Mechanism Design for Virtual Power Plants with Strategic Agents

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Mechanism Design for Virtual Power Plants with Strategic Agents

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Abstract

As power systems increasingly rely on renewable energy, grid services traditionally supplied by central plants must increasingly be sourced from distributed energy resources (DERs). Virtual power plants (VPPs) aggregate DERs to act as a single entity, but coordination is complicated by information asymmetry, possibly resulting in strategic behaviour. This thesis studies how we can design a mechanism for a commercial VPP, having to satisfy a fixed commitment, while optimising the revenue from the VPP operator.

We first develop a tractable, multi-period VPP model with linear costs, local and temporal constraints for DERs and soft system-wide commitments enforced via deviation penalties. On top of this model we design and compare four mechanisms: first-price sealed bid (FPSB), uniform pricing, Vickrey–Clarke–Groves (VCG) and Arrow–d'Aspremont–Gerard-Varet (AGV). We evaluate them on revenue optimality, weak budget balance, incentive compatibility, individual rationality and scalability. Furthermore, we investigate how the composition of a VPP's portfolio could inform mechanism design choices.

FPSB realises payments equalling costs under truthful reports and remains competitive for small strategic fractions, but overpayment grows with the share of strategic agents and with cost dispersion. Uniform pricing is comparatively insensitive to the strategic fraction but highly sensitive to cost dispersion, often leading to large overpayments. VCG is strategy-proof and insensitive to strategic behaviour, yet externality payments increase with cost dispersion and raise total payouts. AGV keeps the payment-to-cost ratio near or below one by relying on expected externalities and scaling, improving operator viability but potentially violating individual rationality in instances.

These results yielded the following guidelines regarding the suitability of mechanisms. FPSB for low strategic participation, uniform pricing for homogeneous portfolios, VCG when truthfulness is vital and external funding is possible, and AGV when operator viability is the hard constraint with safeguards for individual rationality.

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Preface

This research was conducted to fulfil the requirements to graduate as an engineer from the computer science master at Delft University of Technology. After a long fostered interest in electricity — my high-school cross-curricular project as well as my bachelor thesis revolved around the electricity grid — I was happy to find out about the TU Delft AI Energy Lab. I expressed my interest in using algorithmics for fair electricity markets and they proposed to apply this to the area of virtual power plants.

Conducting this master research has been invaluable to my learning experience at Delft University of Technology. Because of the vastness of the research field, I learned the importance of scoping my research by making certain assumptions. I was a bit reluctant doing this at first, but I learned that making assumptions is an indispensable part of doing research. I learned that, as long as they are well argumented and carefully considered, assumptions are a powerful tool.

The most important thing that I have learned during my time at TU Delft is to ask the right questions. Recognising what I do not know has been very meaningful for my approach to solving complex problems. During the bachelor and masters, we were given the tools to find answers to the questions that we learned to ask ourselves.

Readers are expected to have a basic understanding of the workings of the electricity grid. Additionally, basic knowledge of linear algebra concepts and mechanism design is assumed. A nomenclature has been prepended to ensure a correct understanding of the terms.

Readers that are particularly interested in our approach to modelling a virtual power plant are best off reading Chapter 2. Those specifically interested in mechanism design are invited to read Chapter 3. Finally, those who wish to get a general understanding of this research and its results are recommended to read Chapters 1 and 5.

I would like to thank Haiwei for her support, patience and continuous availability to answer all my questions. Our weekly discussions were refreshing to my thinking process, guided me in the right direction and helped me find a perspective how to approach the problems encountered. Thank you Mathijs and Jochen for your mentoring. I really valued the discussions during the joint meetings where you taught me the skill of setting and validating assumptions, which has been an essential skill throughout writing this thesis. Last but not least, my parents, brother, sister, friends and girlfriend for their unconditional support throughout my education.

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Nomenclature

Abbreviations

AGV	Arrow–d'Aspremont–Gerard-Varet
BNIC	Bayesian Nash Incentive Compatible
CVPP	Commercial Virtual Power Plant
DER	Distributed Energy Resource
DSIC	Dominant Strategy Incentive Compatible
EMS	Energy Management System
FPSB	First-Price Sealed Bid
TSO	Transmission System Operator
TVPP	Technical Virtual Power Plant
VCG	Vickrey–Clarke–Groves
VPP	Virtual Power Plant

Sets and Indices

N	Number of DERs aggregated by the VPP
$\mathcal{N} = \{1, \ldots, N\}$	Index set of all DERs
T	Number of discrete timesteps
$\mathcal{T} = \{1, \ldots, T\}$	Index set of timesteps
M	The grid services being delivered
$\mathcal{M} = \{1, \ldots, M\}$	Index set of grid services

Decision Variables

$x_{i,t,m}$	The amount of service $m \in \mathcal{M}$ delivered by DER i at time t
	$x_{i,t}$, x_i and x are used to denote the vector, matrix and tensor respectively.

Cost Parameters and Functions

$u_{i,t,m}$	Cost of DER i to deliver one unit of service $m \in \mathcal{M}$ at time t

$c_{i,t}(x_{i,t})$	Cost of DER i at time t given $x_{i,t}$
$c_i(x_i)$	Total operating cost of DER i under allocation x_i
$c(x)$	Total operating cost across all DERs
$\lambda^+_{t,m}, \lambda^-_{t,m}$	Penalty rates (€ /unit) for surplus and deficit of service m at time t
$f(\epsilon)$	Total penalty cost
$\alpha_{i,t}$	Cost inflation factor applied by agent i at time t
$\theta = (c, \mathbb{X}, g)$	True private information containing cost functions and constraints
$\hat{\theta}$	Reported information set communicated to the VPP operator
$\mathcal{X}$	Allocation function
	$u_{i,t}$, u_i, and u denote the cost vector, matrix, and tensor respectively. λ^+_t, λ^-_t and λ^+, λ^- denote the vectors and matrices respectively. α_i and α denote the vector and matrix respectively.

Feasible Regions and Constraints

$\mathbb{X}_i$	Feasible region denoting local constraints for DER i
$g_i(\cdot) \leqslant 0$	Temporal coupling constraint for DER i
$S = \{i \mid \lVert x_i \rVert \neq 0\}$	Set of DERs with non-zero allocation

Agreements and Slacks

$b_{t,m}$	Commitment for service $m \in \mathcal{M}$ at time $t \in \mathcal{T}$
P_t	Active power commitment at time t (component of b_t)
Q_t	Reserve commitment at time t
$\epsilon^+_{t,m},\ \epsilon^-_{t,m}$	Surplus/deficit slacks for service m at time t
	b_t and b denote the vector and matrix respectively.

Metrics

r_i	Ratio between payment and true cost of DER i
r	Payment-to-cost ratio at the VPP level (weighted average over participating DERs)
s	Proportion of DERs that behave strategically, $s \in [0, 1]$
ϕ	Coefficient of variation for unit costs used in experiments
γ	Target profit margin in the viable VPP condition

Miscellaneous

p_i	The payment from the mechanism to DER i
v_i	Utility of DER i

z	Binary indicator used to enforce mutually exclusive slack directions
M	Big-M constant used in linearisation constraints
φ_t	Normalised solar irradiance profile used in case studies
ψ_t	Normalised wind availability profile used in case studies
$\text{SoC}_{i,t}$	State of charge of storage unit i at time t
E_{max}	Energy capacity of storage
E_t	Energy state variable in storage models

Contents

Chapter 1

Introduction

This introduction focusses on providing important foundations for this research. Therefore, first explaining why and how virtual power plants (VPPs) come into place (Section 1.1). Consequently, we more explicitly describe the problem that we are considering in this thesis (Section 1.2). To introduce the reader to this research field, we provide a brief overview of recent work in this field (Section 1.3). Furthermore, we provide general directions for conducting this research by setting our research questions (Section 1.4). Finally, to provide the reader with a solid understanding of how this thesis is structured, and why it is structured this way, we explain the outline of the thesis in Section 1.6. Note that, for introductory purposes, Section 1.2 and Section 1.3 provide a condensed outline of these topics. A more in-depth discussion takes place in Chapter 2 and 3.1 respectively.

1.1 Background and Motivation

With the transition to renewable energy, the electrical grid is accommodating an increasing number of distributed energy resources (DERs), including solar panels, wind turbines and home batteries. Unlike traditional power plants that offer predictable power generation, the power generation of DERs — often reliant on renewable sources — is influenced by environmental factors such as sunlight and wind. Furthermore, the variability and converter-based nature of those resources present significant challenges for grid operators in balancing electricity supply and demand, respecting network capacity limits and ensuring grid stability [1]. Additionally, DERs are usually small-scale energy resources that, on their own, do not posses enough market capacity to participate in the various electricity markets. To address this challenge, the concept of a virtual power plant (VPP) has been introduced. A VPP aggregates multiple DERs to act as a single, controllable unit. This enables VPPs to offer coordinated energy production and provision of ancillary services, supporting grid stability and participating in electricity markets.

1.2 Problem Statement

In this thesis, we consider the scenario where a VPP must fulfil a fixed day-ahead commitment with a profit maximisation objective. Although interaction with electricity markets is not considered in this thesis, aforementioned commitments could, for example, arise from participation in one of the various electricity markets.

Unifying the DERs to operate as a single entity requires a control mechanism. Moreover, agents need to be incentivised to operate in alignment with the goals of the VPP operator. In the case of a closed system, i.e. the DERs and VPP operator are part of the same company, this is a rather simple problem, since the DERs are under direct control of the VPP and the VPP has perfect information regarding its DERs. However, in cases where the DERs are of different manufacturers, the DERs hold private information. DERs could behave strategically and report untruthful information to the VPP operator, in order to maximise their own utility [2]–[4]. This could compromise the efficient operation of a virtual power plant and hence brings us to the field of mechanism design.

1.3 Research Gap

Despite its practical relevance, there is limited research addressing VPP operation with strategic agents and a VPP revenue maximisation objective. Many studies prioritise social welfare under non-strategic assumptions or decentralised setups [5, Table 2]. Tsaousoglou et al. have taken into account strategic behaviour of agents in energy systems [6]–[11], but their research is mainly focussed on demand response programs. Amongst others, they proposed a near-optimal system for strategic, price-anticipating consumers with private preferences in a demand side management scenario [11]. Further research efforts address the presence of strategic agents in trading frameworks for neighbourhood area networks with shared energy storage [12].

No research addresses our problem formulation, in which the VPP must fulfil a predetermined commitment, under the presence of strategic agents and a profit maximisation objective. Furthermore, to the best of our knowledge, no studies address how the composition of a VPP's portfolio should inform mechanism design choices.

1.4 Research Questions and Objectives

Although our problem formulation has been widely adopted [13]–[15], not enough work has been done to address the presence of strategic agents in this problem formulation. This study aims to explore how a mechanism can be designed to align the incentives of DERs with the goals of the VPP operator. In support of this, this research aims to address three key questions:

1. How can the operational dynamics of a virtual power plant be modelled?
2. How do several mechanisms compare in terms of revenue optimality, weak budget balance, incentive compatibility, individual rationality and computational tractability?
3. How does the composition of a VPP's portfolio, particularly in terms of agent behaviour and difference in cost functions, influence the effectiveness of different allocation mechanisms?

1.5 Contributions

The contributions of this research are twofold. We present a comparison in terms of performance of several mechanisms *and* we provide new insights into how the composition of a VPP's portfolio affects the suitability and performance of those mechanisms. In particular, we pay attention to how several fractions of strategic agents, as well as the spread of cost parameters influence the results. These findings aim to inform the design of more resilient, adaptive and efficient internal market mechanisms for VPPs.

1.6 Thesis Structure

This thesis is structured to consecutively address the research questions and build a coherent understanding of mechanism design for VPPs with strategic agents, more graphically depicted in figure 1.1. This chapter introduced the problem and motivation, defined the research gap and questions. Furthermore, it previewed the approach and contributions. It established the need to model VPP operations and to handle strategic behaviour under private information, setting up Chapters 2 and 3.

Chapter 2 develops an operational model of a VPP with a fixed day-ahead commitment and heterogeneous DERs. It clarifies objectives, constraints, costs and the information structure. The remaining gap is that agents may not report truthfully. The model alone cannot guarantee desired outcomes. This motivates mechanism design in Chapter 3.

Chapter 3 defines design criteria and presents four mechanisms. It analyses their theoretical properties under strategic behaviour. Although the theoretical analysis indicates correlations, it does not provide absolute magnitudes of the metrics related to the design criteria. This motivates empirical validation in Chapter 4.

Chapter 4 applies the mechanisms in a simulated case study to quantify performance, assess robustness to agent mix and cost heterogeneity. This turns theoretical correlations into concrete numbers and practical insights. The remaining need is to further interpret results, discuss implications and limitations for practical usage. This leads to Chapter 5.

Chapter 5 discusses results, limitations and implications for VPP operators. We answer the research questions and distil recommendations for future work. Furthermore, we extrapolate the results to recommendations for VPP mechanism design. Further questions are recommended as directions for future work.

Chapter 6 concludes by summarising contributions, outlining key takeaways and future research directions.

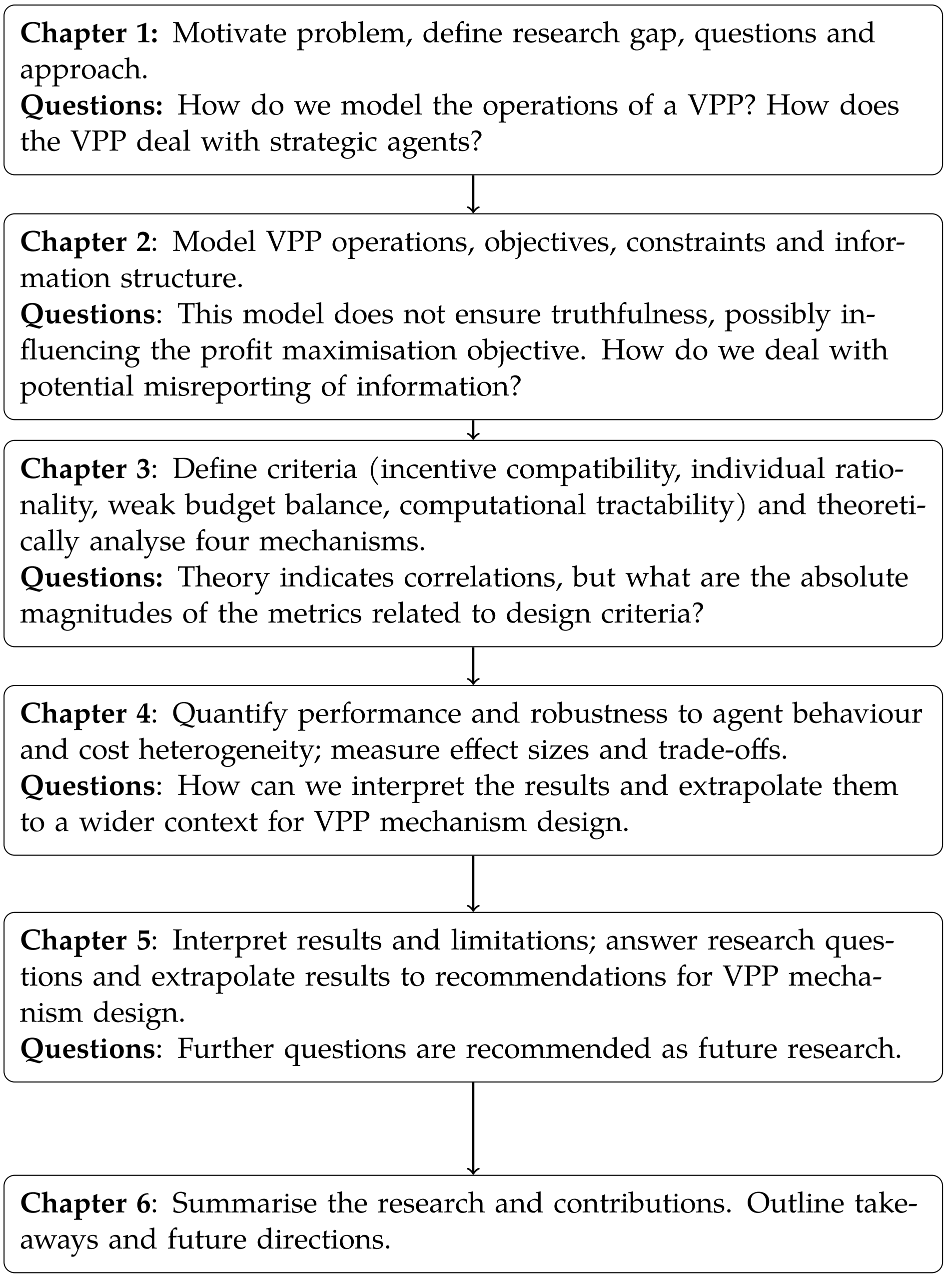


Figure 1.1: Flow of chapters: topic of each chapter and the remaining questions motivating the subsequent chapter(s).

Chapter 2

Modelling a Virtual Power Plant

In order to investigate mechanism design for virtual power plants, we first need to model the operations of a virtual power plant, especially since there is no single adopted definition in academic literature. In order to provide such a model, we first describe DERs, since a VPP comprises of multiple DERs. In Section 2.1, we define key characteristics and behaviour, important to understand how they contribute to VPPs as a whole. Building on this foundation, Section 2.2 formalises the VPP model. We discuss factors such as the VPP's market position, objectives and the communication model, needed to integrate these DERs into a cohesive model. This leads to formalising the optimisation problem that the VPP aims to solve: finding an allocation of grid services to a predetermined commitment, that maximises its revenue. Finally, Section 2.3 reflects on the model's limitations, offering a realistic perspective on its scope.

2.1 Formulation of a Distributed Energy Resource

A DER is generally a small-scale energy resource. Typically it is situated at or near the load site. Therefore, it is usually connected to the local distribution grid rather than the high-voltage transmission network [16]. DERs can include, but are not limited to, renewable energy sources such as photovoltaic systems and wind turbines. They can also include energy storage systems such as batteries (in electric vehicles), fuel cells, engine generators and microturbines [17].

It is important to make a distinction between passive and active generation. Passive generation is considered to be a generation technology that has no control over the fuel input or the power output of the system. These usually include renewable resources that are dependent on the weather such as solar and wind energy. Active generation is a technology that does have control over the power output of the system, such as a gas or diesel generator [17].

Distributed energy resources are characterised by variables, parameters, a cost function, local and temporal constraints that define their operation and performance. Variables capture the dynamic aspects of a DER, such as the units of a certain grid service being provided. Those decision variables can be influenced by a virtual power plant through an incentive-based system. Parameters, on the other hand, represent fixed properties of a DER, such as its technical specifications or operational limits. Constraints impose boundaries on the decision variables, based on the DER's parameters. This ensures that operations stay within safe and feasible ranges determined by these parameters.

In this section we cover the most important concepts to understand how DERs function as part of a VPP. We first introduce decision variables and feasible regions (Section 2.1.1), then capture temporal dependencies (Section 2.1.2). We define the operating cost function (Section 2.1.3) and the resulting utility (Section 2.1.4). Finally, we discuss DER control (Section 2.1.5) and summarise the DER in a formal definition (Section 2.1.6).

We introduce some general notation to facilitate the understanding of the subscripts used in this section. A VPP aggregates N distributed energy resources, the DERs are indexed by the set $\mathcal{N} = \{1, 2, \ldots, N\}$. Furthermore, we consider T discrete time steps, indexed by the set $\mathcal{T} = \{1, 2, \ldots, T\}$. Additionally, we consider the provision of M grid services, indexed by the set $\mathcal{M} = \{1, 2, \ldots, M\}$.

2.1.1 Local Constraints and Decision Variables

An important modelling decision relates to describing the DER's constraints, denoted by feasible region $\mathbb{X}$. Moghaddam et al. [18], Wille-Hausmann et al. [19] and Mashhour et al. [20] include constraints related to the decision variables x of the DERs ($x \in \mathbb{X}$) in the constraint formulation. Moghaddam et al. [18] consider a VPP that aggregates a hydro system and a wind farm. They incorporate various constraints that relate to the specific functioning of hydro and wind generators. Wille-Hausmann et al. [19] consider aggregating cogeneration plants into a VPP. Again, the characteristic behaviour of cogeneration plants is used for the specific formulation of constraints in the problem formulation. Mashhour et al. [20] specifically emphasise how the VPP operator should take into account the feasibility of the schedule concerning the operational characteristics of the DERs and therefore incorporate those in their constraint programming formulation.

In this thesis, we abstract from the specific technical characteristics of individual DER types. A modelling choice is our more general constraint formulation, rather than restricting ourselves to a specific set of DERs and modelling those constraints (as in aforementioned works), we adopt a more flexible approach in which it is assumed that the constraints for all DERs can be captured in the notation $x_i \in \mathbb{X}_i$. This leads to the following definition:

Definition 2.1 (Local Constraints and Decision Variables) *$x_{i,t,m}$ is the decision variable of DER $i \in N$ at time $t \in \mathcal{T}$ for grid service $m \in \mathcal{M}$. This decision variable indicates how much of grid service m the DER provides to the grid. To facilitate writing, $x_{i,t}$ denotes the vector containing all decision variables of DER i per time step and $x_i = \{x_{i,t} \mid t \in \mathcal{T}\}$ is used to note the $T \times M$ matrix, denoting the decision variables across all timesteps for DER i. Consequently, x denotes the $N \times T \times M$ tensor, containing the decision variables for all DERs in the VPP.*

Similarly, $\mathbb{X}_{i,t}$ is the feasible region, constraining the decision variables based on the parameters of the DER such that $x_{i,t} \in \mathbb{X}_{i,t}$. The usage of subscripts follows the same structure as for the decision variables described above.

We recognise that DERs encompass a diverse array of technologies and configurations, each with unique operational characteristics and constraints. Real-world DER deployments may involve more complex control systems, site-specific limitations or regulatory considerations that are not fully captured by $x \in \mathbb{X}$. We would like to stress that the primary objective of this thesis is to evaluate the strategic behaviour and decision-making mechanisms of VPPs. In this context, exhaustively representing every possible DER configuration or operational nuance is not necessary [7].

2.1.2 Temporal Constraints

Temporal constraints define how the decision variables are constrained across time intervals. This is easy to understand when we talk about batteries. The state of charge can never surpass the maximum storage capacity, neither can it fall below 0, or some other minimum. Temporal constraints between the decision variables are denoted by the function g.

$$g_i(\cdot) \leqslant 0 \tag{2.1}$$

Example 2.1 (Temporal Constraints for Battery) *Suppose we have a battery that holds a certain state of charge (SoC) in kWh. The battery engages in delivering active power as a grid service, noted by its decision variable $x_{i,t}$. Note that, since we consider a battery, it can also take electricity from the grid, to charge itself. The decision variable can vary per one hour time interval t. Its capacity is 20kWh and at its initial state of charge is 100% of the capacity. We want to impose constraints such that it can never be discharged below 2kWh and can never exceed its maximum capacity. Therefore:*

$$SoC_{i,t} = \begin{cases} 20 & \textit{if } t = 0 \\ SoC_{i,t-1} + x_{i,t} & \textit{otherwise} \end{cases} \tag{2.2}$$

$$g_i(SoC_{i,t}) = \begin{bmatrix} SoC_{i,t} - 20 \\ 2 - SoC_{i,t} \end{bmatrix} \leqslant 0 \tag{2.3}$$

2.1.3 Cost Function

A DER also has a cost function c, describing the cost at which it operates. If we take an active generation technology (e.g. a diesel generator) as an example, when it generates more electricity it consumes more diesel. For a passive generation technology (e.g. wind turbine), we can say that the cost is related to maintenance, induced by wear and tear of blades and gearboxes when it is dispatched. In other words, we can say that the cost function is dependent on the decision variables of the DER. Each grid service m has a certain cost parameter $u_{i,t,m}$, denoting the cost for der i of delivering one unit of grid service m at time step t. Therefore, we can write down the cost function for DER i at time interval t as:

$$c_{i,t}(x_{i,t}) = \sum_{m=1}^{M} x_{i,t,m} u_{i,t,m} \tag{2.4}$$

For ease of notation in subsequent writing, we also define the total cost for a DER i across all time intervals as c_i and the total cost for a VPP as c.

$$c_i(x_i) = \sum_{t=1}^{T} c_{i,t}(x_{i,t}) \tag{2.5}$$

$$c(x) = \sum_{i=1}^{N} c_i(x_i) \tag{2.6}$$

The cost function plays an important role in the tractability of the problem that needs to be solved by the VPP. In order to keep the problem tractable a monotonicity assumption on the cost function is common in related literature [4], [10], [11] and also adopted in this study.

Assumption 2.1 (Monotonicity of Cost Function) *The cost function $c_{i,t}(x_{i,t})$ is monotonically non-decreasing over its domain. That is, for any two feasible decision vectors $x_{i,t,m}, x'_{i,t,m} \in \mathbb{X}_{i,t,m}$ such that $x_{i,t,m} \leqslant x'_{i,t,m}$, it holds that*

$$c_{i,t,m}(x_{i,t,m}) \leqslant c_{i,t,m}(x'_{i,t,m}). \tag{2.7}$$

2.1.4 Utility

Now that we have defined the cost function, we can define the utility of a DER. The utility is defined as the difference between the payment $p_i(x_i)$ an agent receives, for setting its decision variables as x_i, and its true cost $c_i(x_i)$. We can denote the utility v as

$$v_i(x_i) = p_i(x_i) - c(x_i). \tag{2.8}$$

2.1.5 DER Control

Each DER is controlled by an agent. This agent takes care of the communication with the VPP operator and physically controls the decision variables of the DER. In practice this agent will typically be the software/firmware of the DER that engages in the communication with the VPP operator. It always follows the suggestion from the VPP operator for setting the decision variables. This is for the simple reason that, if the DER fails to do so, it will be considered as unreliable by the VPP operator and will be no longer considered in the allocation of grid services.

Assumption 2.2 *A DER agent will always set its decision variables as the VPP requests. Failing to do so will lead to removal from the VPP, resulting in $v_i(x_i) = 0$ for the respective DER.*

2.1.6 DER Model

Having said that, we can formulate a DER as follows.

Definition 2.2 (Distributed Energy Resource) *A Distributed Energy Resource is defined as a quadruple:*

$$\text{DER} := (g, x, \mathbb{X}, c)$$

where:

x_i denote the decision variables of DER i constrained by $\mathbb{X}_i$ such that $x_i \in \mathbb{X}_i$ (definition 2.1).

$c_{i,t} : x_{i,t} \rightarrow \mathbb{R}$ is a cost function representing the operational cost given the decision variables (Section 2.1.3).

g_i denotes the temporal constraints (Section 2.1.2)

Now, using some examples, we will show that a variety of DER configurations can be fitted to our formulation. Suppose that we have a diesel generator and a wind turbine. For these examples, we consider the provision of a single grid service, active power.

For the diesel generator, the current power output, denoted as p is a variable because it can change. The generator has parameters that define its operational limits, including the minimum generation capacity P_{min}, below which it cannot function without shutting down, and the maximum generation capacity P_{max}, which marks its upper limit. These parameters impose constraints on decision variable p, requiring it to satisfy $P_{min} \leqslant p \leqslant P_{max}$. The diesel generator also has a cost function, which typically rises with increased power output due to higher fuel consumption, satisfying assumption 2.1.

Example 2.2 *A diesel generator can be characterised by its decision variables and corresponding feasible region, cost function and temporal dependencies.*

$$x = [p] \in \mathbb{X} = [P_{min}, P_{max}] \tag{2.9}$$

The cost is described by the monotonically non-decreasing function $c_{i,t}$

$$c_{i,t}(x_{i,t}) = x_{i,t} u_{i,t} \tag{2.10}$$

The diesel generator cannot change its capacity by more than 3 kW across time intervals, therefore:

$$g_i(x_i) = |x_{i,t-1} - x_{i,t}| - 3 \leqslant 0 \tag{2.11}$$

In contrast, a wind turbine represents a passive generation technology, where power output depends on uncontrollable (but predictable) factors like wind speed. Its key parameters include the rated capacity P_{rated}, the power generated at the rated wind speed V_{rated}, the cut-in wind speed V_{min}, below which no power is produced, and the cut-out wind speed V_{max}, above which generation stops for safety reasons [17]. A weather-prediction module estimates the current power output $P_{current}$ and its variability P_{var} due to fluctuating wind conditions. It is assumed that the power of the wind turbine can be curtailed by changing the positions of the blade, to match the current need for energy.

Example 2.3 *A wind turbine provides power based on available wind, but can be curtailed. Its decision variable is the active power* p*, with feasible region:*

$$x = [p] \in \mathbb{X} = [0, P_{current} - P_{var}] \tag{2.12}$$

The cost function captures wear-related expenses, and increases with output:

$$c_{i,t}(x_{i,t}) = x_{i,t} u_{i,t} \tag{2.13}$$

There are no temporal constraints.

2.2 Formulation of a Virtual Power Plant

Now that DERs have been described, we can use this definition to aggregate them in one coherent VPP model. This section focusses on describing this VPP model. Since there is no uniform definition in the academic literature [21], we first adopt one in Section 2.2.1. Consequently, we discuss several modelling choices using related work in Sections 2.2.2 - 2.2.7. After we have made those choices, we present the mathematical formulation of the optimisation problem that the VPP operator needs to address in Section 2.2.8.

2.2.1 Definition of a Virtual Power Plant

In order to construct a model and to provide coherency throughout this thesis, it is important to adopt a single definition of a VPP. We will adopt the definition as in [22], more visually depicted in Figure 2.1.

Definition 2.3 (Virtual Power Plant) *A virtual power plant is a cluster of dispersed generator units, controllable loads and storage systems, aggregated in order to operate as a unique power plant. The generators can use both fossil and renewable energy sources. The heart of a VPP is an energy management system (EMS) which coordinates the power flows coming from the generators, controllable loads and storages. The communication is bidirectional, so that the VPP can not only receive information about the current status of each unit, but it can also send the signals to control the objects.*

A distinction is made between a commercial virtual power plant (CVPP) and a technical virtual power plant (TVPP). A technical VPP takes into account the operating characteristics and corresponding constraints of the underlying distribution network. A commercial VPP does not consider those characteristics and merely serves as an aggregator and its purpose is simply to manage the portfolio of the DERs to optimally participate in the electricity market [23] [24]. Since the main focus of this thesis is designing and evaluating a mechanism taking into account strategic agents, operational characteristics of the grid are of lesser relevance. Therefore, a CVPP will be considered throughout this thesis.

Assumption 2.3 (Commercial Virtual Power Plant Model) *The VPP acts as an aggregator of distributed energy resources and does not account for the physical or operational constraints of the underlying distribution network.*

2.2.2 VPP Market Position

An important decision relates to the market position of the VPP that we will assume. In this thesis, the market position of the VPP is defined as a fixed day-ahead commitment. In other words, the VPP has committed to delivering a certain amount of services to the grid in some day-ahead markets and will seek an allocation among its DERs. This approach contrasts with some existing literature, where the VPP's market position is often more flexible. For instance, in Zamani et al. [25], the VPP participates in both energy and spinning reserve markets with a day-ahead scheduling framework that optimises profit through stochastic bids, allowing dynamic adjustments via storage, demand response and market trades rather than adhering to a rigid commitment. Similarly, Nosratabadi et al. [26] propose a stochastic profit-based scheduling for industrial VPPs, where the day-ahead plan is a flexible strategy adjusted by demand response programs and spot market purchases to maximise profit, not

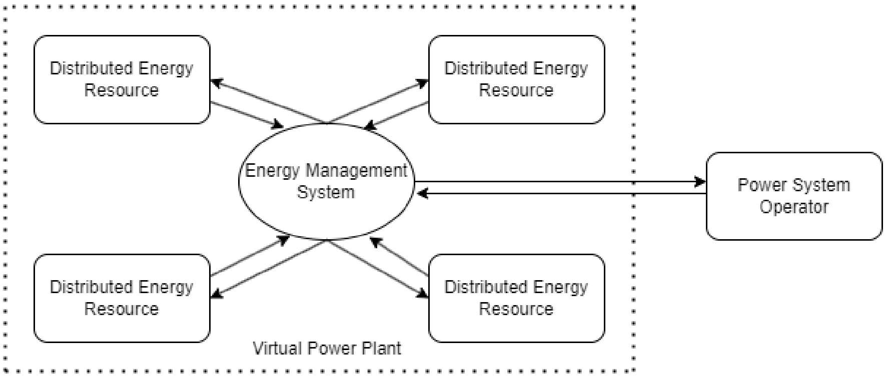


Figure 2.1: A virtual power plant clusters several distributed energy resources. They are aggregated to operate as a unique power plant towards the power system operator.

a fixed obligation. Khorosany et al. [27] propose a two-stage model - day-ahead planning and intraday adjustments - that first allows agents to participate in the day-ahead market and later allows them to adjust their bids using the real-time market. In contrast, Sakr et al. [28] present a closer alignment to this thesis' approach, optimising a day-ahead schedule to maximise profit while using demand response and DER allocation to ensure the VPP meets its market participation goals, though the commitment itself emerges from the optimisation rather than being pre-fixed. While these papers leverage DER allocation and demand response to support market interactions, this thesis assumes a predetermined commitment, shifting the focus to post-commitment resource coordination, as is also followed in [13]–[15].

Within this thesis we do not consider the VPP's interaction with a market, nor do we consider any market specifically. We take it as given that the VPP has participated in some market(s) resulting in a certain commitment, consequently it needs to find an allocation among its DERs to provide the grid services that it has committed to in any of these markets.

Assumption 2.4 (Market Position) *The VPP needs to find an allocation of grid services among its DERs to satisfy a predetermined commitment.*

2.2.3 VPP Objective

A VPP typically aims to maximise its profits [29], often formulated as the difference between system income and total cost [23]. This can be reframed as minimising costs across DERs while meeting market commitments [5], as expressed in Equation 2.14.

$$\begin{gathered} \min \sum_{i=1}^{N} c_i(x_i) \\ \text{s.t.} \\ \sum_{i=1}^{N} x_i = b \\ x_i \in \mathbb{X}_i \end{gathered} \tag{2.14}$$

Here, N DERs have decision variables x_i bounded by operational limits $\mathbb{X}_i$ and costs $c_i(x_i)$. Additionally, we have a coupling constraint $\sum_{i=1}^{N} x_i = b$ to describe that the VPP needs to adhere to commitment b. This cost-minimisation approach is common in VPP optimisation [18]–[20] as well as in microgrid literature [30]–[32]. Despite its differences, both VPPs and microgrids aim to optimise resource allocation and deviations from expected demand, justifying the approach to also have a minimisation of the objective function for VPPs. In addition, [33]–[35] employ this approach of minimising the total cost specific to VPPs as well.

2.2.4 System-wide Constraints

The VPP operator should also take into account the system-wide supply-demand balancing constraint [20]. In addition to aforementioned papers [18]–[20], Xinfa et al. [33] also incorporate these balancing constraints in their VPP model. Additionally, in [34, Eq. 20] they also introduce slack in the supply-demand balancing constraint by making sure that the VPP's total capacity amounts to between 90% and 110% of the contracted amount. This will also be adopted in this research, further elaborated on in Section 2.2.8.

2.2.5 Time Horizon

Liu et al. [36], Zdrilić et al. [37] and Kong et al. [38] model VPPs over multiple time steps, capturing inter-temporal dependencies such as battery charging/discharging. In general, singe-time-step models lack flexibility [4], [7], wherefore we adopt a multi-time-step approach to reflect realistic VPP operations over $T = 24$ hours.

2.2.6 Uncertainty

Uncertainty handling varies across the literature. Deterministic models (e.g. Zdrilić et al. [37]) assume perfect predictions of demand and renewable output, simplifying optimisation. Conversely, Shi et al. [39], incorporate stochastic methods for uncertainty inherent to renewable resources. For feasibility and focus on mechanism evaluation, this thesis adopts perfect predictions, though future work could explore stochastic extensions.

2.2.7 Communication Model

In the communication model, each DER communicates exclusively with the VPP operator. In a graph structure where the DERs and VPP are represented as nodes, this would be a star-like topology (Figure 2.2). Every DER is connected to the central node, representing the VPP operator. This communication model also renders coalition forming beyond the scope of this thesis.

Assumption 2.5 (No Coalition Forming) *The DERs do not form coalitions. They exclusively communicate with the VPP operator.*

To determine the allocation of grid services for each time interval, the DERs share their local information $\theta = (c, \mathbb{X}, g)$ with the VPP operator. Consequently, the VPP operator computes the decision variables by solving its optimisation problem and communicates those decision variables back to the DERs. This is depicted in Figure 2.2.

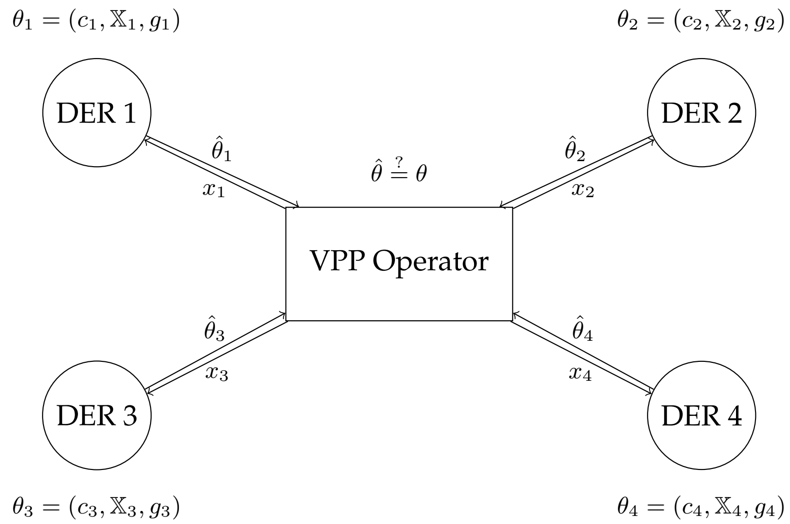


Figure 2.2: Schematic representation of the communication model.

2.2.8 VPP Optimisation Problem

In this section, we present the mathematical formulation of the optimisation problem a VPP aims to solve. I will start of from an example and later generalise this to a general model that will optimise over a horizon of $\mathcal{T} = [1, 2, \dots T]$ time steps.

In this example, the VPP considers itself with the delivery of two grid services, active power and reserve capacity. For every time step $t \in \mathcal{T}$, the VPP has committed to delivering P kW to the grid. Additionally, for each time step t, the VPP has agreed to maintain a minimum reserve capacity of Q_t kW. The grid service provision of each DER i is represented by its decision variables $x_{i,t} := \begin{bmatrix} p_{i,t} & q_{i,t} \end{bmatrix}^T$ and the system wide constraints b_t are denoted $b_t = \begin{bmatrix} P_t & Q_t \end{bmatrix}^T$.

In practice, various factors may prevent a power plant from adhering to its commitment b. To account for such uncertainties, these agreements are modelled as soft constraints, incorporating penalty terms for deviations, whether as shortfalls or surpluses. This approach provides operational flexibility but also maintains an economic incentive to adhere as closely as possible to the commitment.

We introduce slack variable $\epsilon_{P,t} := \sum_{i=1}^{n} p_{i,t} - P_t$ to denote the difference between the required amount of power and the total amount generated across all DERs. Similarly, we introduce slack variable $\epsilon_{Q,t} := \sum_{i=1}^{n} q_{i,t} - Q_t$ to denote the difference between the required amount of reserve capacity and the provided reserve capacity across all DERs. We also introduce monetary penalties related to surplus and shortfall denoted by λ_t^+ and λ_t^-. To that end, we use the notation ϵ^+ to represent the surplus when $\epsilon > 0$ and ϵ^- to represent the shortfall magnitude when $\epsilon \leqslant 0$. Note that ϵ^- is a positive number representing the absolute magnitude of the shortfall when ϵ is negative. The total deviation is then defined as $\epsilon = \epsilon^+ - \epsilon^-$. Because we cannot have shortfall and surplus simultaneously we enforce $\epsilon^+ \epsilon^- = 0$ to indicate that $\epsilon^+ = 0 \lor \epsilon^- = 0$.

This notation is used to formulate a monetary penalty (equation 2.15) incurred by the VPP when it does not adhere to its predetermined grid service commitment.

$$f_t(\epsilon^+_{P,t}, \epsilon^-_{P,t}, \epsilon^+_{Q,t}, \epsilon^-_{Q,t}) := \lambda^+_{P,t}\epsilon^+_{P,t} + \lambda^-_{P,t}\epsilon^-_{P,t} + \lambda^+_{Q,t}\epsilon^+_{Q,t} + \lambda^-_{Q,t}\epsilon^-_{Q,t} \tag{2.15}$$

To eliminate non-linearity, the term $\epsilon^+\epsilon^-$ is reformulated using a big-M parameter. Consequently, incorporating cost minimisation alongside system-wide constraints and penalty terms, the generalised VPP optimisation problem is expressed as shown in equation 2.16.

$$\begin{aligned}
&\min \sum_{t=1}^{T} \left[\sum_{i=1}^{N} c_{i,t}(x_{i,t}) + f_t(\epsilon_t) \right] && \\
&\text{s.t.} && \\
&\sum_{i=1}^{N} x_{i,t} = b_t + \epsilon_t && \forall t \in \mathcal{T} \\
&x_{i,t} \in \mathbb{X}_{i,t} && \forall i \in \mathcal{N} \quad \forall t \in \mathcal{T} \\
&g_i(\cdot) \leqslant 0 && \forall i \in \mathcal{N} \\
&\epsilon^+_{m,t}, \epsilon^-_{m,t} \geqslant 0 && \forall m \in \mathcal{M} \quad \forall t \in \mathcal{T} \\
&\epsilon^+_t \leqslant Mz && \forall t \in \mathcal{T} \\
&\epsilon^-_t \leqslant M(z-1) && \forall t \in \mathcal{T} \\
&z \in \{0,1\} &&
\end{aligned} \tag{2.16}$$

We will denote the solution to this optimisation problem (2.16) as x^*. Of course, x^* differs as the reported information θ varies. Therefore, more precisely, for a set of agent reports θ we denote the optimal allocation x^* using these reports as

$$x^* = \mathcal{X}(\theta), \tag{2.17}$$

where $\mathcal{X}$ is the so-called allocation function.

2.3 Model Limitations

In this section, we briefly reflect on several model limitations in order to provide a realistic perspective on the scope.

2.3.1 No Start-up/Shutdown Costs

A limitation of this model is the assumption that DERs can be dispatched instantaneously without accounting for start-up or shutdown costs. Unlike large-scale power plants such as nuclear, coal or gas facilities, which require extensive start-up and shutdown procedures with significant associated costs, DERs are generally small-scale resources with minimal operational delays. This justifies the assumption that immediate dispatch is feasible without incurring substantial costs. However, exceptions to this generalisation may exist, depending on the specific characteristics of certain DER technologies.

2.3.2 Linearity Assumptions

Furthermore, the cost functions and temporal constraints are expressed in a linear fashion. While this assumption simplifies the optimisation problem and facilitates tractable analysis, it may not fully capture the operational realities of certain DERs. In practice, cost structures can exhibit non-linearities due to factors such as battery degradation, efficiency losses at partial loads or dynamic pricing schemes. Similarly, temporal constraints may involve non-linear dependencies, that are not adequately represented through linear formulations. The current model provides an approximation for high-level analysis which is suitable for this study, since its inherent focus is on mechanism design rather than capturing the full complexity of DER operations.

2.3.3 Physical Grid Limitations

The current formulation does not consider limitations related to the underlying distribution network. All DERs are treated as if they are connected to a single bus. In practice grid services are location-sensitive and the feasibility of the allocation depends on network topology. Again, since the focus on mechanism design these complexities are abstracted away for now.

2.3.4 Heterogeneity in Quality of Grid Services

The model implicitly assumes that all units of a given grid service are substitutable across DERs and time, ignoring possible heterogeneity in the quality or type of service provision. For example, two DERs providing frequency support might do so with different response times or reliability characteristics. These quality differences are not captured in the current formulation, which could lead to suboptimal allocations in practice.

2.3.5 Communication Delays

The model assumes a perfect and instantaneous communication infrastructure between the VPP operator and the DERs. In practice, latency, data loss, or control delays could affect the ability of DERs to respond in real time, particularly when coordination occurs over wide areas or via third-party platforms [40].

Chapter 3

Mechanism Design for VPPs

Although Chapter 2 provided a model describing the operation of a VPP, it did not address how we can achieve revenue maximisation under the presence of strategic agents. This brings us to the area of mechanism design, a field in economics and game theory that focuses on designing systems and incentives to achieve desired outcomes, even when participants act in their own self-interest.

In this chapter, our main focus is investigating how we can design mechanisms that align the incentives of the agents with the goals from the VPP operator. In order to accomplish this, we first discuss background information about mechanism design and identify gaps in recent work (Section 3.1). Consequently, we introduce various design criteria (Section 3.2) to guide us during the design and evaluation process. Based on this, we propose various mechanisms for our problem definition and already provide a theoretical analysis in terms of the design criteria (Section 3.3).

3.1 Background

This section provides background information on market mechanisms for energy markets to facilitate a better understanding of the remainder of this chapter. It covers important aspects of market design, including modelling assumptions, market scope and objectives, allocation and payment rules, communication models and methods for market mechanisms (Sections 3.1.1 - 3.1.6). Tsaousoglou et al. [5] provide an excellent framework for characterising market mechanisms. Even though they focus on local electricity markets, many of the market design principles they outline - such as distributed resource participation and incentive-compatible mechanisms - are very relevant in the context of VPPs, as both local electricity markets and VPPs aim at optimally managing distributed energy resources within a market-based framework. We will adopt this framework throughout this background section. Finally, we provide an overview of recent work regarding mechanism design in local electricity markets in Section 3.1.7.

3.1.1 Modelling Assumptions

Modelling assumptions in DERs cover topics such as cost/utility functions, local constraints, market behaviour and uncertainty. Choices related to those topics affect a mechanism's performance and must therefore be clearly defined. This has been explored in Chapter 2 and we adopt those assumptions when reviewing mechanisms.

3.1.2 Market Scope and Objectives

The literature on market mechanisms shows a range of market scopes and objectives. The market scope includes the set of participants and traded products. The literature on electricity markets exhibits diverse market objectives. Tsaousoglou et al. [5] identify three primary goals: social welfare maximisation [41]–[44], profit maximisation [8], [45]–[47] and fairness [7], [48]–[50]. Social welfare maximisation aims to maximise total utility, profit maximisation targets the monetary surplus of a specific entity (e.g., the VPP operator) and fairness seeks equitable outcomes (e.g., proportionality, envy-freeness, max–min).

3.1.3 Allocation Rule

The allocation rule $\mathcal{X}$ determines how resources or dispatch decisions are assigned to participants in a market mechanism. In the literature, allocation often depends on the mechanism type. For example, Lagrangian methods typically allocate based on optimising a centralised objective like social welfare, using bids or cost functions. Game-theoretic approaches might allocate resources via auctions or equilibrium outcomes, taking into account strategic bidding. Heuristic methods use simpler, rule-based allocations for practicality, while data-driven methods may rely on learned patterns from historical data.

3.1.4 Payment Rule

The payment rule p sets how participants are compensated or charged for their market actions. In the literature, payment rules vary widely. Lagrangian methods often use shadow prices or marginal costs. Game-theoretic mechanisms might employ auction-based payments, like VCG, to encourage truthful bidding. Heuristic methods favour straightforward payments, such as fixed rates, for simplicity, while data-driven approaches might tie payments to predicted outcomes. Payment rules are closely tied to budget balance properties of the mechanism. In a strict budget balanced mechanism, all payments and expenses combined equal zero, whereas in a weakly budget balanced system, the payments may exceed the costs, i.e. the VPP operator can make some profit but should never run a deficit operating the system.

3.1.5 Communication Model

The communication model describes the structure and nature of information exchange among market participants. It consists of two fundamental components: the communication graph and the information format [5].

The communication graph determines the topology of interactions between agents. In a centralised market, all participants communicate directly with a central operator, who collects relevant information and makes allocation or pricing decisions. Conversely, in a decentralised market, agents interact peer-to-peer or within a distributed network without a central coordinator. Such architectures allow for greater autonomy, privacy and potentially enhanced robustness, but require more sophisticated protocols to reach consensus or equilibrium.

The information format refers to the type and extent of data shared. In direct revelation mechanisms, each agent is required to report detailed private information such as cost functions, feasible regions and operational constraints. This full disclosure enables the VPP operator to perform global optimisation based on complete information. While efficient in theory, this approach raises concerns regarding privacy, strategic manipulation and scalability. In contrast, indirect communication mechanisms rely on iterative, limited exchanges, i.e. price signals, bids or marginal costs, without requiring agents to reveal their internal models. These mechanisms, often inspired by auction or game-theoretic principles, preserve privacy and can better align with real-world communication limitations, but may converge slower or fail to reach globally optimal outcomes.

3.1.6 Methods for Market Mechanisms

Tsaousoglou et al. [5] highlight four types of market mechanisms: Lagrangian, game-theoretic, heuristic and data-driven. Lagrangian methods relax coupling constraints and iterate on dual variables (prices) to solve a centralised objective via decomposition (e.g., [51]–[54]). Game-theoretic methods elicit strategic bids or actions and clear the market through auctions or equilibrium concepts (e.g., [11], [55]–[57]). Heuristic methods apply rule-based or greedy dispatch and pricing tailored to practical constraints (e.g., [8], [58]–[60]). Data-driven methods learn dispatch or pricing policies from historical or simulated data using supervised or reinforcement learning (e.g., [61]–[64]).

Each family has trade-offs. Lagrangian methods optimise social welfare for price-taking agents and support privacy-preserving designs but fail in non-convex cases and lack incentive compatibility. Game-theoretic methods excel at social welfare under strategic behaviour and support varied objectives, though payment rules can be complex. Heuristic methods are scalable and practical, ensuring privacy and budget balance, but they are sub-optimal and lack standard feasibility guarantees. Data-driven methods handle uncertainty well and make fast decisions, but they offer no promises on optimality or budget balance.

3.1.7 Related Work

The design of incentive-compatible mechanisms for distributed energy resources in VPPs intersects research areas in mechanism design and energy markets. The literature on incentive-compatible mechanism design for our problem formulation is limited. Therefore, we mainly review literature on the coordination of strategic agents in related problem formulations. The need for mechanisms resilient to strategic behaviour was already motivated in Chapter 1. Consequently, in this section, we particularly focus on studies addressing the challenges of strategic behaviour in aggregators. This section identifies gaps in current approaches and clarifies how our approach builds upon and diverges from prior work.

Tsaousoglou et al. [3] designed a max-min fair flexibility market mechanism for distribution system operators to incentivise strategic aggregators to truthfully report flexibility costs. However, this mechanism is heavily dependent on a proof of payment from the aggregator, used to show how much the aggregator paid to its flexible assets for providing the flexibility.

In another study from the same author [11], a billing rule for a demand side management scenario with strategic users and coupling constraints is designed, preserving budget-balance and individual rationality. Nevertheless, the specifics of this billing rule revolve around rewarding/penalising (in)flexibility which is not applicable to our problem formulation.

A more closely related problem formulation is adopted in [7], wherein the authors propose a personalised-real time pricing scheme for demand response in energy cooperatives and flexibility markets, that incentives selfishly behaving agents to modify their energy consumption pattern towards system-level goals. However, they do not take into account temporal dependencies. Furthermore, the study revolves around demand response, not applicable to our case.

In [10] they propose an auction-theoretic scheme for a community energy management problem with resource constraints. In [6] they present a novel iterative auction mechanism implementing the truthful efficient VCG outcome with a different payment rule. Chen et al. [65] present a novel combinatorial reverse auction framework for aggregating residential users in regulation reserve provision. In order to clear the energy and reserve market in multi-area power systems, an incentive mechanism is designed in [66] to encourage honest bids from generators.

Despite the relevance of our problem formulation [13]–[15] – where the VPP is targeting to satisfy a predetermined commitment, with strategic agents and a revenue maximisation objective – there is no research addressing it with the presence of strategic agents. Because commercial VPPs act as central aggregators, DERs are often independently owned and therefore have both the incentive and the opportunity to act strategically by misreporting private information such as costs or constraints. Failing to account for this reality can lead to inefficient allocations, increased system costs or even the inability of the VPP to meet its contractual obligations. As VPPs become increasingly prominent in grid operations, designing mechanisms that are robust to strategic manipulation is not just a theoretical concern, but an operational requirement.

Furthermore, none of the reviewed papers provide insights into how the composition of the aggregators' portfolio, in terms of the fraction of strategic agents and cost parameter spread, influences mechanism design choices.

3.2 Design Criteria

To design an effective mechanism for virtual power plants, several criteria must be considered. The VPP operator aims to maximise its revenue, yielding revenue optimality as the first design criterium (Section 3.2.2). This implicitly means that the system must be weakly budget balanced in expectation, since running a deficit will negatively impact its revenue maximisation (Section 3.2.3). Furthermore, the mechanism must make sure it is beneficial for DERs to participate, therefore yielding individual rationality as third design criterium (Section 3.2.4). Additionally, incentive compatibility supports revenue optimisation by encouraging truthful reporting, this allows the VPP operator to make the most cost-effective decisions (Section 3.2.5). Finally, an important property is scalability, to handle large-scale VPPs (Section 3.2.6). To facilitate assessing the aforementioned criteria, we first introduce the payment-to-cost ratio in Section 3.2.1.

3.2.1 Payment-to-Cost Ratio

To facilitate assessing the design criteria, we define the payment-to-cost ratio r_i for DER i as:

$$r_i = \frac{p_i(x_i)}{c_i(x_i)} \tag{3.1}$$

Here, $p_i(x_i)$ is the payment to DER i for setting its decision variables as x_i. The true cost incurred is noted as $c_i(x_i)$. To assess the payment-to-cost ratio of the entire VPP we introduce $S = \{i \mid \|x_i\| \neq 0\}$, denoting the set of DERs included in the allocation made by the VPP. Now we can define the payment-to-cost ratio of the entire VPP allocation by taking a weighted average.

$$r = \sum_{i \in S} \frac{c_i(x_i)}{c(x)} r_i, \tag{3.2}$$

Note that $c(x)$ denotes the total cost of the VPP (equation 2.6). The attentive reader may have noticed that $c_i(x_i)$ may be equal to zero. To ensure mathematical validity, we redefine r_i as follows:

$$r_i = \begin{cases} \frac{p_i(x_i)}{c_i(x_i)} & \text{if } c_i(x_i) \neq 0, \\ 1 & \text{if } c_i(x_i) = 0 \text{ and } p_i(x_i) = 0, \\ \text{undefined} & \text{if } c_i(x_i) = 0 \text{ and } p_i(x_i) \neq 0. \end{cases} \tag{3.3}$$

In practice, for the system's revenue optimality metric r, we exclude DERs with undefined r_i from the sum. Alternatively, if $p_i(x_i) = 0$ whenever $c_i(x_i) = 0$, $r_i = 1$ is well-defined.

3.2.2 Revenue Optimality

The primary objective of the VPP is to maximise revenue. This involves two goals: designing an allocation rule that minimises the total cost of grid service provision by optimally assigning tasks to DERs and designing a payment rule such that payments approximate true costs. If we express this using our r metric, we can say that $r_i = 1.0$ ensures the VPP pays DERs their exact costs, maximising revenue whilst also covering expenses (see paragraph on individual rationality).

3.2.3 Weak Budget Balance

In mechanism design, a mechanism is weakly budget balanced when the market mechanism operator does not need to inject money in the system [5]. In other words, a condition stating the total payments made by the mechanism do not exceed the total payments received—ensuring no deficit, but not necessarily any surplus. This definition typically applies when considering only the VPP and the DERs, and does not account for the payouts from the grid operator.

In our context, however, we are interested in the financial sustainability of the VPP operator, who participates in external markets and may therefore earn a profit for providing services to the TSO. To reflect this, we introduce an alternative definition of weak budget balance, which we term the viable VPP condition. This condition allows the VPP to cover its costs and earn a small surplus $\gamma \geqslant 0$. In this case, $0 \leqslant \gamma \leqslant 1$ is the profit margin the VPP makes.

Definition 3.1 (Viable VPP condition) *A VPP is viable if the following holds in expectation.*

$$r \leqslant 1.0 + \gamma \quad \textit{with } \gamma \geqslant 0$$

Here, r denotes the ratio of the total payments made to DERs relative to their true costs and γ captures the VPP's profit margin above aggregated true cost.

Importantly, this condition should hold in expectation over an infinite time horizon. This is assuming the VPP rationally bids in the market to remain financially viable. It does not guarantee a surplus in every time instance and may not prevent short-term losses.

Note that this paper does not address the architecture of any market that the VPP participates in. Therefore, we assume profit margin γ in our model, leaving open any discussion on the wholesale market architecture. A similar approach is followed by Tsaousoglou et al. [11].

3.2.4 Individual Rationality

Individual rationality ensures that DERs are not worse off by participating in the VPP, requiring payments to cover their incurred costs. We can say the system is individually rational if $\mathbb{E}[v_i(x_i)] \geqslant 0 \quad \forall i \in \mathcal{N}$.

We can also express the individual rationality using r.

Proposition 3.1 *The system is individually rational if* $r_i \geqslant 1.0 \quad \forall i \in \mathcal{N}$.

Proof 3.1

$$v_i(x_i) = p_i(x_i) - c_i(x_i) \geqslant 0 \quad (\textit{def. of IR})$$

$$p_i(x_i) \geqslant c_i(x_i)$$

$$\frac{p_i(x_i)}{c_i(x_i)} \geqslant 1.0$$

$$r_i \geqslant 1.0$$

This criterion is closely linked to budget balance, as individual rationality can theoretically be achieved with an infinite budget. The challenge lies in designing a mechanism where payments are just sufficient to ensure individual rationality, minimising excess to support revenue maximisation.

3.2.5 Incentive Compatibility

Incentive compatibility is important to prevent strategic manipulation by DERs, who may misreport costs or constraints to maximise payoffs. A mechanism is dominant-strategy incentive compatible (DSIC) if truthful reporting is optimal for each DER regardless of others' actions [67]. More formally, a system is DSIC if there exists no report $\hat{\theta}_i$ that increases an agents utility over the utility under truthful reporting θ_i.

$$\neg\exists\hat{\theta}_i \quad \text{s.t.} \quad v_i(\mathcal{X}(\hat{\theta}_i)) > v_i(\mathcal{X}(\theta_i)) \quad \forall i \in \mathcal{N} \tag{3.4}$$

By its definition, r_i increases as a result of overpayment, which may be a result from strategic reporting. We can say that no strategic report $\hat{\theta}_i$ should exist that increases r_i. More formally:

$$\neg\exists\hat{\theta}_i \quad \text{s.t.} \quad [r_i]_{\hat{\theta}_i} > [r_i]_{\hat{\theta}_i} \quad \forall i \in \mathcal{N} \tag{3.5}$$

3.2.6 Tractability and Scalability

The mechanism must be computationally tractable to manage the complexity of VPPs, which involve numerous DERs and time steps. Mechanisms requiring excessive computational resources may be impractical.

3.3 Mechanisms

While the reviewed literature provides valuable insights, it does not resolve the challenges posed by strategic agents in our setting. To address this knowledge gap, we investigate a selection of four market mechanisms that we adapt to our problem formulation. Those include the first-price sealed bid (FPSB) auction, a uniform pricing mechanism, the VCG mechanism and an AGV mechanism (Sections 3.3.1 - 3.3.4). The FPSB mechanism mainly serves as a baseline. Uniform price auctions are common in local electricity markets wherefore it is also included in our analysis. Additionally, we study a VCG mechanism since a significant part of related literature is based on VCG systems. Finally, we include an AGV mechanism to address the prior known shortcoming of VCG mechanisms [5].

3.3.1 First-Price Sealed-Bid

The first-price sealed-bid auction is a fundamental mechanism in which distributed energy resources submit their cost functions, reflecting the expenses associated with providing their services. Based on this reported information $\hat{\theta}$, the VPP operator determines the optimal allocation x^* by solving the optimisation problem presented in equation 2.16. Payments to the participating agents are then made according to their submitted cost information, as defined by the payout rule in equation 3.6.

$$p_i(x_i) = \hat{c}_i(x_i) \tag{3.6}$$

Algorithm 1 First-Price Sealed-Bid Mechanism

Require: DERs $\mathcal{N} = \{1, 2, \ldots, N\}$, $\hat{\theta} = \{\hat{\theta}_i \mid \forall i \in \mathcal{N}\}$
Ensure: Allocation x^*, $p = \{p_i \mid \forall i \in \mathcal{N}\}$
1: $x^* \leftarrow$ solution of (2.16)
2: **for** $i \in \mathcal{N}$ **do**
3: $\quad p_i \leftarrow \hat{c}_i(x_i^*)$.
4: **end for**
5: **return** x^*, $p = \{p_i \mid \forall i \in \mathcal{N}\}$.

For this mechanism it is quite trivial, when looking at the payout function, that this mechanism is not incentive compatible. This means that revenue optimality and the viable VPP criterium are dependent on the fraction of strategic DERs s in the portfolio.

Proposition 3.2 *As the fraction of strategic agents s increases, this decreases revenue optimality.*

Proof 3.2

1. *Consider two scenarios, one with strategic fraction s and the second with strategic fraction $s' > s$.*
2. *From equation 3.6 it is trivial that strategic agents cannot benefit from under reporting their cost function, meaning that a strategic agent will increase its reported cost and hence receive higher payout. Therefore, when the portion of strategic agents is higher: $\left[\sum_{i \in S} p_i(x_i^*)\right]_s \leqslant \left[\sum_{i \in S} p_i(x_i^*)\right]_{s'}$*
3. *When we consider the formula for r (equation 3.2) , because the true cost c_i remains the same and the payout increases (2), $r_{s'} \geqslant r_s$; indicating higher payouts to the DERs than strictly necessary, therefore degrading revenue optimality.*

When this r becomes significantly large due to strategic reporting, this will eventually also violate the viable VPP property.

The mechanism is individually rational. When looking at the payout function, we can see that an agent will never be paid less than its reported cost. Furthermore, any rational agent will not under-report its cost function since that cannot improve its utility. Regarding computational efficiency, the mechanism is expected to perform well, since it only requires solving one linear programming problem which can be solved in polynomial time.

The mechanism's prevalence in various markets and its computational simplicity make it a valuable baseline for comparison in the VPP setting. By including the first-price auction, we aim to evaluate under which conditions its practical advantages outweigh its theoretical limitations.

3.3.2 Uniform Price Mechanism

The uniform-price mechanism is prevalent in electricity markets. The operator makes an allocation by solving the optimisation problem using the reported information (equation 2.16). All DERs included in the allocation are paid according to the same cost function. This cost function is determined by combining the cost functions of all DERs included in the allocation S. For each grid service the highest cost parameter is chosen to form the new cost function for determining the payouts (equation 3.7 - 3.9).

$$\bar{u}_{t,m} = \max_{i \in S} u_{i,t,m} \qquad \forall t \in \mathcal{T}, \forall m \in \mathcal{M} \tag{3.7}$$

$$\bar{c}_t(x_{i,t}) = \sum_{m \in \mathcal{M}} x_{i,t,m} \bar{u}_{t,m} \tag{3.8}$$

$$p_i(x_i) = \sum_{t \in \mathcal{T}} \bar{c}_t(x_{i,t}) \tag{3.9}$$

Regarding our evaluation criteria, this mechanism does not necessarily result in optimal revenue, even under non-strategic assumptions. This is because the mechanism pays DERs equal or more than their actual cost. This can also impact the viable VPP property. Nevertheless, because the payment is never lower than the reported cost function, the mechanism is individually rational. The mechanism is not fully incentive compatible. We can easily see that if an agent i overbids just enough such that it still remains in the allocation $i \in S$, it can drive up prices. While not fully incentive-compatible, the uniform-price auction often performs well in practice, especially with many bidders, as strategic bidding is partially mitigated by competition [68].

Algorithm 2 Uniform-Price Mechanism

Require: DERs $\mathcal{N} = \{1, 2, \ldots, N\}$, $\hat{\theta} = \{\hat{\theta}_i \mid \forall i \in \mathcal{N}\}$
Ensure: Allocation x^*, $p = \{p_i \mid \forall i \in \mathcal{N}\}$
1: $x^* \leftarrow$ solution of (2.16)
2: **for** $m \in \mathcal{M}$ **do**
3: $\quad \bar{u}_{t,m} \leftarrow \max_{i \in S} u_{i,t,m}, \quad \forall t \in \mathcal{T}, \forall m \in \mathcal{M}$
4: **end for**
5: **for** $i \in \mathcal{N}$ **do**
6: $\quad p_i \leftarrow \bar{c}(x_i^*)$
7: **end for**
8: **return** x^*, $p = \{p_i \mid \forall i \in \mathcal{N}\}$.

3.3.3 VCG Mechanism

The VCG mechanism is a strategy-proof mechanism that incentivises participants to report truthfully by aligning their payments with the externalities they impose on the system [69]–[71]. First, the DERs communicate their private information $\hat{\theta}_i$ to the VPP operator. The VPP computes an optimal allocation over the total horizon using equation 2.16. Secondly, each DER receives a payment based on the payment rule 3.10 [67, Def. 7.7]. This payment rule determines the payment p_i for DER i as the externality it imposes [70]. Formally, the payment is:

$$p_i(x_i) = \left(\sum_{j \neq i} c_j((x_{-i}^*)_j) + f(\epsilon) \right) - \left(\sum_{j \neq i} c_j(x_j^*) + f(\epsilon^*) \right) \tag{3.10}$$

$$x_{-i}^* = \mathcal{X}(\hat{\theta}_{-i}) \tag{3.11}$$

Here the first term is the total cost of others when agent i is excluded. $\mathcal{X}(\theta_{-i})$ denotes the optimal allocation given all reports except from agent i. The second term is the total cost induced by others under the optimal allocation including i. Their difference equals the negative externality imposed by agent i.

Algorithm 3 VCG mechanism

Require: DERs $\mathcal{N} = \{1, 2, \ldots, N\}$, $\hat{\theta} = \{\hat{\theta}_i \mid \forall i \in \mathcal{N}\}$
Ensure: Allocation x^*, $p = \{p_i \mid \forall i \in \mathcal{N}\}$
1: $x^* \leftarrow$ solution of (2.16)
2: **for** $i \in \mathcal{N}$ **do**
3: $\quad p_i \leftarrow$ solution of (3.10)
4: **end for**
5: **return** x^*, $p = \{p_i \mid \forall i \in \mathcal{N}\}$.

The well-known DSIC property of the VCG mechanism provides zero room to inflate the cost function. However, the spread of cost parameters does influence the VPP in another way.

Proposition 3.3 *Suppose per-unit costs are linear, $c_i(x_i) = x_i u_i$, and i.i.d. $u_i \sim U(d, e)$ with $d < e$. Assume the VPP's commitment b is feasible without using all DERs and is met in both the baseline* *and the $-i$ counterfactual allocations (no penalty, i.e. $f(\epsilon) = f(\epsilon^*) = 0$). Then the expected total VCG payout is strictly increasing in the spread $e - d$.*

Proof 3.3

1. *If $d = e$, all DERs $i, j \in \mathcal{N} \quad i \neq j$ have identical costs ($c_i(x) = c_j(x)$). Excluding any DER i does not alter the optimal allocation or cost, as another DER can substitute at the same cost, yielding $p_i = 0$ in equation* (3.10)
2. *As $e - d$ increases, so does $c_j(x) - c_i(x)$, as the cost parameters are drawn from $\mathcal{U}(d, e)$.*
3. *Now, excluding i requires including a higher cost DER, increasing the first term of equation 3.10.*
4. *In spite of the allocation remaining the same, the payouts increase as the externality is affected by the spread of the costs.*

Whereas VCG mechanisms that use valuations (as in equation 2.8), are known to be individually rational under common restrictions [72, Sec. 10.4.3]. VCG mechanisms that are used in a procurement setting, using costs rather than valuations, are not always individually rational. From this proof we can conclude that for certain cost spreads the mechanism violates individual rationality. Additional rules, such as reserve prices, could be imposed to make the mechanisms also individually rational. However, this could sacrifice other mechanism properties.

3.3.4 AGV Mechanism

The Arrow–d'Aspremont–Gérard-Varet (AGV) mechanism is also called the expected externality mechanism. It is a Groves-type mechanism that achieves budget balance by basing payments on expected, rather than realised, externalities [68, Sec. 5.3.2]. First, the allocation is made using equation 2.16. Following [72] we define

$$ESW_{-i}(\hat{\theta}_i) = \mathbb{E}_{\theta_{-i}} \left[\sum_{j \neq i} c_j(\mathcal{X}(\hat{\theta}_i, \theta_{-i})_j) + f(\epsilon) \right], \tag{3.12}$$

denoting the expected social welfare (ESW). We use this as an intermediate term to make the payment rule more concise. In this equation, we fix the reported information $\hat{\theta}_i$ from agent i and draw the reports from other agents θ_{-i} according to the assumed distribution. $\mathcal{X}(\hat{\theta}_i, \theta_{-i})$ denotes the optimal allocation given these reports. We take the expectation over θ_{-i} to get the expected total cost of everyone except i, given the fact that i announced $\hat{\theta}_i$ and with the cost functions from others according to the prior.

The AGV payment to DER i is then expressed as

$$p_i = ESW_{-i}(\hat{\theta}_i) - \frac{1}{N-1} \sum_{j \neq i} ESW_{-j}(\hat{\theta}_j). \tag{3.13}$$

This is the cost-minimisation counterpart of the expected-externality formula in [72, Def. (10.4.13)].

Algorithm 4 AGV mechanism

Require: DERs $\mathcal{N} = \{1, 2, \ldots, N\}$, $\hat{\theta} = \{\hat{\theta}_i \mid \forall i \in \mathcal{N}\}$
Ensure: Allocation x^*, $p = \{p_i \mid \forall i \in \mathcal{N}\}$
1: $x^* \leftarrow$ solution of (2.16)
2: **for** $i \in \mathcal{N}$ **do**
3: $p_i \leftarrow$ solution of (3.13)
4: **end for**
5: **return** x^*, $p = \{p_i \mid \forall i \in \mathcal{N}\}$.

In general, the AGV mechanism exchanges *ex interim* individual rationality for *ex ante* individual rationality and DSIC for Bayesian-Nash Incentive Compatibility (BNIC) to achieve budget balance [72]. In other words, the mechanism would be IR in expectation but may violate IR for individual instances.

Chapter 4

Case Study

Although the theoretical analysis of the mechanisms in the previous chapter has provided us with a general understanding of correlations between mechanism performance and the experimental dimensions, an understanding of absolute differences in performance across mechanisms is still missing. In order to gain this understanding, we subject the mechanisms to a case study.

First we clarify how we instantiate the model parameters needed for the case study (Section 4.1). Consequently, we discuss the simulation set-up in Section 4.2 and corresponding hypotheses in Section 4.3. Furthermore, we showcase the results of the experiments in Section 4.4 and provide an analysis of those results in Section 4.5.

4.1 Model Instantiation

The model that we use for the case study contains four types of DERs, generators, photovoltaic (PV) systems, electrical storage systems (ESS) and wind turbines. We adopt the model presented in Chapter 2, characterising all DERs through their cost functions, local constraints and temporal constraints. To instantiate the model, we use a hybrid approach combining synthetic data generation based on realistic distributions and real-world-inspired parameters. We discuss the specifics of implementations in their respective subsections 4.1.1 - 4.1.5.

Note: While the data ranges used for model instantiation are informed by real-world implementations [17], the specific numerical values are not essential to the core findings. With this model we aim to illustrate structural patterns rather than reproducing exact outcomes. Consequently, the specific instantiations do not materially affect the qualitative conclusions.

4.1.1 VPP instantiation

For this instantiation we assume that the VPP is providing two grid services, active power p and reserve capacity q, i.e. $|\mathcal{M}| = 2$. Similarly, this approach is followed in [73]. Both grid services are measured in kW over 1 hour time intervals. In this experiment we consider a time horizon of $T = 24$ hours and $N = 100$ DERs. We define the commitment vector per time interval as $b_t := [P_t, Q_t]^T$. The active power commitment is set to a fixed fraction of the aggregate available capacity,

$$P_t = 0.5 \cdot \sum_{i=1}^{N} P_{\max,i,t}, \tag{4.1}$$

reflecting a moderately challenging dispatch. Reserve capacity is set proportionally, based on planning reserve guidelines. [1]

$$Q_t = 0.15 \cdot P_t \tag{4.2}$$

Penalty coefficients for surplus and shortfall enter the soft-constraint term $f_t(\cdot)$ as in equation (2.15). We set $\lambda_P^- > \lambda_P^+$ and $\lambda_R^- > \lambda_R^+$ and keep them time-invariant within a scenario. Those values are derived from historical European market data (EPEX real-time results).

We use common, normalised exogenous profiles: a solar irradiance profile $\varphi_t \in [0, 1]$ and a wind availability profile $\psi_t \in [0, 1]$ shared across agents.

4.1.2 Generators

For generators we need to instantiate its minimum operational capacity P_{min}, its maximum operational capacity P_{max}, its ramping capability, i.e. the amount it can ramp up or down within time frames, and of course its cost function. To establish those parameters we use common ranges as in [17]. We draw the parameters from distributions to introduce variability within the DERs. P_{min} and P_{max} are drawn from uniform distributions $\mathcal{U}(1, 5)$ and $\mathcal{U}(P_{min}, 7)$ respectively to create variation within the DERs. We assume that its ramping capacity P_Δ is 15% of P_{max}, constraining the decision variables across time intervals.

The cost function for generators is linear, reflecting the fuel consumption required for power generation. Cost parameters for active power provision are drawn as

$$u_{i,t,1} \sim \mathcal{N}(\mu_P^{gen} = 0.5,\ \phi\mu_P^{gen};\ [0, \infty)), \tag{4.3}$$

where ϕ is the coefficient of variation. Reserve-capacity unit costs are set proportionally to active-power costs, $u_{i,t,2} = 0.15\, u_{i,t,1}$.

The instantiated local and temporal constraints are

$$P_{min} \leqslant p_{i,t} \leqslant P_{max}, \quad 0 \leqslant q_{i,t} \leqslant P_{max} - p_{i,t}, \quad |p_{i,t} - p_{i,t-1}| \leqslant P_\Delta \tag{4.4}$$

4.1.3 Photovoltaic Systems

Since photovoltaic systems are passive generation technologies, their power output is dependent on weather conditions. However, in this study we adopt perfect predictions and allow curtailment. For each PV system we draw a capacity $\bar{P}_i \sim \mathcal{U}(0.5, 2)$ kW. A common irradiance profile $\varphi_t \in [0, 1]$ captures the expected relative solar intensity at time step $t \in \mathcal{T}$. The time-varying maximum available power is then

$$P_{\max,i,t} = \bar{P}_i \cdot \varphi_t. \tag{4.5}$$

Active-power unit costs are drawn as $u_{i,t,1} \sim \mathcal{N}(\mu_P^{pv} = 0.3,\ \phi\mu_P^{pv};\ [0, \infty))$. In this simulation we assume that PV systems cannot provide controllable reserve capacity due to their weather-dependent nature. Therefore, we constrain the decision variables to

$$0 \leqslant p_{i,t} \leqslant P_{\max,i,t}, \quad q_{i,t} = 0. \tag{4.6}$$

[1] https://www.nerc.com/pa/RAPA/ra/Reliability%20Assessments%20DL/IVGTF1-2.pdf

There are no temporal constraints, as the output depends only on the current solar availability and not on previous operational states.

4.1.4 Electrical Storage Systems

For electrical storage systems, we instantiate multiple parameters to capture their operational characteristics. The maximum charging power $P_{\text{charge,max}}$ and maximum discharging power $P_{\text{discharge,max}}$ are drawn from uniform distributions $\mathcal{U}(1, 10)$ kW. The energy capacity E_{max} is drawn from $\mathcal{U}(1, 10)$ kWh and the initial state of charge is set as $E_0 = 0.5 \cdot E_{\text{max}}$. Active-power unit costs are drawn as $u_{i,t,1} \sim \mathcal{N}(\mu_P^{pv} = 0.2,\ \phi\mu_P^{pv};\ [0, \infty))$. The costs for reserve power are 15% of the active power costs.

The decision variables for ESS include the active power provision $-P_{\text{charge,max}} \leqslant p \leqslant P_{\text{discharge,max}}$ and the reserve capacity q it can provide, $q_t < P_{\text{discharge,max}} - p_t$.

Therefore the local constraints at each time t are:

- $-P_{\text{charge,max}} \leqslant p_t \leqslant P_{\text{discharge,max}}$
- $q_t < P_{\text{discharge,max}} - p_t$
- $0 \leqslant E_t \leqslant E_{\text{max}}$

The temporal constraints use the evolution of the state of charge as follows (with $\Delta t = 1$ h):

$$E_t = E_{t-1} + p_t \cdot \Delta t$$

Furthermore, the temporal constraints can be expressed as in example 2.1.

4.1.5 Wind Turbines

For wind turbines, we instantiate the rated capacity $P_{\text{rated},i} \sim \mathcal{U}(10, 50)$ kW to reflect variation among the DERs. A common wind availability profile $\psi_t \in [0, 1]$ is used to model time variation and the maximum operational capacity at each time step is $P_{\text{max},i,t} = P_{\text{rated},i} \cdot \psi_t$.

Wind turbines are passive generation technologies with output dependent on wind conditions. We assume perfect forecasts and allow curtailment, so the decision variables satisfy $0 \leqslant p_{i,t} \leqslant P_{\text{max},i,t}$ and $q_{i,t} = 0$. The cost parameters for active power provision are drawn from a truncated normal distribution $\mathcal{N}(\mu_P^{wind} = 0.1,\ \phi\mu_P^{wind};\ [0, \infty))$.

Thus, the local constraints are $0 \leqslant p_{i,t} \leqslant P_{\text{max},i,t}$ and $q_{i,t} = 0$. There are no temporal constraints, as their output depends only on the current wind availability and not on previous operational states.

4.1.6 Strategic Behaviour

In this section we specify how strategic behaviour is modelled in our case study. We first discuss among which dimensions agents can exhibit strategic behaviour. Consequently, we introduce a parameter to describe the magnitude of overreporting cost functions. Additionally, we discuss bounded rationality assumptions due to limited information and show how cost spread, in relation with bounded rationality influences the possibilities for DERs to strategise the cost function.

Strategic Dimensions

We focus the strategic dimension on cost reporting. Each agent communicates $\theta_i = (c_i, \mathbb{X}_i, g_i)$ to the VPP, but in the experiments we only allow misreporting of costs, i.e. $\hat{\theta}_i = (\hat{c}_i, \mathbb{X}_i, g_i)$. Misreporting $\mathbb{X}_i$ or g_i is excluded: overstating feasibility would be revealed operationally when requested allocations are infeasible and understating feasibility offers no advantage under our allocation objective.

Misreporting the Cost Function

To describe misreporting the cost function, we introduce a multiplicative factor $\alpha_{i,t}$. Truthful reporting corresponds to $\alpha_{i,t} = 1$. Reported costs are

$$\hat{c}_{i,t}(x_{i,t}) = \alpha_{i,t} x_{i,t} u_{i,t}. \tag{4.7}$$

Influence of Cost Spread

The leeway for a single DER to engage in over reporting its cost function is dependent on the competition within the DER portfolio. We can say that the competition within a VPP portfolio is dependent on the spread of the costs. It is only useful for a DER to over report its cost if this results in the allocation of grid services to that DER, i.e. $x_i \neq 0$. This means that the bounds of α_i are related to the spread of cost parameters within the VPP portfolio.

Proposition 4.1 (Leeway to overreport increases with cost spread) *Consider a single time step ($|\mathcal{T}| = 1$) and a single service ($|\mathcal{M}| = 1$). Let unit costs u_i be i.i.d. $\mathcal{U}(d, e)$ with $0 < d < e$. Let the VPP select a subset S of size $K < N$ that minimises total reported cost subject to the commitment, as in (2.16). Consider a unilateral deviation by some $i \in S$ that scales its reported unit cost by $\alpha_i \geqslant 1$ while other agents' reports are held fixed. Then the maximal factor that keeps i in S, $\bar{\alpha}_i$, satisfies*

$$\frac{\partial \mathbb{E}[\bar{\alpha}_i]}{\partial (e - d)} > 0.$$

Proof 4.1 *Order DERs by reported unit cost. Under truthful reports, $i \in S$ implies $u_i \leqslant u_K$ and the $(K+1)$-th order statistic u_{K+1} is the exclusion threshold. After scaling, i remains selected if and only if*

$$\alpha_i u_i < u_{K+1} \quad \Rightarrow \quad \bar{\alpha}_i = \frac{u_{K+1}}{u_i}.$$

For i.i.d. $\mathcal{U}(d, e)$ draws, u_i and u_{K+1} are order statistics whose ratio's expectation increases with the support width $(e - d)$. A larger spread increases the typical gap between adjacent order statistics, raising $\mathbb{E}[u_{K+1}/u_i]$. Therefore, $\partial\, \mathbb{E}[\bar{\alpha}_i]/\partial(e - d) > 0$.

Bounded Rationality Constraints

Agents attempting to compute the report that maximises their utility is a common phenomenon. However, with incomplete information about others' costs, *exactly* computing the reported cost function to maximise utility (equation 4.8) is unlikely.

Of course, depending on the context, a DER may have information about other DERs' cost. For some technologies (e.g., PV or gas-fired CHP), costs may be similar across agents because they share common sources (i.e. sunlight, gas), allowing DERs to estimate $\hat{\theta}_i^*$.

$$\hat{\theta}_i^* = \arg\max_{\hat{\theta}_i} \left[p_i(\mathcal{X}(\hat{\theta}_i, \theta_{-i})) - c_i(\mathcal{X}(\hat{\theta}_i, \theta_{-i})) \right] \tag{4.8}$$

It is important to note that the optimal report an agent can make is dependent on the type of mechanism. This is because the payment p is part of equation 4.8 and recall that the payment p_i to an agent is dependent on the mechanism. The influence that other agents have on the optimal report is reflected through $\mathcal{X}$, which changes as the reports from other agents change.

To study the effect of bounded rationality on outcomes, we adopt a simple *experimental model* for bounded rationality. Since we instantiate all cost parameters, we can actually calculate $\hat{\theta}_i^*$ and therefore c_i^* according to equation 4.8. Consequently, we can find α_i^* that is associated with c_i^*. In reality, as was pointed out earlier, a DER cannot exactly find c_i^*, due to limited information. Therefore, to propagate this uncertainty into our experiment, for strategic DERs, we draw $\alpha_{i,t} \sim \mathcal{N}(\alpha_{i,t}^*, \frac{\alpha_{i,t}^*}{5})$. To obtain the standard deviation, we divide the mean by 5, such that the deviation scales with the mean. Following proposition 4.1, this approach allows $\alpha_{i,t}$ to change as we vary the cost spread throughout experiments.

Note that this experimental model is not a behavioural claim about the real world, it is a way to model the uncertainty introduced by the limited information. Indicating that a DER is not expected to be able to optimally set its $\alpha_{i,t}$.

4.2 Simulation Set-up

During the simulations we vary two primary factors across scenarios. The first of those is the strategic fraction s, being the proportion of DERs that misreport.

$$s \in \{0.00, 0.05, 0.10, 0.20, 0.40, 0.50, 0.70, 1.00\}$$

The second one is the coefficient of variation ϕ for unit costs.

$$\phi = \frac{\sigma}{\mu} \tag{4.9}$$

$$\phi \in \{0.0, 0.1, 0.5, 1.0, 2.0, 3.0\}$$

For each (s, ϕ) scenario:

1. Instantiate DER parameters and feasible sets as in Section 4.1 with dispersion ϕ; generate shared profiles φ_t, ψ_t.

2. Set commitments b_t and penalties λ as in Section 4.1.1.

3. Select a random subset of DERs of size $\lfloor sN \rfloor$ as strategic. For those, draw $\alpha_{i,t}$; for non-strategic DERs set $\alpha_{i,t} = 1$.

4. For each mechanism: form reported costs $\hat{c}_{i,t}$ using $\alpha_{i,t}$, solve the allocation via (2.16), compute payments by the mechanism's rule and record the overpayment ratio r.

Each scenario is repeated for 10 iterations with a fixed global seed per batch to ensure reproducibility. For each scenario we record the payment-to-cost ratio r (Section 3.2.1) to assess the design criteria (Section 3.2). Furthermore, we record the runtime of the mechanisms for $N \in \{1, 5, 20, 50, 100, 200, 300\}$ in seconds.

The experimental setup is implemented in Python 3.10, using Pyomo for optimisation with the cplex solver to solve the LP problem. The data generation function uses NumPy for random sampling, with a fixed seed to ensure reproducibility. Experiments are run on a Lenovo Ideapad 5 with 16GB of RAM and an AMD Ryzen 5 5500U.

4.3 Hypotheses

By reviewing the theoretical analyses of the mechanisms made in Section 3.3, the bounded rationality model and proposition 4.1, we can form the following hypotheses.

- **H1 (Overbidding raises payments).** For first-price and uniform mechanisms, higher $\bar{\alpha}$ and/or larger s increase the average payout-to-cost ratio r.

- **H2 (Cost spread amplifies effects).** Larger ϕ (greater dispersion of u) amplifies the impact of misreporting on payments, with uniform pricing most sensitive (prices tied to maxima).

- **H3 (Variance to α).** Under VCG and AGV, outcomes are invariant to α, but total payouts still increase with cost spread ϕ via externality payments.

4.4 Results

This section reports observations from the simulations using the payment-to-cost ratio r as primary metric. We vary the strategic fraction s and the coefficient of variation ϕ of unit costs. We provide 2D plots illustrating the impact of the strategic fraction s on the payment-to-cost ratio r for several fixed values of the coefficient of variation ϕ. Similarly, we plot the payment-to-cost ratio versus the coefficient of variation ϕ for several fixed values of the strategic fraction s.

4.4.1 First-Price Sealed-Bid

From Figure 4.1 we can observe the following results. For the FPSB mechanism we can both observe an increase in the payment-to-cost ratio r when the strategic fraction s increases (top), as well as when the coefficient of variation ϕ increases (bottom). Whereas payment-to-cost ratios are modest for a low cost dispersion and strategic fraction they increase for larger strategic fraction s and coefficient of variation ϕ, leading to overpayments of up to 25% in extreme cases.

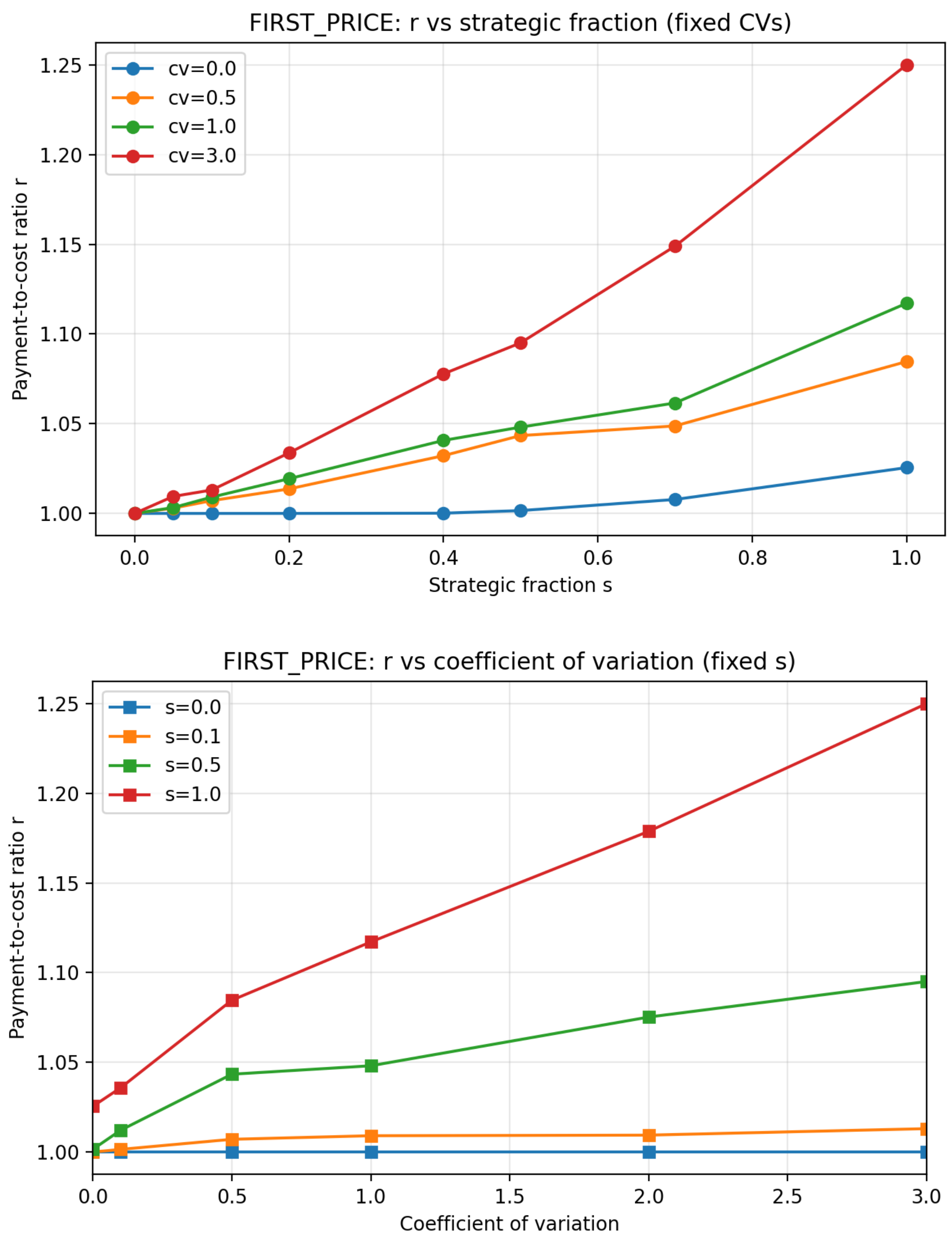
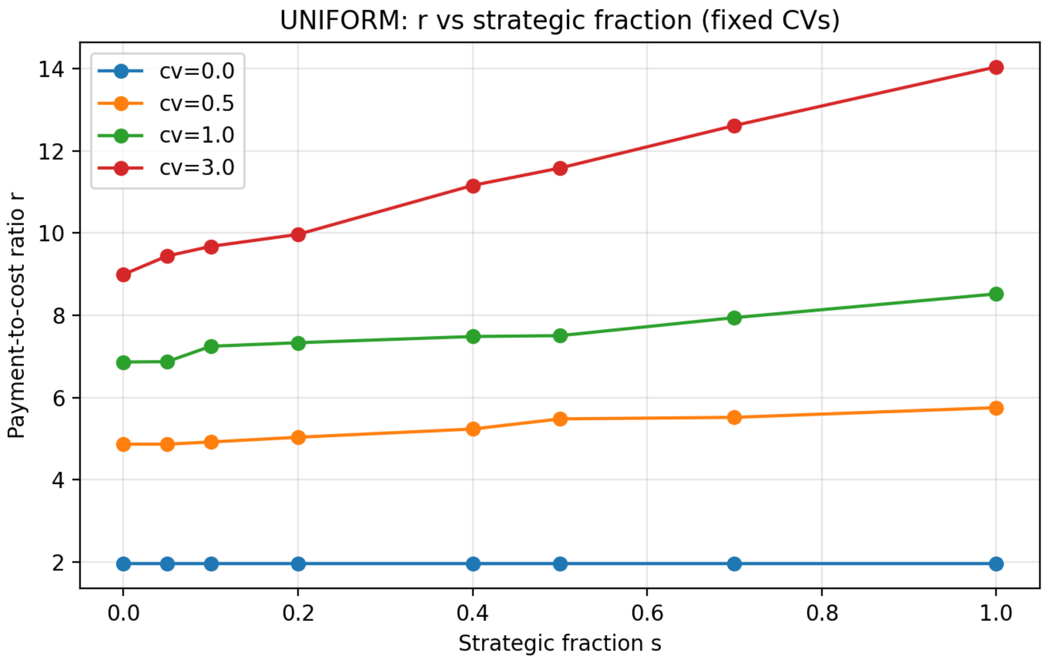


Figure 4.1: FPSB: The payment-to-cost ratio r versus the strategic fraction s for fixed coefficient of variation ϕ (top) and payment-to-cost ratio r versus the coefficient of variation ϕ for a fixed strategic fraction s (bottom).

4.4.2 Uniform Pricing

From Figure 4.2 we can observe that the payment-to-cost ratio r increases significantly when increasing the coefficient of variation ϕ (bottom). Increasing the strategic fraction s also raises the payment-to-cost ratio r but the effect is significantly less. We observe a minimal payment-to-cost ratio of 2, for a coefficient of variation $\phi = 0$ or a strategic fraction $s = 0$. The payment-to-cost ratio attains values that are quite large, ranging from 2 up till 14.



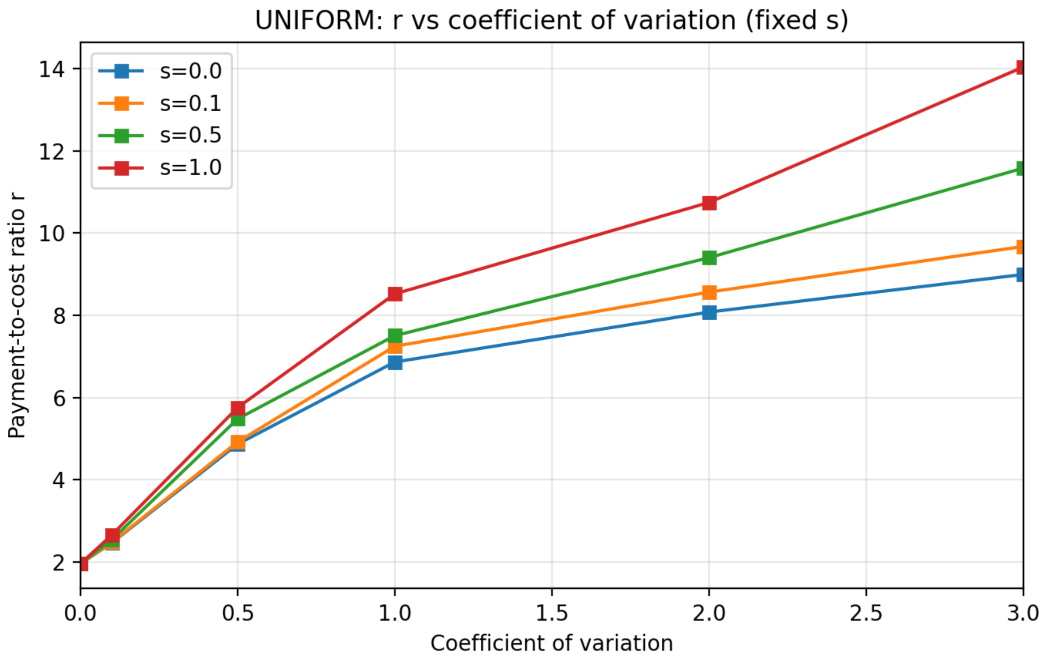
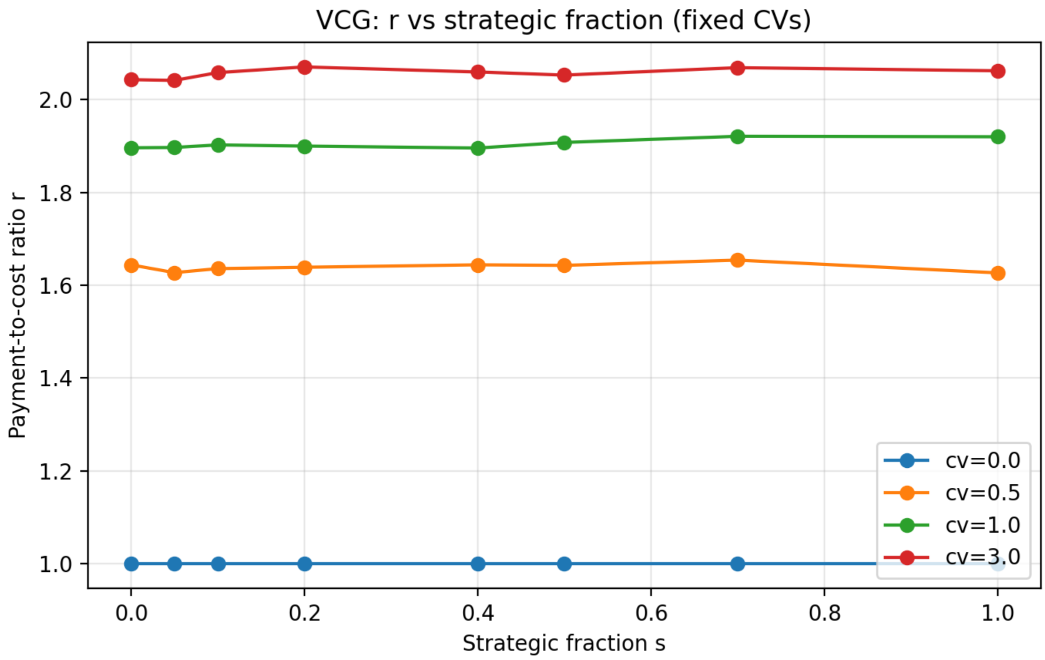


Figure 4.2: Uniform: The payment-to-cost ratio r versus the strategic fraction s for fixed coefficient of variation ϕ (top) and payment-to-cost ratio r versus the coefficient of variation ϕ for a fixed strategic fraction s (bottom).

4.4.3 VCG Mechanism

For VCG, r varies primarily with the coefficient of variation ϕ while variation along the strategic fraction s is negligible (DSIC). Absolute r exceeds 1.0 due to externality payments and rises with the coefficient of variation.



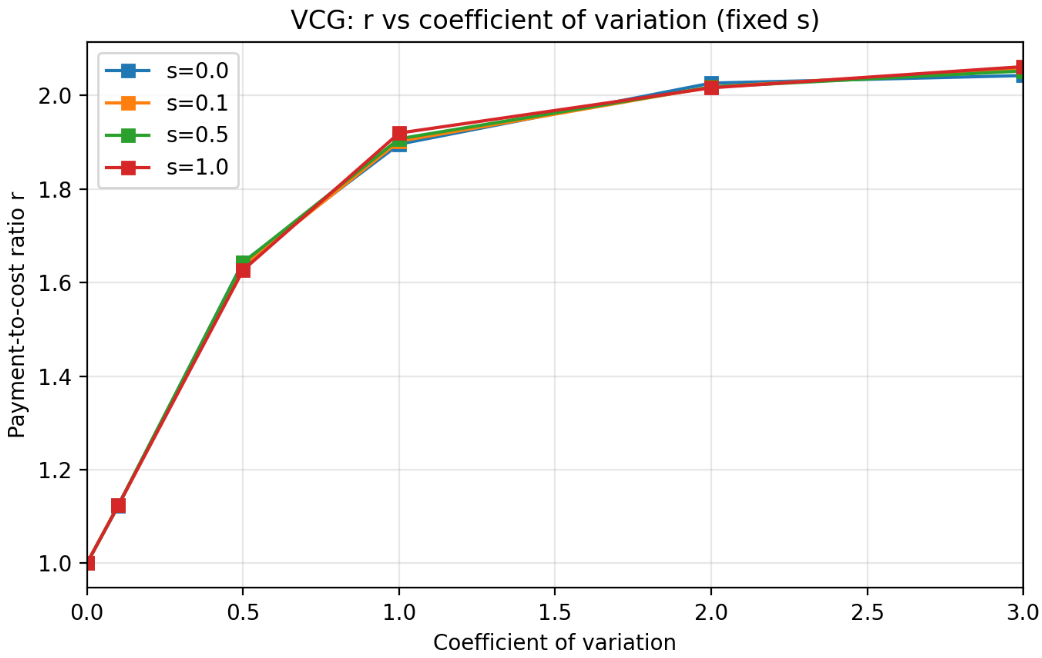


Figure 4.3: VCG: The payment-to-cost ratio r versus the strategic fraction s for fixed coefficient of variation ϕ (top) and payment-to-cost ratio r versus the coefficient of variation ϕ for a fixed strategic fraction s (bottom).

4.4.4 AGV Mechanism

For AGV, r is generally below one, with hardly any sensitivity to the strategic fraction s. Across the coefficient of variation ϕ, moderate differences are to be seen. Absolute variation is limited compared to uniform and VCG.

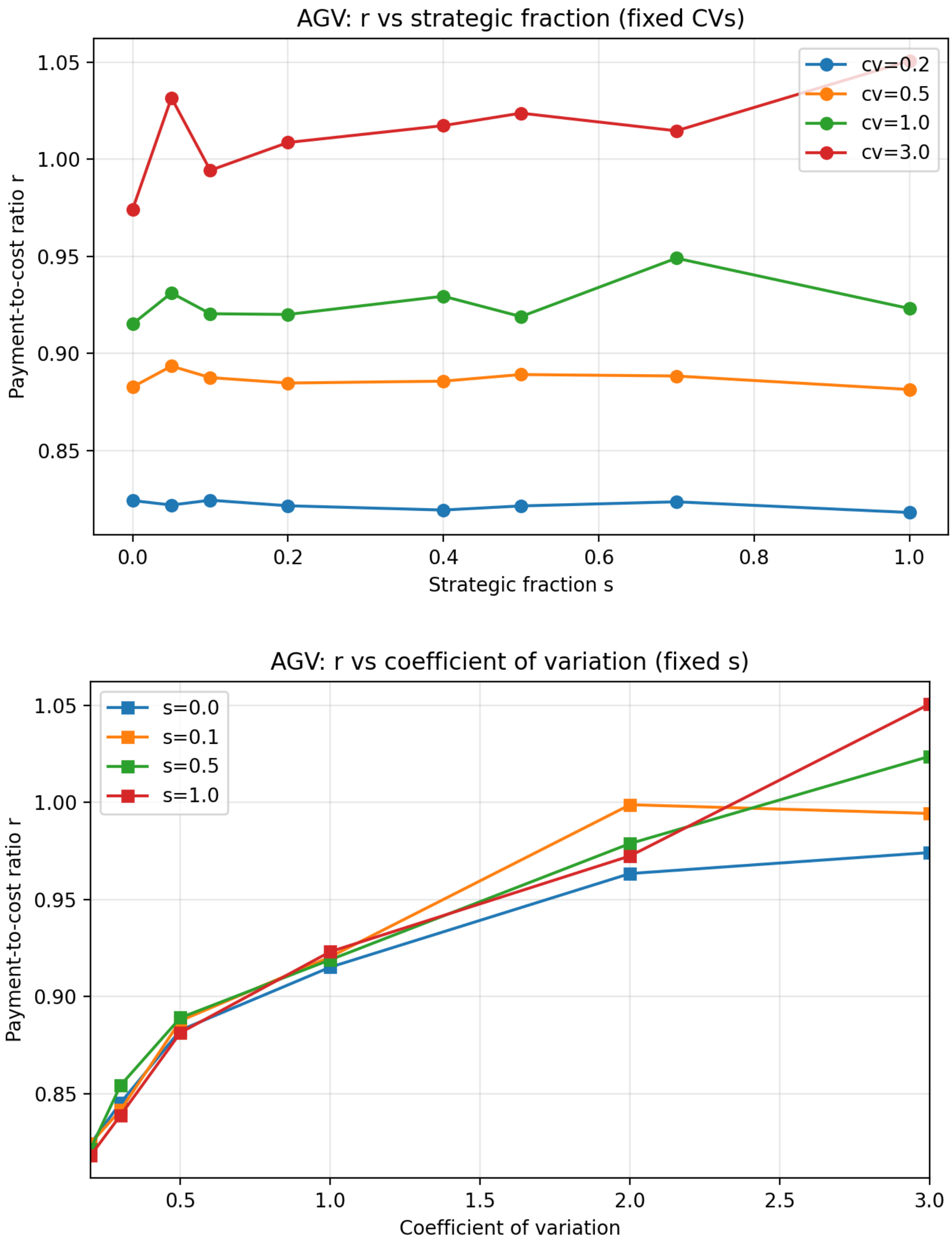


Figure 4.4: AGV: The payment-to-cost ratio r versus the strategic fraction s for fixed coefficient of variation ϕ (top) and payment-to-cost ratio r versus the coefficient of variation ϕ for a fixed strategic fraction s (bottom).

4.4.5 Runtime

Whereas runtimes for VCG increase rapidly, for other mechanisms they remain low as the portfolio size increases.

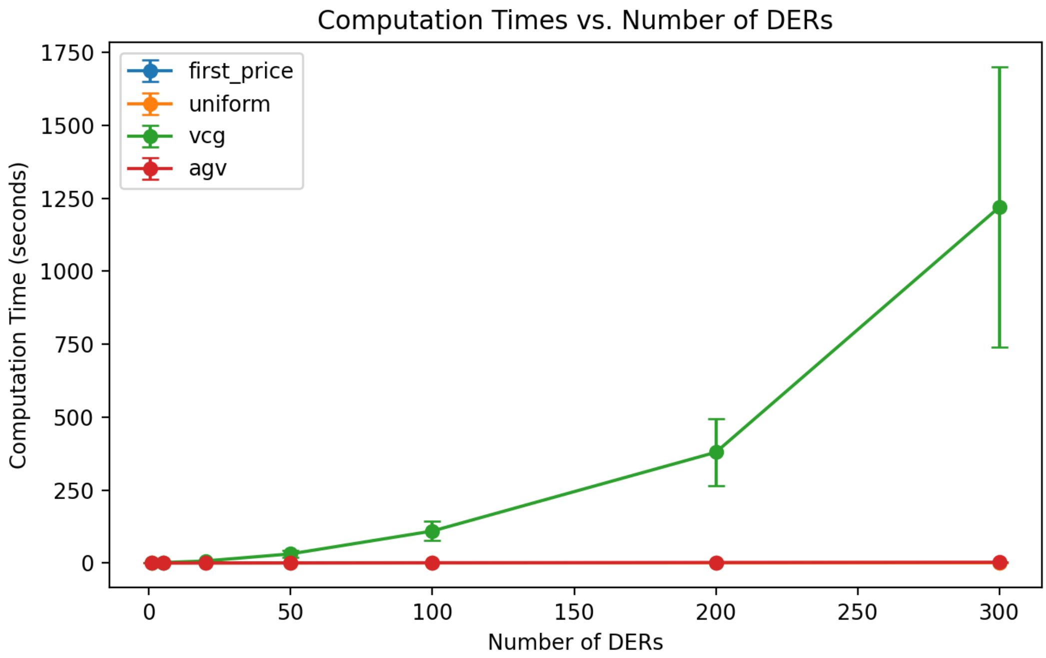


Figure 4.5: Comparison of the runtime (in seconds) for various portfolio sizes.

4.5 Discussion

This section reflects on the results of the case study. A subsection is dedicated to each individual mechanism.

4.5.1 First-Price Sealed-Bid

Figures 4.1 show that the payment-to-cost ratio r increases as the strategic fraction s increases. Similarly, there is a positive correlation between the coefficient of variation ϕ and the payment-to-cost ratio r. The positive correlation between the strategic fraction and the payment-to-cost ratio is consistent with the mechanism's payment rule (equation 3.6) and with proposition 3.2, stating that a larger share of misreporting agents inflates total payments. Increasing the coefficient of variation ϕ changes the leeway for over reporting (proposition 4.1), hence resulting in a higher payment-to-cost ratio.

In terms of design criteria, FPSB is not strategy-proof. Agents have incentives to overreport (Section 3.3.1), so outcomes depend on s and on how aggressively agents misreport. Individual rationality is satisfied in our experiments because agents are paid their reported costs and thus $r \geqslant 1$. Regarding weak budget balance and the viable VPP condition; if all agents are truthful (s=0), FPSB attains r=1 and satisfies the viable VPP condition. As s rises, however, overpayment can push r above $1+\gamma$, threatening both viability and revenue optimality.

4.5.2 Uniform Pricing

For the uniform-price mechanism (figure 4.2), the payment-to-cost ratio r varies strongly with the coefficient of variation ϕ and little with the strategic fraction s. This follows directly from the payment construction (equations 3.7–3.9). The highest unit cost among selected DERs sets the uniform price. As the coefficient of variation ϕ grows, the maximum of the selected costs increases relative to the average, raising the payment-to-cost ratio r. Limited sensitivity to the strategic fraction s is expected because even if some agents overreport, competition among selected DERs constrains the clearing price to the within-allocation maximum, providing some natural robustness as explained in Section 3.3.2.

With respect to the design criteria, uniform pricing is not strategy-proof, DERs can profit from shading upward. Nevertheless, competition provides partial resilience, which aligns with the weak empirical dependence on s. Individual rationality holds by construction because no DER is paid below its reported cost, which is reflected in $r \geqslant 1$. Budget balance and viability are the main concerns: large ϕ produces significant overpayment ($r \gg 1$), which is likely to violate the viable VPP condition and undermines revenue optimality. Interesting to observe is that empirical results never yield a payment-to-cost ratio lower than 2, even when $\phi = 0$. While remarkable at first glance, this is most likely due to the heterogeneity of the portfolio, automatically introducing a spread of costs because different technologies bring different costs.

4.5.3 VCG

The VCG mechanism exhibits almost no variation in the payment-to-cost ratio r with changing strategic fraction s (Figure 4.3), as expected from DSIC. Strategic misreporting does not improve utility, so agents effectively truth-tell (Section 3.3.3). However, r increases with the coefficient of variation ϕ. This aligns with the externality-based payment rule (equation 3.10) and proposition 3.3 in Section 3.3.3, saying that with greater dispersion, replacing a low-cost DER by the next-best alternative becomes more expensive on average, increasing payments.

Considering the design criteria, VCG is DSIC and thus robust to strategic behaviour. Additionally, since $r > 1$ individual rationality is satisfied. Nevertheless, due to this $r > 1$, weak budget balance is not guaranteed. Payments can exceed total costs by a significant margin, jeopardising the viable VPP condition and revenue optimality despite being incentive-compatible. Tractability is lower than for the other mechanisms because naively computing payments requires $N{+}1$ solves per instance, which is consistent with higher runtimes in practice (Figure 4.5).

4.5.4 AGV

For AGV (Figure 4.4), r hardly shows sensitivity to s and increases with ϕ, but overall levels are kept near or below one due to the scaling step explained in Section 3.3.4.

Regarding the design criteria, AGV achieves Bayesian-Nash incentive compatibility, but it is not DSIC. Our implementation appears comparatively insensitive to s. Although, theoretically IR should hold in expectation, we frequently observe $r < 1$, indicating that certain DERs may be compensated below true costs. However, theoretically, the mechanism should be individually rational over an infinite time horizon. Weak budget balance and thus operator viability can be enforced by design through the scaling step, which makes AGV attractive from a revenue management standpoint. Tractability is favourable relative to VCG because actual optimisation problems are replaced by expectations.

4.5.5 Non-Rational Behaviour

Because we have imposed a bounded rationality assumption on the agents, agents will not always show rational behaviour. Under bounded rationality, agents may not compute α_i^* exactly. We use *non-rational behaviour* to refer to deviations from the utility-maximising report (equation 4.8). We are interested in how this influences individual utility and how simultaneous deviations from α_i^* across multiple agents affect the utility from other agents.

For the non-strategy proof mechanisms, we distinguish between $\alpha_i > \alpha_i^*$ and $\alpha_i < \alpha_i^*$. By the definition of optimal α_i^* (equation 4.8), if an agent uses $\alpha_i > \alpha_i^*$ this results in their exclusion from the allocation S, resulting in $v_i(x_i) = 0$ for that agent. Furthermore, when $\alpha_i < \alpha_i^*$, it is trivial that for FPSB this decreases the agents utility. For the uniform pricing mechanism, this is not necessarily the case. If the agent is included in the allocation, using $\alpha_i < \alpha_i^*$ does not influence its own utility, except when it is the agent with the highest cost function. This can be easily inferred when looking at equation 3.9.

Furthermore, we discuss influences on the utility of individual agents when simultaneous deviations from α_i^* occur, i.e. when a significant portion of agents deviates such that $\alpha_i > \alpha_i^*$ or $\alpha_i < \alpha_i^*$. For the FPSB and the uniform pricing mechanism we can see that the first case decreases the competition as in that case those agents are excluded from the allocation, as was discussed in the previous paragraph. This relaxes the inclusion threshold and therefore provides remaining agents with more leeway to inflate alpha. In the latter case, quite trivially, the inclusion threshold is tightened, resulting in a smaller margin for increasing α_i.

For the strategy proof mechanisms this is a different discussion, as those mechanisms are designed in such a way that $\alpha = 1$ results in optimal utility for the agents. However, this means that non-rational agents may still choose $\alpha \neq 1$. From the DSIC or BSIC properties that hold for VCG and AGV respectively, this means that this will decrease their individual utility. Since for AGV the payments are based on expectations it does not influence the mechanism's revenue optimality. Additionally, for the VCG mechanism it neither makes a difference, since collective over, or under-reporting does not influence the difference between the two terms of equation 3.10, i.e. it does not influence the externality.

4.5.6 Runtime

In Figure 4.5 we can observe that the FPSB, uniform and AGV mechanism exhibit low linearly scaling runtimes. On the contrary, VCG runtimes scale much quicker as the portfolio size increases.

Chapter 5

Discussion

The combination of the theoretical analyses of mechanisms in Chapter 3 and the empirical results of the case study (Chapter 4), allow us to discuss the research questions (Section 5.1). Consequently, we combine the results from the three research questions and extrapolate the findings to a broader context (Section 5.2). Finally, we investigate what knowledge is still missing and provide those as directions for future work (Section 5.3).

5.1 Research Questions

RQ1: How can the operational dynamics of a VPP be modelled? The first research question has been an essential question for this research, to cover important preliminaries. Chapter 2 provided a formal description of a tractable multi-period model with local and temporal constraints, soft system-wide commitments and linear costs, sufficient to study internal coordination and mechanism design in a CVPP setting. This laid the groundwork for describing mechanisms and providing subsequent analyses. This chapter concluded with the question how to maximise profit for the VPP operator when agents may engage in misreporting their local information. This brought us to the area of mechanism design, eventually leading us to research question 2.

RQ2: How do mechanisms compare across revenue optimality, weak budget balance, incentive compatibility, individual rationality and tractability? FPSB is simple, IR and tractable. It achieves revenue optimality and viability under truth-telling but is vulnerable as the strategic fraction increases. Uniform pricing is tractable and IR exhibiting fewer dependence on the strategic fraction, but highly sensitive to the spread of costs. This leads to concerns regarding the viable VPP property and revenue optimality. VCG is DSIC and yields efficient allocations, but externality payments threaten viability and revenue optimality. Also, it is often computationally heavier. AGV can be tuned to satisfy budget balance and keep the payment-to-cost ratio near one, offering a middle ground. It did violate individual rationality in various instances in our case study.

RQ3: How does portfolio composition (agent behaviour and cost dispersion) influence mechanism effectiveness? Composition matters. Our results show that FPSB is most sensitive to the fraction of strategic agents. When there are no strategic agents, the payment-to-cost equals one. This indicates the presence of all desired properties, revenue optimality, incentive compatibility, individual rationality and viability. Unfortunately, as the strategic fraction increases these properties quickly fade. Uniform pricing provides more resilience to the presence of strategic agents as the price is reliant on the most expensive agents in the allocation, rendering strategic behaviour for agents with lower cost functions largely unprofitable. On the contrary, it is most sensitive to the dispersion of costs, quickly increases the payment-to-cost ratio as the spread increases. VCG is invariant to s but becomes increasingly expensive as the cost spread grows. AGV is comparatively insensitive to s under our implementation and preserves operator viability across ϕ, albeit with the occasional individual-rationality violations.

5.2 Synthesis

Taken together, these findings imply different mechanism choices for different scenarios. When the strategic fraction is low, FPSB can be particularly useful. Beyond its simplicity, it tends to exhibit relatively low overpayment compared to uniform or VCG. This makes this mechanism especially desirable in cases where only a minor fraction of the portfolio is likely to engage in untruthful reporting. Uniform pricing can fit homogeneous VPP portfolios. In homogeneous portfolios, cost functions are correlated through common drivers (e.g. shared dependencies on solar irradiance, wind availability or gas prices). Therefore, there is a much smaller spread of costs compared to heterogeneous portfolios. Since the impact of the strategic fraction is relatively small, in combination with a low-variance VPP portfolio in terms of cost spread, the uniform pricing strategy is expected to perform well. An important take-away here is that, though both these mechanisms are not strategy proof, under the right circumstances they could outperform mechanisms that are strategy-proof.

In cases where DSIC is important and external subsidisation is feasible, VCG is theoretically ideal. When operator viability is the hard constraint, AGV-style mechanisms with safeguards for individual rationality offer a promising outcome.

5.3 Future Research

From our findings, we propose three directions for future research. First, future work should enhance modelling strategic behaviour by replacing draws of the inflation factor with informed, state-dependent strategies that respond to observables such as fuel prices, solar irradiance and wind availability and possibly by allowing agents to learn over time. This would better capture how the cost spread could amplify strategic behaviour and/or influence the payment-to-cost ratio. Second, the modelling environment can be broadened by relaxing perfect-forecast assumptions, adding additional grid services and richer temporal couplings. Third, evaluating alternative mechanisms, such as iterative schemes, hybrid uniform–pay-as-bid rules or reserve-price Groves variants, could further enhance performance.

Chapter 6

Conclusions and Recommendations

This chapter provides a condensed representation of the work done in this thesis. Starting with an explanation of the context and motivation (Section 6.1), we follow with indicating the research gap (Section 6.2). Consequently, we briefly discuss the mechanisms that were considered in this thesis (Section 6.3) and summarise the contributions resulting from the theoretical analysis and case study in Section 6.4. Finally, we summarise what understanding is still missing and recommend this as future work in Section 6.5.

6.1 Context and Motivation

As power systems increasingly rely on renewable energy, maintaining grid stability becomes more complex. Grid services — such as power balance, ramping, frequency regulation — are essential to ensure secure and reliable system operation. Traditionally provided by large, centralised generators, these services must now be sourced from a growing number of distributed energy resources (DERs), including solar panels, wind turbines and residential batteries. To effectively integrate these small-scale, decentralised resources, the concept of a virtual power plant (VPP) has been introduced. A VPP aggregates the capabilities of multiple DERs and coordinates their operation to collectively provide grid services, allowing grid operators to interact with the VPP as if it were a conventional power plant.

Unlike conventional generation units, DERs are typically owned by independent agents with self-interested objectives. These agents may behave strategically, for example by misreporting costs or constraints, in order to maximise individual benefits. Such behaviour can undermine the collective performance of the VPP and jeopardise service reliability. A key challenge lies in designing coordination mechanisms that align the self-interested objectives (e.g. profit maximisation) of individual DERs with the operational goals of the VPP, ensuring both truthful participation and reliable service provision.

6.2 Research Gap

Whereas strategic behaviour has been studied in related contexts such as demand response programs and community or neighbourhood energy settings, these works rarely address the commercial VPP context in which a central operator must satisfy a fixed commitment while coordinating heterogeneous, independently owned DERs. Many VPP studies treat the day-ahead plan as flexible or do not model strategic reporting at all, which limits their applicability to commercial operations.

This thesis targets a specific and practically relevant formulation that has not been systematically explored: a commercial VPP that must satisfy a predetermined commitment, with a revenue maximisation objective. In this scenario, DERs hold private information and may engage in misreporting those. The operator solves a central allocation with soft penalties for deviation from the predetermined commitment and seeks profit maximisation. What is missing in the literature is an assessment of internal coordination mechanisms tailored to this formulation, including how they trade off revenue optimality, weak budget balance, incentive compatibility, individual rationality and scalability. Equally lacking is an understanding of how portfolio composition, in particular the fraction of strategic agents and the dispersion of unit costs, shapes mechanism performance in this fixed-commitment setting.

6.3 Mechanisms Considered

We evaluated four internal coordination mechanisms. The first-price sealed bid mechanism pays each selected DER its reported cost. The uniform-pricing mechanism pays all selected DERs a common price derived from the highest unit cost among the selected set. The Vickrey–Clarke–Groves mechanism uses the efficient allocation and pays agents according to the externality they impose on others, which induces truthful reports. The Arrow–d'Aspremont–Gerard-Varet mechanism replaces realised externalities by expected externalities and applies a scaling step to target budget balance. Together these mechanisms span the design space from simple and tractable rules to strategy-proof schemes.

6.4 Contributions

The experiments demonstrate clear patterns across the design criteria. FPSB is simple, fast and individually rational. It achieves near-cost payments when agents report truthfully. Payments increase as the fraction of strategic agents grows because DERs can profit from inflating costs. Uniform pricing is comparatively insensitive to the fraction of strategic agents, since the clearing price is anchored to the highest cost within the selected set. It is, however, very sensitive to cost dispersion and can overpay significantly in heterogeneous portfolios with high cost spread. VCG is strategy-proof and invariant to the fraction of strategic agents. It tends to overpay as dispersion grows because externality payments rise when low-cost units are replaced by costlier alternatives in counterfactuals. Runtime is higher because payments require additional optimisation solves. AGV maintains near budget balance and shows limited sensitivity to both strategic participation and dispersion under the chosen scaling. It may violate individual rationality for some agents unless surplus is available for redistribution or minimum-compensation safeguards are added.

These trade-offs imply practical guidance for mechanism selection. FPSB is attractive when the fraction of strategic agents is expected to be small and when operational simplicity is desired. Uniform pricing suits homogeneous portfolios due to tight cost dispersion. It can be robust in practice when competition is strong and technologies are similar. VCG is the preferred choice when dominant-strategy truthfulness is a strict requirement and when the VPP can rely on sufficient margins or external subsidy to absorb overpayment. AGV is well suited when operator viability is the hard constraint. It should be paired with safeguards that protect individual rationality, for example through minimum-compensation floors.

6.5 Future Work

Future research should model strategic behaviour with richer, state-dependent strategies and learning over time, so that misreporting responds to observables such as fuel prices, solar irradiance and wind availability. Furthermore, the modelling environment can be broadened by relaxing perfect-forecast assumptions, adding additional grid services and richer temporal couplings. Additionally, alternative or hybrid mechanisms such as iterative schemes, pay-as-bid with reserves, capped uniform pricing and reserve-price Groves variants under uncertainty could be considered.

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