentally, the following implications have to be considered:

- **Data Issues:**
  Depending on the applied technologies and the extent of their implementation, data issues might arise. These issues refer to both communication and data storage matters, and are usually related to the size of the transmitted and/or stored data, i.e. "Big Data". A typical remedy to these problems is to reduce the temporal resolution of the recorded and/or transmitted data, which, however, weakens the functionality of the SG.

- **Control Frameworks:**
  The major aim of applying DR is to modify the demand according to preset criteria; be it financial or operational. To do so, control algorithms have to be employed. In this respect, their architecture, development, testing, application, coordination etc. has to be carefully contemplated.

- **Operational Costs:**
  Operational costs refer to both physical and service costs. For instance, the excess electricity consumed by smart meters, data storage/communication premises, and potential control centers belong to physical costs [24]. Maintenance costs are also to be credited to physical costs. On the other hand, an example of service costs is the operational cost of the control center(s), e.g. data analytics [25].

- **Market Upgrade:**
  Applying control mechanisms for the load/generation necessitates the introduction of flexibility markets [26], [27]. In those markets the commodity to be traded is the prosumer's flexibility, which can be either sold

locally or globally, that is to say at the distribution or transmission level, respectively. Flexibility markets, however, require the establishment of new market participants, i.e. BRPs, such as the Fleet Operators or other type of flexibility Aggregators [28]. These entities are responsible for merchandising both aggregated and disaggregated flexibility of individual prosumers in a coordinated manner, thereby transforming them into a Commercial Virtual Power Plant (CVPP) [18].

- **Other Complications:**
  Traditional planning procedures have not catered for DR mechanisms; thus, based on the aforementioned factors the DSO has, at the very best, to conduct unprecedented planning of his potential investments [5], [6]. Standardisation, process coordination, software/hardware compatibility, cyber-attack defence and privacy security assurance are only few of the problems to be encountered towards a successful DR utlisation [29]-[32].

Although the aforementioned costs are usually lower than those of grid reinforcement, it is evident that transforming a conventional distribution grid into a SG eminently perplexes the system's configuration while compromising its reliability, i.e. increasing the probability of equipment failure.

1.5 Contemporary Power Systems

Eventually, the grid operator will have to resort to techno-economic analysis in order to define which strategy, namely proceeding to SG or grid reinforcement investments (or both), is more advantageous for the grid. At present time, utilities tend to consider SG as a techno-economically good option; hence, they promote the SG notion, and gradually implement some of its concepts, especially smart metering. In particular, the Dutch company Eneco promotes smart meters in an effort to familiarise consumers with electricity use [33]. Vatenfall reports the experiences of a smart meter roll-out [34], while the Swiss EWZ documents that demand reduction was observed due to smart metering [35]. Finally, the Dannish utility Dong highlights how smart meters benefit the consumer in improving voltage quality and automating some business processes [36]. In a few cases, some SG pilot programs have even been dispatched. For example, the implementation of a prototype SCADA system, which manages a distribution system with high penetration of renewable energy is described in [37]. Additionally, an attempt to fully utilise renewable energy resources by means of active demand is explained in [38]. However, SG deployment has not evolved as expected mainly on the grounds of its complexity [39], [40]. To this end, many research projects have been initiated so as to identify and tackle any arising issues related to SG dispatch [41]-[45].

1.6 Problem Formulation

The current study is part of the "TotalFlex" project, which investigates the applicability of the SG concept. Among the research areas examined in "TotalFlex", this study focuses on the TVPP. The main goal of this project is to develop some new models concerning load, flexibility, and the grid in order to achieve the TVPP's full potential, and ultimately ensure a reliable grid operation by means of exploiting active demand/generation. These models are up to day either absent or incomplete and refer to the following areas:

1. **Load Forecasting:**
   Load Forecasting has traditionally been made at an aggregated level, that is to say the transmission or sub-transmission level. Load forecasting at such a high level has negligible forecast error and is frequently complex and "ad-hoc". Thus, the corresponding purpose oriented models are not suitable for forecasting at a local level, i.e. aggregated consumption of just a few consumers, where the randomness is much higher [46]. This type of forecasting is essential for DSOs and distribution system BRPs in order to realise DR through flexibility markets. Therefore, it should be carefully examined.

2. **Estimation of Flexible Consumption:**
   As explained, one of the major implications in applying DR within the TVPP scope is the amount of data to be recorded, stored, and/or transmitted [23]. The amount of data to be handled along with various other problems, such as bad measurements, malicious attacks, and confidentiality issues, will necessitate the estimation of some variables. From the DSO perspective, flexibility is the most crucial variable to know. In this respect, flexibility estimation techniques should be researched.

3. **Distribution System Load Monitoring:**
   Within the context of a perfect SG, the DSO's task is to monitor the loading of the grid so as to alleviate any grid limit violation problems. Nevertheless, considering that most contemporary distribution grids are not "smart", the problem of resolving grid problems becomes fairly difficult to confront with. Even for existing SGs, prosumer data are usually transmitted at lower temporal resolutions than they are recorded, thus making DR employment considerably troublesome. To this end, approximate monitoring models would be useful in order to boost the intra-day load distribution monitoring potential in return for accuracy compromise.

4. **Reliable Operation of Distribution Systems:**
   Delivering electricity in a reliable and qualitative manner is the prime goal of the DSO. To accomplish that, DSOs have to come up with DSM strategies to proactively and reactively relieve any grid stress [47]. Hence,

appropriate control frameworks have to be proposed which will enable this reliable grid operation, while ensuring that other parameters, like consumer satisfaction, are also respected.

5. **Transactions in Flexibility Markets:**
   Although it is not directly within the technical perspective of the TVPP, the DSO will eventually have to interact with a local flexibility market to purchase flexibility. Hence, the market will have to facilitate flexibility provision which the DSO will be able to bid for. Two major aspects which are crucial for flexibility bidding is the location and the uncertainty of flexibility offers. These two variables have to be linked in order to proceed to reasonable flexibility offers/bids.

The aforementioned problems have been found to be key impairments towards a realistic TVPP implementation. Thus, they have been thoroughly investigated and, consequently, simple, yet efficient, solutions, i.e. models, were devised.

1.7 Limitations

Owing to the complexity of the problems to be solved, in some occasions, the study cases have been simplified. The most significant simplifications, among with their reasoning, are outlined as follows:

1. **Model Verification:**
   The efficacy of the proposed models was tested based on data provided by Danish utilities, namely HEF Net A/S and Nyfors Forsyning A/S. The verification was limited to a specific radial low voltage distribution grid in the area of Støvring in Denmark. The network supplied 129 consumers at 400V. Hourly consumption values for individual consumers were acquired for the year of 2012. As such, any results obtained are based on the characteristics of this case. However, the methodologies proposed should be generalisable to other cases as well.

2. **Balanced 3-phase Steady State Operation:**
   Asymmetrical networks and unbalanced loading have not been considered in this study. Phase unbalance might create additional grid limit violations, for instance, due to high zero sequence current or voltage rise in one or two phases in case of single phase loads. However, for the Danish case, most of the distribution grids have 3-phase connections in residential areas, i.e. in low voltage distribution grids. Moreover, the 3-phases are empirically distributed within the residence so as to proactively balance the load. Additionally, due to the availability of only hourly data, the proposed models consider steady state grid operation. Hence, voltage quality issues arising from load management in high temporal resolutions

are not investigated. Chapter 6 is an exception, since some real time simulations are performed for this reason. Moreover, the potential to incorporate phase unbalance is also discussed there.

3. **Generation:**
   Apart from very particular cases (e.g. Chapter 4), generation has not been considered in this study in the form of renewable energy resources. This is justified on the grounds that these resources can be to some extent considered as negative loads. As such, the active demand frameworks can be adapted to facilitate generation as well. In a sense, generation has been regarded as flexible load reduction in Chapter 6. In the same chapter, the theoretical background to incorporate flexible generation is also presented.

4. **Information and Communications Technology Infrastructure:**
   As outlined in Section 1.4.4, the efficiency of data recording, storage, and communication is important for a successful SG implementation. Nonetheless, this study has focused on TVPP load and grid problems, whereas the Information and Communications Technology issues have been dealt with by other collaborating groups within “TotalFlex”.

5. **CVPP:**
   The prime target of this thesis is to cope with load, flexibility, and grid modeling issues within the scope of a TVPP. It is self-evident, that some setups regarding the flexibility market are chosen, nevertheless, most of these setups are generic and adaptable to various CVPPs. The CVPP case is analytically tackled by other working groups within “TotalFlex”.

These simplifications should not be considered as limitations rather than necessary assumptions in order to obtain an initial simple solution; a solution easy to comprehend, apply and build on.

1.8 Outline

The Ph.D. thesis consists of 9 parts. Their content is documented below:

- ***Chapter 1*** describes the operation and planning procedures of traditional power systems. The new tendency towards decentralised renewable energy resource installation along with the flexible load penetration is signified. The impact of this tendency onn the traditional operation and planning processes of distribution grids is explained. Finally, the importance of SGs is highlighted, whereas relevant SG problems are emphasised.

- ***Chapter 2*** concentrates on the state of the art, that is to say contemporary practices to solve the identified or similar to the identified problems. The theory of these practices is -when deemed useful- shortly described. Finally, the limitations of those practices are explained so as to designate the thesis' contribution.

- ***Chapter 3*** is engaged with the research area of load forecasting, in particular distribution system load forecasting. The impact of load aggregation/disaggregation is thoroughly examined and the prerequisites of regional load forecasting are addressed. Conclusively, a methodology including these features is demonstrated.

- ***Chapter 4*** deals with the area of non-intrusive load monitoring, that is to say estimating the consumption of a particular appliance out of the total consumption of a residence. A novel methodology for identifying the electric signature of power hungry devices is presented, and its application is tested on a flexible load, namely a HP.

- ***Chapter 5*** investigates online load monitoring problems in low voltage distribution networks, both smart and conventional. A framework for power meter allocation is proposed aiming at real-time load distribution estimation by compromising monitoring accuracy. Relevant issues and applications for SGs and conventional networks are discussed.

- ***Chapter 6*** examines the core task of a TVPP, namely resolving grid limit violations. A framework for proactive and reactive load management is suggested. Special attention is paid to the "fair" activation of flexibility.

- ***Chapter 7*** is a special chapter. It is the only methodological chapter which does not restrict to the technical area of a TVPP rather than explaining the DSO's interaction with BRPs when purchasing flexibility. In this concept the trade-off between forecast error and flexibility aggregation is clarified.

- ***Chapter 8*** concludes the thesis. The main contributions are summarised, while ideas for future work are also denoted.

- The ***APPENDIX*** catalogues disemminated work in the form of scientific manuscripts. These manuscripts contain the necessary technical information, e.g. mathematical equations, to apply the proposed methodologies.

The order of the chapters has been selected to gradually acquaint the reader with relevant problems which the DSO might face when implementing a TVPP.

1.9 Publications

The following manuscripts are the outcome of the research performed throughout the Ph.D. study period:

Journal Papers:

J.1: K. Kouzelis, Z. H. Tan, B. Bak Jensen, J. R. Pillai, and E. Ritchie, "Estimation of Residential Heat Pump Consumption for Flexibility Market Applications," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1852-1864, Jul. 2015.

J.2: K. Kouzelis, B. P. Bhattarai, I. Diaz de Cerio Mendaza, B. Bak Jensen, and J. R. Pillai, "Smart Grid Constraint Violation Management for Balancing and Regulating Purposes," *IEEE Trans. Power Syst.*, submitted.

Conference Papers:

C.1: K. Kouzelis, I. Diaz de Cerio Mendaza, and B. Bak Jensen, "Probabilistic Quantification of Potentially Flexible Residential Demand," in *Proc. IEEE PES General Meeting*, National Harbor, MD, 2014.

C.2: K. Kouzelis, B. Bak Jensen, P. Mahat, and J. R. Pillai, "A Simplified Short Term Load Forecasting Method Based on Sequential Patterns," in *Proc. IEEE PES Innovative Smart Grid Technologies Europe*, Istanbul, 2014.

C.3: K. Kouzelis, B. Bak Jensen, and J. R. Pillai, "The Geographical Aspect of Flexibility in Distribution Grids," in *Proc. IEEE PES Innovative Smart Grid Technologies*, Washington, DC, 2015.

C.4: K. Kouzelis, I. Diaz de Cerio Mendaza, B. Bak Jensen, J. R. Pillai, and K. Katsavounis, "Enhancing the Observability of Traditional Distribution Grids by Strategic Meter Allocation," in *Proc. IEEE PES PowerTech*, Eindhoven, 2015.

C.5: K. Kouzelis, I. Diaz de Cerio Mendaza, B. Bak Jensen, J. R. Pillai, and B. P. Bhattarai, "Allocation of Power Meters for Online Load Distribution Estimation in Smart Grids," in *Proc. IEEE PES Innovative Smart Grid Technologies Asia*, Bangkok, 2015.

These publications relate to the upcoming chapters in the following manner:

Table 1.1: Relevance between Chapters and Publications.

Chapter	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Publication	-	-	*C.2, C.3*	*J.1, C.1*	*C.3, C.4, C.5*	*J.2*	*C.3*	-

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Chapter 2

State of the Art

As outlined in the previous chapter, the successful implementation of a TVPP necessitates new, efficient models. This modeling refers to load, generation and grid prototypes. Their purpose is to aid the DSO in coping with the most crucial challenges encountered primarily during operation of the network and subsequently when planning grid investments.

From the DSO perspective, modeling usually relates to creating mathematical formulas or frameworks which describe certain equipment behavior or targets. For instance, a battery model might illustrate the battery's charging behavior, whereas a control model could explain how the consumption patterns of several appliances should be coordinated in order to achieve certain preset goals. In electric power systems, modeling is usually divided into:

- **Load Models:**
  Load models refer to all sorts of mathematical representation of particular appliances, e.g. washing machines, lighting, motors etc. [48]. A simple example of such a model is the battery equivalent depicted in Fig. 2.1. In this figure, the open circuit voltage is referred to as V_{oc}, R represents the battery's internal resistance, while V is the battery voltage at the output. The corresponding mathematical equation for this model is:

  $$V = V_{oc} + IR \tag{2.1}$$

  where I is the current flowing to/from the battery. It has a positive sign when the battery is charging and a negative sign when discharging [49].

- **Grid Models:**
  Grid models relate to frameworks which consider the electrical network as a whole. They range from topology models to optimisation processes, which oftentimes take the components' physical constraints into account.

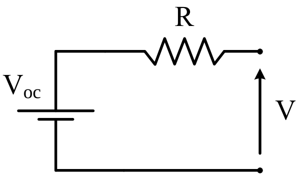

Figure 2.1: Simplified electric equivalent of a battery.

A very common grid model is the power flow calculation[1] [50]. In its simplest form, the voltage and angle of the system's buses are computed based on the network topology, the components' characteristics (e.g. line resistance), and the power requirements/injections of existing loads/generation.

Classifying models into grid and load models is just one out of many possible distinctions. Another popular grouping is the following:

- **Deterministic:**
  Deterministic are those models which do not take uncertainty into account. For example, the battery model shown in Fig. 2.1 is a deterministic one. This can be understood by the fact that no uncertainty is included in its mathematical formulation. Both the open circuit voltage, V_{oc}, and its resistance, R, are fixed deterministic quantities.

- **Stochastic:**
  Stochastic models are those which also account for uncertainty within the model. For instance, a simple linear regression (SLR) model [51]:

$$y = \beta_0 + \beta_1 x + \epsilon \tag{2.2}$$

  incorporates the stochasticity in the ϵ term, which usually is a normal distribution with zero mean and σ^2 variance[2].

It is noteworthy that, to some extent, stochasticity can be replicated even by deterministic models. This approach, also known as Monte Carlo simulation, relies on feeding stochastic input to deterministic models. Multiple runs give multiple outputs and, thus, the stochasticity of the input is transferred to the output.

Finally, it is important to clarify that both load, generation, and grid models can be deterministic or stochastic depending on the application. For instance,

[1] To be more precise, the power flow computes the solution of the grid model, i.e. the Y-matrix or the Jacobian matrix. However, the solution is frequently considered to be a part of the grid model itself.

[2] In case the parameters β_0 and β_1 derive from fitted data, additional variance is expected from those parameters.

State Estimation (SE) is an example of stochastic grid modeling [52]. SE is similar to power flow, yet the solution is weighted according to the variance of the network's input, i.e. the uncertainty of measurements. In this Ph.D. thesis, stochastic and deterministic models are used for the load and grid, respectively.

2.1 Load Forecasting

Load forecasting refers to stochastic load models which aim at predicting load/generation. This task has traditionally been made at the transmission level and is intended for bidding in electricity markets. At the distribution level, load forecasting performs another task for a TVPP. Specifically, local load/generation needs to be forecasted so as to predict, and consequently resolve via DR, any upcoming grid congestions. Load forecasting can principally be categorised as:

- **Long Term Load Forecasting:**
  This type of forecast is usually employed to predict demand peaks and energy requirements in the range of years [53].
- **Medium Term Load Forecasting:**
  Medium term refers to time horizons of a few months ahead.
- **Short Term Load Forecasting:**
  This is the most common prediction horizon for load forecasting. This kind of models conduct daily or hourly predictions.
- **Ultra-Short Term Load Forecasting:**
  Ultra-short term predictions are used for load/generation estimation in the range of minutes ahead [54].

Among these categories, short term load forecasting is the most essential for a TVPP's operation, while long term forecasts are more useful for planning purposes. Medium term load predictions lie within the former and the latter and, as such, they can be utilised for both operation and planning [55]. Finally, ultra-short term load forecasting is, up to day, employed for managing operational reserves and controlling the power flow at the transmission level [56]. Despite its limited contemporary use, its implementation for establishing local flexibility markets in the future might be necessary.

2.1.1 Load Forecasting Models

Load forecasting has been performed within the concept of power systems for a long time. Recently, a series of forecasting competitions have even been organised to propose new forecasting approaches and/or compare them with traditional techniques [57], [58]. The administration of such events further highlights the necessity of load forecasts for proactive load management. Based on the findings of these competitions, Multiple Linear Regression (MLR), the Autoregressive Integrated Moving Average (ARIMA) approach, and Artificial Neural Networks (ANN) are currently considered as benchmark models.

2.1.1.1 Single and Multiple Linear Regression

A SLR model has already been presented in (2.2). The model is regarded as linear owing to the linearity of the parameters β_0 and β_1. Overall, the philosophy of linear regression is depicted in Fig. 2.2. Given an independent variable x, a random variable y, and a set of y, x observations, the reasoning of SLR is to assume a linear underlying model and estimate the parameters β_0 and β_1 so as to encapture this model as best as possible [51]. Typical methods for estimating the parameters β_0 and β_1 are the Least Squares Estimation and the Least Absolute Value Estimation [51], [59].

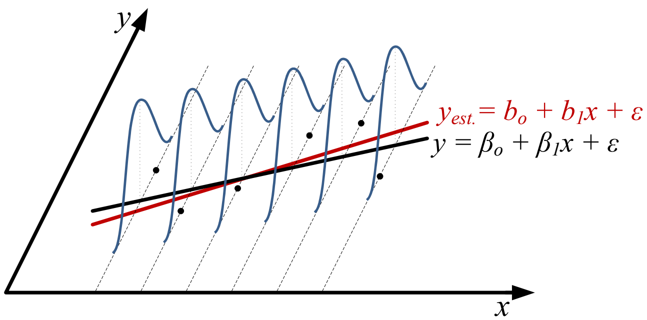

Figure 2.2: Estimated versus real underlying model [51].

The concept of linear regression can be extended to more explanatory variables[3] and regression coefficients, i.e. additional $\beta_i x_i$, resulting in MLR. These variables may refer to environmental conditions or social events. MLR models have been used for forecasting since early times [60]-[64]. The reason is that they are usually efficient, in spite of their simplicity. This also explains why their practicality has endured time [65]-[69]. Recent studies document that MLR is frequently combined with other well-established techniques, like ANNs, Fuzzy Logic, and Support Vector Machines, in order to increase the forecast accuracy and account for non-linearity in the underlying model [70], [71].

[3] The choice of these variables is evaluated by statistical tests, e.g. the t-statistic or the F-statistic [51].

2.1.1.2 Autoregressive Integrated Moving Average

This type of modeling is also known as the Box-Jenkins approach according to the authors who documented it [72]. ARIMA modeling is employed in order to describe and predict weakly stationary[4] processes [74]. Schematically, ARIMA models have the following form:

$$\phi_p(B)(1-B)^d X_t = \theta_q(B)(1-B)^d Z_t \tag{2.3}$$

where X_t is the value of the time series at time point t, Z_t refers to a purely random process with mean zero and variance σ_z, and d is the order of integration. The term $(1-B)^d$, used for the integration, is applied to non-stationary time series in order to transform them to stationary processes. Finally, $\phi_p(B)$, $\theta_q(B)$ are polynomials of order p, q, respectively, so that:

$$\begin{aligned} \phi_p(B) &= 1 - a_1 B - ... - a_p B^p \\ \theta_q(B) &= 1 + \beta_1 B + ... + \beta_q B^q. \end{aligned} \tag{2.4}$$

while B refers to the backshift operator, namely:

$$B^j X_t = X_{t-j} \tag{2.5}$$

The model in (2.3) is called ARIMA (p, d, q). As can be observed, the model is similar to an MLR. The main difference is that the explanatory variables consist of past observations of the output and the corresponding errors of the model. The former are called the Autoregressive (AR) terms, whereas the latter are addressed as the Moving Average (MA) terms. The model type is based on the investigation of the autocorrelation and partial autocorrelation functions, while the determination of the AR and MA terms relies on either the least squares estimation and/or the Yule-Walker equations [74].

ARIMA models have since long time been implemented to conduct load forecasting [65], [75]. Nevertheless, they are still employed due to their accuracy and low training data prerequisites [57], [74]. The models can account for weekday and/or weekend forecasts as well as for load pattern and/or peak demand prediction [76], [77]. Moreover, they can be extended to consider seasonal variations, exogenous parameters, and/or heteroscedasticity [78]-[80]. Lastly, ARIMA models have been combined with other approaches such as ANNs [81].

2.1.1.3 Artificial Neural Networks

ANNs is a type of experience based modeling which, contrary to the previous two models, is able to encapture non-linearities of the underlying model. As

[4] Weakly stationary processes are those processes whose mean is constant and whose autocovariance function depends only on the lag [73].

shown in Fig. 2.3, an ANN is a system of interconnected nodes. Each node receives various inputs and provides one output, thus formulating a "neuron". Moreover, each node is capable of exchanging data with other nodes according to the ANN topology. The data are modified by the interconnection weights, W_{i-j}, and by activation functions associated with every node [82].

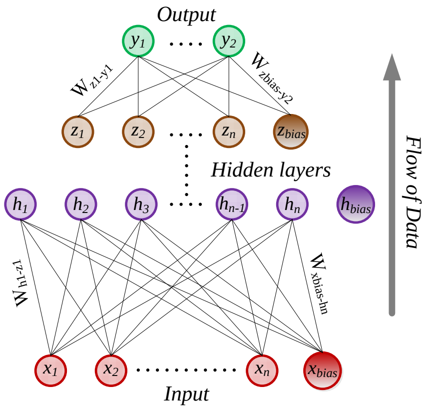

Figure 2.3: Schematic Feed Forward Neural Network [82].

For setting up an ANN, the choice of learning process (e.g. back propagation), activation functions (e.g. linear, sigmoid etc.), and network architecture (i.e. Feedforward or Feedback) are crucial. The most popular ANN model is the Multilayer Perceptron (MLP), which is schematically depicted in Fig. 2.3. This type of model has been broadly used for load forecasting [83]-[86]. Moreover, Probabilistic Neural Networks have been investigated in [87], while Radial Basis Function Networks have been examined in [88]. Additionally, feedback neural networks such as the Elman Neural Networks are proposed in [89], [90]. An example of unsupervised ANN is the Self Organizing Maps which have been applied to load pattern classification for the purpose of load forecasting in [91]-[94]. Finally, hybrid models like, for instance, combining ANN with fuzzy logic have also been suggested [95]-[97].

2.1.2 The Peculiarity of Distribution Systems

Besides the aforementioned models, support vector machines [98]-[100], fuzzy logic [101], Holt Winters [102], expert systems [103], and other approaches have been used for load forecasting in the literature. Nevertheless, a common point of all these studies, is the power aggregation level which they consider. This level refers to the transmission grid, where load uncertainty is quite low. Conversely, forecasting is rarely conducted at the distribution level. In relevant research work, future time series are usually considered as already known [104]-[106].

This is problematic since the implementation of a TVPP will necessitate load forecasting of disaggregated power patterns even up to the consumer level [46], [56]. This implies forecasting at many nodes with high prediction uncertainty [86], [107], [108]. To this end, two topics require further clarification:

1. **Impact of Forecasting in Distribution Systems:**
   In order to assess the applicability of various TVPP applications, the relation between aggregation and forecast accuracy should be studied.

2. **Distribution System Forecast Model:**
   Considering that the aforementioned forecasting methods are "ad-hoc" and additionally require an appropriate model selection and relevant training, they cannot straightforwardly be employed to distribution systems. New generic short term load forecasting models should be suggested.

2.2 Estimation of Flexible Consumption

Within the SG context, the amount of data to be managed will be substantially more than in conventional distribution grids. These data will mostly refer to signals associated with flexibility, which is a prerequisite for applying DR [109]. In this respect, communication and/or data storage implications are bound to affect the potentiality of a TVPP [20]. However, they are not the only endangering factors. Many others, including malicious attacks, consumer privacy, and data sharing issues might also jeopardise the TVPP's functionality [110], [111]. For instance, depending on the market structure, DSOs might not have access to the flexibility potential of individual consumers since they are the buyers, rather than the sellers, of this commodity [112], [113]. Hence, flexibility data might only be available to relevant BRPs, such as the Aggregators. One way or another, DSOs will eventually have to estimate the underlying flexibility of their territory. Moreover, the more disaggregated the flexibility, e.g. device level flexibility, the better.

Essentially, the aforedescribed problem is associated with the research area of Non-Intrusive Load Monitoring (NILM). In NILM, an aggregated measurement referring to the power measurement at the Point of Connection (POC) between the grid and the consumer is usually provided. Subsequently, this aggregated measurement is disaggregated to various device level power patterns. NILM has thoroughly been investigated in the literature. In [114], the possibility of extracting device load signatures from the aggregated consumption data of a house is investigated, while in [115], [116] the authors emphasise the electrical features which should describe equivalent devices for load monitoring. Furthermore, the load identification matter and the load classification problem are considered in [117]-[119] and [120], respectively. Fundamentally, NILM classifies the devices according to some criterion, e.g. ΔP-ΔQ plane, and afterwards associates every device in each class with an electric signature, i.e. a specific power pattern. During real time operation, the power changes of the aggregated residential load are tracked. Then, depending on these changes, i.e. the so-called "events", the operation of each device is identified [121]-[123]. The procedure is principally depicted in Fig. 2.4.

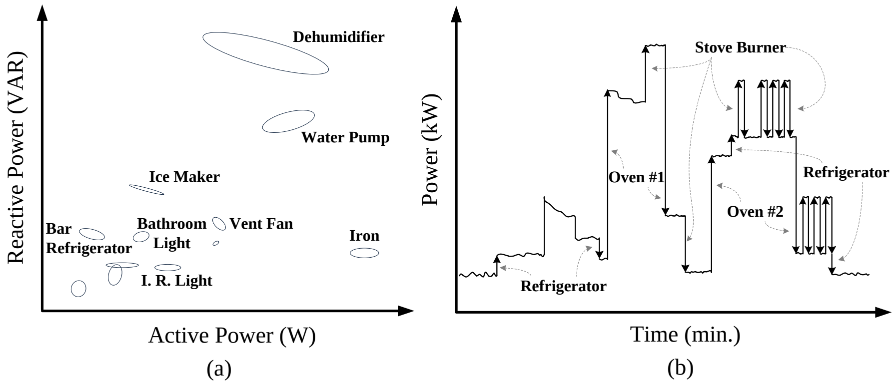

Figure 2.4: NILM [121]. (a) Classification of devices according to ΔP-ΔQ plane. (b) Identification of events.

This methodology is very promising, nevertheless, it relies on very frequent sampling, i.e. milliseconds to seconds. As such, it is neither compatible with smart meters, which usually record at lower temporal resolutions, e.g. per hour [124], nor with the previously indicated communication and/or data storage restrictions. Moreover, some intrusive initial training is necessary for the classification part [121], which might compromise consumer convenience. To this end, NILM techniques for estimating, at least "load intensive", flexible loads should be proposed [122]. Some original attempts to establish these load models have already been done, yet they solely refer to weather dependent loads, and rely on very restrictive assumptions [125], [126]. As such, NILM research compatible with smart metering should be performed.

2.3 Distribution System Load Monitoring

Monitoring the distribution system during operation is vital for a TVPP. Essentially, the DSO should overview the grid's load distribution in order to initiate any corrective actions through DR, either proactively or reactively. Ideally, load monitoring will be conducted by smart meters "online[5]". Unfortunately,

[5]In this context, "online" refers to hourly or half-hourly measurements, considering the time frame of smart meter recording.

as a result of communication limitations [56], the time frame of smart meter recording is oftentimes not equal to the one of transmitting the measurements to the control center. For instance, in the case to be examined in Chapter 5, the utility had smart meters installed throughout the network. These meters were capable of recording the consumption at an hourly basis, yet they were transmitting these recordings to the utility center only once per day.

A straightforward remedy for this situation would be to allocate some few redundant meters which would operate online as a trade off between complete observability and real time operation [127]. The amount of these measurement devices should be rather small on the grounds of potential communication bottlenecks and equipment costs [128]. Apart from its practicality to SGs, this solution would also be useful to traditional distribution grids when perceived as a first step towards a smarter grid.

Regarding the meter allocation strategy, relevant frameworks have been described in the literature. Some of them relate to Power Quality (PQ) monitoring, which is not the same as load monitoring for estimating the load distribution; nonetheless, the scope is similar since they also target partial grid observability. To be more specific, some preliminary work conducted by EPRI suggests allocating metering devices at the substation and at two random places along each feeder [129]. On the other hand, the authors in [130], recommend meter allocation to already installed switching devices which leads to several monitoring spots throughout the feeders. This recommendation is also provided in [131]; however, it is supplemented by meter installations to reconfiguration lines and big loads. Critical load monitoring is also suggested in [132], [133]. Moreover, monitoring the beginning, the middle, and the end of the feeder along with sensitive loads is presented in [134]. Similarly, meter allocation at the substation and along the feeder is proposed in [135]. This allocation is further augmented by typical load profiles to estimate the load distribution. All these approaches are competent, yet they can only serve as generic guidelines, since they are heuristic and inherently vague.

Further research work considers the optimal allocation of PQ meters in the grid [136]-[139]. These methods are promising, but they aim at 100% observability and, as such, they are antithetical to the current scenario. The same holds true for [140] which aims at optimally allocating Phasor Measurement Units. Another perspective is given in a group of references, which base their meter allocation on the minimisation of voltage deviations. In most cases, these deviations are created by performing Monte Carlo simulations of the power flow with stochastic loads, i.e. stochastic output derives from deterministic models with stochastic input. Such an interesting approach is the one presented in [141], which employes dynamic programming to reach a solution efficiently. Likewise, references [128], [142] propound the idea of sequentially installing meters in the grid to enhance its observability capability. Furthermore, reference [143] relies on minimising an entropy function for the optimal allocation of power meters. An exhaustive research of all possible meter allocation combinations is a prerequisite for this study; nevertheless, such a research is not realistic for extensive distribution networks [127]. Lastly, optimal meter allocation frameworks are presented in [113] and [127], whereby the voltage deviations are minimised as a result of state estimation. These approaches are consistent, yet the resulting allocation favors meter placement at the end of the feeders and/or at neighbouring nodes. However, this layout is not advantageous in the scope of load distribution monitoring, since many grid areas remain fairly unobservable, thus reducing the accuracy of the load distribution approximation. As outlined in [132], a more realistic outcome would be a hierarchical frame in order to to achieve the best trade-off between observability and number of allocated meters. This is one of the aims of this Ph.D. study.

2.4 Reliable Operation of Distribution Systems

So far critical aspects for a DSO, such as grid observability, flexibility estimation, and forecasting, have been addressed. By having this tools up and running, a TVPP will be able to identify and locate any upcoming grid issues, i.e. voltage problems and/or equipment overloading, and resolve them by means of flexibility either proactively or reactively. These problems are bound to occur in the future, since high penetration of flexible devices and distributed generation will alter the grid's capacity requirements. In particular, the impact of increasing distributed generation is illustrated in [144], where the possibility of reverse power flow and overvoltage incidences is mentioned. Reference [145] concentrates on potential grid stress due to EV penetration, whereby overloading and undervoltage problems are reported. The same holds true with increasing number of HP installations as indicated in [146]. Depending on the location of these installations, the acceptable penetration level may be very limited [147]. Furthermore, the fact that residential generation, i.e. Photovoltaic (PV) generation, is temporally incompatible with residential active loads, i.e. HPs and/or EVs, is highlighted in [148], whereas its effect to planning procedures is outlined in [149].

Since DSOs are responsible for facilitating the power provision at the low voltage level, they have to devise strategies to cope with the aforementioned problem. As explained in Chapter 1, one solution would be proceeding to grid reinforcement, whereas the alternative would be relying on control strategies. To this end, many researchers have presented active demand control architectures which could be embedded in a TVPP framework. Two types of control are found in the literature, namely centralised and decentralised control schemes. Their advantages and disadvantages are presented in Table 2.1. These features are also described and/or demonstrated in [150]-[152].

Table 2.1: Benefits & Implications of Centralised & Decentralised Control.

Centralised Control	
Benefits	***Implications***
Optimum solution reached	Long computational time
Proactive load management	Predictions necessary
V, I, phase unbalance etc. solved	Reduced scalability
	High communication requirements
	Privacy issues
Decentralised Control	
Benefits	***Implications***
Fast response, suitable for real-time	Sub-optimum solution reached
Increased scalability	Reactive approach
Low communication requirements	Only V problems solved efficiently

Decentralised control algorithms attempt to reactively relieve any grid stress, i.e. the problem is solved while it occurs, by utilising local information at the POC. Examples of decentralised control of EVs in order to cope with grid limit violations are found in [105], [151]-[153]. In these manuscripts, the EV charging process is adjusted according to local voltage information and some prior knowledge of the grid's critical points and/or sensitivities. These methods react fast and perform adequately well for alleviating the voltage problem. However, they are expected to encounter problems when dealing with unprecedented overloading situations in the network.

Centralised control frameworks are counterparts of the decentralised ones when information regarding the whole grid is available [154]. These approaches can only be used for proactive control since their long processing times, especially for extended distribution grids, reduces their scalability [151]. Analytically, references [155]-[157] use linear models to schedule EV charging while respecting grid constraints. On the other hand, nonlinear and quadratic models are used in [158] and [159], respectively. Moreover, financial incentives can also be taken into account when solving the grid congestion problem [160], [161]. Principally, these incentives are either expressed as reference signals corresponding to spot prices [106] or as shadow prices and dynamic node tariffs [162], [163]. These methodologies succeed in embedding both the grid constraints and the financial objectives sought by the Aggregators in one algorithm; an approach which is similar to contemporary market interactions between TSOs and BRPs. Nevertheless, for the distribution system, this scenario is only valid if the DSO and the Aggregator are the same entity or if there is a corresponding long term contract between these two parties [26]. If not, then the relevant capacity issue should be solved by market mechanisms [27] instead.

Finally, it is worth mentioning that some frameworks consider both proactive and reactive demand management, by employing centralised and decentralised control sequentially [164]-[168]. In this manner, the benefits of both types of control are harvested. This perspective of hierarchical control is very appealing for future TVPP implementations, especially considering the high uncertainty stemming from flexible demand and intermittent generation. This last point has been to a great extent neglected by the aforementioned literature; thus, it should be further investigated along with the necessity of interfacing the TVPP's flexibility requirements with potential flexibility market transactions. A final comment considers the fair activation of flexibility. This factor has only been linked to specific devices, e.g. the least charged EV receiving charging priority [169]. Nonetheless, in flexibility terms, "fairness" is generally associated with different consumers offering flexibility in order to resolve permanent grid problems. This issue has not been examined in the literature and should be carefully studied when seeking flexibility services to alleviate grid problems.

2.5 Transactions in Flexibility Markets

Until now, the DSO's option of requesting flexibility services in order to solve upcoming and/or occurring network problems has been discussed. The latter is calculated by decentralised control schemes, whereas the former is computed by centralised control frameworks. In order to realise this concept, relevant flexibility markets should be introduced. To this end, the authors in [170], [171] present a method for integrating HPs and EVs into day ahead pool markets. However, in this framework, the DSO's technical needs are not addressed. These constraints are considered in [106]; yet, like in the previous case, day ahead market clearing is targeted. Day ahead markets have mainly been established for facilitating the participation of large and inflexible in start-up and ramping requirements coal plants. Nonetheless, new markets, which favor distributed energy resources, do not need to adapt to this time frame. On the contrary, due to the volatility of intermittent generation, especially day ahead, shorter time frames for clearing the market would be preferable [172]. In compliance with this observation, the authors in [151] propose a decentralised market mechanism for real-time pricing. On the drawbacks of this method, the current limit violations are not respected. Moreover, real time pricing might create uncertainty and volatility in prices [173].

Another problematic issue in these manuscripts, is the perception of the DSO's role. The DSO is responsible for providing adequate capacity for distribution grid power flows. Failure to comply with this obligation should incur penalties. In the aforementioned research work, the DSO's capacity needs are catered for when formulating market bids. This action is realistic only when the DSO and the Aggregator are the same entity or when long term flexibility contracts are established among them [174]. The existence of these contracts raises the issue of the market structure, i.e. *how should flexibility be traded?* Many researchers support the idea of establishing local flexibility markets [26], [27], which will further deregulate the electricity commerce. On the way to this deregulation, reference [26] suggests the introduction of flexibility contracts between the DSO and the BRPs, whereas three market types are presented in [27], namely bilateral contracts, auctions, and supermarkets. Bilateral contracts offer reliability and predictability, yet they are reported to raise market power and compromise market efficiency [175]. Thus, their use is expected to be limited. Supermarkets and auctions like in [176] pose as more efficient alternatives when trading flexibility; however, they do not facilitate symmetric information provision, thereby raising market power as well [173]. Consequently, the form of local flexibility markets requires further investigation.

A last issue to be clarified concerns the commodity to be traded, i.e. the form of flexibility offers. According to [173], flexibility incorporates multiple attributes such as energy or ramping rate(s) and, thereby, it is considered as a multi-dimensional commodity. Identifying these attributes will aid in establishing local flexibility markets. In [177], some of these attributes are described and flexibility bids are formulated. However, these properties are EV specific and do not cover the general case. Therefore, the last target of this Ph.D. study is to analyse this topic and identify/quantify necessary TVPP related flexibility offer attributes.

2.6 Summary

In this chapter, some crucial matters for successfully implementing a TVPP were addressed. Contemporary practices and experiences from the literature were reported, whereas incentives for further investigation were provided. These may be summarised as a decentralized forecasting method, a SG compatible NILM technique, a hierarchical load monitoring architecture, a proactive and reactive load management scheme and its interface to a flexibility market.

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Chapter 3

Decentralised Short Term Load Forecasting

This chapter is dedicated to present the main problems associated with load forecasting in the SG context. Relevant issues are thoroughly discussed, while simple, yet effective, solutions are proposed. Details of the presented tables and/or figures, e.g. data used, are provided in C.2 and C.3 in the APPENDIX.

3.1 Introduction

One of the most useful features for a utility is the ability to foresee problematic loading situations and proactively react on them. The time horizon of this prediction may vary depending on the scope of the forecast. For instance, foresight of spatial and temporal load growth in the range of years is realised by employing long term forecasts. Consequently, land and electrical equipment are rated and purchased in advance as part of the utility's planning procedure [178]. On the other hand, short term load forecasts are utilised in order to adapt to the load's daily variation. Based on these short term predictions, utilities can resort to control mechanisms to avoid imminent grid complications. If the utility is also an ER, then short term load forecasting will be conducted to formulate appropriate bids for the energy markets as well [1].

In the SG context, a TVPP is principally responsible for identifying any forthcoming grid complications and tackling them proactively. In order to succeed, the TVPP will refer to flexibility markets so as to purchase the estimated amount of flexibility needed to alleviate the problems. On the other hand, ERs should also be able to forecast their consumers' flexibility to formulate their corresponding offers on the market. Moreover, considering the volatility of intermittent renewable generation and the uncertainty of human behaviour which is embedded in the flexibility of consumers, keeping a short horizon for the predictions will be preferable for both sides [158]. As such, short term, i.e. hourly or half-hourly, load forecasting for bidding in intra-day balancing markets is expected to prevail upon other forecast types in SGs.

As explained in Section 2.1.2, short term load forecasting has traditionally been performed at an aggregated level, i.e. the transmission or sub-transmission level. Lack of data and limited local control mechanisms are only two of the reasons leading to aggregated predictions for utilities. Another obvious reason, which relates to ERs, is that participating in contemporary energy markets requires a minimum amount of energy threshold, which cannot be surpassed by a small number of consumers. To this end, several approaches have efficiently been used for traditional load forecasting as presented in Section 2.1.1. However, the applied models deal with reduced volatility due to aggregation and are mainly "ad-hoc". As an example, a region containing thousands of residential, commercial, industrial, and other consumers might be associated with a parametric load model consisting of hundreads of variables. These variables might, for instance, refer to weather dependent variables, e.g. temperature, wind speed, humidity etc., or social events, e.g. an upcoming concert to be held in the region. It is evident that using the same forecast model for a specific consumer would be inappropriate as many of the explanatory variables, e.g. the concert, would probably be irrelevant with the examined case [46]. Furthermore, any relevant variables would require proper estimation, which might be impractical or even impossible for all consumers. This simple example highlights the importance of devising simple, automated, and generic prediction models which will be applicable to different aggregation levels.

In compliance with the short prediction range and the scalability requirements, a straightforward solution to forecasting would be to rely on non-parametric approaches. Thus, in this chapter, a non-parametric prediction model based on sequential pattern mining is proposed. This model, which can be utilised for forecasting at various aggregation levels will aid the DSO in predicting upcoming grid loading conditions. In case a problematic situation is detected, the TVPP will formulate the appropriate flexibility requests as will be shown in Chapter 6.

3.2 Non-Parametric Models

Parametric models rely on incorporating knowledge extracted from a historic database in a number of parameters. These trained parameters are subsequently utilised to forecast future model states. This philosophy can be very accurate; yet, it makes these models purpose-oriented and inflexible to use for different time series. The counterpart of parametric models, namely non-parametric models, do not depend on variable estimation and are, therefore, more flexible. An example of a non-parametric model is the ANN. This empirical method performs the forecasts by imitating a brain-like structure of neurons, which are trained according to historic data. On the downsides of ANNs is the lack of consistent guidelines to select the model structure [179]. Contrary to ANNs, which are to some extent a "black box" approach, sequential pattern mining suggests a simple to comprehend, automatic, and scalable load forecasting solution [180]. This approach, which is similar to a variable order Markov model satisfies all the preset targets of Section 2.1.2 as a trade-off for slightly reducing the prediction accuracy compared to benchmark methods.

3.3 Markov Models

A very common non-parametric prediction model class is the Markov model. The Markov model is a stochastic model utilised when modeling randomly changing systems. The assumption in those systems is that future system states depend only on the present system state and not on the sequence of events that occurred before it. A simple Markov chain example is illustrated in Fig. 3.1. In

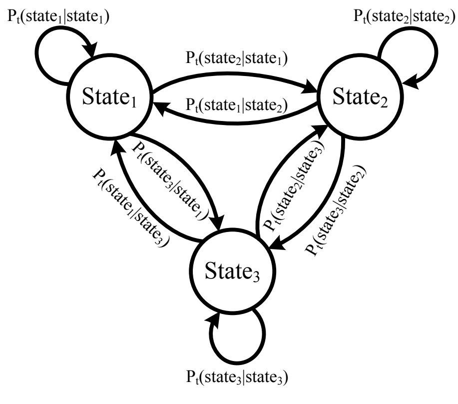

Figure 3.1: Schematic example of a first order Markov model [181].

this figure, a directed graph is used to depict the state transitions. As can be seen the transition between states is based on conditional probabilities. These probabilities are formulated by historic training data. This approach may seem naive, however, it can be surprisingly efficient for very volatile systems while keeping the complexity of the model at a minimum.

3.4 Sequential Patterns

Sequential patterns refer to a machine learning methodology which resembles a higher order Markov chain. Particularly, sequential pattern mining is a data mining process, which aims at identifying statistically relevant patterns among data samples where the values are delivered in a sequence [180]. Thus, sequential pattern mining is closely related to time series analysis; nonetheless, identical to Markov processes, a special prerequisite of sequential pattern mining is the values of the sequences to be discrete. The philosophy of the proposed method is given in Fig. 3.2.

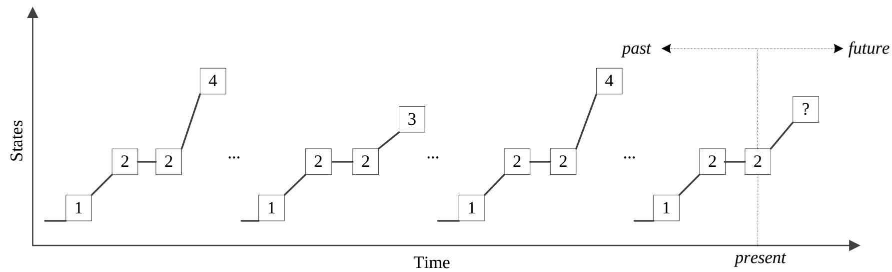

Figure 3.2: Schematic example of sequential pattern forecasting.

As can be seen from that figure, a sequence of states “1-2-2” is recorded at present time. This sequence needs to be forecasted based on past observations. Thus, past sequences with the same order are sought. In this example, three of those have been found. Then, the predicted value is decided based upon the continuation of the past sequences according to a preset criterion. In this study, the most frequent past continuation is selected as the preset criterion. Hence, for the example of Fig. 3.2, the forecasted state would be state “4” since it is more frequent than state “3”. Other studies, however, use other prediction criteria like the average of past continuations [182].

It is apparent that the proposed method resembles a Markov model by perceiving the sequence “1-2-2” as one state which leads to “3” or “4” with certain conditional probabilities. Thus, it can be said that the proposed model is similar to a higher order Markov model. In order to apply this model, two critical features should be defined, that is to say the model states and the length of the sequence. The former can be defined by resorting to clustering techniques, whereas the latter can be variable as will be explained later. This last feature is also a major difference to higher order Markov modeling.

3.5 Clustering

As explained in the previous chapter the model states can be defined by clustering techniques. Clustering techniques are mathematical models which facilitate grouping of similar data into clusters. As such, these models can aid in defining the number of states, but also the values hidden behind those states.

3.5.1 Clustering Techniques

Various clustering techniques can be found in the literature for grouping load data. Some examples are the Kohonen Self Organizing Map [183], the K-Means and the Fuzzy K-Means, Hierarchical Clustering, Expectation Maximisation, and the Modified Follow the Leader [184]-[186]. Additionally, Agglomerative Hierarchical Clustering and Adaptive Vector Quantization were investigated in [94]. Each of these algorithms has certain advantages and disadvantages. For instance, k-means and hierarchical clustering are unsupervised learning techniques which, however, necessitate the definition of the number of clusters. Moreover, k-means requires the initial position of those clusters, while hierarchical clustering needs the definition of the distance formula which is used when comparing clusters. On the other hand, the Kohonen self organizing maps are procedures which can even result in non-linear separation of data without entailing the amount of clusters as an input. Nonetheless, they require visual inspection to determine the clusters themselves. Similarly, Mean-Shift Clustering computes the number of clusters automatically [187]; nevertheless, it requires tuning of an input variable, i.e. the bandwith of the utilised kernel, which can be even harder to assess compared to the number of clusters.

For the problem at hand, simple, linear clustering techniques, like the k-means algorithm, suffice for creating the states of the sequential pattern algorithm.

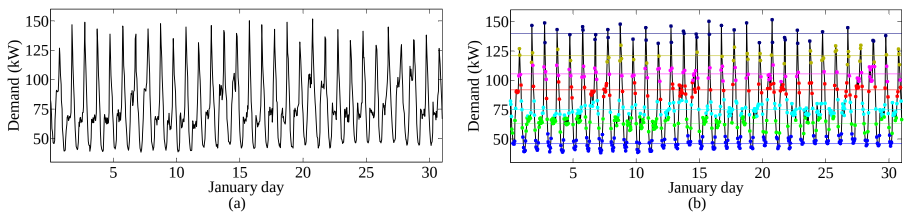

Figure 3.3: Loading of the transformer during January. (a) Load pattern. (b) K-means clustering with 7 clusters.

Given a time series of loading data, such as the one in Fig. 3.3.a, and having assigned the desired number of clusters[1] to the algorithm, k-means results in data grouping as shown in Fig. 3.3.b. The load values in this figure refer to the transformer loading of the consumers described in Section 1.7 during January. One problem with the presented discretisation is the number of clusters to be selected. This value can be decided based on cluster separation measures.

3.5.2 Evaluation of the Clusters

The decision regarding the number of clusters to be used for algorithms which require this input, can be based upon cluster adequacy measures. These mathematical formulas assess the partitioning of the data after clustering. They are useful when comparing the clustering of different techniques utilising the same number of clusters or when comparing trials of the same clustering technique with different number of clusters [94]. The latter is of interest in the current scenario. The evaluation of the clusters is principally performed by comparing the inter-cluster to the intra-cluster data scatter. The inter-cluster data scatter is in most cases interpreted as an evaluation of the distance among data within a cluster as opposed to the intra-cluster data scatter which relates to the distance among clusters [188], [189].

Several cluster adequacy measures have been utilized to assess the cluster validity. Some benchmark examples are the Davies Bouldin Indicator (DBI), the Dunn index, the Clustering Dispersion Indicator, and the Similarity Matrix Indicator [185], [94], [188], [189]. In order to identify the best data partition, a reasonable -for the application- range of potential clusters is selected and then clustering is iteratively applied for all these potential groupings. For each partition, the chosen cluster adequacy measure is calculated to assess the clustering. Then, the best value is identified and the relevant clustering is adopted.

An example of this partition assessment is given in Fig. 3.4 which examines the case of the transformer loading from the 16^{th} to the 20^{th} of January. As can be seen in this figure, a range of 2 to 10 clusters is chosen. Within this range the DBI and Dunn indices are calculated as shown in Fig. 3.4.d and Fig. 3.4.e. Low DBI and high Dunn values are indicators of good clustering, respectively. In both cases, 5 is indicated as the best cluster separation and is, therefore, selected for grouping the data as illustrated in Fig. 3.4.b. Two other partitions are also displayed, namely grouping with 2 and 10 clusters, which are depicted in Fig. 3.4.a and Fig. 3.4.c, accordingly. Fig. 3.4.a is an example of bad clustering, since the data within each cluster are thoroughly scattered. On the other hand, the distribution of the cluster centers, i.e. the colored horizontal lines, is too dense in Fig. 3.4.c. Ultimately, clustering with 5 clusters is a balanced case from both perspectives.

[1] As explained, k-means requires the initial position of the clusters. This initialisation is usually performed by selecting random locations within the data range.

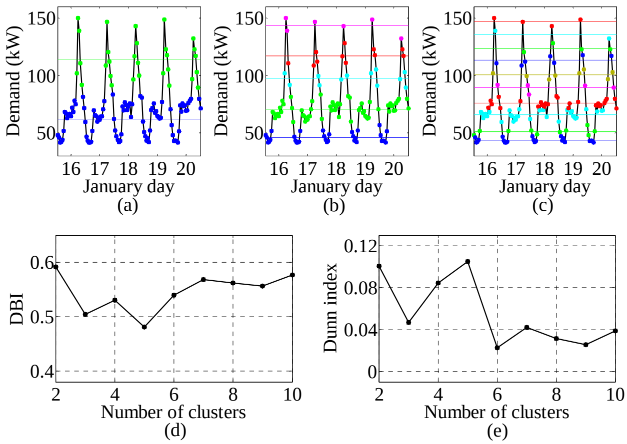

Figure 3.4: Clustering and clustering assessment. (a) k-means with 2 clusters. (b) k-means with 5 clusters. (c) k-means with 10 clusters. (d) Davies Bouldin indices. (e) Dunn indices.

At this point, it should be commented that, although cluster adequacy measures are useful tools for choosing the best number of clusters, there is no indicator for selecting the best method among them. For instance, there is no guarantee that the DBI will perform better than the Dunn index and vice versa. However, relevant studies show that most of the benchmark methods provide similar results when evaluating consumer loading [185], [94]. As such, both the DBI and the Dunn indicators are good choices for such applications. One advantageous feature of the DBI is that values around 0.6 or above are indicators of randomly scattered data which cannot be grouped into natural clusters [188]. This useful-to-know fact is compensated by the DBI's inability to correctly evaluate partitions including clusters with only one datum. For this kind of partitions the Dunn index provides superior results; as such, these two methods should carefully be selected based on the provided data. For simplicity, in this chapter, k-means evaluated by the DBI will be applied.

3.6 Sequential Pattern Forecasting

Sequential pattern forecasting utilises past sequences of states in order to forecast upcoming ones. Thus, the first step is to choose the desired history range and subsequently filter any bad data within it, e.g. missing or erroneous data. For time series of continuous data, a mandatory step would be to discretise those series. As explained in Section 3.5, this is achieved by clustering historic observations. Each historic observation is thereafter associated with its cluster center to create sequences of states. For example, as can be shown in Fig. 3.4.a, each datum is either assigned to the green or the blue cluster center resulting in two possible states of loading. The number of states is decided by means of the selected cluster adequacy measure. This framework is presented at the top half of Fig. 1 in C.2.

Regarding the continuation of the forecasting procedure, a maximum sequence length should firstly be selected. Considering that the forecasted data refer to hourly loading data, a reasonable number, e.g. 12 or 24, is chosen. Next, as shown at the bottom half of Fig. 1 in C.2, the present sequence is recorded and sought in the historic database. If it is spotted, then the most frequent next state is chosen as the prediction value. In case several values are equally frequent continuations of the sequence, then the worst case is selected, i.e. the highest loading state among them. A very interesting feature, which also differentiates this method from a higher order Markov model, is the case when a sequence is not found among past observations. If this occurs, then the sequence is curtailed by one state and the mining process is repeated. Thus, the proposed methodology is flexible in the sense that the sequence length automatically adapts to the current sequence form. Having concluded on the predicted state, the forecasted demand is obtained by assigning the demand value of the corresponding cluster center to the predicted state. Afterwards, the real loading value is classified into one of the existing clusters, i.e. the closest one, and the process is repeated for the next hourly prediction.

The application of the aforedescribed methodology for hour-ahead forecasting is illustrated in Fig. 3.5. In this figure, the load of a single consumer during

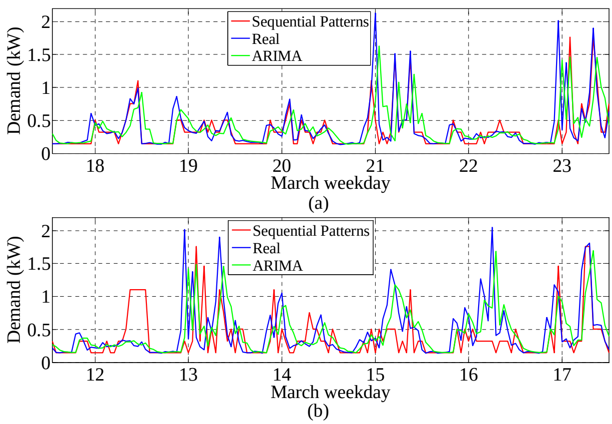

Figure 3.5: ARIMA versus sequential pattern forecasting at the consumer level. (a) Good sequential patterns performance. (b) Bad sequential patterns performance.

March weekdays was examined [190]. It was anticipated that weekdays would express some daily periodicity and, to this end, ARIMA models would be superior to sequential pattern forecasting. However, it is apparent that, apart from night-time, there is barely any periodicity in the load pattern and consequently ARIMA models are incapable to predict the peaks of the loading. They are merely providing a “lag” of the consumption pattern. This highlights in practice why traditional, “ad-hoc”, benchmark models are sometimes inadequate for decentralised forecasting. On the other hand, sequential pattern forecasting is based on replicating past sequences which are not necessarily periodical. Depending on the extent of the historic database, the results can be miraculously good as shown in Fig. 3.5. Particularly, Fig. 3.5.a displays an excellent performance of sequential pattern forecasting, which derives from the fact that relevant pattern sequences were recorded in the historic database and, moreover, the consumer behaved similarly at succeeding time periods. This fact can be justified on the grounds that a consumer might perform the same actions in an order, e.g. turn on the TV, wash the clothes, turn on the oven etc. These actions however do not necessarily need to be periodic as assumed by many parametric models. For this reason, even in cases like in Fig. 3.5.b where the high randomness of a single consumer leads to erroneous predictions, the proposed method may still perform better than the ARIMA approach.

3.7 Aggregation versus Forecasting Accuracy

As shown in the previous section, sequential patterns suggest a new philosophy in residential load forecasting, which can be advantageous in certain occasions. Moreover, the lack of need for a model selection makes them automated and flexible, which are necessary attributes for SG applications. However, these applications do not only restrict to residential level forecasting but also to other levels. To this end, their adequacy in aggregated predictions should be tested, i.e. regional forecasting. These predictions involve new features; for instance, aggregated consumption patterns will probably enhance the daily periodicity identified in individual consumers. The same might be true for other consumer types, i.e. industrial consumers. To investigate this, two simple models were tested to examine their forecasting error performance versus aggregation. The models are the random walk and the “seasonal” random walk, that is to say ARIMA $(0, 1, 0)$ and seasonal ARIMA (SARIMA) $(0, 1, 0)_{24}$, respectively.

As can be seen from Fig. 3.6, the random walk model, which is basically an hourly lag of the original time series, performs better at disaggregated levels. The reason for this is that, as also shown in Fig. 3.5, there is a very daily periodicity in the corresponding load pattern. Nevertheless, as demand patterns are aggregated the situation is reversed and the seasonal random walk, which is a daily lag of the time series, prevails. This implies that after a certain aggregation level at around 20 to 30 consumers, the daily periodicity of the

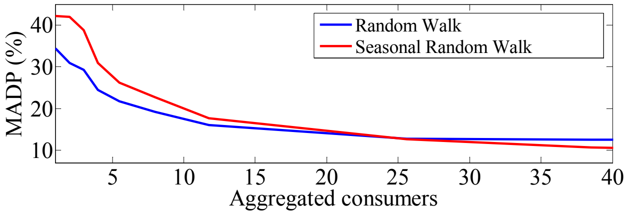

Figure 3.6: Aggregation versus Mean Absolute Deviation Percentage (MADP) error.

power pattern becomes evident; thus, it should be incorporated in the model. Sequential patterns offer such flexibility by modifying the initial model accordingly, as shown in Fig. 6 of C.2. This figure differs from Fig. 1 in C.2 in basically two features. The first one is a parameter inserted which permits the forecast only in case a certain amount of identical historic sequences are found, N_{min}. Experimental results have shown that this variable is useful in acquiring increased forecasting accuracy due to statistically better samples. The second attribute is the introduction of periodicity in the model. As can be observed, to do this, past sequences are only sought at certain time points, i.e. hours, in previous days. One drawback of this approach is that by doing so, there might be cases where no identical past sequences are found in the database. In such an occasion, however, one can either switch to the original model of Fig. 1 in C.2 or resort to a preset simple benchmark forecasting model, e.g. a SARIMA $(1,1,0) \times (0,1,0)_{24}$.

The results of this model upgrade are shown in Fig. 3.7 where the performance of the algorithm is illustrated with and without periodicity. As can be observed, sequential pattern forecasting performs adequately well even when daily periodicity is neglected. Nevertheless, by including this factor the performance is enhanced especially at the beginning of the day.

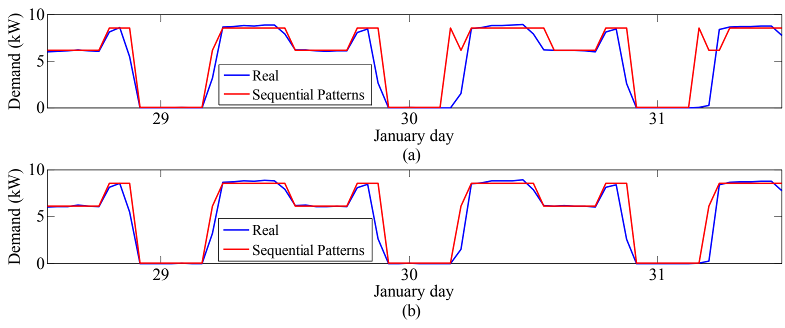

Figure 3.7: Sequential pattern forecasting for an industrial consumer. (a) Neglecting periodicity. (b) Considering periodicity.

As explained, daily periodicity should be considered when forecasting at aggregated levels, i.e. aggregation of more than 20 consumers. Fig. 3.8 depicts the performance of sequential patterns when taking periodicity into account and compares this performance to ARIMA modeling. The loading in this figure refers to the transformer level, while the figure depicts both a good and a bad case of sequential pattern forecasting. Overall, the load forecasting performance

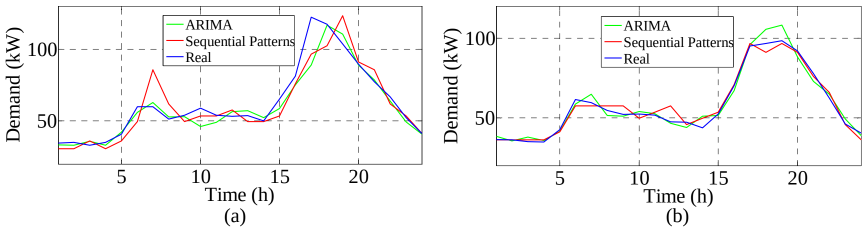

Figure 3.8: ARIMA versus sequential pattern forecasting at the transformer level. (a) Bad sequential pattern performance. (b) Good sequential pattern performance.

at this level is summarised in Table I of C.2, where the forecasting performance of sequential patterns and ARIMA modeling is studied for six months. It is apparent from that table that sequential pattern forecasting offers comparable results to ARIMA modeling. Partially, somewhat worse performance is accredited to the discretisation of the time series in order to formulate the sequences; however, this difference is compensated by lacking the need of model selection, i.e. human intervention. Moreover, even in cases where the forecasts are quite erroneous, like in Fig. 3.8.a, sequential pattern forecasting still provides same result trends to benchmark models, i.e. the ARIMA model fails to predict the peak as well.

3.8 Discussion

Sequential pattern forecasting suggests a new non-parametric, automated, yet flexible, solution for load forecasting at various aggregation/disaggregation levels. It requires minimum input by the user, i.e. maximum number of clusters, maximum sequence length, minimum number of sequence observations to allow inference, and whether to include periodicity. These features[2] may be tuned to increase the forecasting performance if deemed necessary. Some hints on how and when to tune this attributes are given in the preceding sections. Moreover, on the grounds of its simplicity and flexibility, new attributes like, for instance, weather dependency, can be incorporated in the model by regarding them when formulating the sequence states.

[2]These features should not be perceived as estimated parameters, rather than non-parametric attributes similar to the bin number of a histogram.

A very interesting feature of sequential pattern forecasting is the fact that it may not only provide the most probable upcoming loading, but also the second, third, fourth etc. most probable one as well. This is understood by reviewing Fig. 3.2. In that figure, it was concluded that the most probable outcome would be state "4". Nonetheless, as can be seen state "3" is the next most probable outcome for this example. This is controversial to ARIMA modeling, which solely provides one point estimate, and can be proven to be a relatively useful tool when assessing the risk of erroneous forecasts.

Finally, it should be commented that sequential patterns require an extensive historic database. Being a machine learning process, the larger the database, the more the historic sequences, and the more efficient the model becomes. This can be depicted in Fig. 3.9 where it is clearly seen that, unlike ARIMA, sequential pattern forecasting at the transformer level performs gradually better by increasing the training data set.

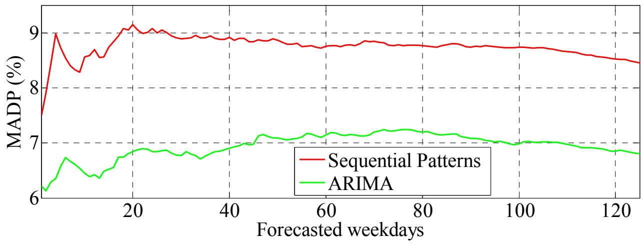

Figure 3.9: Moving average of MADP from 1^{st} of July to the 21^{st} of December.

3.9 Conclusions

In this chapter, a new short term load forecasting philosophy based on sequential patterns was presented. This method showed promising potential at disaggregated consumption levels while being competent to benchmark models when predicting at aggregated demand levels. Furthermore, the importance of periodicity and forecast performance versus aggregation was addressed, assessed, and occasionally accounted for when conducting predictions with the proposed model. As will be discussed in Chapter 6, this method will enable a TVPP to forecast at various aggregation levels so as to identify any grid limit violations and consequently request flexibility services from the market. Moreover, this forecasting technique will also aid in formulating aggregated flexibility offers by Aggregators, as will be shown in Chapter 7.

Chapter 4

Estimation of Flexible Consumption

In this chapter, the possibility of estimating the flexible demand of a residence is attempted. The presented study case concentrates on, but is not limited to, a HP. Ultimately, the HP consumption is approximated to a reasonable degree and its flexibility potential is discussed. More details concerning the study case can be found in J.1 and C.1 in the APPENDIX.

4.1 Introduction

SGs base their operation on increased data availability via smart meters. Although having more monitoring, communication, and control devices can be vital for many grids, it is concurrently the source of many complications. A straightforward consequence of SG infrastructure is that the reliability of the system decreases due to potential data related implications. Examples of this kind are communication and/or data storage problems, equipment failure, consumer data privacy restrictions, malicious cyber-attacks to communication appliances, and bad data [20], [110], [111]. Other incidents challenging the presumed data availability include device coordination and/or compatibility problems, and data sharing limitations between BRPs and grid operators.

All these likely events might compromise the benefits of a SG's enhanced functionality. However, flexibility data should always be available or estimable on the DSO side to manage expected grid congestions. NILM is a relevant research area for this kind of problems. However, as discussed in Section 2.2, most of the proposed methods are incompatible with the granularity of smart meter data and cannot be applied as such [121]. Therefore, a novel stochastic NILM technique for estimating the consumption of flexible devices out of the total consumption of the consumer is presented in this chapter. Unlike conventional NILM methods, which aim at identifying the electrical signature of a device within the total consumption of a residence, the proposed method relies on comparing flexible with non-flexible consumers to estimate the flexible consumption. The technique is to a great extent independent of the selected time frame and, as such, it is easily applicable to smart meter data. Due to its very simple comparison philosophy, it can only be applied to "power hungry" flexible devices; nevertheless, these devices are expected to provide most of the flexibility services from a grid perspective.

4.2 Stochastic NILM framework

The flexibility estimation of a consumer's power pattern is performed by comparing the flexible consumer with electrically similar non-flexible consumers. It is apparent that "flexible" characterises consumers with operationally flexible devices such as EVs or HPs[1]. Their flexibility might refer to time shifting or demand scale up/down capabilities. Having a database of customer consumption data over a reasonably long period, and being interested in estimating the flexibility of one consumer the algorithm is basically performed in three steps:

1. **Clustering:**
   Non-flexible consumers are separated in groups. Each group is differentiated from others in terms of electrical behaviour.
2. **Classification:**
   The flexible consumer of interest is assigned to one of these groups, i.e. the one which has the highest electrical similarity to him/her.
3. **Estimation:**
   The flexible consumer is compared in terms of probabilities with his/her similar non-flexible consumers. Any consumption differences are accredited to load intensive flexibility devices.

Lastly, the same methodology can straightforwardly be applied to generation estimation if deemed necessary.

4.3 Consumer Clustering

A rational way to estimate the flexibility of a particular consumer is to compare his/her power pattern with similar non-flexible consumers. Finding this

[1]The locations of these power hungry devices is expected to be known to the DSO.

electrical similarity can be cast as a classification problem. The classification problem comprises two steps, namely clustering a set of data and assigning a new datum to one of the created clusters. Principally, this process will provide a non-flexible consumer reference group for the flexible consumer. This group can afterwards be utilised for comparing flexible with non-flexible power patterns and eventually estimating any underlying flexibility.

To begin the clustering procedure, a group of non-flexible consumers along with their smart meter data should be selected. At this point, it is important to filter this database from erroneous and/or missing data as this might impact the analysis to follow. Next, a time period for the clustering process should be chosen. Like in most of the methods where training data are involved, there is no unique guideline for selecting the extent of this period. Nevertheless, experimental results in J.1 and C.1 have shown that a month is a sufficient training period for clustering. Assuming that a month is chosen for the analysis, a two-step clustering is performed. As can be seen from Fig. 1.a in J.1, these two steps refer to clustering in terms of energy and clustering in terms of power pattern.

4.3.1 Energy Clustering

This clustering step aims at partitioning the data sample into several clusters each one characterised by an average demand over the reference period, i.e. the selected month for analysis. Hence, the average power consumption of each consumer is calculated for this month. Next, a clustering of those values is performed according to the algorithm of Fig. 1.b in J.1. This procedure, which

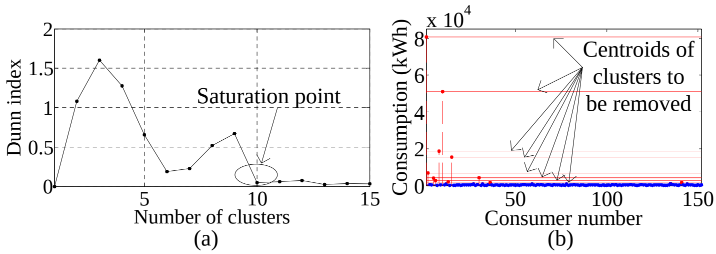

Figure 4.1: Pre-clustering. (a) Dunn index. (b) Clustering.

has thoroughly been discussed in Section 3.5.2 aims at identifying the best data grouping. As explained in that section, a clustering procedure is firstly chosen. For this study hierarchical clustering utilising the complete distance has been selected as it usually results in compact clusters. Then, clustering is iteratively applied for a reasonable cluster range, while cluster adequacy measures are employed to assess the cluster partition at each iteration. In this context, the

Dunn index is employed for evaluating the clusters, whereas the DBI evaluates whether the data are uniformly scattered, i.e. whether they should be grouped in only one cluster.

As can be observed from Fig. 1.a in J.1, energy clustering can itself be performed stepwise. This occurs when great asymmetry is evident in the database, that is to say when industrial and/or large commercial consumers are to be found in the same dataset. These consumers are not of interest for the conducted analysis; therefore, they need to be filtered out. To do so, a pre-clustering step can be employed. As can be seen from Fig. 4.1.a, the clustering partition is assessed utilising the Dunn index. In this scope, the distinction among industrial, (large) commercial, and residential consumers is sought; for this reason, the saturation point of the graph is of interest. This point is reached when all previous cluster categories have already been formulated. As a consequence, assigning more clusters will be penalised by the cluster adequacy measure, thus leading to small values. By adapting the number of clusters as indicated by the saturation point, the industrial and/or commercial consumers can easily be identified and excluded as shown in Fig. 4.1.b.

Following the pre-clustering step, a clustering step among residential and/or small commercial consumers should be performed. The algorithm of Fig. 1.b in J.1 is employed again for the reduced dataset and the highest Dunn index is sought within a reasonable range of possible consumer types [185]. As shown in Fig. 4.2.a Fig. 4.2.b, both the DBI and the Dunn index indicate three to be

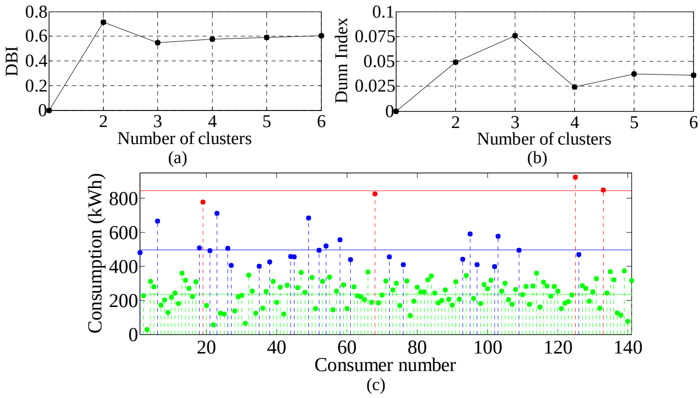

Figure 4.2: Energy clustering. (a) DBI. (b) Dunn indices. (c) Clustering with 3 clusters.

the best number of clusters for the corresponding problem. Moreover, the DBI values are below 0.6 meaning that clustering will indeed make sense. Finally, Fig. 4.2.c depicts the hierarchical clustering result.

4.3.2 Pattern Clustering

The second step of the clustering considers power pattern clustering. To create the power patterns, the consumption data of non-flexible consumers are daily averaged within the reference period. Subsequently, each of these patterns is normalised by its maximum value. This results in obtaining average power patterns rated in per unit. Since per unit values describe the shape but not the power rating of a pattern, pattern clustering is separately conducted within each of the previously formulated energy clusters. This way, both the power rating and the power shape information are respected.

Fig. 4.3.a illustrates the pattern clustering of the green energy cluster of Fig. 4.2. As can be seen, there are five formulated shape clusters. This number is inferred by the algorithm of Fig. 1.b in J.1, albeit in this case the algorithm copes with 24-dimensional data. As can also be observed, hierarchical clustering performs remarkably well in grouping the patterns, whereas irregular shapes, e.g. the black one, are efficiently isolated. This is also the reason for resorting to the Dunn index, rather than the DBI, in this study; it usually shows superior performance when evaluating clusters containing only one datum. Finally, Fig. 4.3.b displays the cluster centers of the resulting power pattern clusters. It is

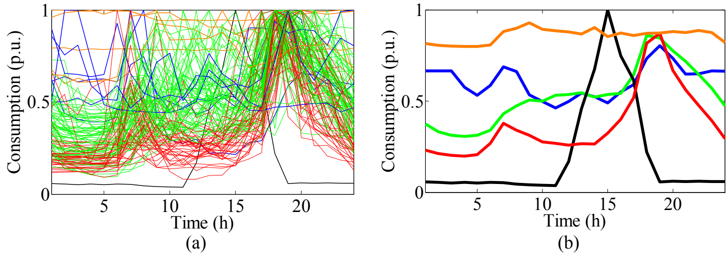

Figure 4.3: Pattern clustering. (a) Clustering. (b) Cluster centers.

apparent from that figure that five is indeed a good number for partitioning the data, since the cluster centers exhibit distinct behaviours.

4.4 Classification

By obtaining all different consumer clusters, i.e. power pattern clusters within energy clusters, the flexible consumer under study may be classified. The classification procedure is very simple as the flexible consumer is classified into the cluster with the shortest Euclidean distance between him/her and the corresponding cluster center. However, classifying the flexible consumer into a non-flexible consumer cluster is only meaningful if he/she does not have any flexible consumption. Thus, the excess demand of the power hungry flexible device(s) should be erased prior to classification. The removal of the flexible device's impact might not be exact, yet it should be realistic for a successful classification. There are various ways to accomplish this each of which might be preferable depending on the working context:

1. **Exploit past observations:**
   Assuming that sufficient historical smart meter data exist, the classification can be easily accomplished prior to the installation of the flexible device. Before installing the flexible device, the currently flexible consumer was still non-flexible. Thus, his/her classification is straightforward for that period. Knowing which consumer is flexible should be readily available by the utility, since the targets of analysis are mostly consumers with major flexible devices like HPs or EVs.

2. **Intrusive load monitoring:**
   One possible solution would be to use intrusive load monitoring in order to explicitly measure the flexible consumption of the consumer; based on this measurement and the aggregated consumption of the premises, the non-flexible consumption can be estimated[2] and, finally, the flexible consumer can be classified. The intrusive load monitoring period can be perceived as a training step, which is a common technique among non-intrusive load monitoring methods.

3. **Utilise expert knowledge:**
   Expertise could be utilized so as to erase, i.e. filter, the flexible device's influence from the total consumption of the flexible consumer as shown in Fig. 1.c of J.1. Among power hungry flexible devices, two types of appliances are distinguished, i.e. weather dependent and behavior dependent loads (or generation). For weather dependent flexible loads/generation, the removal of the flexible consumption can be accomplished in time periods when the flexible load is dominant or absent. For instance, it is easily conceivable that a HP would not operate during very hot summer days or equivalently a cooling system would not consume power during winter. Additionally, a wind generator would steadily produce power during windy days, while a solar system would produce limited power during snowy winter days. For human behavior dependent loads, such as EVs, different kinds of information might be exploited. These might include, for instance, generic statistical distributions of driving habits or specific characteristics of charging patterns.

For the study case presented in J.1, a flexible consumer with a HP was investi-

[2]For grid applications, the flexible consumption of interest derives usually from power hungry devices which are fewer compared to the non-flexible ones. Thus, it would be more efficient to measure the flexible consumption and subtract it from the total consumption, rather than measuring the non-flexible consumption directly.

gated. To filter his/her HP consumption, a cold winter month was examined. In that period, the HP was assumed to operate constantly[3] due to very low temperatures (up to -15 °C). Thus, the HP consumption was approximated by elaborating loading values at time instances of minimum consumption, that is to say instances when approximately only the HP load was present (without the non-flexible consumption). Alternatively, the consumer classification could be performed in a hot summer month, where the HP would barely operate and its effect could, thus, be neglected.

It is important to bear in mind that regardless of the followed procedure, the classification should be perceived as an identification of a non-flexible consumption reference group for the flexible consumer. This representative non-flexible consumption group can then be utilised for estimating the flexible consumption at subsequent time instances. Lastly, it is worth mentioning that if the grouping is believed to be outdated, then the clustering and classification processes shall be redone.

4.5 Estimation

To estimate the flexible consumption of a residence in the presence of power hungry flexible loads, a comparison between the flexible consumer and his/her reference non-flexible group is performed. This procedure is shown in Fig. 4.4,

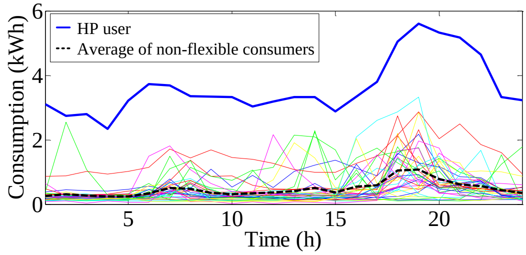

Figure 4.4: HP user versus non-flexible consumers, 6^{th} February, 2012.

in which the HP user's consumption, i.e. blue line, is displayed versus the representative non-flexible users' consumption. Their average consumption is illustrated by the black dashed line. As expected, there is a huge gap between the consumption of the flexible user and the non-flexible users. This also justifies the previous assumption of the HP operating constantly throughout a cold winter period. The gap is most likely caused by the HP operation on the grounds of very low outdoor temperatures.

[3]The constant operation of the HP was perceived on an hourly basis, i.e. average HP consumption at each hour.

To estimate the HP consumption, the aforementioned "gap" should be quantified. One idea would be to straightforwardly subtract the blue from the black line. Nevertheless, by doing this any information regarding the variance of the non-flexible consumption would be lost. A more preferable solution would be to initially evaluate the probability distribution of the non-flexible consumption and subsequently calculate the difference between the flexible consumption and the obtained probability density. In practice, this means identifying the most appropriate Probability Density Function (PDF) for the non-flexible consumption at each of the 24 time points of Fig. 4.4 and comparing the flexible consumer with these PDFs.

To conclude on the non-flexible consumption PDF, parametric and/or non-parametric methods can be exploited. Non-parametric methods, e.g. kernel based methods, are more generic but also more complex; as such, parametric alternatives will be presented in this section. In parametric approaches, PDFs derive from fitting predefined probability distribution functions to sample data. Then, the best fitted PDF is chosen as the representative distribution of the non-flexible consumption. On the downsides of this approach is the fact that there might not be a well fitted function among the chosen ones. However, in the given context the adequacy of parametric approaches can be claimed from the fact that the expected distributions are simple since they refer to already similar, i.e. clustered, consumers. Three goodness of fit approaches are described in the following for selecting the most appropriate distribution:

1. **Empirical Cumulative Distribution Function:**
   The Empirical Cumulative Distribution Function (ECDF) describes the probability that a real-valued random variable X with a given probability distribution will be found to have a value less than or equal to x [191]. This function is associated with the empirical measure of the sample. An example of an ECDF is given in Fig. 4.5. This figure displays the ECDF of the non-flexible consumption as calculated by the sample data

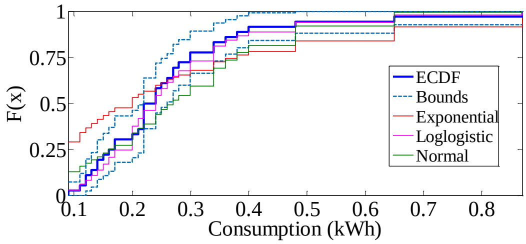

Figure 4.5: ECDF versus fitted distributions.

of Fig. 4.4 at time point 1:00. In the same figure, the 90% confidence bounds of the ECDF are also drawn, along with three fitted cumulative distribution functions based on the "Exponential", the "Loglogistic", and the "Normal" distribution. Good fits are considered those which are within the bounds. As such, the most representative distribution for this ECDf is the "Loglogistic" followed by the "Normal" distribution. Finally, it is apparent that the "Exponential" distribution is a bad fit for the sample data.

2. **Quantile-Quantile plot:**
A Quantile-Quantile (QQ) plot simply plots the sample data values against an empirical assessment of the fraction of observations exceeded by those data values [191]. Practically, this is another representation of the ECDF. Fig. 4.6 presents an example of QQ plots for the same case and distributions as the ones shown in Fig. 4.5. A good fit can be evaluated by

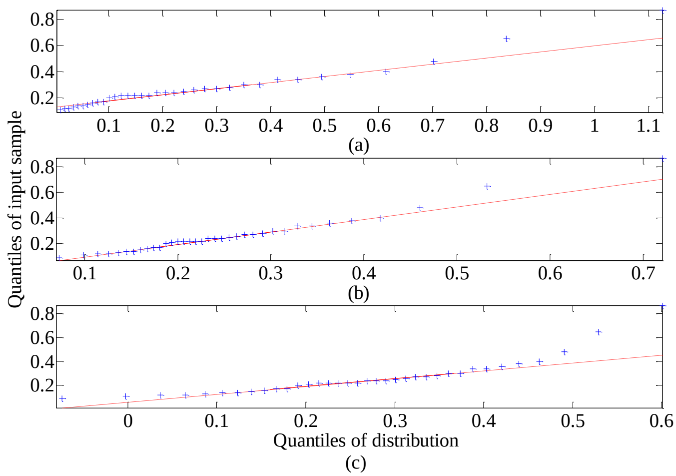

Figure 4.6: QQ plot of preselected fitted distributions. (a) Exponential distribution. (b) Loglogisitc distribution. (c) Normal distribution.

the proximity and alignment of the data values, i.e. blue crosses, to the distribution, i.e. red line. As can be seen the "Loglogistic" distribution provides again the best fit, while the "Exponential" and the "Normal" distributions display worse alignments of the data points to their respective fitted distribution, i.e. red line.

3. **Chi-Squared test:**
The chi-squared test is a goodness of fit test based on hypothesis testing. It principally compares observed, i.e. sample data, with expected, i.e. fitted distribution, frequencies to infer whether their mismatch is likely to belong to a normal distribution at a specific significance level [192]. If it doesn't, then the fitted PDF is considered a bad fit and is disregarded. Although, the chi-squared test does only indicate whether a fitted PDF is a bad fit, this limitation can be circumvented by gradually tightening

the significance level in order to identify the least rejected PDF. This will then become the representative PDF for the non-flexible consumption.

Among the three goodness of fit evaluation methods, the QQ plot is the only one requiring human intervention to evaluate a fit; a feature to be avoided when aiming at automated procedures, as the ones necessitated by a TVPP.

For the case of Fig. 4.4, fitting 24 PDFs, one for each time point, would result in the PDF graph of Fig. 4.7.a and Fig. 4.7.b. These PDFs can be quantified by assuming an Area of Probability (AP) [193]. Different APs of the PDFs are depicted in Fig. 4.7.c in which the flexible consumption is also illustrated. To

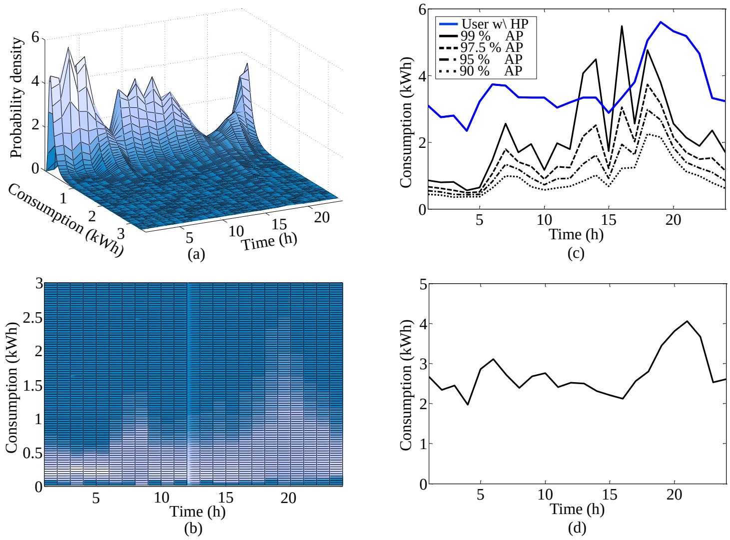

Figure 4.7: February 6^{th}, 2012. (a) Fitted PDFs. (b) Top-view of fitted PDFs. (c) APs compared to the flexible user. (d) Flexible consumption for 90% AP.

estimate the HP consumption, an AP value should first be selected, i.e. 90%, and then the flexible consumption is subtracted from this AP. This way, the estimation of the HP consumption can be obtained as shown in Fig. 4.7.d. It is observable, that due to the high variance of the non-flexible consumption, the estimation of the flexible one is only valid for power hungry loads.

As can be easily perceived, the selection of the AP is crucial for the estimation of the flexible consumption. To interpret these APs, it is important to recall that the non-flexible consumption is represented by the fitted PDFs. Thus, any non-flexible consumption will lie within the selected APs with certain probability, e.g. 90%. Any excess consumption will be non-flexible due to the remaining probability, i.e. 10%, or will equivalently belong to the flexible device with 90% probability. Thus, lower APs will lead to higher flexible consumption estimation, yet with higher uncertainty and vice versa. Lastly, it should be mentioned that if the flexible consumption pattern lies within the AP, it does not necessarily mean that the there is no flexible device operation, rather than it is unclear to infer whether the consumption derives from the flexible or other non-flexible devices such as an oven. This incidence is more likely to occur at time points when the typical non-flexible consumption is quite high.

Ultimately, the relevant entity performing the estimation will have to choose the desired AP. In case of an Aggregator, this will probably be in the context of selling flexibility on the market. Since failure to deliver flexibility will incur penalties, the BRP should make an economic analysis for offering the most flexibility with the lowest uncertainty and the highest financial benefit. This trade-off will be further elaborated in Chapter 7, where the flexibility market framework will be discussed. On the other hand, a DSO would be more interested in the operational aspect of flexibility. Thus, his estimations might be more conservative as reliability is the prime scope for this entity. Generally, experimental results presented in J.1 show that APs of 80% or 90% produce reasonable results which can be used for both operational and financial purposes.

4.6 Flexibility Considerations & Discussion

One issue which should be clarified about the proposed method is that estimating the flexible consumption does not equate to estimating the flexibility of the power pattern. The latter is strongly dependent on the technical limitations of the device as well as the operational preference limits of the user. In case the nature of the flexible device is known, some approximations of the underlying flexibility can be made. For instance, if the flexible consumption is associated with a residential HP then the thermodynamic equations of the house can be used to compute the HP's flexibility potential as exaplained in J.1.

One other issue is the correlation between flexibility potential and seasonality. In Fig. 4.8, the estimation of flexible consumption for a winter, summer, and spring day are shown. Assuming that the TVPP's target would be to reduce the loading of the grid[4] the flexibility potential for these three days is presented as well. It is apparent that during a cold winter day, the HP operates at all hours; thus, flexibility can only stem from scaling down the load as indicated by the blue arrows in Fig. 4.8.a. This can be achieved by lowering the thermostat's indoor temperature setting. On the other hand, during a warm summer day, i.e. Fig. 4.8.b, the HP barely operates. When it does, it is during night time when the non-flexible consumption is also low; hence the value of flexibility during

[4]In networks which are not dominated by dispersed generation, reducing the load is usually the prime target for utilities in grid limit violation cases.

that period is reduced. However, in case of problematic situations due to other

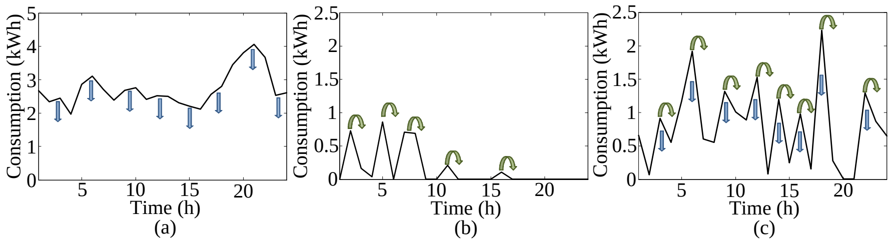

Figure 4.8: Estimated flexible consumption. (a) February 6^{th}, 2012. (b) July 11^{th}, 2012. (c) April 20^{th}, 2012.

types of loading, e.g. charging of EVs during night, some flexibility capabilities via load shifting are present as illustrated by the green arrows. Lastly, Fig. 4.8.c illustrates a spring day. It is apparent that the weather conditions produce a very volatile HP consumption pattern offering both ramping down and load shifting potential. Hence, the value of flexibility at this day is the highest.

The proposed NILM technique has so far been demonstrated for estimating flexible consumption. However, due to its generic nature, it can equally be used for generation estimation. One such case is described in Fig. 4.9, which reflects the consumption pattern of a flexible consumer with both a HP and a PV installed at the residence. As observed, the double sided[5] APs have been

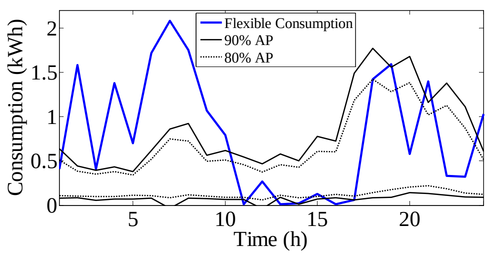

Figure 4.9: Estimation of flexible load and generation.

formulated both for 80% and 90%. It is detected that the consumption of the flexible user goes below the limit set by the APs at around midday. This occurs on the grounds of the PV generation. Although the obtained values reflect only consumption, i.e. reverse flow was not able to be recorded, it is clear that the algorithm is capable of tracking load shifts from consumption to generation. Nevertheless, even if generation values were available, and, thus, subjected to estimation, it should be borne in mind that generation has usually reduced controllability. Moreover, the estimated pattern would be a mix of HP

[5]For more details on how to create these APs refer to J.1.

consumption and PV generation each having its own unknown portion. A remedy to this situation would derive from acquiring an enhanced database with more consumer types. Then, consumers having a PV and a HP would, for example, be compared with consumers only having a HP in order to estimate the PV generation. This setup of different flexible consumer types is realistic for future smart grids.

The aforementioned framework of different consumer types, both flexible and non-flexible, necessitates a fairly big set of recorded consumers. An increased size will not only guarantee a rich mix of distinct consumer types, but will also produce stronger statistical results in relation to the goodness of fit methods of Section 4.5. Nonetheless, the size of the examined area should not be broadened significantly, as demographic, social, financial, environmental and/or other demand affecting factors, which have not been considered in this study, might influence the results.

A final comment considers the time resolution of analysis. Principally, the proposed framework can straightforwardly be applied to SGs, recording data at any resolution in the range of several minutes to hours. For these cases, the method can be claimed to be independent of the smart meter sampling frequency. However, in cases of recording at very high temporal resolution, e.g. seconds to few minutes, the clustering and estimation processes might be affected by the high volatility of the recorded data. However, this scenario is contradicting to the assumption of communication and/or data storage issues which are expected when analysing at these time frames; therefore, it was not examined.

4.7 Conclusions

In this chapter, a novel NILM technique for estimating the flexible demand out of the aggregated demand of a consumer was presented. This technique differs in philosophy with conventional NILM techniques making it compatible with SGs. Applying this technique will substantially reduce the data communication and storage requirements, while providing an efficient estimation alternative in case of false, absent or spurious recordings for grids without data problems. Moreover, as will be discussed in Chapter 6 and Chapter 7, a TVPP can exploit this technique to manage potential grid congestions when having limited information regarding the underlying flexibility in the grid due to market rules.

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Chapter 5

Load Monitoring in Low Voltage Distribution Systems

In this chapter, load monitoring of low voltage distribution systems is investigated. Some problematic issues are identified and a solution based on hierarchical load monitoring is proposed. A detailed explanation of the experiments conducted can be found in C.3, C.4, and C.5 in the APPENDIX.

5.1 Introduction

The gradual electrification of the heating and transportation sector as well as the installation of intermittent dispersed generation is expected to challenge the distribution grid capacity in the upcoming years. To prevent this problematic situation, promote green energy, and further deregulate contemporary electricity markets by introducing a business case for flexibility, the European Union has striven to promote the SG concept, especially smart metering, either by directives or legislation [194], [195]. However, this attempt has not been fruitful so far [39]. The reason for this is that, although SG infrastructure will enhance the network capacity utilisation, there is usually no such need in the short term. The actual penetration of flexible loads and intermittent generation is in most cases not, yet, as high as expected. Thus, considering that most of the developed countries, which are the actual candidates for integrating SG technologies into their networks, have excess grid capacity, the aforeclaimed complications are to be encountered only sporadically in the short run. For these scarce cases, seasonal reconfiguration of power lines and/or tap changing of the secondary distribution transformer would normally suffice to solve the problem. Moreover, taking into account the steadily dropping prices of smart meters and the unprecedented planning entailed with SGs, there is little incentive for utilities to currently invest in smart meters. Furthermore, even for utilities which have installed smart meters to avoid problematic situations in the long run, communication problems impair the functionality of their TVPP. For instance, the utility considered in C.4 and C.5 obtained hourly loading values from each consumer; however, these data were gathered only once per day, leaving little room for online[1] power control. This occurs on the grounds that the amount of data to be recorded by the DSO is substantially more than the ones to be recorded by other BRPs, e.g. HP Aggregators.

To cope with this situation, utilities might have to install some (extra) power meters at strategic locations so as to monitor the loading of their grid online. The number of these meters should be small in order to avoid the previously mentioned communication problems and reduce costs [127]. Naturally, by relying on just a few power meters, the loading distribution of the grid will only be approximate; nevertheless, even this approximation is very important for both planning and operational purposes. Particularly, conventional utilities will benefit by gathering loading data which will aid them in accurate future SG and/or capacity planning. On the other hand, "smart" utilities will be able to monitor their grid online and employ the grid congestion management functionality of the TVPP. This module will then estimate the required flexibility to solve any upcoming grid limit violations as will be shown in Chapter 6.

As explained in Section 2.3, many manuscripts concentrate on the aspect of finding the optimal locations for distribution system monitors. However, most of these approaches are either generic guidelines or approaches not focusing on the load distribution observability [129], [113]. To this end, a new systematic approach for the optimal allocation of power meters in distribution networks is presented in this chapter. This approach aims at enhancing the load distribution observability of low voltage radial distribution networks and is in compliance with literature suggesting a hierarchical framework when performing load monitoring [132].

5.2 Hierarchical Monitoring Structure

Most of the low voltage distribution systems do only possess an online power meter at the secondary distribution transformer point, i.e. the traditional supply point. Based on this measurement and typical consumer load profiles, which are obtained by periodic manual measurements and/or surveys, utilities estimate the load distribution in their grid [135]. Although this approach might

[1] Assuming an hourly temporal resolution for smart meter sampling, online refers to hourly, i.e. average demand within an hour, management of the load.

be to some extent reasonable for planning purposes, it is inadequate for operation. The major problem with it is that generic load profiles do not encompass the daily variation of consumer demand; thus, any information regarding this variation derives from the transformer measurement. Nonetheless, this measurement is at a very aggregated level and provides little insight concerning the load distribution in the grid.

Conceptually, the transformer measurement defines a very extensive load monitoring area, i.e. the whole low voltage network. To circumvent this problematic situation the grid can be split to more monitoring sub-areas [132]. By introducing more online power meters and, hence, more load monitoring sub-areas, the load distribution observability can be enhanced. Moreover, considering that most European low voltage distribution networks are either radial or radially operated, the definition of load monitoring areas can be performed in a hierarchical way. This principal is schematically presented in Fig. 5.1. In particular,

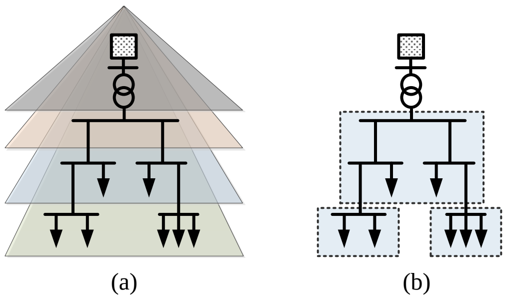

Figure 5.1: Schematic disaggregation. (a) Various disaggregation levels. (b) Monitoring areas at a disaggregation level.

Fig. 5.1.a depicts a sample radial network along with various disaggregations in a top-down hierarchical approach. These disaggregations are illustrated by colored triangles. The first triangle, i.e. the gray one, refers to the case of solely having the transformer measurement. Load variation referring to the grid part below that triangle is estimated by the transformer measurement thus defining one load monitoring area. Equivalently, the lower triangle, i.e. the red one, defines two load monitoring areas, one for the left and one for the right lateral of the grid. Then, the blue triangle refers to even further disaggregation, that is to say three monitoring areas; one formulated by the transformer meter and two by monitoring the two grid sections below the triangle as depicted in Fig. 5.1.b. This figure clearly shows the hierarchical nature of the disaggregation procedure. Finally the green triangle refers to full disaggregation, namely installing a power meter at every single consumer. This last level equates to smart metering.

5.3 Critical Consumers

According to literature studies, monitoring load intensive, also known as "critical", consumers explicitly is a mandatory step towards an efficient load distribution monitoring framework [129], [131]-[134]. Their monitoring is important since they account for a large portion of the grid's total loading. Thus, any abrupt changes in their loading patterns might result to voltage or current issues in the rest of the network. To identify critical consumers, historical consumption values are utilised so as to locate them. The procedure is the same as the pre-clustering step presented in Section 4.3.1. Additionally, it is explained in C.4 and C.5.

5.4 Optimal Allocation of Power Meters

The optimal allocation of power meters can be cast as an optimisation procedure. As shown in C.3, C.4, and C.5, this procedure considers the grid structure and the desired disaggregation level to determine the meter allocation and, hence, formulate the optimal load monitoring areas. An index which refers to the loading of the grid is generated as an objective to be minimised in C.4. Equivalently, in C.3 and C.5, this index is modified according to the forecasting performance of the load. It is concluded that load aggregation and forecasting performance are closely related and, thus, the forecast error can be used as a loading index. Moreover, as shown in the same manuscript, by exploiting this index, the hierarchical disaggregation becomes meaningful for predictive estimation as well. Lastly, it is noteworthy that the optimisation process consists of a set of linear equations including binary variables. This formulation leads to binary integer linear programming which provides a global optimum whenever solvable.

5.4.1 Grid Structure

The grid equations are based on the radial structure of most low voltage distribution networks. As explained in the APPENDIX, two sets of variables are used, namely n and b. The variable b_i determines if a power meter should be placed at the i_{th} element. An element is a grid component where a metering device can be placed (e.g. line, load[2], transformer etc.) excluding nodes. On the other hand, n_i dictates if the relevant element is visible. Neglecting losses, an element is visible when its power can be calculated after the power meter

[2]For describing the node connections, loads are assumed to be grounded and, therefore, connected to the root node of the radial distribution grid [139].

allocation has been performed. For example, in Fig. 5.2, line "2" would be visible if power meters were allocated to "2" or to "4" and "5".

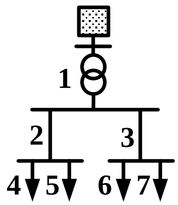

Figure 5.2: Low voltage distribution grid topology example.

The logic behind the formulation of the grid constraints is graphically displayed in Fig. 5.3. In this figure, visible elements are colored orange, whereas power meters are indicated by the relevant blue circle. Fig. 5.3.a depicts that whenever an element leaving a node is visible, all other elements leaving that node are visible as well. Moreover, an element cannot be visible if elements above it

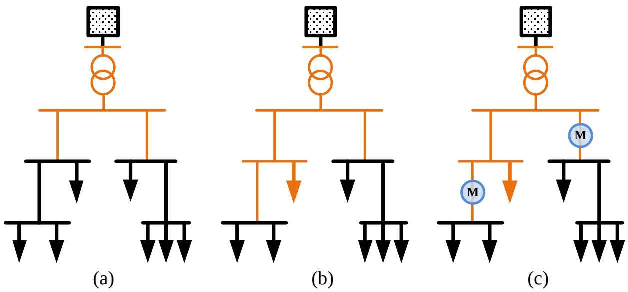

Figure 5.3: Graphical description of grid constraints. (a) Constraints concerning visible elements. (b) Further constraints concerning visible elements. (c) Constraints concerning meter allocation on visible elements.

are not (up to the transformer monitoring point, i.e. the root node) as illustrated in Fig. 5.3.b. Lastly, Fig. 5.3.c shows that power meters should only be assigned to visible branches and should be set as far from the root node as possible. Moreover, only one power meter is permitted for each path established between a visible branch and the root node. Having described all necessary network related constraints, it is important to clarify that these equations can automatically be obtained by means of the grid's incidence matrix [139].

As can be seen, Fig. 5.3.c encompasses all grid related optimisation constraints in a simple example. However, even from this simple meter allocation example, it is clear how the grid is split into several monitoring areas. Particualrly, one area is formulated under the monitoring device on the left and another one under the monitoring device on the right. Finally, a monitoring area between the transformer, which holds a power meter by default, and the two previously defined areas is also established. This partition of the network into several monitoring areas is hierarchical and resembles the one shown in Fig. 5.1.b. To complete the optimisation procedure, a criterion for setting the number of power meters in the grid should also be given. This criterion, which is closely related to the desired disaggregation level, will be explained in the next section.

5.4.2 Disaggregation Level

The disaggregation principle has intuitively been presented in Fig. 5.1.a. As explained, the goal of the disaggregation would be to split the network into several monitoring areas, which would enhance the load distribution observability of the grid. To incorporate this feature into an index, the previously defined visibility term shall be utilised. In particular, the more the visible elements, the more the disaggregation. This can also be observed in Fig. 5.3.c, where it is obvious that the more the orange colored lines, i.e. the visible elements, the better the load distribution understanding. In a similar manner, the number of allocated power meters can be exploited instead of the number of visible elements. The former approach for defining the disaggregation level is adopted in C.3, while the latter in C.4 and C.5.

Assigning maximum disaggregation will lead to monitoring each and every end-consumer separately, which is equivalent to smart metering. Since, the goal is not monitoring at such a detailed level, a desired disaggregation level should be selected. Naturally, this disaggregation level is selected by the system operator, since this entity has both the expertise and the insight regarding the financial restrictions associated with the available number of power meters to be installed. Given a certain disaggregation level (or limit) and a certain grid topology, many different power meter allocation solutions can be achieved. Thus, the optimisation mandates an objective function which will dictate the optimal allocation of these meters. This objective may be driven by loading indices as presented in C.4. Similarly, the forecasting performance can equivalently be exploited as a way to describe the load distribution. It is widely known that the more the aggregation, the less the forecasting error; thus, this property can replace the aforementioned loading indices as explained in C.3 and C.5. Lastly, it is noteworthy that if the prediction performance is decided to substitute the loading indices, then this property should be measured at each element of the grid. Considering that low voltage distribution grids frequently have very extensive topologies, an immense amount of forecasts should be performed. In such applications, the methodology presented in Chapter 3 can take place and automatically conduct the necessary predictions at various disaggregation levels.

5.5 Power Meter Allocation & State Estimation

The outcome of running the presented optimization framework is the indication of strategic positions, i.e. elements, which should be equipped with power meters. A useful feature, which has been embedded in C.4 and C.5, is permitting power meter allocation only to lines and not to loads, since the latter have already been considered for meter allocation at the critical load detection step. Additionally, tactics similar to smart metering should be avoided as commented before. Fig. 5.4 depicts the outcome of the optimization in C.4.

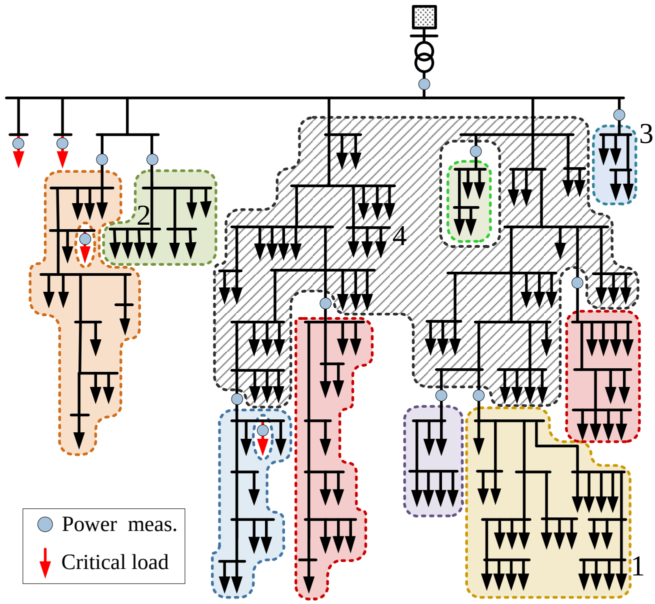

Figure 5.4: Formulation of load monitoring areas.

In this figure, the power meter allocation result is shown along with the corresponding load monitoring areas. It is apparent, that the optimisation ends up in splitting the grid into 9 colored areas. The rest of the loading is monitored by the transformer meter, i.e. hatched area, whereas critical loads are metered explictly formualting their own individual "areas".

Having defined the optimal meter allocation, SE can be employed so as to estimate the load distribution in every grid area [52]. To conduct the SE a redundancy of measurements is required. Thus, apart from the online measurement, load profiles for each consumer should be utilised [135]. These load profiles might originate from utility surveys or past smart meter data. Fig. 5.5 illustrates the consequence of performing SE in hierarchical monitoring areas.

The relevant graphs refer to the enumerated nodes in Fig. 5.4. Specifically, some good results are recorded in Fig. 5.5.a to Fig. 5.5.c, which also display the efficacy of the approach; however, bad estimations do also occur as shown in Fig. 5.5.d. The reason for that is that the consumer load supplied at the

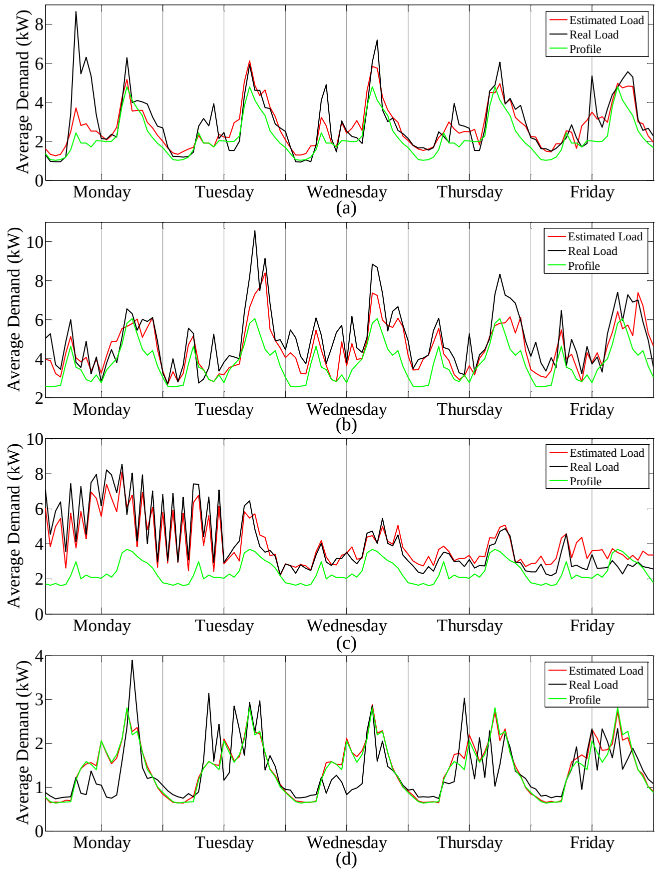

Figure 5.5: Estimation of consumer load supplied at different nodes. (a) Results at node 1. (b) Results at node 2. (c) Results at node 3. (d) Results at node 4.

relevant node belongs to the transformer area which is fairly wide; as such, the online transformer information is shared among too many load profiles and is eventually rendered impactless. Other factors affecting the estimation are the proximity of the load profile to the actual consumption as well as the uncertainty of the pseudomeasurements, i.e. the load profiles. In C.4 and C.5, this attribute has been associated with the average loading of the consumer, that is to say the more the loading of a consumer, the higher the probability that an online recorded loading change would be caused by that consumer.

5.6 Discussion

The problem of ending up with a wide monitoring area has been identified in the previous section. To circumvent this problem, the hierarchical monitoring approach can sequentially be applied to split these wide areas as discussed in C.5. For instance by splitting the "transformer" area of Fig. 5.4, two new monitoring areas are defined which are depicted in Fig. 5.6. It is noteworthy to mention at this point that due to the approximate nature of the load monitoring in this context, and taking into account that the transformer is equipped with a power meter by default, one of the newly introduced measurements (or equivalently the transformer measurement) can be perceived as a virtual measurement without significant loss of estimation accuracy.

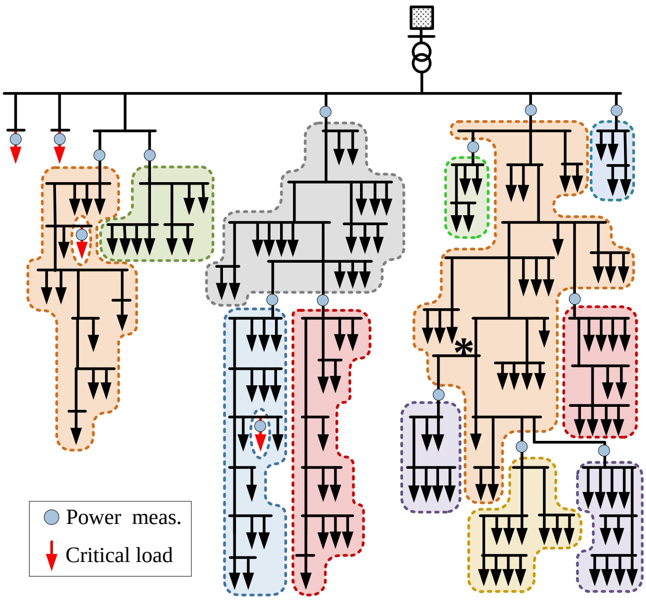

Figure 5.6: Formulation of load monitoring areas with disaggregated transformer area.

Experimental studies in C.5 have proven that installing more measurements with the suggested hierarchical approach will systematically improve the load distribution estimation at both aggregated and disaggregated levels. The former has been demonstrated in Fig. 5.5, whereas the latter can be observed in Fig. 5.7, which displays the load estimation performance at the annotated node, i.e. load entering node, in Fig. 5.6. This estimation result further manifests the fact that employing the proposed framework will dramatically enhance the online load distribution observability.

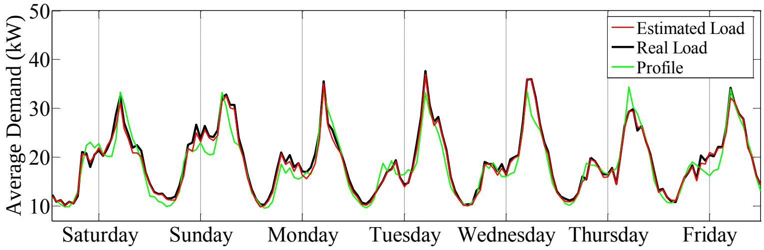

Figure 5.7: Estimation of line loading at an aggregated level.

For load monitoring purposes, the monitoring scheme and the estimation procedure presented so far can effectively be used. According to this scheme, the more the power meters a utility is willing to install, the better, assuming no communication or other data problems. Moreover, measurement redundancy will augment the grid's monitoring reliability and resistance against malicious attacks [110]. Nevertheless, these benefits are mitigated when moving from reactive to predictive aspects. Hence, in case the power meters are allocated so as to predict the load distribution in the grid, the uncertainty of the relevant forecasts at different disaggregation levels should be considered[3]. Therefore, allocating more measurements might in fact have a negative impact for prediction purposes as investigated in C.5. Ultimately, DSOs should decide on the number of power meters they are willing to install depending on both financial and functional criteria.

Lastly, according to experimental results in C.3, C.4, and C.5 it should be reported that the proposed optimisation framework has demonstrated some issues when disaggregating very complex radial structures, i.e. nodes with many leaving elements. The reason for this is that, based on the grid topology constraints, if an element leaving a node becomes visible then all other elements leaving the same node should also become visible. Essentially, this means that in order to disaggregate nodes with many leaving branches, a large number of power meters should be available. To circumvent this restriction, individual loads at each node were aggregated; consequently, the number of leaving elements at each node was drastically reduced. Although, this might seem as a severe limitation at first glance, it is practically not crucial, since individual load monitoring is presumed to be undesirable, whereas critical load monitoring has already been accounted for. Besides, the incentive of a DSO for system monitoring would be to identify grid limit violations in order to reactively/proactively relieve them. These violations are more likely to be encountered at nodes, i.e. voltage problems, or elements feeding numerous consumers, i.e. main lines or

[3] The behaviour of loading versus aggregation has already been discussed in Chapter 3. In this context, the forecast error is incorporated both at the constraints of the optimisation as well as the SE procedure in C.5.

transformers. Thus, individual non-critical consumer overloading is the only undetectable incident with the suggested simplification. Nonetheless, this overloading is eitherway passively handled by the consumer's fuse; it is, therefore, not to be considered when applying grid congestion management.

5.7 Conclusions

In this chapter, a hierarchical grid load monitoring scheme was presented. This scheme was principally devised to aid utilities in alleviating their data problems. Thus, it can be utilised by DSOs without any smart metering in their grids or, alternatively, by smart utilities aiming at online load monitoring. The former can be perceived as a first step towards a smarter grid, while the latter is intended to enhance the situational awareness of a TVPP. Based on the estimated grid condition, the TVPP might further compute the required flexibility for corrective or preventive actions as will be discussed in Chapter 6. Finally, the calculated flexibility will be purchased via a flexibility market as will be shown in Chapter 7.

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Chapter 6

Congestion Management in Low Voltage Distribution Grids

In this chapter, the main functionality of a TVPP is investigated, namely relieving grid limit violations via flexibility activation. Special focus is given on the fair activation of flexibility. Details regarding the study case presented can be found in J.2 in the APPENDIX.

6.1 Introduction

The main task of the DSO is to provide the means of reliable electricity supply to electricity end-users. This involves ensuring sufficient capacity for hosting all consumers within the DSO's territory, while catering for acceptable power quality. This reliable operation of low voltage distribution grids might be compromised due to upcoming penetration of power hungry active loads and intermittent distributed generation. A potential solution to this problem is to invest in SG infrastructure. Thus, DSOs will monitor and forecast their grid loading as demonstrated in Chapter 5 and Chapter 3, respectively. Then, if any grid limit violations are detected, the DSO will request flexibility services.

In case the aforementioned flexibility request is realised via an auction based flexibility market, a necessary condition is to quantify this service into a flexibility demand bid[1]. This means that both the amount and the location of

[1] In a regulated market, utilities will manage flexibility via long term flexibility contracts, that is to say without any bidding process. The same might hold true even for deregulated markets, since flexibility can be bargained in various setups which might or might not include bidding, e.g. bilateral contracts, supermarkets, auction based markets etc.

flexibility should accurately be specified. Various control algorithms in the literature result in this outcome. Some of them rely on centralised approaches [157], while others on decentralised ones [105]. In this chapter, both centralised and decentralised methodologies are combined and their relevance to energy markets is highlighted. Moreover, the "fair" activation of flexibility is embedded to the proposed algorithm. This parameter can provide long term benefits to monopolistic utilities, whereas its applicability in formulating flexibility bids in deregulated market environments is also exhibited.

6.2 Flexibility Market Considerations

Prior to discussing how to calculate the required flexibility for relieving grid stress, the form of flexibility transactions should be regarded. These transactions will basically include two participants, namely BRPs, i.e. Aggregators, and the DSO, the latter buying flexibility services from the former. As will be explained in Chapter 7, due to market performance prerequisites and the high uncertainty associated with local flexibility, the flexibility bargain between these two entities will primarily take place via a double sided auction market and subsequently via bilateral flexibility contracts.

One of the flexibility transaction characteristics is the temporal resolution of their occurrence. For reactive control, the principals of contemporary regulation markets can be adopted; thus, flexibility costs are settled after flexibility has been activated according to either auction based markets or long term flexibility contracts. On the other hand, proactive control is more compatible with auction based markets similar to modern energy markets. Specifically, according to Section 2.5, due to the characteristics of active loads and dispersed generation, i.e. power volatility and moderately stringent ramping requirements, balancing markets are more practical to realise [172]. To this end, hour-ahead flexibility requests will be targeted for proactive control in this chapter.

6.3 Centralised Control

In future deregulated environments, utilities will be able to request flexibility services from local flexibility markets. Hence, they will be able to obtain demand flexibility in advance so as to prevent expected grid stress. Nonetheless, DSOs need to quantify their own flexibility bids in order to participate in these future flexibility markets. A necessary condition to formulate these bids is to forecast the load distribution of their grid and identify any related problems. Hence, based on automated load predictions (see Chapter 3), the TVPP will run the expected power flow in order to identify grid limit violations. These violations mostly refer to voltage and/or current limit violations. However, other electrical quantities such as the power factor or the voltage unbalance may also be considered. Once detected, relevant demand changes, which would relieve the grid congestion, should first be emulated and then converted into flexibility market bids. Centralised control algorithms are most appropriate for this kind of emulations.

Unlike transmission networks, the location of flexibility matters significantly for low voltage distribution networks. As such, before estimating the required flexibility provision, a TVPP should be able to approximate the available flexibility within its territory. Considering a deregulated market scenario, information regarding consumer flexibility might only be available to Aggregators since they are principally the sellers of this commodity. To this end, DSOs should employ estimation techniques, like the one presented in Chapter 4, to approximate the bulk of flexibility in their network. This will aid them in computing realistic bids, i.e. bids for flexibility which will actually exist in the market.

Regarding the centralised control, the TVPP may utilise the power flow sensitivities of the expected power flow in order to relate voltage magnitude changes to active and reactive power changes, that is to say flexibility. These power changes will be restricted by the estimated flexibility potential and by the aforementioned electrical quantity limits as shown in J.2. Since the DSO will pay for the flexibility service, the objective in this context would be to minimise the flexibility required to solve the congestion. Due to its linearity, costs or other properties can easily be embedded in this objective function. For instance, in case different flexibility sources are associated with different expected prices, e.g. flexibility at the end of the feeder might be more expensive, the DSO will have to incorporate this information into the proposed model.

The presented optimisation scheme is simple, fast, and straightforward to implement. Nonetheless, it suffers from the drawback of relying on power flow sensitivities, which are known to be linear approximations at the grid's operation point. This means that the obtained solution will also be an approximation of the optimal solution. Nevertheless, this problem can easily be circumvented by applying the optimisation iteratively. Hence, at each iteration, a new operating condition is found which provides a better linear approximation than the preceding one. Experimental results have shown that two to three iterations suffice even for heavily loaded grids.

The aforedescribed framework was realised in J.2. In that manuscript, hour-ahead flexibility was targeted in accordance with contemporary balancing markets. As will be discussed in Chapter 7, these markets are expected to be particularly compatible with the attributes of flexibility. Since most grids are expected to encounter undervoltage and overloading incidents in the future, hour-ahead load reduction and/or load shedding was simulated so as to resolve grid problems. To demonstrate its efficacy, a five day simulation was performed, whereby the algorithm attempted to relieve the grid stress of an overloaded grid. Fig. 6.1 displays the outcome of the proposed methodology. Particularly, Fig. 6.1.a displays the minimum voltage, whereas Fig. 6.1.b the maximum overcurrent recorded in the grid shown in J.2 before and after control. Accordingly, Fig. 6.1.c shows the injected active power[2] at the transformer point of connection before and after control, while Fig. 6.1.d depicts the available versus the activated power flexibility.

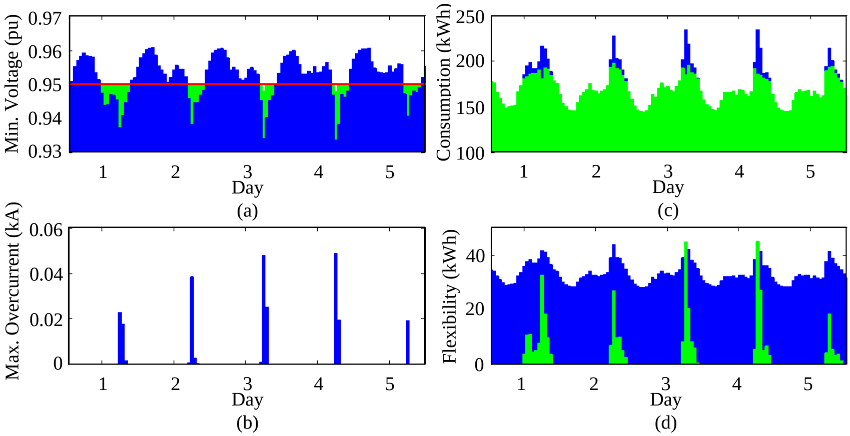

Figure 6.1: Centralised control. (a) Minimum voltage recorded before (blue) and after (green) control. (b) Maximum overloading recorded before (blue) and after (green) control (c) Transformer load before (blue) and after (green) control (d) Activated (green) versus total available (blue) flexibility.

It is apparent, that the control framework succeeds in computing the necessary flexibility, both in magnitude and location, which will restore the voltage at the voltage limit, i.e. red horizontal line, whenever a violation occurs. The same holds true for upcoming overcurrents, which diminish after running the optimisation. Fig. 6.1.c indicates that, as expected, the proposed solution results in peak shaving, whereas Fig. 6.1.d shows that flexibility is actually employed only for a few hours per day and most frequently not at its full capacity. This last point highlights the significance of active networks in managing grid congestions; since grid limit violations are only expected at a few times per day, improving the grid capacity utilisation poses as a more efficient solution than passive approaches like grid reinforcement. Nevertheless, there might be occasions where the available flexibility will not suffice to resolve grid problems. These occasions are apparent in Fig. 6.1.a where the voltage limit violation in two occasions is mitigated, but not resolved, although all available flexibility has been activated. In order to cope with this situation, the utility should

[2]Considering hourly power recording, the average active power within an hour is equal to the energy supplied within this hour.

either reinforce the grid or incentivise consumers to offer more flexibility.

6.4 Decentralised Control

In the previous section, the applicability of a centralised controller to compute the required flexibility services from a market was demonstrated. Nevertheless, in reality, this applicability is to some extent limited by the uncertainty entailed in load forecasts as well as intra-hour loading variations. Thus, similar to modern market structures, a local regulation market should be established in order to manage grid problems reactively. To facilitate such a market, a decentralised controller has been designed, which will calculate the required flexibility of each consumer during grid operation.

Given the flexibility reserved in the balancing market, i.e. by the centralised control, and the consumer flexibility limits, the decentralised controller computes any remaining available flexibility. Then, the same module calculates the flexibility service of individual consumers based on voltage droops; a concept inspired by the frequency control of conventional power plants. Fig. 6.2 introduces the voltage droop functionality scheme. As can be seen, provided the

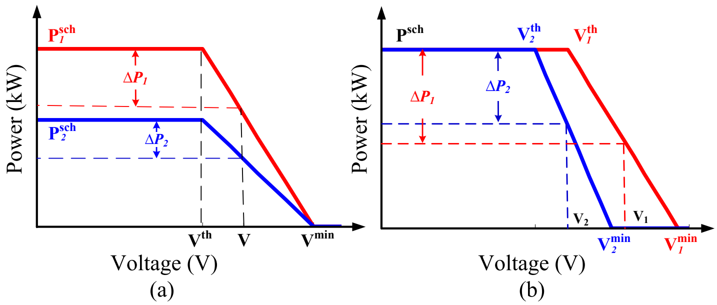

Figure 6.2: Droop characteristics. (a) Different flexibility. (b) Different V^{min}, V^{th}.

available flexibility after scheduling, P^{sch}, the droop is calculated according to two voltage settings, i.e. V^{th} and V^{min}. The former defines the starting operation point of the droop control, while the latter indicates the voltage value which results in activating all of the remaining flexibility. It is apparent from Fig. 6.2.a, that same voltage settings with different P^{sch} set points will result in flexibility activation proportional to the remaining flexibility. Similarly, same P^{sch} with different voltage settings lead to flexibility activation relative to the voltage set points as illustrated in Fig. 6.2.b. The computation of V^{th} and V^{min} is thoroughly described in J.2.

Fig. 6.3 displays the performance of the algorithm for the farthest end node of the study case presented in J.2. For this node, the remaining flexibility from the centralised controller is passed to the decentralised control. Additionally, some noise is added to the flexibility pattern in order to account for the load volatility. As for the control mechanism, in Fig. 6.3.b, the voltage settings are indicated by the two red horizontal lines. Hence, whenever the voltage falls within these boundaries, the voltage droop control is activated as shown in Fig. 6.3.a. It is apparent that in most of the cases, the controller succeeds in

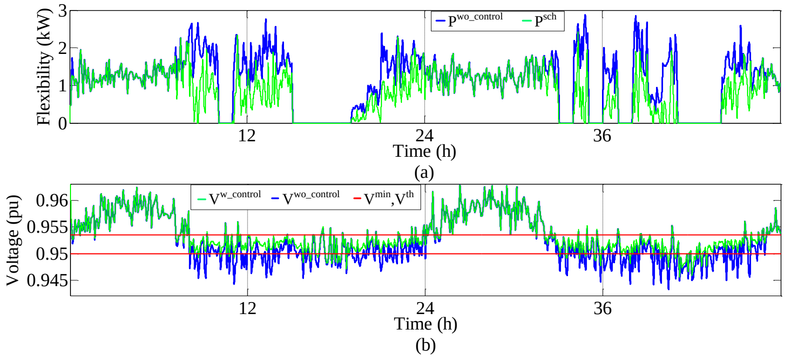

Figure 6.3: Voltage droop control at a particular node. (a) Available flexibility before (blue) and after (green) the control. (b) Voltage before (blue) and after (green) the control.

preserving the voltage over the lower voltage limit. There are cases, however, where the available flexibility is not adequate to keep the voltage at the desired level. For these instances, the DSO will have to either reinforce the grid or motivate the consumers to raise their flexibility provision. A third option considers broadening the voltage range of the droop operation as will be discussed in the next section. It is noteworthy that even in periods of no available flexibility, e.g. at 11:00 in Fig. 6.3.a, there is considerable voltage support. This occurs due to the droop operation share of other nodes in the grid. Lastly, it is important to clarify that since the suggested control does only utilise local voltage information, it can only actively cater for voltage violations. Nevertheless, overcurrent incidents are passively catered for as well on the grounds of overall grid load reduction.

6.5 Fair Activation of Flexibility

The previously formulated control algorithms will enable TVPPs to manage flexibility both actively and proactively according to regulation and balancing markets. Nonetheless, a special feature which has been examined in this Ph.D. study in relation to the control frameworks is the fair activation of flexibility. This term has been associated with specific devices in the past. For instance, fair EV charging schemes would assign charging priority to the least charged vehicle in a network [169]. However, from a grid point of view, fair activation of flexibility has another meaning; it considers the location of flexibility rather than its source. To be more precise, if a problem were to happen many times in the grid, there should possibly be different consumers each time offering their flexibility services to resolve it. The reason for this is that many grid problems, e.g. low voltage issues, are jointly caused by all consumers but are mostly expressed locally, i.e. at the end of long feeders[3]. Consumers located there, i.e. consumers who actually experience the problem, are concurrently the most efficient ones in solving the problem in terms of required flexibility. Therefore, if fairness is disregarded, same consumers would always be asked to contribute with their flexibility to solve a local grid problem. However, these consumers are not responsible for their grid location and, ideally, they should enjoy the same supply services as the rest of the consumers. Even from a technical point of view, considering that the DSO is bound to deliver qualitative power to consumers at all times and assuming that there will be a certain flexibility limit set by each consumer, "penalising" same consumers for the same problem would lead them to lower their flexibility provision limit[4]. This will eventually enforce the DSO to reinforce the grid, which means that "unfair" tactics might in fact raise financial implications in the long run. Antithetically, acquiring flexibility from different consumers each time a certain problem occurs might encourage consumers to broaden their flexibility limit range and, ultimately, aid in further delaying grid reinforcement in the long run.

6.5.1 Fair Centralised Control

As presented in J.2, the fair activation of flexibility has been incorporated in the suggested centralised control scheme by means of a weighted objective function. The relative weights, i.e. coefficients, express a memory effect; whenever a consumer offers flexibility, this flexibility is compared with the total provided flexibility to the grid and the corresponding memory coefficient is computed. The coefficient is calculated in such a way that consumers offering a lot of flexibility during one flexibility request will preferably not be considered for future flexibility requests. The "memory" of the algorithm can be tuned to account for more or less past observations according to the DSO's preference. Nevertheless, experimental results have indicated that a moderate "forgetting" factor, that is to say a value around 0.4 (see J.2), provides rational results.

The effect of the weighted objective function is described in Fig. 6.4. In this

[3]It is not uncommon for low voltage distribution networks to have "weak" points, that is to say grid parts where voltage or current limit violations are frequently encountered.

[4]This course of actions will be more evident in regulated systems, i.e. DSO and ER are the same entity, since the financial benefits from offering flexibility are expected to be lower due to reduced market competition.

figure, the result of Fig. 6.1.d, namely the conventional flexibility activation (green), is compared with the fair activation of flexibility (purple). As can

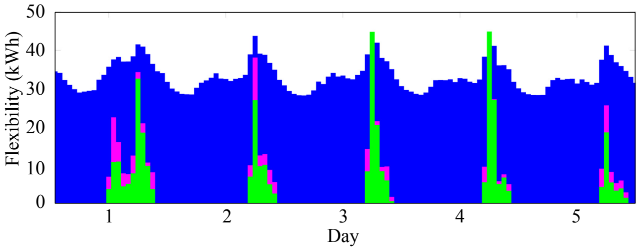

Figure 6.4: Flexibility activated by utilising the fairness factor (purple).

be seen, the memory effect of the weighted objective function results in sub-optimum solutions in terms of utilised flexibility amount. However, this is a toll to be paid for achieving a balanced flexibility contribution among consumers. This balance is demonstrated in Fig. 6.5. In this figure, several trials were performed to alleviate a particular problem, i.e. low voltage at the end of the feeder. In each trial, the corresponding memory coefficients were updated; thus, several solutions for the same problem were reached. Particularly, Fig.

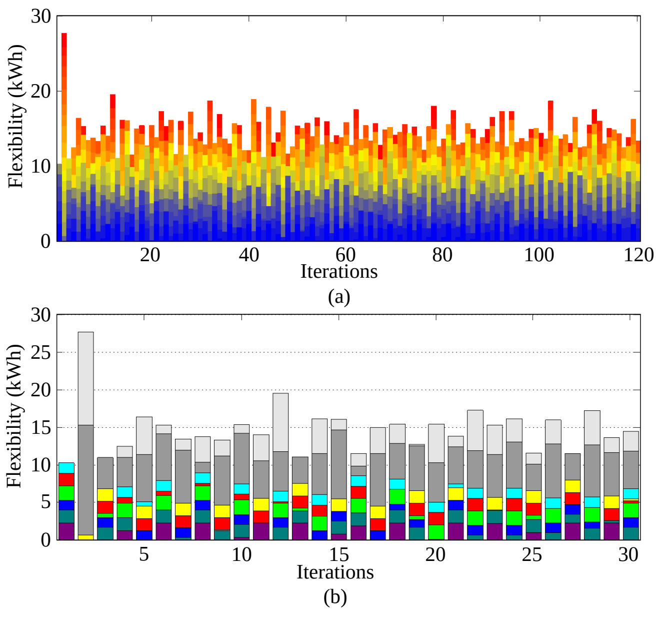

Figure 6.5: Fair activation of flexibility. (a) Flexibility activation at the beginning (red), middle (yellow), and end (blue) of the feeder. (b) Flexibility activation of different consumers at the end of the feeder.

6.5.a depicts these solutions, whereby flexibility is colored red, yellow, or blue depending on its origin being the beginning, the middle, or the end of the feeder, respectively. It is noteworthy that the first trial refers to the optimal solution, i.e. minimum amount of flexibility, since the coefficients were only initialised. Subsequent trials offer alternative solutions, whereby each consumer contributes with more or less flexibility depending on the flexibility provision history. This logic is further analysed in Fig. 6.5.b in which flexibility from the beginning and the middle of the feeder is colored light and dark gray, accordingly, whereas flexibility from the end of the feeder is multicolored. Each of these colors is related to a specific consumer. Since different color and/or color proportions are present in each trial, the goal of "same consumers not offering flexibility for the same problem" is achieved.

As discussed, the fair activation of flexibility will be useful in case of regulated markets, where the DSO is also an ER. In this case, flexibility will solely be bargained via a flexibility contract between the DSO and the consumer. As such, utilising flexibility indiscriminately among consumers will distribute the financial benefits entailed and, thus, motivate consumers to loosen their flexibility provision limits. Eventually, this will benefit the DSO as well, since the utilisation of the existing grid capacity will improve; consequently, costly grid reinforcements will further be delayed.

In case of an auction based flexibility market, the previously analysed logic does no longer hold true. Ideally, all of the grid's flexibility would be sold by the relevant BRP to other BRPs or the DSO in order to maximise profit. However, even in this setup, the weighted objective function can be of use, albeit from a somewhat different perspective. Particularly, in an auction based market, the DSO would have to formulate the corresponding flexibility demand bids. Depending on the flexibility market structure, the DSO would either have to come up with several mutually exclusive bids or with a more generic "grid area" flexibility bid. In the former case the exploitation of the memory coefficients is straightforward; the DSO will simulate several solutions as presented in Fig. 6.5.a and make the relevant bids. In the latter case, the DSO will have to define a "grid area" of interest and utilise the weighted objective function in order to produce multiple solutions in that area. Then, the worst case scenario should be adopted, namely the solution requiring the highest amount of flexibility within that area should be selected.

6.5.2 Fair Decentralised Control

Contrary to the central controller, the decentralised control does only utilise local voltage information in order to issue regulation services. As such, it cannot evaluate how much flexibility is provided to the network by other consumers or which consumers are contributing with their flexibility; thus, the previously analysed logic of selectively activating flexibility based on past activation frequency and extent is impractical for online control. Theoretically, it would be possible to dynamically enable/disable the decentralised control of consumers who have consistently aided the grid; nevertheless, this would considerably limit the total available flexibility in the network.

To circumvent the previously mentioned difficulties in scheduling flexibility selectively during real time operation, the DSO can appropriately adjust the voltage settings of the droop at each supply node. If done systematically, the TVPP's decentralised controller will succeed in a fair activation of flexibility without limiting its capacity substantially. However, choosing the appropriate V^{min} and V^{th} for each node is not a trivial task to do. A methodology to select the values of these variables is introduced in J.2, whereby V^{min} is decided upon past loading analysis of the grid. In this analysis, the centralised controller identifies the most loaded grid situation in the past assuming all loads being fully flexible to avoid constraint relaxation, i.e. the grid constraints are respected. Next, the voltage values recorded in that scenario are set as V^{min}. Regarding V^{th}, an initial setting is chosen by the DSO for the weakest grid node. Then, as explained in J.2, a quadratic function can be used to estimate V^{th} for the rest of the nodes. The quadratic function is suggested to account for the quadratic nature of the power flow equations.

Ultimately, every grid node will have its own voltage settings, which will apply to its connected consumers. Fig. 6.6 depicts the effect of the controller at a node located in the middle of the feeder. It is apparent that if the voltage boundaries, set by V^{min} and V_1^{th} or V_2^{th}, were shifted so that $V^{min} = 0.5$, i.e. same V^{min} as the weakest grid node (see Fig. 6.3), then the controller would never operate. Hence, the decentralised control is "fair" in the sense that it facilitates flexibility provision from all consumers as far as V^{min} is concerned. According to previous discussion, V^{min} is chosen based on technical analysis, whereas the initial V^{th} is decided by the DSO. Then, the rest of the V^{th} settings are computed. The effect of V^{th} in the proposed framework is evident in Fig. 6.6, where the droop operation is illustrated for two such settings, a higher and a lower one. A low V^{th} value originates from an initial low choice of V^{th} at the weakest grid node and vice versa. As can be seen if V^{th} is chosen to be too low, the voltage will less likely fall withing the droop operation region especially for nodes located closer to the beginning of feeder(s). Thus, the total amount of activated flexibility will decrease, i.e. the flexibility regulation costs will be reduced, yet the amount of practically available flexibility will decrease as well. This is shown by the green line in Fig. 6.6.a which indicates that very little flexibility is activated with V_1^{th}. On the contrary, more flexibility is used by choosing V_2^{th} as shown by the purple line in the same figure. This will result in more balanced flexibility provision among consumers, albeit it will increase costs as flexibility might even be initiated way before violating the grid limits. Finally, it should be borne in mind that, regardless of the V^{th} selected, the

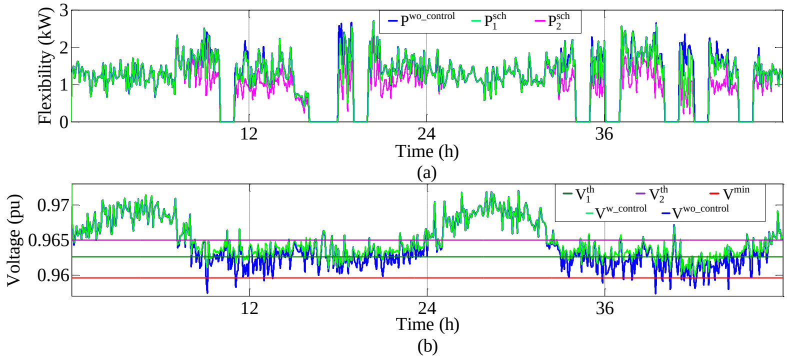

Figure 6.6: Voltage droop control at a particular node. (a) Available flexibility before (blue) and after (green, purple) the control. (b) Voltage before (blue) and after (green) the control.

voltage level is bound to increase at each node. Moreover, the wider the droop operational range the higher the voltage rise. This fact further complicates the choice of V^{th} and signifies the expertise required by the DSO.

Ultimately, the DSO will have to decide regarding the decentralised control operation range. Selecting a short range will considerably save regulation costs but will concurrently endanger the supply reliability by limiting the amount of available flexibility in the grid[5]. On the other hand, an overly wide range will lead to more reliable, yet costly operation. As such, the DSO should wisely choose the appropriate settings based on a technoeconomic analysis. If done efficiently, each consumer will proportionally aid the grid with his/her flexibility in a fair manner.

6.6 Discussion

In the previous sections, two flexibility control frameworks have been presented along with their interoperability. Particularly, a centralised control scheme is responsible for preventing grid issues by scheduling flexibility shortly in advance. This schedule is then passed to the decentralised controller which manages grid problems in real time. The settings of the controller derive from simulations using the centralised control and expert knowledge.

The controllers have been chosen so that they are compatible with contemporary electricity and/or future flexibility markets. As will also be explained in Chapter 7, flexibility is expected to be efficiently traded in balancing and/or

[5]If the voltage range is too short, then many controllers will rarely be initiated, especially at the beginning of the feeder.

regulating markets. The main reason for this is that local loading and distributed generation entail significant forecast uncertainty. Moreover, the value of flexibility will be higher in those markets compared to spot markets. Concerning the control, the centralised controller necessitates loading information from the whole grid. This leads to optimal flexibility requests; nonetheless, it makes the controller computationally slow and less scalable. Thus, it is a control mechanism befitting local balancing markets. On the other hand, the design of the decentralised controller makes it computationally fast and scalable, albeit not optimal in terms of congestion management; hence, it is suitable for online control frameworks such as the ones necessitated by regulation markets.

Lastly, there are three points which require further clarification. The first one is that this chapter has emphasised flexible load management rather than generation. The main reason for this is that the applicability of the methodology to generation is straightforward since generation can be considered as a "negative" load, i.e. load reduction equates generation increase and vice versa. It should be highlighted, however, that, in this case, relevant droops in respect to overvoltage should be formulated as well. Emphasising loading problems is justified taking into account that most grids face consumption rather than generation problems [172]. Moreover, distributed generation is generally less flexible than load. The second point considers that in low voltage distribution grids, the impact of active power in alleviating voltage problems is more dominant than reactive power. This occurs due to the high resistance of distribution grids. Thus, reactive power control is not expected to be as frequent as in transmission grids; it will most likely restrict in correcting the local power factor. Lastly, it is apparent that, in this chapter, flexibility has been treated as a generic commodity; it has not be linked to specific devices. By addressing the source of flexibility for each consumer more constraints, e.g. ramping requirements, payback effects etc., will have to be embedded in the proposed framework. This application will make the suggested control scheme more realistic and will probably favor a 24 hour rolling market [158]. Nonetheless, the scope of this chapter is to describe a generic two-stage control framework which will primarily highlight the fair activation of flexibility.

6.7 Conclusions

In this chapter, a two-stage flexibility control framework has been presented. Special attention has been paid to the fair activation of this commodity. This treatment will encourage consumers to broaden their preference limits in terms of flexibility, which will consequently delay grid reinforcements. Moreover, the fairness factor can be utilised by TVPPs to formulate alternative or grid area bids for double sided auction markets as will be discussed in Chapter 7.

Chapter 7

Flexibility Market

This chapter is dedicated to explore the commodity to be traded in future flexibility markets, namely flexibility. An introduction to its multiple attributes is presented, along with their impact on the structure and operation of future markets. A relevant study is presented in C.3 in the APPENDIX.

7.1 Introduction

Previous chapters have focused on addressing technical limitations when implementing a TVPP. The main problems identified refer to load forecasting, estimation of flexible consumption, and load monitoring. For these matters, simple, yet efficient, solutions were devised. Furthermore, these topics were linked to the ultimate task of a TVPP, that is to say detecting and relieving grid congestions. From a technical point of view, this study has been thorough and has resulted in accurately estimating the amount and location of the DSO's flexibility needs. Contrary to the technical perspective, the commercial counterpart of a TVPP, i.e. the CVPP, will be examined in this chapter. Particularly, the main attributes of flexibility will be addressed and their impact on potential flexibility market structures will be discussed. Furthermore, the interaction among TVPP, local flexibility market, and/or CVPPs will also be explored. This frame is very important to realise a flexibility business case.

7.2 Flexibility as a Commodity

The term "flexibility" has since long been used to describe the potential of generation to follow demand [13]-[17]. Furthermore, its impact has been accounted for in running contemporary energy markets. For example, day ahead markets have been established mainly to incorporate the start-up and ramping requirements of conventional coal and nuclear power plants. However, the traditional definition of flexibility will change in future power systems. The reason for this is that demand will no longer be inflexible; moreover, conventional power plants will be substituted by intermittent dispersed generation, which operates based on different technical requirements than its predecessors. Thus, the structure of modern energy markets will have to be revised and probably altered and/or augmented by new participants and market mechanisms.

A necessary step prior to describing new market mechanisms is to analyse the attributes of the commodity to be traded, namely flexibility [173], [177]. These attributes will actually drive relevant transactions and eventually define the market type. Essentially, flexibility is characterised by the following properties:

- **Energy Scaling:**
  One main feature of flexible loads is their ability to reduce or increase their consumption within the consumer's preset limits. A simple example to conceptualise this action is the light dimer. By lowering its level, i.e. its power consumption, the brightness of the lighting device decreases and vice versa. This type of flexibility has been encountered in Fig. 4.8.a.

- **Energy Shifting:**
  Energy shifting refers to the ability of flexible devices to shift their operation in time. Principally, this action is demonstrated in Fig. 4.8.b. Energy shifting is of uttermost importance for SGs. For instance, as seen from Fig. 6.4, consumption reduction is only required during a few hours per day. Thus, energy shifting can aid in settling the relevant overloading problems by moving energy to time slots with less grid stress. It is noteworthy that energy shifting can be expressed in two forms, namely "spreading"a particular amount of energy consumption across time and/or shifting an energy block in time [196]. Though being a very useful asset in the SG's arsenal, energy shifting can, depending on the flexible device, be also the source of many implications such as payback effects and energy ramping limitations.

- **Location:**
  The geographical location of generation/consumption is also regarded in transmission networks via price area formulation in spot markets. However, low voltage distribution grids differ significantly from transmission networks because of their radial structure and high resistance. This means that these systems have limited power flow controllability and higher voltage drops; thus, as investigated in Chapter 6, the origin of flexibility matters significantly when coping with grid constraint violations.

- **Time:**
  This attribute is well-known from contemporary markets. Essentially, same flexibility services will have different merit depending on the relevant demand/supply requirements at their activation time.

- **Uncertainty:**
  As discussed in C.3, uncertainty is probably the most crucial disadvantage of flexibility, which greatly distinguishes demand and renewable generation flexibility from its contemporary reference to conventional generation[1]. Flexibility uncertainty originates from the type of flexible load or generator. Regarding the former, since flexibility mostly derives from human behavior related devices, individual consumer's flexibility is usually subject to large forecast errors. As an example, an EV which is scheduled to charge at one time slot might be unavailable for charging because its owner decided to drive due to an urgent situation. As for the latter, renewable resources are mostly weather dependent devices; thus, their generation uncertainty stems from weather volatility. One very interesting fact about flexibility predictability, is that it generally decreases with increasing forecast horizon. This can be observed in Fig. 7.1, where the

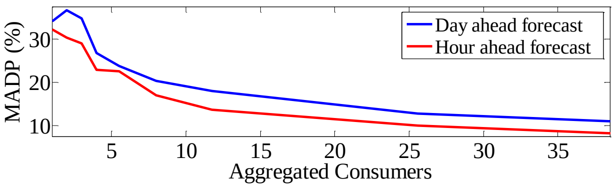

Figure 7.1: Aggregation versus MADP error for two ARIMA models.

  hour ahead and day ahead forecast accuracy was examined for the study case presented in C.3. It is apparent that predicting the hour ahead loading value is more reliable, especially when considering the already high prediction errors encountered in low voltage distribution grids.

It is apparent that the first three properties add value to flexibility, that is to say a fully adjustable energy block of a single consumer is operationally worth more than a less flexible energy block originating from a whole feeder. It should be mentioned that the added value to flexibility according to the time of its activation is not solely driven by the flexibility source itself rather than by other loads/generators as well; thus, it will not be considered in this context. Finally, uncertainty devalues flexibility, that is to say the longer the forecast period and the more local the flexibility source, the higher the prediction uncertainty and, hence, the lower the value of flexibility.

[1]In case no regulation is required, conventional power plants, e.g. coal plants, do only diverse from their planned generation schedule on the grounds of irregular equipment failure.

Overall, it can easily be concluded that flexibility is as a multidimensional commodity, whereby each dimension might add or subtract value to it. To reduce its complexity and improve its interface with future markets researchers have introduced the idea of an Aggregator, which is also referred to as CVPP [43], [197]. The Aggregator is an entity which will cater for the aggregation of flexibility from different devices and/or consumers. The resulting aggregated flexibility will have less scaling, shifting, and locational value but will also entail less uncertainty as explained in Section 3.7. Thus, depending on the expected flexibility demand the Aggregator will decide the optimum aggregation level. For example, if high flexibility needs are expected by the DSO, the importance of the geographical location will prevail and, therefore, less aggregation will be imposed as shown in C.3. On the contrary, more aggregation will be performed when targetting BRPs since the location of flexibility is uninteresting when selling flexibility in wholesale markets.

7.3 Flexibility Market Structure

Traditionally, deregulated energy markets have been operated in three stages to ensure energy balance. Day ahead energy trade has taken place in spot markets, intra-day energy imbalances have been bargained in balancing markets, while real-time imbalances have reactively been settled via regulating markets [1]. Flexibility is intended to be aggregated in order to allow participation in those wholesale markets. However, due to its distributed nature it is anticipated that there will be trading opportunities for flexibility at the distribution level as well.

The flexibility attributes presented in Section 7.2 will to a great extent dictate the time frame of local market operation. Nevertheless, in order to maximise profit and increase competition, these markets should ideally be consistent with wholesale interests, too. Thus, in compliance with contemporary markets and taking into account that flexibility uncertainty decreases for short term forecasts, flexibility markets are expected to be of balancing and/or regulating market form. Although the daily operational requirements of conventional power plants are not to be found in distributed generation, 24 hour markets might still be needed to account for some daily consumer requirements, e.g. charging status of an EV should remain the same after its daily scheduling. Thus, some researchers have proposed the notion of 24 hour rolling markets, which is practically a merge of a balancing and a spot market [16], [158]. This new market will account for both flexibility uncertainty and daily energy requirements, while being compatible with spot and balancing wholesale markets.

Fig. 7.2 schematically depicts the participants of these new flexibility markets in a deregulated environment. As can be seen, there are mainly three entities

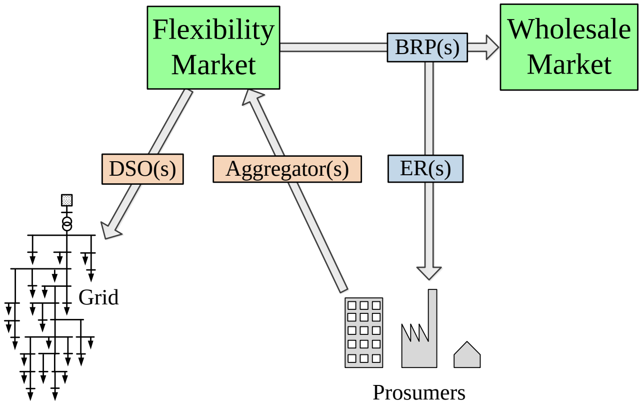

Figure 7.2: Players and transactions in future energy markets [198].

interested in buying/selling flexibility at a local level, namely BRPs, Aggregators, and DSOs. Specifically, local flexibility is managed by the Aggregators; therefore, they are the sole sellers on the market. On the other hand, DSOs do only place flexibility requests to alleviate their grid problems, whereas BRPs buy local flexibility either to correct their own imbalances or to forward flexibility offers to the wholesale market. It should be mentioned that the Aggregator can also be a module of an ER, which principally manages the inflexible load, or even a BRP, therefore having direct access to the wholesale market. Moreover, Aggregators, BRPs, and DSOs might refer to one organisation in case of a regulated environment.

7.4 Interaction between CVPP and TVPP

So far the structure of future flexibility markets has been explored. It has been emphasized that due to low long term prediction capability, these markets will most likely refer to intra-day markets. An additional reason favoring this choice is that Aggregators will eitherway be interested in selling shortly in advance because imminent problems, i.e. upcoming grid constraints for DSOs and energy imbalances on the BRP side, are expected to increase demand value. The same reasoning holds true for local regulating markets.

It should be clarified that among buyers, DSOs are expected to dominate the market. This will occur on the grounds that they will apply for flexibility to solve local grid problems and, hence, they will value local flexibility more than BRPs. Since the majority of transactions is expected to occur between DSOs, i.e. TVPPs, and Aggregators, i.e. CVPPs, their interaction possibilities should be examined. The most probable scenarios include:

- **Fully Regulated Market:**
These markets refer to monopolistic systems, where electricity is generated, transmitted, and distributed by one governmental institution. Although deregulation is usually promoted, there are many countries, e.g. Greece, which operate in a traditional monopolistic way. In those "markets", flexibility provision is settled via long term flexibility contracts between the governmental institution and the consumers. This flexibility is thereafter handled by the institution according to its technical requirements, i.e. grid constraints and energy imbalances. As discussed in Section 6.5, fair activation of flexibility is particularly important in these environments to incentivise flexibility supply when contracting the consumer. This action might incur more costs in the short term, but will eventually pay off in the long run by delaying costly grid reinforcements.

- **Partially Regulated Market:**
In this case power generation, transmission, and distribution are decoupled, yet local distribution is managed by one entity. Thus, in this scenario, Aggregator, DSO, and ER refer to one BRP[2], which has direct access to wholesale markets. This example is operationally similar to the fully regulated environment. As such the BRP is anticipated to handle local flexibility based on long term flexibility contracts. However, more complexity is added by the interaction between the BRP and the wholesale market. This means that fair activation of flexibility will still be able to provide financial benefits in the long run; nonethless, the BRP should weigh these benefits in relation to financial potential which can be achieved by selling flexibility in wholesale markets instead.

- **Deregulated Market:**
Deregulated markets are principally depicted in Fig. 7.2. As discussed, in those cases, Aggregators collect flexibility from several contracted consumers and sell it on a local flexibility market. Accordingly, DSOs[3] and BRPs make their own flexibility requests on the market. Regarding the form of market transactions, various alternatives have been proposed [27]. These include bilateral contracts, supermarkets, and auction based markets. Since the two main participants of these transactions are DSOs, i.e. TVPPs, and Aggregators, i.e. CVPPs, their interaction should thoroughly be described. It is realistic to assume that a flexibility market will refer to a grid area operated by one DSO; hence the interaction between one DSO and one, or more, Aggregators will be presumed in the following.

[2]In this case, TVPP and CVPP are not competing since they belong to the same entity, namely the BRP.

[3]It is noteworthy that DSOs might actually have only access to total consumption smart meter readings due to market rules (see Section 2.2); thus, they might need to perform flexibility estimation in order to make realistic flexibility requests.

Bilateral contracts is one of the most frequently proposed setups between TVPP and CVPP [26], [173]. Particularly, Aggregators will place their flexibility offers on the wholesale market via BRPs. However, these offers will be modified in such a way that no grid limit violations are to occur. The contracts are expected to involve a stand-by cost and an activation cost similar to contemporary regulation agreements. This type of transaction is very effective for reactive control but is not suitable for proactive control. Proactive control in this case is realised similarly to the transmission level, i.e. by utilising shadow prices [162], [163], [199]. Nevertheless, employing shadow prices at the distribution level is not very practical since the load uncertainty in these grids is considerably higher. Hence, there is substantial risk that the flexibility contract will not be respected by the Aggregator. Moreover, some manuscripts assert that contracts might raise market power [175]; therefore, they are not the most efficient market solution.

The second option regarding the flexibility market transaction setup is supermarkets. In this scenario, CVPPs will estimate the location and amount of flexibility services which the DSO might be interested in buying. Then, Aggregators, i.e. CVPPs, will propose and value various flexibility services, just like in a "supermarket", enabling the DSO to purchase the most suitable product. In C.3, the relation between aggregation, uncertainty, and flexibility provision is analysed, thereby establishing framework for formulating the aforementioned flexibility services on behalf of the CVPP. It is concluded that flexibility services should be sold in a "per node" aggregated form to reduce uncertainty and preserve locality, whereas several nodal flexibility offers should be aggregated, especially at the end of long feeders, which usually exhibit voltage issues. One of the problems regarding supermarkets is that market players do not experience symmetric information, which might raise market power.

Lastly, a third solution in setting up flexibility transaction systems is to employ auction based markets. Among these markets, double sided auctions ensure the lowest market power exercised by any of the participants. Contemporary spot and regulating markets are double sided auctions. To this end, Aggregators are expected to place their flexibility services on the market without any information about the DSO's needs. Similarly, the DSO will estimate these needs and bid accordingly. Then, the market will be cleared[4]. In case very local flexibility offers are available by the Aggregator, the DSO might utilise the methodology presented in Section 6.5.1 to formulate multiple mutually exclusive bids. However, due to scalability and uncertainty problems more aggregated offers might be

[4] Although this section focuses on the TVPP-CVPP interaction, BRPs are also expected to bid for flexibility on local flexibility markets. Moreover, in the examined case, grid constraints will not be considered for clearing the market, that is to say no price areas will be established.

provided on flexibility markets. In the latter case, the CVPP might employ the methodology in C.3 to place its mutually exclusive area offers, whereas the DSO might bid accordingly based on the procedure described in Section 6.5.1. Double sided auctions are considered the most efficient market solution for proactive control due to higher competition and lower market power. However, there is considerable risk that selling flexibility services to a BRP will cause grid limit violations which the DSO has not accounted for. To this end, they are expected to be complemented by regulating markets. Equivalently to modern regulating markets, local regulation is expected to be conducted via long term flexibility contracts and/or ultra short term intra day local markets.

Regardless of the case, the interaction between TVPP and CVPP will lead to a business case; be it among BRP and consumers or among Aggregator, DSO, and consumers. Consequently, consumers will be given the opportunity to harvest financial benefits from their flexibility while their supply reliability and power quality will substantially increase. Furthermore, the establishment of flexibility markets will increase competition and decrease market power thus lowering the price of electricity, i.e. both flexible and inflexible.

7.5 Conclusions

Flexibility is a multidimensional commodity, whose nature perplexes the establishment of local flexibility markets. In this chapter, some of the most important features of flexibility were addressed and their impact in defining relevant flexibility markets were discussed. Hopefully, this analysis will shed some light to the, so far, blur perception of flexibility markets and will aid economists in founding efficient market mechanisms for trading flexibility.

Chapter 8

Epilogue

In this chapter, the methodologies and findings of previous chapters are summarised and discussed. Moreover, the scientific contributions of this Ph.D. thesis are outlined. Finally, perspectives for future work are listed.

8.1 Summary & Conclusions

From a technical perspective, SGs are introduced to power systems as an efficient alternative to cope with power imbalances and distribution system capacity limitations. Since this investment is expected to be done by DSOs, the latter seems, up to day, to be the main initiative for SG installations. Particularly, TVPPs are anticipated to handle local flexibility in order to boost the distribution system's functionality, improve its capacity use, and ultimately save costs by delaying expensive grid reinforcements. However, SG scenarios are not ideal. Modernising contemporary grids via SG practices does in fact perplex the system, oftentimes leading to major obstacles. Some of these obstacles include forecasting limitations, lack of flexibility data, and online monitoring deficiencies. To this end, relevant methodologies were devised and/or revised in order to circumvent these issues, hence leading to feasible TVPP setups.

Equivalently to modern operation of power systems, TVPPs are expected to apply both preventive and corrective flexibility control in order to deal with grid limit violations. As such, forecasting is essential to realise preventive control. In this study, the shortcomings of traditional prediction techniques were explained and a new philosophy for forecasting was suggested. This philosophy, which is based on non-parametric machine learning techniques, is automated and adaptable, therefore, being fundamentally compatible with TVPP requirements.

In order to apply control, especially proactive control, the TVPP should have knowledge regarding the available flexible energy in the network. Theoretically, this information derives from smart meter recordings. However, due to communication, data storage and/or data sharing problems among flexibility market participants, flexibility might oftentimes need to be estimated. To this end, a novel NILM technique has been proposed. This technique circumvents the compatibility problems between contemporary NILM algorithms and smart meter sampling frequencies. On the demerits of the method, is its extensive consumer database requirement and its inability to estimate small flexible loads. Nevertheless, these prerequisites are in compliance with SG realisations. In particular, the low sampling times of smart meters are selected due to the massive amount of consumer data to be managed, while small appliances do not reflect the bulk of flexibility.

Another troublesome matter which has been investigated is the lack of online load monitoring in low voltage distribution systems. Even for SGs, the transformer measurement is the sole online tele-measurement, whereas smart meter data are collected with substantial delay. Consequently, an online load monitoring scheme has been proposed to enhance the load distribution observability and aid the DSO in operational and planning decisions and/or procedures. By investing in a few online power meters the load distribution can be approximated to a reasonable degree. Moreover, it was concluded that, as expected, for reactive control, i.e. online monitoring, the more the meters, the better the approximation. Nevertheless, this conclusion is not valid when targeting predictive control, since more meters result in smaller monitoring areas, introducing larger forecast errors. Thus, since both preventive and corrective control is required, an equilibrium between those two choices should be found.

Providing solutions for the aforementioned problems will aid in a smooth TVPP realisation. In this Ph.D. study, this module has been modeled as a two step functionality. The first step refers to a centralised approach which simulates proactive control and generates flexibility requests accordingly to prevent any grid limit violations. In the second step, a decentralised controller is employed for the real-time loading variations which the centralised controller has failed to predict. Moreover, these complementary modules have been designed in a way that flexibility among all users is indiscriminately activated.

Having ensured a realistic and reliable TVPP implementation, its interaction with local and wholesale markets was examined. Though not being within the TVPP's imminent technical constraints, these markets are necessary for an efficient SG operation; be it in monopolistic or deregulated environments. Particularly, they are the driving force of SGs, since they incentivise consumers to provide flexibility in return for financial benefits. It was concluded that flexibility markets do not, yet, exist due to the high complexity of flexibility as a commodity. To this end, some of its attributes were emphasized and linked to potential flexibility market forms. Furthermore, the compatibility of the proposed TVPP framework with several of these market forms was confirmed.

8.2 Scientific Contributions

This Ph.D. study has focused on different aspects mainly regarding the technical implementation of a TVPP. The main contributions are listed as follows:

1. A simple, generic, and automated load forecasting technique based on sequential pattern mining was devised. This non-parametric approach can be used at various aggregation/disaggregation levels by the DSO to detect upcoming grid loading complications.
2. A novel NILM method targeting load intensive flexible devices was conceived. This technique is generic for the most part and occasionally requires adjustment at the classification step depending on the flexible device type.
3. A framework for allocating power meters in a top down disaggregation perspective was presented. It was demonstrated how this approach can result in an online hierarchical load monitoring frame for radial distribution systems. Furthermore, it was shown that the same algorithm can be used to determine the grid areas for trading aggregated flexibility on local flexibility markets.
4. A two-stage control algorithm to define the required flexibility services by the DSO was formulated. Well-known techniques were combined in an innovative way to define both a centralised and a decentralised control scheme, which are compatible with the operating times of contemporary energy markets. Special focus was given on the fair activation of flexibility in the network, which to the extent of the author's knowledge has not, so far, been accounted for in the literature.

8.3 Future Work

This Ph.D. study has addressed and resolved many, up to day, existing issues, which obstruct successful SG implementations, especially on the DSO side. However, since these issues refer to inherently distinct topics, it should be understandable that there is definitely room for further testing and/or improvements. For example, the following matters could potentially be investigated:

- Though different in philosophy, some features of ARIMA modeling, e.g. daily periodicity at aggregated levels, were embedded to the sequential pattern algorithm in order to increase its forecasting accuracy. Other features such as environmental conditions could equally be imported to the model if deemed to be impactive. Moreover, it would be interesting to combine the proposed technique with other established forecasting methodologies to test the efficiency of hybrid models.

- It would be interesting to estimate the consumption of flexible devices, other than the HP. Some obvious candidates are EVs and electric water heaters as well as generation such as PVs and wind turbines. Although the estimation methodology is generic, some of these devices, e.g. the EV, would result in a different classification procedure which is, yet, another challenge.

- The exhibited meter allocation scheme was based on a radial network assumption. In some countries, e.g. the U.S., low voltage distribution grids may not be radial. Moreover, distributed generation and phase unbalance has not been accounted for when designating the optimal positions for installing online power meters. Hence, these issues require further research. Some preliminary ideas involve considering generation as a negative load, breaking the loop of meshed networks and assigning power injections to compensate for the topological change, and treating each phase separately while assigning the corresponding constraints to the optimisation problem.

- Regarding the control algorithms, flexibility has been treated as a generic energy changing feature. However, in reality these energy changes originate from flexible devices, each having its own technical limitations, e.g. payback effect, charging requirements etc. Thus, it would be interesting to incorporate these limitations in the constraints of the optimisation as well as in the droop formulation.

- Lastly, it is expected that integrating the proposed framework in an established flexibility market setup would arise new challenges, whereas it would aid in testing the scalability and efficiency of the system in an interdisciplinary study case.

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