Insurance Mechanisms for the Reliability of Electricity Supply

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Abstract

In the context of rapid shifts in the energy supply mix and the onset of climate change, tail risk in power systems presents an emergent threat to system reliability. Flexible resources like load control, storage and distributed energy resources are potent tools to alleviate system strains during extreme events. However, market participants need appropriate economic incentives to exploit the value of such resources. While spot prices serve as robust indicators of real-time scarcity, a complex challenge lies in translating short-term signals to long-term investment decisions. This is especially pertinent in the context of markets marked by incompleteness, and agents with pronounced aversion to risk.

The financial technology of insurance is targeted at the assessment, pricing, and management of extreme and catastrophic risks. This thesis proposes the novel application of insurance contracts and risk architectures to modern electricity markets, extending existing approaches to reliability risk management. This leads to the central research question of this thesis: *Can the delivery of electricity service to consumers be made more reliable through the application of insurance mechanisms?*

The thesis investigates this question through three main streams of research:

This first stream proposes the novel application of insurance contracts and capital reserving frameworks on the procurement of strategic reserves in electricity markets. A strategic reserve is a reliability mechanism in electricity markets that seeks to contract generation capacity incremental to that incentivised by short-term spot markets, for use in times of critical supply shortage. The insurance contracts allow consumers to elect differentiated reliability preferences, and align the financial interests of the insurer with such preferences. Application to a case study suggests the potential for improved consumer and social welfare while maintaining insurer viability and solvency. The design is also robust to non-transparent market parameters such as generator risk aversion.

The second stream develops a locational insurance model to value resilience in power systems exposed to high-impact low-probability common-mode events. It is demonstrated that the implementation of this scheme in a large-scale power system could reduce load losses via investment in resilient distributed energy resources. However the cost of such insurance may be expensive, and appropriate calibration of consumer expectations and preferences is important.

The final stream examines the interaction between the design of contracts between central agencies and storage resources, and the operation of the resources in the market. Five principles for central agency contracting are proposed, focusing on incentive compatibility with existing spot dispatch and limiting distortions to long-term hedging markets. The principles are applied specifically to contracts with storage resources. It is demonstrated that many early designs for storage auctions may be inconsistent with the identified principles. A novel storage contract 'yardstick' is proposed, which is shown to align participant dispatch incentives, while maintaining revenue support.

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List of Abbreviations

ABM . . . . . Agent-based Modelling

AC-OPF . . . Alternating Current Optimal Power Flow

ACER . . . . . Agency for the Cooperation of Energy Regulators

AEMO . . . . Australian Energy Market Operator

BEV . . . . . . Battery Electric Vehicle

BESS . . . . . Battery Energy Storage Systems

CCGT . . . . . Combined Cycle Gas Turbine

CFD . . . . . . Contracts-for-Difference

CM . . . . . . Capacity Mechanism

CNSW . . . . Central New South Wales

CNQ . . . . . . Central and Northern Queensland

CSIRO . . . . Commonwealth Scientific and Industrial Research Organisation

CV . . . . Coefficient of Variation

CVaR . . . . . Conditional Value-at-Risk

DC-OPF . . . Direct Current Optimal Power Flow

DER . . . . . . Distributed Energy Resources

DI . . . . Dispatch Interval

EBITDA . . . Earnings before Interest, Taxation, Depreciation, and Amortisation

EIM . . . . . . Energy-plus-Insurance Market

EOM . . . . . Energy-Only Market

ERCOT . . . . Electric Reliability Council of Texas

ERM . . . . . Energy Reserve Margin

EUSE . . . . . Expected Unserved Energy

FCAS . . . . . Frequency Control Ancillary Services

FY . . . . Financial Year
GG . . . . Gladstone Grid
GJ . . . . GigaJoule
GW . . . . . . GigaWatt
GWh . . . . . GigaWatt-hour
GNE . . . . . . Generalised Nash Equilibrium
HILP . . . . . High Impact Low Probability
IOLR . . . . . Insurer-of-last-resort
ISP . . . . Integrated System Plan
KKT . . . . . . Karush-Kuhn-Tucker
KW . . . . . . KiloWatt
LP . . . . Linear Programming
LMP . . . . . . Locational Marginal Price
LSE . . . . . . Load-Serving Entity
LOLE . . . . . Loss of Load Expectation
LOLE95 . . . . Loss of Load Expectation 95
LOLP . . . . . Loss of Load Probability
LOLH . . . . . Loss of Load Hours
MILP . . . . . Mixed Integer Linear Programme
MP . . . . Market Price Cap
MWh . . . . . MegaWatt Hour
MWh . . . . . MegaWatt-hour
MW . . . . . . MegaWatt
NEM . . . . . National Electricity Market
NNSW . . . . Northern New South Wales
OCGT . . . . . Open Cycle Gas Turbine
ORDC . . . . . Operating Reserve Demand Curve
PJM . . . . . . Pennyslyvania-New Jersey-Maryland
PRM . . . . . Physical Reserve Margin
RDER . . . . . Resilient Distributed Energy Resources
RRP . . . . . . Regional Reference Price

RN . . . . Risk-Neutral

RTM . . . . . . Real-Time Market

SA . . . . South Australia

SFPFC . . . . Standardized Fixed-Price Forward Contract

SOS . . . . . . Special-Ordered-Set

SoC . . . . . . State of Charge

SNSW . . . . . Southern New South Wales

SNW . . . . . Sydney, Newcastle and Wollongong region

SPP . . . . . . Southwest Power Pool

SQ . . . . Southern Queensland

SST . . . . . . Swiss Solvency Test

SRP . . . . . . Strategic Reserve Procurement

TAS . . . . . . Tasmania region

TSO . . . . . . Transmission System Operator

UC . . . . Unit Commitment

USE . . . . . . Unserved Energy

VaR . . . . . . Value-at-Risk

VIC . . . . . . Victoria region

VRE . . . . . . Variable Renewable Energy

VOLL . . . . . Value of Lost Load

WEM . . . . . Wholesale Electricity Market

WM . . . . . . Winter Energy Margin

Nomenclature

Sets and Indices

$c \in \mathcal{C}$ . . . . . . c denotes a contract and $\mathcal{C}$ represents the set of all contracts.

$d \in \mathcal{D}$ . . . . . . d denotes a consumer and $\mathcal{D}$ represents the set of all consumers.

$\mathcal{D}^M \subset \mathcal{D}$ . . . . The subset of all consumers participating in the wholesale market.

$\mathcal{D}_n \subset \mathcal{D}$ . . . . . The subset of all consumers located at node/region n.

$\mathcal{D}^R \subset \mathcal{D}$ . . . . The subset of all retail consumers participating in the insurance market.

$fr \in FR$ . . . . fr denotes an FCAS market and FR represents the set of FCAS markets.

$\mathcal{G} \subset \mathcal{R}$ . . . . . $\mathcal{G}$ is the subset of all generation resources.

$\mathcal{G}^{der} \subset \mathcal{R}^{der}$ . . The set of all resilient distributed energy generation resources available for investment by the insurer.

$\mathcal{G}^M, \mathcal{S}^M, \mathcal{H}^M \subset \mathcal{R}$ The subset of all resources, generation, and hydro participating in the wholesale market.

$\mathcal{G}_n, \mathcal{S}_n, \mathcal{H}_n \subset \mathcal{R}$ The subset of all generation, storage, and hydro located at node/region n.

$\mathcal{G}^N, \mathcal{S}^N, \mathcal{H}^N \subset \mathcal{R}$ The subset of all resources, generation, and hydro serving as strategic reserves.

$\mathcal{H} \subset \mathcal{R}$ . . . . . $\mathcal{H}$ is the subset of all hydro generation resources[1].

$i \in \mathcal{I}$ . . . . . . i denotes a segment used in the piecewise approximation of the operating reserve demand curve, and $\mathcal{I}$ is the set of segments.

$j \in \mathcal{J}$ . . . . . . j denotes a segment used in the piecewise approximation of the capacity mechanism demand curve, and $\mathcal{J}$ is the set of segments.

$l \in \mathcal{L}$ . . . . . . l denotes a transmission line and $\mathcal{L}$ is the subset of all transmission lines in the network.

[1]It is noted that the set $\mathcal{H}$ only includes hydro generation resources with reservoir storage; this is opposed to 'run-of-river hydro generation' which can be incorporated as a generation resource in $\mathcal{G}$.

$\mathcal{L}_{mn} \subset \mathcal{L}$ . . . . $\mathcal{L}_{mn}$ is the subset of all transmission lines originating from node or region m and terminating at node or region n in the transmission network.

$\mathcal{L}_n \subset \mathcal{L}$ . . . . . $\mathcal{L}_n$ is the subset of all transmission lines originating from node or region n in the transmission network.

$m, n \in \mathcal{N}$ . . . . n denotes a zone/node and $\mathcal{N}$ is the set of all zones/nodes in the network (m is an alternate index).

$\mathcal{R}^{der}$ . . . . . . The set of all resilient distributed energy resources available for investment by the insurer.

$r \in \mathcal{R}$ . . . . r denotes a resource and $\mathcal{R}$ is the set of all resources.

$\mathcal{S} \subset \mathcal{R}$ . . . . . $\mathcal{S}$ is the subset of all storage resources.

$\mathcal{S}^{der} \subset \mathcal{R}^{der}$ . . The set of all resilient distributed energy storage resources available for investment by the insurer.

$t \in \mathcal{T}$ . . . . . . t denotes a dispatch interval (a half-hour) and $\mathcal{T}$ represents the set of all dispatch intervals.

$\omega \in \Omega$ . . . . . . ω denotes a scenario and Ω represents the set of scenarios.

Parameters

A_r^{CM} . . . . . . The capacity de-rating of resource r for the capacity mechanism auction, based on the effective load carrying capacity (dimensionless).

$A_{rt\omega}^{G}$ . . . . The generation availability of resource r at time t in scenario ω (dimensionless).

$\boldsymbol{A}_{r\omega}^{G}$ . . . . The vectorised form of $A_{rt\omega}^{G}$ removing the t subscript (dimensionless).

$A_{nm,t,\omega}$ . . . . . Availability of the transmission line from node m to n at time t in scenario ω (dimensionless).

$\boldsymbol{A}_{nm,\omega}^{L}$ . . . . . . The vectorised form of $A_{nm,t,\omega}$ removing the t subscript (dimensionless).

$\overline{A}$ . . . . Average availability for availability contracts (dimensionless).

B_{nm} . . . . The admittance of the transmission line from node m to n (siemens).

c_r^f . . . . Annual fixed cost for resource r (\$/MW/year).

C_d^{comp} . . . . . . For demand d, the insurance compensation payout per MWh of lost-load (\$/MWh).

C_r^I . . . . The annualised investment cost of resource r (\$/MW/year).

$C_{rt\omega}^{R}$ . . . . The short-run variable cost of providing reserve from resource r at time t in scenario ω (\$/MWh).

$\boldsymbol{C}_{r\omega}^{R}$ . . . . The vectorised form of $C_{rt\omega}^{R}$ removing the t subscript (\$/MWh).

$C_{rt\omega}^{vc}$ . . . . The short-run variable cost of energy delivered from resource r at time t in scenario ω (\$/MWh).

$\boldsymbol{C}_{r\omega}^{vc}$ . . . . The vectorised form of $C_{rt\omega}^{vc}$ removing the t subscript (\$/MWh).

C_i^{rsh} . . . . . . The system penalty cost of unmet reserve for operating reserve demand curve segment i (\$/MWh).

C_d^{sh} . . . . The system value of lost-load for demand d (\$/MWh).

C_j^U . . . . The administrative penalty cost of unmet capacity reserve for capacity mechanism demand curve segment j (\$/MW).

C_d^{voll} . . . . . . For demand d, the value of lost-load specified in the reliability insurance contract (\$/MWh).

C_d^P . . . . Insurance premium levied upon consumer d (\$).

C_d^{voll} . . . . . . The consumer's value of reliability for load shedding for consumer d in \$ per MWh (\$/MWh).

C_d^{comp} . . . . . . The insurance compensation payout value for consumer d in \$ per MWh (\$/MWh).

CFE_{min} . . . . Minimum Cash Flow to Equity ratio for project financing (dimensionless).

CFE_{ave} . . . . Average Cash Flow to Equity ratio for project financing (dimensionless).

d_ω . . . . Depreciation for scenario ω (\$).

$DSCR_{min}$ . . . Minimum Debt Service Coverage Ratio for project financing (dimensionless).

$DSCR_{ave}$ . . . . Average Debt Service Coverage Ratio for project financing (dimensionless).

D_j^{th} . . . . The required capacity demand in MW for capacity mechanism demand curve segment j (MW).

e_r . . . . The maximum energy storage duration of resource r (MWh).

G . . . . Gearing ratio for project financing (dimensionless).

$i_{rt\omega}^{G+}$ . . . . Inflows to the hydrological storage reservoir for resource r at time t in scenario ω (MWh).

i_ω . . . . Interest payment for scenario ω (\$).

k^{fr} . . . . Parameter that reflects the additional utilisation of energy during the actuation of FCAS contingency and regulation reserves (dimensionless).

$p_{dt\omega}^{sh*}$ . . . . Unserved energy of consumer d at time t for scenario ω, as an output of the market equilibrium solution (MWh).

$\boldsymbol{p}_{d\omega}^{sh*}$ . . . . The vectorised form of $p_{dt\omega}^{sh*}$ (MWh).

$\overline{P}_{dt\omega}^{D}$ . . . . . . Consumer energy demand at time t in scenario ω (MW).

$\overline{\boldsymbol{P}}_{d\omega}^{D}$ . . . . The vectorised form of $\overline{P}_{dt\omega}^{D}$ removing the t subscript (MW).

q . . . . Cost of debt capital for project financing (dimensionless).

R_i^{req} . . . . The required reserve for operating reserve demand curve segment i (MW).

$\overline{R^{req}}$ . . . . The total required operating reserves (MW).

v . . . . Parameter that reflects the volumetric exposure, defined as the percentage of operations that the contract is exposed to (dimensionless).

α_d^c . . . . α-tail probability of the conditional-value-at-risk for consumer d (dimensionless).

β_d^c . . . . For a consumer d, the weighting parameter reflects the agent's preference between the expected surplus and the conditional value-at-risk (dimensionless).

α_r^G . . . . α-tail probability of the conditional value-at-risk for market resources (dimensionless).

α^i . . . . α-tail probability of the conditional-value-at-risk for the insurer (dimensionless).

β_r^G . . . . For a market resource r, this is the weighting parameter reflecting the agent's preference between the expected surplus and the conditional value-at-risk (dimensionless).

β^i . . . . For an insurer, the weighting parameter reflects the insurer's preference between the expected surplus and the conditional value-at-risk (dimensionless).

γ . . . . Annualised discount factor for capital investments (dimensionless).

Γ_ω . . . . Taxation liabilities for scenario ω (\$).

δ . . . . Parameter that penalises imbalance in the insurance contract volumes sold and purchased (dimensionless).

$\varepsilon_{t\omega}^E$ . . . . Random variable representing the price forecast error for the marginal price of energy at time t in scenario ω (\$/MWh).

$\varepsilon_{t\omega}^{fr}$ . . . . Random variable representing the price forecast error for the marginal price of FCAS market $fr \in FR$ at time t in scenario ω (\$/MWh).

ζ^{deg} . . . . Parameter that reflects the degradation limit for the BESS resource (MWh).

η_c . . . . Payment thresholds for cap and floor contracts (\$).

κ . . . . Capital investment cost subsidy offered to consumers by the insurer for RDER investments (dimensionless).

π_ω . . . . The probability of scenario ω (dimensionless).

ρ . . . . Annuity payment factor (dimensionless).

ς_r^+ . . . . The charging efficiency of storage resource r (dimensionless).

ς_r^+ . . . . The discharging efficiency of storage resource r (dimensionless).

Decision Problems

CM . . . . This problem represents the clearing of the capacity mechanism.

CON_d . . . . . The risk-averse utility maximisation problem for consumer d.

ED_ω . . . . . . The economic dispatch problem for each scenario ω.

ID_r . . . . The risk-averse utility maximisation problem for resource r.

INS . . . . . . The risk-averse utility maximisation problem for the insurer.

PF_r . . . . . . The storage project finance problem for storage resource r.

SUC_ω . . . . . The storage unit commitment problem for storage resource r.

Decision Variables

$\tilde{c}_r^G$ . . . . Conditional Value-at-Risk (CVaR) for resource r (\$).

$\tilde{c}^i$ . . . . Conditional Value-at-Risk (CVaR) for insurer (\$).

$\tilde{c}_d^c$ . . . . Conditional Value-at-Risk (CVaR) for consumer d (\$).

D . . . . Debt capital raised for project financing (\$).

E . . . . Equity capital raised for project financing (\$).

$p_{rt\omega}^{G+}$ . . . . The dispatch of energy charge of storage resource r at time t in scenario ω (MWh).

$\boldsymbol{p_{r\omega}^{G+}}$ . . . . . . The vectorised form of $p_{rt\omega}^{G+}$ removing the t subscript (MWh).

$p_{rt\omega}^{G-}$ . . . . The dispatch of energy discharge of storage or hydro resource r at time t in scenario ω (MWh).

$\boldsymbol{p_{r\omega}^{G-}}$ . . . . The vectorised form of $p_{rt\omega}^{G-}$ removing the t subscript (MWh).

$p_{dt\omega}^{sh}$ . . . . The unserved demand of consumer d at time t in scenario ω (MWh).

$\boldsymbol{p_{d\omega}^{sh}}$ . . . . The vectorised form of $p_{dt\omega}^{sh}$ removing the t subscript (MWh).

$\overline{P_r}$ . . . . The power capacity of resource r (MW).[2]

$\overline{P_* r'}$ . . . . The optimal power capacity of distributed resource r built by the consumer (MW).

$p_{rt\omega}^{R\uparrow}$ . . . . The dispatch of upward operating reserve of resource r at time t in scenario ω (MW).

$\boldsymbol{p_{r\omega}^{R\uparrow}}$ . . . . The vectorised form of $p_{rt\omega}^{R\uparrow}$ removing the t subscript (MW).

$p_{rt\omega}^{R\downarrow}$ . . . . The dispatch of downward operating reserve of resource r at time t in scenario ω (MW).

$\boldsymbol{p_{r\omega}^{R\downarrow}}$ . . . . The vectorised form of $p_{rt\omega}^{R\downarrow}$ removing the t subscript (MW).

$p_{rt\omega}^{fr}$ . . . . Dispatch of reserve in FCAS market fr for resource r at time t in scenario ω (MW).

$\boldsymbol{p_{r\omega}^{fr}}$ . . . . The vectorised form of $p_{rt\omega}^{fr}$ removing the t subscript (MW).

$p_{it\omega}^{rsh}$ . . . . The unmet reserve for operating reserve demand curve segment i at time t for scenario ω (MW).

$\boldsymbol{p_{i\omega}^{rsh}}$ . . . . The vectorised form of $p_{it\omega}^{rsh}$ (MW).

p_r^{CM} . . . . The cleared capacity of resource r for the capacity auction (MW).

[2] In Chapter 4 this variable is indicated as a parameter for the purposes of the heuristic algorithm for equilibria search.

p_j^U . . . . The unmet quantity of capacity demand for capacity mechanism demand curve segment j (MW).

$p^c d, t, \omega$ . . . . . Quantity of load shed for consumer d at time t for scenario ω (MWh).

$\boldsymbol{p}_{d\omega}^c$ . . . . The vectorised form of $p_{d,t,\omega}^c$ removing the t subscript (MWh).

$p_{rt\omega}^{*G+}$ . . . . . . Optimal dispatch of power charge of storage or hydro resource r at time t in scenario ω (MWh).

$p_{rt\omega}^{*G-}$ . . . . . . Optimal dispatch of power discharge of storage or hydro resource r at time t in scenario ω (MWh).

$p_{rt\omega}^{*fr}$ . . . . Optimal dispatch of reserve in FCAS market fr for resource r at time t in scenario ω (MW).

Q_d^i . . . . Decision variable that reflects the fractional quantity of reliability insurance sold by the insurer to consumer $d \in \mathcal{D}$ (dimensionless).[3]

Q_d^c . . . . Decision variable representing proportional quantity of insurance purchased by consumer d (dimensionless).[3]

$S_{rt\omega}$ . . . . The state of charge of storage or hydro resource r at time t in scenario ω (MWh).

$\boldsymbol{S_{r\omega}}$ . . . . The vectorised form of $S_{rt\omega}$ removing the t subscript (MWh).

$u_r \in \{0, 1\}$ . . . The binary build status of resource r, which takes a value of either zero or one in the decision problem (dimensionless).[2]

U_r^G . . . . Risk-averse utility for resource r (\$).

U^i . . . . Risk-averse utility for insurer (\$).

U_d^c . . . . Risk-averse utility for consumer d (\$).

V_G^r . . . . Auxiliary decision variable representing value-at-risk for resource r (dimensionless).

V^i . . . . Auxiliary decision variable representing value-at-risk for insurer i (dimensionless).

V_d^c . . . . Auxiliary decision variable representing value-at-risk for consumer d (dimensionless).

$\theta_{t\omega n}$ . . . . The phase angle of node n at time t for scenario ω (radians).

$\boldsymbol{\theta_{\omega n}}$ . . . . The vectorised form of $\theta_{t\omega n}$ removing the t subscript (radians).

$\lambda_{t\omega n}^E$ . . . . Locational marginal price for energy for node n at time t for scenario ω (\$/MWh).

[3]In Chapter 4, given the imposition of a mandatory scheme, this is set to 1.0

$\boldsymbol{\lambda^E_{\omega n}}$ . . . . The vectorised form of $\lambda^E_{t\omega n}$ removing the t subscript (\$/MWh).

$\lambda^R_{t\omega}$ . . . . The system marginal price for operating reserve at time t for scenario ω (\$/MWh).

$\boldsymbol{\lambda^R_{\omega}}$ . . . . The vectorized form of $\lambda^R_{t\omega}$ (\$/MWh).

$\lambda^{fr}_{t\omega}$ . . . . The system marginal price for frequency control ancillary services (FCAS) at time t for scenario ω, for all $fr \in FR$ (\$/MWh).

λ^{CM} . . . . . . The system marginal price for capacity based on the clearing of the capacity mechanism (\$/MW).

$\hat{\lambda}^E_{t\omega}$ . . . . Predicted marginal price for energy at time t for scenario ω (\$/MWh).

$\hat{\lambda}^{fr}_{t\omega}$ . . . . Predicted marginal price for FCAS market fr at time t for scenario ω (\$/MWh).

$\underline{\mu^G_{rt\omega}}$ . . . . Dual of the minimum generation capacity constraint for resource r at time t for scenario ω (\$/MWh).

$\overline{\mu^G_{rt\omega}}$ . . . . Dual of the maximum generation capacity constraint for resource r at time t for scenario ω (\$/MWh).

$\underline{\mu^{sh}_{dt\omega}}$ . . . . Dual of the minimum demand shortage constraint for consumer d at time t for scenario ω (\$/MWh).

$\overline{\mu^{sh}_{dt\omega}}$ . . . . Dual of the maximum demand shortage constraint for consumer d at time t for scenario ω (\$/MWh).

Π^{EBITDA}_{ω} . . . . Earnings before Interest, Taxation, Depreciation and Amortization for scenario ω (\$).

Π^{CFADS}_{ω} . . . . Cash Flow Available for Debt Service for scenario ω (\$).

Π^{CFE}_{ω} . . . . . . Cash Flow Available for Equity for scenario ω (\$).

$\varrho^G_{r\omega}$ . . . . CVAR auxiliary decision variable as the positive difference between z^G_r and scenario profits $\Psi^G_{r\omega}$ for resource r (\$).

ϱ^i_{ω} . . . . CVAR auxiliary decision variable as the positive difference between z^i and Ψ^i scenario profits for the insurer (\$).

$\varrho^c_{d\omega}$ . . . . CVAR auxiliary decision variable as the positive difference between z^c_d and Ψ^c_d scenario profits for consumer d (\$).

σ_{ω} . . . . Debt service for scenario ω (\$).

ϕ_c . . . . Fixed contract payment for contract c (\$).

ϕ^i . . . . Required capital reserves for insurer (\$).

$\Phi_{rt\omega}$ . . . . Spot market surplus (operating profit) perceived by the storage unit r for time t in scenario ω (\$).

$\Phi^{C}_{r\omega c}$ . . . . . . Contract difference payment for storage unit r in scenario ω for contract c (\$).

$\varphi_{r\omega}$ . . . . Contract basis for storage unit r in scenario ω (\$).

$\varphi^{*}_{r\omega}$ . . . . Optimal spot surplus over the scenario ω (\$).

$\boldsymbol{\Phi}^{S}_{r\omega}$ . . . . Total spot market surplus (operating profit) perceived by the storage unit r over scenario ω (\$).

$\Psi^{G}_{r\omega}$ . . . . Scenario profits for resource r (\$).

Ψ^{i}_{ω} . . . . Scenario profits for the insurer (\$).

$\Psi^{c}_{d\omega}$ . . . . Scenario profits for consumer d (\$).

Ψ^{S}_{ω} . . . . Scenario surplus for the system (\$).

1 Introduction

Contents

This dissertation addresses the research question:

Can the delivery of electricity service to consumers be made more reliable through the application of insurance mechanisms?

Given the material adverse impacts of extreme events on electricity systems, this thesis investigates the application of insurance risk management to the problem of ensuring reliability of supply. The research coverage comprises applications to market design, contractual frameworks, and system resiliency at the wholesale and consumer level. The purpose of the thesis is to contribute to knowledge by investigating the application of insurance mechanisms that can improve the reliability of electricity systems and support long-term investment.

This chapter commences with a discussion of the motivation for and context of the research in Section 1.1. Section 1.2 sets out the central research question and sub-questions, and specifies the scope of the thesis. The structure of the thesis is described in Section 1.3, followed by a listing of the publications that directly contributed to this thesis in Section 1.4.

1.1 Context and Motivation

The power system is facing many new risks and challenges over the coming decades. To mitigate the harmful effects of anthropogenic climate change, the electricity supply mix needs to rapidly shift from legacy carbon-emitting generation to low carbon forms of generation such as wind and solar [1]. These resources introduce new forms of stochasticity into the system. Weather and climatic conditions now affect not only the performance capability and de-rating of the generation fleet, but the temporal availability of resource base [2]. When combined with the inherent transition risk of managing the roll-off of an ageing legacy fleet, maintaining the reliability of the system is likely to become increasingly complex.

Perhaps more fundamentally, the nature of climate risk at the extremes is changing. The Sixth Assessment Report of the Intergovernmental Panel on Climate Change [3] states, with *high confidence* (except where otherwise indicated) , that:

> The probability of low-likelihood outcomes associated with potentially very large impacts increases with higher global warming levels.
>
> If global warming increases, some compound extreme events will become more frequent, with higher likelihood of unprecedented intensities, durations or spatial extent.
>
> Compound extreme events include increases in the frequency of concurrent heatwaves and droughts; fire weather in some regions (medium confidence); and compound flooding in some locations (medium confidence). Multiple risks interact, generating new sources of vulnerability to climate hazards, and compounding overall risk. Compound climate hazards can overwhelm adaptive capacity and substantially increase damage.

The effects of climate change are expected to have direct impacts on the functioning of the energy system. The findings of [3] suggest climate change will most likely accelerate in the near term, causing increasingly frequent and intense extreme weather events. These so-called High-Impact Low-Probability (HILP) events damage the built environment and impair the serviceability of infrastructure [4]. Global economic losses from extreme natural catastrophes exceeded US$270 billion in 2021 [5]; where such losses are multiples of the levels recorded only a decade earlier (in inflation-adjusted terms). Electricity systems are vulnerable, given existing centralised grid architectures and integrated physical supply and fuel infrastructure [6].

The following three examples demonstrate the impact of extreme or tail events in the power grid and the challenges of managing physical systems and markets under uncertainty. Winter Storm Uri, during late February 2021, caused the outage of over 35 GigaWatts (GW) of electricity generation capacity, leading to emergency load shedding and blackouts across Texas [7]. At the peak, over 5 million residents were left without power with some for more than 3 days, with 200 deaths directly attributed to this event [8]. In Japan, tropical cyclones and earthquakes have repeatedly caused blackouts [9]. Typhoon Faxai damaged the electricity grid in the Tokyo area in September 2019, leaving 900,000 households without power. Typhoon Hagibis, struck the same region one month later, causing further outages. More recently, Winter Storm Elliot in December 2022 brought severe weather conditions and disrupted power supply for millions of electricity consumers across the US [10]. In this case, the storm impacted not only generation and transmission infrastructure in the bulk power system but also caused outages at more localised distribution network levels. While the impacts on distribution infrastructure are an important contributor to supply outages, this issue will not be directly considered in this thesis. Notwithstanding the impacts of extreme events, electric system reliability has been fairly stable in developed markets. For example, total annual power interruptions in the US (excluding major events) have been at a consistent level of around 2 hours per customer between 2013-2022 [11].

Such physical system vulnerability is of growing economic significance, because the optimal decarbonisation pathway calls for the rapid and large-scale electrification of energy use [1]. As a consequence, total global electricity demand is expected to at least double between 2021 and 2050 [12]. Under such a scenario, electricity becomes the largest energy vector and ever more critical to the functioning of society and industry. System vulnerability and service interruption will thus have more widespread adverse effects on the energy consumer base and the economy.

Yet it is not only the scale of impact but the equity of impact that is relevant. Electricity system outages in the context of catastrophic events can result in economic and social upheaval. Remote communities bear a disproportionately higher occurrence [13–15] and impact [16] of electricity service outage. Rates of power restoration following an outage are also consistently slower in such communities [17]. It is important to distinguish between outages caused by the lack of adequate generation capacity (termed adequacy), and outages caused by single points of failure, especially as it relates to electricity networks in rural areas. As a case in point of the latter, a recent study of electricity service in rural indigenous communities of Australia revealed that, of the 3,300 households sampled in the 2018-19 financial year, nearly all (91%) were disconnected at least once, almost three quarters were disconnected more than ten times, and approximately one-in-three disconnections occurred on days with extreme weather [18]. In these cases, restoration is affected not only by the impacts on grid infrastructure, but also by the damage to roads and transport infrastructure that enable local access. While this is an important issue, this thesis focuses only upon the issue of adequacy.

Given the scale, likelihood and inequity of the impacts of emergent risks it becomes imperative to understand the factors that constrain reliability for low-carbon grids. From an engineering perspective, power system decarbonisation requires a rapid shift to technologies that have a fundamentally different technical and uncertainty characterisation relative to legacy fossil-fuel generation. The introduction of variable supply (i.e. wind and solar) and energy-limited resources complicate the challenge of balancing load [19]. Technology advancement has also enabled a fundamental change in the architecture of the physical resources, increasingly trending towards a decentralised paradigm. Distributed energy resources (DER) now enable consumers to self-procure a portion of their energy needs, yet the contribution of such resources to deliver during the extremes requires careful assessment [6].

Economically too, the characteristics of new supply resources are different. The short-run marginal cost of procuring wind and solar resources is effectively zero, but availability is constrained [20]. Cost-effective storage is emerging but its participation in energy markets reflects temporal opportunity costs [21]. Furthermore, managing the roll-off of the fossil-fuelled generation fleet is non-trivial [22]. The replacement of lumpy generation units cannot come from VRE alone, and must be complemented by flexible and firm low-carbon resources [2]

Reflecting the integrated nature of engineering and economic considerations, there is a more fundamental question of incentives. Does the market design create the signals for the right type of investment, at the right time, and location in the grid? The foundations of modern electricity market design are built on an elegant reconciliation between the physics, engineering, and economics of electricity through the concept of spot pricing of electricity [23]. Yet these ideas came about at a time when the technical and economic features of generation and load were intrinsically different from what will likely make up a zero-carbon energy system. Does that invalidate the entire design, or does it involve a more nuanced replacement of specific building blocks? The consideration of which market foundations to reinforce must be carefully considered from an engineering, economic, and social perspective. Lest, removing the wrong block may affect the structural integrity of the entire design edifice, potentially endangering the decarbonisation agenda, consumer costs and system reliability.

This thesis therefore explores alternative reliability mechanism designs that address existing gaps relating to the management of tail risks. In particular, adopting an inter-domain perspective, it draws upon the rich literature in insurance theory and applies it to the management of deep uncertainty in electricity systems.

1.1.1 Definitions of Reliability and Functional Aspects

Before progressing further it is important to define the concept of reliability as used in this thesis, as well as three functional components of reliability - adequacy, system security, and resiliency. While reliability evaluation has a wide scope across many disciplines, its definition in an engineering context tends to coalesce around the capability of a system to perform its required functions [24, 25]. A widely-cited definition in the context of electricity is “the degree to which a system enables the delivery of power to consumers within accepted standards and in the amount desired” [26]. More colloquially the term is often associated with the phrase “keeping the lights on”. This is the context in which the term is used in this thesis, notwithstanding that individual jurisdictions may attach the term to slightly different and distinct applications in power systems [1]. The degree of reliability is measured by the frequency, duration, magnitude, and risk of interruptions to consumer electricity supply [26].

The basic functional aspects of reliability of supply can be further broken down into the concepts of adequacy and security, as shown in Figure 1.1. [26, 29]. Adequacy considers the capacity and capability of power system resources (resource adequacy) and network infrastructure (network adequacy) to supply the aggregate electric energy needs of customers at all times [26]. In economic terms, adequacy refers to achieving an efficient level of involuntary load-shedding in the wholesale market [30]. Power system security is the ability of the power system to withstand and respond to disturbances arising within that system [26]. Security relates to ensuring the stability of key electric system parameters including system

[1]In the National Electricity Market of Australia the term reliability relates to having adequate supply of generation and transmission capacity to meet consumer demand [27]. This is narrower than the definition of reliability adopted in this thesis, and more closely aligns with the concept of adequacy that is used in the thesis. In the US, the North American Reliability Corporation defines operational reliability as the ability of the bulk-power system to withstand sudden disturbances, such as electric short circuits or the unanticipated loss of system elements from credible contingencies, while avoiding uncontrolled cascading blackouts or damage to equipment [28]. This too is narrower that the thesis adopted definition of reliability, and more closely relates to the functional aspect of system security.

frequency, bus voltages, and phase angles (termed frequency security, voltage security, and angular security) [26].

Under a paradigm where consumers have both the ability and willingness to reveal demand preferences for electricity via either direct market participation or priority service, the notion of reliability would tend to focus upon the economic concept of an efficient clearing of the market [31]. That is, with consumers able to indicate preferences for electricity demand, service would be efficiently prioritised via the market mechanism to those consumers that value the service the most. While this tends to relate mostly to system adequacy, it can also extend to the concept of system security – where for example consumers may deliver ancillary services such as frequency response by allowing temporary interruption to supply.

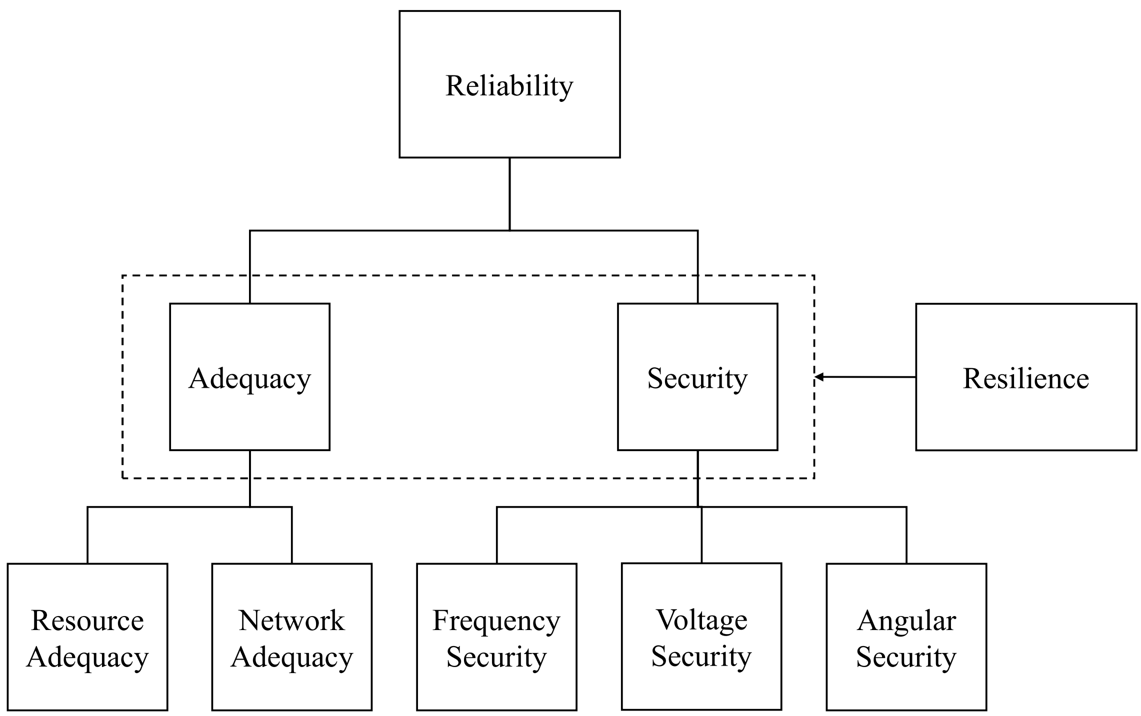

Figure 1.1: Characterisation of the functional aspects of reliability into Adequacy and Security. Resilience, as a concept, adds a new dimension to both Adequacy and Security.

It is important to note that unserved demand in the electricity system can have a range of different causes. The typical categorisations comprise: (i) distribution network causes; (ii) transmission network causes; (iii) insufficient or inadequate supply; and (iv) power system security events. While the scope of this thesis is primarily upon inadequate supply, it is important to note that distribution network causes make up the majority of outages in many major markets (for example, over 94% in the US and 95% in Australia) [32, 33].

Traditional reliability management approaches have tended to focus on having sufficient resources to limit unserved energy on average over a particular time span [24, 30]. This is projected in commonly adopted measures for reliability such as average unserved energy or expected loss of load [34]. More recently and especially in the context of climate change, there has been a recognition of the special relevance of risks relating to adverse extreme outcomes. These outcomes are of low probability but have high impacts on a power system when they do occur [35]. These high-impact low probability (HILP) events require strategies beyond traditional reliability study and towards a focus on ensuring a "resilient" power system[36]. Resilience, as a concept, adds a new dimension to both adequacy and security [37]. An elegant exposition in [38] defines "resiliency" as the ability of a system to anticipate, mitigate, recover from, and adapt to HILP events. HILP risks can arise from both natural and human-induced events (and a combination thereof) [36]. Studies on resilience recognise that it is not possible to avoid adverse outcomes at all times, and propose a more holistic solution beyond system augmentation and expansion, extending to system hardening and smartening [39]. Resilience considers not only the interactions within power systems, but also the broader extent to which the power system is integrated with other systems.

With an increasing awareness of such threats, the resilience of power systems has become a top priority for many countries. The implementation however is fraught with challenges. Addressing the problem requires not only an understanding of technical solutions but also the incorporation of resilience incentives within the market design itself. To this end integrating disciplines that have a specific focus on tail risk management can provide a pathway, given the range of extreme scenarios that need to be considered.

1.1.2 Electricity Market Design and Tail Risks

Historically, electricity service was provided by vertically integrated monopolies that were responsible for the generation, transmission, and distribution of electricity to consumers. In the late 1980s, a program of industry restructuring was initiated [40, 41]. The central precept involved (i) the segregation (commonly accompanied by privatisation) of the electricity value chain into the generation, transmission and distribution, and retailing of electricity; (ii) the creation of licensed monopolies for transmission and distribution network services; and, (iii) the introduction of competition to electricity generation and retail. On the third point, while many regions successfully deregulated electricity generation, the restructuring of retail operations has proven more problematic [42]. Deregulation efforts in many US states were stalled as a consequence of the Californian electricity crisis of 2000-02. While initially implemented in markets such as Australia, New Zealand, and the UK, economic regulation of retail rates has been reimposed in certain jurisdictions and to different degrees [43]. As a consequence, the industrial organization of electricity retailing around the world remains an assortment of different contestable, regulated, and quasi-regulated regimes. This has important implications for retail hedging incentives and in turn, generator investment incentives [44].

Underpinning the evolved industrial organisation of the sector was the concept of a spot market for electricity, the theoretical underpinnings of which can be traced back to the seminal work of Schweppe et al. [23]. The canonical ‘energy only’ market design envisioned by [23] involved the central economic dispatch of generation and load in real time[2]; subject to network and security constraints; with participants settled on the basis of Locational Marginal Prices (LMP) for electricity

[2]Many regions, particularly in the US and Europe, augment the real-time market with a central short-term forward market, typically cleared day-ahead or intra-day. In the US, a security-constrained unit commitment process will accompany a day-ahead security-constrained economic dispatch (SCED) to manage the non-convexities associated with certain plant (minimum generation levels, minimum and maximum run times, startup costs etc). Hogan [45] argues that such multi-settlement markets are an integral part of the market design, while regions such as Australia and New Zealand have operated real-time only markets (with decentralised participant self-commitment). In the latter case, all short-term forward markets are left to the organization of participants and kept out of the centrally dispatched pool.

and ancillary services. The economic price of electricity is sought to reflect, to the greatest extent possible, the physical scarcity of electricity at each time and location in the network. In recent times, design initiatives have been focused on making price increasingly dynamic and responsive to system and network conditions [46]. This is intended to create the right short-term signals for generation and demand, as well as supporting efficient long-term investment.

While full-strength price formation creates strong short-term incentives for efficient dispatch, it can result in volatile electricity prices across time and space. To manage the risks associated with spot prices, participants can hedge or trade risk based on their individual preferences [47]. For example, through forward or option contracts, generators and retailers can exchange volatile spot exposures, for more stable cashflows. Thereby, the execution of longer-term hedge contracts can support the build of new plant, encouraging an efficient level of investment in generation capacity. In the late 1990s, derivative markets for wholesale electricity were introduced in commodity exchanges and over-the-counter markets to enable risk management for buyer and sellers of power[3]. Today a multitude of derivative products exist to trade different forms of risk in the sector (examples of which are provided in Table 1.1), including a suite of contracts that are catered towards hedging risks associated with variable generation [49]. The length of contracts can vary significantly. Bilateral contracts, such as power purchase or tolling agreements, can have terms of 10-20 years. Derivatives traded on multilateral exchanges or over-the-counter (OTC), tend to have shorter terms ranging from months to up to 3-4 years ahead, though liquidity at the long end tends to be limited [48].

Central Risk-Hedging Mechanisms for Low-Carbon Portfolios

While in theory, the energy-only model can deliver efficient levels of investment, in practice it has been critiqued over whether it can guarantee resource adequacy, especially in a transitioning environment. The concerns include (i) the 'missing money' problem - where administrative regulations (such as price caps) prevent prices

[3]The New York Mercantile Exchange issued the first electricity futures contracts in March 1996, the California–Oregon Border and Palo Verde electricity future [48].

Table 1.1: Examples of hedge products in electricity markets.

Contract	Resource Suitability	Trade	Example Trading Hubs / Entities
Forwards	Baseload thermal	Exchange	ASX,EEX
Peak forwards	Intermediate thermal	Exchange	ASX, EEX
Call options	Peaking thermal	Exchange	ASX
Average-rate option	Flexible load	Exchange	ASX
Spark-spread contract	Flexible gas	Exchange/OTC	ICE
Wind power futures	Wind	Exchange/OTC	Nasdaq
Callable forwards	Flexible load	Exchange/OTC	ASX,ICE
Putable forwards	Flexible load	Exchange/OTC	ASX,ICE
Swing options	Portfolio	OTC	
Solar firming product	Solar	OTC	REHM
Floor contract	Renewables	OTC	ASX
Power purchase agreement	Thermal/renewable	Bilateral	
Contract-for-difference	Renewable	Bilateral	
Tolling agreement	Multiple	Bilateral	
Full requirements contract	Portfolio	Bilateral	NJ-BGS
Storage toll	Storage	Bilateral	
Spread contract	Storage	Exchange/OTC	REHM

ASX = Australian Stock Exchange, EEX = European Energy Exchange
ICE = Inter-Continental Exchange, NJ-BGS = New Jersey Basic Generation Service
OTC = Over-the-counter, REHM = Renewable Energy Hub Marketplace
Sources: [48, 50–55]

from reaching their full scarcity value [56], (ii) 'missing markets' - where markets for long-term contracts to support capital intensive investment are largely absent or illiquid [57, 58] and (iii) the lack of appropriate risk-incentives for reliability [57]. Many of these specific issues can be brought under the more generalised concern that markets are in practice "incomplete", leading to muted incentives for risk hedging, investment, and system resilience [8, 59]. Some markets have adopted administrative overlay mechanisms, such as the 'operating reserve demand curve' - which moves from a fixed requirement to a sloping demand curve for operating reserves [56]. This has the practical effect of causing prices for energy and reserves to escalate during periods of scarcity in advance of actual demand curtailment. Other regimes allow the exercise of market power, subject to good faith bidding. Good faith bidding regulatory frameworks, most notably implemented in the NEM, allow generators relative freedom to bid above or below marginal costs and to exercise (but not misuse) market power. This is subject to 'good faith' requirements, which compel generators to bid based on genuine intentions, and to not mislead the market [60]. In other regions, political considerations have constrained the ability to create full-strength spot price signals [61]. In view of concerns with resource adequacy in an energy-only market, regulators have sought to overlay a range of mandatory reliability frameworks. Centralised auctions for generation capacity (also called capacity markets, or capacity mechanisms) were adopted in the US in the late 1990s as a means of ensuring resource adequacy [62, 63]. Strategic reserves have been adopted in markets such as Germany, Sweden, Finland, and Belgium to manage reliability given a trajectory of lumpy fossil generation retirement [64]. A strategic reserve is a reliability mechanism in electricity markets that seeks to contract generation capacity incremental to that incentivised by short-term spot markets, for use in times of critical supply shortage. Decentralised reliability obligations emerged in other regions, such as France, where a central agency sets capacity or reserve targets, thereby obligating electricity suppliers to contract to those targets [65]. The National Electricity Market (NEM) of Australia complements forward contracting obligations on retailers with a reserve trader functionality. This enables the market operator to procure reliability and emergency reserves to meet the reliability standard [66].

The concept of a central framework for resource adequacy has intuitive appeal as a means of completing the market but the design of such mechanisms is fraught with complexity. While a spectrum of structural alternatives is present, they share common challenges.

The issue of quantifying preferences for reliability under a centrally determined framework is non-trivial. In practice, many grids continue to resort to metrics such as the Loss of Load Expectation (LOLE) or Loss of Load Probability (LOLP), as illustrated in Table 1.2. Quantities are also determined in a relatively arbitrary manner - such as the '1 day in ten year' standard that underpins the quantification of peak demand in US capacity auctions [67, 68]. Such standards do not adequately address more complex resiliency challenges like HILP events where both the likelihood and the impact of extreme events are relevant [69]. There can also

Table 1.2: Electricity Reliability Standards Around the World [70]

Jurisdictions (Region)	Metric	Criteria
USA - multiple regions*	LOLE	≤ 0.1 days per year
USA - WECC	LOLP	$\leq 0.02\%$
USA - Hawaii	ERM	$\geq 30\%$
Australia - NEM and WEM	EUSE	$\leq 0.002\%$
Great Britain	LOLH	≤ 3 hours per year
France	LOLH	≤ 3 hours per year
Ireland	LOLH	≤ 8 hours per year (Ireland)
	LOLH	≤ 4.9 hours per year (Nthn Ireland)
Netherlands	LOLH	≤ 4 hours per year
Spain	PRM	$\geq 10\%$
Singapore	LOLH	≤ 3 hours per year
Portugal	LOLH	≤ 5 hours per year
Belgium	LOLH	≤ 3 hours per year
	LOLE95	≤ 20 hours per year
New Zealand	WM	$\geq 14 - 16\%$
Japan	PRM	$\geq 8\%$

ERM = Energy Reserve Margin, EUSE - Expected Unserved Energy
LOLE = Loss of Load Expectation, LOLH = Loss of Load Hours
LOLP = Loss of Load Probability, LOLE95 refers to LOLE 95% probability
PRM = Physical Reserve Margin, WM = Winter Energy Margin
* Includes Midcontinent Independent System Operator (MISO)
Pennsylvania-New Jersey-Maryland (PJM), Southwest Power Pool (SPP)
Electric Reliability Council of Texas (ERCOT)

be a disconnect between the capacity quantity procured under such mechanisms and the actual needs of energy consumers. Key parameters, such as the value of lost load (VOLL), are estimated or surveyed [71]. While certain jurisdictions have adopted granular estimates of VOLL across consumer sub-sectors and types, these are still aggregated or averaged into a central VOLL metric [71]. With technology enabling greater load flexibility and heterogeneity the potential disparity between this aggregated assumption and the actual preferences of individual consumers is a gap that needs to be addressed.

Furthermore, the contractual form of the risk hedge has been called into question given the proliferation of resources with different cost structures (e.g. low or zero marginal costs and high capital costs) and technical characteristics (weather-driven availability for renewables, storage duration limits, etc.) [72, 73].

Payments under traditional capacity auctions can be thought of as a call option with a strike price equal to the price cap for the market. Consumers pay an upfront premium to generators, in exchange for ensuring that the highest price they are exposed to is the price cap. This represents an idealised case where performance incentives on the margin are preserved, noting that this analogy is not exact in practice. The option form has an asymmetric effect on generation risk profiles, tilting the resource mix towards those technologies with lower fixed costs and higher operating costs. In a practical sense this may bias the mechanism against low-carbon forms of generation (such as renewables and storage) which have zero short-run costs, but relatively high capital costs [72].

The question also arises as to whether reliability mechanisms should be designed with a single contract form, or to allow multiple contract structures that can be specifically tailored to the resource being procured [74]. In this context, how such contracts should be adapted to resources such as renewables, demand response, and storage is a significant research question.

Underlying all of these specific design issues is a more general challenge of incentive alignment in administrative reliability mechanisms. Important decisions as to the quantity and type of resource procured are delegated to a central agency, which is typically a non-commercial entity without direct economic incentives. The absence of an economic performance mechanism means that there are no direct rewards or penalties associated with decision-making. In the absence of direct pecuniary incentives, political or other indirect incentives may persist leading to sub-optimal decision-making [57, 75]. An example of potential political influences on resource investment is the decision of the Australian federal government in 2017 to finance a 2.0GW expansion of the Snowy Hydro generation scheme in response to perceived reliability concerns in the Australian market. The project is currently costed at $12 billion and is scheduled for completion by 2029 (compared to $2 billion and 2025 at inception) [76] Hence there is the potential for misalignment between the direct losses borne by consumers and the indirect non-pecuniary incentives of a central agency [77, 78]. There is thus a dilemma between the need to complete the market and the challenge of ensuring contract performance, given imperfect knowledge and deep uncertainty.

To contextualise the impact on market and regulatory design, consider the emergency frameworks in the NEM of Australia. The independent system operator, the Australian Energy Market Operator (AEMO), has a last-resort role as a reliability and emergency reserve trader (RERT), allowing it to enter into reserve contracts with generation and demand-response for up to 12 months to meet a uniform reliability standard [79]. In the past, this mechanism has only been rarely used, with RERT only triggered twice in the 15 years to 2017. Indeed it was proposed to be eliminated given its lack of utility in the market [80, 81]. Since 2017, with ongoing retirements of legacy thermal units and a rapidly shifting supply mix in the NEM, RERT has been exercised in all consecutive years, and often on multiple occasions [82]. Such last-resort measures become increasingly relevant in a world with a rapidly changing climate and a higher likelihood of compound extreme events.

Cross-disciplinary risk frameworks targeting extreme downside losses offer new perspectives on risk characterization and incentive alignment. Specifically, frameworks relating to financial reserving can provide insight how high impact low probability events can be quantified; premium and rate setting in finance and insurance markets provide means of pricing such risks; and reinsurance mechanisms can provide insight into how risk can be contracted and transferred. These concepts link with the insight that reliability mechanisms in electricity markets are in effect financial contracts [45]. Parallels with insurance markets, detailed in Section 1.1.3, indicate the potential for knowledge transfer and enhanced comprehension of the reliability problem in electricity markets.

1.1.3 Alignments between Insurance and Electricity Reliability

Insurance, as a financial tool, manages downside risks for individuals and organizations within the economic system. A risk, as defined by the insurance industry, consists of three components — namely hazard, vulnerability, and exposure [83]. Hazard refers to the potential occurrence of events that may cause damage and loss; exposure indicates the presence of assets, services, resources, and infrastructure that could be affected; and vulnerability is the propensity or predisposition to suffer adverse impacts.

While it does not seek to eliminate risk, insurance provides a contractual mechanism for the trading and allocation of risk. Leveraging extensive historical data on natural disasters, the industry possesses expertise in risk assessment and allocation [83]. Actuarial techniques quantify adverse outcomes, while premium-setting reflects the *price of risk*, and capital reserves align covered risks with institutional financial structures [84]. The field's focus on severe risks has fostered extensive literature on modeling, quantifying, and decision-making for extreme events.

Climate change poses a significant challenge to the insurance sector due to escalating extreme weather impacts [85]. Globally, insurers generate \$1.6 trillion in premiums from property and casualty insurance, the segment most impacted by weather [86]. By 2040, the global property risk pool is projected to increase by 33-41% [87, 88]. It ranks among the paramount risks for insurers and reinsurers [89].

Some hazards might soon become *uninsurable*, necessitating modifications to the conventional insurance model [90]. Kousky and Cooke [84] posit that are three risk factors: fat tails, tail dependence and micro-correlations which are exacerbated in an era of climate change. When insuring risks characterised by these factors the cost of providing insurance rises to levels beyond which budget-constrained households are able to pay, leading to under-insurance. New models of insurance, involving greater localisation and public-private partnerships, are necessary for the development of affordable insurance products under climate change [90].

Insurers could potentially address risks throughout the energy value chain, covering consumers, businesses, and infrastructure related to electric and gas supply [91]. Insurance has spurred innovations, especially in energy efficiency [91]. For example, insurers have provided premium discounts for high-efficiency food and pharmaceutical storage systems, which will maintain critical temperatures longer in the absence of power and thereby limit claim losses. There is also an indirect recognition that electric system unreliability can magnify insurance liabilities, given extended property damage and civil unrest [92].

The earliest reference to insurance in the context of electricity system reliability can be traced back as far as 1941-42 to a scheme for optional load control of domestic electricity by Schiller [93]. Figure 1.2 sets out the operational schematic of the optional load control mechanism in [93]. This scheme maintained a singular supply source but introduced differential charging based on load control execution. Within the scheme's discourse, insurance was suggested as a financial safeguard against extreme events. The paper references the potential for "cold snap[s] which may occur only once in a few years" but which "may revolutionize the load curve and dislocate the finances of the undertaking". This seems to implicitly recognise vulnerability to HILP-style events and the value of an insurance-style product in such a context.

Following on from this early reference, in the late 1980s early work in electricity market design considered the application of insurance in priority service for electricity [94–96]. A compensatory insurance scheme is proposed in [94] as an extension to the basic model of priority service, to the extent that consumers are averse to the risk of service curtailment. An insurance premium, comprising the sum of the actuarial risk and the priority service charge, together with a service priority is proven to yield efficient risk sharing and rationing. The works [95, 96] extend the insurance scheme to include generation and distribution failure under a model of priority service between the utility and consumers. However, since then the development in the field has been slow and sporadic, in part due to the lack of technological support

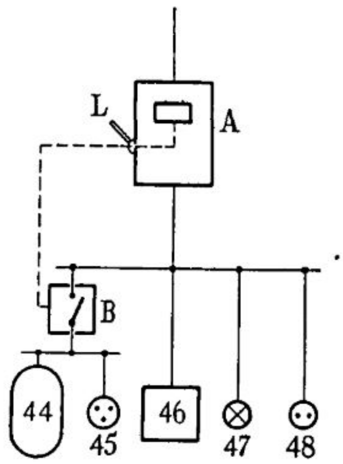

Fig. 2.—Single supply with optional-control feature.

Figure 1.2: Operational schematic of the optional load control mechanism under a single connection, with an insurance scheme to manage outages from extreme weather. Reproduced from [93]

(through load control, communications, metering, etc.) for priority service. Instead, electricity deregulation was predominantly implemented via designs that focused upon centralised spot markets, combined in certain regions with capacity markets.

Three emerging trends underscore the relevance of applying insurance risk management to electricity reliability. Firstly, climate change amplifies the risk of extreme tail events in the system. Secondly, events like Winter Storm Uri in ERCOT exemplify the vulnerabilities of market structures reliant solely on spot markets and scarcity pricing [8]. Lastly, the progression of distributed resources and load technologies presents novel solutions for system reliability and resilience, warranting acknowledgment in market designs. For insurers, DER provides an additional tool to manage risk and limit loss at the consumer site in the event of interruptions to electric service.

However, connecting the two sector is not so straightforward. In 2013, the US Department of Energy undertook a major study on *Insurance as a Risk Management Instrument for Energy Infrastructure Security and Resilience* [83] concluding:

> While insurance instruments can be a useful financial risk mitigation tool for critical infrastructure, they also face a variety of complex challenges. The public sector's engagement may be necessary to develop

> and maintain certain insurance programs; however, the respective roles and responsibilities of public and private partners in providing adequate protection for critical infrastructure against emerging risks through insurance remain unclear.

This dissertation seeks to tackle these challenges through a nuanced application of insurance risk management techniques to managing the financial consequences of extreme physical risks in the electricity system. Special attention is given to the market architecture, as between public and private responsibility. It also explores the impact on incentives and contract designs for emerging firming resources, such as storage and demand-side management.

1.2 Research Question and Scope

Based on this motivation, the central research question of this thesis may be stated as:

Can the delivery of electricity service to consumers be made more reliable through the application of insurance mechanisms?

Given the expansive potential domain, it is essential to delineate the research inquiry's boundaries. As articulated in the research question, this study emphasizes the incorporation and alignment of insurance contracts and risk frameworks into electricity market design, specifically aiming for system reliability. Delving deeper, this thesis primarily addresses reliability facets such as adequacy and resilience, particularly focusing on energy and reserve supply to satisfy demand across varied system states. Although system security, especially dynamic stability and resource control, is crucial for low-carbon power systems, it falls outside the purview of this thesis. An exception is the inclusion of operating and frequency control reserves in the dispatch models presented in Chapters 4 and 5.

This thesis examines contributions to reliability from diverse sources, encompassing generation, storage, and demand-side resources. Consequently, its concepts are exclusively tailored to electricity systems and networks. While analogous ideas might be applicable to natural gas, hydrogen, and integrated energy markets, these are outside this work's ambit. Additionally, from an industrial organization standpoint, the study centers on restructured and competitive electricity markets for generation and supply, rather than on vertically integrated monopolistic frameworks. It is noted that in some cases, transmission augmentation can also be considered a substitute for generation and demand response with respect to system adequacy. As such, an insurance framework can also be applied to transmission and distribution networks (see [97, 98]). Another important area relates to upstream fuel supply risks, such as that relating to coal, natural gas, and in the future hydrogen supply chains. For example, the vulnerability of natural gas supply was a key factor in the reliability of the ERCOT system during Winter Storm Uri [8]. Thus extending the breadth of insurance coverage to the risk of upstream supply interruptions is relevant when considering the reliability of the power system. Finally, the co-optimisation of generation, transmission and supply infrastructure is another potential application of insurance, which has not been explored in the literature to date. However, while these are all important topics, the focus of this thesis is restricted to sources of supply and demand response in the interests of keeping the scope manageable and tractable. Nonetheless each may be considered worthy extensions in their own right (see further in Chapter 6.3).

The review of literature in Chapter 2 identifies three gaps with respect to current work on reliability mechanisms. They are specifically: (1) the potential divergence between revealed consumer preferences for electricity reliability and its aggregated treatment in capacity and reserve market mechanisms; (2) the muted incentives for resilience in an electricity system, and the failure to fully incorporate the contributions of distributed energy resources to local resilience; and (3) the need to develop cohesive principles for the design of contracts between reliability agencies and energy storage projects. Correspondingly, the central research question is deconstructed into three interrelated sub-questions:

1. *How should the decision-making and risk architecture of an energy plus insurance market design be formulated to achieve generation adequacy given the heterogeneous preferences of consumers?* This first question addresses the issue of decision-making frameworks for reliability in an era of flexible load

and heterogeneous consumer preferences. Specifically, it is concerned with the application of an insurance mechanism, one that links physical interruptions to electric service to economic losses of an insurer. Innovative insurance capital reserving techniques are developed with respect to electricity reliability management. In this sub-question the scope is restricted to resource adequacy, focusing primarily on consumer reliability differentiation, and system-firming requirements for peak net load.

2. *Can insurance mechanisms enhance local resilience to extreme events by incentivising efficient investment in distributed energy resources?* System reliability in large-scale electricity systems are affected by a confluence of factors including resource availability, network contingencies and generator outages. This question considers the locational impacts of insurance on the robustness of a large-scale multi-state electricity system. Emphasis is laid upon the role and contribution of distributed energy resources to system resiliency, particularly within remote and non-urban settings and when faced with complex common-mode events.

3. *What are key agency principles that should be addressed in contracts between the storage resource providers and central reliability insurance or procurement agencies?* Given an overarching insurance or reliability framework that aligns agency incentives with consumer reliability preferences, this question contemplates the issue of contract design in low-carbon power grids. The scope is narrowly focused on contracts with energy storage resources given their operational complexity and pivotal role in decarbonised electricity systems. Nevertheless, the principles developed to address this question do have more general application to low-carbon generation and other resources.

1.3 Thesis Structure

Following this motivating section, Chapter 2 undertakes a comprehensive literature review of state-of-the-art electricity market design as it relates to reliability and resiliency. It identifies gaps in architectures for differentiated reliability, incentives for local resilience, and contract design for storage resources. The issue of architectures for differentiated reliability is addressed in Chapter 3 through the application of insurance contracts and a capital reserving framework to generation reserve procurement. While Chapter 3 focuses on resource adequacy, the issue of resiliency to extreme events at local levels still needs to be addressed. As such, in Chapter 4 a locational insurance mechanism is developed to align incentives for local resilience and distributed investment. Given a market architecture that aligns central agency incentives with consumer reliability preferences, the design and structure of contracts between agencies and resources are considered next. Chapter 5 examines a distinct issue relating to the interaction between contract design for storage resources and incentives for market operation. The chapter identifies five principles for contracting by central reliability insurance or procurement agencies and develops a new yardstick contract design between reliability agencies and storage to hedge system risk and maintain incentives for market operation. The thesis concludes in Chapter 6 with an identification of central policy and market design implications, and an assessment of future research direction in this area.

1.4 Contributing Publications

The list of contributing research publications related to this thesis is presented in Table 1.3.

Table 1.3: Contributing Research

Contributing Research	Status	Thesis Section
Billimoria, F., Fele, F., Savelli, I., Morstyn, T., and McCulloch, M. (2022). An insurance mechanism for electricity reliability differentiation under deep decarbonization. Applied Energy, 321, 119356. doi:10.1016/j.apenergy.2022.119356. Awarded **Best Paper** at the MIT AB Applied Energy Symposium 2021	In print	Chapter 3
Billimoria, F., Fele, F., Savelli, I., Morstyn, T. and McCulloch, M., (2023). An Insurance Paradigm for Improving Power System Resilience via Distributed Investment. IEEE Transactions on Energy Markets, Policy and Regulation. doi:10.1109/TEMPR.2023.3301830	In print	Chapter 4.
Poudineh, R., Brandstätt, C. and Billimoria, F., (2022). Electricity distribution networks in the decentralisation era: rethinking economics and regulation. Springer. doi:10.1007/978-3-030-98069-6	In print	Section 4.1.
Billimoria, F. and Simshauser, P., (2023). Contract design for storage in hybrid electricity markets. Joule, vol. 7, no. 8, pp. 1663-1674. doi.org/10.1016/j.joule.2023.07.002	In print	Chapter 5
Yurdakul, O. and Billimoria, F., (2023). Risk-Averse Self-Scheduling of Storage in Decentralized Markets. IEEE Power & Energy Society General Meeting (PESGM). Orlando, FL, July. 2023. doi:10.48550/arXiv.2212.00209	In print	Section 5.2

2
Literature Review

Contents

This chapter conducts a comprehensive literature review on the topic of reliability mechanisms in electricity market design. The objectives of this chapter are to: (i) provide an overview and categorisation of the work being undertaken; (ii) describe how and where this thesis fits into the field; and, (iii) identify gaps in the research that motivate the focus of the thesis.

The literature on electricity market design is extensive, and the question of how to ensure reliability of service is one that has received attention since the genesis of the field. In recent years, given the emergent risks facing electricity systems, the question requires renewed focus and research. In particular, how should market design adapt to the risks of variability and intermittency, extreme common-mode events, and the economic structures of new supply and demand-side resources? In order to investigate the rationale for reform, it is important to understand the origins and evolution of markets for power. The literature review begins in Section 2.1 with an overview of electricity market design, investment equilibrium, and reliability mechanisms. The research is then classified across three categories relevant to reliability, specifically (i) attitudes to risk and uncertainty; (ii) perspectives on market completeness; and, (iii) the analytical approach and methodology. The objective of this section is to provide a high-level portrait of the literature. Section 2.2 considers directional trends in research and identifies three research gaps, all of which will be addressed in detail within the thesis. The directional trends cited relate to architectures for differentiated reliability, distributed resources and local resilience, in addition to contract design and performance incentives. Three research gaps relating to these trends are consequently identified.

2.1 Markets and Investment Equilibrium

The theoretical foundations of modern electricity market design were developed in seminal works [23, 99, 100], which established the concept of a spot market for electricity. The original spot market design, which persists in many markets today, involves the competitive bidding, scheduling, and dispatch of resources in merit order - subject to network and security constraints - in a manner known as Security Constrained Economic Dispatch (SCED). While similar merit-order scheduling and economic dispatch have previously been proposed for power systems [101], the key innovation of these works was the payment mechanism. Applying marginal pricing theory, Schweppe et al. [23] formulated the locational marginal price (LMP) as the clearing price of the supply and consumption of electrical energy, as differentiated by location (per electricity node or bus), and time. In a convex setting, the LMPs are calculated as the dual (or shadow price) of the nodal energy balance constraints [100]. This pricing mechanism creates efficient short-term incentives for generators and load, and has the desirable economic properties of being individually rational and revenue adequate [23, 102] [1]. Moreover,

[1] Four desirable properties of market-clearing mechanisms are: (1) *Cost recovery*, which is one component of the broader concept of *individual rationality*, is the condition in which every market agent is able to recover short-run costs; (2) *Revenue adequacy* refers to the condition under which the market operator never incurs a financial deficit. A stricter condition is *budget balance*, where the market operator has neither financial deficit nor excess; (3) *Incentive compatibility* is the condition that every market agent can maximize objective by revealing true preferences; and (4) *Market efficiency* is the condition where the socially optimal solution is equivalent to a market equilibrium [103, 104]. Hurwicz [103] demonstrates that no mechanism is capable of achieving all

under perfect competition, with truthful energy offers at the short-run marginal cost of production, the socially optimal market clearing solution also represents an equilibrium between market agents [102, 105].

Joskow and Schmalensee [106] developed the new industrial organisation of the sector based on the concept of an electricity spot market cleared on LMP. They proposed a competitive market for the generation and retail supply of electricity, together with economic regulation of monopoly transmission and distribution networks. The design is known as the energy-only market (EOM) design, where the sole source of wholesale revenues were those derived from the sale of energy in the spot market (disregarding any risk-trading, hedging, or contracting activities undertaken outside of the central electricity spot market) [56].

From an investment perspective, LMP can be seen as a signalling and communications mechanism in which participants exchange information upon which investment decisions are made, ultimately converging to a market equilibrium [103]. This design is shown, under a set of ideal assumptions, to create efficient incentives for investment where the theoretical long-term investment equilibrium also coincides with the social optimum [107–110]. Boiteux's seminal analysis [111] shows that high prices for a few hours of the year ensure that optimal capacity is financed and that resource adequacy is secured at an optimal level of unserved energy for the system[2][112]. On this basis, the energy-only market formed the basis of original competitive implementations of electricity markets around the world [56].

2.1.1 Market Distortions

Since its original development, concerns have been raised over whether the energy-only market design is able to deliver investment adequate for a reliable grid. Several factors are argued to distort the investment equilibrium in an energy-only market to the detriment of reliability. Works have challenged the energy-only design and proposed new solutions and enhancements.

four properties at the same time.

[2]Unserved energy relates to the quantity of energy demanded over a period that is not served by the market mechanism. In a market with elastic demand, this can be more precisely interpreted as as the quantity demanded at the market price that is not supplied.

This section sets out the market failures that are argued to distort the investment equilibrium in an EOM, resulting in inadequate and inefficient investment. The primary concerns relate to price formation in spot markets, and incomplete or missing markets for hedging and risk-trading.

Spot Price Formation

The primary concern, in the first instance, relates to those factors that prevent the spot price from reflecting the actual value of lost load during scarcity. Where market prices are capped below the efficient equilibrium price (Figure 2.1), this results in scarcity rents that are insufficient to realise the efficient level of investment. This is known as the *missing money* problem [55, 113].

The majority of papers in this vein focus on the impact of administrative settings and interventions. Generator offer caps and price caps [22, 44, 55–57, 62, 112, 114–120], combined with operator interventions [8, 30, 44, 55, 56, 114] suppress energy prices below the equilibrium value of scarcity. This creates a revenue sufficiency problem (*i.e.,* the *missing money*), which limits the economic returns for generators, and also reduces the incentives for retailers to hedge electricity price risk [56]. This results in resource investment below the efficient level and unserved energy above the social optimum [44]. Other administrative parameters discussed in the literature include the market price floor [121, 122], cumulative price thresholds [123], and simplifications of transmission constraints through definitions of price zones and inter-zone transfer capabilities [124].

Several works [19, 21, 41, 44–46, 58, 125, 126] consider the impact of increasing shares of zero-marginal cost renewables on the equilibrium prices required for firming resources to recover capital costs. Relatedly, price formation under extreme events is explored in [8, 45, 127], gaining prominence in the onset of climate change.

The absence of price-elastic demand has also been an impediment to price formation in wholesale electricity markets [45, 128]. Demand response mechanisms, where 'negative demand' (or NegaWatts) is treated as equivalent to generation, can be problematic from a price-formation, payment, and performance monitoring

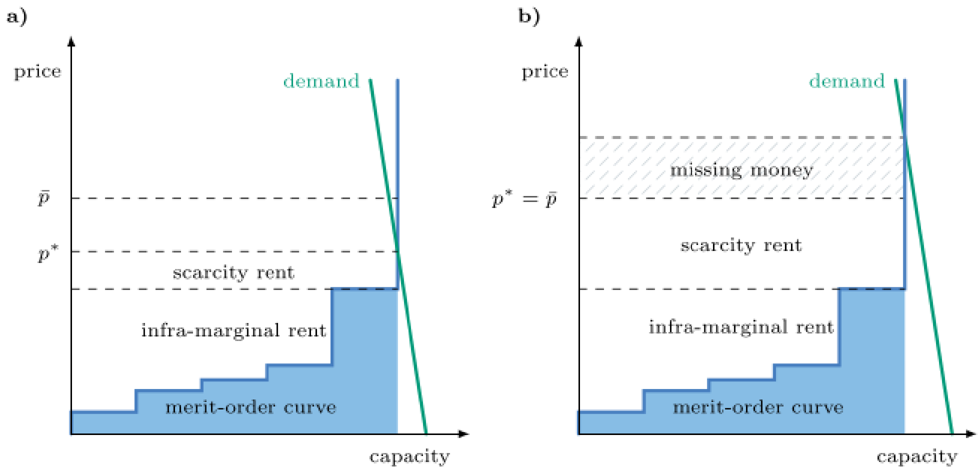

Figure 2.1: Price setting in scarcity situations (from Bublitz et al., 2019); a) where the equilibrium price p^* is below the price cap $\overline{p}$, an efficient outcome is achieved; b) where the equilibrium price p^* is above the price cap $\overline{p}$. However, as the resulting price p^* is equal to the price cap, welfare losses occur (known as missing money). Reproduced from [65]
.

perspective [128]. A recent suite of papers [30, 31, 45, 129] argues that existing restrictions on demand-side bidding and market price caps could be eased given advancements in load technologies and metering.

The development of markets for power system security is also linked to the issue of price formation [130]. The energy transition has led to a fundamental shift in the nature of the interface between resource and grid. Resources like wind, solar and batteries interface with the grid through power electronic converters (converter-connected), in contrast to legacy thermal generation which connects via synchronous turbines. This has led to challenges in managing power system security, such as the loss of inertia and system strength from synchronous resources. As such, the development of markets for power system security are critically important for reliability in low-carbon systems. While it is a growing field of research, and relevant for the future, it has been left out of the scope of this thesis for the purposes of problem tractability, except for one exception. This exception relates to those papers dealing with a subset of services for operating reserves of active power [55]. The demand curves for such reserves can directly impact resource adequacy [56, 131, 132], thereby falling within the scope of this thesis.

The non-convexity associated with resource characteristics is another are important to system reliability. Investment incentives can be significantly impacted by pricing rules, with [133] suggesting that linear or non-discriminatory pricing is more efficient over the long term. The specific form of linear pricing rule can also impact the investment equilibria that is reached, and ultimately the resource mix [134–137]. Non-convexity and the pricing rules adopted are also directly relevant to storage resources, and the form of pricing rule can greatly affect the bidding and dispatch incentives of storage in short term markets, and investment decisions over the long term [138]. The area of non-convexity is important for future electricity markets, but for the purposes of this thesis is excluded from its scope to allow for an appropriately focused and tractable problem.

Missing Markets for Risk

A separate stream of the literature focuses on concerns relating to distortions in markets for long-term risk-hedging and investment.

Discussion focuses on the incompleteness of risk trades in electricity markets. The following papers argue there are '*missing markets*' for long-term contracts required to underpin capital-intensive electricity generation investment [59, 72, 139–145]. This is often linked to broader notions of incompleteness in financial markets [146, 147]. The assumption of completeness is important in characterising the literature on electricity market design, as discussed further in Section 2.1.3 below.

The literature identifies distinct factors leading to market incompleteness in the electricity sector, with a pronounced emphasis on retail markets and tariffs. In competitive retail electricity landscapes marked by by short-term contracts and customer switching, it is posited that retailers lack the creditworthiness to support long-term risk hedges [22, 40, 66, 148]. In markets without retail competition, regulated retail monopolies do not have appropriate incentives to hedge risk [22, 44, 66, 114]. It is also considered that the volumetric nature of retail tariffs provides an implicit load interruption or outage hedge [8].

Electricity markets are integrally linked with fuel markets, which constitute a further source of incompleteness [8, 141]. For example, the insufficient natural gas supply for generators arising during Winter Storm Uri in ERCOT was traced to curtailment and force majeure clauses in gas market regulations [8].

Another important concern in the literature relates to lack of retail price responsiveness to real-time conditions. Traditionally, the retail tariffs in both regulated and competitive retail markets have been formulated as fixed rather than time-varying prices over a specific period. This means that retail consumers have little incentive to modulate demand in response to real-time conditions in the system. A subset of this challenge is the limited political appetite for true scarcity prices [62, 149–151]. This can impose limits on wholesale market settings and the dynamic nature of retail tariff structures that are acceptable in practical implementations [152]

Furthermore, a related problem is the effective socialisation of risk that occurs during supply shortages. In such situations, operators will impose rotating blackouts that disconnect all customers on a particular feeders, regardless of the value they ascribe to consuming electricity at the particular point in time.

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2.1.2 Completing the Market

This section discusses the range of solutions proposed in the literature to address the reliability and resource adequacy concerns of EOMs. These can be subcategorised into *spot market enhancements* (Section 2.1.2) and *reliability mechanisms* (Section 2.1.2).

Spot market enhancements

These proposals focus on improvements and enhancements to spot market design, seeking primarily to rectify the *missing money problem.* An Operating Reserve Demand Curve (ORDC) is proposed by Hogan in [55, 56] as a means of mitigating the *missing money problem* in an energy-only market. The concept involves an administratively determined demand curve for operating reserves in the spot market (as opposed to a fixed requirement). When co-optimizated with energy, both energy and reserve prices approach an assumed value of lost load (VOLL) during scarcity periods before actual involuntary load disruptions occur. The concept has been recently extended to the dynamic sizing and procurement of operating reserves to reflect time-variant uncertainty in resource availability [153–155]. Mehrtash et al. [156] provides a recent review of reserve and energy scarcity pricing in United States.

Related spot market-based proposals include an uplift payment mechanism that seeks to directly pay generators the differential arising between VOLL and the price cap [157]; intervention pricing frameworks to recalculate settlement prices which remove the impact of operator interventions [30, 62]; and a range of price formation enhancements to manage local reliability and out-of-market interventions [158]. The work in [30] goes further to suggest that, under the right circumstances, price caps could potentially be eliminated. Laying the groundwork for a true *two-sided* electricity market, mandatory demand-side bidding is proposed [30, 31]. This is aligned with Scheppe's original power markets vision of using prices to manage demand, rather than supply [159].

Reliability mechanisms

This line of research looks beyond the short-term spot market to develop medium to long-term mechanisms to address *missing money* and *missing markets*. They consider an architecture wherein the spot market is supplemented with a separate mechanism specifically directed toward investment or hedging. In much of the literature to date, they are referred to as *capacity mechanisms* [65]. This chapter uses the term *reliability mechanisms* to signify the overarching objectives of these mechanisms, specifically addressing the reliability gaps in energy-only markets. The term "capacity" is reserved for instances where the mechanism directly pertains to resource capacity. To date, six distinct reliability mechanisms (excluding spot market enhancements) have been identified in the literature. An abridged description of each is provided in the subsequent sections.

Central Capacity Auctions are centralised auctions for physical resource capacity as a complement to short-term spot markets [57, 62, 160]. Central agencies determine the demand for capacity, represented by a fixed volume or a demand curve [161]. Different resource types are derated according to their reliability contributions including for renewables [162] and storage [163]. The Effective Load Carrying Capacity (ELCC) is one such metric for determining qualifying capacity [164]. Market auctions are conducted periodically in accordance with specified auction rules [68]. Contract periods are typically multi-year, usually ranging from one to fifteen years. Successful capacity market awardees have requisite obligations to bid into spot electricity markets. Award payments paid to cleared resources are incremental to revenues accruing from wholesale spot markets. Modern capacity markets also have penalty payment schemes for resource unavailability [165]. Examples of regions with capacity auctions include PJM, MISO, the UK, and the Wholesale Energy Market of Western Australia.

Strategic Reserves are reserves of additional resources procured by a central agency in excess of those delivered by the spot market [165]. As distinct from centralised capacity auctions, resources contracted under strategic reserves do not participate in the spot market. This delineation preserves the option to retain strong scarcity price signals [115]. This is relevant to those jurisdictions seeking to retain a design close to an energy-only model [64]. The quantity of capacity procured is determined by a central agency, either periodically or as triggered by scarcity conditions or projections [66]. The procured resources are available to be utilised by the system operator, to be dispatched when market sources are exhausted. For some strategic reserve designs, decisions on the quantities of reserve procured can be relatively *ad hoc* and subject to high-level capacity or budgetary limits [64]. Though the most common approach to the procurement of strategic reserves involves quantifying the amount of additional generation required to meet a centrally determined reliability metric, such as unserved energy (USE) or loss of load probability (LOLP) [166–169]. Strategic reserves have been adopted in markets such as Germany, Sweden, Finland, Belgium, and now California to manage reliability given a trajectory of lumpy fossil generation retirement [64, 115, 166, 170]. The NEM of Australia combines a triggered strategic reserve with retailer contracting obligations [66].

Central Hedging Mechanisms bear resemblance to central capacity auctions, though the product being traded is a financial product rather than physical capacity [171]. Product demand is determined via an administratively determined demand curve. Several authors have advocated for a financial contract termed 'reliability options', a call option with the payoff defined as the positive difference between the electricity spot price and the strike price [112, 160, 171–173]. A variant of this is an average-rate option, proposed in [152], with the option payoff settled as the positive difference between the average spot price over a period and the strike price. Wolak suggests a load-weighted forward contract form called the Standardized Fixed-Price Forward Contract (SFPFC) [44]. The financial structure creates performance incentives against the forward contract, with resources facing high penalties for under-delivery. Reliability Options have been implemented in Ireland and Italy [174], while the SFPFC is a relatively new concept that has not been adopted yet.

Decentralised Obligations for capacity or financial products create decentralised obligations for market participants, typically retailers or load-serving entities (LSE), to contract a minimum amount of a defined product (*e.g.*, physical dispatchable capacity or financial contracts) [174]. The quantity of such obligations is determined by a central agency, with the responsibility for procurement of the obligation delegated to retailers or LSEs. Obligations are often specified in terms of the quantity of qualifying contract volume or physical capacity, based on *ex-post* or *ex-ante* calculations of retailer demand exposure. Practical implementations include retailer reliability obligations in California, France and the NEM [174].

Priority Service mechanisms allow consumers to elect differentiated reliability preferences through a priority service tariff with the electricity retailer. The concept of quality differentiated service for electricity was developed in the papers of Chao and Wilson [94] and Oren [95], wherein consumers elect from a menu of electric reliability plans provided by the retailer. By selecting the plans, consumers reveal their valuation for power, which can be aggregated and bid into the wholesale electricity market. During times of wholesale scarcity, the reliability preferences are actuated through priority curtailment, where consumer demand is curtailed in the priority of their selected plan [95, 96, 175]. The retailer is responsible for procuring resources to meet the priority service contracts [94]. To date, this has not been implemented in practise as yet.

More recent research on the priority service has focused on the problem of menu design [176–180], resource contracts [181, 182], subscription and consumption interactions [176] and implementation [183]. Under conditions of supply uncertainty and zero marginal cost, Chao, Oren and Wilson [184] establish that priority service Pareto dominates both *ex-ante* time-of-use pricing and integrated resource planning. It is also shown to assure revenue sufficiency for merchant resource investments [184]. To date, research on priority service in electricity markets has focused upon social welfare maximisation as the objective of the utility, rather than profit maximisation [95].

Capacity Subscription mechanisms are similar to priority service, except that the end-consumer is responsible for procuring and capacity contracts with resources [185–187]. During scarcity, consumers who have not contracted sufficient resource capacity are curtailed. This model depends upon the resource having firm dispatchable capacity to support the capacity contract with consumers.

Related concepts include proposals consumer fuse size limits, where energy consumers make elections ex-ante as to a capacity or 'fuse size' that would limit the amount of power consumption below that particular threshold. This limit would only be applicable during times of system scarcity, thereby providing a means for more selective load curtailment of power based on consumer preferences [188]. This amounts to a form of capacity subscription where consumers seeking a higher degree of service continuity can elect for a higher kW level upfront. Alternatively, retail rate reforms that aim to introduce dynamic pricing for consumers, either on a time-of-use basis [189] or in real time [190] are also a means of revealing consumer preferences for energy during times of scarcity.

Table 2.1 classifies the reliability mechanisms based on key design criteria. First, the mechanisms are classified based on the definition of the product being procured and traded. Many reliability mechanisms, such as capacity auctions, strategic reserves, or capacity subscriptions, have focused upon the notion of physical capacity as the product [174]. Alternatively, for hedging mechanisms such as the NEM's Retail Reliability Obligation [73], the traded product is a financial instrument, such as a call option, average rate option, or forward contract. In such cases, the financial incentives for reliability are assumed to be created by the form of the financial obligation. Decentralised frameworks are often supported by a compliance regime that determines contractual and resource eligibility, qualification and accreditation.

Decision-making delegations are considered next; particularly identifying the entities responsible for converting consumer reliability preferences into suitable product quantities and those tasked with product procurement. In capacity auctions, strategic reserves, and central hedging mechanisms, a central agency, such as the market operator, will be responsible for both determining quantities and product procurement (often via a centralised auction) [57]. Decentralised obligations require central agencies to define the product and determine quantities, yet shift the burden of procurement to retail providers. Generator obligations are also possible, where obligations are imposed on variable generation to firm their output via contract, such as for example through an firm insurance contract between variable generation and storage [191]. However, this concept has received relatively little focus in the literature. Mechanisms such as priority service and capacity subscription delegate responsibility for quantity determination and procurement to retailers or consumers, with the consumer responsible for both in the latter [94, 185].

Performance incentives for quantity determination and procurement decisions are also considered. Specifically, whether the agency delegated with the authority to set quantities and procure the product has a reward and penalty framework associated with performance. Mechanisms such as capacity auctions, strategic reserves, and hedging obligations entail penalty or cost allocation frameworks related to the inability to procure an adequate amount of the traded product. However, these penalties are often perceived as ineffective in practice [192]. Performance incentives in relation to quantity setting are non-existent, implicitly assuming that central agencies will be independent and unbiased in decision-making [129]. However, this also means that the agency has no direct incentive for a successful quantification of risk [57]. For priority service and capacity subscription, consumers are subject to priority curtailment, which creates incentives to elect reliability plans in accordance with preferences [94]. For priority service, retailer penalties for any failure to procure depend upon the service contract requirements. Insurance is considered a potential avenue for ensuring incentive compatibility within the design [95]. For consumer subscription models, the incentives for quantity and procurement lie wholly with the consumer, and any consumer with a deficit of capacity contracts during scarcity is at risk of curtailment [185].

The participation of the resources in spot markets is also an important aspect. Strategic reserves are deliberately kept outside of the market so as to preserve price formation signals and limit investment distortion, while all other mechanisms either require or encourage (through profit incentives) participation in the spot markets [64]. Finally, payment structures also vary. Capacity auction payments are based on availability and incremental to spot revenues whereas, for strategic reserves, they are exclusive. For the remaining mechanisms, payment structures are either determined by the form of the contract (*e.g.*, options or futures) or else are privately negotiated between parties.

Table 2.1: Classification of Reliability Mechanisms

Mechanism	Tradeable Product	Decision-making		Performance Incentives		Spot Market Participation	Payment Structure
		Setting Quantities	Procurement	Setting Quantities	Procurement		
Spot market mechanism	Spot energy and ancillary services	Market mechanism	Market mechanism	Market mechanism	Market mechanism	Incentivised, but not required.	Market revenues
Capacity auction	Derated physical capacity	Central agency	Central agency	None	Penalties for non-delivery	Required	Incremental to spot market revenue
Strategic reserves	Derated physical capacity	Central agency	Central agency	None	Penalties for non-delivery	Excluded	Exclusive payments
Central hedging mechanism	Financial contract (Options or Forwards)	Central agency	Central agency	None	Penalty mechanism per contract	As per contract	Based on financial contract
Decentralised obligations	Derated physical capacity or financial contract	Central agency	Retailer	None	Penalty mechanism	Varies	Capacity credit or financial instrument
Priority service	Priority service contract	Retailer sets menu. Consumer selects plan.	Retailer	Priority curtailment	Service obligation, as negotiated	Incentivised, but not required.	As privately negotiated
Capacity subscription	Physical capacity	Consumer sets capacity requirement.	Consumer	Priority curtailment	Priority curtailment	Incentivised, but not required.	As privately negotiated

2.1.3 Characterisation of Methods and Market Assumptions

To further characterise the research, this section considers methodological assumptions and frameworks pivotal to assessment under alternative market designs. Specifically, this section covers (i) risk aversion; (ii) market completeness; and (iii) the modelling framework. Impacts upon mechanism preferences and study outcomes are discussed in due course.

> **Risk Aversion**. This relates to how works consider risk attitudes for the system and of agents in the market. The two main risk attitudes considered are risk-neutral and risk-averse.
>
> **Market Completeness**. Another important assumption (either implied or explicit) relates to market completeness. This describes the degree of liquidity, depth and tradeability of markets for risk over various time horizons relevant to capacity investment. Studies are distinguished between the assumption of complete markets, incomplete markets, and partially complete markets.
>
> **Modelling Approach**. This describes the analytical model adopted, of which the main approaches are optimisation, equilibrium, agent-based, and system dynamics.

Risk and Uncertainty

The literature is distinguished by the extent to which uncertainty and risk are incorporated in agent decision-making under alternative electricity market designs. Risk is an important aspect of investment in capital-intensive assets, and the characterisation of risk impacts market outcomes. A flowchart of approaches and characterisation of uncertainty and risk is shown in Figure 2.2.

Papers can first be distinguished between those that do not consider uncertainty adopting a **deterministic** approach [2, 21, 179, 185, 193–201], and those that incorporate the **stochastic** nature of electricity system variables and parameters. In considering stochasticity it is most common to define the probability space of key system parameters via uncertainty scenarios (*e.g.*, [8, 72, 73, 116, 141, 142,

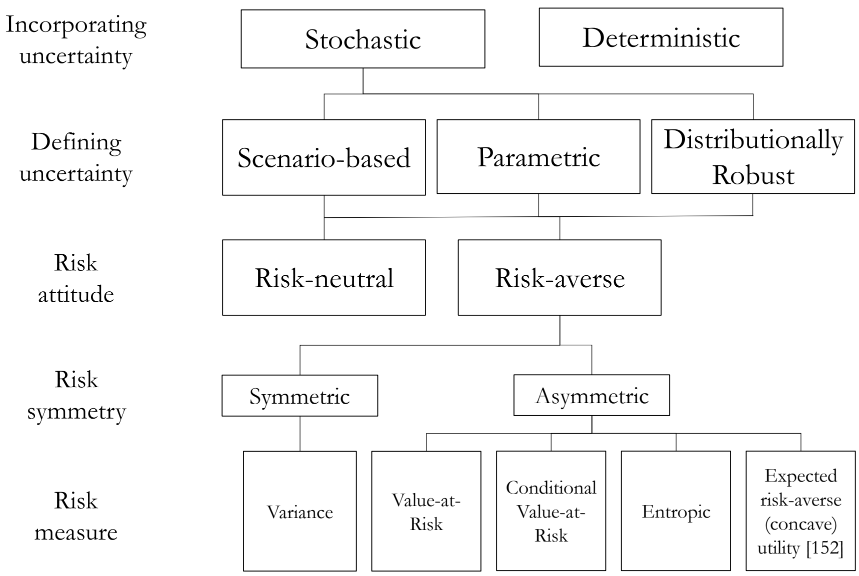

Figure 2.2: Characterisation of Uncertainty and Risk in Electricity Market Design Studies

161, 202–207] or parametric distributions [112, 140, 208, 209]. A less common, though constantly evolving stream of the literature investigates distributionally robust frameworks for decision-making under uncertainty [210].

Of the papers that consider stochastic variation, the approach to characterising the risk attitude of agents varies. Certain papers assume that agents are **risk-neutral** and develop investment equilibria on that basis [112, 116, 157, 196]. Under an assumption of risk-neutrality across all agents and the absence of other market failures (such as market power), the investment market equilibrium is theoretically equivalent to the social optimum [211]. As such, it is unsurprising that adopting this assumption tends to support the efficiency of a scarcity-based design or to equate between energy-only and energy-plus-capacity designs [112, 116, 157, 196, 212].

Other papers incorporate the **risk aversion** of agents and consider how different levels of risk aversion affect participant decision-making and resource investment (*e.g.*, [59, 72–74, 116, 142, 161, 204, 207, 211]). The specification of risk in this context is important. Studies that use a **symmetric** measure of risk, most notably its variance, consider upside and downside variations from a mean to be risk-equivalent [47, 144, 202, 207]. This symmetry provides computationally convenient formulations in the context of searching for equilibria in multi-agent formulations. Across this level, a subset of works makes a further simplifying assumption for risk-hedging, specifically that, in a competitive market, financial instruments trade at or near the expected value of the future payoff [47, 202].

By contrast, asymmetric risk measures consider agents to be averse to downside variation rather than both upside and downside variations. Two common asymmetric risk measures are value-at-risk (VaR) [208] and the conditional value-at-risk (CVaR) (*e.g.*, [8, 59, 72–74, 141, 142, 204]). The latter is more commonly adopted given a convenient linear programming formulation and the coherence of the risk measure (see below).

For a given profit distribution Ψ and risk confidence level $\alpha \in (0, 1)$, the VaR V is defined as the α-quantile of the profit distribution. The CVaR, $\tilde{c}$ is defined as the expected value of profits smaller than the VAR of the profit distribution. Mathematically, for a discrete probability distribution with scenarios $\omega \in \Omega$ of a probability of occurrence π_ω, the CVaR is defined as [213, 214]:

$$\tilde{c} = \max\{V - \frac{1}{\alpha} \sum_{\omega \in \Omega} \pi_\omega \max\{V - \Psi_\omega, 0\}\}, \forall \alpha \in (0, 1) \tag{2.1}$$

Artzner et al. [215] proposes a set of desirable properties that a risk measure should fulfil. Measures satisfying these four properties are defined as coherent risk measures. These properties, for a risk measure $r(\Psi_\omega)$, are:

1. Translation invariance: For all $a \in \mathbb{R}$, it holds that $r(\Psi_\omega + a) = r(\Psi_\omega) + a$
2. Subadditivity: For all $\omega_1, \omega_2 \in \Omega$ $r(\Psi_{\omega_1} + \Psi_{\omega_2}) \leq r(\Psi_{\omega_1}) + r(\Psi_{\omega_2})$
3. Positive homogeneity: For all $a \in \mathbb{R}$, it holds that $r(a\Psi_\omega) = ar(\Psi_\omega)$
4. Monotonicity: For all $\omega_1, \omega_2 \in \Omega$ if $\Psi_{\omega_1} \geq \Psi_{\omega_2}$ then: $r(\Psi_{\omega_1} \geq \Psi_{\omega_2})$

In electricity market literature the CVaR is by far the most commonly used asymmetric risk measure. It has dual properties of convexity and coherence, and its scenario-based formulation can be exactly derived through a convex linear program [214]. This has made it suitable for studies that use operations research or optimisation formulations to assess electricity reliability. Further, it is able to quantify tail risk beyond the VaR [214]. While the VaR measure has also been reported [216], its use as a risk measure upon which decisions are based requires the adoption of multiple binary variables [214]. Another less common risk measure is the entropic risk measure used in [140].

Market Completeness

Works can also be classified on the explicit or implicit assumption made on market completeness. Formally, a complete market in risk is one where there is an Arrow–Debreu security corresponding to any future potential scenario that may arise, allowing participants to construct a portfolio that hedges against uncertainty across future outcomes [142]. This has important implications for how a model will treat the liquidity and depth of risk-hedge contracts and related reliability mechanisms.

The assumption of complete markets is dominant in those works advocating scarcity-based market designs, either explicitly [47, 202], or implicitly [55, 56]. The assumption of incomplete markets, together with participant risk aversion, has tended to support the imposition of additional reliability mechanisms or obligations [8, 44, 59, 116, 141, 204, 212]. A more nuanced posture is adopted in [73], suggesting that markets may vary in degrees of completeness, requiring reliability mechanisms that are adapted to the specific case. The nature and degree of incompleteness in markets can be specified by defining a common set of risk-hedging contracts, by restricting volumes of available contracts, or by limiting the availability of securities to particular scenarios [8, 73, 144].

Analytical Approach

This section reviews four different analytical approaches that are relevant to the study of reliability mechanisms in electricity markets.

System Dynamic Models are applied to electricity market investment to model and observe feedback loops in the system [217]. System dynamic models have been used to assess the viability of EOMs against capacity markets and other reliability mechanisms [193, 195, 197, 218–220] incorporating risk aversion [116, 161, 212, 221, 222] and renewable support schemes [197, 223].

The advantages of system dynamic modelling in the context of electricity market design relate to the capability to model long horizons and transition pathways [195, 220]. However, these models fail to adequately represent the technical constraints of power resources and networks, often relying on simplifications (such as price-duration curves) and neglecting short-term inter-temporal issues (*e.g.*, ramping, short-term storage) [224].

Agent-based modelling (ABM) is similar to system dynamics modelling, but uses programmed decision rules with autonomous agents. ABMs have been adopted in the assessment of investment adequacy in electricity markets under alternative reliability mechanisms under high penetrations of renewables [166, 225–230].

ABMs are capable of representing granular systems and market conditions. This includes imperfect information [226], parameter uncertainty and agency risk [230], and highly granular representations of the power system and market design. Large temporal timescales are prevalent in these studies, where the progressive learning behaviour of agents can also be modelled [228, 231].

The key drawback is that ABMs rely upon the definition of agent strategies and decision rules - where such strategies are typically not endogenous to the problem. In addition, the models are highly parameterised with results highly dependent upon parameterisation By contrast, equilibrium modelling can model the set of all strategies, from which an optimal strategy can be chosen.

The use of ***Optimisation models*** to model power system investment is prevalent throughout the literature. These models are commonly used in planning studies and in developing optimal development pathways for resource and network capacity expansion (*e.g.*, [2, 21, 155, 187, 198, 232–234]). The objective of such models involve a maximisation of the total social welfare of all relevant participants in the system.

These models are scalable and capable of the granular representation of technical and operational elements of the system. Though this comes at a computational cost especially where such elements are represented by binary or integer decision variables. This results in a mixed-integer linear program (MILP), a computationally intensive non-convex problem [2].

Optimisation models are inherently restricted in modelling long-term market design parameters and reliability mechanisms. Typically some approximations are adopted, including minimum capacity constraints [198]. Risk can be represented at the system level, most easily with convex risk measures [235]. Moreover, an important result in [211] shows that a risk-averse equilibrium can be represented by the solution of an appropriately configured risk-averse optimisation problem, under an assumption of complete markets.

Most optimisation models implicitly assume perfect competition and do not well represent participant interactions in markets. As a result, they typically overestimate investment and resource adequacy relative to incomplete market models [8]. Contrasting examples are [236, 237] where a Cournot model is represented by a single optimization problem, which is equivalent to the Nash Cournot game.

Game-theoretic equilibrium models can express the competitive interaction of individual agents and market participants. Consequently, they are well suited to represent agents under alternative electricity market designs. Agents maximise their own utility function given a number of decision variables and constraints, formulated as a mathematical optimisation problem (*e.g.*, [59, 73, 74, 141, 204, 238]).

Here, granular aspects of the market and agent parameters can be modelled, including price formation of energy and ancillary service markets and reliability mechanisms (via dual variables) [74]. Uncertainty can be represented in stochastic formulations, together with symmetric or asymmetric representations of risk. Lending to the modelling of incomplete markets, specific financial instruments and contracts such as forwards, options and contracts-for-difference can be incorporated [8, 72–74].

Several models of competition can be formulated with equilibrium models. Perfect competition is modelled via the zero-profit condition (or in the case of risk-aversion, a zero-risk measure) [72]. Imperfect models of competition are presented in [206, 238, 239], demonstrating the impact of strategic market power on investment efficiency.

Proving the existence and uniqueness of solutions in equilibrium models depends upon the formulation of agent problems and associated interactions [240]. Existence and uniqueness have been proven in certain formulations [140, 238, 241] but are more difficult to establish in models with non-convexity [242], risk-aversion [204] and risk-trading [72, 243]. In such situations, the careful interpretation of equilibria is required. Such cases often adopt distributed or heuristic algorithms for equilibria search [72, 244]. For example, guided search approaches are developed for a specific interpretation, for instance to mimic the process of generator entry and exit in competitive markets [136].

In certain cases, it is possible to reformulate a Cournot model into an equivalent single optimization problem, equivalent to a Nash-Cournot game. This was first adopted in [236], exploiting the properties of the linear inverse demand function, and more recently by [237].

2.2 Research Trends and Gap Analysis

Several research trends and gaps are identified based on the discussion and comparisons presented in this chapter. Given the depth of the literature, the findings have been structured based on topics of particular relevance to this thesis, allowing for comparison and extraction of common results.

2.2.1 Architectures for Differentiated Reliability

An effective organisational decision-making architecture involves the alignment of decision rights (i.e. the space of feasible strategies for each player), performance management systems, and incentives (both rewards and penalties) [245]. Across the literature, reliability mechanisms adopt differing degrees of decentralisation of important elements - including reliability preferences, procurement, risk-hedging and investment.

Across the reliability mechanisms surveyed, only energy-only markets, capacity subscription [185] and priority service models [184] involve the decentralisation of reliability preferences and quantity determination. It is far more common for such roles to be delegated to a central agency, often the ISO or TSO, whereupon an agreed administrative methodology is adopted to translate reliability preferences into a demand curve for quantities of the reliability product to be procured [62]. This process involves the adoption of administrative system-wide targets for reliability, such as the '1 day in 10 years' loss-of-load expectation common in many US jurisdictions [246]. The origin and rationale for this specific metric is not clear. While it is referenced in papers as early as 1950 [247], no justification has been given for the reasonableness of the standard, other than that it is approximately the level that customers were accustomed to [67]. Such criteria have been criticised for being arbitrary, too conservative [77], and acting as an inappropriate reflection of unserved energy preferences [248]. There is also uncertainty as to the interpretation of the standard [67]. Some define it as *one event* in ten years, while others define it as *twenty four hours* of lost load in ten years [249]. [250] offers a unifying reference for defining the LOLE metric, preferring the latter interpretation. Multi-criteria and risk-averse metrics incorporating CVaR have been proposed as enhanced representations of uncertainty and risk [251, 252].

Moreover, the translation of reliability metrics to capacity demand curves or a decentralised capacity requirement requires the central agency to make assumptions of the system-wide value of the lost load, often via estimation or surveys [40]. While some efforts are made at granular VOLL estimations of load segments, such estimates need to be collated or averaged into a single value [71]. Ultimately, this does not reflect the increasingly heterogeneous and flexible nature of the demand side, nor technologies that can discriminate among users or modulate their load. Flexible demand has to date been incorporated into reliability mechanisms by treating demand as if it is a supply resource [167, 253]. This, however, requires the adoption of demand baselines which are non-intuitive and subject to manipulation, given the dynamic nature of electricity consumption [128]. It also depends upon the protocols and technologies used to curtail power, which currently do not allow for discrimination between individuals (e.g. feeder level disconnection)

A unifying concern across all such reliability mechanisms is the lack of direct performance incentives for the central agency [57, 78]. This can result in over-procurement in some cases [57, 77, 254], in others under-procurement [255], and could also subject the agency to political interference [78]. The lack of direct linkage in central reliability mechanisms between revealed consumer preferences and administrative demand curves for reliability leads to **Gap 1** as specified in Section 2.2.4.

2.2.2 Distributed Resources and Local Resilience

While wholesale energy markets can, in theory, ensure a reliable system [23], a range of recent works identifies incompleteness in liberalised market architectures that can leave systems and communities vulnerable to extreme events [8, 44, 192]. Administrative contracting can also distort the fuel mix towards those resources which are particularly vulnerable to weather extremes [72, 138, 256]. Further, extreme events can island particular regions leaving communities disrupted and at risk for sustained periods [16, 18]. Despite best efforts, wholesale market design invariably results in some residual outage exposure for consumers. This has led some to argue that offering full protection through wholesale market frameworks is either excessively expensive or, at worst, illusory [45]. Yet there is a concomitant acknowledgement that leaving open such vulnerability may also be undesirable, particularly given a changing climate [257] and the inequitable impacts of outages from extreme events [14, 16].

While physical protection from service interruptions is impossible due to the range and extremity of events faced by an electricity network, financial protection may still have value in providing a degree of compensation to consumers for service interruptions. The schemes proposed in [95] and [94] discuss the concept of a compensation payment to consumers for electric service outages based on the value of lost load. A contrasting approach is the consideration of full demand side bidding, where consumers (either directly or via agents such as retailers) bid for energy consumption. In such cases, demand is cleared based on revealed preference, and as such any curtailment would not considered as involuntary.

Decentralised technologies offer the technical potential for improved resilience to extreme events as distributed resource availability may have low correlations with the common mode risks that bulk scale resources may have. Specifically, solar photovoltaics, storage, and other resilient DERs (like electric vehicles and smart homes) can be set up to function as micro-, nano-, and pico-grids during emergencies. This arrangement allows them to be islanded and supply power at both community and individual levels when centralized systems fail [6, 258–260], caveated against the reliability of distributed systems themselves.

However, market and regulatory factors can restrict the extent to which such resilience is valued. Examples include incompleteness resulting from price caps; compensation obligations and retailer load hedges[3] [8]; limits and exclusions to liability under service level regulations [261]; and skewed network performance incentives [120, 262]. A well-structured economic framework that aptly appreciates the resilience advantages of DER technologies could stimulate investments (where they are a cost-effective means of improving reliability), thereby unlocking their economic and technical potential. This leads to the identification of **Gap 2** in Section 2.2.4.

2.2.3 Contract Design and Performance Incentives

The issue of alignment between agency incentives and resource performance during scarcity is an important area of focus, especially given the proliferation of zero marginal cost resources [263]. This theme is distinct from the prior two gaps identified and concentrates upon the interactions between the terms and design of contracts and the operational incentives of the resources in wholesale markets.

[3] Currently retail tariffs are typically charged on energy consumption. This implies that during a supply interruption, the retailer does not make any payments to interrupted load - even though such curtailment aids in the re-balancing of supply and demand.

In capacity auctions, this is implemented *ex-ante* through resource accreditation standards [264] and *ex-post* through financial penalties [265]. Nevertheless, underperformance has persisted, as the explicit penalties are too weak to encourage optimal generator behaviour [192]. Stronger penalties have an effective limit given inherent bankruptcy protections.

Hedging obligations, where the traded product is financial rather than physical capacity, enforce performance through the form of contract and the exchange of cash flows. In other words, the generator will need to dispatch in spot markets to offset the financial payments it is liable for under the hedge contract. For example, in reliability option mechanisms, resources writing the option have corresponding incentives to generate energy once prices exceed the option strike price. Such contracts provide stable revenues for generators but require them to produce during high scarcity prices. However, [72] and [144] demonstrate that this form of contract favours low-capital cost resources, such as natural gas, and against low-marginal cost resources, such as renewables and storage. As an alternative, Wolak [44] proposes the Standarized Fixed-Price Forward Contract (SFPFC), a load-weighted forward contract sold by load-serving entities, which creates a portfolio-level incentive to match energy demand across time. If a single standard contract form is mandated, [73] considers the SFPFC preferable against option-style mechanisms. However, market outcomes are more efficient when a single contract form is not mandated, instead allowing for contracts that suit individual resource types [73].

For variable resources, it is instructive to examine renewable support contracts, even though these contracts are not specifically for reliability. Contracts-for-difference (CFD), or variants thereof, are the predominant contract form. Newbery [266] identifies an incentive incompatibility wherein the contract volume is based on actual (wind or solar) generation. This protects the generator from poor network siting choices and mutes the locational market signals provided by LMP. He proposes instead that contract volumes should be based on generator forecast availability rather than actual generation [266]. Similar effects are achieved with 'zero-price thresholds' which suspend the CFD during negative prices or with contract price increments to internalise system-cost externalities [267]. This means that when prices fall negative, in the absence of contractual payments the generators have an incentive to switch off where possible, rather than pay to generate.

Energy storage resources are different in scope and functionality compared to generation, necessitating a detailed review of contracts and financing mechanisms. Much of the historical storage that has existed in power systems had been built and funded by vertically integrated, publicly-owned monopolistic utilities with a captive rate base, and prior to the introduction of competitive electricity spot markets [121]. In the post-reform era, participation models range from the development of projects that are either standalone, part of a portfolio, behind-the-meter, or even operating as network assets.

Broadly speaking, the project financing for standalone storage mirrors that of other electricity generation assets; they are revenue-generating entities with long economic lifespans that can support tranched debt and equity capital [121]. Yet, key distinctions arise when translating storage's intricate operational modes into commercial financing. Storage's true merit lies in its versatile, multi-functional capacity (often termed 'value stacking'), which facilitates its role in various ancillary service markets and serves as a form of arbitrage in spot electricity markets [198]. Thus, traditional contract forms that support generation assets are not wholly suitable for supporting storage in project financing [268]. For example, traditional forward or call option structures do not accurately reflect the energy arbitrage proposition. Moreover, forward markets for ancillary services are either highly illiquid or, in many cases, non-existent (such as in Europe), resulting in an unhedgeable revenue stream [269, 270]. There are also services that storage provides but for markets that do not yet exist [57, 58] (*e.g.,* inertial response, dynamic voltage support, and system strength).

Many of these have a complex 'common pool resource characterisation', making the development of such markets non-trivial. For example, inertia and system strength have different technical characteristics which also implies a different economic characterisation. While both services are non-excludable, the provision of inertia tends to be non-rival – that is the addition of a marginal user does not impact quantity or quality of service, suggestive of traditional public goods. By contrast, the addition of a new user impacts system strength for adjacent nodes in the network, which suggests that a common pool resource characterisation may be more appropriate. Thus, the economic characterisation of the service should be taken into account when designing procurement frameworks, as between spot markets, regulation or contracts.[271]

An important engineering issue relates to the technical capabilities of energy storage systems and other inverter-connected resources to deliver services such as inertia and system strength, that were provided exclusively by synchronous resources. However, given the focus upon market design and contractual frameworks, this is not covered the reader in this thesis. The reader is referred to the following works covering the technical specification and engineering capabilities [272]. A set of works introduces the concept of financial storage rights as a corollary to financial transmission rights which treat energy storage as a communal asset scheduled by a central system operator [216, 273–275]. Central control of storage retains incentive compatibility, though this has only been proven in the absence of uncertainty [276]. While termed differently, both competitive exchanges of trading rights and regulated storage have the financial characteristics of revenue swap style arrangements. The purchaser receives entitlements to the inter-temporal arbitrage gains that storage generates. Correspondingly, the investor receives fixed payments which can support financing. Given shorter timeframes, [191] proposes an insurance contract between storage and a renewable producer to address the problem of imbalance shortfall allocation in two settlement markets. Through the contract, storage commits to reserve some energy to be used in case of renewable shortfall. However, the suitability of such contracts for the application of central reliability mechanisms formulation has not been considered to date. In particular, an important gap relates to the set of contracting principles that should guide a central reliability agency in formulating contracts for storage.

The focus of this identified gap relates to contracts for services that are already incorporated in wholesale spot markets; as well as those for which spot markets do not exist. The first category includes the provision of energy and frequency control ancillary services, and as such the canonical contract forms need to incorporate interactions between the contract terms and the engagement of the resource in such markets. The second category covers grid services such as inertia and system strength, which do not have (as at the time of writing) centrally cleared spot markets. These contracts will generally take the canonical form of availability contracts, where the financial flows cover a payment for the availability of the resource to deliver the service. Such contracts do not need to consider In the absence of spot markets for such services. In relation to this latter category, it is important to caveat however that the identified gap considers the canonical financial form of the contract and is agnostic to the delivery of the grid service, in the absence of a wholesale market for it. As such the capabilities of the technical specification of the non-market service, such as inertia and system strength is not covered by this work. The development and application of principles for storage contracts are further specified in Section 2.2.4 as **Gap 3**.

2.2.4 Gap Analysis

The literature review has identified three critical gaps in the design of electricity markets for reliability.

Gap 1: Integration of Load Heterogeneity into Centralised Decision-making and Risk Architectures. Current reliability mechanisms predominantly factor in load flexibility on the supply side. In contrast, the demand for reliability continues to be determined through administrative means. This approach persists even with the availability of technologies that facilitate varied load profiles and distinguishable consumer preferences regarding reliability. There is a notable research opportunity in this domain to explore how the incentives inherent in insurance can be woven into a centralised reliability mechanism, thereby reflecting differentiated valuations of reliability among consumers and across time and uses.

Gap 2: Incorporating the resilience value of distributed resources in reliability mechanisms. While reliability mechanisms are patently calibrated to meet peak load conditions, power system extremes are likely to reflect common-mode vulnerabilities across load, network, and centralised supply-side resources. Decentralised technologies offer the technical potential for improved resilience to extreme events. An economic framework valuing DER technologies' resilience could spur investments, unlocking their full technical potential for the benefit of consumers. Research could explore using insurance as a method to value local resilience.

Gap 3: Contract structures for storage in reliability mechanisms. It is common, in reliability mechanisms, for central agencies to execute contracts with firming resources to improve system reliability. While contract forms for firm generation resources are well-researched, the design of contracts for energy storage is nascent. There are opportunities for research in the formulation of contracting principles between reliability agencies and storage resources. Particular attention should be given to the incentive compatibility of resource dispatch with energy scarcity signals and consumer welfare.

This gap relates to a range of canonical contract forms that are applicable to storage. The identified gap relates to a range of services relevant for storage resources comprising (i) services for which spot markets already exist, such as energy and frequency control ancillary services and (ii) services which are not covered by spot markets, such as network services and non-market ancillary services, such as system strength and inertia. The focus here is upon financial terms of the contract rather than the technical specification.

3

Architectures for Reliability Insurance

Contents

Chapter 2 identifies a gap in the existing literature relating to the incorporation of load heterogeneity in centralised resource adequacy mechanisms. This chapter addresses the gap by considering the research question: *How should the decision-making and risk architecture of an energy plus insurance market design be formulated to achieve generation adequacy given the heterogeneous preferences of consumers?* It is posited that insurance contracts and risk provisioning frameworks can be adapted to the procurement of reserves in electricity markets to better meet the diverse reliability preferences of consumers.

Energy-only market designs are challenged in their ability to ensure generation adequacy under market incompleteness [8, 59]. Many markets have sought to implement resource adequacy mechanisms to procure reserves in excess of what would ordinarily be incentivised by an energy-only market design. Two common examples of these are strategic reserves and market-wide capacity auctions [165].

These mechanisms require a central agency to determine the type and quantity of resources that are procured.

The prevalent methodology sizes reserves based on a reliability metric such as expected USE or LOLP. Yet, the consumer risk preferences that underpin such metrics are elicited either through surveys or in some cases ad-hoc 'rules-of-thumb' (e.g., the '1-day in 10- years' standard for many US capacity auctions) [67, 249]. Two fundamental and interrelated issues arise with such approaches. The first is the potential for gaps between the indirect (non-pecuniary) incentives of the central procurement agency and the direct losses experienced by consumers [57]. The second is whether consumer preferences for reliability can be more directly revealed in resource adequacy mechanisms [184].

As load technologies have enabled greater differentiation in consumer preferences for electricity service, the alignment between preferences and procurement is of greater relevance today, leading to **Gap 1** identified in Chapter 2.

The micro-economic model of an insurer is as a manager of tail risk. Tail risk relates to financial loss exposures from extreme or low-probability outcomes (*i.e.* the so-called tail of a probability distribution). This suggests a natural applicability to the assessment of resource adequacy in power systems. This chapter takes a fresh look at the market design for resource adequacy through the introduction of an insurance mechanism that allows for differentiated reliability preferences to be directly elected by consumers.

This chapter is focused on strategic reserves. The key differentiation between capacity auctions and strategic reserves relates to market participation of contracted resources - in the former resources participate in the spot market; while in the latter they are only dispatched when market sources are exhausted. The choice was deliberate for two reasons: first, strategic reserve frameworks allow for full-strength scarcity price formation in the energy market. As such, this allows a clearer quantification of those resources deemed to be in excess of what an energy-only market design would deliver. By contrast, the modelling of capacity auctions requires deliberately setting administrative parameters such as energy and offer price caps (usually well below what would be set under full-strength price formation). As this choice affects investment outcomes, this makes results interpretation more challenging given the need to disaggregate the impacts of the resource adequacy mechanism from the price cap. Second, given the tractability challenges of large-scale equilibrium models, there is a computational convenience associated with the game-theoretic modeling of strategic reserves relative to capacity auctions. Taken together this approach yields explicable and tractable results which can, nevertheless, more generally inform the design and policy of resource adequacy mechanisms.

The proposal outlined herein develops an insurance mechanism to monetise the heterogeneous value of lost load when existing demand schemes are capped out by administrative interventions. The approach brings the advantage of applying insurance risk management and loss reserving techniques to a strategic reserve under uncertainty. This *energy plus insurance* model enables (i) the monetisation of the value of lost load based on revealed consumer preference and; (ii) a risk-based decision-making framework for the strategic reserve procurer to make incremental generation investments. Further, by linking this to a scheme for curtailment differentiation, more granular curtailment is enabled to improve the preservation of essential services during extreme scarcity (which ordinarily would be subject to rotating outages).

The scope of the chapter comprises (i) the design of an insurance mechanism for strategic reserves and its interaction with an operational scheme for priority curtailment of load; (ii) the development of decision problems for key agents in the design, including a comprehensive insurance model for the party responsible for reserve procurement; and (iii) a comparison of equilibrium outcomes of the insurance-based design against an energy-only market design. As this work is focused on generation capacity expansion only, network investment is not considered at this stage (*i.e.* a copper plate network is assumed). Operational security reserves considered for the dynamic containment of power system security parameters (such as frequency and voltage) are also not considered.

The chapter begins in Section 3.1 with a formulation of the high-level architecture of the proposed *energy plus insurance* market design; and the development of an applicable insurance loss reserving metric. Adopting this reserving metric, Section 3.2 formalises in mathematical terms the risk-averse decision-making problems of key agents in the design including generators, the insurer, and consumers. This section also provides details on the methods for searching for game-theoretic equilibria and measures used to evaluate performance. In Section 3.3 the formulation is applied to a case study; the assumptions and data used in the case study are described with the results presented and discussed. Section 3.4 elaborates upon the key policy implications of the study. Finally Section 3.5 concludes with implications for the thesis more broadly.

3.1 Market Architecture

A high-level block diagram of the proposed market architecture is provided in Figure 3.1; segmenting the market design into two layers. First, a wholesale electricity market (WEM) layer is constructed which represents the wholesale spot market and capacity investment decisions based on spot market outcomes. Second, a strategic reserve procurement (SRP) layer models the decisions made by the central agency to procure strategic reserves via a novel insurance mechanism. A strategic reserve, by definition, is intended to operate with minimal interference in the spot market and only when market resources are exhausted. Thus the decision-making in each layer can essentially be treated separately, except for information flows from the WEM to the SRP.

With regards to nomenclature, generators that are built based on spot market profits are termed *market generators*, while those generators supported by strategic reserve tolling payments are termed *strategic generators*. There is also a distinction between electricity consumers drawn in the architecture. Certain consumers are able to participate via bid in the spot market (and termed *market consumers*). As these consumers are able to voluntarily indicate curtailment and value preferences via the market, the insurance scheme is of less relevance to them. However, those consumers

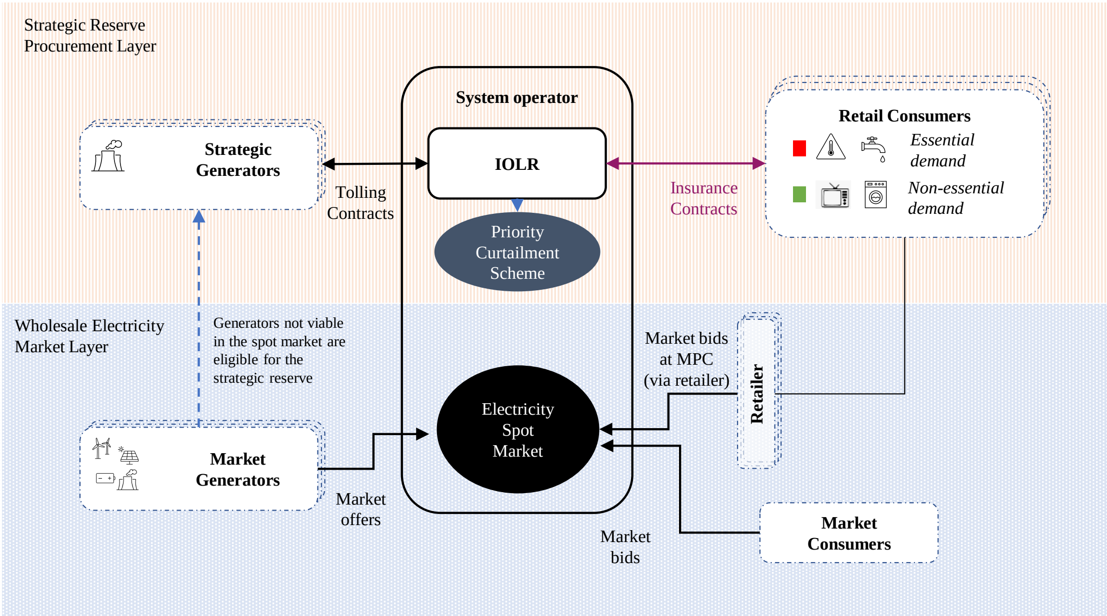

Figure 3.1: Schematic of the market architecture incorporating a wholesale electricity market (WEM) layer incorporating a centrally dispatched spot market settled on marginal prices (managed by the system operator); and a strategic reserve procurement (SRP) layer incorporating a reserve procurement based on a reliability insurance scheme with priority curtailment

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who are not well-suited for direct engagement in spot markets would be eligible to hedge their interruption risks via insurance (and are termed *retail consumers*)In this work, an *open loop system* is assumed in that the SRP decision do not affect physical supply schedules in the WEM, and that a generator or consumer makes an exogenous choice about being a WEM supplier or consumer. Future research could examine alternative game structures that incorporate feedback from the SRP to the WEM.

Beginning with the WEM layer and the electricity spot market, generators offer available generation capacity into a gross pool at short-run marginal cost (SRMC). Consumers bid for energy in the gross pool at their VOLL, limited by the market price cap (MPC) (i.e. their bid to purchase energy is equivalent to $min(MPC, C_d^{voll})$, where C_d^{voll} is the consumer's actual VOLL). Generators are dispatched in economic merit order by the transmission system operator (TSO), and settled at marginal prices with an administrative market price cap (MPC) limiting the price. Complementary administrative mechanisms include generator offer caps and market power mitigation processes [56], though these are not modelled here. A future issue to explore is the existence of such additional regulations on investment appetite between the WEM and the SRP. In the absence of any other sources of revenue for generators, this market design is the *energy-only market* referred to above.

The SRP layer models how decisions are made with respect to the procurement of strategic reserves. As highlighted above, in Section 3.1,in traditional settings SRP capacity quantities are determined unilaterally by a central authority with reference to standardised reliability preferences. In this design, by contrast, the procurement of strategic reserves takes place via the offering of reliability insurance contracts to retail consumers. The insurance scheme is managed by the transmission system operator (TSO), though the term *Insurer-of-last-resort (IOLR)* is used to specify the role of the TSO in managing the strategic reserve as distinguished from its operational role in economic dispatch and market clearing. Key elements of this layer are as follows:

1. The IOLR offers reliability insurance to consumers. In exchange for an upfront insurance premium, reliability insurance provides consumers with financial compensation in the event that load is interrupted, in the form of a payment (in $ per MWh) linked to the marginal VOLL of the particular source of consumption.

2. Consumers can elect whether to purchase insurance based on their risk preferences and the price of insurance (*i.e.* the premium) offered to them by the IOLR. The premium would be expected to be structured on a basis that reflects the consumers level of interruption risk - for example either based on load shape, peak energy, and/or based on consumer type.

3. As the IOLR is financially responsible for paying compensation, it is incentivised to take action to reduce its risk of making such payouts. As such it can procure strategic reserves in the form of tolling contracts with additional generation capacity to mitigate the risk frequency and magnitude of interruptions. It is noted that this framework also allows the IOLR to

actively contract with demand-side resources as an alternative to generation, though only generators are modeled to minimise the formulation complexity.

4. Under the tolling contract, the IOLR pays for all the variable and fixed costs of the generator. Given that this chapter does not consider the issue of contract design, a standard form tolling contract is assumed. Importantly, given the nature of a strategic reserve, these generation resources are excluded from participating in the spot market. The dispatch of such generation reserves takes place only when all available market generators have been dispatched.

5. In the event that consumers are still required to be curtailed, consumers are curtailed in priority based on the VOLL indicated in their reliability insurance contracts (from lowest to highest VOLL). Ordinarily at this stage, many markets resort to rotating/random load shedding (see [277]).

6. Under this priority curtailment scheme, under scarcity or emergency conditions, the load can be *triaged*. The low value or non-essential load is curtailed first with the aim of preserving more essential load. This would be actuated through a real-time communications infrastructure such as an energy router connected to the home [278].

The design could be implemented in phases to allow early benefits to accrue, but also to allow time to integrate with the rollout of load metering, control, and communications technology.

The estimation and revealing of consumer VOLL preferences is an important element in the advancement of this framework, as well as for consumer-centric electricity markets more generally. Research is progressing on this front, with work such as that by Baik et al. [279] elucidating consumer willingness-to-pay (WTP) to avoid long-duration outages. This could also be aided by a phased introduction of insurance. Initially, compensation could be based on average unserved energy at the feeder level and the market price cap, which would provide an initial valuation of lost load and incentivise investment in strategic reserves. As the penetration of digital metering and load technology grows, this would enable consumers to differentiate between different loads in the home or business. Simplified plans, such as those based on the 'traffic light system' by Papalexopoulos et al. [278] could also assist. To the extent that more specific consumer preferences cannot be revealed, the insurance scheme could still be valuable because the election or denial of insurance by consumers at estimated VOLL still provides information (albeit less granular) on preferences.

There are two information flows from the WEM layer to the SRP layer. First, generators that are not viable in the WEM layer are available for investment as strategic reserves; this information is transferred from the WEM to the SRP on a regular but infrequent basis. The second information flow is unserved demand in the wholesale spot market. This is a projection that represents the maximum demand curtailments that can occur from the WEM in the absence of any strategic reserving. It is used by the IOLR to assess whether a reliability insurance contract should be signed with such load, and whether such curtailment can be efficiently reduced via the contracting of additional strategic reserves.

3.1.1 Insurance Principles and Loss Reserving

This section provides the principles governing the viability and solvency of an insurer and that guide the proposed IOLR's decision-making framework are formalised. The operations of the IOLR are managed in accordance with insurance risk management techniques. Tail risks, characterised by rare but severe losses, are managed by setting premiums appropriately, reserving capital against severe losses, and risk transfer or reinsurance [280].

A premium is a payment a policyholder makes for complete or partial insurance cover against a specified risk. An actuarial premium principle is a method for assigning an appropriate price for an insurance premium. The most fundamental and widely used premium principle is the *expected value premium principle* wherein the premium is measured as a multiple of the expected value of the insurer's compensation claims. It is generally applied across classes or segments of customers.

A central insurance scheme is also likely to be subject to regulatory scrutinty to ensure premiums are set at fair actuarial levels and limiting excess rents.

Another key principle of the insurance business model relates to the reserving of capital. In order to maintain solvency the insurer must also provision for potential financial losses from tail risk outcomes, known as a solvency constraint [84]. This means the insurer must carry cash reserves against the possibility that the aggregate value of loss claims will exceed its premium income. These are often termed technical or insurance reserves and are held in cash (or equivalently secure forms of liquid investments). These provide a buffer against extreme outcomes in which the insurer suffers significant losses from paying out large sums in compensation and those cash buffers are drawn down to maintain solvency.

The quantity of reserves required to be held by the insurer is sized by applying a measure of risk to the uncertainty in the insurer's profits, typically guided by best-practice prudential risk standards and industry regulation [281].

A widely used measure for incorporating risk in the insurance sector is the Value-at-Risk (VaR) - the risk measure specified in Solvency II, the European codification of insurance regulation [84]. For a specified risk confidence level α in $(0, 1)$, α-VaR is a lower threshold in which scenario profits are exceeded with probability $1 - \alpha$. The α-VaR of profits associated with a decision is denoted as V. Despite presenting an intuitive representation of losses, VaR exhibits several undesirable properties, including not taking account of the profits below V, non-coherence, and non-convexity when computed using scenarios. The latter two pose significant challenges to computational tractability when seeking to model decision-making via constrained optimisation programmes.

For these reasons the CVaR is used instead as a measure to manage risk in this framework. For continuous distributions, the α-CVaR of profits, denoted by $\tilde{c}$, are those expected given that the profits are less than or equal to V. The definition of CVaR for discrete distributions is yet more subtle, given a set of scenarios $\omega \in \Omega$ used to represent uncertain system outcomes (or states of the world). Rockafellar and Uryasev [213] define $\tilde{c}$ for general distributions as the weighted average of V with the expected profits falling strictly below V. From a mathematical standpoint, CVaR offers several appealing features. Pflug [282] shows that it is a coherent risk measure. Most notably, $\tilde{c}$ can be efficiently computed by minimising a piecewise linear and convex function [213, Theorem 10], which can be cast as a linear programming (LP) problem by introducing an additional variable. From a practical perspective, the CVaR is also used as an insurance risk measure in certain jurisdictions, such as the Swiss Solvency Test (SST) [283].

The principle of loss reserving is applied to this market design, where the IOLR is similarly required to maintain reserves that are sufficient to remain solvent given a portfolio of reliability insurance contracts with electricity consumers. A solvency constraint is formulated in Section 3.2.3 which requires the IOLR to maintain technical (cash) reserves in excess of the (negative) CVaR of its profits. This can be interpreted as requiring the IOLR to have reserves that cover average worst-case outcomes beyond the tail probability[1]. Tail probabilities for insurers are generally set very high to account for tail risk outcomes. For example, Solvency II and SST both require insurers to assess risks at a 99.5% tail probability [283]. Prudent insurance risk management requires that this metric must be met by IOLR.

3.2 Methods

A modelling exercise is conducted in order to understand the impact of market design on the behaviour of market participants and upon system and participant outcomes. An overview of the methodology is set out in Figure 3.2.

A game-theoretic approach was considered most appropriate. It is able to describe the decision-making of individual agents given a particular market design, as well as those interactions arising between agents within the market design. This provides insight into the incentives of agents under risk aversion and market incompleteness. More specifically, given the application to competitive electricity markets, a non-cooperative (as opposed to a cooperative or coalitional) game

[1]It is noted that the application of a 99.5% CVAR tail probability would imply a VAR above this level. However, given the adoption of a similar theshold by the SST it was considered appropriate for this exercise.

framework is considered most appropriate given the contestable nature of electricity generation. The spot market is considered as perfectly competitive, with generators bidding for energy at short-run marginal costs. It is assumed that generators exercise market power with respect to their own capacity in the WEM. For the SRP insurance mechanism, it is assumed that both consumers and insurers are price-takers and negotiate via tatonnement to reach an equilibrium.

In order to construct the game-theoretic model, first the decision-making problems of all relevant agents in the market architecture are formulated. Second, equilibria search algorithms are developed to find equilibria among agents. The assessment of the market design is conducted through the application of a case study using real-world data with results evaluated against success criteria. As noted in 3.1, given that there are two layers of decision-making in the market architecture - the WEM and SRP, the model framework addresses both layers in turn.

In a non-cooperative game, each agent seeks to selfishly maximise its economic utility. However, for the context considered in this problem, each agent must make its individual decision while recognising the inherent uncertainties arising within various global states. Given the uncertainty in outcomes, decisions should reflect the specific risk preferences of the agent. As such decision-making problems of all relevant agents are framed as risk-averse utility maximisation problems. It is assumed that uncertainty is observable (*i.e.* the probability of each state of the world occurring is known in advance) and that knowledge of uncertainty information is common (*i.e.* agents are assumed to have the same knowledge of uncertainty). In this framework, uncertainty is represented by scenarios $\omega \in \Omega$ to represent states of the world and π_ω to represent probabilities.

The specification of risk in this context is important. While risk has traditionally been defined in terms of variance (or standard deviation from a mean), risk aversion is often considered to be asymmetric; that is agents are averse to downside deviations rather than both upside and downside deviations. As such, the utility of each agent is defined as a convex combination of the agent's expected surplus and the CVaR of the surplus [72], where parameter β, ranging between 0 and 1, weights expected

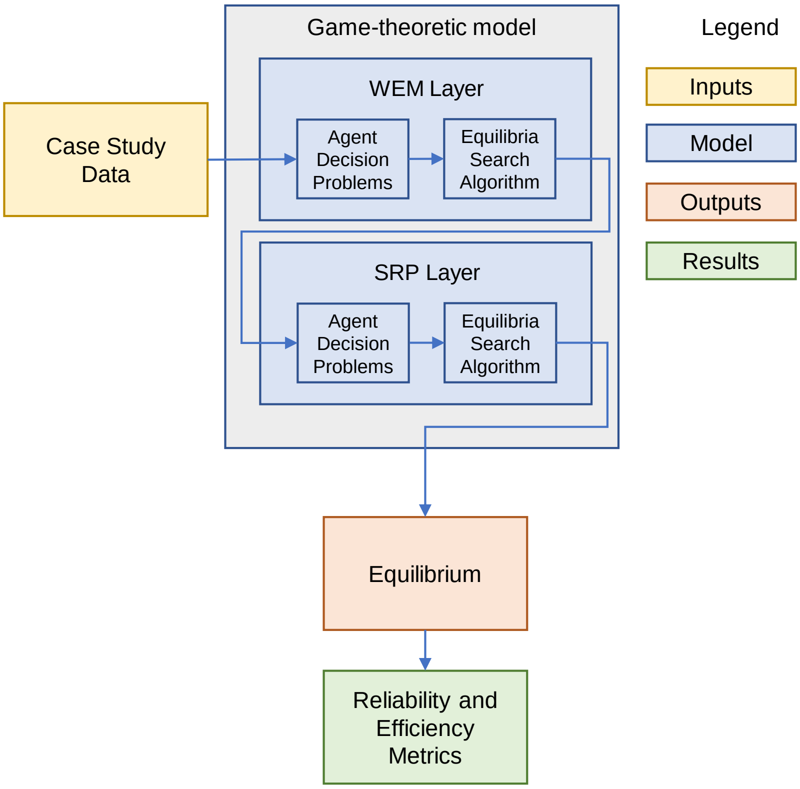

Figure 3.2: Schematic of the methodology for the modelling and assessment of the *energy plus insurance* market architecture.

returns against CVaR based on the agent's preferences. Intuitively this could be considered as a specification of the agent's preference between risk and return [2].

With respect to notation, the relevant variables and parameters of the risk are superscripted to distinguish between the various agents in the game; i for the IOLR, G and c for generators and consumers, respectively.

The mathematical formulations for the decision-making of relevant agents in the market architecture are set out in the following section.

3.2.1 WEM: Decision-making framework for generators

The WEM layer models the operations and investment decisions of generators in the electricity spot market. Market generators are those that choose to build generation

[2]Alternatives here could include Markowitz or von Neumann Morganstern utility functions

capacity based on spot market revenue alone. Hence this section develops the decision-making framework for such a generator. The proposed approach captures the interaction between the generator and the electricity spot market. In particular, this models how a given generator's WEM investment decision and its WEM profits and risks are impacted by WEM spot prices which are the result of the economic merit-order dispatch. A bi-level modelling structure is especially suited and widely used for this application, whereupon a utility-maximising upper-level optimisation problem for the generator's investment decision is constrained by lower-level optimisation problems that represent the short-run market equilibrium [240]. A hierarchical structure of the bi-level model of a generator is assumed (as illustrated in Figure 3.3); the upper-level problem is subject to the solution of primal and dual variables of the lower-level problems. The modelling framework builds upon the approach of [205], which describes a bi-level model for generation capacity expansion, and extended to a stochastic model that incorporates generator risk-aversion. This modification is made with the objective of incorporating a more realistic risk framework for market participants. The spot market game is assumed to be perfectly competitive with participants bidding at short-run marginal costs. Generators are modelled as having the capability to exercise market power with respect to the quantity of capacity investment.

The set of all available generators is represented by $r \in \mathcal{G}$. These are all separate generators, each with an individual profit and CVAR objective. In the upper-level problem (ID_r) the generator seeks to maximise utility (U_r^G), which is defined as the sum of a weighted convex combination of the expected profits and the CVaR of profits ($\Psi_{r\omega}^G$); minus investment capital costs, consistent with [204]. For a generator agent, its profit is defined as the difference between revenues from generating electricity in spot energy markets, and the variable costs incurred in such participation.

The upper level is constrained by spot market clearing outcomes across the set of scenarios $\omega \in \Omega$ modelled at the lower level. For the avoidance of doubt these are the same scenarios observed by the IOLR. As indicated above, the CVaR of profits is annotated as $\tilde{c}_r^G$ with the relevant superscripts.

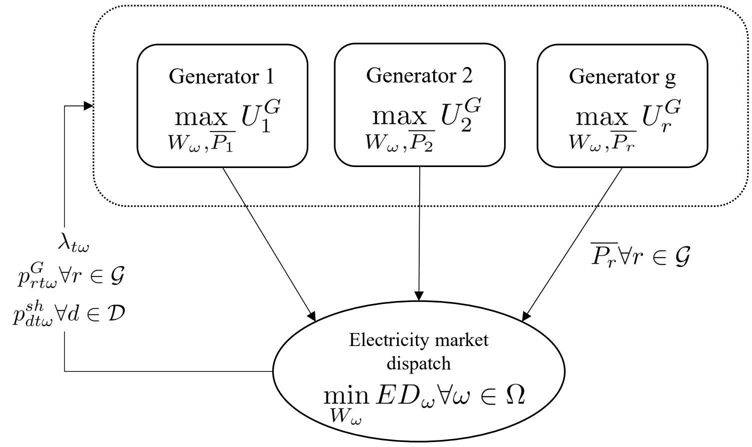

Figure 3.3: Schematic illustrating the hierarchical relationship between generators and the spot market

.

$$\max_{\{W_\omega,\overline{P_r}\}} U_r^G = (1-\beta_r^G)\sum_{\omega\in\Omega}\pi_\omega\Psi^G_{r\omega} + \beta_r^G\tilde{c}_r^G - C_r^I\overline{P_r} \tag{3.1}$$

subject to:

$$\Psi^G_{r\omega} = \sum_{t\in\mathcal{T}}(\lambda^E_{t\omega} - C_r^{vc})p^G_{rt\omega},\ \forall\omega\in\Omega \tag{3.2}$$

$$\tilde{c}_r^G = V_r^G - \frac{1}{\alpha_r^G}\sum_{\omega\in\Omega}\pi_\omega\varrho^G_{r\omega} \tag{3.3}$$

$$V_r^G - \Psi^G_{r\omega} \leq \varrho^G_{r\omega},\ \forall\omega\in\Omega \tag{3.4}$$

$$\varrho^G_{r\omega} \geq 0,\ \forall\omega\in\Omega \tag{3.5}$$

Equation (3.2) represents the profits ($\Psi^G_{r\omega}$) of the generator for scenario ω, as the difference between spot revenues and the variable costs of generation. In this concise model, only spot markets for energy are considered and markets for ancillary services are neglected (Ancillary services are relevant for capacity decisions, especially for storage and will be considered in Chapter 5). Equations (3.3)-(3.5) represent constraints for the scenario-based formulation for CVaR [213] where V_r^G

and $\varrho^G_{r\omega}$ are auxiliary decision variables representing VAR and the positive deviation between VAR and scenario profits, respectively.

The lower level models represent the clearing of the electricity spot market ED_ω under scenarios $\omega \in \Omega$ incorporating generation offers and demand bids for energy. It is assumed that the generators offer available capacity at SRMC and market consumers bid demand at their respective VOLL (each consumer is assumed to have its own unique VOLL, rather than a demand curve), as limited on the upside by the MPC. Retail consumers are assumed to bid at the MPC.

$$\lambda^E_{t\omega}, p^G_{rt\omega} \in \arg\min_{W_\omega} ED_\omega = \sum_{t\in\mathcal{T}}\sum_{r\in\mathcal{G}} C^{vc}_r p^G_{rt\omega} + \sum_{t\in\mathcal{T}}\sum_{d\in\mathcal{D}} C^{sh}_d p^{sh}_{dt\omega}, \forall\omega \in \Omega \tag{3.6}$$

subject to:-

$$\sum_{d\in\mathcal{D}}(\overline{P}^D_{dt\omega} - p^{sh}_{dt\omega}) = \sum_{r\in\mathcal{G}} p^G_{rt\omega},\ \forall t \in \mathcal{T}, [\lambda^E_{t\omega}] \tag{3.7}$$

$$0 \le p^G_{rt\omega} \le \overline{P}_r A^G_{rt\omega},\ \forall r \in \mathcal{G}, t \in \mathcal{T}, [\underline{\mu^G_{rt\omega}}, \overline{\mu^G_{rt\omega}}] \tag{3.8}$$

$$0 \le p^{sh}_{dt\omega} \le \overline{P}^D_{dt\omega},\ \forall d \in \mathcal{D}, t \in \mathcal{T}, [\underline{\mu^{sh}_{dt\omega}}, \overline{\mu^{sh}_{dt\omega}}] \tag{3.9}$$

The objective function (3.6) represents an economic merit-order dispatch that minimises system costs. The lower-level constraints are typical of an economic dispatch under competitive conditions. Equation (3.7) ensures power balance between generation and demand. Equation (3.8) ensures positive generation dispatch but below the maximum available generation capacity, and equation (3.9) limits unserved demand $p^{sh}_{dt\omega}$ to the maximum demand during each time period and scenario. The dual variables of each constraint are shown in square brackets. The vector $W_\omega = \{p^G_{rt\omega}, p^{sh}_{dt\omega}\}$ gathers the decision variables.

As the lower level program is a linear program, the bi-level model can be recast as a single-level program by using the first order necessary and sufficient Karush-Kuhn-Tucker (KKT) conditions of the lower-level problem [284].

$$0 \leq p^G_{rt\omega} \perp \underline{\mu^G_{rt\omega}} \geq 0, \forall r \in \mathcal{G}, t \in \mathcal{T}, \tag{3.10}$$

$$0 \leq (\overline{P_r} A^G_{rt\omega} - p^G_{rt\omega}) \perp \overline{\mu^G_{rt\omega}} \geq 0, \forall r \in \mathcal{G}, t \in \mathcal{T}, \tag{3.11}$$

$$0 \leq p^{sh}_{dt\omega} \perp \underline{\mu^{sh}_{dt\omega}} \geq 0, \forall d \in \mathcal{D}, t \in \mathcal{T} \tag{3.12}$$

$$0 \leq (\overline{P^D_{dt\omega}} - p^{sh}_{dt\omega}) \perp \overline{\mu^{sh}_{dt\omega}} \geq 0, \forall d \in \mathcal{D}, t \in \mathcal{T} \tag{3.13}$$

$$C^{vc}_r - \lambda^E_{t\omega} + \underline{\mu^G_{rt\omega}} - \overline{\mu^G_{rt\omega}} = 0, \forall r \in \mathcal{G}, t \in \mathcal{T}, [p^G_{rt\omega}] \tag{3.14}$$

$$C^{sh}_d - \lambda^E_{t\omega} + \underline{\mu^{sh}_{dt\omega}} - \overline{\mu^{sh}_{dt\omega}} = 0, \forall d \in \mathcal{D}, t \in \mathcal{T}, [p^{sh}_{dt\omega}] \tag{3.15}$$

The complementarity constraints (3.10)-(3.13) can be linearised by replacing $0 \leq a \perp b \geq 0$ with (3.16), where M is a sufficiently large positive constant [285].

$$a \geq 0, b \geq 0, a \leq \zeta M, b \leq (1-\zeta)M, \zeta \in \{0,1\} \tag{3.16}$$

In addition, the bilinear term $\lambda^E_{t\omega} p^G_{rt\omega}$ in (3.2) can be linearised using Lemma 1 [286–288] and by using the strong duality theorem, as stated in [286].

Lemma 1 *The following relationship holds at the optimum of the lower-level problem:*

$$\lambda^E_{t\omega} p^G_{rt\omega} = C^{vc}_r p^G_{gt\omega} + \overline{P_r} A^G_{rt\omega} \overline{\mu^G_{rt\omega}} \tag{3.17}$$

Proof The proof of **Lemma 1** is as follows. The non-linearity $\lambda^E_{t\omega} p^G_{rt\omega}$ can be reformulated as follows based on [286–288]. The dual constraint is restated in (3.18) and multiplied by $p^G_{rt\omega}$.

$$\begin{gathered} C^{vc}_r - \lambda^E_{t\omega} + \overline{\mu_{rt\omega}} - \underline{\mu_{rt\omega}} = 0 \\ \lambda^E_{t\omega} p^G_{rt\omega} = C^{vc}_r p^G_{rt\omega} + \overline{\mu_{rt\omega}} p^G_{rt\omega} - \underline{\mu_{rt\omega}} p^G_{rt\omega} \end{gathered} \tag{3.18}$$

The strong duality condition (3.22) ensures that the complementary slackness conditions hold. Therefore, using the complementary slackness conditions for (3.8), the following is obtained:

$$(p^G_{rt\omega} - \overline{P}_r A^G_{rt\omega}) \overline{\mu^G_{rt\omega}} = 0 \tag{3.19}$$

$$p^G_{rt\omega} \overline{\mu^G_{rt\omega}} = \overline{P}_r A^G_{rt\omega} \overline{\mu^G_{rt\omega}} \tag{3.20}$$

Using similar logic for the minimum generation condition equation (3.21) is obtained. By substituting (3.20) and (3.21) into (3.18) the relation for Lemma 1 is obtained.

$$\underline{\mu^G_{rt\omega}} p^G_{rt\omega} = 0 \tag{3.21}$$

The strong duality theorem, as it relates to linear programs, states that if a problem is convex, then the objective functions of the primal and dual problems have the same value at the optimum [286]. Therefore, with a slight abuse of notation (where $\mathcal{G}$ refers to the set of all generators, and $r^* \in \{\mathcal{G}\setminus r\}$ refers to the set of generators excluding independent generator r) it can be stated that:

$$\begin{aligned}\overline{P_r} A^G_{rt\omega} \overline{\mu^G_{rt\omega}} = \sum_{t\in\mathcal{T}} \sum_{d\in\mathcal{D}} \lambda^E_{t\omega} \overline{P^D_{dt\omega}} - \sum_{d\in\mathcal{D}} \overline{P^D_{dt\omega} \mu^{sh}_{dt\omega}} - \sum_{r^*\in\{\mathcal{G}\setminus r\}} \overline{P_{r^*}} A^G_{r^*t\omega} \overline{\mu^G_{r^*t\omega}} \\ - \sum_{t\in\mathcal{T}} \sum_{d\in\mathcal{D}} C^{sh}_d p^{sh}_{rt\omega} - \sum_{t\in\mathcal{T}} \sum_{\mathcal{G}} C^{vc}_r p^G_{rt\omega}\end{aligned} \tag{3.22}$$

The problem of each individual generator is solved individually, holding all investment decisions of the other generators as constant (we return to this in the diagonalisation algorithm proposed in Section 3.2.2 below). In other words, since the diagonalisation for generator r is run on the basis that that the capacities of all other generators ($r^* \in \{\mathcal{G}\setminus r\}$) are fixed, these are set parameters rather than variables of the decision problem of generator r. It can be observed that the terms of the right hand side of equation 3.22 do not have any bilinear terms in reference to generator r. Thus the remaining bilinear term $\overline{P_{r^*}}\ \mu^{\overline{G}}_{r^*t\omega}$ can be substituted for the linear term on the right-hand side of the equality. This allows each individual generator's decision problem to be recast as a mixed integer linear program that can be solved to global optimality. Thus the bi-level problem introduced above can be recast into the following single equivalent mixed integer linear program that can be solved to global optimality by off-the-shelf commercial solvers. [289]:

Upper level objective function (3.1)

subject to:

Upper level primal constraints (3.2) - (3.5)

Lower level KKT conditions (3.10) - (3.15)

with complementarity constraints (3.10) - (3.13), replaced by (3.16)

Lemma 1 (3.17) and strong duality equality (3.22)

3.2.2 WEM: Market equilibrium

From a game-theoretic perspective, each generator is assumed to be a rational utility-maximising agent and will seek to maximise its individual utility based on the decision-making framework outlined above. Based on the revised bi-level formulation, it is observed that both the objective function and constraints for an agent are coupled to (and dependent upon) the decisions of other agents. The game is thus a Generalised Nash form for which the relevant solution concept is a Generalised Nash Equilibrium (GNE)[3]. A GNE is reached if no generator can increase its utility by deviating unilaterally from the solution.

This section provides an algorithm to search for an equilibrium in the WEM layer. A Gauss-Seidel diagonalisation approach is utilised to search for an equilibrium. Gauss-Seidel diagonalisation solves each agent's individual decision-making problem while considering the decisions of other agents from the previous iteration [240]. The diagonalisation process terminates when the decision of each agent does not deviate from the previous iteration.

The approach taken in this thesis, described in Algorithm 1, is similar to [205]. The algorithm iterates across generators to find an equilibrium between independent generators. Each generator solves its individual decision-making problem while fixing

[3]The two forms can be distinguish in terms of how the agent's decision problem is affected by decision variables of other agents. A Generalised Nash game is one whether the decision variables of other players are in the agents's constraint set. In general, GNE solutions are non-unique. This is exemplified through a simplified example of the capacity problem with two identical generators with the same SRMC (with capacities $PG1$ and $PG2$) in a single time period with load of 1MW. Under a starting point of $PG1 = 1$, the equilibrium would be maintained at the starting points, because neither generator sees benefits from deviating from the current mix. However an alternate starting point of $PG1 = 0$ and $PG1 = 1$ would be maintained at that level.

the decisions of other generators to those values from the previous iteration. An equilibrium is reached when no market generators seek to deviate from their decisions from the previous iteration. As noted in [242, 290–292] the convergence state of the diagonalisation algorithm corresponds by definition to a GNE of the market, since none of the producers can increase their profits by unilaterally modifying their offering strategies. The existence and uniqueness of Nash equilibria in this problem are not guaranteed [292, 293]. As such, in the case study, it is possible to have more than one equilibrium. Furthermore, the iterative diagonalisation approach is not generally guaranteed to converge to an equilibrium, even if such equilibria exist [290, 294, 295]. However, for each of the test cases considered in the numerical study, an equilibrium was reached within a relatively small number of iterations. Each run of the algorithm was tested against a limited range of starting conditions.

Two critical outputs from the spot market equilibrium in the WEM are information flows to the SRP. These are the set of generators that are built in the spot market $\mathcal{G}^M$; and optimal unserved demand outcomes $p^{sh*}_{dt\omega}$ from the spot market given the set of generators $\mathcal{G}^M$. A maximum build capacity of each generator is predefined ex-ante so that the potential capacity that can be built in the SRP is the differential between the predefined maximum capacity and the capacity built in the WEM. These information flows inform the execution of reliability insurance contracts and generator tolling contracts.

3.2.3 Decision-making framework in the SRP layer

Decision-making framework for the Insurer of Last Resort

The formulation of the decision-making framework for an IOLR is set out below. At a high level, the IOLR takes certain information flows from the WEM and makes decisions regarding the execution of reliability insurance contracts with consumers as well as the execution of tolling contracts with generators, subject to prudential requirements to maintain solvency (as described in Section 3.1.1). This takes the form of an optimisation problem (INS) as outlined in equations (3.23)-(3.34) for a single IOLR.

Algorithm 1: Diagonalisation to find spot market equilibrium in the WEM layer.

input : Initial instance of problems (ID_r)
output : Equilibrium solution
initialisation: set ϵ iteration counts k;
while $\max_{r \in \mathcal{G}} |\overline{P}_{r,(k)} - \overline{P}_{r,(k-1)}| > \epsilon$ **do**
  for $r \in \mathcal{G}$ **do**
    solve (ID_r)
    $\overline{P_r} \leftarrow \overline{P}_{r,(k)}$
  end
end
$p^{sh*}_{dt\omega} \leftarrow p^{sh}_{dt\omega} \in \arg\min_{V_\omega} ED_\omega \forall d \in \mathcal{D}, t \in \mathcal{T}, \omega \in \Omega$
$\mathcal{G}^N = \mathcal{G} \backslash \mathcal{G}^M$
return

The information flows from the WEM layer to the SRP layer are the capacity of generation built via the spot market $\mathcal{G}^M$ and demand shortage $p^{sh*}_{dt\omega}$ from the spot market. The set of candidate generators available to the IOLR, $\mathcal{G}^N$ (strategic generators) is that set of all candidate generation $\mathcal{G}$ excluding the set of generators built via the spot market $\mathcal{G}^M$. Thus $\mathcal{G}^N = \mathcal{G} \backslash \mathcal{G}^M$.

$$\max_{W^i} U^i = (1 - \beta^i) \sum_{\omega \in \Omega} \pi_\omega \Psi^i_\omega + \beta_i \tilde{c}^i - \gamma \phi^i \tag{3.23}$$

where $W^i = \{\varrho^i_\omega, V^i, \overline{P_r}, p^G_{rt\omega}, p^c_{dt\omega}, Q^i_d, \phi^i\}$, and subject to:

$$\Psi^i_\omega = \sum_{d \in \mathcal{D}} C^P_d Q^i_d - \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{D}} C^{voll}_d p^c_{dt\omega} Q^i_d - \sum_{r \in \mathcal{G}^N} \sum_{t \in \mathcal{T}} C^{vc}_r p^G_{rt\omega} - \sum_{r \in \mathcal{G}^N} C^I_r \overline{P_r}, \ \forall \omega \in \Omega \tag{3.24}$$

$$\sum_{d \in \mathcal{D}} p^c_{dt\omega} = \sum_{d \in \mathcal{D}} p^{sh*}_{dt\omega} - \sum_{r \in \mathcal{G}^N} p^G_{rt\omega} \forall t \in \mathcal{T}, \omega \in \Omega \tag{3.25}$$

$$0 \leq p^G_{rt\omega} \leq \overline{P_r} A^G_{rt\omega} \forall r \in \mathcal{G}^N, t \in \mathcal{T}, \omega \in \Omega \tag{3.26}$$

$$\tilde{c}^i = V^i - \frac{1}{\alpha^i} \sum_{\omega \in \Omega} \pi_\omega \varrho^i_\omega \tag{3.27}$$

$$V^i - \Psi^i_\omega \leq \varrho^i_\omega, \ \forall \omega \in \Omega \tag{3.28}$$

$$\tilde{c}^i \geq -\phi^i \tag{3.29}$$

$$\overline{P_r} \geq 0 \forall r \in \mathcal{G}^N \tag{3.30}$$

$$0 \leq Q^i_d \leq 1 \forall d \in \mathcal{D} \tag{3.31}$$

$$\varrho^i_\omega \geq 0 \forall \omega \in \Omega \tag{3.32}$$

$$\phi^i \geq 0 triv4 \tag{3.33}$$

$$p^c_{dt\omega} \geq 0 \forall d \in \mathcal{D}, t \in \mathcal{T}, \omega \in \Omega \tag{3.34}$$

The objective function (3.23) is given as a maximisation of the mean-CVaR risk measure of the IOLR's profits (Ψ^i_ω) minus the annualised cost of capital reserved, where γ is an annual discount factor (setting aside of equity capital under a solvency constraint has an opportunity cost and must be incorporated within the insurer's surplus [280]).

Equation (3.24) defines the IOLR's profits. The first term represents premium revenues as the product of parameter C^P_d which is the insurance premium levied upon each consumer d and Q^i_d, a decision variable that reflects the fractional quantity of the maximum possible reliability insurance sold to consumer $d \in \mathcal{D}$; $Q^i_d = 1$ implies the consumer's outages will be perfectly covered. The second term represents insurance compensation payouts as the product of C^{voll}_d (in \$ per MWh), the VOLL compensation parameter as specified in the reliability insurance contract, $p^c_{dt\omega}$ the emergency demand curtailment associated with demand d, and Q^D_d. The next two terms represent the tolling payments made to strategic reserve capacity ($r \in \mathcal{G}^N$). The third term represents compensation for total variable costs incurred by the strategic generator as the product of unit variable cost C^{vc}_r and the out-of-market dispatch of the strategic generator $p^G_{rt\omega}$. The fourth term represents compensation for fixed costs as the product of parameter C^I_r (the annualised investment cost per MW) and $\overline{P_r}$ (the decision variable representing the built (continuous) capacity of strategic generator r).

The unserved demand parameter $p^{sh*}_{dt\omega}$ represents the maximum possible demand curtailment for demand d at time t in scenario ω. As per (3.25) demand curtailment can be reduced through prioritisation (*i.e.* prioritising the lower value load first) and through dispatch of strategic generation. Constraint (3.26) enforces capacity limits for strategic reserve capacity. Trivial constraints in (3.30)-(3.34) ensure that relevant decision variables are non-negative and that the fractional quantities of insurance contracts lie between 0 and 1.

The resultant optimisation problem is a non-convex bilinear program due to the presence of bilinear terms in the formulation $p^c_{dt\omega}Q^i_d$. A binary expansion could be used to convert the continuous Q^i_d into a set of binary variables and the exact McCormick relaxation [296] can be used to convert the problem into an MILP with special-ordered-set (SOS) constraints. However, in this case, the small number of bilinear terms enables the problem to be solved to global optimality by the Gurobi commercial solver under its Branch-and-Bound subroutine. This is able to solve the non-convex bilinear program to global optimality, (but does not provide a guarantee of such) [289, 297] within acceptable time frames).

The result of solving this model includes, for the assumed first stage WEM solution, contract revenues, insurance contract executions, liability coverage and compensation amounts, and the amount of strategic reserve capacity.

Decision-making framework for the Retail Consumer

The decision problem of retail consumer $d \in \mathcal{D}^R$ takes the form of an optimization problem (CON_d) based on a mean-CVaR utility maximisation of the consumer surplus as follows:

$$\max_{W^c_d} U^c_d = (1 - \beta^c_d) \sum_{\omega \in \Omega} \pi_\omega \Psi^c_{d\omega} + \beta^c_d \tilde{c}^c_d \tag{3.35}$$

where $W^c = \{\varrho^c_{d\omega}, z^c, Q^c_d\}$, and subject to:

$$\Psi^c_{d\omega} = (C^{voll}_d - \lambda^{E*}_{t\omega})(\overline{P^D_{dt\omega}} - p^{sh*}_{dt\omega}) - C^P_d Q^c_d + \sum_{t\in\mathcal{T}} C^{voll}_d p^{sh*}_{dt\omega} Q^c_d,\ \forall\omega\in\Omega \tag{3.36}$$

$$0 \leq Q^c_d \leq 1 \tag{3.37}$$

$$\tilde{c}^d_c = V^d_c - \frac{1}{\alpha^d_c}\sum_{\omega\in\Omega}\pi_\omega \varrho^c_{d,\omega} \tag{3.38}$$

$$V^c_d - \Psi^c_{d\omega} \leq \varrho^c_{d\omega},\ \forall\omega\in\Omega \tag{3.39}$$

$$\varrho^c_{d\omega} \geq 0,\ \forall\omega\in\Omega \tag{3.40}$$

The objective function follows the formulation in [204] but includes the ability for the consumer to hedge interruptions via the purchase of an insurance contract. Equation (3.36) defines the consumer surplus as the benefits from electricity consumption, minus the retail costs of electricity, plus any insurance compensation payable minus insurance premium payments. For each consumer, the key decision variable is Q^c_d, the fractional quantity of insurance purchased as a proportion of demand given the insurance premium charged C^P_d (which is provided as a parameter to the decision problem). It is assumed that real-time wholesale marginal costs of electricity are passed on from the retailer to the consumer [4]. Constraint (3.37) limits insurance contract purchases Q^c_d to a fractional quantity between 0 and 1 (as a proportion of demand), while constraints (3.38)-(3.40) define the CVaR. Both $\overline{P^D_{dt\omega}}$ and $p^{sh*}_{dt\omega}$ are not decision variables i.e. determined by the first layer WEM model, and fixed in this SRP layer, with the purchased volume of insurance being the key output of the model.The consumer problem takes the form of a constrained linear program that can be solved to global optimality.

SRP: Insurance equilibrium

This section provides an algorithm to search for an equilibrium in the SRP layer. The IOLR and consumers are both assumed to be rational utility-maximising agents. The key external parameter that affects both types of participant is C^P_d, the insurance premium levied upon consumers. Given that the IOLR and retail

[4] More complex and realistic rate designs should be a subject of future research.

consumers in the SRP are assumed to be price takers and are assumed not to be able to exercise market power, the insurance premium C_d^P is set as a parameter in the decision problem of the insurer of last resort (IOLR), and that of retail consumers. The premium is adjusted as per the tatonnement algorithm to ensure a balance between insurance contract demand and supply.

The multiple of the insurance premium relative to the expected value of losses is used as an ex-post evaluation criterion to provide a relative measure of insurance premium affordability.

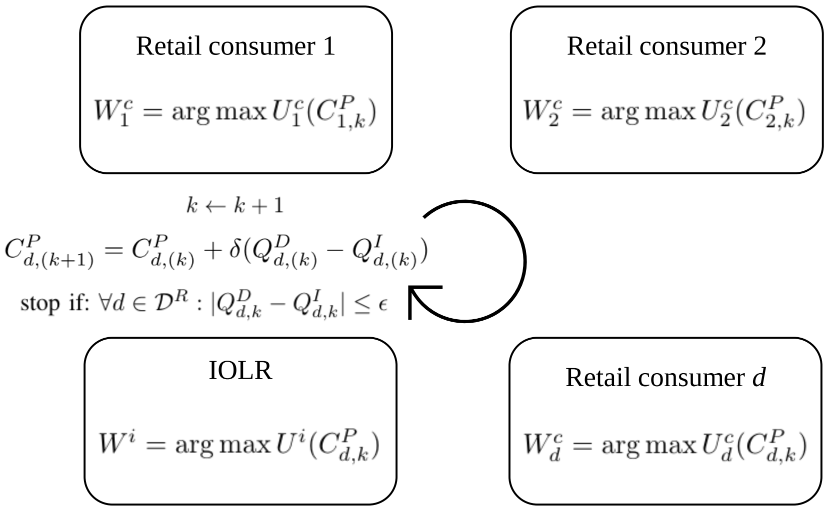

Figure 3.4: Schematic illustrating the tatonnement algorithm used to find an equilibrium in the SRP layer

.

As set out in Algorithm 13, a tatonnement (trial and error) process is developed to compute an equilibrium whereby different values of the insurance premium are trialled based on the insurance quantities sold and purchased by the IOLR and consumers, respectively. The algorithm draws most heavily upon the work of Mays [72] and Hoschle [204] where a price is updated based on the differential between buy and sell quantities of the relevant contract. This approach is a variant of the Gauss-Seidel diagonalisation method [204] and is used for contract balancing and price setting [72]. Uniqueness and existence under such conditions remain an open issue, beyond simple case study analysis. The initialisation of the algorithm begins with an initial instance of problems INS and $CON_d \forall d \in \mathcal{D}$, and initial values for insurance premiums for each insurance contract between the IOLR and consumer $d \in \mathcal{D}$. For iteration k, the problems INS and $CON_d \forall d \in \mathcal{D}$ are run simultaneously, and the insurance premiums for each insurance contract are updated based on the differential arising between the quantities purchased and the quantities sold (*i.e.* if purchase volumes are greater than sell volumes, the price is incremented upward, and vice versa). The algorithm is terminated when the difference between the quantities purchased and sold for each insurance contract is negligible. For the full market design, Algorithms 1 and 2 are run sequentially, with the decision outcomes in Algorithm 1 informing the solution of Algorithm 2. As with the diagonalisation method, this algorithm does not provide guarantees relating to finding a solution or of solution uniqueness. However unique equilibria were found in the case studies, and when tested against a range of alternative initialisation conditions.

Algorithm 2: Tatonnement to find an insurance equilibrium in the SRP layer

input : Initial instance of problems (INS,$CON_d \forall d \in \mathcal{D}$)
output : Equilibrium solution

initialisation:
set ϵ,δ, iteration counts k
set initial value of $C_d^P \forall d \in \mathcal{D}$
while $\max_{d \in \mathcal{D}} |Q^c_{d,(k)} - Q^i_{d,(k)}| > \epsilon$ **do**
  solve (INS)
  for $d \in \mathcal{D}$ **do**
    solve (CON_d)
  end
  $C^P_{d,(k+1)} = C^P_{d,(k)} + \delta(Q^c_{d,(k)} - Q^i_{d,(k)})$
  $k \leftarrow k + 1$
end
return
.

3.2.4 Risk neutral social optima

For comparison, a risk-neutral socially optimal generation expansion model is also constructed. In this setting, the problem is represented as a single large-scale optimisation problem, one that seeks to minimise the total scenario-weighted expected costs of generation and demand. The mathematical formulation for the optimisation problem is written as:

$$\min_{\{p^G_{rt\omega}, p^{sh}_{dt\omega}, \overline{P_r}\}} C^I_r \overline{P_r} + \sum_{\omega \in \Omega} \pi_\omega \Psi^S_\omega \tag{3.41}$$

subject to:

$$\Psi^S_\omega = \sum_{t \in \mathcal{T}} \sum_{r \in \mathcal{G}} C^{vc}_r p^G_{rt\omega} + \sum_{t \in \mathcal{T}} \sum_{d \in \mathcal{D}} C^{sh}_d p^{sh}_{rt\omega}, \forall \omega \in \Omega \tag{3.42}$$

$$\sum_{d \in \mathcal{D}} (\overline{P^D_{rt\omega}} - p^{sh}_{rt\omega}) = \sum_{r \in \mathcal{G}} p^G_{rt\omega}, \ \forall t \in \mathcal{T}, \tag{3.43}$$

$$0 \leq p^G_{rt\omega} \leq \overline{P_r} A^G_{rt\omega}, \ \forall r \in \mathcal{G}, t \in \mathcal{T} \tag{3.44}$$

$$0 \leq p^{sh}_{dt\omega} \leq \overline{P}^D_{dt\omega}, \ \forall d \in \mathcal{D}, t \in \mathcal{T} \tag{3.45}$$

3.3 Case Study

The insurance mechanism design is evaluated on a numerical study based on the South Australian system. The parameters are chosen to best illustrate the operation of the market design, rather than to recreate or predict market outcomes. For this case study, the outcomes from an energy-plus-insurance market (EIM) design are compared with an energy-only market (EOM) design and a risk-neutral socially optimal generation expansion (RN).

The success criteria for this case study are based on quantitative metrics for unserved energy, system welfare, and insurer financial viability. First, the *energy plus insurance* model must ensure that the total system unserved energy (USE) is acceptably small, and materially below an energy-only market design on both probability-weighted scenario-average and worst-case basis. Second, the *energy plus insurance* methodology must deliver total system welfare that is in excess of an energy-only market design. Third, the *energy plus insurance* model must be able to demonstrate reliability differentiation based on revealed consumer preference. Finally the *energy plus insurance* model must demonstrate that the insurer is financially viable, that is it has a net positive utility on a risk-adjusted basis.

3.3.1 Data and Sources

Given the focus on dispatchable generation resources to balance variable renewable energy (VRE), the total capacity of VRE generation is determined exogenously; aligning with explicit renewable generation policy targets across a range of power systems, including the NEM. VRE generation capacity is sized to a target percentage of annual VRE generation as a percentage of demand.

VRE availability projections are sourced from [298], which provides variable generation availability on an asset and regional level for 20 annual scenarios, and with 17520-time intervals in each scenario (*i.e.* every half hour). Availability projections from the South East SA Wind Renewable Energy Zone are adopted, which with a VRE target of 40% of annual South Australian demand, results in 2,100MW of required wind capacity in the system.

Each generator can choose to build the capacity of a particular generation technology based on risk preferences. For the base case, three natural gas-fired dispatchable generation technologies are considered, combined cycle gas turbine (CCGT), open cycle gas turbine (OCGT), and reciprocating engine (RE), with 6 agents for each generation technology. Heat rates and investment costs are adopted based on 2x2x1 GE7HA.02 configuration for CCGT, 1xGE7FA configuration for OCGT, and 12x18 Wärtsilä 50DF dual-fuel configuration for RE. Heat rates and annualised investment costs for CCGT and OCGT technologies are sourced from [299] and converted into Australian $ based on a US $ to Australian $ exchange rate of 1.35, while RE estimates are based on publicly available information for the recently constructed Barker Inlet Power Station [300] (as a relevant comparator was unavailable in [299]). A gas price of $6 per GigaJoule is assumed. Each participant is assumed to have an equal preference between the maximization of the scenario-weighted average profits and the CVaR risk measure (*i.e.* a β_r^G of 0.5) with a risk confidence level of 10% for CVaR (*i.e.* α_r^G of 0.10). Assumptions are summarised in Table 3.1.

Table 3.1: Generation Assumptions for Case Study

.

	CCGT	RE	OCGT
Net heat rate (GJ/MWh)	6.7	7.9	10.4
Variable operating cost ($/MWh)	2.6	2.5	6.1
Total variable cost, C_g^v ($/MWh)	42.9	49.9	68.8
Investment cost annualised, C_g^I ($/MW/yr)	114315	119235	80276
Number of generators	6	6	6
CVaR confidence level, α_r^G	0.1	0.1	0.1
Risk tolerance, β_r^G	0.5	0.5	0.5

Total South Australia system load projections are based on [298], which provides projections for every half-hour of a year, across 20 annual scenarios. Twenty-four representative days for demand and VRE generation are selected from each of the scenarios using a Ward hierarchical clustering algorithm [301]. Figure 3.5 shows the box plot distribution of total demand across the scenarios.

Demand parameters are set out in Table 3.2. Based on benchmark state-of-the-art spot market design, multiple classes of demand have been incorporated. The model distinguishes between retail consumers (whose demand is fixed and inelastic) and market consumers who bid their VOLL in the electricity spot market (and are actively curtailed based on economic dispatch). It is assumed that there exists 102MW of market consumer capacity that is able to bid in spot markets at bids ranging from bid prices ranging from $300/MWh to $14,000/MWh, based on demand side participation projections in [298]. The source of this demand bidding is expected to be primarily commercial demand response and aggregated flexible heating, ventilation, and air-conditioning (HVAC) load. It is assumed that there are four classes of retail consumers, each with a 25% share of the total system load, with VOLL ranging from $15,000/MWh to $30,300/MWh [302].

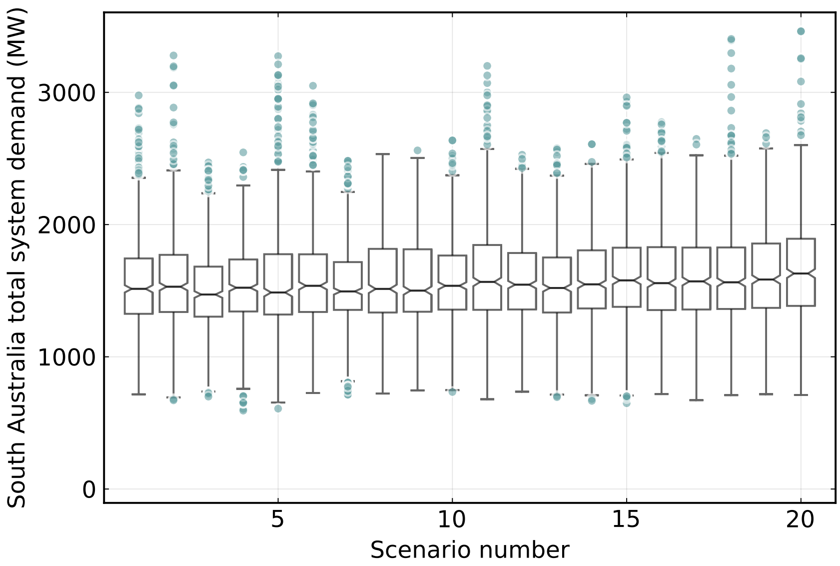

Figure 3.5: Box plot distribution of South Australia total system demand across 20 annual scenarios. The maximum demand across all of the scenarios is 3,464 MW, and the minimum demand is 593 MW.

The insurance compensation value for each demand type is set to the respective VOLL. In the base case, retail consumers are assumed to be risk averse with β_d^c of 1 and tail probability α_d^c of 0.01.

Table 3.2: Demand assumptions for Case Study including demand bidding

Demand type	Demand bidding	Bid C_d^{sh} (\$/MWh)	Quantity $\overline{P_{d,t,\omega}^D}$ (MW)	Insurance	VOLL C_d^{voll} (\$/MWh)
D1 'retail consumer'	x	-	-	✓	15,000
D2 'retail consumer'	x	-	-	✓	20,200
D3 'retail consumer'	x	-	-	✓	25,300
D4 'retail consumer'	x	-	-	✓	30,300
D5 'market consumer'	✓	400	4	x	400
D6 'market consumer'	✓	750	13	x	750
D7 'market consumer'	✓	4,250	15	x	4250
D8 'market consumer'	✓	7,500	35	x	7500
D9 'market consumer'	✓	14,000	35	x	14000

The spot electricity market is cleared on the basis of optimal merit-order dispatch and settled on the marginal price with participants bidding on the basis of short-run marginal cost with an administrative market price cap of $15,000 per MWh.

The IOLR is assumed to have a tail probability α^i for the CVaR risk measure set at 0.5% (consistent with international insurer solvency standards of assessing worst-case outcomes with 99.5% probability [303]). In the base case, it is assumed that the IOLR utility preferences are risk neutral, though risk is incorporated in solution space via the solvency constraint (*i.e.* a β_i of 0.0), which provides a conservative estimate of the potential benefits of the EIM design in incentivising additional generation investment. Premiums are initialised at a 1.0 multiple of expected losses. The code was written in Julia and the solution was obtained using Gurobi 9.5 on an Intel Core i7 (9th-Gen) 2.60 GHz CPU with 16GB RAM. Each WEM bilevel problem has over 600,000 variables, The IOLR decision problem has approximately 700 variables and over 46000 quadratic objective terms. An optimal gap of 0.1% is set for solving each optimisation. Given the non-convex nature of the final set of decision problems, computation times for finding equilibria exceeded a week.

3.3.2 Results

Effects on investment, reliability and social welfare

In Table 3.3 a comparison of outcomes between the EIM, the EOM, and the RN models under base case assumptions is presented. In each case, the same equilibrium was found for the case under consideration when tested against a limited range of starting conditions. Specifically, four additional iterations were run with different starting points based on the following procedure. For each iteration, an individual generator was selected at random (based on a uniform distribution), and its starting capacity set based on a random value selected from a uniform distribution across a range from 0MW to 3500MW (with this level approximately the maximum demand of the system across the scenarios).

Under the EOM, the total capacity of generation built is 2,730MW and, under the EIM, the IOLR supports an additional 398 MW of peaking generation under the strategic reserve. This is relative to 3,317 MW built under the risk-neutral social optimum. The key reason why plant stock is highest in the RN scenario is that it represents a socially optimal outcome, implicit in which is the assumption of complete trading [72]. This enables the optimal selection of plant stock that maximises social welfare, without needing to consider the specific instruments available for risk trading. In incomplete markets, such as the EOM and EIM, risk aversion limits the incentives for future plant build. By providing an additional risk hedging mechanism between the insurer and generators, the EIM provides generators with the missing money to incentivise more plant stock than what is enabled in the EOM alone.

The difference in total generation investment between the EOM case and risk-netural social optimum of 587MW is also indicative of the impact of market power of generators. While not modelled in this work, market power could also persist in the spot market to allow bidding in excess of SRMC, as well as more generally through cross-ownership of generation assets, and vertical integration across generation and retail sectors.

Reliability outcomes are improved under the EIM, with an average system unserved energy (USE) of 0.015%, below the result of 0.035% under an EOM, and relative to that of the risk-neutral social optima of 0.001%. Worst case scenario USE outcomes are also better at 0.116% for the EIM, relative to the EOM at 0.311%. The reliability outcomes from the simulation demonstrate that USE for the EIM is materially improved over the EOM, and is at an acceptable differential against the risk-neutral optimum.

Total changes in system welfare (calculated as the sum of generator, consumer and insurer welfare) relative to the risk-neutral optimum, are shown for the EOM and EIM market designs. The RN case is expected to have the highest (risk neutral) social welfare, as it represents an optimal (risk neutral) utility maximisation. Relative to the RN case, system welfare is $33.7 million and $98.1 million lower for the EIM and EOM, respectively. This demonstrates a relative improvement in social welfare for the EIM over the EOM under the contemplated case study.The EOM and EIM welfare outcomes are also compared to a risk-averse social optimum evaluated under the utility functions of the various agents (i.e., the generators and consumers). This is termed as *RA-Agent* in 3.3. Given the risk-aversion of the agents, total system welfare under RA-Agent social optimum is \$56.6 million lower than that of the risk-neutral social optimum. Thus, comparing the EOM and EIM outcomes to that of RA-Agent, it is found that system welfare under the EOM is \$40.5 million below that of RA-Agent, but the system welfare under the EIM is actually \$23.9 million above the RA-Agent optimum.

Table 3.3: Risk-neutral social optimum (RN), energy-only market (EOM), and energy-plus-insurance market (EIM) outcomes under 40% renewable target
.

Market design	RN	EOM	EIM
Total capacity (MW)	**3317**	**2730**	**3128**
Market generation	3317	2730	2730
Strategic generation	-	-	398
USE - mean (%)	0.001	0.035	0.015
USE - worst (%)	0.020	0.311	0.116
System welfare, Δ to RN (\$m)	-	-98.1	-33.7
System welfare, Δ to RA-Agent (\$m)	-	-40.5	+23.9

It is also important to examine the results relating to reliability outcomes for individual consumers. Market consumers have the same outage experience under the EIM, EOM, and RN, given they bid directly into spot markets. The experiences of retail consumers (D1-D4) are different across designs, as shown in Figure 3.6. In the EOM, the USE experience of all retail consumers is the same with average and worst-case USE across scenarios (at 0.023% and 0.255% respectively). The prioritisation in the EIM allows for the periods of unserved energy to be allocated to lower-value consumers, illustrative of differential reliability experiences between consumers. For example, the average USE for consumer D1 (with the lowest VOLL of all retail consumers) is 0.008%, while D4 (with the highest VOLL) experiences no outage. This illustrates how the scheme enables differential reliability. The insurance premium paid also scales based on the value of the load, at \$11 million for D1 versus \$23 million for D4 (or \$33 to \$67 *per annum* when scaled down based on

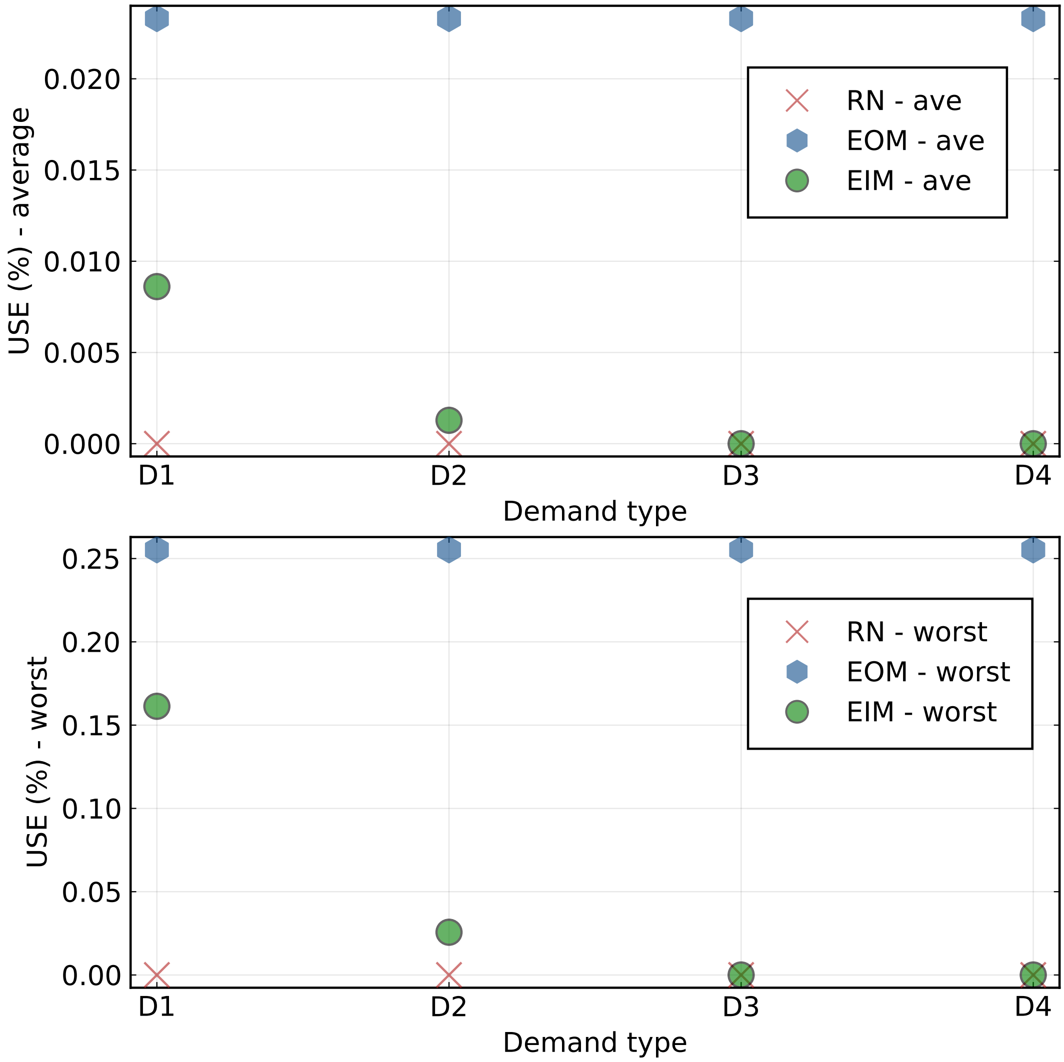

Figure 3.6: Unserved energy (USE) outcomes segregated by demand type compared across an energy-only-market (EOM), energy-plus-insurance market (EIM), and risk-neutral (RN) optimum - illustrating USE under an EOM remain higher than RN outcomes but lower than an EOM.

peak demand to a consumer with a peak load of 10kW). Together with the intraday illustration in 3.7 this demonstrates the capability of the design in differentiating reliability outcomes based on revealed preferences of individual consumers.

Insurer financial outcomes

The financial outcomes of the IOLR are presented in Table 3.4. The insurer is able to generate a positive expected profit (weighted across scenarios) of $32.3 million. The CVaR (under a tail probability 0.5%) is $-61.6 million, which is in line with an insurance business model that is exposed to rare but extreme outcomes. However, the solvency constraints ensure that the IOLR holds sufficient cash reserves to offset financial losses equivalent to a 0.5% CVAR. Moreover, the IOLR invests in material additional generation capacity (in 398MW of OCGT), although the utilisation of the resource is very limited with an average annualised capacity factor (ACF) of 0.1%. The cost of meeting the incremental reduction from the SRP is approximately $9400/MWh. This suggests that the capacity is mainly a reserve and only used in worst-case or emergency scenarios. Given $4.5 million in capital costs associated with holding technical reserves, the IOLR has a positive utility of $27.7 million indicating that it is financially viable in the case study.

Table 3.4: Insurer-of-last-resort financial outcomes

Financial outcome	**Result $ million**
Premium income	69.6
Generator variable costs (range)	0.0 to 1.6
Generator capital costs	31.9
Insurance compensation (range)	0.0 to 97.6
Strategic generation	
OCGT capacity	398MW
RE capacity	0MW
CCGT capacity	0MW
Generation ACF	0.1%
Expected profit	32.3
CVaR of profit	-61.6
Technical reserves	61.6
Technical reserves - annualised cost	4.5
IOLR Utility	27.7

Priority curtailment

Figure 3.7 provides an example of the scheme in operation for a representative day. For both cases, market consumers D5-D9 are curtailed in priority of their demand bids for both an EOM and EIM design. However, for retail consumers D1-D4 (where VOLL is greater than MPC), there are distinct differences in outcomes. Under an EOM (Figure 3.7(a)), the retail load is curtailed on a rotating basis (whereupon each load receives a proportionate share of curtailment). This is reflective of rolling blackouts typically imposed by the system operator during extreme scarcity. Under an EIM (Figure 3.7(b)) with an operational priority curtailment scheme, demand is curtailed in ascending order of the insurance compensation value specified in insurance contracts. Two effects are prominent in this example: first, the quantum of curtailment experienced is lowered due to the incremental generation procured by the IOLR in the EIM scheme (398MW lower at the peak); and second, the prioritisation scheme allows loads with lower VOLL to be curtailed in greater proportion, preserving higher value uses across the representative day (for example, the EIM reduces the curtailment of the highest value D4 load by 557MWh over the day).

Sensitivity to Risk Attitudes of Generation

A sensitivity analysis (Figures 3.8 to 3.11) is run against the risk preferences of market generation; wherein risk aversion of generators are varied from a risk-neutral attitude ($\beta_r^G = 0.0$) to a risk-averse attitude ($\beta_r^G = 1.0$). The intent of running such a scenario is to indicate how reliability outcomes are affected by a changing risk environment. This provides a measure of the robustness of the market design to changing market dynamics.

In Figure 3.8 the quantities of market and strategic generation investment with increased generator risk aversion are shown. As generators become increasingly risk-averse and less willing to take on the downside risk from spot prices, less generation is built varying from 2,819MW (risk-neutral generators) to 2,138MW (risk-averse generators). As the IOLR faces exposures to higher market demand

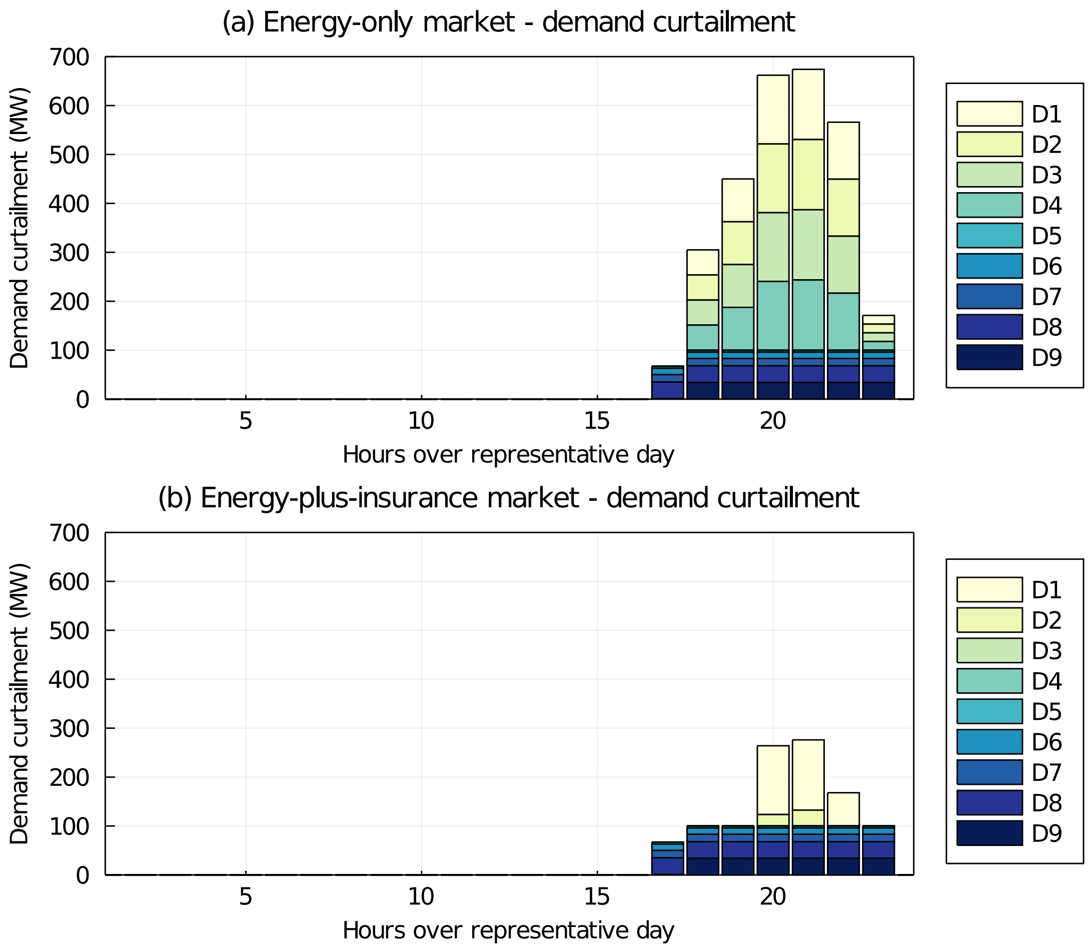

Figure 3.7: Lost load outcomes under (a) EOM with market price cap and (b) an EIM with insurance and priority load curtailment (where the load is curtailed in order of lowest VOLL). The example provided is of lost load outcomes for scenario 18, representative day 12. Load curtailment is reduced in quantum and duration, due to incremental strategic generation capacity being dispatched, and priority curtailment of load in ascending order of value.

shortages from lower market generation capacity, it adjusts its strategic reserve procurement quantities to partially offset the reduction in market generation, with additional strategic reserves procured by the IOLR increasing as market risk-aversion increases. The IOLR procures 942 MW from strategic reserves for the $\beta_r = 1.0$ (risk-averse generation) scenario relative to 364 MW in the $\beta_r = 0.0$ (risk-neutral generation) case.

Figure 3.9 sets out the expected USE outcomes with increased generator risk aversion. Under an EOM design, the reduced investment flowing from higher generator risk aversion impacts reliability, with expected USE increasing non-

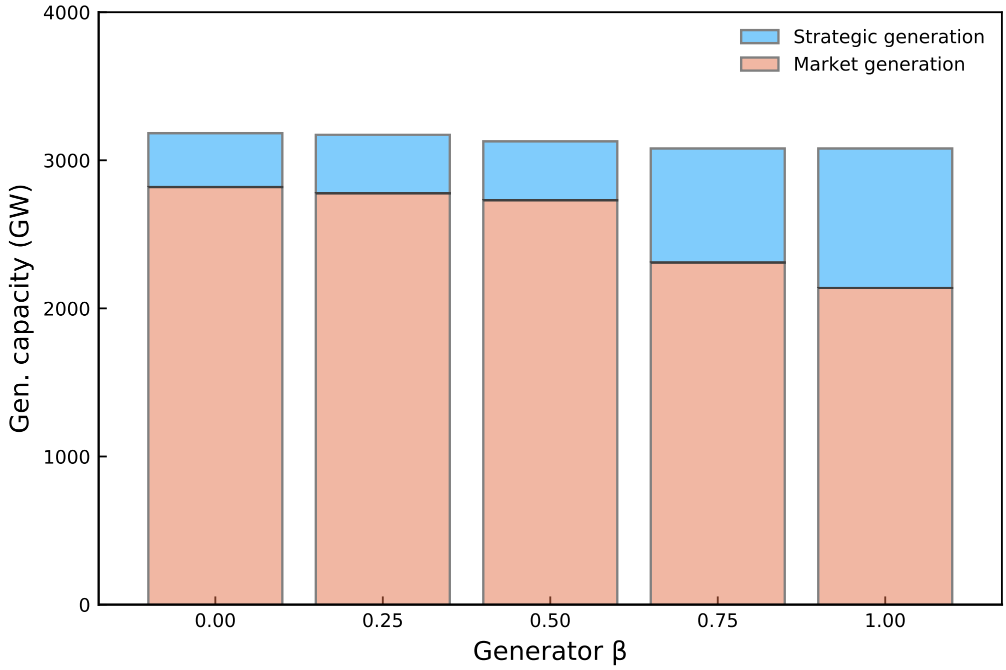

Figure 3.8: Impact of generator risk aversion on the quantities of market and strategic generation capacity, where β_r is varied from 0.0 to 1.0. As risk aversion increases the level of market generation supported via spot prices reduces, with higher offsetting levels of strategic reserve procurement.

linearly with a higher aversion to risk. While the EIM design also records higher USE with greater generator risk aversion, the expected USE is less than half of that experienced in an EOM alone, as higher strategic generation investment offsets the reductions in market generation investment. Intuitively, insurance premiums (Figures 3.10 and 3.11) also rise under higher risk aversion, reflecting the increased demand shortage risks from insufficient market-based generation. Initially, this also requires higher technical reserves (entailing higher capital costs), but at $\beta_r \geq 0.75$, additional premium income supplements the cash position, thereby requiring reduced technical reserves to meet the solvency constraint. Interestingly insurance premiums, in equilibrium, are lower on a relative basis for the risk-averse case at 0.1-0.2 times expected losses, as compared to 0.7-1.0 times for the risk-neutral case. This suggests that, while the absolute cost of insurance rises, the IOLR is incentivised to keep costs lower on a relative basis to avoid customers churning away from insurance.

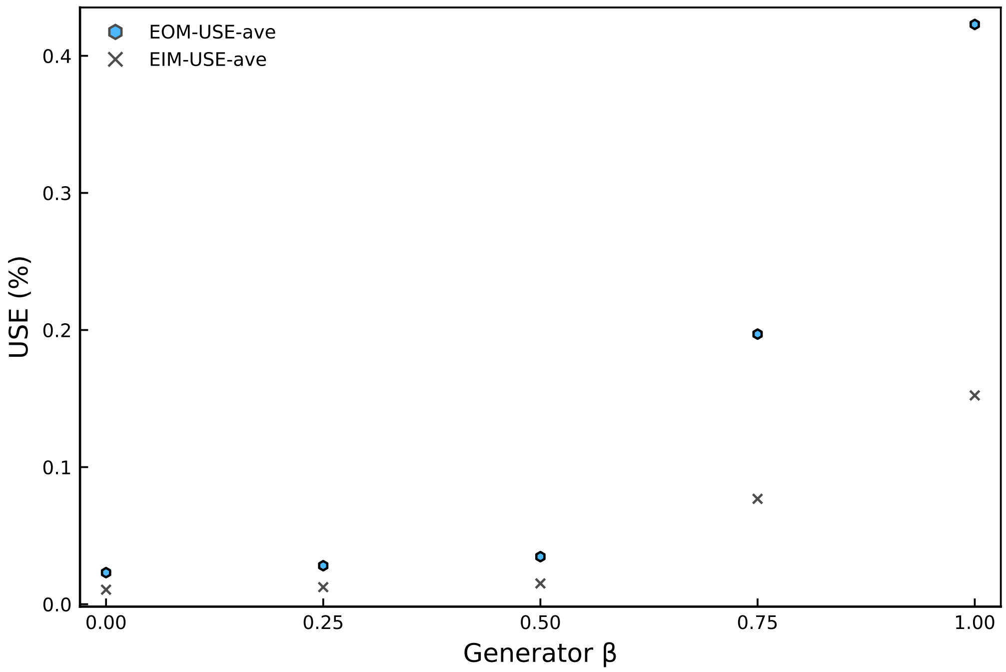

Figure 3.9: Impact of generator risk aversion upon average USE Sensitivity on the impact of generator risk aversion upon average USE, where β_r is varied from 0.0 to 1.0. While USE is higher in a risk-averse case relative to risk-neutral for both EOM and EIM designs, on a relative basis average USE for the EIM is less than half the EOM level

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Sensitivity to Risk Attitudes of Consumers and IOLR

An additional sensitivity has also been run with respect to the risk attitudes of consumers and the IOLR, with both risk aversion of consumers and the IOLR set to 0.5 ($\beta_d^c = 0.5$ & $\beta^i = 0.5$). It is observed that the results are sensitive to the risk-aversion parameters across many aspects. First, in relation to the insurance contracts, a balanced risk-attitude for consumers and the IOLR reduces the willingness to buy and sell insurance respectively. As such, insurance contracts are only signed with retail consumers D3 and D4 (compared to the base case where all retail consumers purchased insurance). It is interesting to note however, that despite the moderated risk attitudes some insurance contracting persists. Second, the level of strategic generation investment is reduced to 287MW (relative to 398MW in the base case). Consequently, the unserved energy outcomes are poorer, with mean USE and worst-case USE at 0.024% and 0.191% respectively (relative to the base case at 0.015% and 0.116%). Thus, while the moderated risk attitudes reduce the level of

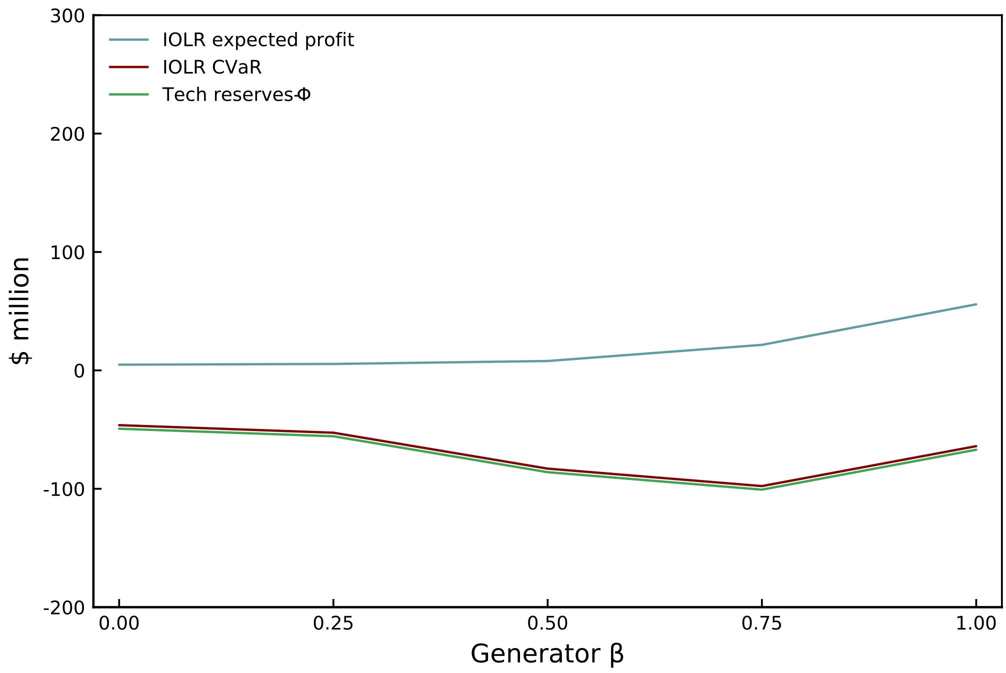

Figure 3.10: Impact of generator risk aversion on IOLR expected profits, CVaR and the level of technical reserves required, where β_r is varied from 0.0 to 1.0. Higher risk aversion drives lower market generation investment, and consequently higher unreliability. This increases the premium income of the IOLR. Initially this means that more technical reserves are required, but at $\beta_r \geq 0.75$, additional premium income supplements the cash position requiring less technical reserves.

contracting and investment, the outcomes remain improved over the EOM results.

Sensitivity to Lower Market Price Cap Settings

A further sensitivity analysis is also run against alternative market price caps settings with the imposition of a lower market price cap of \$5000/MWh for the WEM. The intent of such a sensitivity is understand how insurance and strategic reserve procurement adjust to alternative market settings. The lower market price cap exacerbates the missing problem that persists in wholesale spot markets, resulting in a lower level of market generation investment of 2145MW, relative to the original case of 2730MW. Given the extent of the market distortion, the IOLR adjusts its procurement levels in line the reliability preferences of consumers, procuring more resources to mitigate the gap investment caused by the missing money. To mitigate the gap the IOLR procures additional strategic reserves of 790MW. Comparing the EOM and EIM outcomes for this case the differences in unserved energy outcomes

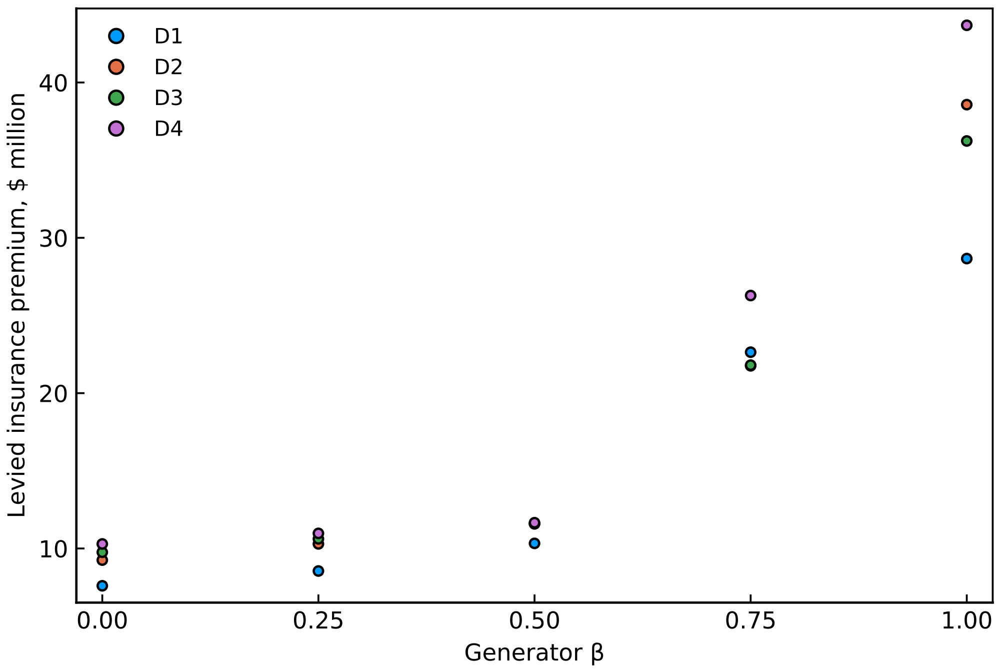

Figure 3.11: Impact of generator risk aversion on consumer insurance premiums, where β_r is varied from 0.0 to 1.0. With higher USE under risk aversion the required premiums to insure reliability risks increase.

are stark. Expected USE for the EOM and EIM at 0.410% and 0.081% respectively. Worst case USE for the EOM and EIM are 1.268% and 0.236% respectively.

3.4 Discussion

The results of the case study suggest that there are benefits associated with market designs that enable the election of differential reliability preferences and an actuarial framework for pricing such heterogeneous preferences. Under the proposed *energy plus insurance* market design, when combined with load control technology, consumers could value essential load in the home differently from non-essential load. This could guide more granular curtailment during emergencies allowing for the preservation of essential services, thereby mitigating against 'all-or-nothing' outcomes. The results point to four further considerations for research inquiry into differential reliability and insurance mechanisms.

3.4.1 Reliability differentiation

The simulation demonstrates the variation of reliability outcomes across heterogeneous demand and the sensitivity to the ascribed VOLL of each demand in the simulation. Taken together with the impact on the investment incentives, this suggests that the valuation and contracting process between retailers and the insuring entity will be a key focus area in the next phase of design. The elicitation of unique consumer preferences must be considered in the practical context of consumer participation in electricity markets. Three layers are important here, specifically the physical layer, the financial layer, and the engagement layer.

A key objective for the physical layer is that the upgrade of physical infrastructure should be aligned with the progression of broader initiatives around grid flexibility and modernization (including, for example, the roll-out of digital metering). While one option for implementation is direct load control at the connection point through, for example, circuit switches, alternative approaches that use indirect forms of control may be more efficient and less intrusive [304]. One example is the energy routing scheme proposed by Papalexopoulos et al. [278]. Another set of approaches would have the insurance contract specifying the functional constraints and charges, with the load controlled and managed at the consumer end (see [305, 306] for illustrations of such controls). Such approaches may also be more acceptable from a consumer privacy perspective.

With respect to the engagement layer, it would be beneficial to retain the existing consumer-retailer relationship in the market. While more sophisticated consumers have shown a capability to interact with multiple agents (retailers, aggregators, risk hedgers, *etc.*), retail consumers are likely to prefer to engage with a single point-of-contact for retail supply. This suggests that, for the financial layer, the insurance premium should be incorporated as a component of the retail tariff. This will also assist with managing bill complexity and customer confusion. Careful engagement and education should take place in introducing the insurance product. Though helpfully in many markets consumers are already familiar with fixed charges in retail bills (*e.g.* through network and access tariffs). In some cases retailers are already offering a price hedging product as a form of insurance [307] and a recent rule change in the NEM allows for multiple electricity retail trading relationships at the same retail site [308]. As this design is intended to facilitate high renewable penetration, the addition of an insurance premium could be complemented by a lower energy charge, to facilitate consumer take-up.

The granular modelling of the impacts of consumer differentiation is an worthwhile natural extension to this work. More granular modelling on prioritisation at individual consumer use levels is desirable (e.g. essential versus non-essential uses) as well as differentiation between customer segment load profiles. Furthermore, it would be important to compare outcomes with and without differentiation (where all consumers pay a common price for contracts, with random curtailment, notwithstanding diverse VOLL and risk preferences).

3.4.2 Extreme events and resilience

This chapter is focused on the adequacy of power systems and, while the uncertainty scenarios modelled here cover a range of weather year outcomes, they do not specifically model extreme weather events. As discussed in Chapter 1, resilience to extreme events represents an important field of risk management in the power system. As such the role of insurance frameworks in the context of extreme events requires further and more granular investigation. Here the role of distributed energy resource (DER) also warrant attention. While DERs offer multiple streams of value, one of the potential benefits in terms of resilience relates to their siting (i.e. at the customer site) and diversity (i.e. multiple small sites rather than a few large scale generation sites). This has the potential to mitigate issues associated with network unreliability. Extreme events in particular have the potential to impact networks and large-scale resources. Thus while DER can provide reliability benefits not just limited to extreme events, considering them in such context would allow a fuller appreciation of their contributions to system resilience. To this end three specific areas of extension are proposed with respect to this area. First, it is suggested that the modelling of the system and network be extended to a more granular representation of the electricity transmission network; secondly, it would be important to integrate the full range of system resources - including distributed energy resources as part of the system mix, and; third, the frameworks for setting regulatory reserves and solvency constraints with respect to system resilience. This extended problem is considered further in the subsequent chapter.

3.4.3 Industrial organisation

The sensitivity of results to risk aversion means that the organisational, ownership, and capital structure of the insurers requires close attention. Organisational models can vary in the level of decentralisation of decision-making, and the nature of contracts executed with resources. While this chapter focuses on a centralised model for the purposes of computational tractability and results interpretation, the implementation could consider both centralised and decentralised models of organisation. The potential for a decentralised investment decision-making model, integrated within existing retailer obligations [309], is a worthwhile consideration for practical application. The benefit of such a model includes private sector innovation in areas including risk assessment; monitoring and mitigation; tariff design; and load control. Integrating priority service tariffs [179] could exploit differentiated reliability given heterogeneous consumer preferences. By contrast, the centralised model allows for a system-wide view of risk and resource investment as well as transparency in resource contracts and insurance pricing.

It is important to this model that the insurer can obtain accurate and timely information regarding the compensation preferences of consumers. The obstacles to getting such information are likely to fall into three broad categories: (i) privacy concerns, (ii) the comprehension of risk; and (iii) to the consumer's awareness of her own preferences. A comprehensive privacy regulation, and consumer education. Initially, insurance compensation amounts may initially be based on market surveys and estimates of VOLL, with the data on consumer elections for or against insurance providing insight from which insurers can provide more granular or specific plans.

Specific areas of extension this regard include: first, the comparison of centralised and decentralised market models of insurance - including the consideration of alternative competitive and regulatory frameworks; second the consideration of privacy aspects of insurance contracts - including decentralised models that could preserve privacy; this also links with the theoretical studies on incentive compatibility and truth revelation as mentioned in Section 3.4.5; finally the regulatory aspect of insurance requires further study including how reserving frameworks are set, modelled and enforced, and impacts upon provider credit worthiness and customer exposure.

3.4.4 Vulnerability and equity

The variation in unserved energy outcomes and levied premiums suggests that further consideration must be given to the treatment of vulnerable consumers. Vulnerable consumers may be less able to afford insurance premiums associated with energy-plus-insurance designs and may seek to insure at low coverage levels or decline insurance completely. This puts the most vulnerable at risk of outage during extremes. These issues are not restricted to an *energy-plus insurance* design, applying similarly to an *energy-only design*, and are part of a broader aggregation of issues concerning consumer equity in energy markets. An *energy-plus insurance* model may have equity benefits over scarcity pricing schemes. Dynamic real-time prices may be highly volatile during scarcity. By contrast, the insurance premium component of an EIM is a fixed payment that does not scale during scarcity. Energy subsidy or safety net schemes currently in place for energy prices, such as the UK Warm Home Discount Scheme [310] can similarly be applied to the energy-plus-insurance model. The treatment of vulnerable consumers represents an important area of future research inquiry for this topic.

3.4.5 Theory and methods

An important set of extensions of this work relates to the theoretical properties of the equilibrium problem of the market design. Specific areas of extension in relation to theory and methods are set out below.

First, the following possible conjecture could be investigated. In a market equilibrium, a generator with short-run marginal cost (SRMC) of C_r^{vc} cannot be idle in the SRP if a generator with a higher short-run marginal cost $C_r^{vc} + \varepsilon$ (where $\varepsilon > 0$) is operating in the WEM. This is under the assumptions of convexity with no discrete decision variables, and generators bidding in the spot market at SRMC. If true, this conjecture could potentially allay the risk that the SRP could result in inefficient dispatch, with cheaper generators being idle, when more expensive generators are operating in the WEM.

Second, the issue of incentive compatibility and truth revelation is an important consideration in design of an energy plus insurance market framework. Incentive compatibility is defined as the consumer selecting the insurance contract intended for her type, given the value of lost load of the particular consumer. Zhao et al. [311] provide sufficient conditions for incentive compatibility under simplified conditions of a risk-neutral insurer that only makes investments in variable renewable energy. However, it would be important to consider incentive compatibility in more complex situations such as with different forms of investment, with multiple insurers and in the presence of a spot market for electricity.

A further important theoretical proof lies in the consideration of EIM and RN outcomes under assumptions of risk neutrality and the absence of market power. In such a case, the WEM equilibrium model could be able to be translated into a single optimisation problem based on a central social welfare maximisation with the consumers cost of demand shortage load based on the market price cap. An understanding of the gap in outcomes between EIM and RN outcomes in such a case would also be an important theoretical contribution.

Finally, notwithstanding the testing of limited alternative starting points, it is entirely possible that other equilibria do exist for this case study. The explainability of equilibria and proof of equilibrium properties is a critical aspect for the furtherance of the market design, and it should be considered as part of future research in this area. This thesis recommends a specific plan for the investigation of equilibrium properties associated with the ‘energy plus insurance’ model, involving four areas of focus.

First, it should be considered and assessed whether the market problem formulation is able to satisfy Rosen’s conditions for the existence and uniqueness of equilibrium points for concave games. Considering an N-person game with shared constraints, by requiring appropriate concavity in the payoff functions of agents, Rosen [312] proves that a unique equilibrium point exists for the concave game. Thus the existing formulation for ’energy-plus-insurance’ market design should be assessed as to whether it meets the concavity conditions specified in [312].

Second, it is proposed that equivalent forms of variational inequality problems for the market formulation be investigated to understand whether uniqueness can be theoretically proved. The uniqueness (or singleton nature) of the solution set can be investigated by deriving the Jacobian matrix of the game map. A symmetric Jacobian matrix implies that the corresponding game is integrable and an equivalent optimization problem can be found. The characteristics (e.g. convexity) of the objective function of the equivalent optimization problem provides an indication of whether unique equilibria exist. By contrast, an asymmetric Jacobian matrix implies that an equivalent optimization problem does not necessarily exist. Vespermann et al. [243] provides an example of such an approach. In addition, The equilibrium in the SRP layer requires the setting of prices such that there is equality between the demand for insurance contracts from consumers; and the supply of insurance contracts from the IOLR (for which both categories of agents are assumed to be price-takers). Thus the existence and uniqueness of equilibria for this problem could be investigated using the P-property, variational inequalities and complementarity problem techniques [313]. This represents an important extension to the current work.

Third, equilibrium interpretation remains a challenge with problems where distributed algorithms are used – see for example Mays et al. [72] and Hoschle et al. [204]. More recently, work by Dimachev et al. [314] sets out a non-algorithmic formulation for the energy market problem. This involves a primal-dual reformulation of the agent decision problems, and uses a set of simplifying assumptions to improve the computational tractability of such an approach. Such an approach could be adopted for the 'energy-plus-insurance' model.

Finally, and complementing the non-algorithmic appraoch, the development of appropriate robustness tests is recommended. Dimachev et al. [314] provides a template of a robustness test of equilibria found via a non-algorithmic approach. This could be adapted to the specific problem under consideration, and could aid in providing further understanding of the nature of the equilibria that are found. The benefit of a robustness test is twofold. First, it allows for seeking of equilibria with particular characteristics - such finding the solution with the lowest unserved energy or the lowest emissions. Using alternative objective functions in the robustness test could be used to check if multiple equilibria can be found.

3.5 Conclusions

This chapter proposes a new reliability insurance mechanism for existing energy-only markets, one that enables efficient generation expansion and reliability differentiation between different types of demand. Relative to an energy-only market design, the energy-plus insurance design has the potential to incentivise additional generation capacity as the insurer is directly exposed to lost load events. It is demonstrated that reliability and social welfare outcomes for a system with an insurance mechanism are significantly improved over energy-only market designs.

If combined with priority curtailment, the scheme enables reliability differentiation when prices have reached the market price cap, directly addressing the *missing money problem* associated with such administrative mechanisms. By aligning financial exposures to electricity interruption between customers and the IOLR, the design also enables economic incentives for additional generation investments in strategic reserves. In addition, if centralised reliability criteria are too stringent this model may also mitigate system over-investment. The results of the case study satisfy the success criteria of (i) acceptable unserved energy outcomes, (ii) improvements in system welfare over alternative models, (iii) demonstrated reliability differentiation, and (iv) insurer financial viability. This confirms the hypothesis and laying the groundwork for future work in this area.

While the simulation of the design suggests that material improvements in unserved energy could be achieved, the model proposed within this chapter is restricted to an assessment of adequacy under a centralised grid. In particular, the risk of extreme low-probability, high-impact weather events and their mitigation with effective siting of distributed resources was not specifically considered. The next chapter thus moves to the issue of resilience in electricity markets and considers insurance mechanisms in the context of investments across both centralised and distributed energy resources.

This work extends the literature in four important ways. First, a practically implementable insurance-based incentive scheme is proposed that has the potential to improve overall efficiency of electricity markets (as measured by social welfare). Relative to other schemes in the literature, this scheme mitigates the missing money problem in a manner aligned with the overall reliability preferences of consumers, by creating an enforceable insurance contract between consumers and the insurer of last resort. Second, relative to existing literature, the insurance model incorporates a novel solvency constraint that links the financial capital exposure of the insurer with the actual reliability experience of consumers. Third, in order to understand the performance of this scheme a novel game-theoretic model is formulated that incorporates an energy spot market layer; an insurance contracting layer; and models the interactions between them. Fourth, a unique sequential equilibria search is developed to find an 'energy-plus-insurance' market equilibrium by combining a diagonalisation-based equilibrium search in the spot market layer; with a tatonnement in the insurance layer to negotiate insurance premiums and volumes.

4
Insurance Paradigms for Resilience

Contents

Up to this point in this thesis, the issue of reliability has only been addressed from the perspective of adequacy of power generation. The prior chapter demonstrated the value of a central insurance reserving framework, but did not consider the resilience of an increasingly decentralised electricity system. The literature review identified a gap in the incorporation of the resilience value of distributed resources in reliability mechanisms. Therefore, this chapter considers the topic under the research question: *Can insurance mechanisms enhance local resilience to extreme events by incentivising efficient investment in distributed energy resources?*. A locational insurance framework is proposed to improve the alignment between residual outage risk exposure and incentives for distributed investment.

Extreme events, exacerbated by climate change, pose significant risks to the energy system and its consumers. With net-zero objectives expected to drive large-scale electrification across many sectors, vulnerabilities in electricity supply are likely to affect increasingly larger portions of society [315]. However, the incompleteness in wholesale energy markets limits agency incentives for risk mitigation of extreme common-mode events [8]. While the technical potential of distributed resources to resilience has been established [6, 258–260] such value is not adequately captured in existing regulatory frameworks [261].

Governments have sought to redress such impacts ex-post, through payments after the event (for example the Prolonged Power Outage Payments in the aftermath of extreme weather events across Australia [316]). However, pre-emptive readiness and enhancements to system resilience are considered better suited to a changing climate [9]. There is thus a need for economic frameworks to align agency incentives for extrema, and value the resilience contributions of distributed technology [317].[1]

This chapter develops a locational model of insurance that differentiates risk on a regional level, recognising regional remoteness and weak network connectivity. This can play an important role in the scalable management of extreme risks by aligning interests for resilience and creating incentives for efficient distributed resource investment. A multi-agent model of the electricity system is formulated to test the effect of the insurance mechanism on three different market designs. The model reflects the spatial topology of the grid with the objective of providing insight into risk-averse participant behaviour; the nature of interactions between participant and design; and system reliability and resiliency impacts. Two investment incentive frameworks for resilient DER are developed – direct investment and subsidisation. It is shown that, while subsidisation can leverage consumer self-insurance benefits, take-up depends upon risk aversion, which is non-transparent to regulators.

The chapter begins in Section 4.1 with a presentation of the technical and market architecture associated with the insurance scheme for resilient distributed energy resource investment. Section 4.2 translates the high-level architecture to a

[1]To build a more resilient system there is a need for responsible parties to incorporate both preventative measures (which includes hardening and building additional resources and network) and reactive measures (including operational responses - selective curtailment, line reconfiguration, power restoration)[318]. While a generalised insurance framework has the potential to improve both aspects, preventative measures are the more relevant paradigm for this chapter more specifically.

game-theoretic model of the market. This includes the formulation of agent decision-making problems and a heuristic algorithm to find equilibria in the multi-agent problem. Section 4.3 applies the model to a numerical case study, with the critical policy implications of the study discussed in Section 4.4. Finally, conclusions and insights relating to the broader thesis are set out in Section 4.5.

4.1 System and Risk Architecture

The approach in this chapter involves the imposition of a locational insurance scheme to insure consumers for interruptions to electricity service. Figure 4.1 illustrates the main elements of the scheme.

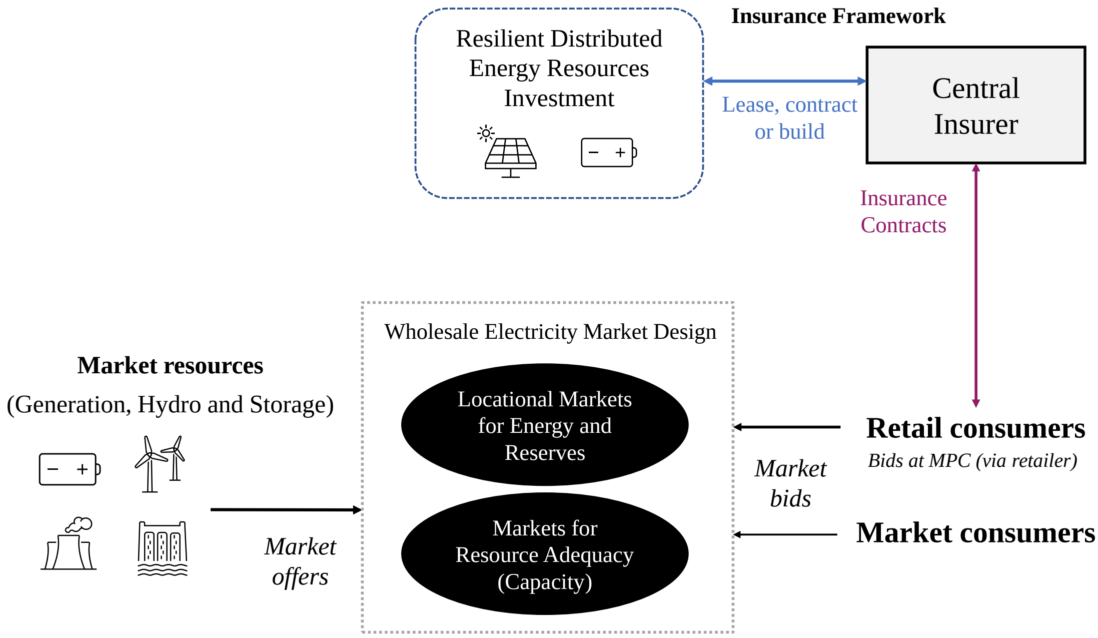

Figure 4.1: Schematic of the market architecture incorporating a wholesale electricity market design with centrally cleared spot markets for energy, reserves, and capacity; combined with an insurance scheme for electricity sector resilience.

Two components make up the market architecture. The first is the wholesale market design which comprises a spot market combined with additional resource adequacy mechanisms. This features a locational spot market for electricity, one that is optionally augmented with an operating reserve demand curve (ORDC) and a capacity mechanism [20].

The second component of the architecture is an insurance mechanism for system resilience. The insurer essentially offers electricity interruption insurance to consumers. In exchange for an upfront insurance premium, the insurer provides consumers with financial compensation in the event that load is interrupted in the form of a payment (represented in $ per MWh) linked to the value of the particular source of consumption. Zhao et al. [311] demonstrates that in a simplified setting (a risk-neutral insurer that only makes investments in variable renewable energy), consumers would select contracts where the compensation payment is closest with the value of lost load of the consumer. Importantly, this mechanism operates as an overlay on the wholesale electricity market (as distinct from the mechanism in Chapter 3, which is part of the resource adequacy market architecture). This allows a holistic consideration of distributed energy resources as a form of resilience-supporting investment, over and above what is delivered in the wholesale market.

Tail risks are managed consistent with the insurance risk principles set out in 3.1.1, through the setting of risk-adjusted premiums, reserving capital against severe losses, and risk mitigation. Under a central insurance scheme, premiums are assumed to be regulated at fair actuarial levels, allowing appropriate returns of and on capital, but no excess rents. This marks a contrast from Chapter 3, where given the focus on establishing a conceptual basis for reliability insurance, insurance premiums were set by tatonnement by negotiation between consumers and suppliers of insurance. In this chapter the mechanism is framed as a mandatory socialised insurance scheme – and as such regulatory setting of the insurance premium was considered appropriate.

The insurer can also offset risk through investment in resilient distributed energy resources (RDER). Investing in RDER could reduce electricity outages, and consequently compensation liabilities for the insurer. Locational diversity (especially under congestion or network outages could contribute to this effect[317]. This can help align interests between the insurer and consumers.

The system architecture for RDER incorporates: (i) a distributed solar system and (ii) a battery energy storage system that is connected to the central grid and enabled for islanded operation if the grid connection is interrupted. This represents one potential setup of DER that could aid in improving resilience to extreme events.[2]

Two forms of investment are considered: (i) direct investment, wherein the insurer bears the full investment cost of RDER; and (ii) subsidy, where the insurer partially subsidises the investment cost of RDER for consumers. The two models are differentiated in how RDER investment is undertaken. In the former, it is the insurer that makes the investment and bears all associated costs. In the latter, the costs are split between the insurer and the consumer, with the investment being made by the consumer. Note that both models only apply after a wholesale investment equilibrium has been reached (i.e. the insurance framework operates as an overlay on wholesale outcomes).

4.2 Methods

The economic rationale for the proposal is demonstrated through an agent-based model of investment in the electricity market and the associated insurance scheme. in which Scenarios with insurance are compared with counterfactuals with no insurance, and reliability and economic efficiency metrics are compared

Subsection 4.2.1 presents the decision formulation for agents in the wholesale electricity market. Subsection 4.2.2 presents the decision-making formulation for the insurer and consumers under an insurance overlay. Subsection 4.2.3 presents an algorithm to find an equilibrium among participants in the market and insurance scheme.

4.2.1 Investment decision-making in wholesale markets

In this subsection the mathematical formulation of the multi-agent model of the electricity market is presented.

[2]Other options include feeder and substation level configurations (see for example [319]). Centralized transmission and distribution network resilience enhancement could be considered and co-optimized with distributed investment options, though this is kept out of scope for this paper to keep the formulation tractable. Cases that included residential diesel gensets as part of the suite of investment options available to the insurer were also evaluated: however, no investment in diesel gensets was recorded in the base case due to their non-competitive capital and variable costs.

For each generation or storage resource, a two-stage decision-making process is adopted. Investment decisions are made in the first stage based on outcomes in the second stage. The second stage represents the co-optimised economic dispatch of energy and dispatch, but not deployment of operating reserves, and the clearing of the capacity mechanism.

Four aspects of uncertainty are modelled (locational demand, resource availability, network availability, and inflows into hydro storage) and reflected in annual scenarios ($\omega \in \Omega$).

Economic dispatch formulation

The electricity spot market ED_ω in (4.1) expresses a centrally cleared bid-based economic dispatch for energy and operating reserves.

As standard in the literature [23], this formulation is based on a convex DC optimal power flow (DC-OPF) model; this grants computational tractability while providing reasonably accurate results for market clearing in the transmission grid [320]. It is assumed that participants bid truthfully in line with their actual costs, as strategic bidding is not considered in this analysis. This is a reasonable assumption under the presence of many bidders, even in complex settings [321]. For the sake of simplicity, only upward reserve procurement is contemplated in (4.1); nonetheless, the formulation can be readily extended to incorporate additional reserve markets.

The set of resources $r \in \mathcal{R}$ comprises generation $\mathcal{G}$, storage $\mathcal{S}$ and hydro $\mathcal{H}$ units ($\mathcal{R} = \mathcal{G} \cup \mathcal{S} \cup \mathcal{H}$), based on capacity investment decisions in the first stage. It is clarified here that set $\mathcal{H}$ only includes hydro generation resources with reservoir storage; as opposed to 'run-of-river hydro generation' which can be incorporated as a generation resource in $\mathcal{G}$.

For ease of notation, any decision variables and parameters that vary over time are denoted in **bold**. For example, the vector of energy dispatched over time from a resource $r \in \mathcal{G} \cup \mathcal{H}$ as: $\boldsymbol{p}^G_{r\omega} \coloneqq [p^G_{r1\omega}, ..., p^G_{rt\omega}, ..., p^G_{rT\omega}]$, where $p^G_{rt\omega}$ denotes the energy dispatched by resource r in scenario ω, time period $t \in \mathcal{T} \coloneqq \{1, \ldots, T\}$. Other vectors are defined similarly. For storage resources, energy dispatch is separated into charge $p^{G+}_{rt\omega}$ and discharge $p^{G-}_{rt\omega}$ with total energy generation defined as the difference between the two $p^{G}_{rt\omega} = p^{G-}_{rt\omega} - p^{G+}_{rt\omega}$. Total upward reserve dispatch is denoted as $p^{R\uparrow}_{rt\omega}$. All mathematical notations are as defined in the **Nomenclature**.

For a given scenario, $\omega \in \Omega$, the economic dispatch optimisation problem ED_ω is defined as follows, where: $Z_{ED} \coloneqq \{\boldsymbol{p}^{G}_{r\omega}, \boldsymbol{p}^{R\uparrow}_{r\omega}, \boldsymbol{p}^{sh}_{d\omega}, \boldsymbol{p}^{rsh}_{i\omega}, \boldsymbol{S}_{r\omega}, \boldsymbol{\theta}_{\omega n}\}$ denotes the set of decision variables.

$$ED_\omega: \quad \min_{Z_{ED}} \sum_{r\in\mathcal{R}} \boldsymbol{C}^{vc}_{r\omega} \cdot \boldsymbol{p}^{G}_{r\omega} + \sum_{d\in\mathcal{D}} \boldsymbol{C}^{sh}_{d\omega} \cdot \boldsymbol{p}^{sh}_{d\omega} + \sum_{r\in\mathcal{R}} \boldsymbol{C}^{R}_{r} \cdot \boldsymbol{p}^{R}_{r\omega} + \sum_{i\in\mathcal{I}} \boldsymbol{C}^{rsh}_{i} \boldsymbol{p}^{rsh}_{i\omega} \tag{4.1a}$$

subject to:

$$\sum_{d\in\mathcal{D}^n} (\overline{\boldsymbol{P}}^{D}_{d\omega} - \boldsymbol{p}^{sh}_{d\omega}) + \sum_{m\in\mathcal{L}^n} B_{nm}(\boldsymbol{\theta}_{n\omega} - \boldsymbol{\theta}_{m\omega}) = \sum_{r\in\mathcal{R}^n} \boldsymbol{p}^{G}_{r\omega},\ n \in \mathcal{N}, \quad [\boldsymbol{\lambda}^{E}_{\omega n}] \tag{4.1b}$$

$$\boldsymbol{p}^{sh}_{d\omega} \le \overline{\boldsymbol{P}}^{D}_{d\omega}, \quad \forall d \in \mathcal{D}, \tag{4.1c}$$

$$\boldsymbol{p}^{G}_{r\omega} + \boldsymbol{p}^{R\uparrow}_{r\omega} \le \overline{P_r} \boldsymbol{A}^{G}_{r\omega} u_r, \quad \forall r \in \mathcal{G} \cup \mathcal{H} \tag{4.1d}$$

$$\boldsymbol{p}^{G-}_{r\omega} - \boldsymbol{p}^{G+}_{r\omega} + \boldsymbol{p}^{R\uparrow}_{r\omega} \le \overline{P_r} \boldsymbol{A}^{G}_{r\omega} u_r, \quad \forall r \in \mathcal{S}, \tag{4.1e}$$

$$\boldsymbol{p}^{G-}_{r\omega} - \boldsymbol{p}^{G+}_{r\omega} + \boldsymbol{p}^{R\uparrow}_{r\omega} \ge -\overline{P_r} \boldsymbol{A}^{G}_{r\omega} u_r, \quad \forall r \in \mathcal{S}, \tag{4.1f}$$

$$-F_{nm} \boldsymbol{A}^{L}_{nm,\omega} \le B_{nm}(\boldsymbol{\theta}_{\omega n} - \boldsymbol{\theta}_{\omega m}) \le F_{nm} \boldsymbol{A}^{L}_{nm,\omega}, \quad \forall n, \forall m \in \mathcal{L}^n, \tag{4.1g}$$

$$S_{rt\omega} = S_{r,t-1,\omega} + \varsigma^{+}_{r} p^{G+}_{rt\omega} - \frac{1}{\varsigma^{-}_{r}} p^{G-}_{rt\omega},\ \forall r \in \mathcal{S},\ t \in \mathcal{T} \tag{4.1h}$$

$$S_{rt\omega} = S_{r,t-1,\omega} + i^{G+}_{rt\omega} - \frac{1}{\varsigma^{-}_{r}} p^{G-}_{rt\omega},\ \forall r \in \mathcal{H},\ t \in \mathcal{T}, \tag{4.1i}$$

$$S_{r1\omega} = S_{rT\omega},\ \forall r \in \mathcal{S} \cup \mathcal{H}, \tag{4.1j}$$

$$\boldsymbol{S}_{r\omega} \le \overline{P_r} u_r e_r, \quad \forall r \in \mathcal{S} \cup \mathcal{H}, \tag{4.1k}$$

$$\sum_{r\in\mathcal{R}} \boldsymbol{p}^{R\uparrow}_{r\omega} + \sum_{i\in\mathcal{I}} \boldsymbol{p}^{rsh}_{i\omega} \ge \overline{R^{req}}, \quad \forall r \in \mathcal{R}, \qquad [\boldsymbol{\lambda}^{R}_{\omega}] \tag{4.1l}$$

$$\boldsymbol{p}^{rsh}_{i\omega} \le R^{req}_{i}, \quad \forall i \in \mathcal{I}, \tag{4.1m}$$

$$\boldsymbol{\theta}_{\omega 1} = 0, \tag{4.1n}$$

$$\overline{P_r} \ge \boldsymbol{p}^{G+}_{r\omega} \ge 0,\ \overline{P_r} \ge \boldsymbol{p}^{G-}_{r\omega} \ge 0,\ 2\overline{P_r} \ge \boldsymbol{p}^{R\uparrow}_{r\omega} \ge 0,\ \boldsymbol{S}_{r\omega} \ge 0. \tag{4.1o}$$

The objective is to minimise the total cost (4.1a). The first term expresses energy generation costs as the product of energy dispatched ($\boldsymbol{p}^G_\omega$) and variable unit costs ($\boldsymbol{C}^{vc}_{r\omega}$). The second term is the cost of unserved demand $\boldsymbol{p}^{sh}_{d\omega}$, where $\boldsymbol{C}^{sh}_{d\omega}$ is the value of lost load. The third term is the cost of dispatched operating reserves $\boldsymbol{p}^{R\uparrow}_{r\omega}$ with unit reserve costs $\boldsymbol{C}^R_r$. The final term expresses the cost of unmet reserves $\boldsymbol{p}^{rsh}_{i\omega}$, penalised at price $\boldsymbol{C}^{rsh}_i$ for each segment $i \in \mathcal{I}$.

Nodal power balance is defined in equation (4.1b), where the associated dual variable $\boldsymbol{\lambda}^E_{\omega n}$ can be interpreted as the locational marginal price of energy. Equation (4.1c) ensures that unserved demand is below actual nodal demand. Equations (4.1d),(4.1e) and (4.1f) ensure the energy and reserve dispatch are below the deliverable capacity, represented as the product of resource capacity $\overline{P_r}$, temporal availability $\boldsymbol{A}^G_{r\omega}$ and the (boolean) build status of the resource u_r. Equation (4.1g) enforces transmission DC flow limits. Equations (4.1h) and (4.1i) define the state-of-charge (SoC) dynamics for storage and hydro, with hydro SoC dependent upon rain flow $i^{G+}_{rt\omega}$. To avoid trivial solutions, in (4.1j) the SoC is constrained to have the same value at the start and end of the considered period. Technical limits on SoC are enforced in (4.1k). Equation (4.1l) determines the reserve amount with the dual variable $\boldsymbol{\lambda}^R_\omega$ indicating the system marginal reserve price. Equation (4.1m) limits the reserves shortage to the corresponding value of the segmented operating reserve demand curve (ORDC) [205]. Equations (4.1n)-(4.1o) set reference phase angles and non-negativity constraints.

Capacity mechanism formulation

The formulation for the capacity mechanism CM envisions a central auction for resource capacity cleared against an administratively determined demand curve. It is noted that this mechanism is not zonal, but applies on a whole-of-system level.

$$CM: \quad \min_{Z_{CM}} \sum_{r\in\mathcal{R}} C^I_r p^{CM}_r + \sum_{j\in\mathcal{J}} C^U_j p^U_j \tag{4.2a}$$

subject to:

$$\sum_{j \in \mathcal{J}} D_j^{th} = \sum_{r \in \mathcal{R}} p_r^{CM} + \sum_{j \in \mathcal{J}} p_j^U, \qquad [\lambda^{CM}] \tag{4.2b}$$

$$0 \leq p_r^{CM} \leq \overline{P_r} A_r^{CM} u_r, \quad \forall r \in \mathcal{R}, \tag{4.2c}$$

$$0 \leq p_j^U \leq D_j^{th}, \qquad \forall j \in \mathcal{J}, \tag{4.2d}$$

$Z_{CM} := \{p_r^{CM}, p_j^U\}$ gathers the decision variables. The first term in (4.2a) represents the total investment in resource r capacity, given by unit capacity costs C_r^I and cleared resource capacity award p_r^{CM}; the second term represents the costs of unmet capacity demand, where the penalty associated to capacity shortage p_j^U in each capacity demand segment $j \in \mathcal{J}$ is denoted by C_j^U. Equation (4.2b) balances auction demand and supply; here, the dual variable λ^{CM} defines the marginal clearing price of the capacity auction. Equation (4.2c) ensures that the cleared capacity award is lower than or equal to the de-rated maximum capacity of the resource (the product of resource capacity $\overline{P_r}$ and the de-rating factor A_r^{CM}). Capacity de-ratings factors are based on the effective load carrying capacity (ELCC) [322]. Capacity demand curve segments are as specified in (4.2d) [205]. The capacity mechanism provides an additional source of revenue to resources based on the marginal price of the capacity auction and cleared resource capacity.

Investment decision

Investment decision-making for each generation, hydro, or storage resource is modelled as a lumpy binary investment optimised separately for each resource with risk endogenised via a risk-weighted utility function. This formulation is aligned with prior literature on capacity investment in electricity markets with risk averse participants [74, 204].

The latter is defined as a convex combination of the expected value of the profit and a coherent risk measure, namely the CVaR, a measure of the expected shortfall [72, 204]. This model is used to determine the risk-averse utility U_r^G of an individual generation, storage, or hydro resource given the set of all committed resources (*i.e.*, all resources $r \in \mathcal{R}$ such that $u_r = 1$) and the market outcomes associated with these (including prices and dispatch of spot energy and reserves, and prices and awards for the capacity mechanism); the coupling is reflected through the dual variables from (4.1) and (4.2).

$$ID_r: \quad U_r^G = \max_{Z_U} \beta_r^G \left(V_r^G - \frac{1}{\alpha_r^G} \sum_{\omega \in \Omega} \pi_\omega \varrho_{g\omega}^G \right) + (1-\beta_r^G) \sum_{\omega \in \Omega} \pi_\omega \Psi_{r\omega}^G - C_r^I \overline{P_r} u_r \tag{4.3a}$$

subject to:

$$\Psi_{r\omega}^G = (\boldsymbol{\lambda}_{\omega n(r)}^E - \boldsymbol{C}_r^{vc}) \cdot \boldsymbol{p}_{r\omega}^G \tag{4.3b}$$

$$+ (\boldsymbol{\lambda}_\omega^R - \boldsymbol{C}_r^R) \cdot \boldsymbol{p}_{r\omega}^R + \lambda^{CM} p_r^{CM}, \tag{4.3c}$$

$$V_r^G - \Psi_{r\omega}^G \leq \varrho_{r\omega}^G, \ \forall \omega \in \Omega, \tag{4.3d}$$

$$\varrho_{r\omega}^G \geq 0, \ \forall \omega \in \Omega, \tag{4.3e}$$

The vector $Z_U \coloneqq \{\Psi_{r\omega}^G, v_r^G, \varrho_{r\omega}^G\}$ gathers the decision variables of the problem, *i.e.*, $\Psi_{r\omega}^G$ and two auxiliary variables v_r^G, $\varrho_{r\omega}^G$ used for the CVaR formulation. The objective function (4.3a) is specified as a maximisation of risk-weighted utility, formulated as a convex combination ($0 \leq \beta_r^G \leq 1$) of the expected value and the α_r^G-CVaR (*i.e.*, relative to the worst-case α_r^G quantile) of scenario profits (4.3c), minus capital costs. Constraints (4.3d) and (4.3e) are required for the scenario formulation of CVaR [213].

In contract to Chapter 3 this chapter does not consider the market power of generations given the application to a large-scale network such as the NEM, where the market for investment at a system level is considered relatively competitive [323][3].

4.2.2 Insurance overlay

The insurer is considered to act as a central agent with contingent liability for consumer electricity service outages. While both decentralised and competitive paradigms for insurance are possible, these deserve a dedicated analysis that is out of the scope of this work. For technical convenience, it is assumed that

[3]As an aside, the ACCC did not competitive concerns with respect to NEM's retail and hedging markets [323]

insurance is mandatory and its regulated to a level that recovers capital and operating costs. It is noted that the analysis in Section 4.3 suggests the scheme could continue to be financially viable if this assumption is dropped. However, in practical implementations, issues related to consumer tail risk estimation (including the willingness and capability to properly assess such risks), and the consequent impacts on take-up of insurance need to be carefully considered through a consumer protection and social justice lens.

The decision making for the insurer (INS) is set out as follows:

$$INS: \quad \max_{Z_{INS}} U^i \coloneqq (1-\beta^i)\sum_{\omega\in\Omega}\pi_\omega\Psi^i_\omega + \beta^i\tilde{c}^i - \gamma\phi^i \tag{4.4a}$$

subject to:

$$\Psi^i_\omega = \sum_{d\in\mathcal{D}}(C^P_d - \boldsymbol{C}^{comp}_d\cdot\boldsymbol{p}^c_{d\omega}) - \sum_{r\in\mathcal{R}^{der}}\kappa C^I_r\overline{P_r},\ \omega\in\Omega \tag{4.4b}$$

$$\tilde{c}^i = V^i - \frac{1}{\alpha^i}\sum_{\omega\in\Omega}\pi_\omega\varrho^i_\omega, \tag{4.4c}$$

$$V^i - \Psi^i_\omega \leq \varrho^i_\omega, \quad \forall\omega\in\Omega, \tag{4.4d}$$

$$\phi^i \geq \max\{0, -\tilde{c}^i\}, \tag{4.4e}$$

$$\overline{P_r}\geq 0, \text{and } \varrho^i_\omega \geq 0,\ \boldsymbol{p}^c_{d\omega}\geq 0,\ \forall\omega\in\Omega, \tag{4.4f}$$

$$\sum_{d\in\mathcal{D}^n}\boldsymbol{p}^c_{d\omega} = \sum_{d\in\mathcal{D}^n}\boldsymbol{p}^{sh*}_{d\omega} - \sum_{r\in\mathcal{R}^{der}}\boldsymbol{p}^G_{r\omega},\ \forall\omega\in\Omega,\ n\in\mathcal{N}, \tag{4.4g}$$

$$0\leq \boldsymbol{p}^G_{r\omega}\leq \overline{P_r}\boldsymbol{A}^G_{r\omega},\ \forall r\in\mathcal{R}^{der},\ \omega\in\Omega \tag{4.4h}$$

$$0\leq \boldsymbol{S}_{r\omega}\leq \overline{P_r}e_r,\ \forall r\in\mathcal{S}^{der},\ \omega\in\Omega, \tag{4.4i}$$

$$S_{rt\omega} = S_{r,t-1,\omega} + \varsigma^+_r p^{G+}_{rt\omega} - \frac{1}{\varsigma^-_r}p^{G-}_{rt\omega}, \quad \forall r\in\mathcal{S}^{der}, t\in\mathcal{T}, \omega\in\Omega, \tag{4.4j}$$

where $Z_{INS} \coloneqq \{\Psi^i_\omega, \tilde{c}^i, \phi^i, \overline{P_r}, v^i, \varrho^i_\omega, \boldsymbol{p}^c_{d\omega}, \boldsymbol{p}^G_{r\omega}, \boldsymbol{S}_{r\omega}\}$ denotes the set of decision variables. The objective is to maximise a convex combination of the expected value and the α^i-CVaR (denoted as $\tilde{c}^i$) of the insurer's profits (first and second term in (4.4a)). In addition, the insurer must also bear the costs associated with reserving capital to meet potential losses [84]: this is expressed by the third term of the objective function, where ϕ^i is the reserved capital and γ its annualised cost. For each scenario $\omega \in \Omega$, insurer profits Ψ^i_ω are defined in (4.4b) as the sum of premium revenues C^P_d, minus insurance compensation costs and the investment costs of RDER, scaled by the subsidy parameter $0 < \kappa < 1$ provided to consumers ($\kappa = 1$ corresponds to direct investment). Note that $\mathcal{R}^{der} \subseteq \mathcal{R}$ designates the subset of RDERs available for investment by the insurer; in particular, $\mathcal{R}^{der} := \mathcal{G}^{der} \cup \mathcal{S}^{der}$, so the term $\sum_{r\in\mathcal{R}^{der}} \kappa C^I_r \overline{P_r}$ can include both (solar) generation and storage investment costs. It is noted that for storage assets $r \in S^{der}$, the net generation term $\boldsymbol{p}^G_{r\omega}$ is equivalent to the difference between storage discharge $\boldsymbol{p}^{G-}_{r\omega}$ and storage charge $\boldsymbol{p}^{G+}_{r\omega}$. Thus $\boldsymbol{p}^G_{r\omega} = \boldsymbol{p}^{G-}_{r\omega} - \boldsymbol{p}^{G+}_{r\omega}$, as in Section 4.2.1.

Equations (4.4c) and (4.4d) define the CVaR $\tilde{c}^i$, whereas (4.4e) sets out the requirements for reserve capital to be in excess of the negative CVaR [4] Load shedding is defined in (4.4g) as the difference between the wholesale unserved demand ($\boldsymbol{p}^{sh*}_{d\omega}$, output of ED_ω) minus generation from RDER. Technical constraints associated with RDER (availability, SoC) are set out in (4.4h)-(4.4j).

Finally, the decision-making framework CON_d is illustrated, upon which consumers base their investments in RDER at a subsidised cost. As this problem pertains to the subsidisation framework, it is only solved for the case $\kappa < 1$.

$$CON_d : \quad \max_{Z_{CON}} U^c_d := (1-\beta_d)\sum_{\omega\in\Omega} \pi_\omega \Psi^c_{d\omega} + \beta_d \tilde{c}^c_d \tag{4.5a}$$

subject to:

$$\Psi^c_{d\omega} = -\boldsymbol{C}^{voll}_d \cdot \boldsymbol{p}^c_{d\omega} - \sum_{r\in\mathcal{R}^{der}} (1-\kappa) C^I_r \overline{P'_r} - C^P_d + \boldsymbol{C}^{comp}_d \cdot \boldsymbol{p}^c_{d\omega}, \ \omega \in \Omega, \tag{4.5b}$$

$$\tilde{c}^c_d = V^c_d - \frac{1}{\alpha^c_d}\sum_{\omega\in\Omega} \pi_\omega \varrho^c_{d\omega}, \tag{4.5c}$$

$$V^c_d - \Psi^c_{d\omega} \le \varrho^c_{d\omega}, \forall\omega\in\Omega, \tag{4.5d}$$

$$\varrho^c_{d\omega} \ge 0, \forall\omega\in\Omega, \tag{4.5e}$$

$$\boldsymbol{p}^c_{d\omega} = \boldsymbol{p}^{sh*}_{d\omega} - \sum_{r\in\mathcal{R}^{der}} \boldsymbol{p}^G_{r\omega}, \forall\omega\in\Omega, \tag{4.5f}$$

$$0 \le \boldsymbol{p}^G_{r\omega} \le \overline{P'_r} \boldsymbol{A}^G_{r\omega} \forall r \in \mathcal{R}^{der}, \omega\in\Omega, \tag{4.5g}$$

$$0 \le \boldsymbol{S}_{r\omega} \le \overline{P}'_r e_r \forall r \in \mathcal{S}^{der}, \omega\in\Omega, \tag{4.5h}$$

[4] Alternative approaches that may also be applicable in assessing extreme or tail risks include robust or "worst case" risk measures [4].

$$S_{rt\omega} = S_{r,t-1,\omega} + \varsigma_r^+ p_{rt\omega}^{G+} - \frac{1}{\varsigma_r^-} p_{rt\omega}^{G-}, \forall r \in \mathcal{S}^{der}, t \in \mathcal{T}, \omega \in \Omega, \quad (4.5i)$$

$Z_{CON} := \{\Psi_{d\omega}^c, \tilde{c}_d^c, \overline{P'_r}, v_c^d, \varrho_{d\omega}^c, \boldsymbol{p}_{d\omega}^c, \boldsymbol{p}_{r\omega}^G, \boldsymbol{S}_{r\omega}\}$ gathers the decision variables. The objective is to maximise a convex combination of the scenario-weighted consumer surplus $\Psi_{d\omega}^c$ and the risk measure given by the α_d^c-CVaR, denoted as $\tilde{c}_d^c$. The consumer surplus, as defined in (4.5b), reflects those losses associated with load shedding; investment costs of RDER (net of subsidy); the insurance premium; plus any insurance compensation payable for load shedding. For each consumer, the key decision variable is the capacity of RDER built ($\overline{P'_r}$). As in the considered subsidisation framework the latter is the result of a co-investment by the insurer and the consumer, the realised capacity is taken to be the minimum of $\overline{P'_r}$ and $\overline{P_r}$ from (4.4) (line 27 in Algorithm 3). The other constraints relate to CVaR (4.5c)-(4.5e) and technical/operational constraints (4.5f)-(4.5i), similar to the INS problem.

4.2.3 Market equilibrium algorithm

A market investment equilibrium is sought where no agent can increase its utility by deviating unilaterally from the solution. To search for an equilibrium, a heuristic algorithm is proposed that seeks to replicate the process of competitive entry and exit in liberalised markets. Figure 4.2 provides a flow chart of the adopted approach, as detailed in Algorithm 3.

The algorithm requires as input the set of resources $\mathcal{R}$, along with their corresponding features and parameters. The main body of the algorithm consists of the *market loop* – which in turn comprises two subsequent processes dealing with resource *retirement* and *investment* – followed by the insurance decision-making. Both inner loops start by finding the dispatch solutions and prices for energy, reserves, and capacity. Based on these, an investment problem is then solved to calculate each respective resource's risk-averse utility. The build status of the relevant resources is assigned to the corresponding binary variables based on whether the investment is considered profitable (an investment with negative risk-weighted utility U_r^G is considered unprofitable). Given the possible multiple equilibria, the algorithm is best described as a guided search through the feasibility

Algorithm 3: Wholesale market investment & insurance framework

Input : Resource mix $\mathcal{R}$ and associated parameters; initial state of assets u_r, $\forall r \in \mathcal{R}$

Output : Equilibrium solution u_r^*, $\forall r \in \mathcal{R}$

Market loop:

repeat
- *Retirement loop*:
- **repeat**
  - solve $(ED_\omega, \forall \omega \in \Omega)$
  - solve (CM)
  - **for** $r \in \mathcal{R}$: $u_r = 1$ **do**
    - $U_r^G \leftarrow$ solve (ID_r)
  - **end**
  - $\underline{U} \leftarrow \min_r(U_r^G)$, $\underline{r} \leftarrow arg\min_r(U_r^G)$
  - **if** $\underline{U} < 0$ **then**
    - $u_{\underline{r}} \leftarrow 0$
  - **end**
- **until** $\underline{U} < 0$;
- *Investment loop*:
- $u_r^{\text{prev}} \leftarrow u_r$, $\forall r \in \mathcal{R}$
- **for** $r \in \mathcal{R}$: $u_r = 0$, *in interconnection queue order* **do**
  - $u_r \leftarrow 1$
  - solve $(ED_\omega, \forall \omega \in \Omega)$
  - solve (CM)
  - $U_r^G \leftarrow$ solve (ID_r)
  - **if** $U_r^G < 0$ **then**
    - $u_r \leftarrow 0$
  - **end**
- **end**

until $\max_r |u_r - u_r^{\text{prev}}| \neq 0$;

Insurance overlay:

solve (INS)

if $\kappa < 1$ **then**
- solve $(CON_d, \forall d \in \mathcal{D})$
- $\overline{P_r}^* = \min\{\overline{P_r}^*, \overline{P_r'}^*\}$, $\forall r \in \mathcal{R}^{der}$

end

return $(u_r^*, \overline{P_r}^*)$, $\forall r \in \mathcal{R}^{der}$

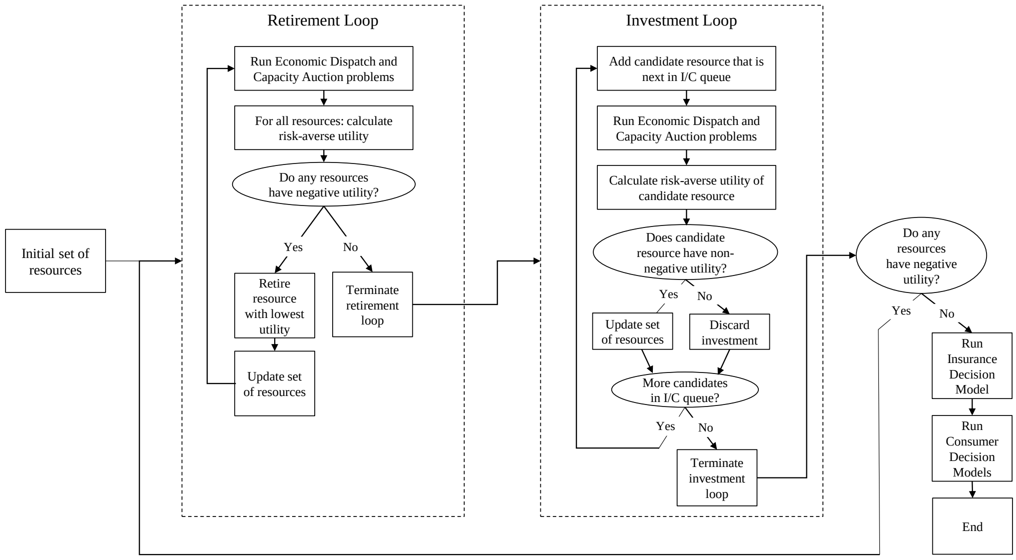

Figure 4.2: Flowchart of Algorithm 3.

set. The rationale of this approach is to seek an equilibrium that is interpretable by nature of retiring following the order of unprofitability and investing by priority of interconnection. In particular, in line 14, it is assumed that a predefined ordering of the set of resources exists; it is pointed out that this ordering is arbitrary, and can reflect the grid interconnection priority that different classes of assets could incur in practice (*e.g.*, according to the project's commitment and financing status [324]). The algorithm terminates when the resource mix does not change over the prior iteration (*i.e.*, no plants seek to retire and no new plants seek to enter the market); note that y is an auxiliary flag variable used to keep track of such changes. Also, note that in line 8 it is assumed that $arg\min_r(U_r^G)$ is a singleton (otherwise any tie-break rule can be applied).

The set of available resources and the relative market outcomes (economic dispatch and capacity) are obtained upon termination of the market loop. These constitute the input for the insurance and consumer decision-making (lines 24–26). Note that the insurance framework is meant to operate as an overlay so as to limit interference in wholesale electricity markets; this is reflected in the model formulation by having the insurer and consumers make decisions sequentially, once the wholesale market equilibrium iterations have terminated.

The heuristic equilibrium-seeking algorithm follows from the concepts of ordered interconnection queue and commercial retirement decision-making. No guarantees of convergence to an equilibrium are provided for the adopted heuristic approach. Nor are there guarantees of uniqueness for the equilibrium, if it exists. Nonetheless, for each of the three test cases considered in the numerical study, an equilibrium was attained within a relatively small number of iterations (it is verified that each of the points reached by the heuristic algorithm was indeed an equilibrium by running an ex-post diagonalisation algorithm of the form outlined in [205]). In terms of solution times, equilibria were typically found in multiple days. The algorithm was also tested against alternative network cases and initial conditions (see Appendix B) and in most instances, an equilibrium was reached; exceptions were those characterised by limited liquidity, wherein a reduced set of resource candidates was available. In such cases, the algorithm would continue to cycle.

4.3 Case Study

A numerical study is developed to illustrate the insurance value of resilient investment. The NEM of Australia provides an apposite case study of a large-scale grid in transition towards a high penetration of VRE and a roll-off of legacy fossil fleet [58]. Moreover, the topology of the grid exposes remote regions to power interruption from extreme weather, evidenced by numerous recent instances of outage and delayed restoration [316, 325].

The market provides a high degree of transparency on demand and generation availability projections across scenarios and locations, technical and financial data for current fleet and project interconnection pipeline, and network topology information. The success criteria for this study are as follows: (i) first, at a system level, acceptable improvements in total unserved energy for a market with an insurance overlay over a purely wholesale market design for extreme percentile risk cases; (ii) second, a reduction in regional USE for non-urban remote regions in extreme percentile cases; (iii) third the incentivisation of appropriate investment in distributed generation and storage; and (iv) finally, the cost-effectiveness of the proposed insurance scheme for consumers with moderate risk aversion. This criterion is specified as consumers with $\beta_c^d \geq 0.5$ recording net positive utility from the imposition of the insurance scheme.

4.3.1 Data and Sources

Plant technical, financial, and cost data are sourced from the Integrated System Plan (ISP) produced by the Australian Energy Market Operator (AEMO) [326] for existing, committed and anticipated resources, supplemented by [324] for new projects. For the network topology, the case study adopts the ISP sub-regional network representation comprising of 10 zones, with specific network transfer capability and seasonal availability limits [326]. Appendix A provides a diagram of the topology and flow limits.

To account for weather uncertainty, a set of annual weather-year scenarios are adopted for demand, variable renewable generation availability, hydro inflows, and transmission network capacity with traces provided for every half-hour over the year. Projections from ten equiprobable 'base' weather years reflect normal weather variability as sourced from AEMO's ISP Step Change projection. These are built upon ensemble projections from downscaled global climate models and reflect inherent correlations between demand and renewable generation availability. Twenty-four representative days are selected from each of the base scenarios using a K-means clustering algorithm [327]. These are used as input to model the VRE resources with 30-minute dispatch intervals. Energy exchange of long-duration storage and hydro between representative periods is approximated through the introduction of additional variables and constraints based on the approach in [233]. Costing and operational assumptions include storage life cycle and degradation cost adjustments, as well as charging and discharging efficiencies [326].

To assess the impact of extreme outcomes, the base weather years are complemented with six equiprobable 'extreme' years, developed as stylised scenarios that reflect the specific risks faced by the NEM. These are built upon extreme scenario calibration work undertaken in [328] and the Electricity Sector Climate Information Risk Assessment Framework, the result of a collaboration between

AEMO and the Commonwealth Scientific and Industrial Research Organisation (CSIRO) [329]. Table 4.1 sets out the specific assumptions used. It is pointed out that all the scenarios used – including demand, generation availability, and hydrological inflows – comprise future projections (in the form of time series) that incorporate climate impacts. They serve to illustrate the range of extreme events that could be expected to form an insurance-based assessment of extreme risks in practice. A real-world analysis would involve a larger number of scenario assessments, which has been limited here for computational tractability. Under the assumption of equiprobability, the tail scenarios were calibrated to similar extremity as informed by the risk assessment. Specifically, each of the six extreme-year scenarios is assumed to have a probability of occurrence of 0.01 (*i.e.*, each is a 1-in-100-year event). Another possible approach could be to fit parametric distributions for uncertainty parameters and obtain a joint distribution through a copula.

Three market designs are tested in the case study: (i) energy-only market (EOM), (ii) energy market with an operating reserve demand curve (ORDC), and (iii) energy market with capacity mechanism (CM). An energy market price cap of $15,000/MWh is adopted for the EOM and ORDC designs, while for the CM a reduced cap of $2000/MWh is applied. The ORDC is characterised by three reserve quantity segments of 2,000 MW, 1,000 MW and 1,000 MW with corresponding price thresholds of $15,000/MWh, $10,000/MWh, and $5,000/MWh. The CM relies on a capacity demand curve with three interpolated points. The highest point is set to 105% of the system's peak demand (equivalent to a reserve margin of 5%). The two remaining interpolated points are set at the peak demand and 95% of the peak demand; the corresponding capacity price thresholds for each interpolated point are based on an assumed cost of new entry (CONE) of $90,000/MW/year and set at 0.5, 1.0 and 1.5 times CONE, respectively. The de-rating factors for numerical study are based on a marginal effective load-carrying capacity (ELCC) methodology. The 'risk-neutral' case is defined as the one where the insurer preferences are skewed towards expected returns, *i.e.*, the insurer is *almost* neutral towards risk; this is

Table 4.1: Description of extreme year scenarios for case study

#	Scenario	Description
1.	Extreme demand & islanding in *Victoria and South Australia*	Demand increased by 20% over peak representative day. Availability for Victoria to South Australia interconnector (VIC-SA) is constrained by 90%.
2.	Extreme demand & islanding in *Tasmania*	Demand increased by 40% over peak representative day. Tasmania-to Victoria interconnector (TAS-VIC) is unavailable.
3.	Extreme demand & islanding in Queensland	Demand increased by 30% over peak representative day. Interconnectors to northern Queensland (SQ-CNQ and CNQ-GG) unavailable.
4.	Thermal generation unavailability due to high temperatures	Demand increased by 10% over peak representative day. Thermal generation availability across all regions reduced by 40%.
5.	Renewables ‘dunkelflaute’	Demand increased by 10% over peak representative day. Variable renewable generation availability across all regions reduced by 80%.
6.	Drought	Hydro inflows across all regions reduced by 20% over the year.

simulated by using $\beta^i = 0.1$, such that some risk aversion is built into the insurance decision making, which would be practically reasonable.

The algorithm is initialised with the Australian NEM resource portfolio as in December 2022. Appendix B describes the solution obtained from an alternative initial generation portfolio. Risk aversion is characterised for resource decision-making by $\beta_r = 0.5$ and $\alpha_r = 0.1$, for all $r \in \mathcal{R}$. The insurance scheme adopts a capital reserving threshold with a tail probability α_i set at 1% (consistent with international insurer solvency standards [303]).

A set of RDER investment options is provided for the insurer. The insurer is able to select from a combination of resources that comprise rooftop solar and distributed battery storage; costs and technical specifications were obtained from

[330]. Two models of investment are considered: (i) a *direct investment* model where the insurer directly funds the investment and bears the associated costs (in this case κ is set to 1) and (ii) a *subsidy* model, where partial capital subsidies are provided to consumers for the deployment of RDER storage (in Figure 4.12 shows results for κ ranging from 0.2 to 0.8). Note that the latter case focuses on storage only, given the array of existing subsidies available to distributed solar technologies. It may also be possible to discriminate by offering different levels of subsidy for different DER technologies or locations.

4.3.2 Results

Impacts on generation and reliability

For each of the three selected market designs, Figure 4.3 illustrates the retired and added capacity, while Figure 4.4 shows the total installed capacity at system level. These plots illustrate both the capacity incentivised through the corresponding wholesale market (resource categories with prefix ‘W’), as well as additional investment in resilient DER resource capacity funded by the insurance scheme (preceded by ‘RDER’).

The results indicate differences in both the total quantities and type of resources incentivised by each of the market designs. At a wholesale level and relative to the current supply mix, the CM design results in a net addition of 0.7 GW of resource capacity, while the EOM and ORDC designs drive net retirements of over 6.7 GW and 6.3 GW, respectively. In the spot-based designs (EOM and ORDC) retirements are mainly from black and brown coal (amounting to $\sim$9.0 GW) and also some gas units; these are replaced by new investment in wind, solar and storage (of 1 and 2-hour durations). New investment in the CM are made in fast-start gas units and storage (though the latter is incremental, once all candidate gas units in the current queue are built).

For each of the three market designs considered, Table 4.2 specifies system reliability and investment outcomes comprising annualised unserved energy (USE) as a proportion of demand on an expected value (mean) basis and for the 90th,

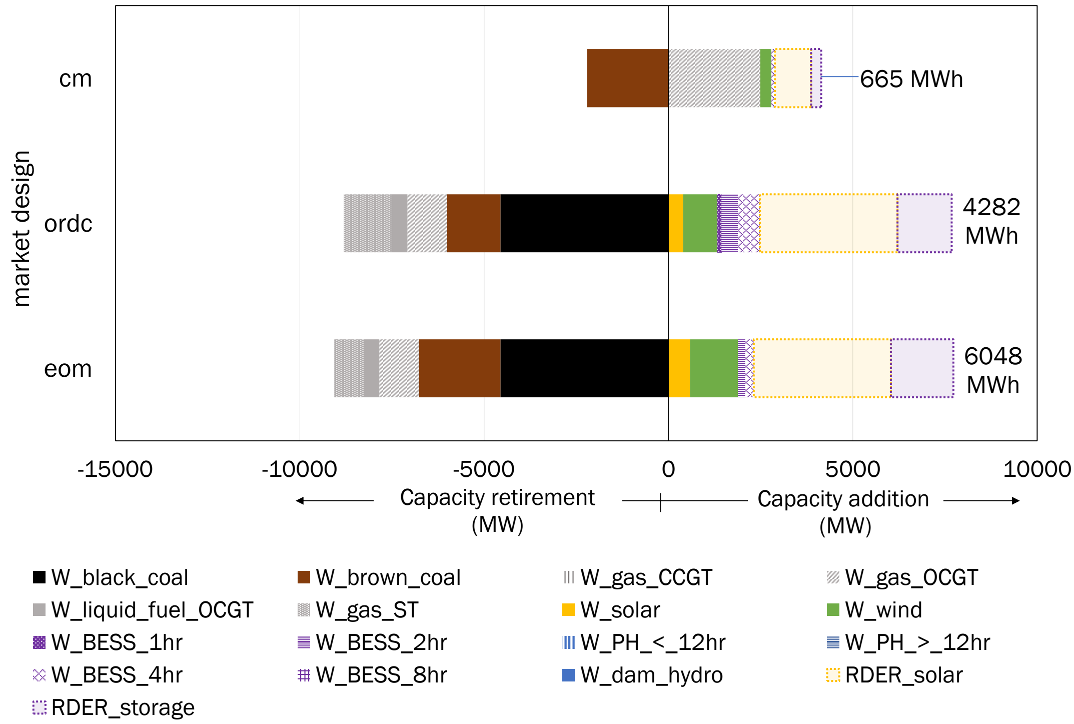

Figure 4.3: Resource capacity additions and retirements under alternative market designs. Resource capacity incentivised by the wholesale market design is preceded with "W". Resilient DER resources incentivised by the insurance overlay are preceded with "RDER". Storage durations in MWh are also detailed in the figure.

95th, and 99th percentile cases, and total investment in RDER generation (on a MW basis) and storage (on a MW and MWh basis). Empirical cumulative density functions for system annualised unserved energy (USE) (which is defined as annual energy demand unserved as a proportion of total annual demand) are shown in Figure 4.5 for each of the three market designs. Figure 4.5 illustrates that prior to the application of the insurance scheme, the base reliability outcomes are better for CM relative to EOM and ORDC across median and higher percentiles. This is expected since the CM design is targeted towards maximal load forecasts.

The impact of the insurance framework on resilience is evident in the quantity of RDER that the insurance agency is incentivised to deploy, which in turn has consequences in terms of unserved energy reduction. For the EOM and ORDC, the insurance scheme drives additional investments of 3.7 GW in RDER-solar and 1.5–1.7 GW in RDER-storage (with an average duration of 3 to 4 hours). For the

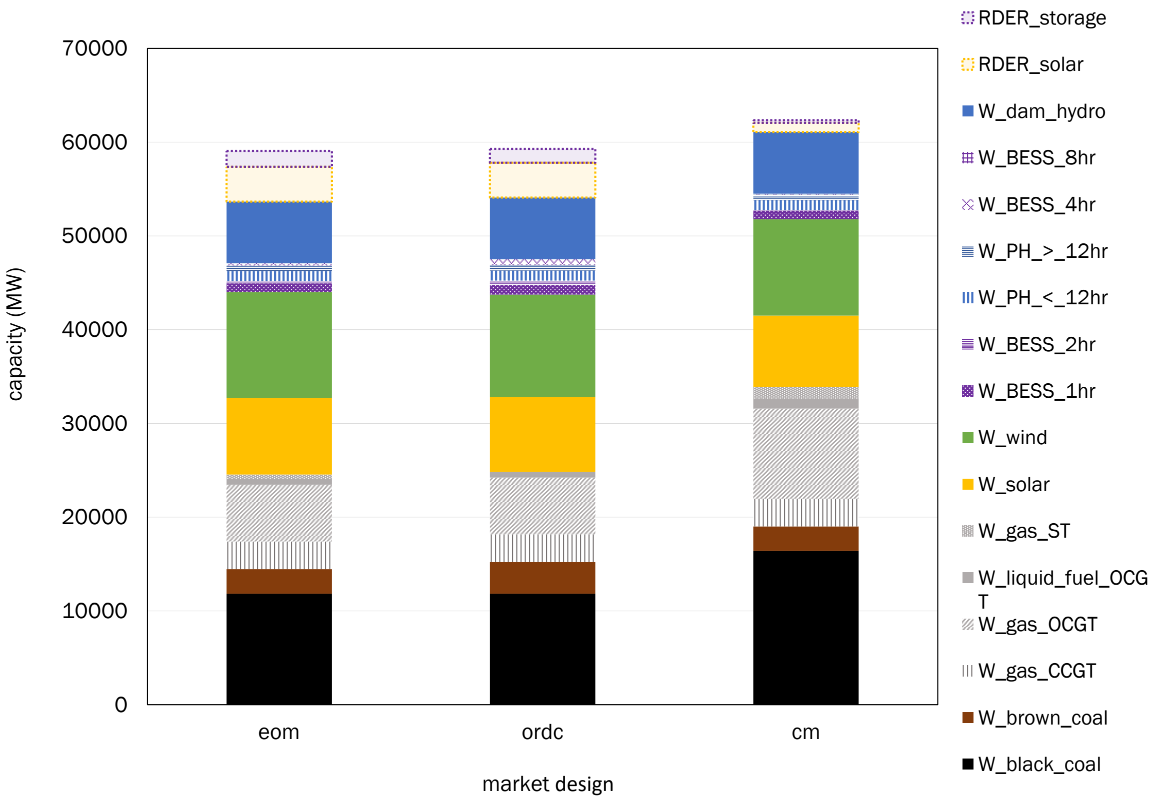

Figure 4.4: Total resource capacity under alternative market designs. Resource capacity incentivised by the wholesale market design is preceded with "W". Resilient DER resources incentivised by the insurance overlay are preceded with "RDER". Storage durations in MWh are also detailed in the legend.

CM, the insurance overlay yields investments that amount to ∼1 GW of solar RDER and 0.3 GW of storage RDER (2 hr duration). Regarding reliability, a reduction in unserved energy for extreme cases is observed for all market designs as a result of the additional investment in RDER. At a probability of exceedance (POE) level of 5%, USE is improved by 0.019-0.025% for EOM/ORDC and 0.003% for CM, while for POE of 1%, improvements recorded are 0.073-0.078% for EOM/ORDC and 0.015% for CM above the wholesale market outcomes.

In terms of the duration curves, it is interesting to note that differential between unserved demand for markets with and without insurance is low at lower percentiles, and only increasing for higher percentiles (i.e. exceeding 90%). Thus, the value of insurance in mitigating unserved demand is skewed towards the rarer events.

Figure 4.6 displays regional unserved energy outcomes on an expected value,

Table 4.2: Reliability and investment outcomes under alternative market designs: Energy-only market (EOM), Energy market with operating reserve demand curve (ORDC), and energy market with capacity auction (CM)

Market design	EOM	ORDC	CM
USE - mean (%)			
wholesale only (%)	0.014	0.012	0.002
with insurance (%)	0.008	0.007	0.002
USE - P90 (%)			
wholesale only (%)	0.016	0.012	0.004
with insurance (%)	0.010	0.008	0.002
USE - P95 (%)			
wholesale only (%)	0.047	0.044	0.004
with insurance (%)	0.022	0.024	0.002
USE - P99 (%)			
wholesale only (%)	0.323	0.324	0.136
with insurance (%)	0.244	0.251	0.120
RDER capacity			
Solar, MW	3720	3731	980
Storage, MW	1696	1471	276
Storage, MWh	6048	4282	665

90th percentile, 95th percentile, and 99th percentile basis for an energy-only market design. Empirical cumulative density functions for unserved energy for regional areas of Central New South Wales (CNSW) and Northern New South Wales (NNSW) for an energy-only market design are shown in Figure 4.7. As the network is characterised by regional areas with weaker connections, such as CNSW and NNSW, local effects can be observed where these regions suffer from poorer supply reliability. This implies that the potential contingent liability exposure investment under an insurance framework is skewed to such regions. As a result, the introduction of the proposed insurance scheme yields noticeable improvements in USE outcomes, following additional investments in RDER driven in these areas, which is observed particularly under the EOM market architecture (see Figure 4.7).

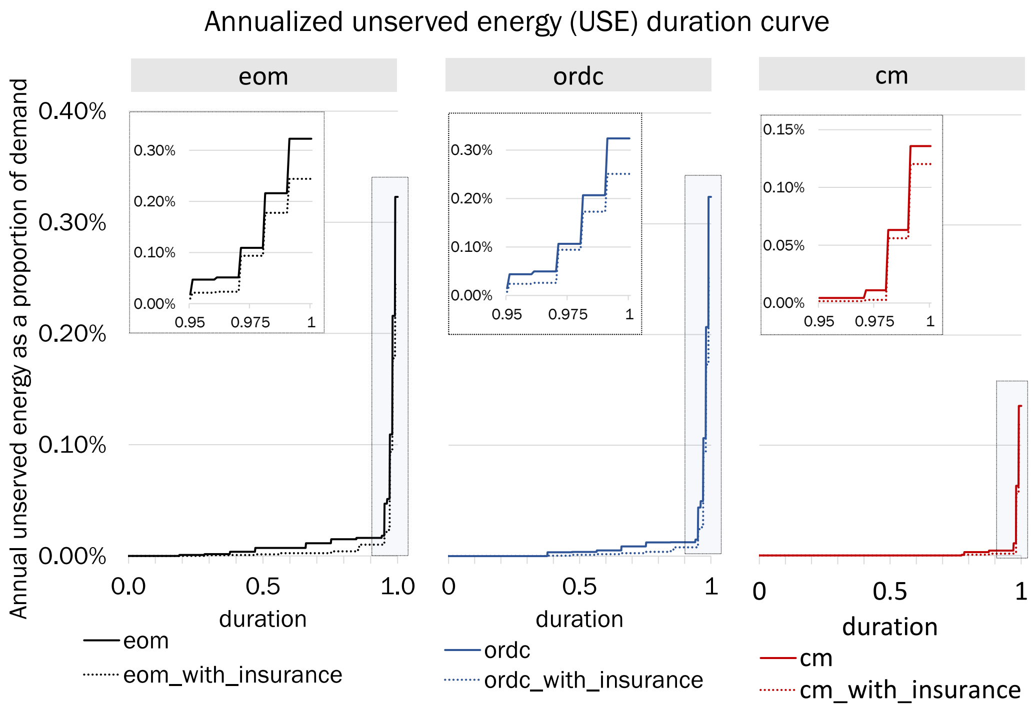

Figure 4.5: Duration curves for system unserved energy (USE), measured as a percentage of demand, under the EOM, ORDC, and CM designs.

Table 4.3 sets out the consumer and insurer surplus from the proposed insurance scheme under each of the modelled scenarios for the EOM. To reflect a regulated recovery of operating and capital costs, the insurance premium is set to a level that provides a zero-utility outcome (eq. (4.4a)) to the insurer; this approach is deemed appropriate to a central scheme such as the one proposed in this work. The total premium is then allocated to consumers (C_d^P in (4.4b)) in proportion to their contribution to peak net load. With the premium set in this way, it is observed that the realisation of surplus for the consumers is hindered by payments of insurance premiums under base weather years, despite the benefit from lowered VOLL. Conversely, a significant surplus can be registered in extreme years, where the role of insurance compensation payouts becomes evident. Correspondingly, the insurer makes small profits in base weather years (primarily from premium payments with only small compensation claims); this profit could be used to lower the premium over subsequent years, making the scheme more appealing to consumers. The insurer can incur significant expenses during extreme years,

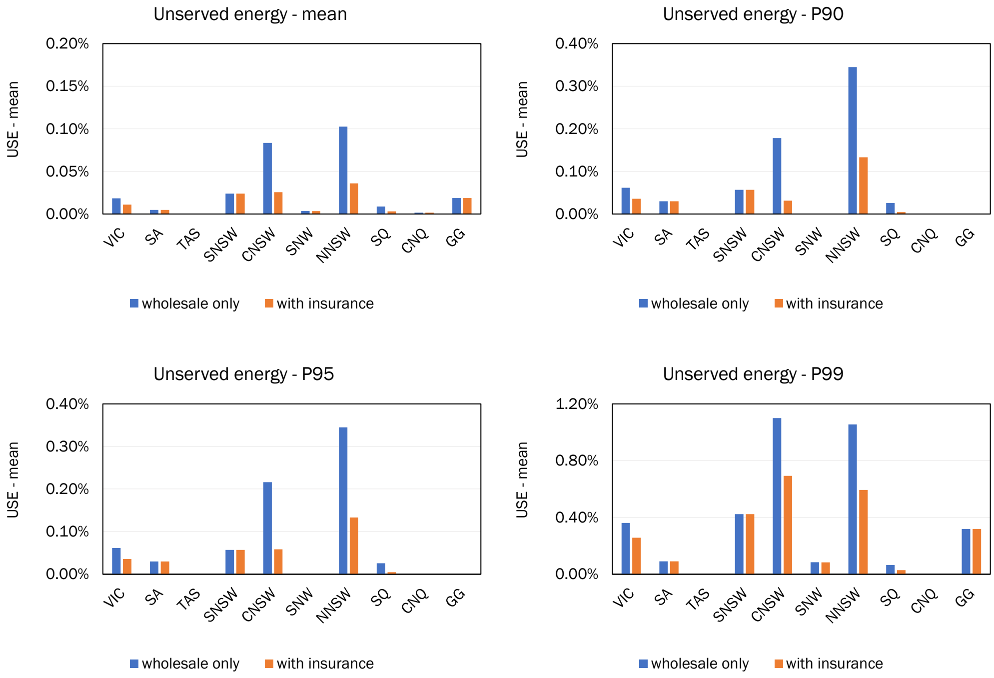

Figure 4.6: Regional unserved energy (USE), measured as a percentage of demand, on an average, 90th percentile, 95th percentile, and 99th percentile basis, under an energy-only market design.

albeit the amount of capital reserves obtained from the solution of (4.4) affords solvency in all the considered scenarios.

To compare the relative efficiency of the scheme, Figure 4.8 illustrates the change in consumer utility arising from the imposition of the insurance scheme under different levels of consumer risk aversion (in the range $0 \leq \beta_d \leq 1.0$). For clarity, consumer utility U_d^c is measured as the weighted mean-CVaR of the consumer surplus, with $\alpha_d^c = 0.05$. For all of the market designs tested, a net positive improvement in total consumer utility is recorded for moderately risk-averse consumers $\beta_d^c \geq 0.5$ across all market designs. For the scarcity-based market designs (EOM and ORDC), the breakeven point of net positive utility improvement is reached at lower levels of risk aversion ($\beta_d^c \sim 0.2 - 0.3$). This result is intuitive due to the incremental resource investments incentivised by the capacity mechanisms. While not directly addressed here, the challenge of designing an incentive-compatible and technology-neutral administrative capacity mechanism is very challenging. [8, 72, 192].

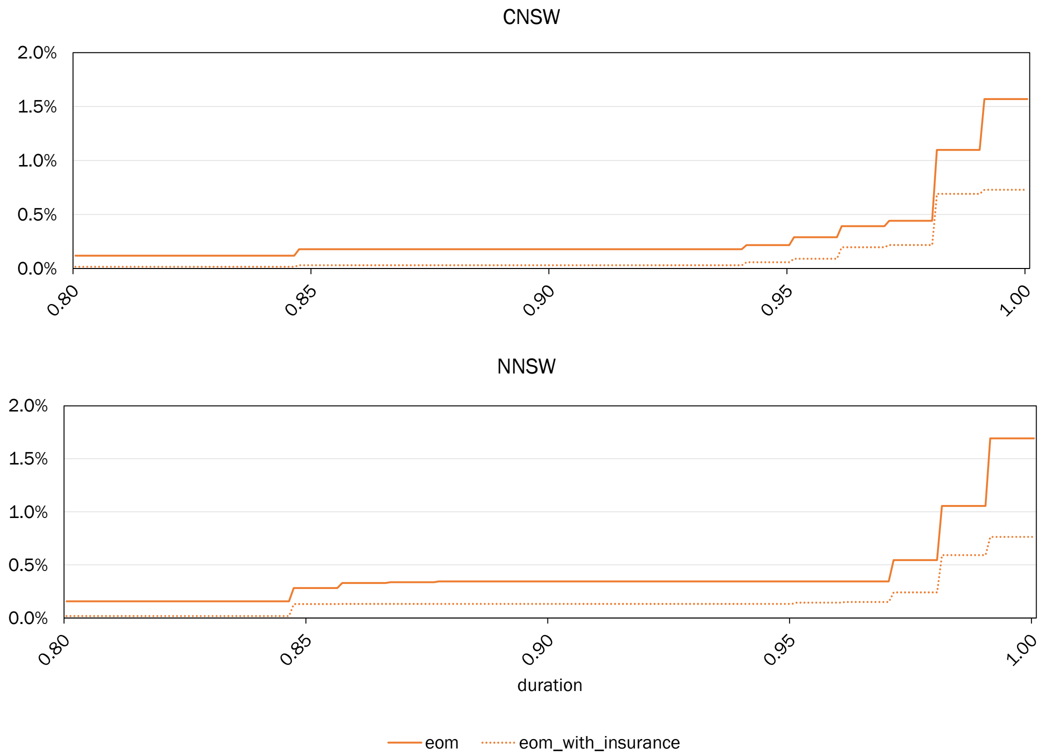

Figure 4.7: Duration curves for unserved energy (USE), measured as percentage of demand, in regional areas of Central New South Wales (CNSW) and Northern New South Wales (NNSW) under an energy-only market design

Table 4.3: Consumer and insurer surplus under EOM design, all figures in \$ billion. "Comp.": insurance compensation, "Res. Cost": cost of provisioning capital reserves, "RDER Cost": operating and investment costs of RDER.

	Base Weather Year Scenarios										Extreme Year Scenarios					
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Consumer Surplus - No insurance scheme																
VOLL	-1.4	-1.0	-0.4	-0.1	0.0	-0.1	-0.6	-1.4	0.0	-0.6	-4.6	-1.6	-12.2	-29.4	-19.1	-4.2
Total (A)	-1.4	-1.0	-0.4	-0.1	0.0	-0.1	-0.6	-1.4	0.0	-0.6	-4.6	-1.6	-12.2	-29.4	-19.1	-4.2
Consumer Surplus - With insurance scheme																
Premium	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8	-1.8
Comp.	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.3	0.0	0.0	0.6	0.2	2.7	7.0	5.1	0.7
VOLL	-0.4	-0.2	-0.1	-0.0	0.0	-0.1	-0.2	-0.9	0.0	-0.1	-1.9	-0.5	-10.8	-22.4	-15.7	-2.1
Total (B)	-2.1	-2.0	-1.9	-1.9	-1.8	-1.9	-2.0	-2.4	-1.8	-1.9	-3.1	-2.2	-9.9	-17.2	-12.4	-3.2
Δ =(B)-(A)	-0.7	-1.0	-1.5	-1.8	-1.8	-1.7	-1.4	-1.0	-1.8	-1.3	1.4	-0.5	2.3	12.2	6.7	0.9
Insurer Surplus - With insurance scheme																
Premium	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.8
Res. Cost	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5
Comp.	-0.1	-0.1	0.0	0.0	0.0	0.0	-0.1	-0.3	0.0	0.0	-0.6	-0.2	-2.7	-7.0	-5.1	-0.7
RDER Cost	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4
Total	0.8	0.8	0.9	0.9	0.9	0.9	0.8	0.6	0.9	0.9	0.3	0.8	-1.8	-6.1	-4.2	0.2
Reserves	7.4	7.4	7.4	7.4	7.4	7.4	7.4	7.4	7.4	7.4	7.4	7.4	7.4	7.4	7.4	7.4

Financial and welfare outcomes

Given the HILP nature of extrema, the cost of insurance for consumers, as measured by the total insurance premium as a proportion of expected compensation payouts, can be relatively high. For the EOM and ORDC designs, premiums are at 4.7 and 5.4 *multiples* of the expected compensation value, respectively. This, however, belies variation across individual regions, ranging from 1-2 *times* in remote regions (*e.g.,* SNSW, CNSW) to 7-20 *times* in urban regions (*e.g.,* SNW, SQ). For the CM design, premiums are at 10.0 times the expected compensation, with similar variations across regions. For individual consumers, the incremental value of insurance varies based on region. For urban centres (SNW, SQ) with strong connectivity, the benefits of insurance are muted relative to more remote areas of the grid, pointing to the need for careful premium allocation and more locationally specific insurance coverage.

Figure 4.9 shows a regional breakdown of the effect of the deployment of the insurance scheme, in terms of mean consumer utility and expected shortfall. In particular, the plots show the sensitivity of these to the insurer's risk aversion. In general, variations of the latter do not produce noticeable differences in the effectiveness of the insurance scheme, once $\beta^i \geq 0.3$. It is noted, however, that for β^i approaching 1, the mean consumer surplus declines abruptly due to the conservative investments made by the insurer, which require an unjustified (on the basis of the considered scenarios) increase in the premium cost. As regards tail events, most regions benefit noticeably from the service of the insurance overlay (considering $\alpha_d^c = 0.05$ for the CVaR). Not all these regions, however, afford a positive mean surplus with the considered premium, which is also a sign of the asymmetrical impact that the different scenarios have at a local level. This suggests that the premium can be readjusted on the basis of the observed regional vulnerability, to keep the scheme attractive to the users.

Sensitivity to insurer risk aversion

Figure 4.10 shows the sensitivity of the amount invested in RDER capacity with respect to the degree of insurer risk aversion. As β^i increases, it is observed that

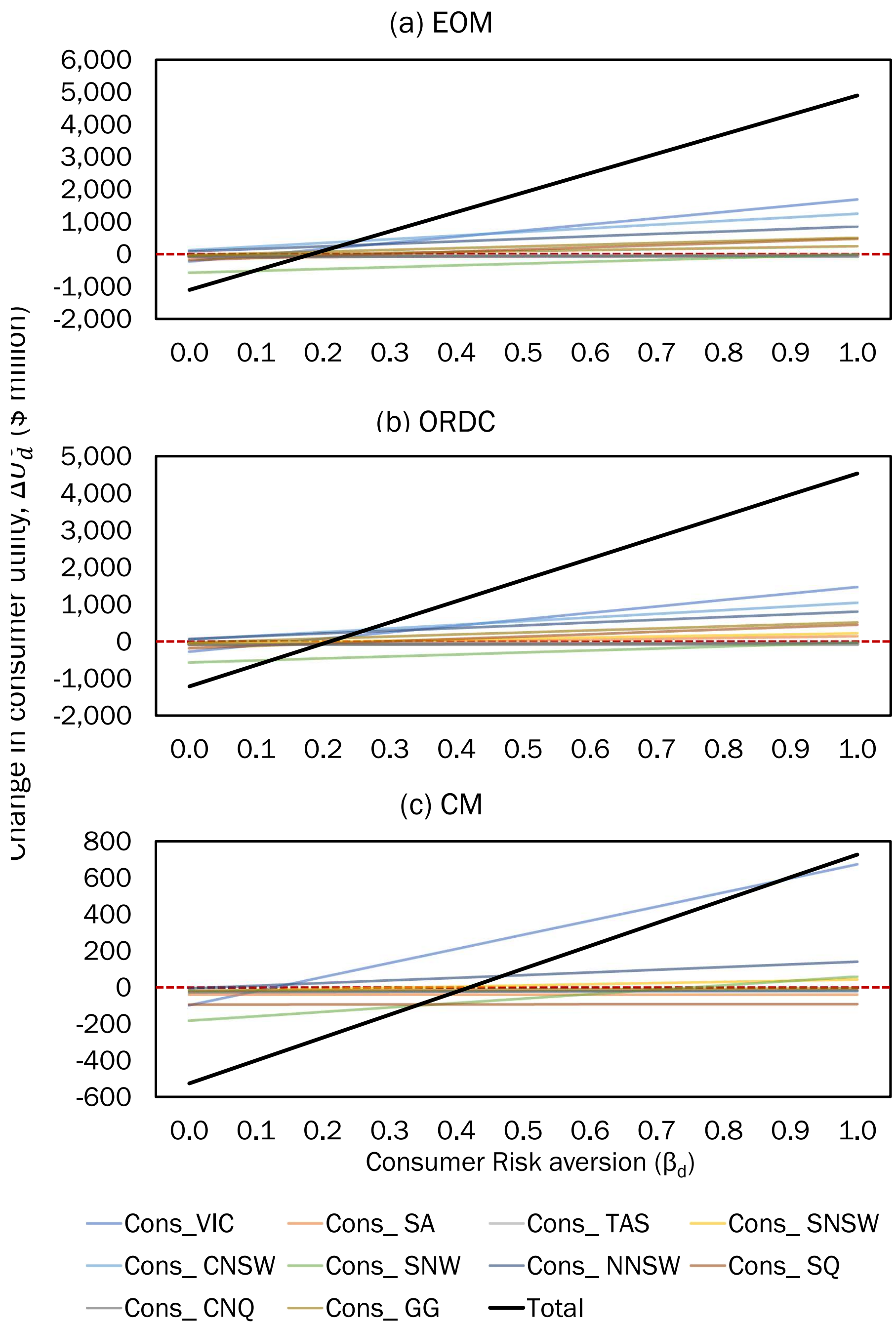

Figure 4.8: Change in consumer utility from the imposition of the insurance scheme ΔU_d^c, in \$ millions under the EOM, ORDC, and CM designs, for differing levels of consumer risk aversion in the range $0 \leq \beta_d \leq 1.0$. Consumer tail probability is set to 0.05 (i.e. $\alpha_d^c = 0.05$) Total consumer utility is shown in black, and consumer utility on a regional basis are shown in colours as per the legend.

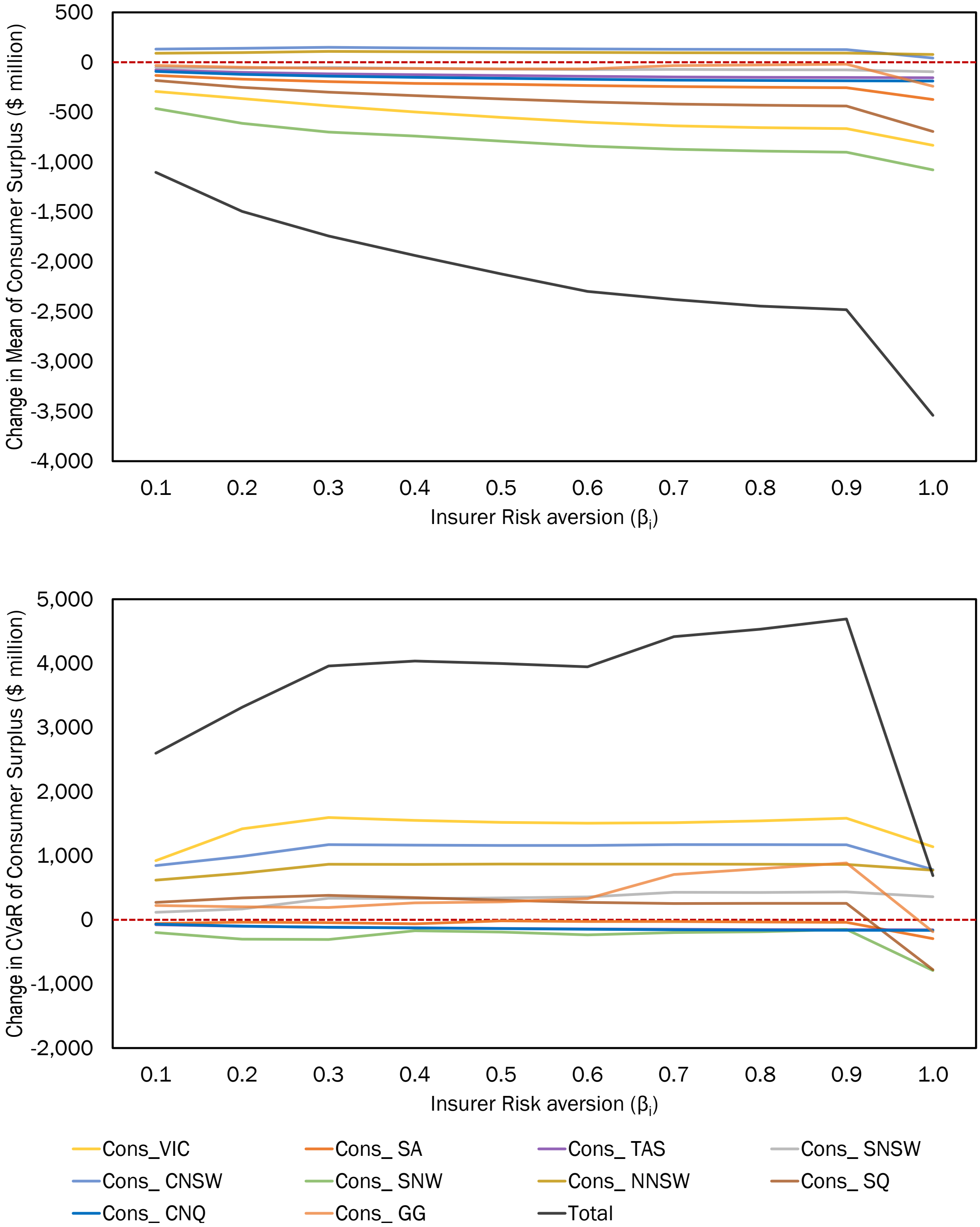

Figure 4.9: Regional breakdown of the effect of the insurance scheme, in terms of mean consumer utility (upper plot) and expected shortfall (bottom plot): sensitivity to variations in the insurer's risk aversion.

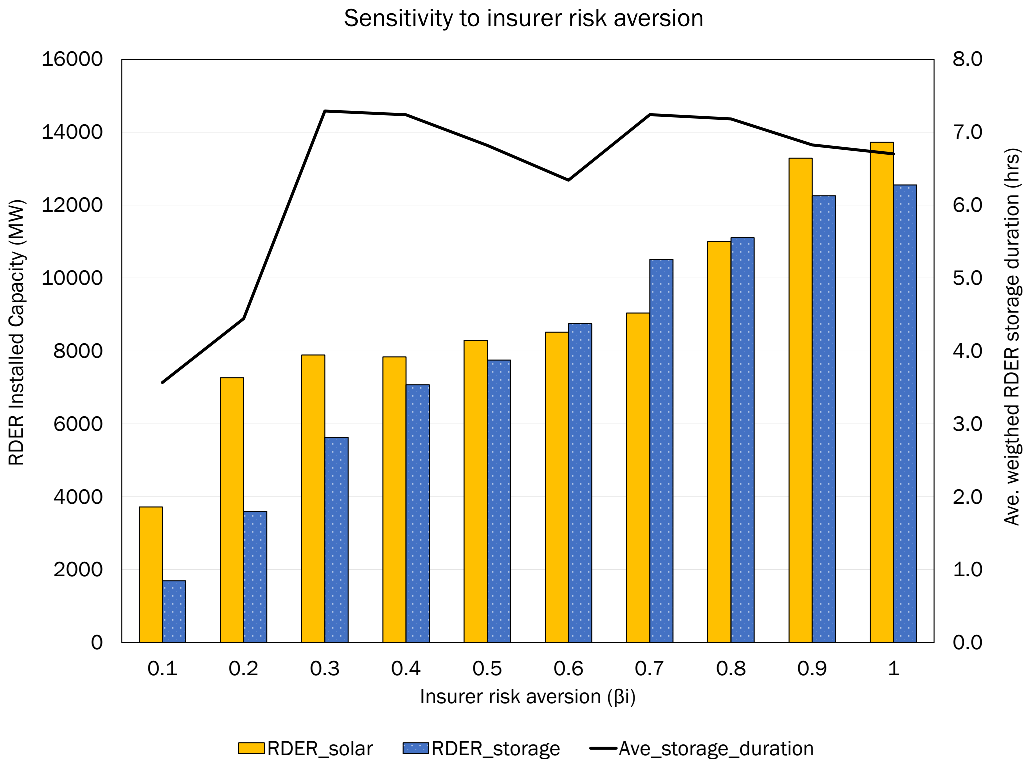

Figure 4.10: Sensitivity of investment on RDER generation and storage capacity to the insurer risk aversion index β^i, under EOM. The solid black trace (relative to the right vertical axis) depicts the average storage duration characterising the assets on which the investments are allocated: this grows from 4 to 7 hours, attained for $\beta^i \geq 0.3$. The average storage duration is weighted by the storage procured in different regions.

the amount invested in RDER (both solar and storage) grows significantly: the investment is twice as large at $\beta^i = 0.5$ and over 3 times under a fully risk-averse case, compared to the case $\beta^i = 0.1$. The average weighted duration of storage also tends to increase with risk aversion from 3-4 hours to 6-7 hours. At higher levels of risk aversion, the insurer is more sensitive to losses flowing from extreme events, especially those precipitated by the loss of transmission interconnection (limiting the ability of wholesale resources to supply energy to load pockets). As such, this sees the insurer investing in distributed resources to mitigate such losses.

Sensitivity against insurance compensation

A sensitivity analysis is conducted against insurance compensation levels with results for the EOM design shown in Figure 4.11. The results indicate that the insurance scheme fails to incentivise investment in RDER at compensation levels

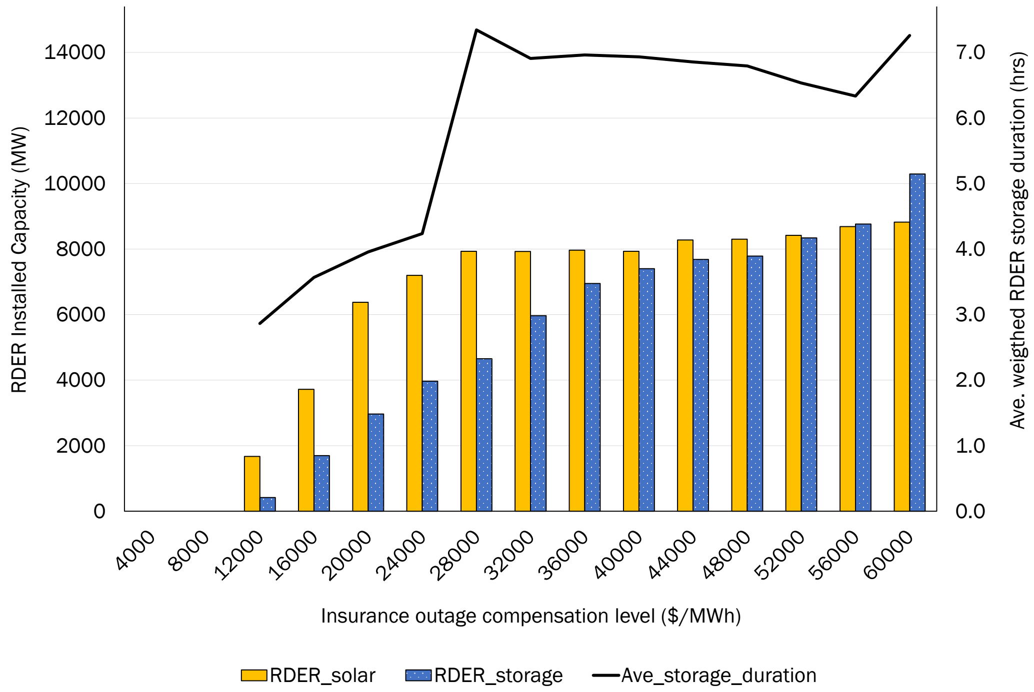

Figure 4.11: Sensitivity of installed RDER generation and storage capacity to insurance outage compensation. The insurance scheme fails to incentivise investment in RDER at compensation levels below \$12,000/MWh. On the other hand, investments reach their maximum at compensations of the order of \$28,000/MWh. This indicates that there are practical bounds to the value of the insurance scheme in a large scale market context.

below \$12,000/MWh. Beyond this level, RDER investment grows but starts to cap out at compensation levels of ∼\$28,000/MWh. This indicates that there are practical bounds to the value of the insurance scheme in a large-scale market context.

Alternative investment models

Finally, while the aforementioned results are obtained under the assumption of direct investment by the insurer in RDER, the study also considers the case where the insurer provides a subsidy to consumers ranging from 20% to 100% of the capital costs of storage RDERs under the EOM framework. The leftmost bars in Figure 4.12 represent the maximum potential investment in storage RDER, expressed by the value $\overline{P_r}$ resulting from (4.4); As expected, the latter decreases as higher subsidies are included in the insurer budget, tending to the direct investment case for κ approaching 1. The blue and red bars represent consumer investments given the level of subsidy provided by the insurance scheme, respectively for near risk-neutral ($\beta_d = 0.2$), and risk-averse ($\beta_d = 1$) preferences. Interestingly, the results show that subsidy levels of 40–80% can drive higher investment compared to the *direct investment* framework. As concerns the RDER storage duration, at lower subsidy levels this is well below the insurer's reference cap, although this gap narrows as subsidies increase and the effective cost of RDER becomes cheaper for the consumer.

While these results point to the viability of the proposed insurance scheme, associated with significant benefits to the energy system reliability, it is important to mention the limitations of this numerical study, which can be overcome in future works. First, to facilitate the analysis, issues related to power system security (*e.g.,* voltage and frequency deviations), were not explicitly modelled. Incorporating these in the model would allow a more precise quantification of the benefits of the proposed approach. Second, scenario risks are presumed to be quantifiable: while the increased availability of data regarding weather and grid operation can facilitate the task, it is acknowledged that not all forms of extreme events could be predicted with the required accuracy. Moreover, while market participants are assumed to be risk averse, it can be challenging to characterise the wide range of preferences and behaviours that can be observed in practice.

4.4 Discussion

The central results of the simulation demonstrate the potential for an insurance overlay to strengthen resilience in the electricity system by driving investment in resilient distributed energy resources and thereby improving reliability outcomes, especially in extreme cases and in more remotely connected regions. The sensitivities also demonstrate the robustness of the core framework, despite emphasising the relative importance of different design aspects. Success criteria are met given the demonstration of acceptable improvements in total unserved energy under extreme risk cases; decreased USE for non-urban remote regions; efficient investment in resilient DER generation and storage; and demonstrated improvements in welfare for consumers with low-to-moderate risk aversion from the introduction of insurance.

There are a number of important policy implications and further areas of inquiry flowing from the results of the case study, as discussed in the following.

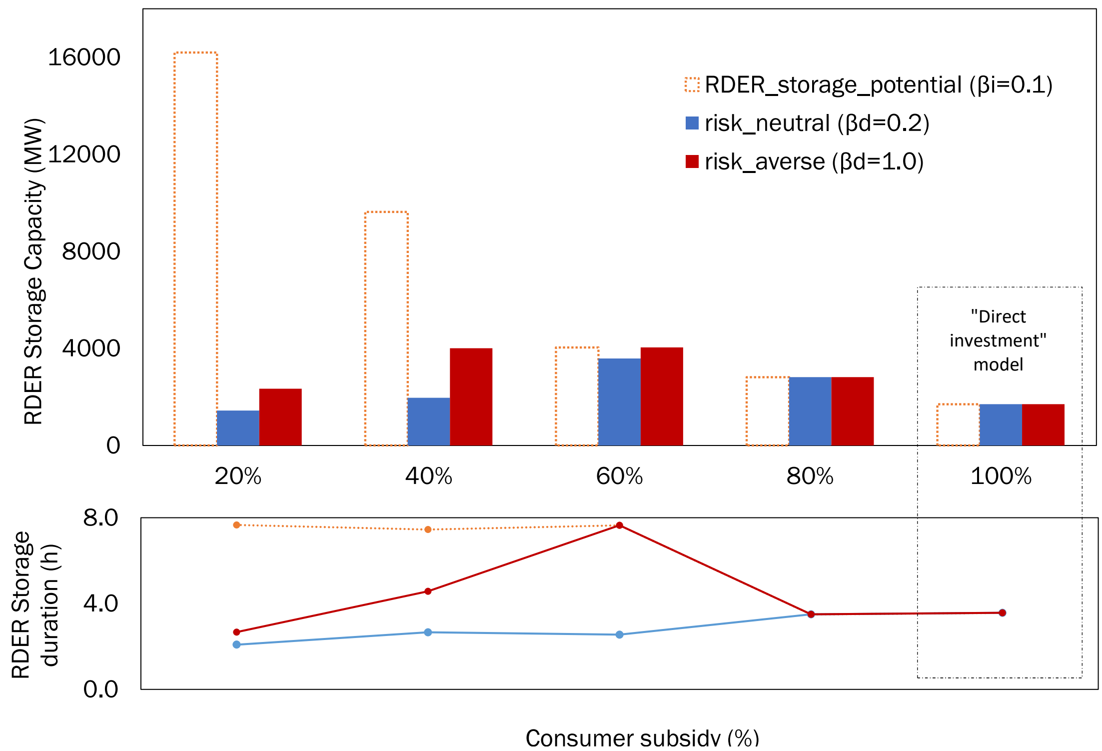

Figure 4.12: Insurance subsidy model: sensitivity of installed RDER storage capacity to the amount of subsidy to consumers. The blue and red bars represent consumer investments given the level of subsidy provided by the insurance scheme, respectively for near risk-neutral ($\beta_d = 0.2$), and risk-averse ($\beta_d = 1$) consumers. The left bars represent the potential investment in storage RDER from the insurer's perspective, expressed by the value $\overline{P_r}$ resulting from (4.4).

4.4.1 Wholesale and distributed approaches to resilience

First, the wholesale market outcomes reinforce the notion that extreme events present real risks for power and energy systems, with particular effects on consumers in poorly connected, remote regions of the grid. This effect remains evident in market designs that incentivise higher levels of investment, such as designs with capacity mechanisms (CMs). Interestingly, in our case study the CM design performed consistently with the inherent bias of such markets towards low capital/high marginal cost resources (such as legacy thermal generation); this has been recognised to be detrimental in scenarios where thermal failure represents the extreme risk [8, 72]. In the current energy system context, the shift from legacy thermal to newer generation technologies (*i.e.*, renewables, storage) underscores the impact of market design on investment mix and the need for careful and transparent parameterisation of risk measures and demand curves for central agencies involved in the procurement of resource capacity to ensure resilience and reliability. Therefore, achieving resilience in large-scale power systems remains an important objective.

Further, the insurance framework provides an economic lens for investment decision making particularly as it relates to high-impact lower probability events. Importantly the RDER investment procured by the insurer and required premiums adjust to the capacity mix yielded by the market design. The cost of insuring extrema is expensive on a relative basis[5], notwithstanding that consumers (with moderate risk-aversion) would still stand to benefit. However, the value of electric reliability insurance is higher in remote *risk-prone* regions, relative to urban centres that are well-supplied. This is consistent with similar assessments across standard insurance lines, like property & casualty [90]. Cost-effective risk mitigation options, such as through distributed resource investment, could be attributed in part to this result. While an insurance scheme has the potential to be viable, regional consumer attitudes and risk exposures should be considered in the allocation of premium costs. Moreover, regional differences in scheme viability may drive a more localised focus for reliability insurance.

While the results do not suggest that all adverse outcomes can be avoided, they nevertheless provide material economic protection to consumers, through the combination of economic loss compensation and loss-mitigating investment. This represents an important alignment with the policy objectives of system resilience which calls for improved resistance and adaptability rather than elimination of extreme impacts altogether [257].

An important area of future research in this area relates to the expansion of the decision set and risks that are considered under an insurance model. Transmission and distribution networks can expose consumers to risk, yet the augmentation, reinforcement or smartening of the network can also be an option to improve

[5]This is consistent with assessments of insurability in traditional insurance lines under climate change. Fat tails, micro-correlations and tail dependence can imply high premiums as a multiple of expected compensation [84]. Appropriate pricing, cost-allocation and risk-sharing frameworks are considered as potential pathways [90]

reliability. As such, it would be useful to investigate an insurance formulation that incorporates transmission network investment (in its multiple forms) as a part of the strategy set of the insurer. More granular consideration and modelling of upstream fuel risks (both in terms of price and availability) should also receive focus in the formulation, and such risk should flow through into the strategy set of available investment options.

4.4.2 Scheme design and risk parameterisation

It is observed that the risk parameters can have a material impact on the level of investment – and given the public nature of the insurance scheme, this would be an important area of consultation and engagement prior to implementation. Furthermore, the results also reflect the trade-offs between insurer 'subsidy' and 'direct' modes of investment. Subsidisation models offer the potential for scalable investment, but are dependent upon consumer risk attitudes and take-up (which may be difficult to ascertain and subject to consumer budget constraints). The insurer has more control over direct investments but must bear all the costs, resulting in lower investment. A granular assessment of consumer attitudes and budgets should accompany any implementation. Finally, the sensitivities also suggest that there are thresholds to scheme operation. With investment benefits only apparent within certain ranges, agencies would need to consider whether they are willing to meet minimum compensation levels over a long-term basis. The success of an insurance scheme depends upon its sustainability both from a capital and income perspective and as such should be considered as part of a programmatic approach to system resilience.

The results of this work support the further development of the central research thesis. The funding of such a scheme requires attention to the economic willingness to pay and social acceptance of premiums to protect and compensate for losses, which are currently all borne by the consumer [279]. The consideration of equity issues related to the allocation of such premiums is an important methodological stream, given that vulnerable consumers can often be located in the regions where risk is highest. The literature on equitable charging of tariffs is a natural starting point here [331]. In terms of scheme design, potential extensions could also consider more detailed terms such as insurance. One example is an insurance deductible which would only compensate consumers above particular thresholds, such as the severity or duration of outages; or total loss amounts. This would allow the scheme to address extreme events more effectively.

Furthermore, government contingent liability is currently an open area of exposure. Comprehensive risk management standards relating to such exposures could aid in developing mitigation and investment plans for resilience. Finally, related streams could look at scheme design and optionality and whether micro-models of insurance could be applied at community levels.

The need for resilience in electricity systems is apparent and immediate. While wholesale market designs should be optimised for resilience, improvements to resilience can also come from distributed architectures, especially for the continuity of essential services during extreme weather. In this proposal for a social insurance scheme for electric service interruptions, the focus is on the alignment of incentives for resilience with capital adequacy and distributed investment. It is illustrated that this can have material positive impacts in encouraging RDER investment, reduction of unserved energy during extremes, while providing financial coverage for consumers.

4.4.3 Theory and methods

Finally, it is desirable that the following potential extensions of the theory and numerical methods be pursued in future research. The understanding of the properties such as existence and uniqueness of equilibria should be investigated. Chapter 3 set out a structured plan for such study, and this remains relevant here. This includes an consideration of the satisfaction or otherwise of Rosen's conditions, variational inequality approaches, non-algorithmic solution strategies and formulation of robustness tests. It would also be worthwhile extending the decision set to incorporate joint DER and transmission investment decision-making in a tractable manner.

4.5 Conclusions

The central thesis of this chapter, as supported by results of the case study, is that the location and decentralisation of power system resources and consumers is a critical aspect of market design. It is important that reliability mechanisms create appropriate locational incentives in respect of resource procurement and cost allocation. Failure to do so may result in inefficient investment, to the detriment of service reliability.

As part of the central contributions of this chapter, for the first time, a novel locational insurance scheme is created that aligns the reliability preferences of consumers in different parts of the electricity network with investment incentives for resilient distributed energy resources. Second, the formulation of a large-scale stochastic risk-averse model of the electricity market reflecting the wholesale spot and resource adequacy market design; and an insurance mechanism for locational resilience. The third contribution relates to the development of a guided search algorithm to seek a market equilibrium reflective of the process of commercial asset retirement and new investment in wholesale equilibrium markets.

Given the vulnerability of the electricity system to extreme events, this chapter develops a model of insurance that applies as an overlay on wholesale market design. Given the natural limits to the degree of protection delivered from a centralised market architecture, the insurance scheme creates incentives for efficient investment in distributed energy resources to add resilience to the energy system. The results of the case study demonstrate that leveraging this framework in large-scale electricity systems could improve consumer welfare outcomes. The distributional impacts of the scheme are also apparent given the benefits of DER investment in reducing service interruptions in regional/non-urban areas. This chapter also highlights the two different mechanisms for activation of the scheme via (i) direct investment, and (ii) consumer subsidy. In the context of the thesis overall, the application of location-specific insurance is demonstrated as being capable of extending the alignment of consumer interests and insurer incentives to more granular representations of the system; and to a richer set of uncertainties that include extreme and common-mode events.

Up to this point in the thesis, the focus has been on the agents in the electricity sector and the impact of insurance mechanisms on investment incentives. It presumes that the insurer will secure investment through direct contracting with new resources that reflect the underlying economic realities. However, the design of risk-hedging contracts for emergent electricity market resources, such as storage, is an important, though as yet unresolved research topic. The next chapter thus moves to the question of incentive-compatible contract design for storage in electricity markets with a central insurance overlay. Specifically, it considers the alignment between the objectives of system reliability, incentives for market dispatch, and the economic interests of the contracted storage resource.

5
Contract Design and Incentives for Storage

Contents

The preceding chapters have been concerned with the development of a market design that addresses the provision of reliable and resilient electricity services in incomplete markets. This is undertaken through an insurance mechanism whereby the insurance agency executes contracts with consumers for reliability insurance; managing liability exposures through priority curtailment and resource contracting.

This chapter shifts focus toward the critical question of how an agency ought to contract with resources, and how such contracts can be structured to ensure reliable and resilient electricity supply. Distinguishing from Chapters 3 and 4 this concentrates upon the interactions between the design of contracts and the operational and market incentives of contracted resources. More specifically, this chapter concentrates on the intricacies of storage contract design, given the crucial role energy storage plays in mitigating the intermittency of renewable energy sources. This chapter thus addresses the research question: *What are key agency principles* *that should be addressed in contracts between the storage resource providers and central procurement agencies?*

Electricity storage serves as an important facilitation resource for decarbonisation. For example, battery energy storage systems (BESS) can provide multiple functions including system balancing, frequency response and more advanced functionality (inertia, dynamic reactive support and grid-formation) [332]. Storage technologies of longer duration, in the region of 8 to 100 hours, will invariably be required to support energy supply from grids with extremely high VRE penetrations [200, 233, 333].

The skewness and variability of electricity spot prices makes it challenging to secure long-term investment finance without some form of hedge [74]. Given the rapid timelines for decarbonisation, an increasing role of governments in incentivising long-duration storage can be predicted. In some jurisdictions, this involvement comes in the form of existing resource adequacy overlays. While in others, most notably Australia, this has come in the form of new central initiation of risk hedging contracts (standalone or as part of a coordinated initiative with renewable and network investments) [334].

One stream of the literature argues for caution or 'judicious use' due to the risk of distortionary impacts on the proper functioning of markets [45]. Another line suggests this is a complementary form of 'hybrid market' (defined further in what follows) [41, 335]. The concept of reliability insurance developed in this thesis is a form of 'hybrid market', recognising the incompleteness of private market incentives [8]. Other more common forms of hybrid market incorporated in the literature include central hedging mechanisms [171] and capacity auctions [62] This chapter considers a hybrid market where a central reliability agency executes contracts with market resources to support investment and reliability. In contracting with projects, the central agency is able to secure resource investment while providing the project with revenue support and cash flow stability. The treatment of contracts between the central agency and storage projects requires careful assessment, given the capability of storage to serve multiple functions in the market.

Contract form is a particularly important aspect of the reliability mechanism design, and can be either explicit (*e.g.* reliability options [171], forward contracts [44]) or implicit (*e.g.* capacity auctions [72]). The assessment of contract form for different forms of generation [48, 73], including renewables [266, 267, 336], has received much research attention. However, academic research on optimal contract designs for storage is still nascent.

The multi-dimensional nature of battery storage complicates the design of an optimal contract. Whereas generation is unidirectional, storage operations require the management of bidirectional energy flows (charge and discharge), co-optimised with ancillary services. This makes the structuring of contracts non-trivial and leads to **Gap 3** as identified in Chapter 2.

The focus of this chapter is on the design of centrally initiated risk-hedging contracts to support long-term financing for standalone energy storage. Such contracts should be structured to meet the objectives of the central insurer or agency. The scope encompasses a spot market design with full-strength price formation, and an appropriately-incentivised central agency to mitigate market incompleteness. There are three limits to the scope. First, it is noted that this analysis is restricted to contracting between a central procurement agency and independent electricity storage projects. It does not consider multi-agent interactions, instead the focus is upon the contract with storage and its impact upon wholesale markets (Chapters 3 and 4 provide frameworks for multi-agent interactions). Second, it presumes a price-taking agent and does not assume any strategic behaviour from either project or central agency. Third, it assumes that there is a capability for the resource to self-commit into the spot market, based on exogenous imperfect forecasts of market prices.

It is noted that the technical capabilities and specifications of services such as inertia and system strength are not covered in this work. Thus, it is assumed implicitly in this chapter that (i) the contracted is able to deliver the service, such as system strength and inertia, to appropriate technical and engineering standards; and (ii) that the more granular terms of the availability contracts will appropriately specify how such service is to be delivered from a technical specification perspective. The following works provide further detail on the technical capabilities and specifications that may be required in such contracts.

This chapter begins, in Section 5.1, with the development of a set of principles for central agency contracting. These principles address the multi-faceted impacts of central agency intervention in risk-trading, with impacts upon wholesale electricity markets and operations. These include preservation of wholesale dispatch incentives, limiting distortions on forward derivative markets, avoiding moral hazards, mitigating impacts on reliability and security, and efficient procurement. The objective is then, to assess a set of fundamental storage contract forms against such principles. As such, Section 5.2 formulates the quantitative model for assessing such impacts. This section also proposes a novel 'yardstick' contract for energy storage that allows for minimum levels of cash flow stability, while preserving incentive compatibility for operational dispatch. In Section 5.3 the model is applied to a case study. It quantitatively demonstrates the challenge of aligning standard contract forms with incentives and the potential of the yardstick contract to satisfy the principles of Section 5.1 whilst improving incentive compatibility. The policy and market implications of designing and structuring long-term contracts for energy storage are set out in Section 5.4, while Section 5.5 concludes with the implications for the overall thesis.

5.1 Contract Principles

The rationale for a hybrid model of electricity market design, involving both private and public participation, is set out a range of works including [8, 41, 66, 73, 335]. They all propose a hybridisation of the market, combining 'competition in the market' with Demsetzian 'competition for the market'. The fundamental trend is well-stated in Joskow [41], p325, in the context of a rapid energy transition:

> "... these developments partially replace the reliance on short-term wholesale prices and voluntary market driven hedging contracts of limited duration to bring forth the targeted quantities and types of wind and solar generating capacity and storage to meet decarbonization

> commitments with competitive procurement of zero-carbon energy and storage."

Yet this has a concomitant acknowledgement that such decision making is, by definition, interventionist and can adversely impact the proper functioning of the market and energy systems. Conversely, if incomplete markets dictate that the alternative fails, what principles might govern how such contracts should be designed to minimise or bound any perceived distortions?

This articulation is relevant for the application of insurance mechanisms in electricity markets. A central reliability insurance framework can be considered a form of hybrid market, whereby incompleteness in private markets are sought to be rectified through extra-market contracting or investment.

Five principles are proposed for government-initiated risk hedging contracts generalised to the procurement of generation or storage resources (though the focus of this work is on the latter). These principles are additional to standard contracting principles relating to the allocation and bearing of risk. The principles are developed with a degree of generality such that they apply to large-scale transactions, auctions and tenders as well as smaller-scale, more bespoke contracting initiatives. The five principles are:

1. Preservation of incentive compatibility in the wholesale market. The first principle is that the design of contracts should ensure that market participants retain sufficient incentives for optimal participation in wholesale spot market – central to the operational reliability and security of the grid [266]. This includes the preservation of locational and temporal signals in the short term market, including for energy, reserves, and ancillary services (such as frequency control).

2. Ensure the proper functioning of forward derivative markets by limiting distortions to short, medium and long term contracting and hedging. The key issue here is to recognise that, by providing a project hedge or incremental revenue source, central agencies inevitably affect project risk balance [337].

However, contract designs should consider how to mitigate adverse impacts on contract availability, liquidity, pricing transparency, and participant incentives.

3. The political economy of central agency contracting also requires a focus on potential moral hazards and equity impacts of decision-making, particular where there is risk of socialisation of losses and privatisation of profits [8].

4. Avoiding adverse impacts on reliability and security of the system. This principle has strong links to (1) but extends further to the operational dispatch and control of storage systems. Thus contracts should consider the transparency of dispatch participation and operational control to limit security risks. Notably some recent contracts have addressed 'missing markets' for security including inertia and grid-formation [338].

5. Finally efficient procurement and value for money *vis-à-vis* costs imposed on the market and consumers given 'benevolent planner' central functionality [334]. To this end, alignment with access and connections, and also with the ability of counterparties to execute, are important.

Consequently, the risk of explicit or implicit bias in contract form under technology agnostic auctions [72, 73] also requires careful consideration. However this is of less relevance to this work given the exclusive focus upon a specific resource type.

5.1.1 Taxonomy of storage contracts

To inform contractual design specifications and templates, a review was conducted of publicly available contract information for existing, proposed and announced storage projects, and announced central procurement processes in the NEM of Australia. The NEM is a jurisdiction with high and growing penetrations of renewables. The market design has strong scarcity price formation, with relatively high market caps (currently at $15,100/MWh). Units self-commit into a centralised market that is dispatched and settled every five-minutes, and co-optimised between energy and eight frequency control ancillary service markets. The market also has a high degree of transparency on project status, financing, and interconnection. While the contracts review has focused upon the Australian NEM, similar trends are observed in international markets for the contracting of storage assets to support project financings, such as the UK, Canada and Europe.

The review's scope was restricted to storage projects that are participating or intending to participate in wholesale spot markets (either wholly or partially). The focus of the review is upon those specifications of risk hedging contracts that express the financial exposures of the project and counterparty (see Appendix C).

The specific approach to the sourcing of information for the contracts review is as follows:

1. The database is populated with all projects on the AEMO Generation Information web page, which provides transparency on, for each NEM region, existing and committed scheduled and semi-scheduled generation capacities; changes and limitations to existing generation; and proposed developments.

2. The database is then filtered for "Storage Units" with the following status: "In-Service", "In-Commissioning", "Committed", and "Announced".

3. For each unit in the list a desktop review of public information is undertaken relating to the contracting status of each project. This is not a legal requirement, but is often publicly disclosed. Search terms include the project name and one or more of "contract", "offtake", "hedge", "derivative", "guarantee", and "service". The public website for the project, owner or developer is also reviewed for information pertaining to contracts or hedges.

Based on the review, while storage contracts themselves can be highly granular, five specifications provide the logic for classifying contracts, as follows:

1. The contract basis (if any) – the derivative index upon which the contract is settled. Unlike standard form generation derivatives, given the inter-temporal and multi-market aspects of storage, it may not be appropriate to have an index based on the energy price at each individual dispatch or trading interval.

For this reason, most storage contracts executed to date (albeit limited) adopt wholesale net revenues generated by the storage unit over a period as the contract basis (or a proxy/yardstick thereof). Net wholesale revenues are calculated as the wholesale spot revenues from storage discharging and ancillary services minus the wholesale costs of storage charging.

2. The contractual form – which at a high level can include a swap of cash flows (predominantly a fixed stream for a floating stream) or options based upon specific triggers and asymmetry (*e.g.* call, put, collars, *etc.*) [48]. While more bespoke structures are possible (*e.g.*, upside revenue sharing, clawbacks, *etc.*), an abstraction from such structures towards fundamental forms is generally sought. It is also important to note that not all contracts are structured as a cash flow exchange. For example, availability payments, grants or other quasi-fixed payment contracts provide a uni-directional and incremental stream of cash flows to the project.

3. The volumetric exposure – this reflects the traded quantity of the contract – which, for storage, is more complex given the focus upon the distinct revenue performance of the underlying asset. As such volumetric exposure is defined as a percentage of the asset's operations – whereupon a full contract will cover the full net revenue generated by the unit, while a partial contract will cover a percentage of net revenue.

4. The periodicity of the contract – for example, whether the cash flow exchange applies on a dispatch interval (DI) basis, or is averaged or summed over longer periods. Where many generation contracts apply on a DI-to-DI basis, storage behaviour can vary across time intervals. Therefore, some form of summation or averaging of the index flows tends to apply.

5. The tenor of the contract (how long the contract is on foot) – *i.e.* monthly, quarterly, or yearly. Generally exchange-traded contracts have to date had maximum tenors of a single year. Bilateral and negotiated contracts tend to

be structured over a longer periods (*e.g.,* 7 to 15 years) to underwrite project financings.

Underpinned by the contracts review, three generalised contractual designs are considered relevant. While it is recognised that real-world contract negotiations will involve more granular terms for the purposes of applying the central design principles, it suffices to adopt a degree of generality in the contract specification. Moreover, in all cases, except for the availability contract, a derivative index of wholesale net revenues over a specific period is adopted. This accounts for the inter-temporal linkages between the dispatch of a storage unit. The three abstracted contract forms are:

- Revenue swaps involving the storage unit exchanging the aggregate net wholesale spot revenues generated by the unit over a period, swapped against a fixed annuity-style payment. The intent is to create revenue certainty for the storage unit (*i.e.,* assisting in 'bankability').

- Revenue floor and cap instruments are intended to set downside and upside limits on net wholesale spot revenues over a period (say a quarter). They are hence structured as call and put options on storage net revenues over a given period (*i.e.,* a revenue floor will effectively limit the quarterly revenues of the unit from falling below a threshold, while a cap will limit the quarterly revenues of the unit from going above a threshold). This can be in the form of a "hard cap" on revenue, or a revenue-sharing arrangement ("soft cap") beyond a specific threshold. A soft cap can be created with partial volumetric exposure. A revenue collar can be created by combining the floor and cap instruments in such a manner so as to ensure that the revenues received by the storage unit are bounded on the downside and the upside (either partially or wholly).

- Availability contracts represent a one-way revenue stream to the storage facility, scaled by the availability of the unit. In some situations, the storage project

> has been required to provide essential system services (such as inertia, fast-frequency response, system integrity, voltage support, and grid formation) in consideration of the financial support provided by the central agency. However, this is neglected for the purposes of the analysis. Availability here represents the operational availability of the unit (*i.e.,* whether it is capable of operating), rather than whether it has sufficient state-of-charge (SoC) to either charge or discharge, as relevant. These can be viewed as relatively fixed revenue streams (assuming that the unit is operationally available), and are thus incremental to any revenues derived from the wholesale spot market. This is often linked to the capability to deliver certain services (such as grid formation, or network support) over particular times.

Motivated by the work of [266] in developing yardstick contracts for renewables, a yardstick contract for storage is proposed (illustrated in Figure 5.1). Rather than a contract that references actual revenues, a yardstick is based on revenues simulated under 'perfect-foresight'. That is, revenues calculated from ex-post simulations of optimal storage dispatch assuming perfect foresight of prices (described further below). For a storage unit operating under imperfect foresight of prices, this creates a performance metric to replicate the perfect foresight outcomes. In doing so, the design preserves revenue stability for the project while ensuring the project has an incentive to match optimal dispatch to the extent possible. Spread contracts, as discussed in [53], appear to have a similar motivation with the derivative index defined as a spread between a set of maximum and minimum energy prices across a period (typically an operating day). Here the energy price spread is considered as the relevant *yardstick*. Ancillary service payments have not been considered to date.

5.2 Methods

To provide further insight into the impact of storage contract design on participant incentives, a modelling framework is required; one that combines a short-run operational model with a long-run investment and financing model. The analysis is

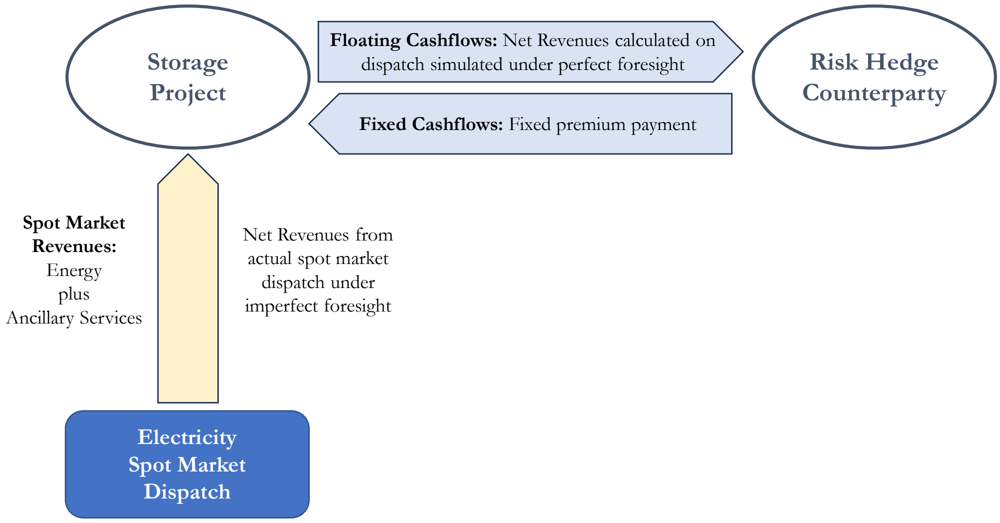

Figure 5.1: Schematic of contractual and spot market cashflows for a storage yardstick contract. The yardstick contract involves the exchange of a fixed premium payment in return for Net Revenues calculated on modelled dispatch simulated ex-post assuming perfect foresight.

focused upon the tractability of standalone storage investments under an array of market conditions and business cycles spanning a multi-year window. The task of simulating these business combinations requires the integration of multiple data sources and a suite of operational and financial simulation models which traverse operational and planning horizons. Standalone storage units are typically funded through project finance (*i.e.* a combination of long-term debt and equity), which is sized based on the quantum and variability of cash flows paid to the project. Contracts are sought to reduce the variability of cash flows and maximise long-dated debt. Project lenders, in particular, seek to ensure that debt is repayable under a range of downside outcomes.

This section presents the formulation for modelling the impact of contract design on short-term and long-term participant incentives. The analysis focuses on the operational dispatch and financial outcomes of a storage unit operating in a wholesale electricity market with decentralised commitment.

5.2.1 Model flow and integration

The methodology integrates two central models – (i) the storage unit commitment model, which models storage commitment and dispatch decisions given a suite of market and technical inputs, and (ii) the dynamic financial model – which integrates outputs from the unit commitment along with technical and capital assumptions to construct a comprehensive set of financial structures, credit metrics, counterparty exposures and minimum viable contract prices. This is consistent with published literature on financing of power generation and storage assets [40, 339].

Operationally, consider a storage unit trading in a decentralised real-time electricity market, settled on the basis of marginal pricing. Agents are assumed to be price takers (who do not act strategically) for both dispatch and investment. They self-commit into multiple energy and reserve markets based on imperfect foresight of exogenous prices. The focus is on battery storage units, though this model and the principles can be readily applied to other forms of storage. To incorporate the impacts of battery cell degradation, a particularly important aspect of BESS operation, a degradation-constrained dispatch is adopted.

In this context, perfect foresight and imperfect foresight relate to the differential between the actual spot price (of energy or reserves) and the forecast price predicted by the storage unit. Scheduling decisions are made on the basis of the forecast prices (and quantities), while the net revenues are outcomes of the unit and are derived from actual prices and quantities. Perfect foresight means that the forecast price is equivalent to the actual price. Under imperfect foresight there is a differential between the forecast prices and quantities, and actual prices and quantities. This differential is modelled as a random variable with a dispersion that represents the accuracy of forecasts. A higher dispersion is indicative of poor forecasting accuracy, and vice versa.

The flows of data inputs to models and outputs are shown in Figure 5.2. Spot market data, prices for energy and frequency control ancillary services (FCAS), and storage technical assumptions are fed into the storage unit commitment model. The key outputs relate to the optimal storage dispatch in response to exogenous prices in the presence of uncertainty. The dispatch outcomes, combined with capital market and technical assumptions, are fed into the dynamic financial model. The latter outputs financial and credit statements, along with counterparty exposures, and a minimum viable contract price. The full specifications of the models are set out in the following subsections. The models are coded on Julia 1.5.3 using

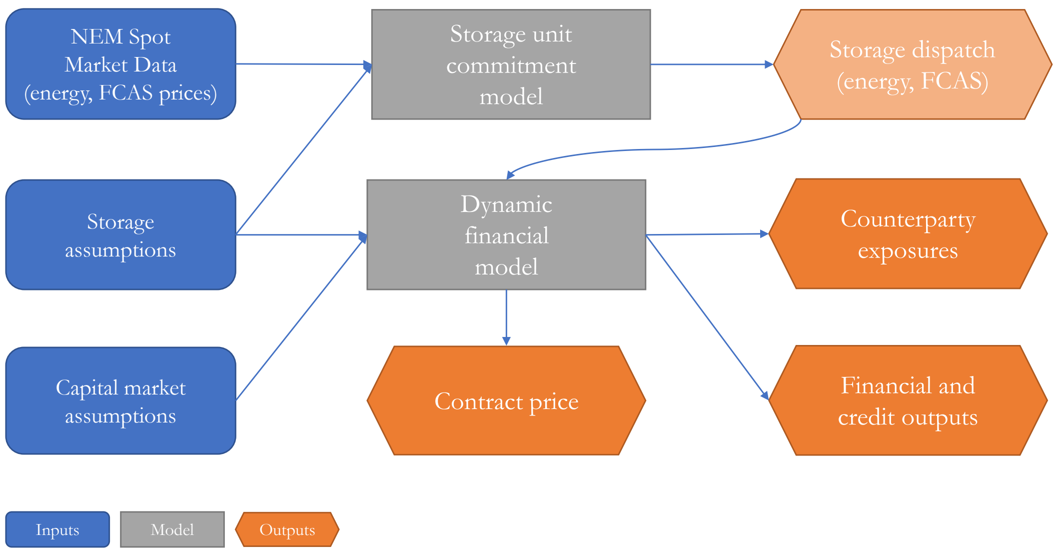

Figure 5.2: Schematic of data sources and modelling framework for assessment of impacts of contract design upon participant incentives. The model framework integrates a short-term unit commitment model with a dynamic financial model.

JuMP 1.4.0 and solved using Gurobi solver 9.5.0 [297].

5.2.2 Storage unit commitment model

Consider a storage unit trading in an electricity market with decentralised unit commitment. The market setting under consideration comprises a real-time market (RTM) for the spot trading of energy and reserves which is settled on the basis of the marginal price. The market setting under consideration does not include a day-ahead market and relies on the real-time market for the spot trading of energy and reserves. The model reflects the current co-optimised markets for energy and eight FCAS services in the NEM. The latter comprises two regulation markets, one in each direction, and six contingency reserve markets (in each direction, and across three time frames, specifically 6 second, 60 second, and 5 minutes). To simplify the analysis, it is assumed that all agents are self-committing price-takers with imperfect foresight of exogenous energy and FCAS prices [1].

Let $t \in \mathcal{T}$ be the ordered set of half-hourly trading intervals over a period $\mathcal{T}$ and $\omega \in \Omega$ the set of agglomerations or sequential scenarios over which the financial outcomes of a storage project are aggregated. For the purposes of this work, each scenario ω relates to a financial quarter, consistent with market practice on financial statement reporting and the typical periodicity of commercial debt interest payments.

The market for energy is denoted with a superscript E. Consistent with NEM market design, a set of eight frequency control reserve services $fr \in FR$ is defined, broken into regulation and contingency services, in *up* and *down* directions. These services are denoted based on the service category, between regulation services REG and contingency services C, and direction $\uparrow$ for upward reserve and $\downarrow$ for downward reserve. Contingency markets are further classified by time period – 6 second (6), 60 second (60) and 5 minutes (5). For example, 60 second contingency down services are denoted as $FR^{C60\downarrow}$, regulation up services are denoted as $FR^{REG\uparrow}$, while the set of all contingency down services are denoted as $FR^{C\downarrow}$.

For each trading interval $t \in \mathcal{T}$ in scenario ω the exogenous locational marginal price of energy is denoted as $\lambda^{E}_{t\omega}$. Similarly, the exogenous marginal price for FCAS reserves is denoted as $\lambda^{fr}_{t\omega}$, for all $fr \in FR$.

However, in the presence of forecast uncertainty the energy price predicted by the storage unit $\hat{\lambda}^{E}_{t\omega}$ will be the sum of the actual price and $\varepsilon^{E}_{t\omega}$, a random variable representing the price forecast error. Therefore, $\hat{\lambda}^{E}_{t\omega} = \lambda^{E}_{t\omega} + \varepsilon^{E}_{t\omega}$ (and similarly for reserves, where $\hat{\lambda}^{fr}_{t\omega} = \lambda^{fr}_{t\omega} + \varepsilon^{fr}_{t\omega}$ for all $fr \in FR$) [340].

[1]This is contrast to some other jurisdictions, which adopt centralised unit commitment processes and short-term ahead markets (day-ahead and intraday).

To model storage unit operations the following is denoted: power charge is p_t^{G+}, power discharge p_t^{G-}, and reserve delivery as $p_{t\omega}^{fr},\ fr \in FR$. Assuming symmetry between charging and discharging efficiencies and assuming netting of charge and discharge a continuous linear formulation of storage dispatch can be used [233].

The vector of energy discharged from a storage resource r over time is defined as $\mathbf{p_{r\omega}^{G-}} = [p_{r1\omega}^{G-}, ..., p_{rt\omega}^{G-}, ..., p_{r\mathcal{T}\omega}^{G-}]$ where $p_{rt\omega}^{G-}$ denotes the energy discharged by resource r in scenario ω, time period $t \in \mathcal{T}$. The vector of energy prices is given by: $\lambda_\omega^{\mathbf{E}} = [\lambda_{1\omega}^E, ..., \lambda_{t\omega}^E, ..., \lambda_{T\omega}^E]$. Similar vectors are defined for energy charged $\mathbf{p_{r\omega}^{G+}}$, FCAS delivered $\mathbf{p_{r\omega}^{fr}}$, and FCAS prices $\lambda_\omega^{\mathbf{fr}}\ \forall fr \in FR$.

For each time interval in a given scenario, the spot market surplus (operating profit) perceived by the storage unit r is $\Phi_{rt\omega}$ is as set out below:

$$\Phi_{rt\omega} = \hat{\lambda}_{t\omega}^E \left(p_{rt\omega}^{G-} - p_{rt\omega}^{G+}\right) + \sum_{fr \in FR} \hat{\lambda}_{t\omega}^{fr} p_{rt\omega}^{fr} + \sum_{fr \in FR} k^{fr} \hat{\lambda}_t^E p_{rt\omega}^{fr} \tag{5.1}$$

The first term comprise the sum of net revenues from energy charge and discharge, while the second term comprises frequency control ancillary service revenues. The third term represents incremental revenues or costs associated with the energy utilised during reserve actuation. The parameter $k^{fr}\ \forall fr \in FR$ reflects the additional utilisation of energy during the actuation of contingency and regulation reserves (upward FCAS involves additional injection of energy, while downward FCAS involves consumption) [270]. In some markets, these costs receive incremental utilisation payments, but in the NEM, metered global settlement processes ensure such flows are incorporated and settled at the relevant regional energy spot price.

Over a time period $\mathcal{T}$, in a given scenario ω, the total spot market surplus is the sum of the surplus over each trading interval as such:

$$\mathbf{\Phi}_{r\omega}^S = \sum_{t \epsilon T} \Phi_{rt\omega} \tag{5.2}$$

Technical constraints also apply to a storage unit, assuming symmetric charge and discharge power capacity of $\overline{P_r}$.

$$0 \leq p^{G-}_{rt\omega} \leq \overline{P_r} \qquad \forall t \in \mathcal{T}, \omega \in \Omega \tag{5.3}$$

$$0 \leq p^{G+}_{rt\omega} \leq \overline{P_r} \qquad \forall t \in \mathcal{T}, \omega \in \Omega \tag{5.4}$$

$$0 \leq p^{fr}_{rt\omega} \leq 2\overline{P_r} \qquad \forall fr \in FR, t \in \mathcal{T}, \omega \in \Omega \tag{5.5}$$

$$S_{rt\omega} = S_{r,t-1,\omega} + \varsigma^{+}_{r} p^{G+}_{rt\omega} - \frac{1}{\varsigma^{-}_{r}} p^{G-}_{rt\omega} \qquad \forall t \in \mathcal{T}, \omega \in \Omega \tag{5.6}$$

$$0 \leq S_{rt\omega} \leq \overline{P_r} e_r \qquad \forall t \in \mathcal{T}, \omega \in \Omega \tag{5.7}$$

$$-\overline{P_r} \leq p^{G-}_{rt\omega} - p^{G+}_{rt\omega} + p^{FR^{REG\uparrow}}_{rt\omega} + p^{fr}_{rt\omega} \leq \overline{P_r} \qquad \forall f \in FR^{C\uparrow}, t \in \mathcal{T}, \omega \in \Omega \tag{5.8}$$

$$-\overline{P_r} \leq p^{G+}_{rt\omega} - p^{G-}_{rt\omega} + p^{FR^{REG\downarrow}}_{rt\omega} + p^{fr}_{rt\omega} \leq \overline{P_r} \qquad \forall f \in FR^{C\downarrow}, t \in \mathcal{T}, \omega \in \Omega \tag{5.9}$$

$$\sum_{t \in \mathcal{T}} (p^{G+}_{rt\omega} + p^{G-}_{rt\omega}) \leq \zeta^{deg} \qquad \forall \omega \in \Omega \tag{5.10}$$

Power limits restrict the delivery of charge and discharge in equations (5.3) and (5.4) for the FCAS reserve delivery in equation (5.5). The state of charge of a unit at each trading interval $S_{rt\omega}$ is defined in 5.6 reflecting symmetric charge and discharge efficiency, ς^{+}_{r} and ς^{-}_{r}. [2]. Limits on the state of charge are defined in constraint 5.7 based on the energy duration e_r.

Constraints on the combined delivery of discharge, charge and FCAS reserves is set out in equations (5.8) and (5.9). It is assumed that regulation and contingency services are mutually exclusive given that regulation operates across the dispatch period overlapping with all contingency services. Contingency services are assumed not to be mutually exclusive, as they each operate over different time frames. Instantaneous ramping capability is assumed for BESS for FCAS delivery [341].

Degradation represents an important aspect of BESS technical parameters and operation. Inevitable cell degradation renders the battery lifetime volatile and highly dependent on battery dispatch, and thus incurs an opportunity cost during operations.

A range of alternative approaches can be adopted to model degradation: A degradation constrained dispatch model is proposed in [342], which imposes an

[2]Note that if regulation services are provided, they will draw on the state of charge; a small expected amount is withdrawn from state of charge in the casae of regulation raise, and a small amount is added for regulation lower [270].

upper limit on the degradation or usage of the battery over a particular time period; explicit cost functions are adopted in [343], based on an estimate of economic usage; further, a rainflow cycle-counting algorithm is proposed in [344] to quantify cycles in the battery's state-of-charge profile. The latter model is specific to lithium-ion battery applications, while the first two are generalised approaches. On balance a degradation constrained dispatch model is adopted in this chapter given it aligns with the warranty conditions imposed by equipment manufacturers on battery owners and operators.

The model incorporates a degradation constrained dispatch of the form adopted in [342] where degradation is constrained to a limit ζ^{deg} over the relevant temporal time frame $t \in \mathcal{T}$. Degradation impacts are proxied by the summated charge and discharge of the unit from cycling (see [340, 342]). A price-taker storage unit will seek to maximise its short-run surplus based on estimates of exogenous prices.

This results in a tractable linear programme SUC_ω, as set out below, which can be solved to optimality by commercial solvers [297]. The decision variables for the linear programme are set out in (5.13).

$$\max_{V_\omega} \mathbf{\Phi}^S_{r\omega} \tag{5.11}$$

$$\text{subject to:}$$

$$(5.3) - (5.10) \, \forall \omega \in \Omega \tag{5.12}$$

$$V_\omega := \{p^{G-}_{rt\omega}, p^{G+}_{rt\omega}, S_{rt\omega}, p^{fr}_{rt\omega} \; \forall fr \in FR\} \tag{5.13}$$

5.2.3 Contract formulation

In the formulation of contracts, the contract difference payment is denoted as $\Phi^C_{r\omega c}$ as the sum of net proceeds from contracts based on the pay-off rules of the contract. It is assumed that contracts are executed ahead of the relevant dispatch period and, as such, that volumes and pay-off rules are fixed. Moreover, the battery is assumed to be perfectly available for all periods and scenarios in which the contract is in operation.

For all contracts considered in this study, the contract basis is assumed to the net revenues from spot markets over a scenario ω. As such, the net revenues comprise those profits realised from participation in energy and FCAS markets over the contract periodicity $t \in \mathcal{T}$. The contract basis is specified in 5.14 as $\varphi_{r\omega}$ for each scenario ω as below:

$$\varphi_{r\omega} = \sum_{t \in \mathcal{T}} \lambda^{E}_{t\omega}(p^{G-}_{rt\omega} - p^{G+}_{rt\omega}) + \sum_{fr \in FR} \lambda^{fr}_{rt\omega} p^{fr}_{rt\omega} \tag{5.14}$$

Revenue swaps $c \in \mathcal{C}^{swap}$ are referenced against the contract basis, *i.e.,* net revenues of the storage unit over the contract periodicity $t \in \mathcal{T}$, swapped against a fixed payment ϕ_c. The volumetric exposure is defined as the percentage of operations that the contract is exposed to and denoted as v.

$$\Phi^{C}_{\omega c} = v\,(\phi_c - \varphi_{r\omega}) \qquad \forall c \in \mathcal{C}^{swap} \tag{5.15}$$

Periodic revenue floor and caps instruments are intended to set downside and upside limits on storage net revenues over a period $\mathcal{T}$. They are hence structured as call and put options on storage net revenues in equations (5.16) and (5.17), respectively, where η_c represents the threshold payment level above or below which the options are exercised. The premium paid or received for the option is ϕ_c (received for caps and paid for floors). A collar can be created by combining the floor and cap instruments, resulting in storage project financing with upside and downside bounded revenues. A partial cap can be created through partial volumetric exposure with $0 < v < 1$.

$$\Phi^{C}_{\omega c} = v.(-\phi_c + \max(\eta_c - \varphi_{r\omega}, 0)) \qquad \forall c \in \mathcal{C}^{floor} \tag{5.16}$$

$$\Phi^{C}_{\omega c} = v.\,(\phi_c + \min(\eta_c - \varphi_{r\omega}, 0)) \qquad \forall c \in \mathcal{C}^{cap} \tag{5.17}$$

For the swaps and options defined above, the contract basis (*i.e.* the financial metric that the derivative contracts are referenced against) is actual net spot revenues $\varphi_{r\omega}$. That is to say that the quantities of energy and reserves delivered are based upon the actual storage unit commitment outcomes of the storage unit under imperfect foresight. This is in contrast with the yardstick contract defined below.

Grants or service contracts represent a one-way revenue stream to the storage facility, scaled by the average availability of the unit $\overline{A}$.

$$\Phi^{C}_{\omega c} = \overline{A}\phi_c \qquad \forall c \in \mathcal{C}^{avail} \tag{5.18}$$

Yardstick contracts for a storage unit, as discussed in Section 5.1, have a contract basis that is the optimal spot surplus over the time period $\varphi^*_{r\omega}$. The optimal spot surplus is the outcome of the storage unit commitment model under perfect foresight. It is an ex-post measure based on the out-turn prices and optimal storage commitment under 'perfect foresight' of prices in the market. For the purposes of the model, the mechanics of the optimal spot surplus involves the following steps. First, setting the price forecast error for energy $\varepsilon^E_{t\omega}$ and reserves $\varepsilon^{fr}_{t\omega}, \forall fr \in FR$ to zero. This is equivalent to a setting of perfect foresight of prices. Second, the storage unit commitment problem is run under this assumption of perfect foresight. This is set out in Algorithm 4. The decision variables from this run of the storage unit commitment model are V^*_ω from which the relevant optimal charge, discharge and reserve schedules $p^{*G+}_{rt\omega}; p^{*G-}_{rt\omega}; p^{*fr}_{rt\omega}\ \forall fr \in FR$ are multiplied by actual energy and reserve prices to calculate the optimal spot surplus. A yardstick revenue swap contract based would have the contract difference payments calculated as per equations (5.19) and (5.20).

Algorithm 4: Calculation of optimal spot market surplus

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input : vector of prices and technical parameters
output : storage dispatch schedules under perfect foresight
initialisation: set $\varepsilon^E_{t\omega} \leftarrow 0, \varepsilon^f_{t\omega}, \forall fr \in FR \leftarrow 0$;
run: $SUC_\omega \forall \omega \in \Omega$
$V^*_\omega \leftarrow V_\omega \in \arg\max_{V_\omega} SUC_\omega$
return

$$\varphi^*_{r\omega} = \sum_{t \in \mathcal{T}} \lambda^E_{t\omega}(p^{*G-}_{rt\omega} - p^{*G+}_{rt\omega}) + \sum_{f \in FR} \lambda^f_{rt\omega} p^{*f}_{rt\omega} \tag{5.19}$$

$$\Phi^C_{\omega c} = v(\phi_c - \varphi^*_{r\omega}) \qquad \forall c \in \mathcal{C}^{swap*} \tag{5.20}$$

5.2.4 Dynamic financial model

The dynamic financial model considers the impact of contract structure on the market financing of a standalone storage resource. Of particular interest is understanding the minimum viable price that can be offered on a particular form of contract in a manner that secures a commercial financing of the asset while reflecting the risk and return preferences of the capital investors. The model takes, as inputs, the results for the storage unit commitment model combined with storage technical assumptions and capital markets input data to produce a comprehensive set of financial structures, credit metrics, buy-side counterparty exposures, and minimum contract price. Given the role of credit quality as a fundamental driver of investment in energy markets, across both independent [49] and vertically integrated operations [40], it is important that the model mimics practical tranched capital structures and financeability metrics. The model develops a cash flow waterfall consistent with generally accepted financial conventions used by project finance banks. These metrics are subject to robust constraints over the financing period, reflecting the requirements of debt and equity capital. The core formulation is set out below along with definitions of financial metrics. The objective function of the model is defined as a minimisation of the contract price ϕ_c subject to the financial constraints. Cash flows and financial metrics are subscripted by ω to represent cumulative cash flows over a quarterly period. This results in a tractable linear programming problem PF_r that is solved to optimality.

$$\min_{W} \phi_c \tag{5.21}$$

subject to:

$$\Pi_{\omega}^{CFADS} \geq DSCR_{min}\sigma_{\omega} \qquad \forall \omega \in \Omega \tag{5.22}$$

$$\sum_{\omega \in \Omega} \Pi_{\omega}^{CFADS} \geq DSCR_{ave} \sum_{\omega \in \Omega} \sigma_{\omega} \tag{5.23}$$

$$\Pi_{\omega}^{CFE} \geq CFE_{min} E \qquad \forall \omega \in \Omega \tag{5.24}$$

$$\sum_{\omega \in \Omega} \Pi_{\omega}^{CFE} \geq CFE_{ave}.|\Omega|.E \tag{5.25}$$

$$W = \{\phi_c, D, E\} \tag{5.26}$$

Equation (5.22) ensures that cash flows available for debt service (CFADS) exceed a scaled quantity of forecast debt service – akin to minimum debt service coverage ratios (DSCR) covenants as a key project financing metric. Equation (5.23) ensures that the average DSCR is in excess of a required threshold, another important debt sizing metric. Equation (5.24) ensures that quarterly cash flows available to equity (CFE) exceed a minimum requirement guided by investor preferences for periodic cash flow yield, while equation 5.25 ensures that equity return thresholds are met in expectation over the investment horizon.

$$\Pi_{\omega}^{EBITDA} = \Phi_{\omega c}^{C} + \Phi_{r\omega}^{S} - c_r^f \overline{P_r} \tag{5.27}$$

$$\Pi_{\omega}^{CFADS} = \Pi_{\omega}^{EBITDA} - \Gamma_{\omega} \tag{5.28}$$

$$\Pi_{\omega}^{CFE} = \Pi_{\omega}^{CFADS} - D\rho \tag{5.29}$$

$$\tag{5.30}$$

Constraints (5.28) to (5.29) define key financial flows in the cash flow waterfall. Earnings before Interest, Taxation, Depreciation and Amortization (EBITDA) Π_{ω}^{EBITDA} is defined as the sum of spot market surplus and contract difference payments, minus fixed operating costs. In equation (5.28), CFADS Π_{ω}^{CFADS} is defined as EBITDA minus quarterly taxation liabilities Γ_{ω}, while CFE Π_{ω}^{CFE} is given as those cash flows accessible to equity investors after accounting for fixed debt service payments, represented as the product of total debt D and the annuity payment factor ρ given the debt horizon and interest rate as set out in equation (5.29). Taxation liabilities are calculated in (5.31) as a multiple of tax rate τ and EBITDA minus quarterly depreciation d_{ω} (with the depreciation schedule based on a flat rate on invested capital over the tax life of the asset) and interest i_{ω} as determined by the debt service schedule, as follows:

$$\Gamma_{\omega} = \tau(\Pi_{\omega}^{EBITDA} - d_{\omega} - i_{\omega}) \tag{5.31}$$

Debt service payments are based on standard annuity mortgage repayment profiles in equations (5.32) and (5.33).

$$\rho = \frac{q}{1 - (1+q)^{-|\Omega|}} \tag{5.32}$$

$$i_{\omega} = \rho - p_{\omega} \tag{5.33}$$

Constraint (5.34) ensures that total invested capital is equivalent to the sum of debt D and equity E tranches.

$$c_r^I \overline{P_r} = D + E \tag{5.34}$$

An analysis of parameter changes on capital returns, given a fixed contract price, is also undertaken. In such exercises, the contract price ϕ_c is set as a fixed parameter rather than a decision variable, and the objective function is defined as a maximisation of equity returns, defined as total distributions over equity capital invested, replacing the previous objective function (5.21) by the objective function (5.35) and constraint (5.36), and introducing a new decision variable E^{-1} which is the inverse of the equity capital decision variable. This results in a non-convex bilinear problem – which can be solved to global optimality by the Gurobi commercial solver under acceptable time frames for the cases considered [297].

$$\min \sum_{\omega \in \Omega} \Pi_\omega^{CFE} . E^{-1} \tag{5.35}$$

$$E \cdot E^{-1} = 1 \tag{5.36}$$

Finally, when running sensitivities against a fixed capital structure, the objective function is nullified (set to a nominal constant of 1) but with adding an additional constraint (5.37) that the debt is sized as the product of the total capital invested c_r^I and a predefined level of financial gearing G (which is defined as the ratio of debt to total capital):

$$D = C_r^I \overline{P_r} \cdot G \tag{5.37}$$

5.3 Case Study

5.3.1 Data and Sources

The case study for this article uses historic, granular 30-minute spot pricing data from the NEM's South Australian region [345]. The period selected from the financial years (FY) FY2012-13 to FY2021-22 represents multiple NEM pricing cycles, where scenarios $\omega \in \Omega$ are the sequential quarterly periods between the selected time periods. The spot market settings comprise a price cap of AUD$15,500/MWh and a price floor of -$1,000/MWh . The model co-optimises and self-schedules dispatch based on energy price traces of the NEM's South Australia regional reference price (SA1 RRP), and eight frequency control ancillary service markets (upwards and downwards regulation service, six contingency services – with 6 second, 60 second and 5 minute durations, each in upwards and downwards directions).

The case study models a 12-hour BESS unit with technical and cost assumptions as set out below in Table 5.1. Capital investment costs are sourced from [345] based on the 2025 projected cost of battery storage in the South Australia low cost region under the step change scenario. Fixed costs are sourced from [345] with economic and tax lives of 25 and 20 years assumed for all assets. Both costs are scaled up to the relevant duration based on the fixed $/MWh for the nearest sized asset. For the degradation constraint a quarterly degradation limit is applied based the BESS duration multiplied by 90, approximately representing the number of days in the quarterly cycle - see [342] (pro-rata to around one BESS duty cycle per day). All assets also incur a transmission access charge of $4,500/MW-yr [334] Charge and discharge efficiencies for BESS are based on the Li-ion design adopted in [342]. Energy utilization is assumed to 0.2 for regulation raise services, 0.1 for regulation lower services, and zero for contingency services [270]. The model was tested against multiple storage units with different durations and technical assumptions yielding the same directionality of results. In addition, a range of economic, financial and capital markets assumptions underpin capital sizing and structuring in the dynamic financial model as per Table 5.2. Debt and equity sizing constraints are assumed to apply quarterly and contract payments are settled at the same periodicity. The financial assumptions are consistent with [49] and updated based on most recent market data. The model is calibrated through a comparison of template unit assumptions with public data on recently approved and constructed projects across the NEM and the US [346], as well comparing consistency of the assumed toll payment requirements with the most recent Lazard levelised cost of storage study [347]

Table 5.1: Case study technical and cost parameters

Parameter	Value
Technology	BESS
Maximum power capacity, $\overline{P_r}$ (MW)	25
Energy duration (hrs)	12
Investment cost per kW, C_r^I (\$/kW)	4046
Investment cost per kWh, C_r^I/e_r (\$/kWh)	337
Fixed operating costs, c_r^f (\$/kW/yr)	46.5
Charge efficiency, ς^+ (%)	0.86
Discharge efficiency, ς^- (%)	0.86

Table 5.2: Financial assumptions and parameters

Assumption	Value
Risk free rate	3.5%
Debt margin	1.0%
Equity risk premium (post-tax)	4.5%
Tax rate	25%
Debt tranche	Standard credit foncier
Tenor	10 years
Debt amortization	20 years
Min DSCR – qtrly	1.05
Average DSCR	1.30
Min equity return – qtrly	0.0

The contractual calibration outcomes are set out in Table 5.3. A base forecast price error standard deviation of \$25/MWh was used to calibrate the contract price for all contract forms. For the revenue swap this leads to an expected equity yield of 9.3% with a minimum viable base contract price (qtrly) of \$2.5m for the revenue swap, with the sensitivities from \$0/MWh to \$50/MWh conducted off the fixed price and gearing implied by the base scenario. Partial contracting of the revenue swap retained the base quarterly contract price of \$2.5m. The revenue floor threshold was calibrated to a level that fully pays debt (*i.e.* a minimum quarterly equity yield of 0.0%), resulting in a floor threshold of \$1.4m. For revenue collar scenarios, the cap threshold was calibrated to an average equity yield of 20.0% resulting in a hard cap threshold of \$6.0m. No premiums are assumed to be paid or received under caps and floors.

Table 5.3: Contract Calibration for Case Study

Contract	**Contract strike, (\$m, qtrly)**	**Gearing**
Uncontracted (v=0)	NA	0.22
Contracted		
Revenue Swap		
$v = 0.25$	2.6 (pro-rata)	0.41
$v = 0.50$	2.6 (pro-rata)	0.60
$v = 0.75$	2.6 (pro-rata)	0.80
$v = 1.00$	2.6	0.80
Floor	1.4	0.57
Cap	6.0	0.57
Collar (floor + cap)	6.0	0.57
Availability \$1m	1.0	0.59
Availability \$1.4m	1.4	0.75
Swap - Yardstick	3.8	0.74

5.3.2 Results

With respect to presentation of results, first the distributions of cashflows under alternative contract designs are illustrated, followed by a presentation of range of volatility and risk measures. Subsequently, there is a specific discussion of results relating to revenue floor and collar contracts, followed by an assessment of incentive alignment and yardstick contracts.

Cashflow distributions

In markets with decentralised commitment, price-taker storage operations use complex algorithms to predict prices and to manage inter-temporal price and dispatch risk in the presence of forecast uncertainty. This is at the core of the value proposition for storage in wholesale spot markets – *i.e.* the ability to rapidly respond to system conditions and arbitrage between periods of low and high prices. In this context, the price error reflects the difference between the actual spot price and the forecast price used by these algorithms. The volatility or standard deviation of the difference between actual and forecast price (forecast price error) is adopted as a proxy for how good the storage unit is in making such price predictions. In other words, a unit with a low volatility of forecast price error is considered better at forecasting prices (and vice versa). In an incentive compatible design such a unit should be rewarded for good predictive performance through better financial outcomes, and vice versa. This preserves the incentives of the unit to seek optimal foresight of price signals.

The quantitative insights are based on a case study of a 12-hour BESS unit operating in the South Australian region of the NEM, an area of extremely high renewable deployment (*i.e.* 60+% VRE market share) over a period of 10 years. This may offer insights for other regions that are not as yet advanced in the scale of intermittent, zero-marginal cost resources but, as a caveat, any extrapolation should consider the comparability of market design, industrial organisation, and regulation.

A set of contract designs is considered based on the templates comprising: (i) revenue swaps with volumetric exposure ranging from 0.0 (uncontracted or merchant) to 1.0 (fully contracted); (ii) revenue collars – comprising a revenue floor with a partial revenue cap with volumetric exposure ranging from 0.0 (floor only) to 1.0 (hard cap); (iii) an availability contract at full volumetric exposure; and, (iv) a yardstick net revenue contract. For each design, the sensitivity of the project's financial outcomes under imperfect foresight is modelled for a range of price-error standard deviations ranging from \$0/MWh-\$50/MWh in \$10/MWh increments.

Figure 5.3 sets out the boxplot (the empirical statistical distribution) of cash flows to equity (CFE) under the full suite of contract designs under price error volatility (as represented by the standard deviation of the price forecast error, ranging from \$0/MWh to \$50/MWh). The results are scaled to a unit equity capital investment of \$100 million to provide a comparable estimate of how cash flows to equity (CFE), the cash flows provided to owners of the storage project, may change under variable forecast price performance.

Figure 5.4 sets out the coefficient of variation (defined as the empirical standard deviation divided by the mean) of CFE for the suite of contract designs under price error volatility (as represented by the standard deviation of the price forecast error, ranging from \$0/MWh to \$50/MWh). Specifically, the coefficients of variation in Figure 5.4 provide an indication of the relationship arising between the dispersion of price error and the dispersion of project equity cash flows for different contracting structures.

A larger set of statistical risk measures, comprising the empirical earnings, or VaR and CVaR, supporting the central thesis is provided in Figures 5.5 and 5.6, at α tail risk thresholds of 5% and 10%, respectively.

Cashflow volatility and risk

The results of the modelling present insights on the alignment between market dispatch and participant financial outcomes. Under a revenue swap arrangement, wherein spot market revenues are exchanged for a fixed payment, the risks and rewards associated with multi-market, inter-temporal revenue arbitrage are transferred from the storage unit to the counterparty. This is emphasised through examining the variability of cash flows for the storage unit.

It is observed that merchant or uncontracted storage (Figure 5.3, panel A) exhibits variation in cash flows from higher price error, particularly relating to downside returns. As the standard deviation of price error increases from \$0/MWh to \$50/MWh, median cash flows to equity for merchant storage declines by 50% and bottom quartile cash flows decline by 68%. This is supported by declines in

VaR and CVaR risk measures (presented in Figures 5.5 and 5.6, Panel A). In other words, a merchant storage resource is penalised for poorer predictive performance. By contrast, cash flows for fully contracted storage (Figure 5.3, panel E) are fixed and remain the same, regardless of changes in the standard price error. This also corresponds with the coefficient of variation (CV) (Figure 5.4, panel A) for merchant storage increasing with higher price error, while the transfer of operational risk results in a coefficient of variation effectively at zero for contracted storage. The key insight is that as forecast errors increases, under a fully contracted swap, the storage owner is essentially protected from price error risk, with such risk shifting to the buy-side counterparty. By contrast, a merchant unit remains fully exposed to such risks.

Partial contracting (Figure 5.3, panels B-E) invariably improves incentive alignment and compatibility, given the unit owner retains meaningful 'skin in the game' via a proportional exposure to the market. Even minimal levels of uncontracted capacity expose the storage unit to risk exposure in terms of cash flow variation compatible with the intended incentives of the spot price as a signal for dispatch.

This suggests that under full contracting, the transfer of operating risk should attach to the counterparty of the contract, for example via the assignment of trading rights. This allows the party with the exposure to price error to maintain operational control of the asset. While it is asserted in the literature on centralised storage that the allocation of operational decision rights can be enabled through the exchange of cash flows, the results above establishes the corollary – that the exchange of cash flows must be accompanied by the allocation of operational decision rights. Central agencies may be motivated to pursue operational decision rights of assets under episodes of power system duress. A fully contracted asset opportunity will motivate the supply side, though the key insight is to ensure that operational control is maintained. This then leads to the question of how operational control might be administered.

It is common in many project structures for operational bidding decisions to be guided or delegated to automated bidding software. Yet, importantly, the allocation of decision rights relating to the selection, renewal and performance

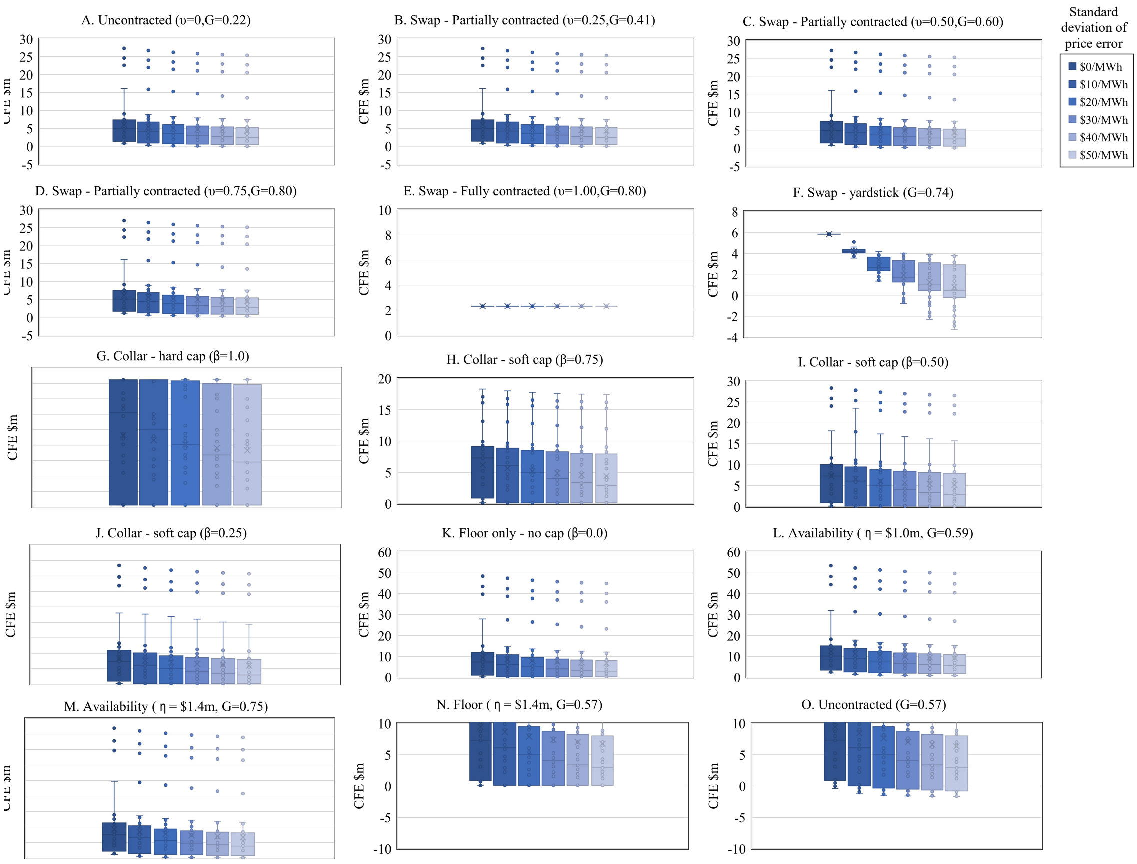

Figure 5.3: Boxplot of distribution of cash flows, for quarterly periods from 1 July 2012 to 30 June 2022, for 12-hr BESS under price error uncertainty – with standard deviation of price error ranging from \$0 to \$50/MWh. Note: Equity and debt levels are optimally sized in the model based on debt service thresholds. The symbol v denotes the volumetric share of the project that is contracted. The gearing ratio (the ratio of debt over total capital) is denoted by G. For the collar, floor and cap thresholds of \$1.4m and \$5.0 million are used, as indicated by the project calibration (see Subsection 5.3.1).

management of such software should ideally attach to the buy-side counterparty. For commercial counterparties of storage, with scalable trading and operational capabilities, this is viable, enabled by partitioning of physical storage at the asset level. Central government agencies as buy-side counterparties will need to specifically consider operational co-ordination, potential delegations or some other objective function. One potential avenue lies in the treatment of such units as centralised assets and integrated within dispatch by the market operator [276]. Though certain adjustments may need to be made to dispatch from the current single-period real-time dispatch to some form of inter-temporal optimisation. The role of

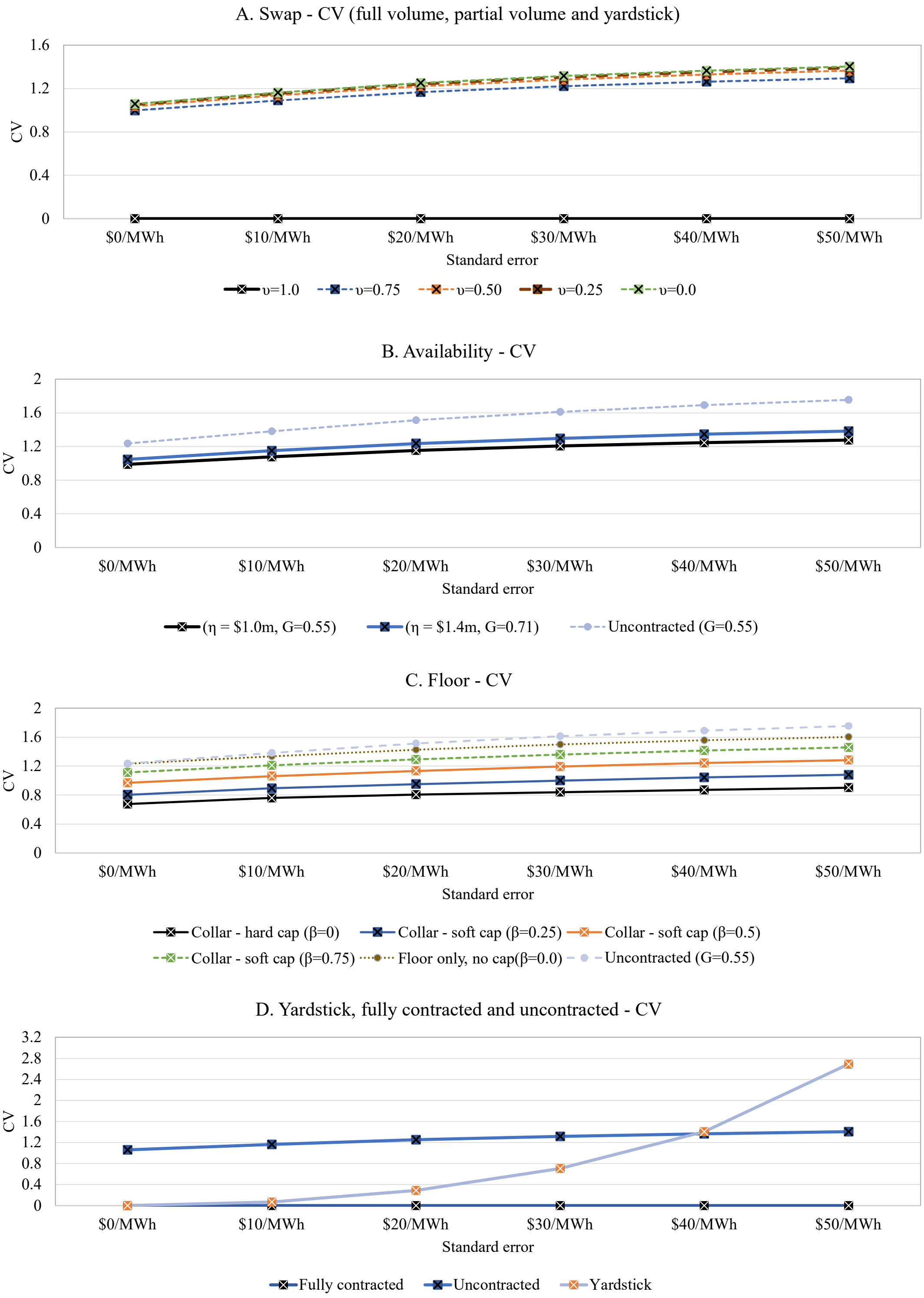

Figure 5.4: Coefficient of variation, for quarterly periods from 1 July 2012 to 30 June 2022 for 12-hr BESS under price error uncertainty – with a standard deviation of price error ranging from \$0 to \$50/MWh

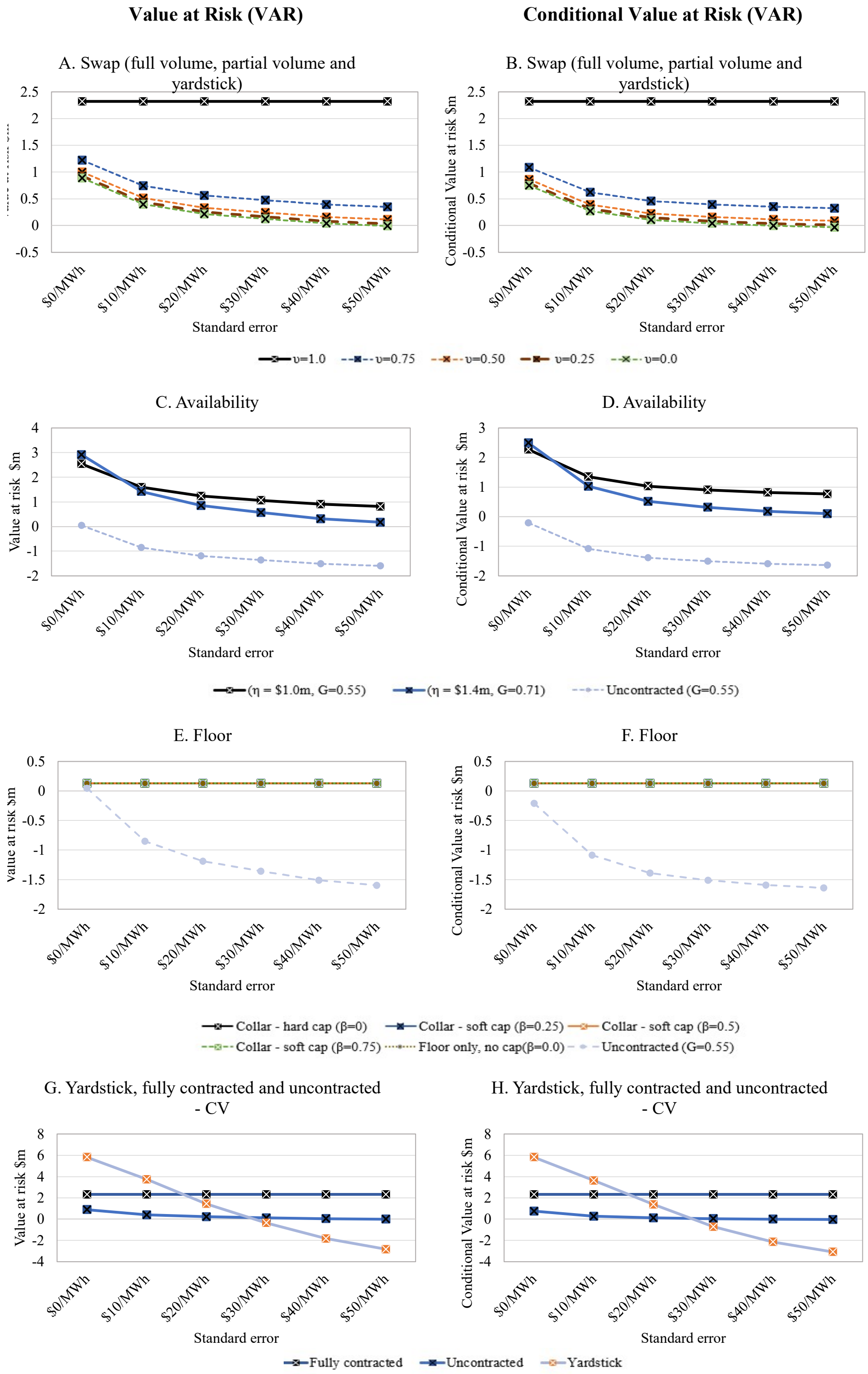

Figure 5.5: Value-at-Risk and Conditional Value-at-Risk (with α tail probability of 5%) for quarterly periods from 1 July 2012 to 30 June 2022, for 12-hr BESS under price error uncertainty – with a standard deviation of price error ranging from \$0 to \$50/MWh

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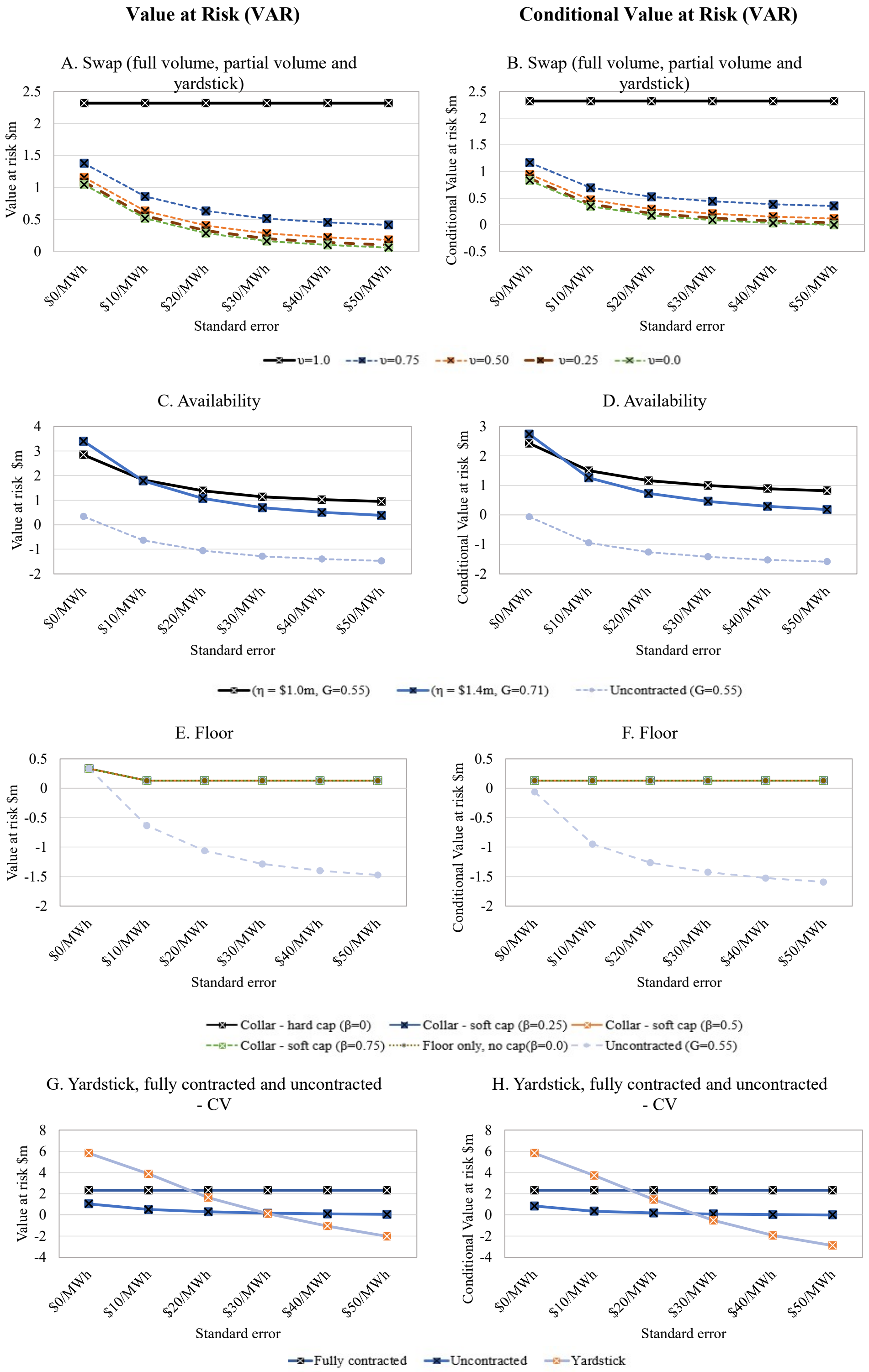

Figure 5.6: Value-at-Risk and Conditional Value-at-Risk (with α tail probability of 10%), for quarterly periods from 1 July 2012 to 30 June 2022, for 12-hr BESS under price error uncertainty – with a standard deviation of price error ranging from \$0 to \$50/MWh

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uncertainty in dispatch scheduling under risk aversion *vis-à-vis* ensuring security of supply also requires consideration.

Revenue floors and collars

Given the cash flow volatility associated with storage operations, governments have considered alternative forms of contract; specifically, variants of caps, floors and availability contracts. Revenue caps and floors are considered attractive for their ability to enable storage to retain revenue risk between bounds. Figure 5.7 below illustrates how a revenue collar instrument, a combination of a revenue floor and revenue cap operates to restrict project revenues and equity returns. The floor restricts downside financial profits; while a hard cap restricts upside financial profits; and a soft cap shares the financial profits above a threshold between the storage project and the counterparty.

By guaranteeing a minimum level of revenue (via the floor), the project is able to secure long-term financing. However, comparing the downside cash flows of a project with a floor, relative to one without a floor, with gearing held constant (Figure 5.3, panels N-O, Figures 5.5 and 5.6 panels E-F), the limiting of downside cash flows to equity is observable. The storage unit with a revenue floor is protected from poor operational performance on the downside. This is because the contract basis is defined by 'actual revenues'; so as these revenues worsen from high price error, the revenue floor comes into effect and protects the unit from such operational performance. Given the asymmetrical relationship observed in equity returns, this risks the privatisation of gains and socialisation of losses, a principle that central counterparties acting as quasi-agents for consumers should be acutely aware of, and indeed wary of.

The basis upon which the collar contracts are settled impacts the allocation of risk as between controllable factors (such as operational performance, accuracy and robustness of price forecasts), and uncontrollable factors (*i.e.,* market and system conditions). For example, floors settled on the basis of actual revenues fail to recognise such distinctions, providing the unit with downside protection from both, which is inconsistent with the objectives of hybrid contracting. Developing an

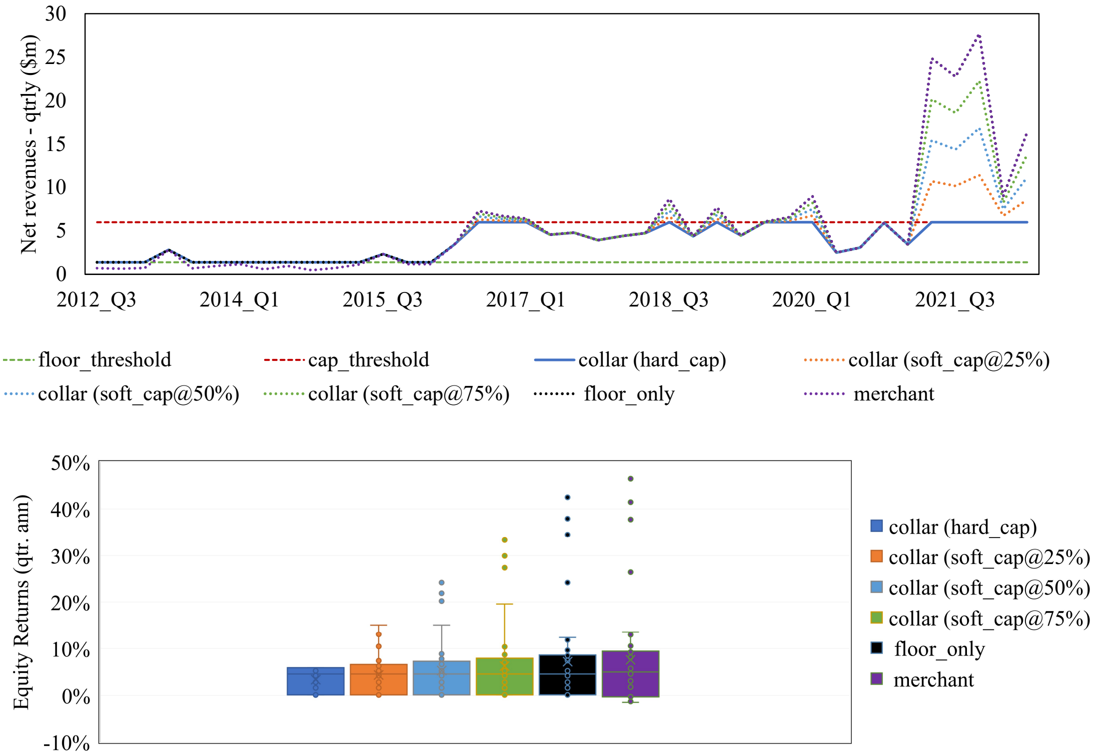


Figure 5.7: Net revenues (top panel) and quarterly equity returns (bottom panel) under a revenue collar (a combination of a revenue cap and revenue floor) with soft cap threshold of \$6 million and floor of \$1.4 million based on a standard deviation of forecast error of \$20/MWh.

appropriate yardstick could create better performance incentives notwithstanding the risk hedge.

While a floor seeks to ensure a minimum net revenue level, availability contracts provide a source of near-fixed revenue that is incremental to spot revenues (Figure 5.3, panels L-M and Figure 5.4, panel B). While both support debt financing and boost equity returns, availability contracts support higher gearing because the revenue source is incremental. It is also observed that equity returns are maximised through leveraging the project based on the revenue support provided by the hedge.

A revenue cap provides a possible means of addressing the asymmetry identified above. By capping revenues above a threshold, windfall gains to the storage unit are limited and instead transferred to the contractual counterparty. However, depending on its structure, a cap can have impacts on dispatch incentives once the specified cap threshold is exceeded. Most notably, Figure 5.8 provides a hypothetical example of such a situation under the modelled timeline, illustrating hypothetical cumulative revenues of a 12-hr BESS project during Q2 2022 under a variety of cap/collar structures (including a hard cap, soft cap under a range of revenue shares, and an uncapped structure). Note that under a hard-cap arrangement, once the threshold is reached, the unit's operating revenue is capped, and it does not accumulate further revenues from spot market operation. Under a partial cap arrangement, the project continues to accumulate net revenue, although the share is dependent upon the soft cap arrangement.

Comparing the hard cap against the soft cap and uncapped arrangement, the project under the former receives no more financial benefit from optimal operation in the market, but rather incurs indirect costs relating to cycling and degradation. This suggests that, in such a situation, the unit would have minimal incentive to continue to make itself available in the market for the remainder of the period. This is despite the occurrence of continued scarcity and extremely high market price volatility. This would be of significant concern to centrally contracted arrangements, and may manifest via split operator incentives of maximising market earnings (*i.e.,* revenue) and attempts to minimise costs (*e.g.,* minimising battery cycling on high-value days rather than using full cycles during such days). This illustrates that, while a hard cap arrangement may have intuitive appeal in minimising windfall profits for market participants, it adversely affects incentives for the resource to continue to participate optimally in the market. The examples above illustrate that certain contract forms, while well-intentioned and straightforward, can lead to challenges in maintaining incentive alignment with socially optimal dispatch. In particular, the hedge offered by particular contract forms can mute incentives to participate in the market.

Incentive alignment and yardstick contracts

The yardstick contract seeks to address the issue of incentive compatibility between incentives for 'best efforts' dispatch and financial outcomes. It is observed

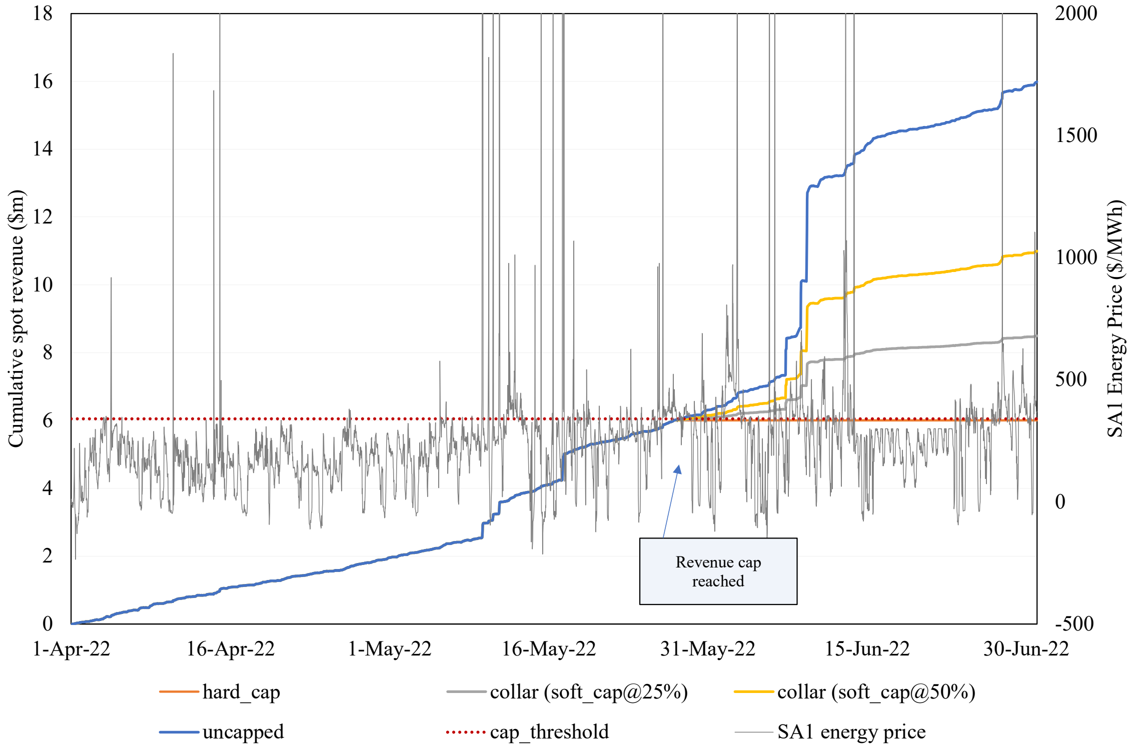


Figure 5.8: Effect of revenue caps on dispatch incentives (12 hr BESS) – Hypothetical cumulative operating revenues during 2Q 2022 under a range of collar/cap structures (hard cap, soft cap, uncapped).

that while the a standard revenue swap preserves a low CV (Figure 5.4, panel D, Figures 5.5 and 5.6, panels G-H), under all price error scenarios thereby muting incentives for optimal dispatch, the stability of cash flows for a yardstick contract scales on how well the unit follows dispatch incentives. In essence, this contract creates an ex-post performance measure for the storage project to meet. A project that is able to better predict prices and follow price signals will benefit from stable cash flows (Figure 5.3, panels A,E-F) and a low CV (Figure 5.4, panel D), while projects with poor price error performance will experience instability and a downside skew to cash flows. This aligns incentives with spot market signals. While it is understood that storage may not realistically expect to be able meet idealised outcomes, and thus parties may reflect that in its contract bid – operational incentives remain for the unit to attempt to do so to the best of its capability, as the settlement is against such behaviour.

Moreover, industry also appears to be already developing performance metrics for electricity storage based on perfect foresight of dispatch, some examples of which include:

- Energy storage company Fluence ranks its battery dispatch forecasting algorithms by a measure termed 'percent-of-perfect' which measures the maximum amount of revenue that an asset can generate with perfect knowledge of future market prices.[348, 349]

- Similar metrics also appear to have been adopted by a range of other participants in the sector (storage software providers, operators etc) [350]

Industrial studies suggest that BESS trading and bidding algorithms can achieve net revenues that 70-90% of that achievable by perfect foresight. For example, regulatory filings by Fluence suggest that its bidding applications have achieved net revenues that are around 90% of perfect foresight in the NEM [349]. A study by Tyba of the CAISO market in 2022 suggests that net revenues of 70-90% of perfect foresight are possible [351]. Benchmarking in the UK market by Modo Energy shows net revenue outcomes at 70-80% of perfect foresight [350]. Participants are likely to reflect their expectations of revenue outcomes into the bid price for the yardstick contract.

5.4 Discussion

The results outlined herein have important policy implications for the procurement and risk management as it relates to storage resources in a hybrid electricity market.

5.4.1 Government initiated tenders for storage

Given the gap in policy action on climate change at both Commonwealth and Federal levels (especially in Australia in recent years), sub-national governments have sought to fill the void with direct contracting via large scale auctions for renewables [337]. Buoyed by the successful execution of these auctions and combined with impetus for more centrally planning, storage procurement strategies are being incorporated into net zero objectives and forming part of certain sub-national government plans.

While parties may retain a preference for simple contract structures, operating resources electricity storage assets represent a higher order of complexity, given the inter-temporal and multi-service dimensions. As such, governments and central agencies need to be acutely aware of the impact of contract form on the incentives of participants across aspects of market operation, risk hedging and investment. In particular, the incentives to participate in real-time dispatch can be directly affected by the structure of the risk hedge, which can be brought to bear in conditions of scarcity.

If central agencies prefer simplicity and broad scale application, then structures such as ‘availability contracts’ as part of a storage certificate scheme may be considered, recognising the inherent subsidisation through revenue additionality. Although incentive compatibility is retained through ongoing market exposure, the contract form is better considered as a revenue subsidy rather than a risk-trade. This should be considered in the context of whether governments seek technological agnosticism among zero-carbon firming strategies or are accepting of more bespoke technology subsidisation. Tolling and revenue swap type arrangements provide a simple reallocation of cash flows although, due to shifts in operating incentives, the reallocation of trading rights must be considered in some detail. This includes, for example, a consideration of risk-constrained behaviour with shorter duration storage in the presence of price volatility. While such scenarios tend to support central control of storage – accompanying inter-temporal dispatch frameworks should be contemplated.

Alternatively, if central agencies are seeking to provide a risk hedge to participants, a granular analysis of incentive compatibility is required. Caps and floors provide a viable alternative by collaring revenue between thresholds – providing minimum returns yet limiting windfall gains. In such situations, the preference is for caps with (i) soft collar arrangements due to operational incentive effects during scarcity and, (ii) that the floor side of the collar be indexed off a yardstick style arrangement – given that it maintains performance incentives. While this may compromise simplicity, the incentive alignment is important for both short-run and long-run investment decision-making.

5.4.2 Development of yardsticks for storage

These results bode positively for the development of yardsticks for storage, noting that the case study necessarily incorporates a generalisation of contracts. Structuring real-world contracts requires consideration of technical constraints, including connection access conditions, manufacturer warranties, environmental permits, safety requirements and water rights (for pumped hydro). Examples include shorter-term duty cycle constraints for BESS, as well as ramping, spill and start-up constraints for pumped hydro. Further implementation considerations include:

- **Model for ex-post simulation**. This model would need to incorporate the parameters and constraints used for actual dispatch to the extent possible. For example, in the NEM, the market operator provides a tool known as NEMDE Queue which allows participants to replicate dispatch outcomes via the actual central dispatch algorithm with full transparency of all constraints and parameters. While there are uncertainties ahead of time, these uncertainties collapse to a single set of parameters at real-time. Under a price-taking assumption, this could be used to develop the 'perfect foresight' dispatch upon which the hedge can be based. Anecdotally, participants appear to be already developing performance metrics for their storage units based on perfect foresight

- **Contingencies and conflict resolution** – the contract should specify the treatment of contingencies such as market suspensions, interventions, *etc*. Conflict resolution procedures would also need to be clarified.

- **Changes to market design** – the contract should specify the allocation of risk as regards to changes in market design (*e.g.*, reserve markets, capacity mechanisms, *etc.*). One potential straw proposal is to incorporate new spot markets within the yardstick, while excluding non-spot revenues.

- Finally, as the 'yardstick' reflects an optimal outcome without curtailment or constraints, it also requires the storage owner to give close consideration to its location in the network, as well as the impact of security constraints.

A yardstick based on an ex-post optimisation is likely to be most applicable to granular and bespoke contracting arrangements, whereby individual specific optimisations are suitable. This work, based on the review of contracts, is one of the first to propose yardsticks based on optimal dispatch, though there are implementations that are approximations thereof as set out below. Larger scale programs would likely require an approximation of an optimal yardstick. One such example are spread contracts – wherein the contract index is defined by the difference between the highest and lowest energy prices over every trading day [53]. It is understood that the Tasmanian 'Battery of the Nation' pumped hydro project has contracted via a spread contract [53]

To date, these contract forms have only focused on energy price spreads. In the near term, a metric for ancillary services could be a worthwhile extension although, over the longer term, energy arbitrage is expected to make up the bulk of revenues for storage.

Alternatively, for longer-duration storage focused on energy price arbitrage, it may be possible to exclude ancillary services from the contract form, leaving it as an upside for participation by the project owner (in a similar way to how generation power-purchase agreements do not account for ancillary services). Further research on yardsticks should consider the applicability of simplified spread contracts to markets with high penetrations of renewables.

5.4.3 Quasi-agency and risk frameworks

By providing risk-trader functionality, governments are seeking to fill 'missing market' gaps arising due to incompleteness in risk-hedging markets. Yet this comes with the risk of entering into complex derivative arrangements without a direct pecuniary incentive, whereupon the brunt of any adverse financial impacts will likely be directly borne by taxpayers. This is probable, especially in light of the dynamic and heavy-tailed nature of energy-only electricity market prices.

Given the programmatic nature of storage and renewable procurement and the complexity of instrument valuation and portfolio exposures, it would behove a central agency to adopt robust and disciplined risk assessment and portfolio construction if hybrid markets are to become a matter of course. An insurance-based framework provides a robust financial framework for alignment between consumer reliability preferences and resource contracting.

Further, while recent price trends offer clues, there is also a broader structural question of how price formation may occur in electricity markets dominated by zero short-run marginal cost renewables and storage.

5.5 Conclusion

In the context of rapid decarbonisation imperatives, the focus on procurement in hybrid electricity markets has broadened beyond renewables to include electricity storage. The analysis suggests that contract design for storage is a complex task, one which requires granular analysis of game theoretic motivations and interactions with market scheduling. Auction designers with a preference for simpler structures may be attracted by availability contracts, though this should recognise the inherent subsidisation. For central agencies seeking to offer a risk hedge, a revenue collar with a soft cap and a yardstick on the floor is proposed, as this mitigates dispatch distortions while maintaining cash flow stability for investors.

The central contributions to the literature in the field relate to the following. First, the framing of canonical principles to guide the design of contracts between reliability agencies and storage resources, in order to align incentives and minimise distortions in wholesale spot and hedging markets. Second, a taxonomy for the classification of financial hedging contracts between storage resources and risk-hedging counterparties; covering central elements of the design and financial structures of the contracts. Third, the formulation of a modelling framework to assess the incentive compatibility of contract designs with spot market dispatch, incorporating short term dispatch commitment decisions with long-term investment and financial decision making. Finally, the proposition of a novel storage yardstick contract between a storage resource and a central reliability agency, which developing a benchmark based to ex-ante optimal dispatch, to ensure incentive alignment between participant incentives and spot market signals.

Future work in this domain could focus upon the following areas. First, further extensions of the theoretical methods to incorporate storage bidding and price formation as opposed to a purely decentralised commitment approach. In particular stochastic opportunity cost and sequential pricing of electricity [352] could be sensible areas of inquiry. Second, it would be useful to extend the multi-agent model in Chapters 3 and 4 to incorporate storage contracts of the form considered herein to understand impacts upon investment incentives. Finally, further research on yardstick contracts could consider the issues of practical implementation e.g., defining contract contingencies and risk allocation, and simplified forms of yardsticks (e.g., spread contracts).

6 Conclusions

Contents

6.1 Concluding Remarks

This thesis addresses the following research question: *Can the delivery of electricity service to consumers be made more reliable through the application of insurance mechanisms?*

Given the scale of the research question, the approach laid out in this thesis has been reduced to three sub-questions. These questions have been designed to address the critical gaps arising in reliability mechanism design in electricity markets. First, to address the gap that centralised reliability mechanisms do not adequately incorporate consumer heterogeneity, the following sub-question is posed. How should the decision-making and risk architecture of an *energy-plus insurance* market design be formulated to achieve generation adequacy given the heterogeneous preferences of consumers? The second identified gap relates to the incorporation of resilience value into reliability mechanisms. Thus, the sub-question asks: can insurance mechanisms enhance local resilience to extreme events by incentivising efficient investment in distributed energy resources? Finally, the thesis considers the research gap relating to incentive-compatible contract designs for storage and interactions with wholesale electricity markets and operations. The sub-question is framed as follows. What are the key agency principles that should be addressed in contracts between the storage resource providers and central reliability insurance or procurement agencies?

Decision architecture for reliability insurance

The growth of load control and communications technologies enables flexibility in consumption and heterogeneous preferences for reliability. The key gap identified in the literature relates to how such heterogeneity is incorporated into existing electricity reliability mechanisms, primarily as a supply side resource with demand administratively set by a central agency. Such frameworks however do not enable diversity of reliability preference to be incorporated into decision-making and resource procurement. Thus, the following research sub-question is posed: *How should the decision-making and risk architecture of an energy-plus insurance market design be formulated to achieve generation adequacy given the heterogeneous preferences of consumers?*.

To address this gap, this thesis (in Chapter 3) formulates an insurance mechanism that is incorporated into wholesale electricity market design. Key elements of the *energy plus insurance* market architecture include: (1) the introduction of a central insurance agency, termed the *insurer of last resort* (IOLR), that executes insurance contracts with consumers in line with reliability preferences; (2) a priority curtailment scheme that prioritises consumers in order of reliability preferences indicated in the insurance contract; and, (3) that the IOLR procures strategic reserves to mitigate its insurance liabilities, where individually optimal. In doing so, the mechanism mitigates the *missing money* and incompleteness associated with energy-only markets in a manner which is aligned to actual consumer reliability preferences. This comprehensive design is termed the *energy-plus insurance* market, or EIM.

A game-theoretical model for the market design has been developed and applied to a case study of the South Australian region in the NEM. The results demonstrate material improvements in system welfare under the EIM model that are well in excess of an energy-only market, even approaching the risk-neutral optimum. The financial viability and solvency of the insurer is preserved through capital provisioning. Further, the EIM model also demonstrates real-time reliability differentiation in harnessing load flexibility. This work answers the sub-question by demonstrating that the novel insurance mechanism can mitigate the issue of *missing money* in a manner consistent with diverse consumer reliability preferences.

Insurance paradigms for resilience

Climate change is expected to magnify the likelihood and intensity of extreme events. In such situations, incompleteness in liberalised market architectures can leave consumers highly vulnerable and exposed. Given the impetus towards large-scale electrification, power system resilience is of critical importance to society. The review of literature identifies that, while *distributed energy resources* (DER) have demonstrated technical capability to improve resilience, such value is largely unrecognised in current regulatory frameworks. Thus in Chapter 4 the following sub-question is posed: *Can insurance mechanisms enhance local resilience to extreme events by incentivising efficient investment in distributed energy resources?*

The gap is addressed through the formulation of a locational insurance scheme, one which recognises regional risks from remoteness, weak network connectivity, and common mode events. The scheme operates as an overlay on wholesale markets and allows the insurer to invest in resilient DER (either directly or via consumer subsidy). A multi-agent game is formulated to model the wholesale market design and the insurance mechanism under a multi-node network topology, with a heuristic guided search algorithm to search for equilibria.

Through a large-scale case study application, improved resilience is demonstrated with investment in DER reducing the incidence of unserved energy during extremes. In particular, the scheme is observed to significantly improve reliability outcomes in remote and poorly-connected areas of the grid. Moreover, the scheme is demonstrated to be financially viable under low to moderate levels of consumer risk aversion, and is robust to risk-aversion and scheme parameters. Two models of investment funding are also proposed – direct investment and consumer subsidy, thereby providing optionality for insurers with respect to implementation. This work thus addresses the second sub-question by demonstrating the potential for improved resilience via locational insurance mechanisms.

Contract Design and Agency Incentives for Storage

The structure of contracts in wholesale reliability mechanisms can have a direct impact on resource incentives and market behaviour. Electricity storage is expected to be an important resource for electricity systems of the future, providing energy and grid services. However, contract designs in traditional reliability mechanisms are generation-centric and do not incorporate the multi-functional and inter-temporal attributes of storage. The literature to date has devoted considerable attention generation contracts, but the application to storage resources remains a gap. Given an aligned risk architecture (via an insurance mechanism or other central reliability mechanism), Chapter 5 considers the issue of how a central agency should structure contracts with storage resources. The research sub-question is posed: *What are key agency principles that should be addressed in contracts between the storage resource providers and central reliability insurance or procurement agencies?* It is noted that the focus of this chapter is distinct from Chapters 3 and 4 focusing upon contract design and market operations. The issue is one of general relevance when considering market designs that incorporate central contracting as a form of hybrid market, including the imposition of an insurance-style mechanism.

The question is addressed in a staged manner. First, a set of principles for contracting by central reliability insurance agencies is formulated. These principles then motivate the development of a cohesive resource decision-making model incorporating storage unit-commitment and long-term financing. Consequently, the model is applied to canonical contract forms for storage via a case study, revealing incentive incompatibility in existing designs. Finally, a novel *yardstick contract* for storage is proposed, one which is demonstrated to achieve the dual objectives of revenue stability for the resource project and incentive compatibility with wholesale market signals. This work thus addresses the final sub-question.

General remarks

Underlying the work of this thesis is the notion that the incentives of market agents should be aligned with the risks facing the electricity system and its consumers. Insurance mechanisms bridge the gap between incomplete agency incentives in electricity markets and emergent tail risks in electricity systems.

Through the introduction of insurance capital provisioning requirements and incentive-compatible contract design, it harnesses the capability of new supply-side and demand-side resources to improve consumer outcomes. This is a powerful approach in the development of tools, technologies, and mechanisms to mitigate those risks likely to arise in the forthcoming era of energy transition and climate change.

6.2 Contributions

This thesis has resulted in the following contributions and publications:

1. The development of the decision-making and risk architecture for an *energy-plus insurance* market design. The key components comprise contracts between a central insurer and consumers, a priority curtailment scheme and a capital risk provisioning constraint to maintain insurer solvency. This architecture aligns central agency incentives for resource adequacy with the heterogeneous reliability preferences of consumers;

    - Billimoria, F., Fele, F., Savelli, I., Morstyn, T., and McCulloch, M. (2022). An insurance mechanism for electricity reliability differentiation under deep decarbonization. Applied Energy, 321, 119356. Awarded **Best Paper** at the MIT AB Applied Energy Symposium 2021. doi:10.1016/j.apenergy.2022.119356.

2. The formulation of a locational design for reliability insurance that differentiates risk on a regional level, recognizing remoteness and weak network connectivity. This mechanism values the resilience contributions of distributed energy resources.

   - Billimoria, F., Fele, F., Savelli, I., Morstyn, T. and McCulloch, M., (2023). An Insurance Paradigm for Improving Power System Resilience via Distributed Investment. Accepted to IEEE Transactions on Energy Markets, Policy and Regulation. doi:10.1109/TEMPR.2023.3301830
   - Poudineh, R., Brandstätt, C. and Billimoria, F., (2022). Electricity distribution networks in the decentralisation era: rethinking economics and regulation. Springer. doi:10.1007/978-3-030-98069-6

3. The enunciation of a set of principles for the design of contracts between energy storage resources and central reliability insurers and agencies. The principles focus upon incentive compatibility between contracts, operational dispatch and long-term hedging markets which can be directly applied to assess contract structures for central auctions of energy storage. A cohesive decision-making model, involving both short-term commitment and long-term financing, is developed to quantify and assess compatibility against the formulated principles.

   - Billimoria, F. and Simshauser, P., (2023). Contract design for storage in hybrid electricity markets. Joule, vol. 7, no. 8, pp. 1663-1674. doi.org/10.1016/j.joule.2023.07.002
   - Yurdakul, O. and Billimoria, F., (2023). Risk-Averse Self-Scheduling of Storage in Decentralized Markets. IEEE Power & Energy Society General Meeting (PESGM). Orlando, FL, July. 2023. doi:10.48550/arXiv.2212.00209

4. The design of a novel storage ‘yardstick’ contract based on an ex-post perfect foresight performance criterion. The contract design is shown to provide

cashflow stability for project investors, and preserve incentive compatibility for operational dispatch.

- Billimoria, F. and Simshauser, P., (2023). Contract design for storage in hybrid electricity markets. Joule, vol. 7, no. 8, pp1663-1674. doi.org/10.1016/j.joule.2023.07.002

6.3 Future Research Directions

Based on the results of this thesis, the areas of future research in this area fall in to the following directions:

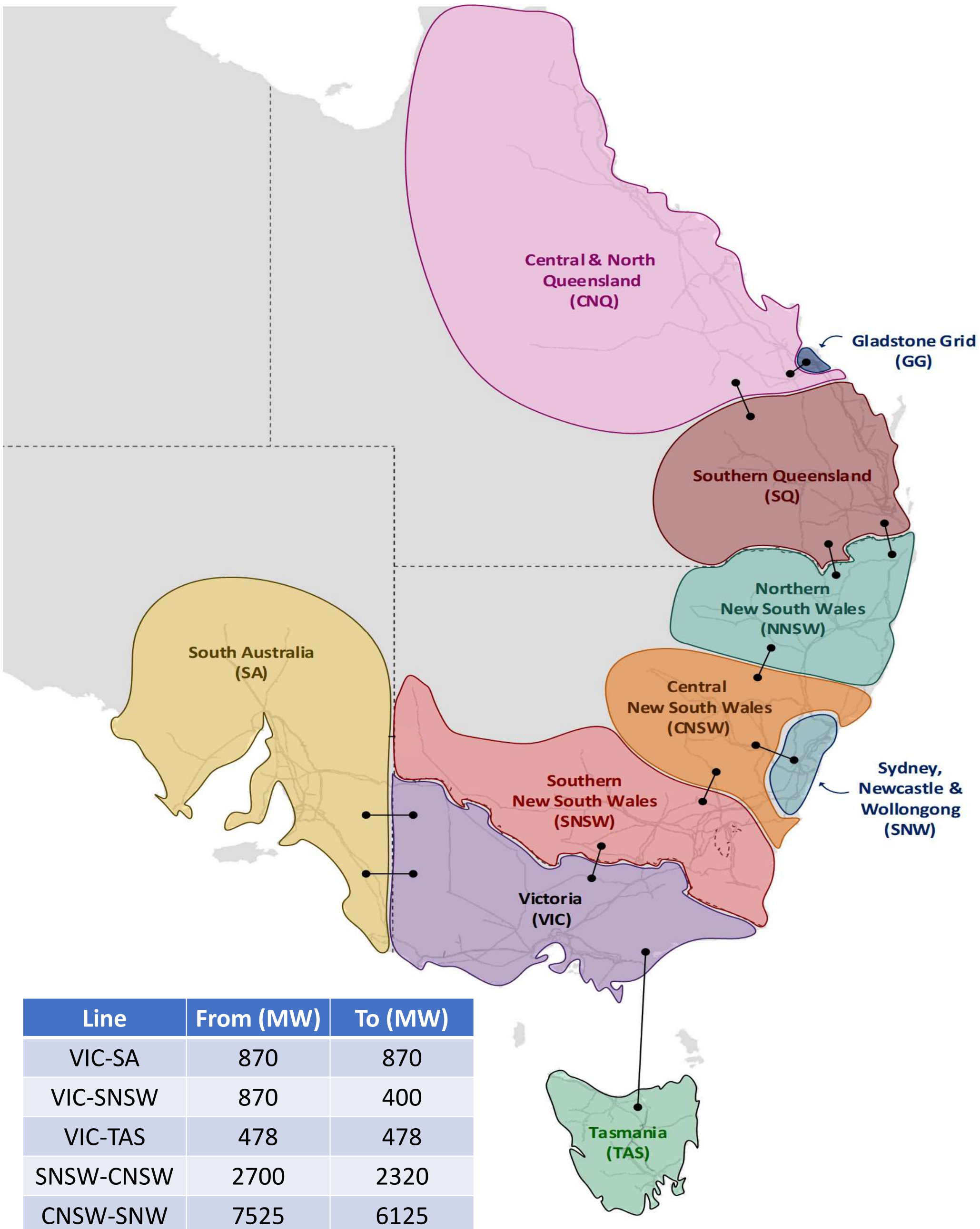
Theory and models. The extension of the theory, models and numerical methods of insurance mechanisms in electricity markets are an important avenue of further research. This could involve the formulation of canonical model that generalize the market architecture and contracts; proof of theoretical properties, and development of computational tools for implementing contract and finding equilibria. Future research could include: integration of risk-hedging contracts into larger-scale equilibrium models of insurance and electricity markets; and theoretical proofs of incentive compatibility, as well as uniqueness and existence of equilibria under alternative models of competition.

Architecture and risk. The second direction of research is the extension of the literature on the architecture of the 'energy-plus-insurance' market design, of which measure and domains of risk are an important component. For example, this thesis predominantly focuses upon a centralised model of insurance. A decentralised model of the sector is referenced in Section 3.4.1 as part of the suite of potential market structure options and is deemed an area worthy of investigation. Future work could, for example, develop a multi-agent competitive framework for insurance, building upon the conceptual development set out in this thesis. This could be applied to understand impacts on premium setting, resource adequacy, and supply mix. The domains of risk that insurance applies to is also an open research question. While this thesis has focused upon generation adequacy, Chapter 4 posits extensions to a more comprehensive range of upstream (fuel) risks; and vertical integration of coverage to transmission and distribution reliability. Further, research into the specification of consumer risk comprehension, and the willingness and ability to pay for resilience could aid in the development of appropriate insurance products. This could involve inter-disciplinary empirical research combining expertise from behavioural economics, social science, and reliability engineering.

Implementation and Equity. The third direction of research could seek to address the challenges of the implementation of the model into practice. While aspects of this model have corollaries in the real world (for example, financial hedge support by central agencies), there are several granular considerations. An important issue, as identified in this thesis, is that remote regions of the grid are often those disproportionately affected by extreme events. Under a purely commercial premium setting approach, those regions would likely bear significantly higher premiums associated with insurance. Consideration of equitable approaches to setting premiums is an important avenue of investigation, leveraging upon the literature on equitable electricity tariff design. Issues around timing and phasing of the design, and the integration with developments in priority service also represent an important focus in guiding this theoretical concept into one capable of practical implementation.

Appendices

A
Modelled Network Topology of the National Electricity Market



Line	From (MW)	To (MW)
VIC-SA	870	870
VIC-SNSW	870	400
VIC-TAS	478	478
SNSW-CNSW	2700	2320
CNSW-SNW	7525	6125
CNSW-NNSW	910	930
NNSW-SQ	685	1335
SQ-CNQ	700	2100
CNQ-GG	700	750

Figure A.1: Modelled network topology of the National Electricity Market with ten local regions. Black Lines with adjoining dots represent transmission links between regions. Transmission network capacities between regions are indicated in the adjoining table. Adapted from [326]

B

Analysis of an insurance market equilibrium reached under an alternative supply mix initialisation

This Appendix describes the solution obtained from an alternative initial generation portfolio relative to the case described in Chapter 4, Section 4.3. The alternative initial generation portfolio problem was initialised with a supply mix that removed (i) all remaining brown coal generation and, (ii) reduced the capacity of black coal generation capacity by approximately 8 GW. Results are shown for the EOM design case in Tables B.1 and B.2.

The major difference in the wholesale supply mix relative to the case in Section 4.3 is the higher investment in flexible gas, renewables, and storage (with total wholesale investment being relatively unchanged). This is because the starting resource mix automatically precludes much of the coal such that it cannot be added to the mix. Distributed generation investment is also similar. Unserved energy outcomes are also similar, both in terms of magnitude and relative impact of the insurance scheme.

Table B.1: Resource mix: alternative equilibrium solution - EOM

Technology	Capacity (GW)	Δ to Orig. Case
W Coal	8.1	-6.3
W Intermediate gas	3.5	0.0
W Flexible gas	10.3	+3.6
W Wind	12.2	+0.7
W Solar	8.8	+0.7
W BESS SD	2.0	+0.8
W BESS LD	0.6	+0.4
W Dam hydro	6.5	0.0
W Pumped hydro	2.3	+0.6
Total wholesale	54.1	+0.5
RDER Solar	4.3	+0.6
RDER BESS	2.3	+0.6

SD = Short duration ($<$ 4hrs), LD = Long duration ($\geq$ 4hrs)

Table B.2: Unserved energy: Alternative equilibrium solution

Unserved Energy (%)	Solution	Δ to Orig. Case
Mean - w/o ins	0.03	0.02
Mean - with ins	0.01	0.0
POE5 - w/o ins	0.06	+0.04
POE5 - with ins	0.03	+0.02

C
Publicly-available information on storage contract specifications

Table C.1: Storage Contract Specifications

Project	Region	Tech.	Size (MW /MWh)	Actual Contract Structure	Assigned Generic Form	Tenor (yrs)	Services
Boulderstone Battery	QLD	BESS	50/100	Floor w/ upside sharing	Soft collar	8	Energy FCAS
Maoneng Portfolio	NSW	BESS	200/400	Call swaption	Soft collar	15	Energy FCAS
Waratah Super Battery	NSW	BESS	850/1680	Service contract	Availability contract	NA	SIPS
Riverina 1&2 Darlington Pt	NSW	BESS	150/300	Operational rights	Revenue swap	10	Grid-form Energy FCAS
Gannawarra BESS	VIC	BESS	25/50	Operational rights	Revenue swap	10	Energy FCAS
Ballarat BESS	VIC	BESS	30/30	Operational rights	Revenue swap	10	Energy FCAS
Hornsdale Reserve	SA	BESS	100/129	Service contract	Availability contract	NA	SIPS PFR
Hornsdale Reserve Extension	SA	BESS	50/64.5	Service contract / grant	Availability contract	NA	Virtual inertia
ESCRI BESS	SA	BESS	30/8	Hybrid structure	Revenue swap	NA	Grid-form FFR
Victorian Big Battery	VIC	BESS	300/450	Service contract	Availability contract	NA	SIPS
Wandoan South BESS	QLD	BESS	100/150	Operational rights	Revenue swap	15	Energy FCAS
Broken Hill BESS	VIC	BESS	50/100	Grant	Availability contract	NA	System strength
Capital Battery	NSW	BESS	70/140	Operational rights	Revenue swap	15	Energy FCAS
Kidston Pumped Hydro	QLD	PH	250/2000	Operational rights	Revenue swap	30	Energy FCAS
BOTN	TAS	PH	600/12000	Spread contract	Yardstick contract	NA	Energy

Abbreviations: BESS = Battery Energy Storage System, FCAS = Frequency Control Ancillary Service, FFR = Fast Frequency Response, PFR = Primary Frequency Response PH = Pumped Hydro, SIPS = System Integrity Protection Scheme

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