Coordination Strategies for Reducing Price Volatility in Local Electricity Markets

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Coordination Strategies for Reducing Price Volatility in Local Electricity Markets

Coordination Strategies for Reducing Price Volatility in Local Electricity Markets

Dissertation

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at Delft University of Technology
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Chair of the Board for Doctorates
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by

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To Maa

Shantanu Chakraborty

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Summary

Introduction

To achieve climate change mitigation goals, it is important to increase the integration of renewable energy in the electricity generation portfolio. Increasing the integration of renewable energy also drives decarbonization of space heating and cooling, and transportation. Accordingly, the energy transition is transforming the socio-technical management of the energy system. However, this transition poses challenges for the operation of the electric power system.

The two main challenges are that renewable energy is intermittent, and cross-sectoral electrification increases demand for electricity. In such a power system, balancing the fluctuations associated with supply and demand of electricity is challenging. The propagation of these fluctuations in electricity markets results in an increase in price volatility. Furthermore, increase in electricity demand also raises concerns for congestion in the electric grid. While congestion management is applicable to both transmission and distribution grids, this thesis focuses on the latter. Distribution grids were previously managed in a passive manner. With the onset of the energy transition distribution grids have become increasingly susceptible to issues of congestion. Increased congestion in the distribution grid could potentially expose consumers to price spikes.

Flexibility, through demand-side management and electric storage have the potential to balance supply-demand fluctuations. This could be used in mitigating the magnitude of price volatility. High electricity price-averse consumers can possibly unite to form an energy community that seeks to reduce price magnitudes through the usage of flexible resources. To aid the community in satisfying their goal, aggregators play an integral role. Aggregators invest in and operate flexible resources on behalf of the consumers in addition to representing them in the electricity market. However, there exists a lack of coordination between the aggregator and the energy community for the utilization of flexibility to reduce price volatility in local electricity markets. This coordination can be facilitated through the involvement of the Distribution System Operator (DSO). In this thesis, the DSO additionally assumes the role of a regulated market operator for local electricity markets. Through this role, the DSO establishes a communication channel between the energy community and aggregator based on electricity price.

Research question and approach

The research objective of this doctoral thesis is: To gain a better understanding of the potential of demand-side flexibility, in a highly electrified and multi-actor distribution grid, to reduce increasing price volatility. Based on this research objective, the following Research Question is formulated: *How can flexible demand and electric stor-*

age be coordinated across multiple actors in an increasingly electrified future to reduce price volatility and congestion in distribution grids?. To address this research question, methods from optimization theory have been used. In particular, using duality theory explicit constraints are placed on the magnitude of electricity price. Assuming strong duality, the introduction of limits on price results in the quantification of the load reduction or demand-side flexibility that must be provided to satisfy the price constraints.

Based on this approach, a high price-averse energy community specifies to the DSO its maximum willingness to pay for electricity in the local market. The DSO using the price constraints quantifies the flexibility required. This flexibility amount is then communicated to an aggregator who is capable of satisfying the requirement. The aggregator satisfies the required flexibility through the dispatch of electric storage and/or through flexible charging of electric vehicles and electric heat pump operation. Once the required flexibility can be satisfied, the aggregator informs the DSO who in turn clears the market. Subsequently, the aggregator is remunerated by the energy community for its services. This establishes the organizational structure, using which demand-side flexibility is coordinated between the different actors for constraining electricity price. Three case studies varying with respect to type and the degree of aggregation of flexible resources are explored in detail in this thesis.

Techno-economic evaluation of electric storage to constrain price

In the first case study, the flexibility source considered is an electric energy storage system. The aggregator for constraining the price of electricity invests in and operates a community energy storage. As the aggregator would need to invest in the storage system, the purpose of this study is to provide an answer to the question: *What is the techno-economic feasibility of coordinating the dispatch of electric storage in distribution grids for reducing price spikes?*

For the considered case, the aggregator enters into a flexibility contract with the energy community to constrain price. It is assumed that the aggregator by discharging storage satisfies the flexibility requests. Additionally, at instances when no flexibility is requested, the aggregator has the option of participating in energy arbitrage. The techno-economic feasibility for the aggregator is evaluated based on the aggregator's revenue from the combination of arbitrage and price constraining under different price limits with the cost of investing in storage. Results indicate that more stringent price limits restrict the level of volatility in the local electricity market. As arbitrage is driven by price volatility, a trade-off emerges when comparing the aggregator's revenue from combined arbitrage and price constraining to arbitrage only. Furthermore, it is observed that the business value proposition for the aggregator depends strongly on the price limit.

Price constraints considering electric vehicles and heat pumps

This scenario builds on the previous by considering the electrification of transport and space heating. For this study, the aggregator constrains price by flexibly scheduling electric vehicle charging and the operation of electric heat pumps. In this study the following research question is answered: *In an increasingly electrified future, to what*

extent is a reduction in price spikes and local congestion possible?

In contrast to electric storage, electric vehicles and electric heat pumps provide load reduction by displacing their power consumption in time. For this study, it is also assumed that both these resources are operated by a single aggregator. Insights on the coordination mechanism are generated through simulation-based case studies. First, as cross-sectoral electrification increases load in the electric grid, an increase in grid capacity is required. Second, the ability of a flexible resource to provide load reduction depends on the underlying assumptions for its power consumption in the reference case. Also, instances may arise where load reduction provided by electric vehicles and heat pumps alone are insufficient to satisfy the required flexibility. In such instances, the aggregator may also operate a community energy storage or request community members for the permission to control their storage systems. The study then investigates the optimal storage capacity required to constrain price assuming both inflexible and flexible operation of the demand. Results indicate that sparing the situation in which both the electric vehicles and electric heat pumps are used inflexibly, the requirement for grid reinforcements is relaxed. Lastly, it is demonstrated that through a combination of demand response and optimal storage dispatch, price can successfully be constrained in local electricity markets.

Coordinating demand-Side flexibility across multiple aggregators

In this scenario, the control and management of flexible resources is distributed across multiple aggregators. Doing so, this study addresses the aspects of scalability and robustness in the supply of demand-side flexibility. Furthermore, each aggregator is assumed to have specialized knowledge about the operation of the flexible resource it manages. Subsequently, the objective of this study is to provide an answer to the following question: *To what extent can flexibility be coordinated in a scalable manner across multiple aggregators for constraining price in local electricity markets?*

To ensure scalable coordination of demand-side flexibility, the Alternating Direction Method of Multipliers distributed optimization approach is used. Using this approach, the study illustrates the feasibility of decomposing the coordination mechanism to a modular structure. In this mechanism, each aggregator earns a revenue that is proportional to its contribution towards satisfying the flexibility requests. Lastly, in contrast to the previous two studies, this study focuses on the impact of distributed decision making under rolling horizon forecasts. It is learned that under such a coordination mechanism capacity requirements from flexible resource for price constraining increase.

Research contribution and future directions

First, a mathematical formulation has been derived through which it is possible to include explicit constraints on price in the local electricity market. Second, through stakeholder analysis this thesis provides the required coordination mechanism essential for the implementation of price constraints in electricity markets. Third, conventional demand response programs have been modified to ensure that demand-side flexibility is coordinated such that price limits are always satisfied. Lastly, through the application of distributed optimization we illustrate price constraining in a modular and scalable manner.

The work conducted in this thesis also provides the foundation for numerous future research directions. One of the possible directions would be the inclusion of uncertainty in the price constraining mechanism. In this thesis deterministic scenarios have been considered. However, uncertainty can emerge from multiple sources and accounting for them would enable more robust planning of the flexible resources. Another direction would be introduction of constraints on the lower bound of electricity price to ensure non-negative price. The inclusion of this constraint would be interpreted as the load increase required to satisfy the constraint. Lastly, the coordination mechanism between the multiple actors considered is assumed to be cooperative. However, the degree of cooperation may vary based on the amount of self-interests of each actor. This would provide the basis for a game-theoretic exploration of the price constraining mechanism.

- Shantanu Tarun Chakraborty

Samenvatting

Introductie

Om de doelstellingen inzake de beperking van de klimaatverandering te bereiken, is het van belang de integratie van hernieuwbare energie in de elektriciteitsproductieportefeuille te vergroten. Een grotere integratie van hernieuwbare energie stimuleert ook het koolstofvrij maken van ruimteverwarming, -koeling en vervoer. De energietransitie zorgt dus voor een transformatie van het socio-technische beheer van het energiesysteem. Deze overgang brengt echter uitdagingen met zich mee voor de werking van het elektrische energiesysteem.

De twee belangrijkste uitdagingen zijn dat hernieuwbare energie variabel is, en dat sectoroverschrijdende elektrificatie de vraag naar elektriciteit doet toenemen. In een dergelijk elektriciteitssysteem is het een uitdaging om de schommelingen in vraag en aanbod van elektriciteit in evenwicht te houden. Deze schommelingen manifesteren zich op de elektriciteitsmarkten als een toename van de prijsvolatiliteit. Bovendien leidt een toename van de vraag naar elektriciteit ook tot bezorgdheid over congestie in het elektriciteitsnet. Hoewel congestiebeheer van toepassing is op zowel transmissie- als distributienetten, richt dit proefschrift zich op de laatste. Distributienetten werden vroeger op een passieve manier beheerd. Met het begin van de energietransitie zijn distributienetten steeds gevoeliger geworden voor congestieproblemen. Toenemende congestie in het distributienet kan consumenten mogelijk blootstellen aan prijspieken.

Flexibiliteit, via beheer aan de vraagzijde en elektrische opslag, kan schommelingen in vraag en aanbod in evenwicht brengen. Dit kan worden gebruikt om de prijsvolatiliteit te beperken. Consumenten die risico-avers zijn voor elektriciteitsprijzen zijn, kunnen zich mogelijk verenigen in een energiegemeenschap die prijsschommelingen probeert te beperken door het gebruik van flexibele bronnen. Om de gemeenschap te helpen bij het bereiken van hun doel, spelen aggregators een integrale rol. Aggregators investeren in en exploiteren flexibele bronnen namens de consumenten en vertegenwoordigen hen op de elektriciteitsmarkt. Er is echter een gebrek aan coördinatie tussen de aggregator en de energiegemeenschap voor het gebruik van flexibiliteit om de prijsvolatiliteit op de lokale elektriciteitsmarkten te verminderen. Deze coördinatie kan worden vergemakkelijkt door de betrokkenheid van de distributienetbeheerder (DNB). In dit proefschrift neemt de DNB bovendien de rol op zich van gereguleerde marktbeheerder voor lokale elektriciteitsmarkten. Door deze rol creëert de DNB een communicatiekanaal tussen de energiegemeenschap en de aggregator op basis van de elektriciteitsprijs.

Onderzoeksvraag en aanpak

De onderzoeksdoelstelling van dit proefschrift is: Het verkrijgen van een beter inzicht in het potentieel van flexibele elektriciteitsvraag in een sterk geëlektrificeerd en multi-actor distributienet, om de toenemende prijsvolatiliteit te verminderen. Gebaseerd op deze onderzoeksdoelstelling, wordt de volgende onderzoeksvraag geformuleerd: *Hoe kunnen flexibele vraag en elektrische opslag worden gecoördineerd tussen meerdere actoren in een steeds meer geëlektrificeerde toekomst om prijsvolatiliteit en congestie in distributienetwerken te verminderen?* Om deze onderzoeksvraag te beantwoorden zijn methoden uit de optimalisatietheorie gebruikt. Meer specifiek: met behulp van de dualiteitstheorie worden expliciete beperkingen opgelegd aan de hoogte van de elektriciteitsprijs. Uitgaande van sterke dualiteit leidt de invoering van prijsbeperkingen tot de kwantificering van het flexibile vermogen aan de vraagzijde dat moet worden geboden om aan de prijsbeperkingen te voldoen.

Op basis van deze benadering specificeert een energiegemeenschap die prijspieken wil voorkomen aan de DNB haar maximale bereidheid om voor elektriciteit op de lokale markt te betalen. Aan de hand van de prijsbeperkingen kwantificeert de DNB de vereiste flexibiliteit. Dit flexibiliteitsbedrag wordt vervolgens meegedeeld aan een aggregator die in staat is aan de eis te voldoen. De aggregator voorziet in de vereiste flexibiliteit door de inzet van elektrische opslag en/of door het flexibel opladen van elektrische voertuigen en het gebruik van elektrische warmtepompen. Zodra aan de vereiste flexibiliteit kan worden voldaan, brengt de aggregator de DNB op de hoogte, die op zijn beurt de marktprijs berekent. Vervolgens wordt de aggregator door de energiegemeenschap vergoed voor zijn diensten. Op die manier wordt de organisatiestructuur tot stand gebracht waarmee de flexibiliteit aan de vraagzijde wordt gecoördineerd tussen de verschillende actoren om de elektriciteitsprijs te beperken. Drie casestudies, variërend in type en mate van aggregatie van flexibele bronnen, worden onderzocht in dit proefschrift.

Techno-economische evaluatie van elektriciteitsopslag om de prijs te beperken

In de eerste casestudy is de flexibiliteitsbron een opslagsysteem voor elektrische energie. De aggregator die zorgt voor het beperken van de elektriciteitsprijs investeert in en exploiteert een gemeenschappelijk energieopslagsysteem. Aangezien de aggregator in het opslagsysteem zou moeten investeren, is het doel van deze studie om een antwoord te geven op de vraag: *Wat is de technisch-economische haalbaarheid van het coördineren van de inschakeling van elektriciteitsopslag in distributienetten om prijspieken te beperken?*

In dit geval sluit de aggregator een flexibiliteitscontract af met de energiegemeenschap om de prijs te beperken. Er wordt verondersteld dat de aggregator door het ontladen van de opslagruimte voldoet aan de flexibiliteitsvereisten. Bovendien heeft de aggregator de optie om deel te nemen aan energiearbitrage wanneer geen flexibiliteit wordt gevraagd. De technisch-economische haalbaarheid voor de aggregator wordt geëvalueerd op basis van de inkomsten uit de combinatie van arbitrage en prijsbeperking onder verschillende prijslimieten en de kosten van investeringen in opslag. Uit de resultaten blijkt dat strengere prijslimieten het volatiliteitsniveau op de lokale elektriciteitsmarkt beperken. Aangezien arbitrage wordt gestuurd door prijsvolatiliteit, ontstaat er een wisselwerking wanneer de inkomsten van de aggregator uit de combinatie van arbitrage en prijsbeperking worden vergeleken met arbitrage alleen. Bovendien wordt vastgesteld dat de zakelijke waardepropositie voor de aggregator sterk afhangt van de prijslimiet.

Prijsbeperkingen voor elektrische voertuigen en warmtepompen

Dit scenario bouwt voort op het vorige door rekening te houden met de elektrificatie van vervoer en ruimteverwarming. In deze studie beperkt de aggregator de prijs door het laden van elektrische voertuigen en de werking van elektrische warmtepompen flexibel in te plannen. In deze studie wordt de volgende onderzoeksvraag beantwoord: *In hoeverre is in een steeds meer geëlektrificeerde toekomst een vermindering van de prijspieken en plaatselijke congestie mogelijk?*

In tegenstelling tot elektrische opslag, zorgen elektrische voertuigen en elektrische warmtepompen voor een vermindering van de belasting door hun stroomverbruik in de tijd te verplaatsen. In deze studie wordt er ook van uitgegaan dat deze twee bronnen door één aggregator worden geëxploiteerd. Inzichten in het coördinatiemechanisme worden verkregen door op simulaties gebaseerde casestudy's. Ten eerste is, naarmate de sectoroverschrijdende elektrificatie de belasting van het elektriciteitsnet verhoogt, een toename van de netcapaciteit vereist. Ten tweede hangt het vermogen van een flexibele bron om de belasting te verlagen af van de onderliggende aannames voor het stroomverbruik in het referentiescenario. Ook kunnen zich gevallen voordoen waarin een vermindering van de belasting door elektrische voertuigen en warmtepompen alleen onvoldoende is om aan de vereiste flexibiliteit te voldoen. In dergelijke gevallen kan de aggregator ook een gemeenschappelijke energieopslag beheren of de leden van de gemeenschap toestemming vragen om hun opslagsystemen te beheren. De studie onderzoekt vervolgens de optimale opslagcapaciteit die nodig is om de prijs in toom te houden, uitgaande van zowel inflexibele als flexibele werking van de vraag. Uit de resultaten blijkt dat, afgezien van de situatie waarin zowel de elektrische voertuigen als de elektrische warmtepompen inflexibel worden gebruikt, de behoefte aan netverzwaringen minder groot is. Ten slotte wordt aangetoond dat door een combinatie van vraagrespons en de optimale inzet van een opslag, de prijs met succes kan worden beperkt op lokale elektriciteitsmarkten.

Coördinatie van flexibiliteit aan de vraagzijde bij meerdere aggregators

In dit scenario wordt de controle en het beheer van flexibele bronnen verdeeld over meerdere aggregators. Op die manier behandelt deze studie de aspecten van schaalbaarheid en robuustheid in het aanbod van flexibiliteit aan de vraagzijde. Bovendien wordt verondersteld dat elke aggregator over gespecialiseerde kennis beschikt over de werking van de flexibele hulpbron die hij beheert. Vervolgens is het doel van deze studie om een antwoord te geven op de volgende vraag: *In welke mate kan flexibiliteit op een schaalbare manier worden gecoördineerd tussen meerdere aggregators om de prijs op lokale elektriciteitsmarkten te beperken?*

Om de coördinatie van de flexibiliteit aan de vraagzijde schaalbaar te maken, wordt gebruik gemaakt van de gedistribueerde optimalisatietechniek van de Alternating Direction Method of Multipliers. Met deze aanpak illustreert de studie de haalbaarheid van het ontleden van het coördinatiemechanisme tot een modulaire structuur. In dit mechanisme verdient elke aggregator een opbrengst die evenredig is met zijn bijdrage aan het voldoen aan de flexibiliteitsverzoeken. Ten slotte wordt in deze studie, in tegenstelling tot de twee vorige studies, de nadruk gelegd op het effect van gedistribueerde besluitvorming bij prognoses met voortschrijdende horizon. Er wordt gevonden dat onder een dergelijk coördinatiemechanisme de capaciteitsbehoeften van flexibele bronnen voor prijsbeperking toenemen.

Bijdrage van het onderzoek en toekomstige richtingen

Ten eerste is een wiskundige formulering afgeleid waarmee het mogelijk is om expliciete prijsrestricties op te nemen in de lokale elektriciteitsmarkt. Ten tweede voorziet dit proefschrift, door middel van een analyse van actoren, in het vereiste coördinatiemechanisme dat essentieel is voor de implementatie van prijsbeperkingen op elektriciteitsmarkten. Ten derde zijn conventionele vraagresponsprogramma's aangepast om ervoor te zorgen dat de flexibiliteit aan de vraagzijde zodanig wordt gecoördineerd dat altijd aan de prijsbeperkingen wordt voldaan. Ten slotte illustreren we, door de toepassing van gedistribueerde optimalisatie, prijsbeperkingen op een modulaire en schaalbare manier.

Het werk dat in deze dissertatie is uitgevoerd vormt ook de basis voor talrijke toekomstige onderzoeksrichtingen. Een van de mogelijke richtingen is het opnemen van onzekerheid in het prijsbeperkende mechanisme. In dit proefschrift zijn deterministische scenario's overwogen. Onzekerheid kan echter uit meerdere bronnen voortkomen en door daarmee rekening te houden zou een robuustere planning van de flexibele middelen mogelijk zijn. Een andere mogelijkheid is de invoering van beperkingen op de ondergrens van de elektriciteitsprijs om een niet-negatieve prijs te garanderen. Het opnemen van deze beperking zou worden geïnterpreteerd als de belastingstoename die nodig is om aan de beperking te voldoen. Tenslotte wordt aangenomen dat het coördinatiemechanisme tussen de verschillende in aanmerking genomen actoren coöperatief is. De mate van samenwerking kan echter variëren naar gelang van de mate van eigenbelang van elke actor. Dit zou de basis vormen voor een speltheoretische verkenning van het prijsbeperkingsmechanisme.

- Shantanu Tarun Chakraborty

Nomenclature

$(UA)_{f,r}$ Heat transfer coefficient between floor and room (in kJ/°Ch)

$(UA)_{r,a}$ Heat transfer coefficient between room and ambient surrounding (in kJ/°Ch)

$(UA)_{w,f}$ Heat transfer coefficient between condenser tank and floor (in kJ/°Ch)

β Coefficient of demand elasticity

ΔP_{hp} Change in heat pump power consumption from one time instant to another

η Charging/discharging efficiency of the electric storage system

η_c Charging efficiency of electric vehicle

η_{hp} Electric heat pump coefficient of performance

λ Dual variable associated with power supply-demand balancing

λ_1 Lagrange variable associated with load balancing coupling constraint

λ_2 Lagrange variable associated with flexibility request balancing coupling constraint

$\mathcal{N}$ Set of nodes in the power network

μ Dual variable associated with generator capacity, load limits or line flows

Ω_{ij} Set of power lines in the power network

$\overline{\lambda^*}$ Contractually agreed electricity price that a community is willing to pay

$\overline{P_{G_i}}$ Maximum power dispatch capacity of generator i

$\overline{P_{ij}}$ Line flow limit from bus i to bus j

$\overline{P_{L_i}}$ Upper bound of a given load i

τ Time constant of the electric storage system

θ_i Phase angle of a given bus i

$\underline{P_{L_i}}$ Lower bound of a given load i

A Area covered by solar panels

A_f Annuity factor

a_i	Marginal cost of generator i
b_i	Utility co-efficient of a given load i
c_t	Day-Ahead electricity market price at time instant t
${c_t}^{FC}$	Electricity price at time instant t with storage dispatch with flexibility contracts
${c_t}^{sto}$	Electricity price at time instant t with storage dispatch without flexibility contracts
c_t^{hedge}	Cost of Financial Hedging at time instant t
$C_{p,f}$	Thermal capacity floor (in kJ/°C)
$C_{p,r}$	Thermal capacity room (in kJ/°C)
$C_{p,w}$	Thermal capacity water (in kJ/°C)
d	Annualized cost of electric storage system
d_{EV}	Distance traveled by the electric vehicle
E_{EV}	Electric vehicle storage capacity
E_{SS}	Electric storage system capacity
H	Solar radiation per unit area
I_F	Income earned by storage operator for constraining price
N_{Opt}	Number of optimization variables associated with the load balancing coupling constraint
N_{Opt_F}	Number of optimization variables associated with the flexibility request balancing coupling constraint
P_E	Power exported to the main grid
P_F	Flexibility required for constraining price to the specified limit
P_I	Power imported from the main grid
P_L	Baseload power consumption
P_R	Set of flexible loads comprising of electric vehicle and electric heat pumps
P_S	Bi-directional variable for indicating charging power ($P_S < 0$) or discharging power ($P_S > 0$) of the electric storage system
P_{avg}	Distributed averaging variable associated with load balancing coupling constraint
P_{ch}	Charging power electric storage system

P_{dis} Discharging power of electric storage system

P_{EV} Charging power of electric vehicle

$P_{F_{avg}}$ Distributed averaging variable associated with flexibility request balancing coupling constraint

P_{G_i} Power dispatch of generator i

P_{hp} Power consumption by electric heat pump

P_{Rat} Performance ratio of solar panels

P_{solar} Solar power generated

$P_{EV_{agg}}$ Aggregated electric vehicle power consumption across energy community

$P_{hp_{agg}}$ Aggregated heat pump power consumption across energy community

P_{new_h} Modified electric heat pump power consumption for household h

P_{new_v} Modified electric vehicle power consumption for vehicle v

r Solar panel efficiency

R_A Net revenue earned from arbitrage

R_F Net revenue from flexibility services

res_1 Residual of the load balancing coupling constraint

res_2 Residual of the flexibility request balancing coupling constraint

T Simulation Time Period

t time instant

T_a Ambient Temperature (in °C)

T_f Floor temperature inside a household (in °C)

T_r Room temperature inside a household (in °C)

T_w Water temperature inside the condenser tank of a household (in °C)

X_{ij} Reactance between bus i and bus j

ϵ Error threshold

ρ_1 Penalty parameter associated with load balancing coupling constraint

ρ_2 Penalty parameter associated with flexibility request balancing coupling constraint

1

Introduction

1.1 Changing energy landscape & energy transition

Climate change is one of the most pertinent issues faced globally. It has resulted in the shrinkage of glaciers, and spread of forest fires. To address this issue, in 2015, the Paris Climate Agreement put forth a global framework 'to avoid dangerous climate change by limiting global warming to well below 2 °C and pursuing efforts to limit it to 1.5 °C' [1]. To achieve these climate change mitigation goals, it is important to increase the integration of renewable energy in the electricity generation mix. Accordingly, Figure 1.1 illustrates that the global share of renewables (solar, wind, geothermal, and hydro) towards electricity generation has been increasing [2].

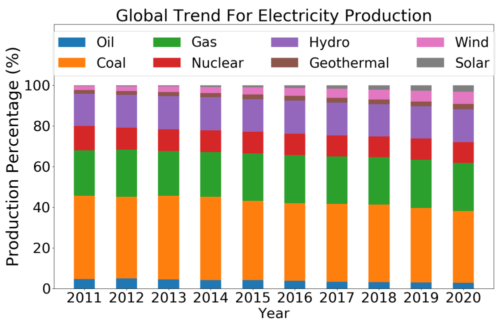

Figure 1.1: Increased contribution of renewable energy for electricity generation (2011 - 2020) [2]

Given that there is disparity in the state of a country's development, not all countries can commit to the same level of renewable energy integration. Figure 1.2 provides an regional overview of installed renewable energy capacity over the period 2011 - 2020. Over this period, renewable integration in Europe grew from 380 TWh/year to 921 TWh/year at a growth rate of 10.35%. Furthermore, countries constituting Asia

Pacific represent the fastest growing region for renewable integration.

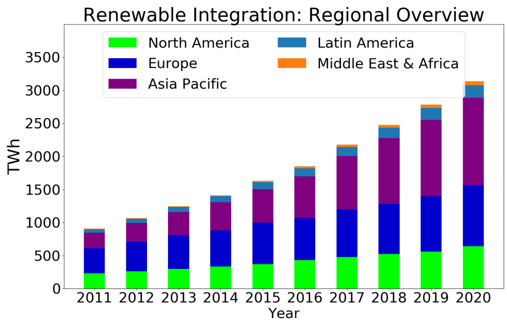

Figure 1.2: Renewable Energy Integration by Region (2011 - 2020) [2]

While these trends are encouraging, the International Renewable Energy Agency (IRENA) [3] analyzed that current emission trends will fall short of satisfying the Paris Agreement goals.

1.1.1 Energy landscape

The electric power system plays a significant role in hosting renewable energy. We provide a brief overview of the evolution of this system for facilitating large scale renewable energy integration. Previously, the electric power system was a monopolistic system having a central and vertically integrated structure. Electric power was generated at large-scale, remotely located fossil-fuel based stations. This power was then transmitted over wide distances through the electric transmission system. Power was then eventually delivered to end-consumers via the distribution system. In this vertically integrated system, power generation, transmission, and distribution was in the domain of a single entity. In the absence of competition, a natural monopoly existed where electricity price was set by a single entity. In this electricity infrastructure, market access to other actors was prohibited.

A solution for enabling market access was through electricity market liberalization. The central premise of market liberalization was to make electricity supply more efficient by integrating competitive forces while maintaining regulation where deemed necessary. Market liberalization, was accompanied by the decoupling of the power system into distinct generation, transmission, and distribution sectors. In such a system, vertically integrated companies were prevented from simultaneously generating, transporting, and supplying electricity while managing the transmission and distribution networks. Electricity markets in Europe were liberalized in 1996, with the adoption of the first European Directive. In the Netherlands, the year 2004 marked the period when the electricity market became fully competitive.

Subsequent European Energy Directives, sought to further decarbonize the electric power system. This was done in parallel with further un-bundling the system and increasing competition amongst market actors. Actors that were able to gain market access comprised of numerous renewable energy-based independent power producers for example solar and wind parks. Concurrently, there was a shift from the central organization and management of the power system to be more decentralized and consumer-centric.

In this decoupled power system, the distribution system was previously operated in a passive manner [4]. However, the energy transition and subsequent large-scale integration of renewable energy, has made the active management of the distribution grid imperative. As renewable energy is intermittent and variable, instances can arise where excess power from the distribution grid flows in a reverse direction. This could lead to possible grid contingencies. Alternatively, renewable energy generation may deviate from their forecasted values, thereby inducing uncertainty into distribution system operation. Integration of storage system aids in alleviating these concerns. However scheduling the operation of electric storage requires a certain degree of computational intelligence. Insights on this were disseminated through the 'Smart Grid Initiative' [5] that provided computational approaches to improve coordination in supply-demand balancing between the transmission, distribution and storage infrastructures.

Lastly, given the presence of a wide array of decision-making actors that influence the operation and economics of the electric power system, it must be acknowledged as a complex socio-technical system. These actors constitute system (transmission and distribution) operators, and market participants (consumers, consumers with integrated renewable energy, and market entities representing an aggregation of consumers). Heading into a future with increasing integration of renewables, the complexity of the interaction between these actors is expected to increase owing to the evolution of the electricity market design and its regulation.

1.1.2 Challenges associated with the energy transition

The distribution grid is becoming increasingly important for the integration and hosting of massive amounts of modular renewable energy systems [6, 7]. While renewable energy contributes towards reduction of carbon emissions, their large-scale integration also poses challenges to the operation of the electric power system. The main challenge emanates from the fact that renewable energy is intermittent and weather-dependent.

To better understand the operational impact of large-scale variable renewable energy on the electric grid, the California Independent System Operator (CAISO) in 2013 conducted a detailed analysis on the projected 'net load' from 2012 to 2020 [8]. 'Net Load' is the residual load that is not satisfied by renewable energy. The study identified a general trend for the curve with a drop in the midday period followed by a ramp in the early evening period. This pattern is in line with increase in solar capacity that results in a midday trough. In contrast, the ramp in the early evening period manifests as a result of simultaneous increase in electrification of end-use appliances and the lack of solar energy in that period. Owing to the distinct characteristic of this demand curve, it was labeled as the 'Duck Curve'.

A similar trend is observed in the Netherlands. Erstwhile, system operators benefited from a predictable and fixed demand curve, characterized by a peak in the morning and evening with a flat back in between. This curve was referred to as the

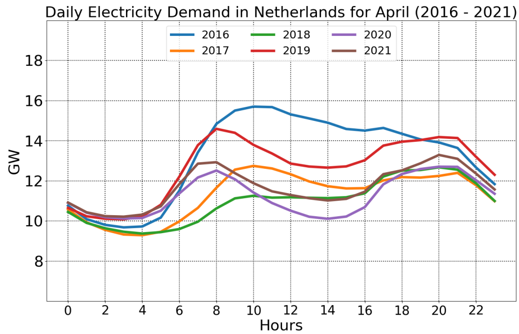

Figure 1.3: Emerging trend of overgeneration and demand spikes as observed in the Netherlands for an average day in April (2016 - 2021) [9]

'Camel Curve' [10]. However, given the recent large-scale of solar energy, the 'duck curve' has also surfaced in the Netherlands as illustrated in Figure 1.3. As of 2020, the Netherlands has an installed capacity of 7.9 GW of solar energy. As studied in the report, the average difference in demand profiles between two consecutive days is increasing from 500 MW in 2017 - 2018, to more than 600 MW during 2019 - 2020. Furthermore, the variability in the demand profile during the daytime has increased and this is attributable to higher generation (or the lack thereof) of solar power. The sharp ramps in the demand profile during the early evenings for the Netherlands is a result of the electrification of heating and transport, and the drop in solar power during that period. Thus, it is imperative that system operators anticipate and proactively take measures to accommodate these demand profiles. Recent reports by the Dutch DSOs [11] indicate that system operators are already having to contend with issues such as congestion management and ensuring voltage-quality. Another issue emerging from the inadequate planning for these demand profiles would be the dispatching of expensive power peaking units, thereby causing stark fluctuations in electricity price.

1.1.3 Electrification of space heating and transportation

To achieve the targets of climate change mitigation and carbon emission reductions set by the European Commission [12] an enormous increase in electricity usage for space heating and cooling as well as transportation is expected. The main reason for electrification is that it is the least expensive decarbonization option.

Historically, the transportation sector has been a notable contributor to carbon emissions and in 1990 it accounted for 15% of aggregated emissions. By 2015, this number increased to 23%. In contrast, the building sector, which comprises of commercial, public and residential buildings accounted for one-third of the total carbon emissions in Europe for the same period. In particular, commercial and public buildings were responsible for as much as 40% and residential dwellings (including buildings) for 60% of total emissions. As a step towards reducing the carbon emissions from these sectors, their electrification through renewable energy has the potential to play a critical role [13].

The European Union has in response laid down a road-map for the electrification of this demand. As per this planning, the electrification of space heating and cooling is expected to increase by 1.3% every year starting 2021. With this projection as the basis, it is expected that by 2050, 80% of this demand would be supplied by renewables [14]. Similarly, the European Union has also set itself ambitious targets for electrification of mobility. The global adoption of passenger electric vehicles is expected to grow to 10% by 2025 and then to 58% in 2040. Of this global forecasted average, 72% of the uptake in electric vehicle adoption is attributable to China and the European Union alone [15].

The electrification of these sectors provide significant carbon emission reductions. If we include the industrial sector as well, then the total emission across the combination of these three sectors would be 68% from 2020 - 2050 [16]. This would equate to a 71% reduction as compared to the 1990 levels. The distribution of these values across the three sectors for a representative country in Northern Europe is illustrated through Figure 1.4.

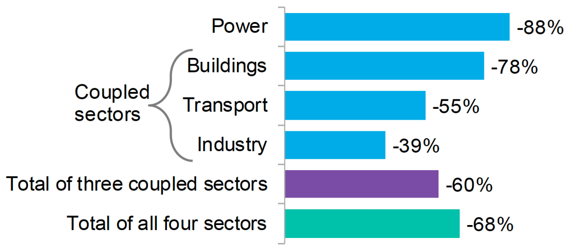

Figure 1.4: Potential of carbon emission reduction across sectors through electrification [16]

In Figure 1.4, the decarbonization of the power sector is achieved by supplanting fossil-fuel based generators with renewable energy systems.

Consequently, the electrification of these sectors would result in a significant increase in electric energy demand. It is expected that this would contribute towards doubling or even tripling of electrification as a share of total energy usage as compared to 23% as of 2015 [17]. To satisfy this increased electrification rate, the amount of renewable energy connected to the grid would also need to increase.

1.1.4 Expected increase in renewable energy integration for cross-sectoral electrification

Decarbonization of the heating and transportation sector, will drive the demand for renewable energy. Many scenarios for the long-term transition from fossil-fuel based power supply to renewables have been generated, and [17] sheds light on them. The report states that in the long-term, the European Union is projected to foresee a significant phase-down of fossil fuel generation capacities from 44% in 2015 to 24% by 2030. This is further accentuated in the year 2050 when fossil fuel power shares drop to a meagre 12%. Additionally, nuclear energy is also expected to be halved in capacity from 12.5% in 2015 to 6% in 2050. Increased integration of renewable energy will thus be critical for satisfying electricity demand in the EU. Wind energy is expected to emerge as the major source of power with its installed capacity anticipated

1

to grow from from 432 GW in 2015 to 870 GW by 2030. Similarly, the capacity for solar energy is expected to increase by 30% over the same period. Overall, under an ambitious scenario, a total of 2,394 GW renewable energy capacity will be made operational by 2050, thus reflecting a five-fold increase compared to 2015.

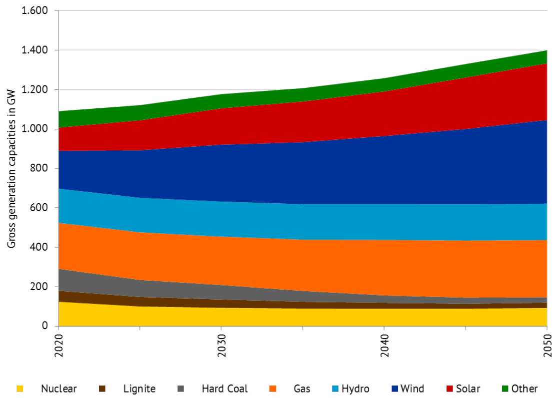

Figure 1.5: Planned Power Capacity in Europe till 2050 [18]

This forecasted trend is also supported by an independent analysis across multiple scenarios performed by [18]. Their analysis shows that wind energy is expected to expand such that it accounts for 30% of overall generation capacity by 2050. Given that renewables are intermittent and non-dispatchable, controllable fossil fuels such as gas will also observe an increase to almost double its capacity by 2050. The energy mix for meeting the additional electrified demand will constitute, 36% of renewables, 44% of dispatchable gas, and the remainder will be controllable renewable energy technologies such as biomass-based power plants. Figure 1.5 illustrates this transition.

1.1.5 Impact of electrification on grid congestion

Increase in renewable energy supply requires an increase in the grid capacity for hosting and transmitting the power. After accounting for a fairly moderate grid expansion between 2020 to 2030, [19] expects a grid expansion of about 25% per decade between 2030 to 2050. This is because the siting of large scale renewable and nuclear energy would be predominantly decoupled from the load centers. As stated in Section 1.1.4, a substantial increase in wind energy is expected, and to transmit this power across central Europe, the transmission grid would need to be upgraded. The net investments for the extension of the transmission grid infrastructure would amount to €100 Billion. However, a more pressing issue with respect to grid capacity planning is the distribution grid, where upgrades are anticipated within the coming decade.

At the distribution grid level, infrastructural investment are required for ensuring the dynamic matching of variable generation and demand. Overall, European DSOs are faced with three key concerns. They constitute the increased electrification of heating and mobility sectors, large scale integration of renewables and reverse power flows, and increasing price volatility in the grid which requires portfolio optimization of decentralized production and load assets [20, 21].

These concerns are already manifesting themselves. In the Netherlands, a huge ramp in solar energy from a capacity of 4.4 GW (in 2018) to 15 GW (by 2024) is expected [11]. This has prompted Dutch DSOs such as Liander and Enexis to advocate for restricting the number of new solar projects [22]. As such an astronomical increase in renewable energy integration was not foreseen, DSOs are increasingly concerned about the growing instances of local congestion and voltage violations. It is anticipated that for facilitating full electrification of sectors and to increase renewable energy integration, an increase in grid capacity of 50% by 2050 is required in the Netherlands [13].

In the interim to alleviate the pressure on the DSOs, demand side management and electric storage will play an important role. Dispatching storage and shifting electricity consumption in time enables system operators to defer costly grid upgrades. In the Netherlands, pilot projects that seek to investigate the potential of grid modernization are being explored in the south of the country [23]. The system operator, Enexis, is responsible for providing adequate network capacity, and for maintaining voltage quality. To achieve its objective, Enexis will interact with an aggregator of flexible demand. Their coordination will focus on predicting, modulating and shifting demand in time, thereby ensuring efficient system operation.

1.2 Changing electricity prices

Effects of the changing energy supply-demand dynamics are expected to influence the electricity market. By 2030, a combined 65% - 70% of electricity output will be provided from renewables and nuclear energy [17]. These energy sources have zero marginal cost, and shift energy prices to a fixed-cost structure. As these energy sources are strongly weather-dependent, they increase the fluctuations in the electricity generation mix thereby contributing to increase in volatility of electricity price. The current electricity market structure in the European Union is characterized as an energy only day-ahead and intra-day markets, where price is set by the intersection of offers and bids for the day. In the advent of demand peaks, or when production from renewable energy sources is intermittent or low, or when there are rapid swings in demand supply, price is expected to increase.

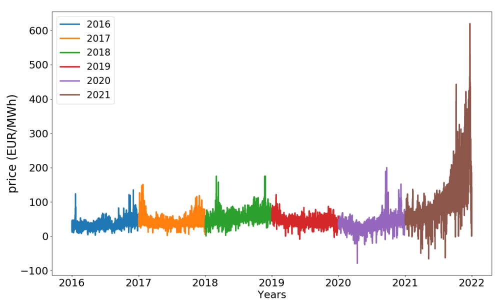

Figure 1.6: Yearly Day-Ahead Market Price Magnitudes from 2016 to 2021 [9]

Figure 1.6 illustrates the electricity price magnitudes in the day-ahead market for the Netherlands from 2016 - 2021. In this thesis, we focus on the day-ahead market as majority of the energy (by volume) in Europe is traded on it. It is observed that other than the end of 2019 and beginning of 2020 (onset of COVID-19), electricity price have been increasing. Winter periods experience comparatively higher price. The increase in electricity price is pronounced in 2021, where price surpassed the €500/MWh mark [9].

In Figure 1.7, a three-week moving variance of the electricity price is presented. For the period 2016 - 2021 while the variance has been in the range of €10/MWh - €20/MWh this value has been trending upwards. This hourly variance in electricity price is underscored in 2021, where the price variance was as high as €80/MWh - €100/MWh.

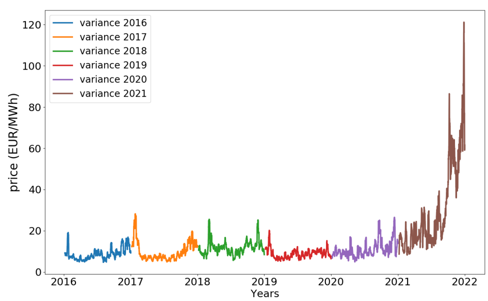

Figure 1.7: Rolling Day-Ahead Market Price Variance 2016 to 2021 [9]

For the period between 2020 to 2030, it is expected that electricity price will comply with the increasing price of gas and CO_2-certificates [18]. This trend will drive consumption more towards being dependent on renewable energy. Again, due to their intermittent nature, it is anticipated that the frequency of periods with extremely high and extremely low price will increase. Extreme price events are defined as those events when the electricity price are equal to/below €0/MWh and those above €100/MWh. These events are illustrated through Figure 1.8, and it is expected that the European Union will begin witnessing these severe extreme price events from as early as 2026.

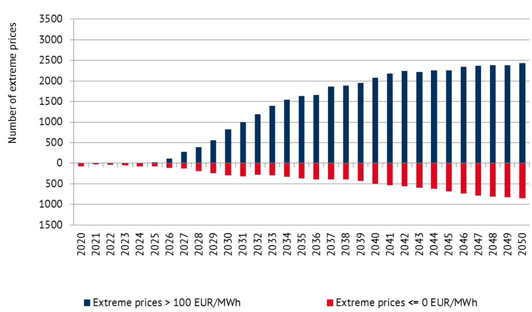

Figure 1.8: Extreme Prices in the European Union [24]

As explained in Section 1.1.5 due to congestion of the electric grid, price spike could also occur thereby exacerbating the price fluctuations faced by consumers. To address these extremes in price, it is quintessential to increase flexibility in the grid. This provides opportunities for new technologies and new participants in the electricity market.

1.3 Importance of flexibility and changing role of actors in future power system

To reliably operate the electric grid under the transitioning energy landscape, and to address increasing price volatility, it is important to increase flexibility in the grid. Flexibility is defined as the ability of the power system to modify generation, and/or consumption patterns in response to external signals [25]. By increasing flexibility, power variability due to demand fluctuations, intermittency of renewable energy generation and unexpected outages can be accounted for. There are multiple options for increasing the flexibility of the electric grid. These options comprise of resources such as micro-turbines whose power dispatch can be controlled in response to supply-demand fluctuations. Another option is demand-side energy management in which power consumption can be controlled in response to external signals. Furthermore, electric storage systems that can either charge if there is overgeneration due to renewables or quickly discharge if there is unsatisfied residual demand. Lastly, power can also be transmitted from one part of the grid to another through interconnections to quickly satisfy power demand thereby increasing the overall flexibility of the grid. These options for enhancing the flexibility of the electric grid are enumerated in Figure 1.9.

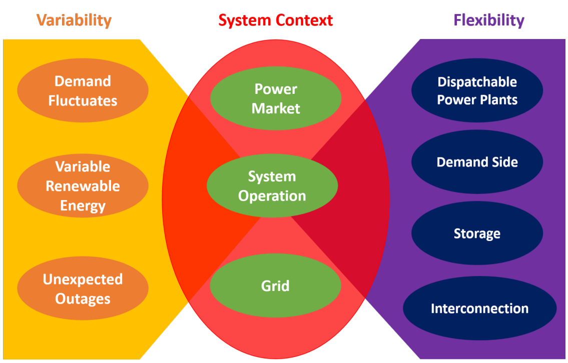

Figure 1.9: The Flexibility Equation [26]

Demand-side flexibility in particular, is the combination of demand response and storage in response to control signals such as changes in electricity price, incentives or requests to support grid reliability [27]. Previously, demand-side flexibility mostly at the industrial consumer level has been investigated [28]. This is in accordance with the potential of these consumers to provide significant amount of flexibility. However, at the residential or commercial consumer level, an individual consumer's potential to offer flexibility is not significant for the power system. To harness this flexibility in a meaningful manner, recent years have witnessed the emergence of a new actor. This entity, the Aggregator, aggregates individual consumer's flexibility and provides services to actors such as power system operators [29]. In parallel, the DSO is also seeking to increase its service portfolio including operating balancing markets at the local level.

1.4 This thesis

1.4.1 Problem description

This thesis aims to address the problem of increasing price volatility associated with the energy transition. Large-scale integration of variable renewable energy and cross-sectoral electrification has made supply-demand balancing challenging. This results in fluctuations that propagate to electricity markets and increase price volatility. Cross-sectoral electrification also raises concerns about grid congestion. Distribution grids that were previously managed in a passive manner, will be subjected to electrified space heating and transport loads. In such a situation, under-dimensioned distribution grids will be susceptible to congestion, thereby exposing consumers to price spikes.

Demand-side flexibility provided through energy storage and demand response, has the potential of fostering a paradigm shift from generation following demand to vice-versa. As a result the fluctuations in energy balancing can be mitigated thereby reducing the potential of increasing price volatility and price spikes. Aggregators, in turn invest in and operate flexible resources on behalf of the consumers and represent them in electricity markets. In this thesis, we focus on local electricity markets, which are operated and cleared by the Distribution System Operator. As DSOs in recent years have expressed the desire to transition from asset-oriented business models to being more service-oriented, in this thesis, we explore the possibility of DSOs assuming the role of being regulated market operators at the distribution grid level.

1.4.2 Research objective

Demand-side flexibility has an important role to play in mitigating the adverse impact of energy transition on price volatility and grid congestion at the distribution grid level. For this flexibility needs to be coordinated across multiple actors; consumers, aggregator, and the DSO. Hence, the objective of this thesis is *to gain a better understanding of the potential of demand-side flexibility, in a highly electrified and multi-actor distribution grid, to reduce increasing price volatility.*

1.4.3 Main research question

The research objective specified in Section 1.4.2 motivates the following research question:

How can flexible demand and electric storage be coordinated across multiple actors in an increasingly electrified future to reduce price volatility and congestion in distribution grids?

1.4.4 Research sub-questions

In order to answer the main research question stated in Section 1.4.3, a number of sub-questions have been formulated.

Research sub-question 1: What is the techno-economic feasibility of coordinating the dispatch of electric storage in distribution grids for reducing price spikes?

Research sub-question 2: In an increasingly electrified future, to what extent is a reduction in price spikes and local congestion possible?

Research sub-question 3: To what extent can flexibility be coordinated in a scalable manner across multiple aggregators for constraining price in local electricity markets?

1.5 Thesis outline and scope

This thesis addresses the questions posed in Section 1.4 in the following order: Chapter 2 provides the necessary background knowledge of the system under consideration. Information pertaining to the technical and economic aspects of the power system is provided. The optimization model used for addressing price volatility and price spikes is described, and institutions for coordinating flexibility is illustrated.

In Chapter 3, we address our first research sub-question. It provides a generic derivation of our proposed optimization model to limit increase in price volatility applied to medium voltage distribution grids. We then investigate the aspect of storage sizing for the provision of flexibility, followed by a techno-economic analysis on a case study. Based on this case study, we identify favorable conditions under which a feasible business case holds for an aggregator.

Chapter 4, addresses the second sub-question by expanding our focus from storage as the only source of flexibility to investigate flexibility provision from demand response. Flexible demand constitute charging of electric vehicles and space heating using electric heat pumps. For this analysis, we investigate the ability of each of these flexible demands to provide flexibility for reducing price volatility, first individually, then together and finally flexible demand in combination with electric storage. Again, we consider the presence of only a single aggregator, and simulate multiple scenarios followed by performing a techno-economic analysis for this actor.

The final sub-question is treated in Chapter 5, which builds on Chapter 4. In this chapter, we consider the presence of multiple aggregators who are involved in the provision of flexibility. We consider an aggregator for each type of flexible resource that is controlled. Furthermore, the research conducted in this chapter focuses on institutional and market analysis through which multiple actors can interact in a scalable and privacy-preserving manner for coordinating flexibility to address increasing price volatility. Final conclusions drawn from our research and recommendations for future work are presented in Chapter 6.

The thesis structure is summarized schematically in Figure 1.10. Chapters 3, and 4 have been published as journal and conference papers, and a choice has been made

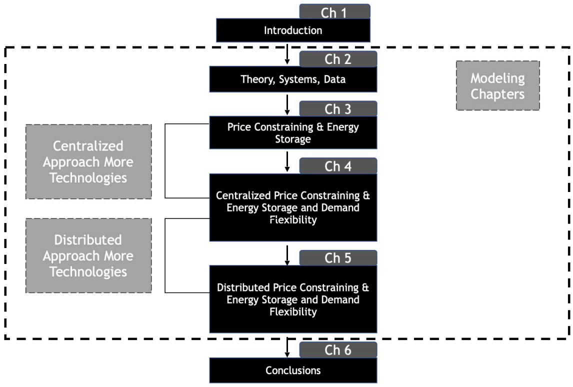

Figure 1.10: Thesis Outline

to include them integrally in this thesis. As a consequence, these chapters themselves start with introductory texts which will inevitably contain some repetitions compared with earlier chapters.

For this research study, different methods and data have been used, and this will be explained in more detail in subsequent chapters. Principally, in this thesis, we have used mathematical optimization models combined with data spanning electricity day-ahead market data for the Netherlands, ambient temperature, baseload profile for residential and commercial consumers in the Netherlands, and electric vehicle driving patterns. We assume traditional, cost-minimizing entities, and for this thesis, optimization models considered are deterministic and executed in a centralized or distributed manner.

There are limitations to the scope of our investigation and they are listed below:

- We limit our investigation to medium voltage distribution grids. The results generated and approach specified can readily be extended to the transmission grid. Additionally, by considering linearized alternating current optimal power flow, our approach can also be extended to low voltage distribution grids. As we limit our focus only to medium voltage distribution grids, which are characterized by higher reactance than resistance, we employ linear decoupled (dc) optimal power flow. Additionally, it should be noted that while the case study considered in Chapter 3 is characteristic of medium voltage grids, a deliberate choice has been made to simplify the case studies in Chapter 4 and 5. The emphasis of these chapters is on the essence of price constraining approach used in the thesis. Furthermore, the flexible loads presented can subsequently be scaled and aggregated to be more representative of the medium voltage distribution grid.
- The IT infrastructure needed to control the flexible resources or for communicating between actors is largely out of scope of this thesis.
- In Chapter 3 and 4, for the techno-economic analysis, we annualize the investment costs for electric storage.

The research conducted in this thesis was performed majorly at the section of

Energy and Industry at the Faculty of Technology, Policy, and Management at the Delft University of Technology. As a part of the Marie Skłodowska Curie Actions Initial Training Network, parts of this research was also conducted at the Department of Electrical Engineering, Politechnico di Torino (Italy) and the Analysis, Modeling and Optimization group at EnergyVille (Belgium).

1.6 Research relevance and audience

Through addressing the questions posed in Section 1.4, we aim to generate insights and contribute to the scientific community. We will also generate insights that are pertinent to actors in society and specify who are intended audience is.

1.6.1 Scientific relevance and contribution

In this thesis, we explore the use of optimization models for quantifying flexibility required to reduce price volatility and price spikes in the distribution grid. This work analysis shows that the presented approach works complementarly to the principle of energy arbitrage, while ensuring price limits on market price. We have also presented the information and money flow between actors at the distribution grid for coordinating the provision of flexibility. The demand-side flexibility considered in this work is provided from electric energy storage and flexible demand comprising of electric vehicle charging and electric heat pumps. Flexibility, in the context of this thesis, has been aggregated assuming the presence of first a single aggregator and then multiple aggregators operating in an energy community and interacting with the DSO for the community. In the case of multiple aggregators, we have investigated multi-actor interactions in a scalable and privacy-preserving manner. Finally, this thesis also performs a techno-economic analysis on behalf of the aggregator that invests in and operates the flexible resources for mitigating increase in price volatility and price spikes.

1.6.2 Societal relevance and intended audience

The insights generated through this thesis are relevant to multiple actors for the economics and operation of the power system. First, we generate insights on the business potential for aggregator companies, to provide services of reducing price volatility and spikes for an energy community that is located in an under-dimensioned distribution grid. Second, consumers in the energy community are protected from these price fluctuations and are ensured that by entering into a contractual agreement with an aggregator do not have to pay a price higher than the contractually agreed limit. Third, a new proposal is made to the DSOs, who are currently seeking new roles and responsibilities. In the flexibility coordination mechanism proposed in this thesis, DSOs assume the role of data handling and market clearing while being a regulated entity. Insights on required institutions for facilitating local electricity markets are also generated for regulators.

Furthermore, these coordination strategies are provided at a time when the electric power system is undergoing a transition, and proposals have been made for withdrawing support schemes to reveal the true value of renewable energy. Finally, the intended audience for this thesis are researchers working on the topic of distribution grids and local electricity markets in the context of the European Union.

2

Constraining price in local electricity markets

In this chapter, we will provide the theoretical foundation of this research. Namely we will first provide an introduction to electric power systems: transmission and distribution networks, followed by an overview of the concept of Active Distribution Grid Management Systems (ADMS). Next we move our attention to electricity markets with an emphasis on local electricity markets. This is followed by an in-depth introduction of the problem, increasing price volatility in electricity markets, that this research aims to address. We then present our proposed solution along with its integral mechanism. This Chapter concludes with an overview of the data used for simulation-based case studies considered in this thesis.

2.1 The electric power system

To ensure power generated in one location can satisfy demand in another, a power network is required. Power networks take different forms and structures such as overhead transmission lines or underground distribution cables. An interconnected power system facilitates efficient and reliable system operation by ensuring sufficient generation capacity for satisfying power demand, and by accounting for unforeseen power generation loss through other units.

The power system comprises of four major subsystems: generation, transmission, distribution and utilization. Generation and utilization subsystems correspond to the actual power supply mix comprising of various generation sources, while the latter comprises of industrial, commercial and residential loads. The Transmission and Distribution systems come together to ensure that the power is supplied from the source to the end demand. We will next briefly comment on these two subsystems.

2.1.1 Transmission grid

Electric power is transferred through the transmission network to the distribution network, which ultimately satisfies load. They enable the economic operation of the power system by connecting neighboring utilities, and also facilitate power transfer across states and countries. Power networks are rated on their voltage levels, and high voltage transmission lines terminate at the primary substation where very large industrial consumers directly consume power. Figure 2.1, illustrates the relationship between the voltage level and the distance spanned.

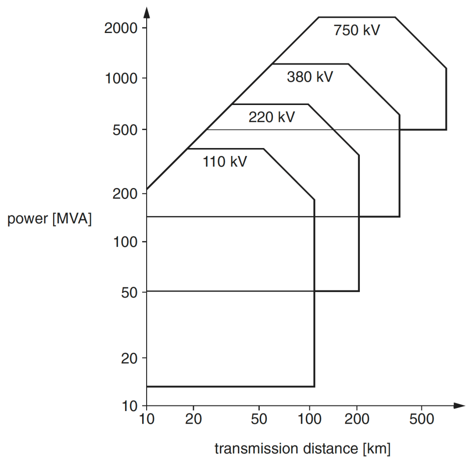

Figure 2.1: Relation between Voltage Levels and Distance of Power Transmission [30]

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2.1.2 Distribution grid

Consumers are connected to the power system through the distribution network. The primary distribution network supplies power to well-defined geographical areas comprising of small industrial consumers. Residential and commercial consumers are connected at the secondary distribution network which has lower voltage values. Figure 2.2 depicts the voltage levels and transformers across the transmission and distribution networks for the Netherlands.

Distribution grids with the voltage range between 10 kV and 20 kV, supply power to the low-voltage networks which in-turn distribute the electrical energy to end consumers. In the Netherlands, the substations at the intermediate voltage levels 50 kV, 110 kV and 150 kV lie 10 - 15 km apart, while the average distance between the 10 kV supply stations is one kilometer or less. On average each 10 kV/ 0.4 kV supply station serves between 50 and 100 houses connected to the low-voltage network. In this thesis, we concern ourselves with the Medium Voltage distribution network.

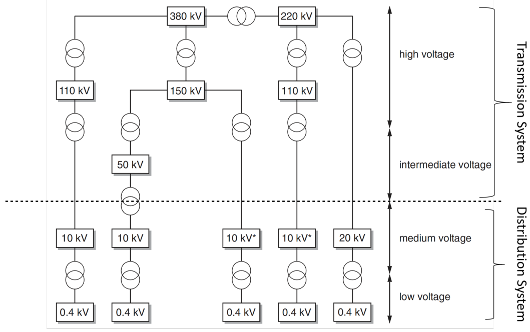

Figure 2.2: Voltage Levels across Transmission and Distribution Networks [30]

2.2 Active distribution grid management systems

The energy transition is characterized by the large-scale integration of wind and solar energy to the electric power system. While wind energy is integrated at scale to the transmission system or at high voltage levels, solar energy is being integrated at large scale to the medium and low-voltage distribution network [31]. Furthermore, electrification of transport and space heating occurs at the distribution network level results in an increase in electricity demand. This new electric demand with increased renewable energy sources are depicted in Figure 2.3.

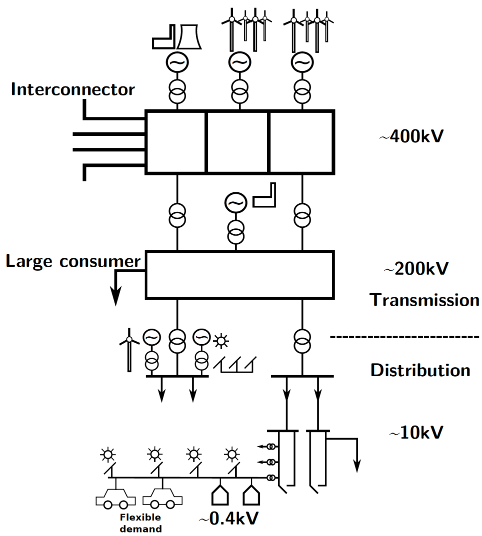

Figure 2.3: Power Grid with increased renewable energy integration and flexible demand [31]

Previously, the distribution grid lacked the capability of monitoring renewable energy profiles, power flows in the grid and grid loading values. Hence, it was not possible to efficiently manage the grid. In such a grid, coordinating supply-demand matching was challenging. This led to instances where excessive solar power generation and reverse power flows resulted in over-voltages. Issues of over-voltages and grid congestion were managed by the Distribution System Operator by reinforcing the grid. Grid reinforcement is costly and may be unsustainable in the long run.

Through the increased application of sensors, computers and communications, it is possible to increase the intelligence or 'smartness' of the grid [32]. Using the data generated, informed decisions are made by distribution system operators with respect to the operation and reliability. This leads to a transition in operation mode from passive to active management.

A number of measures contribute to the active management of distribution grids. Intermittency in renewable energy generation can be countered by increased integration of electric storage systems. This displaces and coordinates supply-demand matching in time. With the rise of distributed energy resources, central management and control of these resources would become cumbersome with limited visibility of individual resource operation. Through distributed control of sensors, and computers across the grid (even at the low voltage level) energy resources can be modularly integrated and supervised. These ICT tools, thus enable system operators in making automatic and robust decisions with high fidelity to ensure the stable operation of the grid.

2.3 Electricity markets and power system economics

This Section provides a general overview of electricity markets. The computation of marginal price which is a prominent feature of electricity market operation is then presented. Lastly, a summary is provided of designs associated with the operation of distribution grid-based local electricity markets.

2.3.1 Introduction to electricity markets

Prior to market liberalization, utility companies were monopolistic. Consumers had no choice but to buy electricity from the utility company serving their area. This was because utilities owned the resources for electricity generation, transmission and its distribution to the consumers. As there was no incentive to operate efficiently, utilities made profligate investments the costs of which were subsequently passed on to consumers.

Contrasting to vertically integrated utilities, in liberalized electricity markets there are several actors having different roles and possibly more than one responsibilities. Entities that produce and sell electricity are called *generating companies*. These companies may additionally sell ancillary services to system operators which aids in maintaining the quality and security of power supply. The transmission and distribution systems are owned and operated by *transmission system operator* and *distribution system operator* respectively. An entity that is responsible for matching bids and offers of electrical energy from buyers and sellers is called the *Market Operator*. *Regulators*, in electricity markets are governmental bodies who are responsible for the efficient and fair operation of the electrical energy system. Finally, the *consumers* comprise of residential and commercial consumers who consume power from the distribution grid. Industrial consumers due to their larger demand profiles are supplied power directly from the transmission grid.

In competitive electricity markets, consumers have the possibility to select their power supplier. These power producers uphold power delivery agreements. Supply-demand matching between producers and consumers takes place through a market-bidding procedure. Subsequently based on the market clearance energy units are dispatched.

2.3.2 Computation of marginal price

The theoretical premise for the restructuring of the electric power market is that the dispatch profile from a market environment with many participants should be the same as a centralized generation system. In such an electricity market, all generating units will increase their output to a point that their marginal cost is equal to the system marginal cost. For an individual generator, its marginal cost is the cost of producing the next unit of power. Similarly, the System Marginal cost, also referred as ‘System Lambda’, pertains to the cost of satisfying one additional unit of demand for the power system.

The market clearing price as determined by the Market Operator thus reflects the marginal cost (MC) of the marginal generator in the system, i.e. the most expensive (based on the merit order of its dispatch) energy source. From micro-economic theory, it is known that in a market environment, the optimal bids are exactly at the marginal costs. This is illustrated from Figure 2.4, where electricity price emerges from demand and supply bid matching resulting in the marginal cost of the marginal generator.

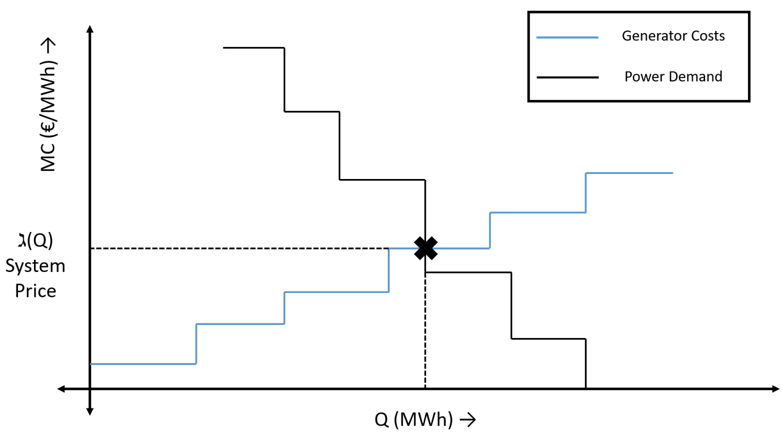

Figure 2.4: Schematic representation of determination of electricity price based on marginal cost (MC) and demand units (Q)

With the energy transition, large-scale integration of renewable energy will also impact the power market. Principally, renewable energy such as solar and wind have zero marginal cost. Even if we account for their operation and maintenance costs, their marginal costs are very close to zero. Assuming that renewable energy is traded in the competitive wholesale market, the merit order of generator dispatch will begin with a large amount of zero bids. This is illustrated in Figure 2.5.

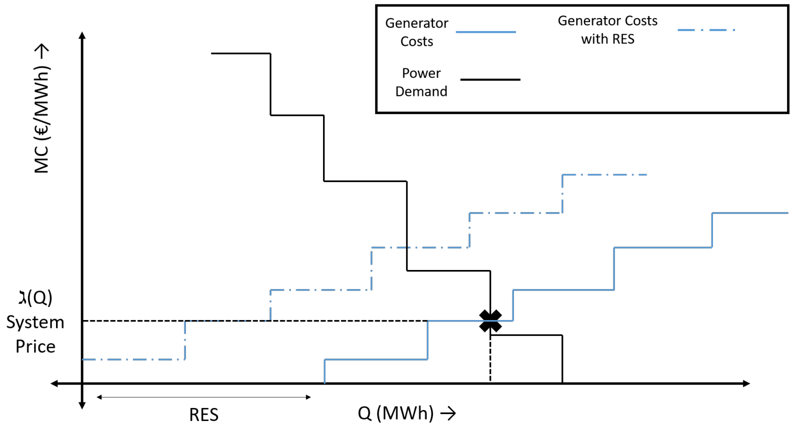

Figure 2.5: Schematic representation of determination of electricity price in a market with large-scale RES

From Figure 2.5, it is clear that for generators with a non-zero marginal cost, the demand would also need to increase for them to recover the cost of operating their generation units. For some countries, it is common to subsidize renewable energy generation as a means to promote their use. As a result, only net demand (after accounting for renewable energy supply) will be considered in the power market.

For conventional generators in the power market, there are numerous constraints that influence their marginal cost. These constraints mostly refer to the time domain, for e.g. the amount of time and cost associated with their startup or shut down or ramping costs. Owing to these factors, a power market inundated with the presence of renewable energy, and weather dependent demand, can possibly experience zero or negative prices. Such cases have been observed in Germany and Denmark.

With increase in renewable energy sources, the power generation portfolio is expected to shift towards generators that are cheaper. However, with renewable energy being variable, if their production is insufficient to satisfy demand, then generation units with a higher marginal cost will be dispatched. Since these generators are dispatched for only a few hours their operational costs are expected to increase. Furthermore, these technologies are also subject to carbon emission taxes, which increases their cost. With the increased marginal costs for these generators, the slope of the price will become steeper as compared to the current scenario. This difference in the slopes manifests as the increase in price volatility as illustrated in Figure 2.6.

The energy transition is also characterized by the electrification of other sectors such as transportation and space heating and cooling. This electrification increases the demand and moves the curve as illustrated in Figure 2.7 towards the right. Hence more expensive generators need to be dispatched for satisfying demand. Given the compound effect of increased variable renewable energy integration, electrified demand, carbon taxes and profit-seeking generators, price is expected to become highly volatile in the near future.

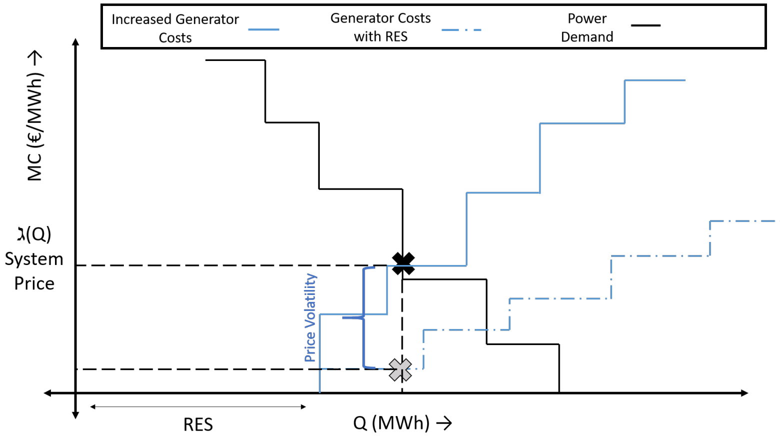

Figure 2.6: Price Volatility due to increase in carbon taxes and generator costs

The marginal cost of the generators is not the only factor determining price in the electricity power market. In deregulated markets, electricity price also subsume a locational component. This means that based on the location of consumers along the power grid, they can potentially be subjected to different price. This price is specified through the Locational Marginal Price (LMP), that comprises of the marginal cost of generators, the cost of congestion management, and the cost of power losses incurred during power transmission and distribution [33].

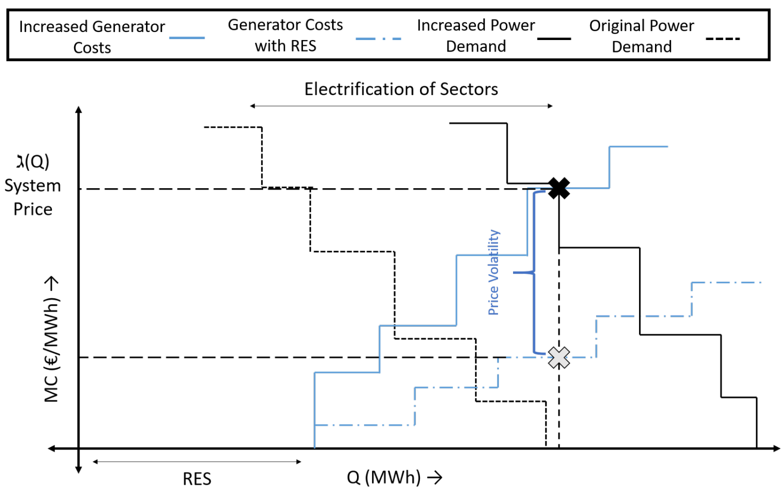

Figure 2.7: Price Volatility due to electrification of transport and heating

It is important to note that LMPs are not universal. For example in the United States, these prices are present in power markets run by Independent System Operators (such as California, Pennsylvania, Maryland). In contrast, in Europe the adoption of

LMP is widely being discussed. Variations of nodal pricing (LMP) such as zonal pricing have been adopted in Denmark [34].

In addition to marginal cost of generators, we focus our attention to the cost of grid congestion. Grid congestion is a function of the capacity of a power line. Power transmission through lines can be restricted during instances of excessive power consumption, or line failures. Under these extreme events, instead of power being drawn from low-cost sources, power is supplied from relatively expensive generators, and this manifests as price spikes that reflect the cost of grid congestion.

The market settings described thus far are applicable for the transmission grid. In recent times due to the active management of the distribution grid these institutions can also be extended to the local electricity market at the distribution grid. Given the energy transition, the distribution grid will undergo significant transformations as described earlier [35–37]. For accommodating these transformations and to reduce the subsequent price volatility, local coordination of flexibility is important.

2.3.3 Distribution grid based local electricity market

Local electricity markets at the distribution grid establish the institutions for interactions between various actors connected to it. These actors include the system operator (DSO) and market participants spanning generation companies, consumers, prosumers, aggregators, and power suppliers (or retailers). We have classified the market settings governing the actor interactions below.

Congestion management

One approach for dealing with the electrification of other sectors is to reinforce the grid. This would result in expensive investments made each year in order to host the additional demand without compromising the integrity of the grid. Another approach for addressing the increased demand is to consider congestion management through market mechanisms. This can be achieved through a congestion market. Under this mechanism as proposed by [38] for Germany, system operators can communicate power quota values directly to flexible power market participants. This communication also entails information pertaining to network constraints and the specific location where flexibility is required. In contrast, [39] proposes a capacity allocation market, in which market participants through a bidding procedure, purchase a certain energy quantity. These capacities are allocated in such a way such that power dispatching will not result in violation of network constraints. Similar work proposals that target flexible energy reservation have also been proposed in [40]. Reserving flexibility in advance enables the DSO to accommodate uncertainties in demand profiles and thus avoid possible grid contingencies.

Flexibility market

Coordination of flexibility in local electricity markets has been reviewed in [41]. The flexibility provided by individual residential and commercial consumers is unsubstantial to be considered for market interaction. Hence an entity that is capable of aggregating flexibility is required. This entity is the aggregator. In local flexibility market it oversees flexibility transactions and provides services to other actors such as system operators for supporting increased integration of intermittent renewables.

It is possible for the aggregator to also direct flexibility services to the transmission grid system operator. This is facilitated through ancillary service markets. Due to the interaction of the aggregator with both the TSO and DSO, providing flexibility services to one grid may create network violations in the other. To account for them, [42] delineates the institutions that must be followed by system actors to coordinate flexibility in ancillary services market. In our research we focus on the local flexibility market, and within this context emphasize the interaction for services between the aggregator and DSO.

Distribution grid locational marginal price

Locational Marginal Price (LMP) is extensible to the distribution grid. LMPs emphasize the efficient operation of the distribution grid and use a price-based mechanism to deter the occurrences of line congestions. It is possible to extend the this price to the distribution grid, where it is termed Distribution-LMP (D-LMP). Previously at the community level, this price has been applied for facilitating the economic operation of distributed energy resources [35, 36]. Through D-LMPs electric vehicles can be optimally charged such that it does not result in violation of distribution grid constraints [37, 43]. Application of D-LMP is a cornerstone of this research, based on which we investigate the coordination of flexible resources to constrain electricity price rise in the subsequent chapters.

2.4 Actors in local electricity markets

The electric power system and its associated market operation can be perceived as a complex multi-actor system. In this physically connected system, the decision made by one actor has an impact on the other. This section focuses on the actors participating in local electricity markets with respect to their roles and responsibilities.

2.4.1 Consumers

They are the users of the electricity, who are connected to the distribution grid across low and medium voltage networks. These entities have a contract with a supplier (or retailer), and through the suppliers pay the DSO for grid access.

2.4.2 Prosumers

These are the end consumers that invest in renewable energy production by installing PV solar panels, or owning other distributed energy resources. The main objective of this entity is to be sustainable by consuming more renewable energy and additionally make use of energy efficient technologies [44]. This entity may also seek a reduction on their electricity bills, or gain more independence from the grid. By taking ownership of power production assets, the passive consumer is transformed to a more active entity in the power market. It is possible that many such entities come together to form an organization that leads to the formation of an energy community.

2.4.3 Energy community

Energy communities are a group of consumers or prosumers that assemble themselves to target shared objectives. These objectives may comprise of reducing carbon emissions from the electric grid, facilitating grid resiliency, increasing their self-sufficiency or reducing electricity costs [45–48]. Communities vary in scale from a few households to cities. A schematic representation of an energy community is provided in Figure 2.8.

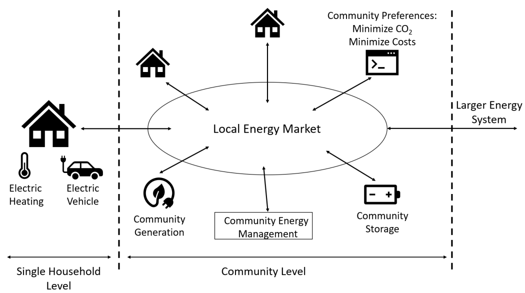

Figure 2.8: Schematic representation of Energy Community [49]

From a technology perspective, communities are characterized by a significant presence of distributed energy resources such as solar, wind, or storage, and may additionally constitute demand response and energy management systems. These resources are generally shared thereby facilitating investments in distributed energy resources (DERs). By coordinating flexible resources at individual community member's households with those shared across the community, it is possible to integrate increased quantities of renewable energy.

2.4.4 Producers and generators

Producers supply electricity to end consumers through different mechanisms such as day-ahead, intra-day and balancing markets or through bilateral contracts. There is a possibility that a producer may also be a balance responsible party. In this case, they have an obligation for ensuring that they comply with a submitted power production profile [39, 44].

2.4.5 Balance responsible parties

A Balance Responsible Party is financially responsible for maintaining energy supply and demand matching within its energy portfolio. Due to the integration of intermittent renewable energy, this task is becoming complicated. However, the supply of demand-side flexibility aids in accommodating the variability and uncertainty in power production of renewable energy.

2.4.6 Transmission system operator / Independent system operator

The Transmission System Operator (TSO) or Independent System Operator (ISO) manages the high-voltage transmission networks and ensures economic transmission of power from large-scale generators to the distribution network. This entity is also responsible for other system functions such as managing congestions and system balance and can also organize different power markets (day-ahead, intraday, balancing).

2.4.7 Distribution system operator

The Distribution System Operator is the entity that owns and operates the distribution grid. It is their responsibility to ensure the reliability of power supply to end consumers. With the introduction of distributed energy resources at the distribution grid, the DSOs have to contend with multiple challenges. Of these, the biggest challenge which a DSO must seek to address is the increase in grid capacity demand caused by electric vehicles, electric heat pumps and solar panels. With the possibility of using flexible resources for reducing the loading levels in the grid, it is possible for the DSO to defer investments for grid reinforcement. For doing so, the DSO must seek a change in its operational mode to become an active manager of the distribution grid.

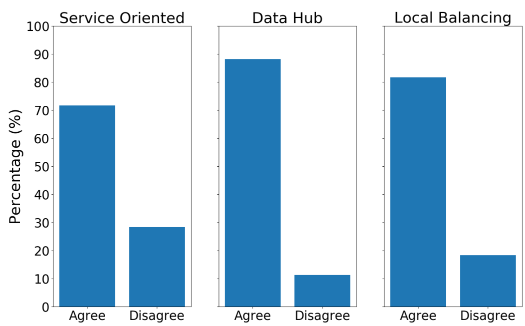

Figure 2.9: Change in DSO roles [50]

The willingness to adapt to an active role has been expressed by several DSOs across Europe [50]. Figure 2.9 represents a census conducted across 108 European DSOs, and it indicates their desire to move towards a service-oriented business model, where they take ownership of the facilitation of market data and its handling while being responsible for local load balancing. It thus becomes compelling to envision the DSO in the role of a regulated market facilitator where it can engage with consumers for the supply of flexibility services either directly or through an aggregator of flexibility [51, 52].

2.4.8 EV owner

An entity, usually a household or company, that owns or rents an Electric Vehicle. It is possible that they have a contract with other market participants such as an aggregator. They have the option to charge their vehicle at home or at other public or private charging stations.

2.4.9 Electric heat pump owners

An entity, usually a household, that owns an electric heat pump for heating their dwelling. Through contractual arrangements, they can give control of the heat pump to an aggregator. It is mostly concerned about having its minimal thermal comfort being satisfied. While it is possible to consider domestic water heating as well, in this thesis the electric heat pumps are used solely for space heating purposes.

2.4.10 Aggregator

An Aggregator is an entity that accumulates flexibility provided through storage or demand response resources. These resources are owned by a set of industrial, commercial and residential end users. An aggregator is able to pool flexibility and transform it into products that are of value to various stakeholders in the electric power market. As power is aggregated across resources, the risk that a particular end-consumer may not be able to provide flexibility is mitigated [44]. As illustrated in Figure 2.10, aggregators in the year 2020 have observed varying degrees of operational success in European markets.

Figure 2.10: State of Aggregator commercial activity in Europe in 2020 [53]

Based on its technical specialization, an aggregator can be designated as an Electric Vehicle or Electric Heat Pump aggregator. Alternatively, they may own and operate either community energy storage or aggregate home energy storage across end-consumers. Under such a setting, the aggregator would serve as an intermediary between the electric vehicle, electric heat pump, electric home energy storage owners and other market participants and the DSO. The aggregator based on contractual agreements with end-consumers may schedule the charging and the operation of flexible resources. By doing this over a sufficiently large population in the context of electricity market operation, an aggregator is able to generate revenue.

2.5 Factors influencing price volatility in electricity markets

The International Energy Agency (IEA) estimates [54] that for the year 2020, approximately 61% of global power demand was satisfied by coal (36%), gas (23%) and to a lesser extent oil (2%). In contrast renewables (wind, solar and hydro-power) provided only 25% of the electricity generated. Presently, it is the fossil fuel power plant that assume the role of the marginal generators and set the price of electricity as per the merit order curve. The price of these fossil fuel power plants are inherently dependent on the cost of the commodity (oil and gas). Commodity price is influenced by macroeconomic factors that are highly unstable and result in increasing price volatility. Additionally, policy interventions may also result in an increase in electricity price. Carbon pricing is one such policy. While integral to the energy transition, its imposition on fossil fuel generators is likely to increase electricity price.

In contrast, wind turbines and solar panels have the potential to lower price. For countries that have large capacities of solar and wind power, on sunny and windy days these renewable sources can supply majority of the demand. This lowers the price of electricity as these resources have nearly zero marginal costs. However, with cross-sectoral increase in electricity demand, price is likely to become more volatile. Electrification of transport, and weather-dependent heating increases the variability of electricity demand which subsequently increases price volatility. This increase in price volatility is propagated along the electric grid from the transmission network to the distribution grid.

When the regulation of the electric grid permits usage of distribution grid LMPs, it is possible that electrification of heating and transport results in increased frequency of price spikes. These price spikes manifest themselves as a result of grid congestion. Figure 2.11 illustrates the aggregate load (baseload) profile of 10 households situated in the distribution grid. In the absence of electricity demand for vehicle charging and space heating, a grid power limit of 12 kW is sufficient for satisfying demand. However, with each household integrating an electric vehicle (EV) and electric heat pump (TCL) to their electricity consumption profile, the grid power limit will be exceeded. At these instances, the grid is considered to be congested. While power consumption from EVs and heat pumps are independent of each other, at certain instances they may even complement each other thereby increasing the stress on the electric grid. For instance between hours 180 - 186 in Figure 2.11 there is a significant spike in power demand due to simultaneous power consumption from both the electric vehicles and heat pumps. However, this spike in power demand also manifests itself as an end-point effect. The increased heat pump power consumption during that time interval ensures that the households thermal comfort limits are not violated till the end of the simulation horizon.

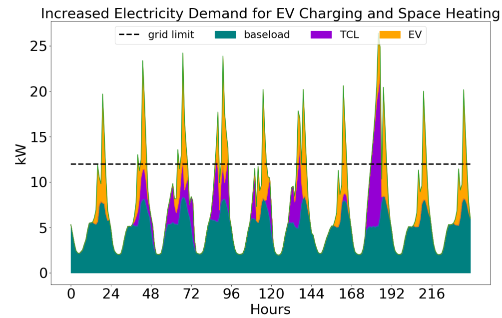

Figure 2.11: Increase in electricity demand due to EV charging and space heating causes grid congestion

Under periods of grid congestion, additional power cannot be delivered to consumers. The unserved power demand is termed as lost load, In Figure 2.12 for illustrative purposes it is assumed that the lost load is satisfied by a generator called the lost load generator. This generator operates at a high marginal cost equal to the cost of lost load, and reflects the price spikes under grid congestion (depicted in red). In this example, it is assumed that the cost of lost load is €200/MWh. It should be noted that the exact value of this lost load is dependent on the load utility curves across consumers and may hence assume a wide range. For comparison, the electricity market price (blue) illustrates the market price in the absence of EV charging and electric heat pump loads. This contrast emphasizes the significant impact that cross-sectoral electrification has on grid congestion and subsequently on electricity price magnitudes.

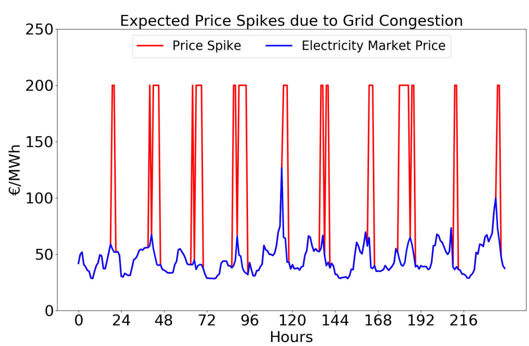

Figure 2.12: Emergence of Price Spikes due to distribution grid congestion

2.6 Addressing increasing price volatility in local electricity markets

To address the issue of increasing price volatility and price spikes, consumers would desire an approach that dampens price fluctuations and arrests its magnitude. Approaches that are capable of effecting these changes involve coordination among actors that participate in electricity markets. Figure 2.13 illustrates a comparison amongst possible approaches to address price volatility. Namely they comprise of purely financial price hedging, scheduling of electric storage systems and flexible loads, and a combination approach that involves introduction of price caps and engaging of flexible resources. In this Section, we explore the benefits and limitations of these approaches.

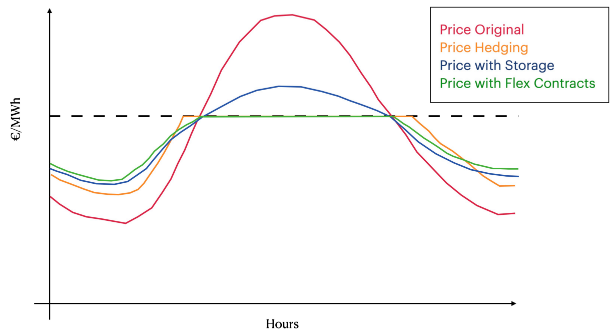

Figure 2.13: Electricity Price Profile Under Different Approaches for Reducing Price Volatility

2.6.1 Financial price hedging

In order to reduce their exposure to increasing price volatility, consumers may opt to use financial instruments. The act of taking a financial position to offset price volatility is called hedging. A commonly used hedging strategy are Forward contracts that are privately negotiated contracts between entities to buy or sell electricity for an agreed price on a certain future date [55].

As presented in Figure 2.13, under a purely financial hedge, an entity such as the energy community specifies the maximum price value that they are willing to be exposed to. At time instants when the electricity market price is higher than this limit, price is hedged and the community pays at the price limit. The issuer of a financial hedge includes a fixed fee for its services. Consumers pay this fee additional to the electricity price at time instants where the price is below the hedged limit. Over a considerable time period the relation between the total price of electricity with and without financial hedging is as follows:

$$\sum_{t=1}^{T}(c_t^{hedge} + \text{Fixed Fee}) \geq \sum_{t=1}^{T} c_t \tag{2.1}$$

In Equation (2.1), the variable c_t^{hedge} is the limit at which price is hedged, while c_t is the price of electricity in the market. The time period considered is denoted as

T. From this relationship it is observed that over the long run due to increasing price volatility financial hedging may not be an adequate means of reducing the total price of electricity [56, 57]. Furthermore, purely financial hedging does not engage any flexible power resources. As a result the approach does not affect the underlying load profile. Hence it cannot leverage the non-linear relationship between electricity price and load for dampening the magnitude of price rise.

2.6.2 Demand-side flexibility

An alternate approach to financial hedging is engaging of demand-side flexibility by the community. Demand-side flexibility constitutes price-aware scheduling of flexible loads (such as electric heat pumps and vehicles) and/or dispatching of electric storage systems. By engaging these resources, demand-side flexibility is able to alter the underlying load profile. Thus it benefits from leveraging the non-linear relationship between price and electric load to achieve price dampening. Figure 2.13, illustrates the price profile (blue) that is dampened by the dispatch of storage units. Storage units seek to exploit inter-temporal dependencies and thus charge at time instants when electricity price is low and discharge when price is high. Charging the storage incurs a nominal price increase at non-peak periods. More importantly, the storage by discharging at peak price periods decreases price rise. However, unlike financial hedging, this approach does not ensure a maximum price limit. In this thesis, we propose an approach that seeks to combine the strengths of both these approaches.

2.6.3 Price capping through flexibility

The foundation of this proposed approach is rooted in duality theory of mathematical optimization. Supply-demand balancing in electricity markets is an optimization problem with which the dual variable of price is associated. This value is usually an output of the optimization problem and is not known a priori. Through the application of duality theory, our proposed approach introduces explicit constraints on the magnitude of electricity price. The addition of this new constraint introduces a new variable in supply-demand balancing that quantifies the amount of flexibility required to constrain price at the desired limit. This required flexibility is made available either through the discharging of storage units or the displacement of power consumption from one time instant to another.

Figure 2.13 illustrates the price profile under this approach (green). Since the required flexibility can be supplied through contractual arrangements with operators of flexible resources the approach may be termed as price capping through flexibility contracts. It is observed that at instances when price exceeds a desired maximum value, the price is capped at the limit. This functionality is akin to that of financial price hedging. However, to ensure this price limit, a storage unit is dispatched for providing flexibility. This is similar to storage dispatching as the underlying load profile is affected in response to price signals. Given that the storage operational profile is similar to that of storage dispatching without the flexibility contract, a similar price profile is observed during non-peak price periods. Nonetheless, as the amount of required storage discharging required differs, the price of electricity during the non-peak price charging periods differs.

Two mathematical relationships exist between these price profiles that emerge from storage dispatching without and with flexibility contracts. The first relation pertains to the total price of electricity. From definition, the flexibility contract is derived by additionally constraining the dual variable associated with supply-demand balancing. The inclusion of this additional constraint in the flexibility contract case further restricts the optimal solution space. This results in a sub-optimal solution in comparison to the case of storage dispatching without flexibility contracts. The relationship for the total price of electricity is thus: $\sum_{t=1}^{T} c_t^{sto} \leq \sum_{t=1}^{T} c_t^{FC}$, where c_t^{sto} and c_t^{FC} are the price profile with storage dispatching without and with the presence of flexibility contracts. Even though these flexibility contracts may result in a higher total price of electricity, it succeeds in ensuring price limits. The second relation is accordingly: $max(c_t^{sto}) \geq max(c_t^{FC})$. These relations suggest that price capping with flexible resource management could combine the benefits of financial hedging with that of demand-side flexibility to address increasing price volatility. In the next sections, we will present the derivation of the price capping formulation and introduce mechanisms for coordinating flexibility supply.

2.7 Application of duality theory for price capping

For placing explicit limits on electricity price our research draws on duality theory of linear programming. To facilitate a better understanding of this theory, in this Section we first present an overview of the relation between the primal and dual linear problems. Properties of this relationship are then leveraged and applied to an illustrative linear electricity market clearing problem.

2.7.1 Computing the dual of linear program

For every linear program there exists a dual problem that is associated with it. While both the programs are constructed based on the same underlying costs and constraint coefficients, minimization of one problem results in the maximization of the other. Furthermore, the optimal values of the corresponding objective functions are finite and equal. The variables of the dual problem represent prices that are associated with the constraints of the primal problem. Assuming that each primal variable is a resource and has a cost associated with it, the dual of a constraint would represent the shadow price of that resource. A shadow price provides insights into the cost sensitivity of a resource. Using this association, the simultaneous consideration of a problem from both the primal and dual perspectives provides significant economic insight [58–61]. The relationship between the primal and the dual problem is displayed below.

Primal:

$$\min_{x} c^T x \tag{2.2}$$

subject to:

$$A_{ineq} x_{ineq} \geq b_{ineq} \tag{2.2a}$$

$$A_{eq}x_{eq} = b_{eq} \tag{2.2b}$$

$$x \geq 0 \tag{2.2c}$$

Equation (2.2) is the primal program where A is an $m * n$ matrix. This matrix represents the primal constraint coefficients. The primal variables are denoted through an m-dimensional column vector, x. Cost coefficients of the primal variables are specified as c^T, which is an n-dimensional row vector. Lastly, the n-dimensional column vector b and m-dimensional row vector λ^T represent the bounds of the primal constraints and the dual variable respectively. Note that the subscript *eq* and *ineq* are used for depicting the coefficients and variables that are associated with the equality and inequality constraints.

The dual for the primal problem expressed in Equation (2.2) is:

$$\max_{\lambda} \lambda^T b \tag{2.3}$$

subject to:

$$\lambda_{ineq}^T A_{ineq} \leq c_{ineq}^T \tag{2.3a}$$

$$\lambda_{eq}^T A_{eq} = c_{eq}^T \tag{2.3b}$$

$$\lambda_{ineq} \geq 0 \tag{2.3c}$$

In Equation (2.3), the dual variable associated with the equality constraint λ_{eq}^T is not restricted to be non-negative. Computation of the dual program also enables assessing of the duality gap. Duality gap is the difference between the primal objective value and the dual objective value and is always non-negative [59–62]. When the primal optimal objective and the dual optimal objective are equal then strong duality holds and the duality gap is zero.

2.7.2 Applying the dual formulation to an economic dispatch problem

In this Section, a linear program representing an economic dispatch for supply-demand balancing is considered. This program is expressed as follows:

$$\begin{aligned}
\underset{P_{G_i}, P_{G_2}}{\text{minimize}} \quad & a_1 P_{G_1} + a_2 P_{G_2} \\
\text{subject to} \quad & P_{G_1} + P_{G_2} = P_L \quad : \quad \lambda \\
& P_{G_1} \leq \overline{P_{G_1}} \quad : \quad \mu_1 \\
& P_{G_2} \leq \overline{P_{G_2}} \quad : \quad \mu_2 \\
& P_{G_1}, P_{G_2} \geq 0
\end{aligned} \tag{2.4}$$

In Equation (2.4) two generators P_{G_1} and P_{G_2} with marginal costs a_1 and a_2 respectively are dispatched for satisfying a load P_L. The objective of this problem is to minimize the cost of satisfying the load. Dual variables associated with the constraints expressed in Equation (2.4) are expressed after a (:) colon. For the equality constraint, the dual variable is λ and it reflects the cost sensitivity of the load. This variable thus captures the ratio of change in power to the change in price. Dual variables μ_1 and μ_2 are associated with the capacity of generators P_{G_1} and P_{G_2} respectively. The dual of Equation (2.4) is expressed as follows:

$$\begin{aligned}
\underset{\lambda,\mu_1,\mu_2}{\text{maximize}} \quad & \lambda P_L - \mu_1\overline{P_{G_1}} - \mu_2\overline{P_{G_2}} \\
\text{subject to} \quad & a_1 - \lambda + \mu_1 \geq 0 \\
& a_2 - \lambda + \mu_2 \geq 0 \\
& \mu_1, \mu_2 \geq 0
\end{aligned} \tag{2.5}$$

For reducing price volatility, constraints are placed on the maximum price of electricity. To quantify the flexibility required for satisfying this price limit, the property of strong duality between primal and dual problem is used. While primal problems (as considered in Equation (2.4)) that are convex usually have strong duality, it is not a given. In addition to convexity, conditions are required for establishing strong duality. These conditions are called constraint qualifiers and Slater's Condition is a well known example of it. Slater's condition states for the set of constraints defined as $f_i(x) < 0,\ i = 1, ..., m$ (where m is the number of inequality constraints) and $Ax = b$, an x exists that satisfies the inequality condition strictly. For problems with affine constraints, this condition can be relaxed. The refined Slater's condition requires a x such that $f_i(x) \leq 0,\ i = 1, ..., m$ and $Ax = b$ is satisfied. In summary, Slater's condition requires that all constraints are convex functions and the set of feasible solutions has non-empty interior [59, 60, 62, 63]. As all optimization problems considered in this thesis are convex with linear or quadratic objective functions and affine constraints, strong duality holds.

For the optimization problem as specified in Equation (2.4) as the primal problem is convex and assuming that Slater's condition holds, strong duality will hold between the primal and the dual problems and subsequently the cost function of the dual problem is the same as that of the primal problem. A constraint to cap the price of electricity λ to a maximum is now introduced. The value of this cap is assumed to be €$\overline{\lambda^*}$. The modified dual problem is now expressed as:

$$\begin{aligned}
\underset{\lambda,\mu_1,\mu_2}{\text{maximize}} \quad & \lambda P_L - \mu_1\overline{P_{G_1}} - \mu_2\overline{P_{G_2}} \\
\text{subject to} \quad & a_1 - \lambda + \mu_1 \geq 0 \\
& a_2 - \lambda + \mu_2 \geq 0 \\
& \lambda \leq \overline{\lambda^*} \\
& \mu_1, \mu_2 \geq 0
\end{aligned} \tag{2.6}$$

Due to strong duality, any update made in the dual problem results in a modification of the primal problem. In this case, adding a constraint on a dual variable, will result in the introduction of a primal variable in the modified problem. This new primal variable quantifies the amount of energy P_F (where F denotes flexibility) required to constrain the price to €$\overline{\lambda^*}$. This flexibility can be provided through additional power supply or through reduction of load through demand response or a combination of the two. The subsequent modified primal problem is expressed below:

$$\begin{aligned} \underset{P_{G_1},P_{G_2},P_F}{\text{minimize}} \quad & a_1 P_{G_1} + a_2 P_{G_2} + \overline{\lambda^*} P_F \\ \text{subject to} \quad & P_{G_1} + P_{G_2} + P_F = P_L \\ & P_{G_1} \leq \overline{P_{G_1}} \\ & P_{G_2} \leq \overline{P_{G_2}} \\ & P_{G_1}, P_{G_2}, P_F \geq 0 \end{aligned} \tag{2.7}$$

In the next section an overview of the mechanism for coordinating the computed flexibility P_F between multiple actors at the local electricity market is presented.

2.8 Coordination of flexibility for constraining price in local electricity markets

In this Section, we focus on three actors that participate in local electricity markets at the distribution grid. These actors interact with each other to coordinate flexibility to constrain the rise in electricity price. The actors considered are the Distribution System Operator (DSO), the aggregator and the energy community. In this market, the DSO functions as the market operator and is responsible for market clearance and distribution grid management. Flexibility required to constrain price is facilitated by the aggregator who invests and manages the operation of demand-side flexible resources. These aggregators are able to influence the local electricity market and can thus also be referred to as price-makers. Institutions are required for governing the information and monetary flow between actors for coordinating flexibility in the market. An overview of three possible mechanisms that characterize these institutions used in the thesis are provided below.

2.8.1 Single aggregator single flexible source coordination

The coordination mechanism is initiated when an energy community in order to protect themselves from high price volatility communicates its maximum willingness to pay for electricity to the DSO. Using the price constraining formulation expressed in Equation (2.7), the DSO then determines a time-varying flexibility signal. The DSO then elicits tenders from multiple aggregators that are willing to provide flexibility against this maximum price stated by the energy community.

An aggregator willing to provide this flexibility service then enters into a contract with the energy community. Once a contract for flexibility service has been established, at time instants when flexibility is required, the aggregator by controlling a flexible resources such as discharging an electric storage system satisfies the required flexibility. The aggregator updates the DSO on its commitment to satisfying the flexibility request, who in turn clears the market. After the market is cleared and the price is constrained, the energy community pays the aggregator the contractually agreed price for its services.

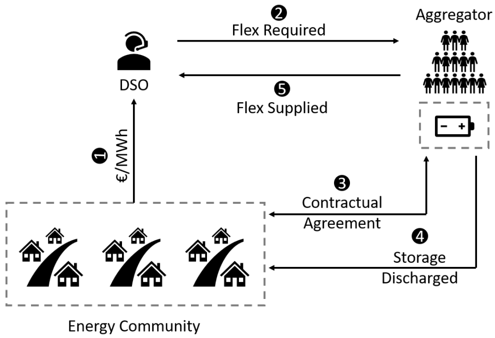

Figure 2.14: Information flow between actors

A schematic representation of the coordination mechanism is presented in Figure 2.14. A detailed explanation of the coordination scheme is provided in Chapter 3.

2.8.2 Single aggregator multiple flexibility sources coordination

It is not necessary that the aggregator concentrate only on one asset to avail flexible power. The aggregator may opt to diversify its sources. In such a case, the aggregator can operate resources such as thermostatically controlled electric loads (TCL) and electric vehicles (EV) additionally to electric storage. The information flow is similar to that as specified in Section 2.8.1. and is presented in Figure 2.15. However, under this coordination mechanism, the aggregator operates multiple resources simultaneously for satisfying the required flexibility.

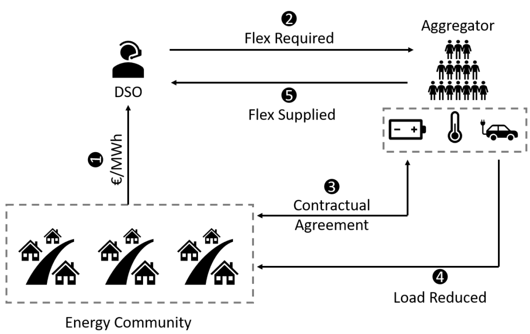

Figure 2.15: Information flow between actors with Single Aggregator controlling multiple flexible sources

The amount of flexible power that can be provided from a resources is characterized by its operational pattern. An electric storage discharges to provide flexible power. The amount of power discharge is contingent on the storage's energy and power capacity as well as factors such as state of charge at a given time instant. In contrast, electric heat pumps and electric vehicles (assuming no vehicle-to-grid discharging) provide flexibility not by discharging but by deviating from their intended power consumption pattern. Electric heat pumps are able to leverage the thermal inertia of households to retain heat in the enclosure. To provide flexibility, the electric heat pump by consuming electricity at an earlier time instant can pre-heat the household ensuring that the temperature does not fall below the household owner's set-point preference. Similarly, owners of electric vehicle may provide flexibility in their preference for a desired state of charge of the vehicle. Instead of completely charging their vehicles, EV owners thus opt to charge their vehicles sufficiently to satisfy their requirements. This would reduce the amount of power consumption by the EV which is then flexibly charged in time so as to satisfy the required state-of-charge for completing the next journey. An aggregator provides the services of flexible operation of EVs and TCLs across the community and is responsible for their coordination. The proposed coordination mechanism has been applied in Chapter 4.

2.8.3 Multiple aggregator multiple flexibility sources coordination

To limit the magnitude of price rise, a single aggregator may opt to diversify its resources to provide flexibility. However, this increases the operational overhead for the aggregator. This is because the operation of a flexible resource may warrant specialized knowledge. For example, an electric vehicle aggregator specialized in the flexible charging of electric vehicles may not be specialized in thermal properties of households or have significant knowledge of heat pump operations. As an alternative, it is possible that multiple aggregators with their own specialized knowledge enter into a flexibility contract with the energy community. This is illustrated in Figure 2.16.

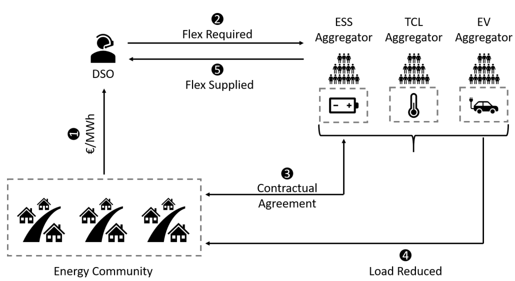

Figure 2.16: Information flow between actors with Multiple Aggregator controlling their own flexible sources

The emerging coordination scheme is one that is more modular. Each aggregator now only has detailed information for the flexible resource that they control. This reduces the information available to a single aggregator and thus preserves privacy of the community members. Aggregators in this coordination mechanism cooperate with each other in a distributed manner for constraining price. The underlying coordination scheme and computational model used are defined in further detail in Chapter 5.

2.9 Modeling of flexible resources and their associated costs

As presented in Section 2.7, using duality theory it is possible to determine the amount of flexibility required for placing price caps in electricity markets. This flexibility is provided by electric storage system and flexible resources (electric vehicles, electric heat pumps) that respond to the external stimuli of price signals. The generalized operational dynamics of these resources is illustrated through a state-space model presented in Equation (2.8).

$$x[t+1] = Ax[t] + Bu[t] + Ed[t] \tag{2.8a}$$

$$y[t] = Cx[t] \tag{2.8b}$$

For a given resource, its state x at a given instance $t+1$ is determined based on its state, input received u and disturbances d at time instant t. The matrices A, B, and E represent the coefficients of the state, input and disturbance vectors respectively. In subsequent simulations, it is assumed that the time-step from one time instant to another is one-hour. The operational output y for a system is expressed in Equation (2.8b) where C is a cost coefficient matrix. Next, for each flexible resource we will illustrate its state-space model and highlight its associated costs. A summary of the state space matrix guiding the operation of the flexible resources is summarized in Table 2.1.

Resource	Electric Storage	Electric Vehicles	Electric Heat Pumps
State Vector (x)	$[E_{SS}]$	$[E_{EV}]$	$[T_r\ T_f\ T_w]^T$
Input Vector (u)	$[P_{ch};\ P_{dis}]$	$[P_{EV}]$	$[P_{hp}]$
Disturbance Vector (d)	[0]	$[d_{EV}]$	$[T_a]$
State Matrix (A)	[1]	[1]	$\begin{bmatrix} \frac{(-(UA)_{fr}-(UA))_{ra})}{C_{p,r}} & \frac{(UA)_{fr}}{C_{p,r}} & 0 \\ \frac{(UA)_{fr}}{C_{p,f}} & \frac{(-(UA)_{wf}-(UA)_{fr})}{C_{p,f}} & \frac{(UA)_{wf}}{C_{p,f}} \\ 0 & \frac{(UA)_{wf}}{C_{p,w}} & -\frac{(UA)_{wf}}{C_{p,w}} \end{bmatrix}$
Input Matrix (B)	$[\eta;\ -\frac{1}{\eta}]$	$[\eta_c]$	$\begin{bmatrix} 0\ 0\ \frac{\eta_{hp}}{C_{p,w}} \end{bmatrix}^T$
Disturbance Matrix (E)	[0]	[-1]	$\begin{bmatrix} \frac{(UA)_{ra}}{C_{p,r}}\ 0\ 0 \end{bmatrix}^T$
Output Matrix (C)	[1]	[1]	$[1\quad 0\quad 0]$

Table 2.1: Coefficients of State Space Matrices

2.9.1 Electric storage systems

Electric storage systems provide flexibility to constrain price by discharging power. In relation to the generalized state-space model, the coefficients of the storage operation are enumerated in Table 2.1. The state vector comprises of the storage's state of charge E. Decisions to charge P_{ch} or discharge P_{dis} the storage constitute the input vector. The charging/discharging efficiency of the storage η is expressed in the corresponding input matrix B. [1]

[1]It is also possible to combine P_{ch} and P_{dis} as one storage variable P_S. This would be the case when storage efficiency is relaxed and subsequently the coefficient matrix $B = [-1]$.

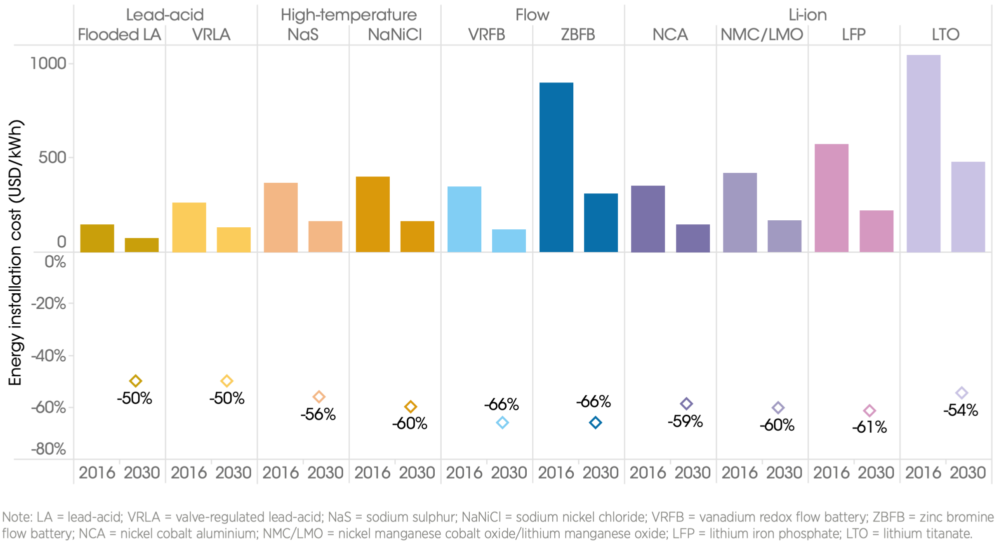

Figure 2.17: Installed Electric Energy Storage Cost Reduction Potential Across Different Technologies 2016 - 2030 [64]

Each storage unit has a maximum state of charge $\overline{E_{SS}}$ which is defined in relation to the maximum storage capacity. Similarly, limits on power charge/discharge capacity is defined as the ratio of the storage size and the time period over which it charges/discharges (τ).

Figure 2.17 presents the installed electric energy storage cost reduction potential across a range of technologies. While electric energy storage systems have historically been expensive, due to economies of scale, their costs have started declining over the past few years. Before investing in a storage system, it is important to consider all aspects associated with its operation. These aspects include the material constituents of the storage system, the storage's charging-discharging times, efficiency and levelized cost of storage (that accounts for life cycle and maintenance).

2.9.2 Electric vehicles

Flexibility can also be provided by price-aware charging of electric vehicles. Electric vehicle owners instead of always charging their vehicles to its maximum capacity, may opt for charging sufficiency that covers their commuting requirements. This provides the flexibility for charging vehicles at low price instances and power consumption may be vastly dispersed in time.

The model for charging of electric vehicles is similar to that of a storage system. However, unlike a storage unit, in this thesis it is assumed that electric vehicles do not inject power back in the grid. As illustrated in Table 2.1, the state vector associated with the EV operation comprises of the EV's state of charge E_{EV}. This state of charge is bounded by a minimum ($\underline{E_{EV}}$)and maximum ($\overline{E_{EV}}$) value based on the vehicle's storage capacity. The input vector u relates to the charging of the electric vehicle P_{EV}, and its charging efficiency η_c is specified in the input coefficient matrix. Discharge of the electric vehicle during commutes is expressed as d and is specified in the disturbance vector.

2.9.3 Electric heat pumps

With the electrification of heating, electric heat pumps consume power from the grid to heat the household. During the winter months, households lose their heat to the ambient surroundings. To keep the temperature within a household within the comfort limits, the heat pump consumes power from the grid. Electric heat pumps may leverage the thermal capacitance of households to flexibly consume power.

Thermal capacitance of a household acts as a buffer that reduces the rate with which heat is lost to the ambient surroundings. This facilitates thermal regulation which prolongs the time period before the heat pump is again required to consume power. This interval is further increased when a household is preheated. The combination of the thermal capacitive properties of a household and the possibility of preheating enables flexible operation. Under a flexible operational schedule, the electric heat pumps consume power in a price-aware mode thereby reducing exposure to high price.

Power consumed by an electric heat pump is propagated to a household through convective currents across three media. The state matrix for the heat pump operation is thus expressed as a heat balance equation across each medium. This matrix comprises of the heat transfer coefficient between the room and ambient surroundings ($(UA)_{ra}$), floor and room ($(UA)_{fr}$), and water and floor ($(UA)_{wf}$). Furthermore, the heat capacities for room air ($C_{p,r}$), floor ($C_{p,f}$), water in condenser tank and heating pipes ($C_{p,w}$), and the electric heater's coefficient of performance (η) are also expressed in the state matrix.

Temperatures recorded across the room (T_r), floor (T_f) and condenser tank (T_w) constitute the state vector. Power consumed by the electric heat pump P_{hp} is expressed as the input vector, while the ambient temperature T_a represents the disturbance vector.

2.10 Simulation data used in the thesis

The data used in this thesis is divided into distinct categories that span electricity demand for urban residential areas, ambient temperatures influencing heat pump operation, solar irradiation data, and electric vehicle usage profiles.

2.10.1 Demand data: Urban residential areas

The data for electricity demand used in this thesis is based on the work presented in [65]. This work focuses on load estimation of households in urban residential areas. Urban areas are characterized by variations in consumer compositions that result in different demand profiles across them. The total annual demand across these consumers was estimated to be 710 GWh.

Figure 2.18 illustrates the load profiles at the daily and monthly values for a winter month i.e. January 2017 for approximately 203,005 houses in the Netherlands. The motivation for selecting the month of January is because residential energy consumption is high during this period on account of the holiday season. Furthermore, while the demand profile is for the whole of the Netherlands, by employing proportional scaling we obtain the demand profiles at the community level.

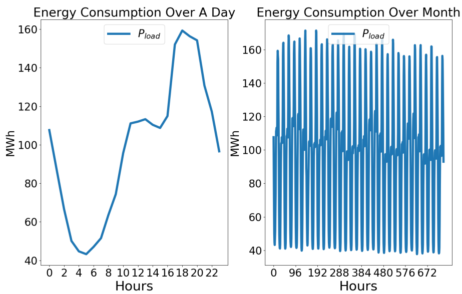

Figure 2.18: Urban Residential Area Power Consumption: (a) Daily and (b) Monthly.

2.10.2 Renewable energy profile

Solar energy is generated by the amount of solar irradiation per unit area (in /cm^2 or /m^2). The solar irradiation value for the Netherlands is obtained from the Dutch Meteorological Institute (KNMI) [66]. To quantify solar power generation from these irradiation values we have made assumptions on the system parameters. Solar power generation is directly proportional to the area that solar panels cover (A), and the solar panel efficiency (r) and the solar radiation on the panels (H). Additionally, solar power generation also depends on the performance ratio (P_{Rat}) which computes the performance of an installation independently of factors such as orientation and inclination of the panels and accounts for all losses. The solar power generated is estimated using Equation (2.9).

$$P_{solar}[t] = ArH[t]P_{Rat} \quad \text{(in MW)} \tag{2.9}$$

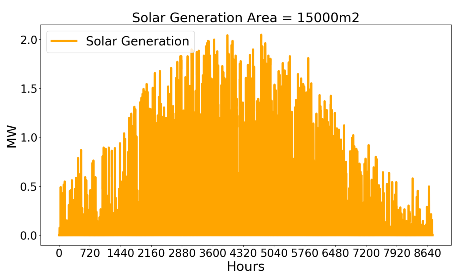

Figure 2.19: Yearly Solar Power Generation

Figure 2.19 presents the amount of solar power generated as an average for the hour assuming system parameter values as $A = 15000m^2$, $r = 20\%$ and $P_{Rat} = 0.75$.

2.10.3 Temperature profiles

Electric heat pumps present one of the flexibility options considered in this thesis. By establishing conductive heat transfer, these heat pumps compensate for the heat loss from a household to its ambient surroundings. Hence, the operation of electric heat pumps is influenced by the ambient temperatures.

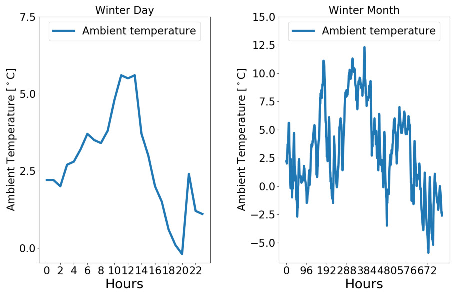

Figure 2.20: (a) Daily and (b) Monthly Ambient Temperature Profile for Winter [66]

The ambient temperatures for the Netherlands at a daily, and monthly time-scale over a winter month is presented in Figure 2.20. These temperature profiles, will be used for our simulation analysis in Chapter 4 and Chapter 5.

2.10.4 Driving profiles

Electric vehicle charging is another flexibility resource considered in this thesis. The electrification of transport is marked with the increase in electric vehicle adoption. Usage of electric vehicles is characterized by their departure time, their arrival time and the distance which they cover per day. As a function of how the vehicle is used its state of charge will evolve. Based on the preference of the owners, these electric vehicles would in turn need to be re-charged to ensure that it is available for subsequent usage. The flexibility provided from electric vehicles is contingent on the ability to displace in time the charging need of the vehicle.

From [31], we retrieve synthetic electric vehicle usage patterns for 25 statistically different profiles as presented in Figure 2.21.

2

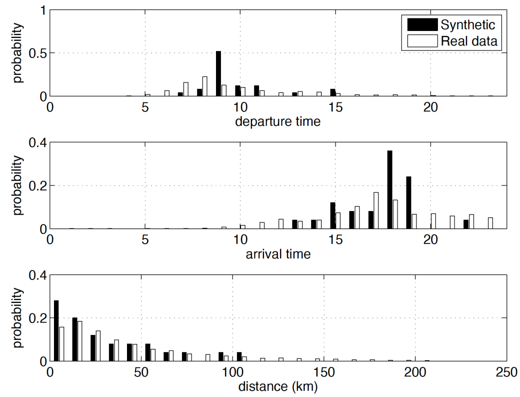

Figure 2.21: Synthetic Driver Profile [31]

2.11 Further reading

In this Chapter, we have reviewed the theory that lays the foundation for this thesis. Particularly, we introduced the different actors participating in the local electricity market, the problem of increasing price volatility being faced by energy communities is then motivated and our proposed solution for price capping through flexibility is introduced. We then briefly discussed the different mechanisms for coordinating flexibility between actors namely the DSO, aggregator and energy community. Lastly we illustrated the input parameters that we will be using in the course of this thesis. In the next three chapters we explore these presented elements in further detail through which we generate and discuss novel insights.

3

A coordination mechanism for reducing price spikes in distribution grids

This chapter is based on [67]

3.1 Introduction

Energy communities are a group of consumers that organize themselves to achieve certain objectives. Recently the topic has received significant attention with the focus in the literature being on techno-economic analysis and institutional arrangements, see e.g. [47] and [48]. These communities are characterized by the significant presence of distributed energy resources such as solar, wind, or storage, in addition to demand response, and they can scale from a few households to cities. Objectives that a community may strive for include the reduction of energy costs, reduction of carbon emissions or enhancing sustainability [68]. As these community based organizations provide a way for consumers to achieve goals that are important for them, they are also referred to as being 'consumer-centric' [69]. Another important driver for a community is that of self-sufficiency. Complete self-sufficiency, however, is rarely achieveable and a connection to the main grid would be needed in many cases. This means that such a community would still be exposed to possibly volatile wholesale prices. In local electricity market at the community level, price can be based on the concept of distribution grid locational marginal price (DLMP), that have previously been investigated with respect to the economic operation of distributed energy resources [35, 36], optimal charging of electric vehicles [37, 43] and transactive energy [70]. Thus, when the community is situated in a part of the grid that faces congestion, price volatility may be more severe due to the activation of the congestion cost that constitutes the locational marginal price. In this paper, we investigate how energy communities can protect themselves from high price volatility and price spikes by constraining marginal price using a local source of flexibility such as an energy storage system.

Energy transactions can take place within the community or between the community and the larger network. Through the local energy market, the wholesale market can interact with the energy community. Surplus energy at the community can be provided to the wholesale market. Alternatively, energy can be consumed from the larger system at the wholesale market price. On the wholesale level, owing to the variable nature of renewable generation and uncertainty in demand, prices can vary significantly [71]. Price volatility is further exacerbated due to lack of coordination between renewable generation and demand, demand spikes, line congestion or generator bids [72, 73]. This increase in price volatility have been observed across the world in Spain [74], Australia [75], Denmark [76], Germany [77] and United States [78].

As experienced in Norway [79] as well as parts of Denmark and Germany [76], supply-side flexibility can address the increase in price volatility. However, these supply-side flexibility options are susceptible to grid constraints which limits their usability. Grid constraints such as line limits can be violated at the distribution grid as a result of uncoordinated operations of flexible resources or very high power consumption during peak hours [80]. In contrast, line congestion may also occur as a result of excessive power supply from distributed energy resources in the distribution grid to the main grid [81]. Currently, distribution grid congestion is not priced explicitly in European electricity markets, but this could change in the future. In particular, the electrification of transport and heating could significantly increase electricity peak demand, leading to more congestion issues on both transmission and distribution grid level [82]. Therefore, congestion may well lead to even higher price volatility in certain parts of the electricity networks. To address network congestion, congestion management schemes such as congestion pricing [83], flexibility markets or direct control methods [80] have previously been investigated.

A complementary approach to supply-side flexibility options for addressing high price volatility and price spikes due to congestion are demand-side flexibility options. Demand-side flexibility can be availed from variable pricing and demand response [84, 85], as well as energy storage. Energy storage provides the opportunity to leverage inter-temporal flexibility that enables shifting supply-demand matching across time. This facilitates the reduction of exposure of consumer demand to periods of extremely steep prices, providing economic benefits to the energy community. Additionally, it is reported in [86] that community energy storage provides increased economic benefits and self-sufficiency for the community as a whole, as compared to storage at individual household levels.

The objective of this paper is to address the knowledge gap on limiting price volatility at the community level. In previous work on local electricity market coordination at the distribution grid, the reduction of price volatility is not considered explicitly as one of the focal points. A review of mechanisms for coordinating flexibility in distribution grids has been performed in [41]. A key entity in local flexibility market is the aggregator, who aggregates flexibility provided from loads, generators or storage units. The aggregator can supervise flexibility transactions at the community level and provide services to the Distribution System Operator (DSO), balance responsible parties or end-users. By providing flexibility services, the aggregator is able to support increased integration of intermittent renewables and reduce energy costs. In [41], while the coordination mechanism proposed centers on the aggregator as a facilitator of the local market, the market activities considered do not take into account system operator constraints and neither do they account for the reduction of price volatility in the market. An alternate coordination mechanism for demand-side flexibility provision is proposed in [87]. This flexibility market is operated by the DSO and is aimed at solving distribution grid congestions. In such a market, after the day-ahead market is cleared, the DSO can avail flexibility from the aggregator for addressing any possible grid violations that are detected. Additionally, [40] builds on [87] by accounting for demand uncertainty and enables the DSO to reserve flexibility in real-time markets to deal with grid contingencies. Thus, previously reviewed coordination mechanisms either focus on business opportunities for aggregator in local flexibility markets or for availing flexibility services by system operators for addressing grid issues, but not explicitly for the reduction of price volatility or mitigation of price spikes. This paper therefore addresses the aforementioned knowledge gap by proposing a mechanism that enables communities to set an upper price limit and to procure the necessary flexibility to achieve this, while considering grid limits.

In this chapter, the process of taking actions in the current time instant to prevent consumers from paying higher than a certain price limit for electricity in the future day ahead market is called *Hedging*. Hedging in electricity markets has traditionally been done using forward contracts or financial transmission rights [88]. However, in decentralized electricity markets with a higher participation of variable distributed energy resources, there is an increased risk of high price volatility. To address this, there is a pressing need for more dynamic mechanisms to deal with price hedging. In relation to price hedging, [89] investigates the possibility of using distribution grid hedging rights as a financial tool to reduce price volatility. Through the proposed hedging rights, market participants such as aggregators that are exposed to price spikes due to grid congestions can use this tool to mitigate the adverse effects of high prices, thereby maintaining their competitiveness iin local electricity markets. Similarly, the work of [90] has investigated the possibility for hedging in day-ahead markets using flexible resources and performs a comparative analysis between forward contracts, call options and incentivizing consumers for flexibility provision. However, previous works do not consider the aspect of price constraints in the hedging formulation, thereby being unable to directly restrain the price in the market to specific levels.

The Hedging approach that we present in this paper is based on optimization duality theory through which explicit constraints can be imposed on prices in the day-ahead market. This results in the ability of consumers to specify a maximum willingness to pay for electricity which sets the foundation for the price limit. Constraining of price below a specific value is contingent on the availability of demand-side flexibility, and in our current work this is provided from an energy storage system operated by an aggregator. Therefore, we propose a mechanism in which physical components (such as energy storage systems) have to be engaged in price hedging, leading to the concept of physical hedging as opposed to purely financial hedging. Thus, the main contribution of our work is that we reduce price volatility at the community level using optimization duality theory to constrain prices to a contractually agreed price limit. This price limit is outcome of a contractual agreement between an energy community and an aggregator, and we illustrate the required information and monetary flow for facilitating this mechanism. Additionally, in this coordination mechanism, to successfully constrain price the optimal size of the storage needs to be determined, for which our work generates insights.

Preliminary results about this hedging mechanism have been reported in [91–93]. The work presented in these papers established the mathematical formulation of physical hedging and explored a few conditions for its implementation, such as probabilistic formulation in the presence of uncertain renewable generation sources and the impact of grid constraints on the effectiveness of the hedging strategy. In contrast, in this paper we show a comprehensive study on the price hedging strategy of an energy storage system owner who seeks to operate its assets for both price constraining and energy arbitrage. We report on the economic viability of such a strategy, including investment analysis under different contractual price limit scenarios. It must be noted that this paper assumes completely deterministic information forecasts, and the aspect of uncertainty analysis is beyond the scope of this work. However, to account for probabilistic forecasts, the work presented can be adapted using methods specified in [94] and [95].

The rest of this paper is organized in the following manner: Section 3.2 introduces the theoretical background for the work presented. The case study that we investigate is presented in Section 3.3. In Section 3.4, details about the data used for the simulation and the analysis of the results is performed. Finally, conclusions are drawn from our investigation and recommendations are made for future research themes.

3.2 Theoretical background

In this section, we present the theoretical basis of our proposed coordination mechanism. This mechanism is based on duality theory of mathematical optimization which plays a fundamental role in electricity markets [96]. The dual variable corresponding to supply demand matching is the marginal price of electricity. In the presented formulation duality theory is used for adding an explicit constraint on this price. The addition of this constraint enables the quantification of the required power for constraining price to a specified price limit. In this paper, we refer to the provision of this additional power as the flexibility required for constraining price, for the given time interval in a market setting.

3.2.1 Capping electricity prices with flexible resources

To illustrate our formulation, we first consider the example of economic dispatch with two generators. This problem can be written as:

$$\begin{aligned} \underset{P_{G_1},P_{G_2}}{\text{minimize}} \quad & a_1 P_{G_1} + a_2 P_{G_2} \\ \text{subject to} \quad & P_{G_1} + P_{G_2} = P_L \quad : \quad \lambda \\ & P_{G_1} \leq \overline{P_{G_1}} \quad : \quad \mu_1 \\ & P_{G_2} \leq \overline{P_{G_2}} \quad : \quad \mu_2 \\ & P_{G_1}, P_{G_2} \geq 0 \end{aligned} \tag{3.1}$$

The generators P_{G_1} and P_{G_2} have to supply a load P_L. These generators have marginal costs a_1 and a_2, and their generation limits are $\overline{P_{G_1}}$ and $\overline{P_{G_2}}$. Associated with the load balance and generator limit constraints are their respective Lagrange multipliers λ, μ_1 and μ_2 which are denoted after a (:) symbol. The value of λ at the optimal solution of Equation (3.1) is known as the system marginal price. In the case with multiple nodes and network constraints, the Lagrange multiplier corresponding to the respective nodal power balance is called the locational marginal price (LMP), and it represents the cost of supplying an additional unit of power to that location. With the objective of applying explicit constraints on price, we first derive the dual formulation of Equation (3.1) which reads as follows:

$$\begin{aligned} \underset{\lambda,\mu_1,\mu_2}{\text{maximize}} \quad & \lambda P_L - \mu_1 \overline{P_{G_1}} - \mu_2 \overline{P_{G_2}} \\ \text{subject to} \quad & a_1 - \lambda + \mu_1 \geq 0 \\ & a_2 - \lambda + \mu_2 \geq 0 \\ & \mu_1, \mu_2 \geq 0 \end{aligned} \tag{3.2}$$

For reducing price volatility, and for quantifying the subsequent flexibility required for constraining price to a desired limit of $\overline{\lambda^*}$, the strong duality between primal and dual problems is leveraged. As the primal problem expressed in Equation (3.1) is convex and its constraints are affine it is assumed that Slater's condition will hold [59, 60, 62]. As a result, the problem has strong duality and the introduction of a constraint to the dual problem is associated with the addition of a new variable in the primal problem. This variable is labeled as P_F, with the subscript F denoting flexibility. The new dual and corresponding primal are then:

$$\begin{aligned} \underset{\lambda,\mu_1,\mu_2}{\text{maximize}} \quad & \lambda P_L - \mu_1 \overline{P_{G_1}} - \mu_2 \overline{P_{G_2}} \\ \text{subject to} \quad & a_1 - \lambda + \mu_1 \geq 0 \\ & a_2 - \lambda + \mu_2 \geq 0 \\ & \lambda \leq \overline{\lambda^*} \\ & \mu_1, \mu_2 \geq 0 \end{aligned} \tag{3.3}$$

and

$$\begin{aligned} \underset{P_{G_1},P_{G_2},P_F}{\text{minimize}} \quad & a_1 P_{G_1} + a_2 P_{G_2} + \overline{\lambda^*} P_F \\ \text{subject to} \quad & P_{G_1} + P_{G_2} + P_F = P_L \\ & P_{G_1} \leq \overline{P_{G_1}} \\ & P_{G_2} \leq \overline{P_{G_2}} \\ & P_{G_1}, P_{G_2}, P_F \geq 0 \end{aligned} \tag{3.4}$$

3

Inclusion of this new term P_F in Equation (3.4) can be interpreted as the introduction of a new flexible generation resource operating with a marginal cost of $\overline{\lambda^*}$ and having infinite capacity. The optimal value P_F^* represents the amount of power needed to cap the price of the system at $\overline{\lambda^*}$.

3.2.2 Capping the electricity price in a more general case

The formulation presented in Subsection 3.2.1 can be extended to a more general case with multiple nodes, generators and time-periods. To do so, we first consider the generalized economic dispatch optimal power flow formulation, which is expressed as:

$$\min_{P_{G_i},P_{L_i}} \sum_{t\in T}\sum_{i\in \mathcal{N}} \big(a_i[t]P_{G_i}[t] - b_i[t]P_{L_i}[t]\big) \tag{3.5}$$

subject to:

$$P_{G_i}[t] - P_{L_i}[t] = \sum_{j\in\Omega_i} \frac{\theta_i[t]-\theta_j[t]}{X_{ij}}, \quad \forall i \in \mathcal{N} \quad : \quad \lambda_i \tag{3.5a}$$

$$\theta_{slack} = 0 \quad : \quad \lambda_{slack} \tag{3.5b}$$

$$-\overline{P_{ij}} \leq \frac{\theta_i[t]-\theta_j[t]}{X_{ij}} \leq \overline{P_{ij}} \quad \forall (i,j) \in \Omega_{ij} \quad : \quad \mu_1, \mu_2 \tag{3.5c}$$

$$0 \leq P_{G_i}[t] \leq \overline{P_{G_i}} \quad \forall i \in \mathcal{N} \quad : \quad \mu_3, \mu_4 \tag{3.5d}$$

$$\underline{P_{L_i}} \leq P_{L_i}[t] \leq \overline{P_{L_i}} \quad \forall i \in \mathcal{N} \quad : \quad \mu_5, \mu_6 \tag{3.5e}$$

The formulation in Equation (3.5) seeks to minimize the difference between cost of generation $a_i P_{G_i}$ and load utility $b_i P_{L_i}$. Power balance at each node in this network is represented through Equation (3.5a). The set $\mathcal{N}$ represents the set of all nodes in the power system. Additionally, in Equation (3.5), sets Ω_i and Ω_{ij} represent the neighbors of node i and all the lines in the network respectively. The bus reference angle at the slack bus is defined as specified in Equation (3.5b). Finally, constraints pertaining to line limits, generator bounds and load limits are expressed through Equations (3.5c), (3.5d) and (3.5e) respectively. It must be noted that in our work, we use dc-opf for modeling the power flow at the distribution grid. This is because our work focuses on medium voltage networks that are much more reactive than resistive. Furthermore, the linear nature of the power flow formulation enables us to readily implement price constraining in these networks as well as other networks such as the transmission grid.

To extend our proposed approach to low voltage networks that are more resistive, linearized power as that specified in [97] can be coupled with our formulation.

In a subset of the nodes specified in Equation (3.5), using flexible power it is possible to cap the nodal price to a specified level of $\overline{\lambda_i^*}$. To apply this price constraint, we first derive the generalized dual formulation, which is expressed as:

$$\max_{\lambda_i,\lambda_{slack},\mu_{1\ldots6}} \sum_{t=1}^{T} \sum_{\forall(i,j)\in\Omega_{ij}} \sum_{\forall i\in\mathcal{N}} \lambda_i[t]\left[\sum_{j\in\Omega_i} \frac{\theta_i[t]-\theta_j[t]}{X_{ij}}\right] - \mu_3[t]\overline{P_{G_i}} - \mu_5[t]\overline{P_{L_i}} + \mu_6[t]\underline{P_{L_i}}$$
$$+\mu_1[t]\left[\frac{\theta_i[t]-\theta_j[t]}{X_{ij}} - \overline{P_{ij}}\right] - \mu_2[t]\left[\frac{\theta_i[t]-\theta_j[t]}{X_{ij}} + \overline{P_{ij}}\right] - \lambda_{slack}\theta_{slack} \tag{3.6}$$

subject to:

$$a_i[t] - \lambda_i[t] + \mu_3[t] - \mu_4[t] \geq 0 \quad \forall t \in T \quad \forall i \in \mathcal{N} \tag{3.6a}$$

$$-b_i[t] - \lambda_i[t] + \mu_5[t] - \mu_6[t] \geq 0 \quad \forall t \in T \quad \forall i \in \mathcal{N} \tag{3.6b}$$

$$\lambda_i[t] \leq \overline{\lambda_i^*} \quad \forall t \in T \quad \forall i \in \mathcal{N} \tag{3.6c}$$

$$\mu_{1\ldots6} \geq 0 \quad \forall t \in T \quad \forall i \in \mathcal{N} \tag{3.6d}$$

The subsequent modified general primal formulation for price constraining is expressed in Equation (3.7). In Equation (3.7), for nodes where no price cap is applicable, the value of $\overline{\lambda_i^*}$ can be assumed to be infinity, thereby enabling the general formulation to hold. The formulation reads as follows:

$$\min_{P_{G_i},P_{F_i},P_{L_i}} \sum_{t\in T}\sum_{i\in\mathcal{N}} \left(a_i[t]P_{G_i}[t] + \overline{\lambda^*}_i[t]P_{F_i}[t] - b_i[t]P_{L_i}[t]\right) \tag{3.7}$$

subject to:

$$P_{G_i}[t] - P_{L_i}[t] + P_{F_i}[t] = \sum_{j\in\Omega_i} \frac{\theta_i[t]-\theta_j[t]}{X_{ij}}, \quad \forall i \in \mathcal{N} \tag{3.7a}$$

$$\theta_{slack} = 0 \tag{3.7b}$$

$$-\overline{P_{ij}} \leq \frac{\theta_i[t]-\theta_j[t]}{X_{ij}} \leq \overline{P_{ij}} \quad \forall (i,j) \in \Omega_{ij} \tag{3.7c}$$

$$0 \leq P_{G_i}[t] \leq \overline{P_{G_i}} \quad \forall i \in \mathcal{N} \tag{3.7d}$$

$$\underline{P_{L_i}} \leq P_{L_i}[t] \leq \overline{P_{L_i}} \quad \forall i \in \mathcal{N} \tag{3.7e}$$

$$P_{F_i}[t] \geq 0 \quad \forall i \in \mathcal{N} \tag{3.7f}$$

By solving Equation (3.7), a system operator can determine the amount of flexibility $P^*_{F_i}[t]$ needed to cap the price at node i to the desired value of $\overline{\lambda^*_i}$. Note that this formulation is completely technology-neutral with respect to the flexible source P_F. Only a time-varying production $P^*_{F_i}[t]$ is required which should be provided by any source of generation (or demand response).

3.2.3 Organizational structure for providing flexibility

To provide the flexibility required for constraining price we need to determine the information and money flow between the actors. A full specification of all roles and responsibilities that would define such an arrangement is beyond the scope of this paper. Hence, we highlight a few key aspects only. It should be noted that the formulation presented so far is general, and we introduce a new organizational structure that can also be implemented for an entire national system or a Transmission System Operator (TSO) / Independent System Operator (ISO) area. In this work, we make a deliberate choice to focus on smaller systems that are embedded at the distribution grid. The DSO in such markets is expected to assume additional responsibilities including being a regulated market operator [98]. Thus, the DSO would be the only entity having information about the grid structure and market bids for supply and demand that are needed to solve the market clearing problem formulated in Equation (3.7).

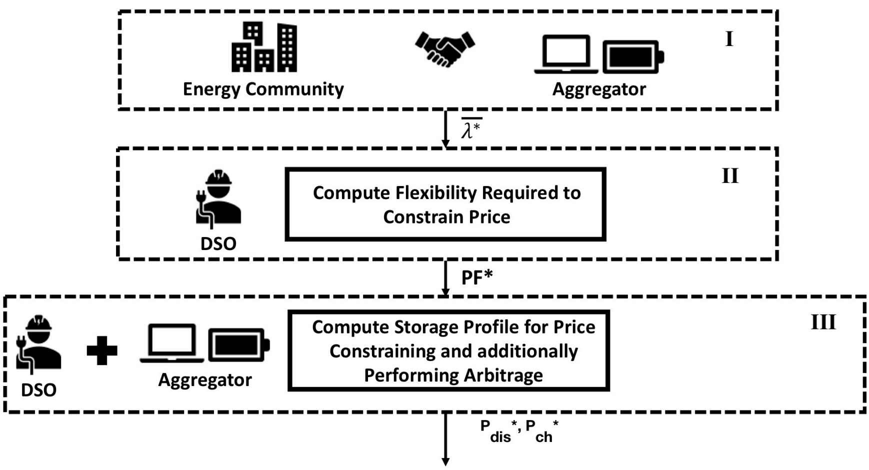

Figure 3.1: Schematics of the information flow between actors

In the case study that we investigate in Section 3.3, we consider an aggregator as the owner and operator of an energy storage system through which flexibility required for constraining price is provided. The reason for choosing an aggregator is that they have technical expertise and professional communication technologies for operating community level storage. Furthermore, we make an assumption that the aggregator behaves perfectly competitively and does not abuse market power. This is a common assumption for neo-classical economics, and while being an optimistic assumption, it leads to a perfect market outcome.

Through Figure 3.1, we illustrate the information flow for facilitating the proposed coordination mechanism. The point of initiation of this coordination mechanism is the determination of the price limit $\overline{\lambda_i^*}$ which is an essential parameter. This is determined in Step I as presented in Figure 3.1 and involves a negotiation between the energy community and aggregator. The contract details could include fixed or variable payments by the community to the aggregator. Once the price limit $\overline{\lambda_i^*}$ is established, it is shared with the DSO. In Step II, the DSO can include this contracted flexibility in the market clearing by solving Equation (3.7). This would result in an allocation of the generation and demand, but also the required $P^*_{F_i}[t]$. The computed volume of required flexible power is then broadcasted to the aggregator, who is then contractually obligated to deliver this in real-time. Determination of the optimal storage profile for satisfying the required flexibility is computed in Step III where the DSO and aggregator cooperate for dispatching the storage thereby ensuring that grid contingencies are mitigated. Once the aggregator provides the required flexibility, it is remunerated for its services by the energy community. Additionally, at intervals when the aggregator is not required to deliver flexible power, it can partake in energy arbitrage to further increase its revenue. In the next Section, we will elaborate further on the case study considered for the implementation of our proposed mechanism.

3.3 Case study

Section 3.2 provided the mathematical foundation for constraining price to a certain price limit and quantified the flexible power required to achieve it. Additionally, we elaborated on an organizational structure that captured the information flow between actors for the coordination of this flexible power. In this Section, we build on these fundamental blocks and apply the proposed mechanism to a case study that focuses on a community of consumers that are faced with high price volatility and price spikes during periods of grid congestion. An energy storage system can be considered as the source of flexibility to reduce price volatility by constraining price to a certain limit. Hence, consumers in this community may decide to collectively buy an energy storage unit to use it during periods of high prices. In principle, these consumers can simply discharge the storage at times of high prices and recharge it when the prices are low. Alternatively, there could be another party that invests in and operates a storage system separately. For such a commercial party, it could be beneficial to discharge during times of congestion as long as it does not resolve the congestion completely (which would reduce the price it gets for its delivered energy). This can be seen as a form of exercising of market power, but it is rational for the storage operator in order to maximize their revenue. The community could make an agreement with the aggregator to pay a fixed yearly fee per unit of energy (€/MWh) to ensure that the price does not exceed a certain price limit $\overline{\lambda^*}$. Thus, in the day-ahead market, the aggregator would discharge the storage when the local price in the community would exceed the agreed on price limit.

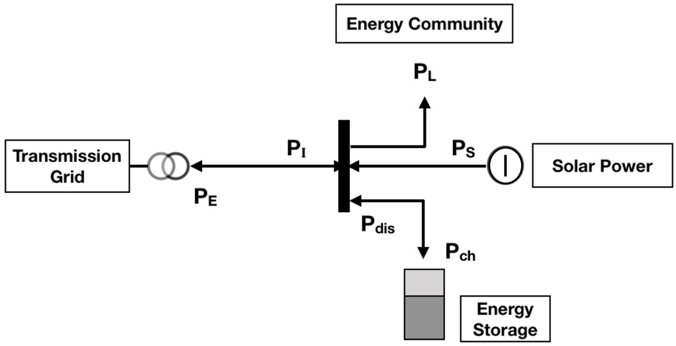

Figure 3.2: Physical Structure

3.3.1 Determining the volume of required flexibility

Equation (3.7) describes the general case of determining the flexibility to cap prices in a multi-node system. For the purpose of our case study we will consider a single node system. In Figure 3.2 we present our case study that considers a system setup where an energy community is connected to a larger network. To model the price spikes as a result of congestion, we assume that the load in our distribution network is elastic, with the following quadratic expression describing its utility B:

$$B = bP_L[t] = \beta(L[t] - P_L[t])P_L[t] \tag{3.8}$$

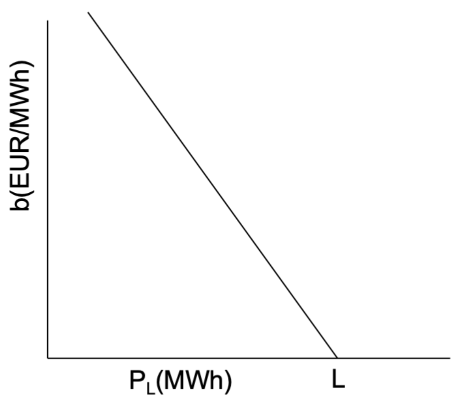

Figure 3.3: Hourly demand function for electricity in the case study grid. The demand function intersects the x-axis at the original value of the demand $L[t]$

In Equation (3.8), the utility function is described for an hourly period. The variable b is the marginal utility and is described as a linearly decreasing function of demand as shown in Figure 3.3. Furthermore, this marginal utility comprises of a relationship between the inelastic load L, elastic load P_L and a coefficient of demand elasticity β.

Power can be supplied to the community from the main grid. Alternatively, power supply to the community can be provided through solar parks. Previously, the formulation presented in Equation (3.7) did not account for power flowing from the distribution grid to the main grid. In this network, we consider the excess of solar power generation to be sold back to the main grid. The flexibility required for capping the local price in the day-ahead market (operating at hourly intervals) experienced by the energy community can be computed as:

$$\begin{aligned}\min_{P_E,P_I,P_F,P_L} & \sum_{t\in T} \Big(a_G[t]\left(P_I[t]-P_E[t]\right) \\ & +\overline{\lambda^*}[t]P_F[t]-\beta\left(L[t]-P_L[t]\right)P_L[t]\Big)\end{aligned} \tag{3.9}$$

subject to:

$$P_I[t]-P_E[t]+P_S[t]-P_L[t]+P_F[t]=0 \tag{3.9a}$$

$$P_E=0 \quad \text{if} \quad a_G[t]>\overline{\lambda^*} \tag{3.9b}$$

$$0\leq P_I[t]\leq \overline{P}_G \tag{3.9c}$$

$$0\leq P_E[t]\leq \overline{P}_G \tag{3.9d}$$

$$P_F(t)\geq 0 \tag{3.9e}$$

The variable a_G represents the cost (in €/MWh) of supplying power from the main grid to the energy community and of supplying the excessive power from the community to the larger network. This value is obtained from the wholesale market price. At a given instance, power can either be imported to (P_I) or exported from (P_E) the energy community. To ensure that the variables P_I and P_E are not simultaneously active, a nominal difference is introduced in the cost terms associated with the two power variables. Equation (3.9a) presents the power balance equation where P_S and P_F represent the solar generation and flexibility required to constrain the price to the value of $\overline{\lambda^*}$ respectively. The solar power is provided at zero marginal cost. At intervals when the market prices are higher than the value of the contractual price limit $\overline{\lambda^*}$, the power provision from the energy community to the larger network is set to zero using constraint (3.9b). The amount of power that can be supplied from the main grid and power that can be supplied to the main grid are limited by the line capacity and is expressed by $\overline{P}_G$. The DSO in its capacity as a regulated market facilitator [98] would have the information about generator and demand bids and the network structure, thereby enabling it to execute the formulation expressed in Equation (3.9) to determine the flexibility that the aggregator would need to supply.

3.3.2 Battery storage as a flexible generation source

The equations presented in Section 3.2 are general for any type of flexibility. In our case study, the focus is on energy storage as a demand-side flexible resource. To model the storage system we will introduce additional essential constraints that enrich the formulation as expressed in Equation (3.7).

Optimal storage size

An energy storage system through charging and discharging can provide the flexibility required to constrain the marginal prices. By executing Equation (3.9), the time series of the required flexibility $P_F(t)$ is determined. An aggregator in order to make an investment decision about the storage capacity would need forecasts about the required flexibility. Then, in order to determine the minimum storage capacity needed by the aggregator to satisfy the time varying signal $P_F(t)$, the following optimization problem would need to be executed:

$$\underset{P_{dis},P_{ch},E_{SS}}{\text{minimize}} \quad dE_{SS} \tag{3.10}$$

subject to:

$$E[t] = E[t-1] - \frac{1}{\eta}P_{dis}[t] + \eta P_{ch}[t] \tag{3.10a}$$

$$P_{dis}[t] - P_F[t] = 0 \quad \text{if} \quad P_F[t] > 0 \tag{3.10b}$$

$$0 \leq P_{dis}[t] \leq \frac{E_{SS}}{\tau} \tag{3.10c}$$

$$0 \leq P_{ch}[t] \leq \frac{E_{SS}}{\tau} \tag{3.10d}$$

$$0 \leq E[t] \leq E_{SS} \tag{3.10e}$$

By executing Equation (3.10) the optimal energy storage system (ESS) size is determined. In Equation (3.10), the variable d represents the annualized per unit cost of the storage expressed in €/MWh-year and E_{SS} is the size of storage. The reason for annualizing the costs of storage is to enable a business feasibility analysis on the basis of comparing investment costs against the yearly operational revenue. Equation (3.10a) expresses the inter-temporal constraint associated with the operation of the storage system. The variables $E[t]$ represents the state of charge, while variables $P_{dis}[t]$ and $P_{ch}[t]$ are the respective variables associated with the discharging and charging of the storage. Equation (3.10b) is the constraint required for satisfying the required flexibility by discharging the storage. The operation of the storage is governed by its physical characteristics, and the amount of energy charged and discharged from the storage at any instance should not exceed the physical size of the inverter which is defined as a function of the storage size and a charging/discharging time constant τ expressed in hours. Note, it is possible that if the storage is inadequately sized, simultaneous charging and discharging of the storage may occur. In order to account for this anomaly, a soft penalty can be introduced in the objective function by adding the expression $\rho\big(P_{dis}[t].P_{ch}[t]\big)$ where ρ is a penalty factor expressed in terms of €/MWh^2 [99].

Providing flexibility with an energy storage system

In the day-to-day operation of the storage, the storage capacity can be reserved to provide the flexible power required for capping the price to the contractual price limit (i.e. provide $P_F[t]$). Thus, whenever the price exceeds the price limit it would be capped thereby enabling the price hedging functionality. The operation of the storage can be modeled using the following optimization problem:

$$\min_{P_I, P_E, P_L, P_{dis}, P_{ch}} \sum_{t \in T} \big(a_G[t] \left(P_I[t] - P_E[t] \right) \\ - \beta \left(L[t] - P_L[t] \right) P_L[t] \big) \tag{3.11}$$

subject to:

$$P_I[t] - P_E[t] + P_S[t] - P_L[t] + P_{dis}[t] - P_{ch}[t] = 0 \tag{3.11a}$$

$$P_{dis}[t] - P_F[t] = 0 \tag{3.11b}$$

$$E[t] = E[t-1] - \frac{1}{\eta} P_{dis}[t] + \eta P_{ch}[t] \tag{3.11c}$$

$$0 \leq P_{dis}[t] \leq \frac{E_{SS}}{\tau} \tag{3.11d}$$

$$0 \leq P_{ch}[t] \leq \frac{E_{SS}}{\tau} \tag{3.11e}$$

$$0 \leq E[t] \leq E_{SS} \tag{3.11f}$$

$$0 \leq P_I[t] \leq \overline{P}_G \tag{3.11g}$$

$$0 \leq P_E[t] \leq \overline{P}_G \tag{3.11h}$$

$$P_F[t] \geq 0 \tag{3.11i}$$

Equation (3.11) determines the optimal storage charging and discharging profile for satisfying the requested flexibility. Constraint (3.11b) enforces that the storage discharge provides the required flexibility. It should be noted that the optimization problem specified is in essence a centralized economic dispatch problem. It represents the most efficient outcome that would emerge in a perfectly functioning local market. The solution provides the cost-optimal schedule of charging the energy storage system that it still meets the obligations to deliver the contracted flexibility $P_F[t]$.

As an artifact of our problem description, the price term $a_G(t)$ is updated to reflect the constrained price $\overline{\lambda}$, obtained by executing Equation (3.9). These prices are such that whenever the cost of electricity in the market would exceed the contractual price limit ($\overline{\lambda^*}$) specified by the community, the prices would be constrained. Equation (3.11a) reflects the power balancing performed at the community inclusive of the storage charging and discharging. Similar to Equation (3.9), the amount of power that can be provided to the community from the main grid or vice versa are restricted by the line capacities. Equations (3.11c) - (3.11f) represent the operation of the storage system as a flexible resource governed by its physical properties. The size of the storage E_{SS} is computed from Equation (3.10). Simultaneity may arise in the presented formulation such that mutually exclusive variables of P_{dis} and P_{ch} may be non-zero. This can be accounted by adding a soft constraint of the form $\rho(P_{dis}[t].P_{ch}[t])$ to the objective function. Finally, given the close interaction between the power flow and storage operation, this step is executed jointly by the DSO and aggregator thereby mitigating additional grid contingencies.

3.3.3 Flexibility and arbitrage with an energy storage system

The problem formulation in the previous Subsection ensures that the energy storage system always delivers the contracted flexibility. However, it may be economically overly conservative, since there could be additional opportunities to perform energy arbitrage i.e. to charge and discharge the storage based on price differences over time, while still meeting the obligations of $P_F[t]$ when needed. In order to allow for this, we only have to change constraint (3.11b) into the following:

$$P_{dis}[t] - P_F[t] = 0 \quad \text{if} \quad P_F[t] > 0 \tag{3.12}$$

This means that the storage is left free to perform additional charging and discharging cycles as long as it delivers $P_F[t]$ when needed i.e. when it is greater than zero.

3.3.4 Arbitrage only with an energy storage system

As a useful comparison case, we also present results of a case where the storage is only used for arbitrage. This setup is exactly as described by Equation (3.11) but *without* constraint (3.11b). In this case the storage will be used to minimize the costs in the distribution grid, thereby flattening price. However, as there is no notion of a price limit, the subsequent flexibility quantification will not be computed, thereby making the formulation incapable of guaranteeing that price does not exceed the community specified limit.

3.3.5 Economic evaluation

In this Section, we shift our focus towards the economic analysis of our proposed formulation. The basis of this analysis is the contractual arrangement made between the energy community and the aggregator. By controlling the energy storage, the aggregator provides the required flexibility for constraining the price experienced by the consumers. For the provision of this flexibility, the energy community is contractually bound to provide remuneration to the aggregator. We make a distinction between the income, costs and operating revenue for the purpose of our analysis. Income refers to the positive cash in-flow for the aggregator, while costs pertain to the cash out-flow that the aggregator incurs for charging the storage. Finally, operational revenue is the term used to denote the net value computed by taking the difference between the income earned and costs incurred by the aggregator.

Without the consideration of a premium, the income earned from hedging i.e. the provision of flexibility to constrain price would consist of:

$$I_F = \sum_{t \in T_F} \overline{\lambda}[t] P_{dis}[t] \tag{3.13}$$

where T_F denotes the time-steps in which $P_F[t] > 0$ i.e. in which flexibility was provided. The variable $\overline{\lambda}$ denotes the constrained marginal price.

For maintaining a sufficient state of charge and for satisfying the flexibility requests over multiple time periods, the aggregator would need to charge the storage. The corresponding cost of charging is:

$$O_C = \sum_{t \in \overline{T_F}} \overline{\lambda}_{ch}[t] P_{ch}[t] \tag{3.14}$$

where $\overline{T_F}$ denotes the time-steps in which the storage charges in order to be able to satisfy the flexibility requests during the periods defined by T_F.

Hence, the net revenue earned by the aggregator from hedging is represented as:

$$R_F = I_F - O_C \tag{3.15}$$

Additionally, the aggregator can earn revenue from arbitrage. The net revenue from arbitrage is defined as:

$$R_A = \sum_{t \in T \setminus (T_F \cup \overline{T_F})} \overline{\lambda}[t] P_{dis}[t] - \overline{\lambda}[t] P_{ch}[t] \tag{3.16}$$

For computing the total operating revenue for the aggregator, we compute:

$$R_{tot} = R_F + R_A \tag{3.17}$$

To participate in the price constraining and arbitrage, a decision needs to be made regarding investing in assets, particularly the storage system. The annualized investment are given by:

$$C = \frac{D E^*_{SS}}{A_f} \equiv d E^*_{SS} \tag{3.18}$$

where D denotes the total capital cost per MWh and A_f denotes the annuity factor:

$$A_f = \frac{1 - \frac{1}{(1+\hat{r})^{T_L}}}{\hat{r}} \tag{3.19}$$

where T_L is the lifetime of the storage and $\hat{r}$ is the interest rate.

In the case when $R_{tot} > C$, a net positive business potential for the given contractual agreement can be realized by the aggregator.

3.4 Simulations and results

Through quantitative analysis we illustrate how the formulation presented in Section 3.3 facilitates the computation of the required flexibility for reducing the impacts of price volatility and price spikes. In this Section, we first introduce the data used for the simulation followed by the analysis of the results.

3.4.1 Simulation setup

We performed numerical simulations to illustrate the case study. To the extent possible, we use realistic data of demand, wholesale prices, solar generation and storage costs. The value of the variable a_G is based on the wholesale market data for the year 2017 which is obtained from the Amsterdam Power Exchange [9]. High price volatility was observed for this year with the prices varying as much as ±€60/MWh between two consecutive hours in the day-ahead market. Power output of the photo-voltaic (PV) systems depends on the solar irradiance of the given region. These irradiance values are converted into the solar generation (in MW) through the formulation:

$$P_{Solar}[t] = ArH[t]P_{Rat} \quad \text{(in MW)} \tag{3.20}$$

where $P_{Solar}[t]$ is then taken as the average for the entire hour. From Equation (3.20) it is clear that the solar power generation depends on the area that solar panels cover (A), the solar panel efficiency (r), the performance ratio (P_R) that accounts for losses. For the purpose of our simulation we set the value as $A = 25000m^2$, $r = 35\%$ and $P_{Rat} = 0.75$. The hourly averaged irradiance values $H[t]$ (converted to MW/m^2) are obtained from the Dutch meteorological institute KNMI [66].

In the case study, we have focused on an energy storage system to provide the contracted flexibility. After reviewing the different storage options presented in [100], Zinc Bromide energy storage was selected due to its economic viability. The cost of this storage system is annualized to represent a yearly investment decision. Using a total capital cost (TCC) of €170/kWh and a lifetime of 20 years from [100] and a near zero interest rate, the annualized cost of storage as given by Equation (3.19) amounts d = €8500/MWh-year. This storage is assumed to have an efficiency $\eta = 95\%$ and a time constant constant of $\tau = 2$ hours is used as an estimation of the converter size. Finally, to ensure that simultaneous charging and discharging of the storage does not occur a penalty factor of ρ=€1000/MWh^2 is introduced.

The demand data used for our simulation is obtained from [65]. This data emulates the load profiles for 5000 residential consumers and is characteristic of medium voltage (MV) distribution grids. It is assumed that the loads are tuned to maximize their utility as expressed in Equation (3.8). In Equation (3.8) the coefficient β=€1000/MW^{2}h. As previously mentioned, power can be supplied to this energy community either from the main grid with the line capacity as 2 MW or from a solar park. Essential to our proposed formulation is the presence of a contractually agreed price and in the simulation of our case study, this value is set to $\overline{\lambda^*}$=€50/MWh. This value is assumed to be constant for the entire year. For simulating the case study we use the IPOPT solver through the Pyomo package [101] provided in Python 3.7.

3.4.2 Simulation results

Using the simulation setup described in Section 3.4.1, we execute the formulation presented in Section 3.3. The efficacy of the proposed coordination mechanism is illustrated by comparing a scenario in which there is no flexibility to a scenario in which flexibility is provided from an energy storage system. This Section is concluded by performing an economic analysis that investigates the optimal storage size, the cost of storage investment and the operational revenue earned by the aggregator assuming different contractual price limits. The aim of this analysis is to determine which price limits would result in feasible business cases.

Reference case

In the reference situation, there is no flexibility in the distribution grid. Due to varying wholesale prices and local congestion, there is a certain level of price volatility. Figures 3.4(a) and 3.4(b) represent the price values and generation and load profiles for a typical week respectively. Price in this scenario exceed the indicated limit of €50/MWh either because the wholesale price exceed this level or because of the grid capacity of 2MW is reached. In Figure 3.4(c) the price duration curve is presented that illustrates the prices experienced by the energy community, organized in a descending order of magnitude. As can be observed, the price rise can be as high as €300/MWh and these high price can be experienced for a considerable time duration. Furthermore, prices in the price duration curve are higher than the example price limit of €50/MWh for approximately 1500 hours. For a few hours during the year, the demand can be satisfied completely by the solar power. This causes the marginal price of power to be €0/MWh.

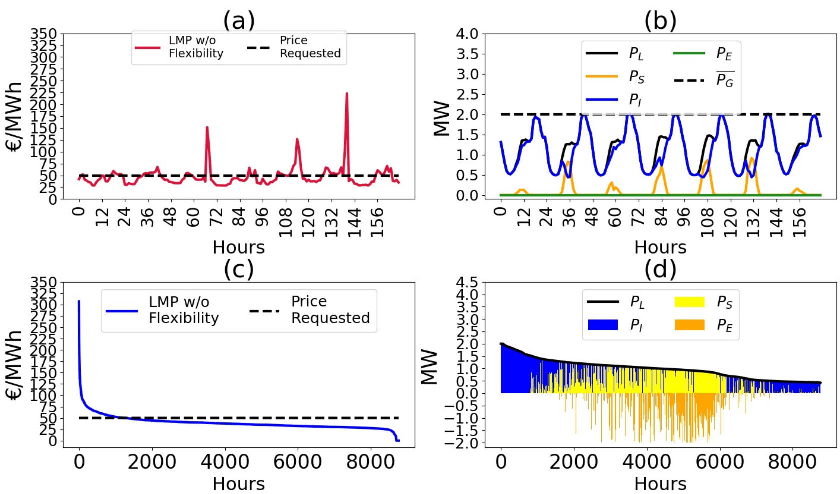

Figure 3.4: Demand, generation and prices in the reference case. (a) Local electricity price for a typical week. (b) demand and generation in the same week. (c) price duration curve (d) load duration curve, the generation and grid imports and exports. An example price limit of €50/MWh is indicated in the price curves.

Figure 3.4(d) presents the generation and demand profiles for the year and is illustrated through a load duration curve. A load duration curve depicts the relationship between demand and supply in a descending order of demand. In this Figure, power can be supplied from solar power (yellow) or can be imported from the main grid (blue) to satisfy the demand (black). Alternatively, excess of solar power generation can be exported (orange) to the main grid and is represented using a negative sign. As the generation of solar energy depends on the magnitude of solar irradiance, which is variable, the demand might not always be satisfied through solar alone. From the load duration curve, it is observed that solar generation is mostly available during the mid-load hours i.e. between 1.0 MW and 1.5 MW. In the advent that no solar power is available, the demand would need to be satisfied by importing power from the main grid, which in turn is constrained by the line limit. However, for majority of the hours, the power import from the main grid and solar power would combine to satisfy the demand, with rules of economic dispatch taking precedence.

Constraining price using energy storage

The coordination mechanism for reducing price volatility and price spikes is demonstrated using Figure 3.5. The results from the implementation of our proposed formulation over a week is presented through Figures 3.5(a) and 3.5(b). From Figure 3.5(a) it can be observed that the marginal price without flexibility provision (red) can exceed the desired price limit. This occurs for a few instances in the given week. At these instances, the DSO issues a request for flexibility to the aggregator on behalf of the energy community.

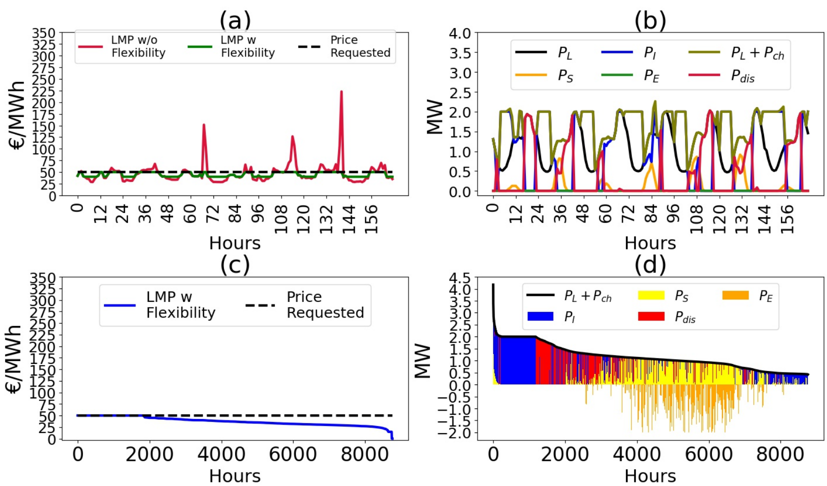

Figure 3.5: Demand, generation and prices in the case of providing flexibility with an energy storage system. (a) local electricity prices for a typical week. (b) demand and generation for the same week (c) price duration curve (d) load duration curve, the generation and grid imports and exports. A price limit of €50/MWh was used in this case and is indicated in the price curves.

This requested flexibility is satisfied by discharging of a storage system as described in Equation (3.11). Figure 3.5(b) depicts the storage operational profile in addition to generation and demand profiles. Once the storage has discharged to constrain the price, it needs to charge in order to constrain prices over multiple periods. Additionally, the aggregator can also participate in arbitrage (not shown in this figure). For charging, the aggregator needs to determine the economically beneficial time periods. From Figure 3.5(b) it is observed that charging mostly takes place during the night when price is low. Furthermore, the aggregator dispatches the storage in coordination with the DSO thereby avoiding additional grid contingencies. The combined load and charging uses the entire grid capacity of 2MW. Finally, charging of the storage results in a net increase in the local demand. This subsequently results in an increase in marginal price as compared to the case without flexibility and can be seen in Figure 3.5(a) where the green line lies above the red line during the low price periods.

The price for the entire year considering price hedging mechanism and the operation of energy storage as a flexible resource are presented in Figure 3.5(c). It is observed that by discharging the storage, the price is capped at $\overline{\lambda^*}$ for the entire year, which exhibits the effectiveness of our proposed mechanism. The net increase in relative price experienced by the energy community due to charging occurs for a period of approximately 1000 hours when the price is most favorable. Additionally, the price increase in most cases are nominal.

The generation, demand, storage and grid exchange for the whole year are summarized in Figure 3.5(d). Storage discharge mostly takes place during hours when the demand is roughly between 1.5MW and 2MW. Comparing Figure 3.4(c) and Figure 3.5(c) it can be observed that these are actually the hours with the highest loads in the distribution grid. During the periods of storage charging, the storage will utilize all of the remaining (other than the consumer demand) available 2MW capacity of the grid connection. For a small amount of hours, the combined load in the grid will exceed 2MW. These are the hours when either the storage discharging or solar generation complement the imports from the main grid.

Economic analysis of contractual arrangements

The economic analysis of different contractual arrangements is performed in this Section. Using the formulation presented in Equation (3.10), we compute the optimal size of the ESS required to constrain the price to the contractual limit of $\overline{\lambda^*}$. Figure 3.6 presents the relation between the values of $\overline{\lambda^*}$ and the optimal size of the storage system. It can be observed that as the price limit is relaxed, the size of the storage required significantly decreases.

The resulting size of the ESS depends on the number of consecutive hours that the marginal price exceeds the value of $\overline{\lambda^*}$ which in turn corresponds to the required depth of discharge and charge that the storage must sustain. For the purpose of our exploratory analysis, the step size in terms of the contractually agreed on price limit $\overline{\lambda^*}$ is €10/MWh for the contractual price ranging between €50/MWh to €110/MWh. For higher values, the step size is then further granulated to reflect a value of €5/MWh. From the value of $\overline{\lambda^*}$ =€50/MWh to $\overline{\lambda^*}$ =€70/MWh a steady drop in storage capacity from 21.3 MWh to 17.93 MWh is observed for constraining the marginal price. However, a nominal decrease in storage capacity is realized when the value of $\overline{\lambda^*}$ is increased from €80/MWh to €90/MWh and then again from €100/MWh to €110/MWh. This is because for the year, the number of consecutive hours in which the price realized is between these pairs of values of $\overline{\lambda^*}$ is scarce. Finally, as the value of $\overline{\lambda^*}$ increases beyond the value of €115/MWh the storage capacity required for constraining marginal prices drastically decreases.

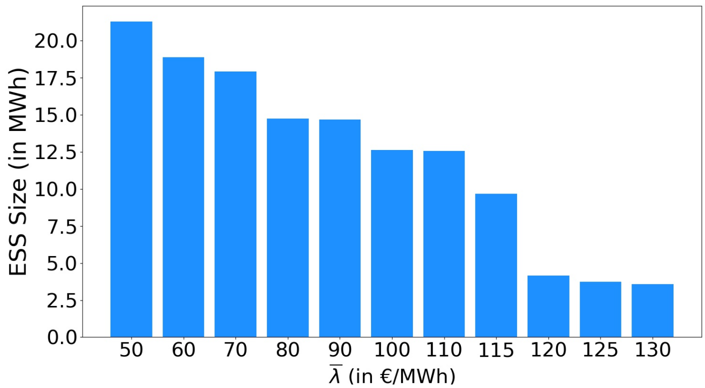

Figure 3.6: Required size of ESS to constrain prices under different contractual arrangements

Figure 3.7 presents a comparison between the capital and operational expenditure incurred by the aggregator to satisfy its contractual obligations. Capital expenditure (CAPEX) values are related to the investment decision which the aggregator needs to make. The total annualized investment cost for the storage system is computed using Equation (3.18). In accordance with Figure 3.6, we can observe that as the value of $\overline{\lambda^*}$ is relaxed, the annualized costs of storage system significantly decreases. The operational expenditure (OPEX) of the aggregator is related to the charging of the ESS and is computed using Equation (3.14).

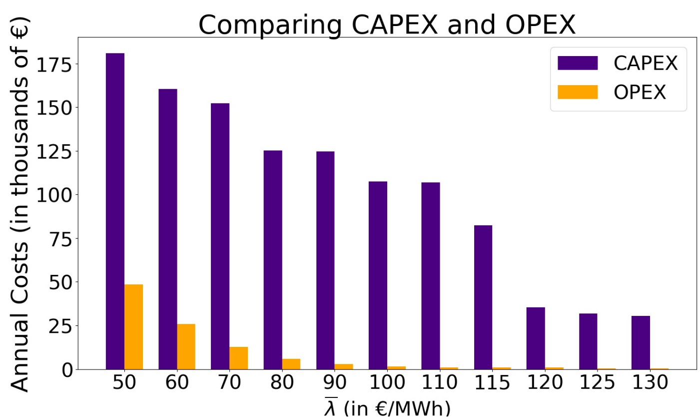

Figure 3.7: Computing Capex and Opex under different contractual arrangements

Charging the ESS during periods of low electricity price ensures that it is able to discharge when the marginal price need to be constrained. As expected, as the price limit for the community is increased, there would be a decrease in the cost of charging due to reduced instances of when flexibility requests are issued. For example, when the price limit for the energy community is aggressive i.e. when the value of $\overline{\lambda^*}$ =€50/MWh then for that case the annualized investment cost for the aggregator is €181,050/year. Correspondingly, given the frequency of the number of hours where the prices realized in the day-ahead market are higher than the value of $\overline{\lambda^*}$ the cost of charging is €48,490.33. Comparatively, when the value of $\overline{\lambda^*}$ =€125/MWh, then the investment and charging costs are significantly lower with values of €31,705/year and €958.714 respectively.

As part of the contractual agreement, the aggregator earns an income from the payments made by the energy community for constraining the prices. The income from hedging is defined by Equation (3.13) and is shown in Figure 3.8. This income decreases sharply for higher price limits. Although the price at which the flexibility is sold increases, the number of hours in which the flexibility is provided falls more rapidly. As a result, the income from hedging (the product of the number of hours flexibility is provided and the price limit, see Equation (3.13)) decreases. For example with $\overline{\lambda^*}$ =€50/MWh the aggregator income is €65,760.55 while at $\overline{\lambda^*}$ =€125/MWh it is only €1444.75.

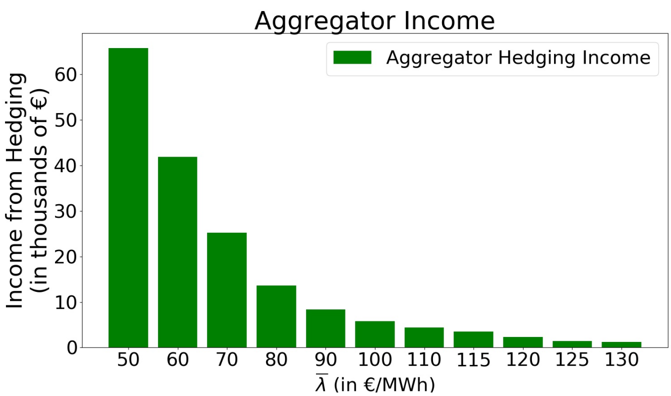

Figure 3.8: Aggregator Income from Hedging under different contractual arrangements

The aggregator can earn additional revenue by partaking in arbitrage during the periods when it is not required to satisfy flexibility requests. To perform arbitrage, the aggregator participates in the wholesale electricity market as a price-taker, charging the storage when the price is low and selling electricity by discharging when the price is high. However, instances may arise when the aggregator is required to forego arbitrage opportunities in order to satisfy its contractual obligations. This in turn limits the revenue potential from performing arbitrage and can be observed clearly for when the price limits are aggressive.

While increasing the price limit results in diminishing return from hedging, the upside is that the storage has more opportunities for arbitrage as the frequency with which constraint (3.12) is to be executed decreases. Figure 3.9 shows the net operational revenue from combined arbitrage and hedging (blue), net hedging revenue only (green) with different price limits as well as corresponding annualized storage investment costs (teal). As a reference, in Figure 3.9 we also consider the revenue potential if an aggregator were to perform only arbitrage (purple) given the same size of storage. Indeed, Figure 3.9 shows that in the combined hedging and arbitrage case, the arbitrage revenue increases when the price limits are relaxed. In fact, they approach the arbitrage revenue of the arbitrage-only case. This makes sense, when realizing that the only difference between these two cases is that constraint (3.12) forces the storage to provide flexibility $P_F[t]$. At more relaxed price limits, this constraint becomes increasingly inactive and the two cases become increasingly alike. The difference between the purple and the blue bars in Figure 3.9 can thus be considered as the cost of imposing a price limit.

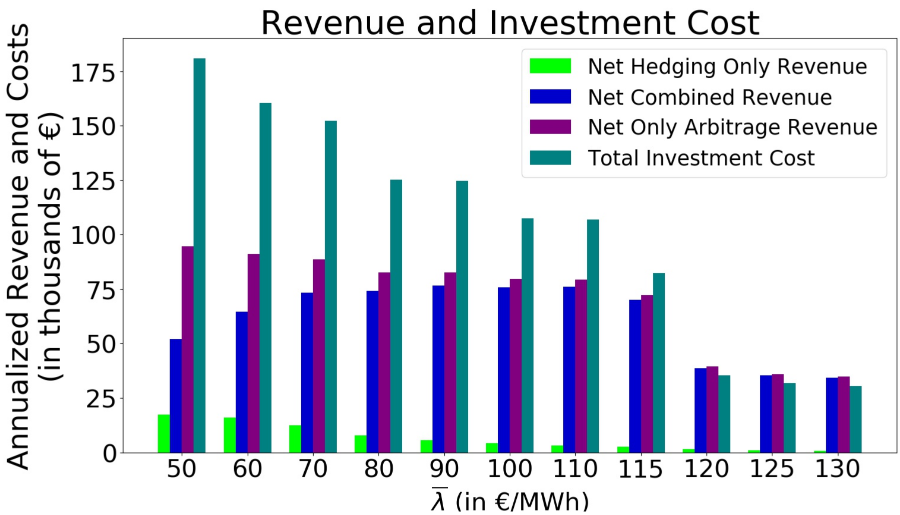

Figure 3.9: Revenue and Investment Analysis under different contractual arrangements

A key observations can be drawn from the analysis of Figure 3.9. The revenue potential from hedging and arbitrage is governed by the size of the storage system. The storage in turn is sized such that it is able to constrain the marginal price to the contractual limits throughout the year. Figure 3.9 also makes clear that with the data used for this case study, there is only a positive business case for values of the price limit of €120/MWh or higher. At the price limit of €120/MWh, the corresponding size of the ESS required is 4.17 MWh and the annualized storage investment costs and combined hedging and arbitrage revenue are €35,431.4/year and €40,118.06/year respectively. Thus, at higher price limits the storage size and its corresponding costs decrease rapidly while the revenues from storage operation falls less sharply. In other words, a relatively small sized storage is able to provide flexibility and arbitrage for a small number of hours, but against very favorable prices.

For this case study, the net revenue from hedging alone is too less for a positive business case. However, we have not considered a premium or fixed fee that the provider of flexibility would receive. In principle, since local price is reduced for the entire grid, a risk neutral consumer could be expected to pay the same amount of money compared to the situation without flexibility.

Comparative analysis: Combined hedging and arbitrage and arbitrage alone

As previously mentioned, the aggregator can integrate to the energy community without entering into a flexibility contract. In this case, the aggregator would operate the storage purely to leverage from the price volatility by performing arbitrage. From Table 3.1 it can be observed that the main benefit of our proposed formulation is that it is able to constrain price to the community specified limit. In contrast, the storage operating purely for arbitrage is unable to guarantee a price limit. For our comparative analysis, the size of storage for each comparison scenario is kept constant. From Table 3.1, it can be noticed that when there is an aggressive price limit $\overline{\lambda}$= €50/MWh, then while the difference between the maximum price in the two cases compared is high, the maximum price in the arbitrage only case is the lowest compared to the other price limit scenarios. This is because the given price limit of €50/MWh requires a larger storage size to successfully constrain price.

Category	$\overline{\lambda}$ =€50/MWh		$\overline{\lambda}$ =€100/MWh		$\overline{\lambda}$ =€130/MWh	
Max. Price and System Benefit	Combined Hedging and Arbitrage	Arbitrage Only	Combined Hedging and Arbitrage	Arbitrage Only	Combined Hedging and Arbitrage	Arbitrage Only
Max Price (in €/MWh)	50.0	84.07	100.0	120.021	130	131.01
System Benefit (in Millions of €/year)	9.897	9.911	9.898	9.904	9.8635	9.868

Table 3.1: Comparative Analysis of maximum price and system benefit (negative of objective function in Equation (3.11)), between combined hedging and arbitrage, and arbitrage only

Furthermore, it can be observed that as the price limit is relaxed, the difference in the maximum price for the two cases being compared also decreases. However, the trade-off of our proposed formulation is that placing a price cap results in a reduced overall system benefit. Subsequently the revenue for the aggregator reduces as compared to a situation in which the aggregator performs arbitrage alone. Additionally, we observe that total system benefits (utility minus costs) are only slightly ($\sim 0.15\%$) higher in the arbitrage only case. This shows that imposing an extra constraint to the system indeed leads to a lower optimum, but the costs in both cases are almost comparable.

3.5 Conclusion

In this chapter, we have presented a coordination mechanism that is used to reduce price volatility and price spikes in electricity systems. The novelty of this mechanism is that it applies an explicit constraint on price which is generally an output of an optimal power flow and not known a priori. Our proposed approach uses duality theory for quantifying the flexible power required to constrain price to the desired limit. An institutional arrangement for the required coordination mechanism is presented that illustrates the information and money flow between consumers, a market facilitator and the operator of a flexible resource.

The concept presented is illustrated with a case study of an energy community located in the distribution grid that faces increasing price volatility and price spikes due to wholesale price and local congestion. An aggregator enters into a flexibility contract with the community, thereby operating an energy storage to satisfy flexibility requests and constrain price. Additionally, at instances when there are no flexibility requests, the aggregator can participate in energy arbitrage. A techno-economic analysis from the aggregator's perspective is considered in this chapter, where the aggregator's revenue from combination of arbitrage and hedging; under different price limits, is compared against the storage investment cost. Results indicate that strict price limits restricts the level of volatility in the local electricity market, and hence a trade-off is observed in the aggregator's revenue when comparing combined arbitrage and hedging case with arbitrage only case. Furthermore, from the techno-economic analysis it is observed that the business case for the storage system depends strongly on the price limit in the grid. For the case study investigated a business case was realized as the value of $\overline{\lambda^*}$ increases over €120/MWh. Finally, a comparison with the arbitrage-only case shows that the reduction in overall system benefit of imposing an additional constraint to the system is modest.

In conclusion, this chapter serves as a preliminary proposal for physical hedging in distribution grids, and future research could provide insights on several aspects that were not addressed here. Firstly, we have considered the flexibility contract to have a constant price limit for the entire year. The shortcoming of such a contract is that when the price of electricity in the market are low, the aggregator is not able to generate revenue through hedging. Alternatively, periods may exist when the price of electricity is consecutively high for long periods. Since the storage capacity sizing is directly related to the number of consecutive hours that the market price are higher than the contractual price limit, it will result in a requirement for large storage units which are expensive. Assigning a time-varying value for the price limit can aid in alleviating this issue. Secondly, we have only considered an energy storage system as a potential source of flexibility in our case study, but it would be interesting to investigate demand response technologies like electric vehicles or flexible heating/cooling systems. This is because the electrification of transport and heating and could contribute to grid congestion thereby resulting in additional price spikes. Thirdly, we have treated everything in a deterministic framework, where full knowledge of future prices and demand was assumed. Uncertainty should be considered to get a more realistic estimate of the operation and economics of the system. Finally, our presented formulation is readily extendable to larger systems ranging multiple nodes and possibly higher voltage levels such as the transmission grid. Thus additional insights from our approach can be generated including the analysis of the computational feasibility of the approach.

4

Potential of flexible loads to contribute towards reduction of price volatility

This chapter is partially based on our paper [102].

4.1 Introduction

In this thesis, energy communities comprise of a group of consumers that organize themselves to achieve the objective of reducing price volatility. To satisfy its electricity demand, the community interacts with the main electric grid. This exposes it to wholesale market price which has become increasingly volatile [71]. As communities undergo the energy transition, an emerging aspect is sector coupling. Sector Coupling [103], is a holistic approach to energy transition, which aims to decarbonize end-use energy consumption by converting the supply-stream to an all electric renewable energy based system. Electrification of end-use appliances for heating and transport will require the electric power grid to satisfy a significant increase in demand magnitude. This increase in demand makes the grid susceptible to congestion. Thus the large-scale integration of variable renewable energy and the expected increase in frequency of grid congestion will result in greater magnitudes of price volatility. To prevent instances of extreme price spikes, and to facilitate sector coupling, increasing energy flexibility is important. This flexibility can be aggregated from demand-side resources such as electric storage, electric vehicles, and electric heat pumps.

In Chapter 3, we focused on the application of electric storage in reducing price volatility. In contrast, the core of this chapter is founded on the flexibility that can be provided from flexible demand. Flexible charging of electric vehicles in response to policy or price instruments, facilitates the alignment of variable load with intermittent generation. This simultaneously mitigates the immediate need for grid reinforcement and price spikes. Integral to this flexibility, are variable pricing schemes and demand response. Research conducted in [104, 105] demonstrate the advantages of flexible charging of electric vehicles while accounting for vehicle owner's behavior and decision making. The coordination of flexible EV charging through the interaction between system operators and EV aggregators as proposed in [106–109] present approaches to minimize deviation in planned energy portfolios while accounting for uncertainty. This increases the power hosting capacity of the electric grid, and reduces the impact of demand ramps and their subsequent grid contingencies.

Electrification of space heating also contributes to increased electricity demand. Flexibility with respect to thermal loads in buildings and households can be harnessed by leveraging their thermal inertia. The thermal inertia of a building envelope enables it to absorb the intermittency and volatility of renewable energy generation. Previous research on thermal load management have considered the aspects of demand response [110, 111], and energy arbitrage [112] while also accounting for aggregation of buildings [113]. The flexibility potential from space heating/cooling is characterized by a number of factors [114] such as the capacitive and conductive property of the building stock, and differences between internal and external temperatures. Using these properties the electric heat pumps can be optimally scheduled to reduce the cost of heating households [115].

It is possible that an energy community comprises of both electric vehicles and electric heating. For these communities, flexibility can be aggregated across both these loads and be leveraged for efficient grid management. In relation, the works conducted in [116, 117] elucidate the combined effect of aggregate load flattening and load shifting for reducing electricity price. An important aspect of aggregated flexibility is that it smoothens the adjustable power profile which can be utilized in market clearing or for grid management [118–120].

However, previous research does not take into account the possibility of invoking an explicit upper price limit in the electricity market to curtail price volatility. To address this research gap, this chapter explores a mechanism by which communities set an upper bound on price in the local electricity market thereby minimizing their exposure to price spikes. The proposed mechanism quantifies the amount of flexibility that the aggregator needs to generate for constraining price.

This Chapter builds on our previous works presented in [67, 91–93]. While these works investigated the potential of electric storage to constrain price, this chapter predominantly focuses on the potential of electric heat pumps and electric vehicles. The chapter contributes to the scientific literature by addressing the following research question: *In an increasingly electrified future, to what extent is a reduction in price spikes and local congestion possible?* Through our results and subsequent discussion, we generate insights on the operational profile of electric vehicle charging, electric heat pump scheduling and the sizing of community energy storage systems to provide the required load reduction for constraining price to a maximum limit. Additionally, we provide a coordination framework for facilitating the price constraining using these diverse flexible assets. It is expected that our formulation will protect consumers against extreme price events as we undergo energy transition and sector coupling.

The structure of this chapter is as follows: first the formulation for estimating the amount of flexibility through load reduction required in the operation of flexible loads is presented. This is followed by the schematics for the information flow between actors required for facilitating the coordination. Next, the data for the simulation and its setup is presented. Simulations are executed at the resolution of a 10-day interval, and later scaled to a yearly time-frame. With this extension in simulation window, insights are generated on the storage size required for mitigating price spikes and grid congestion in the case without and with demand flexibility. Key recommendations are then highlighted, and lastly the main conclusions from this study are drawn.

4.2 Proposed approach to use flexible loads for reducing price volatility

This section focuses on the ability of Thermostatically Controlled Loads (TCLs) and Electric Vehicles (EVs) to limit price magnitudes to a desired maximum in electricity markets. The fundamental idea of the approach is to apply an explicit constraint on price. In an economic dispatch formulation, price is the dual variable associated with load balancing. In addition to the primal problem for economic dispatch being convex, as the constraints associated with it are affine it is assumed that Slater's condition will hold and strong duality exists. Hence, adding an explicit constraint on price in the dual formulation will result in the introduction of a new variable in the load balancing constraint of the primal problem. This newly introduced variable is the flexibility required for constraining price to a desired limit. For example, if we want to constrain price to $\overline{\lambda^*}$, and if the market price is $a : a > \overline{\lambda^*}$, then to constrain the price using our formulation, we will need to supply the required flexibility P_F.

In this chapter, a generalized formulation of the price constraining approach is expressed in Equation (4.1). For a detailed derivation of this formulation, we draw the readers attention to [91, 121].

$$\min_{P_{G_i}, P_{F_i}} \sum_{t \in T} \sum_{i \in \mathcal{N}} \left(a_i[t] P_{G_i}[t] + \overline{\lambda^*}_i[t] P_{F_i}[t] \right) \tag{4.1}$$

subject to:

$$P_{G_i}[t] - P_{L_i}[t] + P_{F_i}[t] = \sum_{j \in \Omega_i} \frac{\theta_i[t] - \theta_j[t]}{X_{ij}} \quad \forall i \in \mathcal{N}, \forall t \in T \tag{4.1a}$$

$$-\overline{P_{ij}} \leq \frac{\theta_i[t] - \theta_j[t]}{X_{ij}} \leq \overline{P_{ij}} \quad \forall (i,j) \in \Omega_{ij}, \forall t \in T \tag{4.1b}$$

$$\theta_{slack} = 0 \tag{4.1c}$$

$$0 \leq P_{G_i}[t] \leq \overline{P_{G_i}} \quad \forall i \in \mathcal{N}, \forall t \in T \tag{4.1d}$$

$$P_{F_i}[t] \geq 0 \quad \forall i \in \mathcal{N}, \forall t \in T \tag{4.1e}$$

Equation (4.1) represents the economic dispatch problem for a medium voltage (MV) distribution grid. This formulation has been modified to account for our proposed price constraining mechanism. The variable $\overline{\lambda_i^*}$ represents the price limit. Load balance at all nodes in the network, denoted by $\mathcal{N}$, is given by Equation (4.1a). At a subset of these nodes which are relatively more susceptible to congestion, flexible resources can be used by a community to mitigate the extent of price spikes. By solving Equation (3.7), we determine a time-varying signal $P_{F_i}[t]$, required for constraining price at a specific node.

In this chapter, flexibility requests $P_F[t]$ are satisfied through the coordination of multiple resources. At first, we consider the flexibility that can be provided by TCLs and EVs alone and then their combination for constraining price. Cases may arise when flexible load by themselves, are insufficient to deliver the required flexibility. For these cases, we additionally consider integration of storage in the flexible resource portfolio.

4.2.1 Reference load profiles

For price-sensitive loads, flexibility is provided by displacing their operation in time. This effectively results in a displacement of power consumption from periods of high price to instances when electricity price is relatively low. In the reference case, power is consumed by consumers, who are unaware of market price. Power is consumed in accordance with consumer preferences and result in a certain reference demand profile. For an energy community, consumers exists, who either possess and operate only thermostatically controlled loads, only electric vehicles, or both. Our initial goal is that given the consumer preferences, we want to estimate a reference load profile across the community.

First, we explain the set of equations governing the base case operation of the TCLs. The TCL considered here is an electric heat pump (EHP). For a household, there are two driving factors: the minimum acceptable temperature that must be satisfied, and achieving this with minimal power consumption. Under this scheme, the heat pump operates only to compensate for the heat loss to the ambient surroundings. The heat pump operation thus restricts the room temperature from decreasing below a specified temperature limit. Based on these conditions, a reference power consumption profile of the electric heat pump is determined. This profile is computed based on the formulation as presented in [112] and is expressed as follows:

$$\underset{P_{hp}}{\text{minimize}} \sum_{t=1}^{T} P_{hp}[t] \tag{4.2}$$

subject to:

$$\begin{aligned} T_{r_h}[t+1] = T_{r_h}[t] + \frac{1}{C_{p,r_h}} \Big\{ (UA)_{f,r_h} (T_{f_h}[t] - T_{r_h}[t]) - \\ (UA)_{r,a_h} (T_{r_h}[t] - T_a[t]) \Big\} \quad \forall t \in T \end{aligned} \tag{4.2a}$$

$$T_{f_h}[t+1] = T_{f_h}[t] + \frac{1}{C_{p,f_h}}\Big\{(UA)_{w,f}(T_{w_h}[t] - T_{f_h}[t]) - (UA)_{f,r_h}(T_{f_h}[t] - T_{r_h}[t])\Big\} \quad \forall t \in T \tag{4.2b}$$

$$T_{w_h}[t+1] = T_{w_h}[t] + \frac{1}{C_{p,w}}\Big\{\eta_{hp} P_{hp_h}[t] - (UA)_{w,f}(T_{w_h}[t] - T_{f_h}[t])\Big\} \quad \forall t \in T \tag{4.2c}$$

$$\underline{P_{hp_h}} \leq P_{hp_h}[t] \leq \overline{P_{hp_h}} \quad \forall t \in T \tag{4.2d}$$

$$\underline{\Delta P_{hp_h}} \leq P_{hp_h}[t+1] - P_{hp_h}[t] \leq \overline{\Delta P_{hp_h}} \; \forall t \in T \tag{4.2e}$$

$$\underline{T_{r_h}} \leq T_{r_h}[t] \leq \overline{T_{r_h}} \quad \forall t \in T \tag{4.2f}$$

The objective of Equation (4.2) is to minimize the amount of power consumed by the heat pump power for a given household. It is denoted by the variable P_{hp_h} where h indicates a given household. Equations (4.2a) - (4.2c) denote the temperature dynamics for the room, floor, and water in the condenser tank. The temperature dynamics inside the household are modeled through conductive heat transfer: they depend linearly on the temperature differences and conductance between the components. In Equation (4.2a) the thermal capacitance of the room, and heat conductivity from the floor to the room, and room to surroundings are given by variables C_{p,r_h}, $(UA)_{f,r_h}$ and $(UA)_{r,a_h}$ respectively. Equation (4.2b) represents the temperature dynamics for the floor temperature. Variables C_{p,f_h} and $(UA)_{w,f}$ represent the thermal capacitance of the floor and the heat conductivity from the condenser tank to the floor. The temperature balance for the condenser tank is expressed in Equation (4.2c). Capacitance of the condenser tank and the coefficient of performance (CoP) of the heat pump is given by $C_{p,w}$ and η respectively. The physical representation of these parameters is illustrated in Figure 4.2. Furthermore, the operational bounds of the heat pump is expressed using Equation (4.2d). Ramp constraints for the heat pump operation and bounds on the temperature values of the room are expressed through Equations (4.2e) - (4.2f) respectively.

Next, we simulate the reference power consumption for the charging of electric vehicles by EV owners. Charging of electric vehicles is also price-sensitive and can be displaced to periods of favorable price. In the reference case, we assume that vehicle owners, have two main prerequisites. First, ensure sufficient charge in the vehicle's storage to satisfy their commute requirements. Second, vehicle owner have a preference to charge the vehicle such that it is always charged to its maximum capacity. Other aspects also concern the possible locations where a vehicle may be charged. In this chapter, it is assumed that electric vehicles can only be charged at the vehicle owner's household. The driving profile for EV owners is based on [31], and the subsequent charging profile is computed using Equation (4.3).

$$\underset{E_{EV}, P_{EV}}{\text{maximize}} \sum_{t=1}^{T} E_{EV}[t] \tag{4.3}$$

subject to:

$$E_{EV}[t+1] = E_{EV}[t] + \eta_c P_{EV}[t] - d_{EV}[t] \quad \forall t \in T \tag{4.3a}$$

$$\underline{E_{EV}} \leq E_{EV}[t] \leq \overline{E_{EV}} \quad \forall t \in T \tag{4.3b}$$

$$\underline{P_{EV}} \leq P_{EV}[t] \leq \overline{P_{EV}} \quad \forall t \in T \tag{4.3c}$$

$$E_{EV}[T] \geq E_{EV}[0] \tag{4.3d}$$

$$P_{EV}[t] = 0 \quad \text{if } t \in T^{away} \tag{4.3e}$$

In Equation (4.3), the state of charge of the electric vehicle is denoted by the variable E_{EV}. As the electric vehicle is used the energy content is updated according to the inter-temporal constraint specified by Equation (4.3a). The variables P_{EV}, η_c, and d_{EV} represent the amount of EV charging at a given instance t, the charging efficiency and the discharging of the electric vehicle due to usage. We implement a discrete-time simulation with an interval of 1 hour. Equation (4.3e) ensures that the vehicle is not charging when it is away from the vehicle owner's household. Limits on the charging amount and storage size are addressed through Equations (4.3b) - (4.3c).

For the energy community, using Equation (4.2) and Equation (4.3), the reference power consumption by each flexible load; P_{hp} and P_{EV} is determined. To estimate, the aggregated power consumption for the community, the cumulative power consumption across constituent households is computed. The aggregation of the heat pump and electric vehicle charging power consumption is denoted as $P_{hp_{agg}}[t]$ and $P_{EV_{agg}}[t]$ respectively, for each time step t.

4.2.2 Potential of flexible loads for providing flexibility

To gain a better understanding of the scheduling of electric heat pumps and electric vehicles for providing flexibility, their schematic representation is compared with electric storage. In Figure 4.1(a) an electric storage is illustrated. The storage's state of charge E_{SS} is governed by its charging P_{ch} and discharging P_{dis} at time instant t. For satisfying flexibility requests, the storage is discharged while accounting for it's state of charge (that is depicted as the dotted line). At instances when no flexibility is required, the storage recharges so that it can be discharged during subsequent time instants.

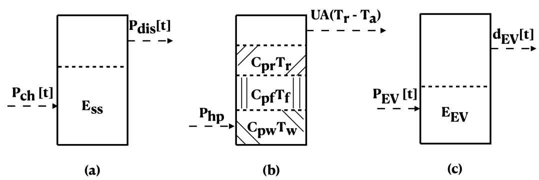

Figure 4.1: Illustration of the similarities between (a) electric storage (b) electric heat pumps (c) electric vehicles for providing flexibility

Similarly, for an electric heat pump illustrated in Figure 4.1(b) its operation is governed by the thermal inertia of a household. This thermal inertia is expressed in terms of the thermal capacitance of surfaces (condenser tank, floor, and room) and the conductivity of heat from one surface to another. Each surface owing to its thermal capacitance is capable of retaining heat and the this thermal energy retention potential (indicated by a dotted line) is akin to the state of charge of an electric storage. The thermal energy retention potential aggregated across different surfaces enables a household to defer the power consumption by an electric heat pump in time. Figure 4.1(c) illustrates the operation of an electric vehicle. For an electric vehicle its state of charge (indicated by dotted line) is governed by the power it discharges while traversing a commute and the power it consumes during charging. While electric vehicles do not provide power back to the electric grid, they again have the potential of providing flexibility by deferring their charging to periods of relatively low electricity price. Thus, both electric heat pumps and electric vehicles have the potential to deviate from a reference power consumption profile to provide flexibility. This is an important property for mitigating the significant extra peak loads that could be created when these loads are scheduled in a 'non-price aware' manner.

4.2.3 Flexible load scheduling

Once the aggregate reference load profile is computed, the amount of flexibility through load reduction required for constraining price needs to be determined. This is achieved by executing Equation (4.1). The power demand term is now decomposed into its three components. These load values are the baseload, aggregated electric heat pump power demand, and aggregated power consumption of the electric vehicles. In the event that a community does not have either one of these flexible loads, the corresponding aggregated power value is set to zero. The total load value $P_{L_i}[t]$ in Equation (4.1a) is now represented as follows:

$$P_{L_i}[t] = \underbrace{\overline{P_{L_i}}[t]}_{\text{agg. baseload}} + \underbrace{P_{hp_{agg}}[t]}_{\text{agg. EHP load}} + \underbrace{P_{EV_{agg}}[t]}_{\text{agg. EV load}} \quad \forall t \in T \tag{4.4}$$

To satisfy the required flexibility P_F, the operational schedule for the heat pumps and EV charging needs to be re-computed using Equation (4.5). The goal of Equation (4.5) is to satisfy load at lowest possible price in addition to providing the requested flexibility. This is achieved through the differences in the heat pump operation and EV charging.

Terms used in the objective function comprise of the time-varying electricity price a_i and the power consumed from the main grid P_{G_i} by an energy community located at node i for time instant t. Equation (4.5a) refers to the load balancing at the community where the variable P_{L_i} is computed using the Equation (4.4) that is updated using the new aggregated power consumption for electric vehicles ($\sum_{v=1}^{V} P_{new_V}[t]$) and thermostatically controlled loads ($\sum_{h=1}^{H} P_{new_h}[t]$). Indices h, v and t constitute the set of households, electric vehicles and the simulation period, H, V and T respectively.

$$\min_{P_{G_i}, P_{new_h}, P_{new_v}} \sum_{t=1}^{\mathcal{T}} \sum_{i=1}^{\mathcal{N}} \left(a_i[t] P_{G_i}[t]\right) \tag{4.5}$$

subject to:

$$P_{G_i}[t] - P_{L_i}[t] = 0 \quad \forall t \in T \tag{4.5a}$$

$$\text{Equation (4.2a) – Equation (4.2f)} \tag{4.5b}$$

$$\text{Equation (4.3a) – Equation (4.3d)} \tag{4.5c}$$

$$P_{F_i}[t] = \left(P_{hp_{agg}}[t] - \sum_{h=1}^{H} P_{new_h}[t] \right) + \left(P_{EV_{agg}}[t] - \sum_{v=1}^{V} P_{new_v}[t] \right) \text{ if } (P_F[t] > 0) \forall t \in T \tag{4.5d}$$

Equation (4.5b) and Equation (4.5c) states that the constraints for individual houses and electric vehicles are the same as specified in Equation (4.2) and Equation (4.3). With Equation (4.5d), we enforce the constraint for satisfying the load reduction requests across the community. Hence when $P_F[t] > 0$, then the difference between the previous aggregated and the new aggregated heating and EV charging profile for the community must satisfy $P_F[t]$ in order to constrain price. The combined flexibility provided from the heat pumps and electric vehicles is thus able to cap the electricity price. A benefit of our proposed approach is that it extends market based approaches for congestion management by enabling direct load control by a market entity to ensure a specified maximum price.

4.2.4 Integration of electric storage for providing flexibility

Instances may arise when the flexibility required to constrain price cannot be provided only through flexible load scheduling. These are the time instants when the baseload (inflexible load) by themselves result in a violation of the grid capacity. For addressing these situations, the work conducted in Chapter 3 can be extended by integrating the flexibility provided through the discharge of an electric storage. As a part of this analysis, the optimal size of the storage and its operational schedule to provide flexibility is computed by making a couple of modifications to Equation (4.5). The first modification is that the objective function is updated by adding the term dE_{SS}. In Chapter 3, the terms d and E_{SS} denoted the per unit size cost of storage and its maximum capacity respectively.

Introducing a storage unit also results in subsequent changes to the set of constraints for Equation (4.5). First, the power balancing constraint specified by Equation (4.5a) is updated as follows:

$$P_{G_i}[t] - P_{L_i}[t] + P_S[t] = 0 \quad \forall t \in \mathfrak{T} \tag{4.6}$$

Additionally, the flexibility balancing constraint expressed in Equation (4.5d) is also updated as follows:

$$P_{F_i}[t] = \left(P_{hp_{agg}}[t] - \sum_{h=1}^{H} P_{new_h}[t]\right) + \left(P_{EV_{agg}}[t] - \sum_{v=1}^{V} P_{new_v}[t]\right) + P_S[t]$$
$$\text{if } (P_F[t] > 0)\forall t \in \mathfrak{T} \quad (4.7)$$

In Equation (4.6) and Equation (4.7) the term $P_S[t]$ is a bi-directional term that represents storage operation at time instant t. The set of constraints that govern the operation of the electric storage is expressed as follows:

$$E[t+1] = E[t] - P_S[t] \quad \forall t \in T \tag{4.8}$$

$$-\frac{E_{SS}}{\tau} \leq P_S[t] \leq \frac{E_{SS}}{\tau} \tag{4.8a}$$

$$0 \leq E[t] \leq E_{SS} \tag{4.8b}$$

Equation (4.8) presents the evolution of the state of charge of the storage. In this equation, when $P_S[t] > 0$ the storage discharges, while charging of the storage is indicated by $P_S[t] < 0$. Additionally, the operation of the electric storage is governed by its physical parameters. These constraints are expressed through Equation (4.8a) - Equation (4.8b) that specify the limits on the maximum charging/discharging limit for the storage and its maximum permissible state of charge respectively.

4.3 Information flow between actors

This Section highlights the information flow between actors for facilitating the proposed coordination mechanism. Actors involved in the coordination include the Distribution System Operator (DSO), an aggregator of flexible loads (EHP and EV), who additionally may own and operate a community energy storage, and an energy community that is connected to the MV network. The proposed coordination mechanism is illustrated through Figure 4.2.

This coordination mechanism is initiated when an energy community, to protect themselves from price spikes, communicate their desired upper price limit to the DSO (1). The DSO as the market operator, participates in this mechanism as a regulated entity with information about market price and grid structure, and executes Equation (3.7) to compute the flexibility required to constrain price. This information is then communicated to the aggregator (2), who seeking a business opportunity can enter into a contract with the community (3), and subsequently operate their heat pumps, identify favorable price periods for vehicle owners to charge their EVs or even discharge the community energy storage (4) to satisfy the requested flexibility. After computing the modified EHP and EV charging schedule using Equation (4.5) and the storage discharge profile, the aggregator informs the DSO about the load reduction achieved

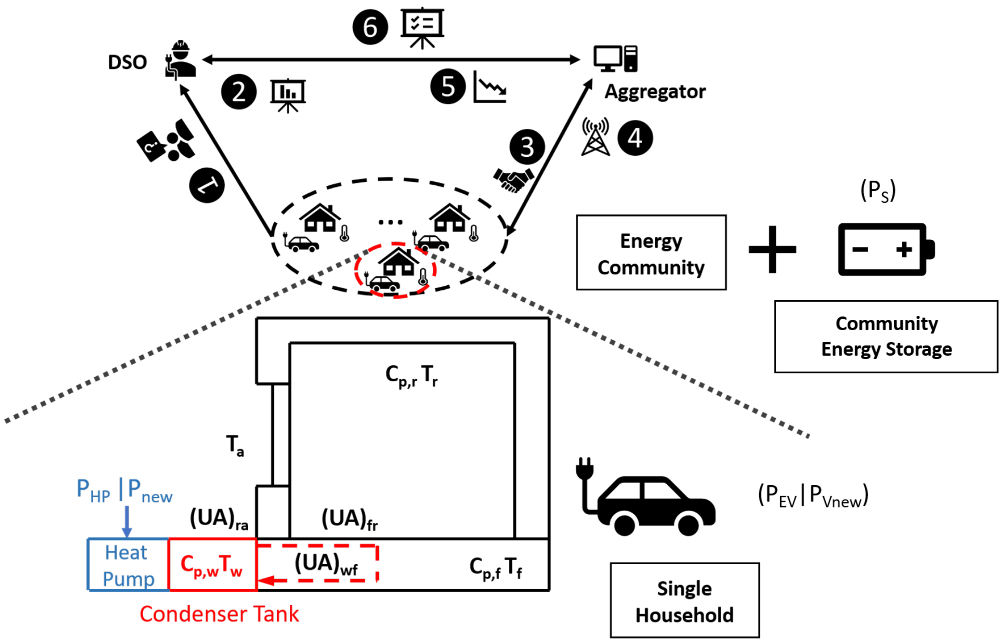

Figure 4.2: Information Flow across flexible load and community storage

(5). Finally, the DSO coordinates with the aggregator for clearing the local market (6).

Thus, through the proposed coordination mechanism, the energy community can engage physical assets; EHPs, EVs, and storage for hedging against price spikes and aggregators receive remuneration for their services. An important aspect of this coordination scheme that must be noted is that it follows the coordination mechanism as introduced in Chapter 2 under a centralized aggregator. This aggregator leverages from large amounts of information pertaining to market price, ambient temperatures, household temperature preferences, electric vehicle owner driving schedules, information about their vehicles storages, and baseload demand patterns. To perform its duties effectively, the aggregator would require to focus on data management, and maintaining specialized knowledge for the operation of flexible resources. It is possible that a single aggregator assumes all the responsibilities for providing flexibility. However, this raises concerns with respect to market power, and it also creates a single point of failure in the supply of flexibility. These aspects will be addressed in the next Chapter 5 of this thesis.

4.4 Simulation and results

In this Section, we first provide information about the data used for the simulation. The simulation tool used will then be presented followed by a discussion of the results generated. A time horizon of 10-days is considered for these simulations.

4.4.1 Electric heat pump

For simulation of the heat pump, we use data provided in [112]. To generate heat pump profiles for a community, the thermal capacitance and conductance values of households are sampled from a normal distribution around the parameters specified for a representative household presented in [112]. These parameters are enumerated in Table 4.1

Parameter Description	**Variable**	**Value**
Thermal Conductance (Floor to Room)	$(UA)_{f,r}$	$624\frac{kJ}{^\circ Ch}$
Thermal Conductance (Room to Ambient Surrounding)	$(UA)_{r,a}$	$28\ \frac{kJ}{^\circ Ch}$
Thermal Conductance (Condenser Tank to Floor)	$(UA)_{w,f}$	$28\frac{kJ}{^\circ Ch}$
Thermal Capacitance (Room)	$C_{p,r}$	$810\frac{kJ}{^\circ C}$
Thermal Capacitance (Floor)	$C_{p,f}$	$3315\ \frac{kJ}{^\circ C}$
Thermal Capacitance (Water in Condenser Tank)	$C_{p,w}$	$836\frac{kJ}{^\circ C}$
Heat Pump Coefficient of Performance (CoP)	η_{hp}	3

Table 4.1: Thermal Parameters for a Representative Household

For the purpose of the simulation, it is assumed that the community comprises of H =14 households. Each community member has their own temperature preferences limits which are in the range of 18°C to 24°C. Additionally, the initial temperature set points of the room, floor and water in the heat pump differs per household which are sampled from a normal distribution curve within the specified range.

Each heat pump is assumed to have a maximum capacity of $\overline{P_{hp}}$ = 1kW and the ramp limit is such that from one time-step to the other the heat pump can completely switch off or on. The time period for the discrete time simulation is one hour.

4.4.2 Electric vehicles

The electric vehicles and their usage profiles considered in this simulation are based on the work presented in [31]. Driving profile based on statistical measures are grouped into 25 unique clusters, that indicate the departure and arrival time of vehicles, as well as the distance traversed d_V. We assign one driver profile cluster to one household. For convenience purposes, minutes within an hour are rounded off to the closest hourly intervals. In our simulations, it is assumed that the electric vehicles charge only at the consumers household. While this usage profile is provided for a 24 hour period only, for the purpose of simplicity we assume that this pattern repeats everyday. The separation of weekday profile from weekend profile is not considered in the simulations.

With respect to the electric vehicle's storage capacity, and its power charge and discharge limits, we assume a constant value of $\overline{E_{EV}}$ = 24 kWh and $\overline{P_{EV}}$ = 3kW across the entire fleet. The time-interval for the discrete-time simulation is set equal to 1 hour. Lastly, the EV storage efficiency is assumed to be $\eta_C = 1$.

4.4.3 Simulation software

As the case study defined is a linear programming problem, the simulations are executed using the GLPK solver through the Pyomo package [101] provided in Python 3.7.

4.4.4 Simulation results electric heat pumps only

From the operational profile of the heat pump, it is observed that it is operated in a way such that it compensates for any heat that is lost by the room to the ambient surroundings. Figure 4.3 provides information on the temperature profiles for each household. The ambient temperature for the community is presented in Figure 4.3(a), and the variations in room, floor and water temperatures are presented in Figures 4.3(b) - 4.3(d). Initial room temperature across the households are randomly sampled from the interval of 22°C - 24°C. As such an initialization effect manifests itself such that in Figure 4.3 the room temperatures fall until the minimum temperature preference limit of a household is hit. Each household compensates for this heat loss to the ambient surroundings through conductive heat transfer across surfaces that ensures a thermal equilibrium is reached.

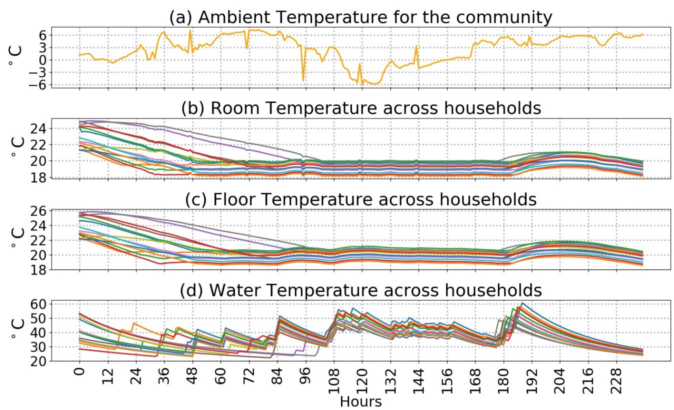

Figure 4.3: Base case values for (a) Ambient, (b) Room, (c) Floor and (d) Water Temperatures

Thereforth, the heat pump will operate by increasing the temperature of the water in the condenser tank which is then propagated to the room. This aids in maintaining a thermal equilibrium with respect to the ambient surroundings. The optimal operation of the heat pump is achieved at the lower bound of consumer's temperature preference.

Next, the aggregate thermal power demand across the community is computed. This is presented in Figure 4.4(b) as $P_{hp_{agg}}$. The baseload profile is obtained from [65] and consists of the load profile $\overline{P_L}$ for an average household in the Netherlands without heating demand. Hence, the aggregated demand in the grid based on Equation (4.4) is composed of the thermal and base loads. Electricity price values are obtained from the wholesale market [9]. In the advent that grid power capacity is violated due to peak demands, then a congestion would occur. As a result of congestion, it would not be possible to satisfy the power demand, thus resulting in lost load. For the simulations

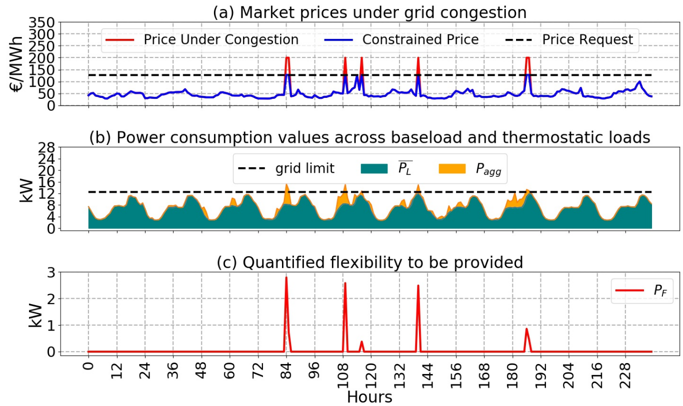

Figure 4.4: Determining flexibility required for constraining prices (a) Market Prices, (b) Load Profiles and (c) Flexibility Needed

considered in this chapter, it is assumed that the value of lost load manifests as the price spikes associated with grid congestion.

Figure 4.4(a) illustrates the electricity price over a 10 day period starting January 1, 2017. It is observed that price spikes occur due to congestion. For this simulation, it is assumed that the community wishes to constrain electricity price at $\overline{\lambda^*}$ = €128/MWh. The grid limit is set to 12.5 kW and is illustrated in Figure 4.4(b) along with the baseload and reference electric heat pump load profiles. Then with the DSO executing Equation (3.7), the flexibility required for constraining price is determined. This required flexibility is illustrated in Figure 4.4(c).

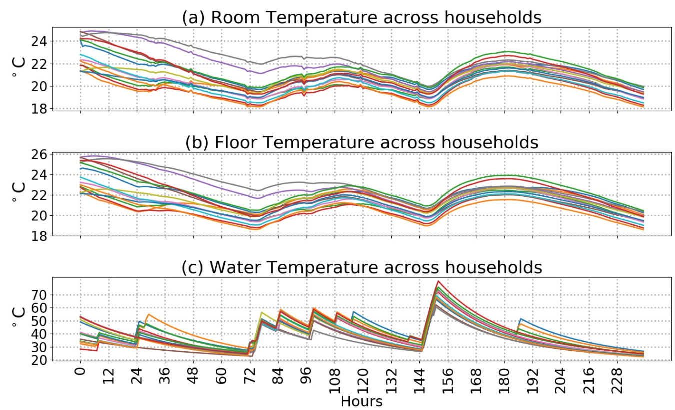

Figure 4.5: Reduced Load case values for (a) Room, (b) Floor and (c) Water Temperatures

In order to evaluate the potential of the heat pump to satisfy the flexibility requests, Equation (4.5) is executed. The results of this simulation are presented in Figure 4.5. The heat pumps are now operated by the aggregated in a price-responsive manner.

Hence, it can be observed that in response to the variations in ambient temperatures, the heat pump operates such that it preheats the water in the condenser tank. Thus the heat pump operation takes advantage of low electricity price periods and this is illustrated in Figure 4.5(c). By leveraging the thermal inertia of the households, power consumption by electric heat pumps are displaced from periods of high price to low.

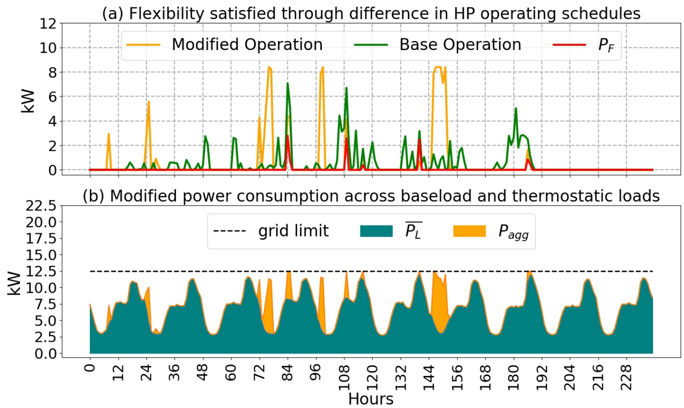

Figure 4.6: Load (a) comparison and (b) profile for modified heat pump operation

Figure 4.6(a) compares the aggregated electric heat pump power consumption without and with flexibility. During periods of price spikes, the aggregator by controlling the heat pump enables load reduction. The load reduction is governed by the proposed mechanism which effectively constrains the price at the community specified price limit. This reduced load profile is then proposed by the aggregator to the DSO. In return, the DSO coordinates with the aggregator to dispatch the load such that subsequent grid contingencies are mitigated. The final cumulative load profile is presented in Figure 4.6(b).

4.4.5 Simulation results electric vehicle charging only

With the objective of consuming electricity produced from renewable sources, increasing amounts of electric vehicles are being integrated to the grid. Vehicle owners charge their vehicles on a daily basis to ensure that the vehicles are sufficiently charged to satisfy their daily commutes. From the work performed in [31], we have identified 25 driving profiles for the Netherlands. Charging of electric vehicles subject to their owner preferences, can be considered as a flexible load. With this assumption, we illustrate the efficacy of the proposed price constraining mechanism when applied to electric vehicles.

For this case study, we assume an energy community of 25 households and focus on the charging of electric vehicles for a period of 10 days. Figures 4.7 (a) and (b) depict the individual EV storage charging operation and its corresponding state-of-charge over this period.

In the simulation, the initial state-of-charge of the EVs is randomly assigned between

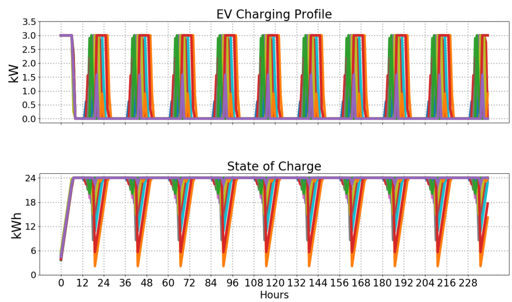

Figure 4.7: Reference Case Charging Profile for EVs (a) Charging Power Consumption (b) State-of-Charge

a value of 0.5kWh to 3.0kWh. As a result it can be observed from Figure 4.7, that for the initial couple of hours, all electric vehicles in the community are charged. This results in a significant ramp in the total demand experienced in the grid as can be observed from Figure 4.8 (b). Later, as vehicle owners depart from their households, Figure 4.7(b) illustrates that there is a decrease in the EV SoC across the fleet. The evolution of the SoC is a function of the distance traversed by the vehicle, its efficiency, and the maximum discharge capacity of the vehicle. On arriving back at their households, the EV owners connect the storage units back to the grid for charging. In accordance with the objective of the EV owner's charging preferences, each vehicle is charged to their maximum capacity. It is assumed that this daily EV charging strategy remains constant over the simulation period considered.

Figure 4.8: Reference case Price and Demand (a) Market Price under Congestion and Price Limit (b) Cumulative Load and Violation of Grid Limit (c) Quantified Flexibility

Figure 4.8 (a) and (b) represent the electricity price in the case of grid congestion (red) and the corresponding baseload (green) and aggregated EV charging load (orange), that results in the grid congestion. The electric grid is sized such that it has a maximum limit of 26 kW for the community. Given the baseload profile, the DSO sizes the grid with an additional buffer for satisfying peak baseloads. However, from this simulation it is realized that the reserve grid capacity is insufficient for satisfying the charging of the electric vehicles. As a result in the reference case without flexibility, grid congestion will occur, which gives rise to subsequent price spikes.

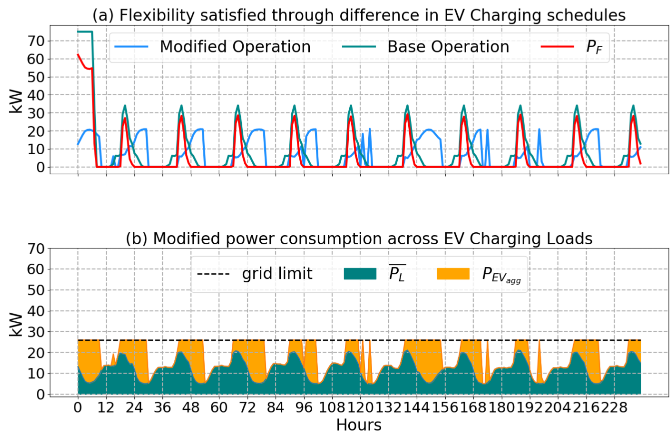

Figure 4.9: Load Reduction and Price Constraining (a) Comparative Load Profile (b) New Cumulative Load Profile

To mitigate these price spikes, we apply the mechanism specified in Equation (3.7). The price limit is set at $\overline{\lambda^*}$ =€128/MWh. This limit is the contractually agreed on price limit between the aggregator adnd the energy community and depicted in Figure 4.8 (a). Following the information flow as described in Section 4.3, the DSO computes and communicates the flexibility values P_F that the aggregator must satisfy through the modification of EV fleet charging profile. The flexibility value to be satisfied over the simulation horizon in depicted in Figure 4.8 (c).

By entering into a flexibility contract with the aggregator, vehicle owners only need to specify the time interval during which they utilise their vehicles and are away from their households. The aggregator then schedules the charging of the electric vehicle fleet in a price-sensitive manner. This change in charging schedule is illustrated in Figure 4.9. Figure 4.9 (a) compares the aggregated power consumption in the inflexible charging case with the flexible one. To constrain price, flexibility quantified P_F (red) by Equation (4.5) must be satisfied. The required load reduction at a given internal is achieved through the difference between modified charging profile (blue) and the reference case profile (cyan).

Figure 4.8 (a) illustrates the difference in aggregated charging profile between the reference case and the flexible case for satisfying the required flexibility. It is observed that by engaging flexible charging, the proposed price constraining mechanism displaces peak consumption over time to constrain price to the specified limit $\overline{\lambda^*}$. Given this flexible EV charging profile, in Figure 4.8(b) it is observed that the cumulative load does not result in grid congestion. As a result price spikes are successfully mitigated.

4.4.6 Simulation results flexible loads

Thus far we have considered energy communities having either only electric heat pumps or only electric vehicles. As we undergo the energy transition, it is likely that communities will adopt both these electricity-driven technologies simultaneously. To investigate the impact on the grid power loading for such a scenario we examine the results of this simulation case study. In this study, we consider an energy community of 25 households, and each household in this community has both an electric heat pump and an electric vehicle. For this simulation, the grid has a capacity of 26 kW. It should be noted that these values are selected for illustrative purposes and for underscoring the impact of cross-sectoral electrification on under-dimensioned distribution grids. As electricity power demand beyond this limit will remain unsatisfied due to grid congestion, it will result in lost load and give rise to price spikes.

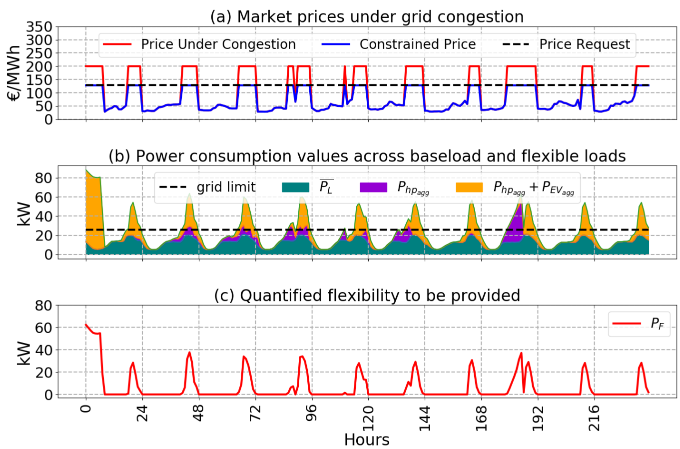

Figure 4.10: Market and Grid Impacts (a) Price Spikes (b) Cumulative Grid Load (c) Required Flexibility

Figure 4.10 illustrates the reference case which is generated by scheduling electric resources in a non-price responsive manner. It is observed that in this reference load case, vehicle charging and heating power consumption results in a significant increase in the cumulative demand as computed using Equation (4.4). This cumulative load, as seen in Figure 4.10 (b), exceeds the grid limit thereby causing grid congestion. The corresponding price spikes are observed in Figure 4.10 (a) (red). It is also noticed that while this excess of electric demand is due to both vehicle charging and heat pumps, it is the former that significantly outstrips the other. Owing to initialization effect, an initial peak load is observed due to electric vehicle charging. In contrast, a peak in electric heat pump power consumption occurs towards the end of the simulation horizon. This is as an end-point effect.

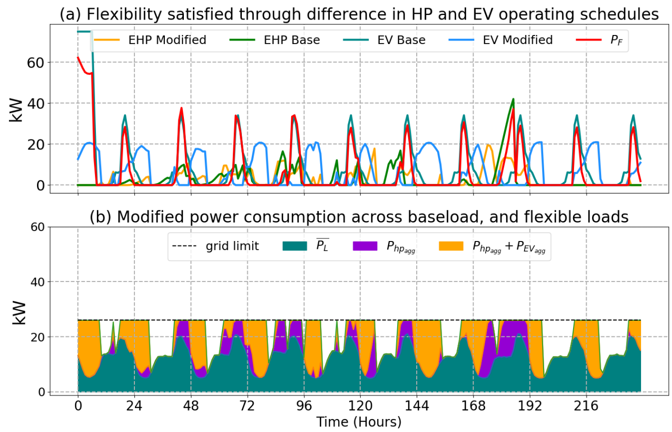

Figure 4.11: Price Constraining and Reduced Load (a) Updated Flexible Load Schedule (b) Updated Cumulative Grid Load

Similar to previous simulations, the community enters into flexibility contracts with flexible load aggregators for constraining price by flexibly scheduling their loads. The price limit is again set to €128/MWh and the flexibility required to constrain price is computed through Equation (3.7). This profile is illustrated in Figure 4.10 (c) and the corresponding constrained price is shown in Figure 4.10 (a) (blue).

The aggregator for satisfying the value P_F schedules the load in a price-responsive manner, as indicated in Figure 4.11 (a). Flexibility requests P_F are indicated in red, and are satisfied through the combined re-scheduling of heat pumps and electric vehicle operation by evaluating Equation (4.5d). This ensures that the aggregated difference between the reference and modified operation of the EV fleet charging and TCL operation, satisfy the flexibility requests. When operated in a price-responsive manner, the aggregator schedules the operation of the electric heat pumps such that the households are pre-heated. Similarly, electric vehicles are charged such that their aggregate charging do not result in peak loads.

With the modified load profiles for EVs and electric heat pumps determined, the aggregator in coordination with the DSO clears the market. As the new cumulative load profiles as illustrated in Figure 4.11 (b) do not exceed grid capacity, electricity price is constrained. Thus the effectiveness of the price constraining mechanism in coordinating flexibility to mitigate price spikes is demonstrated.

4.5 Yearly summary results

Thus far, we have only considered flexibility that is provided from demand to limit price rise. However, cases arise when the price limit is rather conservative or the demand flexibility alone may not be able to successfully constrain price. In these cases, a community energy storage can provide the required flexibility in combination with flexible EV charging and heat pump operation. To estimate the size of the storage required for constraining price, Equation (4.5) is updated to include a storage sizing term in the objective function and additional storage constraints in the power balancing equations. This simulation is analyzed over a period of a year to account for seasonal variations in heat pump operation and variability in electricity price. Daily charging profiles for the EVs are assumed to be constant over the year.

In this yearly simulation, seven scenarios are investigated. For the first scenario, the electrification of transport and space heating is not considered. Storage is required for constraining price given the reference baseload profile. For the remaining scenarios, load inflexibility and flexibility are considered alternatively across the integration of only electric vehicles, only electric heat pumps and their combined operation. This comparative simulation study is performed for a community of 10 households. To estimate the storage capacity and its subsequent operation, the following parameters are assumed: annualized cost of storage (d) is €8.5/kW, the storage time constant (τ) is 1.5. The data used for simulating the electric heat pump and the electric vehicle operation is similar to that described in Section 4.4.1 and Section 4.4.2.

Additionally, for the simulations, it is assumed that the price limit $\overline{\lambda^*} =$ €100/MWh. The decision for this particular price limit is stated in Chapter 1, where electricity price above €100/MWh are defined as extreme events. Lastly, we investigate the impact of price limits, and demand flexibility on storage sizing and cumulative load duration curves experienced by the energy community.

4.5.1 Storage sizing for constraining price

Figure 4.12, illustrates the required sizing of the community electric energy storage to constrain price under different scenarios. We begin first with the scenario where only the baseload is considered. As the integration of electric vehicle charging and electric heat pump loads is not considered here, it is referred to as the reference or 'ref' scenario. In this scenario, the grid power limit for a community of 10 households is set equal to 8 kW.

Given the price limit, the DSO then estimates the flexibility that an aggregator must provide. The aggregator given the flexibility profile that is must satisfy, accordingly invests in the required storage system. In the absence of additional loads, based on the price and load profiles, the optimal size of the storage required to constrain price is 56.5 kWh.

For the 'EVNonFlexCase' scenario, each home owner in the community purchases an electric vehicle. The electric vehicles are charged at households in an inflexible manner which increases the net demand in the grid. As a result the frequency of grid congestion increases. For the yearly simulation in this scenario, to constrain price to the specified limit, the storage size required is 92 kWh. This increase in storage capacity requirements reflects the significant magnitude of increase power consumption attributable to electric vehicle charging.

A contrasting insight is observed through the 'EVFlex' scenario, where the EV owners charge their vehicles flexibly. In this scenario, the size of the storage for alleviating

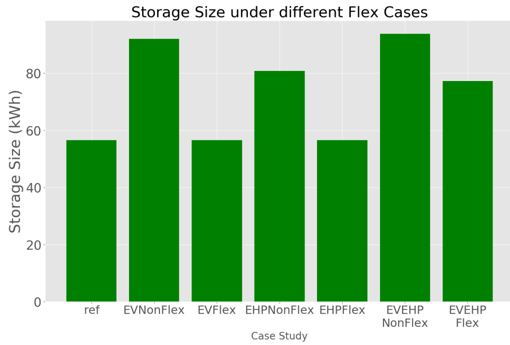

Figure 4.12: Storage Size for different flexibility scenarios

the number of hours of grid congestion significantly decreases. The new storage size with flexible EV charging is the same as in the 'Ref' scenario. This is because during periods of peak load, the storage discharges to satisfy the load. For subsequent hours when the load is relatively low and electricity price is favorable, the electric storage charges. This similar trend is observed in the scenarios when only electric heat pumps are integrated additionally to the baseload. Scenarios 'EHPNonFlex' and 'EHPFlex' illustrate the storage size required for constraining price to the limit $\overline{\lambda^*}$ when the electric heat pumps operate in a inflexible and flexible manner respectively. It is noted that the storage size in the two scenarios differ by 24 kWh with the storage size requirement in the inflexible scenario being 81 kWh.

Finally, the scenarios in which both heating and transport are electrified is considered. This is represented through the 'EVEHPNonFlex', and 'EVEHPFlex' scenarios. In the inflexible scenario the cumulative load requires the DSO to additionally reinforce the grid. Furthermore, to constrain price to the limit, the aggregator also needs an extremely large storage size of 94 kWh. This storage size is the largest amongst all the scenarios. In contrast, when these loads are used in a flexible manner the storage size is limited to 77 kWh.

4.5.2 Load duration curves

Additionally, to the storage size requirements for constraining price, the corresponding load duration curves under inflexible and flexible load scheduling are also investigated. For this the same grid limit is considered across the seven scenarios, and the observed load profiles are illustrated in Figure 4.13. Firstly, it is observed that the maximum load value with non-flexible charging of electric vehicles and heat pump operation (32 kW) is 4 times the maximum load for the reference baseload scenario. Second, the flexibility provided by the loads contributes to a flattening of the curve at the grid limit. This flattening of the demand contributes to constraining of the price, and mitigates the grid congestion.

For periods where flexible loads alone are incapable of providing the required flexibility, their operation can be complemented by discharging of the storage. While

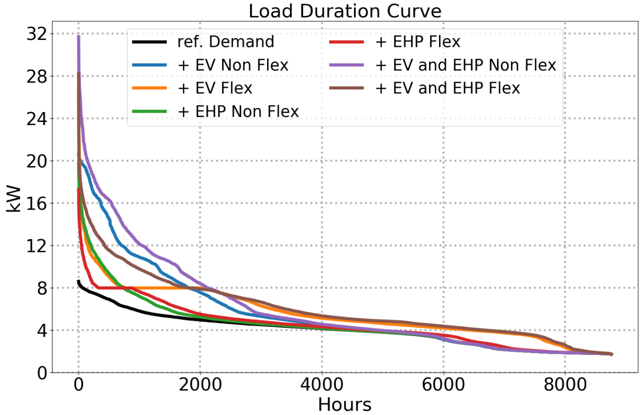

Figure 4.13: Load Duration Curves for different flexibility scenarios

storage operation is not illustrated in Figure 4.13, it is due to their discharging that the load magnitudes are able to exceed the grid limit.

Lastly, in the scenario, where both electric vehicles and electric heat pumps offer flexibility, the magnitude of the load duration curves are on average reduced. However, it is also observed that the highest load magnitude for this curve is higher in comparison to that of a scenario with only a single flexible resource. The increased electricity demand corresponds to periods where both EVs and heat pumps consume power simultaneously. Satisfying these loads may result in multiple consecutive time periods where a storage needs to discharge. Consequently, this would result in larger storage capacity requirements for constraining price.

4.6 Conclusion

In this chapter we have extended our proposed formulation and institutional arrangement from Chapter 3 to account for flexible demand. The flexible demand considered here is from space heating, and transport, two sectors that are transitioning to be powered by electricity. However, electrification of sectors results in an increase in cumulative power consumption across an energy community. This increased power consumption can subsequently increase the frequency with which grid power limit are violated. For electricity markets with locational price, extreme price events would thus become routine.

The efficacy of the proposed price constraining mechanism is investigated under different scenarios. For constraining price, the required flexibility is provided by flexibly operating electric heat pumps and scheduling electric vehicle charging. Thus, load reduction is supplied by deviating from an expected reference operational profile for these resources. The economic benefit derived by the energy community through this mechanism depends on a number of factors. These include, congestion costs or price of lost loads that define the price spike, the grid power capacity, the size of the energy community and the corresponding reference load profile.

We also investigated the scenario where demand flexibility was insufficient to constrain price, and hence a community energy storage was additionally required. Over a one-year period, the optimal storage size required to constrain price to $\overline{\lambda^*} =$ €100/MWh was computed assuming both inflexible and flexible electric load. Except the situation in which both the EVs and EHPs are used in an inflexible manner, the need for grid reinforcement by the DSO is mitigated. As expected, storage requirements are higher in the case of inflexible power demand. For cases where demand-side flexibility is available, the storage reverts back to its reference scenario capacity. Thus, these scenarios exhibit the efficacy of the proposed mechanism.

Results generated in this chapter can be extended in several new directions. First, the information forecasts over the simulation period are assumed to be completely deterministic. In future work, uncertainties arising from ambient temperatures, dwelling parameters, consumer temperature preferences, driver usage profiles and distance traveled can be considered in a probabilistic manner. Second, a sensitivity analysis can be conducted on storage sizing with respect to its cost and evolution of its technical parameters. Third, we have considered a single aggregator to be knowledgeable about a multitude of data pertaining to heat pump and vehicle usage profiles. In practice, this type of approach may not be feasible as it bestows significant authority in a single entity, making the system have a single point of failure. To address this situation, it is possible for multiple aggregators, specializing in a particular source of flexibility and having their own consumers interacting in this type of local market. For ensuring privacy in this type of market, a distributed scheme for communication will be required, and is the subject of the next Chapter.

5

Flexibility coordination in a multi-aggregator local electricity market for constraining price volatility

5.1 Introduction

Concurrent with the energy transition, the power system is evolving from being hierarchically organized to being more decentralized. Energy communities and local electricity markets are a prominent feature of this decentralization. In this thesis, it is assumed that price in local electricity markets is based on distribution grid-based locational marginal price (D-LMP). As such all members of a given energy community would be exposed to the same electricity price. Owing to increasing variability and uncertainty of supply-demand balancing, price volatility has increased. To mitigate price spikes in Chapter 4 we have showed that demand-side flexibility is important. The desired flexibility can be provided by multiple aggregators each controlling a resource of which they have specialized knowledge. Hence, in this chapter a modified market mechanism is presented that emphasizes flexibility coordination across aggregators in a scalable manner.

Local electricity markets present a support mechanism to the DSO for grid management. They also provide market access for distributed energy resources that an aggregator may control for generating revenue. The DSO's need for flexibility and the ability of the aggregator to provide flexibility provides the motivation for their coordination in the electric grid. This coordination between the DSO and the aggregator in the context of a local electricity market requires regulatory and policy consideration for market design, which for the European Union has been reviewed in [122, 123].

From local flexibility markets literature, it is observed that an aspect by which market designs differ pertains to the entity responsible for clearing the market. Studies presented in [41, 124, 125] present a market design where the aggregator is responsible for market clearance. The aggregator in this market optimally schedules flexibility to either maximize its revenue or to satisfy the DSO's flexibility requirements. In contrast, [126] proposes a market design where the DSO assumes the role of a 'neutral market facilitator'. Based on this design [40, 87] proposes a mechanism where the DSO operates and clears a secondary local flexibility market to account for any grid contingencies that occur during the clearing of the day-ahead market.

An approach for clearing local markets is through the application of the transactive energy framework [127]. Transactive energy is a distributed market clearing mechanism that manages the generation, consumption and flow of electric power within a power system while accounting for grid reliability constraints [128]. Application of a distributed control scheme enables a system to be decomposed into modules that are defined by their local constraints. It also reduces the communication overheads between modules thereby improving the scalability of the system. Previously, the transactive energy framework has been applied to enable aggregators in energy communities to reduce peak demand and for resolving real-time congestions [129–131]. Moreover, the implementation of the transactive energy framework and sharing of flexible resources provides increased economic benefits and reduces emissions from electricity consumption [132, 133]. This has been reported both at the industrial [134] and residential [135] levels.

By clearing the electricity market in a distributed manner, autonomous decision making and interaction between market participants is facilitated. A comprehensive review of distributed algorithms applied to power system economics is presented in [136, 137]. The Alternating Method of Multipliers (ADMM) [138] is an often cited approach for clearing electricity marketing using distributed optimization. The method solves convex optimization problems by using a decomposition-coordination approach. The benefit of applying ADMM is that it guarantees convergence for convex problems by combining the robustness of augmented Lagrangian formulation with the distributed computational efficiency of dual decomposition. This thesis applies ADMM for coordinating flexibility in the energy community thereby supporting interaction between the DSO, aggregator and community members. Previously the application of ADMM for clearing local energy markets have been investigated in [69, 139, 140]. In this work the DSO interacts with the aggregator of electric vehicles and electric heat pumps, to access flexibility services for grid management. Furthermore these actors interact with each other without having the need to reveal information about network parameters or the consumer profiles. Similarly, [141] presents a distributed scheduling approach for the operation of flexible resources through which a DSO may perform congestion management.

Nevertheless, previous works on local flexibility markets and distributed optimization aimed at flexibility coordination, have not explicitly considered the issue of increasing electricity price volatility. We address this research gap by answering the following question: *To what extent can flexibility be coordinated in a scalable manner across multiple aggregators for constraining price in local electricity markets*? To answer this question we build on our work presented in Chapter 3 and Chapter 4. In contrast to Chapter 4 that assumes centralized ownership and control of flexible resources, this Chapter focuses on flexible resources that are dispersed across multiple aggregators. Aggregators have specialized knowledge about the resources they control and have information about the preferences and profiles of their consumers. For coordinating the desired flexibility to constrain price to a specified upper limit, aggregators interact with each other in a distributed manner. Through this distributed coordination mechanism aggregators in conjunction with the DSO are able to mitigate grid congestion and reduce price volatility. Secondary insights generated in this chapter provides an overview of the contribution of each aggregator to constraining electricity price and their possible income for it.

The rest of the chapter is organized in the following manner: In Section 5.2 we present the formulation for coordinating flexibility using ADMM to satisfy the load reduction required to constrain price. Section 5.3 illustrates the preliminary organization of the electricity market, highlighting the required information and monetary flows between the energy community, aggregators, and DSO for coordinating flexibility. The data and case-study based simulations are presented in Section 5.4. Drawing on the insights generated we provide concluding remarks and directions for future research and presented in Section 5.5.

5.2 Price constraining using distributed optimization

For reducing the impact of increasing price volatility, using Duality theory in Chapter 3 we placed explicit constraints on price value in local electricity markets. Corresponding equations are expressed in Equation (3.5) - Equation(3.7). Execution of this optimization problem quantifies the time-varying flexibility $P_F[t]$ required to limit price rise. This flexibility is provided through a combination of re-scheduling of flexible resources and the dispatch of electric storage systems.

In previous chapters we have assumed that a single aggregator is responsible for providing the required flexibility. However, there are a couple of shortcomings with this market design. First, a single aggregator represents a single node of failure which increases system vulnerability. Moreover, this aggregator must also undertake significant overheads for maintaining data communications with a large number of consumers. To address these concerns, in this Chapter we consider the presence of multiple aggregators that specialize in the management of each independent flexible resource type.

The DSO as the market operator, when provided with a price limit by the energy community, computes the flexibility required to constrain price. To compute the required flexibility P_F, the DSO uses deterministic forecasts of the baseload profile, and the aggregate power consumption of electric vehicle charging and electric heat pump operation when they are scheduled inflexibly. The centralized formulation for providing flexibility to constrain price over a simulation horizon T is expressed in Equation (5.1)

$$\min_{P_G, P_R, P_S} \sum_{t=1}^{T} f_G(P_G[t]) + f_R(P_R[t]) + f_S(P_S[t]) \tag{5.1}$$

subject to:

$$g_G(P_G[t]) = 0 \tag{5.1a}$$

$$g_R(P_R[t]) = 0 \tag{5.1b}$$

$$g_S(P_S[t]) = 0 \tag{5.1c}$$

$$h_G(P_G[t]) \leq 0 \tag{5.1d}$$

$$h_R(P_R[t]) \leq 0 \tag{5.1e}$$

$$h_S(P_S[t]) \leq 0 \tag{5.1f}$$

$$P_G[t] + P_S[t] - P_{hp}[t] - P_{EV}[t] - P_L[t] = 0 \quad (\lambda_1) \; \forall t \in T \tag{5.1g}$$

$$P_S[t] + (P_{hp}^{ref}[t] - P_{hp}[t]) + (P_{EV}^{ref}[t] - P_{EV}[t]) - P_F[t] = 0 \; (\lambda_2) \; \forall t : P_F[t] > 0 \tag{5.1h}$$

The objective of Equation (5.1) is to satisfy electric demand at the lowest cost. Electric power is drawn from the main grid P_G and the cost of power consumption is evaluated through the function $f_G(P_G)$. This function is the same as expressed in Equation (4.5). The flexible loads of electric vehicle charging and electric heat pump operation are expressed through the set variable $P_R \in \{P_{EV}, P_{hp}\}$. As it is assumed that the operation of these loads do not have a cost associated with them, the function $f_R(P_R) = 0$. This assumption is also extended to the operation of electric storage and thus $f_S(P_S) = 0$.

The equality and inequality constraints associated with the power consumption from the main grid, flexible loads, and electric storage operation are denoted through Equation (5.1a) - Equation (5.1f) respectively. With respect to power consumption from the main grid, only the inequality constraints are active and reflect the grid capacity limits. Constraints corresponding to the scheduling of the flexible loads are expressed through Equations (4.2a) - (4.2f) (for electric heat pump) and though Equations (4.3a) - (4.3d) (for electric vehicles) of Chapter 4. Lastly, the storage constraints are specified in Equation (4.8).

Equations (5.1g) - (5.1h) express the constraints that are associated with load balancing and satisfying the flexibility requests. The dual variables associated with these constraints are denoted as λ_1 and λ_2. As these constraints couple the variables of resources (or sub-systems) that may be owned and operated by independent entities, they are called *coupling constraints*. In Equation (5.1h) the terms P_{hp}^{ref} and P_{EV}^{ref} correspond to the power consumption by electric heat pumps and electric vehicles when they are scheduled inflexibly.

The aggregate flexible resources expressed in this centralized formulation, can be decoupled into modular units using distributed optimization. In addition to the import of power from the main grid, these units represent the independent aggregators that participate in local electricity markets. The DSO being the market operator is responsible for coordinating with these aggregators and clearing the market.

Optimal exchange ADMM for coordinating flexibility

To facilitate the coordination between multiple aggregators, DSO, and the energy community, the Optimal Exchange ADMM algorithm is used. This algorithm summarized in [142] is essentially a *tâtonnement* or *price adjustment* process. It represents a mechanism, where an actor adjusts its consumption or generation in response to price. Under this setting, the DSO as the electricity market operator by adjusting price influences an aggregator's commitment for satisfying the required flexibility. As this price converges to the optimal value, the commitment of each aggregator for providing flexibility is determined.

5

ADMM is implemented iteratively and the algorithm terminates either when the maximum number of iterations is reached or when the error threshold criteria is satisfied. In each iteration, the primal variable of Equation (5.1), are updated. This is achieved by executing the sub-formulations that correspond to each individual aggregator and for power import from the main grid. These updates are computed as follows:

Main grid power import update:

To update the main grid power import variable, P_G^{k+1}, the following sub-formulation is executed.

$$\underset{P_G}{\operatorname{argmin}} f_G(P_G) + \lambda_1^k(P_G) + \underbrace{\frac{\rho_1}{2}(P_G - (P_G^k - P_{avg}^k))^2}_{\text{Deviation from coupling constraint}} \tag{5.2}$$

subject to:

$$g_G(P_G[t]) = 0 \quad \forall t \in T \tag{5.2a}$$

$$h_G(P_G[t]) \leq 0 \quad \forall t \in T \tag{5.2b}$$

In Equation (5.2), the objective function $f_G(P_G)$ is augmented with a lagrangian term λ_1 associated with the power balancing coupling constraint (Equation (5.1g)).

Additionally, a penalty term ρ_1 is introduced that penalizes the deviation of variable P_G from this coupling constraint. To achieve this a distributed averaging term P_{avg} associated with the load coupling constraint is introduced. By minimizing the deviation of P_G from the distributed average, the algorithm ensures that optimal power is imported from the main grid for satisfying demand. Thus, the execution of this formulation over the defined constraint space, results in the update of the grid power import variable at iteration k.

Flexible load update:

Similarly, the flexible load variable P_R at iteration k is updated as follows:

$$\underset{P_R}{\operatorname{argmin}} f_R(P_R) + \lambda_1^k(-P_R) + \frac{\rho_1}{2}(P_R - (P_R^k + P_{avg}^k))^2 + \underbrace{\lambda_2^k(-P_R) + \frac{\rho_2}{2}(P_R - (P_R^k + P_{F_{avg}}^k))^2}_{\text{if } P_F[t] > 0} \tag{5.3}$$

5

subject to:

$$g_R(P_R[t]) = 0 \quad \forall t \in T \tag{5.3a}$$

$$h_R(P_R[t]) \leq 0 \quad \forall t \in T \tag{5.3b}$$

In Equation (5.3), the objective function additionally comprises of the lagrangian term λ_2 that corresponds to the flexibility balancing constraint (Equation (5.1h)). Furthermore, the deviation of the load scheduling from this coupling constraint is also penalized via the penalty factor ρ_2. The variable $P_{F_{avg}}$ is the distributed averaging term associated with satisfying the flexibility requests. By solving Equation (5.3) over the set of equality and inequality constraints pertaining to electric vehicles and electric heat pump operations, P_R^{k+1} is computed.

Electric storage update:

As electric storage is integral to both load balancing and satisfying the required flexibility, its corresponding variable P_S^{k+1} is updated similarly to flexible loads.

$$\underset{P_S}{\operatorname{argmin}} f_S(P_S) + \lambda_1^k(P_S) + \frac{\rho_1}{2}(P_S - (P_S^k - P_{avg}^k))^2 + \underbrace{\lambda_2^k(P_S) + \frac{\rho_2}{2}(P_S - (P_S^k - P_{F_{avg}}^k))^2}_{\text{if } P_F[t] > 0} \tag{5.4}$$

subject to:

$$g_S(P_S[t]) = 0 \quad \forall t \in T \tag{5.4a}$$

$$h_S(P_S[t]) \leq 0 \quad \forall t \in T \tag{5.4b}$$

Thus by solving Equation (5.4) over the set of constraints specified by the storage operation, the variable P_S at iteration k is updated. As P_S is assumed to be bi-directional, it captures both the charging and discharging operation of the storage unit.

Once each of these sub-formulations are executed, their associated primal variables are updated. These updated variables are then sent to DSO. The DSO, using these values subsequently updates the distributed averaging terms and the dual values associated with the coupling constraints. This is expressed as follows:

Updating distributed averaging and dual variable of coupling constraints:

$$P_{avg}^{k+1}[t] = \frac{P_G^{k+1}[t] + P_S^{k+1}[t] - P_{hp}^{k+1}[t] - P_{EV}^{k+1}[t] - P_L[t]}{N_{Opt}} \quad \forall t \in T \tag{5.5}$$

$$\lambda_1^{k+1}[t] = \lambda_1^k[t] + \rho_1 P_{avg}^{k+1}[t] \quad \forall t \in T \tag{5.6}$$

Through Equation (5.5) the update for the distributed averaging term P_{avg}, associated with the load balancing, is computed. This term normalizes the value of coupling constraint by the number of optimization variables N_{Opt} involved in it. After determining P_{avg}, it is subsequently used in updating the dual variable λ_1 expressed in Equation (5.6).

Similarly, the variables $P_{F_{avg}}$, and λ_2 associated with the coupling constraint for satisfying flexibility requests are updated. This is expressed through Equation (5.7) and Equation (5.8).

$$P_{F_{avg}}^{k+1}[t] = \frac{P_S^{k+1}[t] + (P_{hp}^{ref}[t] - P_{hp}^{k+1}[t]) + (P_{EV}^{ref}[t] - P_{EV}^{k+1}[t]) - P_F[t]}{N_{Opt_F}} \qquad t : P_F[t] > 0 \tag{5.7}$$

$$\lambda_2^{k+1}[t] = \lambda_2^k[t] + \rho_2 P_{F_{avg}}^{k+1}[t] \quad t : P_F[t] > 0 \tag{5.8}$$

These variables are only updated for time instants where the flexibility request P_F is non-zero. In Equation (5.7) at iteration k, the storage discharge and deviation of flexible load from a reference profile to satisfy required flexibility is evaluated. This value is then normalized by N_{Opt_F}, which represents the number of optimization variables in the flexibility balancing constraint. The distributed averaging term $P_{F_{avg}}$ thus computed is used for updating λ_2 in Equation (5.8). Once, both λ_1 and λ_2 are updated, these values are distributed across the optimization sub-formulations. This marks the end of one iteration.

Evaluating residual terms:

At the end of each iteration, residual terms res_1 and res_2 associated with the load balancing and flexibility balancing coupling constraints respectively are evaluated. These residual terms are expressed as follows:

$$res_1[t] = \sqrt{(P_G[t]^{k+1} + P_S[t]^{k+1} - P_{hp}[t]^{k+1} - P_{EV}[t]^{k+1} - P_L[t])^2} \quad \forall t \in T \tag{5.9}$$

$$res_2[t] = \sqrt{((P_{hp}^{ref}[t] - P_{hp}[t]^{k+1}) + (P_{EV}^{ref} - P_{EV}^{k+1}[t]) + P_S[t]^{k+1} - P_F[t])^2} \quad t : P_F[t] > 0 \tag{5.10}$$

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If the value for both the residual terms converges to a value $\epsilon \leq 10^{-2}$ and/or if the maximum number of iterations max^{iter} is reached, then ADMM algorithm terminates. Otherwise, the next iteration initiates, until convergence is attained.

Algorithm summary

The ADMM algorithm to coordinate the supply of flexibility is summarized as follows:

This algorithm readily casts itself to a market design paradigm. In the next Section, we illustrate the interactions between the various actors that participate in the local electricity market.

The ADMM algorithm is implemented in Python using the CPLEX 12.7 package. A sequential approach is adopted for updating the primal and dual variables. In this sequential update approach each primal variable is updated one after the other. Once all the primal variables are updated, using distributed averaging the dual variables are also updated sequentially and the next iteration of the algorithm ensues. It must be noted that it is possible to enhance the computation time required for updating the variables through parallel processing. However, investigating methods for enhancing computation time for the ADMM algorithm is beyond the scope of this thesis.

Algorithm 1: ADMM for Distributed Coordination of Flexibility

Input from Price Constraining Formulation: P_L, P_{hp}^{ref}, P_{EV}^{ref}, P_F
Initialize *Distributed Optimization Variables*:
Primal Variables: P_G, P_R, P_S where $P_R \in \{P_{hp}, P_{EV}\}$
Dual Variables: λ_1, λ_2
Penalty Values: ρ_1, ρ_2
Result: P_G^*, P_R^*, P_S^*
for $k = 1; k \leq max^{iter}; k++$ **do**
  Step 1A: Update *Main Grid Power Import* Variable (P_G):
    Execute Equation (5.2)
  Step 1B: Update *Flexible Load* Variables (P_R):
    Execute Equation (5.3)
  Step 1C: Update *Electric Storage* Variable (P_S):
    Execute Equation (5.4)
  Step 2A: Update *Distributed Average for Load Balancing* (P_{avg}):
    Execute Equation (5.5)
  Step 2B: Update *Distributed Average for Satisfying Flexibility* ($P_{F_{avg}}$):
    Execute Equation (5.7)
  Step 3: Update *Dual Variables* (λ_1, λ_2) of Coupling Constraints:
    Execute Equation (5.6)
    Execute Equation (5.8)
  Step 4: Compute *Residual Variables* (res_1, res_2):
    Execute Equation (5.9)
    Execute Equation (5.10)
  if $\mathbf{max}(res_1)$ & $\mathbf{max}(res_2) \leq \epsilon$:
  break
  else:
  continue
end

5.3 Market design and information flow structure

In this Section, the market organization required for coordinating flexibility in the local electricity market to constrain price is presented. Figure 5.1 illustrates the information flow between the aggregators, the energy community, and the DSO.

The DSO, in the proposed market design assumes the role of a 'neutral market operator'. Given this role, the DSO has knowledge about electricity price bids, and network configurations. Furthermore, it is assumed that the DSO generates a deterministic forecast of the power consumption by the energy community. These demand forecasts constitute a baseload component, and the reference case power consumption by flexible resources when they are scheduled inflexibly. The reference case power consumption by electric vehicles is based on the assumption that EV owners always charge their vehicles with the objective of maximizing its state of charge (SoC). For electric heat pumps, the reference case power consumption is estimated based solely on the objective of compensating heat loss to the ambient surroundings. The estimation of these reference load profiles for the flexible resources is presented in Chapter 4 Section 4.2.

The consumers in the local flexibility market have a common objective of minimizing their exposure to increasing price volatility. They thus unite to form an energy community. To screen themselves from price spikes, the community agrees on an upper price limit that represents their maximum willingness to pay for electricity. This

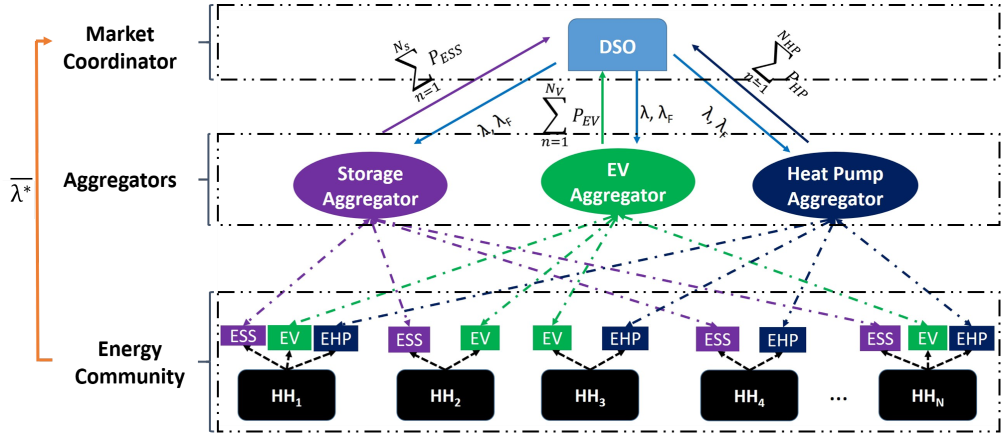

Figure 5.1: Market Design for Constraining Price using ADMM

price limit λ is communicated to the DSO as represented in Figure 5.1. The DSO on receiving this price limit computes a time varying flexibility signal, and broadcasts this to a set of aggregators. Aggregators that are willing to provide this flexibility at the price λ then collectively enter into a flexibility contract with the energy community.

Aggregators, in order to provide flexibility, need to establish a communication and flexible load control channel across the community. In Figure 5.1 this is indicated through dotted arrows. At instances, when load reduction is required, the aggregator schedules the flexible resources in accordance with satisfying the flexibility requests. Each aggregator then independently shares the operational schedule of the flexible loads and storage with the DSO. This is depicted with solid lines between the DSO and the aggregator.

In contrast to the previous coordination mechanisms presented, the DSO does not directly communicate the time-varying signal $P_F[t]$ with the set of aggregators. Rather, drawing on the distributed coordination approach, the DSO translates the primal variables of generation, demand and storage dispatching into dual price variables of λ_1, and λ_2. These price signals associated with load balancing and satisfying flexibility are communicated to the aggregators.

Using the Optimal Exchange ADMM algorithm over a time horizon T, for instances where $P_F[t] = 0$, the local flexibility market is cleared based on the price λ_1. The import of power from the main grid, the scheduling of flexible load and storage by the aggregators, is coordinated through an iterative process that satisfies the balancing of power supply and demand. Alternatively, at time instants where $P_F[t] > 0$, aggregators based on the signal λ_2 in addition to balancing demand, must coordinate amongst themselves iteratively to satisfy the flexibility request. It is the responsibility, of the DSO to oversee the convergence of the algorithm. For each iteration, in the distributed coordination mechanism, the DSO evaluates the residuals of the load balancing and flexibility balancing coupling constraints. Based on the residual magnitudes, the DSO updates the price vectors, and the iterative process terminates when the price updates are negligible. At this point, the optimal values for the generation, storage operation, and flexible load scheduling over the time horizon T is determined, and the market is cleared. Once the market is cleared, the aggregators are remunerated by the energy community in accordance with the scheme proposed in Chapter 3.

5.4 Simulation modeling studies

To illustrate implementation of the proposed distributed coordination mechanism for constraining price, we present the results of simulated case studies. For each case study, information about simulation data and system parameters are provided. The contribution of each aggregator towards satisfying flexibility request is highlighted along with their potential income for this service.

5.4.1 Flexibility from homogeneous flexible resources

Simulations are presented in an increasing order of complexity. First, we consider the case in which flexibility is provided from the same type of flexible resource. Hence, in the following three simulations price constraining is achieved through only storages, only EVs, or only electric heat pumps. The simulation horizon T considered for these simulations is 72 hours.

Only storages

Two households with their individual baseload patterns are considered in this illustrative example. These households mutually agree that they are not willing to pay an electricity price in excess of €50/MWh. Through their communication with the DSO, the two households determine the amount of flexibility required to achieve the price constraining. Being a simple case, it is assumed that the flexible resource of each household is subsequently scheduled by its independent aggregator. Consequently, the ratio between the aggregators and households is 1:1. Simulation data for the baseload is obtained from [65] and is scaled to account for two households. Remaining simulation data and parameters are provided in Table 5.1.

Parameter	Value
Power Import Capacity ($\overline{P_G}$)	2 kW
Storage Capacity (E_{SS_1}, E_{SS_2})	4 kWh, 6 kWh
Initial SoC (SoC_1, SoC_2)	2 kWh, 3 kWh
Storage Power Charge/Discharge Capacity ($\overline{P_{S_1}}$, $\overline{P_{S_2}}$)	2.6 kW, 3 kW
ρ_1	35
ρ_2	40

Table 5.1: Only Storage Simulation Parameters

Figure 5.2(a) illustrates the volatile electricity market price (red), the price limit (black), and the constrained price (blue). Constraining of electricity price quantifies the flexibility required (red) in Figure 5.2(b). From this figure, it is observed that at

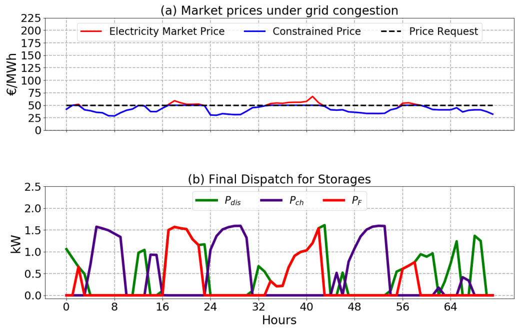

Figure 5.2: Price Constraining Using Only Storages with ADMM

instances when flexibility is requested, the two storages coordinate their dispatch to satisfy it. At the remaining time instants, the households have the option to either self-consume or sell the electricity back to the grid.

In Figure 5.3, the convergence of the ADMM algorithm is illustrated. Convergence is determined by computing the maximum residual over a given time horizon of the coupling constraints associated with the load (blue) and flexibility (orange) balancing. These values are computed as variable res_1 and res_2 in Section 5.2. Figure 5.3 presents the number of iterations on the x-axis and a log-scale y-axis is used for presenting the residual magnitude. It is observed that over a few hundred iterations for both the coupling constraints, the computed maximum residual attains a value lower than 10^-2, which is the threshold limit. At this point, the algorithm converges to an optimal value. Lastly, it must be noted that the rate of convergence of the ADMM algorithm is sensitive to the choice of the penalty parameters ρ_1 and ρ_2.

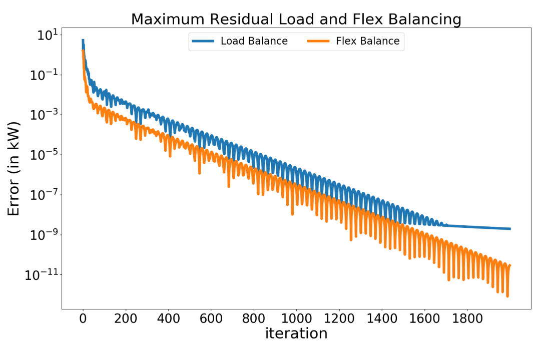

Figure 5.3: Residual Magnitudes for Storage Coupling Constraints

Only electric vehicles

In this case study, flexibility is provided from the charging of electric vehicles that are connected to households. It is assumed that the electric vehicles can only consume power from the grid and not inject power. Under this operating condition, electric vehicles provide flexibility by deviating from a reference power consumption profile, while satisfying the EV owner's driving constraints. In the simulation considered, two households with EVs are assumed to agree on a maximum electricity price of €128/MWh. The data and parameters used in this simulation are presented in Table 5.2.

Parameter	Value
Power Import Capacity ($\overline{P_G}$)	2 kW
Storage Capacity (E_{V_1}, E_{V_2})	24 kWh
Initial SoC ($E_{V_1}[t_0]$)	20 kWh
Distance traveled by EV 1 (d_1)	35.2 km
Departure time EV 1	9:00h
Arrival time EV 1	18:00 h
EV 2 Initial SoC ($E_{V_2}[t_0]$)	22 kWh
Distance traveled by EV 2 (d_2)	24.8 km
Departure time EV 2	9:00h
Arrival time EV 2	16:00 h
Maximum charging power capacity for EVs (P_V)	3 kW
Charging efficiency for EVs (η_c)	1
Discharging efficiency for EVs (η_d)	0.2
Congestion Cost	€250/MWh
Maximum Price Requested	€128/MWh
Simulation Horizon (T)	72 Hours
ρ_1	35
ρ_2	40

Table 5.2: Only Electric Vehicles Simulation Parameters

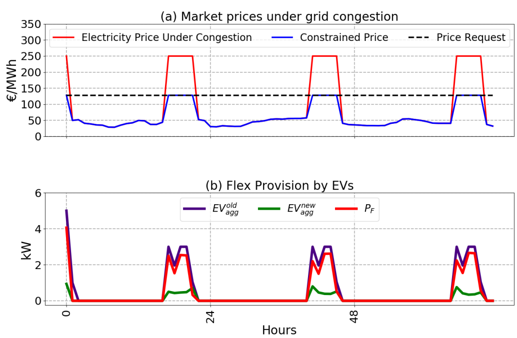

Figure 5.4: Price Constraining Using Only EVs with ADMM

For this simulation, the EV owner's driving profile is obtained from [31]. Over the simulation horizon, it is assumed that the EV owner's have constant daily departure and arrival times. Furthermore, it is assumed that the EVs are charged only at the EV owner's household. As the EVs discharge while commuting, it is required that they are sufficiently charged for satisfying the daily commute requirements. Once the EV owners arrive back to their household, the vehicles are charged. The EVs can either be charged inflexibly or flexibly. This decision on charging strategy impacts the profile of EV power consumption and subsequently impacts the operation and economics of the distribution grid. This impact is visualized in Figure 5.4.

Figure 5.4 (a) illustrates the electricity price without and with grid congestion. The price spike (red) emerges as a result of grid congestion and reflects the value of the lost load. This price profile is generated when the EVs are charged inflexibly in the reference case. Figure 5.4(b) illustrates the reference case aggregate power consumption (red) by the electric vehicles. Under the reference case, when the EV owners return home after their daily commute they charge their vehicles with the objective of maximizing its state of charge. As a result more power than what is required for their daily commute is consumed. This increased power consumption exceeds the grid power capacity thereby resulting in load that cannot be satisfied. Using the proposed price constraining mechanism, we can address these price spikes and constrain the price to the maximum value that is requested while avoiding grid contingencies.

Price constraining results in the quantification of the required load reduction to be provided during the charging of the electric vehicles. This new aggregate power consumption profile EV_{agg}^{new} (green) emerges as a deviation from the reference case profile. This profile satisfies the load reduction requirement which attains the desired price profile (blue) illustrated in Figure 5.4(a).

Only electric heat pumps

This simulation considers the operation of electric heat pumps that are integrated across two households. Electric heat pumps are responsible for compensating the heat that is lost to the ambient surroundings. To do so, water in a condenser tank is heated, and this heat through conductive currents is eventually distributed within the household. The electric power consumed by the heat pump is proportional to the thermal properties (capacity, and conductivity of surfaces) and the household owners minimum temperature preference.

In the reference case, the heat pump is operated with the objective of minimizing electricity consumption alone. As a result the heat pump consumes electricity without taking into consideration electricity price or the state of the distribution grid. Instances can thus emerge where heat pumps consume electricity during high price periods. Additionally, the increase in electricity demand could also result in grid congestion. To reduce their exposure to price spikes, the two households communicate their maximum willingness to pay $\overline{\lambda}$ =€128/MWh to the DSO. The DSO subsequently initiates the distributed price constraining mechanism.

Table 5.3 lists the data used in this simulation. In addition to specifying the thermal properties of the household (based on [112]), the temperature preference of the household owners, and the cost of lost load is provided. Ambient temperatures that

Parameter	Value
Heat Capacity Room ($C_{p,r}$)	810 kJ/°C
Heat Capacity Floor ($C_{p,f}$)	3315 kJ/°C
Heat Capacity Water ($C_{p,w}$)	836 kJ/°C
Heat transfer coefficient between room and ambient ($(UA)_{r,a}$)	28 kJ/°Ch
Heat transfer coefficient between floor and room air ($(UA)_{f,r}$)	624 kJ/°Ch
Heat transfer coefficient between water and floor ($(UA)_{w,f}$)	28 kJ/°Ch
Electric Heat Pump Efficiency (η)	3
Desired Room Temperature (T_r^{ref})	18 °C
Initial room temperature (T_r^{init})	22 °C
Initial floor temperature (T_f^{init})	22 °C
Initial water temperature (T_w^{init})	30 °C

Table 5.3: Only Electric Heat Pumps Simulation Parameters

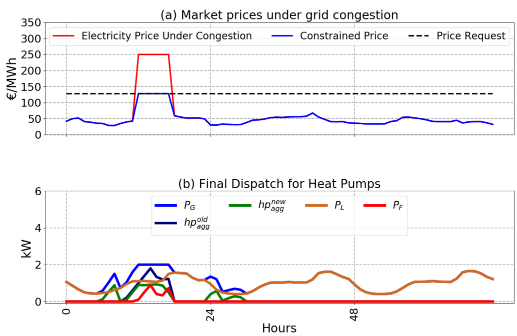

Figure 5.5: Price Constraining Using Only TCLs with ADMM

govern the operation of the electric heat pump are obtained from [66]. The state space equations that capture the thermal dynamics within a household are expressed in Chapter 4, Equations (4.2a) - (4.2f).

Figure 5.5 illustrates the results of price constraining achieved by ADMM to coordinate flexibility provided by the electric heat pumps. From Figure 5.5(b) it is observed that the reference case aggregate power consumption by the electric heat pumps HP_{agg}^{old} (purple) results in grid capacity violation. As a result the load cannot be satisfied. This value of lost load (red) is reflected in Figure 5.5(a). At these time instants, the DSO communicates the amount of load reduction required. The aggregators for the two households then coordinate with each other in a distributed manner through ADMM to determine the new operational profile for the heat pumps. The aggregators now take into consideration the price of electricity. Furthermore, given a time horizon, the aggregators leverage the thermal properties of the household for pre-heating it. Preheating the household enables thermal demand to be moved from one time instant to another. The actions taken by the aggregator results in the determination of the new aggregate electric heat pump operation HP_{agg}^{new} (green) in Figure 5.5(b). Thus through the load reduction provided, the electricity price is constrained and the local electricity market is cleared.

5.4.2 Heterogeneous load aggregators

Thus far, we have focused on case studies where homogeneous flexible resources were responsible for constraining price. However, disparate resources are also able to coordinate among themselves to provide the required flexibility. Hence, in this Subsection we focus on the distributed coordination between heterogeneous demand-side flexible resources.

Simple example

5

In this illustrative example, we consider a community of three households. These households either have a storage, or an electric vehicle or an electric heat pump integrated to them. At time instants when price needs to be constrained, the flexibility aggregated across these households will be used for satisfying the load reduction. For the simulation considered, the price limit is assumed to be $\overline{\lambda}$ =€100/MWh.

The input data used in the simulation is based on values considered in Section 5.4.1. For electric vehicle power consumption the driving profile of Electric Vehicle Owner 1 is assumed from Table 5.2, while for the electric heat pump Table 5.3 data is used. To estimate the reference case power consumption for both these resources, the logic presented in Section 5.4.1 is applied here again. The storage unit is assumed to have a maximum energy capacity and power capacity of 2.2 kWh and 1.5 kW respectively, and an initial state of charge of 1.2 kWh. Lastly, the cost of lost load or grid congestion is assumed to be €250/MWh.

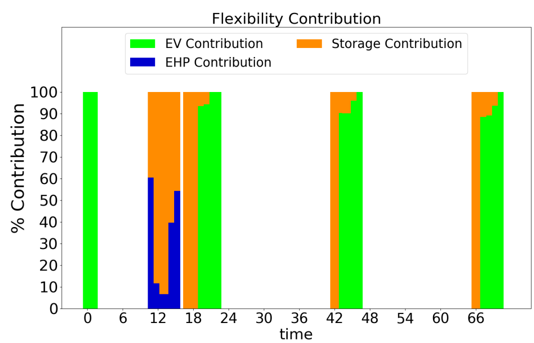

Figure 5.6: Price Constraining Using single Storage, EV, and EHP with ADMM

Figure 5.6 illustrates the contribution of each flexible towards price constraining. The contribution of a resource towards satisfying flexibility is computed as the fraction of the deviation of a flexible load from its reference schedule, or the discharge of a storage, to the total required load reduction. Over the simulation horizon it is observed, that based on a resource's potential it may either satisfy the load reduction by itself or coordinate with other resources to do so.

While this representative community provides an informative overview of the distributed price constraining mechanism with heterogeneous flexible resources, it is rather simplistic. In the next subsection we increase the complexity of the case study by considering a larger system which is simulated over a one year horizon.

Scaled example

With an increase in the scale of the system considered, the number of resources controlled by a given aggregator increases. Given that the simulation horizon is also expanded, it may become infeasible to generate the deterministic forecast for the demand and electricity price for an entire year. Hence, a prominent feature of this simulation case study is the application of a rolling horizon-based Distributed Model Predictive Control (D-MPC) approach.

The D-MPC scheme that has been implemented assumes a deterministic rolling 72-hour forecast horizon. Similar to the previous case studies, over a given 72 hour horizon, using the reference case demand and maximum price limits, the DSO determine the amount of flexibility required. The DSO then communicates this information to the group of aggregators participating in the local electricity market. These group of aggregators then communicate between each other and the DSO to determine the optimal load and storage dispatch profiles for constraining electricity price. As the D-MPC formulation operates under a sliding-window control scheme, only the first 24-hour values of this optimal profile are considered while the remaining are discarded. Furthermore, the state of charge for the storage and EVs, as well as the temperature values for the households are captured at the 24-hour interval. These values in turn become the initial set-points for the next simulation horizon window.

For this case study, we assume that the maximum price limit is €100/MWh and the congestion cost is €250/MWh. The maximum grid capacity is assumed to be 7 kW. Flexible load aggregators are responsible for scheduling of power consumption across 5 heat pumps and 5 electric vehicles. Similarly the storage aggregator is responsible for the dispatch of 5 storage units. Input parameters for simulating the aggregate heat pump power consumption across the community, are based on Table 5.3. To account for variability of thermal properties across the households, the property values are sampled from a normal distribution. Additionally, it is assumed that the minimum household temperature threshold across the community is 18 °C.

Similarly, the aggregate electric vehicle charging profile is determined using the input provided in Table 5.2. Additional driver profiles are sampled from [31] such that the range of distances travelled are 21.7 - 50.8 km, with the departure and arrival time being between 9:00h and 18:00h daily. For the purpose of simplicity we assume that all the EVs are initialized with the same state-of-charge of 20 kWh, and each EV storage has a maximum capacity of 24 kWh. This same logic is used for initializing the storage units. Each storage is assumed to have a maximum capacity of 6 kWh, and initial state-of-charge of 2 kWh. Lastly, the penalty parameters for the execution of the ADMM algorithm are set such that ρ_1=35 and ρ_2=40.

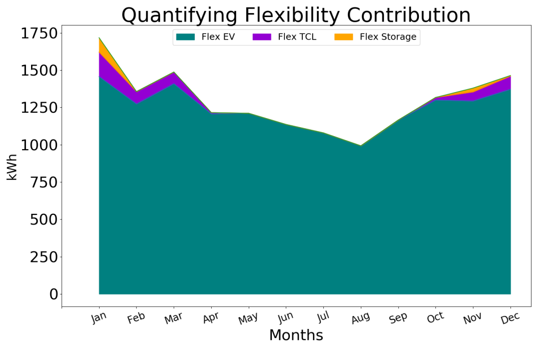

Figure 5.7: Flexibility contribution by each Aggregator

Results from the application of the D-MPC is presented in Figure 5.7. Across the year, whenever the DSO determines a potential violation of the price limit, the request for flexibility is issued. Figure 5.7 illustrates the load reduction provided by each aggregator at a monthly level. It is observed that electric vehicle charging is the main source of flexibility. This is attributable to the amount of load reduction that is made accessible due to switching from an inflexible charging schedule to a flexible one. This also explains the comparatively lower flexibility contribution from the electric heat pump (EHP) aggregators. As the reference case for electric heat pumps already aims to minimize the heat pump power consumption, it restricts the amount of load reduction that they can provide when flexibly scheduled. Furthermore, the heat pumps are operated only in the winter months. Hence, they are not capable of contributing towards the load reduction during the summer period.

Additionally, from Chapter 3, we learned that when the price limit is in excess of €100/MWh, the amount of storage discharge required for price constraining reduces. Correspondingly, the size of the storage required is also reduced. It must be noted that Figure 5.7 only indicates the storage discharge for constraining price. Hence, the participation of storage in energy arbitrage is not illustrated here.

For their contribution towards providing flexibility, aggregators based on their contractual arrangement with the energy community earn an income. While, there are numerous possible arrangement schemes for computing the income for an aggregator, we only consider a proportional scheme in this Chapter. Under this proportional scheme, it is possible for an aggregator to earn the product of the quantity of flexibility they provide times the difference in price without the provision of flexibility and the upper price limit. We have tabulated results from this assumption in the following table:

In accordance with Figure 5.7, EV aggregators realize the most value proposition in entering such a contractual arrangement. There is definitely a case for the future consideration of cooling loads which would increase the business potential for aggregators of thermostatically controlled loads. However, for storage aggregators it is more

Price Limit	EV Aggregator	EHP Aggregator	Storage Aggregator
€100/MWh	€1325.08	€34.5	€13.27

Table 5.4: Yearly-aggregated income per aggregtor-type

beneficial to partake in arbitrage opportunities. Thus, participating in price constraining should be observed by storage operators as a possible option for diversifying their revenue streams. Hence, through this simulation-based study it is demonstrated that a Distributed-MPC approach can be used for facilitating a local flexibility market in which communities can reduce their exposure to extreme price values.

5.5 Conclusion and future work

This Chapter, contributes to the thesis by building on the coordination mechanisms we have presented thus far. The price constraining mechanism has been implemented using distributed optimization thereby achieving more modular coordination while reducing communication overheads. Under such a setting, it is not necessary for a single aggregator to be responsible for the control and scheduling of flexible resources. Multiple aggregators can now be responsible for the control of these resources and contribute towards the required load reduction for constraining price. Furthermore, the presented coordination mechanism provides the foundation on which households within the community could self-organize to provide the flexibility required to protect them from price volatility. However, this is not considered in the scope of this thesis.

The benefits of the ADMM-based optimization are also applicable to the distributed price constraining mechanism. One of these benefits is scalability that refers to the computational tractability of the algorithm and the increased robustness of the solution. ADMM also provides benefits of strong convergence properties. This serves as a main motivation to use this approach over other distributed optimization approaches. However, it is to be noted that ADMM is sensitive to the value of the penalty parameters used while defining the augmented lagrangian functions.

Insights are also generated on the impact of information forecasts on flexibility coordination. First, the unavailability of a complete year's information impacts the sizing of the resources. This is because under the presence of centralized and deterministic information, resources can be optimally scheduled which results in a lower capacity requirement. However, when information is decentralized and forecasts are known on a rolling basis, resources may not be scheduled optimally over the entire time horizon. As a result an increased storage capacity is required to constrain price. Second, the potential to contribute towards flexibility and the subsequent income generated are contingent on the price limit and the power consumption defined in the reference case. This explains the higher contribution by EV aggregators for price constraining. Finally, we have also assumed a rather simplistic contractual arrangement between the aggregator and the community for constraining price. The aggregators income are highly contingent on the respective contractual arrangement they enter into.

A number of future research directions emanate from the research conducted in this chapter. We have assumed, equal number of EVs, EHPs, and storage for our simulation. It will be of interest to determine the impact of flexibility contribution and income derived by considering a different distribution of these resources. Additionally, selecting a time-varying price-limit could also provide interesting insights on the value proposition of the proposed approach. Next, we have assumed deterministic information forecast for the distributed-MPC based study. Uncertainties can arise in this forecast from multiple sources such as building envelope parameters, EV capacities and usage profiles. Accounting for these uncertainties is important for implementing a closer to real-world coordination mechanism. Finally, in this chapter we have considered that the aggregators and DSOs cooperate with each other towards providing the required flexibility for constraining price. This might not always be the case. Aaggregators motivated by their own goals may decide not to cooperate with others. To account for these behaviors, it is important to consider the problem from the perspective of game theory.

6

Conclusion

This final chapter concludes the work described in this thesis by summarizing its main results and insights. Answers to the main research question and sub-research questions are presented along with a summary of their main contributions. The chapter also discusses critical reflections of this thesis and enumerates recommendations for future research. Lastly, policy considerations for regulators, aggregators and energy communities are provided.

6.1 Conclusions and answers to research questions

This thesis has the objective of gaining a better understanding of the potential of demand-side flexibility, in a highly electrified and multi-actor distribution grid, for reducing the increase in price volatility. In line with this objective, the main research question addressed in this thesis is:

How can demand-side flexibility be coordinated across multiple actors in an increasingly electrified future to reduce price volatility and congestion in distribution grids?

To answer the main research question, we decompose it into a set of sub-questions. The following paragraphs summarize the main findings in these sub-questions.

Sub-question 1: What is the techno-economic feasibility of coordinating the dispatch of electric storage in distribution grids for reducing price spikes?

The first research sub-question that we have addressed, focuses on the introduction of a coordination mechanism for reducing price spikes in the distribution grid. In Chapter 3, drawing on duality theory we provide a mathematical formulation to quantify the flexibility required to constrain electricity price to a specified upper limit. Next, we describe the coordination mechanism between the DSO, aggregator and energy community for providing this required flexibility. This mechanism outlines the actors roles and responsibility, as well as the information and money flow between them.

Provided with a request to constrain price from the energy community, the DSO determines the required flexibility. This profile is then broadcasted to aggregators. Aggregators that are willing to provide flexibility services against an agreeable price then enter into a contract with the energy community.

To analyze the techno-economic feasibility of the proposed formulation, we executed yearly simulations. In this analysis, a range of upper bounds on price were selected. Based on this upper price limit, we determined the optimal size of storage required and the economics associated with the charging/discharging of the storage unit.

Insights generated from our analysis indicate that imposing strict limits on electricity price restricts the level of volatility in the local market. Thus in contrast to pure arbitrage revenue streams, a trade-off exists in the storage aggregator's revenue stream when arbitrage and price constraining are combined. Lastly, it is observed that the business value proposition from the provision of flexibility depends strongly on the price limit considered.

Sub-question 2: In an increasingly electrified future, to what extent is a reduction in price spikes and local congestion possible?

For addressing the second research sub-question, we extend our scope to account for flexible resources of electric vehicles and heat pumps. These resources by responding to demand response events provide the flexibility to constrain price. In the considered simulation study, these resources are coordinated by a single aggregator. Similar to the first research sub-question, on detecting price limit violations, the DSO requests the aggregator to provide flexibility. Load reduction is achieved by coordinating power consumption such that it deviates from an uncoordinated reference power consumption profile for EV charging and EHP operation. The essence of this research sub-question is that it focuses on space heating, and transport. These sectors are undergoing a transition to being driven by electricity thereby adding substantial load to the electric grid. Our investigation using the proposed price constraining mechanism reveals several novel insights. First, as cross-sectoral electrification will increase the load in the electric grid, grid capacity will need to be increased. Reinforcing the grid is a cost-intensive and time consuming process. Increasing energy flexibility aids in reducing the load magnitude while mitigating instances of price spikes. Second, it is observed that EVs overall provide more flexibility than EHPs. This manifests as a result of the underlying definition used for estimating the power consumption by these resources in the reference case. For EHPs, the reference power consumption profile is such that it only compensates for the heat loss to the ambient surroundings. This minimizes the amount of power required. In contrast, the EV charging reference case assumes that EV owners charge the EVs to maximize their state of charge leading to increased power consumption. This highlights that the amount of flexibility that can be rendered by flexible demand is contingent on the modeling of the reference scenario.

Lastly, instances arise when the aggregated flexibility from demand by themselves may not be sufficient to constrain price. This necessitates the inclusion of community energy storage, which could either be controlled and owned by an aggregator. Alternatively an aggregator could request individual community members for permission to control their storage systems. Using this as the basis, we determined the optimal storage capacity to constrain price assuming both inflexible and flexible demand. Results indicate that except the situation in which both the EVs and TCLs are inflexible, the need for grid reinforcement is relaxed. Thus by optimally implementing a combination of demand response and storage dispatch price in the local electricity market is constrained.

Sub-question 3: To what extent can flexibility be coordinated in a scalable manner across multiple aggregators for constraining price in local electricity markets?

Our third research sub-question builds on the second by addressing the aspect of scalability, and inclusion of multiple stakeholders in the coordination of demand-side flexibility to constrain price. In contrast to the previous sub-question this sub-question focuses on the aspect of reducing reliance on a single aggregator. The control and management of flexible resources is thus distributed across multiple aggregators. Each of these aggregators specializes in the operation of the underlying flexibility resource that they control. During periods of extreme price events, these aggregators coordinate with the system operator and the energy community to provide the required flexibility. This coordination occurs in a distributed manner and is based on the Alternating Direction Method of Multipliers (ADMM) approach.

The ADMM approach applied is a price adjustment procedure. The DSO using the constrained electricity price profile communicates with a set of specialized aggregators for coordinating flexibility provision. Aggregators then adjust either the storage dispatch or power consumption by the flexible demand to supply the required flexibility. This is achieved through a series of iterations, until the convergence criteria is satisfied. In contrast to the previous two sub-questions, it is assumed that information is made available on a rolling forecast basis of 72 hours. Based on information forecasts, the optimal operational profile of flexible resources is determined using distributed model predictive control (D-MPC).

The main finding from the simulation-based study is that it is feasible to decompose the coordination mechanism into a modular structure. This enhances the computational scalability and robustness of the price constraining mechanism. Aggregators earn a revenue proportional to the amount of flexibility they provide to constrain price. For the selected study, EV aggregators are able to contribute the most towards providing the required flexibility. In the future, owing to the emergence of electric cooling, aggregators of thermostatically controlled loads could increase their contribution towards flexibility provision. This would subsequently increase the revenue accrued by them. Lastly, the information forecast horizon influences capacity planning and the operational profile of flexible resources. In contrast to yearly, centralized and deterministic planning, when information is made available on a rolling horizon basis and is distributed across different actors, the capacity requirements of flexible resources increases.

6.2 Research contributions

Through the insights generated in this thesis, we contribute to scientific literature. These contributions are highlighted below.

Price Constraining mechanism applied to distribution grid-based electricity markets. The first contribution of our work is that we have derived a mathematical formulation to include explicit constraints on price in distribution grid-based local electricity markets. Inspiration for this formulation stems from [143]. Previously, price has only been treated as an output of an optimization problem which is not known a priori. As a result constraints cannot be explicitly placed on its magnitude. By leveraging optimization duality theory it is possible to place constraints directly on price. Addition of this new constraint translates to a new power balancing variable in the original optimization problem. In particular, this variable corresponds to the amount of load reduction or additional power supply required to constrain electricity price.

Our work builds on this formulation by applying it in the context of distribution grid-based local electricity markets. By constraining the distribution grid locational marginal price, the required flexible power is quantified. For satisfying this required flexibility, our work subsequently computes the optimal storage size and determines the optimal schedule for charging electric vehicles and operating electric heat pumps.

Coordination mechanism under detailed case studies. Through stakeholder analysis, we have contributed the required coordination mechanism essential for the implementation of price constraining in electricity markets. To achieve this, we have performed actor analysis, by determining the data possessed by each actor (DSO, aggregator, energy community), the decisions that they make, and the interactions between them. This interaction comprises of the maximum price contracts that are established between the aggregator, and the energy community. Furthermore it entails the required sequence of information flow for providing the flexibility services to constrain price. Lastly, we investigated the influence of price limits on the aggregator revenue and business potential by varying the maximum electricity price limits.

Demand response role in price constraining. In this thesis, demand-side flexibility is accrued by engaging electric storage systems, electric vehicles, and electric heat pumps. These resources are optimally managed for satisfying the load reduction values as generated by the price constraining formulation. It is important to note here that storage and flexible loads under demand response schemes do contribute towards reducing price volatility in electricity markets. However, as evidenced from our investigation, this operation does not mathematically satisfy constraining of price to specified limits. To address this explicitly, we modify the conventional demand response programs. Thus by ensuring that the demand response events are triggered based on violation of price limits, demand-side flexibility is coordinated such that the price limits are always satisfied.

Application of distributed optimization to price constraining. In this thesis, ADMM-based distributed optimization has been incorporated in the execution of the price constraining mechanism. Previously, in relation to the operation of the electricity market, distributed optimization has been investigated for unlocking the flexibility provided from building clusters or electric vehicle charging. However, limited attention has been focused towards mitigating price spikes and grid congestion in the context of multi-stakeholder local electricity markets while accounting for cross-sectoral electrification. Through our explorative analysis, we contribute to the scientific literature by investigating the aspect of price constraining achieved through demand-side flexibility coordination in a modular, scalable and privacy-preserving manner.

6.3 Reflections

Approach used

To reduce the complexity of our modeling efforts in this thesis, and to focus on the true essence of the thesis we have made certain assumptions. We aim to make them apparent in this Section. This thesis, assumes deterministic modeling of the case studies considered. It is not necessary that all EVs have the same storage capacity, or that perfect prediction of load consumption and solar power generation is available. Additionally uncertainties may also exist with the estimation of the thermal properties of households. While these uncertainties could be better addressed through stochastic optimization based approach, for the purpose of simplicity we have focused exclusively on deterministic analysis.

With respect to aggregators in Chapter 3 - Chapter 5, we have assumed them to be price makers. Under the existing regulatory setup, this is possible only under limited circumstances. Aggregators can be price makers instead of price takers during instances where price differences exist in the electric grid. At the local electricity market level, we have assumed price to be governed by distribution grid locational marginal price. By definition these values in addition to the marginal generation costs comprise of a congestion and power loss component. Hence, during periods of grid congestion, price spikes occur which are experienced by the community. By providing flexibility services, aggregators may act as price makers.

Furthermore, in Chapter 3, we have assumed that electric storage system can completely charge and discharge. However, this would compromise the health of the system. Hence limits must be placed on the state of charge which in turn impacts the optimal sizes of the electric storage system. Lastly, we made a deliberate decision to focus on distribution networks for the application of the price constraining mechanism. Given the modeling similarities with the medium voltage distribution grid, the proposed mechanism can be readily extended to the transmission grid.

Research scope

Given the growing complexity of the electric grid undergoing transition, to perform an explorative analysis, it is important to restrict the thesis' scope. This applies to the regulatory aspect of the electricity market, the geographical context of the research and its modeling aspects. With respect to the data used in our simulations; electricity market price, load consumption profiles, EV driver profiles, and thermal properties of residential dwellings; we have restricted it to the Netherlands. Many of these profiles such as electricity market price, residential dwelling thermal capacities, and load consumption profiles are extensible to other locations in the European Union such as Denmark as well as the West Coast of the United States such as Seattle. Hence, results generated in this thesis could also provide valuable insights in those locations.

From a regulatory standpoint, long-term electricity markets such as bilateral contracts, forward contracts are not considered in the course of this thesis. This is because there is a lack of good overview on this topic. Furthermore, intra-day markets owing to their low liquidity, and lack of publicly available data were left out of the scope of this thesis. We have restricted our focus only to the day-ahead market due to its more established presence and the presence of significant price volatility in their operation. This price volatility as discussed in Chapter 1 is only expected to increase in the near future. Additionally, we extend the day-ahead market price consideration to account for price in the local electricity market. To do this we couple it with distribution grid-based locational marginal price which have previously largely been investigated in deregulated markets. At the moment, this price does not exist in the Netherlands, but it is expected that zonal price which is similar to D-LMPs will be introduced in European markets.

Furthermore, we have not investigated the frequency with which grid congestion occurs and the magnitude of the subsequent price spikes. Advanced econometric models could be used for generating better insights on the associated price volatility. To address the price volatility, we have not considered a detailed comparison between our proposed mechanism and a purely financial hedge. Another option to address price volatility is through reliability options. However, these have previously been applied at the ISO/TSO level and could be extended to the distribution grid.

From a modeling aspect, we have assumed that all actors in the local electricity market cooperate with each other. In markets that have multiple peers, they can aggregate into mini pool markets and/or engage in peer-to-peer trading. To satisfy their self-objectives, peer could be motivated to compete with each other thereby challenging the assumption of cooperation. To account for this competitive behavior, game theoretic methods could be applied for identifying equilibrium conditions. However, we have not considered game theoretic models in this thesis.

6.4 Recommendations

6.4.1 Future research

In this thesis, we have performed an exhaustive exploration of our proposed price constraining mechanism to mitigate the adverse impact of price spikes and contributed to the scientific literature on congestion management. Through our work we hope to have provided the foundation for numerous future research directions. We enumerate a few of these research directions here:

- **Time-varying price limit**. In this thesis, we have only considered the case extreme price values i.e. price that are greater than €100/MWh. This price limit directly influences the magnitude of the demand-side flexibility required, and subsequently has an impact on the optimal capacity of flexible resources required. However, it is possible for this upper price limit to be time-varying. By varying this price limit it becomes possible to adjust the energy communities attitude towards the risk of extreme price events, which could result in more economical flexible resources capacity planning.

- **Inclusion of uncertainty.** In this thesis, we have considered deterministic scenarios for the investigation of our simulation-based studies. Nonetheless, there are multiple input parameters that are of a stochastic nature. Uncertainties can emerge from parameters such as solar irradiation that impact solar power generation, storage degradation/efficiencies which impact the depth of charge/discharge for storage operation, thermal conductance and capacitance properties of households that impacts the potential of thermal flexibility provided by households, and the EV owner usage profiles. Consideration of uncertainty would enable a more realistic determination of the availability of demand-side flexibility to constrain price. An example of uncertainty accommodation has been investigated in [93].

- **Price constraining to ensure non-negative electricity price** Inversely to the usage of duality theory for placing an upper limit on price, it is also feasible to place a lower limit i.e. enforcing a positive value on electricity price. The addition of this constraint in the dual formulation introduces a new primal variable which is the increase in power consumption at a given instance. The increased power consumption can be allocated to EV charging, or to pre-heat households.

- **Extension of our formulation across voltage levels**. For this thesis, we have limited our scope to an economic dispatch formulation, and addressed the aspect of peak load and congestion management. Hence, limited attention was given to the underlying power network. Our formulation is readily extensible to the transmission grid, but would require the aggregation of larger capacity of flexible resources to facilitate price constraining. Additionally, the price constraining formulation can also be applied to the low voltage distribution grid. The low voltage grid is highly resistive and incurs higher line losses. In relation to this, it is important to mention that it is feasible to linearize the ac power flow [144] as a quadratic programming problem, which also has a zero duality gap. This enables the application of our proposed price constraining formulation.

- **Game-theroetic aspect to price constraining**. We have assumed a cooperative coordination mechanism. However, different actors may cooperate with each other to varying degrees. As an example, aggregators may not completely cooperate with the energy community on the upper price limit if it does not result in a business case for them. This would provide the basis for the exploration of an equilibrium price which is agreeable to both actors. Similarly, the game-theoretic approach can also be extended to the case of determining the contribution across different aggregators towards providing the required demand-side flexibility to constrain price.

- **Extending the application of price constraining to other fields**. While this thesis was focused on the application of the price constraining approach to power system economics, it can be extended to other fields. In essence the dual variable can be constrained in applications where it has a clear economic interpretation and the conditions for verifying strong duality holds. One such application is the transportation sector where the application of the price constraining approach could be used for congestion management in the presence of dynamic road tariffs.

6.4.2 Policy considerations for decision-makers and actors

Through this thesis, we have generated insights for the different decision-makers and actors at the distribution-grid. These actors are impacted either by the issue of increasing price volatility, facing the need for re-defining their value proposition, seeking additional viable revenue streams, and those that are responsible for defining the rules of coordination in local electricity markets.

Distribution System Operator: With the integration of large-scale renewables at the distribution grid, the cross-sectoral electrification of transport and heat, challenges faced by the DSO are only expected to increase. Passive management of the distribution grid in which the DSOs role was primarily to reinforce the grid, a rather cost-intensive measure, would not be able to cope with these changes. Hence, DSOs expressed desire to reassess and re-define their role. Main themes that emerged were the DSOs willingness to focus on active distribution grid management, and emerging as a service-oriented entity. Additionally, the DSO would assume the role of a regulated data facilitator to facilitate the operation of local electricity markets.

In this thesis, we explored the scenario in which DSOs are responsible for market clearance at the local electricity market level. Through the involvement of the DSO it is possible to provide price constraining services to energy communities. This is achieved by incorporating bids solely based on price limits. Furthermore, the DSO communicates with the aggregator pertaining the magnitude of demand-side flexibility to be provided. It is important to note, that the DSO provides all these services while still remaining a regulated entity. The DSO can also extend this role by becoming a coordinator between actors that participate in the management of the distribution grid. In this case, the DSO could broadcast signals to actors, and based on their responses, make informed decisions for resolving grid contingencies.

Aggregator: In 2017, only limited countries had explored the potential role of aggregators in electricity markets. Since then, the presence of aggregators has increased globally. To integrate aggregators as a market participant, policies are required for determining their nature and business models.

Presently, a vast majority of aggregators participate in wholesale markets and provide services to the TSO. In contrast, this work has generated insights that aggregators may consider for participating in local electricity markets. Aggregators can then provide services to the DSO for improving operational flexibility required for efficiently managing the distribution grid. Doing so would provide another revenue stream to aggregators, while also delay the need for grid reinforcements by the DSO.

Additionally, aggregators may also provide flexibility services to energy communities. With the increase in price volatility, aggregators could enter into contracts with energy communities that constrain the price to which consumers are exposed to. Through these price-constraining contracts, aggregators could augment their business model. However, aggregators are advised to thoroughly evaluate the agreed on price limit as it significantly influences income from this service.

Energy Communities: To assist with the energy transition, communities have adopted renewable energy and switched to electric vehicles and heat pumps. However, with variability in power generation and uncertainty in power consumption, price volatility is increasing. Increased power consumption may also cause grid congestion which results in price spikes. Energy communities in an uncoordinated manner by themselves might not be able to reduce their exposure to price volatility. Through this research, communities are made aware of these issues. For addressing these issues, this thesis also provides a possible solution to the communities. Communities can consider engaging in flexibility contracts with the aggregator, who would represent them in electricity markets. In such a market, the aggregator would place a demand-side bid that indicates the community's maximum willingness to pay for electricity. This bid when cleared, would ensure that the upper price limit of electricity is not violated. In the future, as price volatility worsens, such a price constraining contract will prove increasingly valuable to energy communities.

Regulators: Regulators have a multitude of challenges to address throughout the energy transition. While price become increasingly more volatile, new actors such as aggregators are emerging, and existing actors such as DSOs are restructuring. Under these complex situations, informed decision-making is required from the regulators for developing institutions that engage multiple actor interactions. The price constraining mechanism proposed, provides regulators with a comprehensive analysis required for engaging actors in local electricity market to mitigate price spikes. Although the price constraining mechanism as studied does not result in the overall minimization of costs, it does protect consumers from price spikes. This insight could provide an additional aspect that regulators may consider while designing electricity markets. Lastly, the proposed coordination mechanism could give rise to instances of strategic behavior and collusion amongst the actors. To address this and other similar concerns, regulators must direct additional research to fully understand the complexities of local flexibility markets.

6.4.3 Final remarks

Increasing electricity price volatility is a concern that could have adverse economic impact on consumers. This thesis provided coordination strategies between multiple actors through which price constraining in electricity markets can be achieved. For achieving coordination, the role and responsibilities of each actor in addressing the issue needs to be accounted for. Additionally, to motivate them it is important to identify the value proposition that an actor may derive. This makes a techno-economic analysis approach imperative for conducting this research. Insights generated through this thesis highlight the importance of collaboration in addressing complex issues.

Additionally, this thesis is being published at a time when electricity price across Europe is spiking. While, the research conducted in this thesis was focused at the local community level, the method and results can be scaled for constraining price regionally. However, a significantly greater capacity of flexible resources would be required to achieve this. Lastly, the coordination mechanism presented in this thesis provides a foundation by which other pertinent issues facing the energy transition can be addressed. Capping carbon emissions related to the power system is one such issue. To illustrate how the proposed mechanism can be extended, consider a problem where the goal is to plan the dispatch of a generator to satisfy power demand, while minimizing the amount of carbon emitted. In this case, explicit limits would be placed on marginal emissions. This would then aid in estimating the capacity of clean energy resources required for satisfying power demand.

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About the author

Shantanu Tarun Chakraborty was born on December 23, 1989 in Mumbai, India. After studying Computer Engineering for his Bachelor's degree, Shantanu obtained a Master of Science degree in Energy Science, Technology & Policy from Carnegie Mellon University in the US. For his M.Sc. thesis Shantanu focused on the 'Hierarchical Control of Energy Management Systems at Carnegie Mellon University'. After obtaining his M.Sc. degree Shantanu worked as a Data Scientist for enhancing residential and commercial energy efficiency at Tendril Networks (now Uplight) in Boulder, Colorado, US. Later, having an interest in learning more about fuel cell systems, he worked as an Engineer Data Analysis at Bloom Energy in their Advanced Process Control and Data Analysis teams.

Having a desire for gaining in-depth knowledge and analysis in power system economics, operational research, and local energy systems, in 2016 Shantanu joined the Energy & Industry section at TU Delft's Faculty of Technology, Policy, and Management. His thesis was funded by the Innovative controls for renewable source integration into smart energy systems (INCITE) which was a Marie Sklodowska-Curie European Training Network (ITN-ETN) funded by the HORIZON 2020 Programme. Throughout his PhD, Shantanu presented his work at multiple international conferences. At the IEEE Power & Energy Society General Meeting 2019 in Atlanta, Shantanu's work was recognized as one of the best paper's submitted. During his term as a doctoral candidate, Shantanu undertook research visits at Politechnico di Torino and at EnergyVille. Additionally, Shantanu also served as a teaching assistant for the course on Energy System Optimization and supervised master thesis projects on this subject.

Currently, Shantanu is a Managing Consultant and Senior Research Analyst - Hydrogen at Guidehouse Consulting in Utrecht, The Netherlands.