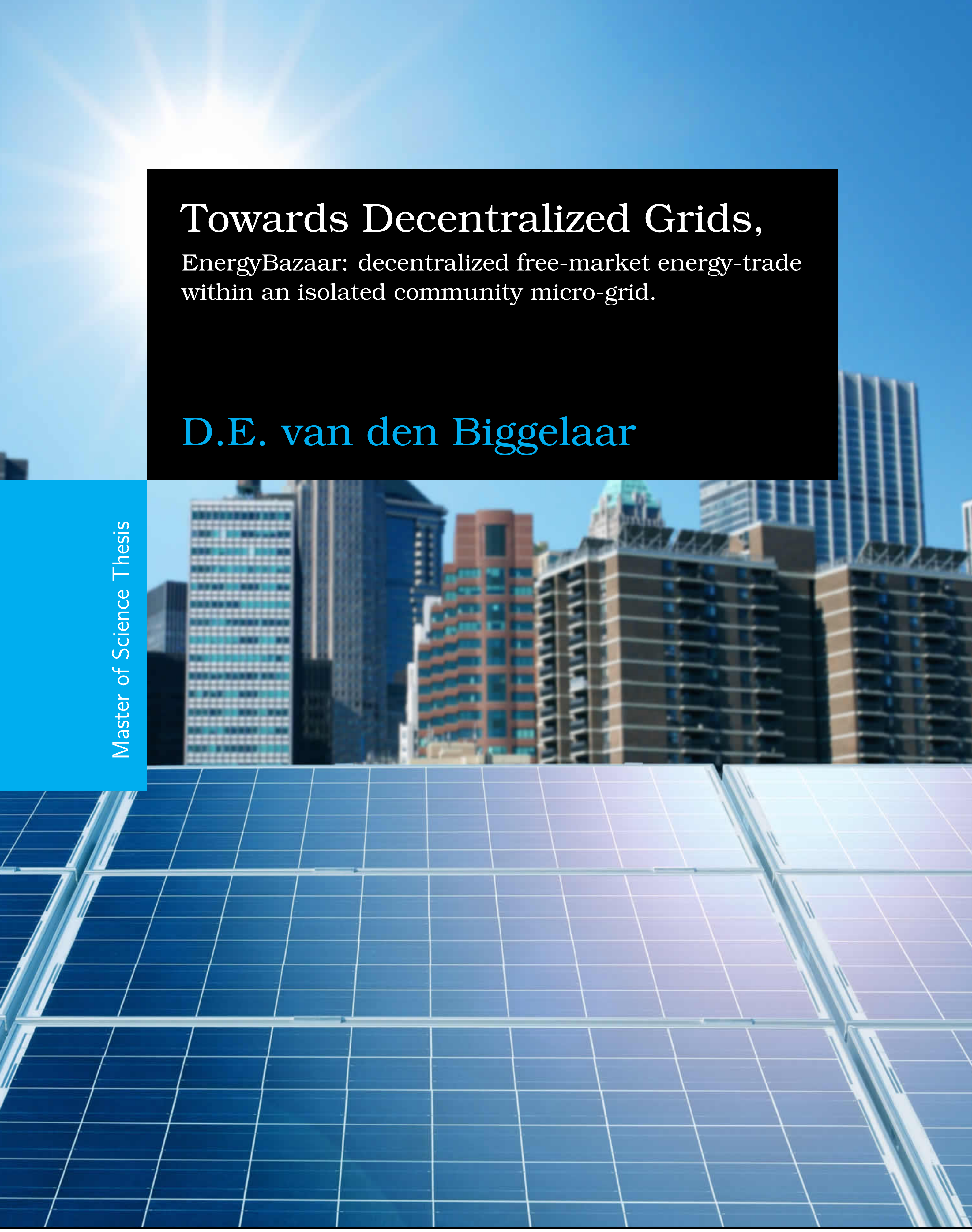
Towards Decentralized Grids,

EnergyBazaar: decentralized free-market energy-trade within an isolated community micro-grid.

D.E. van den Biggelaar

Master of Science Thesis



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Abstract

We witness the rise of prosumers: consumers that produce a surplus of energy that can be supplied back into the grid. However, for energy-trade between prosumers and consumers, a centralized and undesirable middle-man is still necessary. We developed a method to decentralize essential aspects of energy distribution between households. Macro-grids are divided into various neighborhood sized community-grids; a micro-grid. A micro-grid as a community yields a degree of self-sustainability. Nevertheless, micro-grids currently still possess centralized elements. The presence of central controllers, trading-agents or banks, maintains this undesirable situation. Decentralization of a power-grid increases end-user autonomy, independency and fairness in the system.

We propose to establish a truly transactive micro-grid: decentralized in its energy distribution, control and money-flow by deploying EnergyBazaar, a distributed trading algorithm. Concepts of game theory are used in the design to enable EnergyBazaar to solve the economic dispatch problem: agents want to individually optimize their social welfare, while the collective task is to stabilize the grid. Micro-grids make use of a decoupled hierarchical structure: primary control is responsible for fast dynamics of voltage and frequency, secondary control coordinates the economics within the micro-grid. In its core, EnergyBazaar coordinates inverter-based droop parameters within the Energy Storage System (ESS) of each agent, managing their charging/discharging behaviour. A trade-off is identified between economical gain and the necessity of surviving energy scarcity. For this, energy patterns are predicted and acted upon. In contrast to a coordinator dictating a centralized solution, EnergyBazaar creates a free market, where agents individually converge to a global Nash equilibrium. A comparison is made to show performance of both.

By rejecting centralized institutions in the micro-grid, trust challenges are introduced: achieving decentralized money-flows, the necessity of shared information during distributed optimization and the manipulation of the free-market by malicious agents. We introduce an approach of mitigating these issues in a decentralized paradigm by embedding EnergyBazaar in a smart-contract deployed on a blockchain platform.

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Chapter 1

Decentralized energy-trade

> Once there is a convenient way to sell energy into the grid, not only will homeowners be compelled to hop onto the grid and supply energy, but there will also be a brand new market to develop and allocate renewable energy.
>
> — Al Gore

In recent years, a paradigm shift has taken place in the energy sector. Next-generation power-grids are being designed with renewable energy in mind. The necessity of reducing green house gasses has become larger than ever [1]. In parallel, universal requirement of a robust power-grid is of continuous importance ever-since dependency on energy in modern day society has become a capability for social welfare [2]. Nevertheless, in bulky, old and poorly maintained grids around the world, reliability is not a given fact. Illustratively, headlines in newspapers regularly light up with messages as "India blackouts leave 700 million without power" [3]. A trend is developing wherein dependency on the flawed macro-grid is substituted with self-sustainable and semi-isolated communities.

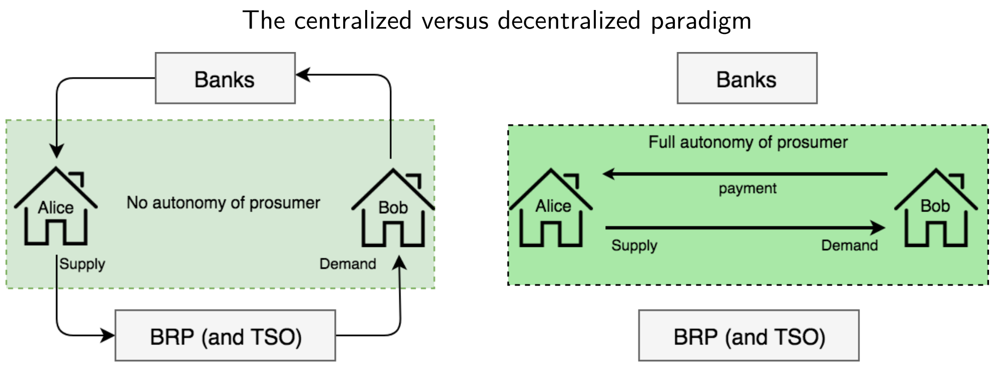

Figure 1-1: Centralized energy trade at the left figure, in which Alice and Bob have limited autonomy and are depending on a TTP; BRP, TSO and banks, while in the figure on the right, Alice and Bob are owner of their energy and trading independently from outside-institutions.

Towards a decentralized utility-grid

One of the reasons of the lack of reliability originates in the degree of centralization of the grid. In a centralized paradigm, when the central power-plant fails, the whole grid can fail with it. A decision has to be taken; optimizing the reliability of the single power-plant, or distribute the grid. Distributed Energy Resources (DER) is an umbrella term for the combination of Distributed Generation (DG) units and Energy Storage System (ESS). With DER, production responsibility is distributed among various smaller-scale energy harvesters. Another argument against centralization are costs of transmission from centralized production to more distant areas. Costs of transmission in a centralized grid are substantial, even in relatively small and modern grids such as in the Netherlands [4, 5]. The combined arguments of increased reliability with decreased costs per unit of energy forms a strong case against a centralized power-grid. Stating these arguments, it does not amaze to hear that the power-grid is already in the process of being more distributed in nature [6]. Innovation in the power-grid fuels the emergence of DG, local ESSs and small-scale communication networks by Advanced Metering Infrastructure (AMI), i.e. smart-meters. Combining these tools, a smart micro-grid is created, able to manage generation, storage and distribution within an isolated community grid. DGs in the form of Photo Voltaic (PV) panels are widely available and have become a part of the scenery. Grid parity for DG, where home-produced solar power is cheaper than centralized energy, is a huge milestone to be reached within this decade [7]. The traditional consumer is slowly transforming into consuming producers, also known as prosumers.

The dilemma of autonomy and energy-ownership

Nevertheless, considering the power-grid of today, there is still no method of trading a surplus of energy without a BRP. A BRP is an energy retailer that originally retails and trades energy between centralized power-plants and households [8]. We celebrate decentralization not only because of its efficiency and increase in reliability, but also because in the decentralized paradigm, we can reject the notion of dependency on BRPs. BRPs offer fixed price reimbursement to surplus-supplying prosumers, in a range of 7 to 11 cents/kWh [9]. However, these fixed prices are often below par with dynamic market prices for energy. With an increasing portion of retailed energy originating from prosumers, they should be able to actively participate in trading their own energy. Reducing the scope to isolated communities, we propose a community wherein agents are regaining autonomy over their energy. Switching to a global-south perspective, the impact of a decentralized community is even more noticeable. Not so much economically, but societal in nature. In countries stricken by wide-spread inefficiency, corruption, or even war, communities that are self-sufficient and independent from corrupted central institutions still have a chance to thrive. Communities have both an economical as a societal motivation for decentralization. In summary, it should be possible to create an isolated community, as a local-scale micro-grid, without the meddling of centralized coordinating agents, wherein energy can be traded within a free-market.

Challenges introduced by decentralization

With decentralization come challenges. A substantial part of grid-control is lifted out of the hands of the nation-wide macro-grid. Balancing the supply and demand is among the most significant control tasks in a power-grid. In centralized grids, power-plants can supply according demand and are very quick to ramp up- or down-production when needed, see fig. 1-2. In a decentralized paradigm, dependency within a micro-grid shifts to DG. However, DG units produce power that is highly variable and intermittent; e.g.solar-panels that produce energy only during the day. A micro-grid community needs an effective and fair way to distribute the available energy among its households, reducing community-wide deficits and dependency on the macro-grid. Parallel to dependency on a TTP for energy distribution, households currently depend on the service of a bank for facilitate payment. Nevertheless, a transaction platform that is independent from a TTP is a necessary feature to a decentralized micro-grid. With recent technological advances and widespread adoption by society, a blockchain database might provide for the need of a decentralized transaction method, in-line with a local energy market, completing the decentralized cycle between energy and payment. A micro-grid where end-users can participate in energy-trade by decentralized transactions is called a *transactive grid*.

Conclusively, there is a need for a community grid in which neighbors Alice and Bob can trade energy independently, *with the exclusion of other parties*. In section 1-1, contextual background to the problem is provided. Distilled from this, a research question is posed in section 1-2.

1-1 Contextual introduction

Before defining the research question, this section briefly glances at four fields of research this thesis will touch; what are current innovations, what is trending research and what are the real-world, state-of-the-art implementations of these technologies.

1-1-1 Energy transition and innovation in the power-grid

Since the introduction of the notion "energy transition" in the Dutch National Environmental Policy Plan [10], the Netherlands are making an effort towards a sustainable future. The urgency of an energy transition into sustainability was recently underlined again during the 2015 climate talks in Paris, when a great number of countries united to halt climate change [1].

The current energy market

Currently, maintaining the balance between load and supply is a task for the TSO of the power-system. The balancing market is an institutional arrangement that aims to fulfill this control task. BRPs are parties that participate in energy-trade and are constrained by their responsibility to keep balance. Deviation from balance results in the TSO to allocate its energy reserves, for which the BRP pays a penalty. BRPs are subjected to an Program Time Unit (PTU), e.g. a time-unit on which energy schedules have to be submitted to the TSO. In the Nordic region, including the Netherlands, the PTU ranges from 15 to 60 minutes [8].

Emergence of the smart-grid

The term smart-grid was coined to define a new sort of power-grid with a high degree of decentralization in the production and trading of energy [4]. Micro-grids are small-scale versions of the centralized electricity grid. In smart micro-grids, appliances are equipped with sensors capable of measuring and communicating essential data [11]. The advantages of a smart-grid are evident; deployment of DER leading to distribution of generation, interaction of end-users with the system and real-time measurement, giving insight into the state of the system. Ultimately, this accumulates into an increase of reliability and sustainability of the power-grid [12]. Additionally, prosumers start to become more autonomously by installing DG at their households and thus supplying their own needs. Nonetheless, surplus energy is still provided back into the system, to be retailed by BRPs. Opportunities for smart micro-grids in distributed renewable energy and peak-load reduction by integration of smart battery storage are surveyed in [13]. Distributed energy is the utilization of smaller power generation and storage systems used for powering homes, businesses and communities [14].

ESSs are introduced as a promising new development. The potential of deploying ESSs in smart micro-grids lies in creating a buffer between demand and supply: storing energy at low-demand

and selling when demand rises [15]. ESS in combination with Renewable Energy Sources (RES) can keep a micro-grid operable even when the main grid is down. Above all, ESSs can solve the notorious 'duck curve' problem [16]. The duck curve visualizes the needs for quick ramping-up of energy supply, and thus production in a grid during the start of the evening. Turbine-based power-plants are well equipped to ramp up production, while renewable DG produces only during periods of sun and wind. ESSs are capable to store energy, saving it for when demand rises above natural supply. Since investment costs of ESS are still high, finding the minimum capacity that is still capable of achieving the balancing-act is a challenge that is mostly economically driven. In the Netherlands, exemplary ESS research projects are innovations such as [17] and [18]. For a extensive view of all smart-grid research projects under auspices of the Dutch government see [19, 20]

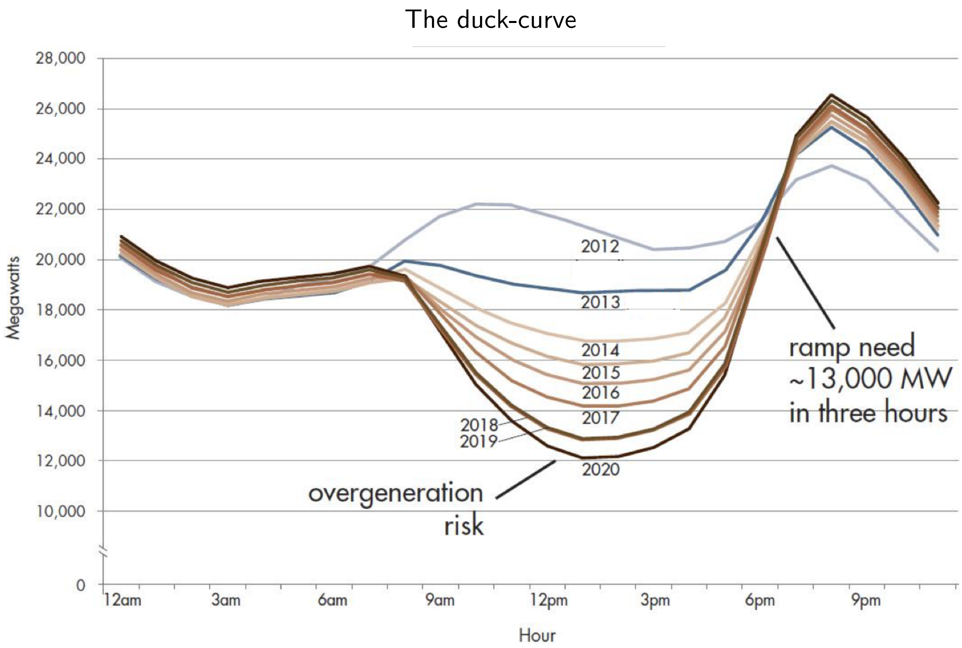

Figure 1-2: A pressing matter in modern-day 'green' power-grids is the severe mismatch between peak-demand and renewable energy supply. With the steady rise of renewable energy, the duck-curve is becoming more extreme. Main energy-consumption starts after sun-set, when solar-panel already stopped generating. We modelled our input-data such that is captures this behaviour, see section 3-2-2. Adoption of ESS could offer a solution for bridging the gap within micro-grids. Figure from [21].

1-1-2 Methods for optimizing energy distribution in a smart-grid

After the the mid-1980's, liberalization efforts took effect in Europe, aimed at making the sector more efficient through the introduction of competition among players [22]. Although a sudden switch to a decentralized grid is unwise [23], careful experimentation is incentivized through the introduction of new policy [24]. New trends in influencing consumers in their energy consumption behaviour, called Demand Response (DR), are surveyed in [25]. In DR, voluntary energy rationing is incentivized through economic rewards and allows for distribution of energy for peak-shaving but is often governed by the utility company [26]. DR strategies fall under Demand Side Management (DSM) techniques. In this thesis, a more autonomous solution is proposed using distributed computing using smart-meters installed in households. The authors of [27] initiated work on abstracting electricity markets as multi-commodity markets and showed how agents trading energy could allocated energy more efficiently by partitioning the day in time-slots. In [28], the authors introduce the notion real-time-pricing, the first of the family of DR strategies. Its poor performance was concluded to be due to the exclusion of human behaviour in the model, since the acting agents in the grid are ultimately representing human households. A game-theoretical approach to this method could mitigate these issues [29].

1-1-3 Blockchain as a market platform

In 2008 the identity known as Sathoshi Nakamoto published a new payment system Bitcoin [30], revolutionizing the payment paradigm after the banking crisis. The blockchain behind Bitcoin technology has been proved to be inherently secure by design, albeit lacking scalability in terms of transaction throughput and costs per transaction. Blockchain is a combination of a Peer to Peer (P2P) network and a distributed time-stamping server to make the system completely decentralized while relying heavily on cryptology to guarantee security. As a result, Bitcoin proved to be the first digital payment scheme able to solve the double spending problem without artificially created trust in the form of a TTP. A more detailed technical explanation is given in section 2-4. Some blockchain platforms, such as the widely known Ethereum, enable programming environments. These, so called smart-contracts, can provide a secure escrow service in real-time without a TTP. The interpretation of smart-contracts by various popular blockchain platforms is surveyed in [31]. In [32], the characteristics of block-chains that allow smart-contracts is analyzed, while also looking at issues caused by negligent design. A more cautious tone was set by showing the criminal potential in [33]. A distributed energy sharing network, where stakeholders cannot rely on trust among players, could heavily benefit from a public ledger as database. Among the few trials of energy sharing blockchain platforms are PowerLedger [34] and the Brooklyn MicroGrid [35].

1-2 Research goals

In chapter 1, we expressed the motivation for this thesis. We briefly discussed various fields of study. In chapter 2, these are discussed in more detail. The aim of this research is to establish truly decentralized energy trade in a micro-grid. The research question for this thesis is:

Can a transactive grid be established through deployment of a promise-keeping smart-contract triggered by a distributed algorithm that enables free-market trade?

To divide this research in manageable parts, the research question is divided up into sub-questions. Answering these sub-questions will shed light on the framework in which the sharing-algorithm should function:

- How does a smart micro-grid operate, how is micro-grid stability controlled and what are the boundary conditions for energy-trade with such a micro-grid? (See section 2-1)
- What are the concepts of game-theory and can elements of game-theory be used in the design of a decentralized energy trading algorithm between agents? (See section 2-3)
- What are trust issues that are introduced by decentralization of the power-grid and can those issues be mitigated by a smart-contact deployed on Blockchain? (See section 2-4)

1-3 Contributions

We present a novel method towards a truly transactive grids. We propose the distributed algorithm called EnergyBazaar which makes use of a hierarchical structure derived from Stackelberg games, introduced in section 2-3. EnergyBazaar has as task the coordination of DER for load-balancing, while optimizing individual welfare of the set of agents. The agents employing EnergyBazaar are model predictive by determining their cost-functions according to an anticipation horizon, predicting scarcity or abundance in the future. Constraints to optimization are set by linking our secondary-level energy-distributing algorithm to the dynamics of primary-level frequency control in order to safeguard load-balancing. We present a smart-contract capable of logging initial shared information before optimization to check the validity of trade deals, forcing agents to keep to their promised supply or demand. Used this way, the smart-contract is able to detect agents that artificially attain a higher utility by breaking their initial promises. The smart-contract is deployed on a Blockchain in order to make verified state-changing transactions to the smart-contract. In summary, we show the following:

- An analysis of the solution-space of the Economic Dispatch Problem (EDP) optimization, looking at grid-stability constraints. (See section 2-1-4)
- A novel approach to trade locally produced energy through a distributed game-theoretical algorithm governed by free-market trade inside an isolated micro-grid. (See chapter 3)
- The inclusion of prediction on future energy scarcity and abundance in the micro-grid, increasing the utility of the agent on average over time. (See section 4-1-2)
- A system integrated with EnergyBazaar managing trust issues introduced by decentralization, used by agents to settle trade by a smart-contract deployed on a Blockchain. (See section 3-4-2)
- An evaluation of EnergyBazaar compared to a central EDP solution according to a performance metric-based on cost reduction and operability of households. (See section 4-1-5)

The source-code is available on https://github.com/dirkbig/master_thesis.

1-4 Thesis outline

In chapter 2, the application setting, a micro-grid is discussed in detail and existing solutions to energy-trading are investigated. Following, in chapter 3, the proposed algorithm called EnergyBazaar is presented as a novel approach to energy-trading in a community. Chapter 4 shows the performance of EnergyBazaar compared with a centralized method according to an evaluation metric. Finally, in chapter 5 we end with a conclusion and recommendations for future work.

Chapter 2

Preliminaries

This chapter presents the state-of-the-art of technology used within the scope of this thesis. Smart micro-grids are discussed in section 2-1. In section 2-3, a basic introduction to game theory is given and game theoretical approaches regarding energy trading are examined. Following, in section 2-4, we introduce Blockchain and consider it as a solution to decentralized transactions.

2-1 Smart micro-grids

Micro-grids are small-scale grids that are designed to be self-sufficient from the macro-grid with respect to control such as grid balancing and power supply [36] and energy generation. Seen from the perspective of the macro-grid, a micro-grid can be considered as a large Distributed Generation (DG) unit operating in either three modes; idle, importing energy or exporting energy. Figure 2-1 shows a linear structured micro-grid. The Micro Grid Central Controller (MGCC) is the gateway to the macro-grid and traditionally is the residence of the central dispatch controller, which coordinates all sources of energy in the micro-grid. Households are linked such that all Distributed Energy Resources (DER) are inter-connected. In addition, an Advanced Metering Infrastructure (AMI) enables all household to communicate with each other. In section 2-1-1, we discuss the application setting of our micro-grid households.

Micro-grids are either radial or meshed [37]. In a radial grid, households are connected only to their two neighbors, while in a radial grid, households are connected to more than two households. Research into stability of micro-grids, especially in decentralized grid-control, often assumes radial grids, which simplifies the model substantially [38, 39]. Inverters transform Direct Current (DC) power of DG into Alternating Current (AC) power [40]. We consider a AC micro-grid infrastructure as an uniform and loss-less black-box, considering only in- and outputs of energy at the doorstep of households. Additionally, we do not consider topological impedance differences throughout the grid. Nevertheless, a topology is introduced in chapter 5 to analyze the effects of limited range of communications.

2-1-1 Application setting: household agents

We consider a micro-grid consisting of n buses, each representing a household in the set of households $\mathcal{N}$. The applications of each household consist of household DER and energy consuming loads. The following application setting is assumed [41] for each household; DG, Energy Storage System (ESS) and AMI.

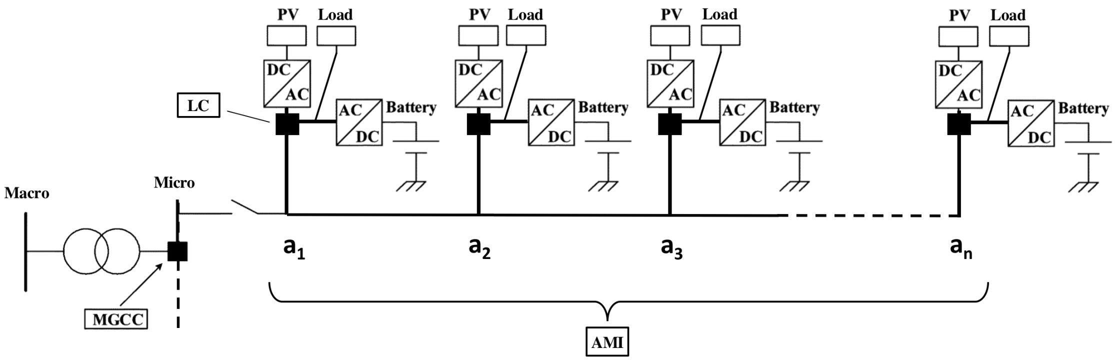

Figure 2-1: Simplified lay-out of a micro-grid. LCs are tasked with primary control, where behind the DER reside, linked by bi-directional AC/DC converters. $E_{\text{consumption}}$ originates from the load, $E_{\text{production}}$ from its PV panels and SOC_{actual} from the battery. All households in the community are communicating with each other using an AMI network.

- **Distributed Generation**. DGs are local energy generators, for example in the form of roof-top solar panels. Since the costs of solar power is predicted to pair with grid-power in the near future, market penetration roof-top solar panels are rising. DERs are equipped with local controllers that govern frequency regulation through closed-loop feedback control:

$$\Delta\dot{\omega}_k = M^{-1}\left(\Delta P_{mech} - \Delta P_{elec}(\delta) - g\Delta\omega_k\right). \tag{2-1}$$

  In eq. (2-1), $\dot{\omega_k}$ is frequency deviation rade at DG unit k, M^{-1} a matrix representing the dynamical model of DG$_k$, P_{mech} and P_{elec} respectively the mechanical power 'applied' and the electrical power injected into the grid. Finally, g represents a control constant. See eq. (2-7) for a generalized set of equations for frequency and voltage control. DG units can ramp up/down their generation within bounds of $[P_{\text{min}}, P_{\text{max}}]$ according to the Automatic Generation Control (AGC) frequency set-point given. Normal operation is at their Maximum Power Point (MPP).

- **Energy Storage Systems**. ESSs are essential to introduce flexibility in energy supply within the micro-grid [42]. ESSs provide a buffer of power supply needed in self-sufficient micro-grids that are making use of DER, often renewable sources that do not guarantee constant power supply. Electric Vehicles (EV) batteries using Vehicle to Grid (V2G) technology are now able to both charge and discharge, effectively introducing a mobile ESS into the micro-grid, discussed in [43] and [44]. ESSs are, from a control perspective, a class of actuators with broad bandwidth, suitable for control of fast dynamics though with narrow situation limits [45]. By equipping households with ESSs, a buffer is build in between production and load, changing the mapping from eq. (2-2) to eq. (2-3), further discussed in section 2-1-3:

$$\text{Production} \longleftrightarrow \text{Consumption}, \tag{2-2}$$

$$\text{Production} \rightarrow (\text{Supply} \longleftrightarrow \text{Demand}) \rightarrow \text{Consumption}. \tag{2-3}$$

- **Advanced Metering Infrastructure**. Smart-meters enable bidirectional measurements of power-flow and communication among households. Also, smart-meters have basic computational power [46]. A network of smart-meters is known as an AMI [47]. The typically limited geographical radius of micro-grids facilitates communication through affordable and simple standard network protocols. A promising means of communication is Long Range Wide Area Network (LoRaWAN). [48, 49]. The limits of LoRaWAN are discussed in [50, 51]. Concluding from [50, 51], LoRaWAN is a suitable communication technology for small-scale smart-grids.

2-1-2 Power flows within the micro-grid

We consider a micro-grid consisting of n buses, each representing an ESS of each household. The ESS is placed in between the household and the micro-grid, see fig. 2-1. For inductive lines of reactance $X_{i,j}$ connecting bus i to bus j, the active and reactive power injections P_i and Q_i at bus i are given [52]:

$$P_i = \sum_{j=1}^{n} \frac{V_i \cdot V_j}{X_{i,j}} \sin(\theta_i - \theta_j), \tag{2-4}$$

$$Q_i = \frac{V_i^2}{X_i} - \sum_{j=1}^{n} \frac{V_i \cdot V_j}{X_{i,j}} \cos(\theta_i - \theta_j). \tag{2-5}$$

In eq. (2-4) and eq. (2-5), V_i, V_j and θ_i, θ_2 are the respective voltages and phase angles at bus i and j. Also, in eq. (2-5), $X_i = 1/(\sum_{j=1}^{n} X_{i,j}^{-1})$. Active power is decoupled from reactive power, for example by a control method described in [53]. Even though ESS are capable of providing support to reactive power regulation, we focus on the interplay of active power and frequency, the economic dispatch problem. Nevertheless, for completion, the interplay between reactive power Q and voltage V is given as well.

2-1-3 Micro-grid stability

The predominant tasks for micro-grid control are frequency and voltage regulation; values for V and ω should stay within bounds, allowing only small deviations [14]. Stability issues that occur due to poor mirco-grid control include:

- **Failure in DER coordination**. Poor damping of certain modes in the grid can be the cause of mis-interaction of control systems or poor deployment of DER units. These disturbances can disrupt stability of the micro-grid by causing voltage oscillations [54].
- **Loss of inertia**. Because DER often do not provide necessary inertial reserves serving as inertia buffers to frequency-control, small-scale micro-grids can suffer from frequency deviations when proper reserves are absent [55]. In contrast to a macro-grid, a micro-grids does not posses a virtually unlimited inertial reserve. This is due to the low-inertia characteristics of DG often deployed in micro-grids. In the macro-grid, synchronized generators can balance supply and demand by increasing or decreasing the rotating frequency of its turbines. In isolated micro-grids, an absence of a synchronized infinite bus means load-balancing becomes more complex. Load-shedding and inclusion of ESS strategies are discussed in [56]. Fluctuations of frequency above the allowable bounds can result in damage to equipment [14].

Control values in an AC power-system

Control variables that are involved in micro-grid control are voltage, frequency, reactive and active power, measured at each bus of the micro-grid according eq. (2-4) and eq. (2-5).

- **Frequency**. Maximum grid frequency deviations in Northern Europe is kept at 0.1 Hz. Comparing AGC set-point frequency ω_{agc} to ω_{local} results in a control parameter u_{freq} used in Europe for simple PI-control [37]. Frequency control is explained in a couple of steps by [57]. A clear distinction of solutions for frequency control between macro-grids and micro-grids are given in [45]. By eq. (2-4), frequency is coupled to active power P.

- **Voltage magnitude**. Resistance R is large compared to Reactance X. Adjusting the flow of reactive power in the grid will influence the voltage amplitude. The voltage control holds the voltage between the limits defined by the European standard EN50160 [58]. A short mismatch in amplitude, phase or frequency of voltage can lead to high oscillating currents and damaged hardware; forcing DER to automatically shut-off and leading to a cascading collapse of the grid [14]. By eq. (2-5), voltage is coupled to reactive power Q.
- **Active and reactive power**. In AC-grids, active power is power generated by currents and voltages that are in phase, used in appliances. Reactive power is created when current and voltage are shifted in phase, creating a non-working oscillating power. For example, introducing capacitors creates a phase shift in a electrical circuit.

Inverter-based droop-control

Among technologies for grid-control such as master-slave control and average current-sharing, inverter-based droop control is the most renowned for frequency-control for micro-grid systems [39]. In addition, power output can be controlled by actuating the droop-frequency and output-voltage. In medium- to high-voltage power systems, where reactance $X << R$ with R being resistance, the reactive power Q is coupled to voltage V, while active power P is coupled to frequency ω. To obtain a reference set-point frequency ω_i^* and voltage V_i^*, $P-V$ and $Q-\omega$ droop-control is used [59];

$$\omega_i^* = \omega_n - m_i(P_{i,n} - P_i), \tag{2-6}$$
$$V_i^* = V_n - n_i(Q_{n,i} - Q_i). \tag{2-7}$$

In eq. (2-7), n_i and m_i represent droop-gains that prescribe the actuation magnitude. Index n represents either the nominal value in the power system, or the set-point AGC in case of DG controlled through secondary control. In [57] and [59] droop-control is further described. Among others, new droop-control methods are proposed in [60] and [61] that utilize a fast control-loop to emulate line impedance. Droop-control does have a few drawbacks such as a inherent trade-off between accuracy and voltage deviations and unbalance in harmonic current sharing [62]. Most importantly, dependence on droop-control that relies heavily on high-inertia turbines, is not ideal for a micro-grid with low-inertial DG deployed. For this, virtual inertia can be injected in the system [59]. In [63], clear dynamical models are provided of DG and a battery based droop-control method applicable to both inverter-based or rotating DG.

Hierarchically structured micro-grid control: decoupling control and coordination

Micro-grids employ hierarchical control by decoupling dynamics with different response times and thus controllers with varying impact. This hierarchical control is useful as it decouples various actors that independently influence the main control task of frequency/voltage regulation [64]. The three different control layers are identified as:

- **Primary control**. Ran by LC, it is exclusively based on local measurements, requiring no communications and is characterized by quick response. Under primary control fall micro-grid islanding detection and transition, output balancing and rudimentary power sharing. [65, 62, 66]. Governing the system's fast dynamics, LCs operate autonomously, but track AGC set-points coordinated by secondary control.
- **Secondary control**. This control-layer is often referred to as the micro-grid Energy Management System (EMS), is introduced for coordination of demand and supply in the grid.

On a secondary-control level, DG units communicate through a Peer to Peer (P2P) network. Especially when the grid heavily depends on DER, potentially causing sudden changes in power generation and fluctuations in voltages and frequency, coordination is essential to maintain load-balance. Whether the EMS in micro-gird should be decentralized is under debate in [37]. In terms of dynamics, secondary control operates in a region slower primary control, effectively *decoupling* the two. Secondary control coordinates the power DG units will produce at given moments by communication of frequency set-points, called AGC signals. The coordination of energy with regards to economics is called the Economic Dispatch Problem (EDP), formally introduced in section 2-1-3.

- **Tertiary control**. The highest control layer and is responsible for long term goals in the system, such as trading on the year-ahead market; characterized by a high all-round impact but with extremely slow sampling time. Responsible for operations between micro-grids and reactive power injection control. Tertiary control is often not embedded in the micro-grid but applied as a link between micro-grid and the macro-grid. Thus, tertiary control is often not regarded as part of the micro-grid control system [37].

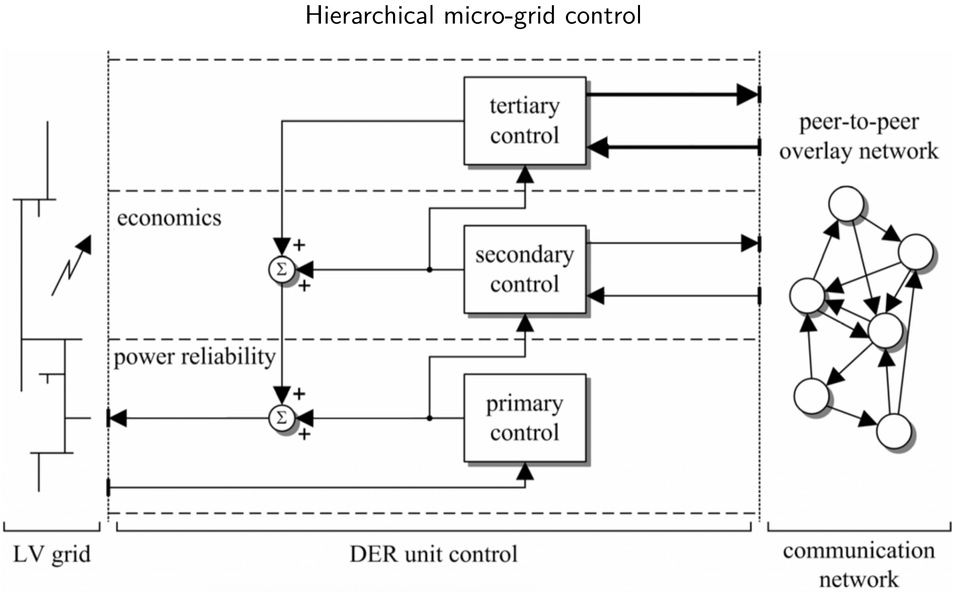

Figure 2-2: A DG unit utilizes a three-folded control decoupled structure. Standalone primary control has fast sample time/dynamics and does not communicate with neighbors. Secondary control governs energy dispatch at a larger timescale, with higher sampling time and slower dynamics. Tertiary control is involved in the day-to-day markets. From a micro grid perspective, tertiary control governs connection to the macro-grid.

The economic dispatch problem

Secondary control encompasses the economic dispatch problem. Briefly discussed in section 1-1-1, the economic dispatch problem can be simply formulated as [67]:

$$\min U_T = \sum_{i=1}^{N} U_i(P_i) \text{ subject to:} \tag{2-8}$$

$$\sum_{i=1}^{N} P_i = 0 \text{ and } P_{\min,i} \le P_i \le P_{\max,i}. \tag{2-9}$$

Here, U_T is the sum of social welfare of each agent i, expressed by U_i. P_i is the power-flux at bus i, which is constrained by actuator saturation in a range of $[P_{\min,i}, P_{\max,i}]$. Equation (2-8) is often solved through a centralized controller. Section 2-3 discusses solutions to EDP. Subsequently in chapter 3, EnergyBazaar is presented as a decentralized solution to the EDP. Firstly however, we discuss how DER technology influences the EDP.

Energy storage acting as a buffer to Demand Side Management (DSM)

In order to effectively balance between energy supply and demand within a micro-grid, two directions can be taken; either influence variable demand so to match fixed supply, or match variable supply to a fixed demand. Currently, methods such as real-time pricing, time-of-use and critical-peak-pricing are used in micro-grids to influence energy demand, described in [68] and [69]. End-users are rewarded for voluntarily reducing electricity consumption on peak-hours during. Real-time-pricing portrays the dynamic costs of energy according to the imbalance between supply and demand. With an incentive presented, end-users shift their energy demand to low-price time-slots. In [70], energy consumption indicators that provide real-time feedback on energy prices are installed at households. Results of these tests show that the economic benefits are small though non-negligible, see [70] and [71]. Conclusively, assuming end-users to actively change their behaviour, restricting their freedom and comfort for low cost reduction, is not the most elegant of solutions. Concluding: DSM is a field that is heavily researched and many practical solutions are proposed.

A second approach is creating energy reserves at households. With this, DSM can preform load-balancing by allocating the energy reserve instead of directly influencing end-user behaviour. Thus, we can implement an energy dispatch method that autonomously manages the ESS of each household to optimize load-balancing. In this scenario, energy consumption is fixed and energy demand is variable, with the ESS decoupling the two. In this thesis, we use this principle as a basis: the solution proposed in chapter 3 focuses on satisfying energy demand, while DSM methods can be applied added to influence energy consumption.

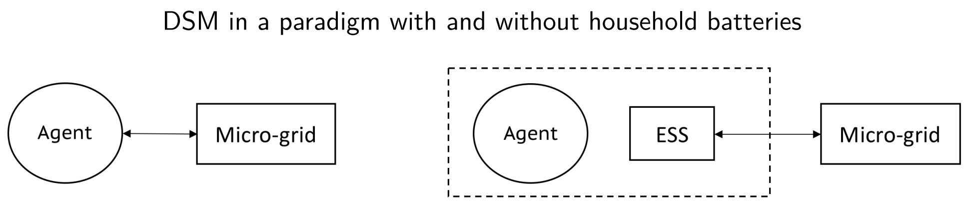

Figure 2-3: The direct and indirect influence that end-users have; with demand response, in the figure on the left and with ESS demand response, the figure on the right

In fig. 2-3, the ESS negotiates energy prices using a distributed algorithm based on free-market mechanics, through methods that are discussed in section section 2-3. The energy-balancing problem can be used to define the economic incentive that drives the load-balancing optimization. When demand is low, prices are low and vice-versa, driving supply and demand back together. This is a key-concept that lies at the foundation of EnergyBazaar. In [15], costs for various ESSs are discussed in detail. Prices vary in a domain of 200-1500 €/kWh.

The micro-grid as an isolated token-based economy

An islanded micro-grid can be considered as a isolated economy and the EDP as a zero-sum game, with the sum of cash-balances is zero. In case of a connection to the adjacent macro-grid, the micro-grids economy is pulled out of isolation and forcibly linked to the fiat-economic macro-grid. In this case, internally submitted bids of buying agents should always be lower than macro-grid buying prices, while higher than external selling prices. This will ensure that sellers sell, and buyers buy, internally [72]. Domain $\mathcal{C}_{\text{macro}}$ represents the solution-space wherein buying agents set their prices:

$$\mathcal{C}_{\text{macro}} = [c_B, c_S], \tag{2-10}$$

$$c_i \leq c_S \text{ and } c_i \geq c_B \quad \forall i \in \mathcal{I}. \tag{2-11}$$

In eq. (2-11), the macro-grid buying price is c_B and its selling price is c_S. Furthermore, c_i is the bidding price of agent i in set of buying agents $\mathcal{I}$ within the micro-grid. Within domain $\mathcal{C}_{\text{macro}}$, a distributed algorithm solves the EDP by modeling a utility function that captures the economics of the micro-grid and the behaviour of agents reacting with their bidding prices $\mathbf{c}$.

Contrary to the mean-field game played in [73], within the micro-grids economy agents influence on the nominal bidding prices is non-negligible, assuming a small enough community. Malicious agent can artificially raise prices by sharing dishonest information. Since free-market pricing revolves around fluctuating supply or demand; agents can pretend to have a lower supply, an effect shown in fig. 3-4. Mitigating this attack is a show-case of the potential a promise-logging public ledger has, discussed in chapter 3 to be solved in section 3-4-2.

2-1-4 Impact of disruptive technology

Summarizing section 2-1-3, control of a micro-grid focuses mostly on frequency and voltage, and the EDP is constrained by actuator saturation of the primary controllers responsible this task. By satisfying this requirement, grid-stability is assured. This subsection looks at the impact various DER have on the stability of the micro-grid and how to translate this into dynamical constraints.

Deployment of DER in the micro-grid

As the portion of power supplied in the grid originating from inertia-less DER increases, these DER should become providers of grid support functions that were traditionally performed by rotating generation. The following is an overview of various proposals on how to actively deploy DER in supportive roles.

The authors of [74] look into various methods to coordinate DER for managing the grid. In [75] a particle swarm optimization is used to determine the best location of DER dispatch. The loss sensitivity is used to find the optimal long-term deployment of DER. In [76], the CERTS paradigm states that in a decentralized power grid, DER should be deployed at locations of vital- or sensitive loads. Then, less important loads could even be switched off to save the functioning of the grid. They propose to balance the grid through passive plug-and-play electronic interfaces on time scales less than minutes. In [77], a robust control scheme is implemented in a small DC micro-grid to regulate current and voltage sharing among DG by imposing constraints to the solution manifold. In [78], the authors develop maximum-power-point-tracking control for $V-\omega$ coordination of PV panels and ESSs. The authors of [79] propose a distributed algorithm to supply ancillary services in a micro-grid by solving the following distributed problem at time-step k: minimize $\sum_j \pi_j(k)$. Let $\pi_j(k)$ be the amount of P or Q demanded from a DER unit located at j at time-step k. Then:

$$\pi_j(k+1) = p_{j,i}(k) \cdot \pi_j(k) + \sum_{i \in \mathcal{N}_j} p_{j,i}(k) \cdot \pi_i(k), \tag{2-12}$$

with $p_{j,i}(k)$ representing the set of weights between j and other DER units in connection with j through a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with $\mathcal{V}$ the vertex set and $\mathcal{E}$ the set of edges. This way, the

Inverter droop-control and power curve of a PV panel

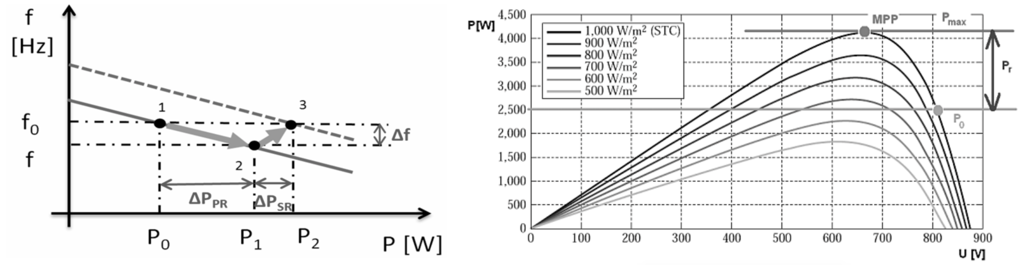

Figure 2-4: The AGC signal dictates DG units how much power it should be supplying. As long the requested power, P_{AGC}, is within bounds of $[P_{\min}, P_{\max}]$ (see section 2-1-4 for bounds for PV panels), primary control is able to serve secondary control demands. Secondary control manages the pricing behind the supply of P_{AGC}. In the left figure: primary control regulates frequency ω by tracking the set-point signal f_{AGC}. In the right figure: PV panels output can operate within bounds $[0, P_{\text{MPP}}]$ where MPP is the maximum power-production.

authors of [79] include a topology and are able to consider the geography and infrastructure in their optimization.

The authors of [80] show that without voltage-control and with a 50% EV penetration rate, events take place where voltage drops well below the allowed minimum, destabilizing the grid. As a solution, [80] places constraints on voltage. In [81], an optimal generation dispatch algorithm is constrained by two constraints: an upper-bound to be able to ramp-up during peak-demand and a lower-bound to keep the generator within the area covered by the stability analysis. Also, the relation between the frequency-droop gain k_p is linked to stability-margins.

We consider an application setting where households have access to PV panels and ESS in the form of batteries. A DER portfolio of only PV panels causes the most intermittent power supply, spikes at day-time and zero at night. We take this extreme situation to test the limits of our algorithm, see chapter 3. A quick overview of respective PV and ESS dynamics are given.

PV dynamics

The authors of [82] provide a review is on the impact of PV panels on a power-grid. In [83] a dynamical model of PV panel output power P_{pv} is given:

$$P_{\text{pv}} = \frac{P_{\text{stc}} \cdot S_{\text{ing}}}{S_{\text{stc}} \cdot \big(1 + K(T_c - T_r)\big)}, \tag{2-13}$$

with P_{pv} representing the output of the PV panel, P_{stc} is the maximum power output point. S_{stc} and S_{ing} are the irradiance of respectively the sun at standard testing conditions and at time of measurement. In eq. (2-13), K is a coefficient relating to power and T_c and T_r respectively the ambient and reference temperatures. However, it is preferable to use observation data instead of try to model the output by a dynamical model: the noisy and erratic behaviour of the weather pattern is not included in eq. (2-13). However, it can be used as an estimator model to a prediction of PV power output.

ESS dynamics

The dynamics of an ESS mentioned throughout our work can be modelled according the method used in [84]. The State of Charge (SOC) of an ESS at time step k is denoted by $x_{\text{soc}}(k)$, having the following discrete-time model:

$$SOC(k+1) = SOC(k) + \eta P^b(k) - E_{\text{sb}}, \tag{2-14}$$

$$\text{where} \quad \eta = \begin{cases} \eta^c, & \text{when charging,} \\ 1/\eta^d, & \text{when discharging.} \end{cases} \tag{2-15}$$

In eq. (2-15), the updated battery SOC is dependant on the previous SOC $x_{\text{soc}}(k)$, the exchanged power $P^b(k)$ times an either charging or discharging return rate η minus a constant battery degradation x_{sb}. Constraints to battery storage are given in [85]:

$$\Delta P_{\max} \leq \frac{0.2 V_{\text{sys}} \cdot C_b}{\delta t}, \tag{2-16}$$

with the maximum of output power of an ESS over time interval δt is depending on the systems voltage V_{sys}, the battery capacity C_b in Ah. For a visualization of the charging and discharging by set-point frequency droop-control, see fig. 2-5. We model the battery capacity of households at a typical 13.5 kWh, corresponding to the capacity of a Tesla Powerwall. An average household has a load of 4500 kWh, thus a daily load of 13.2 kWh. For a Tesla Powerwall, maximum charge/discharge power in literature is set on between 3.4 and 5 kW [86],

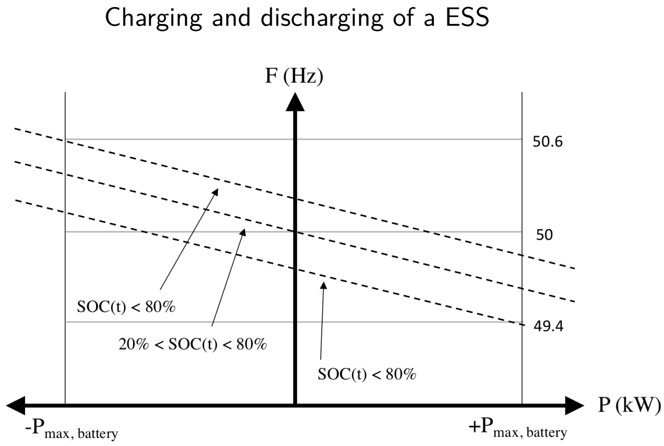

Figure 2-5: ESS units manage their charging and discharging behaviour by shifting their droop-parameter upwards or downwards with respect to the prime-mover ω_n. ω_{ess} has to stay within bounds of European standards $[49.9, 50.1]$ in Hertz and cannot exceed its power limits $[P_{\min}, P_{\max}]$

Rise of the EVs

A substantial part of research is conducted on methods to include EVs in the micro-grid. EVs could greatly contribute to stability of micro-grids in terms of voltage control and congestion management, but also pose a significant hazard due to high loads EV demand from the grid. In either case, the emergence of EV is a profoundly disruptive trend. Increasing EV penetration raises concern about the impact of a fleet EV poses to the balance act of a micro-grid. Concerns range from system losses, voltage drops or oscillations, phase unbalances, general increase of power demand and equipment overloading [44]. Both in [43] and [87] this impact on a regular macro-grid is recognized as well. On the other hand, the batteries in EVs can also be used for good. In [88], EVs are used to coordinate frequency-control while providing a energy reserve to the grid. Realistically though, EVs are still economically unsuitable for tasks other than voltage regulation

[44, 80]. In [80], charge and discharge coordination is implemented while constraining the charging pattern to ensure stability of the grid with respect to voltage.

The authors of [89] examine the pay-back time of EV when the potential of voltage regulation, load-balancing and costs due to decrease in performance due to the increase in charge cycles are included. In [90] it is stated that EV can greatly contribute to ancillary services, providing a power buffer to supply primary and secondary control. The authors of [91] and [87] show the possible impact of EV draining local micro-grids. Firstly it is shown that EV's can cause unpredictable power loads through-out the micro-grid. Secondly, a game-theoretical solution is provided.

The author of [92] proposes a novel method to allow power-systems to benefit from a EV fleet, with each EV checking for an array of constraints before allowing itself to start charging. An aggregator agents keeps score of fairness in the system w.r.t. energy allocation to EVs. Consequently, the method achieves an effective peak-shaving effect on load, relieving DG from high production ramping at dawn. Selfish-draining behaviour of individual EV is restrained.

Contract based control: actuator saturation as secondary control constraint

In contract-based control, elements of a control-structure can form contracts to negotiate assumptions and guarantees for which these elements are decoupled from others. Contracts are represented as $\mathcal{C}_n(A, G)$, contract n guarantees G_1 under the set of assumptions A_1.

We use contract-based control to model the interactions between primary and secondary control. The requirements any EDP solving algorithm should satisfy to allow primary control to stabilize the micro-grid can be expressed in such a contract

$$\mathcal{C}_n = \begin{cases} \mathcal{C}_1 : A_1 \to G_1 \\ \mathcal{C}_2 : A_2 \to G_2 \end{cases} \text{with } G_2 = A_1 \tag{2-17}$$

Here, primary control is represented by $\mathcal{C}_1$ and a secondary control solution by $\mathcal{C}_2$. The guarantee made by primary control that it will deliver a stable micro-grid is represented by G_1; voltage and frequency will be within required bounds grid-wide. The assumption $\mathcal{C}_1$ makes for this guarantee is that secondary control $\mathcal{C}_2$ manages to restrict power surges within certain bounds, represented by guarantee G_2. The assumption that $\mathcal{C}_2$ makes is that there is a certain energy reserve left. In eq. (2-17), $\mathcal{C}_1$ and $\mathcal{C}_2$ are coupled through $G_2 = A_1$; as long $\mathcal{C}_2$ honours G_2, it has free reign on providing set-points (AGC signals) to DER units, while being assured of G_1; a stable micro-grid (regarding frequency control):

$$\mathcal{C} = \begin{cases} \mathcal{C}_{\text{PC}}: & \sum_{i=0}^{N} P_i = 0 \text{ and } P_{\min} \leq P_i \leq P_{\max} \;\; \to \;\; \|\omega_n - \omega_i^*\| < \epsilon_\omega, \\ \mathcal{C}_{\text{EDP}}: & \|E_{\text{storage},n} \nleq E_{\text{sc}}\| \;\; \to \;\; \sum_{i=0}^{N} P_i = 0 \text{ and } P_{\min} \leq P_i \leq P_{\max}. \end{cases} \tag{2-18}$$

A design requirement to $\mathcal{C}_{\text{EDP}}$, the proposed trading algorithm in chapter 3, should be that guarantee G_2 holds, that is, power demand of DER units will not exceed their bounds and total energy flux within the grid at each step k equals zero. With G_2 as a boundary condition to secondary control, it can be decoupled from primary control. Actuator saturation of DER is discussed in section 2-1-4. The effect of actuator saturation on the solution of the EDP is discussed in section 4-1-3.

2-2 State-of-the-art: grid coordination on secondary level

With constraints to secondary control determined in section 2-1, focus can be shifted towards the problem residing within this level of control. This section discusses the current state-of-the-art of approaches of the economic dispatch problem.

2-2-1 Methods for economic dispatch in micro-grids

Dynamic economic dispatching of a micro-grid is an optimization problem that is often non-linear, with high dimensionality and multi-index constraints. Many methods for solving these non-linear problems have been introduced over the years; e.g. neural networks, evolutionary programs and model predictive control are among the most recent innovations.

In [93], an ESS is modeled by an agent-based system and a management technique is developed to converge to efficient behaviour. In [94] a game is formulated that combines prediction and price elasticity to achieve lower a Peak to Average Ratio (PAR). The authors in [95] make use of droop-control to stabilize the grid by reactive power sharing. While including more grid-dynamics than conventional game-theoretical approaches, control solutions exclude human behaviour. In [96] a micro-grid is modelled as an Multi Agent System (MAS) and uses the contract-net procedure as an DER coordination technique.

Of all literature available, a summary of the following three methods is used to illustrate the diversity of the problem and their solutions; inclusion of prediction, the modelling of a hierarchical structure and the problem of convergence in large non-cooperative populations.

Model predictive control

The authors in [84] make use of Model Predictive Control (MPC) for secondary-level economic dispatch of DER in a micro-grid. MPC is a control method where optimization of time-step k is influenced by a prediction of coming time-steps up to a receding horizon; $(k_h) = (k + j)$. In [84], an objective function, eq. (2-19), aiming at including all relevant earnings and costs for DER units within the micro-grid, calculated over a time period $k \to k_h$:

$$\begin{aligned}
&\sum_{k=0}^{k_h}\sum_{i=0}^{N}[C_i^{DG}(P_i(k)) + SU_i(k) + SD_i(k)] \\
&\qquad + OM^b[2z^b(k) - P^b(k)] + C^g(k) + \rho_c \sum_{h=1}^{N_c} \beta_h(k) D_h^c(k), \\
&\qquad = \sum_{k=0}^{k_h}[\mathbf{c}_u'(k)u(k) - OM^b\mathbf{F}'(k)u(k) - OM^b\mathbf{f}'\mathbf{w}(k) + \mathbf{c}_z'\mathbf{z}(k)] \qquad (2\text{-}19)
\end{aligned}$$

In eq. (2-19), C_i^{DG} describes the cost-function of DER unit that is taken variable over $P_i(k)$, which is the power exchanged with unit i. Also, SU and SD are costs involved with start-up and shut-down of the DER unit. Import/export to the macro-grid with the macro-grid is described by C^g, operational costs with OM^b. Additionally, $[2z^b(k) - P^b(k)]$ is a cost involved with changing a ESS from charging to discharging mode. Finally, $\rho_c \sum_{h=1}^{N_c} \beta_h(k) D_h^c(k)$ represents consumer discomfort when their consumption pattern is influence by rescheduling [84]. The equation is rewritten in a notation where variables for DER units are combined in vectors and the control variable $\mathbf{u}$(k) is visible. Note that accurate prediction up to the end of horizon k_h is necessary for a optimal solution.

At each step k, given initial storage x_k^b and horizon k_h, this MPC controller computes an optimal control strategy $u_k^{k_j}$ through solving the following finite horizon control problem:

$$\mathcal{J}(x_k^b) = \min_{\mathbf{u}_{k=0}^{k_h}} \sum_{j=0}^{N} [\mathbf{c}_u(k+j)\mathbf{u}(k+j) + \mathbf{c}_z\mathbf{z}(k+j) - OM^b\mathbf{F}'(k+j)\mathbf{u}(k+j) - OM^b\mathbf{f}'\mathbf{w}(k+j)]. \tag{2-20}$$

In eq. (2-20), a minimization is made over the (rewritten) cost-function on a time period of $k \rightarrow k_h$ eq. (2-19). By minimization, an optimal control sequence $\mathbf{u}_k^{k_b}$ is found, a vector that provides an optimal control input for the coming time-steps up until k_b. Of $\mathbf{u}_k^{k_b}$, only u_k is used. A feedback loop is created by repeating this process at time $(k+1)$, with new measured and estimated state-values. This method of applying MPC to economic dispatch yielded cost savings of up to 34,7 % with a horizon of $k_h = 72$.

Hybrid weighted bi-level planning

The proposed method in [97] combines bi-level planning with an internal genetic algorithm. Bi-level planning is a subject of decision-making problems, modelled in a hierarchical structure. In the case of micro-grid control, there are various layers that have to cooperate while having different objectives and constraints (e.g. primary/secondary control, day/day-ahead markets). In [97] this is illustrated. Upper-level contains optimal allocation, which aims at minimizing the daily fixed cost, lower level contains economic dispatch. Upper and lower level solutions are influencing each other, such that a trade-off exists. Upper-level costs are daily fixed cost of investment (DFCI), load loss probability (LLP) and excess energy rate (EER). Lower-level costs are cost of operation and management (COM) and cost of pollutant disposal (CPD):

$$P = \begin{cases} \mathcal{U}_l = \min(\eta_{1,2} \cdot C_{\text{COM}} + \eta_{1,2} \cdot C_{\text{CPD}} + r\Delta P), \\ \mathcal{U}_u = \min(\eta_{2,1} \cdot C_{\text{LLP}} + \eta_{2,2} \cdot C_{\text{DFCI}} + \eta_{2,3} \cdot C_{\text{EER}}). \end{cases} \tag{2-21}$$

In eq. (2-21), $\eta_{1,i}$ and $\eta_{2,j}$ are weights to various costs $[C_{\text{COM}}, C_{\text{CPD}}, C_{\text{LLP}}, C_{\text{DFCI}}, C_{\text{EER}}]$ and $r \cdot \Delta P$ is a penalty for unbalanced power. The hybrid weighted solution for optimal allocation between these two levels is found by combining the two objective function through normalization and weight determination. The resulting weights $\in I$ and J are $\eta_{=}a\eta_{1,i} + (1-a)\eta_{2,i}$, with $\eta_{1,i}$ and $\eta_{2,j}$ being weights that are determined by respectively the judgment matrix method (a weight ranking matrix) and the variation coefficient method (an analysis of the ratio of the standard deviation to the mean value) [97]. With this function, a genetic algorithm is subsequently used to find the optimal solution in the non-linear trade-off between $\mathcal{U}_l$ and $\mathcal{U}_u$. The authors of [97] propose a solution to divergent objective functions and a method to decide on a trade-off in benefits within the micro-grid. In [97], a case-study is made into high-level control of day-markets, while in this thesis we focus on primary and secondary control-levels within the range of seconds and minutes.

Mean-field games

The authors of [73] assume a population of non-cooperative agents in the community that tend to infinity. This way, agents are influenced by the mean field of the community, as their personal contribution vanishes statistically. Here, the interactions between agents are modeled by two coupled differential equations; the individual optimal responses and the dynamical behaviour of agents. Instead of regular mean-field games, agents do not need properties of the statistical distribution of states of all agents in order to solve the problem decentrally. In contrary, the author of [73] solves the problem by introducing a central coordinator that broadcasts a reference signal. The costs that influence unit coordination are captured in the individual cost-function $\mathcal{J}_i$:

$$\mathcal{J}_i(\mathbf{s}_i, \mathbf{u}_i, \mathbf{s}_j) = \sum_{t=0}^{t_h} \left\| s_{i,t+1} - \left(\eta + \frac{1}{N} \sum_{j=1}^{N} s_{j,t+1} \right) \right\|_{Q_{t+1}}^2 + \|u_{i,t}\|_{R_t}^2 . \tag{2-22}$$

In eq. (2-22), s^i is the state variable of the dynamical model of agent i, u^i, constrained by actuator saturation: $s_t^i \in \mathcal{S}_{i,t}$ and $u_t^i \in \mathcal{U}_{i,t}$. The function is comprised out of two parts; firstly, a penalty of deviations from the average population behaviour plus some constant off-set η, secondly the the control-effort of agent i. Q and R are time-varying weights. Note that s^i statistically insignificant to the average 'mean field' σ of the community, $\frac{1}{N}\sum_{j=1}^{N} \mathbf{s}^j$. From a reversed perspective, the mean-field does influence the behaviour of agent i, resulting in an aggregative game where agent i needs to minimize its individual deterministic cost $\mathcal{J}(x^i, \epsilon)$. In, [73] it is shown that there exists a population size $N_\epsilon \in N$ such that populations $N \geq N_\epsilon$ converge to a Nash equilibrium (see section 2-3), as long $\mathbf{z}$ is a fixed point of $\mathcal{A}$, thus $\mathbf{z} = \mathcal{A}(\mathbf{z})$, reducing the problem of population convergence to:

$$\mathbf{z} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{x}^{i*}(\mathbf{z}) = \mathcal{A}(\mathbf{z}), \tag{2-23}$$

with $\mathcal{A}$ being the mapping of optimal response by all agents to the macroscopic reference signal z. The mean-field control problem then focuses on finding the reference signal z. Mean-field assumes agents responding to a macroscopic reference z. This results in allowing a centralized agent in the system, while achieving minimal information exchange thus anonymization. For a continuation on game theory, please be referred to section 2-3.

2-2-2 Solution schemes

We have seen that the economic dispatch problem which the proposed energy trading algorithm deals with is the optimization of a best-solution to a cost function that includes a set of costs, profits and penalties that influence the optimal coordination of DER in the micro-grid. In section 2-1 we analyzed the constraints to primary control that have to be met, defining the solution space of dispatch algorithms. Depending on the cost-functions and constraints, the problem becomes, linear, convex or even non-linear. In case of non-linear problems, new solution methods are used to find heuristic solutions. Specifically, the following two methods are used in a wide variety of literature.

Genetic Algorithms (GA)

GA is a solution search algorithm that copies evolutionary theory, relying on genetic crossovers, mutations and selection on a population of solutions. The goal is to abandon the low-utility population and only allow the high-utility to survive and cross-breed. The authors of [98] use simulated annealing, allowing certain randomly picked solutions to survive regardless of performance, in order to accelerate the solution search, that exponentially increases with the increase of agents and time. To search for the best solution, the initial solution is coded into a chromosome that evolves over a number of generations until the process finds a solution that meets the convergence criteria.

Although acceptable for finding heuristic (sub-)optimal solutions for a non-linear problem, these approaches are necessarily centralized because of their computational complexity. In addition these central controllers use information on consumption and production of *all* agents in order to find an acceptable solution. In a decentralized control paradigm, agents should be able to converge to a global optimum individually using only limited localized information. GA is an optimization technique meant to be applied in a discrete search-space. For a continuous search-space, such as a range of bidding-prices, a Particle Swarm Optimization (PSO) is better suited.

Particle Swarm Optimization

A PSO mimics the behaviour of natural groups of agent; e.g. flocks of birds or a swarm of bees. PSO explores the solution-space by looking at both particle velocity and position. The modeling of particle momentum allows for faster convergence. The author of [99] proposes a heuristic method to find a solution to dynamic non-linear dispatch problem by PSO. Solutions are represented as particles that have the states of position x_i and velocity v_i. Movement of each particle is influenced by the current state and the best positions found by any particle. The search-space is defined by the constraints to the problem. In a one-dimensional case, states x_i and v_i are updated as follows:

$$v_{k+1} = a \cdot v_k + b_1 \cdot r_1(o_1 - x_k) + b_2 \cdot r_2(o_2 - x_k), \tag{2-24}$$

$$x_{k+1} = c \cdot x_k + d \cdot v_{k+_1}, \tag{2-25}$$

with a as a momentum factor and b, c, d as gravity coefficients that attract particles to the respectively previous local and global optimal positions o_1 and o_2. PSO is inspired by social behaviour of bird flocking or fish schooling. A community of 'solution' particles is formed by random initialization, where after particles compute both an individual optimum and a global 'grouped' optimum, influencing x and v, until termination criteria are met. A method found in [99] improves on the standard PSO algorithm by including variable weighting to constraints and learning factors. Subsequently, this requires PSO to deal with a variable solution-space.

2-2-3 Forecasting methods

Since coordination strategies discussed and proposed in this thesis often include model-predictive control, forecasting within a micro-grid is discussed in this sub-section. Because of the non-linearity of nature, it is a relatively hard task to capture its dynamics and fit a model. Broadly exploited methodologies for non-linear forecasting are Neural Network (NN)s and Support Vector Machines (SVM)s.

In [100], a forecasting method is proposed in which SVM are used. Traditional approaches to forecasting, such as numerical weather predictions (NWP) based on satellite images are used in PV generation prediction, yielding an Root Mean Square Error (RMSE) = $\sqrt{(\sum P_{\text{forecast}} - P_{\text{true}})^2/N}$, of around 15 %. However, during dusk and dawn, and under rainy conditions, the RMSE can rise to an unacceptable 50 %. Two approaches can be identified; direct, by analyzing the measured output, or indirect, by analyzing the radiance of sunlight, coupling this to PV output by $P_i = S \cdot A \cdot \eta$; the power output P of panel i being dependant on the radiation intensity S, the PV area A_i and the efficiency $\eta = \eta_0[1 - \gamma(T_p - T_y)]$. Here, η_0 is a reference efficiency at surrounding temperature T_γ (298 K) and γ is a temperature coefficient of the ESS linked to the PV panel.

SVM is a learning method rooted in statistical learning theory, solving the problem of limited sample learning. For a given data-set, a regression function is: $F = \{f | f(x) = g^T \cdot x + b,\ g \in R,$ with $||g||^2$ as the describing function. The goal is minimizing risk on deviation, with a structure risk function introduced:

$$\min R_{\text{reg}} = \min \frac{1}{2} \|g\|^2 + C \cdot R_{\text{emp}}(f), \tag{2-26}$$

with $\|g\|^2$ is the describing function, C is a trade-off constant between empirical risk R_{emp} and the model complexity f. The PV output is classified into four types: sunny, foggy, cloudy and rainy, determining which SVM model configuration is chosen to forecast the one-day-ahead output. On average, the SVM approach yields a RMSE of 8.64 %. On sunny days the RMSE drops as low as 4.85 %.

2-3 A Game-theoretical approach to energy trade in a micro-grid

All happy families are alike; all unhappy families are unhappy in their own way.

Anna Karenina - Leo Tolstoy

In section 2-1, we concluded that frequency control is coupled with load-balancing. Section 2-1-1 examines the hierarchical control-structure of a micro-grid; allowing decoupling; the trade-algorithm has free-reign within certain bounds prescribed by actuator saturation of primary-controllers, captured a contract described by eq. (2-18). Section 2-2 presents the EDP to be solved within bounds of eq. (2-18) and relevant solutions. In this section, an introduction to game theory is given. In section 2-3-1, an theoretical outline is given. An extensive survey on game theory for solving the EDP is given in section 2-3-2.

2-3-1 Game theory: an outline

Game theory can be defined as the study of mathematical models of conflict and cooperation between intelligent rational decision makers [101]. Formally, a branch of mathematics, it has many applications to economics, political science, biology, physics, engineering and many other fields [102]. When using game theory to model, the assumption of intelligent rational behaviour is made, meaning that a player in a game has not only a clearly defined goal but also can figure out how to achieve that goal given the circumstances. Tolstoy was interested in diversity and thus wrote about unhappiness; game theory would rather use the similarity of happy families as a gauge. Predictable rationality as a benchmark can simplify complex behaviour significantly. A very usefull summary on the basics of game theory is discussed in [103].

Interestingly enough, great potential game theory lies in its distributed nature. A game is divided into rounds and players can autonomously participate and optimize within their own context. A game can be played with players entering in between each round of the game, resembling an P2P network like Bit-Torrent, a relatively stable network where nodes can freely enter and leave the network [104]. With the right game design, game theory can pose solution to distributed control and thus used as a decentralized approach to the EDP [105].

A normal-form game can be seen as the basic structure of a game [103]. It has the following elements:

- The set of players is $N = \{1,..., n\}$.
- Player i has a set of actions, a_i, available. These are generally referred to as strategies.
- The set of all profiles of strategies or actions denoted by $a = (a_1, ..., a_n)$
- Player i's pay-off as a function of the vector of actions taken. The pay-off for player i is $U_i(a)$ if i plays the game according to strategy a.

Two ways to formulate a game are in extensive form and the strategic form. Extensive formulation allow for more explicit treatment of time and information, while a strategic formulation game does not [106]. The basics of a extensive form game consist out of the following structure [107]:

- **Representation of moments of choice**. A node represents a decision moment for the player. The first node is the root, the beginning of the game. From thereon, a tree branches of representing all options of the player that initiates the game, leading to new nodes. These nodes represent next steps, or responses of other players to the initial action of the initiator.

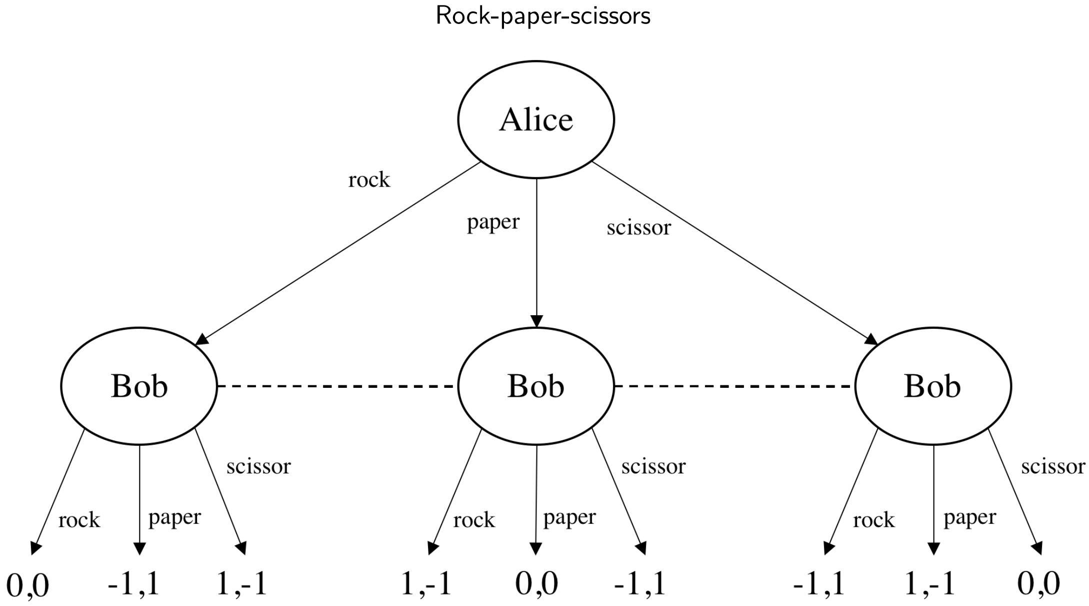

Figure 2-6: Alice and Bob play a game of Rock-Paper-Scissors. The pay-off vector in this game is defined like $[U_{Alice}, U_{Bob}]$. Bob plays a game of imperfect information: he has to pick a strategy regardless of the strategy of Alice. With imperfect information, the response time (that in a game of rock/paper/scissor is zero) to the other player is modelled.

- **Path of play**. The path of play represents the path through this game tree, translated to the actions taken by all players resulting in the actual choices made.
- **Labels**. Players are represented by labels linked to nodes. A players label defines the player that is permitted to make a choice between its available actions at that specific node. The *information state* label specifies the information that is available at that node. Games can be of perfect or imperfect information. When the game is information imperfect, players cannot always respond to strategies of other players. see fig. 2-6
- **Action space**. The action space represents the available choices to the player. The action space is linked to the information state.
- **Terminal node**. Terminal nodes are placed at the end of a path of play. They represent the pay-offs, the outcome of the game for that specific set of actions taken by all players during the game. A pay-off can be maximized with a best response strategy. The vector u_i gives an overview of the pay-offs for all paths of play.

An extensive-form game Γ_{EXT} can be formulated as the tuple of the combination of all items discussed in section 2-3-1:

$$\Gamma_{\text{EXT}} = (N, a_i, U_i)_{i \in N} \tag{2-27}$$

Game theory is divided into cooperative and non-cooperative game. Non-cooperative games are mainly used to analyze strategic decision-making within a group of independent players that have conflicting interests over the outcome of a game. It captures a distributed decision-making process that allows players to optimize without communication or coordination during the game [29]. Cooperative games capture situations where players can increase their individual social welfare by working together with other players.

Temporal games are played in rounds, known as repeated or dynamic games. An important concept to mention is the horizon of the game H_i. Players in an infinite repeating game might prefer to choose for a strategy that pays off less in the near-future than a strategy with a higher pay-off in the distant-future [108, 109]. One way of modeling this anticipation on future utility is by incorporating a discount δ [110].

Solution schemes

Solution concepts are formal rules of what strategies will be adopted by the players, a prediction to the outcome of the game. For example, a Nash equilibrium is a solution concept where each player′s strategy is a best response against the equilibrium strategies of the other players [106], where $a_{\{-i\}}$ is the set of strategies of all other players, and a_i' is a arbitrary strategy not equal to the Nash strategy a_i. The Nash equilibrium is formulated as:

$$\mathcal{U}_{\text{Nash},i}(a_i, a_{-i}) \geq \mathcal{U}_i(a_i', a_{-i}) \quad \forall i \in I. \tag{2-28}$$

Here, $U_i(a_i, a_{-i}$ is the utility of player i. It depends on its own strategy as well as strategies of other players. $\mathcal{U}_{\text{Nash},i}(a_i, a_{-i})$ is the best response player i can make as reaction to other players $\{-i\}$. If all players are in a situation where there is no incentive to change, the game converged into its Nash equilibrium. In dynamic games, a reinforcement of a Nash equilibrium is a sub-game perfect Nash equilibrium [111]. For any node x in Γ, let $F(x)$ be the set of all branches and nodes thereafter, including x. In this sub-game $F(x) = \Gamma_{sub}$. Behaviour in sub-game Γ_{sub} should also appear rational when viewed in the scope of the full game Γ. The sub-game perfect Nash equilibrium is then a solution for the game Γ that is a Nash equilibrium solution for every sub-game Γ_{sub}.

A Stackelberg equilibrium is found when a hierarchy is introduced in the game and where the players that lead can anticipate on the strategies of the followers. In an energy trading game, there is a distinction between prosumers with a surplus of energy and prosumers with a deficit of energy. The surplus that then be shared to balance out the deficit. Prosumers with a surplus are identified as leaders of the game and those with a deficit as followers. With this, a Stackelberg equilibrium is found as a sub-game perfect equilibrium, given the extensive-form game $\Gamma_{\text{EXT}} = (N, a_i, U_i)_{i \in N}$. The followers strategy, $F$is also depending on that of the leader L: $a_F = T(a_L)$.

Execution of the game: utility function and learning schemes

The utility function captures the behaviour of agents w.r.t. certain values such as social welfare or economic profit. Maximizing utility U_i is the goal of agent i. This optimization problem is solved by a so called learning algorithm, see section 2-3-1. The inputs given to the function represent the incentive given to the players. Within a power-grid, players are often focused on maximizing their profit or minimizing costs. In literature this is called the 'rationality axiom' and will be further discussed in section 3-2-1. In [112], the utility function is an representation of costs due to certain scheduling of appliances in different time slots:

$$\mathcal{U}(\mathbf{x}_n, \mathbf{x}_{-n}) = \Omega \cdot \sum_{h=1}^{H} C_h \bigg(\sum_{a \in A_n} x_{n,a}^h + \sum_{m \in N \setminus \{n\}} l_m^h \bigg). \tag{2-29}$$

Minimization of this 'cost' with respect of the action argument $\mathbf{x}_n$ will result in a local best response strategy $\mathbf{x}_n^*$ and a optimized utility β_n:

$$\beta_n = \underset{\mathbf{x}_n \in X_n}{\text{argmin}} \sum_{h=1}^{H} C_h \bigg(\sum_{a \in A_n} x_{n,a}^h + \sum_{m \in N \setminus \{n\}} l_m^h \bigg). \tag{2-30}$$

In eq. (2-29) and eq. (2-30), $h \in \mathrm{H}$ is the time-slot vector dividing the day, C_h is an convex function (i.e. quadratic) enabling convex optimization, A_n are load appliances of players with x and l being, respectively, an energy consumption scheduling vector and the total load per player over each hour. In eq. (2-29), $\mathbf{x}_n = x_{n,a}^h$ is the playing argument that can be influenced by the player, Ω is a constant representing the conversion from load to costs. The utility function is reliant on other players information, that is; the utility function needs l_m^h with $m \in N \setminus \{n\}$. After every round played, l_m^h has to be shared to update the local optimization problem of player i. Equation (2-30) yields a peak-shaving result in terms of average energy demand of agents over time.

After choosing a solution concept, the way to reach the solution equilibrium is the next step in designing a suitable game. A learning scheme that forms the backbone of the energy trading algorithm. In literature, four variants of learning schemes are commonly used:

- **Best response**. Best response is a concept where after each iteration, players simply pick the strategy that maximizes its utility function. Choosing best response strategy requires the utility function to be convex since only convex function will converge into a global equilibrium using this method [113].
- **Fictitious play**. Fictitious play is a scheme where after each iteration, all players are informed on choices made by all other players and a estimation of other players response is made through a simulation of further game play. Afterwards, a best response function is picked based on a empirical estimation [114].
- **Regret matching**. Regret matching is based on the minimization of regret under choosing certain action. The regret function provides an insight in the missed potential of not playing s over time t; $R^t(s) = U^t - U^t(s)$, with U is the pay-off from the played strategy and $U^t(s)$ is the missed potential from strategy s that was not played. Not focusing on the modeling of other players forms a distinction between fictitious play. A regret matching learning rule chooses an action with probability proportional to its regret [115, 116].
- **Reinforcement learning**. Reinforcement learning is observed in nature; every species learns through trial and error. By remembering the pay-off of previous action and classifying those 'trials' by its success i.e. pay-off, one can learn from its successes and more importantly, their mistakes. An simply model is cumulative pay-off matching for strategy vector α; $\alpha^{t+1} = \alpha^t + u^t e^t$ with the term $U^t e^t$ being the reinforcement for each strategy with utility U at time t [114].

2-3-2 Game theory and energy trade

From a control-theory point-of-view, balancing the decentralized micro-grid is a control task. Intuitively, the aim of the controller should be to match supply and demand to stabilize the grid. With further consideration, more factors and diverse optimization goals arise in this control problem, discussed in section 2-1 and in [117]. Practically, with conscious agents as actuators, the challenge becomes more complex. In a situation where actuators adopt human behaviour, individual local goals often diverge from the global balancing goal. This is illustrated with a thought-experiment:

A neighborhood plans to collectively invest in a playground. Neighbor i resists investing his share, reasoning that in a large enough community, the fund will be filled anyhow. With this strategy, neighbor i does not invest and still gains a playground; a maximum pay-off. However, the inevitable result is that every rational neighbor will deduct the same strategy. Resulting in neighbors refusing investment, no fund is collected and no playground is built; zero pay-off.

Thus, a mechanism needs to be designed that fulfills each agents individual goals, while indirectly establishes our main control task of load balancing. We identify a collective task of maintaining balance by solving the EDP, and a individual task of optimizing personal welfare. The agent's utility function should be designed such that these tasks are aligned. Additionally, a game type and a solution concept are to be selected. Before we present our proposed decentral solution to the EDP in chapter 3, we give an overview of game-theoretical approaches to solve the EDP, categorizing the examples as either cooperative or non-cooperative games.

Cooperative or coalitional games

Cooperative game theory investigates the forming of coalitions in communities acting according to a behavioural model. Coalitions are formed through matching games; played such that a 'greater good' utility function is optimized. A cooperative solution concept is the Shapely value [118]. This value represents the unique distribution of the total pay-off over the contribution members of the coalition [119]. The Shapely value Φ for player i is the result of evaluating the contribution of i over all possible coalition combinations π:

$$\Phi_i = \frac{1}{n!}\sum_{i=1}^{\pi}(v\{1,...,\pi(i)\} - v\{1,...,\pi(i)-1\}). \tag{2-31}$$

The authors in [120] propose a solution by extending on the cooperative game introduced in [121] and [122] by including a more sophisticated model for power routing and matching of supply and demand. A traditional coalitional game is played in [123] where initially, a group of energy consumers are matched with prosumers in a matching optimization. Afterwards, the Shapely value Φ is used to express individual contribution to the general good, deciding on the pay-off vector. On a higher level, the author of [122] matches micro-grids with an energy surplus to those with a deficit.

Algorithm 1 Coalitional game, from [122], minimizes the amount of energy imported/exported to the macro-grid.

procedure Coalitional game
Stage 0: initiation
The network is partitioned by $S = S_1, ..., S_k$ (initially $S = N = 1, ..., N$ with micro-grids that are initially non-cooperative).
Stage 1: coalition forming.
repeat:
1) $M = Merge(S)$: micro-grid coalitions $\in M$ decide to merge.
2) $S = Split(M)$: micro-grid coalitions $\in M$ decide to split.
until convergence w.r.t. solution scheme into final partition S_{optimal}.
Stage 2: cooperative power transfer
Coalitions of micro-grid players $S_i \in S_{\text{optimal}}$ orders its seller to play strategy a_{optimal}.
repeat:
Buyers in $S_i \in S_{\text{optimal}}$ attempts to satisfy demand Q_j by allocation of sellers $\in S_i$.
until no local power transfer is possible.
Stage 3: wrap-up
Within coalition $S_i \in S_{\text{final}}$, any seller or buyer, which still has reserves left, can trade by buying or selling from the macro-grid.

Voluntary games, also known as voluntary contribution games, are a separate class within cooperative games. They model a realization event of a public good [124, 125, 126]. Players have the option to voluntarily participate; an action that influences game dynamics. The authors of [127] theorize that multiple rounds could increase probability of donors contributing to a public cause. In

[128] the authors aim to measure discomfort from rescheduling energy consumption for Dynamic Pricing (DP) after which the agent is able to reduce this discomfort utility through voluntary rescheduling. In algorithm 1, an example of a coalitional game is expressed in pseudo-code.

Non-Cooperative Games

Non-cooperative games, in contrast with cooperative games, focus on situations where players do not cooperate with each other. Players individually optimize their strategies according to the their context to optimize their utility, not by joining certain strategy coalitions. A Nash equilibrium is found when all players decide on a strategy that is a best response to all other players. The degree of information exchange between players dictate the height of the optimum.

In [129] a game is modeled between a single energy retailer and multiple consumers, while different revenue stream models were used to influence the outcome. A model that includes large-scale micro-storage while introducing an adaptive consumer strategy is developed in [130]. The ability to adapt to the model makes the consumer more versatile and increases all over efficiency. The paper [131] stands out by including an online learning algorithm focusing heavily on prediction on EV price elasticity, introduced in [69]. In [29], EV batteries were used to store energy traded in a non-cooperative game. Prices are determined via an auction mechanism. A subclass of non-cooperative games are congestion games, or exact potential games [132]. Able to efficiently allocate resources to players, congestion games are especially useful when modeling the charging behaviour of EVs [133]. [134] extends this model by allowing EVs to discharge as well, supplying back during peak-hours. In [91], the author tries to bridge the gap between the micro-grid and EV by playing a scheduling game between EVs and charging stations. The authors of [135] aim to control peak-load by distributed load management in smart-grids through dynamic pricing. In algorithm 2, an example of a non-cooperative game is expressed in pseudo-code.

Algorithm 2 Non-cooperative game from [112], yields a peak-shaving result.

```
procedure AUTONOMOUS DEMAND SIDE MANAGEMENT
    Stage 0: initiation
    For each agent: initialize l_n and l_{-n}.
    Stage 1: individual optimization
    repeat
        while listening to broadcasts of l_n ∈ N do:
            Solve local convex-optimization problem in eq. (2-30).
            if x_n changes compared to current schedule then:
                Update x_n according to the new solution.
                Broadcast control message announcing updated l_i to other players.
            if a control message is received then:
                Update l_{-n} with new schedule.
    until no players announce new schedules l_i.
    Stage 2: wrap-up
    Execute schedules l_i.
```

Stackelberg games

The, already briefly introduced in section 2-3-1, Stackelberg game enables the inclusion of a player hierarchy. In non-cooperative trading games, Nash equilibria can prove to be Pareto inefficient; agent could increase their own utility without harming others utility, thus a sub-optimal solution

[136]. The authors of [137] manage to improve the pay-off of best-responses by introducing a players hierarchy. In [72], a distinction between buyers and sellers is made through a leader-follower two-step Stackelberg game. A major advantage is within each step, a global Nash equilibrium is agreed on within one iteration. An iterative process is thus not needed. This is called backward induction, which is possible when the game is played with perfect information.

A Stackelberg game approach is used in [113], where utility companies are identified as the leaders, while not including DER in the model. [138], contributing to [139] by introducing V2G, models an aggregator that owns arrays of DER. The optimization is performed by stochastic programming, useful to handle optimization with uncertainties, where multiple plausible realizations (or scenarios) of each stochastic variable are generated [140]. A Stackelberg framework is used in [141] to model the interaction between the micro-grid and a following fleet of EVs. A Stackelberg game has a certain advantage over normal non-cooperative games in that, by dividing the pool of players into a hierarchy, the optimization pools are smaller. Also, leaders can anticipate on the best response of the follower, and thus can algebraically find their strategy. Additionally, by including hierarchy, the traditional market mechanism is modeled more accurately. Numerical solutions to Stackelberg games can be found in [142], providing a practical overview on approaches to solve the optimization problems stated by an Stackelberg-game. Closed-form Stackelberg games can be algebraically solved, as done in [72].

Algorithm 3 Stackelberg game, from [72], allows sellers (leaders) and buyers (followers) to trade among each other. Sellers are able to algebraically find their best response strategy if they know about followers utility function.

procedure HIERARCHICAL-BIDDING OPEN-FORM GAME
Stage 0: initialization
Divide players in buyers-pool $\mathcal{I}$ and sellers-pool $\mathcal{J}$ according to measurements.
Determine energy surplus. $\hat{E}_j$ and bidding range $\mathcal{C}_i = [c_B, c_S]$.
Initialize c_i and w_j $\forall j$ $\forall i$.
Stage 1: hierarchical game
repeat:
→ Level-1 Game: buyers optimize iteratively, results in c_i^*.
$\hat{\mathcal{B}}_i(\mathbf{b}) = \text{argmin}_{c_i} \ \hat{U}_i(c_i, c_{-i}, \mathbf{w}) \ \forall i$.
Buyers broadcast c_i^* to sellers.
→ Level-2 game: sellers $\in \mathcal{I}$ optimization using c_i^* in $\hat{\mathcal{B}}_j(\mathbf{c})$ for w_j^*.
$\hat{\mathcal{B}}_j(\mathbf{c}) = \text{argmin}_{w_j} \ \hat{U}_j(w_j, \mathbf{c}) \ \forall j$.
Sellers converge and broadcast w_j^*.
until 2-layered distributed optimization converges to (**c**,**w**).
Stage 2: wrap-up
Execute c_i^* $\forall i \in I$ and w_j^* $\forall j \in J$.

The authors in [143] deal with a central energy supplier while consumers can choose whether to participate in the collective trade or not. In algorithm 3, a Stackelberg game is expressed in pseudo-code.

We model our algorithm, discussed in chapter 3 as a non-cooperative game since we expect households to be individualistic non-collaborative in nature; a Nash equilibrium is a solution-scheme that captures this. As framework, we adopt the hierarchical structure of the Stackelberg game in [72]. A Stackelberg game, such as in [72], is restricted to using only standard functions as follower utility function $\mathcal{U}_{\text{follower}}$. Although the algorithm presented in chapter 3 is open-loop, standardness is still requirement (source: personal correspondence with S. Bahrami, author of [144]). We prove standardness of $\mathcal{U}_{\text{follower}}$ in appendix A-1-3.

2-4 Blockchain for decentralized energy trading

> The Blockchain does one thing: it replaces third-party trust, in whether something happened, with mathematical proof.
>
> Adam Draper

A Blockchain is a public ledger that keeps record of all transactions preformed among participating nodes in a P2P network. Transactions are grouped together into blocks, while blocks are linked together to form a chain, establishing a Blockchain. Due to the fact that every node keeps track of its own version of the public ledger, nodes independently verify transactions announced over the P2P network. Consensus is reached on the validity of transactions through a consensus protocol, comparable to a democratic election with all nodes casting votes. A crucial result is a data-base that is governed by all and owned by none. By doing so, a Blockchain effectively cuts out the middle-man during a transaction of value.

An brief outline of Blockchain is given in section 2-4-1. In addition, in section 2-3 it has become evident that agents are sharing information among each other in order to converge to a global optimum. A method to counter malicious agents that provide licentious information is discussed in section 2-4-1.

2-4-1 Outline of Blockchain

The notion of digital money started out with the first attempt of building cryptocurrencies with projects like described in [145]. These currencies did still depend on a centralized trusted authority to validate the transactions. In case two friends, Alice and Bob, want to transfer value, Alice could announce to a group of people a signed contract stating "a transferal of a certain value to Bob". This contract would be called the transaction. With signatures, this transaction can be considered valid, while it is not forgery-proof. Normally, a centralized institution is needed to generate trust by enforcing regulation, for example by issuing serial numbers to each contract to counter replayability. In the absence of a bank, what is needed to establish transactions in a trust-less asynchronous environment are the following features [30]:

- **Tokens**. A token is a chain of digital signatures, showing a trail of previous owners of this coin. Tokens need to be uniquely identifiable, while not making use of serial numbers. Namely, a mapping between serial numbers and tokens has to be issued by an Third Trusted Party (TTP), not allowed in a decentralized paradigm; Blockchain solves this problem. Ownership of tokens is moved around by transactions, which are grouped together in blocks for time-stamping.
- **Procedure in time**. A time-stamping server is needed to show a temporal order. The trail of owners of a specific coin can be rightly sequenced. The server proves the existence of transactions at a certain location of the sequence by referring back all future transaction to this block wherein the transaction resides [146]. The genesis block is the first block in the Blockchain to be mined.
- **Consensus protocol**. In a decentralized network of nodes, a dependable and fair consensus protocol picks out a specific node to suggest a new block of transactions collected by listening to announcements in the network. To exclude forging of identities in a the network (e.g. Sybil attacks [147], explained in section 2-4-1), the consensus protocol allocates 'voting power' according to certain schemes that proof an entity instead of an identity by demanding an investment of real-world resources.

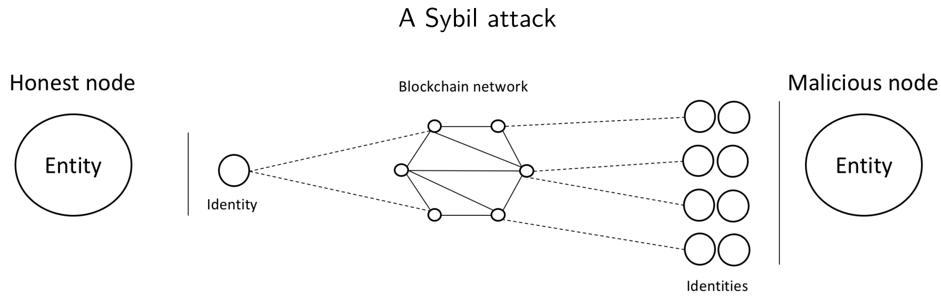

Figure 2-7: Sybil Attack: a honest node represents itself as a single identity while a malicious node cheats by representing itself as multiple identities, gaining a majority of voting power in the network. Testing entities instead of identities is the solution

- **Network participation**. To make nodes contribute to the network by participating in the consensus protocol whereby the participating entity has to invest its resources, a financial incentive is given. Often, this results in a reward of crypto-coins to those nodes selected by the consensus protocol to suggest a block of transactions or through transaction fees.
- **P2P network**. All nodes participating in a Blockchain form a P2P network similar to data-sharing networks such as employed by Bit-Torrent [104]. In this network nodes are responsible for announcing new transactions, gathering transactions into blocks by listening, preforming a resource-intensive calculation to prove entity before allowed to propose a formed and valid block to other nodes in the network.

An in-depth review on Blockchain is given in [148]. Requiring every node to keep its own public ledger enables decentralization but evidently opens up numerous possibilities for nodes to cheat. The problem of replayability of transactions, also known as double-spending, was resolved in [149] in 1998, but with a unrealistic assumption of a completely synchronous network. In a real-world P2P network, latency between a transaction and all nodes receiving the respective announcement results in a distributed consensus problem.

Double-spending in a decentralized paradigm

Figure 2-8 portrays an example of a double-spending attack of Alice on Bob. In the example, Bob is owner of a innovative pizza-restaurant and Alice is a customer able to pay by Blockchain. Alice executes a double-spending attack on the transaction with which she payed Bob for a pizza she just ate. According to the ground-rule that the longest chain is accepted by the network as the truthful chain, Alice has to make an effort to make her fork, b, longer than the previously accepted fork a, containing her pizza-payment. The probability of winning the leader-election and thus the right of proposing a new block increases with the amount of voting power. Statistically, only a $> 50\,\%$ majority of the voting-power can keep up winning the election over time. Nevertheless, it is not impossible for Alice to make some progress with only a small percentage of the voting power. This is why k blocks have to be chained after block 2_a for Bob to be assured that Alice paid for her pizza, basically waiting for fork a to be provided with a head-start to any double-spend attack aimed at a transaction in block 2_a. Bob thus waits a while with serving Alice her pizza, allowing other customers to make transactions and mine blocks. Consequently, after k blocks have been mined, Alice has to win the leadership-election for k consecutive times to over take fork a. Statistically, if Alice continuously owns $> 50\,\%$ of voting-power, she is certain of a successfully executed double-spending attack. If so, Alice ate here pizza, while not paying for it. With this premise, and assuming that the total voting-power in the network is large, the key-concept of a consensus protocol is that it should counter the fraudulent use of forged identities. The consensus protocol requires of Alice real-world resources in the form of computing power; translated into

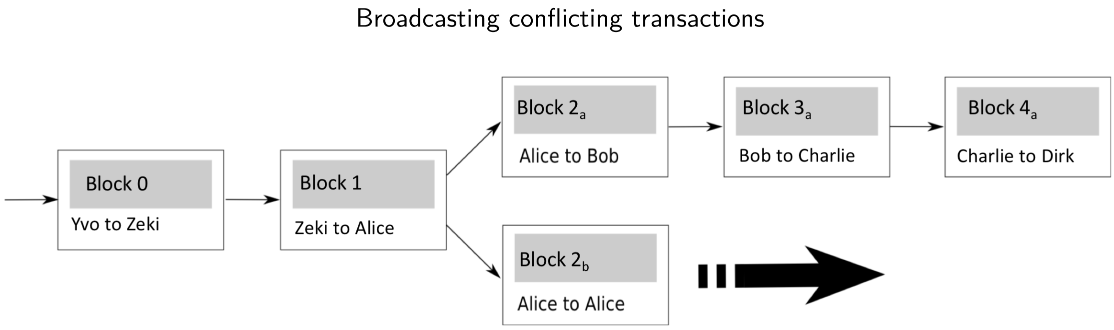

Figure 2-8: Bob is an owner of a pizza-restaurant and Alice is a customer. After block 2_a is proposed and accepted by Bob, Alice is allowed to eat her pizza, paid for by token transfer on the Blockchain. If Alice, after finishing her pizza, tries to propose a new block 2_b at the height of her original pizza-payment, in which her pizza-payment does not exist. A fork is created, and a leader-election race initiated between Alice and the network is initiated. Figure from [148], but modified.

hardware investments and electricity, this amounts to real-word fiat-resources. An attack on consensus of Alice by trying to represent here entity by multiple identities (Sybil attack) to gain artificial voting power in a consensus vote-count is thus not viable. The consensus protocol makes it impossible for Alice to gain $> 50\%$ voting power by fraud.

Solving double-spending: Consensus protocols

In order to give voting power proportional to entities instead of identities, a consensus protocol trades voting power for a task that consumes real-world resources. For this a proof is needed that is generated by a 'Proof-of-X' scheme. Multiple ways of measuring the contribution of the entity are possible. Among the best known are Proof of Work (PoW) and Proof of Stake (PoS). PoW makes use of the computing power of the hardware of the node. PoW is used most often and by the better known Blockchains but is wasteful w.r.t. real-world resources. PoW was first introduced in [150] and later adopted by Bitcoin [30]. PoS works by counting the invested stake of each entity in the Blockchain; the larger the amount of so-called coin-age, the larger the chance of winning the leader-ship election and to suggest a new block to the chain.

A cryptographic hash function $H(m) = h$ is a one-way mapping from a variable-length input bit string m to a fixed-length output string h: h is called the hash of the message m. The mathematical puzzle to be solved in a PoW scheme is based on a hash-function. An in-dept look at the commonly used and yet unbroken hash function SHA-256 is given in [151]. A cryptographic hash function has three distinct features:

- It is computationally simple to compute a hash value from any amount of alpha-numerical piece of data m.
- It is computational unfeasible to compute the original alpha-numerical piece of data m from its hash value.
- The probability of two pieces of data m_1 and m_2, with $m_1 \neq m_2$, having the same hash is beyond negligible: $H(m_1) \neq H(m_2)$.

A celebrated consequence of these features is that a small change in the input data m results in an uncorrelated change of its hash value. PoW requires the node to compute a hash value of the block-format m_{block} that the node wants to propose with a certain structure, such that h_{block} is a string beginning with a certain amount of zeros. The data to be hashed is the block information. To change the hash value, a small piece of information (a nonce) is added into the block-format data. At each try, the nonce is changed to a different value and thus a different hash value is yielded. Since it is impossible to predict what nonce will yield a block hash with the right structure, the only way is to try. The first node that yields a rightly structured hash h_{new} wins. Other nodes then easily verify whether this node truly should be the winner by recreating h_{new} using the provided nonce and block-format provided by the winning node. The proposed block then is adopted by the network and thus added to the Blockchain, adding the transactions included in the new block to the public ledger.

By ordering transactions into blocks and adding blocks behind each other, a network-wide consensus is reached on an arrangement of blocks, similar to a time-stamping server. Since the hash value h_{prev} of the previous block is included in the block-format of the new block, an unbreakable link is made from the most recent block to previous block. Without this previous block hash, the block is not deemed valid by the network, who again can easily verify by recreating the new hash value h_{new} using the previous block-format and h_{prev}. This mechanism creates a trail from the newest block all the way back to the genesis block, ordering the blocks in time in the process.

Blockchain transactions

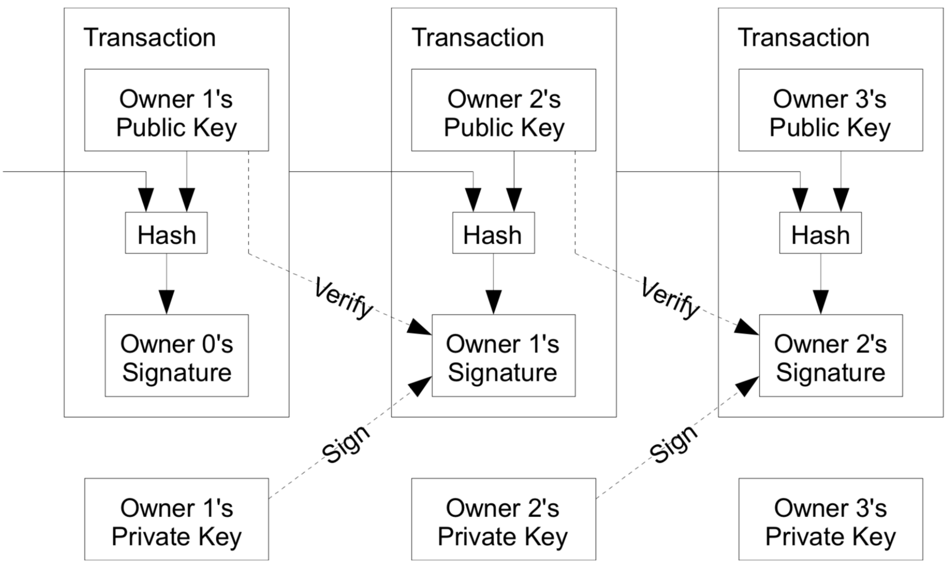

Figure 2-9: Blockchain uses uniquely identifiable tokens to represent value and transactions to move around this value among users. Transactions are digital 'contracts' stating ownership of tokens, signed using **PKI!**. A trail of transactions regarding a token is equal to a certificate of ownership of that token. In order to verify whether a pretender is truly owner of a token, one need to be able to trace back the trail from genesis up-to the current moment and verify the trail ends up with. The figure is taken from [30].

To transfer value between Alice and Bob, both need a virtual wallet, consisting of a public-private key-pair for signing transactions. The transaction-format includes a previous transaction hash $h_{\text{prev,tx}}$ to create a easily verifiable trail back to the genesis transaction, much like the time-stamping mechanism for blocks. Alice proves that she is able to to mandate over the value-transfer referenced on the input side by providing her public-key and a signature. The network rejects the proposed transaction if it becomes apparent that Alice does not own the needed amount of tokens. In [152] and [153], extended information on the method of signing a transaction using the Elliptic Curve Digital Signature (ECDS) algorithm is given. The transaction process is visualized in fig. 2-9. Requirements of a Blockchain platform are the following:

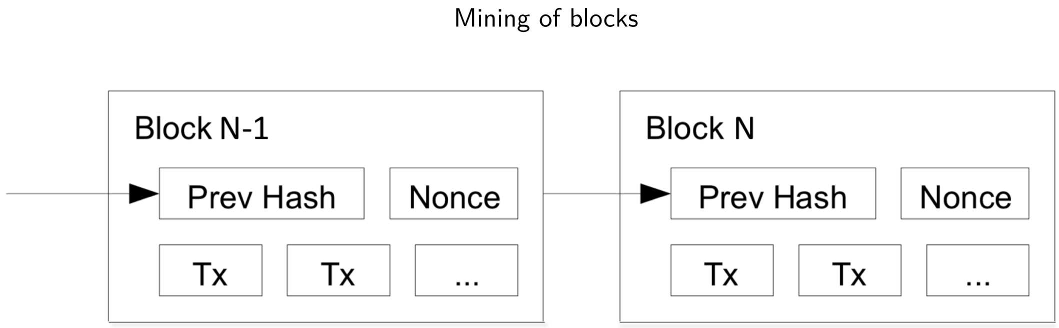

Figure 2-10: All participating nodes collect transactions by listening in on the P2P network. When collected enough transactions, they form a valid block by preforming resource-intensive iterations on the consensus protocol. The first node to present a valid solution wins the leader-election and is allowed to propose their block to the Blockchain, receiving a financial incentive in the process. The figure is taken from [30].

- **High transaction throughput**. With every node in the network validating every transaction, validation rate is low with Blockchains such as Bitcoin and Ethereum [154]. Scaling issues are widespread.

- **Low transactions fees**. Aim is to have near real-time transaction among nodes to allow for near real-time energy trade within the micro-grid. Following the duration of deployment of primary control services as a guideline, the maximum amount between each algorithm time slot is 15 minutes [88]. Transaction costs should not exceed the added value of the Blockchain.

- **A resource-light consensus protocol**. PoW intentionally wastes energy during its leadership election. This is not a sensible doctrine when *trading* energy, since again, costs should not exceed added value. PoS, the Tangle [155], or a permissioned practial Byzantine Fault Tolerance (pBFT) network offer a better solution.

The platform Ethermint provides these criteria, as it utilizes the on pBFT based consensus protocol PoS. A detailed explanation of PoS is given in [156]. In [157], a lengthy comparison is made between PoW and PoS schemes.

Smart-contracts: verified and decentralized state-change

A smart-contract is a computer protocol to digitally facilitate and enforce negotiation between agents. It can be triggered by making a transaction to it, causing the smart-contract to execute independently and automatically on every node in the network, according to the data that was included in the triggering transaction [158].

By deploying a computer program on Blockchain and allowing state-changes through Blockchain transactions, the contract is honoured in a decentral paradigm with distrusting agents. Solidity is a contract-oriented programming language developed by the creators of Ethereum. As of this date, it is the most practical approach to writing Blockchain deployed smart-contracts, as it has the most extensive documentation and is backed by a strong developing community. In section 3-4-1, we present a smart-contract capable of accounting a zero-sum game between agents in a micro-grid, keeping track of a promise system and providing a time-stamp server in order to recognize.

2-4-2 Application of Blockchain in energy-trade

Research of Blockchain applied in energy-trade has only recently picked up pace. Most existing work has been on permission-less, public platforms such as Bitcoin and Ethereum, focusing mainly on interesting problems such as security, privacy and scalability. The ability of participants on a Blockchain network to reach an universal agreement on a certain state while in the presence of an asynchronous network or malicious nodes is valuable in decentralized optimization. Nevertheless, parallels made in literature with distributed energy trading are few, with examples as [159] and [160]. We slightly modify the realizations of [159] to find requirements to an EDP solving distributed algorithm:

- Aggregation of information should be protected against cyber attacks or malicious agents.
- Agents in the network should have means to verify payments to and from their wallets.
- Essential network elements of distributed optimization such as brokering and negotiation need to take place among agents on a secure and 'trust-less' platform.

In [160], the authors propose NRGcoin, a decentralized digital currency generated by smart-meter that prove they supplied back energy, generated in household DERs. Incentive given is proportional to supply and demand, thus achieving a DSM mechanism, flattening energy peaks throughout the grid. However, extensive testing is in order to prove the effectiveness of the system. The authors of [159] approach the problem of integrating disruptive fleets of EV's in small-scale grids by introducing a P2P energy trading model. Trade is auction-based with a set of central auctioneers that also serve as a consortium among which a Blockchain platform is created. Conclusively, not much literature is available in the field of Blockchain application in energy trading. In [158], distributed control is achieved by function-blocks deployed as smart-contract to enable edge-computing. a methodology that shows more similarity with our proposed smart-contract in section 3-4-2.

Chapter 3

EnergyBazaar: a decentralized energy market

Although acting independently, all household agents are charged with the collective task of maintaining a stable micro grid: when supply and demand are balanced. Introducing storage capacity in the grid allows a buffer in both: the mapping of production to supply and demand to consumption, such that this margin can be used for economical optimization. The goal of the distributed optimization is to allow for free-market pricing.

3-1 Problem formulation

The micro-grid Economic Dispatch Problem (EDP) consists of taking decisions on how to optimally schedule charging and discharging of Energy Storage System (ESS)s, meeting the micro-grid balance in demand and supply, section 2-1-3. In addition, we do not want to include a central controller subject to a central control law that steers agents with a certain behaviour towards an equilibrium, such as proposed [73]. Instead, we want to design the agents behaviour by modeling their utility function; such that they autonomously steers themselves towards an equilibrium. The micro-grid is considered in a fail-state when it needs the macro-grid for energy-import (deficits) or load-shedding (overflows). The goal is minimized deficit while economical optimization of agents $a \in \mathcal{N}$ and while dynamical constraints are met. Additionally, the battery dynamics pose a constraint. The challenge for the community as a micro-grid, $\mathcal{B}_{\text{mg}}$, is to minimize the total deficit in the micro-grid:

$$\mathcal{B}_{\text{mg}} = \min \frac{\sum_{k=0}^{t_d} E_{\text{deficit},a}(k)}{k} \quad \text{subject to:} \tag{3-1}$$

$$\sum_{j \in J} E_{\text{supply},j}(k) - \sum_{i \in I} E_{\text{allocation},i}(k) = 0, \tag{3-2}$$

$$P_{\min,a} \leq P_a(k) \leq P_{\max,a} \quad \forall a \in \mathcal{N}, \tag{3-3}$$

$$SOC_a(k+1) = SOC_a(k) + \eta \cdot E_{\text{flux},a}(k) + SOC_{d,a} \quad \forall a. \tag{3-4}$$

The optimization problem is described by eq. (3-1) and is subjected to three requirements: The total flux of energy in the system on time-step k is equal to zero, see eq. (3-2); the actuation of the ESS installed at households cannot exceed its saturation limits and the State of Charge (SOC) of all batteries are subject to its dynamical model, eq. (3-4).

3-2 Modelling a micro-grid community

We model the micro-grid with an agent-based model, see appendix B-1 for a layout of the system. Assumptions are made for the agent-based system's environment and its agents; respectively the micro-grid and its households. First, we discuss the assumptions and claims regarding households situated in the micro-grid. Afterwards, the micro-grid itself is discussed.

3-2-1 Smart households

A very significant assumption made in this research is that households are rational actors that pursue economical gain. We investigate the validity this assumption in the following discussion.

Rationality of agents

The classical model of economy is a concept introduced by Adam Smith published in [161]. The classical model described the world as actors in constant pursue of welfare, but constrained by their empathy to others. Opposing this, the neoclassical model of economics simplifies economy down to a set of actors, either firms or households, each respectively maximizing profit and utility, with no regard to empathy. All actors are assumed to interact in perfectly competitive markets [162]. In [162], the 'rationality axiom' is introduced; the economic agent maximizes its own utility or self-interest, a premise used throughout this thesis for modeling human behaviour. However, the rationality axiom is strained under criticism, since it exempts altruism as a drive for human behaviour. Game-theoretical rationality therefore is loosing ground in softer area's as political science [163]. Nevertheless, the argumentation to use the rationality axiom is two-fold:

- It is assumed that micro-grids are formed within a neighborhood with negligible social inequality, excluding altruism from our model. In case this assumption fails, methods to mitigate the social inequality are needed, methods provided in [164].
- With assuming rationality, it is possible to anticipate actions of players, the model becomes deterministic. It allows designing an utility function that captures the behavioural dynamics of all agents, making analysis practical [165].

Although a community can be considered as a social entity were cooperation takes place among its neighbors, economic gain can still be assumed to be a personal drive for agents in the system. Within the scope of this thesis, agents are modelled to be non-cooperative in their pursuit of profit, such that agents will compete with each other in a free-market economy. Making use of element of non-cooperative gametheory, we use the Nash equilibrium to express the utility of the players. The Nash equilibrium is used because in a free-market, prices are driven by supply and demand, i.e. players respond to the situation within the environment, that is comprised of the strategies of all other players [29]. Irrational behaviour such as discrimination, induced for example by the Indian caste system [164], is not considered. The primary drive for each agent is to optimize its revenue or decrease costs. We design a mechanism that ensures the stability of the grid while abstaining to force its members into alignment with a global pursuit that conflicts with personal goals.

Household characteristics

Households are given three characteristics: energy consumption, storage capacity and energy production by Photo Voltaic (PV) panels. We assume all Distributed Energy Resources (DER) units to have equal characteristics and efficiency. $E_{\text{consumption},i}$ is the amount of energy needed to saturate the consumption of household i. The load of a household is not variable since load-shifting (e.g. as done in [112]), does not lie within the scope of this research. $E_{\text{production},i}$ is the energy produced by Distributed Generation (DG) units, modeled as PV panels. Only if $E_{\text{production},i}$ is greater than $E_{\text{consumption},i}$, the surplus $E_{\text{surplus},i}$ is traded on the local energy-market, because using self-produced energy is more economical. This is due to the incentive given to consumers with a smaller $E_{\text{demand},i}$ according to proportional allocation, see section 3-2-2. To satisfy $E_{\text{demand},i}$, a rational buyer will allocate its own $E_{\text{production},i}$ first. The capacity of the household battery, $E_{\text{capacity},i}$ represents the amount of energy that can be stored in each house. Each agent will aim to maintain a preferred SOC, $SOC_{\text{preferred}i}$. This level is determined by a prediction model and acts like a set-point parameter the agent uses to determine its trading-behaviour; the gap between the actual SOC, $SOC_{actual i}$, and $SOC_{\text{preferred}i}$ will influence the size of $E_{\text{demand},i}$. Thus, the household battery acts as a buffer and mediator between demand and imported supply. $E_{\text{demand},i}$ is thus the demand requested by agent i from the micro-grid to maintain $SOC_{\text{preferred}i}$

Prediction of supply and demand patterns

In [72] prediction on future supply and demand is not included. In [72], the law of diminishing return, compared to direct revenue, is the sole drive for selling-agents to decide on their strategies. We explore the inclusion of prediction to actively anticipate coming scarceness or abundance of energy in the micro-grid.

Information on agent specific consumption and production is sensitive and cannot be simply shared among the community. Agents thus can only predict future supply and demand based on data from their own household and on data generated by the community as an entity, such as global equilibria on nominal bidding price c_n and sharing factor w_n. In addition, open-source data such as the weather forecast are used by agents. The number of agents participating in the micro-grid is known by all agents, analogous to an permissioned network.

Smart-meters and the communications network

It is assumed that smart-meters are able to perform accordingly and deployment of smart-meters is (economically) feasible, discussed in [47]. We assume a network that is synchronous: there are no agents lagging due to latency in the network and broadcasts are not jammed.

3-2-2 The micro-grid

In this section, we discuss the assumptions made while modelling the micro-grid.

PV panels in the Californian sun

The test-data used to model the community originates from Laboratory for Advanced System Software (LASS). LASS offers an open-source repository for smart-home data [166]. For 114 single-family homes the consumption has been monitored through 1-minute interval data-points. For production, 1-minute interval monitored solar panels situated in California, USA are used to provide the generation data [167]. The pattern in the consumption data is highly erratic, and does not compare to standard average household spikes in morning/evening times. However, this spike-pattern is proven to exist [168]. Thus, the behaviour of the algorithm should be analyzed with inclusion of morning/evening spikes. These spike characteristics are added using a sine-wave function. The finalized data spans a week for both production and consumption. We assume that generation capacity in the micro-grid is as high as energy consumption, the very basic requirement for a self-sufficient system.

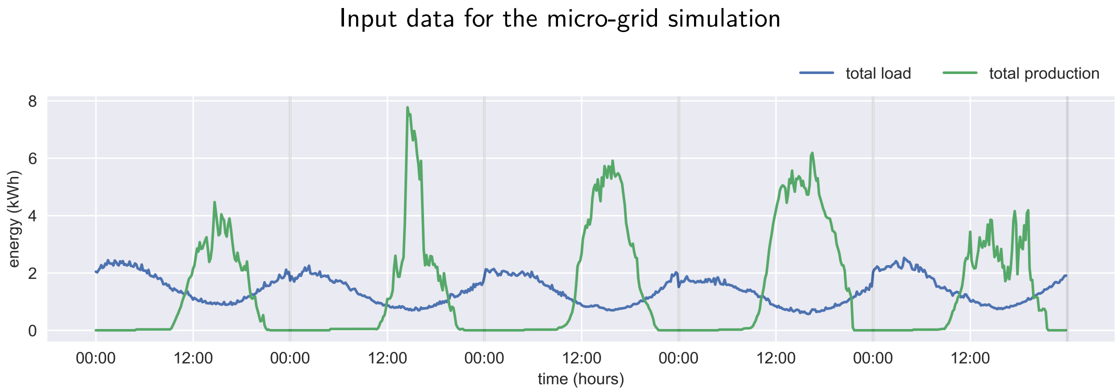

Figure 3-1: Total production and consumption of energy in a micro-grid with 12 agents. We capture the characteristics of the duck-curve, see fig. 1-2: a constant base-load with spikes in morning and evening; production peaks during solar hours and drops to zero during the nights. Data-set, after grooming, has a 5-day duration, with 1440 data-points per day.

Proportional Allocation

Proportional allocation is a method of distribution of goods from a seller to potential buyers. We use proportional allocation in our implementation of EnergyBazaar, see section 3-3. The allocated share to agent i is $a_i(x, y)$, when x is the bid of i and y is the sum of all other bids of agents, $\mathcal{I}_{/i}$:

$$a(x, y) = min\left(x, \frac{x}{x+y}K\right).$$

This method ensures that buyers will never receive zero goods, opposed to, for example, linear allocation [169]. In addition, the more agent i bids relative to the total other bids y, the bigger the share of K is allocated to i. Usually, x and y would represent the quantity of the order. In EnergyBazaar, this is substituted with the bidding price per unit of energy of buying agents $\in \mathcal{I}$. Not using proportional allocation, buying agents $\in \mathcal{I}$ would simply order more than the actual demand $E_{\text{demand},i}$ without consequences. Now, a higher allocation means a higher bidding price c_i. This is fair in a isolated system where energy is considered a scarce resource; there is an incentive to have a low $E_{\text{demand},i}$ thus introducing an incentive to invest in increasing $E_{\text{production},i}$ or lowering E_{load}, resulting in a more sustainable community.

When using proportional allocation, it is preferred to decrease $E_{\text{demand},i}$, for it allows the agent to lower the share of energy allocated $x/(x + y)$ by lowering x. Since x is a bidding price, it is preferable for it to be low, see eq. (2-29). This reinforces the claim that agents will first use $E_{\text{production},i}$ to (partially) satisfy $E_{\text{load},i}$, reducing or even satisfying $E_{\text{demand},i}$.

Over- and under-capacity of the micro-grid

A situation can occur wherein the community's combined production eventually overflows the total storage capacity in the grid:

$$\sum_{i=1}^{N} E_{\text{supply},i} + \sum_{i=1}^{N} E_{\text{actual},i} > \sum_{i=1}^{N} E_{\text{capacity},i}. \tag{3-5}$$

Either the excess energy has to leave the grid by exporting to the macro-grid, or production has to halt. An approach to production-shedding coordination for DER in a community during over-production beyond the scope of this thesis. For research in this area, see [79].

$$\sum_{i=1}^{N} E_{\text{supply},i} + \sum_{i=1}^{N} E_{\text{actual},i} < \sum_{i=1}^{N} E_{\text{demand},i} \tag{3-6}$$

On the other hand, it can happen that the combined total supply of the community cannot satisfy its demand, see eq. (3-6). In this case, energy has to be imported from an adjacent grid, or operations will have to halt. The community can supply its total deficit by importing energy, but either-way this case is considered as a fail-event for the community:

- The algorithm is not capable of distributing the energy efficiently through the system or does not provide enough incentive to store enough energy to survive periods of scarcity. Individual agents witness depletion-events.
- The micro-grid hardware failed: the production of energy or storage capacity in the isolated micro-grid is not high enough to survive periods of scarcity and has to import energy from the macro-grid. There is consistent deficit of allocated energy throughout the micro-grid.

Connection to the Macro-Grid.

We make an assumption of semi-isolation: local trade within the grid is motivated by a two-fold of reasons; firstly, transmission costs within grid will be more efficient due to smaller transmission costs and second, dependence and autonomy of the micro-grid is increased, reducing the demand on the national grid [29]. Only in case of depletion or overflow, see **??** and eq. (3-5), the macro-grid will either provide or adsorb energy.

3-3 Mechanism design: the EnergyBazaar algorithm

EnergyBazaar establishes interaction between buying and selling agents, ensuring that enough energy is stored within the micro-grid to provide a smooth and reliable supply throughout time, depending on E_{demand}. Time is modelled as discrete time-steps k of 10-minute intervals. At each time-step, a game is played between players $n \in \mathcal{N}$, either classified as a buyer $i \in \mathcal{I}$, or as seller $j \in \mathcal{J}$, introducing a hierarchical structure. Buyers are deciding among themselves on a bidding-price while sellers react by fine-tuning the amount of the amount of energy willing to supply to the community. The action-space a_i of buyers i, at k is governed by utility function U_i. Its best-response strategy is c_i; the bidding price. Meanwhile, the action-space a_j of seller j is governed by utility function U_j, with the sharing-factor w_j as strategy. Both utility functions are designed to capture rational behaviour of the agents. The community is assumed to be non-cooperative and rational, letting agents to pursue individual economical gain.

3-3-1 Dynamics of the game

With the assumption of uncontrollable energy load $E_{\text{consumption},n}$, the trading-algorithm is designed to portion the amount of stored energy passed from time-step (t) to $(t+1)$. Nominal sharing factor w_n governs the share of available energy in the grid to be stored or to the be spent. For a buying household, the demanded energy will not always be fully allocated. In this case, its battery will supply the remainder to satisfy $E_{\text{consumption}n}$. A discrete-time model for the total amount of energy available in the system:

$$E_{\text{stored,total}}(t+1) = \left[(E_{\text{stored,total}}(t) - E_{\text{consumed,total}}(t) + E_{\text{produced,total}}(t))(1 - w_n(t))\right]. \quad (3\text{-}7)$$

At time-step t, a game is played to determine the nominal sharing factor, $w_n(t)$. At the start, a participating player is either a buyer i or seller j: according their production, consumption and the preferred SOC of its battery. Ultimately, $w_n(t)$ is the control variable that influences the state of the micro-grid, seen in eq. (3-7). $w_n(t)$ is to be determined by the interaction of agents. A hierarchical structure is introduced to separate a buyers-level game from a sellers-level game, respectively optimizing in rounds to find global equilibria $\mathbf{c}_i^*(k_{\text{final}})$ and $\mathbf{w}_j^*(k_{\text{final}})$, with k being the number of the round played, within game at time-step t. The EnergyBazaar game EBZ, played at k, is defined as:

$$EBZ(t) = \begin{bmatrix} c_i(k_b) \\ w_i(k_s) \end{bmatrix} = \begin{bmatrix} \text{argmin}_{c_i} \mathcal{U}_{\text{buyers}} \\ \text{argmax}_{w_j} \mathcal{U}_{\text{sellers}} \end{bmatrix}, \quad (3\text{-}8)$$

$$= \begin{bmatrix} \gamma_i \cdot \left| E_{\text{demand},i} - E_{\text{allocation}i}\big(w_n(k_s-1), \mathbf{c}(k_b)\big) \right|^{\lambda_{i,1}} + \Big(C_i\big(w_n(k_s-1), \mathbf{c}(k_b)\big) \Big)^{\lambda_{i,2}} \\ \gamma_j \cdot \left| SOC_{\text{gap},j} - E_{\text{storage},j}(w_j) \right|^{\lambda_{j,1}} + \Big(R_j\big(c_n(k_b), \mathbf{w}(k_s)\big) \Big)^{\lambda_{j,2}} \end{bmatrix}. \quad (3\text{-}9)$$

In eq. (3-9), C_i stands for the costs made by buyer i and R_j stands for the share of total revenue seller j receives. The input to the game is $E_{\text{surplus}}(t)$, the nominal (grid-wide) sharing factor $w_n(k_s-1)$ of the previous step and prediction data on the energy pattern of the micro-grid. The result is $w_n(k)$, used to determine $E_{\text{supply}}(k+1)$, the energy supplied for that time-step. Round k, consisting of respectively the buyers-level k_b and sellers-level k_s is initialized with values $c_i(k_b-1)$ and $w_j(k_s-1)$. At $k=0$, random values within reasonable bounds are generated (convex-optimization guarantees the discovery of a global-optimum).

3-3-2 Predicting abundance and scarcity: selling or storing

The household ESS plays a role in determining the amount of surplus energy available to the buyers, or energy demanded by buyers. The ESS gives incentive to buy or sell energy by pursuing a certain preferred SOC:

$$E_{\text{surplus},j}(k) = E_{\text{production},j}(k) - E_{\text{consumption},j}(k) - \big(SOC_{\text{preferred},j} - SOC_{\text{actual},j}\big). \quad (3\text{-}10)$$

The value $E_{\text{soc preferred},j}$ is deduced from the difference of the actual SOC of agents battery and the preferred SOC. The preferred SOC is determined by evaluation of the energy needed to survive until the prediction-horizon h:

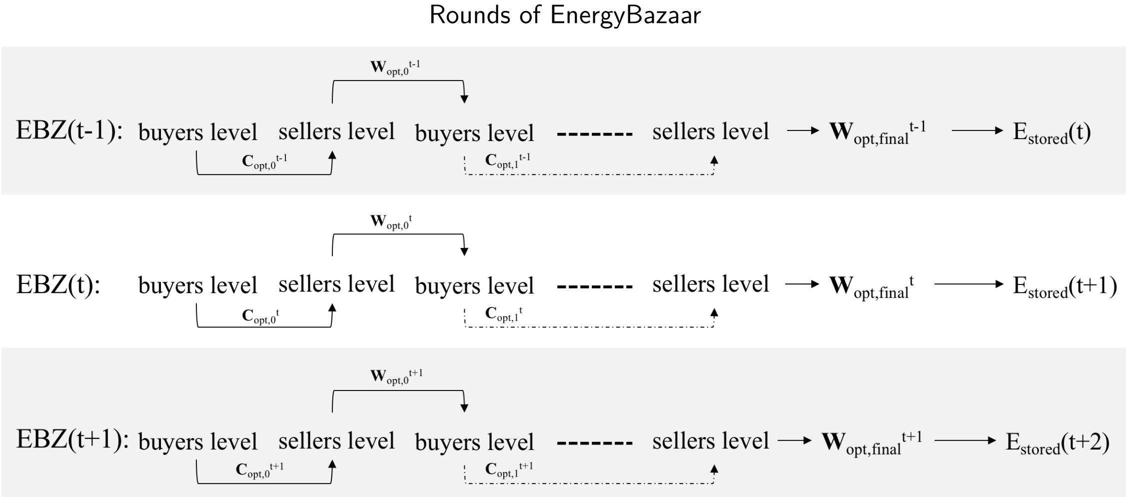

Figure 3-2: Progress of rounds and time of the EnergyBazaar algorithm. At each time-step k, an EBZ game is player to yield an w_n, that decided the amount of energy that is left in the micro-grid. Tuning the game is done by giving agents the right utility functions such that supply and demand are balanced while social welfare is optimized.

$$\hat{E}_{\text{balance},j} = \sum_{k_p=0}^{h} \hat{E}_{\text{production},j}(k_p) - \sum_{k_p=0}^{h} \hat{E}_{\text{consumption},j}(k_p) \tag{3-11}$$

$$SOC_{\text{preferred},j} = \begin{cases} \hat{E}_{\text{balance},j} & \text{if } \hat{E}_{\text{balance},j} > 0 \\ 0 & \text{if } \hat{E}_{\text{balance},j} \leq 0 \end{cases} \tag{3-12}$$

Here, h is the distance of the prediction horizon the agent uses. Receding horizon h_i is the number of steps the agent anticipates on. In eq. (3-12) this method is used as well in a micro-grid context. Prediction $\hat{E}_{\text{prediction}}$ is retrieved from the data-set, but this should be extended on with real prediction curve-fitting on past data. As discussed in [170] and [171], neural networks are well-suited for this task. That said, more simplistic methods could prove as efficient, due to the easily recognizable patterns within the grid [172], see section 2-2-3.

3-3-3 Buyers-level game

Buyers start off by playing a distributed optimization game using information on demand, E_{demand} and energy supply by sellers, E_{supply}. Since sellers did not yet decide on a w_n, this it is randomly initialized within the domain $[0, 1]$, creating a random E_{supply}. With a convex utility function, buyers can converge to a buyers-level Nash equilibrium, see the proof in appendix A-1. Buyer i needs information on the outcome of the sellers game with which the buyers game is initialized, $\mathbf{w}(k_{b,opt})$, as well as information on utility function $\mathcal{U}_i$ and its corresponding optimization is given:

$$\mathcal{U}_i(\mathbf{c}, w_n) = \gamma_i \cdot \left| E_{\text{demand},i} - E_{\text{supply}} \cdot \frac{c_i}{\sum_{l \in \mathcal{I}} c_l} \right|^{\lambda_{i,1}} + \left(E_{\text{supply}} \cdot \frac{c_i^2}{\sum_{l \in \mathcal{I}} c_l} \right)^{\lambda_{i,2}} \tag{3-13}$$

$$\mathcal{B}_i = c_i^*(k_b) = \underset{c_i}{\operatorname{argmin}} \, \mathcal{U}_{\text{buyers}}\big(\mathbf{c}(k_{b,opt} - 1), w_n(k_s - 1)\big). \tag{3-14}$$

In eq. (3-14), $\mathcal{B}_i$ is the best response of buyer i. Logically, buyers want to close the gap between their energy demand $E_{\text{demand},i}$ and the energy that is allocated to the agent, $E_{\text{allocation},i}$, as much as possible, while minimizing their costs of doing so. The parameters $\lambda_{i,1}$ and $\lambda_{i,2}$ are set to two and one to make the utility function convex, while γ_i is a weight used to express preference for either deficit minimization or costs suppression. E_{demand} consists of the in- and out-flux of energy and the difference between the actual and preferred SOC of its household battery. $E_{\text{allocation},i}$ is the amount of energy allocated to agent i through proportional allocation derived from the total supply at (k_s-1), E_{supply}:

$$E_{\text{demand},i} = E_{\text{load},i} - E_{\text{production},i} + (SOC_{\text{preferred},i} - SOC_{\text{actual},i}), \tag{3-15}$$

$$E_{\text{allocation},i} = E_{\text{supply}} \cdot \frac{c_i}{\sum_{l\in\mathcal{I}} c_l}. \tag{3-16}$$

Within $E_{\text{demand},i}$, the preferred battery SOC is accounted for; agent i uses battery energy to supply energy to the load of its household. Since the load is invariable, the agent has to make sure it can consistently provide demanded energy. It needs to anticipate on the necessary SOC of its battery. For this, the agent combines a prediction model on its own load, on E_{supply} from sellers and on $E_{\text{demand}i}$ from buyers in the community. Value $SOC_{\text{preferred},i}$ is the SOC that represents this minimum amount of energy needed to sustain operations on the respective time-step k. $SOC_{\text{preferred},i}$ is a set-point variable that is used by the agent to control $E_{\text{demand},i}$. By changing $SOC_{\text{preferred},i}$ in the next buyers-round (k_b+1), the agent is able to close the gap between $E_{\text{demand},i}$ and $E_{\text{allocation},i}$, the same way a buyer would artificially increase its order in a traditional proportional allocation game [169].

3-3-4 Sellers-level game

E_{supply} is decided in the sellers game. Rational seller $j \in \mathcal{J}$ wants to optimize revenue gained by selling energy in the buyer-seller game. Decisions on sharing-factor vector for all sellers, $\mathbf{w}$, governs total supply E_{supply}, the share of total surplus energy E_{surplus} to be supplied. $\sum_{j\in\mathcal{J}} E_{\text{surplus}j} \cdot w_j$ can also be expressed as $E_{\text{surplus}} \cdot w_n$, with w_n as the community-wide nominal sharing factor. Utility function $\mathcal{U}_j$ and its corresponding optimization is given:

$$\mathcal{U}_j(\mathbf{w}, c_n) = \gamma_j \cdot \left|SOC_{\text{gap},j} - E_{\text{surplus}}(1-w_j)\right|^{\lambda_{j,1}} - \left(R_{\text{direct}} \frac{w_j}{\sum_{l\in\mathcal{J}} w_l}\right)^{\lambda_{j,2}} \tag{3-17}$$

$$\mathcal{B}_j = w_j^*(k_s) = \underset{w_j}{\operatorname{argmin}}\ \mathcal{U}_{\text{sellers}}(\mathbf{w}(k_{\text{opt},s}opt), c_n(k_b-1),) \tag{3-18}$$

Utility function $\mathcal{U}_j$ is a trade-off between storing energy and selling energy. The share to be saved for future sales is $(1-w_j)$ and thus w_j is the share to be directly supplied to the community for direct revenue. Total revenue R_{direct} is governed by total energy allocated to buyers, $\sum_{i\in\mathcal{I}}(E_{\text{demand},i} * c_i)$ and the nominal price c_{n}, decided upon by the buyers urgency for energy in section 3-3-3. $\lambda_{j,1}$ and $\lambda_{j,2}$ are both set to two to make function $\mathcal{U}_j$ convex. The total direct revenue R_{direct} is then divided between sellers, proportional to the share of total E_{supply} that seller j supplies. The potential share of predicted revenue seller j will receive is the utility gained by storing energy. Besides pursuing revenue, sellers want to replenish their batteries by covering $SOC_{\text{gap},j}$ with $E_{\text{surplus},j}(1-w_j)$. The weight γ_j expresses the preference of either covering the storage gap or selling for revenue. Absolute values are taken since no incentive should be given to store more energy than needed.

3-3-5 Interaction between buyers and sellers

Since both utility functions $\mathcal{U}_i$ and $\mathcal{U}_j$ are convex functions, local optima are found through convex optimization. For this, Sequential Least Squares Programming (SLSQP) is used in both games. SLSQP makes use of the Han-Powell quasi-Newton method [173]. A merit function $\mathcal{M}$ is constructed that makes a trade-off between loyalty to constraints and utility maximization [173]. Optimization should have been constrained, see section 3-3-5 but implementation in Python using `scipy.optimize` was not successful. The control variable w_j is bounded in the domain $[0, 1]$.

Buyers communicate value c_n to the sellers to give insight in the direct revenue R_{direct} to be made. The nominal price c_n of all bidding prices $\mathbf{c}$ is defined as:

$$c_n = \frac{\sum_{i\in\mathcal{I}} \left(E_{\text{allocation},i} \cdot c_i\right)}{\sum_{i\in\mathcal{I}} E_{\text{allocation},i}} \tag{3-19}$$

Subsequently, the sellers use c_n within their sellers-level round (k_s). The sellers-level game produces w_n which is defined as:

$$w_n = \frac{\sum_{j\in\mathcal{J}} \left(E_{\text{surplus},j} \cdot w_j\right)}{\sum_{j\in\mathcal{J}} E_{\text{surplus}j}} \tag{3-20}$$

Finally, w_n is plugged into the buyers-level game, providing insight in the amount of E_{supply} available in the community, given the fact that E_{surplus} is know by all. In a decentralized paradigm, establishing both c_n and w_n is a task of a smart-contract: agents update their private state within the smart-contract with respectively their c_i or w_j and a time-stamp k, after which the smart-contract is able produce public values c_n and w_n.

Actuator saturation of ESS

To constraint the optimization in order to satisfy the contract-based requirement to primary control, discussed in section 2-1-4, we should pose upper-bounds to c_i and w_j. An approach is to algebraically derive these upper-bounds from equations of $E_{\text{allocation},i}$, and $E_{\text{supply},j}$. Upper-bounds for discharging and charging are:

$$E_{\text{supply},j} = E_{\text{surplus},j} \cdot w_j \qquad \leq P_{max,j}, \tag{3-21}$$

$$E_{\text{allocation},i} = E_{\text{supply,total}} \cdot \frac{c_i}{\sum_{i\in\mathcal{I}} c_a} \quad \leq P_{min,i}. \tag{3-22}$$

For $w_{max,j}$ and $c_{max,i}$, an upper-bound is algebraically derived:

$$w_{max,j} = \frac{P_{max,j}}{E_{\text{surplus},j}}, \tag{3-23}$$

$$c_{max,i} = \frac{\sum_{a\in\mathcal{N}/\{i\}} c_a}{E_{\text{supply,total}} - P_{max,i}}. \tag{3-24}$$

Here, $c_{max,i}$ would only be imposed when $E_{\text{supply,total}} - P_{max,i} > 0$. An issue arises when implementing upper-bound $c_{max,i}$ in a hierarchical game; buyers respond to each other by altering their price. An constraint on bidding price c_i that depends on the sum of all other bidding prices, expressed as $\sum_{a\in\mathcal{N}/\{i\}} c_a$, will eventually decrease c_i to zero. In eq. (3-24), we clearly see the relationship between c_i and $\sum_{a\in\mathcal{N}/\{i\}} c_a$. Since $w_{max,j}$ depends on local values, we do not experience this issue at the sellers-level game. We further discuss the method and the unconstrained behaviour of ESSs in section 4-1-3. Note that chapter 4 discusses results of unconstrained optimization.

3-3-6 Proof of convergence: existence of a Nash equilibrium

We use a Nash equilibrium as solution concept, motivated in section 2-3. A Nash equilibrium is a situation wherein all players cannot further improve their utility $\mathcal{U}_i$ by changing their personal strategies c_i^* in response to all other player's strategies:

$$\mathcal{U}_i(c_i^*, \mathbf{c}) \geq \mathcal{U}_i(c_i', \mathbf{c}) \quad \forall i \in I \tag{3-25}$$

For player i to find the optimal response to the strategies of others, $-i$, it optimizes utility function U_i over c_i, its game variable. For agents to converge in a round-based game, it is essential that U_i is convex, since convex optimization guarantees a unique local optimum [72]. To prove the a function to be convex, the second derivative is required to be positive.

$$\frac{\partial^2 \mathcal{U}_i}{\partial c_i^2} > 0 \tag{3-26}$$

$$\frac{\partial^2 \mathcal{U}_j}{\partial w_j^2} > 0 \tag{3-27}$$

For c_i bounded from below at 0 and for w_j bounded in the domain $[0, 1]$, this is the case. For this proof of both $\mathcal{U}_i$ and $\mathcal{U}_j$, please be referred to appendix A-1. For households to converge to a Nashequilibrium, an unique Nashequilibrium must exist where each player [101]. In case of the Stackelberg-game framework taken from [72], the followers utility function, in this case the buyer-function $\mathcal{U}_i$, must be a standard function [174, 72]. For function $f(p) = (f_1(p), ..., f_N(p)$ with $\mathbf{p} = (p_1, ..., p_N)$, $f(p)$ is a standard function when the following three properties are satisfied for $\mathbf{p} \geq 0$ [174]:

- Positivity: $\mathbf{f}(\mathbf{p}) > 0$,
- Monotonicity: For all $\mathbf{p}$ and $\mathbf{p}'$, if $\mathbf{p} \geq \mathbf{p}'$, then $\mathbf{f}(\mathbf{p}) \geq \mathbf{f}(\mathbf{p'})$,
- Scalability: For all $\mu > 1, \mu\mathbf{f}(\mathbf{p}) > \mathbf{f}(\mu\mathbf{p})$.

With $f(c_i) = \mathcal{U}_i$, these properties need to hold in order for the iterative interaction between buyers (outputting $c_n^*(k)$) and sellers (outputting $w_n^*(k)$) to converge towards a global Nash equilibrium. Please be referred to appendix A-1-3 for proof of standardness of $\mathcal{U}_i$. Utility functions $\mathcal{U}_i$ and $\mathcal{U}_j$ are depicted in fig. 3-3.

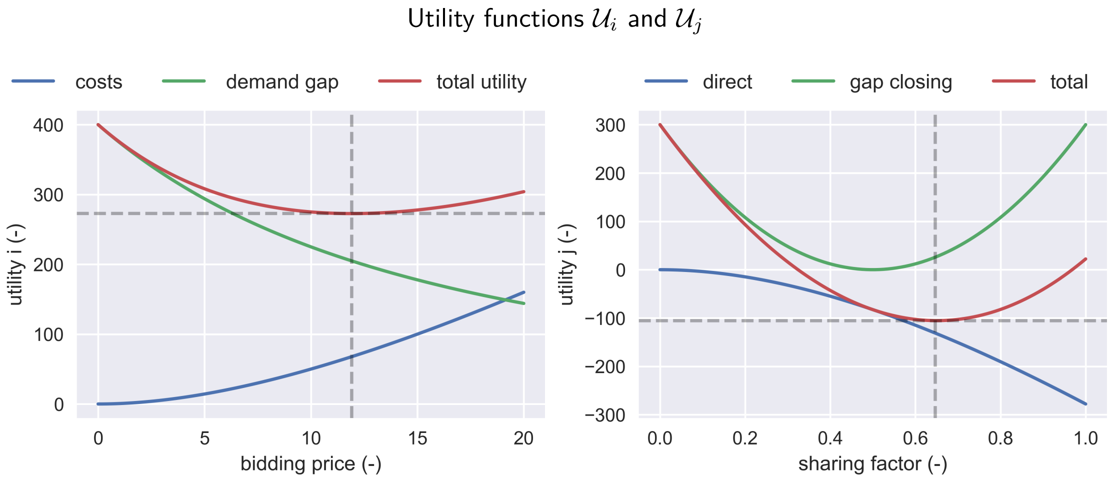

Figure 3-3: Shape of utility functions $\mathcal{U}_i$ and $\mathcal{U}_j$. Clearly visible are the trade-offs; for $\mathcal{U}_i$ between the closing the gap and corresponding costs, for $\mathcal{U}_j$ between closing the gap and missed revenue. Grey lines indicate the local optima. $\mathcal{U}_j$ actually is a concave function, while $\mathcal{U}_i$ is convex.

3-4 EnergyBazaar on Blockchain

Using Blockchain within the micro-grid solves three distinct problems that arise when introducing decentralization. Firstly, introducing a smart-contract as a substitute for a centralized institute governs the payments made by buyers to sellers in a decentralized fashion. This way the micro-grid becomes a transactive grid. Secondly, a smart-contract can function as a record keeping of promises made during trading, countering fraudulence manipulation of prices. Lastly, the communications network between agents cannot simply be assumed synchronous and the smart-contract can function as a time-stamping server to create an temporal order in transactions made in the micro-grid.

3-4-1 Blockchain applied to energy-trade

With the micro-grid as a closed community in which the number of participating agents is known, we can implement EnergyBazaar as a permissioned Blockchain. In a permissioned network, an identity based practial Byzantine Fault Tolerance (pBFT) consensus protocol suffices, whereas in a permissionless network a more extensive entity-based consensus protocol, such as Proof of Work (PoW) is needed since leader-election according to voting power has to be linked to entities instead of identities. In a permission-less network, Sybil attacks can be made by malicious nodes to represent a its entity with multiple identities, increasing its voting power in case of a identity-based consensus protocol. In a closed community micro-grid, the number of agents is known and thus voting power can be divided according to identities; it can be easily verified whether the number of nodes (identities) is equal to the number of households (entities).

A Blockchain platform that combines a permissioned network with smart-contract is Ethermint: a combination of Ethereum and Tendermint. Tendermint is a secure state-machine replication algorithm, originally making use of the pBFT consensus protocol. With a pBFT protocol, in a network of $2f + 1$ nodes, up to $f < \frac{N}{3}$ of nodes can arbitrarily fail, while still achieving consensus in an asynchronous network. For a complete overview of Tendermint, see [175]. Ethereum provides a smart-contract programming language; Solidity. We write in Solidity since it will be used by Ethermint. See appendix B-2 for a walk-through of the smart-contract.

3-4-2 Design of the EnergyBazaar smart-contract

We wrote a smart-contract that we deployed on Ethereum. It has the purpose to settle deals agreed upon by a buyers and sellers and to act as a negotiator between buyers and sellers. Either directly deployed on the Ethereum Virtual Machine (VM) or used by a permissioned Blockchain on Ethermint, the smart-contract is written in Solidity, a smart-contract orientated and Turing-complete programming language. We use the Application Programming Interface (API) Web3.py to connect the smart-contract to the micro-grid model in Python. In appendix B-2, further explanation on certain functions is given.

Broadcasting minimal information to the community

Agents make use of a smart-contract to share their optimization context with the rest of the network. Preferably, EnergyBazaar maintains the privacy of agents and is confidential. Privacy means that the identity of the agent is not given away when an agent participates in energy-trade. Confidentiality of EnergyBazaar makes sure that the information that is shared with the smart-contract is not shared with all other agents. Privacy and confidentiality on Blockchain is a challenge since all state-changing transactions to the smart-contract are per definition shared with all nodes in the Blockchain network. This is a major drawback of a smart-contract: information cannot be privately stored.

Considering information shared in EnergyBazaar: $E_{\text{demand}i}$ is sensitive since it tells about the characteristics of the household of agent i. For example, malicious agents could identify agents that away from home by looking for periods of time where $E_{\text{demand}h}$ of honest agent h is zero. Thus, effort is made to keep $E_{\text{demand}i}$ concealed from other agents. The distributed optimization algorithm of EnergyBazaar is designed such that agent i does not have to share $E_{\text{demand}i}$, but only its bidding price c_i. The information sensitivity of sellers is lower: both $E_{\text{surplus}i}$ and w_j, combined to be the product of the trade $E_{\text{supply}i}$, are necessarily shared. The mapping of shared information in EnergyBazaar among buyers and sellers is:

$$\begin{array}{rlc} \text{buyer}_i \rightarrow & \text{buyers}_{-j}: & c_i \\ \text{buyers} \rightarrow & \text{sellers}_{all}: & c_n \\ \text{seller}_j \rightarrow & \text{sellers}_{-j}: & (E_{\text{surplus},j}, w_j) \\ \text{sellers} \rightarrow & \text{buyers}_{all}: & (E_{\text{surplus},j}, w_j). \end{array}$$

Bidding price c_i expresses the necessity for energy; even with this information, behavioural patterns can be derived [176]. An ideal situation would be to obscure c_i as well. Currently, this is not possible, since buyers necessarily have to be updated by other agents to solve the optimization game.

Market manipulation of malicious nodes

EnergyBazaar opens a way to fraud the system: a malicious agent a_m could yield a higher revenue when mid-optimization it lowers its $E_{\text{surplus},m}$. Since this incentive applies to all sellers, prices can artificially surge through this mechanism when all sellers participate. The promise system requires all agents to record their surplus and maximum demand prior to optimization. After the market game has been played by participating agents, the smart-contract verifies through an internal function whether $\{E_{\text{surplus},j} \cdot w_j = E_{\text{supply},j} \text{ is True}\}$. If so, the payment is executed.

For this, the first smart-contract state-change initialized in a trading agent is a promise, see eq. (3-28). After optimization, the output of the game consists of trading-deal, see eq. (3-29).

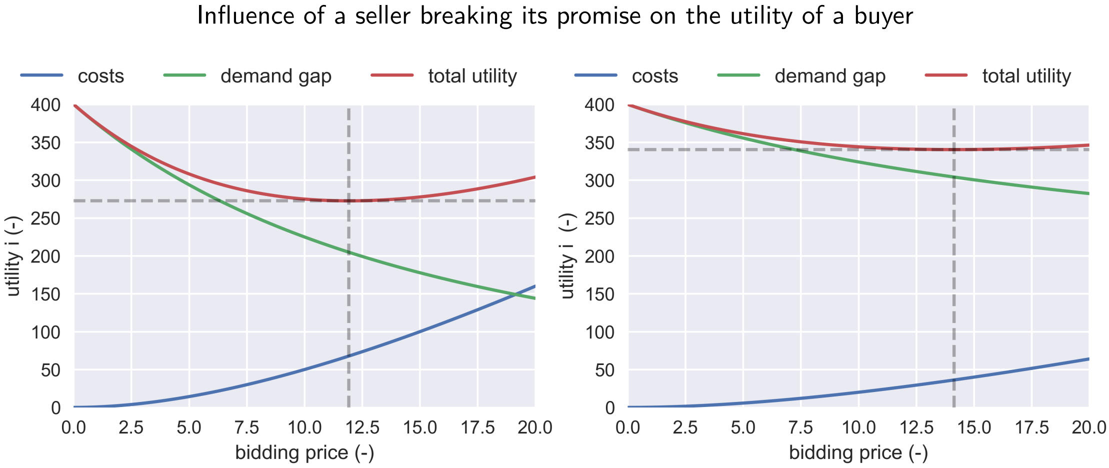

Figure 3-4: Selling agent a_m increases the minimum utility of buying agents by reducing its promised supply at the last moment. To counter this, sellers have to update their promised E_{surplus} in the state of the smart-contract prior to the optimization round. The buyer has to bid a higher prices for the same amount of energy.

$$M_{\text{promise},a} = \{E_{\text{demand,promise},a}, E_{\text{surplus,promise},a}, k_a\}, \tag{3-28}$$

$$M_{\text{execute}a} = \{E_{\text{allocated,real},a}, E_{\text{supply,real},a}, k_a\}. \tag{3-29}$$

As mentioned before, in between seller and buyer-level rounds, $\mathbf{c}$ and $\mathbf{w}$ are transformed to c_n and w_n. Function `computeNominalc` receives the set of bidding prices and internally computes and afterwards discloses c_n. The same is done for w_n. For each agent to know who is momentarily participating in solving the EDP, the smart-contract acts as a time-stamping server. All agents include their current time-step k_a within each message. Agents thus are able to exempt lagging agents from the current optimization at round k. These lagging agents are then excluded from that particular trading-round, since they are not able to provide up-to-date information on either demand, supply, bidding price or sharing factor. The complete mapping between agent i its address and smart-contract state at agents time-step k_i:

$$\text{address}_i \rightarrow \{\text{balance}_i, \text{ update}_{\text{promise},i}, \text{ update}_{\text{action},i}, \text{ promise}_{\text{sell},i}, \text{ promise}_{\text{buy},i} | k_i\}. \tag{3-30}$$

The mapping 3-30 is a state in the smart-contract and is public to all participating nodes.

Chapter 4

Results and Validation

In chapter 3, a trading mechanism has been designed that coordinates the charging/discharging of a Energy Storage System (ESS) of households in a distributed fashion. To be able to draw conclusions, performance and comparison to existing methods investigated in chapter 2, we analyze results and comparisons in this chapter.

4-1 EnergyBazaar: evaluation of performance

This section will present the results achieved by deploying the EnergyBazaar algorithm as a distributed solution to the Economic Dispatch Problem (EDP).

4-1-1 Testing EnergyBazaar

Evaluation is three-fold; the measure of self-sustainability of a micro-grid from the macro-grid, the costs involved with decentralization, and the ability to link EnergyBazaar to the macro-grid. For this we identify three areas in which EnergyBazaar must be tested:

- **Decentralization and independence**. We look at the measure of independence from the macro-grid. A conclusion is drawn on the optimal battery capacity of a household.
- **Cost of Anarchy**. We make a comparison between EnergyBazaar and a centralized EDP solution to investigate the sense of fairness and computational viability of the micro-grid with EnergyBazaar as a solution to the EDP.
- **Linking micro-grid and macro-grid**. We make a statement regarding the tipping point where communities would decide to decentralize and about the link that remains with the outside world.

Key Performance Indicator (KPI)

To show the performance of our algorithm, we compare a micro-grid running on EnergyBazaar to a situation where no trading is allowed. Additionally, a half-way approach is given in order to benchmark the utility functions of EnergyBazaar with agent behaviour used in [72]. In a 'no-trade' situation, households are fully isolated from each other in terms of energy trade. In a situation where EnergyBazaar is implemented, households are able to trade energy with each other. Energy shortages are expressed in deficits: the amount of energy that was needed satisfy the households original energy load. To maintain operations, this deficit needs to be imported from an other source; the macro-grid. EnergyBazaar should make a micro-grid independent from the macro-grid in terms of energy import. Thus the performance indicator that is used is the deficit of agents in the micro-grid:

$$E_{\text{balance},i}(k) = E_{\text{SOC},i}(k-1) + E_{\text{production},i}(k) + E_{\text{allocation},i}(k) - E_{\text{load},i}(k), \tag{4-1}$$

$$E_{\text{deficit},i}(k) = \begin{cases} E_{\text{balance},i}(k) & \text{when} \quad E_{\text{balance},i}(k) < 0, \\ 0 & \text{when} \quad E_{\text{balance},i}(k) \geq 0. \end{cases} \tag{4-2}$$

To maintain grid-stability; considering our assumption that all E_{load} is critical, all households have to be able to satisfy E_{load} using either battery reserves, personal energy production or allocated energy. If not, the total deficit at step k, $\sum_{i=0}^{N} E_{\text{deficit},i}(k)$, has to be imported from the macro-grid, ruling out independency. Beside the average deficit, we look at the overflow of energy; energy that is produced but cannot be stored or sold. If batteries overflow, energy is not used and goes to waste. Overflow occurs when production is too high, battery capacity is too low or when EnergyBazaar is not effective in distributing energy among all agents, and thus has to be minimized.

Table 4-1: An overview of relevant control parameters.

Parameters	Symbol	Value	Unit
Battery Capacity	C_i	19	kWh
Prosumers	p	50	%
Prediction horizon	h	90	steps
Population size	N	40	-
Buyers weight	γ_{buyers}	1	-
Sellers weight	γ_{sellers}	1/3	-

In table 4-1, all initialization parameters are given that influence the outcome of the simulation. Effects of capacity C_i, prosumer participation p and the horizon h are investigated in section 4-1-3. Weights γ_{buyers} and γ_{sellers} are fixed at 1 and 1/3 after tuning trials.

Simulation in Python

We run our micro-grid model, of which the systems-layout is as discussed in appendix B-1, in a 5-day simulation, using the input-data discussed in section 3-2-2, with a resolution of 1-minute. Time is divided into discrete time-steps k. In this work, the interval of $(k+1) - k$ is 10 minutes. This interval prescribed that energy-trade within the grid operates in a 10-minutes ahead market, slightly faster than the German Program Time Unit (PTU) interval of 15-minutes [177]. However, the interval resolution can be set to arbitrary intervals, with a minimum of 1 minute.

The default size of the agent population N is 40, but can vary between 6 and 100 agents. See section 4-1-6 for an evaluation of variable complexity of solving the EDP within the range of N. Total energy generation is assumed to be equal to total energy consumption. Prosumer penetration p is set to 0.5, meaning that 50% of agents are households with Photo Voltaic (PV) panels installed. On default, the prediction horizon h is at $(k + 72)$. With a 720 minute horizon, agents can anticipate on the coming 12 hours. All households are given an ESS with a capacity of 19 kWh. A battery of 19 kWh is considered very large for a household ESS: ≈ 1.5 times as large as a Tesla Powerwall. Maximum charge and discharge limits are set according to battery saturation, see eq. (2-16).

Due to discontinuation of the simulation, the final day of 144 steps shows irregular charging behaviour in all situations, resulting in higher overflows of batteries. These overflows are caused by the prediction horizon h shrinking to zero steps, resulting in consumer demand $E_{\text{demand},i}$ to drop to zero. When comparing between methods, these irregularities are not omitted. Irregularities only occur at boundaries of the simulation.

To simplify our model, we assume all households to have uniform utility functions, either $\mathcal{U}_i$ when buying or $\mathcal{U}_j$ when selling. In a real application, utility functions might differ: agents could have a preference towards economical gain or a zero-deficit, see section 5-2.

4-1-2 A week in the life of a semi-isolated micro-grid

We monitor the trading behaviour within the micro-grid for a duration of five days. A comparison is made between a 'no-trade' paradigm and the 'EnergyBazaar' paradigm. We compare EnergyBazaar to the energy-trading framework discussed in [72] as a benchmark. Batteries are given an initial State of Charge (SOC) of half of their total capacity to minimize the boundary irregularities but also witness the agents coping with initial scarcity.

Regarding the coming figures (figures 4-1, 4-2, 4-4 and 4-5), we show for each method both SOC progression over the week and the deficits and overflows occurring over the week. in the upper plot, the averaged SOC (kWh) of consumers and prosumers is showed for the duration of five days. The standard deviation is given as a blue fill-in and the both extremes of all batteries is given in a red fill-in. In the lower-plots, the total mean deficit and the prosumer mean deficits shown along-side with the total overflow in the systems at each time-step k.

No inter-trade among agents

A 'no-trade' situation is simulated, seen in fig. 4-1. Trade among agents has been disabled, showing the natural deficit that would occur. This situation is comparable with households residing in a normal utility-grid where prosumers are not given opportunity to sell their energy. Buyers import from the macro-grid and sellers export to the macro-grid. Although prosumers are able to survive energy scarcity by replenishing their batteries and are thus autonomous, consumers experience depletion early on in the week and are thus forced to import energy from the macro-grid. Independence from the macro-grid is not possible since at all times, there is a deficit for both consumer as for prosumer.

EnergyBazaar deployed in full

Figure 4-2 shows the micro-grid when EnergyBazaar is deployed. An extensive formulation of EnergyBazaar is given in chapter 3. With EnergyBazaar, agents are able to trade among each other. The result is that energy, previously aggregated at prosumers, is dispersed over all agents, thus reducing neatly distributed are consumers and overflow at prosumers. We see a drastic reduce in overflow and deficit, fig. 4-2; which means that energy is efficiently distributed throughout the micro-grid. Prosumer energy is able to reach the consumers, for which they pay a price, see lower left figure in fig. 4-7. Consumers have a stronger preference to maintain a high SOC, thus start loading their ESS earlier than prosumers. This process derails slightly at the end of the simulation, due to boundary issues discussed in section 4-1-1.

H(s)

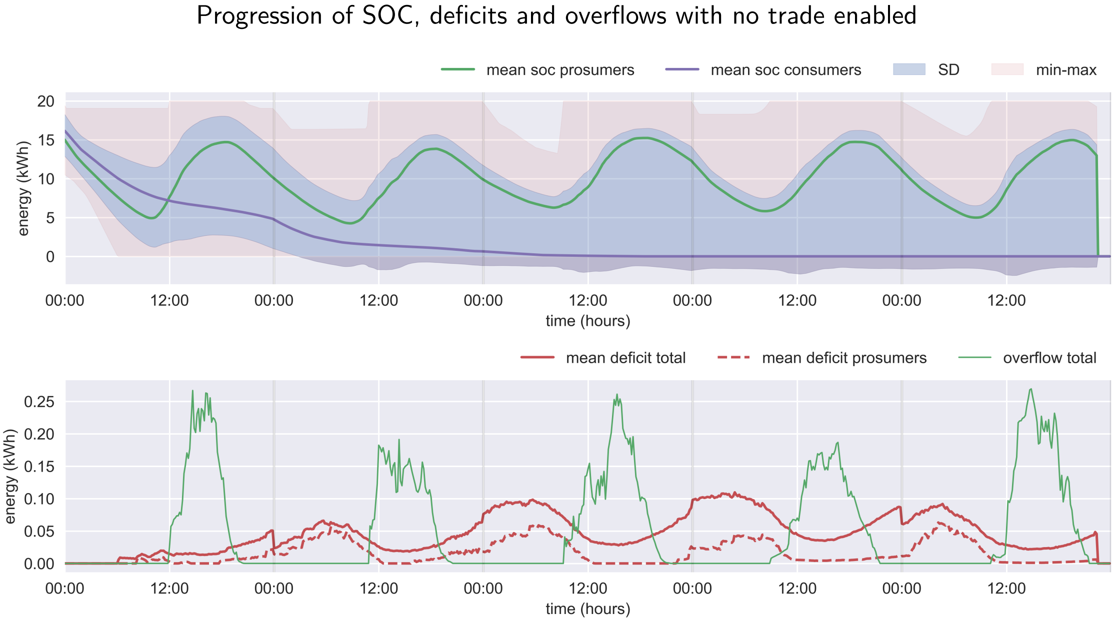

Figure 4-1: Micro-grid consisting of 40 household agents, without EnergyBazaar deployed; agents are not allowed to trade energy. Only prosumers are barely able to survive scarcity by night, consumers experience a depletion event early on in the week.

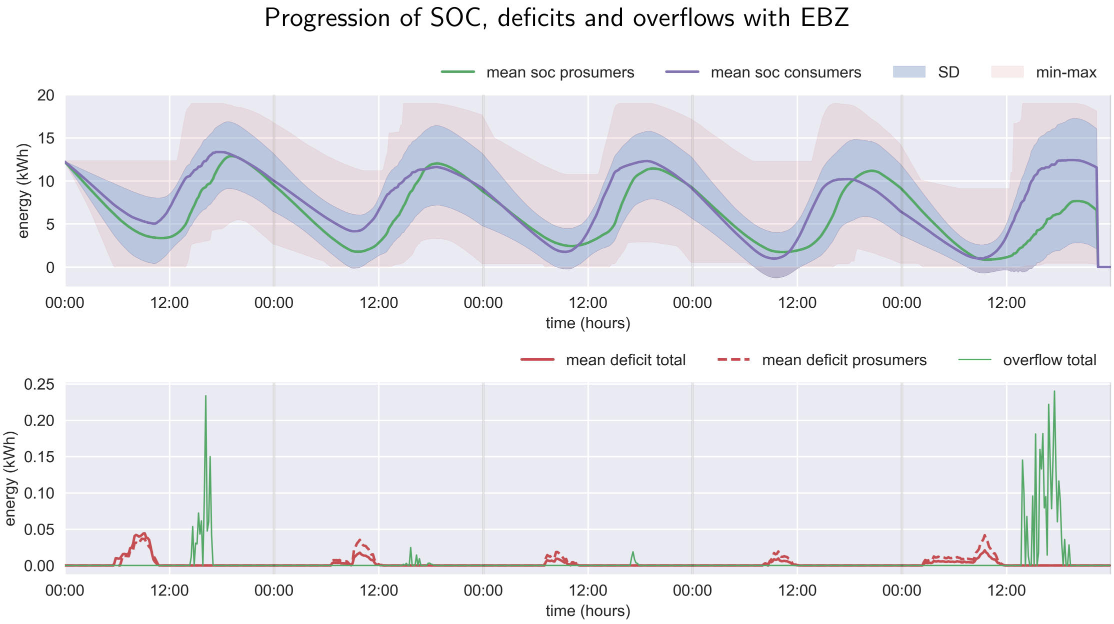

Figure 4-2: Micro-grid consisting of 40 household agents, with EnergyBazaar deployed; agents are trading energy among each others according to a hierarchical round-based game, where in energy demand is expressed in higher prices, creating incentive to trade.

Bench-marking agent behaviour

The Stackelberg-game framework of [72] is an inspiration to the hierarchical game structure of EnergyBazaar. However, the game played in [72] is closed-loop where sellers anticipate buyers plugging an algebraically computed $\mathbf{c}$ into their utility function $\mathcal{U}_j$. Also, [72] does not utilize prediction and needs a distinct link to the macro-grid for agents to establish bidding prices $\mathbf{c}$. To see the increase in performance that EnergyBazaar's inclusion of prediction yields, we replace utility function for selling agents, see eq. (3-18), with a function proposed in [72], where a trade-off for sellers is modelled between battery degradation and the revenue R_j and does not look at the preferred SOC of its battery w.r.t future needs. Sellers utility function $\mathcal{U}_j$ of [72]:

$$\mathcal{U}_{j,new}(\mathbf{w},\mathbf{c}) = \ln[1 + E_{\text{surplus},i}(1 - w_j)] + \gamma_j \cdot \left(R_{\text{direct}} \frac{E_j w_j}{\sum_{l \in \mathcal{J}} E_l w_l} \right), \tag{4-3}$$

with utility of agent j being is a trade-off between a diminishing return function of battery storage, expressed by the natural logarithm, and a direct revenue R_j. γ_j is tuned to 0.4, relaxing the trade-off function such that the bandwidth of optimal w_j^* is extended, see appendix A-1-4.

4-1-3 Parameters influencing total deficit in the micro-grid

As default, we chose a battery size of 19 kWh, a prosumer participation of 50 % and a prediction horizon of 15 hours (i.e. 90 time-steps). The value of these parameters have a big influence on the applicability of EnergyBazaar to a real-world setting.

Battery size

Assuming that in the micro-grid, $\sum_{i=0}^{N} E_{\text{production}} \approx \sum_{i=0}^{N} E_{\text{load}}$, deficit and overflow is decided by the initial battery SOC, the battery size and the efficiency of EnergyBazaar in distributing E_{surplus} to consumers. The initial battery SOC really only influences deficit and overflows during the first 12 hours. More importantly, the battery capacity decides whether agents are able to have enough storage capacity to survive the night. For a household with an average energy demand of 15 kWh per day, we look at different battery sizes and compare deficits.

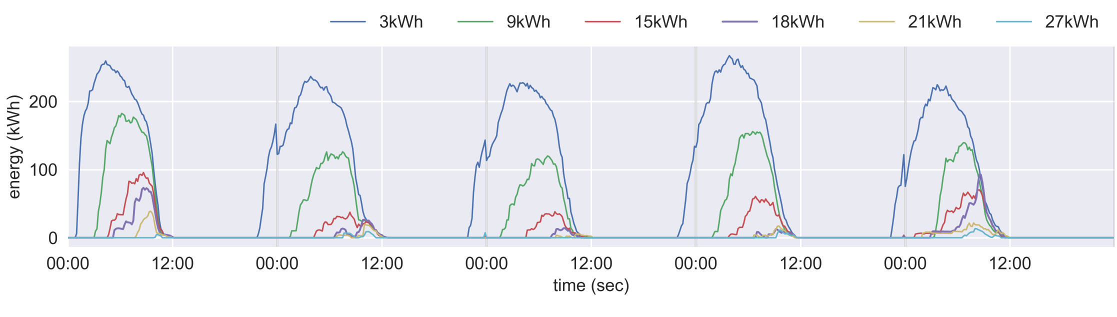

Figure 4-3: Influence of battery sizes on total deficit: by increasing the maximum battery capacity, deficits in the micro-grid decrease. The rate of deficit reductions slows down with higher battery sizes. On default, we chose a battery size of 19 kWh.

On default, all households in the community own a personal ESS with a capacity of 19 kWh. This capacity yielded the best results: since we modelled the load-patterns to mostly have their 15 kWh energy consumption during the night, batteries have to be large to survive this nightly scarcity. However, with this we intended to show a worst-case scenario. Since costs (€/kWh) for chemical

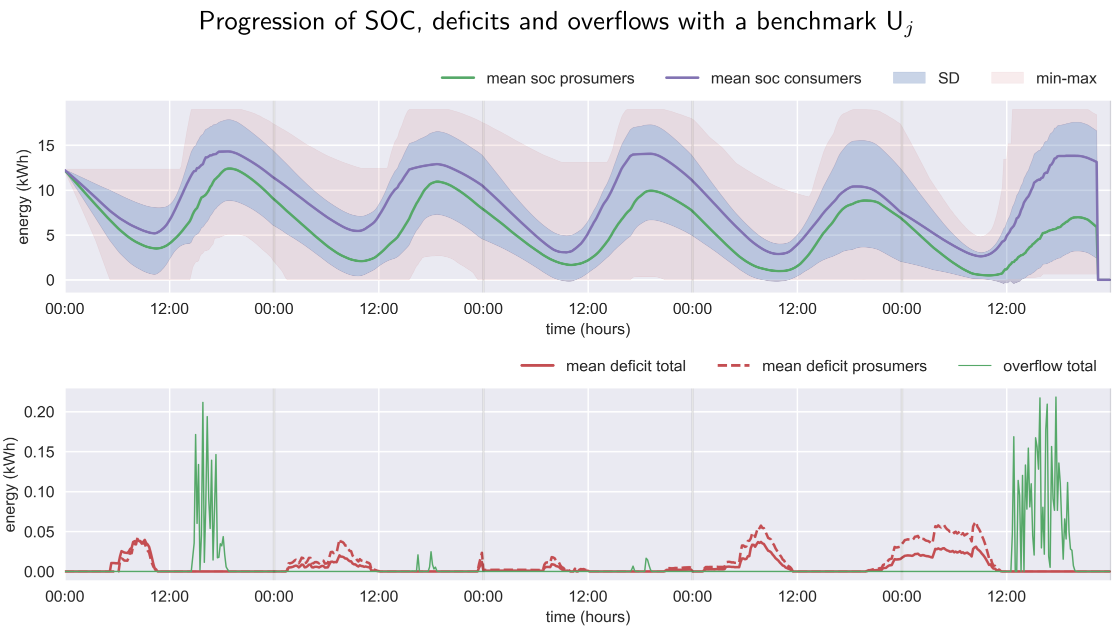

Figure 4-4: Micro-grid state-of-charge and deficits in a EnergyBazaar deployed paradigm using a bench-mark utility function for sellers, $\mathcal{U}_j$, from [72].

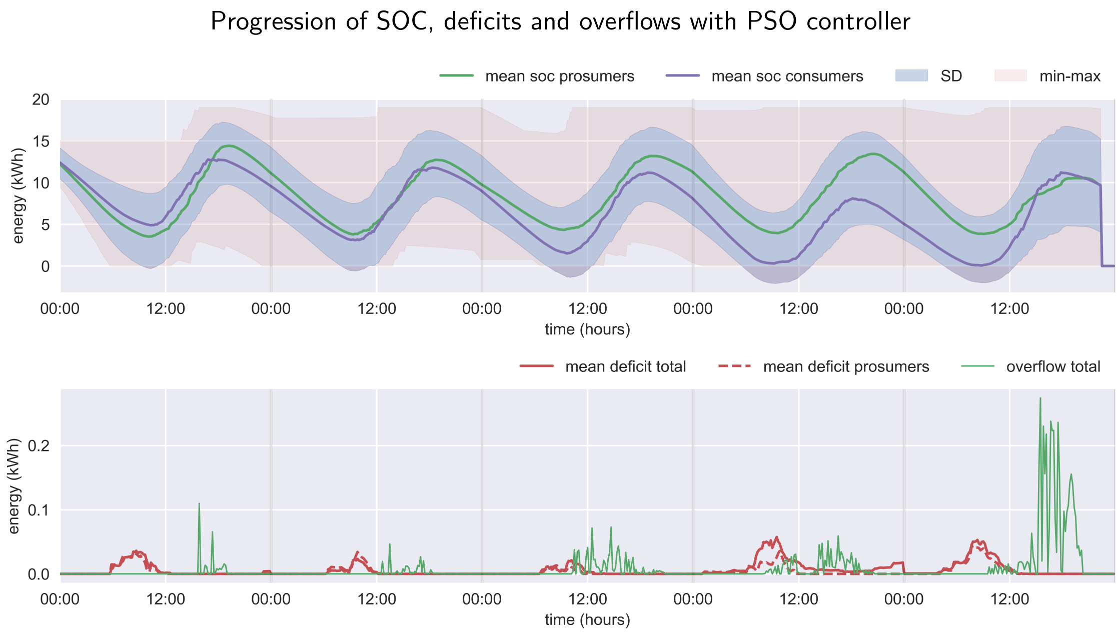

Figure 4-5: Micro-grid state-of-charge and deficits of trade dictated by a central controller replacing the hierarchical game structure with a PSO.

batteries are still high, we foresee a combination of technologies to be used in unison [15], such a combination of a low-friction and inexpensive community-shared fly-wheel for long term storage and smaller personal household chemical batteries. Using ESS shared by the community, discussed in [178], could greatly decrease capital costs and could be easily managed by a smart-contract that leases out virtual space of the community energy storage.

Prosumer participation

Less prosumers means less sellers but equal demand thus higher allocations. An increase of $E_{\text{allocation},i}$ is allowed until actuator saturation occurs. For an Tesla Powerwall, actuator saturation lies at 0.83 kWh for each time-step k (kWh/k, k being a 10 minutes interval), discussed in eq. (2-16). Sellers are thus physically not able to deliver more at one time-step. We showed in section 3-3-5 that a naive method of charging/discharging behaviour of ESS does not prove effective. Although additional research on actuator saturation within the trading-game EnergyBazaar is needed, we already look at the actual behaviour of ESS in the micro-grid.

In fig. 4-6 we see the most extreme (dis)charging at given k. Although the averages lie below the saturation boundary of 0.83 kWh, certain batteries show spikes, especially at the end of the day, that gravely exceed boundaries. Furthermore we see the effect of an increase of prosumer participation in the micro-grid. With an increase of 20% to 50 % of prosumers, the extremes are limited significantly. An even higher increase in prosumer participation, e.g. from 50 % to 80 % does not yield an as big of an improvement w.r.t. lowering extreme dis(charging) behaviour. Three measures should be taken in parallel to mitigate restriction of trading by actuator saturation: have a sufficiently high participation of prosumers in the micro-grid, lowering the burden of individual sellers; increase the actuator limits of ESS by improvement in battery technology and; develop hard-coded constraints to the trading optimization.

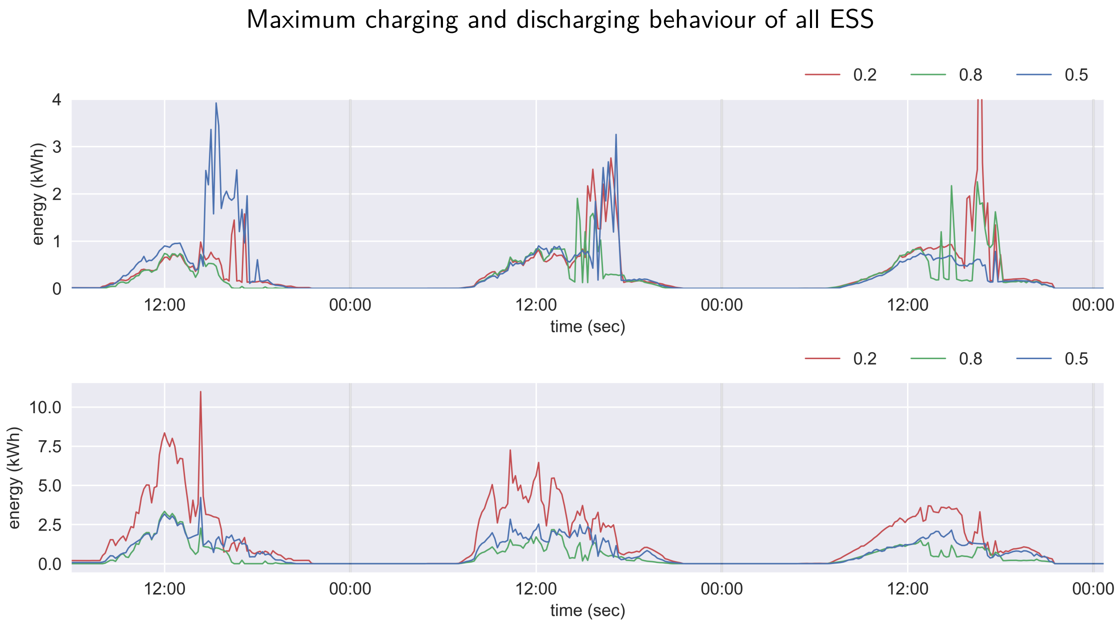

Figure 4-6: Maximum charging and discharging behaviour of agents with a variable prosumer participation p. Increasing p lowers the maxima. Upper figure is charging behaviour, below which the discharging behaviour is depicted.

Prediction horizon p

Additionally, the performance of EnergyBazaar depends on prediction horizon h. To investigate the optimal value for h, we preform a parameter-sweep in the range of $[50-110]$ steps. The default horizon is set to 90 steps, since for this horizon distance, total deficits are the lowest, see table 4-6. The accuracy of weather and consumption pattern prediction for a horizon of 15 hours ($90 \cdot 10$ minutes) should be sufficiently high using simple forecasting techniques discussed in section 2-2-3.

Table 4-2: Deficits and overflows for respectively prosumers and consumers. Over the range of [50, 110] it is clear that an optimum is found around a horizon distance of 90 steps. This distance also roughly equals the average length of the production scarce periods.

h length	50	60	70	80	90	100	110
deficit consumers	42.55	54.92	33.57	16.63	11.24	17.40	30.04
deficit prosumers	239.13	159.33	99.61	70.13	37.60	84.32	111.46
overflow consumers	236.70	196.02	135.08	121.27	134.26	156.91	192.24
overflow prosumers	36.15	83.54	38.02	52.54	39.58	43.20	18.45

4-1-4 Central control by PSO

A optimal solution for the economic dispatch problem is found using a PSO algorithm. We used this as comparison scenario to EnergyBazaar in terms of agent costs and computational complexity. By solving the EDP by using PSO we substitute the hierarchical distributed game by a central controller. Although the behaviour captured in utility functions $\mathcal{U}_i$ and $\mathcal{U}_j$ remains the same, we change the means of reaching the optimal configuration for this behaviour.

PSO is a non-linear, centralized and collaborative optimization method: particles are created and are assigned a position and velocity, with which a momentum is calculated. After initiation, particles search the multi-dimensional solution space. This solution space consists of all possible combinations for $\mathbf{c}$, bounded by $[0, \infty)$ and $\mathbf{w}$, bounded by [0,1]. Particles with an high utility have less incentive to search an other location in the solution-space, while particles with a low utility do have this incentive. Particles are drawn to locations with a high-density of fellow-particles, mimicking the behaviour of a swarm, school or flock of animals. These three mechanisms cause particles to conglomerate at locations of high utility, thus pin-pointing the optimal configuration of $\mathbf{c}$ and $\mathbf{w}$. See section 2-2-2 for more information on PSO.

We do not include the hierarchical game in the PSO, since PSO is meant to evaluate all dynamics at once. Thus, an combined utility function $\mathcal{U}_j$ is created and tuned:

$$\mathcal{U}_{\text{pso}}(\mathbf{c}, \mathbf{w}) = \gamma_{\text{pso}} \cdot \mathcal{U}_j(\mathbf{w}) + \frac{\mathcal{U}_i(\mathbf{c})}{\gamma_{\text{pso}}}, \tag{4-4}$$

with a γ_{pso} set to 1.5, increasing slightly the resolution of the evaluation of $\mathcal{U}_j$, yielding an slightly lower total deficit. Parameters used during the PSO: the minimum change of swarm's best utility before termination, $\min_{\text{func}}$, is set to 0.01 and the swarm consists of 1000 particles.

Evidently, the PSO has to be executed at a central controller that necessarily needs information on $E_{\text{demand},i}$ for all buying agents and $E_{\text{surplus},j}$ of selling agents. Since especially $E_{\text{surplus},j}$ is sensitive, see section 3-4-2 for a discussion on this topic, a centralized PSO approach is not privacy preserving and creates a single-point of failure; if the controller fails the grid will fall back into a 'no-trade' situation. The result that this approach yields is seen in fig. 4-5.

Looking at control values of both EnergyBazaar and PSO, we see that the pricing appears more predictable for the case of EnergyBazaar. The PSO does not regard buyers responding to each other, omitting the game-theoretical part of EnergyBazaar. Thus, PSO solves the EDP problem, but not through a more natural free-market mechanism. Because of a less efficient solution, E_{demand} is higher later in the week than in the case of EnergyBazaar. We see that under EnergyBazaar, prices drop to zero when supply is higher than demand, which is not the case with our PSO method. The combined size of set of sellers $\mathcal{J}$ and buyers set $\mathcal{I}$ is not necessarily equal to the total number of agents N. This is because agents can decide not to participate in trade and live off their battery reserve, thus become 'passive'.

A peculiarity is that during EnergyBazaar trading, sellers either sell all their $E_{\text{surplus},j}$ or nothing at all. This originates from the utility function $\mathcal{U}_j$ that provides an incentive to close the gap between a preferred battery charge and the actual battery charge. Under EnergyBazaar, sellers decide to become sellers only to when their preferred SOC is reached, thus with the gap already closed. With the PSO algorithm, this gap is not always closed.

4-1-5 Comparison of deficit and overflow over all methods

We give an overview of deficits and overflows during 5 days of micro-grid simulation. In fig. 4-9 and fig. 4-10, we plot the deficit per time-step k in kWh/k over time-steps k. In a no-trade situation, energy is not distributed among agents, creating deficits at consumers and energy overflows (i.e. waste) at prosumers. By introducing a trading algorithm, energy is distributed according supply and demand, resulting in a lower deficit and overflow. EnergyBazaar out-performs both its benchmark and the centralized PSO method w.r.t. distribution efficiency.

In table 4-3 the total deficits and overflows for both the set of consumers and set of prosumers is given. EnergyBazaar (EBZ) manages to attain the best energy distribution in general, but does not yet completely reduce the deficit and overflow to zero: consumers tend to buy to much energy, resulting in a consumer overflow.

Table 4-3: Deficit and overflow comparison between various methods. No trade is a worst-case scenario. EnergyBazaar improves deficit for both prosumers and consumers.

KPI (in kWh)	No trade	Benchmark	EBZ	PSO
Deficit consumers	1111.21	24.23	17.99	118.66
Deficit prosumers	222.78	129.79	43.47	56.64
Overflow consumers	0.0	146.35	133.840	144.43
Overflow prosumers	1460.76	70.96	12.14	95.56

No method used yields a deficit of zero. This means that no method is able to isolate the micro-grid from the macro-grid completely. Nevertheless, we expect that with EnergyBazaar, deficits are reduced to a point that load-shifting strategies, discussed in section 2-1-3, could mitigate the remaining deficit, as discussed in section 5-2.

4-1-6 Computational complexity

To look at computational scalability, we preformed a batch-run on both EBZ and PSO over an increasing number of agents. Since the PSO approach is a non-linear 'shot-gun' approach, the computational difficulty increases exponentially when increasing the amount of agents in the grid. See table 4-4 for the experimental set-up specifications. On the contrary, EnergyBazaar performs better: with a linear increase of complexity as N increases. The PSO complexity progression is fitted by a second order polynomial, while the progression under EnergyBazaar is a best fit with a linear function.

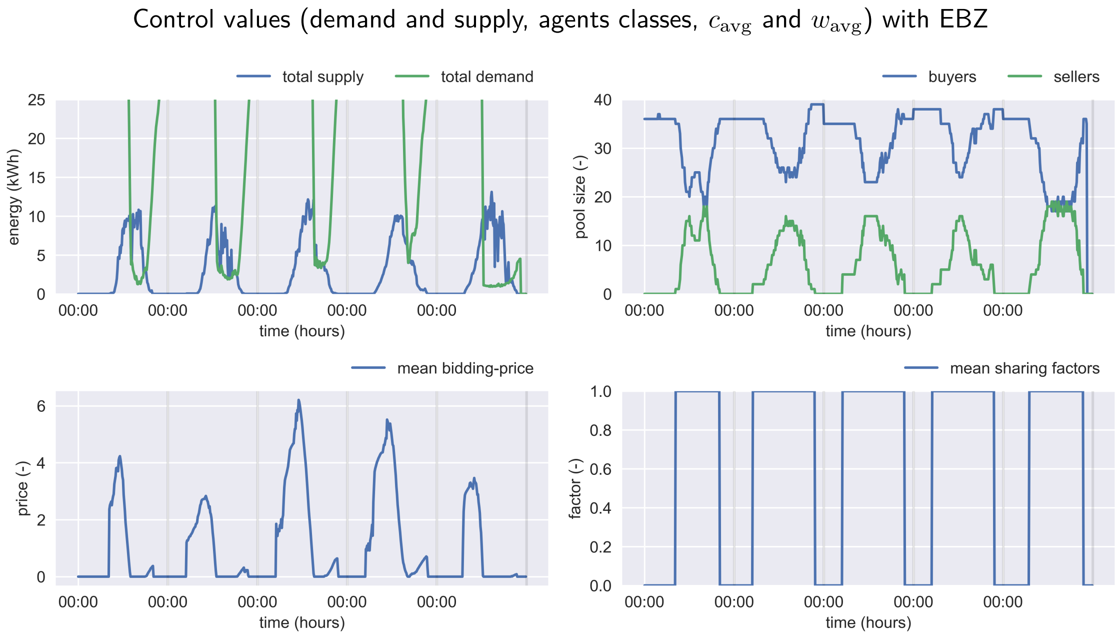

Figure 4-7: From upper-left plot, clock-wise: supplied energy and energy demand; buyers and sellers pools; sharing factor w_j; average bidding-price c_i, all plotted over the duration of 5 days. Simulation of the micro-grid with EnergyBazaar. We see bidding prices that intuitively correspond to demand and supply in the system.

Figure 4-8: From upper-left plot, clock-wise: supplied energy and energy demand; buyers and sellers pools; sharing factor w_j; average bidding-price c_i, all plotted over the duration of 5 days. Simulation of the micro-grid using the centralized PSO approach. We see that the bidding prices is erratic, while supply factors are not 1 even-though demand is higher than supply.

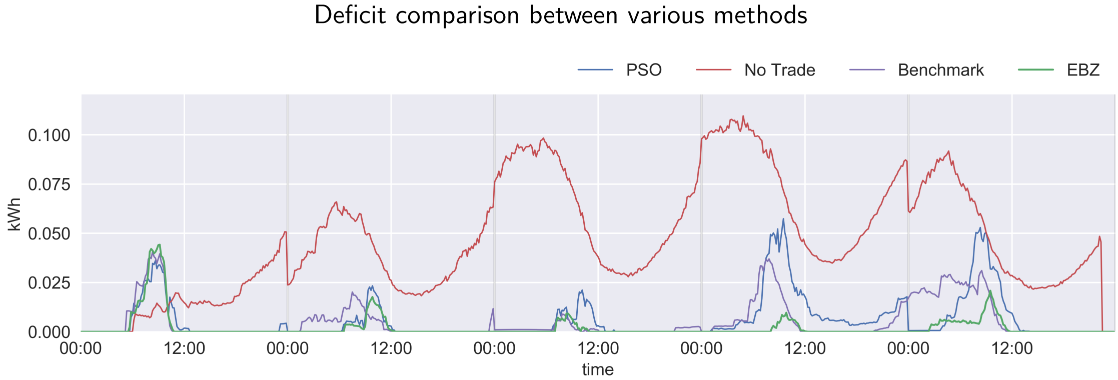

Figure 4-9: A comparison of deficits during the week in various situations; No-trading, see section 4-1-2, EnergyBazaar deployed, see section 4-1-2, a benchmark to EnergyBazaar, see section 4-1-2 and the centralized PSO approach, see section 4-1-4. At every night and day cycle, EnergyBazaar is better at reducing energy deficit in the grid than other methods. Deficit over all is reduced by a factor ≈ 50, but not reduced to zero.

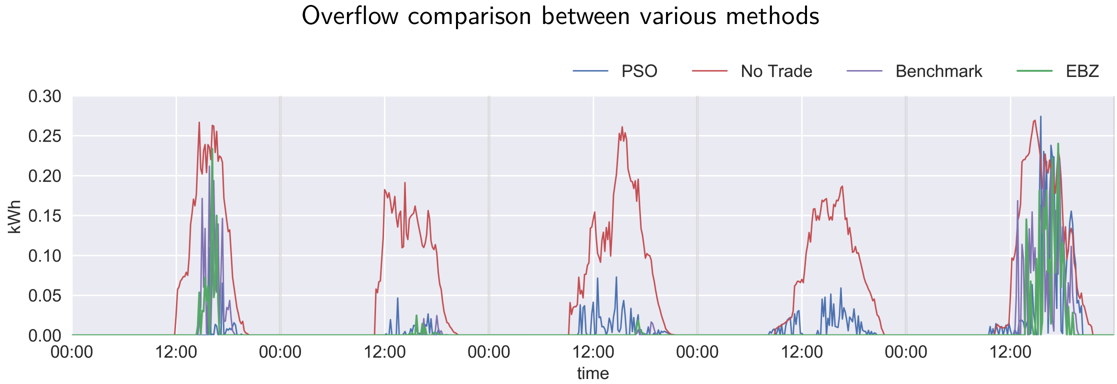

Figure 4-10: A comparison of overflows during the week in various situations; No-trading, see section 4-1-2, EnergyBazaar deployed, see section 4-1-2, a bench-mark to EnergyBazaar, see section 4-1-2 and the centralized PSO approach, see section 4-1-4. At every night and day cycle, EnergyBazaar is better at reducing energy overflow in the grid than other methods.

Nevertheless, a centralized controller is able to aggregate computational power and communication is solely intern, while EnergyBazaar requires agents to communicate with each through a blockchain with a smart-contract. This is not included but is expected to deal a considerable blow to the performance of EnergyBazaar. The creators of the practial Byzantine Fault Tolerance (pBFT) discuss in [179] the performance of the protocol w.r.t. the communications network, but only on a limited scale of 4 nodes (one of which malicious). A model accounting for network latency should aid in testing the scalability of an EnergyBazaar micro-grid.

Table 4-4: Experimental set-up: Mac-Book pro 2014

2.6 Ghz Intel Core i
8 GB 1600 Mhz DDR3
Intel Iris 1536 MB

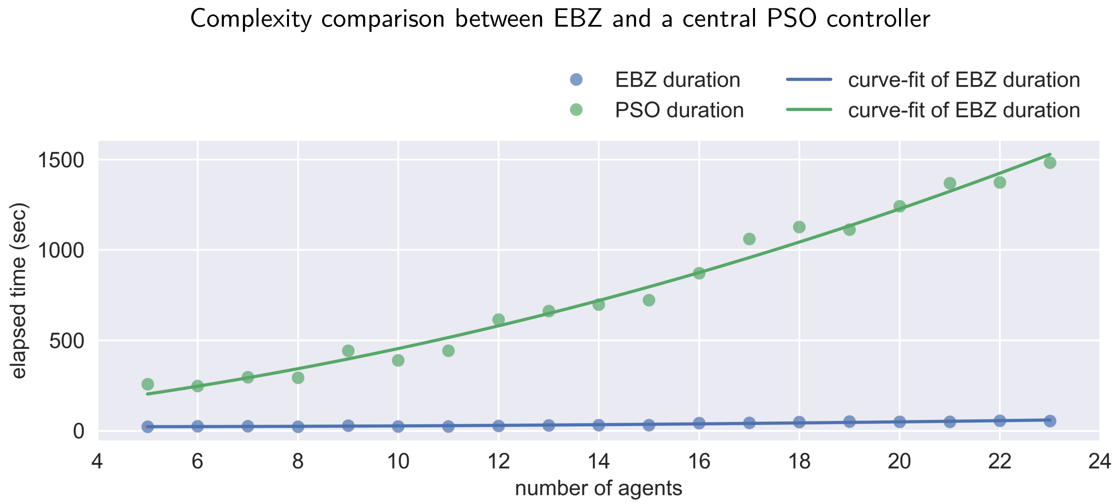

Figure 4-11: Elapsed computation-time comparison between PSO and EBZ; with increasing the number of agent in the micro-grid, EnergyBazaar linearly increases in computational complexity while the centralized PSO method shows an exponential increase

4-1-7 EnergyBazaar on Blockchain

To test the performance of EnergyBazaar running over the Ethereum Virtual Machine (VM), with the `TestRPC` provide we create a test-network using the Web3.py Application Programming Interface (API). Agents are assigned an address and use it to sign transactions. With Blockchain enabled in the implementation of EnergyBazaar in Python, agents communicate over the blockchain. State-changing transactions are made towards the smart-contract. This way, the shared values of c_i, w_j, $E_{\text{surplus},j}$, c_n and w_n are shared through the smart-contract. In `TestRPC`, blocks are immediately mined after transactions are broadcast. The elapsed time of a simulation with communications over Blockchain greatly increases, see table 4-5.

Table 4-5: EnergyBazaar on-chain versus off-chain. Adding the communications through Blockchain in the `TestRPC` network increases the elapsed time with factor 37. In this simulation, community contains nine participating households.

EnergyBazaar off-chain	≈ 1.5 min
EnergyBazaar on-chain	≈ 56 min

Regarding on-chain communications, especially buyers have a high communication burden. Before each game, buyers and sellers make a promise transaction $\text{Tx}_{\text{promise},n}$. For each optimization round, both buyers and sellers communicate their c_i and w_j to the smart-contract by making an action-transaction $\text{Tx}_{\text{action},n}$ for all agents in $\mathcal{N}$. Thus the number of transactions made in the micro-gird at time-step k is $NTx = (N_\mathcal{I} + N_\mathcal{J}) + (it_{\text{buyers}} \cdot N_\mathcal{I} + it_{\text{sellers}} \cdot N_\mathcal{J})$. Here, N is the number of participating households, $N_\mathcal{I}$ is the amount of buyers and $N_\mathcal{J}$ is the number of sellers. Respectively, $\text{it}_{\text{buyers}}$ and $\text{it}_{\text{sellers}}$ is the number of iterations in the buyers and sellers game.

The most iteration intense time-step is during the third day in the afternoon. The transaction rate over Blockchain reaches $\approx 2\,\text{Tx/sec}$, when k is 10 minutes. For a permissioned Blockchain such as Ethermint, with its Proof of Stake (PoS) protocol that takes up to 200 Tx/sec, this is not a problem [180]. The transaction rate scales linearly when increasing the number of agents, since the average number of iterations does not increase significantly when increasing the number of agents. This was tested up to 100 agent; but with duplicated data-sets for agents $i > 44$ where noise was added to.

Iterations for buyers and sellers rounds

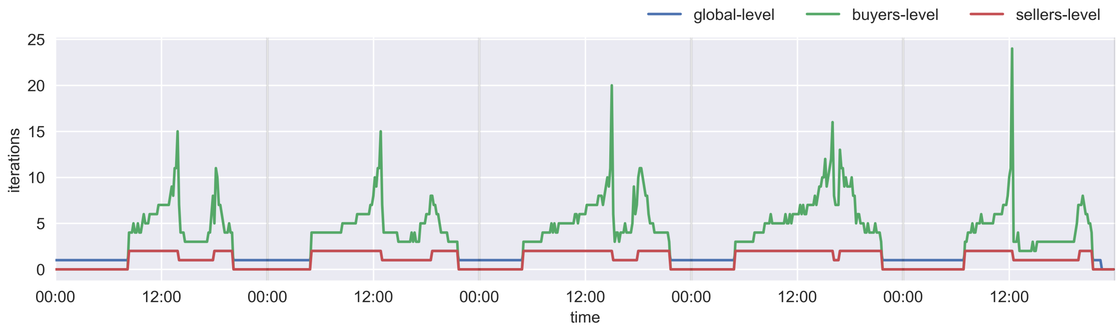

Figure 4-12: Iterations for buyers-level, sellers-level and global-level game.

Transaction throughput rate of EnergyBazaar with 40 households

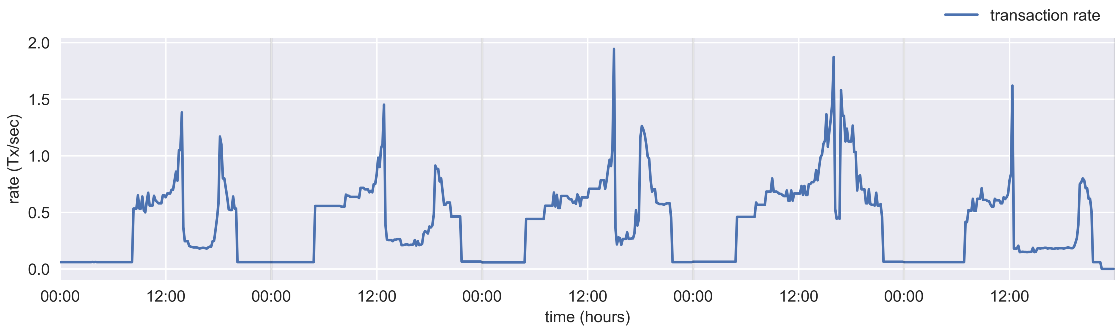

Figure 4-13: Transaction rate of agent communication to the Blockchain. Maximum transaction rate is ≈ 2 Tx/sec for a micro-grid of 40 households.

4-2 Micro-grid versus the macro-grid: when to decentralize?

When a community cannot rely on central institutions it might decide to decentralize, decentralization fueled by a social motivation. A community can also decide to decentralize its grid because it is cheaper, an economical motivation: for this case it is important we investigate in a methodology to find this tipping-point.

Levelized Cost of Electricity (LCOE) for a micro-grid

Within the micro-grid, buyer i gives prosumers tokens in return of their $E_{\text{allocation},i}$. Since prosumers have a steady E_{surplus} to be sold, prosumers will aggregate token within the grid, while consumers will constantly buy energy, thus spend tokens. Without circulation of token consumers will soon run out of initial token reserves. Additionally, without a way to use tokens, they will be worthless to the prosumer, stealing away the incentive to trade on the micro-grid market and thus help consumers. We search for a way to vitalize token-exchange in the micro-grid.

For both problems, two solution can be found. Firstly, establish a circular token-based economy with the EnergyBazaar token as a decentralized corner-stone. Then, energy-tokens can be spend by prosumers for services or products consumers offer in return. However, the commitment of a community to reject a fiat-currency must be large and infrastructure must be developed for this. A more realistic method is to link the energy-token to a fiat-currency.

One clue is the fiat-investment in hardware made by prosumers at the creation of the micro-grid.We calculate the LCOE of both prosumer and consumer, a calculation used to express generalized €/kWh for generation plants [181]:

$$LCOE = \frac{I_c + \sum_{t=1}^{n} \frac{O_{c,t}}{(1+i)^t}}{\sum_{t=1}^{n} \frac{E_{\text{production,t}}}{(1+i)^t}}. \tag{4-5}$$

In eq. (4-5), the levelized costs of electricity in €/kWh for any power-plant is described. I_c is the base investment, $E_{production,y}$ is the annual power output and $O_{c,y}$ are annual costs. n is the life-span of the plant, in this case the PV panels and ESS and the year of operation t is included to express interest rates over the years.

The LCOE for a consumer buying from the macro-grid is the average price for a kWh, 0.204 €/kWh [182]. For a consumer in a micro-grid running on EnergyBazaar, the LCOE within the Energy-Bazaar community is calculated by eq. (4-5):

$$LCOE_{EBZ} = \frac{(I_c + O_c) \cdot \frac{E_{supply,y}}{E_{production,y}}}{n \cdot E_{supply,y}}. \tag{4-6}$$

Here, a prosumer sells surplus energy for a price that accounts for its investment in hardware and for the LCOE: the price the agent would pay as a consumer to the utility grid if not producing energy himself. In eq. (4-6), a few assumptions have been made for simplification. The missed interest rate is omitted, thus t is 1. Also, $O_{c,y}$ is a constant, yielding O_c which is the total expected operational costs for the total lifespan. An economic assumption is that the prosumer wants to break even with its costs, through reimbursements with tokens. With these assumption, an expression for the token value T_v is derived:

$$(I_c + O_c) \cdot \frac{n \cdot E_{supply,y}}{n \cdot E_{production,y}} - N_t \cdot T_v = 0. \tag{4-7}$$

In eq. (4-7), N_t is the average amount of tokens received by a prosumer over the year. A payment at a given time-step k of : $N_t = c_i \cdot E_{\text{allocation},i}$. The energy originates from prosumers, who in return receive tokens for their supplied energy. Economically motivated consumers will refuse to pay more than macro-grid prices.

Table 4-6: Parameters that are used for a calculation of LCOE in the micro-grid.

Parameter	Symbol	Value	Origin
Life-span PV panel	n	25-30 years	from [181]
Installed investment	I_c	56,000 €	7 €/Wp, from [181]
Operational costs	O_c	10,000 €	from [181]
Annual production	$E_{production,y}$	10950 kWh	from assumption, 8kWp
Annual supply	$E_{supply,y}$	5111 kWh	from simulation
LCOE of macro-grid	LCOE$_{utility}$	0.204 €	from [182]
Aggregated tokens	N_t	222	from simulation
Token value	T_v	€	

An simplified LCOE example

A token should be carefully linked; if token value T_v proves too high, consumers would rather buy energy from the macro-grid. If T_v is too low, prosumers won't invest and maintain hardware, see eq. (4-7). A calibration for T_v with fiat-currency (€) is algebraically derived from eq. (4-5):

$$T_v = \frac{(I_c + O_c) \cdot E_{\text{supply,y}}}{N_t \cdot E_{\text{production,y}}} \tag{4-8}$$

Filling in the variables in eq. (4-8) and eq. (4-7) produces an example:

$$T_v = \frac{(56,000 + 10,000) \cdot 5111}{222 \cdot 10950} = 138,12\,€ \tag{4-9}$$

$$mLCOE_{EBZ} = \frac{(56,000 + 10,000) \cdot \frac{5111}{10950}}{25 * 5111} = 0.241\,€/kWh \tag{4-10}$$

With these two values, a rudimentary answer is given to two questions posed in this subsection. When should a community decentralize? And what is a method of calibrating a token to a fiat-currency. With a method to set the token value T_v to a value in €, an bona fide exchange is possible between prosumer and consumer and with it, the rest of the world, solving the problem of prosumers aggregating 'useless' tokens.

Secondly, a community grid should decentralize when prosumers can get break-even in their costs of energy generation, yielding LCOE_{EBZ}. In addition, consumers pay less to sellers in the micro-grid than to the macro-grid. For this last requirement, $\text{LCOE}_{\text{EBZ}} \leq \text{LCOE}_{utility}$ needs to hold. In the example given above, this is not yet the case with current prosumer-costs; with the LCOE_{EBZ} being 0,0370 €/kWh (or a factor 1.18) more expensive than buying energy from the macro-grid. We can make a statement on the relation between prosumer costs, its energy production during the lifespan of the Distributed Generation (DG) plant and the prices on the competing macro-grid (i.e. utility-grid).

$$LCOE_{\text{EBZ}} = \frac{(I_c + O_c) \cdot \frac{E_{\text{supply,y}}}{E_{\text{production,y}}}}{n \cdot E_{\text{supply},y}} \leq LCOE_{\text{utility}} \tag{4-11}$$

$$(I_c + O_c) \leq \text{LCOE}_{\text{utility}} \cdot n \cdot E_{\text{production,total}} \tag{4-12}$$

As seen in fig. 4-14, the requirement $\text{LCOE}_{\text{EBZ}} \leq \text{LCOE}_{\text{utility}}$ in case of solar based grids, so-called 'grid-parity', is expected to be reached in more and more countries in the near future. Grid-parity, as seen in eq. (4-6), depends on production capacity of the power-plant, on costs I_c, O_c, and on prices of macro-grid energy. Our results compares well to the global trend of grid-parity; with a costs decrease of 18 %, our micro-grid would achieve grid-parity as well.

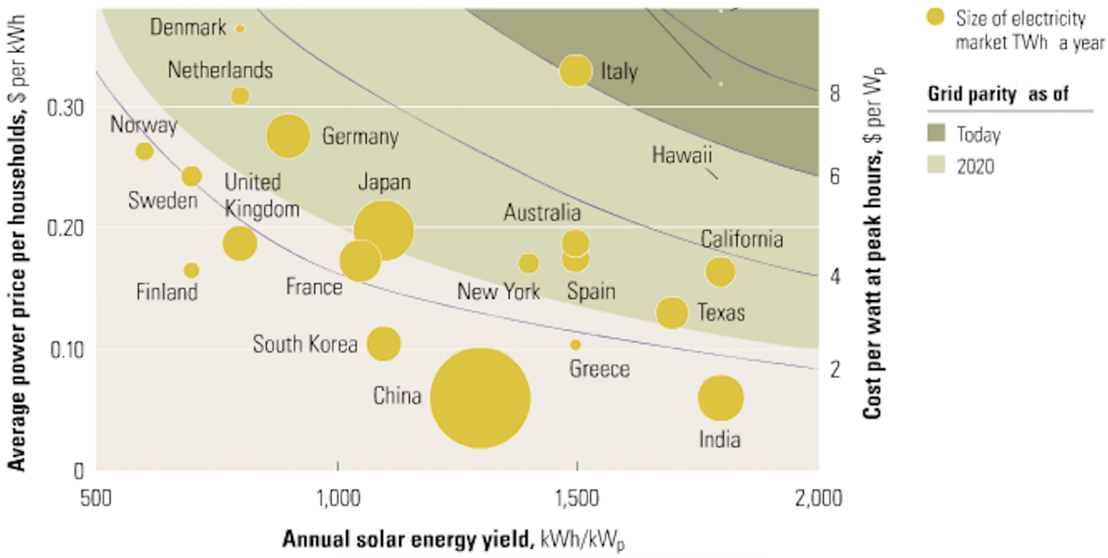

Figure 4-14: Expected grid parity around the world, a situation where $\text{LCOE}_{\text{EBZ}} \leq \text{LCOE}_{\text{utility}}$ holds. Figure is taken from [183].

4-3 Discussion

In chapter 4, the performance of EnergyBazaar is tested and compared to other methods. We tested EnergyBazaar both off-chain as on-chain and were able to make a statement on its scalability using a platform such as Ethermint.

The solution EnergyBazaar yields is better than its centralized counterpart when looking at the total energy deficit in the micro-grid. Agents make bids as a response to each other, in contrast to the centralized solution; energy prices become erratic. We see that, with EnergyBazaar and with default settings, deficits and overflows are small compared to a no-trade situation. Demand Side Management (DSM) solutions, to shift consumption away from the locations where deficits do not disappear completely, are easily added to EnergyBazaar. This is because E_{demand} and $E_{\text{consumption}}$ are decoupled by the batteries.

The pricing mechanism makes use of proportional allocation: for a larger piece of the total available energy, buyers have to increase their bidding price. Thus costs scale quadratically. This way, the utility functions of buyers have a suitable trade-off for convex optimization. Meanwhile, proportional allocation is also a fair way to divide a scarce asset: large consumers have proportionally higher costs; in a real-world micro-grid this would encourage efficient energy use. The pricing mechanism only works when demand is higher that supply. If not, energy is not a scarcity and proportional allocation fails to create a bidding market. In a real-world setting this works a bit different: in a power-grid, over-generation is a burden for the prosumers. Consumers can charge a price for taking over the extra energy, as a grid-balancing service. EnergyBazaar can be extended to also capture load-shedding services. Currently, consumers have the tendency to buy more energy than necessary, creating overflows at their batteries. Even after tuning of consumer utility parameters, this behaviour did not completely vanish.

In [72], the presence of a macro-grid that ushers external energy prices (possibly by dynamic pricing), creating a (variable) price domain for the buyers to make bids in. In this work, the macro-grid is modelled by overflows and deficits that are exported/imported from the micro-grid. Currently, the buyers in the micro-grid are not provided with the choice to buy from either the macro-grid or from sellers in the micro-grid. In case a micro-grid is not fully isolated from the macro-grid, this is a not a realistic assumption.

Agents take no regard to trade-minimization. Battery degradation is negligible over 5 days, but over the life-span of a battery, this is a real cause of concern. Batteries degrade especially with extreme (dis)charging, thus agents have a distinct incentive to have a constant supply or energy allocation to preserve their batteries. This is not captured in the utility functions. Other infrastructure considerations are not included as well: for example line-congestion and the introduction of Electric Vehicles (EV). Above all, functional actuator constraints is the most important feature that is missing. Even more so since we showed that current dis(charging) exceeds the limit on interval k at multiple moments throughout the day.

We considered a simplified micro-grid model. In a real-world setting, a more diverse portfolio of Distributed Energy Resources (DER) would be available. A more diverse portfolio decreases the dependency of agents on the solar energy spike in the afternoon. Previously mentioned EV could act as mobile ESS, further complicating the model but also assist in an efficient solution.

Furthermore, the assumption of an ESS installed at each household is not realistic. Households that have an ESS installed could lease virtual battery space to consumers that have none. This is a perfect extra use-case for a Blockchain: the smart-contract could be extended to record this agreements among agents. Generalizing this concept, communities could install an aggregated ESS and cover its costs by decentralized lease-contracts on Blockchain.

We implemented EnergyBazaar on Ethereum as a proof-of-concept. We saw that money-flows can be accounted for by a smart-contract deployed on the public ledger of Blockchain, albeit for a heavy toll on simulation execution time. How this will translate into a real-world setting is still unclear. The performance of a large scale micro-grid has not sufficiently been researched to conclude on scalability of on-chain EnergyBazaar, but transaction rate appears to scale almost linearly for up to 100 agents. For an micro-grid of 40 agents, a maximal average of 2 Tx/sec is needed to fit all transactions necessary at k within the time-frame prescribed by k. Ethermint has a maximum transaction rate of 200 Tx/sec. This shows great promise for scale-up of an order of magnitude: a community of 400 households would be a realistic real-world setting.

The 'cost of anarchy' is estimated at 0.046 €/kWh, although this estimation is by far not sophisticated enough. Costs have to be better defined; such as including battery costs and degradation, infrastructure costs and pricing strategies of the adjacent macro-grid. An effect shown in [72], where a macro-grid influences the energy prices within the micro-grid will be present in any real-world micro-grid that is not completely isolated. Especially for economically motivated micro-grids, this effect will greatly influence the decision whether to decentralize. Additionally, the installation and maintenance of the micro-grid is not accounted for. The Transmission System Operator (TSO) could still play an important role in this.

With an ideology such as EnergyBazaar, a self-sufficient community with an independent token-based economy has transgressed form being an Utopian concept into something that could be applied in the real-world in the foreseeable future.

Chapter 5

Conclusion and recommendations

5-1 Conclusion

In the future, communities will have an incentive to quit their dependency on centralized institutions. This incentive will have both: a economical basis as a societal basis. In order to investigate the possibilities of returning autonomy and energy ownership to such communities, we started our research with the question:

Can a transactive grid be established through deployment of a promise-keeping smart-contract triggered by a distributed algorithm that enables free-market trade?

As an answer, we proposed EnergyBazaar, a method that allows free-market energy trade within a micro-grid, allocating generated energy of prosumers to consumers. By doing this, EnergyBazaar minimizes the total energy deficit of any consuming household within the community, energy that otherwise should have been imported from the macro-grid. Additionally, prosumers obtain a way of trading their surplus energy, energy that otherwise would have been wasted after overflowing household batteries, or sold to the macro-grid for an unfair fixed price. With EnergyBazaar, consumers and prosumers within the community have a fair and dynamic market-place for energy, while completely decentralized.

This marketplace proves to be as efficient in its energy distribution as a centralized dispatching solution; which dictates rather than trades. With EnergyBazaar, households automatically full-fill the most important control task in any power-grid; balancing of demand and supply, a task normally reserved for a Balance Responsible Party (BRP)s. We compared the distributed algorithm of EnergyBazaar create energy prices that are intuitive; they are proportional to the degree of scarcity of energy in the community and form a solid basis to a true smart-grid; combining an energy market place with other Demand Side Management (DSM) solutions. This is in stark contrast with a centralized controller, which yields erratic prices.

Aiming for a complete decentralized paradigm, the value flows of EnergyBazaar cannot depend on a Third Trusted Party (TTP). As a proof-of-concept, we deployed EnergyBazaar as a smart-contract on an Ethereum Blockchain. Through it, we established decentralized payment. A major draw-back of using Blockchain is that all agent states are completely public. We reduced the amount of sensitive data to be shared among agents, yet through public bidding prices, network participants can still derive load-patterns of households.

Considerable costs are involved in creating an independent micro-grid. Prosumers have to invest in Distributed Generation (DG) units while all households need some sort of energy storage.

Although energy production by means of Photo Voltaic (PV) panels is becoming as inexpensive as energy imported from the macro-grid, the same cannot yet be said about energy storage. A considerable technological advancement is needed to decrease battery costs. Once a community is decentralized, its energy economy becomes a token-based zero-sum game. We showed the drawback of this situation; prosumers aggregate 'useless' tokens in case tokens cannot be exchanged with the outside-world. By linking tokens with fiat-currencies, this problem is mitigated and a cautious statement can be made about the economics of decentralization.

Although EnergyBazaar yields satisfying results, additional research is needed to apply this concept to a real world setting. We discuss this in the following section.

5-2 Recommendations for future work

In this thesis, we proposed a concept of decentralized energy markets. We provided a ground-layer; on top of which extra work can be added to make the complete system more sophisticated. Future work is categorized in different sections. Improvements on the algorithm itself, the Blockchain structure and further research necessary for the application of a real-world micro-grid with EnergyBazaar.

5-2-1 Continuation on EnergyBazaar

The EnergyBazaar algorithm was modeled as a hierarchical game, a structure borrowed from [72], in which a Stackelberg formulation is used. Although EnergyBazaar is an open-loop iterative game, the utility function of buyers, $\mathcal{U}_i$ is a standard function: a requirement for a traditional Stackelberg game. Thus, the algorithm could possible be improved by adopting this method. Besides extending the non-cooperative game, a comparison can be made with collaborative games. Although outside the scope of this thesis, coalitional games discussed in section 2-3 have proven to be able to tackle the Economic Dispatch Problem (EDP) as well.

Considering agents behaviour, the current utility functions $\mathcal{U}_i$ and $\mathcal{U}_j$ can still be sophisticated. The ability of a certain agent to predict community-wide energy scarcities would create an incentive to store energy, waiting until energy demand rises; even-though there is sufficient energy-demand. This can thus be included in the behaviour of agents. Currently, EnergyBazaar does not provide this foresight; an agent is merely able to predict its own production and consumption. An ethical study should also be conducted to see how in how far this behaviour should be before agents are considered to manipulate the market.

Furthermore, we made the assumption that sellers and buyers are uniform in their behaviour. When this assumption does not hold, agents will use varying and personal utility function. Research should be conducted into the real-world behaviour of agents in a community and this behaviour should be captured and accounted for. For example, altruism, where agents show irrationality in that they share energy without pursuing the highest possible personal utility. In this example, a collective welfare could be modeled: individual agents that strive against energy-poverty across the community. Afterwards, an investigation should conclude whether agents with diverse behaviour still converge to a solution to the EDP problem.

A feature that was unsuccessfully implemented in EnergyBazaar where battery saturation limits $P_{\max}$. We looked at the charging behaviour of a Energy Storage System (ESS) in an unconstrained optimization and concluded that certain spikes surpass the limit $P_{\max}$, which is not physical possible. Although discharging can be constrained by an upper-bound of w_j, constraining charging behaviour with c_i using the same method is not possible without destroying the free-market pricing mechanism, with plummeting prices as a result. A constraint to battery charging needs to be added.

Continuing on the pricing mechanism; EnergyBazaar currently does not allow negative prices of c_i. Negative prices make sense when overflows occur in a real-world situation. The problem of overflow or over-generation and its solutions (load-shedding) are discussed in [184]. Adding such strategies to EnergyBazaar would enable consumers to take on the burden of over-generation for a price. A mobile fleet of autonomous Electric Vehicles (EV) could play a very interesting role in a load-shedding solution, if allowed to roam the grid in search for overflows in the system.

In a real-world setting, the micro-grid infrastructure should be accounted for in the EDP. Power congestion in a power-grid is an issue that cannot be omitted. The methodology used in [185] can be added to the EnergyBazaar concept to account for line-congestion. To model this, a cooperative games can be used such as the authors in [132] do. For this, a realistic topology of the grid should be modeled, discussed in [4]. Another feature that is omitted is the presence of a fleets of EV in the micro-grid, discussed in section 2-1-4. The integration of a fleet of EV in a grid is the topic of [92] and its method can be layered over EnergyBazaar.

Finally, prediction is omitted in the scope of this thesis. We provided agents with the real data. In a real-world application, this obviously is not possible. Thus a prediction methods should be implemented. Beforehand, it is already possible to discover what the impact of prediction accuracy has on the micro-grid. An uncertainty in prediction data will always remain and needs to be accounted for by the agents in the form of a minimum energy reserve.

5-2-2 Blockchain and EnergyBazaar

We proposed a smart-contract layer for EnergyBazaar. EnergyBazaar, implemented in Python, makes use of a Python - Ethereum Application Programming Interface (API) called Web3.py. The newest version 4.0.0 will contain the feature `eth.account`, which enables adding accounts. Only then, a test-environment can be created with more that 9 agents, essential for testing scalability of the smart-contract feature of EnergyBazaar. Afterwards, implementation of EnergyBazaar on Ethermint is the next step. Ethermint makes use of a Proof of Stake (PoS) consensus protocol based on a practial Byzantine Fault Tolerance (pBFT) protocol and does not require the waste of physical resources such as the Proof of Work (PoW) of Ethereum. Whether distributed optimization over Blockchain is realistic should then be answered.

An important next step in the development of EnergyBazaar is shifting the focus from a synchronous network assumption to assuming an asynchronous network. In such network, agent need to know what agents are jammed or lagging. Namely, this will influence distributed optimization: if a transaction that updates $E_{\text{surplus},j}(k)$ of agent j is jammed, other agents have the chance either to use $E_{\text{surplus},j}(k-1)$ or omit agent j from the optimization.

The biggest draw-back of the implementation of EnergyBazaar on Blockchain is the issue of privacy and confidentiality. All information stored within the smart-contract is per definition shared and public to all nodes. Although the most sensitive data on energy consumption $E_{\text{demand},i}$ is not shared over the network, bidding prices are. Bidding prices are only needed by buyers. Nevertheless, sellers also receive c_i, while they only need c_n. For EnergyBazaar to become privacy conserving and confidential, features of privacy-preserving Blockchains such as pseudonymous transactions used by Monero [186] and Hawk [187] should be adopted, discussed in appendix C-2.

Appendix A

EnergyBazaar: proofs

A-1 Proof of convexity for utility functions $\mathcal{U}_i$ and $\mathcal{U}_j$

A-1-1 Utility function $\mathcal{U}_i$

To proof a Nash equilibrium exists for $\mathcal{U}_i$, we must prove $\frac{\partial^2 \mathcal{U}_i}{\partial c_i^2} > 0$, see [72]. Settings are $\lambda_{i,1} = 2$ and $\lambda_{i,2} = 1$. We derive $\mathcal{U}_i$ twice over c_j to yield $\frac{\mathcal{U}_i}{\partial c_i^2}$:

$$\mathcal{U}_i(w_n, \mathbf{c}) = \left(E_d - E_s \frac{c_i}{c_i + c_o}\right)^2 + \ E_\mathrm{s} \frac{c_i^2}{c_i + c_o} \tag{A-1}$$

$$\frac{\partial \mathcal{U}_i}{\partial c_i} = -2E_d E_s \frac{c_o}{(c_i c_o)^2} + E_s^2 \frac{c_i c_o}{(c_i + c_o)^3} + E_s \frac{c_i^2 + 2c_i c_o}{(c_i + c_o)^2} \tag{A-2}$$

$$\begin{aligned} \frac{\partial^2 \mathcal{U}_i}{\partial c_i^2} = 2E_d E_s \frac{2c_i c_o + 2c_o^2}{(c_i + c_o)^4} \\ + E_s^2 \frac{c_o(c_i + c_o) - 3c_o}{(c_i + c_o)^4} + E_s \frac{(2c_i + c_o) + 2(c_i + c_o)(c_i^2 + c_i c_o)}{(c_i + c_o)^4} \end{aligned} \tag{A-3}$$

$\frac{\partial^2 \mathcal{U}_i}{\partial c_i^2} > 0$: the negative term $-3c_o$ is countered by positive quadratic terms of c_o in the first of the three parts of $\frac{\partial^2 \mathcal{U}_i}{\partial c_i^2}$, when $E_d > E_s$. Indeed, when $E_d < E_s$, prices in the micro-grid drop to zero immediately.

A-1-2 Utility function $\mathcal{U}_j$

To proof a Nash equilibrium exists for $\mathcal{U}_j$, we must prove $\frac{\partial^2 \mathcal{U}_j}{\partial w_j^2} > 0$, see [72]. Settings are $\lambda_{j,1} = 2$ and $\lambda_{j,2} = 2$. We derive $\mathcal{U}_j$ twice over w_j to yield $\frac{\mathcal{U}_j}{\partial w_j^2}$:

$$\mathcal{U}_j(\mathbf{c}) = \left(SOC_{gap} - E_j(1-w_j) \right)^2 - \left(R_{\mathrm{d}} \; \frac{E_j w_j}{E_o w_j + E_l w_l} \right)^2 \tag{A-4}$$

$$\frac{\partial \mathcal{U}_j}{\partial w_j} = 2SOC_{gap}E_j - E_j^2 + E_j^2 w_j - 2R_d \frac{E_j^2 E_o w_j}{(E_o + E_j w_j)^3} \tag{A-5}$$

$$\frac{\partial^2 \mathcal{U}_j}{\partial w_j^2} = E_j^2 - 2R_d \frac{E_j^2 E_o (E_o + E_j w_j)^3 - 2E_j^3 E_o w_j}{(E_o + E_j w_j)^3} \tag{A-6}$$

Here, $\frac{\partial^2 \mathcal{U}_j}{\partial w_j^2} \geq 0$ does not hold for all situations. To be more specific, only when $R_d(E_o + \frac{E_j w_j}{E_o}) \leq 2R_d(E_j w_j)$, the second term of $\frac{\partial^2 \mathcal{U}_j}{\partial w_j^2} \leq 0$. This is also see in fig. 3-3: if utility from direct revenue would be high enough, it would bend $\mathcal{U}_j$ into a non-convex function. If this situation occurs, posing an upper-bound on w_j at 1 still constrains w_j within physical bounds. Clearly, when the gap of $SOC_{gap} - E_j(1-w_j)$ is fully closed, there is incentive for the seller to sell all its E_{surplus}, causing w_j to hit its upper-bound of 1.

A-1-3 Standardness of functions $\mathcal{U}_i$

In a closed-loop Stackelberg game, the best-response $\mathcal{B}_i = \mathrm{argmax}_{c_i} \mathcal{U}_i$ is algebraically plugged-in at the sellers level game. Using this formal Stackelberg game structure as a hierarchical distributed optimization is possible only when utility function $\mathcal{U}_i$, of the followers, is a standard function, see proposition 2 and definition 3 in [72]. Although EnergyBazaar is not closed-loop, personal correspondence with S. Bahrami, author of [144] convinced us to verify standardness of $\mathcal{U}_i(c_i)$:

- Positivity: $\mathbf{f}(\mathbf{p}) > 0$ with $p \geq 0$.
  - $\mathcal{U}_i(c_i)$: Since both terms are squared, both terms will be positive. $\mathcal{U}_i(c_i)$ is positive only when $c_i > 0$. Positivity thus does not strictly hold for $\mathcal{U}_i(c_i)$. However, given the fact that $c_i \neq 0$, positivity holds. In [72], this relaxation has been applied as well.
- Monotonicity: For all $\mathbf{p}$ and $\mathbf{p}'$, if $\mathbf{p} \geq \mathbf{p}'$, then $\mathbf{f}(\mathbf{p}) \geq \mathbf{f}(\mathbf{p'})$.
  - $\mathcal{U}_i(c_i)$: if $c_i > c_0$, then $\mathcal{U}_i(c_i) > \mathcal{U}_i(c_0)$. With $\frac{c_i}{c_o} = \alpha$, $\mathcal{U}_i(c_i) = \frac{\alpha \cdot c_i}{E_d - E_s \cdot \alpha}$. With $\alpha > \alpha_0$ and $c_i > c_0$, $\frac{\alpha \cdot c_i}{E_d - E_s \cdot \alpha} - \alpha > \frac{\alpha_0 \cdot c_i}{E_d - E_s \cdot \alpha_0} - \alpha_0$, when $E_d < E_s$, which is easily verifiable numerically. E_d and E_s are initialized values and are fixed during the game. If at the beginning $E_d < E_s$ holds, a bidding game is played among buyers. When $E_d \not> E_s$, bidding prices drop to zero, as observed in chapter 4. Under normal conditions with $E_d < E_s$, monotonicity holds for $\mathcal{U}_i(c_i)$.
- Scalability: For all $\mu > 1$, $\mu \mathbf{f}(\mathbf{p}) > \mathbf{f}(\mu \mathbf{p})$.
  - $\mathcal{U}_i(c_i)$: for the first term of $\mathcal{U}_i(c_i)$ scalability holds since $\mu E_d - E_s \frac{\mu c_i}{c_i + c_o} > E_d - E_s \frac{\mu \cdot c_i}{c_i + c_o}$. For the second term it holds as well, since $\frac{1}{c_i + c_o} > \frac{1}{\mu \cdot c_i + c_o}$. Conclusively, scalability holds for $\mathcal{U}_i(c_i)$ with the first and second term being added up.

Summarily, $\mathcal{U}_i(c_i)$ is a standard-function, allowing us to apply the Stackelberg framework, albeit in open-loop form. For a revisit to open-loop discrete dynamic Stackelberg games, see [188].

A-1-4 Benchmark to utility function $\mathcal{U}_j$

We substituted $\mathcal{U}_j$ with a utility function that does not regard prediction. This utility function is used in [72]. In figure fig. A-1, its shape for different trade-off weights γ_j is visualized. In section 4-1-2, we chose γ_j to 0.4. This yielded the best result.

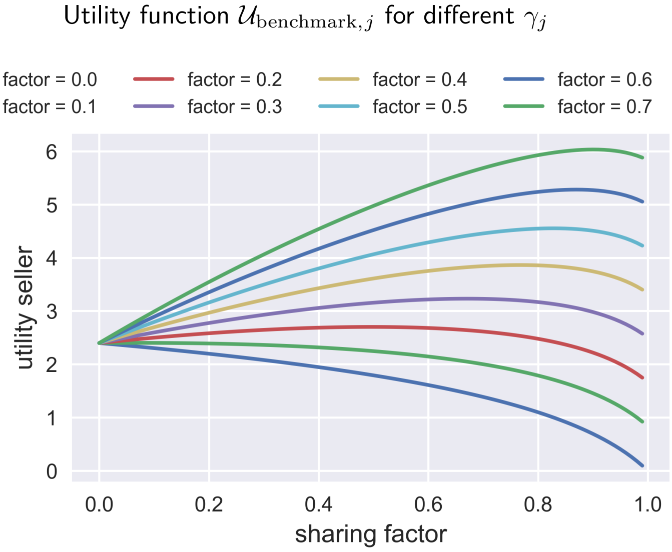

Figure A-1: Prediction-less utility function for seller j in a 'no-prediction' paradigm, from [72]. Plotted over a range of weights γ_j, it becomes clear that at a γ_j of 0.4, the convex function is sufficiently relaxed to find an optimum over a wide range of w_j.

Appendix B

EnergyBazaar: implementation in Python and Solidity

B-1 System high-level lay-out

The implementation of EnergyBazaar is done in Python. We made use of the `MESA` package to make an agent-based model [189]. Two classes are created: an micro-grid class called `MicroGrid` and an agent class `HouseholdAgent`. A high-level overview of the implementation is given in fig. B-1. For the actual code, please be referred to https://github.com/dirkbig/master_thesis.

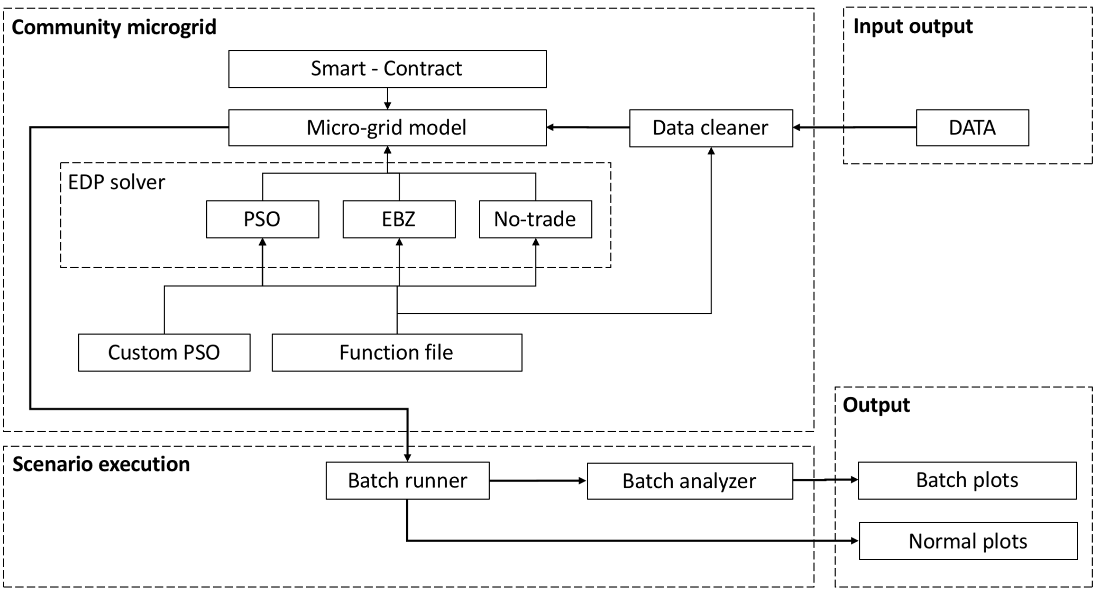

Figure B-1: High-level system-layout of the implementation of EnergyBazaar in Python. The smart-contract is written in Solidity and compiled through an API to Python called Web3.py.

Data is loaded in by the micro-grid model, wherein agents are communicating through state-changes on the smart-contract while either executing the distributed optimization algorithm EBZ, or being directed by the central PSO controller. The batchrunner preforms simulations for various parameter settings and outputs the results into files. These files are used to make plots.

B-2 Smart-contract pseudo-code

The smart-contract written in Solidity is used to store the mappings between accounts and their states. In the smart-contract, `getter`-functions call on these states and `setter`-functions make transactions to the Blockchain in order to change states. Functions can be either external or internal: external functions can be called by all agents, internal functions can only be called by other functions within the smart-contract. Functions consist out of simple logical rules that check where some requirement is satisfied. If so, the function proceeds to a next rule or action. The smart-contract has an escrow structure, wherein a decentralized aggregation of tokens pays-out and receives tokens from respectively sellers and buyers after a proof of supply of E_{supplied} or E_{demand}, provided by the smart-meter. An other option would be a token-mint and token-burn contract, where no aggregation of tokens exists, but where they are created and destroyed on the spot.

The contract is deployed by the function `MyToken()`, which signifies the origin of the transaction as the creator, saving its account in the `supplier`-state. A one-time function `giveStartingMoney()` pays-out an amount of tokens as a starting capital to agents that call this function. The mapping `startingMoneyGiven` is initialized at zero, and set to one when `giveStartingMoney()` is called by this address. This way, the smart-contract knows whether this address already received a starting capital.

In `mapping (address => uint256) public lastUpdatePromise`, promises are being stored. Actual trade-deals are stored in `mapping (address => uint256) public lastUpdateAction`. These mappings are public such that they can be seen by all agents. These states are updated by `makePromiseOfsell(value, timestamp)` and `makePromiseOfbuy(value, timestamp)`, providing the promised amount of energy and timestamp as inputs. Afterwards, the optimization rounds of EnergyBazaar begins, during which nominal bidding price c_n and nominal sharing factor w_n are updated by an internal function `computeNominalc` and `computeNominalw`. The mappings where c_n and w_n are stored are public and thus call-able. After optimization, deals are settled by functions `allocatedEnergy(value, timestamp)` and `suppliedEnergy(value, timestamp)`.

Blocks that are mined consist out of transactions of agents calling `setter`-functions. In appendix B-2, a 'receipt' of the 156^{th} block is given.

Algorithm 5

```
procedure SMART-CONTRACT ENERGYBAZAAR
    I: deployment of contract:
    MyToken()
        supplier = sender
        balanceOf[sender] = totalSupply
        timestampSmartcontract = 0
    giveStartingMoney()
        require(startingMoneyGiven[sender] ≠ 1)
        balanceOf[sender] = startingCapital
        startingMoneyGiven[sender] = 1

    II: initialization trading round:
    makePromiseOfsell(value, timestamp):
        promiseOfsell[sender] = value
        promiseOfbuy[sender] = 0
        lastUpdatePromise[sender] = timestamp
    makePromiseOfbuy(value, timestamp):
        promiseOfbuy[sender] = value
        promiseOfsell[sender] = 0
        lastUpdatePromise[sender] = timestamp

    III: optimization rounds:
    repeat
        repeat
            biddingpriceOf(price, allocation, timestamp):
                biddingpriceOf[sender] = price
                allocationOf[sender] = allocation
                lastUpdateAction[sender] = timestamp
        until all buying agents reported
        computeNominalc():
            cNominal = sum(biddingpriceOf[i]*E_allocation[i])/∑(E_allocation[i])
        repeat
            sharingfactorOf(value, timestamp):
                sharingfactorOf[sender] = value
                lastUpdateAction[sender] = timestamp
        until all selling agents reported
        computeNominalw():
            wNominal = sum(sharingfactorOf[i]*E_surplus[i])/∑(E_surplus[i])
    until wNominaltolerance < ε_sellers and cNominaltolerance < ε_buyers

    IV: settling deals:
    allocatedEnergy(value, timestamp):
        require(balanceOf[sender] >= value)
        require(promiseOfbuy[sender] >= allocatedTo[sender]
        balanceOf[sender] -= value
        balanceOf[supplier] += value
    suppliedEnergy(value, timestamp):
        require([sender] != 0x0)
        require(balanceOf[sender] >= value)
        require(promiseOfsell[sender] >= suppliedFrom[sender]
        balanceOf[sender] += value
        balanceOf[supplier] -= value
```

```
AttributeDict({ 'number': 156, 'hash': '0
    xa4ac7c3c6c54e810755d40fe8ade29a60e27fd3fc7a18ff79876ffbf7fdb261e', '
    parentHash': '0
    x0fa3bf4a6e25bd23516ea6f6f2929e223389316f5146b9ccfab9dcb62211b7c6', '
    nonce': '0x0000000000000000', 'sha3Uncles': '0
    x1dcc4de8dec75d7aab85b567b6ccd41ad312451b948a7413f0a142fd40d49347', '
    logsBloom': '0x00000000000000000000000000000200004000000000000000...',
    'transactionsRoot': '0
    x6444c25820c66ea509037120d6060e658ef5561a15baa18f848dc312a8656668', '
    stateRoot': '0
    x7afacd0368c2821b177e666686b4bb839315f736949d8c51db7058ced9a4204e', '
    miner': '0x82a978b3f5962a5b0957d9ee9eef472ee55b42f1', 'difficulty':
    134745, 'totalDifficulty': 20874617, 'size': 674, 'extraData': '0
    x0000000000000000000000000000000000000000000000000000000000000000', '
    gasLimit': 4000000, 'gasUsed': 41586, 'timestamp': 1410974997, '
    transactions':['0
    x2ae22f862c6d2862671f6c15dbc68e35cf69586dfe03f80445d7a6ee5593489d'], '
    uncles': []})
```

Figure B-2: Block format of an arbitrary block (number 156) mined at time step 15. Since the `TestRPC` network immediately mines blocks, the nonce value is still its initial value.

Appendix C

Blockchain

C-1 Blockchain overview

An overview of Blockchains is given in table C-1. We chose Ethereum as a platform to test EnergyBazaar. Our motivation was that we could test a smart-contract using Ethereum with Solidity as smart-contract programming language. An Application Programming Interface (API) from Python to Ethereum, Web3.py, is available, though not yet all necessary functions are available, which made testing difficult. Ethereum makes use of a Proof of Work (PoW) consensus protocol that is unsuitable for energy-trading with a high transaction rate and necessary scaling. Ethermint is a combination Ethereum and Tendermint, that is based on the practial Byzantine Fault Tolerance (pBFT) consensus protocol. Ethermint makes use of a fast and scalable Proof of Stake (PoS) protocol that is not wasteful.

List of various Blockchains

Name	Persmission	Protocol	Tx/s	SC [1]	Ref
Ethereum	permission-less	Proof of Work	Low	Yes	[190]
Iota	permission-less	the Tangle	High	No [2]	[155]
Hyperledger Fabric	permissioned	Custom	High	Yes	[191]
Tendermint	permissioned	pBFT	Medium	No	[192]
Ripple	permissioned	RCPA	High	No [3]	[193]
Chain	permissioned	Federated	High	Yes	[194]
MultiChain	permissioned	pBFT [4]	High	No	[195]
ZCash	permissioned	Proof of Work	Medium	No	[196]
Hawk	permission-less	Proof of Work	Low	Yes	[187]
Ethermint	permissioned	PoS	High	Yes	[180]

Table C-1: Overview of Blockchain platforms.

C-2 Privacy and confidentiality

Oracle published guidelines to follow in order to conform to new General Data Protection Regulation (GDPR) legislation within the European Union. On the topic of anonymization and pseudonymization: the application of pseudonymization to personal data can reduce the risks for the data subjects concerned and help controllers and processors meet their data protection obligations [197]. Through the public ledger of a Blockchain, any agents could gather gain information on load-patterns of households in the grid.

To protect the privacy of the end-user, different cryptographic techniques are capable of providing solutions for privacy safe-guarding both Blockchain and off-chain. Homomorphic encryption is used to obscure the information on the public ledger. Ring-signatures are used to obscure the identity of the node in a communications network.

Homomorphic encryption

In [198], a basic definition on homomorphic encryption is given. Let $\mathcal{M}$ denote the message in plain-text and $\mathcal{C}$ the cipher-text. Encryption is called homomorphic if for any encryption key k the encryption function E satisfies:

$$\forall m_1, m_2 \in \mathcal{M}, \quad E(m_1 \odot_{\mathcal{M}} m_2) \leftarrow E(m_1) \odot_{\mathcal{C}} E(m_2), \tag{C-1}$$

using operator $\odot_{\mathcal{M}}$ and $\odot_{\mathcal{C}}$, with $\leftarrow$ representing direct decryption. For a fixed key k, it is equivalent to perform math operations on $\mathcal{M}$ or $\mathcal{C}$. This property enables remote modification of encrypted data without decryption. Applying homomorphic encryption on a Blockchain could means that information inside of transactions could be completely hidden while still allowing for the prover and verifier to prove the validity of a transaction.

Homomorphic encryption is applied in zero knowledge Succinct Non Interactive Arguments of Knowledge (zk-SNARKs), a proof construction where interaction between prover and validator is not necessary. This reduces the communication necessary, saving valuable computational resources. Both in Hawk [187] and ZCash [196], zk-SNARKs are used in order to encrypt transactions on the public ledger.

Ring-signatures

Group-signatures allow a group master to set up a pool of member that becomes authorized to produce a signature for messages on behalf of the whole group [199]. The authors of [200] improve this scheme by anonymization of the signer within the group itself. Adversaries have negligible probability of specifying the original sender within the group. Among different issues, the key drawback of group-signatures is that a trusted group-master is needed to set up the group [201]. To solve this issue, ring-signatures are created. Ring-signatures are first introduced in [202]. Unlike group-signatures, ring signatures are completely decentralized, a key feature that makes application for anonymization in decentralized systems possible. Monero utilized ring-signatures for hiding of the destination and origin of transactions [186]. Link-able ring-signatures go one step further by making the anonymous transactions linked to each other, linking transaction according to the anonymous signer, useful for example in e-voting [203].

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Glossary

List of Acronyms

AC	Alternating Current
AGC	Automatic Generation Control
AMI	Advanced Metering Infrastructure
API	Application Programming Interface
pBFT	practial Byzantine Fault Tolerance
BRP	Balance Responsible Party
DC	Direct Current
DER	Distributed Energy Resources
DG	Distributed Generation
DSM	Demand Side Management
DP	Dynamic Pricing
DR	Demand Response
EBZ	EnergyBazaar
ECDS	Elliptic Curve Digital Signature
EDP	Economic Dispatch Problem
EMS	Energy Management System
ESS	Energy Storage System
EV	Electric Vehicles
GA	Genetic Algorithms
GDPR	General Data Protection Regulation
KPI	Key Performance Indicator
LASS	Laboratory for Advanced System Software

LC	Local Controllers
LCOE	Levelized Cost of Electricity
LoRaWAN	Long Range Wide Area Network
MAS	Multi Agent System
MGCC	Micro Grid Central Controller
MPC	Model Predictive Control
MPP	Maximum Power Point
NN	Neural Network
P2P	Peer to Peer
PAR	Peak to Average Ratio
PoS	Proof of Stake
PSO	Particle Swarm Optimization
PTU	Program Time Unit
PV	Photo Voltaic
PoW	Proof of Work
RES	Renewable Energy Sources
RMSE	Root Mean Square Error
SLSQP	Sequential Least Squares Programming
zk-SNARKs	zero knowledge Succinct Non Interactive Arguments of Knowledge
SOC	State of Charge
SVM	Support Vector Machines
TSO	Transmission System Operator
TTP	Third Trusted Party
V2G	Vehicle to Grid
VM	Virtual Machine

List of Symbols

A list of recurring symbols, listed in order of appearance:

ω	Frequency
M	Dynamical Model Matrix
P	Active Power
Q	Reactive Power
V	Voltage
X	Reactance
R	Resistance
θ	Phase Angle
U	Utility
c	Bidding Price
w_j	Sharing Factor
$\mathcal{I}$	Set of Buyers
$\mathcal{J}$	Set of Sellers
S	Solar Irradiance
T	Temperature
E	Energy
$\mathcal{C}$	Contract
G	Guarantee
A	Assumption
u	Control Action
C	Costs
s	State Variable
$\mathcal{A}$	Mapping of Optimal Response
z	Fixed Point
x	Position State
v	Velocity State
a	Momentum
o	Optimal position
g	SVM Describing Function
γ	Weight
N	Number of Agents
a	Strategy
h	Horizon
δ	Discount
$\mathcal{U}$	Utility Function
$\mathcal{B}$	Best Response
l	Load Schedule
Φ	Shapely Value
π	Coalitions
M	Message
H	Hash Function
h	Hash Value
SOC	State of Charge
k	Time Step
R	Revenue
p	Prosumer Participation
Tx	Transaction
$\mathcal{T}$	Number of Tokens
I	Capital Costs
O	Operational Costs

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