Optimaal en schaalbaar beheer van slimme elektrische netten met elektrische voertuigen

Optimal and Scalable Management of Smart Power Grids with Electric Vehicles

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Putte-Kapellen, februari 2015
Kevin Mets

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List of Acronyms

List of Acronyms

A

AC	Alternating Current
AS	Ancillary Services
AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
AMR	Advanced Meter Reading
API	Application Programming Interface

B

BAU	Business-as-Usual
BAN	Building Area Network

C

CDI	Cluster Dispersion Indicator
CHP	Combined Heat Power
COM	Component Object Model
CPF	Continuation Power Flows
CSP	Curtailment Service Providers
CSV	Comma-separated values
CIM	Common Information Model

D

DBI	Davies-Bouldin Index
DC	Direct Current
DLL	Dynamic Link Library
DSM	Demand Side Management
DG	Distributed Generation
DR	Demand Response
DER	Distributed Energy Resource
DES	Discrete Event Simulation
DRES	Distributed Renewable Energy Source
DSO	Distribution System Operator
DEVS	Discrete Event System Specification

E

EV	Electric Vehicle
EMT	Electro Magnetic Transients
EMS	Energy Management System

F

FAN	Field Area Network
FFT	Fast Fourier Transform
FOM	Federation Object Model
FWT	Fast Wavelet Transform

G

GUI	Graphical User Interface
GPS	Global Positioning System

H

HAN	Home Area Network
HIL	Hardware-in-the-Loop
HLA	High-Level Architecture
HVDC	High Voltage Direct Current

I

ICE	Internal Combustion Engine
IDE	Integrated Development Environment
ICT	Information and Communication Technology
ILP	Integer Linear Program
IAN	Industrial Area Network
IP	Internet Protocol
IEC	International Electrotechnical Commission
IED	Intelligent Electronic Device

L

LP	Linear Program
LV	Low Voltage
LTE	Long-Term Evolution

M

MAS	Multi-Agent Sysem
MCP	Master Control Program
MIA	Mean Index Adequacy
MV	Medium Voltage

O

OPC	Open Process Control
OPF	Optimal Power Flow
OFDM	Orthogonal Frequency-Division Multiplexing

P

PCA	Principal Component Analysis

PEV	Plug-In Electric Vehicle
PHEV	Plug-In Hybrid Electric Vehicle
PMU	Phasor Measurement Unit
PDC	Phasor Data Concentrators
PLC	Power Line Communication
PF	Power Flow
PV	Photo Voltaic

Q

QP	Quadratic Program

R

RES	Renewable Energy Source
RMS	Root Mean Square
RT	Real-Time
RTI	Runtime Infrastructure
RTSE	Real-Time State Estimators
RPC	Remote Procedure Call
RDF	Resource Description Framework

S

SCADA	Supervisory Control and Data Acquisition
SMI	Similarity Matrix Indicator
SSA	Small-Signal Stability Analysis

T

TCP	Transmission Control Protocol
TLT	Transmission Line Theory

U

UDP	User Datagram Protocol
UMTS	Universal Mobile Telecommunications System

V

V2G	Vehicle-to-Grid
VPP	Virtual Power Plant

W

WAMPAC	Wide-Area Monitoring, Protection, and Control
WAN	Wide Area Network
WCBCR	The ratio of "within cluster sum of squares to between cluster variation"
WLAN	Wireless Local Area Network

X

XML	EXtensible Markup Language

Nederlandse samenvatting –Summary in Dutch–

Het streven naar duurzaamheid, betrouwbaarheid en energie-efficiëntie zorgt ervoor dat de wijze waarop we energie produceren en consumeren veranderingen ondergaat. Overheden stimuleren technologieën zoals hernieuwbare energie en elektrische voertuigen. Dit gaat echter gepaard met uitdagingen. We hebben geen controle over zonne- en windenergie vermits deze afhankelijk zijn van het weer. Het opladen van elektrische voertuigen vertegenwoordigt een aanzienlijke vraag naar elektriciteit. Het elektriciteitsnetwerk is hier echter niet voor ontworpen en ondergaat daarom een transformatie naar een slimmer elektriciteitsnetwerk, een zogenaamd *smart grid*. Smart grids integreren informatie- en communicatietechnologie om zo te komen tot een efficiëntere opwekking, transport, en distributie van energie. Vraagsturing *(demand side management)* is een essentieel onderdeel van smart grids. Zonder vraagsturing volgt de productie de vraag naar energie. Bij vraagsturing daarentegen zal de vraag naar energie gestuurd worden om zo bijvoorbeeld de belasting van het net te verminderen, of samen te vallen met de productie van groene energie. Dit proefschrift richt zich op het optimaal integreren van elektrische voertuigen in smart grids en levert daarbij contributies in drie domeinen: (i) simuleren van smart grids, (ii) vraagsturing van elektrische voertuigen, en (iii) analyse van energieverbruik met het oog op toepassingen in vraagsturing.

Simulatoren zijn kostefficiënte, veilige, flexibele en volledig gecontroleerde omgevingen om concepten voor smart grids te evalueren. De gecombineerde simulatie van het elektriciteitsnetwerk, het communicatienetwerk en de controlelogica (bv. vraagsturing) bovenop is essentieel. Het zijn net de interacties tussen die onderdelen die de kern vormen van het smart grid concept. Het is dan ook normaal dat simulatiehulpmiddelen dit moeten reflecteren. Dit is echter niet altijd het geval. We bestuderen drie types van simulatoren die toepasbaar zijn in het smart grid domein: (i) simulatoren voor het elektriciteitsnetwerk, (ii) simulatoren voor het communicatienetwerk, en (iii) simulatoren die beide combineren. Simulatoren voor het elektriciteitsnetwerk kunnen onderverdeeld worden in twee toepassingsdomeinen, enerzijds deze die zich richting op simulaties van het elektriciteitsnetwerk in stabiele toestand, anderzijds deze die zich richten op simulaties wanneer het elektriciteitsnetwerk veranderingen ondergaat. Het gecombineerd simuleren van elektriciteitsnetwerk en communicatienetwerk wordt vaak bereikt met een zogenaamde co-simulatie aanpak, waarbij verschillende simulatoren gecombineerd worden. Dit introduceert echter extra complexiteit, omdat de verschillende simulatoren en hun modellen gesynchroniseerd moeten worden. De smart grid simulator die ontwikkeld werd tijdens dit onderzoek biedt echter een meer geïntegreerde oplossing. De modellen voor het elektriciteitsnetwerk, communicatienetwerk en controle logica worden gedefinieerd in dezelfde omgeving. De simulator is reeds gebruikt voor toepassingen met betrekking tot het opladen van elektrische voertuigen, residentieel energiebeheer, en de integratie van hernieuwbare energiebronnen.

Met de nodige hulpmiddelen ter beschikking kunnen we de invloed van het opladen van elektrische voertuigen op het elektriciteitsnetwerk bestuderen. Elektrische voertuigen moeten frequent opgeladen worden vanwege hun beperkt bereik en de daaruit voortvloeiende *range anxiety* bij gebruikers. Het herladen van elektrische voertuigen kan er echter toe leiden dat het elektriciteitsnetwerk overbelast raakt of dat er spanningsproblemen optreden. We kunnen hier tegen optreden door gebruik te maken van vraagsturing, waardoor de vraag naar energie voor het herladen verschoven wordt naar periodes met weinig vraag, ook wel *load shifting* genoemd. We beschouwen een aantal van deze methodes die telkens een ander perspectief bekijken. Op deze manier bekomen we meer inzicht in wat de invloed is van de architectuur en de informatie en communicatie vereisten op de efficiëntie van dergelijke methodes. We maken gebruik van kwadratisch programmeren om de verschillende methodes te modelleren en hun invloed op de efficiëntie te evalueren in termen van piekbelasting, variabiliteit van de vraag, en spanningswijzigingen. We bekijken in onze experimenten een groep residentiële gebruikers.

De eerste methode is actief op woningniveau en maakt geen gebruik van externe informatiebronnen of controlesignalen. Het energiebeheersysteem berekent een oplaadschema op basis van de tijd die beschikbaar is voor het laden, de benodigde energie, en het verwachte verbruik in de woning. Een oplaadschema geeft aan wanneer een voertuig mag laden, en het vermogen dat daarvoor gebruikt mag worden. Uit de experimenten blijkt dat deze lokale aanpak reeds een groot deel van de anders bijkomende piekbelasting op het net kan vermijden. Het spreiden van de vraag op zeer lokaal niveau heeft dus een positief effect.

De tweede methode gebruikt een centrale planner die het herladen van meerdere voertuigen coördineert. Van zodra een voertuig wil laden, zal het energiebeheersysteem contact opnemen met de centrale planner en de nodige informatie aanleveren. Die zal op zijn beurt een oplaadschema opstellen, rekening houdend met het verwachte verbruik in de omgeving inclusief wagens die reeds aan het laden zijn. Door deze gecoördineerde aanpak kunnen we de piekbelasting verder verlagen. Het systeem wordt echter wel complexer door gebruik te maken van een centrale planner.

We vergeleken deze methodes met een multi-agent systeem dat gebruikt maakt van op marktprincipes gebaseerde coördinatie en niet afhankelijk is van voorspellingen. Simulaties tonen aan dat vraagsturing in alle gevallen de piekbelasting kon verlagen. Bovendien konden spanningsproblemen in vele gevallen vermeden worden. De methodes gebaseerd op kwadratische programmeren bekwamen de beste resultaten. Hierbij moet wel opgemerkt worden dat deze methodes eerder als referentiescenario's beschouwd moeten worden, vanwege hun gebruik van voorspellingen die mogelijk moeilijk te bekomen zijn. De studie geeft echter wel een beeld welke ruimte voor verbetering er nog is en wat de invloed van bepaalde ontwerpkeuzes is.

Na het behandelen van de mogelijke negatieve effecten van het herladen, werd gekeken naar mogelijkheden waarbij herladen kan gebruikt worden om diensten te leveren aan het elektriciteitsnetwerk. Zo varieert de productie van groene energie doorheen de tijd, wat het moeilijk maakt om productie en consumptie te balanceren. Deze balans moet ten allen tijde behouden worden. We hebben echter reeds gezien dat door middel van vraagsturing de piekbelasting van het elektriciteitsnetwerk beperkt kan worden. We kunnen diezelfde flexibiliteit inzetten om productie en consumptie te balanceren. We verschuiven dan het herladen naar periodes waarin er veel productie is, waardoor we minder energie van conventionele bronnen nodig hebben.

We bereiken dit door gebruik te maken van een hiërarchische aanpak waar zogenaamde aggregatoren instaan om de flexibiliteit van elektrische voertuigen te beheren. We combineren daarbij elementen van centrale en decentrale methodes voor vraagsturing en bekomen op die manier een schaalbaar en privacy vriendelijk systeem. Dit wordt onder meer bereikt met behulp van de aggregatoren die flexibiliteitsinformatie aggregeren vooraleer het aangeboden wordt hogerop in de hiërarchie. Op basis daarvan worden aggregatoren een planning toegekend. Aggregatoren faciliteren op basis daarvan het onderhandelingsproces dat gebruikt wordt voor het bepalen van oplaadschema's. Gebruikers krijgen de mogelijkheid om zekere voorkeuren in te stellen over hoe hun flexibiliteit ingezet wordt. Deze voorkeuren moeten zij bovendien niet delen met de aggregatoren, maar bepalen wel op welke wijze zij deelnemen aan de onderhandelingen. Simulaties tonen aan dat we op basis van dergelijk systeem efficiënter gebruik kunnen maken van groene energie en op hetzelfde moment ook rekening houden met de wensen van de gebruikers.

De integratie van elektrische voertuigen in smart grids is het hoofdonderwerp van dit proefschrift. We bestudeerden verschillende methodes van vraagsturing voor het reduceren van de piekbelasting en het balanceren van groene energie. Willen we echter het volledige potentieel van dergelijke methodes benutten, dan moeten we meer weten over de omgeving waarin ze te werk gaan. Slimme meters meten het verbruik en de productie in detail en bieden ondersteuning voor dynamische tarieven. Deze meters kunnen vanop afstand uitgelezen worden en eveneens aan- of uitgeschakeld worden. De gegevens die deze meters verzamelen bieden een waardevolle bron van informatie over de consumptie- en productiepatronen die we met vraagsturing bespelen.

We beperken ons even tot consumptiepatronen die per dag verzameld worden gedurende een jaar. Het doel is om hieruit een beperkt aantal representatieve consumptiepatronen op te stellen die een gebruiker of groep van gebruikers karakteriseren. We maken hiervoor gebruik van een zogenaamde clustering aanpak die uit twee fases bestaat. De eerste fase zal voor elke gebruiker zijn of haar representatieve consumptiepatronen bepalen, door middel van het groeperen van gelijkaardige patronen. De tweede fase verloopt analoog, maar gebruikt de resultaten van de eerste als invoer. Op die manier karakteriseren we zowel individuele gebruikers, als de groep van gebruikers.

Karakteriserend aan onze aanpak, is dat we slechts een beperkte set van eigenschappen gebruiken tijdens het clusteren die robuust zijn voor verschuivingen in de tijd. Hierdoor zullen identieke consumptiepatronen die ten opzichte van elkaar verschoven zijn in de tijd, ook als gelijkaardig beschouwd worden. Dit is in andere methodes vaak niet het geval. Hierdoor benadrukken we het achterliggende gedrag. We bekomen bovendien een schaalbaar systeem door gebruik te maken van de twee fases en de beperkte set van features. De resultaten die voortvloeien uit deze methode kunnen gebruikt worden om het verbruik te voorspellen, of mogelijk om de flexibiliteit van een gebruiker in te schatten.

English summary

Sustainability, reliability, and energy efficiency concerns are changing the way energy is produced and consumed. Governments worldwide are for example stimulating the adoption of renewable energy and electric vehicles. However, this does not come without challenges. Solar and wind power depend on weather factors over which we have no control, and electric vehicles represent a considerable load to the grid. However, the power grid was not designed with these changes in mind. As a result, the power grid is transitioning to a so-called smart grid. In the smart grid, power grid and information and communication technologies (ICT) are integrated to generate, transport, and consume energy in a more efficient way. Key to the smart grid concept is demand side management (DSM). In a traditional power grid structure, power generation follows the changes in demand. Instead, DSM influences demand to follow generation, reduce peak loads, or balance renewable energy. This dissertations focuses on the optimal integration of electric vehicles in smart grids. It presents contributions in three areas: (i) smart grid simulation, (ii) demand side management of EVs, and (iii) energy consumption analysis.

Simulators are cost effective, safe, flexible, and fully controlled environments to evaluate new smart grid concepts. In the context of smart grids, the combined simulation of the power grid, communication infrastructure, and control algorithms on top is essential. It are the interactions between them are at the core of the smart grid concept, and thus simulation tools should reflect that. However, this is not always the case. An in depth survey presents three types of simulators in the smart grid area: power system simulators, communication network simulators, and combined power and communication simulators. Power system simulation tools can be organized in two main application areas: (i) steady state analysis typically dealing with power flow studies, or (ii) transient dynamics simulations for disturbances or sudden system changes. Combined power system and communication network simulation often follows a co-simulation approach, where different domain simulators are combined, requiring careful synchronization of simulation models. However, the smart grid simulator developed as part of this research offers a more integrated solution, that has a tighter coupling between different domain models. Models for the power system, communication network, and control logic are defined in a single environment. The simulator has been used in context of EV charging, home energy management, and integration of renewable energy sources.

Provided with the necessary simulation tools, we can assess the impact of EV charging on the power grid. Electric vehicles (EV) need to be recharged frequently because of their limited range and the resulting range anxiety of users. However,

charging electric vehicles can lead to problems such as excessive peak load, and voltage fluctuations outside the permissible range. To deal with such problems, DSM approaches can be used to control and coordinate EV charging by shifting charging to times of low demand (i.e., load shifting). We consider such load shifting approaches from different perspectives (e.g., local, global) to gain more insight into the architecture, and information and communication requirements. Quadratic programming is used to model these different approaches and we asses their performance in terms of peak load, demand variability, and voltage fluctuations. We consider a scenario in a residential area.

We first considered an approach that operates at the residential level, using no external information or control signal. Based on the time available for charging, the energy requirement, and the expected household consumption during that time, the home energy management system determines a charging schedule when the vehicle is plugged-in. Such a charging schedule specifies when the EV can charge, together with the charging power. This purely local approach is already able to shift most of the additional peak load that would have otherwise come from EV charging, and demonstrates the positive effect of spreading demand at a local level.

Next, we assessed the performance of an approach where a central controller coordinates charging of multiple vehicles. If a vehicle requests to charge, the home energy management system connects to a controller that determines a charging schedule based on the expected consumption of the neighborhood (incl. EVs already charging), and the charging constraints. This reduces the peak load even further to the level that it would be without EV charging. However, extra complexity is added by using a central controller.

We compared these approaches to a multi-agent system (MAS) that uses market based coordination and does not require consumption forecasts. Simulations of a residential area show that controlled charging reduces peak load, load variability, and deviations from the nominal grid voltage. Also, local approaches already lead to substantial peak load reduction. The approaches based on quadratic programming obtained the best results, but mainly served as benchmark, since the requirement of consumption forecasts makes them less practical. However, it allowed us to identify the room for improvement in the MAS approach. In addition, we showed that controlled charging reduces the number of voltage fluctuations outside of the permissible range.

After considering the challenges stemming from EV charging, we considered the opportunities where EV charging could provide an additional service to the grid. The output from renewable energy sources varies over time, making it difficult to balance supply and demand. However, we have already seen that DSM approaches can shift flexible charging load such that the peak load and voltage fluctuations are reduced. That same flexibility can be used for balancing supply and demand. More specifically, we can shift electric vehicle charging in time, so it coincides with renewable energy production, thereby reducing the need for additional generation from conventional sources.

To achieve this, we propose a hierarchical approach that uses aggregators to manage the flexibility from EVs. It combines elements from centralized and decentralized DSM to obtain a scalable and privacy-friendly system. This achieved by using aggregators that aggregate the flexibility information before passing it higher up in the hierarchy. Based on this aggregated flexibility information, the aggregators are assigned a target load schedule. Based on this, aggregators facilitate the negotiation process that is used to determine the charging schedules of each EV. Users can specify certain charging preferences, that are not shared with the aggregator, but that influence how they respond during the negotiations. Simulations have shown that this leads to a more efficient use of wind energy, while at the same time accounting for user preferences.

The integration of electric vehicles in the smart grid is the main topic of this dissertation. We studied different approaches for load shifting and matching renewable energy and demand. However, to achieve their full potential, we need to have a full understanding of the environment in which they operate. Smart meters support detailed measurements of energy consumption and production, dynamic pricing, remote control and meter reading, etc. Data collected by those smart meters provides a valuable source of information about the energy consumption and production patterns we are changing with DSM.

We used a two-stage clustering approach to identify typical daily consumption patterns (load profiles) of individual customers and customer groups. The first stage derives typical daily load profiles from individual users based on smart meter data. The second stage uses the typical load profiles from all those users combined, and groups those. We use a limited set of features that are robust to shifts in time, thereby emphasizing the type of patterns occurring in the load profiles instead of the times at which they occur. The combination of our feature choice, and two-stage architecture leads to a scalable system. The results obtained from this, could be used as input for load forecasting methods, or even for assessing the flexibility of customers.

1 Introduction

1.1 Smart Power Grids

The electrical power grid since its inception was designed to deliver power from a small number of large centralized generation units over transmission networks towards the consumers connected to distribution networks. However, the power grid is currently undergoing profound changes towards the so-called smart grid, with the main drivers being sustainability, energy efficiency, and reliability [1]. Initiatives such as the EU 20-20-20 targets demonstrate the interest in smart grids. These targets are to be met by 2020 and aim for (i) a reduction in greenhouse gas emissions of at least 20%, (ii) 20% of energy consumption to come from renewable energy sources, and (iii) a 20% reduction of energy consumption [2]. Figure 1.1 illustrates the smart grid and brings forward several concepts that are key to the smart grid concept and the work presented in this dissertation:

- Distributed renewable energy sources (e.g., wind, solar, wave).
- Electric vehicles (EVs).
- Smart meters.
- Demand side management (e.g., smart charging).
- ICT infrastructure and services.

The ongoing transition to renewable energy sources (e.g., solar and wind) and new sources of energy demand (e.g., electric vehicles, heat pumps) are (among

Figure 1.1: The smart grid of the future.
(Image source: European Technology Platform Smart Grids: Future Network Vision)

others) driving forces behind the smart grid. It is clear that those changes in demand and supply will have an impact on the power grid, e.g., supply planning becomes more complicated because of the intermittent nature of renewable energy sources and changing demand patterns, especially considering that electricity has to be used the moment it is generated. Indeed, the power grid represents the ultimate example of just-in-time product delivery [3].

To tackle these supply and demand challenges, smart grids will integrate power grid technologies, and information and communication technologies (ICT) to generate, transport, distribute and consume electricity in a more efficient manner.

Smart meters can be considered a first step towards a smarter power grid, and support detailed measurements of energy consumption and production, dynamic pricing, remote control and meter reading, etc. Monthly bills are based on measured energy consumption, instead of estimates. However, smart meters and other smart grid technologies have also raised concerns, e.g., because of privacy issues. Indeed, monitoring of energy consumption patterns provides much insight about the end-users and their activities [4].

Households equipped with home energy management systems will make better use of the available resources, taking advantage of local generation, storage, and flexibility in demand. Public and private parking areas equipped with smart charging infrastructure will ensure that charging is coordinated to avoid overloading the grid. This is achieved using demand side management (DSM) techniques, that modify energy usage patterns in response to financial or other incentives.

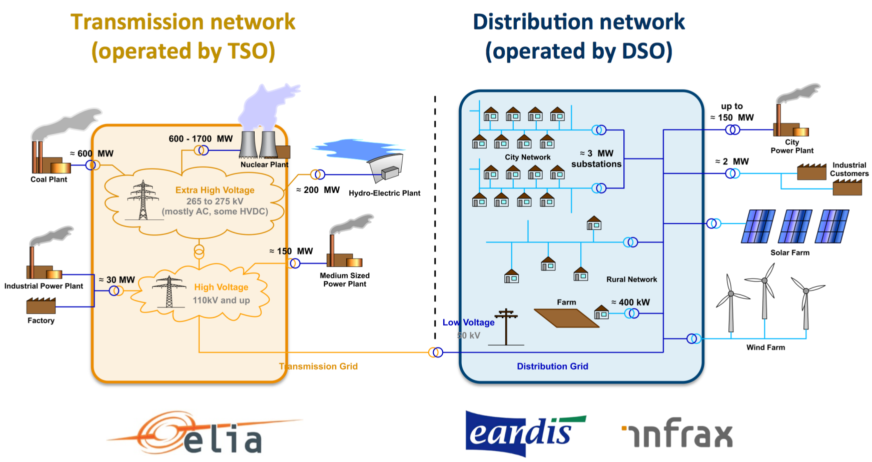

Figure 1.2: Illustration of the structure of the power grid in Belgium [6].

New services, business models, and regulatory frameworks need to be defined to reach the full potential of the smart grid. For example, demand side management applications benefit from accurate forecasts of demand and renewable supply. Consumers connected to the distribution grid are taking on an active role in the energy market, being so-called *prosumers*, i.e., consumers and producers of energy at the same time. Retail energy markets [5] are therefore being considered to facilitate active participation of those consumers, as a way to control their energy costs and consumption.

The integration of electric vehicles in the smart grid is the primary topic of this dissertation. However, let us first consider renewable energy a bit closer, before going deeper into which challenges and opportunities EVs pose.

1.2 Renewable Energy

The power grid was designed to deliver power from a few large centralized generation units over transmission networks towards the consumers connected to distribution networks. However, the power grid is moving away from such a centralized power generation paradigm. With governments actively promoting renewable energy, distributed generation is happening throughout the grid. We illustrate this in Figure 1.2. Conventional power plants (e.g., nuclear, coal, gas) are connected to the high-voltage transmission grid. In contrast, distributed generation from renewable energy sources takes place in the distribution grid at medium (e.g., wind turbines) and low voltage level (e.g., rooftop photovoltaic (PV) installations).

However, the intermittent nature of renewable energy sources, such as wind and solar, makes it difficult to balance demand and supply, which must be maintained at all times for the correct operation of the power grid. In addition, the power grid was originally designed for power flowing in one direction, from producer to consumer. However, the rise of distributed energy sources, which are placed throughout the grid, leads to bi-directional power flows. Typical issues of stemming from the presence of such distributed generation (DG) include: voltage and frequency instabilities as a result of local power generation, and power security issues resulting from bidirectional energy flows [7]. Therefore careful management of these energy sources is required.

In residential neighborhoods with PV installations there is often a mismatch between production and consumption of power generated by these installations. Peak PV output is reached around noon, however demand peaks in the evening when people arrive at home and start cooking, washing, etc., when output from PV installations is low, especially in winter. When PV power production exceeds consumption, power is injected into the grid, possibly causing the voltage to rise beyond its permissible range. In such cases, the PV installation must automatically disconnect from the grid. To solve this, we can use local energy storage (e.g., batteries, thermal), or try to (automatically) shift demand in order to coincide with supply. In both cases, power injection into the grid is reduced or avoided.

1.3 Electric Vehicles

To achieve cleaner and more energy-efficient transportation, governments worldwide are providing incentives to promote the use of (hybrid) electrical vehicles. Through financial incentives (e.g., tax reductions) and free additional services (e.g., free parking, battery charging), consumers, public organizations, and companies are being stimulated to adopt electric vehicles. As a result, (hybrid) electric vehicles are gaining in popularity.

However, as the electrification of the vehicle fleet is gaining momentum, changing demand patterns caused by it will have an impact on the power grid. Electric vehicles represent an additional load on the power grid that originates from the need to recharge the batteries of plug-in hybrid electric vehicles (PHEVs), especially in high-concentration areas such as residential areas and public parking places. Electric vehicles not only require significant amounts of electricity to recharge their batteries, the location where the charging will take place is not fixed. Electric vehicles are what could be called “mobile energy consumers”, as their demand for energy is not limited to a single location. Adequately dealing with such electric vehicles forms part of the challenges and opportunities in the evolution towards smart grids.

Let us first consider the different types, before further discussing their unique role in the smart grid. Electric vehicles (EV) are vehicles that can be recharged from an external source of electricity, e.g., from regular wall outlet or dedicated EV charger. Plug-in hybrid electric vehicles (PHEV) combine a conventional internal combustion engine (ICE) with an electric motor and can also be recharged from an external source. Hybrid electric vehicles (HEV) without external recharging capabilities do also exist. Further distinctions can be made, but are not essential for the remainder of this work. In the remainder of this dissertation, we focus on vehicles with plug-in capabilities. For our purposes, the distinction between an EV and PHEV lies mostly in the dimension of their batteries. Two examples are given to get an impression of their characteristics.

The Nissan Leaf [8] is an EV with a range of approximately 200 km. The time required to recharge, depends on the type of charger used: up to 12 hours using a regular wall socket, between 4 to 8 hours using a dedicated charger, or 30 minutes using a fast charger (limited to 80%). It is equipped with a battery of 24 kWh. The Opel Ampera [9] is an example of a PHEV. It has a full electric range of 40 to 80 km, which is extended to 500 km by a range extender. In can be recharged in less than 4 hours using a regular wall socket. It is equipped with a 16 kWh battery, of which only 10 kWh is effectively used to maximize its lifetime. Recharging at home will typically be in the range of 2 to 7 kW, depending on the type of installation. In Belgium, a typical single phase household grid connection (40A, 230V) supports up to 9.2 kW. This puts EV charging in perspective, and already indicates that EV charging is not just another load.

1.3.1 Challenges

P(H)EVs will represent a significant new load on the existing distribution grids, especially as their penetration level increases. Their limited range and the resulting range exiguity of the users will lead to frequent charging. Research estimated that their number in Belgium would reach 30% by 2030 [10]. Additional generation would thus be required to recharge the batteries of these vehicles as this requires large amounts of electrical energy. However the energy required to charge these vehicles is estimated to be only 5% of total consumption in Belgium [11] in 2030. The impact on the generation and transmission levels of the power grid are therefore considered manageable on a short to medium term. However, the impact on the (residential) distribution network can be substantial, especially for high penetration levels of EVs: a single EV is estimated to double average household load during charging [1]. Related studies have also been done abroad. According to a US study, the current power grid infrastructure has enough spare generating capacity to support PHEV penetration levels ranging from 30% to 70% when being considered at large scale (e.g., nation wide) [12]. This spare generating capacity however is mostly available during off-peak moments such as night time. Hence, there is an opportunity to limit the extra electricity required to satisfy the PHEV charging demand by shifting it in time. To make optimal use of this spare generating capacity, we need control mechanisms that achieve shifting the resulting charger loads to times at which spare generating capacity is available.

This bring us to the problem of peak load. An increase in peak load is a concern because charging of EVs is expected to coincide with existing (e.g., evening) peaks and hence increase them. To deal with these peak loads, additional and more expensive peak power would need to be generated. As costs are low for base load capacity, but high for peak load capacity, there is thus a need to manage the peak load to reduce energy costs. In addition, these changes in load patterns may require upgrades to (distribution) power grid components such as transformers. The peak load is also an important factor when dimensioning the infrastructure of the power grid. Besides such economical concerns, technical concerns such as maintaining the power quality (e.g., voltage, unbalance) are also important to assure the correct operation of the power grid. Indeed, voltage deviations, power losses [13], transformer and feeder overloads, reduced operating efficiency [14], etc. could occur as a result of higher peak loads. Therefore, it is important to control and coordinate the charging of (plug)-in hybrid electric vehicles.

1.3.2 Opportunities

Electric vehicles are examples of so-called flexible consumers. The main concern of vehicle owners is to have the batteries charged by the time they need their vehicle again. Thus, a certain degree of flexibility is available, because vehicles are often parked for periods of time that are longer than the time required to charge their batteries, for example during the night. A study has shown that personal vehicles are only used 4% of the time for transportation, and the remaining 96% they are not used and thus can be used for other purposes [15]. This flexibility leads to new opportunities, especially in the context of green energy.

If power generation becomes increasingly dependent on renewable sources, supply and demand matching will obviously become more challenging. However, EVs can be used to store energy on a wide-scale. Exploiting the flexibility in deciding when to charge an EV battery can partly alleviate this problem of intermittent (and unpredictable) energy supply. Moreover, the batteries may also be exploited as temporary storage of the fluctuating energy supply, and serve as energy storage resource that can give energy back to the grid while parked, also known as vehicle-to-grid (V2G) power [15]. Thus, not only can the renewable energy be used to power the transport functions of the PHEV, but V2G can also be exploited to provide ancillary grid services (e.g., peak power, spinning reserves, regulation).

We can also exploit this flexibility in charging and discharging, to reduce the peak load that would otherwise be caused by EV charging. Both these cases present opportunities for the development of intelligent charging algorithms that utilize this flexibility to avoid issues in the distribution grid and even provide additional services. These algorithms will decide on when to charge which vehicle, and potentially at what charging rate (if this can be tuned), as to achieve a certain objective (e.g., peak shaving, load shifting, maximally use available green energy). These techniques are not limited to electric vehicles, but also extend to other use cases. This fits in the more general context of demand side management.

1.4 Demand Side Management

Demand side management (DSM) is a key smart grid concept. DSM influences the demand for electricity, which is achieved by switching consumers on and off (i.e., binary control), or by regulating their power consumption during operation (i.e., modular control). We have already seen examples of DSM in the context of EVs (e.g., avoiding excessive peak loads). However, DSM is also applied in other contexts, e.g., households, and industries. The amount of flexibility depends on this context, e.g., household flexibility is in the watt to kilowatt (kW) range, whereas industrial flexibility is in the megawatt (MW) range.

The Linear project [16] [1] is financed by the Flemish government and studies how demand side management can tailor residential energy consumption to the amount of solar or wind production. Several devices were identified as potential candidates for DSM: electric boiler, heat pump, EV, dishwasher, washing machine, and clothes dryers [17]. The following business cases for residential DSM are evaluated in the project:

- **Portfolio management:** Households get six different rate categories per day, which are based on wind, solar, supply, and demand forecasts. Manual and automated control can be used to respond to these dynamic tariffs.

- **Wind balancing:** Regional variations make wind energy difficult to predict. DSM is used to correct forecast errors in real time, by automatically switching devices on or off in real time.

- **Transformer aging:** Transformers that supply neighborhoods have difficulty processing the peaks from renewable energy. By reducing the peak load, the temperature of the transformer is reduced, thereby extending its lifetime. To achieve this, consumption is tailored to the amount of locally generated energy.

- **Line voltage profile:** Local energy production (e.g., PV installation) can lead to fluctuating voltage levels in the distribution lines, making it difficult

[1] http://www.linear-smartgrid.be

for the grid operator to keep the voltage within the permissible range. Automated control can be used to optimize the voltage level at the household grid connections.

The e-harbours [2] project focuses on large industrial consumers and producers in harbor areas, and aims to improve local energy efficiency and increase the share of renewable energy. The following business cases for industrial DSM are evaluated in the project [18]:

- **Trade on the wholesale market:** The variable price of electricity on wholesale markets, and the presence of flexibility, can be exploited to reduce energy cost.
- **Balancing group settlement:** Balancing responsible parties (BRP) are responsible for balancing consumption and production in their portfolio. Flexible consumption and production can help to maintain that balance.
- **Offer reserve capacity:** In cases that BRPs are not always able to maintain balance, the transmission system operator (TSO) has to use reserve capacity in order to restore balance. Flexible customers can offer their flexibility to the TSO for balancing purposes.
- **Local system management:** Local energy production can lead to local problems in the distribution grid (e.g., transformer and line congestion). Again, flexibility can be used to to keep the grid operating in an optimal way within its constraints.

These two projects give a good indication of the business-cases that are being evaluated for demand side management.

1.5 Contributions

The ongoing transition towards a smart grid comes with challenges and opportunities. This dissertation proposes three key research contributions that deal with both from the perspective of integrating electric vehicles in our evolving infrastructure. First, a *smart grid simulator* that models and simulates the communication and power networks, and the control mechanisms. Second, *demand side management algorithms* for the optimal integration of electric vehicles by avoiding excessive peak loads from charging, or by providing additional services to the grid (e.g., vehicle-to-grid, balancing renewable energy sources). Third, a *two-stage clustering algorithm* to group similar energy consumption or production patterns, e.g., obtained from smart meters. Following is a detailed overview of the contributions.

[2] `http://www.eharbours.eu`

Simulation is key to asses the effectiveness of control mechanisms, architectures, and network technologies that are being proposed to realize the smart grid. Simulation in both the areas of communication networks and power systems has been widely adopted. However, the coupling of those two worlds in the frame of smart grids calls for tools able to address both. To understand the interaction between these two areas, it is essential that we can model and study both at the same time. We propose an innovative integrated framework [19] that models and simulates both the communication and power networks. The flexibility of the framework is demonstrated in various applications: (i) demand side management algorithms for electric vehicles [20], (ii) multi-agent based residential energy management [21], and (iii) assessment and mitigation of voltage violations caused by PV [22]). Further, an in-depth survey [23] of power system, communication network, and smart grid simulators, provides a classification and comparison in terms of their application domains, supported features, limitations, design, etc. In addition we point out the challenges and methods to deal with challenges stemming from the combined simulation of power systems, communication network and smart grid applications.

Demand side management algorithms are used to modify the energy consumption patterns of end-users, e.g., to avoid excessive peak loads, increase local consumption of renewable energy, balance supply and demand, or adapt to dynamic prices. Electric vehicles are the primary focus in this dissertation, because they represent a significant load to the grid, but at the same time are flexible in meeting their charging requirements. Demand side management algorithms are proposed for two key application domains: (i) load shifting to avoid high peak loads, and (ii) balancing renewable energy. Those algorithms are benchmarked to so-called business-as-usual or uncontrolled scenarios where no form of control of coordination exists, theoretical upper bounds, and other state-of-the-art algorithms.

Load shifting is concerned with avoiding increased peak loads (e.g., evening hours) stemming from electric vehicle charging. Charging demand is shifted towards low demand periods, leading to a more stable base load. In our work, load shifting is approached from different architectural perspectives, ranging from completely local mechanisms (e.g., household level) where decisions are made locally with limited or no external inputs, to global mechanisms [24] where decisions are made by a central entity with a system wide view. Extensions to these strategies also consider vehicle-to-grid operation during which power is injected back into the grid [25], which reduces the peak load even further. The limitations that may be imposed by the charging infrastructure and their impact have been considered [26]. In addition, we show that voltage limit violations can be avoided, event without taking those explicitly in account [20]. Combined, this gives a broad view on how to avoid avoid negative effects such as peak load and voltage violations caused by electric vehicle charging.

Matching supply and demand is complicated by renewable energy sources. However, the adoption of electric vehicle also introduces new opportunities, i.e., their charging can be coordinated in such a way that charging demand is shifted in time to periods of high availability of renewable energy, thereby reducing the need for additional generation from conventional sources. To achieve this, we propose a privacy-friendly decentralized strategy [27] that can be extended to a hierarchical approach [28] that combines elements from centralized and decentralized strategies. Although centralized strategies lead to the most optimal results, decentralized strategies are shown to be more scalable and privacy-friendly. However, by combining elements from both, hybrid solutions emerge. Privacy is enhanced because limited information is shared and the end-user can specify preferences for how his or her flexibility is used. Those preferences are not shared, but are kept confidential. In addition, the hierarchical structure provides inherent support for different control levels, possibly operated by different market entities.

Extracting information from raw data (e.g., obtained from smart meter or demand side management programs) will be crucial to reach the full potential of the smart grid. Smart meter data are considered a valuable source of information for tariff purposes, demand forecasting, demand side management, etc. A **two-stage clustering** algorithm [29] is proposed to analyze daily energy consumption patterns or load profiles from individual end-users and groups of end-users. The first stage groups similar load profiles on a per user basis, from which representative profiles are derived. Those provide end-users insight in their consumption patterns, or can be used for demand side management applications (e.g., evaluation of the impact of DSM, identification of flexibility). The representative load profiles from all users are used as input for stage two, leading to clusters of different energy consumption patterns that exist within group of end-users. We focus on a heterogeneous set of customers connected to the distribution grid, whereas related work is often limited to industrial consumers with more regular patterns. The careful selection of our features and clustering algorithm is translated to a scalable system with unique features for demand side management applications.

1.6 Outline

The discussion of the key research contributions provides references to articles published or submitted to peer-reviewed journals and conference proceedings that describe these contributions in detail. A selection of these contributions is included in this dissertation. The outline of this dissertation is as follows. Chapter 2 provides an in depth survey of power system, communication network, and smart grid simulators. We motivate the need for such simulation tools and provide an overview of the different application domains. In addition, the survey includes a summary of the integrated smart grid simulator framework developed for our research. We classify the different simulators according to targeted use cases, simulation model level of detail, and architecture. Chapter 3 compares charging algorithms (local, iterative, global, and multi-agent based) for electric vehicles that reduce peak load and demand variability in a distribution grid. Their effectiveness is evaluated in terms of reducing the peak load, and in terms of their impact on the voltage levels in the grid. Chapter 4 proposes a privacy-friendly hierarchical approach to balance renewable energy and electric vehicle charging demand, while respecting user preferences with regard to how their flexibility is used. Chapter 5 proposes the two-stage approach to cluster daily load profiles from individual and groups of end-users. Finally, Chapter 6 summarizes the conclusions and future research perspectives.

1.7 Publications

1.7.1 Publications in international journals

1. **Kevin Mets**, Reinhilde Dhulst, and Chris Develder. *Comparison of Intelligent Charging Algorithms for Electric Vehicles to Reduce Peak Load and Demand Variability in a Distribution Grid.* Journal of Communications and Networks, 14(6):672–681,2012.

2. **Kevin Mets**, Juan Aparicio, and Chris Develder. *Combining power and communication network simulation for cost-effective smart grid analysis*. IEEE Communications Surveys and Tutorials, 16(3):1771–1796, 2014.

3. **Kevin Mets**, Gary Atkinson, Marina Thottan, Chris Develder. *Privacy-friendly hierarchical demand side management with user preferences.* Submitted to IEEE Transactions on Smart Grid, 2014.

4. **Kevin Mets**, Frederick Depuydt, and Chris Develder. *Two-stage load profile clustering using fast wavelet transformation*. Submitted to IEEE Transactions on Smart Grid, 2014.

1.7.2 Publications in international conferences

1. **Kevin Mets**, Tom Verschueren, Wouter Haerick, Chris Develder, and Filip De Turck. *Optimizing smart energy control strategies for plug-in hybrid electric vehicle charging*. In Proc. 1st IFIP/IEEE Int. Workshop on Management of Smart Grids, at 2010 IEEE/IFIP Netw. Operations and Management Symp. (NOMS 2010), pages 293–299, Osaka, Japan, 19-23 Apr. 2010.

2. Tom Verschueren, Wouter Haerick, **Kevin Mets**, Chris Develder, Filip De Turck, and Thierry Pollet. *Architectures for smart end-user services in the power grid.* In Proc. 1st IFIP/IEEE Int. Workshop on Management of Smart Grids, at 2010 IEEE/IFIP Netw. Operations and Management Symp. (NOMS 2010), pages 316–322, Osaka, Japan, 19-23 Apr., 2010.

3. **Kevin Mets**, Tom Verschueren, Filip De Turck, and Chris Develder. *Evaluation of multiple design options for smart charging algorithms.* In Proc. 2nd IEEE ICC Int. Workshop on Smart Grid Commun., Kyoto, Japan, 5 Jun. 2011.

4. **Kevin Mets**, Tom Verschueren, Chris Develder, Tine Vandoorn, and Lieven Vandevelde. *Integrated simulation of power and communication networks for smart grid applications*. In Proc. 16th IEEE Int. Workshop Computer Aided Modeling, Analysis and Design of Commun. Links and Netw. (CAMAD 2011), pages 61–65, Kyoto, Japan, 1011 Jun. 2011.

5. **Kevin Mets**, Tom Verschueren, Filip De Turck, and Chris Develder. *Exploiting V2G to Optimize Residential Energy Consumption with Electrical Vehicle (Dis)Charging*. In Proc. 1st Int. Workshop Smart Grid Modeling and Simulation (SGMS 2011) at IEEE SmartGridComm 2011, pages 7–12, Brussels, Belgium, 17 Oct. 2011.

6. Tom Verschueren, **Kevin Mets**, Bart Meersman, Matthias Strobbe, Chris Develder, and Lieven Vandevelde. *Assessment and mitigation of voltage violations by solar panels in a residential distribution grid*. In Proc. 2nd IEEE Int. Conf. Smart Grid Communications (SmartGridComm 2011), pages 540–545, Brussels, Belgium, 17–20 Oct. 2011.

7. **Kevin Mets**, Matthias Strobbe, Tom Verschueren, Thomas Roelens, Chris Develder, and Filip De Turck. *Distributed multi-agent algorithm for residential energy management in smart grids.* In Proc. IEEE/IFIP Netw. Operations and Management Symp. (NOMS 2012), Maui, Hawaii, USA, 16–20 Apr. 2012.

8. Matthias Strobbe, Tom Verschueren, **Kevin Mets**, Stijn Melis, Chris Develder, Filip De Turck, Thierry Pollet, and Stijn Van De Veire. *Design and evaluation of an architecture for future smart grid service provisioning*. In Proc. 4th IEEE/IFIP Int. Workshop on Management of the Future Internet (ManFI 2012). Maui, Hawaii, USA, 2012, pages 1203–1206.

9. Wouter Labeeuw, Sven Claessens, **Kevin Mets**, Chris Develder, and Geert Deconinck. *Infrastructure for collaborating data-researchers in a smart grid pilot.* In Proc. 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGTEU 2012). pages 1–8, Berlin, Germany, 14–17 Oct. 2012.

10. **Kevin Mets**, Filip De Turck, and Chris Develder. *Distributed smart charging of electric vehicles for balancing wind energy*. In Proc. IEEE 3rd Int. Conf. on Smart Grid Communications (SmartGridComm), pages 133–138, Tainan, Taiwan, 5–8 Nov 2012.

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1.7.3 Publications in national conferences

1. **Kevin Mets**, Wouter Haerick, and Chris Develder. *A simulator for the control network of smart grid architectures.* In Proc. 2nd Int. Conf. Innovation for Sustainable Production (i-SUP 2010). pages 50–54. Bruges, Belgium, 2010.

2. **Kevin Mets**. *Optimal and scalable management of electric vehicles in smart power grids*. In Proc. Ghent University Faculty of Engineering and Architecture (FEA) 12th PhD Symposium, Ghent, Belgium, 2011.

3. **Kevin Mets**. *Optimizing energy consumption in residential smart grids*. In 5th Strategic Energy Forum (Poster Session). Brussels, 2011.

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2

Combining power and communication network simulation for cost-effective smart grid analysis

In this chapter, we look at how simulation is used in the context of smart grids. It provides an overview of power system, communication network, and combined power and communication simulators (i.e., smart grid simulators). In addition, it introduces our integrated smart grid simulation framework used for use cases such as the assessment of approaches for the optimal integration of electric vehicles in the smart grid.

⋆ ⋆ ⋆

Kevin Mets, Juan Aparicio, and Chris Develder.

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Abstract Today's electricity grid is transitioning to a so-called smart grid. The associated challenges and funding initiatives have spurred great efforts from the research community to propose innovative smart grid solutions. To assess the performance of possible solutions, simulation tools offer a cost effective and safe approach. In this paper we will provide a comprehensive overview of various tools and their characteristics, applicable in smart grid research: we will cover both the

communication and associated ICT infrastructure, on top of the power grid. First, we discuss the motivation for the development of smart grid simulators, as well as their associated research questions and design challenges. Next, we discuss three types of simulators in the smart grid area: power system simulators, communication network simulators, and combined power and communication simulators. To summarize the findings from this survey, we classify the different simulators according to targeted use cases, simulation model level of detail, and architecture. To conclude, we discuss the use of standards and multi-agent based modeling in smart grid simulation.

2.1 Introduction

Today's electricity grid is transitioning to a so-called *smart grid*. This is driven by the objective of making electricity delivery more reliable, economical and sustainable. Given the reliance of critical services (e.g., transportation, communication, finance) on the power grid, demand for a resilient and self-healing grid is high. The challenge to realize it is complicated by the ever increasing penetration of renewable and distributed energy, adding an extra uncertainty dimension and thus the need for efficient responses to not only varying customer demand, but also to varying (and less controllable) production levels: demand-side management (DSM), in particular demand response (DR) is increasingly important to keep the grid operation economically viable (i.e., feasible without excessive infrastructure investments). Indeed, the power grid since its inception was designed to deliver power from large centralized generation units unidirectional over transmission networks towards the consumers connected to distribution nets. To make it more economical, distributed sources could help reduce the distance between production and consumption (thus limiting transmission losses, which typically amount to 8% [1]). Further, DSM/DR approaches can help to reduce required generation capacity to deal with peak demand only (for which around 20% of current generation capacity is deployed [1]).

While the smart grid transition happens at the various grid levels (i.e., generation, transmission and distribution), much research attention is going to the distribution grid, where today limited control is available. Also, typically the roots of power system issues trace back to this distribution level [1].

Central to the smart grid concept, is the convergence of information and communication technology with power system engineering. Modern monitoring, analysis, control, and communication capabilities are being added to the aging infrastructure of the electricity grid, to more accurately get insight in the current grid state and use that knowledge to operate it more efficiently. The latter also implies environmental constraints, which are an important underlying motivation for the smart grid evolution, as exemplified by e.g., the European Union's "Climate and

Energy Package" definition of the famous 20-20-20 targets, to be met by 2020: (i) 20% of energy supply should stem from renewable energy sources, (ii) reduce greenhouse gasses with 20%, (iii) 20% increase in energy efficiency.

Undeniably, aforementioned challenges and associated funding initiatives have spurred great efforts from the research community to propose innovative smart grid solutions. Smart grid technology typically results in an increased complexity of the power grid, and implies uncertainty (to be dealt with by, e.g., stochastic control models). To assess the performance of possible solutions, simulation tools offer a cost effective approach. In this paper, we will provide a comprehensive overview of the various tools and their characteristics, applicable in smart grid research: we will cover both the communication and associated ICT infrastructure, on top of the power grid.

The aim of our work is to assist (i) smart grid *researchers* looking for tools that target a certain use case, as well as (ii) smart grid simulator *developers* that wish to gain insights and learn more about simulator paradigms, architectures, standards, etc. However, it is not our intention to provide a detailed implementation guide for smart grid simulators.

The remainder of this introduction outlines the main power grid challenges and indicates how they call for communication infrastructure to be added. In Section 2.2 in general, and more specifically in Section 2.2.1, we motivate the choice for a simulation approach in the domain of smart grids. Section 2.2.2 points out possible pitfalls to aspiring developers of a smart grid simulator, through an overview of the related design challenges. From a researcher's perspective, the same overview of design challenges can serve as a guide whether to develop custom simulation tools, or rather aim to reuse existing tools where possible. A general overview of smart grid simulation paradigms is given in Section 2.3. Specifically, Section 2.3.1 provides insights into the two main approaches used to achieve combined simulation of communication networks and power grids, and Section 2.3.2 goes into more detail regarding the differences in modeling time in both domains. Although this survey is focused on software based simulation, we briefly discuss the related concepts such as emulation, real-time simulation, and hardware-in-the-loop in Section 2.3.3. Next, we will discuss the three types of simulators in the smart grid area: power system simulators in Section 2.4, communication network simulation tools in Section 2.5, and combined power and communication simulation in Section 2.6. From a researcher's perspective, these respective overviews can help to assist in the tools to select for a particular task, while for a developer it might be worthwhile to select one (or more) as a starting point (resp. building block(s) in a co-simulation approach, see further). We will finally provide a summarizing discussion in Section 2.7 and conclude in Section 2.8.

2.1.1 The role of communication networks in smart grids

Communication networks already play an important role in the power system. However, from a communication perspective, existing power grid networks suffer from several drawbacks [2], such as: (i) fragmented architectures, (ii) a lack of adequate bandwidth for two-way communications, (iii) a lack of interoperability between system components, and (iv) the inability to handle increasing amount of data from smart devices. As we will show in the next sections, communication networks will play an even more crucial role in the development of smart grids, and hence are subject of many research efforts, studying the most efficient topology of the communication network, physical media, protocols, etc. [3]. To gain a better understanding of the type of communication networks present in smart grids, the overall smart grid communications layer is often considered to consist of three types of networks, each having a distinct scale and range:

- *Wide Area Networks (WAN)* provide communication between the electric utility and substations, and as such operate at the scale of the medium voltage network and beyond. WAN are typically high-bandwidth backbone communication networks that handle long-distance data transmission.

- *Field Area Networks (FAN), Neighborhood Area Networks (NAN), and Advanced Metering Infrastructure (AMI)* provide communication for power distribution areas (LV grid). FAN/NAN/AMI interconnect WAN and the Home/Building/Industrial Area Networks of the end-users.

- *Home Area Networks (HAN), Building Area Networks (BAN), and Industrial Area Networks (IAN)* provide communication between electrical appliances and smart meters within the home, building or industrial complex.

Various smart grid applications have specific (challenging) communication requirements (see [4]), and in the next subsections we present some high level examples showcasing the need for communication for both measurement/monitoring and control. The latter calls for combining accurate models of information and communications technology (ICT) components as well as power networks, e.g., allowing the impact of such control on power system transients [5]. In the context of such smart grid applications, some examples of communication requirements and performance metrics are [2, 4]:

- *Latency* requirements are concerned with the time required to send data from a source to a destination. Certain applications, such as real-time state estimation using PMU data requires very low latency (few tens of ms). For applications such as smart meters data collection or demand response the latency requirements are less critical (up to seconds).

- *Data rate* requirements are concerned with the speed at which data can be sent, i.e., the data volume that can be sent within a certain period of time. For example, video data used in wide area monitoring and control requires high data rates, whereas data rates for AMI can be low.
- *Reliability* requirements deal with ensuring the communication system remains available and is able to send data. Remote protection applications require a very reliable communication network to ensure the safe operation of the grid.
- *Security* requirements aim to protect the system from a wide range of attacks. Concepts related to security are confidentiality (i.e., prevent the disclosure of information to unauthorized parties), integrity (i.e., maintain and assure the accuracy and consistency of data over its entire life-cycle), availability (i.e., the information must be available when needed), authenticity (i.e., validate that parties are who they claim to be), and non-repudiation.

Power line communication (PLC) reuses existing power wires for data communication. i.e., the power grid itself becomes the communication network. Different types of PLC technology exist [6]: (i) ultra narrowband PLC technology operating in 300 to 3000 Hz range with very low bit rate (100 bps), (ii) low data rate (few kilobits per seconds) narrowband PLC operating in the 3-500 kHz range, (iii) high data rate narrowband PLC (500 kbps), (iv) broadband PLC operating in 1.5–30 MHz range and data rates up to 200 Mbps.

Narrowband PLC technologies that operate over the medium voltage or low voltage power grids have been proposed by e.g., PRIME [7], PLC G3 [8], and IEEE 1901.2 initiatives. Targeted applications include monitoring (e.g., AMI), grid control, etc. Broadband PLC is being used for e.g., home multimedia services. However, PLC is challenging because the communication channel, i.e., the power grid, was not designed for that purpose.

2.1.2 Advanced metering and demand response

Distribution grids have limited monitoring and control capabilities and today in practice still depend largely on manual actions. As part of the efforts to transition to more automated solutions, advanced metering infrastructure (AMI) has been the focus on the distribution system level. It provides distribution system operators not only with system state information, but also provides remote control capabilities. AMI systems originate from automated meter reading (AMR) systems capable of remotely reading consumption and production records, alarms and status information from the customer. However, AMR is limited by one-way communication capabilities and does not enable control actions based on received information. AMI on the other hand provides two-way communication, and therefore supports control over the demand: AMI is considered as a possible basis for distributed command and control strategies [1]. Note that AMI will need to scale to very large number of participants (e.g., every electricity meter).

Indeed, energy demand levels and their patterns over time are undergoing changes as a result of emerging technologies such as electric vehicles, heat pumps, μ-CHP, etc. Demand response (DR) technologies aim to adapt the energy demanded over time. A classic example of DR is a dual tariff scheme for energy consumption, i.e., an expensive peak hour tariff, and a cheap off-peak hour tariff. In such a scheme, consumers are provided an incentive to modify their energy consumption patterns. Communication technologies such as AMI will enable much more fine-grained levels of control using variable pricing or even real-time pricing. Electric appliances that are equipped with a smart grid interface could react automatically to these price signals (thus relieving the consumer from having to take manual actions based on the changing prices).

One particular area of specific interest in the DR sphere is the charging of plug-in (hybrid) electric vehicles (P(H)EV), which show great promise for the transport sector in reducing the associated emissions and costs (esp. if the energy is supplied by renewable sources). However, such vehicles represent a significant new load to the power grid, especially for distribution grids that are already operating near their limits. The load stemming from uncontrolled EV charging (which for full-electric EVs amounts to the same order of magnitude of a complete household!) thus may require substantial (distribution) grid infrastructure investments. Hence the importance of applying DR-like techniques to avoid overloading the grid. On the other hand, electric vehicles also present new opportunities for utilities. For example, the vehicle batteries could be used for so-called vehicle-to-grid (V2G) applications [9, 10]: provide peak power, or cope with the intermittent behavior of renewable energy sources by storing excess energy and feeding it back into the grid when needed. Intelligent management (based on ICT technology in the power grid) of these vehicles will be essential to deal with these challenges and to benefit from the opportunities.

2.1.3 Distributed renewable energy sources (DRES)

Another major cause of the smart grid challenges stems from distributed renewable energy sources (DRES): their large scale deployment has a significant impact on the power system, since the output of solar and wind power is difficult to control given its dependence on variable local weather conditions. Therefore, the effect of such distributed generation (DG) units on system stability is less predictable than on-demand sources such as coal or hydroelectric. As such, large amounts of distributed energy sources have to be monitored and managed [11] to ensure optimal integration. Demand and supply must be in balance in the power grid. As a result, large shares of renewable energy require stand-by controllable generation or the presence of storage to cope with sudden changes in power output. Small controllable energy sources can be aggregated in so called virtual power plants. Distributed algorithms must be developed to make decisions on power system state and control actions [3]. In this context, communication protocols, standards and data formats will be essential to make these components inter operable. Therefore, it is essential that these are evaluated in detail before deployment [3, 11]. Also, DRES may be located in regions where no communication infrastructure is currently available and possibly difficult to deploy. For example, DRES located in mountainous terrain or offshore may require wireless or power line communication based solutions due to the complexity and cost of deploying alternative wired solutions (e.g., fiber).

2.1.4 Wide-Area Monitoring, Protection & Control

To prevent instability and collapse of the system (e.g., because of DG behavior), wide-area monitoring, protection, and control schemes (WAMPAC) are essential. Traditional protection schemes depend on local measurements sent to a central control system that is part of the supervisory control and data acquisition (SCADA) system [12], and which sends adjusting (low bandwidth) control signals over dedicated communication networks. However, modern protection and control schemes measure and send information at a much higher rate: e.g., measurement and communication of coherent real-time data is considered an enabling technology for improving monitoring and control of the power grid [13]. Synchronized phasor measurements (synchrophasors), representing both magnitude and phase angle of voltage or current waveform at particular points in the grid, are obtained by phasor measurement units (PMU) devices and further collected by phasor data concentrators (PDC). This offers real-time state information with microsecond time accuracy, thanks to synchronization using Global Positioning System (GPS) clocks. Such PMU data supports detailed and accurate state estimation, and enables multiple applications including distributed wide area control, protection, wide-area situational awareness, post-event analysis, etc. While such PMU networks initially were considered in the context of transmission networks, today PMU applications are considered to also improve the observability of the distribution grid. These safety- and time-critical applications clearly need fast communication networks, with requirements beyond best-effort internet technologies. Therefore, there is a need for modeling the communication network and evaluating its impact on modern protection and control schemes [14, 15].

2.2 Motivation

To study aforementioned smart grid innovations, simulation is considered an important tool. However, writing a new simulation engine from scratch is complex, costly and time consuming [3, 14], especially if we consider the interdisciplinary nature of the smart grid comprising both power system engineering and ICT as key components. The alternative, i.e., reuse existing (off-the shelf, commercial) simulation environments as is, or combine them into a (distributed) simulation environment, may have the benefit of better reliability and scalability [3]. However, the interdisciplinary nature of the smart grid complicates the assurance of the model validity for both power and communication networks, requiring extensive expertise of the most appropriate tools (and their settings) for both domains.

As such, the primary objective of this survey is to provide a comprehensive overview of existing simulation tools in the individual fields of power systems and communication networks, and the interdisciplinary field of smart grids combining power and ICT simulation. To assist in selection of the right tool for the job, this survey provides a detailed overview and classification of existing tools and their capabilities, illustrated by example use cases.

Although reusing existing simulation tools offers many benefits, it is sometimes necessary to design custom tools, e.g., due to missing features. Therefore, the secondary objective of this survey is to give insights in the design and implementation of smart grid simulators, indicating common pitfalls, lessons learned from earlier experiences, and methods to integrate different simulators.

Next we first motivate the use of simulation tools for smart grid research, and continue by pointing out the most apparent challenges in designing such tools.

2.2.1 Why simulation?

Historically, simulation is an important tool for the design of power systems [16–18] as well as communication networks [19]. Communication network simulation environments are used to develop and evaluate new ICT architectures and network protocols, while similarly power system engineers use simulation environments for power system planning and operations. In a smart grid context, simulators allow to study complex interactions between these interconnected systems and the monitoring and control elements on top of them [20]. Motivations for resorting to simulation has both economical and practical origins. Simulation is used to reduce the costs associated with upgrades to the power system and communication network infrastructures: costs related to performing the upgrades (installation, testing, etc.), but also to the potential loss of service that can occur as a consequence. Indeed, upgrades can have severe economic and social impacts, even for a short period of time [21]. Simulation reduces these risks, enabling the design and evaluation of different solutions before actually deploying them the in the field, and moreover in a fully controlled environment. The latter implies that future power systems or communication networks can be studied under varying conditions and for different scenarios [20]. Another benefit is that simulation can happen faster than real-time, depending on the complexity of the simulation model [22]. This can reduce the time required to develop new technologies. Therefore, simulation offers much more flexibility compared to studies that depend on real-life deployments. Simulation is also considered an important tool for educational and research support [17].

2.2.2 Smart grid simulator design challenges

In this section, we further motivate the need for smart grid simulators, and also discuss the challenges associated with the design and development of smart grid simulators. The provided information not only assists developers in the development process, but also enables users to evaluate the different solutions. We discuss (i) the need for combined simulation of the power system and ICT infrastructure, (ii) selection of the appropriate abstraction level for simulation models, (iii) requirements for simulation scenarios, (iv) differences in modeling time, and (v) practical considerations such as user friendliness, flexibility, etc.

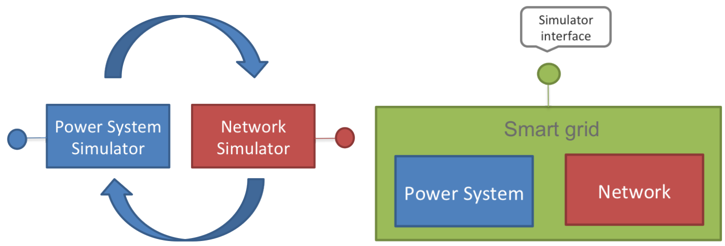
The underlying challenge associated with smart grid simulation is that it requires combined simulation of both the power system and the ICT infrastructure, as well as the applications (e.g., control algorithms) running on top of them, especially considering the large scale those systems [17, 18]. As pointed out previously, the operation of the power grid increasingly depends on ICT [21] and it is therefore crucial to understand the impact of the performance of the communication network on the operation of the power grid [17, 23]. The smart grid, comprising many heterogeneous communicating devices, thus needs to deal with issues such as safety, security (including protection against potential cyber attacks [17]), interoperability, and performance [24]. Yet, current power grid simulators typically do not model the network communication protocols, or even traffic patterns involved in such a smart grid [14, 24]. On the other hand, the operating mode of the smart grid has an impact on the traffic in the communication network [23]. Thus, integration of power and ICT components in the operational power grid also requires similarly integrated simulation frameworks [17].

A first main challenge that thus arises is to decide on the appropriate abstraction level for smart grid simulator models, that should cover the power grid, and ICT components ranging from the communication network, middleware (e.g., [13, 25]), control strategies (which constitute the key smart grid innovations, see Section 2.1), etc. One of the key challenges is the different time resolution (see below) and fidelity of the simulation [20]. Furthermore, the simulator should allow flexible specification of varying scenarios [20], and possibly definition of the level of detail (e.g., time resolution). In this respect, scalability is an important concern: simulators should scale to support the complexity of modern large scale smart grid scenarios, e.g., when considering nation wide smart grids. As such, deciding on the level of modeling detail has to account for computational efficiency [17]. Furthermore, simulations should not only aim to achieve technical objectives, but also consider financial and business criteria as dictated in industry standards [26].

On the modeling part, it should be noted that traditional simulation tools will need to be extended with models specific of the advanced smart grid scenarios. On the power side, this includes appropriate characterization of renewable sources: e.g., dealing with their intermittent and stochastic behavior is a crucial research topic [17]. In view of the DR approaches, correct modeling of the user behavior [26], and especially the flexibility of his load (e.g., time shifting of appliance usage, state-of-charge and charging deadlines for EVs), is crucial. Such models should be accompanied by explanatory meta-data to allow correct application of the models, respecting the assumptions under which they were constructed.

Another complexity stems from different models of time by various simulators: continuous simulation is common in power systems, whereas communication network simulators typically are discrete event simulators [3, 15, 20, 27]. Thus, when combining such tools in so-called co-simulation approaches (see Section 2.3), synchronizing the time of different co-simulation components is a recurring topic [3, 14, 22, 28]. Clearly, the synchronization of various simulation model constituents has to be carefully managed, as we will explain in Section 2.3.2.

Beyond aforementioned technical aspects, the design of a smart grid simulator should also take into account more practical aspects, including user friendliness. Not only is simulation an important tool to support education and research [17, 29, 30], consumer involvement in smart grid simulation is also considered [17, 30]. As such, a smart simulator should be an open and flexible environment, that supports user-defined models [17], and easy reuse of already established and validated models. The latter suggests that possible integration with different programming languages could give such support to a broad audience [17, 20]. To achieve this, the use of a common simulation interface and existing communication methods (e.g., web services) is suggested, as to enable integration of existing models, independent of the programming language or simulation tools used [20]. Related to this is the use of data formats for input/output: simulators should limit the dependency on proprietary input formats, operating systems or third party libraries. Ideally, a smart grid simulator should be able to incorporate actual power system components, i.e., hardware-in-the-loop simulations [17, 18, 23]: thus, existing components can be tested in a controlled environment, or used as building blocks to speed up development. However, this requires real-time operation of the simulator and hence appropriate modeling of time.



(a) Co-simulation (b) Integrated simulation

Figure 2.1: Conceptual approaches to combining power and communication network simulation: (a) Co-simulation*: Multiple simulators with specialized tasks, each having their own simulation interface for data input/output, control, etc. The arrows indicate that interaction between the simulators is required. (b)* Integrated or comprehensive simulation*: One combined simulator provides an integrated environment for combined simulation of power system and ICT.*

2.3 Smart Grid Simulation Paradigms

In the following sections we will present simulation environments that are used for simulating power systems, communication networks, as well as their combination in the context of smart grids. First however, we will discuss the overall simulation paradigms they are built on. After sketching how to combine power and ICT simulation constituents, we will outline specific time modeling approaches and the complexity of combining them.

2.3.1 Combined simulation of power and communication systems

We briefly discuss the combined simulation of the power system and communication network. Although power system or communication network simulators are being used extensively in both domains, it is the combined simulation of the power system and communication network that has recently attracted more attention due to rising interest in smart grid from governments, industry, and academia. It can be achieved using a variety of approaches, of which two will be discussed in more detail: (i) co-simulation, (ii) comprehensive or integrated simulation.

Constructing a new combined simulation environment is potentially time consuming and expensive. Therefore, a *co-simulation* approach combines existing specialized simulators. In the context of smart grid co-simulation, a co-simulator would consist of a specialized communication network simulator (e.g., OMNeT++) and a specialized power system simulator (e.g., OpenDSS). Figure 2.1(a) illustrates the co-simulation approach. Multiple simulators are used, each having their own distinct simulation interface for data input, configuration, result output, control, etc. Therefore, the main challenge is to connect, handle and synchronize data and interactions between both simulators using their respective simulator interfaces. Especially time management between both simulators is challenging, because each simulator manages their simulation time individually. Nonetheless, the main advantage is that existing simulation models, algorithms, etc. that have already been implemented and validated can be reused. Indeed, the majority of the development effort is put into modeling of additional, smart grid specific components: systems such as photovoltaics, wind turbines, etc. and composite subsystems such as low or medium voltage power grids [20]. Hence, a co-simulation approach reduces development time and the risk of errors.

Notwithstanding the development advantages, running the simulators separately and the necessary synchronization likely will imply performance penalties. E.g., in [31] the authors present an example in the context of video streaming where synchronization overhead accounted for 90% of the total simulation time. To further illustrate potential performance examples, we consider a co-simulation approach in which each simulator is run in sequence. For each simulation run, the simulation environment must be loaded (i.e., start-up time is the performance penalty), configured and input data must be provided (i.e., reading and processing configuration and input data is the performance penalty). Next, the simulation model is executed and results are gathered and output. Data input/output often requires intermediaries to store the data, e.g., files on a file system, a database, web services, etc., in which case the access time and the time required to read the data will incur a performance penalty. Also, input/output data must be pre-processed before using it in a next step (e.g., due to different file formats used), introducing pre-processing delay.

An alternative for co-simulation is an *integrated* or *comprehensive* approach to simulation, in which both the power system and communication network are simulated in one environment. Figure 2.1(b) illustrates the concept. A single simulation interface is provided, instead of having distinct interfaces for each simulator. Another advantage of this tightly coupled approach is that the management of time, data, and power/communication system interactions can be shared among the simulator constituents. Hence, no performance penalty due to synchronization is expected. However, the main challenge is the combination of both models in one environment. The main challenge is to provide a simulation interface that provides sufficient level of detail for the different aspects of the smart grid simulation model. A possible implementation approach to integrated simulation is to select a communication network, power system or other platform as the basis for the smart grid simulator, and implement the other components from scratch or link existing libraries or tools.

2.3.2 Continuous time and discrete event simulation models

As stated earlier, power system and communication network simulators tend to adopt different modeling approaches. Dynamic power system simulation commonly uses continuous time modeling, where state variables are described as continuous functions of time. Thus, power system element dynamics are expressed by differential equations defining the relations between continuous state variables. However, some discrete dynamics are introduced by circuit breakers, relays, etc. Hence, a time stepped approach is used: since exactly solving the equations analytically is only possible for trivial cases, numerical algorithms using discrete time slots are used. This leads to the time model illustrated in Figure 2.2(a).

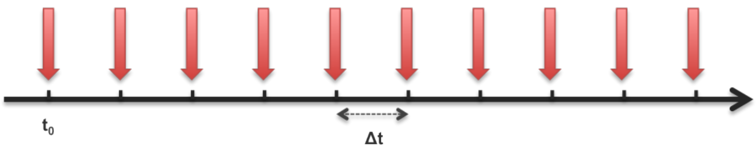
Communication networks typically are packet switching networks (cf. IP based technologies), which are adequately modeled as discrete event systems characterized by events such as sending and receiving of packets, expiration of timers, etc. Such events occur unevenly distributed in time. This is clearly different from the time stepped approach commonly used for power system dynamic simulation, where a fixed interval between events is selected. An event scheduler is responsible for maintaining a time-ordered list of all scheduled events, and simulation time progresses from event to event as sketched in Figure 2.2(b).

One approach to combine both approaches is the use of predefined synchronization points, indicated by the dashed lines in Figure 2.2(c). Each simulator pauses when their simulation clock reaches a synchronization point. After each simulator is paused, information is exchanged. This however can lead to simulation inaccuracies: messages that need to be exchanged between both simulators are delayed if they occur between synchronization points. A solution to this problem is to reduce the time step between synchronization points (and possibly refining the timescale used for the continuous time simulator), yet this clearly degrades performance. Thus, co-simulation needs to strike the right balance between accuracy and simulation speed. Also, not all time instants at which communication between the different simulators must occur are known a priori.

2.3.3 Emulation, Real-Time Simulation and Hardware-in-the-Loop Simulation

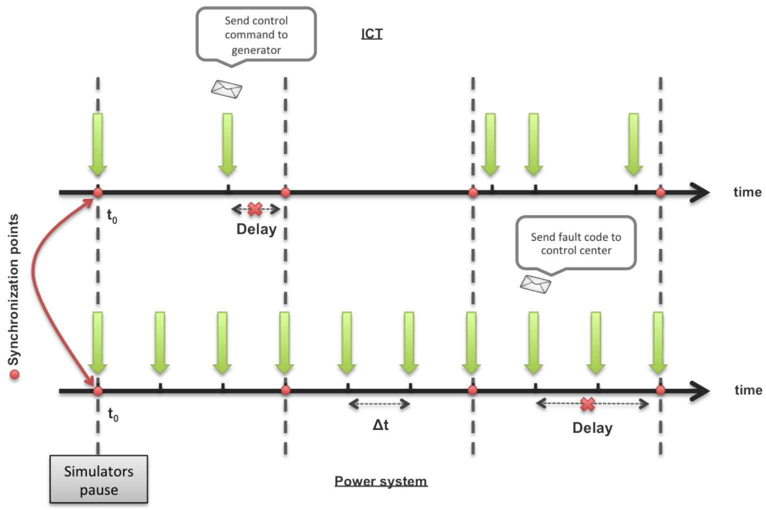
So far we only considered pure software-based simulation approaches, i.e., both power grid and ICT infrastructure are simulated: the physical world components are abstracted as software models. However, some approaches aim for more realism and therefore provide support for emulation, real-time simulation, and/or hardware-in-the-loop experiments. In this section, we provide an introduction to these concepts.

In an *emulation* approach (integrated or co-simulation), the emulated component more closely mimics the real world in hardware. For example, a network



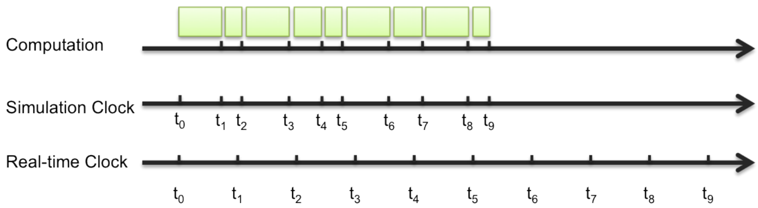
(a) Continuous time simulation

(b) Discrete event simulation

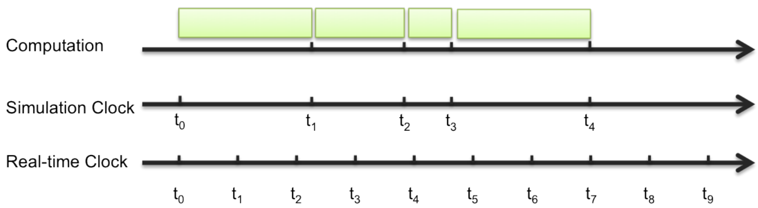


(c) Synchronisation issues

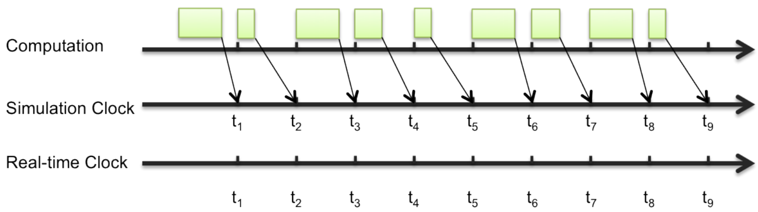
Figure 2.2: Continous time vs discrete event simulation: (a) Time stepped simulation of a continuous time simulation model. (b) Discrete event simulation (DES). (c) Example of simulation errors in an approach based on predefined synchronization points.



(a) Offline or non real-time simulation: fast



(b) Offline or non real-time simulation: slow



(c) Real-time simulation

Figure 2.3: Difference between non real-time (offline) simulation and real-time simulation: (a) Non real-time simulation in which computation takes less time than the simulated event: simulation clock progresses faster than the real-time clock. (b) Non real-time simulation in which computation takes more time than the simulated event: simulation clock progresses slower than the real-time clock. (c) Real-time simulation: simulation clock and real-time clock are synchronized.

emulator such as Emulab [32] can be used instead of simulators such as ns-2/ns-3 or OMNeT++, resulting in a more realistic but still controllable environment: i.e., Emulab allows specifying an arbitrary network topology, resulting in a controllable, predictable, and repeatable environment. To provide an even higher level of detail, it is possible to use actual smart grid components, e.g., GridSim [18] uses the GridStat [33] communication middleware platform.

Next, we discuss *real-time simulation*. The difference with non *real-time or offline simulation* is illustrated in Figure 2.3. Figure 2.3(a) and Figure 2.3(b) illustrate two possible scenarios for non real-time simulation: the simulation clock can progress either faster than the real-time clock (i.e., time in the real world) or slower. However, in a real-time simulation approach, the simulation clock and real-time clock are synchronized as illustrated in Figure 2.3(c). For these examples, we have assumed a simulation model with discrete time and constant time step (see also Section 2.3.2). Note that techniques exist for supporting variable time steps, but they are less suitable for real-time simulation [34]. Put more formally, a real-time simulator must accurately produce the internal variables and outputs of the simulation model within the same length of time as its real-world counterpart would. I.e., the correctness of a real-time model not only depends upon the numerical computation, but also on the timeliness with which the simulation model interacts with external components (hardware or software). Applications of real-time simulation include testing of physical control and protection equipment.

Hardware-in-the-loop (HIL) simulation is a technique used to develop complex real-time embedded systems (e.g., in the domain of power electronics) in which some components are real hardware, whereas others are simulated. Components may be simulated because they are unavailable, or because experiments with the real components are too costly, time consuming, or are too hazardous. Typically, a mathematical model of the simulated system is used to provide electrical emulation of sensors and actuators that are connected to real hardware.

2.4 Power System Simulation

In this section we discuss power simulation, mainly targeting readers with an ICT background: we introduce different power simulation types, and an overview of existing power simulators, in terms of their main features, example studies, and options for integration of external tools.

Simulators for power system analysis have been extensively used by professionals for network planning, operations and price forecasting. Over-voltages, harmonics, short circuits, transient stability, power flow, and optimal dispatch of generating units are examples of important power system phenomena that need to be captured and parameterized in the simulations. Power system simulations are usually classified into one of these two categories:

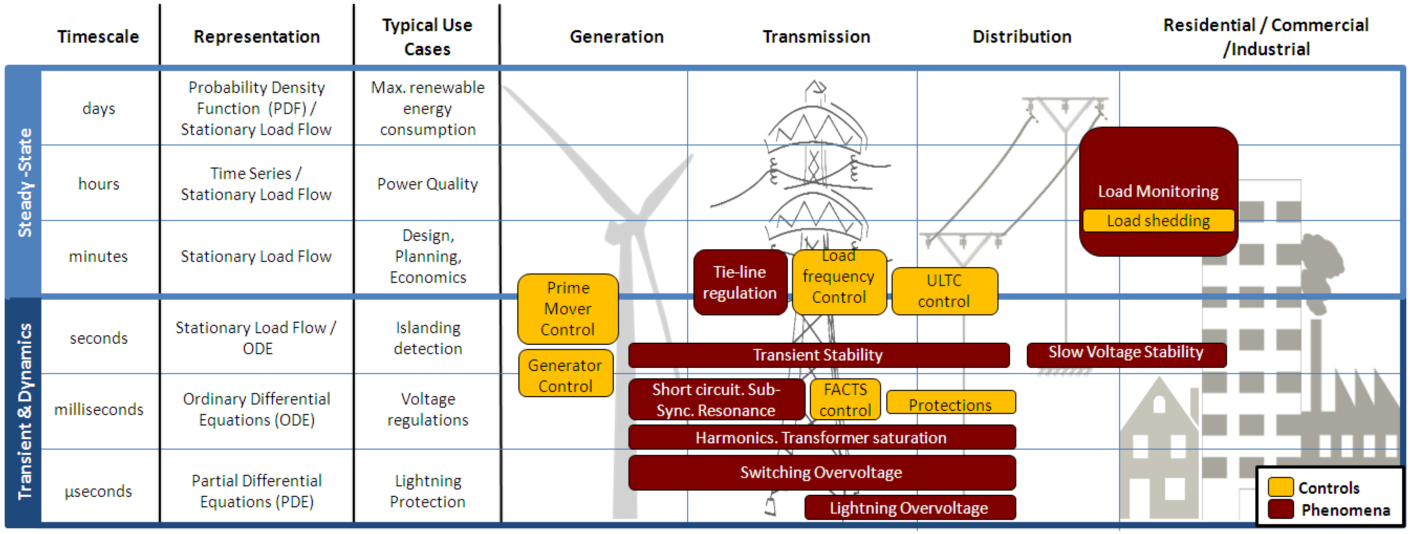


Figure 2.4: Time scales of power phenomena and power control: depending on the time scale, different model representations are adopted. The time scale considered depends on the use case, which typically is related to a particular part of the grid (generation, transmission, distribution, etc.).

1) Steady state simulations form the basis for power grid network planning studies. Researchers and engineers perform "what-if" studies to measure the impact of modifications in the power system. The system is analyzed in a stable equilibrium state, and focus lies on checking whether the power system variables are within proper boundaries (e.g., validation of voltage limits). The different simulators specialized in steady state studies offer a full range of analysis methods, from power flow studies, load estimation and load balancing, to fault analysis or optimal capacitor placement. Steady state simulations also cover optimal power flow studies. In these studies, the system conditions that minimize the cost per kWh delivered are analyzed using linear optimization. Other optimal power flow methods that incorporate Artificial Intelligence (AI) techniques are described in [35].

2) Transient dynamics simulations study transitions between equilibrium points due to a major changes in the power grid configuration, e.g., disturbances. A major goal of such studies is to determine if the load angle reaches a new optimal steady state. Simulations performed include electromagnetic transient studies with finer time granularity (in the order of microseconds to milliseconds) than the steady state ones. In these simulations, time varying and short term signals are studied. If the equilibrium is lost due to continuous small disturbances, dynamic stability simulations, also known as small-signal stability simulations, are needed. Simulators specialized in transient dynamic power characteristics enable to model the network at circuit level, reproducing the time domain wave forms of state variables at any point in the system.

In addition to the "steady state" vs "transient dynamics" classification, power system simulations usually focus to one of the hierarchical power grid domains: Power Generation, Transmission, Distribution or Utilization (residential, commercial and industrial loads). Depending on the domain of interest and the power phenomena, the time steps of the simulation would vary. Figure 2.4 gives an overview of the timescale for different phenomena and control strategies in power systems. Phenomena that require higher frequency studies (transients) would require a smaller duration of calculation time steps. Note that such smaller time steps would deliver more accurate results, but come at the price of increasing the total simulation runtime [11]. Figure 2.4 also captures the different power system domains, example studies and the mathematical representation of the various power phenomena. The top part of the diagram focuses on steady-state analysis, while the bottom groups the transient dynamics.

As pointed out in Section 2.2.2, smart grids pose specific challenges, such as high penetration of renewable DG units and microgrid operation, implying importance of energy storage and decentralized energy management. In energy transmission and distribution, the increment in sensing and communication capabilities enables new automation and control strategies for remote condition monitoring or blackout prevention. Moreover, new intelligent consumption strategies are possible thanks to more frequent meter readings, demand response plans and smart appliances with different load management features. These all need to be appropriately modeled. In the following subsections, we present an overview of the main simulators found in research literature and illustrative applications thereof in smart grid studies. We also indicate interfaces offered by the simulation tools to expand its functionality, and e.g., link with other components to realize co-simulation.

2.4.1 PSCAD/EMTDC

PSCAD/EMTDC is a commercial simulation tool for the Power System Computer Aided Design and Electromagnetic transients for DC. An example of simulations of power system control in a smart grid context is [36], where Fazeli et al. present a novel integration of wind farm energy storage systems within microgrids. PSCAD/EMTDC can be coupled with external tools like Matlab, as exemplified in [37], where Luo et al. combine PSCAD/EMTDS's electromagnetic transient simulation capability and with advanced matrix calculations in Matlab for testing a new network based protection scheme for the power distribution grid. Similarly, Mahmood et al. have designed a three-phase Voltage Source Converter (VSC) for distributed generation, developed their linear model in Matlab and validated it using a detailed switching model in PSCAD/EMTDC [38].

2.4.2 DigSilent - PowerFactory

DigSilent Power Factory allows the modeling of generation, transmission, distribution and industrial grids, and the analysis of their mutual interactions. Load flow, electromechanical RMS fluctuations and electromagnetic transient events can be simulated. Thus, both transient grid fault and longer-term power quality and control issues can be studied. As an example of power flow studies using DigSilent, Coroiu et al. evaluate the continuity of power supply using the comparative methods of the probabilistic load flow and the stochastic load flow [39]. Transient studies is performed by e.g., Chen et al. who studied the transient stability of a micro-grid supplied by multiple distributed generators [40]. Models of voltage controllers, generators, motors, dynamic and passive loads, transformers, etc. are part of DigSilent's built-in electrical components library, but the algorithms inside these models are not accessible. However, users can create models using the DigSilent Simulation Language (DSL). An example of such a study on dynamic wind models can be found in [41]. In addition, DigSilent supports the exchange of power data with external tools. For example, in [42] Andren et al. combine DigSilent with Matlab and present a framework for the simulation of power networks and their components, using an Open Process Control (OPC) interface for exchanging data between simulators.

Table 2.1: Classification of power simulators

	Simulation Type		**Power Subsystem - Domain**			**License**	
Simulator	Steady State (min, hours, days)	Transient Dynamics (s, ms, μs)	Generation	Transmission	Distribution + RCI loads	Commercial	Open Source
Cymdist	x		x		x		
DigSilent	x	x	x	x	x	x	
EMTP-RV		x		x	x	x	
ETAP PSMS	x	x	x	x	x	x	
EuroStag	x		x	x	x	x	
homer			x			x	x (v.2.68Beta)
ObjectStab		x	x	x			x
OpenDSS	x	x	x		x		x
PowerWorld	x	AO		x			
PSCAD/EMTDC		x		x	x	x	
PSSE̊	x	x	x	x		x	
PSSS̊incal	x	AO	x		x	x	

RCI: Residential, Commercial and Industrial loads **AO**: Add-on

2.4.3 Siemens PSS

The Power Systems Simulator (PSS) product suite includes several software solutions targeting different domains and time scales. Among others, PSS includes PSS SINCAL and PSS E. PSS SINCAL targets utility distribution system analysis: it is a commercial (with special licenses for research and education) network planning and analysis tool with capability to perform, among others, power flow, load balancing, load flow optimization and optimal branching simulations. PSS SINCAL's COM-server interface facilitates the integration into existing IT architectures. The COM interfaces can be exploited in Smart Grid simulations, where PSS SINCAL can be used in the analysis of distributed generation and smart meter data. As an example of such studies, Chant et al. investigate the impacts on integrating photo voltaic panels on the utility grid in terms of harmonic distortion, voltage fluctuation and load rejection issues [43]. PSS SINCAL allows users to link each Smart Grid equipment model (e.g., e-cars, micro-turbine, smart meter, etc.) with their correspondent generation and load profiles [44]. For transmission system planning, the PSS E tool allows users to perform load flow analysis and transient analysis. For example, Mohamad et al. use PSS E for transient stability analysis [45].

PSS E can interact with user scripts using the Python scripting language. Such integration is used by Hernandez et al. : modeling Synchronous Series Compensators (SSSC) in Python, they simulate the control of power flow through transmission lines [46].

2.4.4 EMTP-RV

EMTP-RV is a commercial software for simulations of electromagnetic, electromechanical and control systems transients in multiphase electric power systems. For instance, Napolitano et al. use transient modeling using EMTP-RV software to model the MV feeder response to indirect lightning strokes [47]. Other potential uses of EMTP-RV include studies in insulation coordination, switching surges, capacitor bank switching, motor starting, etc. Users can develop customized modules and interface them to EMTP-RV via dynamic-link library (DLL) functionality.

2.4.5 PowerWorld

PowerWorld Simulator is an interactive, visual-approach, power system simulation package designed to simulate high voltage power system operation on a time frame ranging from several minutes to several days. PowerWorld's add-on SimAuto allows to control the simulator from external applications. SimAuto acts as a Component Object Model (COM) object for interfacing with external tools, such as Matlab or Visual Basic. Such combination is illustrated by Roche et al. , who combine PowerWorld with external artificial intelligence (AI) decision making tools to realize smart grid simulations studying feeder reconfiguration and large-scale demand response [48].

2.4.6 ETAP PSMS

ETAP PSMS is a real time power management system. ETAP software has more than 40 modules for load flow analysis, short-circuit analysis, device coordination analysis, motor starting analysis, transient stability analysis, harmonic analysis, etc. In [49], Mehra et al. applied principal component analysis (PCA) to simulated phasor data, generated by ETAP software.

2.4.7 Cymdist

Cymdist is designed for planning studies and simulating the behavior of electrical distribution networks under different operating conditions and scenarios. It offers a full network editor and it is suitable for unbalanced load flow and load balancing studies. The software workspace is fully customizable. The graphical representation of network components, results and reports can be built and modified to supply the level of detail needed. Furthermore, the CYME COM module allows different environments to communicate with the CYMDIST software for accessing different pre-defined functions and calculations. An illustrative distribution system modeling study using Cymdist can be found in [50].

2.4.8 EuroStag

EuroStag is a power systems dynamics simulator developed by Tractebel Engineering GDF SUEZ and RTE (electricity system operator of France). It allows a range of transient and stability studies. Supplementary tools, such as Smart Flow, enable load flow calculations. An example of such studies can be found in [51], where Asimakopoulou et al. compared various load control scenarios for the power system in the island of Crete, using EuroStag as the basis for their simulations.

2.4.9 Homer

HOMER is a power generation simulator. It can be used for designing hybrid power systems containing a mix of energy sources: conventional generators, combined heat and power, wind turbines, photo voltaics, batteries, etc. Both grid tied or standalone systems can be simulated. In addition, green house calculations are also possible. An illustrative micro grid sizing and dynamic analysis study using Homer and EuroStag is presented in [52].

2.4.10 OpenDSS

OpenDSS is an open-source distribution system simulator developed and maintained by EPRI. It is designed to support power distribution planning analysis associated with the interconnection of distributed generation to the utility system. Other targeted applications include harmonic studies, neutral-earth voltage studies, volt-var control studies, etc. Co-simulation interfaces (e.g., COM and scripting interfaces) are provided and users can define their own models [53]. OpenDSS is considered a suitable platform for smart grid research as it supports the analysis of intermittent and stochastic processes associated with renewable energy sources [17].

2.4.11 ObjectStab

ObjectStab [54] is an open source power system library with capabilities to perform power system transient simulations. It is based on Modelica, a general purpose object oriented modeling language. An example of high voltage DC (HVDC) power transmission studies can be found in [55], where Meere et al. designed optimized power system models for variable speed wind turbine machines with a HVDC link for grid interconnection. The electrical performance of the system is verified using ObjectStab.

2.4.12 Real-time hardware-based simulation

Opal-RT [56] develops real-time digital simulators and hardware-in-the-loop testing equipment. eMEGAsim from Opal-RT is a real-time hardware-based simulator that has been developed to study, test, and simulate large power grids, industrial power systems, etc. It supports simulation of very large power grids with a time step as low as 20 microseconds. It can also be used for simulation of power electronics found in distributed generation (e.g., wind farms, photo voltaic cells) and Plug-in Hybrid Electric Vehicles (PHEV). RT-LAB [57] is the core technology behind eMEGAsim and enables distributed real-time simulation and hardware-in-the-loop testing of electrical, mechanical, and power electronic systems, and related controllers. ARTEMIS is a suite of fixed-step solvers and algorithms that optimize real-time simulation of SimPowerSystems [58] models of electrical, power electronic, and electromechanical systems. Opal-RT products are fully integrated with MATLAB/SimuLink.

The Real-Time Digital Simulator (RTDS) [16] from RTDS Technologies [59] is a power system simulator that solves electromagnetic transient simulations in real-time. It supports high-speed simulations, closed-loop testing of protection and control equipment, and hardware-in-the-loop applications. Parallel processing techniques enable the simulation of large scale power systems: power system

Package	PF	CPF	OPF	TD	EMT	SSA
DCOPFJ			x			
EST	x			x		x
INTERPSSS	x	x	x	x		
MatEMTP				x	x	
MATPOWER	x		x			x
PAT	x			x		x
PSAT	x	x	x	x		x
PST	x	x		x		x
PYLON	x		x			
SIMPOWER	x			x		
SPS	x			x	x	x
TEFTS	x			x		
VST	x	x		x		x

PF: Power Flow
CPF: Continuation Power Flows
OPF: Optimal Power Flow
TD: Time Domain
EMT: Electromagnetic transients
SSA: Small-signal Stability Analysis

Table 2.2: Classification of Matlab-based power simulators

equations are solved fast enough to continuously produce output conditions that realistically represent conditions in the real network. RTDS supports IEC 61850 device testing. As a result, the simulator can be connected directly to power system control and protective relay equipment.

2.4.13 Classification

A characterization of the previously mentioned simulators can be found in Table 2.1, which presents a classification of popular power simulators according to the time-scale of the simulations (steady-state vs transient), the domain (power generation, transmission, distribution, consumption) and their licensing (open-source vs commercial).

In addition, simulation platforms based on Matlab/Simulink environments are also widely used. Examples of power system simulators based on MATLAB include Power System Analysis Toolbox (PSAT) [60], Power System Toolbox (PST) [61], Educational Simulation Tool (EST) [62], SimPowerSystem [58], Power Analysis Toolbox (PAT) [63], Voltage Stability Toolbox (VST) [64] and MATPOWER [65]. Note that although several of these tools are open source, MATLAB is a commercial and closed product. Yet, PSAT can also run on GNU/Octave, which is a free Matlab clone, therefore resulting in a complete open source solution that is freely available. In addition, PYPOWER is a translation of MAT-

POWER to the Python programming language. Table 2.2 summarizes the different MATLAB modules and their capabilities, based on [17, 60, 64]

Note that in addition to the major tools discussed above, additional open source tools are described by Milano et al. in [66]: UWPFLOW (power flow, implemented in the C programming language), TEFTS (transient stability, C), InterPSS (load flow and transient studies, in Java), AMES (whole sale power market, Java), DCOPFJ (DC optimal power flow, Java) and PYPOWER (DC and AC power flow and DC and AC optimal power flow).

2.5 Communication Network Simulation

In this section, we present an overview of communication network simulators, which are widely used for the development and evaluation of communication architectures and protocols. We present a short overview of the different simulators that have been successfully used in a smart grid context: ns-2/ns-3, OMNeT++, NeSSi and OPNET Modeler. This section will primarily serve readers with a power systems background, since ICT experts will be presumably be familiar with some of these tools. Yet of particular interest for ICT researchers will be the highlighted sample smart grid use cases for which they have been used. We limit our selection of examples to those that focus on the communication aspects in the smart grid, and as such do not require (detailed) modeling or simulation of the electric behavior of the power grid. Simulators and use cases that focus on the combined simulation of the power system and communication network are considered in Section 2.6. Note that general purpose tools such as MATLAB have also been applied to study communication networks in a smart grid context [67, 68], but we will not further elaborate on those studies here.

2.5.1 Network Simulator (ns-2 and ns-3)

The *Network Simulator version 2 (ns-2)* is a widely used open source discrete event network simulator created for research and educational purposes. It is targeted at networking research, with a strong focus on internet systems. Therefore, it includes a rich library of network models to support simulation of e.g., IP-based applications (including TCP, UDP, etc.), routing, multicast protocols, over wired and/or wireless networks. The *ns-2* core is written in the C++ programming language. Users can create new network models or protocols using the C++ language. Simulation scripts to control the simulation and configure aspects such as the network topology are created using the OTcl language interface. As a result, users can create and modify simulations without having to resort to C++ programming and recompiling *ns-2*. Development of *ns-3*, the successor to *ns-2*, is ongoing: new features include support for the Python programming language as a scripting interface (instead of OTcl), improved scalability, more attention to realism, better software integration, etc. [69]. However, when selecting a specific version of *ns*, it is important to consider that *ns-3* is not backwards compatible with *ns-2*: i.e., existing *ns-2* simulation models must implemented again for *ns-3*. Both are widely used for networking research in general, and unsurprisingly also in a smart grid context both *ns-2* and *ns-3* are adopted in e.g., a co-simulation approach [11, 22, 24, 27, 70, 71]. In [72] a suite of software modules for simulation of PLC networks using ns-3 is presented and source code is made available at [73]. The simulation model is based on transmission line theory (TLT), which relies on the knowledge of the topology, wires, and the load characteristics of the power grid underlying the PLC system. This approach supports networks with multiple node-to-node links. An interface to the ns-3 framework is provided, which allows the integration of higher level protocols such as TCP/IP. A GUI is provided that enables users to draw the topology and specify node and line properties, and also noise present in the network.

2.5.2 OMNeT++

The open-source OMNeT++ discrete event simulation environment [74] has been designed for the simulation of communication networks (wired and wireless) and distributed systems in general. The simulation environment has a general design (i.e., it is not limited to simulating communication networks) and therefore has been used in various domains, such as wireless network simulations, business process simulation and peer-to-peer networking. However, OMNeT++ is mostly applied in the domain of communication network simulation. A comprehensive set of internet based protocols is provided by means of the INET framework extension which includes support for IPv4, IPv6, TCP, UDP, Ethernet, and many other protocols. Other extensions provide simulation support for mobility scenarios (e.g., VNS), ad-hoc wireless networks (e.g., INET-MANET), wireless sensor networks (e.g., MiXiM, Castalia), etc. Distributed parallel simulation is supported to enable simulation of large scale networks. Additionally, federation support based on the High-Level Architecture (HLA) standard is provided in OMNEST, the commercial version of OMNeT++. An OMNeT++ simulation model consists of simple modules implemented in C++. Compound modules consist of other simple or compound modules, and are defined using the OMNeT++ Network Description Language (NED). Modules communicate by passing messages via gates, which are the input and output interfaces of the modules that are linked to each other by so-called connections forming communication links between modules. Apart from the networking community, OMNeT++ has also received substantial attention from the smart grid community for developing smart grid simulators [5, 29, 75–80].

Example use cases that focus on the communication aspect of the smart grid include the design and evaluation of different smart grid communication architectures, performance of smart grid protocols, etc. For example, a demand side management communication architecture based on orthogonal frequency-division multiplexing (OFDM) power line communication (PLC) is proposed in [76, 77]: the authors test business cases and benchmark overall network performance in a controlled environment, and use OMNeT++ results to iteratively improve the network design. As part of that research, a full simulation model of PRIME protocols has been developed that enables simulation of IP communication over a PLC network. Another PLC simulation model for OMNeT++ is presented in [81]. It is a generic model that does not implement a specific variant of PLC, but provides a toolkit that should enable the user to model the desired PLC variant. Simulation of broadband PLC in a home environment is demonstrated.

Another example is a simulation environment to study geographical routing in multi-hop wireless networks in the context of smart grid energy applications [78]. There, the authors purely focus on communication, i.e., without power system modeling and simulation. That work is extended and a modular and distributed simulation environment is proposed in [79], focusing on scalability analysis of smart grid ICT infrastructures. It allows distributed simulation and provides additional simulation management features (scenario generation, model repository, dependency management, management GUI, etc.). Main research questions include topology-specific influences on the scalability of different technologies and various traffic patterns for smart grid applications.

A last example is related to the evaluation of smart grid standards and protocols. An important standard in smart grids is the IEC 61850 standard, targeted at substation automation. An IEC 61850 simulation platform is described in [29] based on OMNeT++. The platform is designed to support communication network performance analysis, hardware-in-the-loop simulations, and algorithm development and evaluation. An overview of other IEC 61850 simulation platforms that are limited to communication network performance analysis is also presented in [29].

2.5.3 NeSSi

NeSSi (Network Security Simulator) is an open source discrete event network simulator developed at DAI-Labor (Distributed Artificial Intelligence Laboratory) and sponsored by Deutsche Telekom Laboratories. We include NeSSI because the primary focus of the tool is on network security related scenarios in IP networks [82]. Features described to support security related scenarios are attack modeling, attack detection, security metrics, etc. Distributed simulation is supported to enable simulation of large scale networks. Example uses in the smart grid domain include a security analysis of a smart measuring scenario through federated simulation [83] and to use an integrated approach for evaluating and optimizing an agent-based smart grid management system [82].

2.5.4 OPNET Modeler

OPNET Modeler is a powerful commercial discrete event network simulator with built-in, validated models including LTE, WIMAX, UMTS, ZigBee, Wi-Fi, etc. It enables modeling of various kinds of communication networks, incorporating terrain, mobility, and path-loss characteristics in the simulation models. OPNET Modeler has a visual high-level user interface offering access to a large library of C and C++ source code blocks, representing the different models and functions. It comes with an open interface for integrating external object files, libraries, other simulators (co-simulation) and even hardware-in-the-loop.

The Smart Grid Communications Assessment Tool (SG-CAT), introduced in [84], is a simulation, modeling and analysis platform, targeted to utilities that want to develop a holistic smart grid communications strategy. It has been developed to assess the performance of different smart grid applications under various terrains, asset topologies, technologies and application configurations. SG-CAT has been built on top of OPNET Modeler, taking advantage of OPNET's modular design, which allows the exchange and customization of applications, communication technologies, terrain profiles and path-loss models. The same authors also discuss the scale-up concerns when approaching large scale simulations in OPNET, and offer a solutions to these challenges based on the unique characteristics of smart grid scenarios [85].

Furthermore, OPNET is used in multiple co-simulation approaches (see further in Section 2.6) that consider both the communication network and power system in detail [15, 28, 86–88]. Smart grid use cases that focus on the communication network without detailed modeling of the power grid are described in [89–91]. The authors of [89] consider a wide area monitoring and control scenario system that uses a WiMAX/IEEE 802.16 network to transport delay-sensitive PMU data: several IEEE 802.16 scheduling services (UGS, rtPS, BE) are evaluated in terms of delay, uplink use and signaling overhead, using a simulation model developed in OPNET. The same authors also propose a heterogeneous WiMAX-WLAN network architecture for advanced metering infrastructure (AMI) communications [90], and compare the performance of the WiMAX-WLAN network architecture to that of a pure WLAN network architecture. In [91], the authors study the performance of a Long Term Evolution (LTE) based networks (frequency- vs time-division multiplexing mode) for up-link biased smart grid communication in terms of latency and channel utilization.

2.5.5 Discussion

The communication network simulators discussed in this section have been used successfully in context of smart grid research. OMNeT++ and ns-2/ns-3 are used extensively in academia due to their open-source nature. In terms of supported simulation models, we believe that a wide range of models is available for each simulator, and the choice mainly depends on prior knowledge and preferences of the user regarding modeling language and tools, extensibility and supported programming languages, presence of extensive GUI tools, etc. For example, OMNeT++ and NeSSi provide an integrated development environment (IDE) that includes GUI's for building and configuring simulation models, visualization of topologies, result processing, etc. However, ns-2/ns-3 lacks an extensive set of GUI tools as found in OMNeT++, making it more complex in its usage. OPNET Modeler on the other hand is a commercial simulator that has a visual high-level interface. Another aspect that may influence the choice of simulator is commercial support, which is available for OMNeT++ (i.e., OMNEST) and OPNET. NeSSi, also an open-source simulator, distinguishes itself from the other tools due to its primary focus being network security.

2.6 Smart Grid Simulation

In this section, we present an extensive overview of smart grid simulators, i.e., those that support the combined simulation of the power system and the communication network, and/or model and study higher layers such as market mechanisms (e.g., for the development of demand response algorithms). We will categorize such smart grid simulators in two types, which we dub tools, resp. environments. A smart grid simulation *tool* is defined as providing a combined simulation of the power grid and communication network for a specific use case, i.e., the simulation tool is designed for that specific use case and others are not supported. As such, these tools are used to provide answers to very specific research questions, and are not extensible. On the other hand, smart grid simulation *environments* do not target a specific use case, but their design supports a wide range of use cases. As such, these environments are used to provide answers to a broad range of research questions, and are much more extensible.

2.6.1 Specialized smart grid simulation tools

A smart grid co-simulation tool to study the impact of delays in the communication network on the performance of the power grid is presented in [24]. A wireless communication network is simulated. A control strategy uses the wireless network to activate distributed storage units to compensate for temporary loss of power from a photo voltaic (PV) array, a phenomenon called “cloud transient” or

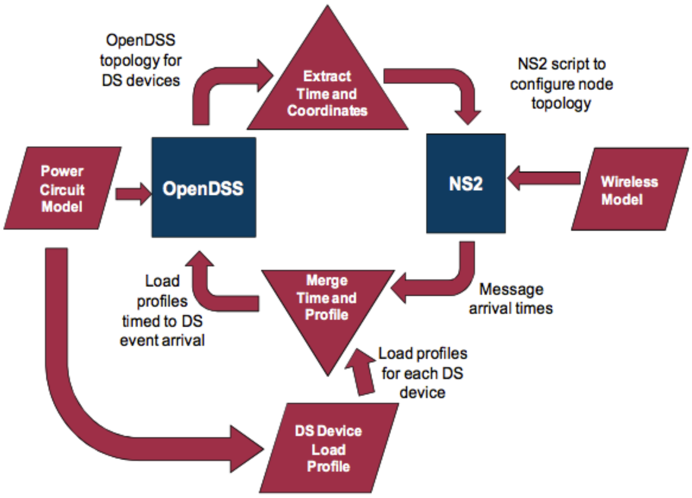


Figure 2.5: Example of a co-simulation approach [24].

"solar ramping"). The tool is used to determine if the distributed storage units can be dispatched quickly enough in case such a cloud transient occurs. A model of an actual distribution feeder is used to which small-scale storage batteries and a large scale PV array are connected. The wireless communication system is based on IEEE 802.11 (Wi-Fi). OpenDSS is employed to simulate the distribution system and the ns-2 network simulator is used to simulate the wireless communication network. Figure 2.5 illustrates the sequential co-simulation approach that is employed. OpenDSS outputs data regarding the time of the PV ramp event, the geographical coordinates of the storage nodes, and the power output of the storage nodes. Scripts parse this output and configure ns-2 with the storage node topology. Ns-2 then simulates the arrival of the dispatching messages at the storage units. Next, the arrival times of these messages are used to create OpenDSS scripts that are fed back to the OpenDSS environment, which then performs a sequence of power flow solutions. Note that this implies careful synchronization, as discussed in Section 2.3.2.

2.6.2 Smart grid distribution system

In this section we discuss (i) the power distribution system simulation and analysis tool GridLAB-D, and (ii) a hardware-in-the-loop test platform for real-time state estimation in distribution networks.We include GridLAB-D in the smart grid simulator overview instead of the power system simulator overview because it focuses on smart grid technologies and aims to incorporate simulation of the communication network.

2.6.2.1 GridLAB-D

GridLAB-D can be considered as a power distribution system simulation and analysis tool [92] targeted at the smart grid. It allows the simultaneous simulation of power flow, end use loads, and market functions and interactions. The software consists of a system core that can determine the simultaneous state of millions of independent devices (each can be described by multiple differential or difference equations) resulting in a detailed and accurate system model. GridLAB-D is designed as a modular system: the system core can load additional modules that add specific functions and models to the simulation environment. Modules can be developed and distributed independently. Basic features provided by these modules include power flow calculations and device control, end use loads and controls, data collection, etc. Additional, more advanced features, such as consumer behavior models (e.g., different types of demand profiles, price response, contract choice), energy operations (e.g., distribution automation, load-shedding programs, emergency operations), and business operations (e.g., retail rate, billing, market-based incentive programs) are also provided or under development [93]. Although the original focus of GridLAB-D was on the distribution system, research into the transmission system is also supported (e.g., the power flow module consists of both a distribution module and a transmission module [93]) as illustrated by [94] in which the influence of distributed energy sources on the transmission grid is evaluated. Although the current version (2.3.1) of GridLAB-D does not support explicit modeling of the communication network, a communication network module and a co-simulation approach are mentioned in the context of the next version (3.0): i.e., a *communications module* will allow users to simulate latency and dropped messages [95, 96]. The addition of such a module will enable users to determine the impact communications systems have on the operations of smart grid technologies. GridLAB-D is is also reported to be used as a basis for other smart grid simulation frameworks [97, 98] (although some raise concerns on the limited flexibility of composing GridLAB-D with other modules [20]). An electricity market simulator and GridLAB-D distribution system simulator are combined to simulate integrated retail and wholesale power system operation in [97]. In [98] the authors show that demand response resources can be used to maintain a flat and stable voltage profile over the feeder. For this, the authors extended GridLAB-D with a demand response controller, and adapted the existing volt/var controller is adapted to make use of the added demand response controller. Note that no communication network is simulated in [97, 98].

2.6.2.2 Hardware-in-the-loop test platform

A hardware-in-the-loop [99] test platform for real-time state estimation of active distribution networks using phasor measurement units is presented. Active distribution networks refer to electrical grids of which the resources are controlled by an energy management systems (EMS) to perform optimal voltage control, fault detection and management, etc. Such functions are deployed in time frames that vary between a few hundreds of milliseconds (fault management) to few tens of seconds. As such, they require real-time information about the network state. For this purpose, real-time state estimators (RTSE) that use PMU measurements are being developed. However, it is difficult to assess the accuracy of such RTSE in a real operational grid, as the true network state is unknown. Real-time simulators overcome this problem by enabling researchers to reproduce realistic power network conditions in a controlled environment.

The authors use the eMEGASim PowerGrid Real-Time Digital Simulator from Opal-RT to generate three-phase voltage and current analog signals of the monitored network buses, which are captured by a number of PMUs, which encapsulate the processed signals according to IEEE Std. C37.118.2-2011 [100] and send them over a real communication network to a workstation running a Phasor Data Concentrator (PDC) that processes and stores the information. The RTSE, also running on the workstation, uses the information to estimate the network state in real-time.

The real-time digital simulator accurately simulates the electromagnetic transients required by power grid and fast power electronic and converters systems. The true network state is known because it is recorded by the real-time simulator. Therefore, the performance of the RTSE algorithm can be assessed. Also, because a real communication network is used, the impact thereof (e.g., latency and/or data errors and loss) can be evaluated.

2.6.3 Electricity Markets

In this section we discuss smart grid simulators that focus on simulation of electricity markets in smart grids. Although these simulators do not explicitly model the communication network, we include them because of they incorporate specific smart grid technologies (e.g., VPP). Also, agent based simulators for electricity markets such as SEPIA could be seen as the predecessors of the smart grid simulators of today. Agent based approaches were gaining attention as a concept for self-healing distributed control of the power grid. Clearly, concepts such as self-healing, distributed control, and agent based system are currently still active research domains in the smart grid. Modeling thereof started with tools such as SEPIA [12] to which additional control strategies would be added. Hence, our reasoning for including SEPIA in this discussion of smart grid simulators.

2.6.3.1 SEPIA

Simulator for Electric Power Industry Agents (SEPIA) [26] is an agent-based simulation approach to modeling and simulation of physical and business operations in an electric power system. SEPIA is aimed to be a proof-of-concept to illustrate an agent-based simulation approach for the power industry. Possible applications targeted by SEPIA relate to the integration of physical and business operations in a power system. A power system structure can be defined by components that represent generators, loads, and business entities. These components are interconnected by links, representing power grid links, ownership, or money flows. Basic AC and DC power flow simulations are supported. SEPIA consists of three main components: (i) a graphical user interface to design, monitor and steer simulations, (ii) domain specific agents, and (iii) a simulation engine. Domain specific agents consist of traditional power system agents (e.g., generators, loads, transmission lines) and ancillary agents (e.g., markets, weather and speculators). Agents can transmit messages to each other. Each message is sent with an associated delivery time, which enables modeling of communication delay. The simulation engine has three major functions: (i) keeping track of simulated time, (ii) managing all communication between agents, and (iii) enforcing constraints set by the model topology. SEPIA supports studying agent learning in a power system by including a learning module that is based on the Q-learning algorithm (for agents to learn actions to take based on their observations of the system state). An example use case considers generator agents that learn how to take price decisions in electricity markets.

2.6.3.2 MASGriP

Similarly to SEPIA, the authors of [101] propose a multi-agent based smart grid environment, but explicitly focuses on smart grid use cases e.g., in the context of residential demand response. The simulation environment consists of two parts that are integrated in one environment: (i) the multi-agent smart grid simulation platform (MASGriP), and (ii) the multi-agent system for competitive electricity markets (MASCEM) [102]. Thus, MASGriP considers the technical aspects, whereas MASCEM considers the economical aspects of the smart grid, as discussed in more detail below.

MASGriP models the distribution network and the involved players. Power system entities such as consumers (residential, commercial, industrial) and (distributed) generators are modeled as agents. Each agent represents a physical entity in the smart grid and includes information regarding the electrical properties, location, etc. Additionally, demand response (DR) functions, micro-generation units, and/or electric vehicles can be assigned to these consumer types. These consumer agents establish contracts with aggregator agents: Virtual Power Players (VPP) or Curtailment Service Providers (CSP). Since individual consumers have insufficient flexibility required by for example DR programs, a CSP aggregates the demand response participation from small and medium consumers. CSP tasks include: identifying curtailable loads, enrolling customers, manage curtailment events, and calculate payments and penalties for participators. A VPP manages energy resources (DG, DR, SS, EV) and participates in the energy negotiation process (DR contracts, markets, etc.). Hence, a CSP is responsible for the technical management of energy resources, whereas a VPP is responsible for the economical activities associated with these resources.

MASCEM is a modeling and simulation tool to study complex and restructured electricity markets. Following agents are defined: market operator, system operator, market facilitator, buyer agents, seller agents, VPP agents, and VPP facilitators. Although the focus of MASCEM is on the economical aspects (i.e., electricity markets), technical constraints influence the operation of electricity markets (e.g., supply and demand must be balanced). Therefore, the system operator agent ensures that all constraints are met in the system and is therefore connected to a power system simulator to perform power flow analysis.

2.6.4 Wide-Area Monitoring, Protection and Control

Now we discuss three approaches that target use cases related to wide-area monitoring, protection and control: (i) two co-simulation approaches (GECO [3] and ORNL PSS [27]), (ii) a federated co-simulation approach (EPOCHS), and (iii) A real-time co-simulation approach (GridSim).

2.6.4.1 GECO

A global event-driven co-simulation framework for interconnected power systems and communication networks (GECO) is proposed [3, 70]. It is based on the PSLF (steady state and dynamic power system simulations) and ns-2 (communication network) simulation environments. GECO has been used to evaluate wide area monitoring, protection and control schemes [3, 103].

The GECO architecture is illustrated in Figure 2.6. A subcomponent in ns-2 is responsible for managing the co-simulation. It implements a global event scheduler designed as the global time reference and coordinator. A bidirectional interface between ns-2 and PSLF is used to exchange information (e.g., power system data, control commands), which is a tighter coupling than the co-simulation approach of e.g., [24]. Network-based power system control strategies are implemented in ns-2 based on the Application class in ns-2: control models for digital relays, phasor measurement units, and intelligent electronic devices. Agents make control decisions that are communicated using the simulated network and communication protocols based on TCP and UDP. Synchronization of the simulators is based on a global event driven mechanism, therefore it does not exhibit the accuracy problems illustrated in Section 2.3.

An example use case discussed is a communication-based backup distance relay protection scheme. The present distance relay protection framework is ex-

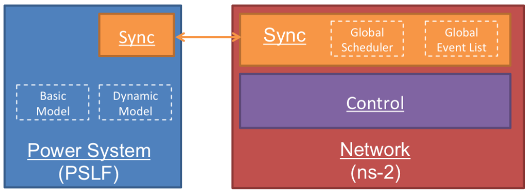


Figure 2.6: The GECO Architecture. Power system is simulated by PSLF and state information and control commands are exchanged between PSLF and ns-2 using a bidirectional interface (indicated by Sync*). Control models (PMU, intelligent agents, etc.) are implemented in ns-2.*

tended with an underlying network infrastructure. Distance relays can communicate with each other through their software agents thereby forming a coordinated system protection scheme. The objective of the scheme is to have faster backup relay protection and additional robustness to prevent tripping. Depending on the type of communication, two related protection schemes are discussed: supervisory (master-slave) and ad-hoc (peer-to-peer). Both schemes achieve faster backup relay protection than traditional non-communication based schemes, and also false-tripping (i.e., due to faulty measurements) is avoided.

2.6.4.2 ORNL Power System Simulator

Another example, based on a co-simulation approach using the ns-2 and A Discrete EVent system Simulator (adevs) simulation tools, is presented in [27], and in [5] the authors present a similar approach using OMNeT++ instead of ns-2. In [27], the authors discuss in detail the problem of integrating the discrete event nature of communication systems and the continuous time models of power systems. An approach based on Discrete Event System Specification (DEVS) is proposed to ensure formally that simulation correctness is preserved, enabling an integrated simulation of both domains. DEVS is a formalism to model and analyze general discrete event systems. The Toolkit for HYbrid Modeling of Electric power systems (THYME) is built on adevs and provides power system models (loads, transmission lines, generators, etc.), a power flow model, and a limited model for electro-mechanical transients [5]. A wide area load control use case demonstrates the simulation environment. Example results link the performance of the communication network to the operation of the power system: e.g., network flows affect load shed order and available bandwidth and network latency affects the control behavior.

2.6.4.3 EPOCHS

The electric power and communication synchronizing simulator (EPOCHS) [14, 104] is a platform for agent-based electric power and communication simulation. The main use cases supported by the EPOCHS simulation framework are related to wide area monitoring, protection and control. Example use cases are: (i) evaluation of the benefits and drawbacks of using communication in an agent-based special protection system, (ii) a backup protection system, (iii) monitoring of power system to prevent blackouts caused by voltage collapse. Instead of designing and building a new combined simulation environment, multiple specialized simulation environments (PSCAD/EMTDC, PSLF, ns-2) are linked into a distributed environment (federation).

EPOCHS is a combined simulation environment that links a power system simulator and communication network simulator ("federates") in a distributed environment (a "federation"). Figure 2.7 gives an overview of the EPOCHS architecture. The user of the simulation environment has the choice between two power system simulators, depending on the target use case: the PSCAD/EMTDC electromagnetic transient simulator (power system modeling), or the PSLF electromechanical transient simulator (transient timescales). Support for these different power system simulators is required due to the large differences in time scales between the electromagnetic and electromechanical simulations. The communication network is modeled in Network Simulator 2 (ns-2). The federation is managed by a central component, the runtime infrastructure (RTI). The RTI routes all messages between simulation components and ensures that the simulation time is synchronized across all components. The AgentHQ provides a unified view on the federation and provides a framework for implementation of intelligent agents, for example to implement distributed wide-area control and protection schemes. EPOCHS uses a time stepped synchronization approach as discussed in section Section 2.3 and as such may exhibit accuracy problems.

Summarized, EPOCHS is a distributed simulation environment that considers the combined simulation of the power grid and communication network. Supported use cases are related to wide-area monitoring, protection and control.

2.6.4.4 GridSim

GridSim simulates the power grid, the ICT infrastructure that overlays the grid, and the control systems running on top of it, in real-time. It focuses on the design and testing of wide area control and protection applications using PMU and other high-rate time stamped data. Distinctive about GridSim is that it operates in real-time to ensure optimal interfacing with actual power system elements, either hardware or software, i.e., it enables hardware-in-the-loop (HiL) experiments.

GridSim provides a flexible simulation framework that supports power system

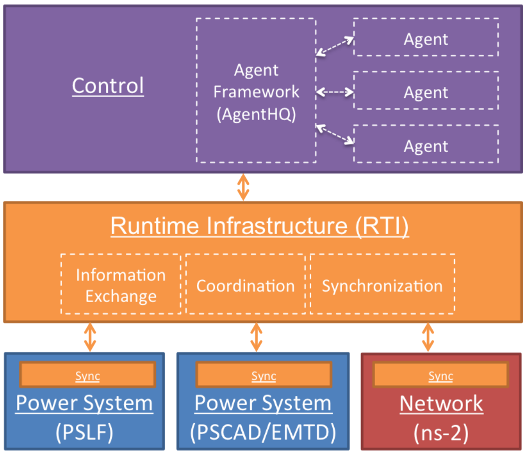


Figure 2.7: EPOCHS Architecture. Intelligent agents implement distributed wide area control and protection schemes. RTI routes all messages between simulation components and manages simulation time.

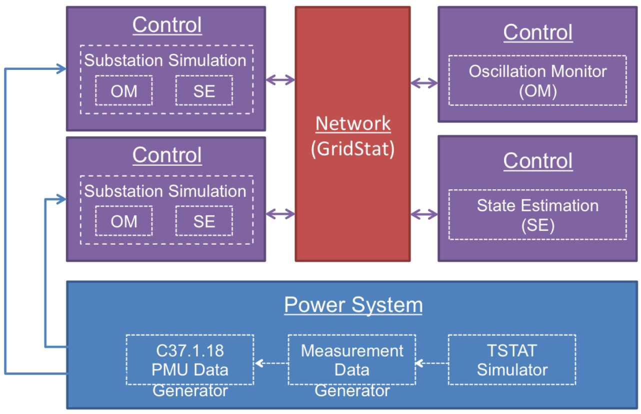


Figure 2.8: The GridSim Architecture. The Power System *component generates PMU measurements that are encapsulated in C37.1.18 data format and forwarded to simulated substations that use real communication middleware (GridStat) to transmit them to OM and SE applications.*

simulation, data delivery, flexible sensor deployments, and integration of actual power system components, protocols, and algorithms. GridSim components can be organized in four groups: power system simulation, substation simulation, communication and data delivery, and control center applications. TSTAT, a transient stability simulator, is used for power system simulation. GridStat, is used to deliver data between the different components in GridSim. GridStat is a wide area data delivery framework based on a publish-subscribe architecture. Examples of control center applications that are included in GridSim are: (i) an oscillation monitor, and (ii) a state estimator, both built using the OpenPDC applications set, which is an open-source software system for collecting and processing PMU measurements.

Summarized, GridSim is a real-time simulator for the power grid, the communication network and the control systems. Real-time operation ensures that actual power system elements can be integrated. Instead of using a communication network simulator, a real communication middleware platform is used.

2.6.5 Demand-Response/Demand-Side Management

This section gives an overview of simulators that are used to perform simulations related to demand-response or demand-side management applications. The simulators have been selected because they have distinct features. The IBCN smart grid simulator provides an integrated environment that has been used to evaluate DSM algorithms for electric vehicles. The SGiC simulator for example aims to involve end-users in their simulations, whereas GridSpice demonstrates how cloud technology can be used to enhance smart grid simulation scalability.

2.6.5.1 IBCN Smart Grid Simulator

An integrated smart grid simulator that considers the combined simulation of the power system and ICT infrastructure is proposed in [75]. A case study demonstrates the capabilities of the environment by investigating the impact of control algorithms for distributed generators (i.e., PV panels) has on a distribution grid, i.e., on the voltage profile and load profile of a household. Another area for which the simulator has been used extensively is demand side management of electric vehicles, e.g., [105].

The smart grid simulation environment is designed as layered architecture in which three layers are defined: application, middleware and support layers. The architecture is illustrated in Figure 2.9. The simulation environment is implemented in OMNeT++ using the INET framework, and power system simulator module implemented in Matlab is integrated into the environment.

The application layer consists of high-level applications or services, for example AMI, DSM/DR, or billing services. The services in the application layer make

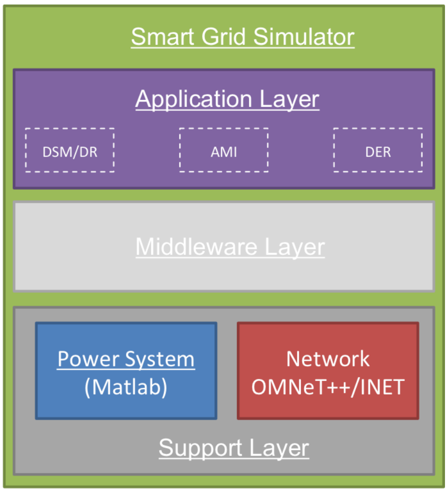


Figure 2.9: IBCN Smart Grid Simulator presented in [75]

use of the middleware layer, which provides generic functionality that can be used by any service. This includes a communication interface which can be used to send messages between components independent of the underlying networking technology (e.g., ZigBee or PLC; TCP or UDP) that is being simulated, discovery of devices or services, etc. The goal of this middleware layer is to support a broad range of applications while reducing the effort required to develop these services to a minimum. The support layer, composed of the network and electrical components, provides support functions for the layers above. Communication between services is simulated by the network component that provides simulation models for multiple types of physical media and communication protocols. The simulation environment must be able to model and interact with (virtual) electrical devices. This is supported by the power system component of the simulator which provides power flow simulations. Basic electrical models are provided (e.g. PV panel, battery, electric vehicle), but the user can add his own models.

2.6.5.2 SGiC

The Smart Grids Information & Communication (SGiC) [17] is web-based software for distributed decision support and performance analysis. Target use cases for the SGiC framework are power routing, power balancing, virtual power plants, or price based control. The software enables active participation of researchers, engineers and customers (residential or commercial). The latter is the unique aspect of this simulation tools. SGiC provides a end-user interface that supports social network interactions, which are considered appropriate incentives for consumers

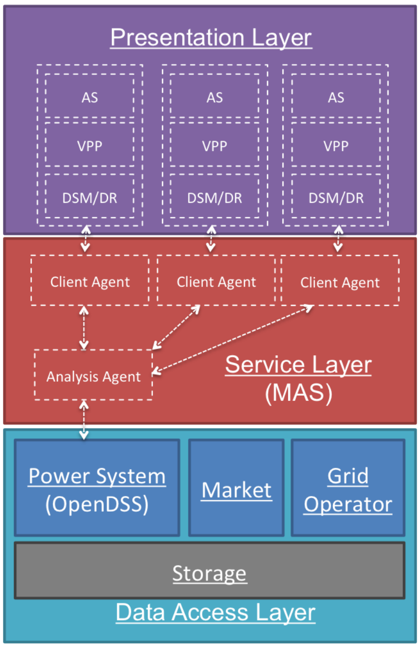


Figure 2.10: The layered SGiC architecture [17]. AS: ancillary services, VPP: virtual power plant, DSM: demand side management, DR: demand response, MAS: multi-agent system.

participating in DR, DSM, and virtual power plant (VPP) programs.

The SGiC software has a three-layer architecture, illustrated in Figure 2.10: presentation, service, and data access layers. The presentation layer provides web-based services to the end user that assist in participating in VPP, DSM, DR and local balancing programs. Customers are encouraged to share information, in order to obtain information on interesting programs in which to participate. An agent framework is used in the service layer to share information between users, network operators, and markets. Based on input from the users, an analysis agent (based on OpenDSS) will perform power system simulations and send decisions back to the users. Data from network operators, markets, DR participation, etc. is recorded in a common database in the data access layer.

2.6.5.3 GridSpice

GridSpice is a cloud-based simulation package developed to provide a framework to model all interactions of a smart grid, i.e., power flows, communication and market operations, in distribution and transmission networks. Built on top of GridLab-D and MATPOWER, the initial applications it targets are: renewable energy inte-

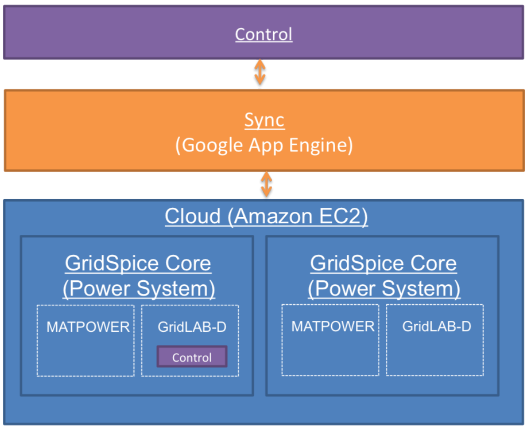


Figure 2.11: The GridSpice Architecture [98]

gration, home area control and smart algorithms, electric vehicle infrastructure, distributed energy resources, micro-grids, demand response and distribution operation, and utility scale storage. In [98] the authors use the GridSpice simulation platform to simulate volt/var control, demand response, and distribution automation in order to maintain a flat and stable voltage profile over the feeder.

2.6.6 Generic smart grid simulation environment

In this section we discuss generic smart grid simulation environments. Such environments do not target a specific use case, but aim to be general enough to support a wide range of use cases. The coupled simulator presented in [11] uses IEC 61850 to provide standards based distributed simulations. Mosaik [106] is an automatic simulation composition framework for the smart grid.

2.6.6.1 The Coupled Simulator

A coupled power system and communication network simulator is presented in [11]. Example use cases include the monitoring and control of large amounts of distributed energy resources in the context virtual power plants. Nevertheless, the simulator is described as not being limited to specific use cases (e.g., time step can be chosen in function of the phenomena under study). A message format and communication protocol based on the IEC 61850 specification is used to communicate over sockets, enabling a standards based distributed approach.

An overview of the architecture is given in Figure 2.12. The authors define the concept of interaction points, which are a subset of the IEC 61850 logical nodes. These nodes are the elements of the data model used for communication. Access

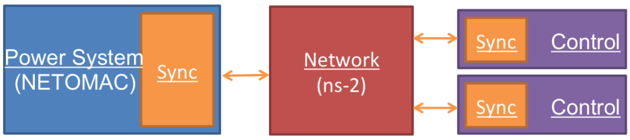


Figure 2.12: Architecture of the Coupled Simulator described in [11]

(reading/writing) to those interaction points is provided via JNI (Java Native Interface) interfaces. A network simulator is placed between the smart grid applications and the power simulator. All messages are routed through this network. A GUI enables the user to view the topology and simulation results of the simulated smart grid. Real-time simulation is supported enabling real-time testing of hardware.

2.6.6.2 Mosaik

Mosaik is a modular smart grid simulation framework supporting automatic composition of existing, heterogeneous simulation models for the evaluation of control strategies for heterogeneous DER and loads [106]. As such, the framework aims to provide support for scenario specification, simulation composition and scenario result analysis.

Mosaik adopts a layered approach to the simulation composition problem, which deals with the selection and combination of simulation components into valid simulation systems, according to specific user requirements. The layered architecture is illustrated in Figure 2.13. The *syntactic level* defines the interactions between the simulation models: i.e., to integrate a simulation model in Mosaik, the modeler has to provide an implementation of a predefined interface (SimAPI – XML/RPC API) that enables Mosaik to progress time of the simulation model and to get and set model data in a uniform way. The *semantic level* uses a reference data flow model to add a semantic description (i.e., data type, units) of the data that can be exchanged using the interfaces defined at the syntactic level. The *scenario level* deals with scenario definition and depends on a scenario meta model which is a formal scenario description. A prototype scenario meta model has been implemented using domain specific language (DSL). The *control level layer* provides a standardized API for the control strategies to analyze and manipulate the system at run-time. The Mosaik prototype consists of two components (both implemented in Python) [20]: (i) Master Control Program (MCP), (ii) simulation interface (SimAPI). The MCP manages the composition of the simulation scenarios and controls the execution of the scenarios. SimAPI must be implemented by the simulation models to integrate with Mosaik. An example use case is presented that composes a variety of simulation models: (i) electric vehicles (Python/SimPy and JADE), (ii) photovoltaics (MATLAB/Simulink), (iii) residential loads (CSV time-

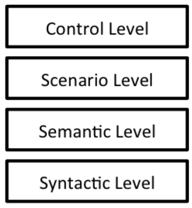


Figure 2.13: The Mosaik architecture for the selection and combination of simulation components into valid smart grid simulation systems

series), (iv) distribution grids (single-phase power flow analyses with Python/Pylon). Although not described, the SimAPI should allow a communication network simulator to be part of the framework. A future resource management component will enable simulations to be distributed over multiple machines thereby enhancing scalability.

2.6.7 Summary

Figure 2.14 displays a classification of smart grid simulators according to their modeling capabilities in terms of communication network and power system. The communication network model level of detail is divided in three parts: (i) no model, (ii) black box communication network model, (iii) detailed communication network model.

Figure 2.15(a) illustrates the cases where no communication network simulation model is implemented by the smart grid simulator. Information is exchanged without modeling message sizes, bandwidth, delay, errors, congestion, protocols, etc. In other words, an ideal network with infinite bandwidth, zero delay, no errors, etc. is modeled.

Figure 2.15(b) illustrates a black-box communication network model which provides a simplified and abstract model of the simulated communication network. The example black-box communication network is modeled using two parameters: the delay and errors. For simplicity, we assume a fixed delay, independent of the source, destination, message size, etc. In such a scenario, a source that wants to transmit a message to a destination, forwards the message to the black-box communication network model, which delivers the message to the destination after the specified delay. An example of a possible "error" model could be a given probability that a message is lost in the network, and as a result is not received at the destination. Note that other parameters (e.g., bandwidth, congestion, message sizes) could also be included in the black-box model.

Figure 2.15(c) illustrates a detailed communication network model which provides a realistic model of the simulated communication network. The example network consists of a source and destination host connected to a switch, which

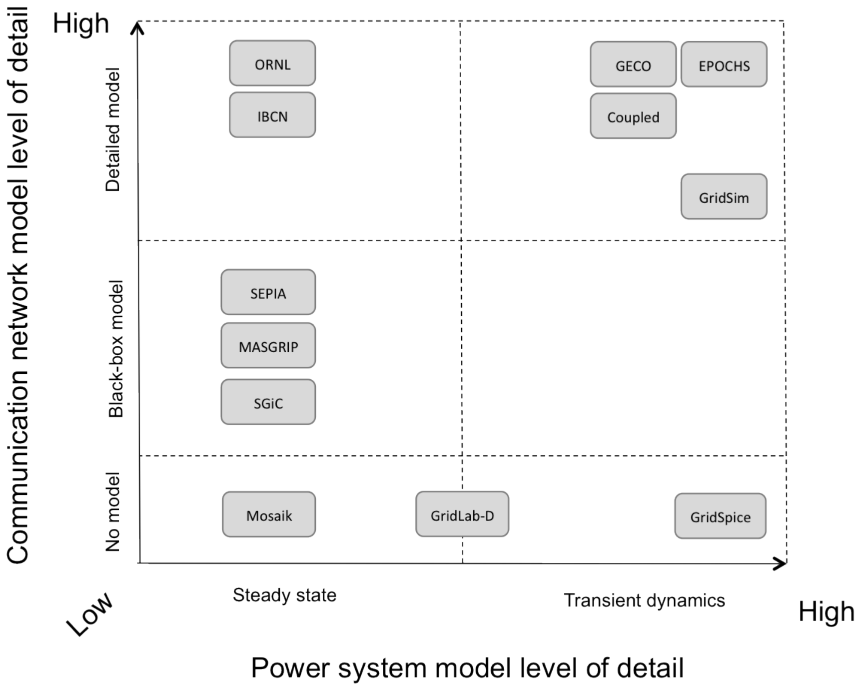


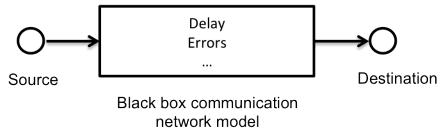
Figure 2.14: Classification of smart grid simulators according to power grid simulation type and communication network model.

are connected to the core network that consists of multiple interconnected routers. Each communication link may be configured with specific bandwidth, delay, error, etc. parameters. Source and destination hosts contain models for the application, transport, network, link and the physical layers of the network. Switches contain models for the link and physical layers of the network. Routers contain models for the network, link and physical layers of the network.

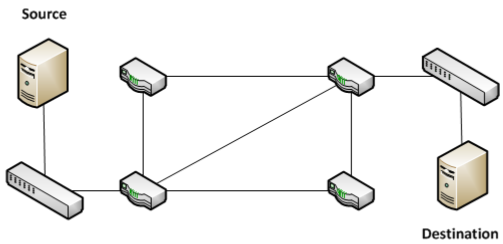
Summarized, a black-box model does not explicitly model the network topology, links, protocols, background traffic, etc., whereas a detailed communication network model provides support for this.

The power system model level of detail is divided in two levels: (i) steady state, (ii) transient dynamics. Summarized, steady state simulations analyze the system in a stable equilibrium state, and focus lies on checking whether the power system variables are within proper boundaries (e.g., validation of voltage limits). Transient dynamics simulations study transitions between equilibrium points due to a major changes in the power grid configuration, e.g., disturbances. We refer to Section 2.4 for more information about these power system simulation types.

(a) None



(b) Black-box



(c) Detailed

Figure 2.15: Level of detail of the communication network simulation model: (a) No communication network simulation model. (b) Black-box: high level abstract simulation model. (c) Detailed communication network simulation model.

2.7 Discussion

Above, we presented a survey of power system, communication network and smart grid simulators. In this section, we first synthesize the architectural schemes these smart grid simulators are built on. Next, we will discuss the use of standards, communication protocols, data formats, etc. in smart grid simulators. Finally, we briefly indicate the role of multi-agent based systems in smart grid simulators.

2.7.1 Smart grid simulator architectures

In this section we give an overview of the different smart grid simulator architectures, for which we will indicate the relationship between the four high level functional components:

Power system models the power grid.

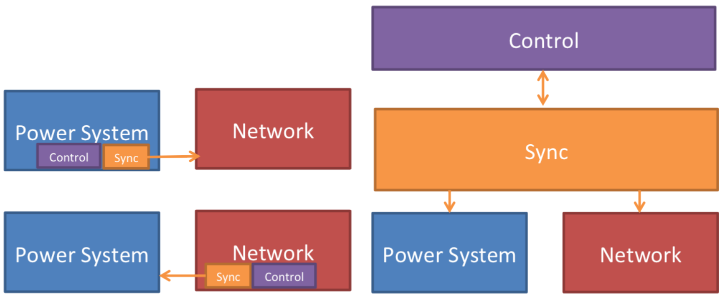
Network models the communication network.

Control models the smart grid applications (WAMS, DSM/DR, AMI, etc.).

Sync synchronizes time, data and interactions between the different simulator constituents.

As discussed in Section 2.3, in an *integrated simulation* architecture (see Figure 2.1(b)) a single simulation environment combines simulation of the power system, communication network and control. Synchronization between the various components in this approach is straightforward, since there is only one core simulation engine keeping track of (simulated) time. This is the approach taken in, e.g., [75, 107].

In a *co-simulation* approach (recall Figure 2.1(a)), multiple specialized simulators are used, thus requiring synchronization between them. Therefore, in practice typically one simulator is selected as a master simulator for the synchronization logic, which usually (although not strictly required) is also the one where control logic is implemented: this amounts to a master-slave configuration, as illustrated in Figure 2.16(a). Control and synchronization thus are possibly limited by the capabilities of the master simulator. An example of this approach is [22], combining ns-2 (master) and Modelica, which identified possible drawbacks: (i) the master controls the slave model, therefore, sending data from slave to master is not possible (i.e., slave cannot push messages in response to internal events to master) (ii) no parallelism is exploited, both run each in turn. Also, such an architecture does not naturally lend itself to distributed or federated simulation. Other examples that use this approach are GECO [3], the ORNL Power System Simulator [5, 27], VPNET [28].



(a) Master-slave (b) Dedicated synchronization and control

Figure 2.16: Two fundamentally different approaches to co-simulation.

Figure 2.16(b) illustrates a co-simulation architecture in which a single dedicated component is responsible for synchronizing and connecting all the different components. Not only does it provide synchronization between the multiple simulators, it also offers a unified interface for the control logic. This approach also lends itself to distributed or federated simulation: dedicated hosts could be used for each individual host. Examples that use this approach are EPOCHS [14] and GridSpice [18], Mosaik, and the HLA-based simulator proposed in [15].

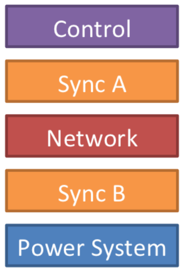


Figure 2.17: Layered simulation architecture. Sync A *is responsible for synchronization between* Control *and* Network *components whereas* Sync B *provides synchronization between the* Power System *and* Network *components. The difference in naming indicates that completely different approaches/technologies may be used.*

Figure 2.17 illustrates a layered approach using different synchronization layers between each simulator. An example that uses this approach is [11]. Also, we could consider the co-simulation approach presented in [24] to be of this type. Although the SGiC does not explicitly model the communication network, it also uses a layered approach. Mapping the SGiC architecture [17] to the functional blocks defined in this section (power system, network, control, sync), we could say that network and synchronization layers have been merged in the service layer.

Table 2.3 provides an overview of smart grid simulators using an integrated or co-simulation approach. It can be used to identify simulators based on the targeted use case, illustrate different co-simulators that have been used, etc. Emphasis is put on simulators that consider the combined simulation of the power grid and ICT infrastructure. However, certain examples do not consider both components, but are still included due to the specific smart grid applications they target. For each simulator, we indicate the main use case that is being targeted, the power and network communication components, and lastly if the simulator can be used in a distributed setting. The support for distributed simulation can be beneficial the increase the scalability of the simulator, and enables easier integration with other simulators (e.g., based on HLA, see below).

2.7.2 Standards and smart grid simulation

Federation is identified as a common mechanism to co-simulation in this survey and in [82]. The High Level Architecture (HLA) is an open standard developed by the Simulation Interoperability Standards Organization and published in IEEE Standard 1516. It is a technology for developing distributed simulation and describes the components of HLA, their interfaces and properties. Several smart grid simulators use this technology or a similar approach to perform a combined simulation of the power system and ICT infrastructure [14, 15, 83]. A federation con-

Table 2.3: Overview of smart grid simulators.

Reference	Use Case	Power	Communication	Distributed
GridLab-D [92]	Distribution system	-	-	No
GridSim [18]	Wide Area Monitoring and Control	TSTAT	GridStat	Yes
ORNL [5, 27]	Wide Area Monitoring and Control	adevs	ns-2, OMNeT++	No
EPOCHS [14]	Wide Area Monitoring and Control	PSCAD/EMTDC, PSLF	ns-2	Yes
GECO [3]	Wide Area Monitoring and Control	PSLF	ns-2	No
Zhu et al. [87]	Wide Area Monitoring and Control	Matlab/Simulink	OPNET	No
Georg et al. [15]	Wide Area Monitoring and Control	DigSilent	OPNET	Yes
Lugaric et al. [21]	Wide Area Monitoring and Control	PowerWorld	Anylogic	No
Mets et al. [75]	DSM/DR	Matlab	OMNeT++	No
GridSpice [98]	DSM/DR	GridLab-D, MATPOWER	-	Yes
Godfrey et al. [24]	DSM/DR	OpenDSS	ns-2	No
SEPIA [26]	Electricity Markets	MP_2	-	Yes
MASGrip [101]	Electricity Markets	-	-	No
Bergmann et al. [11]	Virtual Power Plants	PSS NETOMAC	ns-2	Yes
Davis et al. [108]	SCADA Security	PowerWorld	RINSE	?
Mallouhi et al. [109]	SCADA Security	PowerWorld	OPNET	?
Liberatore et al. [22]	Networked control	Modelica	ns-2	No
VPNET [28]	Networked control	VTB	OPNET	No
Xiaoyang et al. [88]	Networked control	-	OPNET	No

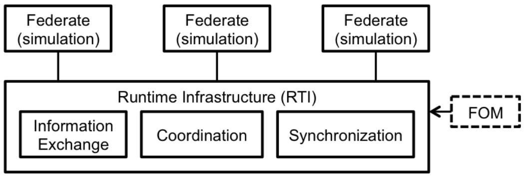


Figure 2.18: Topology of a HLA Federation

sists of a number of simulators (federates) that are connected to a service bus called the Runtime Infrastructure (RTI). Figure 2.18 gives an overview of a topology of a HLA federation. The RTI provides information, synchronization, and coordination services. Information exchange occurs according to a publish/subscribe paradigm. Synchronization services handle time, synchronization points, snapshots, etc. Coordination services are used to manage the execution of the federation and the different federates. A Federation Agreement is a document that describes how federates are exchanging services. It consists of Federation Object Models (FOM) that contain a description of the data exchange in the federation (e.g., objects, interactions). Main advantages of the HLA are standardized interface specifications and documentation. However, concerns are also raised regarding: (i) added complexity of developing a federated simulation, (ii) the requirement to modify existing simulators to make them HLA conform.

The smart grid simulators presented in [11, 15] make extensive use of smart grid standards such as *IEC 61970 Common Information Model (CIM)/Energy Management*, *IEC 61968 Common Information Model (CIM)/Distribution Management* and *IEC 61850 Power Utility Automation*. In [15], the power system topology is provided as input to the simulator using CIM, which defines a description language used for the power system topology. Ontology matching is used to convert the CIM topology to the IEC 61850 based model description used internally. Support for both technologies using ontology matching approaches is considered beneficial considering the ongoing CIM and IEC 61850 harmonization. Similarly, Mosaik [20] supports CIM to define the topology of the power system. A message format and communication protocol based on the IEC 61850 specification is used to communicate over sockets between the different simulator components [11]. GridSim [18] uses a communication protocol defined by IEEE C37.118 when simulating the exchange of PMU data. For static power flow analysis, a CIM compliant tool chain for Python has been identified in [110], comprising: (i) PyCIM to import grid topology as CIM XML/RDF file (ii) CIM2BusBranch to convert CIM node breaker topology to the bus branch topology, and (iii) PyPOWER to perform load flow analysis.

Use of standards based approaches (HLA, IEC 61850, CIM, etc.) facilitates the interoperability of different simulators that are acquired or developed over time, as well as the exchange of simulation models. It also adds an extra level of realism to the simulation models. Another advantage is that users can easily select and combine components according to their specific requirements, reducing cost, time and risk.

2.7.3 Multi-agent based systems

Agents are a natural way to extend the power system without drastic changes in the architecture of the power system [14]. Main benefits that are associated with agent based approaches are their (i) autonomous nature, (ii) ability to share information, (iii) ability to coordinate actions. Hence, multi-agent based systems are being used in a variety of ways for smart grid applications [111]. For example, protection schemes, demand side algorithms, etc. are being implemented using (market based) multi-agent systems, in which the agents contain the intelligence required to take appropriate actions. As such, the (simulated) multi-agent architecture and the intelligence implemented in the agents could eventually be implemented in the field and thus is not only for simulation purposes. Another example of the application of multi-agent systems is the increased use of agents that is observed in devices deployed in the field such as Intelligent Electronic Devices (IED) [14].

This survey on smart grid simulation has pointed out that also in the context of simulation, agent based approaches play a significant role: i.e., agents are used as a model for simulator components, which would not necessarily correspond to an actual components in the real world. Agent based approaches are typically used in simulators that consider electricity markets such as SEPIA and MASGriP. Examples of other smart grid simulators that use agent models include GECO, EPOCHS and SGiC. The ILIas framework presented in [82] focuses on integration of simulation and multi-agent based management systems. For the requirements analysis for Mosaik, additional emphasis was put on supporting agent based control strategies [106]. In [112] the authors describe a simulator based on software agents that simulates the dynamic behavior of a smart city: heterogeneous devices that consume and/or produce energy, and that are able to act autonomously and collaborate. Agents are also considered to model the human factor within simulations [21].

2.8 Conclusion

Smart grid technology typically results in an increased complexity of the power grid, and implies uncertainty (to be dealt with by, e.g., stochastic control models). To assess the performance of possible solutions, simulation tools offer a cost effective approach. A comprehensive overview of the various tools applicable in smart grid research, as well as their main characteristics, shows they fall into three groups: (i) power system, (ii) communication network, and (iii) smart grid simulators. Power simulation tools broadly are either targeted at steady state analysis (typically power flow studies), or at transient dynamics simulations (typically upon disturbances or sudden system changes). They typically adopt a continuous time model, studying the system state at fixed, equidistant points in time. Communication network simulators on the other hand typically adopt a discrete event simulation approach, where time intervals between successive events (i.e., system changes) can greatly vary. Thus, combining them both into real smart grid simulators requires careful synchronization when a so-called *co-simulation* approach is followed, where models from both domains in different tools are combined. More *integrated* solutions have a tighter coupling between the two domain models, avoiding more tedious model synchronization interactions. In terms of use cases, we found two major types of studies: either on wide-area monitoring, protection and control (WAMPAC), or on demand-response (DR). The latter also imply extensive models studying market-based control, where typically multi-agent system (MAS) approaches are adopted.

Our survey details current state-of-the-art grid simulation approaches, in terms of their use cases, architecture and example studies. We believe this synthesis thus will assist (i) smart grid researchers looking for tools that target a certain use case, as well as (ii) smart grid simulator developers that wish to learn more about simulator paradigms, architectures, standards, etc. To conclude, lessons learned from the current state of the art seem to be:

- Power system simulation is supported by a wide variety of tools that can be classified in *steady state* and *transient dynamic* simulators according to the phenomenon under investigation.

- For well-defined, specific use cases, *dedicated simulation tools* exist in both power and communications domains, but for cross-domain issues, combined simulations are required.

- Combined simulation of power system and ICT infrastructure can be achieved using a *co-simulation* or *integrated approach*.

- *Power line communication (PLC)* technologies transform the power grid into a data communication network, and are being considered for a wide range of smart grid applications. However, support for simulation of PLC networks in popular network simulators is only limited and not available by default.

- Smart grid simulators that offer a combined simulation or focus on applications that characterize smart grids are found for *use cases* related to *active distribution systems*, *electricity markets*, *wide-area monitoring*, *protection and control (WAMPAC)*, and *demand-response/demand side management*.

- *Generic smart grid simulation tools* are being developed that support a wide range of use cases instead of focusing on one specific area. However, most simulators focus on one specific area.

- When power network (resp. communication) details can be highly abstracted, an *integrated* simulator taking a detailed power (resp. communication) simulator as a base seems appropriate.

- When a *detailed simulation* of both domains can be most efficiently (esp. in terms of development effort) realized using a *co-simulation* approach that reuses existing tools.

- However, supporting combined simulation remains challenging because of the need to manage and synchronize actions and state (especially time) of the components.

- *Federated* smart grid simulators are a promising to achieve large-scale and detailed smart grid simulations: distributed simulation is supported and other co-simulator components could be added more easily (e.g., transportation, weather). Use of standards (e.g., HLA, IEC 61850, CIM) may play an important role in this.

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3

Comparison of intelligent charging algorithms for electric vehicles to reduce peak load and demand variability in a distribution grid

In this chapter, we take the first step towards optimal integration of electric vehicles. We study how electric vehicle charging can lead to excessive peak loads, and how this can cause problems such as transformer overloads and voltage fluctuations. To avoid such problems, different demand side management approaches are considered, and their performance is compared in terms of peak load, demand variability, and voltage fluctuations using the smart grid simulator introduced in Chapter 2.

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Abstract A potential breakthrough of the electrification of the vehicle fleet will incur a steep rise in the load on the electrical power grid. To avoid huge grid investments, coordinated charging of those vehicles is a must. In this paper we assess algorithms to schedule charging of plug-in (hybrid) electric vehicles as to minimize

the additional peak load they might cause. We first introduce two approaches, one based on a classical optimization approach using quadratic programming, and a second one, market based coordination, which is a multi-agent system that uses bidding on a virtual market to reach an equilibrium price that matches demand and supply. We benchmark these two methods against each other, as well as to a baseline scenario of uncontrolled charging. Our simulation results covering a residential area with 63 households show that controlled charging reduces peak load, load variability, and deviations from the nominal grid voltage.

3.1 Introduction

Electric vehicles (EV) and plug-in hybrid electric vehicles (PHEV) are expected to gain in popularity the following years. Research estimates the number of hybrid electric vehicles in Belgium to reach 30% by 2030 [1]. This evolution is mostly driven by environmental benefits such as lowered emissions and improved fuel efficiency. However, as the electrification of the vehicle fleet is gaining momentum, it will also have an impact on the generation, transmission and distribution levels of the power grid.

Additional generation will be required to recharge the batteries of these vehicles as this requires large amounts of electrical energy which results in additional load on the power grid. However the energy required to charge these vehicles is estimated to be only 5% of total consumption in Belgium [2] in 2030. The impact on the generation and transmission levels of the power grid are therefore considered manageable on a short to medium term. However, the impact on the (residential) distribution network can be substantial, especially for high penetration levels of EVs: a single EV is estimated to double average household load during charging [3] (120V/15A 1.4kW Level 1 charger, and average residential load Southern California).

Charging electric vehicles can lead to large peak loads. Equipment installed in the power grid can be overloaded as a result. Maintaining the power quality (e.g., voltage, unbalance, etc.) is also important to assure the correct operation of the power grid. Therefore, it is important to control and coordinate the charging of electric and plug-in hybrid electric vehicles.

The main concern of vehicle owners is to have the batteries charged by the time they need their vehicle. A certain degree of flexibility is available, because vehicles are often parked for periods of time that are longer than the time required to charge their batteries, for example during the night. We can exploit this flexibility and shift consumption to times of lower demand. This presents opportunities for the development of intelligent charging algorithms that utilize this flexibility to avoid issues in the distribution grid. These algorithms will decide on when to charge what vehicle, and potentially at what charging rate (if this can be tuned), as to achieve a certain objective (e.g., peak shaving, maximally use available green energy).

Such approaches to control and coordinate the charging of electric vehicles, that for example reduce peak load or balance demand and supply from renewable energy sources, are part of a broader context called demand side management (DSM) or demand response (DR). Instead of adapting power generation to power demand, power demand is adapted to support the optimal operation of the power grid. The application of DSM or DR is not limited to controlling the charging of electric vehicles, but also targets other residential, commercial, or industrial devices. Different approaches are considered in literature. In this work, we focus on approaches that are based on mathematical optimization and multi-agent systems. A mathematical optimization approach based on quadratic programming is presented in [4]. The aim is to minimize energy losses, and maximize the grid load factor. In earlier work [5, 6], we also explored approaches based on quadratic programming, that reduce peak load and load variability. An example of a multi-agent system is PowerMatcher [7], which is based on virtual markets, where agents bid on an electronic market to determine an equilibrium price matching demand and supply. Distributed algorithms based on dual decomposition are proposed in [8] and [9]. Other approaches are based on game theory to perform demand side management [10]. Control schemes for charging electric vehicles based on queuing theory are proposed in [11] and [12]. Clearly, there is much interest in DSM or DR algorithms, and a wide variety of methods has been proposed, to improve the operation of the distribution grid by controlling and coordinating the charging of electric vehicles (or other electrical loads).

Yet, often the proposed coordination mechanism is only benchmarked against a "business-as-usual" scenario without coordination. In this paper, we present a quadratic programming based coordinated charging algorithm that can serve as optimal control benchmark. We will demonstrate its usefulness in comparing it with a realistically deployable price-based coordination mechanism for DSM, in casu a market-based multi-agent system (MAS).

The contributions of this paper are: (i) an extensive analysis (beyond [5, 6]) of quadratic programming (QP) based assessment of attainable peak load reduction, (ii) including associated effects on power quality, and (iii) benchmarking of a fully distributed market-based multi-agent system against the optimal QP results.

We also note that electric vehicles could also be used to provide ancillary services to the power grid [13], a concept known as vehicle-to-grid (V2G). An example of V2G services is storage of renewable energy. Solar and wind energy is intermittent and often the availability thereof does not coincide with the demand for energy. Electric vehicles can be charged at these moments and help balance supply and demand. The energy stored in the EVs' batteries obviously can be used later for transportation, but it could also be delivered back to the grid while the EV is still stationed at the charging point. Although this is a promising concept, we will not consider it in this work. However, both approaches we consider, can be adapted to V2G services [6].

The remainder of this paper is structured as follows: our problem statement is summarized in Section 3.2. We discuss the algorithms considered in this paper in Section 3.3. The case study used to evaluate the different algorithms is presented in Section 3.4 and results are discussed in Section 3.5. Finally, conclusions are synthesized in Section 3.6.

3.2 Problem statement

Charging algorithms that determine optimized charging schedules can reduce the negative effects that the additional load has on the distribution grid, and also optimize the consumption of renewable and intermittent energy sources. This paper discusses two approaches used to determine charging schedules of electric vehicles. The first approach adopts *quadratic programming (QP)*, whereas the second approach is based on *multi-agent systems (MAS)* and *electronic markets*. The goal of both approaches is to minimize the peak load and load profile variability of the transformer load profile resulting from charging electric vehicles. This is achieved by shifting the charger loads in time and controlling the rate of charging.

The two approaches have a fundamental difference in their design. We use the QP approach in an offline setting, where we assume all events (cars arriving, departing, evolution of base load of other electrical consumers) are known in advance: the QP solution hence will result in an optimal answer to the EV charging scheduling problem. (Note that some online approaches can be straightforwardly be derived, which would lead to sub-optimal results, but these are not further discussed in this paper.) The second approach, MAS, will reflect the more realistic online situation, where we do not know beforehand what car will arrive when, but rather (re)compute the charging schedule dynamically upon each arrival. The goal of this work is to measure the differences between the two approaches.

3.3 Charging algorithms

The algorithms that form the topic of this paper determine charging schedules that control the recharging of electric vehicles. Each schedule indicates when a certain vehicle can be charged and at which charging rate.

The following sections will describe the different approaches taken. Afterwards, we compare the results from each approach to a *"business-as-usual" (BAU)* case in which we assume that the car immediately starts charging upon arrival at the charging point, without any form of coordination, until it is fully charged. In this BAU scenario, the charging rate is not controlled, but is fixed by the car/battery properties.

3.3.1 Quadratic Programming

In the following sections we discuss three algorithms based on quadratic programming (QP): the *local*, *iterative global*, and *global* algorithms. The local and iterative global algorithms have been introduced in earlier work [5]. However, we here expand on this earlier work by introducing a third algorithm, and by comparing these algorithms to an algorithm based on multi-agent systems and electronic markets.

Quadratic programming is a specific type of optimization problem in which a quadratic function of several variables subject to linear constraints on these variables is optimized (minimizing or maximizing). The three algorithms are similar in nature, but differ in the amount of knowledge they possess about their surroundings, i.e. regarding the power consumption of other households and vehicles.

3.3.1.1 Model parameters

We first discuss the parameters that are present in the different quadratic programming models. The models consists of K households, identified individually by the variable k. The simulated period of time (e.g. 24 hours) is divided in T discrete time slots (e.g. 5 minutes) which are identified by the variable t.

We assume that the load resulting from the usage of electric appliances in each household is uncontrollable; we call this load the uncontrollable load. Each household k has a load profile for the uncontrollable loads $B_k(t)$ that indicates the average uncontrollable load (stemming from household appliances etc.) during each time slot t. The aggregated power demand of each household is limited to L_{max} (representing the grid connection capacity), expressed in Watt.

Charging electric vehicles will result in an additional load in the households. This load however is flexible as it can be shifted in time and therefore it is not part of the uncontrollable load of a household. Each vehicle has an arrival and departure time slot, respectively α_k and β_k. BC_k indicates the maximal capacity of the battery, expressed in Wh. C_k indicates the energy contained in the battery pack upon arrival and is also expressed in Wh. The charging rate is controllable but limited by $X_{k,max}$.

The equations use a conversion factor, δ, to calculate the energy consumed (expressed in Wh) during a certain time slot based on the load (expressed in W) during that time slot (e.g. $\delta = 0.25$ assuming 15 minute time slots).

3.3.1.2 Local algorithm (QP1)

The local (i.e. single household) scheduling method uses information about local power consumption to determine a charging schedule, i.e., we assume that the household energy consumption is known between arrival and departure time. A home energy management system could provide this information, e.g. based on historical data. The impact of other households and vehicles on the global load profile is not considered in this case. Therefore, the schedules resulting from this approach minimize local peak load and load profile variability. The quadratic programming model described below is solved for each vehicle separately upon arrival at the charging point at home.

A target load profile $T_k(t)$ is calculated for $t \in \{\alpha_k, ..., \beta_k\}$, the duration of the charging session, before determining the optimal charging schedule. The goal is for the household load profile, which includes the uncontrollable load and charger load, to approach this target profile as closely as possible. The optimal target load profile, considering the goals of minimizing the peak load and load profile variability, is formed by a constant load. The target load profile represents the constant power that should be supplied, to provision the energy requirements of the household and electric vehicle. Of course, this is not achievable, because not all devices have flexibility. The calculation of the target load at each household is defined in equation (3.1) and is based on the battery capacity BC_k, the current battery state C_k, the uncontrollable load $B_k(t)$, and the charging session duration.

$$T_k(t) = \frac{(BC_k - C_k) \cdot \delta + \sum_{t'=\alpha_k}^{\beta_k} B_k(t')}{\beta_i - \alpha_i} \tag{3.1}$$

The following constraints apply to the optimization problem. The decision variables $X_k(t)$ of the optimization problem form the charging schedule and indicate the charing rate during each time slot. We define decision variables for one vehicle. The charging rate is limited by $X_{k,max}$, and can be any as defined by constraint (3.2). Constraint (3.3) assures that the load of the household does not exceed a certain limit L_{max}, e.g. set by the supplier, distribution system operator (DSO), or technical constraints (e.g. household circuitry). Finally, constraint (3.4) assures that the battery is fully charged after applying the charging schedule. Note that we use a very simple battery model. However, this should not significantly influence the results [14].

$$0 \leq X_k(t) \leq X_{k,max} \tag{3.2}$$

$$B_k(t) + X_k(t) \leq L_{max} \tag{3.3}$$

$$C_k + \sum_{t=\alpha_k}^{\beta_k} \big(X_k\,(t) \cdot \delta\big) = BC_k \tag{3.4}$$

The objective function is defined in equation (3.5). A charging schedule $X_k(t)$ is obtained by minimizing the squared euclidean distance between the target load profile and the household load profile.

$$\sum_{t=\alpha_k}^{\beta_k} \Big(T_k(t) - \big(B_k(t) + X_k(t)\big) \Big)^2 \tag{3.5}$$

3.3.1.3 Iterative global algorithm (QP2)

The iterative global algorithm also uses power consumption information, but it is not limited to local information. The algorithm is initialized by determining the load profile observed by the transformer to which the households are connected. Equation (3.6) is used to calculate this global load profile. The global load during each time slot t is the sum of all household loads during time slot t.

$$GB(t) = \sum_{k=1}^{K} B_k(t) \tag{3.6}$$

The following quadratic programming model is solved separately for each vehicle that wishes to recharge its batteries. The algorithm calculates a target load profile using the global load profile instead of the local load profile as done by the local algorithms.

$$T_k(t) = \frac{(BC_k - C_k) \cdot \delta + \sum_{t'=\alpha_k}^{\beta_k} GB(t')}{\beta_i - \alpha_i} \tag{3.7}$$

The constraints applied to the quadratic programming model are identical to the constraints of the local algorithm and are therefore defined in constraints (3.2), (3.3), and (3.4).

The objective function that is minimized to determine the charging schedule is defined by equation (3.8). It is based on the same principle as the local algorithm, but utilizes the global load profile instead of the local load profile. As a result, we obtain a global optimum, instead of a local optimum as is the case of the local algorithm.

$$\sum_{t=\alpha_k}^{\beta_k} \Big(T_k(t) - \big(GB(t) + X_k(t)\big) \Big)^2 \tag{3.8}$$

After determining the charging schedule, the global load profile is updated with the load originating from the charging schedule (3.9), hence the iterative nature of the algorithm. As a result, future iterations will account for other households and electric vehicles that have been scheduled. This is the main difference between the local and global iterative algorithms: other households and electric vehicles that have been scheduled are accounted for when a charging schedule is determined by the iterative global algorithm.

$$GB(t) = GB(t) + X_k(t), \forall t \in [\alpha_k, \beta_k] \tag{3.9}$$

The iterative global algorithm is performed on a first-come-first-serve basis for each vehicle that arrives. However, the order in which vehicles arrive will have an impact on the charging schedule. To evaluate the impact of this order, and also to evaluate the benefits of accounting for future arrivals, we developed a third approach, which is presented in section 3.3.1.4.

3.3.1.4 Global algorithm (QP3)

The third approach based on quadratic programming assumes knowledge about household energy consumption, and even more importantly, each future charging session that will occur over a certain time frame.

A scheduling period, e.g. corresponding to a calendar day, is defined for which the charging schedules of all vehicles are determined beforehand. For each vehicle, the algorithm has to know in advance the arrival time, departure time, state-of-charge, etc. Based on this information, charging schedules for each vehicle are determined simultaneously by solving the quadratic programming model. Note that in contrast to the local and iterative global quadratic programming model, the global model only has to be solved once to determine the charging schedule for each vehicle. The advantage of this approach is that all information is known, and therefore the flexibility is maximally used.

The global algorithm is initialized in the same way as the iterative global algorithm by calculating the global load profile using equation (3.6). A set of decision variables $X_k(t)$ and constraints is defined for each vehicle k. These variables will define the charging schedule for each vehicle after minimizing the objective function (3.10). Again, the constraints are identical to those defined by the local algorithm in equations (3.2), (3.3), and (3.4).

Equation (3.10) illustrates that the objective function is again based on the same principle as the local and iterative global algorithm. In contrast to the local and iterative global method, the quadratic programming model now contains decision variables for each vehicle. As a result the charging schedules for each vehicle k will be determined after minimizing the objective function.

$$\sum_{t=0}^{T} \left\{ T(t) - \left(GB(t) + \sum_{k=1}^{K} X_k(t) \right) \right\}^2 \tag{3.10}$$

3.3.1.5 Discussion on the different QP models

Sections 3.3.1.2, 3.3.1.3, and 3.3.1.4 discuss approaches based on quadratic programming. The objective of each approach is to minimize the peak load, and reduce the variability between demand over time. Although the objective of each approach is the same (i.e. reduce the peak load), the information used to determine optimal charging schedules is different for each approach. Therefore, we can evaluate what information is needed, and has to be shared between participants, to obtain suitable results. Also, the required ICT infrastructure depends on the specific approach, as illustrated in Fig. 3.1.

For example, the local algorithm depends on the arrival and departure time, the energy requirements, battery charger and/or electric vehicle properties, and the predicted household energy consumption. We consider it realistic that the user provides an expected departure time (while the arrival can be detected automatically from the insertion of the plug), and battery/vehicle properties be acquired automatically (e.g. through communication with the EV). Household energy consumption information can be provided by an energy management system (e.g. the home energy box in Fig. 3.1), based on e.g. historical data. Therefore, all information required for the local algorithm is locally available, and assuming the household is equipped with an energy management system, the optimal charging schedule can be determined locally, and no connection to a wide-area network is required.

The iterative global and global approaches on the other hand, require information from households and vehicles to be either communicated amongst all local systems (i.e. the home energy boxes), or sent to a central controller (e.g. the Global Energy Controller in Fig. 3.1). Energy consumption information from all households must be aggregated, and the central controller requires information regarding arrival and departure times, energy requirements, battery and/or electric vehicle properties. Therefore, a network spanning at least the complete residential area will be required, connecting the households with the central controller. Note that privacy concerns could be raised against the global and iterative approaches, regarding the amount of information shared (since user presence and behavior could be inferred from it, e.g. through load disaggregation). We will not delve into such discussions in this paper, but rather focus on the potential technical advantages stemming from sharing that information, in terms of load shaping and power grid effects.

3.3.2 Market based coordination (MAS)

We benchmark aforementioned (rather theoretical) QP-based approaches, with a more pragmatic coordination mechanism for EV charging coordination: a single-shot multi-unit auction market mechanism. This market based coordination mechanism also aims to prevent unwanted power peaks. The distribution grid is organized as a commodity market where agents act on behalf of the transformer and the households. An agent is a software or hardware computer system that is able to [15]:

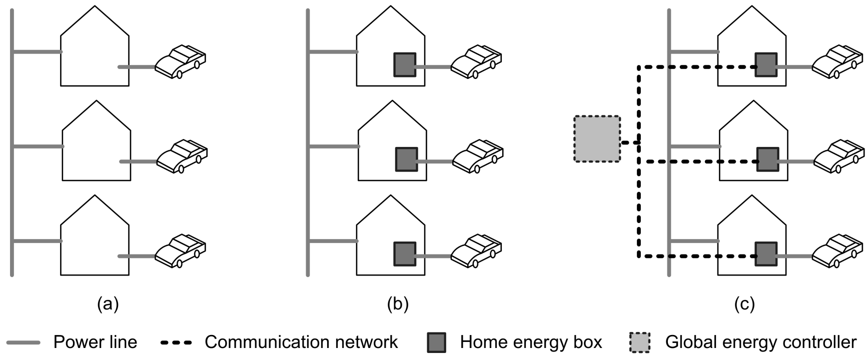
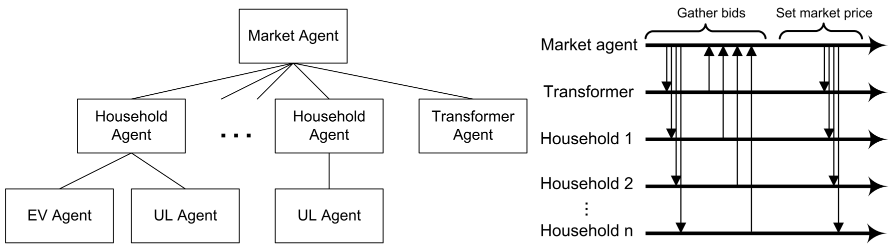


Figure 3.1: ICT infrastructure required for (a) the uncontrolled BAU case, (b) local control, (c) global/iterative control.

- Make autonomous decisions
- Interact with other agents
- React, reactively and pro-actively, to changes in its environment

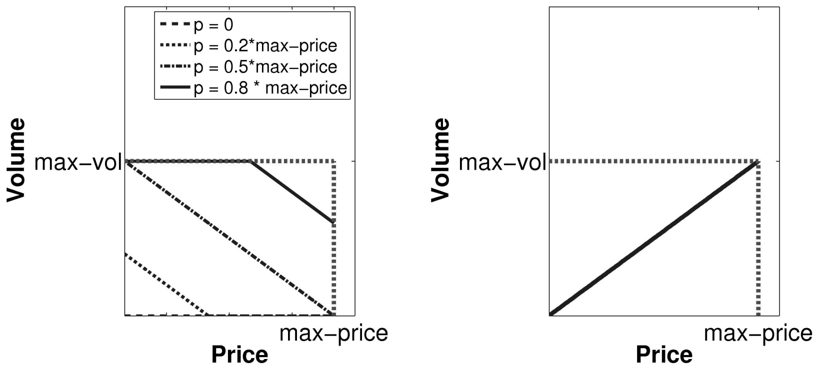
The commodity that is bought and sold in the market is electrical energy. In a single-shot multi-unit auction, buyers and sellers submit their bids and offers for a commodity, after which a clearing price is established to balance supply and demand [7, 16, 17]. A bidding function indicates what volume a buyer or seller is willing to trade for which price. A bidding function is constrained by the maximum volume a buyer or seller is willing or able to trade. Each buyer is allocated to consume the amount of electrical energy that he is willing to buy for the clearing price. The sellers are allocated to produce the amount of goods they are willing to sell for the clearing price. All players on the market do not know each others strategies nor bids. It should be noted that this market-based coordination approach assumes the price is only used as a control signal to stimulate devices to postpone or advance their consumption and no real-time pricing system is connected to our coordination system. The main advantage of a market based approach to coordination is that it requires no centralized planning algorithm, it scales well to a large numbers of devices as well as a large diversity of devices. Furthermore, since the only interaction between the market players is by means of bidding functions, a market based approach has less privacy issues than a centralized coordination approach.

The market-based coordination organized in the distribution grid functions as follows (see Fig. 3.2(a)). Each household is represented by an agent that bids for electricity on the market. The transformer is represented by an agent as well, which acts as the sole supplier of electricity. Within a household, each device is



(a) Agent Organization (b) Agent Interactions

Figure 3.2: Multi-Agent System



(a) EV bidding function (b) transformer bidding function

Figure 3.3: Bidding functions

also represented by an agent. These device agents send their bids to the household agent who aggregates these bids before sending the aggregated bid to the market. The household agents bid for an amount of electrical energy that they want to use for the next time slot and the transformer agent bids for the amount of energy it wants to deliver. In every bidding round, the market agent sends a signal to the transformer agent and the household agents, after which each agent will submit its bid. When all bids are received, the market agent aggregates the bid functions and determines the market price. This market price is communicated to the agents and based on their bids, the agents know how much energy to consume or produce. The interaction between all agents during one bidding round is depicted in Fig. 3.2(b). We assume the agents know how much their consumption will be in the next time slot when submitting a bid function.

Every household contains at least one agent representing the uncontrollable load (UL). Because the UL agent needs to be sure that the uncontrollable loads will actually get their required energy, the UL agent will always bid the maximum price for its load, as to reflect its inflexibility. The controllable device we consider in this paper will be the EV, which hence will have its separate EV agent. In this work, we assume that the EVs are able to modulate their demand, i.e., the EV chargers can demand a power between zero and the maximal power. Consequently, the bidding functions they submit are linear functions, shown in Fig. 3.3(a). The shape of the linear bidding functions depends on the price p, as shown in Fig. 3.3(a). The bidding strategy of the EV agent is to bid a price p that increases linearly as the charging deadline approaches. This charging deadline is the time at which the electric vehicle has to start charging in order to be fully charged in time. An important assumption is that, in order to estimate its bid price, an EV agent is able to obtain an accurate estimation of the state-of-charge of the battery. The exact shape of the aggregated bid of a household agent thus depends on whether an EV is present or not, the bid price of that EV, the EV consumption and the consumption of the uncontrollable load.

The transformer submits a linear bid function, shown in Fig. 3.3(b): we assume that higher costs are associated with a higher power transmitted by the transformer.

3.4 Case study

The algorithms are evaluated using three scenarios, each simulating a distribution network with a certain penetration degree of electric and plug-in hybrid electric vehicles. The different scenarios and their corresponding number of electric and plug-in hybrid electric vehicles together with the type of battery charger are defined in Table 3.1. We simulate a time frame of 24 hours, divided in time slots of 5 minutes.

3.4.1 Power grid

The simulated three phase distribution network is illustrated in Fig. 3.4, and consists of 63 households distributed over three feeders, that are connected to a distribution transformer with a rating of 250 kVA. Each household is connected to the distribution grid using a single-phase connection, which is randomly assigned to either of the three phases using a uniform distribution. The load profiles that model the power drawn by each household are based on measurements performed by VITO on a number of households in Flanders during different winter days, representing a worst case scenario, as the grid load is highest during winter in Belgium. Each house is randomly assigned one of these real-life measured load profiles which is randomly shifted in time using a uniform distribution to avoid unrealistic synchronization of loads amongst houses.

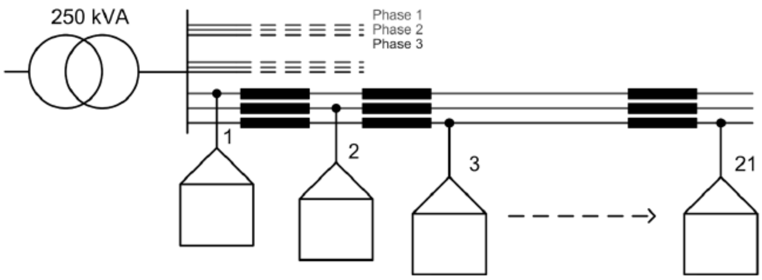


Figure 3.4: Topology of the three phase distribution grid used in the simulation. It consists of 63 households, distributed over 3 feeders, and a distribution transformer with a rating of 250 kVA.

Scenario	PHEV 3.6 kW	PHEV 7.4 kW	EV 3.6 kW	EV 7.4 kW
Light	4	3	2	1
Medium	10	10	5	4
Heavy	17	16	7	7

Table 3.1: Amount of PHEV and EV and their type of battery charger in the three different scenarios.

3.4.2 Electric vehicles

We assume a PHEV to have a battery capacity of 15 kWh and an EV a battery capacity of 25 kWh. We use a linear approximation of the non-linear battery behavior. In this model, we neglect battery inefficiency and assume all power is transferred lossless through the charger into the battery. However, this should not significantly influence the results [14]. The households are provided with a single-phase connection and either a standard charger of 3.6 kW, using 230V 16A, or a fast charger of 7.4kW, using 230V 32A. These specifications are based on the IEC 62196 standard which describes conductive charging of electric vehicles.

3.4.3 User behavior

It is assumed that most of the times, vehicles will be recharged at home or at work. In this paper we focus on charging at home. The plug-in times of electric vehicles are varied around 17:00 using a normal distribution with a standard deviation of 45 minutes. The charging deadline times are similarly assumed to be normally distributed around 06:00 AM.

3.5 Results

For each scenario (light, medium, and heavy) we selected 100 seeds to initialize the random parameters (i.e. arrival and departure times) and evaluated each algorithm for each of these 100 seeds. To compare the results from the different charging approaches, we obtained the peak load and standard deviation of each load profile and calculated the average over 100 instances for these metrics. The results presented below were obtained using our simulation environment that incorporates models of both the ICT infrastructure and the power network [18]. Fig. 3.6 illustrates the average transformer load profiles obtained for each scenario and algorithm. Clearly, uncontrolled charging leads to a substantial increase in peak load. However, controlled charging approaches are able to reduce this peak load. A more detailed discussion is provided in the following sections.

3.5.1 Total energy consumption

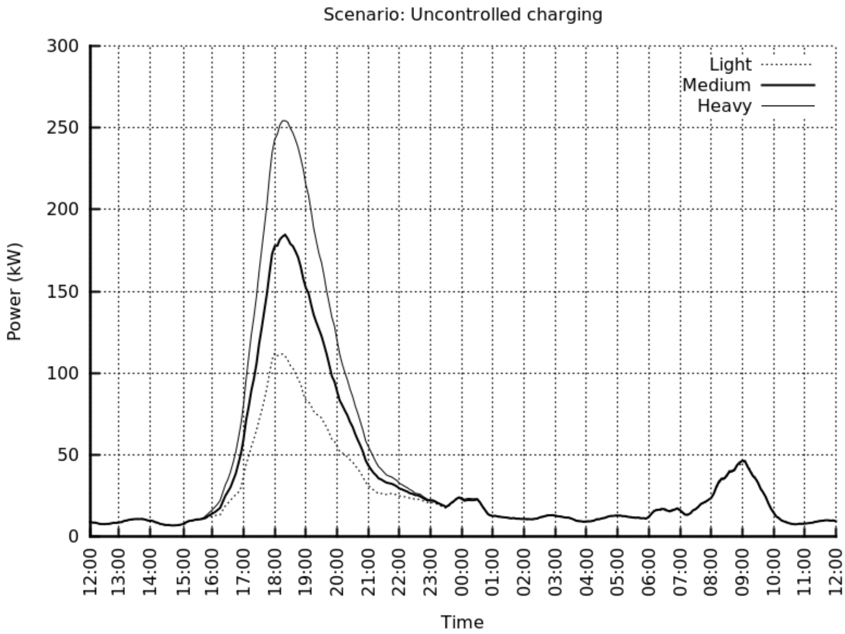
Electric vehicles form an additional load on the power grid when being recharged. This additional load obviously leads to more energy consumption than the case without EVs. This is observed in the light and medium scenarios where total energy consumption rises with 22% and 63%. In the heavy scenario energy consumption is doubled. Clearly, no coordination mechanism can reduce that total load increase, but rather shift the EV load in time as to minimize peak load increases. This is discussed next.

3.5.2 Impact of uncontrolled charging on the peak load

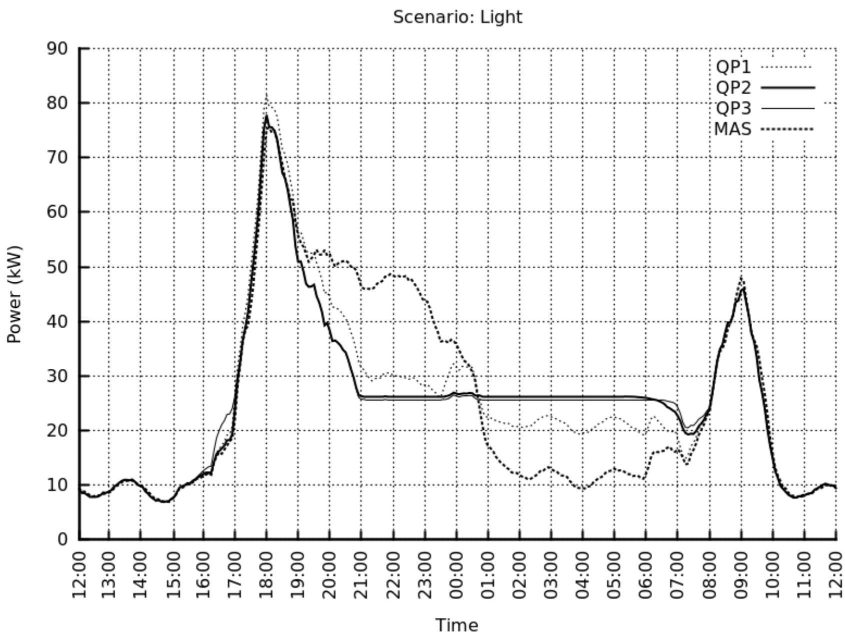
We start the discussion of the results by looking at the impact of uncontrolled charging on the peak load. Uncontrolled charging has a significant impact on the peak load because the charging coincides with the existing evening peak load. On average it leads to almost 1.5 times the peak load of current electricity consumption in a residential area if we consider the light scenario. Uncontrolled charging in the medium and heavy scenario on average leads to a peak load that is 2.4 and 3.3 times the existing peak load. The peak load does not exceed the transformer rating in the light and medium scenarios, however it exceeds the transformer rating in 88% of the simulated cases (i.e. for 88 out of 100 random seed choices).

3.5.3 Peak load reduction by controlled charging

As we have seen in the previous section, uncontrolled charging leads to a higher peak load, because the charging coincides with the existing evening peak load. The charging algorithms presented in this paper aim to reduce the peak load as much as possible, preferably to the same level as in the case without EVs.

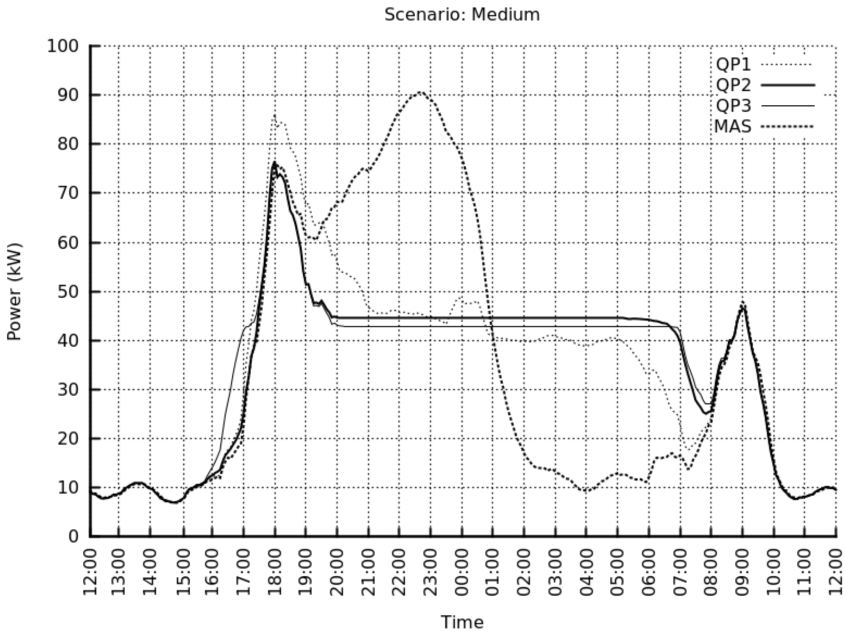


(a) Uncontrolled charging

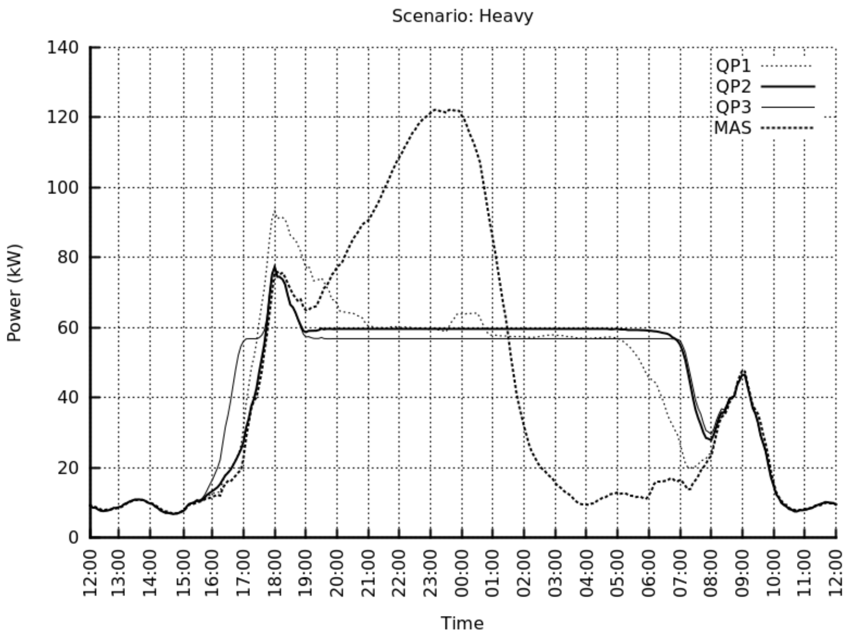


(b) Ligt scenario (10 P(H)EVs)

Figure 3.5: Average load profiles measured at the distribution transformer. Every load profile is the average of 100 individual load profiles that were obtained for the uncontrolled and light scenarios



(a) Medium scenario (29 P(H)EVs)



(b) Heavy scenario (47 P(H)EVs)

Figure 3.6: Average load profiles measured at the distribution transformer. Every load profile is the average of 100 individual load profiles that were obtained for the medium and heavy scenarios.

Scenario	Algorithm	Minimum	Mean	Maximum
Light	QP1	76.34	85.23	98.36
	QP2	71.96	82.15	95.23
	QP3	71.96	82.15	95.23
	MAS	71.98	82.28	95.23
Medium	QP1	83.71	91.89	102.84
	QP2	71.96	82.15	95.23
	QP3	71.96	82.15	95.23
	MAS	86.71	93.19	99.09
Heavy	QP1	90.20	99.23	110.21
	QP2	71.96	82.15	95.23
	QP3	71.96	82.15	95.23
	MAS	116.91	125.78	137.88

Table 3.2: Overview of the peak loads observed (kW). The peak load is determined for each scenario and algorithm. The minimum, average, and maximum peak load are given for 100 simulations.

	Peak Load ↘			
Scenario	QP1	QP2	QP3	MAS
Light	29.62%	32.16%	32.16%	32.00%
Medium	53.84%	58.73%	58.73%	53.19%
Heavy	63.76%	70.00%	70.00%	54.04%

Table 3.3: Peak load reductions. QP1 = Local, QP2 = Iterative Global, QP3 = Global, MAS = Multi Agent

Table 3.2 and Table 3.3 summarize the impact on the peak load by the different energy control strategies. The energy control strategies are able to reduce the peak load of uncontrolled charging, by shifting the vehicle loads in time and controlling the rate of charging. In the light scenario, the local method (QP1) achieves a peak load reduction of 29.62% compared to the BAU scenario (i.e. uncontrolled charging), while the iterative (QP2), global (QP3) and multi-agent market (MAS) based methods all achieve a peak reduction of approximately 32%. In the medium scenario, the local and multi-agent market based method achieve similar results: 53.84% and 53.19%. The iterative and global methods both achieve a peak reduction of 58.73%. When we consider the heavy scenario, the multi-agent market based method achieves a reduction of 54.04%, the local method 63.76%, and the iterative and global method both achieve a reduction of 70.00% compared to the BAU scenario. These results give an indication of what the impact is on the peak load, but we are more interested in knowing how much of the additional peak load that was the result of uncontrolled charging can be shifted.

The iterative and global methods are able to fully reduce the peak load to the original level before electric vehicles were introduced to the distribution grid. The local method however, removes only 92% of the additional peak load that is added by uncontrolled charging. The reason for this being that the local algorithm only considers peak loads in each household individually. The vehicle load is shifted in time to not coincide with the peak loads in that household. However, that local peak does not necessarily coincide with the overall peak load. The market based method is also unable to fully remove the additional peak load that is the result of charging electric vehicles: 99.64% of the additional peak load is removed in the light scenario, 90.64% in the medium scenario and 77.15% in the heavy scenario.

3.5.4 Load profile variability

The load profile variability is another interesting factor as it influences dispatching of generators. We measure it by calculating the standard deviation between the values of the load profile. We list the standard deviation of the transformer load over time in Table 3.4, and summarize its reduction compared to the BAU case in Table 3.5. Each algorithm is able to reduce the standard deviation of the values of the load profile compared to the BAU scenario. However, there is a big difference between the methods based on quadratic programming and the market based multi-agent system. The results regarding the peak load for the iterative and global algorithm where identical, however there is a difference when considering the variance of the load profiles. The global algorithm is able to determine the most optimal solution as it has the most information available, whereas if we only consider peak load, the iterative and global method have the same results. Note that the market based MAS system does not seem to be able to reach the flat load

Scenario	Algorithm	Minimum	Mean	Maximum
Light	QP1	15.66	16.17	16.85
	QP2	14.18	14.57	15.24
	QP3	14.11	14.49	15.18
	MAS	17.95	18.65	19.48
Medium	QP1	18.79	19.80	20.80
	QP2	16.56	17.38	18.19
	QP3	15.55	16.78	17.76
	MAS	27.19	28.64	29.89
Heavy	QP1	23.35	24.80	26.20
	QP2	21.34	22.56	24.02
	QP3	19.46	21.30	22.62
	MAS	36.66	38.71	40.57

Table 3.4: Assessment of the demand variability based on the standard deviation of the load profiles.

	Standard deviation ↘			
Scenario	QP1	QP2	QP3	MAS
Light	35.24%	41.63%	41.94%	25.29%
Medium	55.01%	60.50%	61.88%	34.91%
Heavy	60.22%	63.82%	65.84%	38.80%

Table 3.5: Reduction of the standard deviation. QP1 = Local, QP2 = Iterative Global, QP3 = Global, MAS = Multi Agent

profile as achieved by the QP methods.

3.5.5 Effect on voltages

The peak load and load profile variability are mainly of concern to assess production and grid capacity. Yet, as noted before, the introduction of EVs risks to cause additional problems in the distribution grid that historically was not dimensioned to cater for EVs. Using our integrated ICT- and power network simulator [18], we also assessed the impact of coordination mechanisms QP1 and QP2 on the power quality in terms of variations in voltage magnitude. As just discussed, we achieve substantial improvements in terms of peak power and demand variability reduction, using realistic assumptions on the required information. According to the EN50160 standard, voltage deviations up to 10% are acceptable in distribution grids.

First, we evaluated how often voltage deviations exceeding 10% occur during a 24 hour time period, divided in 288 time slots of 5 minutes. Table 3.6 gives an overview of the average number of time slots during which such deviations occur. We obtained these averages by counting the number of time slots in which deviations exceeding 10% occurred somewhere in the residential area for each experiment (using a different random seed), and calculated the average. Large P(H)EV penetration degrees lead to deviations occurring more often. For the heavy scenario, which corresponds to the worst case, uncontrolled charging on average leads to voltage deviations exceeding 10% for 45.51 time slots, or approximately 16% of the time slots. However, controlled charging reduces this number: if we consider the heavy scenario again, QP1 leads to 3.92 time slots, or approximately 1% of the time slots, and QP2 leads to 9.30 time slots, or approximately 3% of the time slots.

Next, we evaluated how large the deviations from the nominal voltage are. Results are summarized in Table 3.7. We only considered experiments during which at least one voltage deviation exceeding 10% occurred. For each of those experiments, we determined the maximum voltage deviation that occurred. The maximum and average values are given for each set of experiments in Table 3.7. Large penetration degrees of P(H)EV lead to larger voltage deviations. For the heavy scenario, the average maximum deviation observed for uncontrolled charging is 37% of the nominal voltage, and the maximum deviation observed over all experiments is 65%. These deviations are much larger than the 10% required by the EN50160 standard. However, controlled charging reduces the magnitude of the deviations. The average maximum deviation for QP1 is 12% in the heavy scenario, and the maximum deviation observed over all experiments is 20%. For QP2 we obtain respectively 14% and 22%.

Based on the results summarized in Table 3.6 and Table 3.7, we can conclude that the QP1 approach in general results in the most optimal results. The QP1 or local approach aims to reduce the local or household peak load. Therefore, the load at each node in the grid will be as low as possible, resulting in smaller voltage deviations. The QP2 or iterative approach on the other hand, aims at reducing the transformer peak load. Individual household peak loads do not necessarily coincide with the peak load at the transformer level. Therefore, it is possible that household peak load is increased, which increases the voltage deviation.

3.5.6 Discussion

The results from the approaches based on quadratic programming are superior in terms of peak load and load profile variance reduction compared to those of the

Scenario	BAU	QP1	QP2
Light	22.17	3.90	3.31
Medium	38.01	4.52	5.32
Heavy	45.51	3.92	9.30

Table 3.6: Average number of 15 minute time slots (out of the 288 time slots over the course of the considered one day period) during which voltage deviations exceeding 10% are observed.

	BAU		QP1		QP2	
Scenario	AVG	MAX	AVG	MAX	AVG	MAX
Light	20%	29%	13%	19%	13%	18%
Medium	29%	60%	13%	22%	13%	20%
Heavy	37%	65%	12%	20%	14%	22%

Table 3.7: Average and maximum magnitude of voltage deviations.

multi-agent system. However, the results from the market based MAS system require less stringent knowledge of the load profiles, and also only exchange very limited information compared to the QP-methods. The multi-agent system has the added advantage of being a truly dynamic and flexible approach: via tweaking of the bidding curves, the optimization can be steered towards other objectives. The QP approach is more strict, and more cumbersome to adapt to different objectives. Nevertheless, the QP method is extremely useful to assess what the best possible result is, and hence serves as an optimal benchmark. In our case, it thus reveals that there is still substantial room for improving the market based MAS approach (e.g. peak reduction of 54.04% vs 70.00% for QP, variability reduction of 38.80% vs 65.84% for QP). This does not mean that the approaches based on quadratic programming are useless, as they determine the most optimal solutions and therefore can be used to benchmark other algorithms.

3.6 Conclusion

Uncontrolled charging of electric vehicles for substantial penetration would result in increases in peak load (we noted for the worst case scenario more than doubling the peak load observed in the distribution grid without electric vehicles). We presented two classes of EV charging coordination: based on classical quadratic programming (QP) on the one hand, and market-based multi-agent systems (MAS) on the other. The aim of both in the considered case studies is to reduce the peak load and the load variability in a distribution grid. We considered three quadratic programming approaches, assuming different knowledge of components within the grid. We provide simulation results, using a combined ICT and power simulator [18] for a residential area consisting of 63 households and different penetration degrees of electric vehicles. Peak reductions ranging from 29% up to 70% are achievable, compared to a business-as-usual scenario in which vehicles are charged without control and coordination. Variability in demand is decreased ranging from 25% up to 65%. The QP method mainly serves as benchmark, since real-life deployment may be hampered by its requirement to communicate expected load profiles (e.g. based on historical measurements). The MAS approach, while requiring modest knowledge of the expected future load and imposing little communication, achieves in the range of 32.00% to 54.04% (vs. 32.16% to 70.00% for QP-global) peak reduction. We conclude that future work is required to further tune and optimize e.g. MAS systems to closer achieve the optimum found by QP. We also evaluated the impact of our coordinated charging approaches in terms of power quality, under the form of voltage magnitude variations. While the objectives as formulated in our approaches do not explicitly include the voltage as a parameter to be optimized, we do note that the coordinated charging strategies reduce the observed voltage deviations (measured as differences from the nominal voltage greater than 10%).

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4

Privacy-friendly hierarchical demand side management with user preferences

In Chapter 3 we showed how demand side management reduces the peak load, variability in demand, and voltage fluctuations caused by electric vehicle charging. We now consider opportunities where flexible EV charging could provide an additional service to the grid. This chapter studies a hierarchical demand side management approach for balancing wind energy with EV charging, while respecting user preferences with regard to how their flexibility is used.

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Abstract This paper presents a privacy-friendly hierarchical demand side management approach for the optimal integration of wind energy and electric vehicles in the smart grid. The algorithm combines elements from centralized and decentralized approaches to improve the supply and demand balance by exploiting demand flexibility of electric vehicles. In addition, we focus on how to integrate user preferences with regard to how their flexibility is used. We evaluate the approach in a simulated case study and demonstrate that the supply and demand balance is improved, and user preferences are respected. We compare our approach to a business-as-usual scenario and a theoretical upper bound.

4.1 Introduction

Traditionally, power is generated by large controllable power generators (e.g., nuclear, coal, gas) and transported to the consumers over the transmission and distribution grids. In power systems, demand and supply must be balanced to ensure reliable operation. Nowadays however, renewable energy sources (RES) such as wind and solar are increasingly being deployed in the power system. However, because their energy production cannot be easily controlled, integrating these RES significantly complicates demand and supply balancing. We also observe changes on the demand side, e.g., an increased interest in the electrification of transportation in the form of Electric Vehicles (EV). The shift away from fossil fuels will increase demand for electricity and change the demand patterns (e.g., increased peak loads). Demand side management (DSM) or demand response (DR) techniques have been suggested to cope with the challenges associated with the changing supply and demand: instead of depending on controllable generation and/or storage, demand is steered, e.g., to coincide with renewable energy generation.

4.2 Related work: demand side management

DSM approaches can broadly be classified in (i) *centralized*, (ii) *decentralized*, and (iii) *hybrid* approaches. In *centralized* approaches, a central controller has full knowledge about the DSM participants and their flexibility. Decisions are made by the controller and communicated to the participants: direct load control. In *decentralized* approaches, decisions are made by the participants themselves. *Hybrid* approaches combine aspects from centralized and decentralized approaches. We now describe these different approaches in more detail.

4.2.1 Centralized approaches

In *centralized* approaches, a central controller takes decisions on behalf of DSM participants. For this, it requires knowledge about those participants and their flexibility: location, appliances and possible control actions, usage preferences, constraints, etc. Compared to distributed approaches, centralized approaches have been shown to provide the most optimal results in terms of energy costs and peak-to-average ratio [1], resource usage [2], etc. However, participants lose control and are required to share privacy sensitive information [1, 3]. Another drawback associated with centralized approaches is that they have been shown to scale poorly in terms of computation time [2, 3] or memory requirements [4] when dealing with large groups of participants.

4.2.2 Decentralized approaches

In *decentralized* approaches, there is no central controller that has detailed information about the participants and participants make decisions locally: flexibility information is not shared and decisions are made by the participants themselves (e.g., based on financial incentives). The main motivation for decentralized approaches include privacy [1, 5], scalability [2, 3], and reliability [6, 7], while still obtaining (near) optimal solutions. However, the system operator loses direct control and can only provide incentives to obtain the desired behavior, making it difficult to anticipate the end result. An example of a decentralized approach that only requires one-way communication between the utility and flexible consumers is proposed in [7] for avoiding congestion problems and the invocation of protection mechanisms.

4.2.3 Hybrid approaches

Hybrid approaches combine aspects from centralized and decentralized approaches, leading to results comparable to those from centralized approaches while improving scalability [8, 9]. A two-stage market model for microgrid power transactions via aggregators is proposed in [8]. Microgrids sell their surplus power to a utility via aggregators, because direct participation in the retail markets is not scalable. Surplus power from microgrids is aggregated sold to the utility. An iterative market mechanism (decentralized) is used in the first stage between aggregators and the utility, whereas supply function bidding (centralized) is used for the second stage market between microgrids and aggregators, both leading to improved scalability and localized responsibilities. In [9], a three-step approach for DSM of plug-in hybrid electrical vehicles is proposed. The three steps are: (i) aggregation, (ii) optimization, and (iii) control. During the aggregation step, individual charging constraints (i.e., energy and power constraints) are aggregated upwards in a tree structure. In the optimization step, the aggregated constraints are used for the scalable computation (centralized) of a collective charging plan, which minimizes costs for electricity supply. In the real-time control step, this charging plan is used to create an incentive signal for all vehicles, determined by a market-based priority scheme (decentralized).

4.2.4 Mathematical optimization

We conclude from Sections 4.2.1, 4.2.2, and 4.2.3 that although centralized approaches demonstrate the best results, hybrid and distributed approaches are preferred, motivated by improved scalability, privacy, reliability, etc. We now take a closer look at related work from a more algorithmic perspective. We consider balancing renewable energy supply with demand by exploiting flexibility from end-users. We formulate this as a mathematical optimization problem. In this section, we give an overview of related (distributed) approaches.

In [5] a real-time pricing algorithm is proposed to steer consumption patterns of end-users. Preferences and consumption patterns of end-users are modeled using power consumption intervals and a generic utility function that can be tailored to individual end-users. A distributed algorithm is proposed to determine optimal energy consumption levels for each end-user, thereby maximizing their utility and minimizing their energy cost. Although a generic utility model is proposed, no instantiations are provided for different appliance types or user preferences. A distributed multi-timeslot scheduling approach is considered in [6]. Different appliance types (e.g., EVs and airconditioning unit) are considered, but again no specific user profiles within a certain appliance type. For example, EV flexibility is based on time, energy and power constraints, but no additional preferences (utility) can be given (e.g., fast but still flexible). User preferences are considered in more detail in [1], which defines generic device models for shiftable and throttleable devices. User preferences can balance different objectives: energy costs, operational delay, and power gap (i.e., deviation from preferred maximal power).

4.2.5 Relation to our work

Motivated by scalability benefits we have chosen a hybrid approach, that uses a hierarchical (tree) architecture similar to that in [8] and [9]. Additionally, the hierarchical architecture localizes information sharing and communication. To offer users more freedom in defining their flexibility, we investigate the concept of (dis)utility functions [5, 6] in more detail, and propose a generic and intuitive model that can be tailored to the end-users and demonstrate this in the context of charging EVs. In contrast, related work focuses on specific appliances (e.g., EV, A/C unit [6]) or groups (e.g., shiftable, throttleable [1]), whereas we emphasize on usage models that characterize the usage preferences of the *user* instead of the (technical) appliance characteristics. Rather than a single timeslot approach as in [5], we consider a multi-timeslot scheduling approach as in [6]. Such pro-active approaches have been shown to improve balancing performance [10], and at the same time the user can be provided with more detailed information on the current and future progress of their charging session.

4.3 Focus and Contributions

Demand and supply of electricity must be balanced at all times in the power grid. Typically this is achieved by controlling the output from power generators, but this is limited or even impossible in the context of RES. Instead, we use flexibility in demand (e.g., EV charging) to balance supply and demand. The main contributions of our work include:

- We propose a hierarchical architecture and hybrid algorithm and evaluate it in the context of a wind power balancing case with EV charging. We focus on the energy mix used (technical objective), instead of a pure energy cost objective (economical objective) typically used in related work [1, 5, 6]. We model the energy mix as the combination of conventional energy (e.g., nuclear, coal, gas) and renewable energy and the objective is to increase the renewable energy consumption.

- We define different user flexibility profiles (e.g., “fast” and “flex”) for EV users and evaluate the impact thereof from a system operator and user perspective. Related work typically focuses on the device characteristics, whereas we focus on usage characteristics.

- The flexibility profiles are not shared with other components in the system, but are private to the EV user.

- We compare our method with two reference cases: (i) a business-as-usual or uncontrolled scenario, and (ii) a theoretical upper bound.

- We show how to leverage the flexibility from specific users (i.e., those with “flex” profiles) to circumvent potential optimization issues that may arise in the decentralized setting. We achieve this by incorporating a random element in how they respond to demand response incentives.

- A theoretical analysis of the proposed algorithm that gives more insight into potential (optimization) problems. Additionally, we show how the problem search space can be limited to improve convergence rate and avoid sub-optimal solutions.

4.4 System model

We propose a hierarchical architecture and hybrid smart charging algorithm for maximizing the match between of renewable power supply and demand. The hierarchical architecture for smart charging consists of three components and is illustrated in Figure 4.1: (i) a grid controller, (ii) aggregators, and (iii) flexible consumers. For flexible consumers, we focus on EVs, even though similar modeling could also apply for other time-shiftable loads (e.g., washing machines and dishwashers). **Electric vehicles** are characterized by their flexibility constraints (e.g., charging rates, energy requirement, and time available for charging) and their preferences on how to use their flexibility. The EV flexibility constraints are shared with the aggregator, but the flexibility preferences are kept private. **Aggregators**

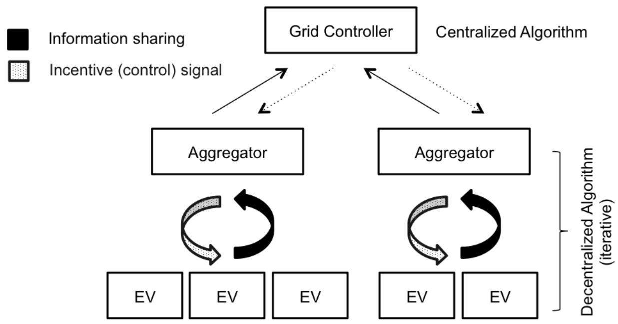

Figure 4.1: Hierarchical architecture and hybrid smart charging algorithm for matching supply and demand.

manage a fleet of EVs and have two main responsibilities: (i) aggregate the EVs into one large (virtual) flexible consumer and offer the aggregated flexibility to the grid controller, and (ii) to negotiate charging schedules with the EVs. The **grid controller** uses the aggregated flexibility constraints of the aggregators to determine optimal (aggregated) target load profiles for the aggregators. The aggregators in turn are responsible for translating the target load profiles in individual charging schedules.

The algorithm is **hybrid** in the sense that the grid controller uses a centralized algorithm to determine the target load schedules of the aggregators, whereas the aggregator uses a distributed algorithm to determine the charging schedules of the EVs in order to improve the scalability and maintain privacy. Compared to fully distributed approaches, the communication overhead is reduced because of: (i) data aggregation, and (ii) localization of the communication intensive (iterative) aspects of the algorithm. Users are however required to share some but not all of the flexibility information, but this is again localized at the aggregator level and the grid controller does not know any details of individual users.

4.4.1 Electric vehicle flexibility constraints

EVs offer great potential as flexible loads to provide services to the grid, i.e., charging can be shifted in time and/or charging power can be increased or decreased. We model the flexibility of an EV $v \in V$, where V is the set of EVs, with the following scalar parameters. We assume a time-slotted approach and arrival timeslot s_v and departure timeslot t_v. The energy required by the time of departure is expressed by E_v. The minimum and maximum charging rates are expressed by P_v^{min} and P_v^{max} respectively. In other words, the flexibility constraints are expressed in terms of *time*, *power*, and *energy* constraints. Assuming a planning window of T time slots, the flexibility constraints are sent to the aggregator in the form of constraint vectors of length T. The maximum and minimum charging power for each timeslot are listed in the power constraint vectors $\mathbf{p_v^{max}}$ and $\mathbf{p_v^{min}}$, and we similarly define an energy requirement vector $\mathbf{e_v}$. This provides a generic model and also decouples the aggregator from the specific device or user characteristics. It is thus conceivable to have the grid controller and aggregator roles to be performed by distinct business entities.

4.4.2 Aggregator flexibility

A set of aggregators A aggregate flexibility information from EVs and offer their combined flexibility to the grid controller. The flexibility model for an aggregator $a \in A$ assuming a planning window of T timeslots is characterized by the following parameters: (i) vectors $\mathbf{p_a^{min}}$ and $\mathbf{p_a^{max}}$ specify respectively the minimum and maximum load for each timeslot, and (ii) a vector $\mathbf{e_a}$ expresses the energy requirements. In other words, the flexibility is again expressed in terms of *power* constraints and *energy* constraints over a planning window of length T time slots. V_a is the set of EVs managed by an aggregator a. Power constraints from individual EV users can easily be aggregated by the aggregator:

$$\mathbf{p_a^{min}} = \sum_{v \in V_a} \mathbf{p_v^{min}} \tag{4.1}$$

$$\mathbf{p_a^{max}} = \sum_{v \in V_a} \mathbf{p_v^{max}} \tag{4.2}$$

To obtain the energy requirement vector e_a, we first aggregate the energy constraints of the individual vehicles:

$$\mathbf{e'_a} = \sum_{v \in V_a} \mathbf{e_v} \tag{4.3}$$

We then obtain the final vector $\mathbf{e_a}$, that describes the minimal energy requirements by the end of each timeslot, as follows:

$$e_{a,t} = \sum_{t'=1}^{t} e'_{a,t'} \tag{4.4}$$

4.5 Optimization model for grid controller and aggregators

The grid controller is provided with a target load profile $\mathbf{q}$ (e.g., wind turbine output forecast) that is used to steer the load profiles of a set of aggregators A for a planning window of T timeslots. The primary objective of the grid controller is to maximize the "green" energy consumption from RES by exploiting the flexibility provided by the aggregators. Secondary objectives may include additional load shaping objectives, e.g., to obtain smooth load profiles that change gradually instead of abruptly. Additionally, the aggregated grey and green generation profiles are also determined, giving insight in the energy mix used over time. A linear optimization problem is formulated to determine the load profiles for all aggregators:

$$\min_{\{\mathbf{x_a},\mathbf{u},\mathbf{v}\}} \quad \sum\nolimits_{t\in\{1,\ldots,T\}} u_t\gamma_t + v_t\epsilon_t + \tag{4.5}$$

$$\sum\nolimits_{t\in\{1,\ldots,T-1\}} \sum\nolimits_{a\in A} \sigma_a \cdot |x_{a,t} - x_{a,t+1}| \tag{4.6}$$

subject to:

$$\sum_{a\in A} x_{a,t} - y_t = q_t \qquad \forall t \in \{1,...,T\} \tag{4.7}$$

$$y_t = u_t - v_t \qquad \forall t \in \{1,...,T\} \tag{4.8}$$

$$\sum_{t'=1}^{t} x_{a,t'} \geq e_{a,t} \qquad \forall t \in \{1,...,T-1\}, a \in A \tag{4.9}$$

$$\sum_{t=1}^{T} x_{a,t} = e_{a,T} \qquad \forall a \in A \tag{4.10}$$

$$p_{a,t}^{min} \leq x_{a,t} \leq p_{a,t}^{max} \qquad \forall t \in \{1,...,T\} \tag{4.11}$$

$$u_t, v_t \geq 0 \qquad \forall t \in \{1,...,T\} \tag{4.12}$$

The objective function is composed of two parts: the energy cost (4.5), and the load shape cost (4.6). Three types of decision variable vectors of length T are used: (i) a load schedule $\mathbf{x_a}$ for each aggregator $a \in A$, (ii) the amount of "grey" energy $\mathbf{u}$, to be purchased from the grid when insufficient energy is available, and (iii) the amount of "green" energy $\mathbf{v}$ rejected when excess energy is available. To create an incentive to consume green energy, a high cost γ_t will typically be assigned to grey energy consumption (i.e., aggregator load exceeds target load) and a low cost ϵ_t to surplus green energy (i.e., target load exceeds aggregator load). Note that different aggregator schedules can be obtained depending on the definition of γ and ϵ vectors, e.g., to schedule green energy consumption as soon as possible (or as late as possible). For now, due to our focus on the technical objective of balancing supply and demand, we consider these to be *virtual* costs used to steer demand, and not "real" monetary costs (e.g., current market prices). Nevertheless, such economical parameters can easily replace or be combined with the virtual costs to deal with both technical (i.e., balancing) and economical objectives (i.e., energy costs). In addition, the load shape term can be used to obtain smooth aggregator profiles. Constraints (4.7), (4.8), and (4.12) are used to assign the grey and green loads. Note that either u_t or v_t (but not both) can be greater than 0 at any time t. In other words, we do not schedule grey consumption when green consumption is still available. Constraints (4.9), (4.10), and (4.11) ensure that the power and energy constraints are met.

Note that the complexity of the model in terms of number of constraints and decision variables only depends on the number of aggregators $|A|$ (and the number of timeslots T), and not on the number of EVs. This is the result from the aggregated flexibility model and improves the scalability because the number of aggregators will typically be much lower and constant compared to that of the flexible consumers such as EVs. In addition, the aggregated flexibility information only describes power, time, and energy constraints. In Section 4.6 we show that individual users have additional means for defining their flexibility, which are kept confidential. This also leads to a simpler and more scalable model.

The load schedules $\mathbf{x_a}$ of the aggregators need to be post-processed before assigning them to the aggregators: the load schedules $\mathbf{x_a}$ obtained by solving the optimization problem include grey and green power. The goal of the post-processing step is to extract a green target profile $\mathbf{q_a}$ for each aggregator a, to emphasize our primary green energy objective. Nevertheless, this will still include the effects from additional load shaping objectives. This ensures that aggregators focus on the energy mix. For now, we assume that the amount of green power during each timeslot is assigned to each aggregator proportionally to their assigned load and available green energy.

4.6 Optimization model for aggregator and EVs

In this section we discuss the optimization model of the aggregators and EVs, that is used to determine individual charging schedules. We first describe the optimization model in detail, and then a distributed solution method.

4.6.1 Optimization model

The aggregator is assigned a target load profile $\mathbf{q_a}$. Three types of decision variable vectors of length T are used: (i) a charging schedule $\mathbf{z_v}$ for each EV $v \in V_a$, (ii) the amount of "grey" energy $\mathbf{g_a}$, and (iii) the amount of "green" energy $\mathbf{b_a}$, rejected when excess energy is available. Note that we use $\cdot$ for the dot product between vectors:

$$\min_{\{\mathbf{z_v},\mathbf{g_a},\mathbf{b_a}\}} \quad \gamma \cdot \mathbf{g_a} + \epsilon \cdot \mathbf{b_a} + \tag{4.13}$$

$$\sum_{v \in V_a} \beta_\mathbf{v} \cdot (\mathbf{p_v^{max}} - \mathbf{z_v}) \tag{4.14}$$

subject to:

$$\sum_{v \in V_a} \mathbf{z_v} - \mathbf{g_a} + \mathbf{b_a} = \mathbf{q_a} \tag{4.15}$$

$$\mathbf{1} \cdot \mathbf{z_v} = E_v \quad , \quad \forall v \in V_a \tag{4.16}$$

$$\mathbf{p_v^{min}} \leq \mathbf{z_v} \leq \mathbf{p_v^{max}} \quad , \quad \forall v \in V_a \tag{4.17}$$

$$\mathbf{b_a} \geq \mathbf{0}, \mathbf{g_a} \geq \mathbf{0} \tag{4.18}$$

The objective function again consists of two components: (i) an energy mix cost (4.13), and (ii) the flexibility model (4.14) of the EV users that models their willingness to deviate from their preferred schedule. The constraints (4.16), (4.17) ensure that time, energy and power constraints of users are met, with some additional bookkeeping constraints (4.15) and (4.18) for the energy mix objective. From an **aggregator perspective** we have the energy mix cost (4.13) that is similar to that of the grid controller model. We again make the distinction between the energy supply available from RES, additional grey energy that might be required, and possible over-supply of green energy at certain times. From a **user perspective** we have the flexibility model, discussed in more detail in Section 4.6.4.

4.6.2 Lagrangian relaxation

Although the linear optimization problem can be solved as a linear program, this would be a centralized approach solved by the aggregator, and EVs would be required to share all flexibility info. A transformation to a distributed approach is found by reformulating the linear problem using Lagrangian relaxation and then distributing the subproblems: introduce a (timeslot) vector of Lagrange multipliers $\lambda \in \mathbb{R}^T$ and relax the aggregator profile constraint set into the objective. The new objective function becomes:

$$\begin{aligned} L(\mathbf{g_a}, \mathbf{b_a}, \mathbf{z_v}, \lambda) \quad = \quad & \gamma \cdot \mathbf{g_a} + \epsilon \cdot \mathbf{b_a} + \\ & \sum_{v \in V_a} \beta_\mathbf{v} \cdot (\mathbf{p_v^{max}} - \mathbf{z_v}) + \\ & \lambda \cdot \left(\sum_{v \in V_a} \mathbf{z_v} + \mathbf{b_a} - \mathbf{g_a} - \mathbf{q_a} \right) \end{aligned} \tag{4.19}$$

The Lagrangian dual function is:

$$\begin{aligned} F(\lambda) \quad &= \min_{\{\mathbf{g_a} \geq 0, \mathbf{b_a} \geq 0, \mathbf{z_v} \in Z_v\}} L(\lambda, \mathbf{g_a}, \mathbf{b_a}, \mathbf{z_v}) && (4.20) \\ &= F_g(\lambda) + F_b(\lambda) + \sum_{v \in V_a} F_v(\lambda) - \lambda \cdot \mathbf{q_a} && (4.21) \end{aligned}$$

where

$$F_g(\lambda) = \min_{\mathbf{g_a} \geq 0} (\gamma - \lambda) \cdot \mathbf{g_a} \tag{4.22}$$

$$F_b(\lambda) = \min_{\mathbf{b_a} \geq 0} (\epsilon + \lambda) \cdot \mathbf{b_a} \tag{4.23}$$

and $\forall v \in V_a$:

$$F_v(\lambda) = \min_{\mathbf{z_v} \in Z_v} \beta_\mathbf{v} \cdot (\mathbf{p_v^{max}} - \mathbf{z_v}) + \lambda \cdot \mathbf{z_v} \tag{4.24}$$

$$= \min_{\mathbf{z_v} \in Z_v} (\lambda - \beta_\mathbf{v}) \cdot \mathbf{z_v} \tag{4.25}$$

These problems are separable and can be solved independently in a distributed manner for given λ. Since strong duality holds, solving the original problem is equivalent to solving the dual problem:

$$\max_{\lambda \in \mathbb{R}^T} F(\lambda) \tag{4.26}$$

The objective function $F(\lambda)$ is concave, so the problem is convex. The subproblems $F_g(\lambda)$, $F_b(\lambda)$, and $\{F_v(\lambda)\}$ are each convex and can be solved independently for a given λ. One approach to solving the dual (master) problem is using the subgradient search method for λ. After the i^{th} iteration:

$$\lambda^{(\mathbf{i+1})} = \lambda^{(\mathbf{i})} + \sigma^{(i)} \mathbf{s}^{(\mathbf{i})} \tag{4.27}$$

where $\mathbf{s}^{(\mathbf{i})}$ is a subgradient of the master problem $F(\lambda)$, and $\sigma^{(\mathbf{i})}$ is the stepsize. For Lagrangian relaxation, the relaxed constraints can be used as subgradients:

$$s = \mathbf{b_a}^{(i)} - \mathbf{g_a}^{(i)} - \mathbf{q_a}^{(i)} + \sum_{v \in V_a} \mathbf{z_v}^{(i)} \tag{4.28}$$

For selecting the step size(s), some known results are [11]:

- If $\sigma^{(i)} = h$ is constant and $\|\mathbf{s}^{(\mathbf{i})}\| < K$, then $|\lim_{i \to \infty} F(\lambda^{(i)}) - max_{\lambda \in \mathbb{R}^T} F(\lambda)| < \frac{1}{2} h K^2$.
- For a positive step size sequence $\{\sigma^{(i)}\}$, $\lim_{i \to \infty} \sigma^{(i)} = 0$ and $\sum_{i \in \{0,\ldots,\infty\}} \sigma^{(i)} = \infty \implies \lim_{i \to \infty} F(\lambda^{(i)}) \to max_{\lambda \in \mathbb{R}^T} F(\lambda)$

An alternative to these step size rules is given by Held and Karp's adaptive step size rule:

$$\sigma^{(i)} = \mu^{(i)} \frac{(F^{bound} - F(\lambda^{(i)}))}{\|\mathbf{s}^{(\mathbf{i})}\|^2} \tag{4.29}$$

where

- F^{bound} is an upper bound on the problem $\max_{\lambda \in \mathbb{R}^T} F(\lambda)$.
- $\mu^{(i)} = \alpha \mu^{(i-1)}$ if $F(\lambda^{(i)})$ has not increased in the last N iterations where $\alpha \in [0, 1]$, $N > 1$ or $\mu^{(i)} = \mu^{(i-1)}$ otherwise. $\mu^{(0)} \in]0, 2]$.

Experimental results (Section 4.7) have demonstrated that the Held and Karp's rule is less sensitive to hyper parameter settings (e.g., $\mu^{(0)}$ and α), exhibits more consistent convergence behavior, and in general converges relatively fast.

4.6.3 Properties

The EV sub-problem (4.25) lends itself to an analytic solution that highlights potential issues. First, we consider a special case, namely when the lower bound on the variables is zero. The following proposition simplifies the solution finding for this special case.

Proposition 1. *Consider the problem V_0:*

$$\min_{z \in Z} \mathbf{c} \cdot \mathbf{z}, Z_0 = \{z \in \mathbb{R}^n | \mathbf{1} \cdot z = b > 0, \mathbf{0} \leq \mathbf{z} \leq \mathbf{u}\} \tag{4.30}$$

Without loss of generality, assume that $\mathbf{c}$ is such that $c_1 \leq c_2 \leq \ldots \leq c_n$. Let $U = \sum_{i \in \{1,\ldots,k\}} u_i$, where k is such that $U \leq b \leq U + u_{k+1}$. Then an optimal solution to problem V_0 is $\mathbf{z}^* = (u_1, u_2, \ldots, u_k, b - U, 0, \ldots, 0)$.

Note that the general form of the vehicle problem differs slightly from Problem V_0 in that there may be non-zero lower bounds on $\mathbf{z}$. However, this problem can be transformed into Problem V_0. The next observations indicate how alternative optima can exist in the vehicle problem. When using dual-inspired methods (such as subgradient search) with a vertex solver for the sub-problems, alternative solutions may be needed to build primal feasible solutions to the overall aggregator-EV problem: e.g., existence of alternative optima can be exploited to explicitly impose complementary slackness.

Observation 1. *If $\mathbf{z}^* = (z_1^*, z_2^*, \ldots, z_n^*)$ is an optimal solution to Problem V and for some $i < j, i, j \in \{1, \ldots, n\}, c_i = c_j$ and $z_i^* \neq z_j^*$, then they can be swapped, i.e., the following is a (distinct) alternative optimal solution for Problem V:*

$$\mathbf{z}^* = (z_1^*, \ldots, z_{i-1}^*, z_j^*, z_{i+1}^*, \ldots, z_{j-1}^*, z_i^*, z_{j+1}^*, \ldots, z_n^*)$$

Observation 2. *If $\mathbf{z}^* = (z_1^*, z_2^*, \ldots, z_n^*)$ is an optimal solution to Problem V and for some $i < j, i, j \in \{1, \ldots, n\}, c_i = c_j$, then the following are also optimal solutions for Problem V:*

$$\mathbf{z}^* = (z_1^*, \ldots, z_{i-1}^*, w_i^*, z_{i+1}^*, \ldots, z_{j-1}^*, w_j^*, z_{j+1}^*, \ldots, z_n^*)$$

where $w_j^* = b - w_i^* - \sum_{i \in \{1,\ldots,i-1,i+1,\ldots,j-1,j+1,\ldots,n\}} z_i^*$ for $w_i^* \in [l_i, u_i]$.

Observation 3. *If $\mathbf{c} = C \cdot \mathbf{1}$ for some constant C, i.e., $c_1 = c_2 = \ldots = c_n$, then any $z \in Z = \{z \in \mathbb{R}^n | \mathbf{1} \cdot z = b > 0, \mathbf{0} \leq \mathbf{l} \leq \mathbf{z} \leq \mathbf{u}\}$ is an optimal solution to Problem V.*

While these are special cases of alternative optima that might be useful to call attention to, the general pattern is: if a face of the feasible region polytope is in the optimal solution (as indicated by the equality of cost coefficients in a subset of the dimensions), then any point on that face can be used in an optimal solution, e.g., by taking a convex combination of all polytope vertices on the face.

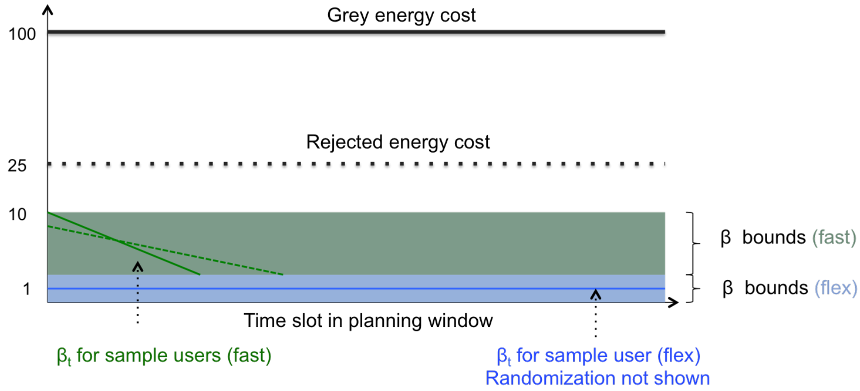

Figure 4.2: Example cost graphs: grey energy cost, rejected energy cost, and flexibility costs (fast and flex profiles).

4.6.4 Models for charging flexibility and preferences

We now describe the user flexibility model (4.14). We consider two types of users and show how to model them.

4.6.4.1 Flex users

First, we consider users without any preference with regard to their charging schedule: their only constraint is being charged on time. In other words, they do not care how their flexibility is used. One way to model these users in the proposed framework is to assume:

$$\beta_t^{(v)} = \beta^*, \forall t \in \{1, ..., T\} \tag{4.31}$$

with β^* some pre-defined constant, independent of time (and possibly even the individual user). In a quadratic model [12] this leads to demand spreading. However, in the linear model multiple optimal solutions exist due to the model being convex instead of strictly convex. Removing the flexibility model still leads to multiple optima, a topic also discussed in [6, 13]. From a user perspective this may not matter, but from a system perspective it could, e.g., to avoid excessive peak loads caused by identical user responses. Therefore, precautions should be taken to avoid such situations. A similar problem is encountered in [13, 14] when considering discontinuities in price responses. The authors solve this by limiting the maximum charging rate, essentially spreading demand. We on the other hand propose a simple but yet effective alternative: *randomization*. For example, by modeling their flexibility costs β using random values sampled from a pre-defined interval:

$$\beta_t^{(v)} = \beta^* + \xi_t, \forall t \in \{1, ..., T\} \tag{4.32}$$

where each ξ_t is drawn from a random (e.g., uniform) distribution. Note that we again assume a constant base value β^* to indicate the potential for user differentiation. The proposed (linear) model corresponds more to shifting demand in time than to demand spreading by reducing the power drawn from the grid. Consequently, simpler charging infrastructure with only on/off control actions is required, at the cost of balancing performance due to less fine grained control.

4.6.4.2 Fast users

The second type of users consists of users that have flexibility, but still prefer to be charged sooner rather than later. We can use decreasing flexibility costs for this type of users, i.e., high costs are assigned to deviations from their maximal charging rate at the start of the session. Important: we define the flexibility costs over the duration d_v of the charging session. Let us assume a (linear) decreasing sequence of $\beta_t^{(v)}$ values:

$$\beta_1^{(v)} > \beta_2^{(v)} > \cdots > \beta_{d_v}^{(v)} \tag{4.33}$$

Again we risk of synchronizing responses from similar users. This problem is however alleviated because the sequence depends on the arrival and departure time: only users with exactly the same time constraints will respond the same. We could again add randomization to avoid this, but in our experiments we did not see any noticeable improvements.

4.6.4.3 Example flexibility profiles

Figure 4.2 gives an example of a possible configuration for *flex* and *fast* flexibility profiles. From a system perspective we can interpret the β values as flexibility costs, i.e., costs associated with using flexibility from consumers at a certain time. Flex profiles exhibit the lowest flexibility costs: their flexibility will be put to action first. Flexibility costs associated with fast profiles are higher, and thus will only be put to action when other options are exhausted. Preference for fast charging is given by the linear decreasing slopes in the flexibility costs. The highest costs are assigned to the costs associated to the energy mix used, our primary objective. Note the ordering of the different cost types. The energy mix costs are the highest and our primary objective to steer demand. Flexibility costs are related to so-called flexibility profiles that can be tailored to each user type: low costs for flexible consumers, high costs for less flexible consumers.

4.6.4.4 Additional measures

We could employ additional techniques such as discussed in [13, 14] that limit the maximum charging rate to further spread demand and avoid optimization problems. This however comes at the cost of a computational and communication penalty: for each users, multiple optimization problems are solved (i.e., for each P^{max}), and the results of those are sent back. Our method however, does not limit the maximum charging rate of users, without additional computational and communication penalty. Note that randomization has also been applied in other contexts, e.g., frequency regulation [15], where randomized response times are used for charging actions (e.g., charge, discharge, idle) based on local measurements of the system frequency.

4.7 Case Study

In this section we present experimental results to illustrate and evaluate the proposed system. We evaluate the architecture (i.e., number of aggregators) and algorithms from a user and system perspective.

4.7.1 Scenario

We evaluate the hybrid algorithm with a scenario that simulates 2 aggregators and 100 EVs over the course of one month (31 days), with charging sessions based on the availability model in [16]. We execute the hybrid algorithm every 15 minutes using the new system state. We consider a number of flexibility profile mixes (i.e., flex and fast) and evaluate the impact thereof on the balancing capabilities. The simulated output from the wind turbine was scaled such that the cumulative (green) energy produced matched the sum of all charging requests over the complete period. The model uses real wind speed measurements taken over the period of one month, therefore there are time periods with high demand and low supply and vice versa. In addition, there is a theoretically infinite amount of conventional (grey) energy available from the grid. In this paper the primary focus is demonstrating the workings of the smart charging algorithm, i.e., we focus on the technical aspects. Alternative scenarios should be considered in addition to perform a complete feasibility study for DR services in the context of wind balancing, i.e., to study the feasibility of the business case.

4.7.2 Algorithm Parameters

The cost model used is illustrated in Figure 4.2 and discussed in Section 4.6.4.3. Individual EV charging sessions are randomly assigned to an aggregator. Flexibility profiles are assigned randomly to sessions according to the ratios specified in each experiment. The Held-Karp adaptive step size rule was used with $\mu = 0.1$, $\alpha = 0.01$, $N = 5$, and $F^{bound} = 10^{10}$. A maximum number of 100 iterations was used to speed up simulations.

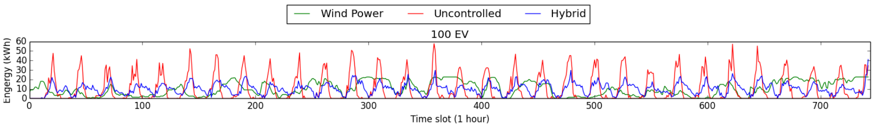

Figure 4.3: Example demand and supply curves.

4.7.3 Reference Scenarios

We compare the results of the hybrid algorithm to two reference scenarios: (i) uncontrolled charging, and (ii) an (offline) benchmark. The uncontrolled charging (or so called "business-as-usual") reference scenario assumes that EVs start charging at the maximum charging rate immediately after being plugged in. The uncontrolled scenario amounts to 39.49% green energy consumption, i.e., the amount of charging demand that is matched to the wind supply. The offline benchmark provides an upper bound on the amount of green energy consumption, which is 71.17% for this scenario, and is obtained by solving an optimization problem assuming a-priori knowledge of all supply and charging information. For certain scenarios we also include the results of a centralized implementation of the aggregator algorithm (Section 4.6.1) to study the impact of the decentralized implementation and configuration thereof.

4.7.4 Experimental Results

4.7.4.1 User mix

We first consider the impact of the user mix on the wind balancing results shown in Table 4.1. Green energy demand ranges from 48.85% to 67.91% depending on the user mix, i.e., the flexibility model has an impact on the balancing capabilities. The former result is obtained when all users prefer fast charging, and the latter is obtained when the users have no preference with regard to their charging schedule. Hence, as expected, energy consumption is more optimal when users provide more flexibility. Nevertheless, we are able to improve green demand compared to the uncontrolled scenario, even when users that offer flexibility prefer fast charging. An example is given in Figure 4.3.

The distributed implementation only has binary (on/off) states for the chargers (Section 4.6.3), whereas in the centralized implementation the charger state can be anywhere between P^{min} and P^{max}, leading to better balancing performance. In other words, there is a trade-off to be made between balancing performance and charging infrastructure requirements. Even when the centralized implementation is used, the results do not match those of the offline benchmark, due to a lack of future knowledge. Forecasting methods could be used to reduce the gap between these results (Figure 4.4).

Fast	Flex	Green demand	Green Demand (*)
100%	0%	48.85 %	62.65 %
75%	25%	56.57 %	63.51 %
50%	50%	61.73 %	64.13 %
25%	75%	63.76 %	64.87 %
0%	100%	63.97 %	65.28 %

Table 4.1: Results for the hybrid algorithm and different mixes of user types. Uncontrolled charging results in 39.49% green demand. The upper bound for green demand in this scenario is 71.17%. We also include as reference the green demand when a centralized algorithm (*) is used for the aggregator problem instead of a decentralized algorithm implementation.

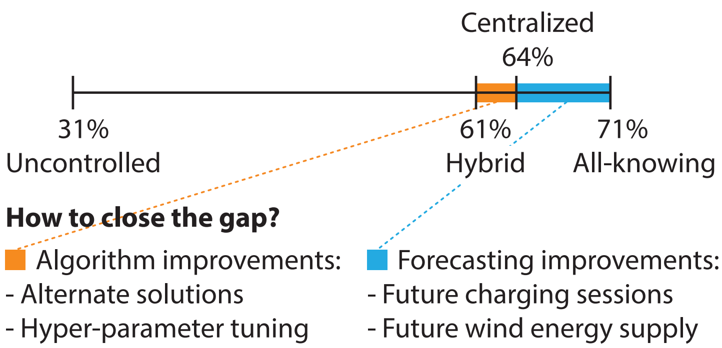

Figure 4.4: Qualitative illustration of the results obtained for an example scenario using various demand management approaches and potential improvements to close the gap.

Let us now consider the impact of the different flexibility models from a user perspective. Fast users prefer fast charging, i.e., their preferred schedule matches the uncontrolled charging schedule. Flex users have no preference. We expect that, given the same time, power, and energy flexibility, fast users will be charged in less time than flex users. Figure 4.5 shows that the available flexibility in terms of time slots is the same in both groups of users. How this flexibility is used however differs between the two user groups. Figure 4.5 shows that only a small amount of the fast users their flexibility is used, i.e., they only experience a minor increase in the time required to achieve a 100% state-of-charge.

4.7.4.2 Load profile shaping (smoothing)

We now consider the impact of the aggregator "smoothing cost term" in the grid controller objective function (see Section 4.5 and equation (4.6)). The smoothing cost term shapes the load profile of each aggregator, i.e., obtain load profiles that change gradually. Table 4.2 shows that the smoothness cost $\sum_{t=1}^{T-1} |x'_{a,t} - x'_{a,t+1}|$

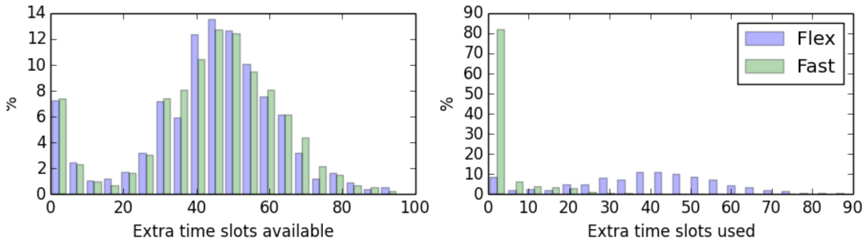

Figure 4.5: Available and used flexibility for the 50% fast and 50% flex scenario in Table 4.1.

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σ	Aggregator 1	Aggregator 2
0.0	7475980	7339128
0.1	5528916	5672472
1.0	5520308	5352320
10.0	5364276	5626720

Table 4.2: Evaluation of the smoothness of the aggregator load profiles (lower is better). The smoothness of the aggregator load profiles is improved as a result of the smoothness cost term introduced in the objective function. σ corresponds to the weight assigned to that cost term (see also Section 4.5 and Eq. (4.6)).

for the aggregator load profiles x'_a decreases when applying a smoothing cost term, which indicates that changes in aggregator load profiles occur more gradually.

Table 4.3 provides experimental results that applying a smoothing cost term in the grid controller objective function improves the balancing performance, i.e., green energy demand. We have verified this behavior for the decentralized and a centralized reference implementation of the aggregator/EV algorithm. The offline benchmark is not included in this comparison because it does not consider smoothing, i.e., the only objective is balancing (i.e., green demand).

4.7.4.3 Number of aggregators

Until now we assumed 2 aggregators for the experiments. However, the number of aggregators has an impact on the balancing performance shown in Table 4.4: for the decentralized implementation it degrades as we add more aggregators, but for the decentralized implementation, the performance depends on whether smoothing is applied or not. Smoothing results in demand spreading by reducing the charging rate. Consider the extreme case where each session is managed by a different aggregator. The target profiles for the aggregator then define the target of the single managed session instead of a group of sessions. In case of the decentralized imple-

σ	Green	Green (*)
0.0	58.21%	61.31 %
0.1	61.36%	64.16 %
1.0	61.73%	64.13 %
10.0	61.52%	64.06 %

Table 4.3: The use of an aggregator load profile smoothing term in the grid controller objective function has a positive impact on the balancing performance, i.e., green energy demand. We experimentally verified this for both the decentralized and the centralized$^{(*)}$ reference implementation.

	Smoothing		No smoothing	
#	Green	Green (*)	Green	Green (*)
1	62.45%	63.30 %	59.96%	61.33%
10	56.44%	65.76 %	54.39%	60.76%

Table 4.4: Impact of the number of aggregators on the balancing performance for the decentralized and centralized (*) implementation of the aggregator algorithm.

mentation and a smooth target profile, the EV will not be able to reach this target because it only has on/off control actions and the smooth target requires more fine grained control, which is available in the centralized implementation. In addition, it has been shown that a so-called pro-active approach, which is related to demand spreading, gives better balancing performance [10]. To verify this, we disabled smoothing, and then observed a similar decrease in balancing performance for the centralized implementation as for the decentralized implementation.

4.7.4.4 Randomization

We now consider the proposed randomization approach used to obtain diverse user responses. We repeat the scenario in which all charging sessions are considered *flex* sessions. Applying the randomization method results in 63.97% green demand, however without randomization we obtain only 37.21% green demand, which is even less than the uncontrolled benchmark that results in 39.40% of green demand.

4.8 Conclusion

In this paper we present a smart charging algorithm that combines ideas from centralized and decentralized DR approaches for the integration of RES using the flexibility in time for charging EVs. We emphasized the user preferences in this work and define a generic charging flexibility model that can be tailored to accommodate different user types. We have also shown how the system operator can shape the demand and go beyond the objective of just a balancing perspective. We provide a theoretical and experimental analysis of our algorithms. Future work could include heuristics to reduce the number of iterations in the distributed part of the algorithm, and the inclusion of grid constraints (e.g., voltage limits).

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5

Two-stage Load Profile Clustering Using Fast Wavelet Transformation

The challenges and opportunities introduced by electric vehicle charging have been considered in Chapter 3 and Chapter 4. However, to reach the full potential of demand side management approaches such as those, it is essential to understand the environment in which they operate. Smart grid systems aggregate large volumes of data, e.g., from smart meters. Data collected by those smart meters provides a valuable source of information about the energy consumption and production patterns we are changing with demand side management.

⋆ ⋆ ⋆

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Abstract Smart grid systems aggregate large volumes of smart meter data in the form of time-series or so called load profiles. To support the analysis thereof, we propose a scalable and flexible two-stage load profile clustering approach. The *first stage* is performed on a per user basis and takes as input a set of load profiles and groups similar load profiles, from which typical load profiles can be derived. The *second stage* uses as input the typical load profiles from all users combined, and again groups similar profiles. We use features extracted from the fast wavelet

transformation of the load profile time series data, thereby reducing the dimensionality of the data and emphasizing the type of patterns occurring in the load profiles instead of the times at which they occur. We provide experimental results to demonstrate and evaluate our approach.

5.1 Introduction

Smart meters are being deployed worldwide, to support detailed measurements of energy consumption and production, dynamic pricing, remote meter reading, etc. Whereas traditional electricity meters are often only read manually once a year, we focus on such measurements that give insight in the energy consumption patterns over time that occur at the grid end-points (e.g., households, commercial). One challenge lies in the large volume of data that results from this process, making it difficult to interpret. Machine learning techniques, specifically clustering algorithms, are being used to group similar load profiles, making it easier to analyze and interpret the data [1]. Load profiles represent the demand over time for a specific period of time, e.g., 24 hours with a resolution of 15 or 60 minute intervals. Load profile classification is then used for applications such as customer segmentation, load forecasting, power system planning and operation.

To support the analysis of large volumes of smart meter data we propose a scalable two-stage approach and a feature extraction procedure based on the fast wavelet transformation (FWT) of the load profile, instead of features directly derived from the time domain data [2] or based on fast Fourier transform (FFT) [3]. In addition, we propose the g-means algorithm [4], as an alternative clustering algorithm, because it automatically selects the optimal number of clusters, and makes fewer assumptions about the cluster shapes. We focus on a heterogeneous customer group connected to the low voltage distribution grid, instead of industrial medium voltage customers [1, 5] or nationwide demand data [6]. We show that our choice of features, which also reduces the dimensionality of our data, can be used to cluster daily load profiles from a heterogeneous group of end users. Benchmarks are provided for features derived from the time domain and the k-means algorithm.

The structure of this paper is as follows. In Section 5.2 we given an overview of the related work. In Section 5.3 we present our feature extraction method and two-stage load profiling approach. In Section 5.4 we provide experimental results. We summarize our conclusions and discuss future work in Section 5.5.

5.2 Related Work

Load profiling, load profile clustering, segmentation, etc. are terms frequently used to describe the process of grouping similar load profiles into groups. Instead of describing related algorithms in detail (which has already been done extensively, e.g., in [1]), we have chosen to emphasize the potential applications. We then provide background information on clustering algorithms that are relevant to our proposed approach. Next we give an overview of the feature extraction and selection methods used in related work. We conclude this section with an overview of evaluation criteria that are frequently used and will also be used to evaluate our approach in Section 5.4.

5.2.1 Applications

In this section, we present the applications that benefit from load profiling. Clustering or profiling of customer load profiles has many applications, including tariff design, load forecasting, power grid planning and operations, demand response, and energy efficiency programs.

5.2.1.1 Electricity demand analysis

From a high-level perspective, the power system consists of *generation*, *transmission*, and *distribution*. Load profiling is used to study demand patterns at these levels: e.g., nation wide [6] (e.g., for generation planning), substations [7], distribution stations [8], large (industrial) customers [1, 9, 10], and more recently small residential or commercial customers [2].

5.2.1.2 Customer segmentation, tariffs, billing and markets

Currently the utility companies use demographic data (family size, house size, location, etc.) as the basis for customer segmentation and tariff design [11]. However, technological (e.g., smart meters), and liberalized energy markets lead to new possibilities in defining tariffs, by benefiting from detailed knowledge of customers' energy consumption behavior [1] to better suit the customer and utility needs. In [10, 12], the authors propose load profiling for the purpose of pricing differentiation or designing demand response tariffs. In [13] the authors suggest to use load profiling information as input for billing of consumers who have deviated from their contracted schedules. It could also be used to handle cases with multiple suppliers [5]. Load profiling can also be used to assist customers select an adequate tariff [5].

5.2.1.3 Load Forecasting

Load forecasting is an essential part of generation, grid operations, power markets, and regulation. Load estimation or forecasting forms the basis for system state estimation, which is used for power system planning (e.g., transformer, conductor sizing). Customer classification based on load profiles may provide relevant information for short-term and mid-term load forecasting. In [14, 15], power system load is estimated by the aggregation of representative load patterns, and the use of clustering for the definition thereof is proposed in [16]. Techniques that use information on similar days for forecasting purposes [17] may benefit from load profiling to identify similar days. In [18] the authors use clustering for dis-aggregated electricity load forecasting. The benefits from customer grouping on load forecasting accuracy in the context of market participation are considered in [19]. In [20], it shown that consumption of groups of customers with similar consumption patterns can be forecasted more accurately than that of random groups of customers.

5.2.1.4 Demand response and demand side management

Load profiling is proposed as a means for enhancing targeting and tailoring of demand response and energy efficiency programs as well as improving energy reduction recommendations [2, 21–24]. Segmentation results are used to study the variability in energy consumption in [2]: e.g., it might be easier to target customers with low variability for demand response programs, and those with high variability for suggesting behavioral changes and energy efficiency programs. Load profiling is proposed to estimate the impact of demand response programs [5, 16] and energy efficiency programs [25]. Regression models for demand reduction based on cluster analysis of load profiles are presented in [26]. In [27] load profile data is used to infer occupancy states, group users, and determine demographic, household, and appliance stock characteristics. Clustering is used to extract controllable heating loads from smart meter data in [28].

5.2.1.5 Power system planning and operation

Load profiling may also be used to improve the planning and operation of the power system, especially in low-voltage networks for which limited knowledge is available related to, e.g., the consumption patterns of households. Highly generalized profiles are typically used for decision making, but in reality domestic consumption patterns are highly diverse. Load flow simulations are often used as a tool for power system planning and operations, and in [11] the authors suggest the use of load profiling results to improve the accuracy of such power grid simulations. In an example case study, maximum line currents and minimum node voltages were calculated and compared to the values calculated with real network loads and those using highly generalized profiles. The values obtained by the proposed model are very close to the real values, compared to those using the generalized profiles. In [8], clustering is used for analysis of the load profiles of distribution substations.

5.2.2 Features

In Section 5.2.1 we discussed several application domains in which clustering of load profiles can play are role. We will now discuss the features that are typically extracted from those load profiles to be used as input data for the clustering algorithms.

The most commonly used features are directly derived from the data of the (daily) load profile time series. Load profiles are typically pre-processed before clustering. A common step is to normalize the daily load profiles, e.g., (i) by rescaling it relatively between the minimum and maximum loads of the period under study [5], (ii) by dividing it by the user's reference power (e.g., peak power [1]), or (iii) by dividing it by its total consumption [2]. Normalization method such as these are used to emphasize the shape of the load profiles, rather than to focus on the absolute value of their amplitude.

Pre-processing (e.g., normalization) is not only done on a per profile basis. The authors in [1] first group the daily load profiles according to pre-defined *loading conditions* (e.g., season, day) for the period under study. A single *typical daily load profile* is then determined for each customer and loading condition: i.e., multiple daily load profiles are combined according to a statistical criterion (e.g., mean or median). Non-regular patterns (e.g., peaks) that occur will have a limited impact on the typical daily load profile. In addition, the amount of data to be clustered is reduced significantly. However, because the typical load profiles are much smoother compared to the individual load profiles, details and extremes of the behavioral patterns are lost and only general trends remain.

We, on the other hand, have chosen not to create such typical daily load profiles from a priori defined loading conditions, i.e., our input data consist of all available load profiles. Certain use cases may benefit more from detailed behavioral patterns: e.g., demand response applications may want to identify specific behaviors (e.g., to target relevant customers, identify flexibility, steer demand), energy efficiency applications may target old or faulty appliances which exhibit non-regular behavior. In addition, we focus on all types of low voltage customers, for which it is difficult to specify loading conditions that are applicable to all of them. For example, stores in Belgium are typically open on Saturday but not on Sunday, and have an additional closing day during the week. Making the distinction between week and weekend days does not make sense in this case, but it does in case of most residential customers. We therefore derive typical daily load profiles and their corresponding loading conditions from the data itself, instead of defining a priori loading conditions.

Alternative approaches sometimes use frequency domain features, based on a Fast Fourier Transform (FFT) [3, 29]. However, the FFT is designed for stationary behavior, whereas load profile time series typically exhibit non-stationary behavior. Wavelet transformations on the other hand are more suitable. Related work has also shown promising results when using wavelet-based features for clustering nation wide energy demand profiles [6]. Therefore, we have chosen to use an approach based on wavelet-based features for low voltage distribution grid customers. Details on the feature extraction process are given in section Section 5.3.1.

5.2.3 Clustering Algorithms

A wide variety of approaches has been proposed for clustering load profiles: e.g., k-means, fuzzy k-means, hierarchical clustering, modified follow the leader [1], Gaussian mixtures [11], self-organizing maps [3, 30]. We describe the k-means and g-means algorithms. The former forms the basis for the g-means algorithm that is used in our approach. We limit our discussion to these two, because other algorithms have been covered extensively in literature, e.g., in [1].

5.2.3.1 K-means

The k-means algorithm partitions a data set $X = \{x_1, x_2, \dots, x_N\}$ with $x_i \in \mathbb{R}^n$ in a set of K clusters $\{C_1, C_2, \dots, C_K\} \in C$. A cluster centroid μ_k is associated with each cluster C_k. Each data point $x_i \in X$ is assigned to exactly one cluster $C_k \in C$. The algorithm is initialized by selecting K initial cluster centroids $\{\mu_1, \mu_2, \dots, \mu_K\}$. The algorithm consists of two steps, which are repeated until the clusters converge (i.e., the members of each cluster do not change): (i) the *cluster assignment step* assigns each data point to its nearest cluster centroid, and (ii) the *cluster update step* updates each cluster centroid according to the current cluster members. The k-means algorithm takes two inputs: (i) the data set X to be clustered, and (ii) the number of clusters K.

During *initialization*, K data points $x_i \in X$ are typically selected at random as initial cluster centroids $\{\mu_1, \mu_2, \dots, \mu_K\}$. The objective of the algorithm is to minimize the *cost function* J (also called *distortion function*):

$$J = \frac{1}{N} \sum_{k=1}^{K} \sum_{x_i \in C_k} \|x_i - \mu_k\|^2 \tag{5.1}$$

The *cluster assignment step* of the k-means algorithm assigns each data point x_i to the cluster of which the centroid μ_k is located nearest to x_i according to a certain distance metric, typically the (squared) Euclidean distance:

$$\min_{k \in \{1,\dots,K\}} \|x_i - \mu_k\|^2 \tag{5.2}$$

The *cluster update step* of the k-means algorithm updates each cluster centroid according to the current cluster members: i.e., it calculates the average over all data points assigned to the cluster.

$$\mu_k = \frac{1}{|C_k|} \sum_{x_i \in C_k} x_i \tag{5.3}$$

The k-means algorithm is a simple and widely used algorithm. Nevertheless, certain drawbacks must be accounted for when using k-means. The number of clusters K must be specified as input parameter, which is a non-trivial problem in many applications. The resulting clusters will be spherical because of the L2 cost metric, i.e., there is a prior assumption that the data is distributed in spherical clusters. The algorithm is also sensitive to the selection of the initial cluster centroids: i.e., the algorithm does not necessarily reach a global optimum, and instead may reach a local optimum. To reduce the risk of ending up in a local optimum, the algorithm can be executed multiple times from which the best solution is selected according to some criterion (e.g., minimum value of J), and alternate means of selecting initial cluster centroids can be used.

5.2.3.2 G-means

The g-means algorithm [4] can be seen as a wrapper around the k-means algorithm, that determines the optimal number of clusters and makes less prior assumptions about how data points are distributed within clusters.

It is an iterative algorithm that starts with a small number of clusters, and increases the number of clusters as it progresses. During each iteration, it determines if existing clusters should be split into two new clusters. Between each round of splitting, k-means is executed on the entire dataset using the current cluster centroids in order to refine the solution.

The decision to split a cluster or not is based on a statistical test performed on the data points assigned to each cluster. The user is required to provide the statistical significance level α for the test. The test is simplified by first projecting the data to one dimension. If the data appear to be Gaussian, then do not split the cluster. Otherwise, split the cluster. The test used is based on the Anderson-Darling statistic, a powerful one-dimensional normality test.

5.2.4 Evaluation Criteria

Multiple evaluation criteria have been defined for the task of load profile clustering. A detailed overview is given in [1] and summarized below. We use these evaluation criteria to analyze the clustering results in Section 5.4. First we define three distance functions used to define other metrics.

The distance between two n dimensional vectors (e.g., load profiles):

$$d(x_i, x_j) = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(x_{i,k} - x_{j,k})^2} \tag{5.4}$$

The average distance between a vector x_j and the members of cluster C_j:

$$d(x_j, C_j) = \sqrt{\frac{1}{|C_j|}\sum_{x_k \in C_j} d^2(x_j, x_k)} \tag{5.5}$$

The infra-set mean distance of a set, defined as the average of the pairwise distances between the members of the set C_j:

$$d(C_j) = \sqrt{\frac{1}{2|C_j|}\sum_{x_k \in C_j} d^2(x_k, C_j)} \tag{5.6}$$

The Mean Index Adequacy (MIA) is used to measure the compactness or homogeneity of the clusters.

$$MIA = \sqrt{\frac{1}{K}\sum_{k=1}^{K} d^2(\mu_k, C_k)} \tag{5.7}$$

Other indicators consider not only the compactness of the cluster, but also the separation of clusters or distance between clusters. Assuming R the set of cluster centroids, the Cluster Dispersion Indicator (CDI) is:

$$CDI = \frac{1}{d(R)}\sqrt{\frac{1}{K}\sum_{k=1}^{K} d^2(C_k)} \tag{5.8}$$

The Davies-Bouldin index represents the system-wide average of the similarity measures of each cluster with its most similar cluster:

$$DBI = \frac{1}{K}\sum_{k=1}^{K}\max_{i \neq j}\left\{\frac{d(x_i, C_k) + d(x_j, C_k)}{d(R)}\right\} \tag{5.9}$$

The Similarity Matrix Indicator (SMI) is defined as the maximum off-diagonal element of the symmetrical similarity matrix, whose terms are built by computing a logarithmic function of the Euclidean distance between any pair of cluster representative load diagrams:

$$SMI = \max_{\substack{i>j \\ i,j \in \{1,\ldots,K\}}}\left\{\left(1 - \frac{1}{ln[d(\mu_i, \mu_j)]}\right)^{-1}\right\} \tag{5.10}$$

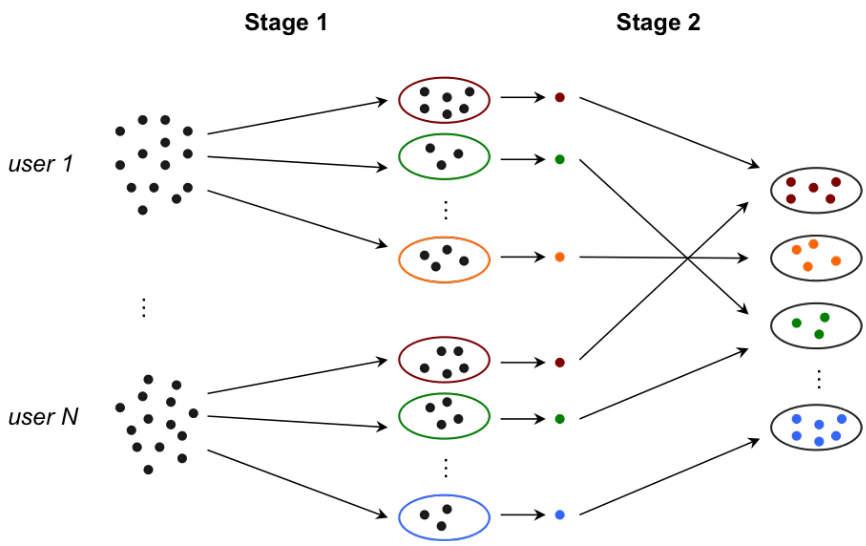

Figure 5.1: Two-stage load profile clustering algorithm.

The ratio of "within cluster sum of squares to between cluster variation" is the ratio of the sums of the square distances between each input vector and its cluster's centroid vector and the distances between the clusters' centroids:

$$WCBCR = \frac{\sum_{k=1}^{K} \sum_{x_k \in C_k} d^2(\mu_k, x_k)}{\sum_{1 \leq q < p}^{K} d^2(\mu_p, \mu_q)} \tag{5.11}$$

Compactness and cluster separation show opposing trends, e.g., compactness increases with the number of clusters, but separation decreases.

5.3 Two-stage load profile clustering algorithm

We propose a two-stage load profile clustering approach similar to [5] and illustrated in Figure 5.1. The *first stage* is performed on a per user basis, and finds their "representative day load profiles". The *second stage* uses all users' representative profiles, to group similarities between users. Both stages employ the same approach to process their input data: i.e., FWT based feature vectors [6] are clustered using the g-means algorithm [4]. The practical benefits are:

- The two-stage approach groups load profiles on a per user level, and on a user group level. The former leads to insights specific to each user and their behavioral patterns, whereas the latter lead to insights into the behavior of the group.

- Results from the first stage can be used for, e.g., load forecasting of customers, tariff selection, demand side management, energy awareness programs, etc. Results from the second stage can be used for power system planning, customer segmentation, tariff design, etc.
- We avoid a priori definition of loading conditions and corresponding typical load profiles (supervised), but instead derive the typical load profiles and corresponding loading conditions from the data itself (unsupervised).
- We focus on grouping load profiles that exhibit similar behavior, and do not care so much about the exact timing: we want to treat (slightly) time-shifted but otherwise similar shaped profiles as "similar".
- The selection of input data for stage two of the algorithm can be customized to the specific application.

The more technical benefits of this approach are:

- The number of clusters is determined automatically using a single intuitive configuration parameter: the confidence level used to determine whether to split a cluster or not.
- Features computed from the wavelet transform result in a significant reduction of the dimension of the feature vectors, thereby reducing computation time, memory, and storage requirements.
- Time invariance is incorporated in our features, instead of in the clustering algorithm (e.g., K-Spectral Centroids (KSC) algorithm in [24]).
- The two-stage approaches improves scaling to large datasets of many users. Stage 1 can be executed in parallel for each user, and results in a reduced set of load profiles to cluster in stage 2.

5.3.1 Stage 0: Data pre-processing and feature extraction

We deal with time-series data describing energy consumption of low voltage customers, e.g., households or small businesses. The time-series data are most often obtained from smart meters and logging (e.g., average power in kW) is typically performed on a 15 minute interval basis which results in load profiles of 96 samples per day. Our objective is to group these load profiles in such a way that we obtain compact and distinct groups. Instead of using the time series directly, as is typically done, we transform the time series to reduce the number of features and introduce a degree of invariance to temporal translations, i.e., we focus on which behavioral patterns occur, and less on when they occur. The approach is shown in 5.2

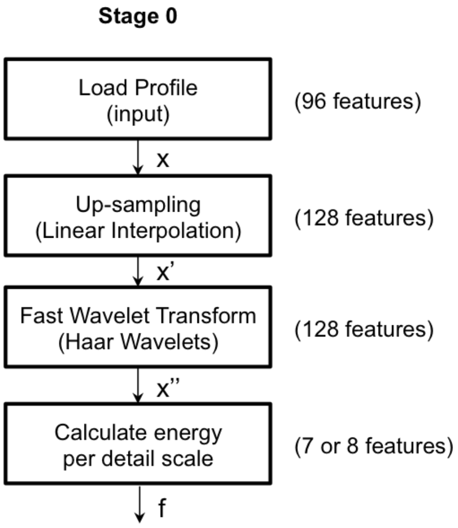

Figure 5.2: Stage 0: Date pre-processing and feature extraction. Each load profile x is pre-processed to obtain a feature vector f.

We employ FWT and Haar wavelets to transform a time-series data vector (load profile) x as proposed in [6]. Wavelets capture the general trend of the input data in an approximation component, while the localized changes are kept in the detail components. Wavelet representation describes the time series in both time and frequency domain. However, before the FWT can be applied, the time series must be up-sampled to obtain $N = 2^L$ samples (e.g., using linear interpolation). The FWT transformation W is applied to the up-sampled load profile x' and the result describes the data at different detail scales (frequencies) $(d_0, \dots, d_{L-1})$ and an approximation term c_0.

$$W : \mathbb{R}^N \to \mathbb{R}^N, x' \to (d_0, \dots, d_{L-1}, c_0) \tag{5.12}$$

$$d_j = \{d_{j,0}, \dots, d_{j,2^j-1}\} \tag{5.13}$$

From the FWT result $x'' = (d_0, \dots, d_{L-1}, c_0)$, we extract the coefficients for each detail scale (i.e., frequency) and calculate the energy therein to obtain our final feature vector $f = (f_0, \dots, f_{L-1})$. Note that we disregard the approximation term.

$$f_j = ||d_j||^2 \tag{5.14}$$

Detailed time information is removed, leading to dimensionality reduction. We are using the way the global energy $||x''||^2$ is distributed over the scales to generate our features. Note that because of Parseval's theorem, $||x'||^2 = ||x''||^2$.

An important consequence of disregarding the approximation term is that the features will be invariant to vertical shifts of the load profiles. Alternatively, if the application requires it, the approximation term of the wavelet coefficients can also be used, leading to a feature vector $f' = (f_0, \ldots, f_{L-1}, c_0)$.

The final result of the feature extraction process is a set of feature vectors for each user on which we perform range normalization before using them as input to the first stage of the clustering algorithm.

Our feature choice is in addition motivated by our focus on behavioral patterns, with less attention to the times at which they occur. In such context, time domain features combined with the L2 norm used in many clustering algorithms has been shown to cause problems [24] (e.g., a "double penalty" is applied to profiles that are only slightly different in timing when peaks occur) and the k-spectral centroids algorithm (KSC) is used to incorporate a certain degree of time invariance. We achieve a similar result purely by our choice of features. Reducing the dimensionality of the data was another concern, especially if in the future higher frequency measurements may become available.

5.3.2 Stage 1: Determine typical load profiles on a per user basis

Stage 1 consists of two steps: (i) analysis of individual customers, and (ii) selection of representative data to be used as input for Stage 2 . In a certain sense this step corresponds to a data driven unsupervised alternative to the a-priori definition of loading conditions and derivation of typical load profiles.

5.3.2.1 Analysis of individual customers

The daily load profiles haven been grouped and pre-processed (Stage 0) per customer. The resulting dataset is then clustered in Stage 1 using the g-means algorithm. Note that individual customers can easily be clustered independently and in parallel. Loading conditions [1] can be determined from these results, and used as selection criteria for stage 2 inputs.

5.3.2.2 Selection of representative data

We select representative data from the stage one results to be used as input for stage two. In [5] the cluster centroid (time domain features) from the largest cluster is chosen in the context of setting tariffs. Instead, we have chosen to select a representative, also cluster centroid (wavelet based features), from each of the user's clusters to keep as much information as possible. Alternatively, we could select the mean load profile in the time domain [5] or a representative load profile (e.g., the load profile for which the wavelet based features have the smallest distance to the cluster center). However, choosing a time domain representative requires an extra step of wavelet based feature extraction (or one could choose to perform stage two in the time domain). It also leads to information loss: e.g., detailed behavior gets lost in mean load profiles, or a single representative profile only captures a single day.

5.3.3 Stage 2: Determine typical load profiles of a user group

The input for Stage 2 consists of the combined representative data from all users (Stage 1 results). After range normalization, the dataset is clustered using the g-means algorithm. The resulting clusters group similar patterns from multiple users.

5.4 Experiments

In this section we evaluate the two-stage load profiling algorithm. We use the evaluation criteria defined in Section 5.2.4. We obtained a data set with measurements covering one year (15 minute intervals) of Belgian users. The data set was first filtered to remove customers for which less than a year of data was available (e.g., equipment failures, or because the smart meters were installed later in the year), leading to a set of 244 customers.

In Section 5.4.1 we analyze stage one of the algorithm in detail. We analyze the number of clusters per customer. We compare our wavelet transformation based features to times series load profile data. We also compare the performance of k-means and g-means. In Section 5.4.2 we conclude with the complete two-stage algorithm.

5.4.1 Stage 1: Typical load profiles on a per user basis

5.4.1.1 Example user

Figure 5.3 gives an example of the clusters obtained after stage one of the algorithm using a significance level $\alpha = 0.01\%$ as input for the g-means algorithm. The user exhibits three distinct patterns. The first group contains load profiles for when there is not much activity (e.g., when the customer is on vacation): low activity with few peaks. Although the peaks occur at different times, the pattern is similar. This demonstrates the time invariance built into our features. The second group contains the load profiles associated with the general demand pattern at the household. The third group contains load patterns that exhibit high demand around midday, which occurs typically on Wednesdays and in spring and summer, possibly indicating a family with children home on Wednesday. Choosing larger

	significance level α					
	15%	10%	5%	2.5%	1%	0.01%
Wavelet	28	21	15	12	10	6
Time	54	41	27	20	14	6

Table 5.1: Average number of clusters per user obtained after Stage 1.

values for α will result in more clusters and thus a more detailed view, however low values are useful to determine the general trends as we did in this example.

5.4.1.2 Number of clusters per user

The main benefit of the g-means clustering algorithm is that it automatically determines the number of clusters. Let us therefore first consider the number of clusters obtained for each user. Figure 5.4 and Table 5.1 summarize the number of clusters per user that are obtained after stage one. The confidence level used by the g-means algorithm influences the number of clusters that are obtained per user. Because we are also interested in the difference between using time based or wavelet based feature, we performed the experiment using two feature representations: (i) wavelet based features, (ii) time series features . We see that time series based features typically result in more clusters per user, which can be explained by the higher dimensionality of the input data. Note that for a confidence level of 0.01% the average number of clusters per user converges for both feature representations.

5.4.1.3 Comparison between time and wavelet based clustering

In this section, we analyze the use of different feature sets: (i) time series features, and (ii) wavelet based features. We have already shown that the choice of features has an impact on the number of clusters (Figure 5.4) when using g-means, making comparisons more difficult. We therefore use the k-means algorithm to emphasize the influence of the data representation. We use the approach discussed in [29] for comparing results obtained from different feature sets.

For this evaluation we use the g-means algorithm using different values for the significance level α to determine the number of clusters for each user using both feature representations. We use these cluster counts as input for the k-means algorithm, which was again executed for both feature types. We have chosen this approach because the main benefit of g-means is the automatic determination of the number of clusters. As such, we wanted to focus on cases that would be realized by g-means. Performance metrics were calculated on the load profiles and their associated clusters. We ensured that the same pre-processing was applied when calculating the performance metrics in the time domain. The results in Fig-

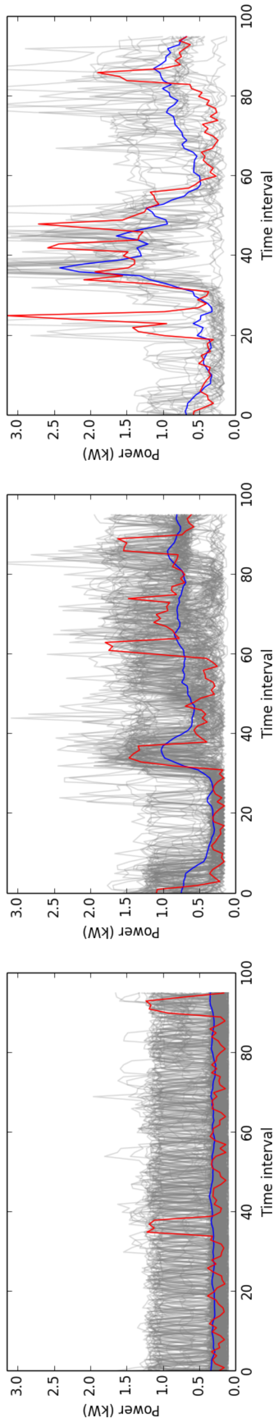

Figure 5.3: Example user with three distinct patterns obtained for $\alpha = 0.01\%$. For each cluster, we show the average load profile (blue) and a real representative load profile (red) corresponding to the profile nearest to the cluster centroid. The actual load profiles obtained from the smart meter are shown in grey.

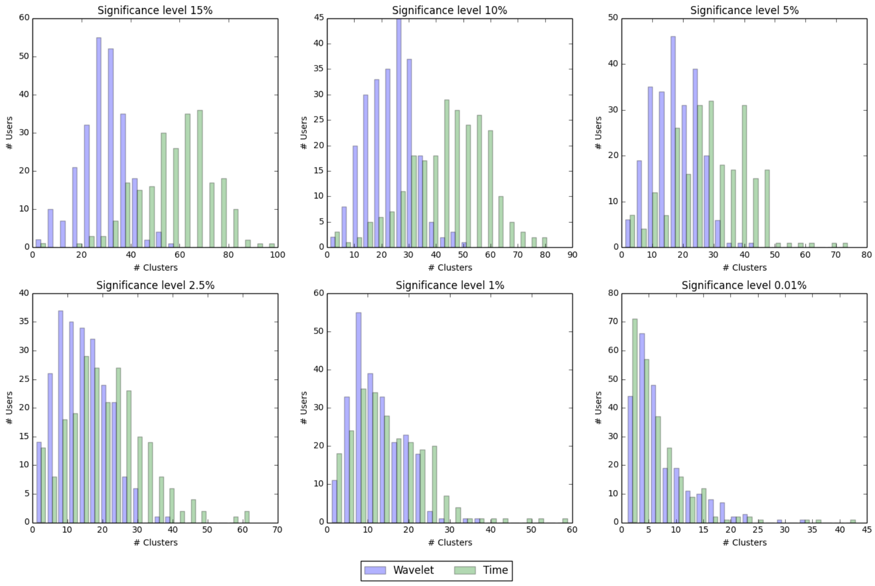

Figure 5.4: Histograms of the number of clusters per user (obtained after Stage 1) obtained from the g-means algorithm using time series or wavelet based features. The x-axis represents the number of clusters, and the y-axis represents the number of users.

ure 5.5 show the average performance in function of the number of clusters for both feature types. The time series based features lead to the best result (i.e., lower values for the evaluation criteria). This should be no surprise because the evaluation criteria are designed for and calculated using load profile time series data. Nevertheless, the wavelet based features demonstrate very similar trends.

5.4.1.4 Comparison with alternative algorithms

In this section we compare the performance of the g-means algorithm with the k-means algorithm. We cluster the load profiles of a single user with the g-means algorithm. We then take the number of clusters found by the g-means algorithm as input for the k-means algorithm. We calculate various cluster quality indicators for both algorithms. We repeated this procedure for all users in the data set. Figure 5.6 and Figure 5.7 give an overview of the cluster quality indicators for the g-means and k-means algorithms. We observe that the results are comparable for both algorithms, independent of the features used. This can be explained by the prior assumptions made by the different algorithms. The k-means algorithm assumes that data points in each cluster are spherically distributed. More generally, the Gaussian expectation maximization algorithm assumes that the data points in each cluster to come from a multi-dimensional Gaussian distribution. The Gaus-

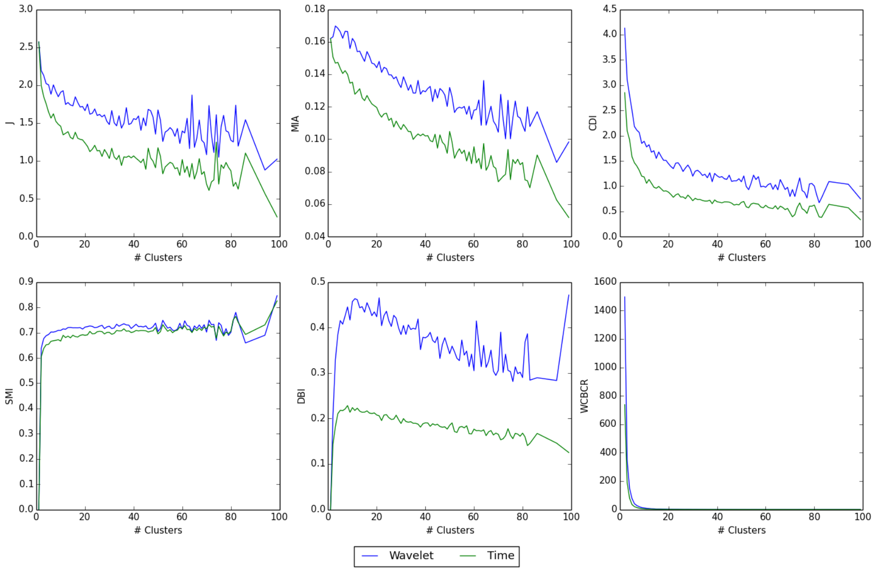

Figure 5.5: Comparison of the time and wavelet based approaches. Performance metrics are compared in the time domain. Lower values correspond to higher quality clusters.

sian distribution test used by the g-means algorithm accounts for both.

5.4.2 Stage 2: Typical load profiles of a user group

In Section 5.4.1 we limited ourselves to the analysis of the first stage of the load profiling algorithm. We now analyze the complete two-stage algorithm. Figure 5.8 visualizes the ten largest stage two clusters in the time domain. Performance metrics are given in Table 5.2 for different values of α. Cluster 8 could be considered a commercial cluster (e.g., shop or office) because of most consumption occurs during working hours. The remaining clusters correspond to profiles associated to different types of residential customers.

5.4.2.1 Number of clusters

Let us again start with the number of clusters discovered by the two-stage approach and wavelet based features. Table 5.2 shows the number of clusters obtained after stage one and two for different hyper-parameter choices. We assumed the same choice of α for both stages of the algorithm. We used the cluster centroids from the individual users as input data for stage 2. Alternatively, we could assume different significance levels for stage 1 and stage 2. For example, a high significance level may be specified for stage 1 to maintain a more detailed view of individual

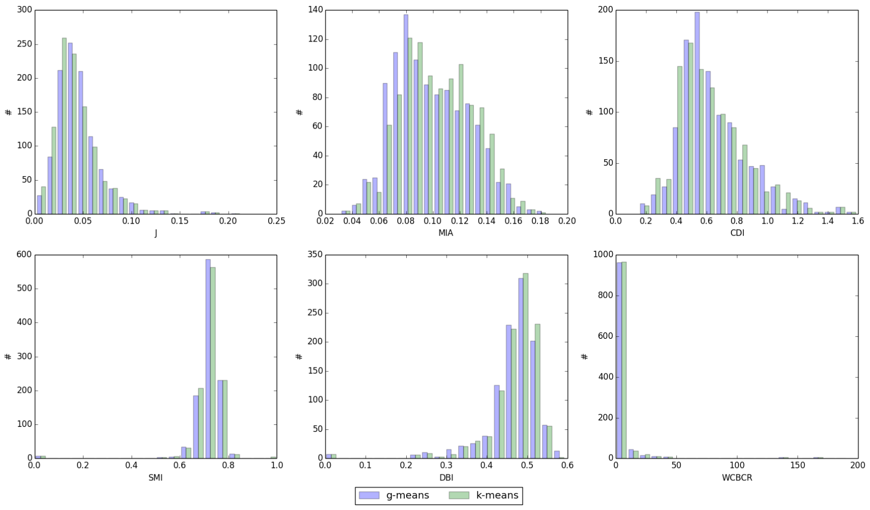

Figure 5.6: Histograms comparing the cluster quality indicators for the g-means and k-means algorithms using wavelet based features. The x-axis corresponds to the values of the quality indicator.

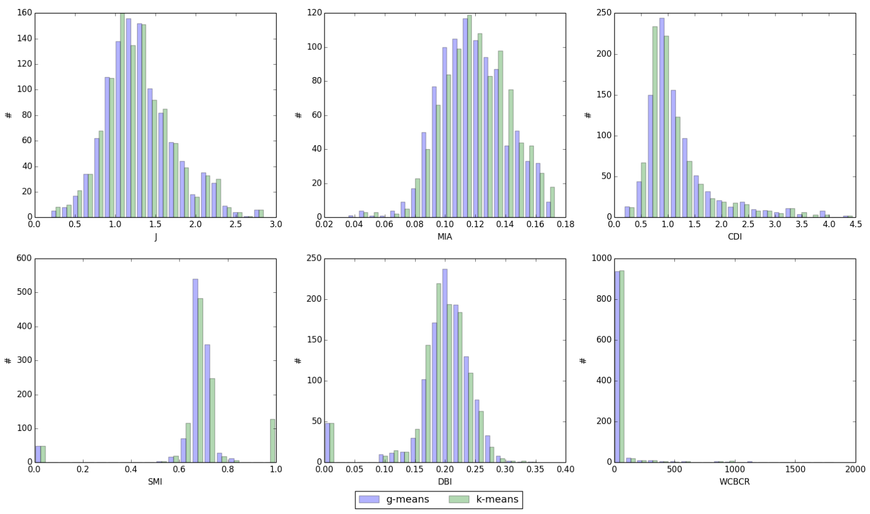

Figure 5.7: Histograms comparing the cluster quality indicators for the g-means and k-means algorithms using time domain features. The x-axis corresponds to the values of the quality indicator.

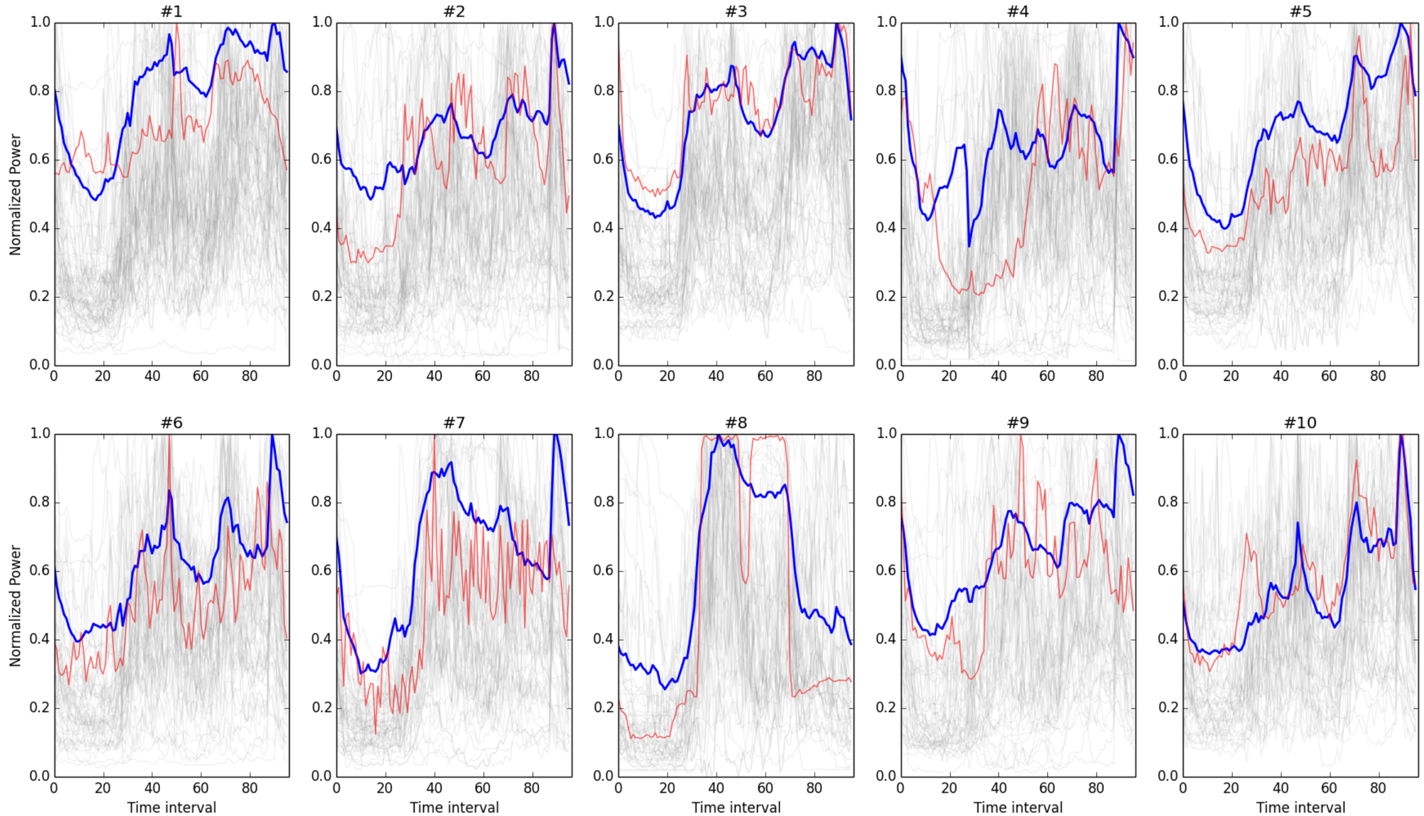

Figure 5.8: Ten largest stage two ($\alpha = 1\%$) clusters visualized in time domain, normalized to emphasize load profile shape. Grey load profiles correspond to the average load profiles derived from stage one clusters (Figure 5.3). Blue is the average load profile of the shown cluster. Red is a representative profile (nearest to cluster center), and corresponds to one of the grey load profiles.

	# Clusters		Cluster Quality Metric					
α	S1	S2	J	MIA	CDI	SMI	DBI	WCBCR
15.00%	7045	476	0.017	0.050	0.269	0.815	0.502	0.002
10.00%	5486	291	0.020	0.054	0.299	0.801	0.505	0.006
5.00%	4261	175	0.025	0.057	0.327	0.795	0.519	0.016
2.50%	3523	112	0.028	0.058	0.350	0.795	0.515	0.041
1.00%	2892	112	0.027	0.055	0.338	0.800	0.490	0.034
0.01%	1775	68	0.033	0.058	0.334	0.821	0.495	0.060

Table 5.2: Performance indicators of the two-stage algorithm using wavelet based features. S1: Stage 1, S2: Stage 2.

behavior. However, it is difficult to specify an optimal choice for the significance level and therefore the significance level should be chosen in function of the target application of the clustering results.

5.4.2.2 Clustering performance evaluation

Table 5.2 also provides an overview of the values for the evaluation criteria defined in Section 5.2.4 for different choices of the confidence level α. We do not provide a comparison to a time domain feature set because the two-stage approach and g-means clustering algorithm would make comparisons difficult (e.g., different number of clusters). However, the results presented in Section 5.4.1.3 provide more information on the impact of feature extraction and selection.

5.5 Conclusions and Future Work

We presented a two stage approach for grouping similar daily load profiles of a group of low voltage distribution grid customers. The first stage groups similar load profiles on a per user basis. The second stage takes as input the results from stage one and performs a similar grouping over all users. We extract features obtained from a fast wavelet transformation of the load profiles, thereby reducing the dimensionality of the data. These features are used to analyze low voltage load profiles, instead of the nationwide demand profiles considered in related work. The former is a more challenging task because of the larger variety in load profiles. The main contributions of our work are:

- Feature extraction from load profile time series based on a wavelet transformation to reduce the dimensionality of the input data and emphasize behavioral patterns independent of when they occur.
- The results from stage one summarizes energy consumption behavior of individual customers, which can be used to provide feedback on, e.g., energy

consumption, tariffs selection, and load forecasting (e.g., for demand response). Representative data from stage one is selected an used as input for stage two. The selection strategy can be adapted to the specific application, therefore it is not required to define a priori a representative day or mean day as suggested by other authors [5].

- The two stage approach leads to a more scalable system. Stage one can be performed in parallel for each user, and stage 2 operates on representative data from stage one, instead of all data of individual customers. Alternative methods instead use all available load profile data execute a clustering algorithm on the full dataset.

- Our approach automatically selects the optimal number of clusters for both stages using an intuitive parameter, the significance level for the statistical test used by the g-means algorithm.

- The wavelet based features show the same trend when comparing to the features in the time domain, although a much smaller representation is used. The comparison is however biased towards features in the time domain, due to temporal invariance built into our features, which is penalized heavily in the performance metrics [24].

- The performance of the g-means algorithm is comparable to the k-means algorithm for the same number of clusters.

Future work will incorporate the the two-stage approach in demand response applications, e.g., :

- Detect energy consumption flexibility for targeted demand response campaigns.

- Development of demand response algorithms that learn the flexibility from individual or a group of users, reducing the need of manual user input

- Load forecasting of individual customers and/or a group of customers.

- The clustering results give insights in the typical energy consumption patters of customers, which can be used to evaluate the impact of demand response programs, e.g., by comparing ”business-as-usual” behavior with behaviors resulting from demand response programs.

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6 Conclusion

In this dissertation we focused on the optimal and scalable integration of EVs in the smart grid. EVs require frequent recharging because of their limited range. Therefore, they will represent an additional load to the grid, especially in high-concentration areas such as residential areas and public parking places. However, the power grid was not designed with electric vehicle charging in mind. Charging can lead to excessive peak loads if not managed carefully. On the other hand, flexibility in EV charging offers new opportunities, e.g., for increasing the share of renewable energy sources. As we move towards a more electrified transportation, the large number of EVs will become challenging, therefore it is essential to provide a scalable solution.

Chapter 2 introduces the smart grid simulator developed to support this research. Further, it provides an in-depth survey of power system, communication, and smart grid simulators combining both. The classification and comparison in terms of their application domains, supported features, limitations, design, etc. forms an extensive resource for both end-users and developers. In addition, it provides perspectives on current trends and future directions. Although simulation is key to assess smart grid paradigms, and thus is used widely, this is the first in-depth overview of all simulation tools that are applicable in a smart grid context. It reaches a wide audience by targeting both the end-users and the developers of smart grid simulation tools.

Firsthand experiences and an extensive survey have shown that several aspects should be considered when selecting or developing a smart grid simulator. The supported use cases are the first aspect to consider and already provide a strong guideline when selecting or designing simulators. The second aspect to consider is the level of detail required for the simulation models. Specialized tools are required when the use cases require detailed simulation models for both power system and communication. In such cases, combining and extending existing and proven tools would be recommended. Such a co-simulation approach supports in-depth simulations, but also requires expert knowledge in both domains to develop, combine, use and extend these tools. More integrated approaches may reduce the need for expert knowledge when using them, e.g., by providing additional layers of abstraction and user-friendly modeling and analysis tools. However, we have experienced that this may come at the cost less detailed simulation models, or a limited set of supported use cases. Therefore, in case parts of the simulation models can be highly abstracted and a wider audience must be reached, such integrated approaches possibly tailored to the specific use cases can be an option. This brings us to the third aspect to consider, which is the user-friendlyness when using or extending the simulators, or analyzing the results obtained from them.

In Chapter 3 we show that the peak load can become up to three times as high as it was without the presence of uncontrolled EV charging, which leads to overloading of power grid components (e.g., transformers). Instead, demand side management algorithms for EV charging are proposed to control and coordinate EV charging to avoid such excessive peak loads. We achieve this by shifting charging in time, and/or changing the charging power. In addition, we ensure that a more stable demand for energy is obtained. However, the peak load and load profile variability are mainly used to assess production and grid capacity. EV charging also influences the power quality, e.g., in terms of variations in voltage magnitude. The proposed strategies also reduce the number of voltage deviations and the magnitude thereof, even without explicitly accounting for them. This study also demonstrated the capabilities of the smart grid simulator in terms of simulating both power system and communication.

In Chapter 3 we reduce the negative impact stemming from uncontrolled and uncoordinated electric vehicle charging. In Chapter 4 we take this one step further and focus on how smart charging can be used to provide additional services to the grid. We consider an application where charging demand is matched to the output from wind turbines, i.e., we ensure that charging uses as much renewable energy as possible, thereby reducing the need for additional generation from conventional sources (e.g., gas, coal). We consider a scenario where renewable energy can only provide 40% of uncontrolled charging demand. We propose a privacy-friendly hierarchical demand-side management approach that leads to renewable energy providing 49% up to 64% of charging demand, depending on the preferences of the users that participate. Novel to this approach is the strong emphasis on user preferences, expressed in flexibility profiles only known to the user. In addition, we make the trade-off between charging infrastructure requirements and effectiveness of the proposed approach. More advanced charging infrastructure can lead to an additional 14% of renewable energy being used for charging demand. Although we do not consider forecasting of charging demand, we show that improvements in that area can lead to 71% of charging demand being provided by renewable energy sources.

Reaching the full potential of the smart grid not only requires intelligent control strategies, but it also requires methods to make sense of the large amounts of data being collected from smart meter or demand side management programs. In Chapter 5 we proposed a two-stage clustering algorithm to derive representative load profiles for individual users and groups of users. Representative load profiles describe the typical energy consumption patterns, and therefore provide valuable information for applications such as tariff design, energy efficiency, power system planning, load forecasting, and demand side management. Until recently, related work often focused on large industrial customers. Instead, we consider a heterogeneous group of end-users connected to the distribution grid. Scalability of the method comes from the two-stage approach combined with a limited set of features being used. Only a minimal amount of configuration is required, making the approach accessible to a wide audience.

To summarize, the optimal integration of electric vehicles and charging thereof in the context smart grids was considered from different perspectives: (i) evaluate the impact on the grid (e.g., high peak loads, voltage issues), (ii) load shifting approaches to avoid high peak loads, and (iii) matching forecasted supply (e.g., wind or solar) and demand. Approaches ranging from decentralized to centralized and hybrids thereof were considered. Local and fully decentralized approaches (e.g., household level) already offer substantial benefits in terms of avoiding excessive peak loads, while other use cases such as matching demand and supply are achieved using more coordinated approaches. The latter approaches benefit from more detailed information, e.g., about forecasted demand, supply, and flexibility patterns. The load profiling algorithm has been developed with this in mind, e.g., to provide data for demand and flexibility forecasting models.

Over the course of the past years, demand side management algorithms (e.g., smart charging) have gotten considerable amounts of attention and are proposed for a wide range of use cases in different contexts (e.g., residential, industrial). Certain use cases focus on economical aspects such as minimizing energy costs (e.g., in a dynamic pricing environment, energy markets), whereas others focus on more technical aspects (e.g., load shifting, voltage regulation, frequency control, matching supply and demand). However, further refinement of these methods is still needed when we want to combine both economical and technical aspects, especially in decentralized settings where only limited information might be available compared to more centralized settings where a detailed and system wide view is available. At the same time, we must ensure that the end-user does not experience discomfort and benefits (e.g., financially) from offering flexibility and participating in demand side management programs.

The term *smart* charging is frequently used to describe controlled and coordinated charging methods, however in a sense those methods are not yet truly smart. Indeed, many of these methods are not yet able to autonomously learn from their environment, forecast future events, and take appropriate actions. Techniques from artificial intelligence (e.g., reinforcement learning) are expected to bring us closer to such a self-learning system that can adapt and anticipate to the changing environment. For example, instead of depending on users or appliances to provide flexibility information (e.g., based on arrival and departure time, energy requirement), the system should learn this on its own. As a result, demand side management algorithms would act pro-actively, instead of reactively to changes. In addition, the need for manual user interactions would be reduced or eliminated altogether. Understanding energy consumption, production patterns, and the flexibility in them is a first step to achieve this.

In conclusion, although the integration of electric vehicles must be managed carefully, this dissertation proposes different approaches to ensure the optimal integration by carefully managing how and when they are charged and/or discharged. In doing so, we avoid EVs having a negative impact on the power grid. In addition, further integration of renewable energy sources is facilitated by proposing approaches to match supply and demand, reducing the need for additional power from conventional sources. However, to obtain the full potential of these approaches, we will need to make them better understand their environment, e.g., the energy consumption and production patterns. To that end, we are only at the beginning of a truly “smart” grid.