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An insurance mechanism for electricity reliability differentiation under deep decarbonization

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ABSTRACT

Securing an adequate supply of dispatchable resources is critical for keeping a power system reliable under high penetrations of variable generation. Strategic reserves have been used by a range of jurisdictions to procure investment in additional generation reserves given the missing money problem in energy only market designs. Given the growing flexibility and heterogeneity of load enabled by advancements in distributed resource and control technology, strategic reserve procurement needs to be able to reflect the different preferences of energy consumers. To address this challenge this paper develops an insurance risk mechanism for the procurement of strategic reserves that is adapted to a future with variable generation and flexible demand. The proposed design introduces a central insurance scheme with prudential requirements that align diverse consumer reliability preferences with the financial objectives of an insurer-of-last-resort. We illustrate the benefits of the scheme in (i) differentiating load by usage to enable better management of the system during times of extreme scarcity, (ii) incentivizing incremental investment in generation infrastructure that is aligned with consumer reliability preferences and (iii) improving overall reliability outcomes for consumers.

1. Introduction

This paper addresses the question: Can we adapt the procurement of strategic reserves in electricity markets to efficiently meet the heterogeneous reliability preferences of consumers? Resource adequacy is particularly relevant today as the de-carbonization of the electricity sector requires the deployment of large amounts of variable renewable energy (VRE), which is expected to supply 70%–90% of global electricity demand by 2050 [1]. An electricity system with large penetrations of VRE will require an adequate capacity of dispatchable resources to balance periods of intermittent or low renewable resource availability [2].

In most liberalized markets, electricity is dispatched in economic merit-order and cleared on the basis of a marginal price [2]. In theory, the marginal price is capable of stimulating generation investment to ensure long-term generation capacity adequacy with consumers able to indicate preferences via bidding into markets either directly or indirectly (via aggregation) [3]. However, in practice a range of factors, including system operator interventions and administrative caps on market prices, restrict power prices from reaching the theoretical value of lost load (VOLL) [3]. This leads to the well-studied *missing money problem* where generators face a chronic shortage of revenue, while retailers avoid the full financial impact of lost load, resulting in under-hedging of load and underinvestment in resource capacity [4]. This becomes increasingly challenging as markets become dominated by variable resources with zero or negligible short-run marginal costs [4], leading to a view among some that additional investment frameworks are required given incomplete energy markets [5,6].

While some markets have moved to market-wide capacity mechanisms, others have sought to implement a strategic reserve as an overlay on the spot market. A strategic reserve for power system reliability seeks to procure additional generation capacity in excess of that delivered by the spot market [7]. Resources contracted under strategic reserves do not participate in the spot market, and are only dispatched when market sources are exhausted [8]. Hence this reserve is intended to apply to resources that may not be viable in the spot market, but may nevertheless be valuable in mitigating the reliability externality associated with administrative mechanisms [9]. This delineation preserves the option to retain strong scarcity price signals [8], relevant for jurisdictions seeking to retain a design close to an energy-only model [7]. 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 [7,8,

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10]. The National Electricity Market (NEM) of Australia complements forward contracting obligations on retailers with a strategic reserve. 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 other resources) for up to 12 months to meet a uniform reliability standard [11]. These reserves are only called into action where market responses are insufficient. 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 [7]. 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) [10,12–14]. In the context of variable generation an expected value of the metric (e.g. expected USE) is typically used, underpinned by stochastic modeling [13].

The advent of distributed energy and storage technology, and enhanced load controllability has enabled greater differentiation in consumer preferences for electricity service [15]. VOLL studies that underpin strategic reserve procurement are becoming increasingly granular to reflect the heterogeneous value of load across different consumers [16] and forms of demand response are eligible for strategic reserve procurement [17]. However, given the potential for differentiated preferences for reliability itself, a key question that arises is how to value such preferences in strategic reserve decision making. While the indirect elicitation of VOLL through surveys and other methodologies provide an estimate of the differentiated value of load, the question arises as to whether consumer preferences for reliability can be more directly revealed. We take a fresh look at the design of strategic reserves through the introduction of an insurance mechanism which allows for differentiated reliability preferences to be directly elected by consumers, and the procurement of strategic reserves to reflect those preferences.

The microeconomic model of an insurer is as a manager of tail risk [18]. 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 assessment of resource adequacy in power systems. The theory of reliability insurance was originally proposed in [19] as a contractual mechanism for priority service. Reliability insurance offers consumers compensation for electricity interruptions in return for an upfront premium [20]. This in turn creates an incentive for the insurance counterparty to mitigate interruption risk through portfolio diversification and investment in or contracting with generators [21]. In [11,22,23] insurance is considered as a logical pricing mechanism for systems with higher levels of variability and uncertainty in generation and demand.

Our proposal develops an insurance mechanism to monetize the heterogeneous value of lost load when existing demand schemes are capped out by administrative interventions. The novelty of the proposed design is the application of insurance risk management and loss reserving techniques to a strategic reserve, which to the best of author's knowledge has not been proposed to date in the literature. An insurance mechanism enables (i) the monetization of the value of lost load based on revealed consumer preference; (ii) a risk-based decision-making framework for the strategic reserve procurer to make incremental generation investment. Further by linking this to a scheme for curtailment differentiation we enable more granular curtailment to improve the preservation of essential services during extreme scarcity (which ordinarily would be subject to rotating outages). The scope of the paper is as follows: (i) the design of a strategic reserve mechanism and the 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 strategic reserve procurement; and (iii) a comparison of equilibrium outcomes of the insurance-based design against an energy-only market design. We are focused in this paper on generation capacity expansion only and do not consider network investment at this stage (i.e. a copper plate network is assumed).

The rest of this paper is organized as follows. In Section 2 we begin with a high-level architecture of our proposed *energy plus insurance* market design. In Section 3 we enunciate key principles of insurance risk and loss reserving and use them to develop a reliability insurance risk provisioning metric. Using this metric, in Section 4, we formalize in mathematical terms the risk-averse decision making problems of key agents in the design, including generators, the insurer (i.e. the procurer of strategic reserves) and consumers. In Section 5 we apply the design to a case study and present the results. Section 6 concludes with policy implications and extensions.

2. An "Energy plus Insurance" market design

In this section we describe the architecture of the proposed *energy plus insurance* market design. A high level block diagram of the proposed market architecture is provided in Fig. 1. We segment the market design into two layers. A wholesale electricity market (WEM) layer which represents capacity investment decisions given outcomes from the wholesale spot market, and a strategic reserve procurement (SRP) layer which models the decisions made in respect of the strategic reserve (using a novel insurance mechanism). A strategic reserve by definition is intended to operate as an overlay on and 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 we call generators that are built based on spot market profits as market generators, and generators supported by strategic reserve tolling payments as strategic generators. There is also a distinction between electricity consumers drawn in the architecture. Certain consumers are able to participate, via bidding in the spot market (we term these 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 consumers that are not suited for direct engagement in spot markets and/or have a VOLL above the market price cap would be eligible for to hedge their interruption risks via insurance (we term these retail consumers).

We begin with the WEM layer and the electricity spot market. Generators offer their available capacity into a gross pool at the short-run marginal cost. Consumers bid at their VOLL, limited by the market price cap (MPC). 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 [3]. 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 traditional settings quantities are determined unilaterally by a central authority with reference to standardized reliability preferences. In this design 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 we use the term Insurer-of-last-resort (IOLR) to specify the role of TSO in managing the strategic reserve as distinguished from its operational role in optimal 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 payment (in $ per MWh) linked to the VOLL of the particular source of consumption.

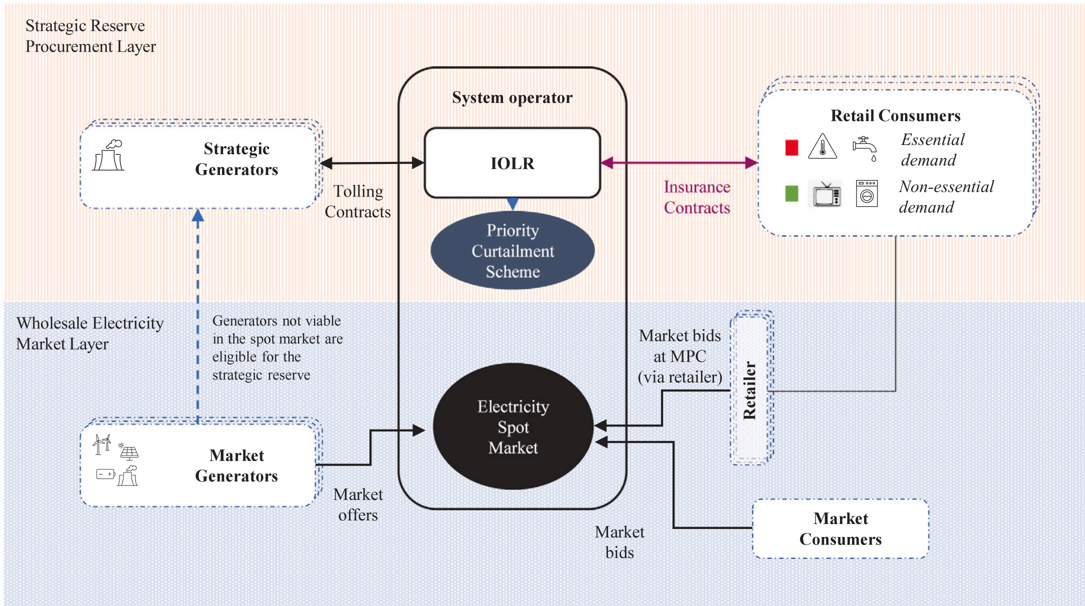

Fig. 1. Schematic of the market architecture incorporating a wholesale electricity market (WEM) layer incorporating a centrally dispatched spot market settled on marginal prices (managed by the system operator); and a strategic reserve procurement (SRP) layer incorporating a reserve procurement based on an reliability insurance scheme with priority curtailment.

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.
3. As the IOLR is financially responsible for paying compensation, it is incentivized 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 of interruptions. We note that this framework also allows the IOLR to actively contract with demand-side resources as an alternative to generation, though we only model generators in this paper to minimize the formulation complexity.
4. Under the tolling contract, the IOLR pays for all variable and fixed costs of the generator. 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 VOLL to highest VOLL). Ordinarily at this stage many markets resort to rotating/random load shedding (see [5,24,25]).
6. With this priority curtailment scheme, under scarcity or emergency conditions, load is able to be *triaged* with low value or non-essential load curtailed first, with the aim of preserving more essential load. This would be actuated through real-time communications infrastructure such as an energy router connected to the home [26].

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. Initially compensation could be based on average unserved energy at the feeder level and the market price cap, as proposed in [22], which would provide an initial valuation of lost load and incentivize 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.

There are two information flows from the WEM layer to the SRP layer. First, as 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. The second information flow is demand shortages forecasted in the spot market. This information represents the maximum demand curtailments that can occur, is used by the IOLR to assess whether a reliability insurance contract should be signed with such load, and whether such curtailment can be reduced via the contracting of additional strategic generation.

3. Insurance principles and loss reserving

In this section we describe the principles governing the viability and solvency of an insurer, and use these principles to formalize prudential metrics that guide the proposed IOLR's decision-making framework. The operations of the IOLR are managed in accordance with insurance risk management techniques where tail risks, characterized by rare but severe losses, are managed by setting premiums appropriately, by reserving capital against severe losses and by risk transfer [27–29].

A premium is the payment that a policyholder makes for complete or partial insurance cover against a risk. An actuarial premium principle is a method for assigning an appropriate price for an insurance premium [18]. The most fundamental and widely used premium principle, is the *expected value premium principle* where the premium is measured as multiple of the expected value of the insurer's compensation claims.

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 [27]. This means the insurer must carry cash reserves against the possibility that the aggregate value of loss claims will exceed its premium income [28]. These are often termed technical or insurance reserves and held in cash or equivalently secure and liquid investments, and provide a buffer against extreme outcomes. As such in rare but extreme scenarios where the insurer suffers significant losses from paying out large sums of compensation, those cash buffers are drawn down to maintain solvency. The quantity of reserves required to be held by the insurer are sized by applying a risk measure to the insurer's profits for a particular tail probability, and are typically guided by best-practice prudential risk standards and industry regulation [30]. We apply the principle of reserving 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. In this paper the conditional value-at-risk (CVAR) is used as the tail risk measure given its coherency properties [18] and its prevalence in insurance solvency regulation [31]. A solvency constraint is formulated in Section 4 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. Tail probabilities for insurers are generally set very high to account for tail risk outcomes. For example, the European Solvency II insurer financial risk framework requires insurers to assess risks at 99.5% tail probability [31]. Prudent insurance risk management requires this metric must be met by IOLR.

4. Problem formulation

This section proposes mathematical formulations for the decision-making model of the IOLR, of consumers and that of generators in the market. Consequently it proposes algorithms to find equilibria (i) in the WEM layer between market generators in the spot market, and (ii) in SRP layer between the IOLR, consumers and strategic generators. The decision problems of all relevant agents are framed as risk-averse utility maximization problems, where utility is defined as a risk measure of the agent's surplus. The risk measure chosen is a convex combination of the agent's expected profits and the CVAR of profits [32], where the parameter β ranging between 0 and 1 weights expected returns against CVAR based on the agent's preferences. As described above, there are two layers of decision making in the architecture — the WEM and SRP layers. We superscript relevant variables and parameters by i to distinguish between the CVAR of the IOLR and that of generators and consumers (calculated using the same approach), which are superscripted by G and c respectively.

4.1. WEM: Decision-making framework for generators

The WEM layer models the investment decisions of generators in the electricity spot market. Market generators are those that choose to build generation 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 we seek to model how a generator's strategic investment decision is impacted by spot prices that are the result of the economic merit-order dispatch. A bilevel modeling structure is especially suited and widely used for this application [33–36], where a utility-maximizing upper-level optimization problem for the generator's investment decisions is constrained by lower-level optimization problems that represent market equilibriums. We assume a hierarchical structure of the bi-level model of a generator (as illustrated in Fig. 2); the upper-level problem is subject to the solution of primal and dual variables of the lower-level problems. Our modeling framework builds upon the approach of [33], which describes a bi-level model for generation capacity expansion but we extend the model from a deterministic model to a stochastic model that incorporates generator risk-aversion. This modification are made with the objective of incorporating a more realistic risk framework for market participants.

The set of all available generators in represented by $g \in \mathcal{G}$. In upper level problem (GMP_g) the generator seeks to maximize utility (U_g^G) as a mean-CVAR measure of profits ($\Psi_{g,\omega}^G$) minus capital costs, which are constrained by spot market clearing outcomes across the set of scenarios $\omega \in \Omega$ modeled at the lower level (for avoidance of doubt these are the same scenarios observed by the IOLR). The CVAR of profits is notated as $\tilde{c}_g^G$ with the relevant superscripts (A description of all relevant nomenclature is set out at the end of the paper).

$$\max_{\{V_\omega, \overline{P_g^G}\}} U_g^G = (1-\beta_g)\sum_{\omega\in\Omega}\pi_\omega \Psi_{g,\omega}^G + \beta_g \tilde{c}_g^G - C_g^I \overline{P_g^G} \tag{1}$$

subject to:

$$\Psi_{g,\omega}^G = \sum_{t\in\mathcal{T}}(\lambda_{t,\omega} - C_g^v)p_{g,t,\omega}^G, \ \forall\omega \in\Omega \tag{2}$$

$$\tilde{c}_g^G = z_g^G - \frac{1}{\alpha_g^G}\sum_{\omega\in\Omega}\pi_\omega \varrho_{g,\omega}^G \tag{3}$$

$$z_g^G - \Psi_{g,\omega}^G \le \varrho_{g,\omega}^G, \ \forall\omega \in\Omega \tag{4}$$

$$\varrho_{g,\omega}^G \ge 0, \ \forall\omega\in\Omega \tag{5}$$

Eq. (2) represents the profits ($\Psi_{g,\omega}^G$) of the generator for scenario ω, as spot revenues minus variable costs of generation. Eqs. (2)–(5) represents constraints for scenario-based formulation for CVAR [37] where z_g^G and $\varrho_{g,\omega}^G$ are auxiliary decision variables representing value-at-risk (VAR) and the positive deviation between VAR and scenario profits.

The lower level models represents the clearing of the electricity spot market ED_ω under scenarios $\omega \in \Omega$ incorporating generation offers and demand bids (it is assumed that the generator offer at variable cost and demand bids at its VOLL, limited by the MPC).

$$\lambda_{t,\omega}, p_{g,t,\omega}^G \in \arg\min_{V_\omega} ED_\omega = \sum_{t\in\mathcal{T}}\sum_{g\in\mathcal{G}} C_g^{vc} p_{g,t,\omega}^G + \sum_{t\in\mathcal{T}}\sum_{d\in D} C_d^{sh} p_{d,t,\omega}^{sh}, \forall\omega\in\Omega \tag{6}$$

where $V_\omega = \{p_{g,t,\omega}^G, p_{d,t,\omega}^{sh}\}$ and subject to:-

$$\sum_{d\in D}(\overline{P_{d,t,\omega}^D} - p_{d,t,\omega}^{sh}) = \sum_{g\in\mathcal{G}} p_{g,t,\omega}^G, \ \forall t\in\mathcal{T}, [\lambda_{t,\omega}] \tag{7}$$

$$0 \le p_{g,t,\omega}^G \le \overline{P_g^G} A_{g,t,\omega}^G, \ \forall g\in\mathcal{G}, t\in\mathcal{T}, [\underline{\mu_{g,t,\omega}^G}, \overline{\mu_{g,t,\omega}^G}] \tag{8}$$

$$0 \le p_{d,t,\omega}^{sh} \le \overline{P_{d,t,\omega}^D}, \ \forall d\in\mathcal{D}, t\in\mathcal{T}, [\underline{\mu_{d,t,\omega}^{sh}}, \overline{\mu_{d,t,\omega}^{sh}}] \tag{9}$$

The objective function (6) represents an economic merit-order dispatch that minimizes system costs. The lower level constraints are typical of an economic dispatch. Eq. (7) ensures power balance as the sum of generation and demand shortage. Eq. (8) ensures positive generation dispatch but below the maximum available generation capacity, and Eq. (9) enforced demand shortage limits. The dual variables of each constraint are shown in square brackets.

As the lower level program is a linear program, the bilevel 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 [38].

$$0 \le p_{g,t,\omega}^G \perp \underline{\mu_{g,t,\omega}^G} \ge 0, \forall g\in\mathcal{G}, t\in\mathcal{T}, \tag{10}$$

$$0 \le (\overline{P_g^G} A_{g,t,\omega}^G - p_{g,t,\omega}^G) \perp \overline{\mu_{g,t,\omega}^G} \ge 0, \forall g\in\mathcal{G}, t\in\mathcal{T}, \tag{11}$$

$$0 \le p_{d,t,\omega}^{sh} \perp \underline{\mu_{d,t,\omega}^{sh}} \ge 0, \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{12}$$

$$0 \le (\overline{P_{d,t,\omega}^D} - p_{d,t,\omega}^{sh}) \perp \overline{\mu_{d,t,\omega}^{sh}} \ge 0, \forall d\in\mathcal{D}, t\in\mathcal{T} \tag{13}$$

$$C_g^{vc} - \lambda_{t,\omega} + \underline{\mu_{g,t,\omega}^G} - \overline{\mu_{g,t,\omega}^G} = 0, \forall g\in\mathcal{G}, t\in\mathcal{T}, [p_{g,t,\omega}^G] \tag{14}$$

$$C_d^{sh} - \lambda_{t,\omega} + \underline{\mu_{d,t,\omega}^{sh}} - \overline{\mu_{d,t,\omega}^{sh}} = 0, \forall d\in\mathcal{D}, t\in\mathcal{T}, [p_{d,t,\omega}^{sh}] \tag{15}$$

The complementarity constraints (10)–(13) can be linearized by replacing $0 \le a \perp b \ge 0$ with (16), where M is a large enough positive constant [39].

$$a \ge 0, b\ge 0, a \le \zeta M, b \le (1-\zeta)M, \zeta\in\{0,1\} \tag{16}$$

In addition the bilinear term $\lambda_{t,\omega} p_{g,t,\omega}^G$ in (2) can be linearized using Lemma 1 [35,40,41] (with proof provided in the Appendix) and by using the strong duality theorem, as stated in [40].

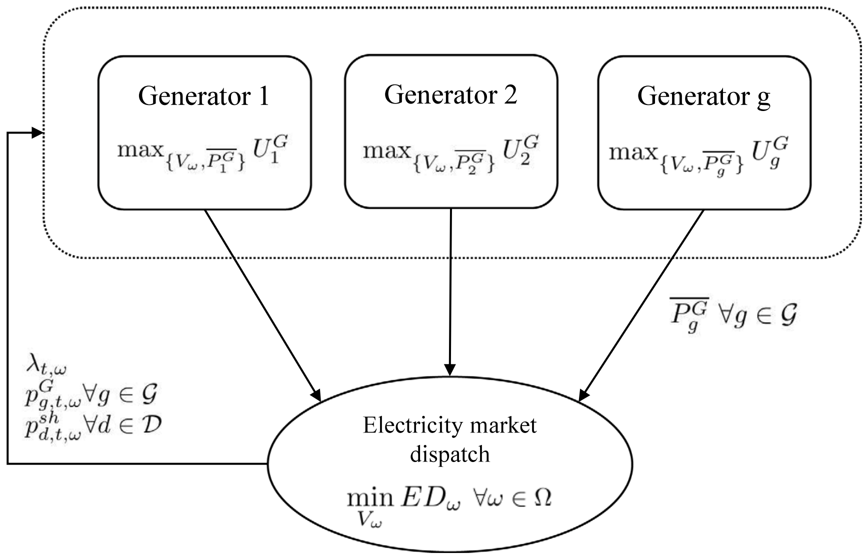

Fig. 2. Schematic illustrating the hierarchical relationship between generators and the spot market.

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

$$\lambda_{t,\omega} p^G_{g,t,\omega} = C^{vc}_g p^G_{g,t,\omega} + \overline{P^G_g} A^G_{g,t,\omega} \overline{\mu^G_{g,t,\omega}} \tag{17}$$

The strong duality theorem, as it relates to linear programs, says that if a problem is convex, the objective functions of the primal and dual problems have the same value at the optimum [40]. Therefore with a slight abuse of notation (where $\mathcal{G}$ refers to the set of all generators, and $\{\mathcal{G} \backslash g\}$ refers to the set of generators excluding independent generator g) we can state :

$$\overline{P^G_g} A^g_{g,t,\omega} \overline{\mu^G_{g,t,\omega}} = \sum_{t \in \mathcal{T}} \sum_{d \in D} \lambda_{t,\omega} \overline{P^D_{d,t,\omega}} - \sum_{d \in D} \overline{P^D_{d,t,\omega} \mu^{sh}_{d,t,\omega}} - \sum_{\{\mathcal{G} \backslash g\}} \overline{P^G_g} A^g_{g,t,\omega} \overline{\mu^G_{g,t,\omega}}$$
$$- \sum_{t \in \mathcal{T}} \sum_{d \in D} C^{sh}_d p^{sh}_{d,t,\omega} - \sum_{t \in \mathcal{T}} \sum_{\mathcal{G}} C^{vc}_g p^G_{g,t,\omega} \tag{18}$$

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 [42]:

Upper level objective function (1)

subject to:

Upper level primal constraints (2)–(5)
Lower level KKT conditions (10)–(15)
with complementarity constraints (10)–(13), replaced by (16)
Lemma 1 (17) and strong duality equality (18)

4.2. WEM: Market equilibrium

This section provides an algorithm to search for an equilibrium in the WEM layer. Each generator is assumed to be a rational utility maximizing agent. Each participant will seek to maximize its individual utility based on the decision making framework outlined above. An equilibrium is reached if no generator can increase its utility by deviating unilaterally from the solution. We use a Gauss–Seidel diagonalization approach to search for an equilibrium. Gauss–Seidel diagonalization solves each agent's individual decision-making problem while considering the decisions of other agents from the previous iteration [43]. The diagonalization process terminates when the decision of each agent does not deviate from the last iteration.

The approach taken in this paper, described in Algorithm 1, is similar to [33]. The algorithm iterates across generators to find an equilibrium between independent generators. Each generator solves its individual decision-making problem while fixing the decisions of other generators to the values from the previous iteration. An equilibrium is reached when no independent generators seek to deviate from their decisions from the previous iteration. As noted in [44–47] the convergence state of the diagonalization algorithm corresponds by definition to a Nash equilibrium 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 is not guaranteed [47,48]. As such in the case study it is possible to have more than one equilibrium. Furthermore, the iterative diagonalization approach is not generally guaranteed to converge to an equilibrium, even if equilibria exist [44,49,50]. However, for each of the test cases considered in the numerical study (Section 5), an equilibrium was reached within a relatively small number of iterations. Each run of the algorithm was tested against a range of starting conditions. In all cases the algorithm converged to the same equilibria under a range of different 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 demand shortage $p^{sh*}_{d,t,\omega}$ outcomes from the spot market given generators $\mathcal{G}^M$. These information flows inform the execution of reliability insurance contracts and generator tolling contracts.

Algorithm 1: Diagonalization to find spot market equilibrium in WEM layer

```
input  : Initial instance of problems (GMP_g)
output: Equilibrium solution
initialization: set ε iteration counts n;
while max_{g∈G} |P^G_{g,(n)} − P^G_{g,(n−1)}| > ε do
    for g ∈ G do
        solve (GMP_g) ;
        P^G_g ← P^G_{g,(n)};
    end
end
p^{sh*}_{d,t,ω} ← p^{sh}_{d,t,ω} ∈ arg min_{V_ω} ED_ω ∀d ∈ D, t ∈ T, ω ∈ Ω;
G^N = G \ G^M;
return
```

4.3. Decision-making framework in SRP layer

4.3.1. 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, and the execution of tolling contracts with generators, subject to prudential requirements to maintain solvency (as described in Section 3). This takes the form of an optimization problem (INS) outlined in Eqs. (19)–(26), and described in detail thereafter.

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

$$\max_{V^i} U^i = (1-\beta_i) \sum_{\omega\in\Omega} \pi_\omega \Psi^i_\omega + \beta_i \tilde{c}^i - \gamma\phi^i \tag{19}$$

where $V^i = \{\varrho^i_\omega, z^i, \overline{P^G_g}, p^G_{g,t,\omega}, p^c_{d,t,\omega}, Q^i_d, \phi^i\}$, and subject to:

$$\Psi^i_\omega = \sum_{d\in D} C^P_d Q^i_d - \sum_{t\in\mathcal{T}}\sum_{d\in D} C^{voll}_d p^c_{d,t,\omega} Q^i_d - \sum_{g\in\mathcal{G}^N}\sum_{t\in\mathcal{T}} C^{vc}_g p^G_{g,t,\omega} - \sum_{g\in\mathcal{G}^N} C^I_g \overline{P^G_g}, \ \forall\omega\in\Omega \tag{20}$$

$$\sum_{d\in D} p^c_{d,t,\omega} = \sum_{d\in D} p^{sh*}_{d,t,\omega} - \sum_{g\in\mathcal{G}^N} p^G_{g,t,\omega} \forall t\in\mathcal{T}, \omega\in\Omega \tag{21}$$

$$0 \le p^G_{g,t,\omega} \le \overline{P^G_g} A^G_{g,t,\omega} \forall g\in\mathcal{G}^N, t\in\mathcal{T}, \omega\in\Omega \tag{22}$$

$$\tilde{c}^i = z^i - \frac{1}{\alpha^i}\sum_{\omega\in\Omega} \pi_\omega \varrho^i_\omega \tag{23}$$

$$z^i - \Psi^i_\omega \le \varrho^i_\omega, \ \forall\omega\in\Omega \tag{24}$$

$$\tilde{c}^i \ge -\phi^i \tag{25}$$

$$\overline{P^G_g} \ge 0, 0 \le Q^I_d \le 1, \varrho^i_\omega \ge 0, \phi^i \ge 0, p^c_{d,t,\omega} \ge 0 \tag{26}$$

The objective function (19) is given as a maximization of the mean-CVAR risk measure of the IOLR's profits (Ψ^i_ω) minus the annualized cost of capital reserved, where γ is an annual discount factor (The setting aside of equity capital under a solvency constraint has an opportunity cost and must be incorporated within the insurer's surplus [29]).

Eq. (20) 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 reliability insurance sold to consumer $d \in \mathcal{D}$. The second term represents insurance compensation payouts as the product of the VOLL compensation parameter specified in the reliability insurance contract C^{voll}_d (in \$ per MWh), $p^c_{d,t,\omega}$ the emergency demand curtailment associated with demand d, and Q^D_d. The third term represents the tolling payments made to strategic generators ($g \in \mathcal{G}^N$), which comprises investment costs as the product of parameter C^I_g, the annualized investment cost per MW and P^G_g, the decision variable representing the built capacity of strategic generator g, and variable costs as the product of unit variable cost C^{vc}_g and the out-of-market dispatch of the strategic generator $p^G_{g,t,\omega}$.

The demand shortage $p^{sh*}_{d,t,\omega}$ represents the maximum possible demand curtailment for demand d at time t in scenario ω. As per (21) demand curtailment can be reduced through prioritization (i.e. prioritizing lower value load first) and through dispatch of strategic generation. Constraint (22) enforces capacity limits for strategic generators and the trivial constraints in (26) ensure that relevant decision variables are non-negative, and that the fractional quantities of insurance contracts are between 0 and 1.

The resultant optimization problem is a non-convex bilinear program due to the presence of bilinear terms in the formulation $p^c_{d,t,\omega} Q^D_d$. A binary expansion could be used to convert the continuous Q^I_d into a set of binary variables and the exact McCormick relaxation [51] can be used to convert the problem into a 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 (which is now able to solve non-convex bilinear programs to global optimality) [42,52] within acceptable timeframes.

4.3.2. 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 maximization of the consumer surplus as follows:

$$\max_{V^c_d} U^c_d = (1-\beta_d) \sum_{\omega\in\Omega} \pi_\omega \Psi^c_{d,\omega} + \beta_d \tilde{c}^c_d \tag{27}$$

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

$$\Psi^c_{d,\omega} = (C^{voll}_d - \lambda^*_{t,\omega})(\overline{P^D_{d,t,\omega}} - p^{sh*}_{d,t,\omega}) - C^P_d Q^D_d + \sum_{t\in\mathcal{T}} C^{voll}_d p^{sh*}_{d,t,\omega} Q^D_d, \ \forall\omega\in\Omega \tag{28}$$

$$0 \le Q^D_d \le 1 \tag{29}$$

$$\tilde{c}^d_c = z^d_c - \frac{1}{\alpha^d_c}\sum_{\omega\in\Omega} \pi_\omega \varrho^c_{d,\omega} \tag{30}$$

$$z^c_d - \Psi^c_{d,\omega} \le \varrho^c_{d,\omega}, \ \forall\omega\in\Omega \tag{31}$$

$$\varrho^c_{d,\omega} \ge 0, \ \forall\omega\in\Omega \tag{32}$$

The objective function follows the formulation in [53] but includes the ability for the consumer to hedge interruptions via the purchase of an insurance contract. Eq. (28) 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 relates to the fractional quantity of insurance purchased as a proportion of demand Q^D_d given the insurance premium charged C^P_d (which is provided as a parameter to the decision problem). It is assumed that wholesale costs of electricity are passed on from the retailer to the consumer. Constraint (29) limits insurance contract purchases Q^D_d to a fractional quantity between 0 and 1 (as a proportion of demand), while constraints (30)–(32) define the CVAR. The consumer problem takes the form of constrained linear program that can be solved to global optimality.

4.3.3. SRP: Insurance equilibrium

This section provides an algorithm to search for an equilibrium in the SRP layer (see Fig. 3). The IOLR and consumers are both assumed to be rational utility-maximizing agents. The key external parameter that effects both types of the participants is C^P_d, the insurance premium levied upon consumers .

We use a tatonnement (trial and error) process, set out in Algorithm 2 to compute an equilibrium where 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 [5] and Hoschle [53] 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 diagonalization method [53] and is used for contract balancing and price setting [5,32]. Uniqueness and existence under such conditions remain an open issue, beyond simple cases. The initialization of the algorithm begins with an initial instance of problems INS and $CON_d \forall d \in \mathcal{D}$, and initial values for insurance premia 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 and the insurance premia for each insurance contract is updated based on the differential 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

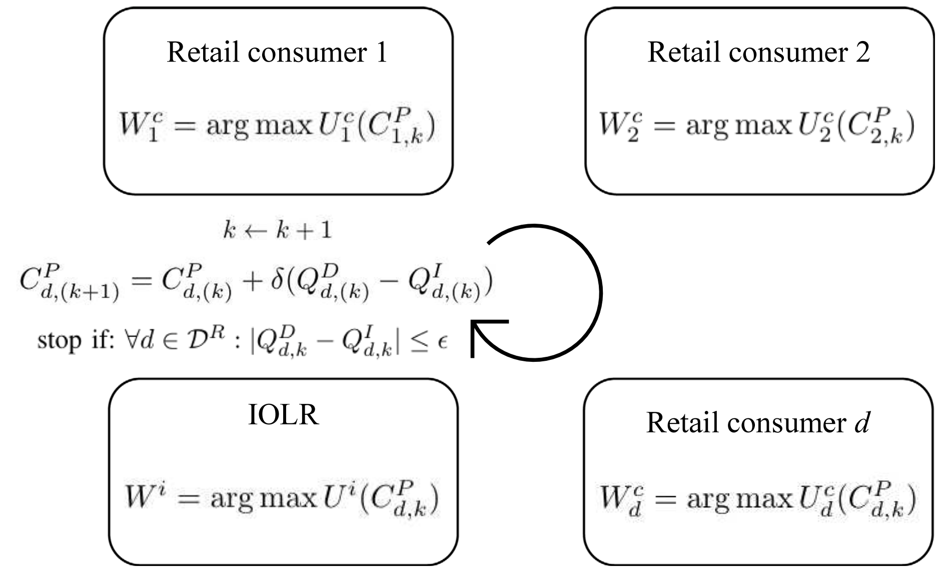

Fig. 3. Schematic illustrating the tatonnement algorithm used to find an equilibrium in the SRP layer.

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 diagonalization method, this algorithm does not provide guarantees relating to finding a solution or of solution uniqueness though equilibria were found in all of the test cases run, against multiple starting points.

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

input : Initial instance of problems (INS,$CON_d \forall d \in \mathcal{D}$)
output: Equilibrium solution
initialization:
set ϵ,δ, iteration counts k;
set initial value of $C_d^P \forall d \in \mathcal{D}$;
while $\max_{d \in \mathcal{D}} |Q_{d,(k)}^D - Q_{d,(k)}^I| > \epsilon$ **do**
    solve (INS) ;
    for $d \in \mathcal{D}$ **do**
        solve (CON_d)
    end
    $C_{d,(k+1)}^P = C_{d,(k)}^P + \delta(Q_{d,(k)}^D - Q_{d,(k)}^I)$;
    $k \leftarrow k+1$;
end
return

4.4. Risk neutral social optima

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

$$\min_{\{p_{g,t,\omega}^G, p_{d,t,\omega}^{sh}, \overline{P_g^G}\}} C_g^I \overline{P_g^G} + \sum_{\omega \in \Omega} \pi_\omega \Psi_\omega^S \tag{33}$$

subject to:

$$\Psi_\omega^S = \sum_{t \in \mathcal{T}} \sum_{g \in \mathcal{G}} C_g^{vc} p_{g,t,\omega}^G + \sum_{t \in \mathcal{T}} \sum_{d \in D} C_d^{voll} p_{d,t,\omega}^{sh}, \forall \omega \in \Omega \tag{34}$$

$$\sum_{d \in D} (\overline{P_{d,t,\omega}^D} - p_{d,t,\omega}^{sh}) = \sum_{g \in \mathcal{G}} p_{g,t,\omega}^G, \ \forall t \in \mathcal{T}, \tag{35}$$

$$0 \leq p_{g,t,\omega}^G \leq \overline{P_g^G} A_{g,t,\omega}^G, \ \forall g \in \mathcal{G}, t \in \mathcal{T} \tag{36}$$

$$0 \leq p_{d,t,\omega}^{sh} \leq \overline{P_{d,t,\omega}^D}, \ \forall d \in \mathcal{D}, t \in \mathcal{T} \tag{37}$$

5. Numerical study

We evaluate the insurance mechanism design 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, we compare the outcomes from an energy-plus-insurance market (EIM) design with an energy-only market (EOM) design and a risk-neutral socially optimal generation expansion (RN).

Given the focus on dispatchable generation resources to balance VRE, the capacity of VRE generation is determined exogenously, aligning with explicit renewable generation policy targets in 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 [54], which provides variable generation availability on an asset and regional level for 20 annual scenarios, and with 8760 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 a 40% of annual South Australian demand, results in 2100 MW of required wind capacity in the system.

Each generator can choose to build 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) and open cycle gas turbine (OCGT) and reciprocating engine (RE), with 6 agents for each generation technology. We adopt heat rates and investment costs based on $2 \times 2 \times 1$ GE7HA.02 configuration for CCGT, $1 \times$ GE7FA configuration for OCGT and 12×18 Wärtsilä 50DF dual-fuel configuration for RE. Heat rates and annualized investment costs for CCGT and OCGT technologies are sourced from [55] 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 recent constructed Barker Inlet Power Station [56] (as a relevant comparator was unavailable in [55]). 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. $\beta_g = 0.5$) with

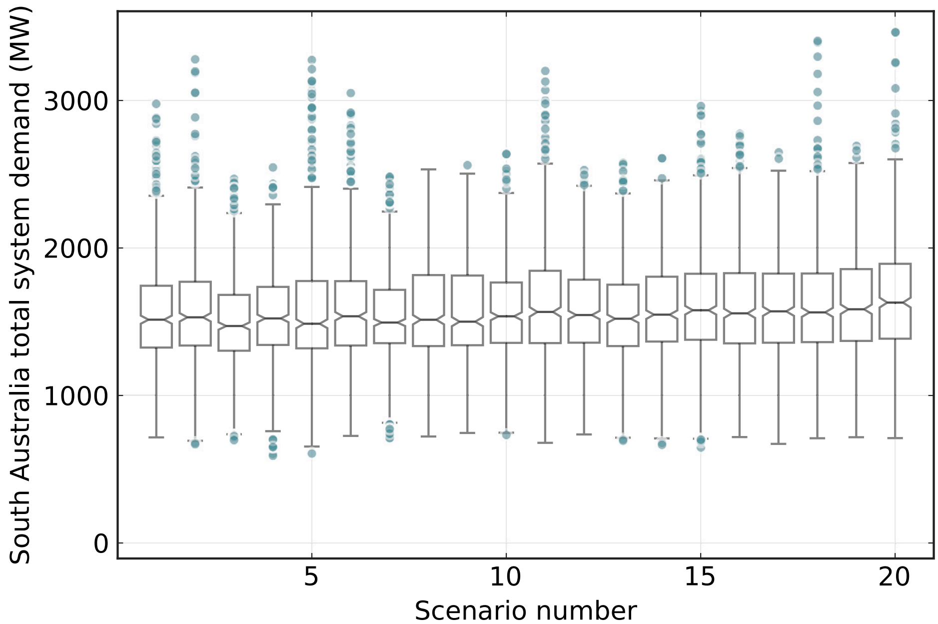

Fig. 4. Boxplot distribution of South Australia total system demand across 20 annual scenarios. The maximum demand across all of the scenarios is 3464 MW, and the minimum demand is 593 MW.

Table 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 annualized, C_g^I ($/MW/yr)	114 315	119 235	80 276
Number of generators	6	6	6
CVAR confidence level, α_g^G	0.9	0.9	0.9
Risk tolerance, β_g	0.5	0.5	0.5

Table 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’	✓	4250	15	x	4250
D8 ‘market consumer’	✓	7500	35	x	7500
D9 ‘market consumer’	✓	14 000	35	x	14 000

a confidence level of 90% for CVAR (i.e. $\alpha_g^G = 0.90$). Assumptions are summarized in Table 1.

Total South Australia system load projections are based on [54], 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 [57]. Fig. 4 shows boxplot distribution of total demand across the scenarios.

Demand parameters are set out in Table 2. Based on benchmark state-of-the-art spot market design, multiple classes of demand have been incorporated. We distinguish between retail consumers (whose demand is fixed and inelastic) and market consumer that bid their VOLL in the electricity spot market (and are actively curtailed based on optimal dispatch outcomes). It is assumed that there is 102 MW 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 [54]). The source of this demand bidding is expected to be primarily commercial demand response and aggregated flexible heating, ventilation and air-conditioning (HVAC) load. We also assumed that there are four classes of retail consumers, each with a 25% share of total system load, with VOLL ranging from $15 000/MWh to $30,300/MWh [16]. 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 $\beta_d = 1$ and tail probability $\alpha_d = 0.99$.

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 0.995 (consistent with international insurer solvency standards [31]). In the base case we assume that the IOLR utility preferences are skewed towards expected returns i.e. $\beta_i = 0$, which provides a conservative estimate of the potential benefits of the EIM design in incentivizing additional generation investment. Premiums are initialized at a 1.0 multiple of expected losses. The code was written in Julia and solution obtained using Gurobi 9.5 on an Intel Core i7 (9th-Gen) 2.60 GHz CPU 16 GB RAM. We set an optimality gap of 0.1% for solving each optimization.

Fig. 5 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 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 (the first panel), retail load is curtailed on a rotating basis (where 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 (second panel) with an operational priority curtailment scheme, demand is curtailed in order of priority based on 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 IOLR in the EIM scheme (398 MW lower at the peak), and second the prioritization scheme allows loads with lower VOLL to be

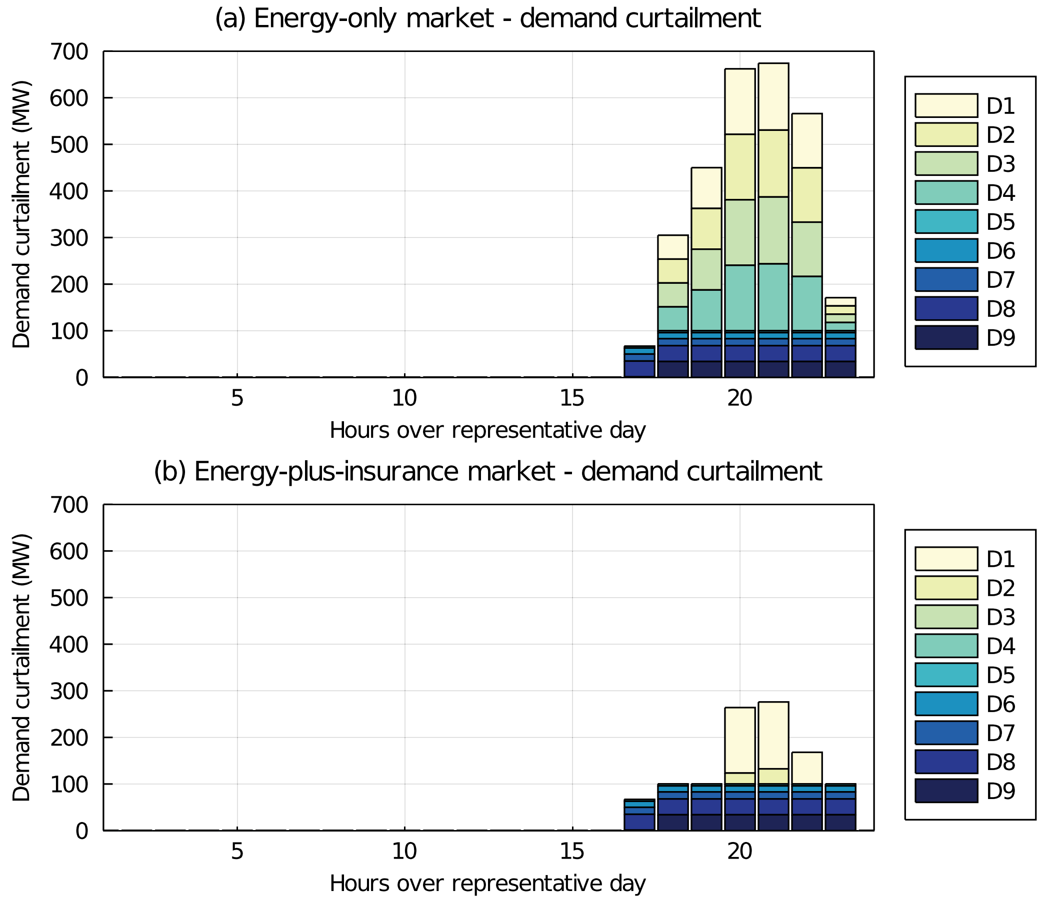

Fig. 5. Lost load outcomes under (a) EOM with market price cap and (b) an EIM with insurance and priority load curtailment (where load is curtailed in order of lowest VOLL). The example provided is of lost load outcomes for scenario 18, representative day 12. Load curtailment is reduced in quantum and duration, due to incremental strategic generation capacity being dispatched, and priority curtailment of load in order of value.

Table 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)	**3361**	**2730**	**3128**
Market generation	3361	2730	2730
Strategic generation	–	–	398
USE - mean (%)	0.001	0.035	0.015
USE - worst (%)	0.020	0.311	0.116

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 557 MWh over the day).

In Table 3 we present a comparison of outcomes between the EIM, the EOM and the RN models under base case assumptions. In each case, the same equilibrium was found for the case under consideration when tested against a range of starting conditions. Under the EOM the total capacity of generation built is 2730 MW — and under the EIM the IOLR supports an additional 398 MW of peaking generation under the strategic reserve. This is relative to 3361 MW built under the risk neutral social optimum. Reliability outcomes are improved under the base case, with an average system unserved energy (USE) of 0.015%, relative to 0.035% under an EOM, though short of the risk-neutral social optima of 0.001%. Worst case scenario USE outcomes for the EIM also lower relative to the EOM. The key reason for 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 [32]. This enables the optimal selection of plant stock that maximizes 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 incentivize more plant stock than what is enabled in the EOM alone.

The financial outcomes of the IOLR are presented in Table 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 in the worst case. Moreover, the IOLR invests in material additional generation capacity (in 398 MW of OCGT) though the utilization of the resource is very limited with an average annualized capacity factor (ACF) of 0.1%. This suggests that the capacity is mainly a reserve and only used in worst-case or emergency scenarios.

Of interest is also the more granular outcomes with respect to USE for individual consumers. Market consumers experience the same outage experience under all designs, as they are able to bid into spot markets. The experience of retail consumers (D1–D4) are different across designs, and we concentrate on those in Fig. 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 prioritization 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, 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. The

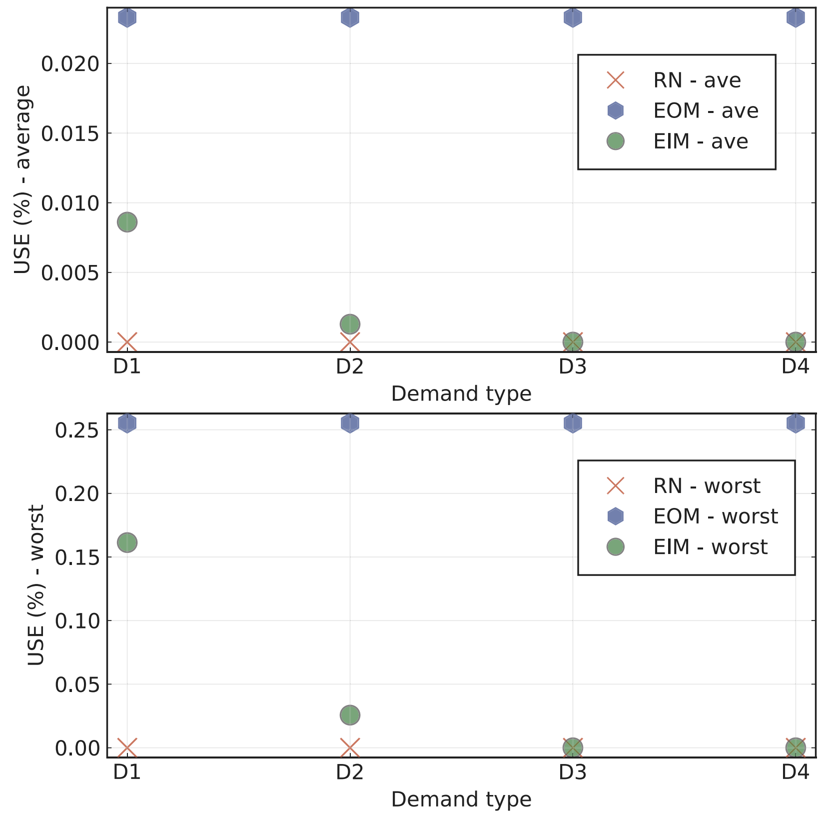

Fig. 6. Unserved energy (USE) outcomes segregated by demand type compared across an energy-only-market (EOM), energy-plus-insurance market (EIM) and risk-neutral (RN) optimum — illustrating USE under an EOM remain higher than RN outcomes but lower than an EOM.

Table 4
Insurer-of-last-resort financial outcomes.

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

insurance premium paid also scales based on the value of load, at $11 million for D1 versus $23 million for D4 (or $33 to $67 per annum when scaled down based on peak demand to a consumer with a peak load of 10 kW).

In Fig. 7 we run a sensitivity against the risk preferences of market generation where β_g is varied from a risk-neutral to a risk-averse preference (0 to 1.0). The intent of running such a scenario is to indicate how outcomes are affected by a changing environment for risk. As generators become risk averse and less willing to take on the downside risk from spot prices, less generation is built varying from 2819 MW (risk-neutral generators) to 2138 MW (risk-averse generators). As the IOLR faces exposures to higher levels of USE 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 $\beta_g = 1.0$ (risk-averse generation) scenario relative to 364 MW in the $\beta_g = 0.0$ (risk-neutral generation) case. While a higher level of unserved energy is experienced with risk-averse market generators, the expected USE is less than half of that experienced in an EOM alone. Intuitively insurance premia also rise under higher risk aversion, reflecting the increased outage risk from insufficient market based generation. Interestingly insurance premiums, in equilibrium, are lower on a relative basis for risk averse when compared as against the expected value of losses ranging from 0.1–0.2 times expected losses for the risk-averse case relative to 0.7–1.0 times for the risk-neutral case. This suggests that while the absolute cost of insurance rises, the IOLR is incentivized to keep costs lower on a relative basis to avoid customers churning away from insurance.

The application of the results of this case study suggests that there are benefits associated with market designs that encourage differential reliability standards. With granular control infrastructure consumers could value essential load in the home differently to non-essential load. This could guide more granular curtailment during emergencies allowing for preservation of essential services, mitigating against 'all-or-nothing' outcomes experienced during recent extreme events where consumers either experience complete outage or retail full electric service. As against this there are five points of further consideration and analysis leading to avenues for research inquiry of differential reliability. First, the reliability outcomes exhibit significant variation across different types of demand and are sensitive to the VOLL of each demand. As such, the approach to the specification of VOLL for different uses requires further analysis to ensure that customers are appropriately valuing the service during scarcity. Secondly, the variation in levied premiums suggests that further consideration must be given to how vulnerable consumers are to be treated, and whether similar subsidy or safety net schemes currently in place for energy prices can be applied to the energy-plus-insurance model. Third, the sensitivity

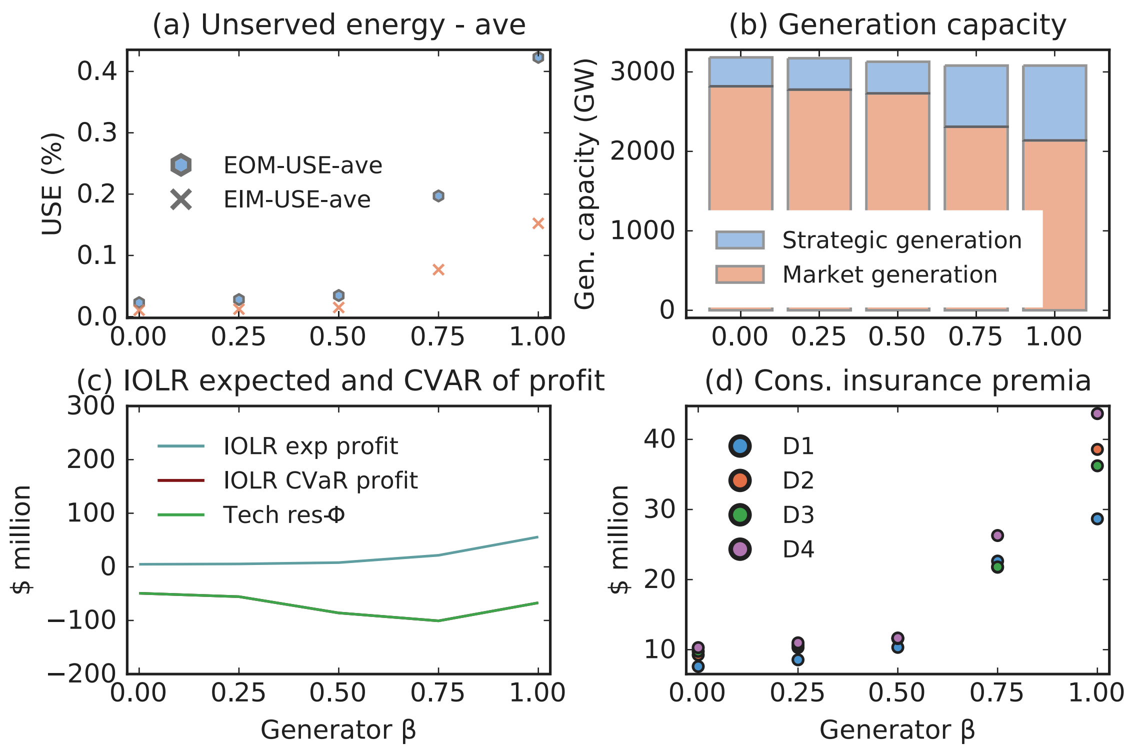

Fig. 7. Sensitivity of EOM and EIM market designs to different levels of risk aversion, where β_g is varied from 0.0 to 1.0. Panel (a) illustrates the impact of generator risk aversion upon average USE. Panel (b) illustrates the quantities of market and strategic generation capacity. Panel (c) illustrates the impact of generator risk aversion on IOLR expected profits, CVAR and the level of technical reserves required. Panel (d) illustrates the impact upon consumer insurance premiums. As risk aversion increases the level of market generation supported via spot prices reduces, with higher offsetting levels of strategic reserve procurement. 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 is less than half the EOM level.

of results to risk aversion means that the organizational, ownership and capital structure of the insurers requires close attention in order to guide appropriate risk-based decision making. The potential for a decentralized investment decision-making model integrated within existing retailer reliability obligations, such as in [22], is a worthwhile extension. Fourth, while the uncertainty scenarios modeled here cover a range of weather year outcomes they do not specifically model extreme weather events, such as winter storms. As such the role of insurance frameworks in the context of extreme events requires further more granular investigation. Finally the frameworks for setting regulatory reserves and solvency constraints are an important area of focus given the importance of technical reserve levels to the design.

6. Conclusions and future work

In this paper, we have proposed a new reliability insurance overlay on existing energy-only markets 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 incentivize additional generation capacity as the insurer is directly exposed to lost load events. 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. Key areas of further investigation include consideration of consumer vulnerability and technical approaches to setting VOLL and reserve levels.

Nomenclature

This section sets out relevant nomenclature for the mathematical formulation:

Sets

$g \in \mathcal{G}$ Set of generators
$g \in \mathcal{G}^M$ Set of market generators
$g \in \mathcal{G}^N$ Set of strategic generators
$d \in \mathcal{D}$ Set of consumers
$d \in \mathcal{D}^M$ Set of market consumers
$d \in \mathcal{D}^N$ Set of retail consumers
$\omega \in \Omega$ Set of scenarios
$t \in \mathcal{T}$ Set of dispatch intervals

Parameters

$\alpha_{g/d/i}$ Tail probability for CVAR for generator g, consumer d, and IOLR i
$\beta_{g/d/i}$ Weight given to the CVAR for generator g, consumer d, and IOLR i
π_ω Scenario probability
C^v_g Short-run variable cost of generator
C^I_g Annualized investment cost of generator
C^{sh}_d Demand shortage cost
$\overline{P^D_{d,t,\omega}}$ Consumer demand
$A^G_{g,t,\omega}$ Availability of generator
$p^{sh*}_{d,t,\omega}$ Demand shortage of consumer, as output from WEM market equilibrium
γ Annualized discount factor
C^P_d Reliability insurance premium for consumer d
C^{voll}_d Value of lost-load for consumer d
δ Parameter that penalizes imbalance in the insurance contract volumes sold and purchased

Decision variables

$p^G_{g,t,\omega}$ Dispatch of generator
$p^{sh}_{d,t,\omega}$ Demand shortage of consumer
$\lambda_{t,\omega}$ Spot market marginal price

$\overline{P^G_g}$ Generation capacity

z^G_g CVAR auxiliary decision variable representing value-at-risk for generator

z^i CVAR auxiliary decision variable representing value-at-risk for IOLR

z^c_d CVAR auxiliary decision variable representing value-at-risk for consumer

$\varrho^G_{g,\omega}$ CVAR auxiliary decision variable as positive difference between z^G_g and scenario profits for generator

ϱ^i_ω CVAR auxiliary decision variable as positive difference between z^i and scenario profits for IOLR

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

ϕ^i Insurance technical reserves

Q^i_d Decision variable representing proportional quantity of insurance sold

Q^d_d Decision variable representing proportional quantity of insurance purchased

$p^c_{d,t,\omega}$ Demand curtailment associated with consumer d

CRediT authorship contribution statement

Farhad Billimoria: Conceptualization, Methodology, Investigation, Software, Writing – original draft, Writing – review & editing, Visualization. **Filiberto Fele:** Methodology, Writing – review & editing. **Iacopo Savelli:** Validation, Writing – review & editing. **Thomas Morstyn:** Writing – review & editing, Validation, Supervision. **Malcolm McCulloch:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Proof of Lemma 1

The non-linearity $\lambda_{t,\omega} p^G_{g,t,\omega}$ can be reformulated as follows based on [35,40,41]. The dual constraint is restated in (38) and multiplied by $p^G_{g,t,\omega}$.

$$
\begin{gathered}
C^{vc}_g - \lambda_{t,\omega} + \overline{\mu^G_{g,t,\omega}} - \underline{\mu^G_{g,t,\omega}} = 0 \\
\lambda_{t,\omega} p^G_{g,t,\omega} = C^{vc}_g p^G_{g,t,\omega} + \overline{\mu^G_{g,t,\omega}} p^G_{g,t,\omega} - \underline{\mu^G_{g,t,\omega}} p^G_{g,t,\omega}
\end{gathered}
\tag{38}
$$

The strong duality condition (18) ensures that the complementary slackness conditions hold. Therefore using the complementary slackness conditions for (8) we obtain:

$$(p^G_{g,t,\omega} - \overline{P^G}_g A^G_{g,t,\omega})\overline{\mu^G_{g,t,\omega}} = 0 \tag{39}$$

$$p^G_{g,t,\omega}\overline{\mu^G_{g,t,\omega}} = \overline{P^G}_g A^G_{g,t,\omega}\overline{\mu^G_{g,t,\omega}} \tag{40}$$

Using similar logic we obtain for the minimum generation condition we obtain (40). By substituting (40) and (41) into (38) the relation for Lemma 1 is obtained.

$$\underline{\mu^G_{g,t,\omega}} p^G_{g,t,\omega} = 0 \tag{41}$$

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