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Computational analysis of demand-side management in smart grids

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Dissertation presented in partial fulfillment of the requirements for the degree of Doctor of Engineering Science (PhD): Computer Science

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Beknopte samenvatting

Hoogtechnologische softwareoplossingen zullen een belangrijk deel uitmaken van toekomstige elektriciteitsnetten. Software maakt efficiënte communicatie en beheer van verschillende energieproductie- of consumptietoestellen mogelijk en zal tegelijkertijd instrumenteel zijn in het analyseren van de complexe scenario‘s die zich voordoen wanneer verschillende partijen, met elk hun eigen doelen, met elkaar interageren om een veilig en stabiel elektriciteitsnet te realiseren.

Met de stijgende integratie van hernieuwbare energiebronnen in elektriciteitsnetten wordt het almaar meer uitdagend om de stabiliteit van de netten te vrijwaren. De huidige energie-infrastructuur is immers niet altijd ontworpen met decentrale energieproductie in het achterhoofd. De variërende productie van hernieuwbare energiebronnen maakt het daarbij nog moeilijker om energieproductie- en consumptie in balans te houden. Flexibiliteit aan de productie en consumptiekant van deze balans is daarom nodig om de Europese 20-20-20 doelstellingen omtrent klimaat en energie te behalen zonder de veiligheid van het elektriciteitsnet in gebaar te brengen.

Vraagsturingsprogramma’s proberen partijen in te schakelen die flexibel kunnen zijn in hun energieconsumptie voor doeleindes zoals het behouden van de elektrische netstabiliteit wanneer er rekening gehouden moet worden met hernieuwbare energiebronnen. Het succesvol implementeren van zulke programma’s vereist dat energieproducenten, -consumenten en systeembeheerders goed omgaan met strategische keuzesituaties omtrent de verscheidene aspecten van vraagsturing. Literatuur focust zich vaak op de technische aspecten van consumptieflexibiliteit terwijl eigenlijk de combinatie van technische en economische aspecten de doeltreffendheid van vraagsturingsprogramma’s bepalen. Deze verhandeling spitst zich toe op verschillende technieken uit computerwetenschappen om strategische keuzesituaties te onderzoeken in verschillende aspecten van het gebruik van vraagsturing om problemen aan te pakken die te wijten zijn aan de integratie van hernieuwbare energiebronnen in de huidige elektriciteitsnetten.

In deze verhandeling wordt de keuze tussen verschillende financiële compensatiestructuren voor partijen die flexibiliteit aanbieden computationeel geanalyseerd met behulp van evolutionaire speltheorie om zo inzicht te krijgen in hoe financiële compensatie deze partijen motiveert om deel te nemen aan vraagsturingsprogramma's. Computationele analyse met heuristische resultatenmatrices, opgebouwd door microsimulatie, toont aan dat gebruikers van flexibiliteit een hoger marktaandeel kunnen krijgen aan partijen die flexibiliteit aanbieden, door te kiezen voor een systeem van reservatiebetalingen in plaats van activatiebetalingen.

Naast financiële compensatie moeten gebruikers van flexibiliteit ook beslissen welke aanbieders van flexibiliteit het meest geschikt zijn om op een bepaald moment de flexibiliteit ervan in te zetten. Hiertoe worden algoritmes geïmplementeerd uit de literatuur over multi-agentsystemen en mechanismeontwerp voor het coördineren van en het onderhandelen tussen gebruikers en aanbieders van consumptieflexibiliteit.

Om balanceringsproblemen in elektriciteitsnetten effectief op te lossen, moet er aanzienlijk geïnvesteerd worden in technologische oplossingen voor het beheren en activeren van consumptieflexibiliteit. In welke mate deze investeringen kosteneffectief zijn, wordt bepaald door de kosten en baten van de oplossingen in kwestie. Een analyse van investeringskosten wordt voorgesteld en geëvalueerd voor een gecombineerde oplossing voor overtollige windproductie die gebruik maakt van verschillende actieve netwerkbeheertechnieken waaronder dynamische kabellimieten, vraagsturing en batterij-opslag.

Naast de investeringsbeslissingen waar gebruikers van flexibiliteit voor staan, moeten ook aanbieders van flexibiliteit beslissen welke partijen ze van hun flexibiliteit zullen voorzien. Als laatste contributie wordt de deelname in verschillende ondernemingsplannen gesimuleerd en geanalyseerd met behulp van evolutionaire speltheorie. In deze analyse wordt de evolutie van deze keuze tussen deze ondernemingsplannen geanalyseerd afhankelijk van hoe gebruikers van flexibiliteit de aangeboden flexibiliteit gebruiken en compenseren.

Het toepassen van technieken uit de literatuur rond evolutionaire speltheorie op strategische keuzesituaties heeft aangetoond dat evolutionaire speltheorie waardevolle inzichten kan geven in de complexe interacties die zich voordoen wanneer verscheidene partijen samen interageren in het energiedomein.

Abstract

High tech software solutions will form a fundamental part of the future electricity grid. Software enables real time efficient communication and control of various devices for producing and consuming electrical energy and will be instrumental in analyzing the complex scenarios that arise when multiple parties with varying goals interact to create a safe and stable delivery system for electricity.

With the increasing adoption of renewable energy sources (RES), maintaining grid stability becomes increasingly challenging because legacy power infrastructure was often not designed with decentralized generation in mind. The varying nature of RES also further complicates maintaining a balance between electricity production and consumption. Flexibility is needed in both production and consumption in order to achieve the European union's 20-20-20 climate and energy targets while maintaining a safely balanced electricity grid.

Demand-side management (DSM) programs attempt to harness consumption flexibility for goals that include maintaining grid stability when dealing with RES. Successfully implementing these programs requires producers, consumers and system operators to deal with strategic choice situations concerning various aspects of DSM. Literature often focuses on singular technical aspects of consumption flexibility while the combination of various technical and economic aspects determine the actual long term efficacy of DSM programs. This dissertation focuses on computational analysis techniques for studying strategic choice situations in various aspects of using DSM to address problems related to the integration of RES into contemporary electricity grids.

In this dissertation the choice in compensation payment structures for flexibility providers are analyzed using evolutionary game theory (EGT) with replicator dynamics to gain insight into how financial compensation influences DSM participation willingness. Computational analysis with heuristic payoff matrices determined through microsimulation shows that users of flexibility can gain a higher market share of flexibility providers by favoring reservation payment structures.

Besides financial compensation, users of flexibility must decide which provider is best suited at any given time to activate their flexibility. To this end, algorithms for the coordination of the use of consumption flexibility and the negotiation between users and providers of this flexibility are implemented from multi-agent and mechanism design literature. Both cooperative contract net protocol (CNP) and competitive qualitative Vickrey auction (QVA) mechanisms are compared and evaluated in terms of allocation efficiency.

To solve grid balancing problems effectively, sizable investments in technological solutions for managing and activating consumption flexibility are necessary. Whether these investments are cost effective depends on the costs and benefits associated with these technology investments. An investment cost model is proposed and evaluated for an optimized end to end solution for excess wind power production using various active network management (ANM) techniques including dynamic line rating (DLR), DSM and battery storage.

In addition to investment decisions faced by users of flexibility, flexibility providers also must decide on which flexibility program to take part in. As a last contribution, participation in different competing business cases is simulated and computationally analyzed using EGT. The choice dynamics of flexibility providers choosing business partners, are evaluated in terms of how flexibility users employ and compensate for the consumption flexibility offered by flexibility providers. This evaluation also includes a sensitivity analysis on the influence that contractual activation constraints have on the efficiency of the DSM program in use.

Applying techniques from EGT literature to analyze strategic choice scenarios has shown that EGT can offer valuable insights into the complex interactions that occur between the multitude of parties in the energy domain.

List of Abbreviations

AC alternating current.
ANM active network management.
ARP access responsible party.

BRP balance responsible party.

CNP contract net protocol.
CS computer science.

DLR dynamic line rating.
DR demand response.
DSM demand-side management.
DSO distribution system operator.

EGT evolutionary game theory.
ESS evolutionary stable strategy.
EV electric vehicle.

FFD first fit decreasing.

GenCo generation company.
GT game theory.

ICT information and communication technology.

MAS multi-agent system.
MD mechanism design.
MIP mixed-integer programming.

NE Nash equilibrium.

ODE ordinary differential equation.

QVA qualitative Vickrey auction.

RES renewable energy sources.

TSO transmission system operator.

Nomenclature

C^f_{dlr} Fixed cost of the dynamic line rating solution.

C^m_{dlr} Maintenance cost of the dynamic line rating solution.

C^f_{dsm} Fixed cost of the demand side management solution.

C^m_{dsm} Maintenance cost of the demand side management solution.

C^r_{dsm} Marginal cost of the demand side management solution.

C^f_{net} Cost of network reinforcement.

C^f_{sto} Fixed cost of the storage solution.

C^m_{sto} Maintenance cost of the storage solution.

$E_s^{\max}$ The total amount of excess energy handled by storage. Capacity of the battery in the storage solution.

NPV Net Present Value.

$P_s^{\max}$ The peak of the excess power handled by storage. Peak power rate that can be handled by storage.

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Chapter 1

Introduction

Software and high-tech solutions from the domain of computer science (CS) form a crucial part of the transformation that conventional electricity grids are undergoing in becoming ‘smart’ grids. This transformation is in part driven by the ambition to lessen the dependency on fossil fuel resources in favor of more sustainable renewable energy sources (RES). The European Commission’s 20-20-20 objectives state that 13% of the gross total energy consumption in Belgium alone should come from RES such as wind and solar in 2020. Maintaining a safe and stable electricity grid becomes increasingly challenging as more energy is produced by RES. Legacy infrastructure was not originally designed with decentralized generation in mind and the variable nature of RES further complicates maintaining a production-consumption balance in real time. Flexibility in consumption and production alike is therefore a necessity to achieve the 20-20-20 climate goals and especially the more ambitious 2050 climate goals, without compromising the stability of the electricity grid. The successful employment of this flexibility in future electricity grids with high levels of RES penetration cannot be accomplished without technological support. Software for simulating new technologies, for coordinating power producers and consumers and for computing key performance indicators are but a few examples of CS applications in smart grids.

In this dissertation the role of power consumption flexibility in smart grids is analyzed from a CS perspective. Various aspects of employing power consumption flexibility are analyzed in the context of integrating RES into existing electricity grids. Common to all of these aspects is the notion of strategic decision making scenarios that have an impact on how effectively consumption flexibility can be used. CS literature offers tools and frameworks for analyzing such strategic decision making scenarios. Specifically, tools from game theory (GT) literature are used for analyzing strategic choice situations in the following aspects of using consumption flexibility.

The financial compensation offered to providers of consumption flexibility will determine the willingness of these providers to make consumption flexibility available for use. To gain insight into how financial compensation influences participation willingness, the choice between different financial compensation payment structures are computationally analyzed in [1]. Besides financial compensation mechanisms, users of flexibility must decide which provider is best suited at any given time to activate their flexibility. To this end, algorithms for the coordination of consumption flexibility and the negotiation between users and providers of this flexibility are discussed in [2]. To solve grid balancing problems effectively, sizable investments in technological solutions for managing and activating consumption flexibility are necessary. Whether these investments are cost effective depends on the costs and benefits associated with these technology investments. An investment cost model is proposed and evaluated for an optimized end to end solution for excess wind power production using both consumption flexibility and battery storage in [3]. In addition to investment decisions faced by users of flexibility, flexibility providers also must decide on which flexibility program to take part in. In [4], participation in different competing business cases is simulated and evaluated in terms of how flexibility users employ and compensate for consumption flexibility offered by flexibility providers. For these business cases, the influence of the contractual flexibility activation constraints are also analyzed.

The remainder of this chapter discusses the context (section 1.1), the scope (section 1.2) , the objectives (section 1.3) and the concrete contributions (section 1.4), in more detail.

1.1 Context

The effort to reduce the carbon footprint of electrical power generation has resulted in an increasing share of electrical energy produced by RES. Data from the European commission shown in Fig. 1.1 shows that the share of renewables in the gross energy consumption in Belgium rose from 3.6% in 2008 to 7.9% in 2015. The goal for Belgium, set by the European commission is to achieve 13% by 2020. This increase in RES adoption forces a reevaluation of how conventional power systems are designed. In conventional power grids, electrical power or electricity is produced by generation companys (GenCos). The transmission system operator (TSO) is in charge of maintaining the transmission grid that

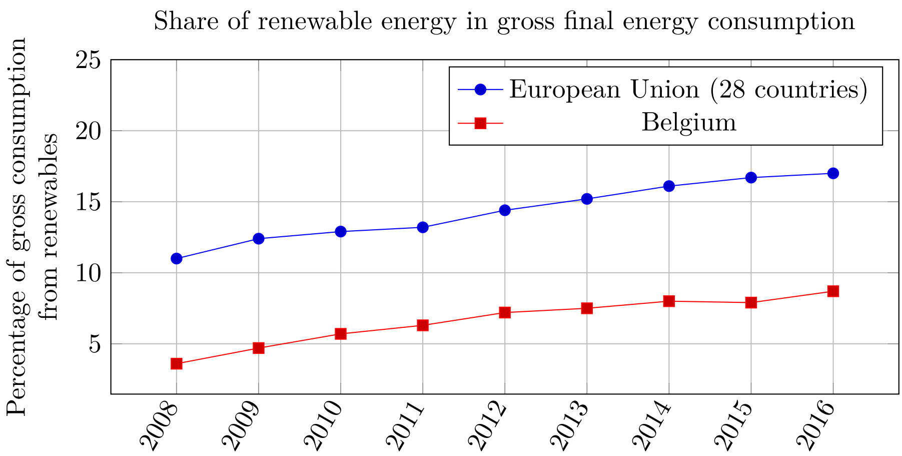

Figure 1.1: The increasing share of renewables in gross energy consumption of Belgium toward the target of 13% by 2020.

is used for transporting electricity over long distances using high voltage power lines. Distribution system operators (DSOs) in turn, use low to medium voltage grids for the last mile transport of electricity to industrial and residential consumers. Traditionally electricity flows unidirectionally and in a hierarchical fashion. Integrating RES requires injection of power at all levels in this hierarchy. Residential solar panels can, for example, produce energy for consumption miles away and wind turbines can be integrated into local distribution infrastructure to directly supply industrial consumers or to augment conventional generation for residential consumers. Figure 1.2 illustrates the conceptual differences in electricity transfer between conventional and future electricity grids and how information and communication technology (ICT) infrastructure will form an integral part of their operation.

1.1.1 Production/consumption balancing

One important aspect of electrical power systems in general is that a balance between the energy produced and the energy consumed should at all times be maintained. For example, power lines in perfectly balanced grids in Europe offer an alternating current (AC) that oscillates 50 times per second or at a frequency of 50Hz. When production and consumption are not in balance, this grid frequency can become greater or less than 50Hz causing, among other

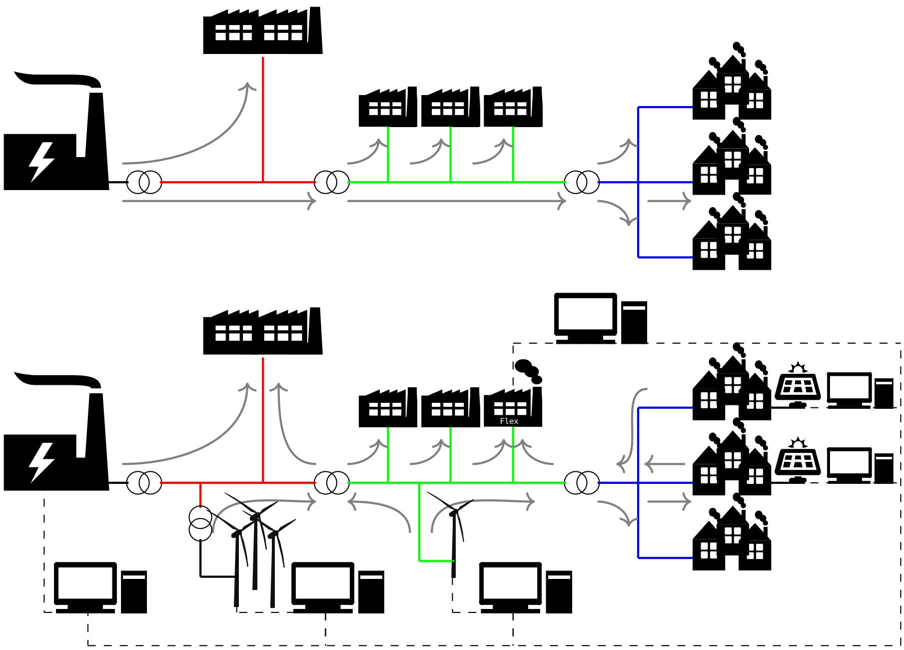

Figure 1.2: In conventional electricity grids (top), electricity is transported (gray) from generation to consumption via the high voltage transmission grid (red), before being distributed via medium voltage distribution grids (green) to low voltage distribution grids (blue). In smart grids (bottom), electricity can flow in both ways through the network (gray), requiring ICT based control centers to maintain operational safety.

things, electrical motors and clocks to run faster or slower than what they were designed for. Larger imbalances can even cause brownouts or black outs.

Maintaining this balance is an ongoing process involving multiple stakeholders from system operators to GenCos and consumers all interacting to ensure the safe operation of electricity grids. Effectively coordinating different stakeholders towards a common goal can be challenging in its own right. Grid balancing is becoming even more challenging as increasing shares of RES are integrated into the electricity grid. Compared to conventional generation, RES such as wind and solar are know to be more variable in their power production because wind speeds can vary during the day and solar power is dependent on daylight. The following stakeholders are all involved in grid balancing.

Transmission system operators

TSOs (e.g. Elia in Belgium) are responsible for operating and maintaining the transmission grid and for making sure the electricity grid in general remains balanced. The TSO indirectly monitors the production/consumption balance of the different grid access points for its control perimeter. When imbalances are observes, the TSO activates production or consumption reserves to restore balance and mediates financial settlements between the parties that were respectively causing and resolving the imbalances.

Balance responsible parties

For each grid access point, whether it is used by a consumer, producer or a combination of the two, a responsible party is assigned. Balance responsible parties (BRPs), or access responsible parties (ARPs) in Belgium, are companies that manage a portfolio of grid access points beside performing their main business activities. Some companies consume or produce so much electricity that they are considered as singular BRPs themselves. Each BRP monitors the balance of the access points in their portfolio and provides the TSO with this information.

Distribution system operators

DSOs (e.g. Eandis, Infrax in Flanders) are responsible for operating and maintaining the distribution system and for ensuring consumers, whether residential or industrial, have a stable connection to the electricity grid. With the integration of RES at the distribution level, the DSO has to take care that local imbalances do not cause damage to the physical cable infrastructure (e.g. when excess power production causes cables to overheat).

Renewable energy sources

RES are a crucial part of the effort to reduce carbon based electricity generation. Because of their variable production characteristics and less predictable nature, RES are prone to cause imbalances which have to be dealt with. While support schemes for promoting the integration of RES are in effect, curtailing RES production is not always an option, making RES a significant driver of grid imbalance.

Flexible consumers

Maintaining the production/consumption balance requires flexibility on the production and on the consumption side. Consumers capable and willing to modify their power consumption on demand are valuable resources towards this end. Some form of compensation, often financial in nature, is often required to motivate consumers to allow the use of their consumption flexibility.

The distinction can be made between industrial and residential scale consumers. Consumption flexibility can be found on both the industrial [5] and the residential [6] level but the particular implementation often differs.

Industrial scale consumers can often provide consumption flexibility from the processes they operate. Cold storage or waste processing facilities can leverage inherent buffers in their processes to regulate their power consumption. Residential consumers often find consumption flexibility in shifting loads from household appliances or from regulating heating appliances (e.g. electric heating or heat pumps).

Aggregators

Aggregators (e.g. REstore) have a business case in mediating between providers and users of flexibility. They abstract away the technical responsibilities from the providers while streamlining the financial responsibilities of the flexibility users. Relatively small amounts of consumption flexibility can also be bundled and offered as a whole towards stakeholders that require larger amounts of consumption flexibility. In doing so, aggregators act as virtual steerable power plants in the energy landscape.

1.1.2 Demand side management (DSM)

With larger shares of energy production coming from wind turbines, sudden changes in wind speed can affect the power generated and consequently influence the production side of the balancing equation. Similarly, clouds and other weather patterns can influence the output of solar production installations. Dealing with this increasing production variability in the context of grid balancing requires flexibility both in energy production and consumption. Demand-side management (DSM) is the umbrella term used to describe techniques and mechanisms for employing consumption flexibility to modify the demand side of the balancing equation and it has already shown potential in enabling wind power integration [7]. The long term goals of DSM often include reducing the carbon footprint from generation and improving the overall security and efficiency of power systems.

DSM programs can be classified according to either the goals of the program or by how program participants are motivated to provide consumption flexibility. For example, DSM programs can be used to improve power system reliability by using consumption flexibility to maintain grid balance and thus avoid outages [8]. Another example is that demand-side flexibility can be used to curb the effect large consumers and producers can have on the market prices of electricity [9].

Motivating consumers to modify their consumption on demand requires some form of financial compensation. A distinction can be made between direct incentive programs where fees are paid directly by the party making use of the consumption flexibility to the flexibility provider. These fees are often contractually specified and can be paid as a flat rate or on a per use basis [10]. Another way of incentivizing consumers to modify their consumption is by modifying the prices consumers have to pay for electricity. Popular examples of pricing based DSM are the use of peak/off-peak or day/night tariff distinctions for residential customers [11].

1.1.3 Smart grids

Effecting real time coordination between generation and consumption of electricity on a sub-second scale is not trivial. Moving forward toward future implementations of safe and efficient electricity grids supporting both increasingly varying production and consumption requires significant technological support. The conceptual term used for describing the future electricity grid that depends largely on digital ICT is the smart grid. Smart grids are defined by the computing and communication technology that allows more efficient transmission of electricity, increased integration of RES, reduced operation and management costs and improved operational safety and security [12].

The field of CS is fundamental to the development of these smart grid technologies by advancing the state of the art of both hard- and software and in particular their applications to the monitoring, managing and automation of critical power system services in real time. The CS research domain has contributed to the technical know-how and development of smart grid technologies in multiple ways including, but not limited to:

- algorithms for coordinating energy dispatch between generation and consumption [13][14]

- algorithms for optimizing flexible load schedules [15]
- software architecture for energy management systems [16]
- security and privacy of smart grid information systems [17][18]
- data analysis techniques for smart grid monitoring systems [19][1]
- simulation tools for prototyping future technologies [20][21]

The work presented in this dissertation fits the research on multi-agent system (MAS) and the interaction of self-interested and autonomous agents. Different stakeholders that each have their own goals and responsibilities, have to interact in the power systems domain to guarantee a safe delivery of electrical power to myriad consumers. By their very nature, power systems are a prime application domain for MAS research.

1.2 Scope

This dissertation focuses on analyzing various aspects of employing consumption flexibility to address problems caused by integrating RES into existing electricity grids. The research questions addressed in this dissertation are partially inspired through collaboration with industry through the icon projects SWiFT [22] and MonIEFlex [23]. By participating in these projects, more accurate problem modeling was made possible by means of industry validation and problem-specific data. Consequentially, the following scoping decisions have been made concerning this dissertation.

This work focuses on balancing problems caused by the integration of wind turbines into existing distribution grids. High resolution wind power production data, available through industry collaboration, has been used to analyze imbalance problems while taking into account location and seasonal variety of wind production. Similar high resolution data concerning other RES (e.g. solar) can be used for similar analyses that can lead to interesting results. Other RES are considered out of scope for this work.

This work focuses on the use of industrial consumption flexibility to address grid balancing problems. As a solution to imbalances, industrial DSM has the technical potential in terms of locality and scale to deal with the grid balancing problems discussed in this work. Other sources of consumption flexibility such as residential or electric vehicle (EV) charging based flexibility could also be valuable to such imbalance problems, but the complexity involved would warrant a study in its own right. Besides industrial consumption flexibility, other forms of flexibility are considered out of scope for this work.

1.3 Objectives

As part of the effort to reduce the dependency on fossil fuel resources, wind farms are being deployed all across Europe [24]. This effort is part of the ongoing process of effecting the change from conventional power grids to a safer, more efficient and greener ‘smart’ grid. Transitioning to the future smart grid requires different stakeholders to interact and collaborate to face the challenges that are presented when integrating wind production resources into contemporary electricity grids. Challenges such as legacy power infrastructure that is not designed with local injection in mind but also the growing dependency on technological support to maintain a safe production-consumption balance on both a local and a system-wide scale, are but a few examples. Stakeholders in the power domain need to be mindful of the opportunities and the consequences of dealing with these challenges. As part of the research performed in the context of the icon-SWiFT project, industrial consumption flexibility was proposed to support the integration of wind turbines into existing electricity grids [22]. Industrial consumers capable of increasing or decreasing their energy demand at will, are presented with new business opportunities in providing such flexibility for financial compensation. Besides industrial consumers, system operators and also generation companies all face strategic choice situations in figuring out how to navigate the uncharted technological and legislative waters that RES and DSM create. Flexibility providers and users must all make well-informed decisions with long-term effects in doing business with each other. Flexibility providers, for example, must decide which business cases are most beneficial. In turn, the users of flexibility must decide on whether DSM or infrastructure reinforcement is a more cost-effective long term solution for grid stability problems.

To harness industrial power consumption flexibility successfully, insight into the different aspects of consumption flexibility is required. Not only the technical solutions, but also the business-economical aspects of deploying DSM are important to consider because these aspects together determine the overall effectiveness of specific DSM programs.

In this dissertation the following aspects of employing consumption flexibility are computationally analyzed:

- The influence that different financial compensation mechanisms such as activation and reservation pricing have on flexibility provider willingness.
- The coordination of flexible consumption between flexibility providers and users in both cooperative and competitive settings

- The efficient scheduling of consumption flexibility allocations for various business cases including distribution grid congestion avoidance and portfolio balancing under various activation constraints.
- The strategic choice flexibility providers face in choosing the business party to provide their flexibility to.

Common to all these consumption flexibility aspects is the notion of strategic choice. Evaluating the long term effects of strategic decisions can aid the decision makers involved. The analysis of strategic choice situations is one of the key applications of game theory (GT). Game theory (GT) is a multidisciplinary field of study that has seen theory and applications in economics, mathematics and CS [25][26]. In this dissertation, computational analysis techniques based on game theoretic abstractions and solution concepts are employed to analyze strategic decision making in the context of harnessing consumption flexibility. Concretely evolutionary game theory (EGT) and mechanism design (MD) are used for analyzing how choices change over time and how the rules governing interactions affect such choices respectively. Detailed technical and business models are implemented in an open simulation framework developed for the purpose of this research alone. Source code and results are made available online to aid reproducibility and extensibility of this research [21]. Transparency into the methods and data used is a key aspect of fostering better understanding of the research and improving the reuse potential whether for future work or for future validation of current work [27].

1.3.1 Why evolutionary game theory (EGT)?

In this dissertation, complex interactions between different stakeholders in the energy domain are analyzed from a strategic choice perspective. For modeling and analyzing complex systems, generally two more or less opposing paradigms can be adopted. Mathematical modeling and analysis techniques focus on complex systems on an aggregate level. Observable behavior of system components is modeled using mathematical equations and formulas which can then be analyzed using a wide range of tested and proven tools for system analysis. The downside of such modeling techniques is often the higher abstraction level based on aggregated behavior and data. Agent-based modeling and analysis, on the other hand, focuses on fine grained, low level models of action and interaction between agents. Simulating these models enables the analysis of emergent behavior that arises from low level interactions. Analyzing emergent behavior in this sense often requires tailored techniques for observing and analyzing specific aspects of simulation results.

Our approach in using evolutionary game theory (EGT) to analyze strategic interactions in complex systems, combines the benefits of agent-based modeling with formal mathematics based game theoretic analysis techniques. The various stakeholders involved in DSM are explicitly modeled as agents pursuing their own goals, in the simulation framework `GridFlex` together with the protocols governing agent interactions. Through simulation, the strategic choice dynamics are analyzed using well-founded techniques from EGT literature. EGT adds the notion of a population of agents in which each agent can change its choice of action over time, based on the expected rewards from making certain choices. By adding this notion, EGT builds on classical game theory (GT) by weakening the assumption of perfect rationality among agents.

1.3.2 Why mechanism design (MD)?

Where classical GT focuses on analyzing the outcomes of agents choosing specific actions, mechanism design (MD) or inverse GT focuses on the game rules necessary to guide agents towards certain desirable outcomes. The rules governing the interaction between different agents are not always fixed. MD offers useful tools for decisions makers to analyze the effects of different interaction protocols that are not available in classical GT literature. For example, parties that are in a position to dictate how interaction with other parties occurs, can benefit from choosing interaction protocols that best lead to their own desired outcomes.

1.4 Summary of contributions and outline

This section provides a summary of the contributions of this dissertation. The contributions are presented as content chapters containing self contained scientific articles. Each content chapter (Chapter 2 to 6) contains a full paper verbatim, save for minor editorial changes. Chapters 2 to 4 are published conference papers. Chapter 5 contains a published journal paper and chapter 6 is currently accepted for presentation at a conference. This dissertation is concluded in chapter 7.

1.4.1 Analysis of compensation pricing structures for consumption flexibility

A common aspect of DSM is that flexibility providers are financially compensated or motivated for their efforts in modifying their consumption on demand. Chapter 2 provides an analysis of different payment strategies for delivered consumption flexibility. Concretely, flexibility providers face a binary choice in doing business with flexibility aggregators implementing activation (per use) or reservation (flat rate) payment strategies. Aggregators employ the offered flexibility to minimize a common imbalance signal. This strategic choice is modeled using replicator dynamics and analyzed using EGT.

The contribution in chapter 2 is the description of a EGT analysis framework for modeling and analyzing strategic choice dynamics for varying numbers of participating agents. When this approach is applied to financial compensation strategies, empirical evidence shows that in general, rational providers prefer reservation payments over activation payments.

The implementation of the open source `GridFlex` simulation framework further discussed as a technical contribution in appendix A `GridFlex` forms the basis for all simulations performed for all content in this dissertation.

This paper on which chapter 2 is based, was awarded the Best Paper Award at the conference for self-organizing and self-adaptive systems in Boston, USA (2015).

1.4.2 Analysis of coordination mechanisms for employing consumption flexibility

Smart-Grids are known for their complex dynamical environment where different self-interested parties interact and negotiate toward their respective goals. Negotiating the activation of flexible consumption resources with multiple providers and users of flexibility requires coordination mechanisms. Chapter 3 provides an analysis on the efficiency of flexibility activations using different coordination mechanisms. The distinction is made between off- and on-line flexibility activation method to distinguish between best-case investment scenarios and real-time effectiveness of DSM programs. For the on-line case, both competitive and cooperative coordination mechanisms are evaluated. These mechanisms are based on the qualitative Vickrey auction (QVA) and the contract net protocol (CNP) respectively, both state-of-the-art in MD literature.

As a first contribution presented in chapter 3, empirical evidence shows that cooperative flexibility scheduling mechanisms are more efficient than competitive mechanisms in distribution grid congestion cases with small numbers of participating agents. Systems operators operating such mechanisms are therefore better off retaining the full rights on deciding which flexibility to activate at which times.

As a second contribution we argue that DSM alone is not sufficient for resolving all congestion in these cases, even in off-line activation scheduling scenarios. Besides DSM, other active network management (ANM) techniques should be employed to ensure all congested energy can be dealt with.

Besides these major contributions, chapter 3 also defines the allocative efficiency metric that is used for evaluation sections of the following chapters.

1.4.3 Analysis of investment costs for deploying and maintaining infrastructure for using consumption flexibility

Chapter 3 described the need for other ANM techniques besides DSM as a comprehensive solution to deal with distribution grid congestion. Battery storage is proposed in chapter 4 as a fallback solution to offer the necessary power flexibility to deal with congestion that is not resolved through DSM. To evaluate the cost efficiency of this combined approach, an investment and operation cost model is proposed based on optimal storage dimensioning in combination with DSM as a first choice mechanism.

The contributions presented in chapter 4 are twofold. As a first contribution, the parametrized investment and operation cost model is described for an integrated solution to distribution grid congestion using dynamic line rating (DLR), DSM and energy storage. A second contribution is the evaluation of two cases using real world data from two different locations and industry validated cost projections. The evaluation is performed in terms of cost effectiveness for the DSO as a main stakeholder. The cost-effectiveness of this approach is also compared to grid reinforcement. Results based on current data suggest that grid reinforcement is a more cost-effective solution to deal with distribution grid congestion.

1.4.4 Analysis of strategic choice between different business cases from a flexibility provider point of view

Increasing the amount of energy produced by RES can present challenges in different ways. Similarly, power consumption flexibility can be harnessed toward different goals. Chapters 3 and 4 have provided one example of wind power integration challenges in a distribution grid congestion problem case. In addition to distribution grid congestion, chapter 5 improves on the grid balancing case described in chapter 2 by modeling wind power production forecast induced imbalances faced by BRPs that have wind power production resources in their portfolios. Chapter 5 focuses on how both problem cases differ in their need for consumption flexibility and what this difference might mean for flexibility providers from an economic point of view. The strategic choice faced by flexibility providers in choosing to do business with a DSO facing grid congestion on the one hand and a BRP on the other is analyzed in terms of expected compensation payments. Analysis tools from EGT proposed in chapter 2 are employed to study the choice dynamics in different scenarios.

The main contributions in chapter 5 are twofold. The first contribution is the formulation and modeling of two business cases for employing consumption flexibility in function of value exchanges between relevant parties active in European power systems. The second contribution is the analysis of market share dynamics of two competing companies requiring consumption flexibility for different business cases. These market share dynamics reflect the results of the strategic choice faced by flexibility providers.

1.4.5 Analysis of contractual flexibility activation constraints in different flexibility use cases

This dissertation shows that consumption flexibility can be employed to deal with wind power production excesses in different forms. Realizing the employ of consumption flexibility to address these excesses requires formalized agreements in the form of contracts between providers and users of flexibility. These contracts often specify constraints on when and how much flexibility can be called upon for the duration of the contract. Chapters 3 to 5 have indicated that the activation constraints used can influence the effectiveness of flexible power scheduling. Chapter 6 presents a sensitivity study on the effect of flexibility activation constraint parameters when flexibility is used do deal with different problem cases related to wind power production excesses. This study is performed for the problem cases discussed in chapter 5.

The two main contributions of chapter 6 are the following. A first contribution is the results indicating that the allowed inter-activation time dimension of flexibility activation constraints is only influential for distribution grid congestion cases and not for portfolio balancing cases. A second contribution is that there exists a clear relation between the DLR mechanism used to determine congested energy volumes and the activation duration parameter dimension of the activation constraints employed.

Chapter 2

Darwin in Smart Power Grids - Evolutionary Game Theory for Analyzing Self-Organization in Demand-Side Aggregation

Common to all DSM programs is that flexibility providers receive financial compensation for providing consumption flexibility. How providers are financially compensated can determine their willingness to deliver this consumption flexibility. This chapter presents the analysis of two pricing strategies employed by competing users of flexibility and contains the paper:

> Kristof Coninx and Tom Holvoet. 2015. Darwin in Smart Power Grids - Evolutionary Game Theory for Analyzing Self-Organization in Demand-Side Aggregation. In 2015 IEEE 9th International Conference on Self-Adaptive and Self-Organizing Systems, 101–110. DOI:10.1109/SASO.2015.18

The definitions, analysis and supporting software are the result of discussions between both authors. Kristof Coninx did all the programming and the writing. Tom Holvoet gave feedback on the writing. This paper was awarded the Best Paper award at SASO 2015.

Abstract

Maintaining a balance between power consumption and production is paramount for the safe and efficient usage of our power infrastructure. With the increased adoption of less predictable producers such as windmills and photovoltaics, maintaining this balance has become even more challenging. Demand-side aggregators are relatively new actors in smart power systems, offering balancing services. Aggregators maintain a portfolio of flexible consumers (e.g. production plants, electric vehicles or shiftable household appliances) that they can use for such balancing purposes. Typically, these balancing actions involve some form of financial compensation.

Together these actors form a complex, interacting, self-organizing system, where an individual's behavior fluctuates as a result of maximizing their own objectives. In this chapter, we analyze the influence of competing aggregator's pricing strategies on the flexibility providers by using evolutionary game theory (EGT) with replicator dynamics. Applying this analysis approach to concrete multi-aggregator scenarios allows for predictions on stable system states under varying conditions. Concrete results show that pricing strategies favoring reservation payments over activation payments increases the aggregator's market share size and its associated balancing potential in stable equilibrium.

2.1 Introduction

Power systems are known to be complex dynamical systems and are a good example of a domain where a multitude of different parties, each having their own goals, interact and self-organize to maintain a stable system of electricity production, transmission, distribution and finally consumption. In such systems, maintaining a balance between consumption and production is paramount to the safe and efficient use of existing infrastructure. Maintaining this balance has become even more of a challenge with the advent of decentralized production elements like wind turbines and solar panels.

Demand-side management (DSM) techniques describe the ability to influence or control the demand side of the balance equation to compensate for sudden changes in production because of less predictable production instances. To this effect, demand-side flexibility has become a highly valued commodity in current-day smart grid contexts. This flexibility can be found in industrial sites capable of finetuning their processes in order to consume less or more power when asked to [28] but also shiftable household appliances [29] and electric vehicles can offer flexibility that can be used to help balance the grid [30].

Together with the emergence of techniques for identifying this form of flexibility, the opportunity for capitalizing on this demand-side flexibility has led to the emergence of demand-side aggregators.

Demand-side aggregation can employ a variety of different DSM techniques for aggregating and using demand-side flexibility [31] but one thing all different aggregation business cases have in common is that participating clients need to be compensated for providing power consumption flexibility [9] and that this compensation has a direct effect on the willingness of a flexibility provider to participate in a DSM program. In turn, the availability of flexibility has a direct effect on the performance of an aggregation technique because a larger amount of flexibility per definition allows for more ways to correct imbalances. Most often, these compensations are of a financial nature and in cases where more aggregators are competing for the business of flexibility providers, the effects of an aggregator's payment strategies towards their clients can become an even bigger influence on a provider's willingness to do business. The influence of these payment strategies are the focus of this paper because current literature mainly focuses on designing and evaluating aggregation techniques in general without taking into account that competing aggregators and pricing strategies can have a profound influence on aggregator performance in a self-organizing setting.

The complexity of the resulting dynamics at play in self-organizing balancing systems is considerable. Analyzing these dynamics requires the use of tools that are able to capture this complexity. In this chapter we show how evolutionary game theory (EGT) can prove useful in this regard. EGT [32] is a field of study originating in the biology discipline but with a great track record across other disciplines as well (e.g. economics, computer science). EGT provides tools for modeling the concept of strategic choice in a population of self-interested agents. EGT extends classical game theory [33] by modeling Darwinian selection into the choice making process of these agents. In this chapter, EGT is applied to the field of power systems to analyze the influence of aggregator pricing strategies on the dynamics between multiple flexibility providers and multiple competing aggregators and the effects of these dynamics on power systems in terms of balancing consumption and production. The remainder of this chapter is structured as follows. First the problem description will be presented and illustrated in section 2.2 while the approach used in this chapter to address this problem is described in 2.3. The concrete scenario description of the performed experiments is described in section 2.4 and the results of these experiments are discussed in section 2.5. Finally, related work in the fields of EGT and smart grids is discussed in section 2.6 and the conclusion of this chapter and some future research directions are provided in section 2.7.

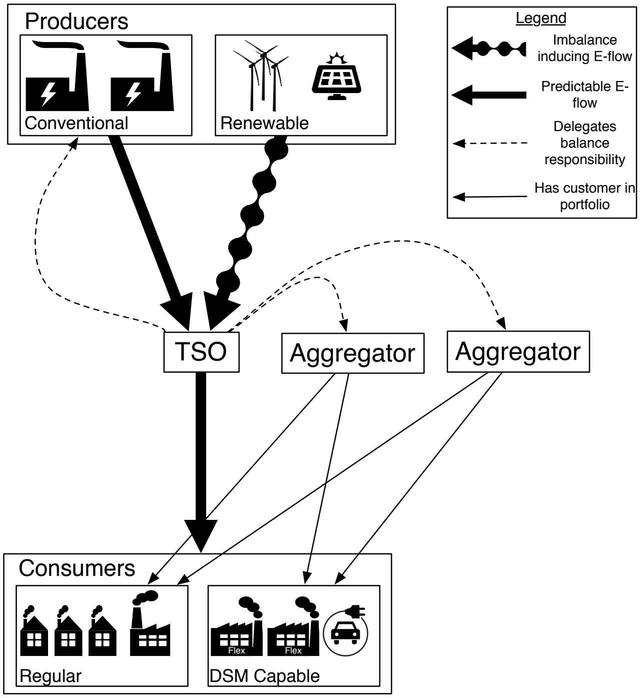

Figure 2.1: Simplified representation of the problem domain where multiple aggregators are responsible for compensating imbalances caused by less predictable, renewable energy sources.

2.2 Problem description

The electricity grid can be divided into two main components. The transmission grid is responsible for transporting electricity from large power plants to the distribution grid, while the distribution grid in turn distributes the electricity to end users (i.e. households, factories, traffic lights, ...). The transmission grid is governed by the transmission system operator (TSO) and one of its responsibilities entails making sure the total electricity produced and injected into the net equals the total amount consumed. To this effect, the TSO employs a mechanism where every transmission grid access point is managed by a balance responsible party (BRP). In Belgium, these responsible parties are called access responsible party (ARP). Electricity producers, major consumers or electricity suppliers can all be BRPs [34]. The main responsibility for BRPs is to balance their respective portfolios of consumers and producers. BRPs can meet this responsibility by buying or selling electricity on the day-ahead electricity market or through longterm bilateral contracts. When buying or selling electricity on the day-ahead market, this electricity needs to be delivered one day later. This implies the need for consumption and production forecasts to guide the decision of how much electricity to buy or sell. At the same time, BRPs are required to provide the TSO with nominations for the electricity bought and/or sold. These nominations represent the consumption and production forecasts of the BRPs. The nominations are needed so that the TSO can make the necessary adjustments to keep the production-consumption balance within the grid. The TSO continuously monitors actual production and consumption values and compares it with the reported values in the nominations from the BRPs. If the production does not cover the consumption, extra production reserves are deployed and if the consumption does not cover the production, consumption reserves are deployed. The costs that the TSO suffers for employing consumption reserves and the revenues for employing production reserves are settled with the BRPs causing the imbalance. These settlements are generally less profitable for a BRP than buying or selling electricity on the day-ahead market and the revenues that are lost, are therefore called the imbalance cost (also known as opportunity costs in economics). This mechanism is used continuously in time steps of 15 minutes.

When considering electricity suppliers being a BRP, the supplier needs to provide electricity for a whole portfolio of customers. With a time horizon of one day, consumption forecasts can be off, which leads to imbalance costs. The integration of distributed generation instances into a customer portfolio can further increase the difficulty to accurately forecast production-consumption balances. Demand-side flexibility providers and aggregators can help compensate these forecast error related imbalances.

2.2.1 Aggregator business cases

This section describes some examples of how independent aggregators can formulate a business case around aggregating and providing flexibility to other parties. Flexibility aggregators can be differentiated between further in terms of the techniques used to aggregate, the goal of their techniques (determined by the party they are offering their services to), and the payment structures used. The examples given describe business cases from the point of view of third party companies. However, keep in mind that the services that independent aggregators provide can also be taken up as a responsibility by the party aggregators provide services to, themselves. That is why in the remainder of this paper, we will use the term aggregator to describe a party that has taken up the responsibility of aggregation.

Ancillary services for the TSO

TSOs have the responsibility to employ reserves (either production or consumption side) to correct imbalances in real time. These reserves can be contractual or based on a flexibility market [35]. Aggregators have a business case in providing these reserves by aggregating flexibility providers who would otherwise be incapable of meeting contractual obligations with the TSO, or would not be willing to deal with the required administration.

Distribution grid optimization for the DSO

Distribution system operators (DSOs) have the responsibility of making sure electricity is distributed from the distribution grid to local consumers. They are among other things responsible for managing and maintaining the infrastructure between the transmission grid and the consumers. Maintaining this infrastructure incurs a maintenance and investment cost when existing infrastructure needs to be upgraded to cope with increasing peak infrastructure loads. These load increases can be caused by increased consumption from electric vehicles (EVs) or by increased production by local distributed generation instances. Aggregators can provide DSOs with the needed flexibility to optimize their local power flows and to shave peak loads [36]. In this business case, the geographical location of the flexibility providers is also of significant importance however because infrastructure peak congestion points depend heavily on the local distribution grid topology. The aggregator business case in this example is more client dependent and the benefit for the flexibility providers is mostly based on a reduction in administration overhead when compared to the case where the DSO would contract suitable flexibility providers directly to offer flexibility when needed.

Portfolio balancing for BRPs

A final example business case is where an aggregator provides aggregated flexibility towards a BRP. BRPs are interested in minimizing the imbalance cost from forecast error. Aggregators can use provided flexibility to minimize the real time imbalance to more accurately match the forecasted portfolio balance and the volumes bought or sold on the day-ahead market [37].

2.2.2 Payment structures

An important aspect of DSM programs is the incentive mechanism used. When DSM programs form the core of self-organizing systems, the incentive mechanism used is the driving force behind the self-organization. These incentive mechanisms are necessary because flexibility providers capable of providing flexibility often do so with a certain amount of inconvenience for which they need to be compensated. These compensations are often of a financial nature. In literature, two aspect of DSM payment structures are discerned, namely reservation pricing and activation pricing.

Reservation pricing

Reservation pricing describes a payment method where flexibility providers are compensated for offering flexibility without any condition on how or when the flexibility is used. The aggregator compensates the providers relative to the amount of flexibility the provider makes available to the aggregator. Often these reservation prices correspond to a fixed amount that is paid for the duration of a contract for a contractually defined volume of flexibility that has to be available when asked. In this work, we assume reservation fees are determined and paid for each time slot separately.

Activation pricing

Activation pricing describes a payment method where flexibility providers are compensated for actual curtailment or increases in energy consumption. The aggregator compensates the providers relative to the amount of power that is increased or decreased multiplied by the duration of the event.

2.2.3 Concrete problem case

This paper focuses on a concrete case of imbalance correction through the use of aggregators by focusing on the business case of providing services to BRPs. This case describes two different electricity utility companies selling electricity to a portfolio of clients. Both utility providers serve as BRPs from the TSO's point of view. The utility providers have contracted distributed generation instances in the form of wind turbines to lower the amount of electricity that has to be bought on the day-ahead market. This means that both these utility companies potentially suffer from forecast error related imbalances because of these less predictable generation units.

To offset these imbalances in real time, the utility companies employ the aggregator business case described in section 2.2.1. From this point forward, the utility companies will be referred to as aggregators. These aggregators now have a business case in using the budget otherwise spent paying the imbalance costs, to contract flexibility providers. This budget is divided into 2 distinct portions: a reservation budget and an activation budget. These portions are to be used for respectively reservation and activation fees towards the flexibility providers.

In this case we assume a liberalized market structure where selecting between and signing up with different utility providers or aggregators is relatively easy. Flexibility providers in this case are modeled as industrial processing plants with the ability to offer flexibility by increasing or decreasing the power consumption of machines on site. For example, at a frozen goods food processing facility, certain cold [38] stores may be deactivated for a limited period of time while the current temperatures are well below the allowed maximum temperature. These cold stores consume less energy for this time period but afterwards might need to compensate to get the temperature back down to well below allowed maximum levels. Similarly, these cold stores might be used to consume more energy by lowering the current temperature even further than necessary but allowing for a period of decreased energy consumption afterwards.

2.3 Approach

Where classical game theory (GT) [33] provides tools for static analysis of games focusing purely on the payoffs for individual actions, evolutionary game theory focuses on the payoffs for actions in combination with the amount of agents playing the actions [39]. So while classical GT offers ways for eliciting the possible Nash equilibria [40], evolutionary game theory can offer insight into which Nash equilibria are more likely to occur in practice. EGT can mainly be categorized into two approaches. There is the static approach proposed by Maynard Smith where the solution concept of an evolutionary stable strategy (ESS) is introduced for populations wherein all agents play the same mixed strategy [41]. ESS extends the Nash equilibrium solution concept from classical GT with a notion of robustness to a small invading subpopulation of agents playing a different strategy. The second approach describes modeling biological evolution or in this case the agent's rational choice more explicitly using a system of differential equations. This system regards agents in a population as playing only pure strategies while population states are described by vectors akin to mixed strategies. In this approach the solution concept of evolutionary stable states is used. Evolutionary stable states can be formally equivalent to evolutionary stable strategies [42] in some cases including the cases described in this work where the comparison between the two approaches is made. Using explicit dynamical system modeling allows using the wide range of tools for analyzing dynamical systems [43]. We mainly follow the second approach for analyzing the population evolution in this work by modeling the dynamics of a population of agents in a self-organizing system and by analyzing the properties of equilibrium states in these population dynamics. Some interpretations for the resulting dynamics are also given from the viewpoint of the first approach where appropriate.

As input for defining these dynamical systems, we follow the approach taken in [44] and treat heuristic strategies as primitive actions for a game theoretic analysis, meaning that an action in this game formulation represents choosing an algorithm implementation or in this case choosing an aggregator using a specific payment strategy. For the entities involved in this self-organizing systems case, empirical expected values are estimated using simulation and the resulting heuristic payoff table will be used as a starting point for the analysis. Similar to the approach described in [45], agent's choices are assumed to be independent of their types which allows for a compact representation of the payoff table. In a game of n players and k heuristic strategies to choose from, this payoff table will contain entries of the form

$$p = (p_1, ..., p_k) \tag{2.1}$$

with p_i representing the number of players bound to action i. The function f maps a vector $p \in P$ onto a vector $q \in Q$ of the form

$$q = (q_1, ..., q_k) \tag{2.2}$$

representing the expected payoff for agents bound to action i. This expected payoff is an average over all players playing this strategy. The total number of entries in this payoff table is given by s in (2.3).

$$s = \frac{(n+k-1)!}{n!(k-1)!} \tag{2.3}$$

This corresponds to one entry per possible population state, taking into account agent symmetry. In a setting with two agents choosing between two options, there are three population states and therefore entries in the payoff table. Assigning parameters a, b, c and d to the possible payoffs produces the set $\mathcal{Q} = \{(a,0), (b,c), (0,d)\}$ from applying f to set $\mathcal{P} = \{(2,0), (1,1), (0,2)\}$ For brevity, the payoff matrix can be written as

$$A = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \tag{2.4}$$

Applied to the case of power system self-organization described in section 2.2.3 where flexibility providers choose an aggregator to do business with, selection dynamics are used to model the rational choice between two aggregators in repeated pairwise interaction where the providers compare their choice of aggregator and the gained revenues with other providers. These providers base their choice on their fitness. In this context, fitness is described by an agent's financial costs and especially the rewards arising from doing business with the chosen aggregator. The selection dynamics used in this work are the replicator dynamics [46] because stable states in these dynamics are closely linked to Maynard Smith's definition of evolutionary stable strategies and because the replicator dynamics have been well covered in literature [47].

The replicator dynamics are a set of ordinary differential equations describing the population dynamics in terms of the fitness of agents choosing the strategy compared to the overall average fitness of the whole population. The replicator dynamics equations describe how a population share of providers following a specific aggregator will increase or decrease in size as the payoffs for those agents are better or worse than the average payoff of the whole population. Consider a mixed strategy profile x for the population as a population state where each component x_i represents the population share choosing aggregator i instead of one agent's randomization over the choice of aggregators with $\sum_{i=0}^{k} x_i = 1$. The general replicator equations are then given in (2.5) following the notation used in [32].

$$\dot{x_i} = x_i[u(e_i, x) - u(x, x)] \tag{2.5}$$

with $u(e_i, x)$ representing the average expected payoff of an agent choosing aggregator i when the population is in state x and $u(x, x)$ representing the overall average expected payoff for an agent from a population in state x. In this formula e_i is the base vector in $\mathcal{R}^k$ and it represents the pure strategy of choosing aggregator i in a system where strategies are encoded as vectors from the unit simplex.

We can also represent the dynamics from (2.5) in terms of the 2×2 payoff matrix from (2.4) as

$$\dot{x_1} = x_1[(Ax)_1 - x^T Ax)] \tag{2.6}$$

with $\dot{x_2} = -\dot{x_1}$ because we assume a constant population size. In this notation $(Ax)_1$ represents the first element of the vector that results from multiplying A with the population state vector x.

From (2.6) we generalize the replicator dynamics for N agents and 2 actions in terms of the heuristic payoff table entries represented by the function f by defining $u(e_i, x)$ in (2.7) and $u(x, x)$ in (2.8).

$$u(e_1, x) = \sum_{i=0}^{N-1} \binom{N-1}{i} x_1^{N-i-1} x_2^i f(N-i, i)_1 \tag{2.7}$$

$$\begin{aligned} u(x, x) = &\sum_{i=1}^{2} x_i^N f(N - N(i-1), N(i-1))_i + \\ &\sum_{j=1}^{N-1} x_1^{N-j} x_2^j \sum_{k=1}^{S} \binom{N-1}{j-k-1} f(N-j, j)_k \end{aligned} \tag{2.8}$$

with N specifying the number of agents and S the number of actions to choose from (in this case 2). The definition for $u(e_i, x)$ is similar to work in [48] which defines the payoff to individual players playing a strategy $r = (r_1, r_2)$ against a set of opponents, each of which is playing $p = (p_1, p_2)$. In this case, however, expected payoffs are drawn from a heuristic payoff table provided by simulations and represented by the function f. The definition for $u(x, x)$ is given by using the same intuition that led to the definition of $u(e_i, x)$.

Finally, we analyze the critical points of these equations in terms of stability and draw conclusions about the probability of a certain stable state in the population occurring given the initial population.

2.4 Scenario setup

2.4.1 Aggregators

The concrete scenario consists of two competing aggregators attempting to balance their portfolio of clients in 15 minute time periods. For each period, the inputs for the aggregator consist of a value for the current imbalance in its portfolio drawn from a function $\mathcal{I}_i(t)$ and a value for the imbalance price in that time period, drawn from a function $\mathcal{C}(t)$. These two values determine the budget cap ($C_{i,b}$) for an aggregator. This cap is the maximum amount of money available to dispense towards flexibility providers to compensate for the imbalance. The budget is further divided between a budget for reservation payments ($C_{i,r}$) and a budget for activation payments ($C_{i,a}$) according to a ratio r_i such that $C_{i,r} = r_i C_{i,b}$ and $C_{i,a} = (1-r)C_{i,b}$. This budget division is also depicted graphically in Figure 2.2.

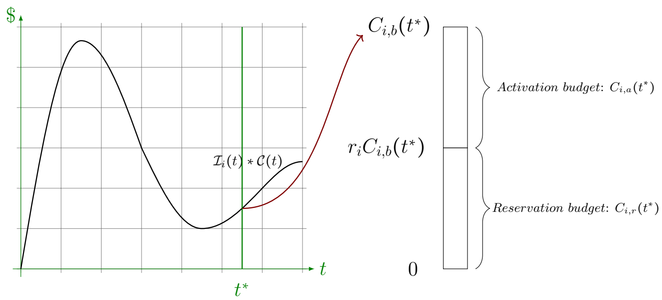

Figure 2.2: For each 15 minute time step, the amount of imbalance in the portfolio is determined and together with the imbalance price at that time, the upper bound of the aggregator's budget is set. This budget is weighted between reservation and activation fees according to a parameter r_i.

2.4.2 Flexibility providers

Flexibility providers are conceptually modeled as production factories working with production lines consisting of workstations and buffers. These production factories are able to offer power consumption flexibility by shutting down or starting up parallel workstations and relying on existing buffers between stations to continue production. The rebound effect often described in literature [31] as the increased consumption following a period of curtailment because a total decrease of consumed energy would impact the business output. As stated in [31] DSM is a mechanism for changing consumption patterns not for decreasing total consumption. However, the current model for the production factories does not take the rebound effect into account.

The available flexibility a provider can offer is represented by flexibility profiles of the form $(id, \delta P, \delta T, \delta Tc)$ where δP represents the amount of power the provider can curtail or consume additionally, δT the duration this profile will remain active when activated and δTc the recovery time representing the time after an activation that a provider is unavailable for providing flexibility. The providers are assumed to immediately activate the profile when the contracted aggregator signals an activation event.

2.4.3 Protocol

Aggregators query flexibility providers for their flexibility profiles and subsequently determine the best combination of profiles and providers to correct the current imbalance. Concretely, the combination of flexibility profiles (denoted by the set F) is chosen that minimizes $|\mathcal{I}_i(t) - \sum_{f \in F} \delta P(f)|$ under the assumption that for each client only one flexibility profile can be active. The full protocol modeled in this case is described in Figure 2.3. This protocol models three distinct phases: appropriation, nomination and remuneration, which occur for every time period continuously.

In the appropriation phase, the discrepancy between the current portfolio balance and the balance forecast provided to the TSO in $d-1$ is determined. All the flexibility profiles available from the contracted flexibility providers are gathered by using the flexibility provider APIs and the opportunity cost from not paying imbalance costs is determined and set as the budget for this period.

In the nomination phase, the flexibility profiles that compensate for the current imbalance are determined, activated and nominated with the TSO.

In the remuneration phase, the appropriate funds are used to pay reservation and activation fees to the providers.

2.4.4 Experiments

Flexibility providers are modeled with parameters for base load and flexibility provided by deterministic random generators drawing from normal distributions. Each provider can offer flexible power on par with the imbalance signal ranges of the aggregators but they offer this flexibility in discreet steps. Aggregators have two distinct input signals, one representing the current portfolio imbalance and one representing the imbalance price for the current time slot.

For a first experiment, the same imbalance ($\mathcal{I}_i(t)$) and pricing ($\mathcal{C}_i(t)$) signals are used for both aggregators while for a second experiment, distinct signals are used for each aggregator with the first aggregator having a larger total imbalance over time than the second aggregator ($\int |\mathcal{I}_1(t)|dt >> \int |\mathcal{I}_2(t)|dt$). The combination of the r_i parameters for the aggregators span a two dimensional parameter space. This parameter space is sampled with a sampling resolution of $10 * 10$ possible combinations of r_i values for the two aggregators. These experiments are performed with N flexibility providers with N ranging from 2 to 7.

Performing similar experiments with more agents can be problematic because of the combinatorial explosion from filling in all combinations in the payoff matrix for all parameter combinations using micro-simulations. Work in [49] can offer interesting techniques for sampling such solutions spaces and allowing for a higher number of participating providers with a computational cost similar to that of the current approach.

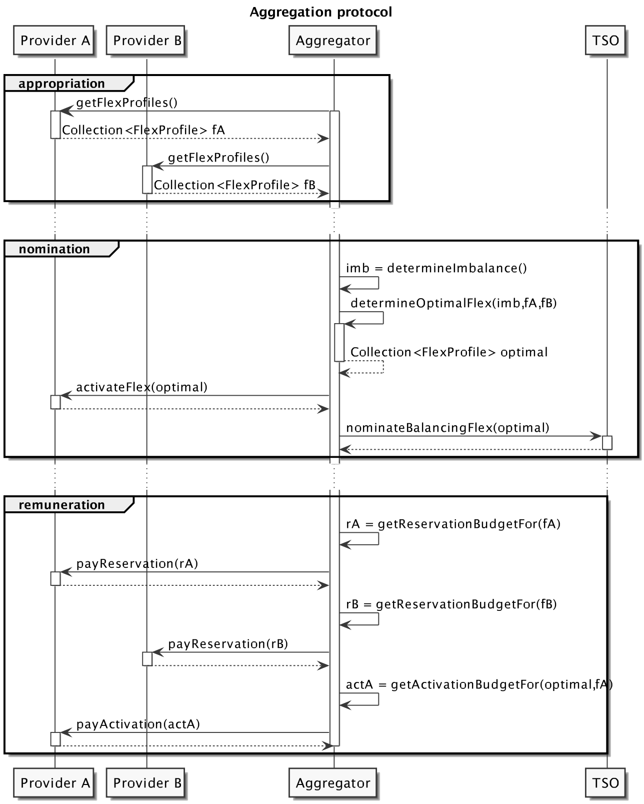

Figure 2.3: A UML sequence diagram describing the interaction protocol between an aggregator and two flexibility providers participating in the DSM program in a case where provider A supplies the best match to compensate for the imbalance.

All cases discussed in this paper are simulated using the simulation framework `GridFlex` [21]. `GridFlex` is a simulation framework capable of simulating smart grid scenarios with different flexibility providers models, input signals and different aggregator implementations while providing abstractions for performing game-theoretic analyzes. Simulation experiments are performed multiple times ($n = 500$) with different seeds for the random generators.

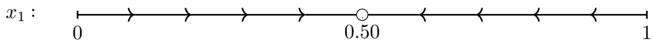

Figure 2.4: This phase plot shows the replicator dynamics for the game played by two clients. Any initial population proportion choosing the first aggregator would move to the stable equilibrium of 50% of clients choosing that aggregator.

2.5 Evaluation and discussion

Considering DSM programs as self-organizing balancing systems, the incentive mechanism used to compensate flexibility providers has a big influence on shaping the dynamics of these systems. This section uses EGT to analyze the dynamics as a result of the simulation experiments described in subsection 2.4.4.

Concretely, we analyze the influence of the budget division parameter r_i on the population dynamics of flexibility providers in a self-organizing balancing mechanism. A first analysis case will discuss two flexibility providers participating in an environment with two aggregators having both equal division parameters $r_1 = r_2 = 0.5$. Intuitively, with equal division parameters and equal imbalance and pricing signals, it is trivial that a client should feel indifferent between choosing one aggregator over the other. We will first validate this assumption with a game theoretic analysis and then follow the same approach to analyze cases where the r parameters differ.

2.5.1 Indifference case analysis

Simulation results provide a normalized payoff matrix A similar to (2.4). Payoff table A can be normalized further to

$$A' = \begin{pmatrix} s_1 & 0 \\ 0 & s_2 \end{pmatrix} \tag{2.9}$$

by subtracting c from the first column and b from the second column without loss of generality because the set of Nash equilibrium (NE) and the set of ESS are invariant under local payoff shifts in symmetric games when $s_1, s_2 \neq 0$ with s_1 and s_2 being the resulting matrix entries [32]. The numerical results from simulations are given in (2.10).

$$A = \begin{pmatrix} 2310 & 3849 \\ 3820 & 2304 \end{pmatrix} \rightarrow A' = \begin{pmatrix} -1510 & 0 \\ 0 & -1545 \end{pmatrix} \tag{2.10}$$

Based on the signs of s_1 and s_2, Weibull [32] categorizes 3 different cases, corresponding respectively to variants of the Prisoner's Dilemma [50] if $s_1 * s_2 < 0$, the coordination game [51] if $s_1, s_2 > 0$, and the hawk-dove game [41] if $s_1, s_2 < 0$. The simulation results for this case results in a payoff matrix that corresponds to a class of games that contains the hawk-dove game. In the hawk-dove game there are 3 Nash equilibria, one symmetric mixed strategy equilibrium $(\hat{x}, \hat{x})$ and two asymmetric strict equilibria $\{(e_1, e_2), (e_2, e_1)\}$. We are only interested in the symmetric equilibrium because only symmetric equilibria can be evolutionary stable states in single population models (which are modeled here). In this case, the symmetric equilibrium is defined as $x = (\lambda, 1 - \lambda)$ with $\lambda = \frac{-1545}{-1510-1545} = 0.51$ supporting the assumption made earlier that clients are (more or less) indifferent between the two aggregators. This symmetric equilibrium corresponds to an evolutionary stable state because for every other strategy $y = (y_1, y_2)$, the expected payoff of a client playing strategy y against x is always equal and the expected payoff of a client playing strategy y against itself will always be less than the expected payoff for a client playing y against a client playing x. This is indicated by (2.11) and (2.12).

$\forall y = (y_1, y_2) : y_1 + y_2 = 1 :$

$$\begin{aligned} u(x, y) &= -1510\lambda y_1 - 1545(1 - \lambda)y_2 \\ &= \frac{-1510*(-1545)}{-1510-1545} = 763.6 \end{aligned} \tag{2.11}$$

$\forall y \neq x :$

$$u(y, y) = -1510y_1^2 - 1545y_2^2 < 763,6 = u(x, y) \tag{2.12}$$

This verifies the assumption of indifference from the point of view of single agents playing mixed strategies. These results can also be interpreted from the viewpoint of evolutionary stable population states as discussed in section 2.3. When considering populations of clients participating in this self-organizing system, the optimal division between two equal aggregators with each their own imbalance to correct would be an approximately equal division between the two aggregators. In the case of two participating clients, a 50-50 population division would mean that each aggregator only has one client and that the available budget can be used to compensate one client fully. None of the clients would be better off doing business with the other aggregator as then the budget of one aggregator would have to be used to compensate two clients. The interpretation of client indifference from an individual agent point of view and optimal rewards in the population model can both be explained by using the same mathematical formalisms, but for further analyzes, we adopt the population model point of view.

Replicator dynamics are used to explicitly model population dynamics. The replicator dynamics, derived from applying (2.5) to A in (2.10), also supports the same conclusions from previous paragraphs. The resulting dynamics shown in (2.13) are illustrated by a one dimensional phase plot in figure 2.4. Phase

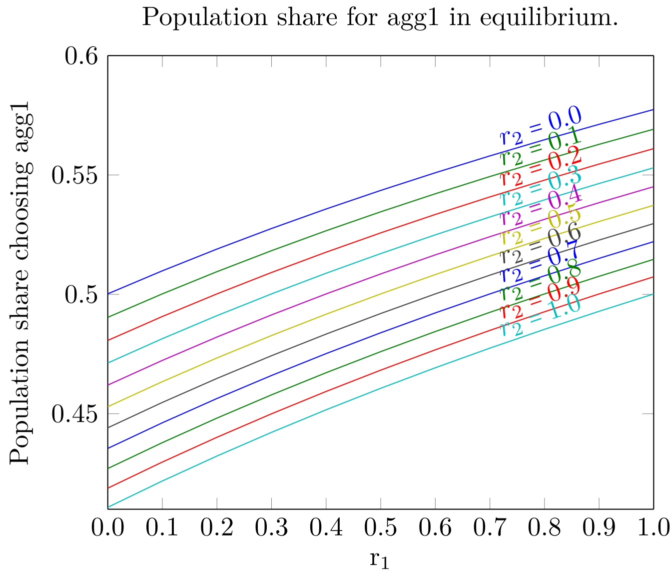

Figure 2.5: Plot showing the solution plane for r-parameters. Using more of the available budget for reservation payments improves your population share in equilibrium.

plots show the fixed points in the dynamics and whether these fixed points are attractors or repulsors. Clients are limited to a binary choice between aggregators so the dynamics can be displayed in one dimension by only showing the proportion of clients choosing the first aggregator while the complement of that proportion signifies the proportion choosing the second aggregator. Figure 2.4 shows one attracting fixed point at 0.5 indicating that all initial population distributions move towards a 50-50 distribution.

$$\begin{cases} \dot{x_1} = x_1\big[(2310x_1 + 3849x_2) \\ -(2310x_1^2 + 7669x_1x_2 + 2304x_2^2)\big] \\ \dot{x_2} = -\dot{x_1} \end{cases} \tag{2.13}$$

$$\Leftrightarrow \begin{cases} \dot{x_1} = (-1510x_1 - 1545x_2)x_1x_2 \\ \dot{x_2} = -\dot{x_1} \end{cases} \tag{2.14}$$

2.5.2 Influence of budget division parameter

Equal imbalance profiles

The previously explained case illustrated how evolutionary stable states can be found. In this subsection, we study the influence of the budget division parameter r_i on the evolutionary stable states of the population dynamics. Restricting the amount of free variables in the experiment setup and only varying the r_i parameters in 10% increments allows for sampling the solution plane. The results in Figure 2.5 show the population share of providers choosing the first aggregator in function of the r_i parameters chosen by both aggregators. From the point of view of an aggregator, increasing the r_i-parameter to increase the portion of the budget that is allocated to reservation fees, increases the client population share that chooses the aggregator in stable equilibrium. These results are gathered from simulations performed by two providers, but simulations using 3,4 or 5 providers show the same trend of results, yet less convincingly. The total amount of imbalance and therefore the total budget that is available for each aggregator has to be divided among more providers, which lowers the power of persuasion a certain payment structure can exert on the population.

Figure 2.6 shows how the equilibrium planes show a gentler incline when simulations are performed with more agents meaning that the same conclusion about changing the r_i-parameter can be drawn but that the effect of changing this parameter for an aggregator becomes less pronounced under equal imbalance profiles as the number of participating clients increases. More generally stated, when the ratio of total imbalance in the system to flexibility providers is low (e.g. when the available flexibility outweighs the needed flexibility), these effects are less pronounced. We call this ratio the Needed-to-Available flex ratio (NtAf).

If the assumption is made that from an aggregator's point of view that a larger client base allows for a more efficient way of performing portfolio balancing, then increasing the portion of the budget that is allocated to reservation payments can improve the balancing efficiency. This increase in efficiency can be negligible when the number of flexibility providers that want to participate outweighs the needed flexibility to perform portfolio balancing.

Different imbalance profiles

In this case we discuss whether the same results hold when the overall amount of imbalance differs between 2 aggregators. The results in Figure 2.7 show that when the first aggregator has an overall imbalance that is significantly larger than the imbalance of the second aggregator ($\int |\mathcal{I}_1(t)|dt >> \int |\mathcal{I}_2(t)|dt$),

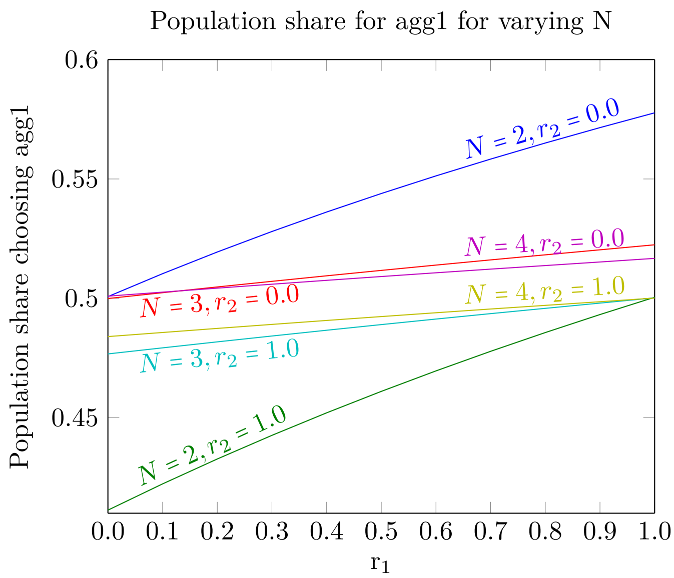

Figure 2.6: Shows the influence of the amount of simulated clients on the solution planes. Only $r_1 = 0$ and $r_1 = 0$ solutions are plotted for $N = 1$ to $N = 4$. Similar to previous plots, solutions for other r_1 parameters are parallel and equidistant between the plotted solutions. The results for $N > 5$ have been omitted to avoid decreasing the readability. The trend of the results also holds for $N = 5, 6$ and 7.

the solution plane undergoes a translation to match the fact that the budget available to the first aggregator is also significantly larger. The aggregator with a larger budget to divide amongst its clients, can provide a larger number of clients with at least as much expected payment than the other aggregator would be able to. In this case, increasing the portion of the budget that is allocated to reservation payments (r_i) still has a positive effect on the expected payments of the providers. This increases the population share in stable equilibrium when reservation payments are being favored by an aggregator.

Other conclusions concerning the influence of the r_i parameters still apply to this case. In situations with a large number of flexibility providers, the population division in equilibrium is mainly determined by the differences in budgets and less so by the choice of r_i parameters. With large numbers of flexibility providers, the available budgets need to be divided amongst an aggregator's clients. The expected payments from a provider's point of view decreases when more providers are doing business with the same aggregator. When

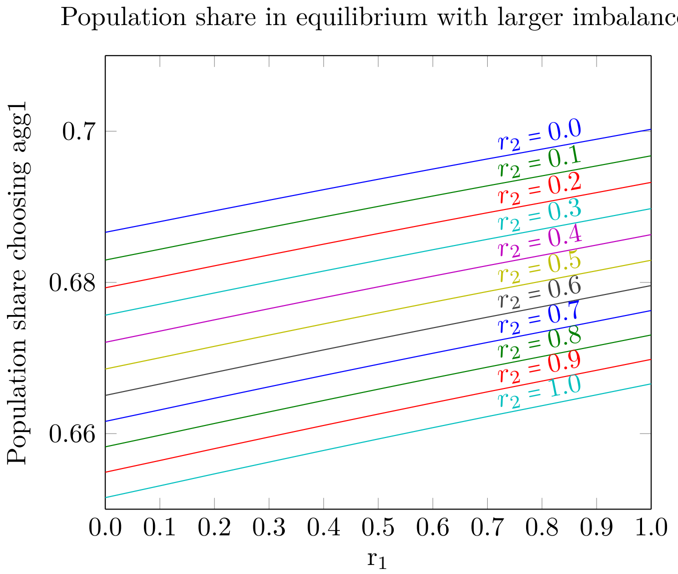

Figure 2.7: Shows the translation of the solution plane of the results towards the aggregator with more imbalance to correct and therefore with a higher budget to distribute among the providers.

the number of competitors increases, choosing another aggregator with less clients increases the expected payment values more than a change in aggregator payment structure would.

2.5.3 Lessons learned

We summarize the lessons learned from evaluating these results for cases where multiple aggregators compete for the business of flexibility providers. We assume that the flexibility providers are profit maximizing, the aggregator budget volume is determined by the opportunity costs from imbalance prices and that flexibility providers have the means for gaining information about the payoffs of fellow providers. The lessons learned from the point of view of individual aggregators are the following.

- As an incentive mechanism, reservation payments are more likely to increase market share than activation payments.
- A larger portfolio imbalance results in a larger market share in equilibrium.

- In systems with lower Needed-to-Available flexibility ratios, the likelihood of increased market share through using reservation payments, is less pronounced.

These lessons learned are subject to the assumptions made in this work and the simulation model used to produce the results. Real world scenarios concerning flexibility providers and aggregator dynamics are in all likelihood more complex than modeled in this case. It is therefore important that these assumptions and models are also improved upon in future work to verify if these results continue to hold in real world scenarios. However, our experiences does show the potential of using EGT to analyze the dynamics of such scenarios and to draw conclusions about the influence of specific scenario parameters.

2.6 Related work

Applications of EGT have gained momentum in other research fields. For example, in the field of economics research, Walsh et al. offer an analysis of strategic interaction between price bots in different market settings [44]. Phelps et al. compare two double-auction market designs using evolutionary game theory [45]. But applications are not limited to the economics domain. Sandholm offers an extensive overview of applications in social sciences besides applications in economics [52]. To the best of our knowledge, the application of EGT in the context of smart grids has been limited. This work attempts to address that.

The smart grids domain by now is a well established field for coordination and self-organization research ranging from DSM [31] to coordinated charging of electric vehicles [53][14]. A popular approach towards smart grid coordination in literature is the application of optimization algorithms in coordination protocols [54]. Designing coordination protocols starts from the assumption of willing participants that can be governed easily. When dealing with self-interested agents that are outside the scope of control from the perspective of the protocol designer, a framework capable of modeling strategic interaction is required. GT [33] and more specifically inverse game theory, otherwise known as mechanism design (MD) [55], allows for taking into account multiple individual goals for designing incentive compatible coordination mechanisms while accounting for strategic agents [26]. One example of such mechanisms is proposed in [56] where the authors propose a mechanism for scheduling uncertain demand given uncertain supply while dealing with strategic agents.

This work focuses on scenarios with multiple aggregators where strategic choice between aggregators influences self-organization. The smart grid literature considering similar scenarios is also rather limited. To the best of our knowledge, only the work in [57] describes a similar scenario with self-interested agents and multiple aggregators. The authors discuss a scenario where these agents are hierarchically structured under different aggregators but differs from this work because the agents are not modeled to choose strategically between different aggregators. Instead of using GT, the authors formulate a multilevel optimization problem and provide solution characteristics for different scenarios. An examples of related work concerning single aggregator scenarios can be found in [35] where self-organized coalitions of agents are used for trading active power and ancillary services.

This work proposes the Replicator Dynamics for modeling selection between aggregators in population dynamics [46]. The replicator dynamics is in itself a special case of a class of dynamical systems that has been analyzed in terms of limit behavior and stability in general [58]. This makes the replicator dynamics attractive as a way of modeling selection dynamics. When it comes to deterministic selection dynamics, other examples and studies of using differential equations for modeling evolutionary dynamics are also available. Hoffbauer and Sigmund [59] and Sandholm [60] have provided excellent surveys on this topic. Besides these selection dynamics, the evolution aspect in EGT does not necessarily have to be biologically inspired. Other selection dynamics that are used for modeling evolutionary dynamics are based on learning [61] and imitation [62]. However, not all of these selection dynamics bare the strong link to Maynard Smith's definition of evolutionary stable states and classical game theoretic notions of the NE [40] that the replicator dynamics do.

2.7 Conclusion and future work

The smart grid domain is host to situations of complex interplay between various parties. These parties self-organize by adapting to their own objectives. These objectives often, if not always involve maximizing financial revenue.

One of the most important aspects in safely operating the current power infrastructure is that the balance between power consumption and production always needs to be maintained. Demand-side flexibility aggregators can offer balancing services to this effect by using flexibility providing parties. Convincing these flexibility providers to do business with them instead of with a competing aggregator involves choosing the appropriate payment structures to incentivize these providers. As a result, aggregators and flexibility providers interact and form a complex self-organizing system. In this work, the dynamics of this system is analyzed using evolutionary game theory.

Concretely, a case of BRP portfolio balancing is analyzed to gauge the influence of overall budget divisions between reservation and activation payments on a population of flexibility providers. In this case, flexibility providers are capable of making a choice between multiple aggregators acting as BRP, based on their compensation for services offered. EGT is an ideal tool for analyzing such self-* systems because it allows for capturing notions like rational strategic behavior and best response strategies while using these notions to reason about populations of interacting agents. In this case, analyzing such scenarios using EGT provides insight into how population distributions might change under the influence of certain changing scenario parameters like the payment structures used by aggregators. Simulation results show that preferring the allocation of a budget to reservation payments for one BRP can increase its client population share in stable equilibrium but that this effect is dampened when the amount of flexibility offered greatly outweighs the flexibility needed.

In this work, among others, the assumption is made that a larger client population share increases the portfolio balancing efficiency by having more flexibility to balance with. In future work this assumption will be verified by improving on the scenario setup such that the effect of budget division on global system imbalance can also be analyzed. The input signals that represent imbalance volumes and imbalance costs for BRPs will also be studied more exhaustively in future work. In this work we have already seen that the overall size of an aggregator's imbalance influences its budget and by extension the power of persuasion it can exert on the population of flexibility providers. It is likely that the imbalance volumes and shapes therefore also influences the population dynamics.

In this work, the opportunity cost from not having to pay imbalance costs is used as a budget for using DSM to compensate for imbalances. In future work, business cases where only a selective part of these opportunity costs are used for DSM compensation fees are considered. In these cases, BRP profit margins influence the budget caps and could therefore influence the population dynamics similar to how the budget division between reservation and activation payments can be an influencing factor on these dynamics.

Finally, even though more complex models of interaction dynamics are needed to bride the gap between results from simulation models and expected behavior in the real world, EGT remains useful in capturing this complexity during analysis.

Acknowledgment

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Chapter 3

Coordinating Wind Turbines and Flexible Consumers with Cooperative and Competitive Agents

In chapter 2 the strategic choice between financial compensation structures was computationally analyzed. Besides compensation structures, flexibility users must also decide on which flexibility providers to activate when dealing with imbalances. How and when these decisions are made, influences how efficiently consumption flexibility can be used to address imbalances. This chapter presents and evaluates various coordination mechanisms for employing consumption flexibility and contains the full workshop paper that corresponds to the following published extended abstract:

> Kristof Coninx and Tom Holvoet. 2016. Coordinating Wind Turbines and Flexible Consumers with Cooperative and Competitive Agents. In Proceedings of the 15th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2016), 1407–1408.

The definitions, analysis and supporting software are the result of discussions between both authors. Kristof Coninx did all the programming and the writing. Tom Holvoet gave feedback on the writing.

Abstract

Integrating wind farms into existing distribution grids is challenging because of potential congestion caused by imbalance between wind turbine energy production and consumers' energy offtake. Demand-side management (DSM) techniques address this imbalances by dynamically increasing the consumers' offtake, thereby allowing unrestrained power generation by wind farms. In practice, distribution grids are constrained by power line capacity, a fact often ignored by existing literature. Present chapter describes a novel and realistic application of DSM to a constrained distribution grid where multiple self-interested agents can provide flexibility to the distribution system operator (DSO). DSM is evaluated online, where agents' flexibility is allocated in real time using limited local forecasts, and offline, where a central agent has complete foresight to compute a theoretical upper bound and enables the DSO to evaluate its infrastructure investments. In online simulations a cooperative mechanism is compared to a competitive strategy proof auction mechanism. The results indicate that the competitive mechanism has a lower allocative efficiency compared to the cooperative mechanism. This online result questions the trend of increased usage of markets in industry while the offline experiment shows that the current activation constraints of the DSO prevents the system from reaching global allocation optima.

3.1 Introduction and problem

Meeting the 20-20-20 objectives put forward by the European Commission to increase the share of renewable energy production in Belgium to 13% of the gross final energy consumption by 2020, requires the installation of large wind farms both on- and offshore [63]. Integrating these wind farms into existing distribution infrastructure is challenging because of potential congestion caused by imbalance between wind turbine energy production and consumers' energy offtake [64].

One technical constraint that needs to be considered is guaranteeing that existing cables can cope with the increased wind energy injection into the grid. Adding energy production elements to existing grids can cause power rates to increase past the rates that would ensure safe cable operation. Upgrading existing cable infrastructure to cope with increased power rates would lead to a costly replacement of existing cables. Experience in industrial projects shows that this is an actual problem distribution system operators (DSOs) are facing when incorporating wind turbines into existing distribution infrastructure.

Considering that these excessive power rates only occur occasionally, alternative remedies are investigated.

Literature describes active network management (ANM) techniques for dealing with these forms of increased power production related current congestion in a more cost effective manner [65]. ANM techniques describe a class of techniques for actively performing steering actions in the management of a distribution network to minimize or alleviate congestion problems from excessive wind power production.

Smart grids are known for their complex dynamical environments where different self-interested parties interact to trade energy and to maintain the stability of power grids [1]. Multi-agent systems (MASs) can provide solutions and analysis frameworks for these systems [66]. Most work situated in the intersection of smart grids and MAS deals with smart devices or smart agents representing the interest or preferences of prosumers in a multi-agent context where the agents can negotiate in some form an outcome that is beneficial to them [30] [31].

The work described in this chapter focuses on applying MAS techniques to solve a concrete and current real world problem. Demand-side management (DSM) is used as the ANM technique of choice to resolve the problem of upstream current congestion. The distinction is made between two phases and we propose algorithms for both phases. The first phase deals with an ahead of time planning phase where grid investment or reinforcement has to be outweighed against demand-side management. A second phase considers a real time situation for online allocation of ANM resources based on local wind production forecasts. For online power flexibility allocation, two mechanisms, a cooperative contract-net based mechanisms and a competitive qualitative Vickrey auction (QVA) are implemented and compared in terms of allocative efficiency.

3.2 Remedying congestion

This work defines a flexibility model that closely resembles the real world products available. We focus on tertiary reserve under a dynamic profile (R3DP) as the closest matching product that is relevant to this work because of its focus on DSO-connected grid users to offer strategic reserve. Primary and secondary reserves are not of use in this case because these reserves are meant for transmission scale balancing. The problem discussed here is distribution local. Furthermore, primary reserve is used for frequency control and secondary reserve specifies injection by production reserves. The flexibility product description that is used in this work is therefore proposed for DSO-connected grid users

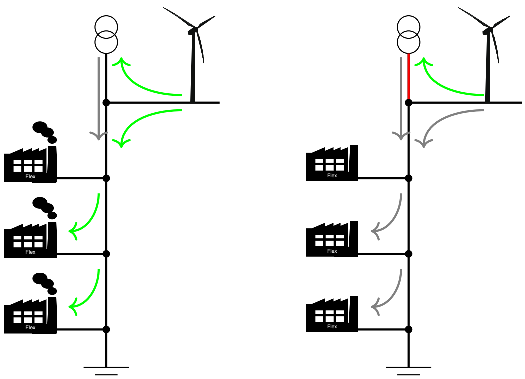

Figure 3.1: Example scenario for upstream current congestion. Left: Energy flows from wind turbine to factories downstream and all excess production flows upstream towards the TSO transformer for grid injection. Right: Factories downstream are inactive and all energy flows upstream towards the TSO transformer causing upstream current congestion.

that offer consumption increase flexibility according to the following constraints, which are similar to the R3DP activation constraints specified by Elia, the Belgian TSO:

- A maximum of 40 activations/year is allowed.
- All activations last max. 2 hours.
- The time between 2 consecutive activations should be at least 12 hours.

3.2.1 Offline allocation

Primarily, an offline optimal solution can provide an upper bound on the maximum allocative efficiency that is attainable for given wind profiles and flexibility in the system, constrained by activation constraints such as described in the previous section. Optimally solving the allocation problem is done in mixed-integer programming (MIP) model 1 by maximizing the remedied congestion over time $s(t)$ which in turn maximizes the allocation efficiency of flexibility activations.

This problem formulation is shown in Model 1. The decision variable $x(t, j)$ represents the time periods t, each flexibility provider j is activating its flexibility, defined by $p(j)$. The main input for this model is the congestion profile

$c(t)$. Constraint (3.1) maps the remedied congestion variable $s(t)$ to the boolean variable $x(t,j)$ where δT represents the number of settlements per hour. Together, constraint (3.1) and (3.2) model the remedied congestion as being the minimum of both the available congestion to remedy and the activated flexibility. Constraints (3.3), (3.4) and (3.5) model the duration d_a of each activation while constraint (3.6) models the inter-activation time d_i between two consecutive events. Finally, constraints (3.7), (3.8) enforce the maximum number of activations m_a per provider. This model is the result of a process in which constraints are defined in a mathematical model which are then transformed into linear equations that can be used in a MIP model.

$$s(t) - \sum_j x(t,j) * \frac{p(j)}{\delta T} \leq 0 \tag{3.1}$$

$$s(t) - c(t) \leq 0 \tag{3.2}$$

$$x(0+k,j) - x(1+k,j) \leq 0 \tag{3.3}$$

$$d_a - \sum_{k=0}^{d_a-1} x(t+k,j) + (1 - x(t+d_a,j)) \geq 1 \tag{3.4}$$

$$\begin{aligned}(1-d_a) &- \eta^- * x(t,j) + \gamma \\ &-\gamma * x(t+1,j) + \sum_{m=0}^{d_a-1} x(t-m,j) \geq 0\end{aligned} \tag{3.5}$$

$$\sum_{k=0}^{d_a+d_i-1} x(t+k,j) - d_a \leq 0 \tag{3.6}$$

$$\sum_{t=0}^{N_I} x(t,j) - m_a * d_a \leq 0 \tag{3.7}$$

$$\sum_{t=0}^{N_I} x(t,j) - m_a * d_a \geq 0 \tag{3.8}$$

Model 1

$$
\begin{aligned}
\underset{t}{\textbf{maximize}} \quad & \sum \mathrm{s(t)} \\
\textbf{subject to} \quad & (3.1),\ \forall t \in T, \forall j \in J \\
& (3.2),\ \forall t \in T \\
& (3.3),\ 0 \le k \le d_a - 1, \forall j \in J \\
& (3.4),\ 0 \le t \le N_T - d_a, \forall j \in J \\
& (3.5),\ d_a \le t \le N_T - 1, \forall j \in J, \gamma = \eta^{-} - \epsilon \\
& (3.6),\ 0 \le t \le N_T - d_a - d_i + 1, \forall j \in J \\
& (3.7),\ \forall j \in J \\
& (3.8),\ \forall j \in J
\end{aligned}
$$

3.2.2 Online allocation

For solving the real-time allocation problem we study two different approaches to the flexibility allocation problem. A cooperative setting relating to current practice in industry is modeled. DSM participation is currently often regulated by contracts and these contracts are enforced with significant fines and complete exclusion from DSM programs. A strategy proof, qualitative Vickrey auction (QVA) is implemented as a counterpart to the cooperative setting to follow state-of-art proof of concept cases where flexibility market mechanisms are modeled to allow all parties to act as market participants.

Both approaches are evaluated in terms of allocative efficiency which is defined as the amount of excess energy that is actually reduced by DSM activations. Any activation that leads to more energy reduced than the amount that was causing congestion is considered inefficient. Both mechanisms are implemented to follow a similar message protocol, shown in Figure 3.2. Every time period of 15 minutes, the center agent (DSO) evaluates whether forecasts show that congestion will occur and if so, will send out a *call for proposals* to all agents. Agents then respond with a bid depending on their capabilities at that time and the winning bid is sent an activation signal.

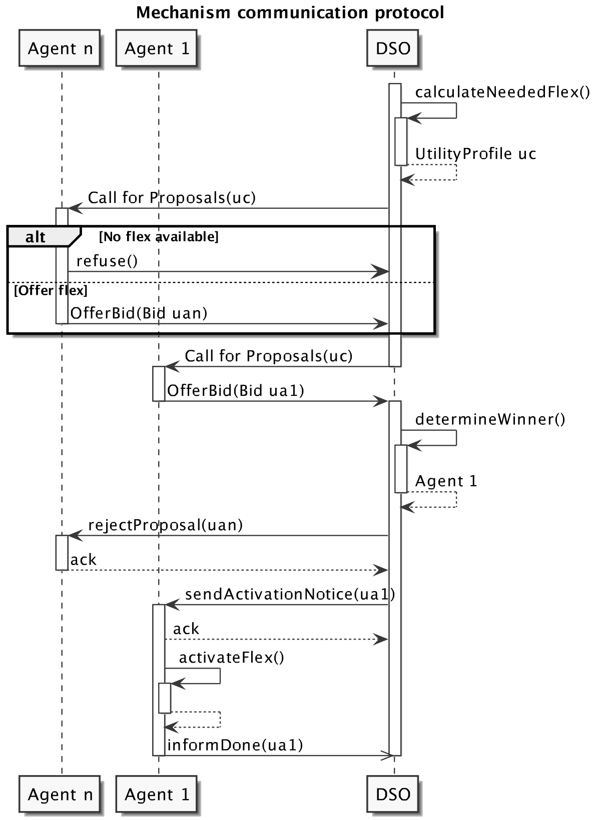

Figure 3.2: A UML sequence diagram showing the communication flow for both the cooperative and competitive mechanisms. All agents (agent n) submit bids (ua1 from agent 1, etc.) to the DSO

Cooperative mechanism

In the cooperative mechanism, the winner is determined by a social choice function $\mathcal{F}(R^n)$ which favors the closest bid of the form $x = (x_p, x_s, x_e)$ that could resolve most of the congestion among all the bids, with x_p representing the capacity for increasing consumption in kW, x_s and x_e marking the start and end times of the activation in units of time t. This function is defined in (3.9) where $C(t)$ is the function representing the congestion over time and $\epsilon(x)$ represents the allocative efficiency for that bid.

$$\mathcal{F}(R^n) = \arg\max_{y \in R^n}(\epsilon(y)) \tag{3.9}$$

$$\epsilon(x) = \int_{x_{start}}^{x_{end}} \min(C(t), x_p)dt \tag{3.10}$$

Ties are broken in favor of the bid offering the lowest amount of power (x_p) to increase consumption with. Without this tie-breaking rule any agent offering a contract with $\hat{x}_p \geq \max_{t|x_s<t<x_e} C(t)$ has equal chance of being determined the winner and subsequently getting the allocation.

Competitive mechanism

In the competitive mechanism, contract auctions are implemented. Contract auctions are an application of qualitative Vickrey auctions (QVAs) [67], which are known to be the only mechanisms that are individually rational, dominant strategy proof and capable of selecting stable, Pareto efficient outcomes given the assumption of weakly transferable utility [68]. The assumption of weakly transferable utility does not hold because the center has single (positively) peaked preferences which introduces a local maximum. Inspired by the work in [68], a fixed and publicly announced tie breaking rule is used to guarantee strategy proofness in the absence of weakly transferable utility. In this case, however, Pareto efficient outcomes cannot be guaranteed.

The application of the QVA contract auction to this congestion case leads to the following mechanism formulation in similar fashion to the formulations in [68].

(1) Initially, the utility function of the DSO agent is announced by way of communicating the required power to remedy the congestion in this round alongside a fixed tie breaking order over the outcomes.

(2) Each DSM agent in turn provides an offer to the DSO agent by way of a sealed bid containing the tuple $x = (x_p, x_s, x_e)$ similar to the definition in section 3.2.2.

(3) The agent that provided the highest bid is declared the winner with ties broken according to the fixed tie breaking order in step (1). The agents are informed of the outcomes and the winner is informed of the minimum allowed bid that would have made him the winner.

(4) Lastly, the winning agent can activate the smallest amount of power that would have still made him the winner were he to have provided that value in his bid in step (2).

#agents	1	2	3	4	5
Optimal	0.9896	0.9815	0.9863	0.9620	0.9574

Table 3.1: Optimal sample results

3.3 Evaluation and discussion

The optimal full knowledge allocation approach can deliver very efficient allocations in general. The main drawback is that optimally allocating agent power flexibility over a one year time horizon in 15 minute increments, leads to very high resource requirements, in both CPU time and memory for the branch-and-bound technique used for solving MIP problems.

The first result is that attaining 100% total efficiency is not possible in the simplest case with 1 participating agent using the optimal allocation algorithm. The results of the optimal allocation experiment are shown in Table 3.1 for up to 5 agents. Further study into the flexibility required to solve these specific current congestion problems is needed because currently available flexibility products can not be used to attain 100% efficient allocations in the best case scenario.

The second result in Figure 3.3 shows that the cooperative approach manages to attain a higher allocative efficiency than the competitive approach. These results also indicate that the difference in mean efficiency between both approaches decreases significantly as the number of participating agents increases making the difference between the two approaches negligible in terms of result when many agents participate. Assuming that more than 10 agents would be located in such a way that they can all be used to resolve congestion is, however, unreasonable because all agents need to be connected to the same feeder, as is illustrated in Figure 3.3. This is an interesting result because the use of more market oriented mechanism like the QVA has useful properties such as strategy proofness and the selection of stable outcomes. As more agents participate, these benefits will outweigh the difference in allocative efficiency. These results also indicate that from the point of view of the DSO it is beneficial to maintain full control over the social choice rule used in the mechanism while enforcing cooperation when the number of participating agents is low. This occurs often in problems similar to the one discussed in this work because of the location requirement where agents need to be physically connected to the grid at locations that allow congestion to be resolved by their actions. This results also indicate that in similar problems where this location requirement is not in place and the number of participating agents can be significantly higher, that the benefits from a competitive mechanism might outweigh that of a cooperative

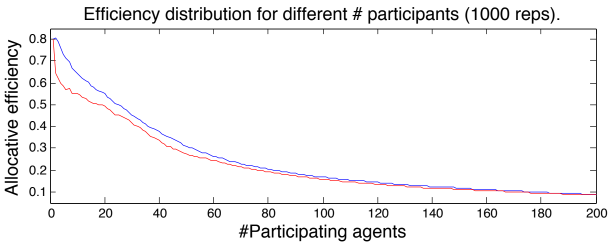

Figure 3.3: Results for up to 200 participating agents show higher allocative efficiency of the cooperative (blue/higher) setting when compared to the competitive (red/lower) solution.

mechanism. Transmission grid scale congestion problems might offer examples where these locality requirements are less strict,

3.4 Conclusion

This work presents initial findings in a study to apply cooperative and competitive MAS techniques to the problem of upstream current congestion. Further results analyzing different metrics such as the actually resolved congestion and different wind profiles are underway.

Further work is necessary to specify the exact flexibility product requirements that are necessary for dealing with these current congestion problems. In future work we will also analyze investment costs and compare these costs to other ANM techniques such as storage.

Chapter 4

Combining DSM and Storage to Alleviate Current Congestion in Distribution Grids

Chapter 3 showed that consumption flexibility alone is often not enough to address local imbalances. Combining different ANM techniques such as DSM and energy storage, can provide a technically feasible but possibly costly solution. This chapter presents an evaluated investment and operational cost model for an optimized combination of ANM techniques and contains the paper:

> Kristof Coninx, Mohammad Moradzadeh, and Tom Holvoet. 2016. Combining DSM and storage to alleviate current congestion in distribution grids. In 2016 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 1–6. DOI:10.1109/ISGTEurope.2016.7856202

The definitions, analysis and supporting software are the result of discussions between all authors. Kristof Coninx led the discussions and did most of the programming and the writing. Mohammad Moradzadeh contributed the source code for the prototype storage dimensioning algorithm and early versions of the energy storage section in the article and Tom Holvoet gave feedback on the writing.

Abstract

Storing energy is one possible active network management (ANM) technique for reducing wind turbine induced distribution grid congestion. However, in most cases investment costs for installing storage solutions far outweigh the cost for infrastructure upgrades. Our research shows that combining demand-side management (DSM) and storage techniques can prove effective in reducing the total investment costs in certain cases while increasing these costs in other cases. In this work we qualify when DSM can prove beneficial to the total investment cost of deploying ANM techniques and we quantify the amount of cost decrease DSM can offer. We present cost models for storage and DSM and describe ANM resource allocation techniques while considering real world regulatory constraints.

4.1 Introduction

In efforts to meet the European Commission's 20-20-20 objectives of increasing the renewable energy production share in Belgium to 13% of the gross final energy consumption by 2020, requires the installation of large wind farms both on- and offshore[2]. Integrating wind turbines into existing distribution grids can be troublesome when the existing cable infrastructure is not rated to cope with increased current flows caused by added production elements [69]. Distribution grid congestion in this form can be harmful to the correct operation of these grids and repairing damages caused by overheating power cables can be costly. Measures to prevent damage exist in the form of curtailing wind turbine production or upgrading existing infrastructure with more heat resistant cables. Both of these options are costly because curtailment can mean that wind farm owners might have to be compensated for the loss of income from their wind turbines. Upgrading existing infrastructure is also a costly endeavor.

In this chapter we consider a combination of different active network management (ANM) techniques as alternative measures to address distribution grid congestion from increased wind turbine integration. These ANM techniques are evaluated in projected investment costs over a 20 year business case and compared to the cost of upgrading existing infrastructure.

This chapter is structured as follows. First, the problem context is described in section 4.2 while the approach to addressing these problems by proposing cost models and ANM allocation mechanisms are discussed in section 4.3. Simulation results are discussed in section 4.4. Conclusions and future work are described in section 4.5.

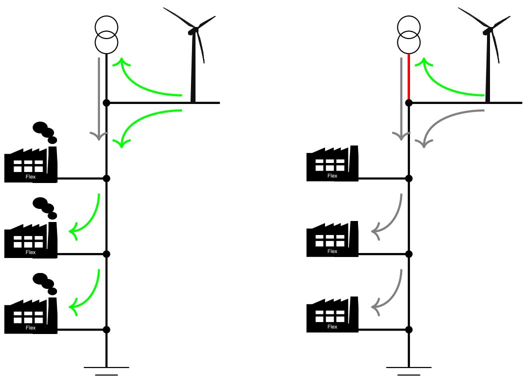

Figure 4.1: Example scenario for upstream current congestion. Left: Energy flows from wind turbine to factories downstream and all excess production flows upstream toward the TSO transformer for grid injection. Right: Factories downstream are inactive and all energy flows upstream toward the TSO transformer causing upstream current congestion.

4.2 Problem context

A common problem with existing distribution infrastructure is related to the static ampacity ratings of installed cables in a distribution grid [2]. When new renewable energy generators are added to this infrastructure, the increase in electric current in some parts of the cable network can cause temperatures inside these cables to reach unsafe levels. The power rates of these generators are then often limited or curtailed as a measure to ensure safe cable operation. Figure 4.1 shows a scenario where excessive wind power production rates combined with low energy offtake from energy consumers can lead to upstream current congestion. Considering that these excessive power rates only occur occasionally, alternative remedies are investigated.

Literature describes ANM techniques for dealing with these forms of increased power production related current congestion as alternatives to infrastructure upgrades. While economic evaluation of different ANM techniques is not novel [65], we focus in this work on the combination of multiple ANM techniques and their associated installation and operation costs.

4.2.1 Active network management

ANM techniques describe a class of techniques for actively performing steering actions in the management of a distribution network to minimize or alleviate congestion problems from excessive wind power production. In this work several techniques are considered: dynamic line rating (DLR), energy storage and demand-side management (DSM).

Dynamic line rating

DLR consists of temporarily increasing the static current limit on the cables based on the actual cable temperature. Because temperature increases from increased electrical current through a cable follow a hysteresis effect, the cables are actually capable of dealing with increased current for a short while before dangerous temperatures are reached. DLR makes use of these effects to allow short peak power rates without wind power curtailment by changing the static current limit to a dynamic current limit [70]. This dynamic limit is dependent on external factors such as the make, model and type of cable, the surrounding environment and the load profiles of production and consumption elements on that cable. The main cost of such a solution is in installing temperature sensors on existing cables which makes this technique an ideal complement to any other ANM technique used [71]. Concrete test cases implementing DLR in Belgium, have been positive [72].

Energy Storage

Energy storage elements installed at key location can deal with excess energy by taking in a portion of the produced excess energy before it causes congestion problems down the line. Existing work in the domain of storage allocation describes the possibility of achieving up to 13% savings on consumer electricity bills by installing residential storage devices [66]. At the moment, installing consumer/industrial batteries for energy storage, remains expensive however. Considering industry projects experiences in this field, recompensating green energy certificates by curtailing wind energy is generally less expensive than implementing a storage solution. Work in literature focusing on economic viability of battery storage solutions to increase the penetration of renewable energy sources in general are not in all cases positive [73].

Demand side management

DSM is employed to increasing energy offtake from the grid at key moments. In general, DSM is an umbrella term of techniques for influencing or controlling the demand side of the balance equation between energy production and consumption [9]. Different to most work in literature, this case requires power flexibility providers capable of increasing their energy consumption to offtake excess energy from the grid in stead of curtailing their energy consumption on demand.

Drawbacks of using DSM in this context is that the physical location on the grid of the flexibility provider is important [2]. Flexibility providers located upstream of the wind turbines and behind the congestion points cannot alleviate the congestion. This limits the scale of the DSM allocation problem because a large number of available flexibility providers would not be a realistic assumption. Assuming that for a specific problem, flexibility providers can be found in adequate locations, we focus on solving congestion by using DSM.

4.3 Approach

In this work two profiles of wind turbine production over a period of one year, in 15 minute increments are considered. These wind production profiles cover two distinct locations in Belgium. The wind profiles are boosted by 30% in terms of produced power to simulate locally added generation capacity. Excess energy in these profiles is defined as the amount of energy that surpasses the static ampacity limits of existing cables. *XLPE240* cables rated at 300A are taken as reference cables deployed in a 15kV distribution grid with wind turbines providing 3.2MW at 100% nominal power rates.

To remedy distribution grid current congestion, DLR is used first. The resulting profile of excess energy is then used as input for DSM and Storage allocation mechanisms, in that order. DSM is assumed to be employed first because DSM activation constraints make it a less flexible ANM technique than storage. Lastly, storage solutions are dimensioned and used for remedying all remaining excess energy that is not taken care of by DLR or DSM. All ANM allocation mechanisms are offline algorithms that employ full historic knowledge of the wind profiles. Offline allocation can provide a lower bound on the associated investment costs as online allocation is generally less efficient and can require more ANM resources to achieve the same effects [2].

4.3.1 Investment costs

Cost models are proposed for a 20 year investment business case and evaluated against infrastructure reinforcement costs. These models define the yearly costs for the employed ANM techniques by discerning fixed costs (Table 4.1), marginal costs (Table 4.2) and maintenance costs (Table 4.3) with all monetary values in euro (€) where N_{dsm} represents the number of flexibility providers and $(E_s^{\max}, P_s^{\max})$ represents the storage dimensions. The parameter values chosen in this work have been evaluated by a Belgian distribution system operator (DSO) as reasonable. Final costs are calculated as the NPV over a 20 year business case.

Table 4.1: Fixed costs for ANM techniques include DLR installation cost, DSM cost for on site installation of DSM equipment and costs for buying energy storage batteries.

Technique	Symbol	Value
DLR	C^f_{dlr}	€1000
DSM	C^f_{dsm}	€15000 × N_{dsm}
Storage	C^f_{sto}	€150 × $E_s^{\max}$+€150 × $P_s^{\max}$
Grid reinforcement	C^f_{net}	104/meter cable

Table 4.2: Marginal costs for DSM includes reservation costs for reserving flexible load capacity and is paid upfront.

Technique	Aspect	Symbol	Value
DSM	reservation cost	C^r_{dsm}	€30/MW

Table 4.3: Marginal costs include upkeep and maintenance cost for on site equipment and maintenance cost for Storage. No maintenance cost for DLR is assumed.

Technique	Symbol	Value
DSM	C^m_{dsm}	10%×€15000 × N_{dsm}
Storage	C^m_{sto}	€2 × $P_s^{\max}$
DLR	C^m_{dlr}	€0

Besides many technical benefits, ANM is also capable of generating revenue. In this work, curtailment reduction (R^2) is also considered as a positive revenue stream because revenue is generated for DSOs by not having to compensate wind turbine owners for green certificates lost because of curtailment. For energy storage, a negative revenue stream (or cost) of compensating wind turbine owners for energy lost during charging/discharging (R^1) is also included in the cost model.

4.3.2 ANM allocation

Dynamic line rating

DLR is applied to the base wind production profile using an activation mechanism that allows four quarter hours of increased current, followed by four quarter hours of limited current flow. Without other ANM techniques, all excess production output is curtailed to maintain this limit. It is the DLR mechanism that shapes the excess energy profile for other ANM techniques.

Demand side management

DSM allocation of a set of flexibility providers is performed using Algorithm 1. Algorithm 1 finds the largest volumes excess energy that is feasible given the activation constraints and allocates DSM resources until no more feasible allocations are possible. The activation constraints in this work are similar to the constraints described in [2], which are the following:

- A maximum of 40 activations/year is allowed.
- All activations last max. 2 hours.
- The time between 2 consecutive activations should be at least 12 hours.

These constraints are similar to the constraints of the R3DP flexibility product, the Belgian TSO offers for grid connected users. Our definition differs in that we assume flexibility providers to be able to increase their consumption in stead of limiting it. For this work, we draw realizations of power rates for simulations from a gamma distribution $\Gamma(a,r)$ with $a = 1.37012, r = 677.926$. This Γ distribution passes the classical goodness-of-fit tests for a confidential industry data set of R3DP clients in Belgium. These tests include the Komolgorov-Smirnov [74] and the Anderson-Darling [75] goodness-of-fit tests.

In Algorithm 1, the `findMaxFeasibleActivation` procedure maximizes the volume of excess energy present in the input profile $congestion(T)$ by grouping d contiguous time periods with d the activation duration. For each allocation, the activation period d and the inter-activation time ia after the activation time are marked in a binary data structure $unavailable(T, J)$. This data structure represents the availability of all flexibility providers (J) for all time steps (T). The function `findMaxFeasibleActivation` returns the start index of the activation period containing the highest volume of excess energy or a negative number indicating that no feasible allocations are possible.

Algorithm 1 DSM allocation algorithm

```
procedure GreedyCongestionReduction
    done ← false
    while ¬done do
        activationStart = findMaxFeasibleActivation()
        if activationStart < 0 then
            done ← true
        else
            reduceCongestion(activationStart)
            markActivation(activationStart)
        end if
    end while
end procedure
```

findMaxFeasibleActivation():

$$\underset{t_s \in \mathrm{T}}{\textbf{maximize}} \quad \sum_{\mathrm{t=t_s}}^{\mathrm{tsm}} \mathrm{congestion(t)}$$

$$\textbf{subject to} \quad 0 = \prod_{j \in J} 1 - \prod_{t=t_s}^{tcm} 1 - unavailable(t, j)$$

$$tsm = min(t_s, max(T))$$

$$tcm = min(t_s + d, max(T))$$

Energy storage

To solve the excess energy that remains after the allocation of DSM, storage dimensioning will have to be performed. This section describes a generic discrete-time model for energy storage and a storage dimensioning optimization problem formulation similar to [76] but diverges from [76] in the specific implementation of this model for the congestion cases and cost models used in this work to evaluate the influence of DSM on total investment costs. First, the following generic discrete-time model for energy storage is used for storage capacity allocation.

$$E_s(k+1) = E_s(k) + E_{\text{ex}}(k) \tag{4.1}$$

$$E_{\text{ex}}(k) = \eta P_s(k).\Delta T \tag{4.2}$$

where

$$\eta = \begin{cases} \eta_c, & \text{if } P_s(k) \geq 0 \text{ (charging)} \\ \frac{1}{\eta_d}, & \text{otherwise (discharging)} \end{cases} \tag{4.3}$$

subject to

$$0 \leq E_s(k) \leq E_s^{\max} \tag{4.4}$$

$$|P_s(k)| \leq P_s^{\max} \tag{4.5}$$

where k denotes the present time instant $t_k = k.\Delta T$, $E_s(k)$ the level of stored energy at present time k (internal state of the storage), $E_{\text{ex}}(k)$ the energy exchange with the storage at time k, $P_s(k)$ the **grid-side** power exchange with the storage at time k (charging from the grid (+ sign) and discharging to the grid (- sign)), η_c and η_d charging resp. discharging efficiencies. Note that we assume that $\eta_c = \eta_d$ (round-trip efficiency η_{rt} is defined as the product of the efficiency of charge and discharge $\eta_{\text{rt}} = \eta_c.\eta_d$). $\Delta T = t_{k+1} - t_k$ is the duration of each interval (time difference between two subsequent time instants e.g. $k+1$ and k). Note that depending on the type of the storage technology, different operational constraints on maximum power exchange as well as on maximum energy capacity itself may apply. $E_s^{\max}$ denotes the maximum energy capacity of the storage, and $P_s^{\max}$ is the maximum rate of charge/discharge. We assume in this work that the (absolute value of) maximum rate of charge $P_s^{\text{max-c}}$ and maximum rate of discharge $P_s^{\text{max-d}}$ are equal. Thus,

$$|P_s^{\text{max-c}}| = P_s^{\max} = |P_s^{\text{max-d}}|. \tag{4.6}$$

Using this storage allocation mechanism, it is relatively straightforward to calculate cost metrics R^1, the amount of revenue lost from not being able to sell energy lost during charging and discharging of the batteries and R^2 the amount of revenue lost for compensating lost green certificates. Similarly, calculating operational metrics such as E^c, the volume of excess energy remaining or curtailed, is relatively straightforward. The following optimization procedure is used to dimension the storage in order to minimize the associated investment costs while resolving the remaining congestion.

We will size the storage based on the following maximization problem:

$$\begin{aligned}
\underset{(P_s^{\max}, E_s^{\max})}{\textbf{maximize}} \quad & \mathrm{NPV}(\mathrm{P_s^{max}}, \mathrm{E_s^{max}}) \\
& = -\left(C_{sto}^{f} + C_{sto}^{m} \cdot \sum_{n=1}^{N} \frac{1}{(1+r)^n} \right) \\
& + R^1 \cdot \sum_{n=1}^{N} \frac{1}{(1+r)^n} + R^2 \cdot \sum_{n=1}^{N_{\mathrm{GC}}} \frac{1}{(1+r)^n} \\
\textbf{subject to} \quad & \frac{E^c}{E^{produced}} < E_c^{allowed}
\end{aligned}$$

In this formulation $E_c^{allowed}$ represents the maximum allowed percentage of curtailment or remaining congestion according to the regulatory framework. This percentage is relative to the total amount of energy produced by the generators ($E^{produced}$) over the study horizon.

Other parameters for setting up the business case are defined as follows. Green certificate compensation (R_{gc}) is rated at 68.80 €/MWh, lost energy is compensated at 50 €/MWh, the business case duration (N) is 20 years while green certificates are compensated for 15 years. All cost are calculated in terms of NPV at a discount rate $r(\%)$ of 3.5291.

4.3.3 Regulatory constraints

Because of the novelty of integrating green energy into the grid, the regulatory framework wherein DSO, TSO and other parties have to operate can change in the future. These frameworks provide guidelines and constraints for how much curtailment is allowed and how generation side entities are compensated for curtailment. In this work, different regulatory frameworks are considered because the question of whether curtailment should be avoided at all cost is still under debate [77]. These frameworks influence the cost model and allocation requirements in the experiments. Concretely, the distinction is made between a scenario where no curtailment is allowed and all renewable energy should be injected into the grid and a scenario where 2% of the gross produced energy per generator is allowed to be curtailed. In the latter case, lost green certificates must be compensated to the wind turbine owner.

4.4 Simulation results and discussion

In this section we discuss simulation results from applying the ANM techniques to two different wind profiles P_1 and P_2. We consider both a regulatory scenario where curtailment is allowed, but constrained to maximally 2% of the gross output and a scenario where no curtailment is allowed and where storage must cover all of the remaining congestion from DSM.

4.4.1 Setup

Two wind profiles are used as input for this work. Both profiles are gathered from locations in Belgium. P_1 represents a one year wind production profile in the Antwerp harbor and P_2 represents a one year wind production profile in Zeebrugge. Figure 4.2 shows that P_2 has significantly lower peak congestion volumes than P_1 and contrary to P_1, P_2 induces no congestion events that last for more than 1 hour after the application of the same DLR activation mechanism.

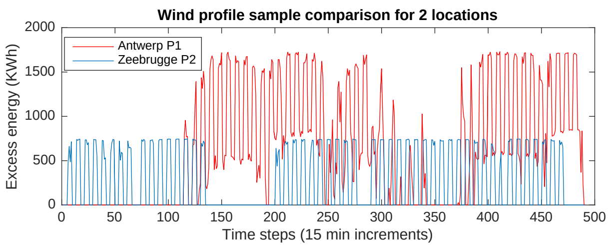

Figure 4.2: A 125 hours sample of the two congestion profiles after DLR shows that P_2 is never congested for longer than 1 hour and has considerable lower peak congestion.

4.4.2 2% curtailment allowed

For the regulatory scenario where 2% curtailment is allowed, the difference between the two locations represented by P_1 and P_2 is clearly noticeable. Shown in Figure 4.3, there is a distinct benefit in using DSM in combination with Storage solutions in terms of total costs. This total cost benefit reaches an optimum for around 6-8 agents indicating that the benefit is not linear in terms of participating flexibility providers. Because the problem of distribution grid current congestion is a very local problem and the location of the flexibility

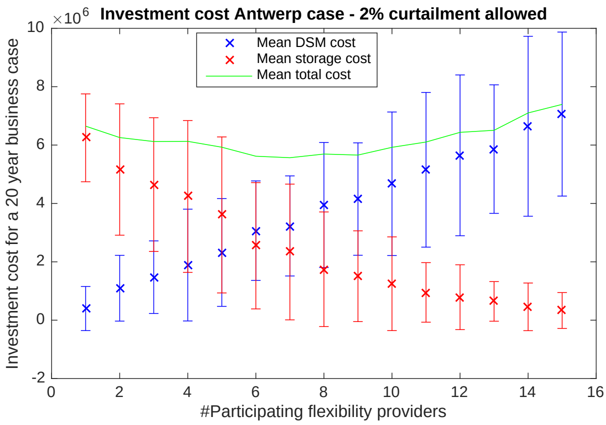

Figure 4.3: 90%CI for ANM investment cost for Antwerp, given 2% allowed curtailment shows limited positive influence of DSM on total costs.

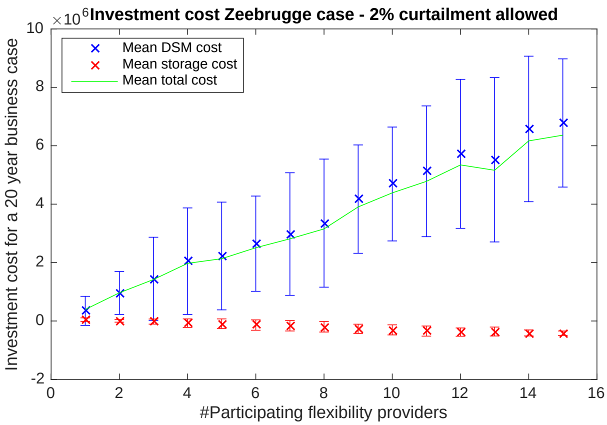

Figure 4.4: 90%CI for ANM investment cost for Zeebrugge, given 2% allowed curtailment shows negative influence of DSM on total costs.

provider is a crucial factor in its ability to help reduce congestion, it is not unreasonable to assume that it will be hard to find large numbers of suitable flexibility providers to participate.

For the Zeebrugge case P_2, DSM is ineffective in reducing total investment costs. This is shown in Figure 4.4. The cost for storage in case P_2 is also considerably lower because the total congestion remaining after the application of DSM is in all cases much closer to the allowed 2% curtailment boundary.

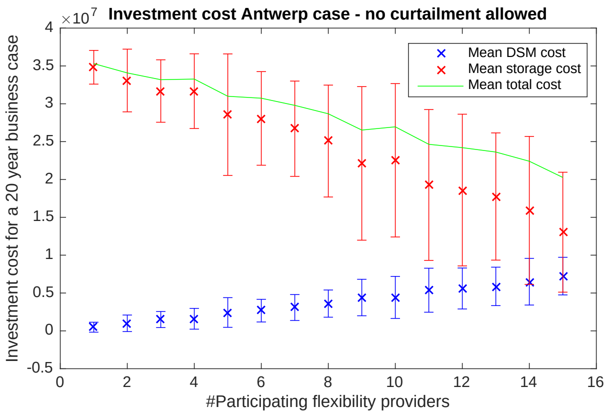

Figure 4.5: 90%CI for ANM investment cost for Antwerp, with any curtailment prohibited, shows positive influence of DSM on total costs.

4.4.3 No curtailment allowed

Considering the regulatory scenario where no curtailment is allowed at all, the overall installation cost are obviously higher because, in the end, up to 2% more excess energy needs to be reduced by DSM and storage. Figure 4.5 shows a total cost reduction benefit from using DSM to lower the storage dimensioning requirements for the P_1 case where for the P_2 case, we see a similar ineffectiveness of DSM to reduce the total cost as in the previous regulatory framework. The main reason DSM is so ineffective in the P_2 case shown in Figure 4.6 is that each congestion event lasts for maximally 1 hour, while the DSM activation constraints are specified to activate for hours after which the activated provider is unavailable for 12 hours. This results in each activation having at least a 50% efficiency penalty for the same cost to the DSO with more excess energy that needs to be handled by storage.

4.4.4 Grid investment

In all of the discussed cases, the total investment cost for the proposed ANM mechanisms to reduce distribution grid current congestion is significant. Projecting the one time infrastructure reinforcement cost for the lifetime of the business case and comparing these costs with the best case total investment cost for the four different cases discussed in this section, allows for computing the lower bound on the length of cable needed before ANM techniques pose a viable alternative. Table 4.4 shows the minimal cable length needed to achieve

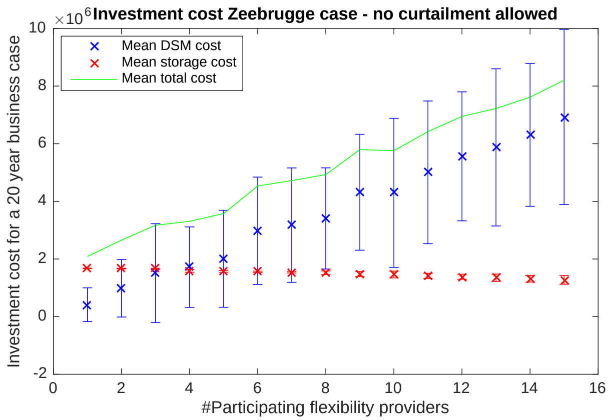

Figure 4.6: 90%CI for ANM investment cost for Zeebrugge, with any curtailment prohibited, shows negative influence of DSM on total costs.

a positive business case for the different cases discussed under the pricing model described in section 4.3.1.

Table 4.4: Best case minimal cable length needed for positive ANM business case.

	Antwerp P_1	Zeebrugge P_2
2%curt. allowed	~ 53km	~ 3km
No curt. allowed	~ 200km	~ 20km

4.5 Conclusion

In this work, different active network management techniques, such as DLR, DSM and energy storage are combined to address the problem of distribution grid congestion from wind turbine integration. ANM resource allocation mechanisms and cost models are proposed for a 20-year business case and evaluated using real world wind production profiles from a Belgian DSO covering two different locations in Belgium where the alternative to ANM is wind turbine curtailment. The distinction is made between two different regulatory frameworks of which one allows up to 2% of curtailment and the other allows no curtailment at all.

Simulation results indicate that the influence that the DSM activation constraints employed have on the cost effectiveness of DSM in combination with storage, is not negligible. DSM activation constraints can impact the efficiency of DSM in reducing congestion, leaving more excess energy to be handled by storage. This in turn leads to higher required storage dimensions and associated costs. Matching DSM activation constraints to the specific profile of excess energy is therefore warranted when using DSM to augment other ANM techniques in reducing distribution grid congestion.

Simulation results also show that generally higher peak congestion combined with longer congestion event durations can lead to better cost effectiveness for DSM when the remaining congestion needs to be solved by storage, for which the costs increase linearly in both peak power rates and energy volumes storage should cope with.

Finally, although there are cases where DSM can provide a reduction in total ANM investment cost, in most cases, grid reinforcement seems to be a more cost effective solution to address distribution grid congestion.

Future work includes investigating the precise influence of the DSM activation constraints on DSM allocation efficiency and cost effectiveness of DSM. Also, quantifying the sub-optimality of the allocation algorithms to provide a hard lower bound on the resource requirements for operational ANM mechanisms will be included in future work.

Acknowledgment

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Chapter 5

Who Gets My Flex? An Evolutionary Game Theory Analysis of Flexibility Market Dynamics

Chapters 2 and 3 have discussed multiple use cases for consumption flexibility illustrating that consumption flexibility can be employed towards various goals and in various ways. Until flexibility markets facilitate the trading of consumption flexibility among different parties, the nature of bilateral agreements force flexibility providers to choose between which flexibility users to do business with. This chapter presents an analysis of the strategic choice flexibility providers face in choosing a partner to do business with and contains the paper:

> Kristof Coninx, Geert Deconinck, and Tom Holvoet. 2018. Who Gets My Flex? An Evolutionary Game Theory Analysis of Flexibility Market Dynamics. Appl. Energy 218, (May 2018), 104–113. DOI:10.1016/j.apenergy.2018.02.098

The definitions, analysis and supporting software are the result of discussions between all authors, led by Kristof Coninx. Kristof Coninx did all of the programming and the writing. Tom Holvoet and Geert Deconinck gave feedback on the writing.

Abstract

Maintaining a real time balance between energy consumption and production is challenging when faced with increasing penetration of renewable energy sources (RES) because of the increased variability in generation output. Demand-side management (DSM) techniques address this issue by steering consumers' energy offtake, thereby enabling further penetration of RES. This chapter addresses the problem of overproduction from distribution grid connected wind generation. We present and analyze two business cases in the Belgian-European energy landscape for using upward consumption flexibility to deal with excessive wind power injection. We focus on the perspective of the flexibility providers and the strategic choice they face in choosing the business partner that maximizes their expected financial compensation. Evolutionary game theory is used to model this strategic choice and to provide a framework for quantifying realistic financial compensation bounds based on real world market and wind production data for multiple locations in Belgium. Results show that in a competitive market setting compensation payments for flexible power consumption are higher when dealing with higher wind forecast error levels. These results validate the economic benefits of having accurate wind production forecasts.

5.1 Introduction

The ability to monitor and manage power delivery in real time has been defined as one of the key components that distinguishes smart grids from conventional power grids [78]. This component is crucial in supporting the adoption of more secure, sustainable and innovative practices in energy consumption and production. To this effect, the European Commission has put forth the 20-20-20 objectives [79] causing a gradual increase of installed renewable energy sources (RES) capacity in Europe [80]. This increase in RES penetration has also lead to an increase in energy production variability because of the less predictable nature of renewables such as wind and solar.

Energy production variability combined with a growing energy demand, partially caused by the increased adoption of electric vehicles (EVs) and plug-in hybrids, has made it more challenging for system operators to maintain the consumption-production balance. Maintaining this balance is paramount to the safe and stable operation of power systems in general. In order to achieve this, flexibility is a necessity both on the consumption and on the production side.

Although wind production resources have successfully participated in ancillary service programs [81], these resources are still often subject to various incentive and support mechanisms that impede their entry into ancillary service markets. In the Belgium energy domain, wind energy production is supported by green certificates and priority dispatch. Energy produced under priority dispatch should at all times be prioritized over other energy sources when satisfying customer energy demands. For ancillary services from wind production to remain economically viable, the loss of green certificates should also be compensated when production curtailment is called for. With decreasing support for new conventional power production facilities in favor of renewables, the flexibility needed to curb system imbalances needs to come from the consumption side until regulatory frameworks properly incentivize the use of RES in the ancillary service markets. The authors of [82] further describe the relationship between support schemes and system balancing with increasing wind production in more detail and from a market perspective. Policy recommendations are made to address challenges and issues stemming from certain support schemes used. This work focuses on the use of consumption flexibility to address similar issues but while retaining these support schemes. To the best of the authors' knowledge, addressing technical issues arising from renewable support schemes has gained limited attention in literature.

Upward Consumption Flexibility

The use of consumption flexibility to modify the energy demand can be categorized as demand-side management (DSM). For DSM, a distinction can be made between upward and downward flexibility. In literature these two aspects of DSM are often considered together in the form of load shifting. Load shifting can be accomplished either through direct consumption shifting [83], by using energy storage solutions [84] or through both simultaneously in the form of the scheduling and charging of EVs and plug-in hybrids [30]. In literature the two aspects are also considered separately. Making the distinction between upward and downward flexibility products can lower the entry barrier for flexibility providers by allowing them to only provide upward or downward flexibility.

A large body of DSM research is focused on the use of downward flexibility, or the ability to decrease one's consumption to satisfy a shortage of energy (negative system imbalance) [9]. Examples of negative imbalance occurrences can be found in winter times when heating requirements are generally higher and solar production might under-perform because of the limited amount of daylight hours.

On the other hand, the potential for production surpluses has been identified as one of the major challenges faced in the effort to increase RES penetration [85]. This work focuses on using upward consumption flexibility or the ability to increase one's power consumption to satisfy production surpluses (positive system imbalances). Upward consumption flexibility has been proposed as a valuable resource for facilitating wind production integration in contemporary power grids as demonstrated in [86]. Positive system imbalances can, for example, occur when unexpected peak production from renewables meets RES under priority dispatch and conventional generation in must-run conditions [87]. Some conventional generation units cannot be curtailed because they provide frequency regulation services needed to maintain grid stability while other generation units can be very uneconomic to scale down (e.g. nuclear generation). This phenomenon has also been labeled as the incompressibility of power systems [88]. Clear market signals for the need of upward consumption flexibility during periods with incompressible positive system imbalances have been observed for Belgian and other European energy markets in the form of negative prices [89]. Negative prices can occur in the day-ahead, intra-day and balancing markets under different conditions but all supporting the need for upward consumption flexibility.

DSM literature often assumes the availability of flexibility providers. Such an assumption is not unreasonable. The potential for upward consumption flexibility in energy intensive industries has been described in the context of increasing RES penetration in Germany by Paulus and Borggrefe [5]. Processes capable of load shifting are demonstrated to be valuable by providing upward flexibility. Similarly Lund et al. offer a comprehensive survey of DSM flexibility potential in the context of variable RES. This survey includes load shifting potential and upward flexibility in industry [90]. Upward flexibility is in literature often defined as one aspect of load shifting. In terms of residential flexibility, D'Hulst et al. illustrate the asymmetry of estimated available flexibility in favor of upward flexibility [6]. In this work, similar assumptions are made on the availability of consumption flexibility and more specifically, upward consumption flexibility. Where literature often focuses on employing consumption flexibility towards singular goals [91], this work contrastingly considers competing interests in contracting flexibility providers for different business cases.

Beside the use case of providing upward flexibility as an ancillary service to the transmission system operator (TSO), two business cases for employing this upward flexibility cost effectively are identified and presented. The first business case benefits a balance responsible party (BRP) suffering imbalances from wind forecast errors because of the wind production in their portfolios. These imbalances usually incur imbalance costs that can be partially avoided by harnessing consumption flexibility to offset these imbalances. Literature shows that balancing of up to 1.5 MW of overproduction from wind generation can be achieved using demand-side flexibility [92]. The second business case benefits a distribution system operator (DSO) aiming to avoid distribution grid congestion from increased wind injection in medium voltage grids. Integrating new wind production elements into existing distribution grids can cause congestion problems that are usually mitigated by curtailing wind production. In such cases, DSOs have to compensate the wind generation owners for their loss of income. Employing consumption flexibility can, in some of these cases, avoid curtailing wind generation [3].

To render these business cases positive for all parties involved, some form of financial compensation must be offered to the flexibility providers participating in these demand-response programs. From the point of view of the flexibility provider, it is beneficial to choose the most lucrative business partner to offer their flexibility. Depending on the business case, this flexibility might be activated differently and therefore, financial remuneration can also vary between business cases. Another factor influencing the amount of financial reward that can be reaped from these programs is the amount of other flexibility providers participating in the same program. Maximizing the expected reward gained by making choices while these rewards depend on the choices of other parties, is one of the application domains of game theory. The concrete focus of this work is analyzing the strategic choice that flexibility providers face in deciding which business partner to offer their flexibility by using tools from evolutionary game theory (EGT).

Evolutionary Game Theory

In general, game theory provides tools and solution concepts for analyzing strategic choice situations in terms of expected payoffs or rewards [26]. Concretely, game theory provides a mathematical framework for explicitly modeling strategic behavior and interaction and analyzing resulting decisions, making it ideally suited for evaluating different business cases from an economic optimization point of view. Classical game theory has been well used to model and analyze DSM mechanisms in literature. Direct negotiation between consumers to achieve consumption peak shaving is analyzed in [93] while load shifting is encouraged by a mechanism between consumers and utilities in [94].

In this work specifically, we use evolutionary game theory to model and analyze how this strategic choice of multiple flexibility providers might change over time given different parameters such as activation fees and the location of wind energy resources. Tools from EGT literature can provide insight into how robust the market shares of two different business cases competing for a common resource, in this case the flexibility providers, are to changes in economical and environmental parameters [95]. In general, EGT expands the notion of static games based on rational choice from classical game theory (GT) literature to settings where populations of agents myopically improve their decisions based on observed rewards [1]. Complete rationality is therefore not a strict requirement when modeling evolutionary games, making EGT a useful tool for both modeling and analyzing strategic choice situations in multiple domains. Though not as prevalent as classical GT, applications of EGT can be found in literature of various domains.

In the field of economics Agastya studies a refinement of the evolutionary stable state solution concept from EGT in the context of k-double auctions [96]. EGT is also used for analysis in the field of sociology where Kuran et al. focus on cultural integration [97] and computer science where Altman et al. focus on transport protocol in computer networks [98]. Even in the physics domain EGT is used to study the thermodynamic limit of interacting particles [99]. The use of EGT in smart grids literature, however, has been limited. To the best of our knowledge, examples of the use of EGT in smart grids research are limited to [100] where the benefits of participating in DSM for consumption peak shaving are analyzed, [1] where consumption flexibility remuneration strategies are compared and [66] where the adoption rate of micro-storage devices is predicted using EGT. This work attempts to further close the gap between applications of EGT and the energy domain literature.

Contributions and Outline

Our contributions in this work are threefold.

- We formulate two business cases for employing upward consumption flexibility to address issues arising from wind turbine integration under renewable energy support schemes. These business cases offer a novel perspective on the use of consumption flexibility under support schemes and are situated in the current-day European power systems context. The value streams relevant to these business cases are elicited in section section 5.2.
- We describe an approach for performing strategic choice analysis between two competing alternatives using EGT (section 5.3) to demonstrate the applicability of EGT in energy literature.
- We present an analysis of market share dynamics with two competing actors having their own business case in employing upward consumption flexibility to alleviate problems caused by wind generation and renewable energy support schemes (section 5.5). This analysis is performed using

real world market and wind production data through simulation using the model described in section 5.4.

Finally, the conclusion and future research directions are presented in section 5.6.

5.2 Business cases

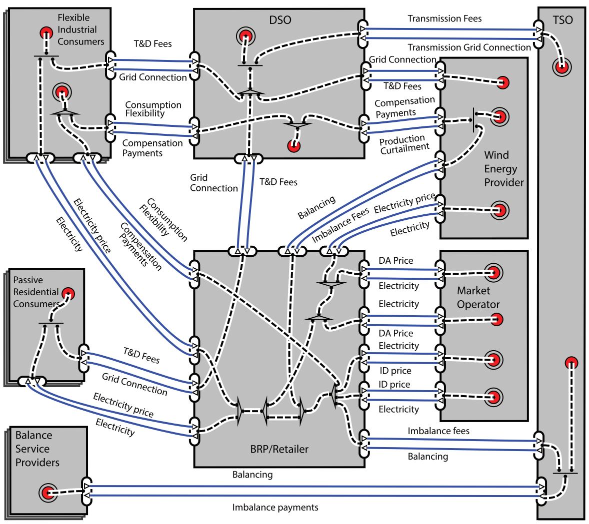

Figure 5.1: Multi-actor business model for the use of upward flexibility.

Multiple actors are involved in the smart grid domain, each with their own business cases. In this section we present a selection of business cases for actors involved in grid balancing and their main activities in the Belgian power systems context, relevant to this work. Although this study focuses on the Belgian energy landscape, the concepts presented here can be generalized to different European settings, especially when considering the current efforts in European energy market harmonization [101]. The e3value notation [102] is used to concisely represent the business case model in Figure 5.1. This notation allows for a graphical representation of the value streams and exchanges between different actors. The exchanged values can be both of a financial nature e.g. money or of a material nature, e.g. goods such as electricity. For example, in the model shown in Fig. 5.1 the electricity requirement of industrial and residential consumers alike is satisfied by a electricity retailer that also serves as a BRP for customers in its portfolio. Electricity is delivered to the consumers at a certain price which includes transmission, distribution and other fees. The retailer satisfies customer electricity needs through the market operator or by using the wind energy providers in their portfolio.

Our model differs from the model in [103] by assuming that the connection of industrial consumers to the distribution grid is a direct contract or transaction between the DSO and the industrial consumers in stead of an agreement brokered by the retailer as is the case with residential consumers. Another difference from [103] is in the assumption that wind energy producers cannot financially be held responsible for BRP imbalances caused by forecast errors.

The first of the two main business cases discussed in this work is the case of a BRP looking to avoid costly imbalance payments by using upward consumption flexibility to compensate wind forecast induced imbalances in their portfolio. The second case describes a DSO that avoids wind turbine curtailment compensation by using those same flexible energy consumers.

5.2.1 Portfolio imbalance reduction

The TSO is responsible for the real time balancing of production and consumption. In the current balancing mechanism every grid access point is managed by a BRP. In Belgium these BRPs are called Access Responsible Parties (ARP) but we will keep to the BRP nomenclature for the remainder of this work.

The balancing mechanism works in part by having BRPs nominate their projected production and consumption to the TSO. These projections are based on the amount of energy sold and bought on the day-ahead market, through bilateral trading or production from their own RES. Nominations should be submitted before the gate closure time the day before the delivery day.

With increasing penetration of RES such as wind energy producers, generating accurate production-consumption balance forecasts has become increasingly challenging [104]. Realtime imbalances, i.e. unpredicted imbalances occurring after the nomination but before delivery, are usually settled using the intra-day or the balance market where prices can be high, or through the TSO's ancillary services, for which imbalance fees must be paid to the TSO. These imbalance fees or penalties can also be quite costly compared to regular energy tariffs. It is possible that the imbalance of a BRP portfolio is of opposite sign as the global system imbalance. In such cases the portfolio imbalance is seen as beneficial to the grid as a whole and the BRP can be compensated accordingly.

As an alternative to paying the imbalance fees to the TSO, this business case employs flexible industrial consumers to provide demand response services with relatively short term activation. These services are only used in situations where the portfolio imbalance is aggravating the global system imbalance. In this particular implementation, we only focus on flexible consumers providing upward flexibility (i.e. the ability to increase consumption on demand). Upward flexibility is only useful for correcting positive portfolio imbalances. In theory, the business case could easily be extended to use both upward and downward flexibility to reduce imbalances. We limit ourselves to upward flexibility, however, because this allows for a more fair comparison between the grid congestion avoidance business case in section 5.2.2.

5.2.2 Distribution grid congestion avoidance

The main business case of DSOs is in maintaining and operating a distribution grid that transports electrical energy from the transmission grid to the end user. Ensuring the infrastructure remains stable and capable of handling increasing volumes of electricity is a costly endeavor. This effort has become even more challenging with the increasing demand from EVs and increased production by local distributed generation instances [1].

A specific problem with integrating wind turbines into existing distribution grids is that some parts of the distribution cable network can overheat because of excess currents from peak wind power injection [2]. Current practices by DSOs involves curtailing wind energy producers when peak injection tends to overload grid segments. Wind energy providers lose green certificate bonuses during these curtailment events and have to be compensated by the DSO for both the lost green certificates and the lost income from renewable generation. As an alternative to production curtailment, this work presents an alternative for the DSO in using distribution connected industrial consumers.

If connected at key locations in the distribution grid topology to consume energy excesses during peak injection events, industrial consumers with upwards consumption flexibility can be used to avoid production curtailment. In practice, flexibility providers will divert the flow of excess energy away from congestion points by increasing their own consumption. These flexible consumers will be financially compensated for the activation of their flexibility by making use of budget resources otherwise spent on grid reinforcement and/or curtailment compensation.

5.2.3 Relation between business cases

The business cases described in this work are assumed to be mutually exclusive from the point of view of the flexibility provider. The reason for this exclusivity pertains to the formal contracts that represent the bilateral agreements between flexibility users and providers. These contracts specify activation constraints for how and when consumption flexibility is available for use. Activation constraints benefit the flexibility user or contractor by guaranteeing the availability of consumption flexibility when required within the bounds specified in the contract. The benefits for the flexibility provider in formalizing activation constraints is that providers are protected from disruptive use of consumption flexibility by setting bounds on when this flexibility can be called upon. Contracts guaranteeing availability of a service from one party while simultaneously setting bounds on this availability often requires exclusivity clauses.

5.3 Approach

In this chapter we follow the modeling and analysis approach described in chapter 2 where we use evolutionary game theory (EGT) to model a population of agents facing a choice between two alternative actions. Agents in this terminology are flexibility providers willing to provide consumption increase flexibility on demand expecting financial compensation. A concrete action translates to choosing a party to do business with. This party requires consumption flexibility and is willing to pay for it. The percentage of agents choosing to do business with a flexibility user represents the market share within the population of agents and provides insights into the business case viability of that particular flexibility user. A common problem with game theory (GT) and its use in applied research is that relying too heavily on game theoretic modeling abstractions can negatively impact the relation to the real world concepts being modeled. In other words, the real world applicability of the research can be damaged by models made to fit the game theoretic framework more than the real world abstractions. To avoid this issue, EGT tools are in this work mainly used for analysis purposes. Agent payoffs for participating in DSM business cases are heuristically determined through micro-simulation. To acquire concrete market share data, extensive simulations are performed for different population configurations to fill a payoff matrix. This payoff matrix contains entries mapping a vector representing the number of agents choosing each action to a vector with expected payoffs for each agent.

In classic GT, strong assumptions are made concerning the rational behavior of all players. EGT requires less strict rationality assumptions. The only assumption is that players myopically improve their choice based on some imitation scheme [60]. We employ selection dynamics [58] to gain insight into how the market shares evolve over time when agents interact and compare payoffs with each other. Selection dynamics are used to model rational choice between two different business cases for employing flexibility in repeated pairwise interaction where the providers compare the gained revenues from their choice of business parter and change their choice accordingly. As concrete selection dynamics, we use the replicator dynamics to model market share over time as a system of ordinary differential equations (ODEs). This allows the use of classic well known techniques for analyzing dynamical systems [43].

The general replicator equations for N agents and two actions to choose from are then given in (5.1) following the notation used in [32].

$$\begin{cases} \dot{x_1} = x_1[u(e_1, x) - u(x, x)] \\ \dot{x_2} = -\dot{x_1} \end{cases} \tag{5.1}$$

with $u(e_1, x)$ representing the average expected payoff of an agent choosing action 1 when the population is in state x and $u(x, x)$ representing the overall average expected payoff for an agent from a population in state x. $u(e_1, x)$ and $u(x, x)$ are given by (5.2) and (5.3) in function of the payoff matrix that can be accessed by function $f(i)_k$ where $f(i)$ returns an expected payoff vector for a population state where i agents choose the first action and $N - i$ agents the second action.

$$u(e_1, x) = \sum_{i=0}^{N-1} \binom{N-1}{i} x_1^{N-i-1} x_2^i f(N-i)_1 \tag{5.2}$$

$$\begin{aligned} u(x, x) = &\sum_{i=1}^{2} x_i^N f(N - N(i-1))_i + \\ &\sum_{j=1}^{N-1} x_1^{N-j} x_2^j \sum_{k=1}^{S} \binom{N-1}{j-k-1} f(N-j)_k \end{aligned} \tag{5.3}$$

Finally, we analyze the critical points of these equations in terms of stability and draw conclusions about the probability of a certain stable state in the population occurring given the initial population. We take into account the worst case and best case bounds based on the 95% confidence intervals of the simulated payoff results.

5.4 Simulation model

The concrete scenario in this work involves a group of flexibility providers having to choose between a BRP employing the portfolio balancing business case discussed in section 5.2.1 and a DSO employing the congestion avoidance business case discussed in section 5.2.2. The flexibility providers sign up for one year contracts with either flexibility user, discretized in 15 min. time windows.

5.4.1 Flexibility providers

Flexibility providers or agents in this model, represent small to medium size industrial consumers. The model used in this work makes several assumptions concerning the agents that represent the flexibility providers. Agents are for example capable of increasing their energy consumption on demand. Examples of upward flexibility providers are companies with processes containing thermal buffers or companies with on site energy storage solutions. The agents can be asked to activate their flexibility, which corresponds to increasing their energy consumption, within 15 min. after activation. Flexibility provider agents are also assumed to be physically connected to the congested feeder of a 15 kV distribution grid in such a way that increasing the consumption of the provider would mitigate the congestion. Additionally, the agents are part of a BRP portfolio.

Flexibility providers are realized with flexible power rates drawn from a gamma distribution $\Gamma(a, r)$ with $a = 1.37012, r = 677.926$ fitted to a confidential industry data set of clients of the R3DP flexibility product offered by the Belgian TSO. This Γ distribution passes the classical goodness-of-fit tests for the industry data set. These tests include the Komolgorov-Smirnov [74] and the Anderson-Darling [75] goodness-of-fit tests. The offered flexibility is then, in turn, subject to activation constraints similar to the constraints of R3DP to mimic strategic reserve constraints found in industry today. As such, the number of activations is limited to 40 times in a single year, each activation is restricted in duration to two hours and an activation cannot occur within 12h after a previous activation [2].

Finally, flexibility providers can myopically compare financial compensation results with other flexibility providers facing the same choice between doing business with either the DSO or BRP. Business is conceptually modeled by short term bilateral agreements between the provider and user of flexibility.

5.4.2 Flexibility users

The two main parties requiring consumption flexibility considered in this work are the DSO and the BRP, with their relevant business cases discussed in section 5.2.

Input data

Both flexibility users in this scenario share a common data source as a business case driver. Wind energy resources are a cause of BRP portfolio imbalances when wind production forecasts differ from actual production values. These resources can also cause distribution grid congestion when existing infrastructure cannot cope with excessive production.

Industry datasets containing wind power production profiles are used as input data for the flexibility users. They represent distribution grid connected wind turbines that are also part of a BRP's production portfolio. These datasets contain profiles for different locations in Belgium with their own wind conditions and span 12 month periods in 15 min. increments. Other data sources containing publicly available market price data and system imbalance data are also used. Three major assumptions are made in this model. First, flexibility activation is assumed to not influence market prices. This is called the price taker assumption in literature [105]. Secondly, perfect foresight of the input data is assumed to allow business case comparisons at allocation efficiency upper bounds. Both assumptions are common in demand-side flexibility literature [106]. Finally, modeling the rebound effect is reserved for future work.

For the BRP business case, the wind production profiles are transformed to imbalance data by applying power forecast error data from literature to the production profile data. ERCOT error data from [19] is used to generate forecast error induced imbalance data. In this work, forecast errors are assumed to be normally distributed and this assumption has gained valid critique in literature. For example, [107] proposes the beta distributions as a better fit while Hodge et al. propose Cauchy-Lorenz distributions [108]. In future work we will analyze the difference that the choice in error distribution has on the results. Finally, not all imbalances incur imbalance penalties. In some situations a local portfolio imbalance can help compensate a global system imbalance. In such cases, consumption flexibility should not be used to reduce a portfolio imbalance. To account for these situations, industry data sets containing net regulated volume information per quarter hour are used. The imbalance is not considered when the total net regulated volume is of opposite sign than the current portfolio imbalance.

For the DSO, excess energy is identified as energy that should be curtailed according to the dynamic line rating (DLR) mechanisms used. DLR is an active network management (ANM) technique that differs from using static cable ampacity limits by allowing excess currents for a limited time because of the temperature hysteresis effect inside the cables [3]. The DLR mechanisms used, shapes the congestion profile by marking which energy volumes are excessive and require production curtailment or consumption increase to avoid dangerous cable temperature levels. The specifics of the DLR mechanism used are outside the scope of this article and merely provide a means to define excessive energy volumes as a static ampacity limit would have.

Flexibility allocation

To ensure a fair comparison between the two business cases, both users competing with each other for market share are provided with the same wind based input data and employ the same flexibility allocation mechanisms. The OptaPlanner [109] optimization library is used to optimize the off-line scheduling of flexibility to imbalance or congestion volumes depending on the business case. OptaPlanner is well known as a constraint satisfaction solver and planning engine and combines optimization heuristics and meta-heuristics with efficient score calculation and constraint modeling. The flexibility activation allocation problem is formally defined as the tuple:

$$\langle \mathcal{T}, \mathcal{C}, \mathcal{P}, \mathcal{R}, \mathcal{D}, \mathcal{I}, \mathcal{N} \rangle \coloneqq \textit{activation scheduling problem}$$

where

$\mathcal{T} \coloneqq$	number of "time periods",	$\mathcal{T} > 0$
$\mathcal{C} \coloneqq$	function mapping time periods to excess energy volumes,	$\mathcal{C} : \{1, ..., \mathcal{T}\} \mapsto \mathbb{R}$
$\mathcal{P} \coloneqq$	set of flexibility providers,	$\lvert\mathcal{P}\rvert > 0$
$\mathcal{R} \coloneqq$	function mapping providers to flexible power rates,	$\mathcal{R} : \mathcal{P} \mapsto \mathbb{R}$
$\mathcal{D} \coloneqq$	activation duration	$\mathcal{D} > 0$
$\mathcal{I} \coloneqq$	minimum time between two consecutive activations	$\mathcal{I} > 0$
$\mathcal{N} \coloneqq$	amount of allowed flexibility activations	$\mathcal{N} > 0$

This problem defines excess energy volumes for $\mathcal{T}$ 15 min. time periods and a set of flexibility providers along with the contractually determined activation constraints described in section 5.4.1.

For solving the activation scheduling problem, the set of flexibility activations $\mathcal{A} \subseteq \{1,...,\mathcal{T}\} \times \mathcal{P}$ is constructed along with the helper functions $\mathcal{M} : \mathcal{A} \mapsto \{1,...,\mathcal{T}\}$ which yields the start time for activations and $\mathcal{B} : \mathcal{A} \mapsto \mathcal{P}$ which yields the flexibility provider that is being activated for each tuple $(t_i, p_i) \in \mathcal{A}$. These helper functions are defined merely for the sake of convenience. For each flexibility provider $p \in \mathcal{P}$, $\mathcal{A}$ contains $\mathcal{N}$ activation events $a_i \in \mathcal{A}$ for which $\mathcal{B}(a_i) = p$. This is enforced by maintaining constraints (5.4) and (5.5) on $\mathcal{A}$ where $\mathcal{S}$ represents all subsets of $\mathcal{A}$ for which the condition holds that all activation events in the subset map to the same flexibility provider under mapping function $\mathcal{B}$. Alternatively, $\mathcal{S}$ can be more elegantly defined as the quotient space $\mathcal{S} \coloneqq A/R\_\mathcal{B}$ when the equivalence relation, induced by function $\mathcal{B}$ is denoted by $R\_\mathcal{B}$.

$$\forall \mathcal{S}^* \in \mathcal{S} : |\mathcal{S}^*| = \mathcal{N} \tag{5.4}$$

$$|\mathcal{A}| = \mathcal{N} \times |\mathcal{P}| \tag{5.5}$$

$$\mathcal{S} \coloneqq \{\mathcal{A}^* \subseteq \mathcal{A} | (\forall a_i, a_j \in A^*)[\mathcal{B}(a_i) = \mathcal{B}(a_j)]\} \tag{5.6}$$

The optimization of the flexibility activation allocation problem is achieved by determining the start times (t_i) of the individual activations that maximize the objective function. The objective function given in (5.8) maximizes the excess energy volumes resolved by activating flexible consumption where the function $\mathcal{G} : \{1,...,\mathcal{T}\} \mapsto \mathbb{R}$ denoted in (5.7) defines the amount of flexibility activated during any given time period. [1]

$$\mathcal{G}(t) \coloneqq \sum_{a_i \in \mathcal{A}} \mathcal{R}(\mathcal{B}(a_i))[\mathcal{M}(a_i) \leq t < \mathcal{M}(a_i) + \mathcal{D}]) \tag{5.7}$$

$$max : \sum_{t \in \{1,...,\mathcal{T}\}} min(\mathcal{C}(t), \mathcal{G}(t)) \tag{5.8}$$

To ensure that an activation schedule adheres to the activation constraints agreed upon by flexibility providers and users, the following hard constraints are enforced:

[1] The definition given in (5.7) employs the conditional summation notation used in [110]. In this notation the condition that must resolve to true before the value of a variable is allowed to be taken into account for summation, is put in square brackets behind the variable in question.

$$\forall a_i, a_j \in \mathcal{A}: \ \mathcal{B}(a_i) = \mathcal{B}(a_j) \implies \tag{5.9}$$

$$|\mathcal{M}(a_i) - \mathcal{M}(a_j)| \geq \mathcal{D} + \mathcal{I} \tag{5.10}$$

$$\forall a_i \in \mathcal{A}: \ \mathcal{M}(a_i) + \mathcal{D} \leq \mathcal{T} \tag{5.11}$$

Constraint (5.10) enforces that no two activations of a single provider may occur within the inter-activation time period determined by the contract between provider and user. Constraint (5.11) enforces that activations start within the time frame bounds.

We use a state of the art heuristic search algorithm for solving the allocation problem [111][112]. The optimization algorithm consists of two phases. In a first phase, the first fit decreasing (FFD) construction heuristic from bin packing literature [113] provides a planning solution that satisfies the activation constraints for all participating flexibility providers. The construction heuristic allocates first the activation events that are most difficult to plan, only considering activation events already allocated before. Difficulty is determined by the flexible power rate of the flexibility provider and the activation constraints the flexibility user must adhere to. The second phase is a local search phase using Tabu Search [114] to further increase the planning solution by maximizing the congestion or imbalance resolved by the flexibility providers. The local search phase is bound in time in a hardware independent way to ensure fair comparison between different simulation runs. It must be noted that the flexibility activations are allocated to the complete imbalance or congestion profiles. Complete foresight is assumed and results in this work provide upper bounds on the efficiency of the allocations attainable within the time bounds set. The objective function and constraints are modeled in OptaPlanner using the Drools rule engine [115].

Remuneration

In terms of financial compensation all flexibility providers are remunerated on a pro rata activation basis. This means that for every activation of flexibility, which all last for 2h, the activated energy volume is compensated in proportion to the available budget for the time periods during which the activation occurs. The size of the budget available to flexibility users, varies per business case.

For the BRP, public datasets of imbalance prices per quarter hour are used to seed the budget caps. Whenever an imbalance fee should be paid, a portion of that fee is used to compensate a flexibility provider for their activation in proportion to the imbalance fee that has been avoided by that activation.

For the DSO, activations are compensated at a fixed price/kWh rate as part of a sensitivity analysis to determine which price rates can maintain positive business cases. It should be noted that a price point exceeding the green certificate compensation value in case of wind turbine curtailment is unfavorable.

5.4.3 Deployment

Simulations are deterministic and repeatedly ($R = 400$) performed with different random seeds using the open source GridFlex simulation framework [21]. This simulation framework has been developed in house and uses JPPF [116] to deploy simulation experiments on a computing cluster consisting of up to 95 quad core desktop computers.

5.5 Results

This section presents the analysis results of the market share dynamics of flexibility users competing for the business of flexibility providers. The financial compensation offered by flexibility users is the main component influencing these dynamics over time. The systems representing these market share dynamics are defined by the heuristic payoff values described in section 5.3. These dynamical systems and their critical points can be visualized by phase plots as shown in the example in Fig. 5.2. Phase plots for games where two distinct actions are possible are used to represent the critical points of the dynamics. Depending on the specific payoff results, these critical points can either form the boundary between two basins of attraction. In this case critical points are called repulsors and are denoted by λ_R. Critical points can also be the center of a basin of attraction in which case they are called attractors, denoted by λ_A. In the latter case, the critical point is an evolutionary stable strategy (ESS) of the game when using replicator dynamics [32].

Results in this work all present unique ESSs even though the number of critical points in a system of replicator dynamics can maximally equal the number of flexibility providers participating. These results correspond to a market that converges to a stable market share equilibrium over time, as illustrated in Fig. 5.2. In stable equilibrium, flexibility providers will not rationally want to change the partner they are in business with because it would mean an expected loss of income.

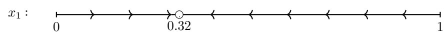

Figure 5.2: This phase plot example shows the replicator dynamics for a game played by N providers. Any initial population proportion choosing to do business with the BRP would move to the stable equilibrium of 32% of clients choosing the BRP in stead of the DSO.

Results are shown for varying compensation values offered by the DSO with both 95% confidence lower and upper bounds for these values to indicate the effective financial range the DSO needs to operate in to remain competitive. These bounds are based on the 95% confidence intervals of the payoff samples generated by simulation. These results are shown for sites at two different locations, one for wind production profiles from the Antwerp harbor and one for profiles from the coastal city of Zeebrugge in Belgium. While relatively close in geographic distance, different patterns of power production can be observed for these locations, possibly caused by different micro-climates at these locations. Both sites are therefore analyzed and compared to qualify the effect of locational differences on the market dynamics.

The number of participating flexibility providers has been denoted as N. Low values for N can provide too small a sample for inferring stable market equilibrium points. The delta between a stable market share equilibrium and the closest actually attainable population distribution can be as high as 25% (e.g. in games with only 2 agents). In such cases simulation results for varying flexibility provider parameters show higher variability than results obtained from simulation with more participating flexibility providers. For a fixed price point, results shown in Fig. 5.3 illustrate this decrease in variability as the number of participating agents increases. These simulation results are obtained with equal sample sizes for every number of participating agents. While too few participating providers leads to unfavorably high variability, assuming that many flexibility providers are located at key points of distribution grid infrastructure to reduce current congest is also unreasonable. Simulation results are therefore shown for $N = 8$. Fig. 5.3 shows that equilibrium results and confidence somewhat stabilize from 8 flexibility providers and more.

Because of lacking forecast error data for the specific locations used in this study, multiple forecast error data profiles are used as part of a sensitivity study. We distinguish between three levels of power forecast error with the baseline corresponding to a normal distribution $X \sim \mathcal{N}(0.0117, 0.1187)$, modeled after the day-ahead forecast error data for the ERCOT system described in [19]. To analyze the effects of forecast error data variation we also consider distributions $Y \sim 2 * X$ and $Z \sim \frac{X}{2}$.

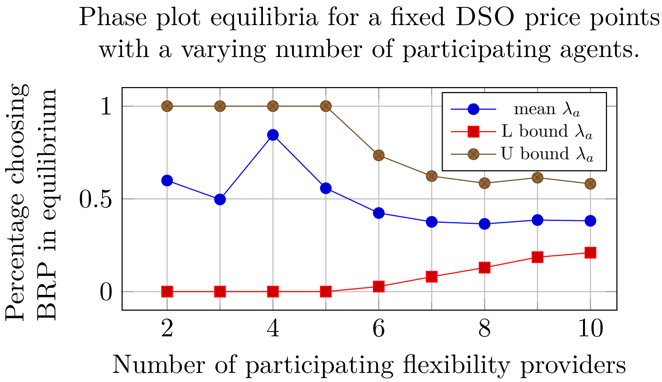

Figure 5.3: These results show that uncertainty decreases as the number of participating flexibility providers increases for a fixed DSO price point using the Antwerp data set.

5.5.1 Antwerp

The results for the Antwerp harbor location, shown in Fig. 5.5, shows the stable market share equilibrium for different DSO compensation price points. BRP imbalance data is generated based on power forecast error distribution X. Fig. 5.6 and Fig. 5.7 show simulation results for respectively higher and lower power forecast error distributions Y and Z. These results indicate that the price points for DSOs to remain competitive are higher when competing BRP portfolios contain higher imbalance volumes. Higher imbalance volumes in BRP portfolios intuitively allow for more opportunities to use consumption flexibility than portfolios with lower imbalance volumes. This leads to a larger compensation budget that can be used by BRPs to pay providers for their flexibility. This in turn drives up the compensation prices for competing DSOs wanting to remain competitive.

As BRP portfolio imbalance volumes increase, the competitive margins for DSOs also become larger. This is primarily caused by the increase in BRP payoff results that follows the increased opportunity costs from larger imbalance volumes that the BRP has to correct. Compensation budgets are determined by the imbalance penalties that would be incurred if no consumption flexibility is used. Another factor driving up compensation prices for competing DSO that want to remain competitive is the direct effect that power forecast error distribution variability has on the percentage of useful allocation of consumption flexibility to the imbalance data. The allocative efficiency metric $\mathcal{E}$ can be defined by the ratio of resolved excess energy to activated flexibility. This metric, described in (5.12), is used to show the difference in allocative efficiency when using the power forecast error distributions X, Y and Z. These result in Fig. 5.4 show less efficient allocations with lower imbalance volumes. Besides a lower mean allocative efficiency results from using the Z distribution, also a lower variability in allocative efficiency can be noted.

$$\mathcal{E} := \sum_{t \in \{1,\dots,\mathcal{T}\}} \frac{min(\mathcal{C}(t), \mathcal{G}(t))}{\mathcal{G}(t)} \tag{5.12}$$

The amount of compensation to be expected from doing business with the BRP decreases as the imbalance volumes that are effectively resolved by consumption flexibility decreases.

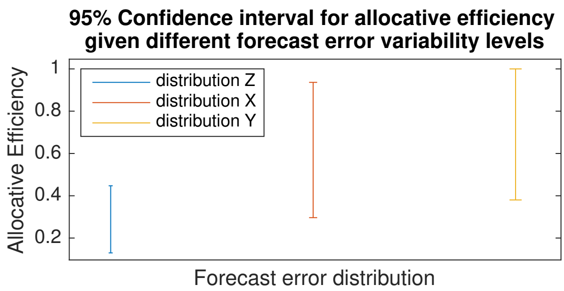

Figure 5.4: 95% confidence intervals of allocative efficiency show that lower forecast error volumes cause lower efficiency in flexibility activations.

5.5.2 Zeebrugge

The results for the Zeebrugge location in Belgium are based on the same relative power forecast error data discussed in section 5.5.1 but with different power production profiles because of the difference in location. Fig. 5.8 shows the stable market share equilibrium for different DSO compensation price points with forecast error data distributed according to X. Fig. 5.9 and Fig. 5.10 show simulation results for respectively higher and lower power forecast error distributions Y and Z.

The trends in the results for this location show significant similarities to the results of the Antwerp location discussed in section 5.5.1 in that higher forecast error induced imbalances at BRP side lead to higher competitive price ranges. Similar to the Antwerp case lower imbalance volumes again lead to decreased efficiency in allocation for BRPs, which in turn leads to lower competitive price

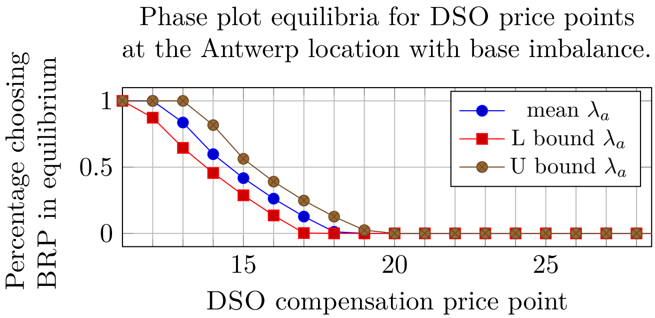

Figure 5.5: Phase plot results for multiple DSO compensation price points show the competitive price ranges for the Antwerp location at base imbalance levels.

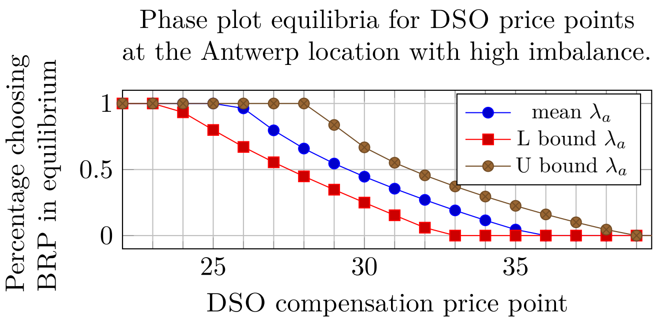

Figure 5.6: Phase plot results for multiple DSO compensation price points show the competitive price ranges for the Antwerp location at high imbalance levels.

ranges in equilibrium. It is interesting to note, however, that the competitive price ranges observed in the results between these two different locations do quantitatively differ under similar BRP forecast error data profiles. This difference is more pronounced with higher forecast error volume profiles and become negligible as lower forecast error volumes are used.

5.5.3 Lessons learned

Summarizing the lessons learned from analyzing simulation results where a DSO and a BRP compete for consumption flexibility provided by small to medium sized industrial consumers we note that:

- Higher BRP power forecast inaccuracies lead to higher imbalance volumes,

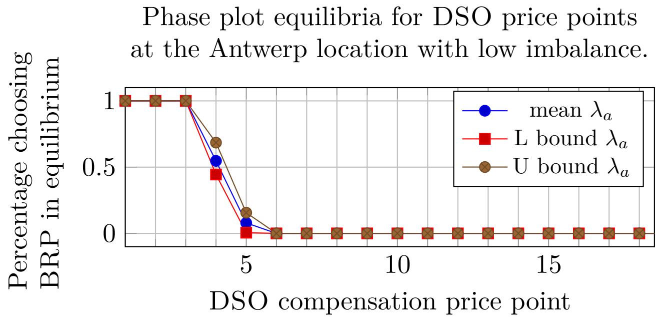

Figure 5.7: Phase plot results for multiple DSO compensation price points show the competitive price ranges for the Antwerp location at low imbalance levels.

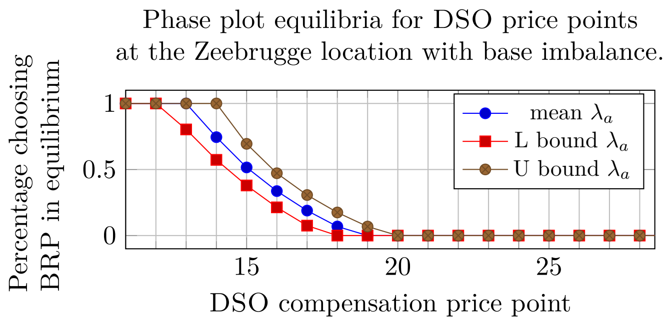

Figure 5.8: Phase plot results for multiple DSO compensation price points show the competitive price ranges for the Zeebrugge location at base imbalance levels.

which in turn lead to higher possible compensation budgets. In these cases, DSOs are forced to increase their financial compensation margins to remain competitive.

- Different locations have different power production characteristics which in turn lead to different base BRP portfolio imbalance levels. Quantitative conclusions drawn from this study are therefore location specific.
- The location specific differences in equilibrium results are less pronounced with lower forecast error levels.

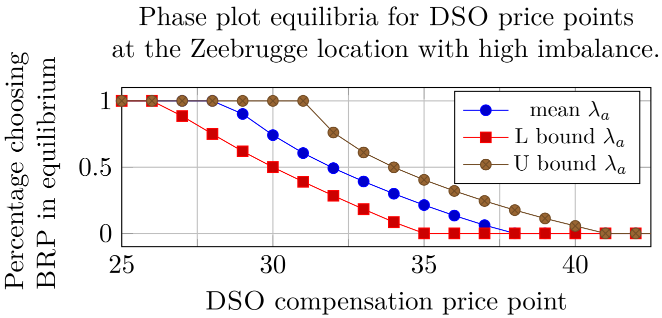

Figure 5.9: Phase plot results for multiple DSO compensation price points show the competitive price ranges for the Zeebrugge location at high imbalance levels.

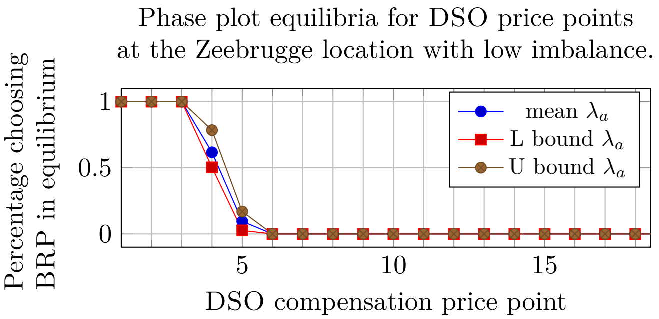

Figure 5.10: Phase plot results for multiple DSO compensation price points show the competitive price ranges for the Zeebrugge location at low imbalance levels.

5.6 Conclusion

Maintaining the balance between production and consumption becomes increasingly challenging with the adoption of more RES in efforts to create more sustainable future power grids. Both consumption flexibility and the technical know-how to employ this flexibility will be required in order to maintain this balance in real time. Using DSM techniques effectively towards this goal in light of increasing integration challenges, is one of the key features that defines smart grids.

In this work, different business cases are presented for using upward consumption flexibility to deal with issues related to the integration of wind turbines into existing distribution grids. We focus on the strategic choice faced by flexibility providers in choosing which business partner to do business with in order to maximize financial rewards for offering consumption flexibility.

In our model, several assumptions are made. The wind turbines that serve as the primary input data source are assumed to be connected to 15 kV distribution feeders and part of a BRP portfolio. Another assumption is that flexibility providers are located on the same distribution feeder as the wind turbines and that these flexibility providers are able to provide upward consumption flexibility on demand. More specifically, they are physically connected at a location that allows the reduction of current congestion. We also assume that all participating flexibility providers have a means of pairwise comparing payoffs with other providers. Lastly, the allocation of flexibility to imbalance or current congestion profiles is done with perfect foresight to provide upper bounds on the effectiveness of DSM. In reality, real time planning of flexibility activations will result in less efficient allocations and less possible value for money for the flexibility users.

Results from extensive simulations show that higher BRP forecast inaccuracies lead to higher compensation budgets needed by DSOs to remain competitive. These results stress the importance of having accurate wind power production forecasts when faced with increased penetration of variable RES. Results also show that depending on the location where wind production data is gathered, DSO margins for remaining competitive will differ. The framework for analyzing business partner choice dynamics of flexibility providers can be used by DSOs to estimate their market position and to help inform future investments decisions regarding the optimal use of RES. Other power system involved parties can also benefit from this framework. Flexibility providers can make informed decisions on who to provide flexibility to and flexibility aggregators can employ these tools to help schedule flexible consumption to different parties requiring flexibility.

Future work includes analyzing the effects that different BRP forecast error distributions and different activation constraints can have on the payoff dynamics. Validating these results while weakening the assumption of perfect foresight is also important future work. Incorporating real time resource allocation techniques might shed a different light on the market dynamics at play between two competing parties that can use consumption flexibility. Furthermore, the model presented in this work assumes two mutually exclusive business cases for flexibility providers. In future work this assumption can be weakened by assuming the availability of flexibility providers that do not require the guarantees that activation constraints provide. EGT can offer insights such situations as well.

Finally, even though future work is needed to validate actual commercial viability of the business cases presented here, these results provide a base line quantification of the market dynamics of real world smart grid entities with real world industry data. This work also presents how EGT can be used as a methodology for evaluating such market dynamics in complex domains such as smart grids and to eventually further assist the cause of creating sustainable energy systems.

Acknowledgment

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Chapter 6

Analysis of Activation Constraints and their Effect on Demand-Side Flexibility Allocations

Bilateral agreements on harnessing consumption flexibility often constrain the availability of consumption flexibility to both guarantee this availability and to protect the providers. Chapters 4 and 5 have indicated that the specific constraints used for scheduling flexibility can influence how efficiently flexibility providers can be used to address various imbalance problems. This chapter presents a sensitivity analysis on flexibility activation constraints and their effects on DSM efficiency and contains the paper currently in submission to PES ISGT Europe 2018 titled:

> Analysis of Activation Constraints and their Effect on Demand-Side Flexibility Allocations

The definitions, analysis and supporting software are the result of discussions between all authors, led by Kristof Coninx. Kristof Coninx did all of the programming and the writing. Tom Holvoet and Geert Deconinck gave feedback on the writing.

Abstract

Demand-side management (DSM) programs in literature and industry alike often enforce constraints on the activation of flexible power provided by customers. Constraining consumption flexibility used in DSM can lower the entry barrier for flexibility providers but the specific constraints used can also have an impact on the efficacy of employing such flexibility. While different problems requiring their own form of consumption flexibility are described in literature, systematic analyses of the impact of activation constraints on such DSM programs are limited. This chapter addresses this by analyzing the effects that different activation constraints for power flexibility used in industry have on different problem cases involving renewable production resources. This sensitivity study of activation constraints is performed using real world electricity production and imbalance data for different locations in Belgium. Our work shows that depending on the use case, some constraint dimensions influence the efficiency attained in best case flexibility scheduling while other constraint dimensions do not have any influence in certain other cases. These results are compared against constraint parameters used in flexibility products by system operators today and provide insights into possible improvements of constraint parameters in different use cases.

6.1 Introduction

With the increasing adoption of renewable energy production resources, maintaining a production/consumption balance in the current day electric power grid requires flexibility on both the production and consumption side. demand-side management (DSM) describes techniques for controlling the demand side of the equation to achieve and maintain this balance.

DSM programs can be implemented with different goals in mind. For example, DSM is often considered for flattening peak consumption demand [117][118]. Improving power system reliability by employing flexible consumption to match intermittent production from renewable energy sources (RES), is also a valid use case of DSM [119]. Other examples exist in both literature [5] and industry [120] of consumption flexibility being harnessed towards a more stable and safe operation of power systems.

Through DSM, consumption flexibility can be employed in different ways to achieve these goals. One category of DSM techniques is called demand response (DR). In DR, utilities and system operators indirectly influence the energy demand of consumers. This is achieved by offering financial incentives (e.g. tariff reductions) for changes in consumption patterns [121].

Another form of DSM employed in industry is achieved through bilateral agreements between industrial consumers and utilities or system operators [122]. For industrial consumers, bilateral agreements allow consumers to negotiate the form and the availability of their flexibility [123]. Utilities, system operators and other parties that can make use of consumption side flexibility can, in turn, offer standardized flexibility products. Clearly delineated and constrained product offers can lower the entry barrier to potential customers. An integral part of these product are the activation constraints specifying when, how often and for how long flexible power consumption can be used by a contractor. With different ways of employing this constrained flexibility, the specific constraints can have different effects on the global effectiveness of employed flexibility on a case by case basis. Insights into these effects can greatly benefit stakeholders employing consumption flexibility such as distribution system operators (DSOs), transmission system operators (TSOs) and utilities in general.

The presence of systematic evaluations of flexibility activation constraints for industry purposes is limited. This work attempts to remedy that by empirically evaluating the most commonly used flexibility activation constraint dimensions for two different problem cases with real data. A portfolio balancing problem case is compared to a distribution grid congestion case. The portfolio balancing case concerns a balance responsible party (BRP) that balances its portfolio of production and consumption. The production part of this portfolio includes wind production resources. Wind production forecast errors can lead to real time portfolio imbalances that can be offset by consumption flexibility [122][1]. The distribution grid congestion cases concern DSOs that face grid congestion from wind production during periods with high wind and low consumption. Consumption flexibility can offset overproduction to avoid damaging the infrastructure during congestion events [3]. Both cases have different flexibility needs but can make use of the same consumption flexibility offered by industrial consumers. The effects of flexibility activation constraint parameters and their influence on the effectiveness of scheduling flexible consumption to reduce excess energy are analyzed for both cases.

Following this introduction, a description of the input data and modeling is given in section 6.2. The analysis approach is described in section 6.3. Analysis results are described in section 6.4. Finally, the contributions are summarized and described in context of future work in section 6.5.

6.2 Model and data

Small to medium sized companies willing to increase their consumption on demand are modeled to provide consumption flexibility. The amount of flexibility provided at any given time is determined by their flexible power rate. Flexibility providers are realized with flexible power rates drawn from a gamma distribution Γ fitted to a confidential industry data set of clients of the tertiary reserve under a dynamic profile (R3DP). This Γ distribution $\Gamma(a, r)$ with $a = 1.37012, r = 677.926$ passes the classical goodness-of-fit such as the Komolgorov-Smirnov [74] and the Anderson-Darling [75] tests for a confidential industry data set of R3DP clients in Belgium. R3DP is a flexibility product offered by the Belgian TSO to distribution grid connected industrial consumers [124].

All flexibility activations are subject to activation constraints. The activation constraint dimensions modeled in this work are inspired by the constraints specified by the R3DP product. These constraints specify an activation duration of two hours with a minimum of twelve hours of inactivity between two consecutive events and a maximum of 40 activations per year. The flexibility modeled in this work will have the same constraint dimensions but with varying parameters as part of a sensitivity analysis. This sensitivity analysis of flexibility activation constraints is performed for different problem cases and real world data from two different locations.

The portfolio balancing case describes the employment of flexible industrial consumers as an alternative to paying imbalance fees to the TSO. When balance responsible parties have portfolios which include sizable amounts of RES, real time balancing becomes more difficult because of the variable nature of these RES. Power production forecasts are an important aspect of minimizing these balances in real time. The imbalances assumed here are caused by wind power production forecast errors between the nomination date of expected production-consumption balance and the actual balance at time of delivery. Imbalance data is generated from proprietary power production time series and forecast error data from literature. These data sets span 12 month periods in 15 min. time periods.

In literature multiple models for wind production forecast error have been proposed based on different underlying distributions. Both the normal distribution and the Cauchy-Lorentz distribution among others have been used to model production forecast errors [125]. In this work we model normally distributed errors with the ERCOT data distribution parameters described in [19]. This imbalance data is compared to imbalance data based on Cauchy distributed production error data artificially created to bear the same total yearly production error volume as the normally distributed data from literature.

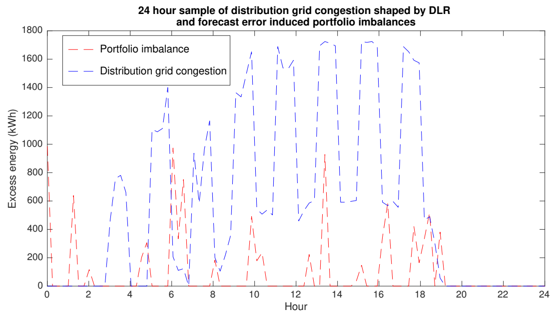

Figure 6.1: A random sample of congested energy volumes spanning 24 consecutive hours shows the distinct DLR shaped congestion.

The distribution grid congestion case describes distribution congestion caused by excessive wind power injection. In such cases the cable infrastructure is not rated to cope with excessive currents flowing through the cables at times. The distinction is made between static line rating and dynamic line rating (DLR). Both line rating schemes define which injected power is actually deemed excessive. DLR shows great potential in reducing grid congestion by temporarily allowing excess currents followed by stricter ampacity limits in favor of a universal static ampacity limit [126]. Another useful side effect of using DLR is the window of opportunity it allows in which other flexible power resources can be employed and ramped up to take over when long periods of increased injection are causing problems. Different DLR algorithms produce different congested energy profiles however. In this work two different DLR algorithms are discussed. A first algorithm allows two quarters of an hour of excessive currents up to 30% more than the static ampacity limit, followed by enforcing a 12.8% more strict ampacity limit for two quarters hours. A second algorithm allows four quarters of an hour of similar excesses, followed by the same more strict ampacity limit for four quarter hours. Both profiles are discussed in terms of varying activation constraints. Both these cases are discussed for multiple wind power production profiles that differ in the location of the respective wind farms. Concretely, production sites in Zeebrugge and in Antwerp have both provided data for this study detailing a yearly output of 43 GWh and 36 GWh respectively.

Samples of the distribution grid congestion and the portfolio imbalance data are shown in Fig. 6.1. This sample shows the distinct form of the DLR shaped grid congestion and the sparser portfolio imbalances.

6.3 Analysis approach

The sensitivity analysis focuses on the effects of flexibility activation constraint parameters and their influence on the effectiveness of scheduling flexible consumption to reduce excess energy. Power consumption flexibility is offered by flexibility providers in the form of a fixed number of flexibility activations (c) that are scheduled off line, on fully available historical data. The time series data spans 12 months of excessive energy volumes in 15 min. time periods $t \in \{1, ..., 35040\}$. Off line allocation of flexibility provides a view on the upper bound of allocation effectiveness compared to the on line allocation algorithms that correspond to the day to day decision making faced by flexibility users when dealing with uncertain production.

The optimal-within-bounds activation schedule is produced using a heuristic local-search algorithm that schedules activations to optimize the actually resolved energy excesses given the following activation constraints:

- An activation event spans a period of $4 * d$ time periods with d representing the activation duration in hours.
- An activation can not start within $4 * (i + d)$ time periods following the start of another activation with i representing the inter-activation time in hours.
- The total number of c activations must be respected.

The heuristic optimization library OptaPlanner [109] is used in the open source simulation framework GridFlex [21]. The first fit decreasing (FFD) construction heuristic from bin packing literature is used to produce an initial allocation schedule [113]. Tabu Search is used as a local search algorithm to further improve the initial allocation schedule [127]. All experiments execute a fixed number of search steps to maintain a fair comparison with varying simulation hardware performance.

Allocation schedules for the different scenarios and combinations of activation constraint parameters are evaluated using the allocative efficiency metric. This metric represents the actual volumes of excess energy that are reduced with the flexibility allocations compared to the total theoretically available flexibility offered by the providers over a 12 month period.

For all analysis scenarios, the relative allocative efficiency metric $\mathcal{E}$ is defined by equation (6.1) where $C(t)$ represents the congested energy volume function for each 15 min. time period t and $F(t)$ represents the total activated energy volume in the same time periods $(C, F : \{1, ..., 35040\} \mapsto \mathbb{R}^{+})$. This metric $\mathcal{E}$

is plotted in function of the flexibility activation duration and the minimum inter-activation time parameters.

$$\mathcal{E} \coloneqq \sum_{t \in \{1,\ldots,35040\}} \frac{\min(C(t), F(t))}{F(t)} \tag{6.1}$$

6.4 Simulation results and discussion

This section presents simulation results for the flexibility activation constraint sensitivity analysis. This analysis is performed for the distribution grid congestion case and the portfolio balancing case.

6.4.1 Distribution grid congestion

When dealing with distribution grid congestion, volumes of excess energy are defined by the electrical current that exceeds the allowed current ratings of cable infrastructure. DLR makes use of the hysteresis effect of current-temperature curves when defining excess energy. We distinguish between the two different line rating algorithms described in section 6.2. The first scenario features a DLR algorithm that allows two quarter hours of excessive current ratings before employing a more strict current rating. A second scenario features an alternative DLR algorithm that allows four quarter hours of excessive current ratings before employing the same strict rating.

Influence of dynamic line rating parameters

Results in Fig. 6.2 shows the relative allocative efficiency metric for the first scenario using the Antwerp data set. These results show a gradual decrease in relative efficiency as the activation duration increases. A small preference for smaller inter-activation times is also noticeable. This effect becomes more noticeable when more activation events need to be scheduled, which is shown in Fig 6.3.

For the second scenario, results shown in Fig. 6.4 show a similar decrease in efficiency with increasing activation durations in general. One important difference in these results is the markable increase in efficiency relative to the observed results from the first scenario when using activation durations of odd hours.

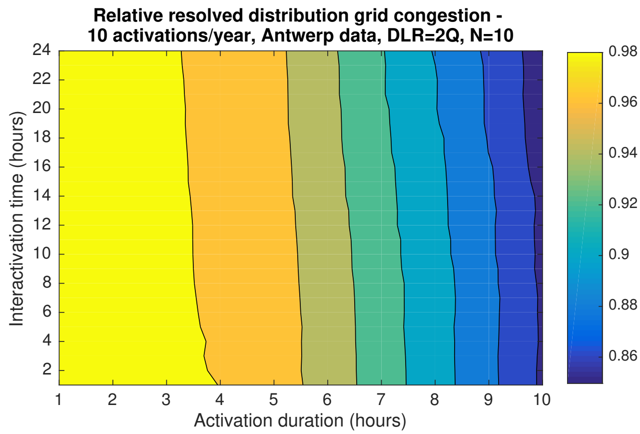

Figure 6.2: A gradual decrease of allocative efficiency is shown as the activation duration parameter increases. A small preference for low inter-activation times is noticeable.

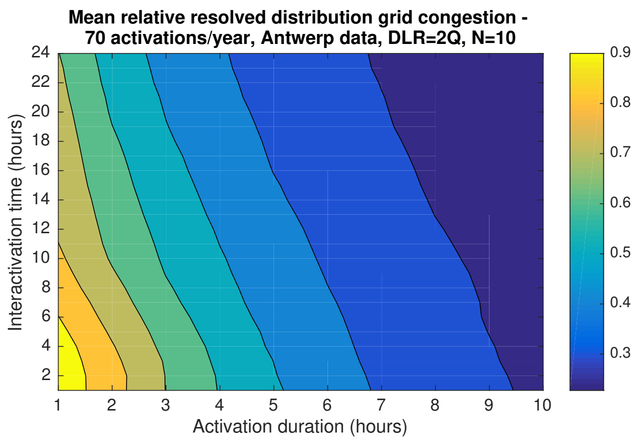

Figure 6.3: A gradual decrease of allocative efficiency is shown as the activation duration parameter increases. A preference for low inter-activation times is more pronounced with higher activation events to schedule.

Results for the second scenario using the Zeebrugge data set are shown in Fig. 6.5. Comparing these results with the Antwerp data set shows that the inter-activation time parameter bears no effect on the allocative efficiency metric by itself in this case. A general decrease of allocative efficiency as the activation duration increases is noticeable however. Similar to the second scenario of

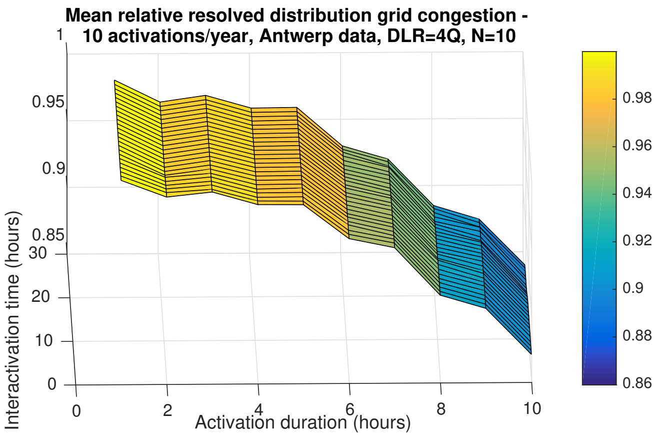

Figure 6.4: A general benefit for odd activation durations over even durations is noticeable.

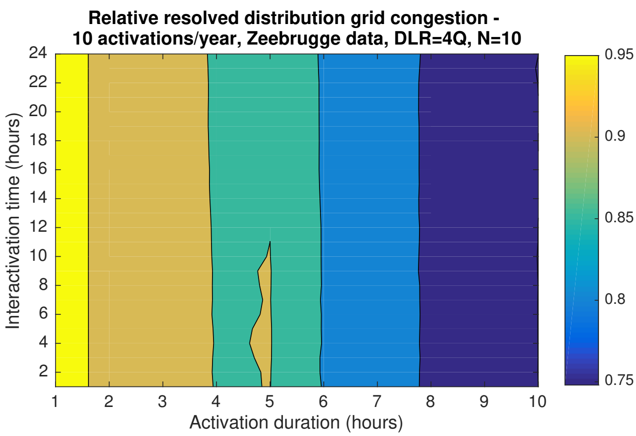

Figure 6.5: The preference of lower inter-activation times is less pronounced in the Zeebrugge data set. These results show similar benefits for odd activation durations as the results in Fig.6.4

the Antwerp dataset, odd hours of activation durations yield greater or equal allocation efficiency than using smaller but even hours of activation durations.

Intuitively, allocating activation events with even hour durations to congestion which oscillates hourly between high and low values results in the best case in allocations that have at least 50% of the time spanning the low values. Activation events with odd hour can both start and end on the high values, thereby possibly yielding higher efficiencies. This is supported analytically by first examining a stylized congestion function that produces a similar congestion profile as DLR algorithms that allow k quarter hours of high cable ratings followed by k quarter hours of lower ratings. Function (6.2) represents such a binary step function.

$$C^*(x) = 1 - \left\lfloor \frac{x}{k} \right\rfloor \bmod 2 \tag{6.2}$$

The relative amount of congestion r that can be resolved by an activation of d hours is given in (6.3).

$$r = \frac{1}{d} \int_0^{4d} C^*(x)dx \tag{6.3}$$

For $k = 2$, equation (6.3) yields a constant $r = 2$ for all values of $d \in \mathbb{N}^+$. For $k = 4$, equation (6.3) yields a case distinction between even and odd values of d. This case distinction resulting from evaluating (6.3) is given in (6.4) and shows a similar limit behavior as for $k = 2$ but with possible higher fractions of resolved congestion for smaller odd values of d. This concurs with the results shown in Fig. 6.4 and Fig. 6.5.

$$r = \begin{cases} 2, & \frac{d}{2} \in \mathbb{N}^+ \\ \frac{4\lceil \frac{d}{2} \rceil}{d}, & \frac{d}{2} \notin \mathbb{N}^+ \end{cases} \tag{6.4}$$

Influence of offered flexibility volumes

The least constrained activations to schedule are those activations that last only an hour and can be activated again with only an hour of down time between two consecutive activations. In all scenarios shown, those conditions offer the highest allocative efficiency. When varying the number of activations that have to be scheduled at once, these conditions remain dominant in their effectiveness. Even when increasing the number of activations that have to be scheduled eightfold, the relative allocative efficiency metric attains higher than 90% efficiency in these conditions. When looking at activation durations that last longer, the allocation efficiency decreases when the number of allocations to schedule increases. This is apparent when comparing Fig. 6.2 with Fig. 6.3 for the Antwerp data set. But also comparing Fig. 6.5 with Fig. 6.6 shows a similar trend.

When keeping to a fixed number of allocations and varying the activation durations within a scenario, the total amount of flexibility offered by a flexibility provider varies also. To avoid presenting a skewed view of optimal constraints for providers willing to provide a set amount of flexibility, Fig. 6.7 and Fig. 6.8 show results in terms of allocative efficiency for which the number of allocation

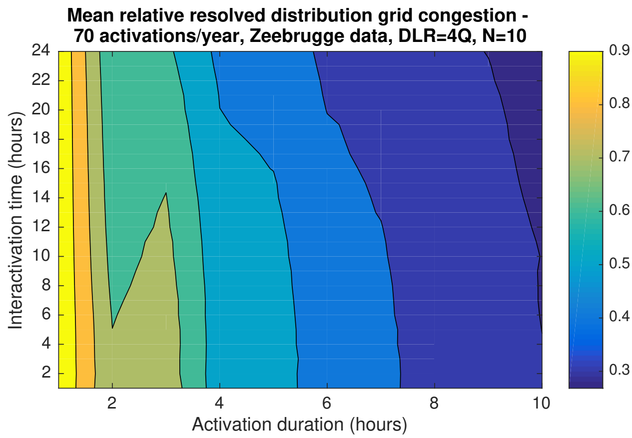

Figure 6.6: Scheduling 70 allocation events causes the allocative efficiency to decrease when using high duration activations, when compared to lower numbers of allocations to schedule.

events to schedule is scaled in function of the activation duration as to keep total amount of flexibility offered by providers constant.

Results for the Antwerp data shown in Fig. 6.7 show unsurprisingly a preference for highly flexible activations with short activation durations and short inter-activation times. It is also noticeable that short activation durations need to be paired with short inter-activation times to produce relatively effective allocations. Increasing the activation duration consecutively allows for higher inter-activation times as well without losing significant efficiency in flexibility allocations.

For the Zeebrugge data shown in Fig. 6.8 a general disinterest in the inter-activation time is observed for all activation durations except durations ranging from two to four hours. Furthermore, short activation durations of one hour are preferred to produce optimally efficient allocations. If one hour activation durations are not feasibly, however, a local optimum can be found for activation durations ranging from five to six hours.

It can also be noted that in all simulation results, the parameters used by the R3DP product (40 activations of two hours per year with an inter-activation time of 12 hours), can be improved upon to provide more efficient activation schedules.

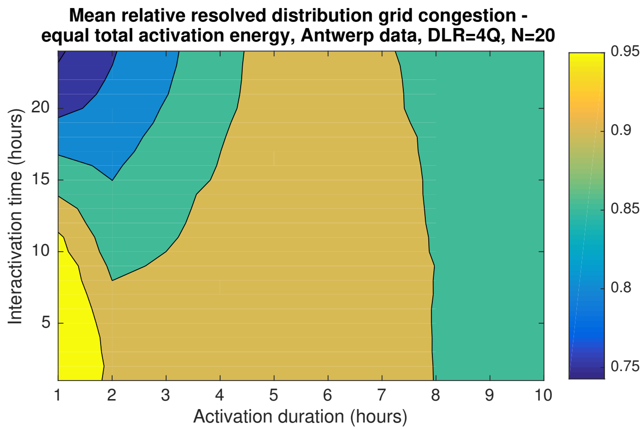

Figure 6.7: When the total flexibility offered is assumed constant over varying activation constraints then a clear preference for minimally constrained flex is noticeable.

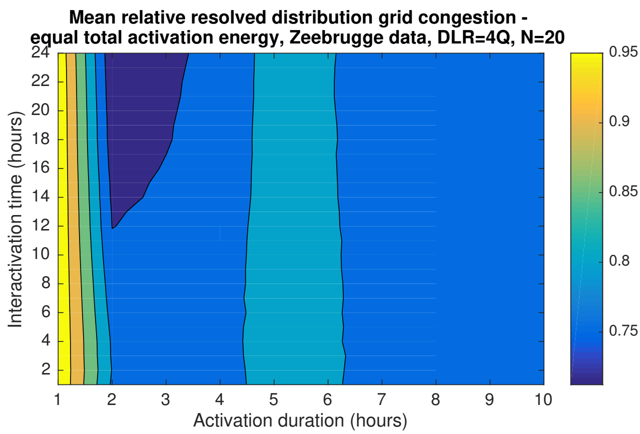

Figure 6.8: When the total flexibility offered is assumed constant over varying activation constraints then a clear preference for minimally constrained flex is noticeable. A local maximum can also be found with activation durations of 5-6 hours.

6.4.2 Portfolio balancing

The difference between normally distributed forecast errors and Cauchy distributed errors is that, in the latter case, higher error peaks can be observed,

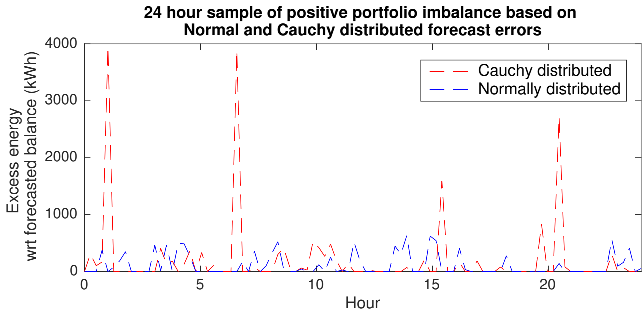

Figure 6.9: This 24 hour sample of the normally and Cauchy distributed forecast errors shows a difference in peak error levels and the frequency of the occurring peaks.

but at a lower frequency than the normally distributed error peaks. Figure 6.9 shows a sample period for each distribution.

Simulation results from allocating flexibility under different activation constraints are shown in Fig. 6.10 for the normally distributed forecast errors and in Fig. 6.11 for the Cauchy distributed errors using the Antwerp power production data. Literature has indicated that the use of different forecast error distributions can yield different results. No such discernible differences in trends were observed in these results. Results using the normal distribution show an overall small ($< 5\%$) increase in allocative efficiency over the Cauchy distributed errors. Results from the Zeebrugge production data set show trends similar to the Antwerp data.

Compared to the problem cases discussed in section 6.4.1, in portfolio balancing cases, the inter-activation time parameter of the activation constraints has no influence on the allocative efficiency of these activations. Forecast errors are less subject to seasonal variations than the distribution grid congestion case because of the different origin of the error. This limited seasonality in the problem data means that for a limited amount of activations to schedule, the probability of finding volumes of excessive energy for an activation that does not conflict with other activations is high enough for the inter-activation time parameter not to matter.

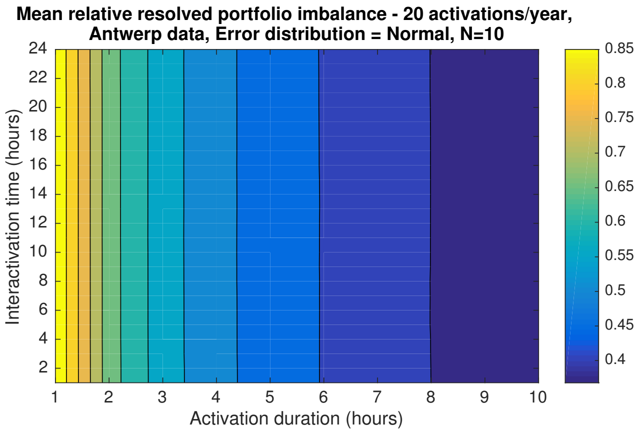

Figure 6.10: Relative resolved portfolio imbalance for the Antwerp data shows that the inter activation time parameter has no influence on the efficiency of flexibility activation.

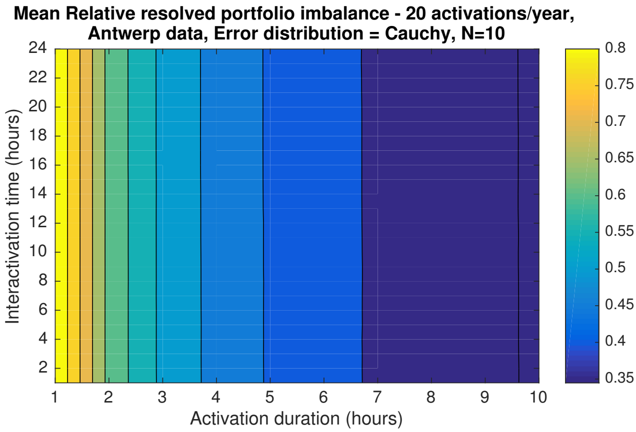

Figure 6.11: The results using the Cauchy distributed forecast error shows no difference in trend when compared to normal distributions.

6.5 Conclusion

Maintaining a real time production/consumption balance is challenging in light of increased adoption of renewable energy sources. Bilateral contracts between utilities and flexible consumers can regulate the use of consumption flexibility to maintain this balance in real time. In this work we perform a sensitivity analysis of flexibility activation constraint parameters when used to schedule flexibility activations in two problem cases for two locations in Belgium. This analysis is performed for the off line scheduling of consumption flexibility activations based on real world data spanning 12 consecutive months.

Simulation results show that constraining the required down time that follows an activation of consumption flexibility can only influence the efficiency of flexibility scheduling in distribution grid congestion cases and not in portfolio balancing cases. Results also show that whether a normal or a Cauchy distribution is used to model forecast errors has no effect on the efficiency of flexibility scheduling. Finally, results also indicate that when DLR is used to shape congestion in distribution grid congestion cases, there is a clear relation between the DLR algorithm and the activation duration parameters used. Results presented in this work can offer insights into how the design of flexibility products offered by system operators and other parties requiring flexibility can be improved upon in terms of activation constraints. For distribution grid congestion cases specifically, more efficient flexibility activations are possible when activation duration and inter-activation times can be lowered, compared to R3DP.

Future work into the use of other DLR algorithms in the sensitivity study can prove useful in providing a better understanding of the effects of DLR on flexibility activation constraints. Expanding this sensitivity analysis to on line allocation mechanisms as well to gain understanding of optimal constraints to use when dealing with uncertain future production excesses is another opportunity for future work.

Acknowledgment

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Chapter 7

Conclusion

Software is increasingly crucial in the transformation from electrical grids to smart grids. An integral part of implementing smart grid technologies is developing and maintaining software for monitoring and managing consumption data, whether for smart meters or for industrial energy management systems. Similarly, software to simulate future technologies or demand-side management software for scheduling flexible loads will be fundamental to building and operating smart grids.

Electricity grids are evolving to more high tech and dynamic grids where electricity no longer flows from generation to consumption in a hierarchical and unidirectional fashion. New renewable energy sources (RES) are connected at all conceptual levels of the electricity grid. Wind farms are, for example, connected to the transmission grid, individual turbines can provide locally produced energy for industrial consumers and solar panels are being deployed on a residential scale. Together with the digitalization of energy management systems, RES offer new business opportunities in the energy landscape. Business cases for managing and selling consumption flexibility are implemented by aggregators and system operators invest in active network management (ANM) techniques to minimize costly grid imbalances. All stakeholders operating in the power systems domain face strategic choice situations that require informed decision making processes in capitalizing on these opportunities. Software capable of supporting these business opportunities and providing information for informed decision making, will be instrumental in producing positive end results. The field of computer science (CS) is ideally positioned to providing the necessary software, algorithms and analysis tools.

In this dissertation various aspects of employing consumption flexibility are analyzed in the context of increased adoption of RES such as wind. This analysis is performed from a strategic choice perspective using evolutionary game theory (EGT). EGT is an ideal tool for modeling and analyzing strategic choice dynamics over time.

The remainder of this chapter summarizes the contributions of the previous chapters in more detail (section 7.1). This dissertation is concluded with a discussion of the lessens learned and interesting directions of future work (section 7.2).

7.1 Summary of contributions

This section summarizes the contributions of each of the content chapters in chronological order.

7.1.1 Evolutionary game theory analysis framework for analyzing strategic choice

A common aspect of demand-side management (DSM) is that flexibility providers are financially compensated for providing power consumption flexibility on demand. Chapter 2 provides an analysis of different payment strategies for offered consumption flexibility. Concretely, flexibility providers face a binary choice in doing business with flexibility aggregators implementing activation (per use) or reservation (flat rate) payment strategies. balance responsible parties (BRPs) employ the offered flexibility to minimize a common imbalance signal.

The first contribution in this dissertation is the description of the approach for analyzing strategic choice dynamics using replicator dynamics with varying numbers of participating agents. The analysis approach is based on heuristic payoff matrices determined through microsimulation.

The application of this approach in chapter 2 yields empirical evidence indicating that BRPs can gain larger flexibility provider client population shares when employing reservation payment over activation payments when assuming that flexibility providers determine their choice in BRP based on expected financial rewards. This effect is shown to be less outspoken when the amount of flexibility offered largely outweighs the flexibility needed for balancing.

Parallel with the contributions in chapter 2, the development of the open source simulation framework `GridFlex` is considered as a technical contribution. This framework has been in continuous development over the course of this research project and is the basis for work in all following chapters. A more thorough description of `GridFlex` is found in Appendix A.

7.1.2 On-line and off-line coordination mechanisms for employing consumption flexibility

Negotiating the activation of flexible consumption resources with multiple providers and users of flexibility requires coordination mechanisms. The second contribution spans the content of chapter 3 in formulating on- and off-line flexibility allocation algorithms. For on-line flexibility allocations, the distinction is made between a cooperative algorithm, based on the contract net protocol (CNP) and a competitive algorithm, based on the strategy proof qualitative Vickrey auction (QVA). A less computationally tractable off-line optimal mixed-integer programming (MIP) formulation is also presented to provide efficiency upper bounds for scenarios with few participating agents.

Chapter 3 provides an analysis of flexibility activation efficiency using different coordination mechanisms for using consumption flexibility to address distribution grid congestion. Empirical results show that cooperative activation mechanisms can yield more efficient allocations than competitive mechanisms for scenarios where the number of participating agents is limited. For system operators, retaining full control over the decision of which providers to activate when encountering congestion events, is shown to be better in terms of allocation efficiency compared to employing a more market oriented mechanism. The problem context does not often allow large numbers of participating agents. Such scenarios would minimize the efficiency penalty for using a competitive mechanism in which case the positive features of QVAs might be preferred.

7.1.3 Investment cost model for an integrated ANM solution to address distribution grid congestion

Chapter 3 proposed the need for other ANM techniques besides DSM as a comprehensive solution to deal with distribution grid congestion. A third contribution described in chapter 4 concerns the presentation of a operation and investment cost model for employing an integrated ANM solution using dynamic line rating (DLR), DSM and storage solutions to address distribution grid congestion. DLR is used as a first line solution to provide a buffer for activating DSM resources and to define the energy volumes that need to be addressed by the other ANM techniques. Energy storage solutions are used as a last line solution to address remaining excesses that are not handled by DSM. The storage solution is dimensioned appropriately to resolve energy excesses while minimizing costs. The investment cost model contains initial investment, maintenance and operation costs for the integrated approach. The specific model parameter choices were validated by a Belgian distribution system operator (DSO).

Investment case cost projections for two different locations show that depending on the regulatory framework in place, DSM can significantly reduce the total investment cost for 20 year business cases. Because storage solutions are sized in two dimensions: peak power rate (kW) and energy volume (kWh), congestion events with larger peaks and durations can reduce the dimensions of the storage solution required as a fallback solution. In such situations the use of DSM can reduce the total cost associated with an integrated ANM solution. Comparing the total investment costs to grid reinforcement cost projections has also shown that with current storage prices, grid reinforcement is still often the more cost effective solution to dealing with grid reinforcement.

The investment cost analysis is based on activation constraints used in an existing Belgian strategic reserve program. The empirical results indicate that the DSM activation constraint that are used, have non negligible effects on the efficiency of DSM. This phenomenon has been further investigated in chapter 6.

7.1.4 Computational analysis of flexibility provider strategic choice between multiple business cases

Power consumption flexibility can be harnessed toward different goals. Financial compensation of flexibility providers participating in DSM programs can also vary depending on the specific implementation of the such programs. In chapter 5 flexibility providers face a strategic choice situation in deciding whether to participate in a DSM program where consumption flexibility is used to address distribution grid congestion, as described in chapters 3 and 4 or to address a BRP portfolio imbalance. This latter case improves on the grid balancing case described in chapter 2 by modeling wind power production forecast induced imbalances faced by BRPs that have wind power production resources in their portfolios.

The fourth contribution in this dissertation is the formulation of two business cases for using consumption flexibility and the description of the value streams that make up these business cases. The first business case pertains to DSOs that want to avoid distribution grid congestion by using flexible consumption.

The second business case refers to BRPs that want to avoid imbalance penalties by employing consumption flexibility to balance their portfolio.

The fifth contribution is the approach for defining a base line quantification of flexibility market dynamics in environments where flexibility providers must choose between parties competing for consumption flexibility. This approach can be used for deriving competitive price ranges for flexibility compensation payments, when used with the appropriate data.

Strategic choice analysis of situations where flexibility providers must choose between two different business cases show that quantitative results of competitive price ranges for DSOs dealing with competition from BRPs are location specific. Although concrete quantification of these price ranges are location specific, empirical evidence is presented in chapter 5 indicating that higher wind forecast inaccuracies in BRP portfolios lead to higher compensation payment upper bounds, which in turn drive up price ranges that other parties must adhere to if they want to remain competitive.

7.1.5 Sensitivity analysis of allocation efficiency under different flexibility activation constraints

Realizing the successful use of consumption flexibility to address various wind production excess related problems, requires formalized agreements in the form of contracts between providers and users of flexibility. These contracts often specify constraints on when and how much flexibility can be called upon for the duration of the contract. Chapters 3 to 5 have indicated that the activation constraints used can influence the effectiveness of flexible power scheduling. The last contribution is described in chapter 6 and concerns a sensitivity analysis on the effect of flexibility activation constraint parameters when flexibility is used do deal with different problem cases related to wind power production excesses. Based on this analysis, possible improvements on existing flexibility products are proposed for when they are used in different use cases.

Concerning the use of flexibility to address distribution grid congestion, both empirical and analytical results indicate a relationship between the parameters of the DLR algorithm used to shape the congestion and the activation duration parameter of the activation constraints.

Concerning the use of flexibility to address portfolio imbalances induced by wind forecast errors, literature has often disputed the use of some specific distributions in favor of others. Based on empirical data described in chapter 6, no discernible differences in allocation efficiency have been observed when comparing two popular distributions for modeling wind forecast errors (Cauchy and normal).

7.2 Lessons learned and future work

The domain of power systems is complex. The various stakeholders that each have their own goals and concerns must interact to ensure a safe and responsible delivery of electrical energy. Coordinating the interaction of these stakeholders to certain outcomes fairly and efficiently, will create challenges as the electricity grid as a whole becomes 'smarter'. This section presents some of the lessons learned over the course of this research project and discusses possible future research directions.

Smart grid development presents technical, economical and political challenges

Consumption flexibility will be an important part of maintaining the equilibrium between consumption and generation, especially in light of RES. Experience in industry projects has shown that the challenges involved in employing consumption flexibility to address imbalance problems are not strictly technical.

Both economic and political arguments feature heavily in discussions on future implementations of electrical power delivery systems. System operators are charged with maintaining safe and stable electricity grids, but still have to account any strategic investment decisions against their bottom line and shareholders. Similarly, renewable and nuclear energy sources are hot topics on political platforms. The regulatory frameworks in place for governing curtailment and green certificate compensations have already been shown to influence to what degree the use of consumption flexibility is economically viable for system operators. So while DSM can offer technical benefits, its implementation in future electricity grids is still subject to economical and political decision making, which makes its future not completely clear. With careful guidance, however, the smart grid can transform contemporary electricity grids into more cost effective and sustainable power systems.

Allocation mechanisms can benefit from forecasting and optimization

RES are characterized by their production variability and less predictable nature. The importance of forecasting techniques for dealing with this variability became clean in chapter 5 where wind production forecast errors caused costly portfolio imbalances. Also in the general sense, having limited foresight in dealing with problems related to RES is challenging. Deciding in real time which flexibility resources to activate is but one example where the foresight horizon is an important factor. Penalties in consumption flexibility allocation efficiency are to be expected in real time scenarios when compared to scenarios using full historic knowledge as described in chapter 3 but also other ANM techniques such as storage are subject to these penalties. Our experience with research in this dissertation and the icon-SWiFT project has shown the benefits that can be gained from developing and utilizing machine learning and forecasting techniques in dealing with RES in real time and further research in this area is warranted.

The work in this dissertation is in most cases focused on off-line best case analysis using full historic knowledge. Besides the comparison of on-line flexibility allocation mechanisms discussed in chapter 3, future work can benefit from an even stronger focus on on-line allocation mechanisms and the analysis of strategic choice situations in the context of on-line operational results. State-of-the-art forecasting techniques will play an important role in studying on-line mechanisms and should be further incorporated into future work in this field.

The allocations mechanisms used, although state-of-the-art, can also be further improved. In this dissertation, the use of common flexibility allocation mechanisms allows for a fair comparison across business cases, but further case-specific improvements and optimizations could improve the efficiency of the mechanisms even further.

EGT applications can have weaker dependencies on complete rationality than game theory (GT) applications

When first discovering GT, applications can be seen everywhere from bartering for produce in local markets to playing sports. The use of GT in academic literature is similarly plenty. Also in the energy domain, game theory offers popular tools for modeling and analysis purposes. Though often alluring because of the elegant models that can be created at high abstraction levels, care should be taken with the assumptions that are made when using GT for modeling purposes. The heavy reliance on the assumption of complete rationality of the players, while fundamental to the theory, is not often realized by real world players. This can limit the real world application value of game theoretic modeling. Experience taught us that one of the most challenging aspect of pursuing game theoretic research is effectively applying game theoretic modeling to real world problems.

Two approaches for dealing with assumption of complete rationality are often encountered. The first approach considers the use of software agents that embody the goals and motivations of their proprietors. These software agents are then assumed to be programmed to act perfectly rational in all situations. The danger here being that perfectly designed and programmed software is a rarity and that even the most subtle of bugs could technically lead to irrational behavior for certain agents. The second approach is the one taken in this work and it concern the use of EGT. EGT builds on classical GT but offers tools that have a much weaker assumption on rationality. In EGT, and specifically with replicator dynamics in play, choosing which action to take, is determined not based on knowing agent payoffs and decisions but on observation and imitation behavior. Agents are only assumed to change decisions when observing other agents that are gaining more from making similar decisions. This approach also puts less focus on the modeling aspect of GT, thereby allowing a more pure focus on the analysis aspect. When considering GT for real world practical purposes, EGT should not be overlooked. In our experience, EGT is not a silver bullet but it can produce valuable insights. It is not always suitable to the problem at hand but when suitable, its smaller dependence on complete rationality increases its usefulness to analyzing real world problems. In this regard, EGT is in our opinion still undervalued.

Besides replicator dynamics, which has been used in this dissertation to model choice dynamics, other dynamics exist in literature (e.g. based on learning behavior). Future research directions include exploring how other choice dynamics might be applicable to problems concerning strategic choice and how these dynamics might influence analysis results.

The strategic choice analysis results in this dissertation particularly, concern exclusive binary strategic choice situations. Although the rationale for assuming exclusivity has been explained in chapter 5, weakening this assumption can open up avenues of future work in analyzing strategic choice situations where flexibility providers face a more diverse set of alternatives. Improving the EGT analysis framework to support such analyses will increase the applicability of this work to also include more general market oriented settings.

Accurate data is crucial to effective problem solving

One of the fundamental goals of CS as a research field is problem solving. Effectively solving problems first requires the problem to be well defined and for information to be available on the problem. In this dissertation the necessity for accurate problem data and information has become clear. In our experience, even the most promising of analysis fall short in usefulness when data is lacking.

Even though a strong reliance on realistic data from industry is present throughout the work in this dissertation, there is always room for improvement. Problem input data for different locations in Belgium or Europe might shed more light on commonalities and differences of location-specific results. The energy landscape is also constantly changing, making results based on more recent data a welcome addition to the state-of-the art insights into the use of consumption flexibility. Besides problem data, more specific cost data is necessary for industry stakeholders wishing to use the proposed analysis techniques to drive business decisions concerning consumption flexibility exploitation. In general, finding and using data to more accurately model and analyze problems is challenging but it is a challenge that should not be ignored for it can lead to valuable contributions.

Many companies in the energy domain are fostering an attitude of transparency by making data available to the public. Further efforts by public companies in making data concerning production, consumption, etc. available, can aid in improving general understanding, enable more detailed research projects and improve informed decision making for different stakeholders active in the energy landscape.

Combining active network management techniques can enable valuable collaborative research efforts

Different ANM techniques exist in literature and practice for improving grid stability and for dealing with RES. Each of these ANM techniques has its own strengths and weaknesses, making it hard for one specific ANM technique to suffice in solving particular problems. In this dissertation the main ANM technique of interest is DSM. In chapter 3 empirical evidence showed that DSM alone was not sufficient for solving grid congestion problem. This opens up opportunities for collaborative research where experts in specific techniques can work together toward integrated solutions that can more adequately deal with such problems. In our experience, such collaborative contributions can be highly worthwhile to pursue. In chapter 4, our DSM approach was combined with energy storage expertise from *EELab-UGent* and DLR expertise from a

Belgian DSO. Future research directions include the inclusion of different DLR and storage models in integrated ANM solutions for RES related problems. For example, the use of different DLR parameters was shown to have an effect on the allocation efficiency of specific constrained flexibility products in chapter 6. To gain a better understanding in how to tailor these flexibility product for specific use cases, further analysis into the relation between parameters of different ANM techniques can be useful.

7.3 Reflection

The energy domain is a complex beast. Different stakeholders, each with their own goals and concerns, interact in various market settings and mechanisms to realize a stable electricity delivery system. As a society, transforming conventional power grids into more sustainable and smart versions will be a daunting but necessary task in mitigating the effects of man made climate change. The challenges in generating clean co_2 neutral electricity from RES are numerous and not only technical in nature. Political and economical challenges must be overcome in efforts to integrate larger shares of RES into the grid.

Our contribution in addressing these challenges are only a small part of what is required. As far as RES go, we only focus on wind energy and the grid imbalance problems it can cause. We only focus on industrial consumption flexibility as a means for dealing with grid imbalances and we only focus on two different wind production locations for analyzing specific imbalance problem cases. The grid imbalance problems are analyzed from a strategic choice perspective using EGT and mechanism design (MD). Other RES and the integration problems that they can cause, other sources of consumption flexibility and other techniques for analyzing strategic choice scenarios are left for future work. These research avenues, although valuable, are considered out of scope for this work.

The research questions and therefore the scoping of this work is partially inspired through collaboration with industry. Industrial validation has therefore been a part of the research process pertaining to this dissertation but future validation remains necessary. Many choices in scenarios, interactions and data were driven from the current grid setting at that particular time to promote the extrapolation of practical rules of thumb. With the ever changing energy landscape, whether the results of this work and the usefulness of the analysis techniques holds for the future, will have be shown. Further validation of present work, both academically and industrial in nature, will be useful in determining the validity of our approaches when e.g. regulatory frameworks change or grid technologies evolve. Even though the scope of this work is limited in the face of myriad challenges in integrating RES, the concrete results presented in this dissertation are interesting and they provide a stable foundation for future work.

Appendix A

`GridFlex` simulation framework

A.1 Introduction

Over the years, multiple simulation frameworks have been developed for supporting multi-agent systems and smart grids research [128]. Choosing the appropriate modeling simulation tools is an important aspect of bootstrapping this research project. Even when limiting the choice to free open source software for research purposes, simulation software is always designed with specific purposes in mind. Simulation software is often designed with clear abstractions and extension points that other developers can use to implement their own scenarios. However, solving large scale optimization problems with varying parameters is computationally heavy. The time and effort required to adapt simulation frameworks to offer features for dealing with this complexity was deemed to be better spent developing `GridFlex`. As such, `GridFlex` offers features tailored to the specific requirements of the research in this dissertation.

The remainder of this appendix will discuss the objectives, features and high level architecture of the `GridFlex` simulator [21].

A.2 Features

In this section some of the most valuable features that the `GridFlex` simulator offers, are explained in more detail.

A.2.1 Distributed execution

To draw useful conclusions based on experimental data, the statistical confidence of the observed results needs to be sufficiently high. One way of increasing the statistical confidence is to increase the independent repetitions of the experiments. `GridFlex` supports both single and multi-threaded experiment executions through the Java *ExecutorService* framework for local experiments. Besides local execution, `GridFlex` also supports distributed remote execution through the open source grid computing solution *JPPF* [116]. Switching between local and remote execution can be done seamlessly by providing the appropriate run-time arguments and experiment modeling and processing is agnostic of the execution framework to facilitate easy switching between local and remote execution.

A.2.2 Multi-solver support

Optimization solver technology was a fundamental part of various experiments described in this dissertation. The problem of allocating consumption flexibility to imbalance problems was modeled both mathematically as a mixed-integer programming (MIP) to support commercial solvers such as *Gurobi* and *CPLEX* and in a domain based fashion to which constraints apply, to support the open source heuristic optimization framework: *OptaPlanner* [109].

Switching between solver implementations can be done seamlessly by providing the appropriate run-time arguments. This allows easy comparison between optimal and heuristically optimized approaches and allows users to choose the appropriate solvers for problem cases with varying computational complexity and resource requirements.

A.2.3 Game theoretic modeling abstractions

`GridFlex` is primarily developed for game theoretic modeling and analysis. This simulator supports the modeling of multi-player games with multiple actions where heuristic payoff tables are populated at run time. `GridFlex` provides tools for performing evolutionary game theoretic analyses on the generated payoff tables. The game theoretic abstractions are generic and completely agnostic of the specifics of how payoff data is generated, thereby leaving it up to the users to define the specific game rules and participators.

A.2.4 Extensive test base

`GridFlex` is developed using a largely test-driven approach to ensure correct operation of the implemented concepts. Because of the simulator produces results intended for scientific purposes, a well developed test base is crucial. Tests for this simulator include unit, scenario, integration and regression tests. The software was developed using a continuous integration approach with code quality analysis to allow problems to be discovered and fixed early in the development process.

A.3 Architecture

`GridFlex` is a modular simulation framework where each module is self-contained in terms of the functionality it offers to other modules. The dependencies and major functionality offered by the modules is shown in the component diagram in Figure A.1. The following modules make up the `GridFlex` simulator:

A.3.1 Core

The core module offers multiple core functionalities for the software. Discrete-time simulation abstractions are offered for other modules to use. Participation in these simulations can be done by registering as a *SimulationComponent* to an instance of *Simulator*. Besides simulation abstractions, this core module offers access to general utilities for mathematical operations and transformations, development utilities for streamlining realizations of particular design patterns in this software and some general IO functionality.

A.3.2 Domain

The domain module offers implementations of various concepts related to the problem domain of smart power grids and the use of consumption flexibility. In this module, a distinction is made between representations of operational

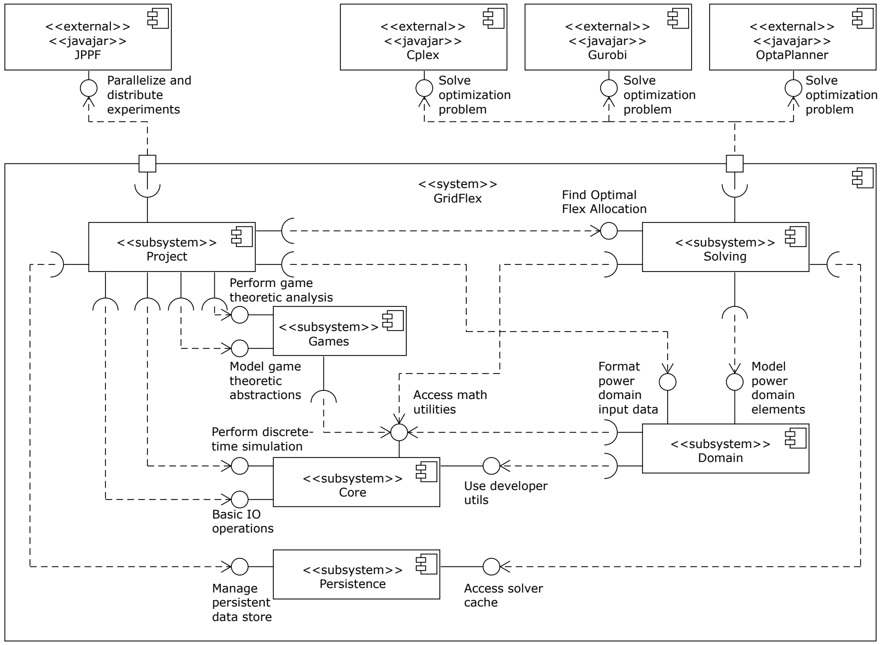

Figure A.1: The component diagram describes the modular design of the GridFlex simulator. Reuse and extensions of the software are promoted through a minimally coupled architecture.

application logic software elements and power system specific problem data representations.

A.3.3 Persistence

The persistence module offers persistent storage functionality to other modules. In this simulator, persistence functionality is mainly used for storing computationally expensive experiment results.

A.3.4 Solving

The solving module provides optimization problem representations of the flexibility allocation problem studied in this dissertation. This module offers

MIP solvers using *Gurobi* and *CPLEX* and also offers heuristic optimization solvers using *OptaPlanner*. For computationally intensive experiments the solver module can make use of persistence module to perform memoization. Results calculated for expensive experiments can be stored so that in future experiment runs, the stored result can be used in stead of executing the expensive experiments again.

A.3.5 Games

The games module offers abstractions for modeling multi-player games. This module is problem independent and can be used to guide to populating a heuristic payoff matrix by traversing the result space spanned by players and their actions. The resulting payoff data can be used to calculate player choice dynamics using the evolutionary game theory (EGT) analysis functionality provided by this module.

A.3.6 Project

The project module is the main module that combines the functionality provided by the other modules to realize the simulation experiments that produced the results discussed in this dissertation. This module coordinates the basic IO and manages the run-time configuration of the experiments and guides their execution whether local or remote. Concrete experiments are modeled separately for each separate research question while using the functionality provided by the other modules.

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Curriculum Vitae

Kristof Coninx was born in Genk on March 31st 1990. He finished his secondary education at the Onze-Lieve-Vrouwlyceum in Genk in 2008. In 2013 he graduated from the KU Leuven, obtaining his master's degree in Computer Science. His master thesis was written under supervision of Prof. dr. Tom Holvoet and Prof. dr. Ir. Geert Deconinck and was titled: "Coordinated charging of electric vehicles at public charging stations using Delegate MAS." Later that year he joined the imec-DistriNet research group under supervision of Prof. dr. Tom Holvoet. He did research work on evolutionary game theory and smart grids and participated in the icon-SWiFT and icon-MonIEFlex projects.

List of publications

IT (Articles in internationally reviewed academic journals)

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