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An Insurance Paradigm for Improving Power System Resilience via Distributed Investment

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***Abstract*—Extreme events, exacerbated by climate change, pose significant risks to the energy system and its consumers. However there are natural limits to the degree of protection that can be delivered from a centralised market architecture. Distributed energy resources provide resilience to the energy system, but their value remains inadequately recognized by regulatory frameworks. We propose an insurance framework to align residual outage risk exposure with locational incentives for distributed investment. We demonstrate that leveraging this framework in large-scale electricity systems could improve consumer welfare outcomes in the face of growing risks from extreme events via investment in distributed energy.**

***Index Terms*—resilience; insurance; distributed energy resources; capacity market; energy dispatch.**

I. Introduction

This paper addresses the issue of incentive frameworks for decentralised resilience investments by proposing an electricity interruption insurance scheme to price residual outage risk. In doing so it presents a defensible rationale for efficient investment in resilient distributed energy resources (DER).

The nature of risks faced by the electricity system is changing. The impetus for sectoral decarbonisation is expected to drive order-of-magnitude increases in generation supply from variable renewable energy (VRE), along with the rolloff of an ageing and increasingly unreliable thermal fleet [1], [2]. With climate change already occurring, the frequency and severity of extreme weather events are expected to magnify with particularly significant impacts on centralised grid architectures [3].

While wholesale energy markets can in theory ensure a reliable system [4] a range of recent works identify incompleteness in liberalized market architectures that can leave systems and communities vulnerable to extreme events [5]–[7]. Administrative contracting too can distort the fuel mix towards resources that are particularly vulnerable to weather extremes [8], [9]. Furthermore, to no flaw of market design, extreme events can island particular regions leaving communities disrupted and at risk for sustained periods. The recognition that, despite best efforts, wholesale market design inevitably leaves residual outage exposure for consumers leads to a view by some that promising complete protection from wholesale market frameworks is at best inordinately costly, and at worst illusory [10]. Yet there is a concomitant acknowledgement that leaving open such vulnerability may also be undesirable, particularly given a changing climate [11] and the inequitable impacts of outages from extreme events [12], [13].

Decentralised technologies offer the technical potential for improved resilience to extreme events. In particular, solar PV, storage and other RDER (EVs, smart home etc), can be configured to act as micro-, nano-, and pico- grids during emergencies providing power at community and consumer levels when centralised system architectures fail [3], [14]–[16]. An economic framework that appropriately values the resilience benefits of DER technologies could catalyse investment that enables the realization of this technical potential. In this paper we are primarily interested in the concept of reliability insurance as an economic framework for valuing resilience via distributed investment.

A. Related Work and Contributions

The concept of reliability insurance in electricity market design was introduced in [17]–[19] as a means of pricing priority service. The central precept of this line of work involves an insurance contract between an energy consumer and an insurance agency which provides economic compensation for electricity interruption in exchange for an upfront premium. The application of insurance schemes to incentives for backup generation was investigated in [20], [21] and [7]. A key result of [20] was that, under full insurance, an individual's economic incentives to install onsite backup generation to minimise premia will supplant the utility's incentive to mitigate compensation liabilities. [21] uses an agent-based model that confirms that insurance contracts converge to theoretical optima under bounded perception of risks and losses. The authors in [7] establish that a compensatory insurance scheme can improve consumer outcomes in the presence of reliability externalities. More recently, [22] establishes that priority service Pareto dominates both ex-ante time-of-use pricing and integrated resource planning under supply uncertainty. However, all of these works adopted a simplified copper-plate network model and a generalised definition of reserves.

Our paper uses a more detailed model of the network and the market design to understand the regional and temporal aspects of reliability insurance as an incentive framework for distributed investment. Specifically the contributions and novel aspects of this paper are as follows:

1) we develop a locational model of reliability insurance that differentiates risk on a regional level, recognizing remoteness and weak network connectivity. This can

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play an important role in scalable management of extreme risks;

2) we formulate a multi-agent model of the electricity system 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 on participant behaviour, the nature of interactions between participant and design, and system reliability and resiliency impacts;
3) we propose two investment incentive frameworks for resilient DER – direct investment and subsidization. It is shown that while subsidization can leverage consumer self-insurance benefits, take-up depends upon risk aversion, which is non-transparent to regulators.

The structure of this paper is as follows. Section II presents the technical and market architecture associated with the insurance scheme for resilient distributed energy resource investment. In Section III we present the multi-agent model of the market and the program formulation for insurance-based decision making. Section IV applies the model to a numerical case study, followed in Section V by policy implications and conclusions.

II. System and Risk Architecture

Our approach in this paper involves the imposition of an insurance scheme to insure consumers for long-duration outages. Figure 1 illustrates the main elements of the scheme.

Two components make up the market architecture. First, the wholesale market design, which comprises a spot market combined with additional resource adequacy mechanisms. In this paper, we consider a locational spot market for electricity, that is optionally augmented with an operating reserve demand curve (ORDC) and a capacity mechanism [23].

The second component of the architecture is an insurance mechanism for system resiliency. The insurer offers electricity interruption insurance to consumers. In exchange for an upfront premium, insurance 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, consistent with optimal contract selection [24]. The insurer manages the tail risks by setting premia and reserving capital against severe losses. In addition, to reduce compensation liability exposure the insurer can also offset risk through investment in resilient distributed energy resources (in the following shortly referred as RDER). The incentive to invest depends on the potential service interruption mitigation, thus aligning interests between the insurer and consumers. We consider two forms of investment in RDER : (i) direct investment, where the insurer bears the full investment cost of RDER; and (ii) subsidy, where the insurer 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 cost. In the latter, the costs are split between the insurer and consumer, with the investment made by the consumer. Note that both models only apply after a wholesale investment equilibrium has been reached.

We adopt a RDER system architecture that incorporates (i) a distributed solar system and (ii) a battery energy storage system (BESS) that is connected to the central grid and enabled for islanded operation if the grid connection is interrupted. This represents one potential setup of RDER that could aid in improving resilience to extreme events.[1]

III. Methods

To illustrate the economic rationale for the proposal we develop an agent-based model of investment in the electricity market via the associated insurance scheme.

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

A. Investment decision-making in wholesale markets

In this subsection we present the mathematical formulation of the multi-agent model of the electricity market.

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 economic dispatch of energy and operating reserves and clearing of the capacity mechanism. Four aspects of uncertainty are modelled (locational demand, resource availability, network availability and inflows into hydro storage) reflected in annual scenarios ($\omega \in \Omega$).

1) Economic dispatch: The electricity spot market ED_ω in (1) expresses a centrally cleared bid-based economic dispatch for energy and operating reserves. As standard in the literature, 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 [**?**]. It is assumed that participants bid truthfully in line with their actual costs, and strategic bidding is not considered in this analysis. This is a reasonable assumption under the presence of many bidders, even in complex settings [25]. For simplicity, only upward reserve procurement is contemplated in (1); nonetheless, the formulation can be readily extended to incorporate additional reserve markets.

The set of resources $r \in \mathcal{R}$ comprise 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. We clarify here 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 $\mathcal{G}$.

For ease of notation, any decision variables and parameters that vary over time are denoted in **bold**. For example, we

[1] Other options include feeder and substation level configurations (see for example [**?**]). 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. We also evaluated cases that included residential diesel gensets as part of the suite of investment options available to the insurer: however, no investment in diesel gensets was recorded in the base case due to their non-competitive capital and variable costs.

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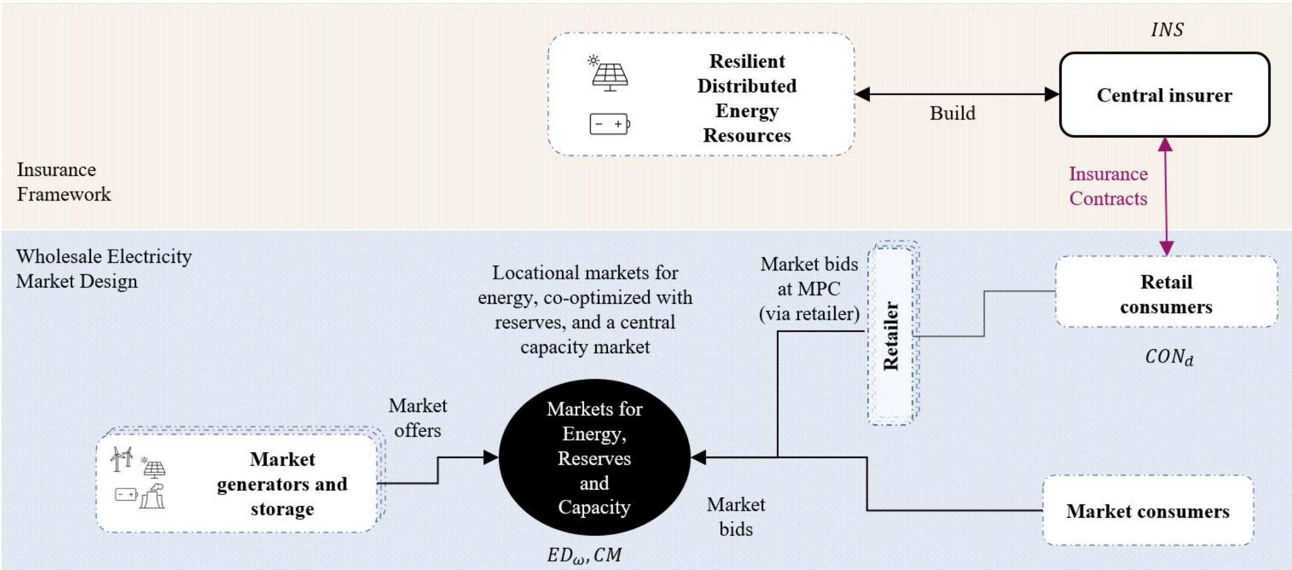

Fig. 1: Schematic of the market architecture incorporating a wholesale electricity market design with centrally cleared spot markets for energy, reserves and capacity; combined with an insurance scheme for electricity sector resilience.

define the vector of energy dispatched over time from a resource $r \in \mathcal{G} \cup \mathcal{H}$ as $\boldsymbol{p}^G_{r\omega} := [p^G_{r1\omega}, ..., p^G_{rt\omega}, ..., p^G_{rT\omega}]$ where $p^G_{rt\omega}$ denotes the energy dispatched by resource r in scenario ω, time period $t \in \mathcal{T} := \{1, \ldots, T\}$. Other vectors are defined similarly. For storage resources, energy dispatch is separated into charge $p^{G+}_{st\omega}$ and discharge $p^{G-}_{st\omega}$ with total energy generation defined as the difference between the two $p^G_{st\omega} = p^{G-}_{st\omega} - p^{G+}_{st\omega}$. Total reserve dispatch is defined as the sum of reserve delivery from $p^R_{st\omega} = p^{R-}_{st\omega} + p^{R+}_{st\omega}$. All mathematical notation is defined in Supplementary Information Section I [26].

For a given scenario $\omega \in \Omega$, we define the economic dispatch optimization problem ED_ω as follows, where $Z_{ED} := \{\boldsymbol{p}^G_{r\omega}, \boldsymbol{p}^R_{r\omega}, \boldsymbol{p}^{sh}_{d\omega}, \boldsymbol{p}^{rsh}_{i\omega}, \boldsymbol{S}_{r\omega}, \boldsymbol{\theta}_{\omega n}\}$ denotes the set of decision variables.

$$ED_\omega : \quad \min_{Z_{ED}} \sum_{r\in\mathcal{R}} \boldsymbol{C}^{vc}_{r\omega} \cdot \boldsymbol{p}^G_{r\omega} + \sum_{d\in\mathcal{D}} \boldsymbol{C}^{sh}_{d\omega} \cdot \boldsymbol{p}^{sh}_{d\omega} + \sum_{r\in\mathcal{R}} \boldsymbol{C}^R_r \cdot \boldsymbol{p}^R_{r\omega} + \sum_{i\in\mathcal{I}} \boldsymbol{C}^{rsh}_i \boldsymbol{p}^{rsh}_{i\omega} \quad (1a)$$

subject to:

$$\sum_{d\in\mathcal{D}^n} (\overline{\boldsymbol{P}}^D_{d\omega} - \boldsymbol{p}^{sh}_{d\omega}) + \sum_{m\in\mathcal{L}^n} B_{nm}(\boldsymbol{\theta}_{n\omega} - \boldsymbol{\theta}_{m\omega}) = \sum_{r\in\mathcal{R}^n} \boldsymbol{p}^G_{r\omega}, \; n \in \mathcal{N}, \quad [\boldsymbol{\lambda}^E_{\omega n}] \quad (1b)$$

$$\boldsymbol{p}^{sh}_{d\omega} \le \overline{\boldsymbol{P}}^D_{d\omega}, \quad \forall d \in \mathcal{D}, \quad (1c)$$

$$\boldsymbol{p}^G_{r\omega} + \boldsymbol{p}^R_{r\omega} \le \overline{P_r} \boldsymbol{A}^G_{r\omega} u_r, \quad \forall r \in \mathcal{G} \cup \mathcal{H} \quad (1d)$$

$$-\boldsymbol{p}^{G+}_{r\omega} + \boldsymbol{p}^{R+}_{r\omega} \le \overline{P_r} \boldsymbol{A}^G_{r\omega} u_r, \quad \forall r \in \mathcal{S}, \quad (1e)$$

$$\boldsymbol{p}^{G-}_{r\omega} + \boldsymbol{p}^{R-}_{r\omega} \le \overline{P_r} \boldsymbol{A}^G_{r\omega} u_r, \quad \forall r \in \mathcal{S}, \quad (1f)$$

$$-F_{nm} \boldsymbol{A}^L_{nm,\omega} \le B_{nm}(\boldsymbol{\theta}_{\omega n} - \boldsymbol{\theta}_{\omega m}) \le F_{nm} \boldsymbol{A}^L_{nm,\omega}, \quad \forall n, \forall m \in \mathcal{L}^n, \quad (1g)$$

$$S_{rt\omega} = S_{r,t-1,\omega} + q^+_r p^{G+}_{rt\omega} - \frac{1}{q^-_r} p^{G-}_{rt\omega}, \; \forall r \in \mathcal{S}, \; t \in \mathcal{T} \quad (1h)$$

$$S_{rt\omega} = S_{r,t-1,\omega} + i^{G+}_{rt\omega} - \frac{1}{q^-_r} p^{G-}_{rt\omega}, \; \forall r \in \mathcal{H}, \; t \in \mathcal{T}, \quad (1i)$$

$$S_{r1\omega} = S_{rT\omega}, \; \forall r \in \mathcal{S} \cup \mathcal{H}, \quad (1j)$$

$$\boldsymbol{S}_{r\omega} \le \overline{P_r} u_r e_r, \quad \forall r \in \mathcal{S} \cup \mathcal{H}, \quad (1k)$$

$$\sum_{r\in\mathcal{R}} \boldsymbol{p}^R_{r\omega} + \sum_{i\in\mathcal{I}} \boldsymbol{p}^{rsh}_{i\omega} \ge \overline{R^{req}}, \quad \forall r \in \mathcal{R}, \quad [\boldsymbol{\lambda}^R_\omega] \quad (1l)$$

$$\boldsymbol{p}^{rsh}_{i\omega} \le R^{req}_i, \quad \forall i \in \mathcal{I}, \quad (1m)$$

$$\boldsymbol{\theta}_{\omega 1} = 0, \quad (1n)$$

$$\overline{P_r} \ge \boldsymbol{p}^{G+}_{r\omega} \ge 0, \; \overline{P_r} \ge \boldsymbol{p}^{G-}_{r\omega} \ge 0, \; \boldsymbol{p}^{R+}_{r\omega} \ge 0, \; \boldsymbol{p}^{R-}_{r\omega} \ge 0, \; \boldsymbol{S}_{r\omega} \ge 0. \quad (1o)$$

The objective is to minimise the total cost (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 $\boldsymbol{p}^R_{r\omega}$ 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 (1b), where the associated dual variable $\boldsymbol{\lambda}^E_{\omega n}$ can be interpreted as the locational marginal price of energy. Equation (1c) ensures that unserved demand is below actual nodal demand. Equations (1d),(1e) and (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 (1g) enforces transmission DC flow limits. Equations (1h) and (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 (1j) the SoC is constrained to have the same value at start and end of the considered period. Technical limits on SoC are enforced in (1k). Equation (1l) determines the reserve amount with the dual variable $\boldsymbol{\lambda}^R_\omega$ indicating the system marginal reserve price. Equation (1m) limits the reserves shortage to the corresponding value of the segmented operating reserve demand curve (ORDC) [27]. Equations (1n)-(1o) set reference phase angles and non-negativity constraints.

2) Capacity mechanism formulation: The formulation for the capacity mechanism CM envisions a central auction for resource capacity cleared against an administratively determined demand curve.

$$CM: \quad \min_{Z_{CM}} \sum_{r\in\mathcal{R}} C^I_r p^{CM}_r + \sum_{j\in\mathcal{J}} C^U_j p^U_j \tag{2a}$$

subject to:

$$\sum_{j\in\mathcal{J}} D^{th}_j = \sum_{r\in\mathcal{R}} p^{CM}_r + \sum_{j\in\mathcal{J}} p^U_j, \qquad [\lambda^{CM}] \tag{2b}$$
$$0 \le p^{CM}_r \le \overline{P_r} A^{CM}_r u_r, \quad \forall r\in\mathcal{R}, \tag{2c}$$
$$0 \le p^U_j \le D^{th}_j, \qquad \forall j\in\mathcal{J}, \tag{2d}$$

where $Z_{CM} \coloneqq \{p^{CM}_r, p^U_j\}$ gathers the decision variables. The first term in (2a) represents the total investment in resource r capacity, given by unit capacity costs C^I_r and cleared resource capacity award p^{CM}_r; the second term represents the costs of unmet capacity demand, where the penalty associated to capacity shortage p^U_j in each capacity demand segment $j\in\mathcal{J}$ is denoted by C^U_j. Equation (2b) balances auction demand and supply; here, the dual variable λ^{CM} defines the marginal clearing price of the capacity auction. Equation (2c) ensures that cleared capacity award is lower than or equal to the derated maximum capacity of resource (the product of resource capacity $\overline{P_r}$ and the derating factor A^{CM}_r). Capacity deratings factors are based on the effective load carrying capacity (ELCC) [28]. Capacity demand curve segments are specified in (2d) [27]. The capacity mechanism provides an additional source of revenue to resources based on the marginal price of the capacity auction and cleared resource capacity.

3) Investment decision: Investment decision making for each generation, hydro or storage resource is modelled as a lumpy binary investment with risk endogenised via a risk-weighted utility function. The latter is defined as a convex combination of expected value of the profit and a coherent risk measure, namely the conditional value-at-risk (CVaR), a measure of the expected shortfall [8], [29]. This model is used to determine the risk averse utility U^G_r 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, prices and awards for the capacity mechanism); the coupling is reflected through the dual variables from (1) and (2).

$$ID_r: \quad U^G_r = \max_{Z_U} \beta_r\Big(v^G_r - \frac{1}{\alpha^G_r}\sum_{\omega\in\Omega}\pi_\omega \varrho^G_{g\omega}\Big) + (1-\beta_r)\sum_{\omega\in\Omega}\pi_\omega \Psi^G_{r\omega} - C^I_r\overline{P_r}u_r \tag{3a}$$

subject to:

$$\Psi^G_{r\omega} = (\boldsymbol{\lambda}^E_{\omega n(r)} - \boldsymbol{C}^{vc}_r)\cdot \boldsymbol{p}^G_{r\omega} \tag{3b}$$
$$+ (\boldsymbol{\lambda}^R_\omega - \boldsymbol{C}^R_r)\cdot \boldsymbol{p}^R_{r\omega} + \lambda^{CM} p^{CM}_r, \tag{3c}$$
$$v^G_r - \Psi^G_{r\omega} \le \varrho^G_{r\omega}, \ \forall\omega\in\Omega, \tag{3d}$$
$$\varrho^G_{r\omega} \ge 0, \ \forall\omega\in\Omega, \tag{3e}$$

where $Z_U \coloneqq \{\Psi^G_{r\omega}, v^G_r, \varrho^G_{r\omega}\}$ gathers the decision variables of the problem, i.e., $\Psi^G_{r\omega}$ and two auxiliary variables $v^G_r, \varrho^G_{r\omega}$ used for the CVaR formulation. The objective function (3a) is specified as a maximization of risk-weighted utility, formulated as convex combination ($0\le\beta_r\le 1$) of the expected value and the $(1-\alpha^G_r)$-CVaR (i.e., relative to the worst-case $1-\alpha^G_r$ quantile) of scenario profits (3c), minus capital costs. Constraints (3d) and (3e) are required for the scenario formulation of CVaR [30].

B. Insurance overlay

We consider the insurer to act as a central agent with contingent liability for consumer electricity service outages; while decentralized and competitive paradigms for insurance are possible, these deserve a dedicated analysis that is out of the scope of this work. For technical convenience, we assume the insurance is mandatory. We note that the analysis in Section IV 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 willingness and capability to properly assess such risks), and the consequent impacts on take-up of insurance, need to be carefully considered also through a consumer protection and social justice lens.

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

$$INS: \quad \max_{Z_{INS}} U^i \coloneqq (1-\beta_i)\sum_{\omega\in\Omega}\pi_\omega\Psi^i_\omega + \beta_i\tilde{c}^i - \gamma\phi^i \tag{4a}$$

subject to:

$$\Psi^i_\omega = \sum_{d\in\mathcal{D}}(C^P_d - \boldsymbol{C}^{comp}_d\cdot\boldsymbol{p}^c_{d\omega}) - \sum_{r\in\mathcal{R}^{der}} \kappa C^I_r\overline{P_r}, \ \omega\in\Omega \tag{4b}$$
$$\tilde{c}^i = v^i - \frac{1}{\alpha^i}\sum_{\omega\in\Omega}\pi_\omega\varrho^i_\omega, \tag{4c}$$
$$v^i - \Psi^i_\omega \le \varrho^i_\omega, \quad \forall\omega\in\Omega, \tag{4d}$$
$$\phi^i \ge \max\{0, -\tilde{c}^i\}, \tag{4e}$$
$$\overline{P_r}\ge 0, \text{and } \varrho^i_\omega \ge 0, \ \boldsymbol{p}^c_{d\omega}\ge 0, \ \forall\omega\in\Omega, \tag{4f}$$
$$\sum_{d\in\mathcal{D}^n}\boldsymbol{p}^c_{d\omega} = \sum_{d\in\mathcal{D}^n}\boldsymbol{p}^{sh*}_{d\omega} - \sum_{r\in\mathcal{R}^{der}}\boldsymbol{p}^G_{r\omega}, \ \forall\omega\in\Omega, \ n\in\mathcal{N}, \tag{4g}$$
$$0 \le \boldsymbol{p}^G_{r\omega} \le \overline{P_r}\boldsymbol{A}^G_{r\omega}, \ \forall r\in\mathcal{R}^{der}, \ \omega\in\Omega \tag{4h}$$
$$0 \le \boldsymbol{S}_{r\omega} \le \overline{P_r}e_r, \ \forall r\in\mathcal{S}^{der}, \ \omega\in\Omega, \tag{4i}$$
$$S_{rt\omega} = S_{r,t-1,\omega} + q^+_r p^{G+}_{rt\omega} - \frac{1}{q^-_r}p^{G-}_{rt\omega}, \quad \forall r\in\mathcal{S}^{der}, t\in\mathcal{T}, \omega\in\Omega, \tag{4j}$$

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 $(1-\alpha^i)$-CVaR (denoted as $\tilde{c}^i$) of the insurer's profits (first and second term in (4a)). In addition, the insurer must also bear the costs associated with reserving capital to meet potential losses [7]: this is expressed by the third term of the objective function, where ϕ^i is the reserved capital and γ its annualized cost. For each scenario $\omega \in \Omega$, insurer profits Ψ^i_ω are defined in (4b) as the sum of premium revenues C^P_d, minus insurance compensation costs and the investment costs of RDER, scaled by the subsidy $0 < \kappa < 1$ 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. We note 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 III-A1.

Equations (4c) and (4d) define the CVaR $\tilde{c}^i$, whereas (4e) sets out the requirements for reserve capital to be in excess of the negative CVaR. Alternative approaches that may also be applicable in assessing extreme or tail risks include robust or "worst case" risk measures. Load shedding is defined in (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 (4h)-(4j).

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

$$CON_d: \quad \max_{Z_{CON}} U^c_d := (1-\beta_d)\sum_{\omega\in\Omega}\pi_\omega \Psi^c_{d\omega} + \beta_d \tilde{c}^c_d \quad (5a)$$

subject to:

$$\Psi^c_{d\omega} = -\boldsymbol{C}^{voll}_d \cdot \boldsymbol{p}^c_{d\omega} - \sum_{r\in\mathcal{R}^{der}} (1-\kappa) C^I_r \overline{P'_r} - C^P_d + \boldsymbol{C}^{comp}_d \cdot \boldsymbol{p}^c_{d\omega},\ \omega \in \Omega, \quad (5b)$$

$$\tilde{c}^c_d = v^c_d - \frac{1}{\alpha^c_d}\sum_{\omega\in\Omega}\pi_\omega \varrho^c_{d\omega}, \quad (5c)$$

$$v^c_d - \Psi^c_{d\omega} \le \varrho^c_{d\omega}, \quad \forall\omega\in\Omega, \quad (5d)$$

$$\varrho^c_{d\omega} \ge 0, \quad \forall\omega\in\Omega, \quad (5e)$$

$$\boldsymbol{p}^c_{d\omega} = \boldsymbol{p}^{sh*}_{d\omega} - \sum_{r\in\mathcal{R}^{der}} \boldsymbol{p}^G_{r\omega}, \quad \forall\omega\in\Omega, \quad (5f)$$

$$0 \le \boldsymbol{p}^G_{r\omega} \le \overline{P'_r}\boldsymbol{A}^G_{r\omega} \quad \forall r \in \mathcal{R}^{der}, \omega\in\Omega, \quad (5g)$$

$$0 \le \boldsymbol{S}_{r\omega} \le \overline{P}'_r e_r \quad \forall r \in \mathcal{S}^{der}, \omega\in\Omega, \quad (5h)$$

$$S_{rt\omega} = S_{r,t-1,\omega} + q^+_r p^{G+}_{rt\omega} - \frac{1}{q^-_r} p^{G-}_{rt\omega}, \quad \forall r \in \mathcal{S}^{der}, t\in\mathcal{T}, \omega\in\Omega, \quad (5i)$$

where $Z_{CON} := \{\Psi^c_{d\omega}, \tilde{c}^c_d, \overline{P'_r}, v^d_c, \varrho^c_{d\omega}, \boldsymbol{p}^c_{d\omega}, \boldsymbol{p}^G_{r\omega}, \boldsymbol{S}_{r\omega}\}$ gathers the decision variables. The objective is to maximise a convex combination of the scenario-weighted consumer surplus $\Psi^c_{d\omega}$ and the risk measure given by the $(1-\alpha^c_d)$-CVaR denoted as $\tilde{c}^c_d$. The consumer surplus, as defined in (5b), reflects 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 subsidization 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) (line 27 in Algorithm 1). The other constraints relate to CVaR (5c)-(5e) and technical/operational constraints (5f)-(5i), similar to the INS problem.

C. Market equilibrium algorithm

We seek to find a market investment equilibrium where no agent can increase its utility by deviating unilaterally from the solution. To search for equilibria we propose a heuristic algorithm that seeks to replicate the process of competitive entry and exit in liberalised markets. Fig. 2 provides a flow chart of the adopted approach, detailed in Algorithm 1.

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 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 or not (an investment with negative risk-weighted utility U^G_r is considered unprofitable). Given the possibly multiple equilibria, our algorithm is best described as a guided search through the feasibility 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 we assume that a predefined ordering of the set of resources exists; we point 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 unit commitment status [31]). 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 $\arg\min_r(U^G_r)$ 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 taking decisions sequentially, once the wholesale market equilibrium iterations have terminated.

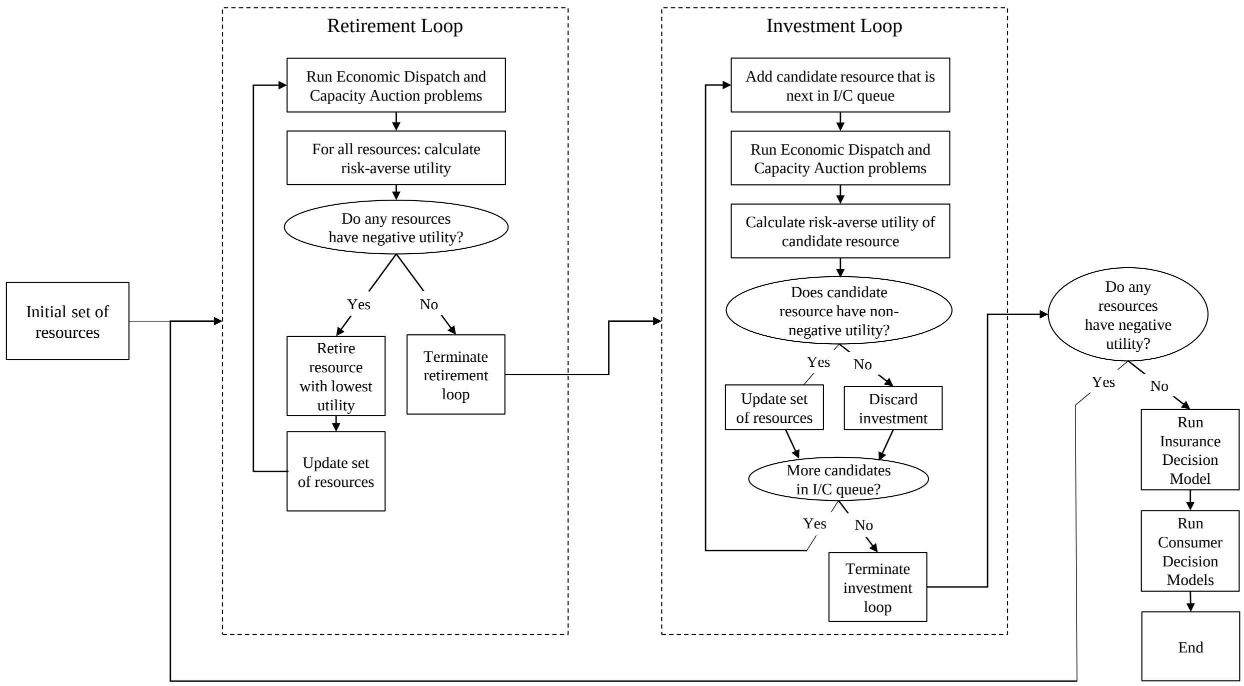

Fig. 2: Flowchart of Algorithm 1.

Our heuristic equilibrium-seeking algorithm follows from the concepts of ordered interconnection queue, and commercial retirement decision making. We do not provide guarantees of convergence to an equilibrium for the adopted heuristic approach. Nonetheless, for each of the test cases considered in the numerical study, an equilibrium was attained within a relatively small number of iterations (we verified that each of the points reached by the heuristic algorithm was indeed an equilibrium by running an ex-post diagonalization algorithm of the form outlined in [27]). We also tested the algorithm against alternative network cases and initial conditions and in most instances an equilibrium was reached; exceptions were those characterised by a limited liquidity, where a reduced set of resource candidates was available.

IV. Numerical Study

Our numerical study is developed to illustrate the insurance value of resilient investment. The National Electricity Market (NEM) of Australia provides an apposite case study of a large scale grid in transition towards a high penetration of VRE and the rolloff of legacy fossil fleet. We also benefit from a high degree of transparency on demand and generation availability projections across scenarios and locations, technical and financial data for current fleet and network topology information, as well as projected interconnection pipeline.

A. Data and assumptions

Plant technical, financial and cost data are sourced from the Integrated System Plan (ISP) produced by the Australian Energy Market Operator (AEMO) for existing, committed and anticipated resources [32], supplemented by [31] for new projects. For the network topology we adopt the ISP sub-regional network representation comprising 10 zones, with their transfer capability and seasonal availability limits [32]; a diagram of the network along with further details are provided in Supplementary Information Section II [26].

To account for weather uncertainty, a set of annual weather-year scenarios are adopted for demand, VRE availability, hydro inflows and transmission network capacity with data 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 [33]. These are used as input to model the VRE resources with 30 minute dispatch intervals. We approximate energy exchange of long duration storage and hydro between representative periods through the introduction of additional variables and constraints based on the approach in [34]. Costing and operational assumptions include storage life cycle and degradation cost adjustments, as well as charging and discharging efficiencies [32].

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 [35] and the Electricity Sector Climate Information Risk Assessment Framework, result of a collaboration between AEMO and the Commonwealth Scientific and Industrial Research Organisation (CSIRO) [36]; we refer the reader to Supplementary Information Section III

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Algorithm 1: 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 $r \in \mathcal{R}\colon u_r = 1$ **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 $r \in \mathcal{R}\colon u_r = 0$, *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 $(u_r^*, \overline{P_r}^*)$, $\forall r \in \mathcal{R}^{der}$

[26] for details on the specific assumptions used. We wish to point 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 we have 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 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.)

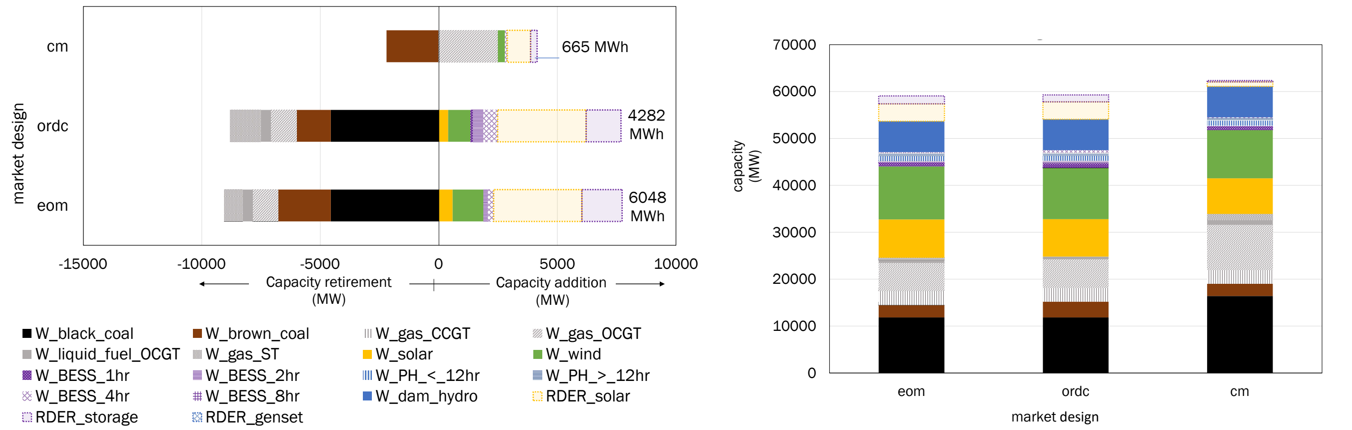
Three market designs are tested in the case study: (i) energy only market (EOM), (ii) energy market with an operating reserve demand curve (ORDC) and (iii) energy market with capacity auctions (CM). An energy market price cap of \$15000/MWh is adopted for the EOM and ORDC designs, while for the CM we consider a reduced cap of \$2000/MWh. The ORDC is characterised by three reserve quantity segments of 2000 MW, 1000 MW and 1000 MW with corresponding price thresholds of \$15000/MWh, \$10000/MWh and \$5000/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 \$90000/MW/year and set at 0.5, 1.0 and 1.5 times CONE respectively. The derating factors for numerical study are based on a marginal effective load-carrying capacity (ELCC) methodology. We define the 'risk-neutral' case as the one where the insurer preferences are skewed towards expected returns, i.e., the insurer is *almost* neutral towards risk; we simulate this 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. We characterise risk aversion for resource decision-making by $\beta_r = 0.5$ and $\alpha_r = 0.9$, for all $r \in \mathcal{R}$. The insurance scheme adopts a capital reserving threshold with a tail probability $1 - \alpha_i$ set at 1% (consistent with international insurer solvency standards [37]).

We provide a set of RDER investment options 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 [38]. We consider both (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 Fig. 9 we show results for κ ranging from 0.2 to 0.8). Note that in the latter case, we focus on storage only, given the array of subsidies available to distributed solar technologies.

B. Results

For each of the three selected market designs, Figure 3a illustrates the retired and added capacity, while Fig. 3b 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'). Empirical cumulative density functions for system annualized unserved energy (USE) (which is defined as annual energy demand unserved as a proportion of total annual demand) are shown in Fig. 4 for each of the three market designs. The



(a) (b)

Fig. 3: Outcome of EOM, ORDC and CM markets on (a) resource capacity additions and retirements, and (b) total resource capacity. Storage durations in MWh are also detailed in the legend.

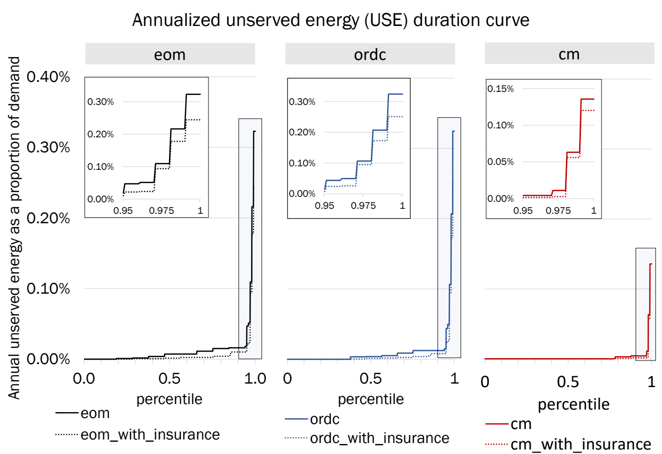


Fig. 4: Duration curves for system unserved energy (USE), measured as percentage of demand, under the EOM, ORDC and CM markets.

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 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 & brown coal (amounting to ∼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 on fast-start gas units and storage (though the latter is incremental, as all candidate gas units in the current queue are built). Fig. 4 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 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, reduction in unserved energy for extreme cases are 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. As the network is characterised by regional areas with weaker connections, such as Central New South Wales (CNSW) and Northern New South Wales (NNSW), local effects can be observed where these regions suffer from a poorer supply reliability. This implies that the potential contingent liability exposures 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 could be observed particularly under the EOM market architecture (see Fig. 5).

Table I 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, we set the insurance premium to a level that provides a zero-utility outcome (eq. (4a)) to the insurer; we deemed this approach 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 (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 premia under base weather years, despite the benefit from lowered VOLL. Conversely, significant surplus can be registered in extreme years, where the role of insurance compensation

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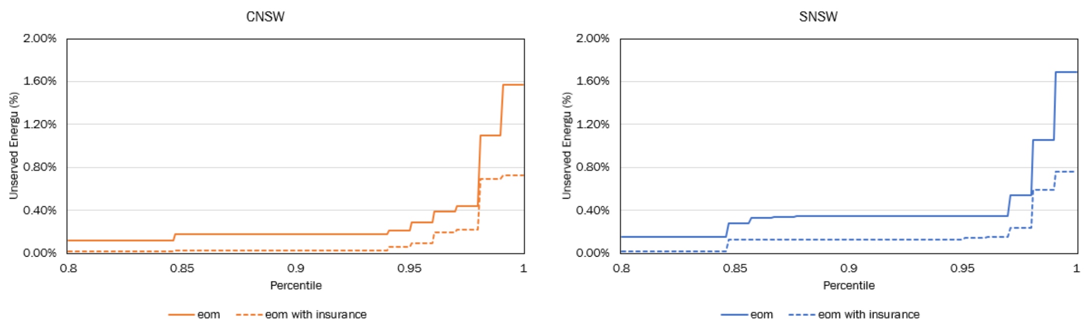

Fig. 5: Duration curves for unserved energy (USE), measured as percentage of demand, in regional areas of Central New South Wales (CNSW) and Northern New South Wales (NNSW) under an energy only market design.

TABLE I: 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

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, albeit the amount of capital reserves obtained from the solution of (4) affords solvency in all the considered scenarios.

Fig. 6 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 $\beta_i \geq 0.3$. We note, 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 $1 - \alpha_d^c = 0.01$ 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 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.

Fig. 7 shows the sensitivity of the amount invested in RDER capacity with respect to the degree of insurer risk aversion. As β_i increases we observe that 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.

A sensitivity analysis is conducted against insurance compensation levels with results for the EOM design shown in Fig. 8. The results indicate that the insurance scheme fails to incentivise investment in RDER at compensation levels below $12000/MWh. Beyond this level, RDER investment grows but starts to cap out at compensation levels of $\sim$$28000/MWh. This indicates that there are practical bounds to the value of the insurance scheme in a large scale market context.

Finally, while the above results are obtained under the assumption of direct investment by the insurer in RDER, we also consider the case where the insurer provides a subsidy

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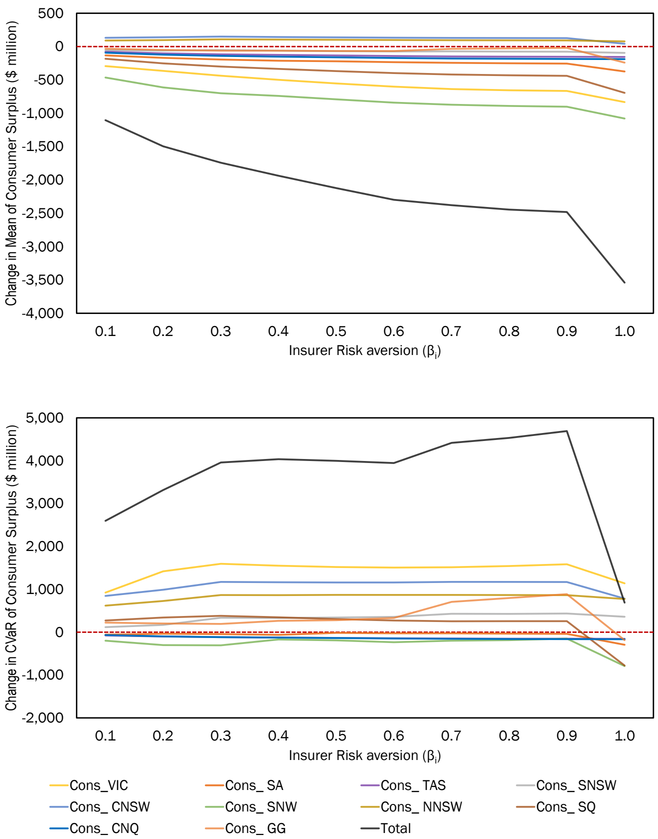

Fig. 6: Regional breakdown of the effect of the insurance scheme, in terms of mean consumer utility (upper plot) and expected shortfall (bottom plot): sensitivity to variations in the insurer's risk aversion.

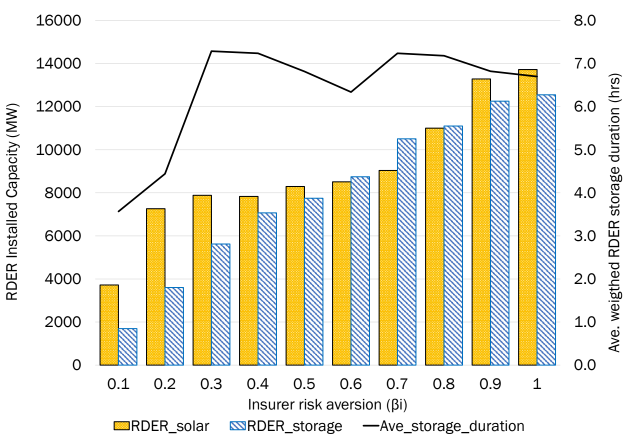

Fig. 7: Sensitivity of investment on RDER generation and storage capacity to the insurer risk aversion index β_i, under EOM. The solid black trace (relative to the right vertical axis) depicts the average storage duration characterising the assets on which the investments are allocated: this grows from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

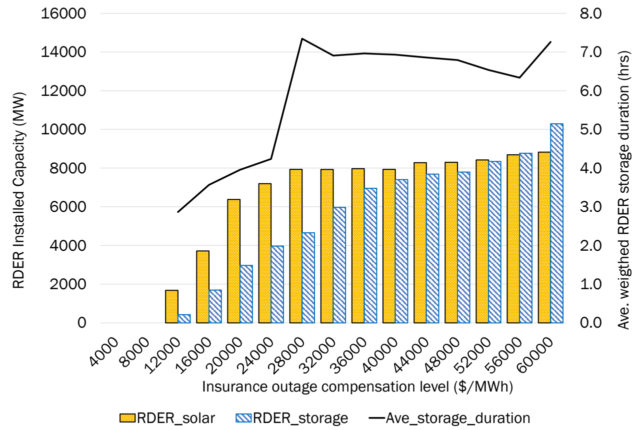

Fig. 8: Sensitivity of installed RDER generation and storage capacity to insurance outage compensation. The insurance scheme fails to incentivise investment in RDER at compensation levels below \$12000/MWh. On the other hand, investments reach their maximum at compensations of the order of \$28000/MWh. This indicates that there are practical bounds to the value of the insurance scheme in a large scale market context.

to consumers ranging from 20% to 100% of the capital costs of storage RDERs, under the EOM framework. The leftmost bars in Fig. 9 represent the maximum potential investment in storage RDER, expressed by the value $\overline{P_r}$ resulting from (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.

In the next section, we discuss some policy implications based on the results of this study. While these results point to the viability of the proposed insurance scheme, associated with significant benefits to the energy system reliability, we should mention some important 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 from 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, we acknowledge 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

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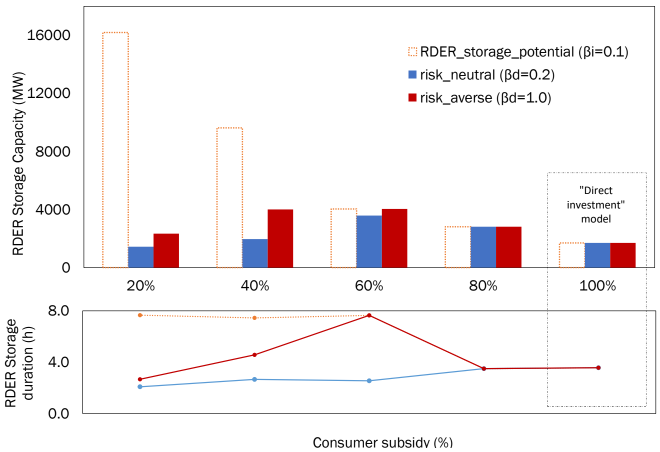

Fig. 9: Insurance subsidy model: sensitivity of installed RDER storage capacity to the amount of subsidy to consumers. The blue and red bars represent consumer investments given the level of subsidy provided by the insurance scheme, respectively for near risk-neutral ($\beta_d = 0.2$), and risk averse ($\beta_d = 1$) 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).

practice.

V. Policy Implications and Conclusions

There are a number of important policy implications and further areas of inquiry flowing from the results of the case study. 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 (CM). 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], [9]. In the current energy system context, the shift from legacy thermal to newer generation technologies (renewables, storage) underscores the impact of market design on investment mix, and the need for careful structuring and parameterisation of schemes for resilience and reliability. Therefore, achieving resilience in large scale power systems remains an important objective.

Second, the insurance framework provides an economic lens for investment decision making particularly as it relates to high-impact lower probability events. The results support a rational economic case for investment in resilience by central agencies. Importantly the RDER investment procured by the insurer and required premia adjust to the capacity mix yielded by the market design. 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, the proposed insurance-based approach provides material economic protection to consumers, through the combination of economic loss compensation and loss-mitigating investment. This aligns with the policy objectives of system resilience, which calls for improved resistance and adaptability rather than elimination of extreme impacts altogether [11].

We observe 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 tradeoffs between insurer 'subsidy' and 'direct' modes of investment. Subsidisation models offer the potential for scalable investment, but dependent upon consumer risk attitudes and take-up (which may be variant and subject to consumer budget constraints). The insurer has more control over direct investments but must bear all the costs, resulting in lower investment. 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.

Going forward we consider that this paper supports further development of the research thesis. The funding of such a scheme requires attention to the economic willingness to pay and social acceptance of premia to protect and compensate for losses, which are currently all borne by the consumer [39]. The consideration of equity issues related to the allocation of such premia 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 [40]. Given the challenges of tail risk estimation for vulnerable consumers, opt-out provisions of such schemes must also be considered carefully from a consumer protection and social justice lens. 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 to 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 in the continuity of essential services during extreme weather. In our proposal for a social insurance scheme for electric service interruptions we align incentives for capital investment, and provide consumers with physical and financial risk mitigation. We illustrate that

TABLE II: 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 III: 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

this can have material positive impacts in encouraging RDER investment, reduction of unserved energy during extremes, while providing financial coverage for consumers.

Appendix A: Analysis of a different case

This section briefly describes the solution obtained from an alternative initial generation portfolio: relative to the case described in Section IV, the 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 II and III.

The major difference in the wholesale supply mix relative to the case in Section IV 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 into 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.

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