Risk Tolerance and Attitudes in the Economics of Electric Power and Gas Utilities: Case of Wildfire for Community Resilience

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ABSTRACT
Electric and gas investor-owned utilities operate in a regulated environment, and are scrutinized by media and stakeholders for key strategic and operational decisions. Some decisions entail significant risk requiring a special attention to risk tolerances and attitudes. Utilities typically institute enterprise risk management programs to efficiently and effectively manage safety, reliability and financial risks for their customers, employees and communities in a changing climate with intensifying risks, such as wildfire. Consequences from such events could include human life and property losses, health effects, environmental damage, service loss, and other indirect financial and economic impacts. A spectrum of risk quantification and management methods are available for assessing these hazards. Varying risk tolerances and attitudes of stakeholders, typically ranging from neutrality to risk aversion, create situations that are central to decision-making where the safety, service delivery reliability, rate affordability and the financial wellbeing of entities come together in a complex manner. This paper sets context, defines key terms, and develops an innovative approach for methodically reflecting risk tolerance and attitude in informing risk management decisions by offering flexibility to account for preferences by stakeholders in a structured manner. The proposed methods are illustrated in the context of wildfire risk management including calibration and validation approaches.

ELECTRIC POWER AND GAS UTILITIES: BACKGROUND AND CONTEXT
Investor-Owned Utilities (IOUs), particularly with electric and gas operations, are regulated by governmental entities, and scrutinized by media and stakeholders. IOUs engage in strategic and operational decisions that entail significant uncertainties and risks. These decisions are challenged by many considerations including and reflecting risk tolerances and attitudes. Public trust is predicated on how an IOU manages risks both within its control, such as operational risks, and external risks including non-stationary natural hazards in a changing climate such as weather extremes, wildfires, etc. IOUs typically institute Enterprise Risk Management (ERM) and other programs to efficiently, effectively and consistently manage safety, reliability and financial risks for their customers, employees and communities. For example, wildfires have increased in annual counts and severities within the U.S. and globally, with an annual U.S. average of about 70,000 fires since 1983 (EPA 2022). California Public Utilities Commission (CPUC) reported that California wildfires originating from utility infrastructure accounted for 42% of the damaged acreage in the reported period of 2014-2017, with only 9% of the total

wildfire ignitions, and 35% of the fatalities in the top 20 deadliest wildfires in California. The total economic burden of wildfire in the US is estimated to be between $71.1 to $347.8 ($2016) billion annually. Consequences from such events generally include human life and property losses, health effects, environmental damage, service loss, and financial and economic impacts. Utilities face other safety risks, e.g., gas pipeline ruptures, cyber-attacks, dam failures, workforce safety, etc.

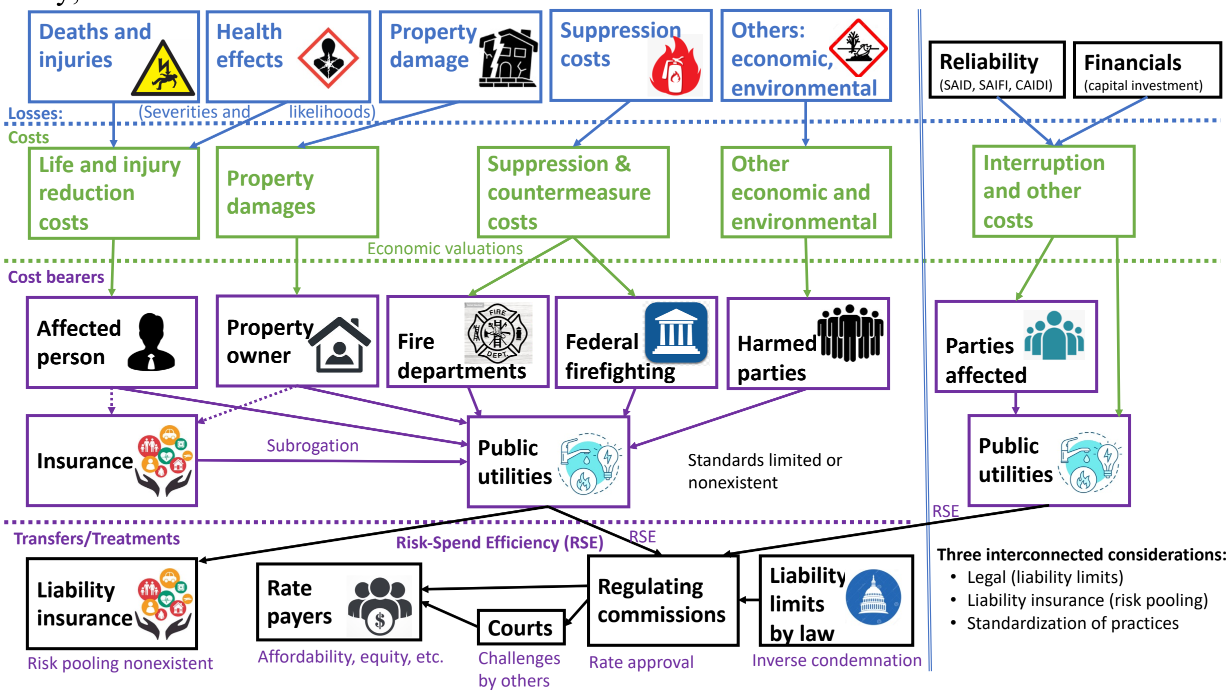

Figure 1. Stakeholders, compliance, economics for utilities.

To determine appropriate rules and requirements for managing such risks, the CPUC instituted a Rulemaking to develop a Risk-based Decision-Making Framework (RDF) (formerly known as Safety Model Assessment Proceeding, S-MAP). Through the S-MAP, CPUC set a requirement for a regulatory review and public-vetting process known as the Risk Assessment and Mitigation Phase (RAMP) to ensure the four major IOUs (i.e., Pacific Gas and Electric (PG&E), San Diego Gas and Electric (SDG&E), Southern California Edison (SCE), and the Southern California Gas Company (SoCalGas)) to carefully consider and fully disclose safety risks associated with their service and activities, and explain how those risks are identified, quantified and managed at the lowest practicable costs. The RAMP requirements were set to incorporate RDF into the regulatory process of approving utilities' funding requests, as a pre-requisite to the IOUs' General Rate Case (GRC) applications. Figure 1 illustrates the complexity associated with decision-making by engaging stakeholders, and considering hazards, risks including safety consequences measured by injury and death, reliability consequences measured by different metrics such as System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), Customer Average Interruption Duration Index (CAIDI) and Customer-Minutes Interrupted, and costs, impacts, and valuations within legal, insurance, and economic efficiency requirements. This decision-making by IOUs requires balancing public and private/investor interests with transparency, and a formal treatment for the quantification of risk tolerances and attitudes for compliance, economic efficiency and consistency is necessary for fulfilling missions in equitable terms. From community resilience perspectives (for example ASTM E3130-21) risk preferences and tolerance have not been formally incorporated although noted as a need (Gilbert et al. 2015, Helgeson et al. 2020). Terminology and novel methods are presented next.

RISK TERMINOLOGY AND METHODS

Terminology provided herein is based on CPUC (2022), ISO (2009a, 2009b), IAA (2015), Hertwig et al. (2018), Gilbert et al. (2015), and Ayyub (2014). **Risk** is the effect of uncertainty on objectives, and commonly measured in terms of potential loss resulting from an uncertain exposure to a hazard, as a potential source for harm, or event scenario that exploits the system's vulnerability. At an enterprise level, **risk appetite** is willingness to pursue for return particular risk types with respective maximum loss amounts; whereas **risk tolerance** is the loss amount by risk type after applying risk treatment for achieving objectives within legal or regulatory bounds as set by **risk criteria**. **Risk preference** is an element of choice in the behavioral sciences, often conceptualized in economics by focusing on the variance of monetary payoffs; whereas in psychology by focusing on propensity to engage in behavior with the potential for loss or harm. Hence, it is respectively associated with distinct measurement traditions, behavioral measures in economics, and self-reporting in psychology. **Risk attitude** is the analytics associated with risk preference for informing decisions that account for subjectivity of a decision makers, within risk appetite and tolerance by (1) turning away from heightened risks as a case of **risk aversion**, or (2) pursuing, retaining or undertaking the risk for potential return as the case of **risk-seeking**, or (3) maintaining proportionality in decisions based on expected loss, i.e., maintaining same attitude, as the case of **risk neutrality**. **Risk acceptance** is the degree of risk that a decision maker perceives and accepts in actions under a given set of circumstances and associated net costs. Always some **residual risk** remains, and sometimes **risk retention** is considered needed for potential benefit of gain. **Risk sharing** is an option in the form of insurance or contracts sometimes per legal or regulatory requirements, including **risk finance** by funds to meet or modify the financial consequences. **Safety** is the judgment of risk tolerance, or acceptability, commonly associated with human injury or loss. **Resilience** is ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions (PPD 2013).

A **utility function** is a relationship between preferences and some measure of value (e.g., wealth or benefit). For goods, utility functions are upward sloping, as more value (i.e., greater quantity) is preferred to less. Risk aversion implies a **diminishing marginal utility** of value (utility increases at a decreasing rate), which results in a concave utility function (Friedman 1976). Following from **expected utility theory**, the utility of the **expected return on investment** is greater than the expected utility of the return on investment (Varian 1992), implying that a smaller return on investment is preferred, if known with certainty, over a larger expected return that carries more uncertainty. Planning for hazards under an assumed equal investment cost, a risk-averse preference favors planning scenarios that are developed based on larger potential loss estimates (i.e., smaller net benefits), when there is greater certainty that the losses will not be exceeded, opposed to smaller potential loss estimates (i.e., larger net benefits) associated with greater uncertainty. The methods proposed offer options to explicitly introduce risk adjustments to build in risk averse preference on values from risk neutrality.

A spectrum of risk quantification and management methods are available for addressing hazards and gaps in community resilience associated with electric-power and gas utilities. The methods favored in recent RAMP submission utilize event and fault trees with a bowtie framework consisting of (1) defining risk drivers and triggers for each hazard, (2) identifying existing and proposed barriers or controls, (3) examining impacts and consequences, and (4) identifying mitigation measures (see Ayyub (2014) for other methods). Figure 2 illustrates a bowtie framework for wildfire triggered by equipment as an example risk concern. The different events are used to construct event-fault trees for assessing and quantifying risk in terms of loss exceedance curves. The figure shows several wildfire-related (1) triggers, such as downed conductor (T1), general equipment failure (T2), etc.; (2) effects or outcomes, such as serious injuries and/or fatalities (E), property loss for third party (E2), etc.; and (3) consequences, such as claims (C1), financials (C4), etc. Figure 2 shows barriers placed between triggers and events, and containment, such as controls, placed between events and effects.

The proposed risk methodology in this paper is consistent with accepted practices (IOS 2009a and Ayyub 2014), is compliant with CPUC's RDF, and is illustrated at a high level in Figure 3 by four steps. The fourth step is of particular interest because it allows for the introduction of risk aversion into the decision-making process. It starts by setting risk tolerances with residual risks, and using risk attitudes for loss accumulation by utilizing subjectively-set risk-attitude amplification factors elicited from experts and subjected to calibration including public elicitation, e.g., collective intelligence methods.

For example, risk tolerance in the case of wildfire from the perspective of an IOU in the context of Figure 1 can be set as a risk type to be managed with a level defined by three ranges of potential losses: loss range 1 (L1) from zero to $300 million; loss range 2 (L2) from $300 to $600 millions; and loss range 3 (L3) from $600 to $3000 millions as the largest possible level. The risk attitude of the IOU in this case is a mixture depending on the uncertain potential loss level, ranging from risk neutrality for lower loss levels to varied risk aversion for higher loss levels. Risk-seeking typically is an inappropriate attitude in this case. The analytics and quantification associated with such risk attitudes reflect the decision situation where the public interest, safety, service delivery reliability, rate affordability and the financial wellbeing of entities come together in a complex manner. Subsequent sections offer methods for setting risk tolerances and attitudes by offering flexibility to account for preferences by stakeholders.

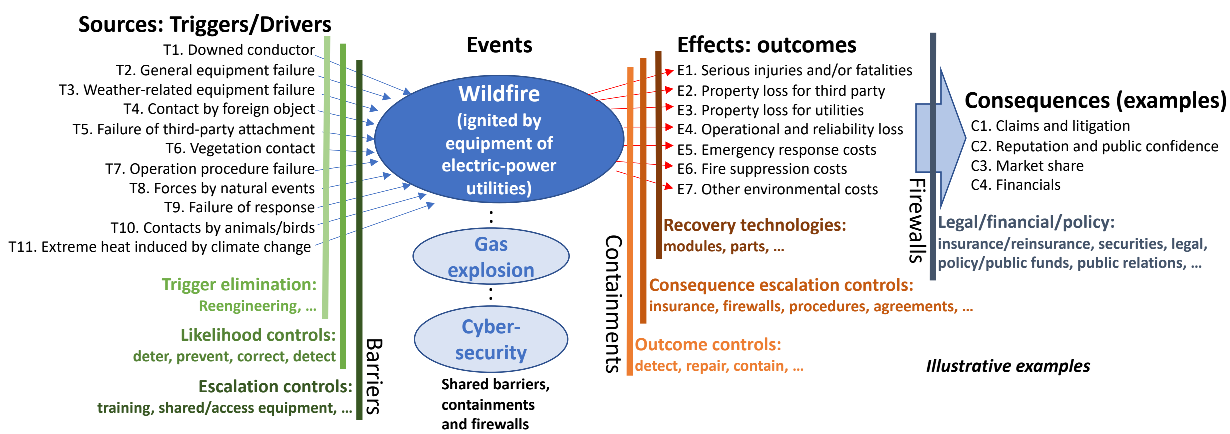

Figure 2. Example wildfire bow-tie framework.

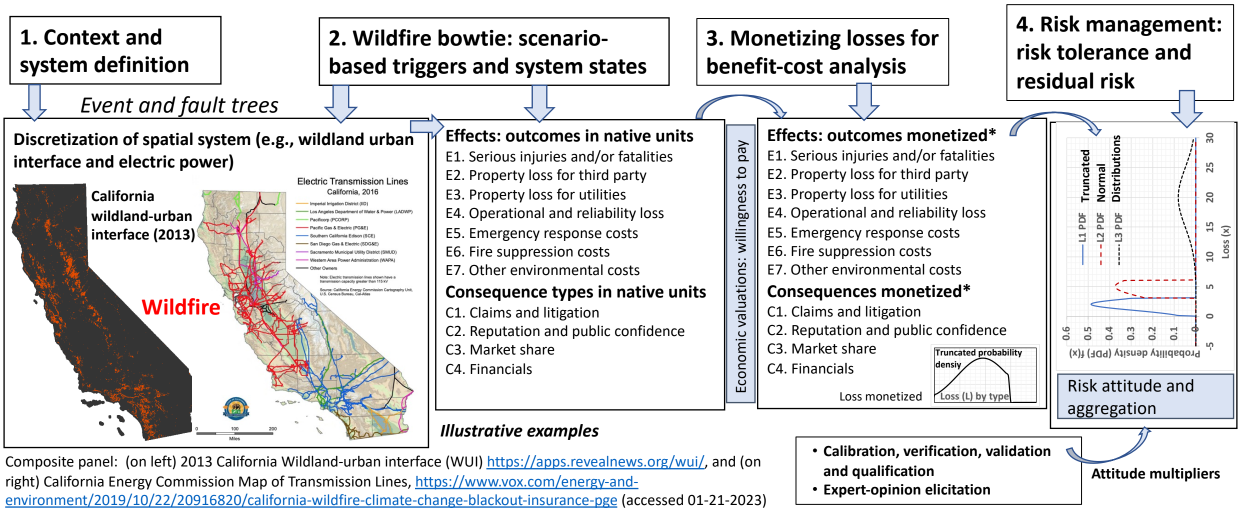

Figure 3. Quantitative risk assessment steps explained and illustrated.

SETTING RISK TOLERANCES AND QUANTIFYING RISK ATTITUDES

Risk tolerance is typically set by adverse (i.e., risk) event types and respective maximum possible losses in native or monetized measurements over a range of exposures. A monetized loss distribution over its range can be represented by a truncated probability distribution, e.g., the truncated normal used herein and can be treated by a mixture distribution (Ayyub 2014) as discussed in a subsequent section.

For each risk type, an overall loss (L) range is defined for setting the risk tolerance and divided in practical or readily comprehensible ranges (L1, L2, L3, etc.) based on a decision-maker or community's preferences and uncertainty levels. These ranges can be named using terms such as operational, critical and catastrophic regions as illustrated by L1, L2 and L3 in Figure 4. Some of these ranges are tolerable (i.e., acceptable) without any changes, and other are subjected to risk treatments in economically efficient terms for reduction to acceptable levels. Other ranges can be included that are tolerable but requiring particular treatments through changes to an underlying system, market, regulations and policies, or demonstrating the attainment in its risk reduction to *as low as reasonably practicable levels* (ALARP) as set in for risk criteria (see Figure 5 developed for major hazards of transport study (HSE 1992, HSE 2023 and TRB 2018). Such layering of losses (or in general liability) is a common practice in the insurance and re-insurance marketplace. For example, (1) the 1957 Price-Anderson Act on limiting liability of its reactor licensees for radioactive damages to members of the public (Ayyub and Parker 2009); (2) the 1980 U. S. Supreme Court ruling in the AFL-CIO (oil and chemicals industry) v. American Petroleum Institute for the OSHA standard limiting Benzene in workplace (U.S. Supreme Court 1980); and (3) ALARP by weighing risks against efforts or costs needed to respectively control them (HSE 1992 and 2023, TRB 2018). It should be noted that the 1980 Supreme Court ruling made distinctions according to the following two items: (1) a significant safety concern defined by scientific evidence requiring regulatory action, and (2) the use benefit-cost analysis for safety enhancement. This ruling affirmed that reducing benzene exposure from 10 to 1ppm (per OSHA new standard) does not meet item 1 by lacking scientific evidence. Additionally, the ruling states that benefit-cost analysis per item 2 can be used only after meeting item 1, and benefit-cost analysis can go as far as technologically and economically possible to eliminate the safety concern. This 1980 case founded the rulemaking space for safety threshold setting applicable to other risks including ones encountered by utilities, and the monetization and economics for safety enhancement in efficient economic terms after thresholds are met.

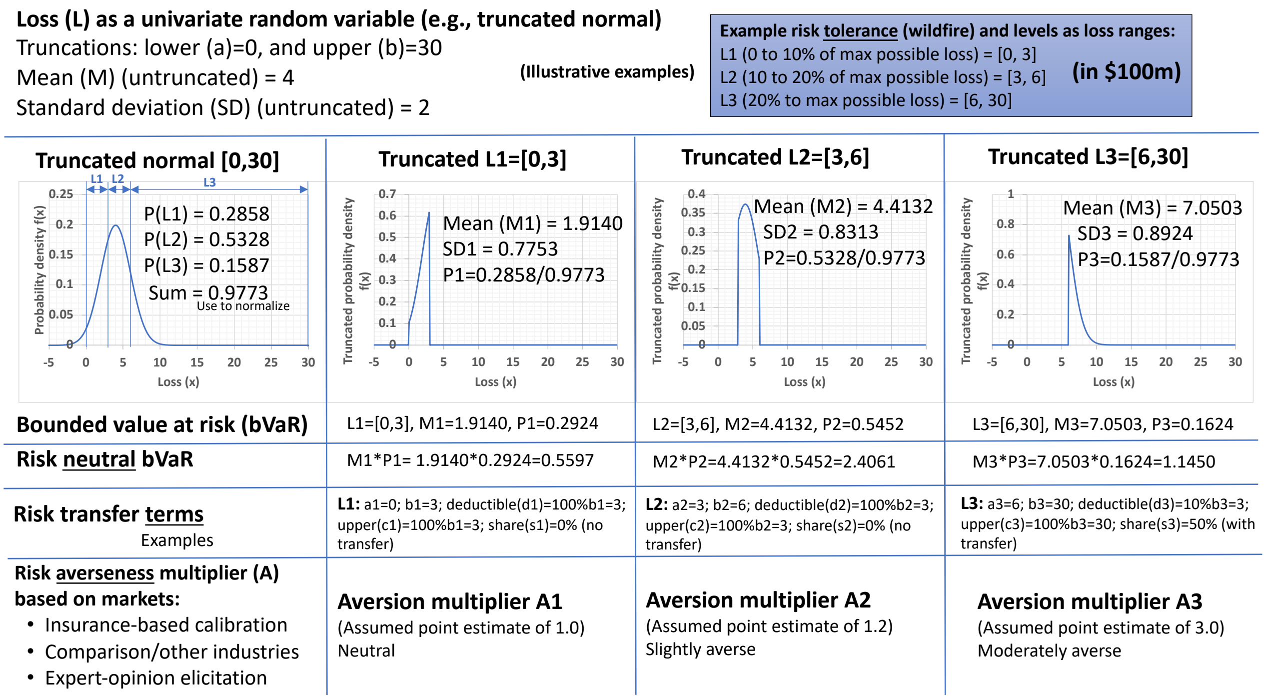

Figure 4. Loss ranges for risk tolerance setting and risk-attitude analytics.

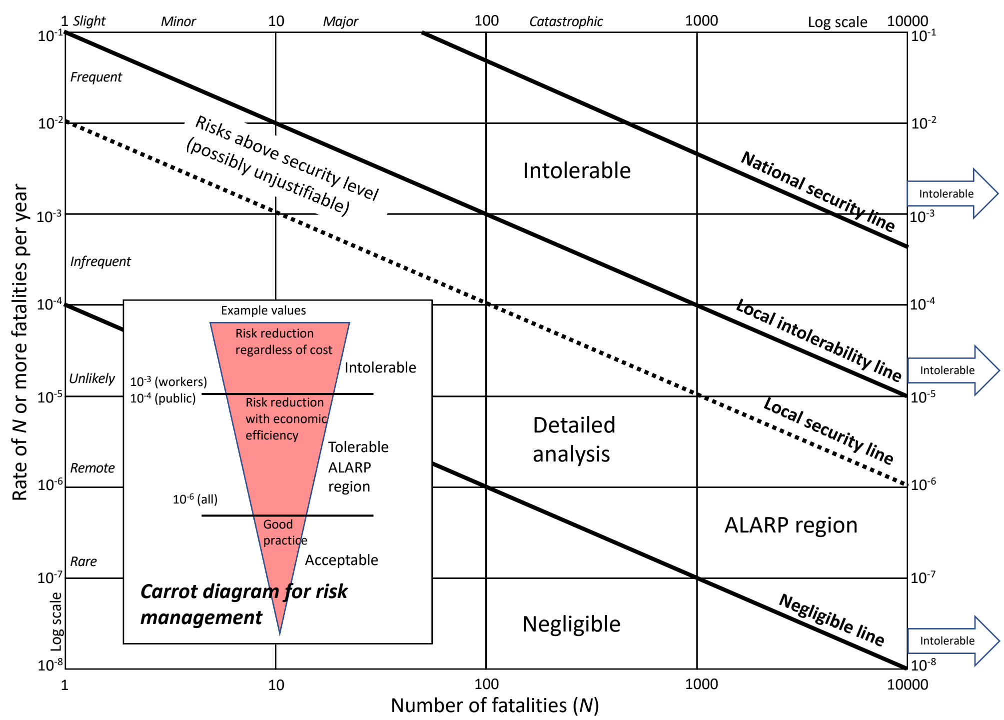

Figure 5. Risk criteria for major hazards of transport study (adapted from HSE 1992).

Tolerable losses are then managed further by analytics for economic efficiency in a manner to reflect the risk attitudes of a decision maker. Figure 5 illustrates the risk tolerance concepts, and the definition of loss ranges and associated uncertainties. The case of wildfire is considered in this figure by defining L from 0 to $3 billions, i.e., [0,30] in $100 millions, and dividing it in L1, L2 and L3. The distribution of L is assumed to be a [0,30] truncated normal with a non-truncated mean and standard deviation of 4 and 2, respectively (in $100 millions). Each loss range of L1, L2 and L3 are truncated from the distribution of L, and the corresponding Bounded Value at Risk (bVaR) in terms of its mean (M) and probability (P) is introduced herein to further illustrate risk attitudes and associated analytics as provided in Figure 5.

The concept of the Bounded Value at Risk (bVaR) introduced herein builds on the Value at Risk (VaR) defined as a single-valued, i.e., threshold-like loss associated with an exceedance probability. Also, it is related to the Conditional Value at Risk (cVaR) defined as the mean value of the loss exceeding VaR. While VaR represents a threshold loss associated with an exceedance probability, and cVaR is the expected loss of exceeding VaR, i.e., cVaR is greater than VaR; bVaR is the expected value of losses in the range from VaR and an upper-bounded maximum possible loss, with infinite maximum possible loss bVaR becoming cVaR.

To account for risk attitude in assessing risk treatments for risk reduction, the corresponding expected losses (monetized) are computed under the assumption of risk neutrality, followed by their adjustment to higher levels corresponding to the respective market-related, such as willingness-to-pay, amounts on the basis of hypothetically transferring them fully or partially by agreement for premium-receiving other entities such as insurers or re-insurers, guided by existing practices and judgement within regulatory constraints. These higher amounts can be viewed as sure-loss premiums for risk transfers, reflecting the entire range from risk neutrality to averseness. Then, the ratios of risk-averse premiums to the risk-neutral expected loss values are used as estimates of the extent of risk averseness as the reciprocal of loss ratios used in actuarial insurance studies (US Treasury 2022), and called herein as risk-aversion amplification factors. These factors are further adjusted by the product of the reciprocals of satisfactory outcomes of loss-psychological aspects; therefore, reflecting both the psychological and micro-econometric considerations in risk preference, noting that other considerations, such as prioritization for Disadvantaged and Vulnerable Communities (DVCs) can be reflected under influences (see Figure 6). The use of reciprocals is illustrative of the process proposed, and can be applied for each loss range and for each risk event including wildfires, earthquakes, gas pipeline ruptures, etc. In this paper, this proposed approach is illustrated by loss-ratio and probability reciprocals for incorporating such information into risk-aversion amplification factors. These amplification factors can be treated as random variables to recommend point estimates for use. Such factors offer a workable scaling function to reflect risk-aversion premiums associated with losses and used into loss accumulation models (Gilbert and Ayyub 2016). This method is not limited to a particular risk type, and is applicable broadly for risks associated with electric power and gas IOUs, and other industries. It can reflect individual entity and societal risk preferences, and can be empirically constructed to reflect the prevailing general aversion with variability across hazards, events and decisions. Risk attitudes are generally non-stationary, dynamic and evolving, and this method can accommodate any applicable trend. The degree of risk aversion according to portfolio theory is defined by the additional marginal return an investor demands for any additional loss exposure represented by greater bounds or greater standard deviations of the return; noting that the concept of loss bounds more applicable to hazard types encountered by IOUs than standard deviations.

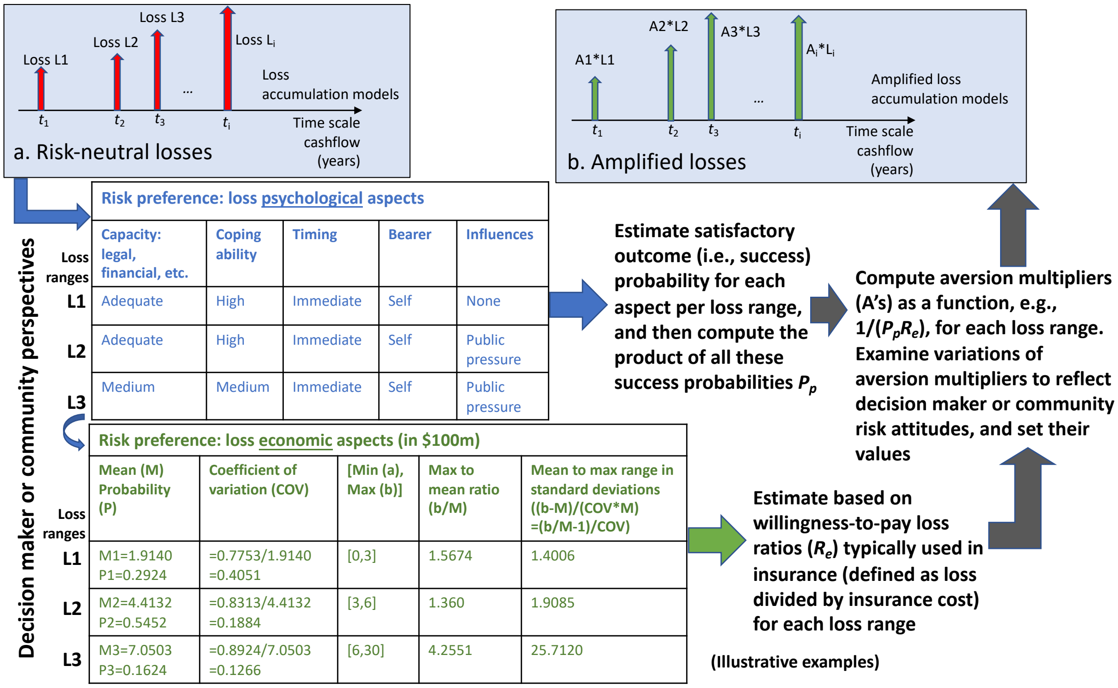

Figure 6. Risk preferences and considerations for risk aversion amplification factors.

MIXTURE LOSS DISTRIBUTIONS: AN EXAMPLE

In this section, each loss range of L1, L2 and L3, as introduced in previous sections, is separately modeled using a truncated normal distribution with respective bounds and moments as shown in Figure 7. Other distributions may be used to meet the characteristics of the potential loss being modeled. Then, the individual probability density functions (PDFs) of L1, L2 and L3 are aggregated to construct a mixture PDF as the weighted sum of the three PDFs using respective weight factors of 0.6, 0.3 and 0.1 as examples. The weight factors must add up to one. The resulting truncated mixture distribution shows as expected tri-modality. Alternatively, the loss distribution for entire range can be initially examined for appropriateness prior to truncating at the tails for each loss range. Also, instead of using weight factors, loss occurrences for L1, L2 and L3 can be modeled by stochastic Poisson processes with losses that are independently identically distributed (IID) having respective occurrence rates λ_1, λ_2 and λ_3. The loss (L) accumulated over a planning period (t) can be estimated as follows (Ayyub 2014) for any of the ranges to obtain a mixture loss distribution:

$$F(l;t,\lambda) = \sum_{n=0}^{\infty}\left(e^{-\lambda t}\frac{(\lambda t)^n}{n!}F_L^{(n)}(l)\right) \tag{1}$$

where F = cumulative distribution function, l = loss, n = event count in time period t, and $F^{(n)}$ = n-fold convolution of F with ∞ symbolizing infinity; noting that using instead the largest possible number of events in the planning period requires normalizing by the sum of all the Poisson probabilities over the range of n used. Equation 1 can be generalized to cover loss accumulation of multiple loss Poisson processes. For the case of a untruncated normal, Eq. 1 is expressed as:

$$F(l;t,\lambda) = \sum_{n=0}^{\infty}\left(e^{-\lambda t}\frac{(\lambda t)^n}{n!}F_L\left(l;n\mu,\sqrt{n}\sigma\right)\right) \tag{2}$$

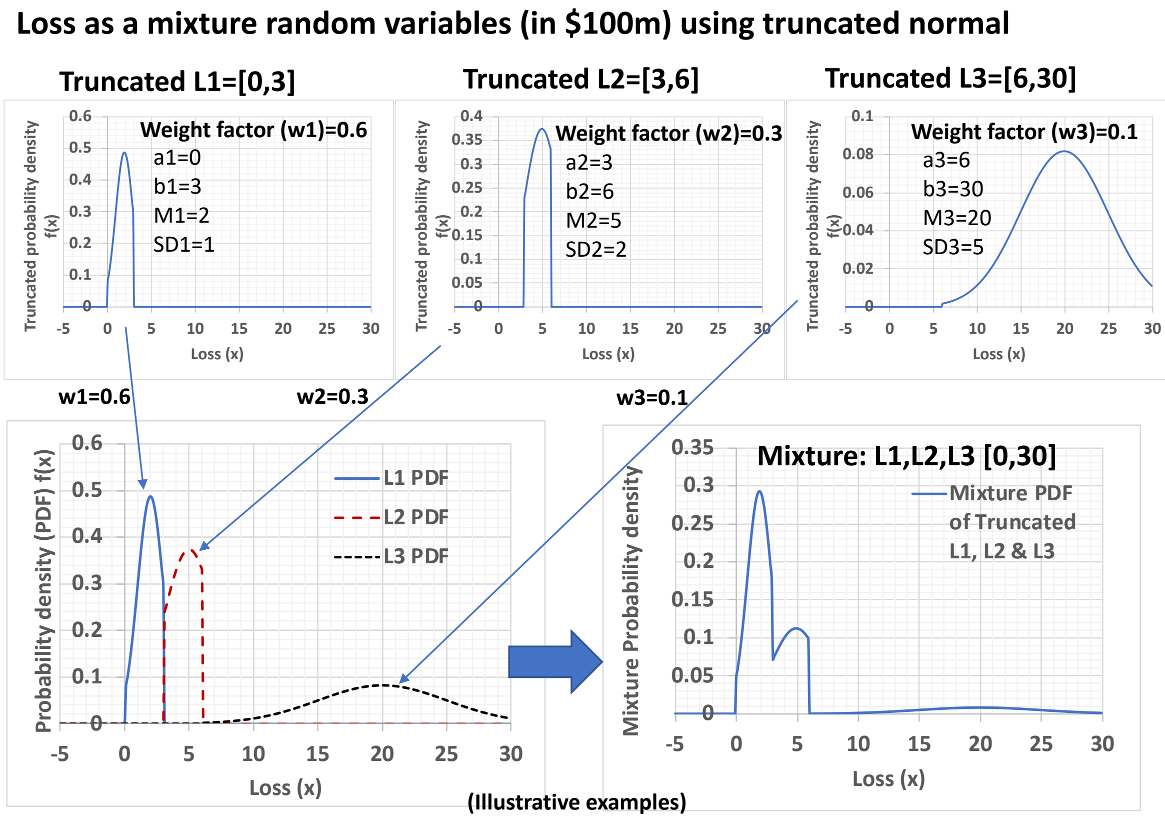

Figure 7. Loss as a mixture of truncated random variables.

USE OF RISK-AVERSION AMPLIFICATION FACTORS

The use of risk-aversion amplification factors, i.e., aversion multipliers in Figure 5, is straightforward and works of loss-accumulation models as provided by Eqs. 1 and 2 as introduced by Gilbert and Ayyub (2016). The risk-aversion amplification factors are applied to each loss component, and the amplified losses reflecting aversion are treated in these models in the same manner as other losses that were not amplified for cases of risk neutrality. Such an approach offers simplicity, compatibility with existing practices, and transferability across decision situations and industries for the goal of achieving consistency and transparency.

ELICITING AND QUANTIFYING RISK TOLERANCES AND ATTITUDES: FUTURE NEXT STEPS

Risk tolerances and attitudes can be set based on explicit objectives of decision makers by public or corporate policy or best practice within legal bounds. Risk tolerances can be calibrated based on existing public policies and translated into loss ranges. Such risk tolerance policies affect investment planning decisions and should be carefully examined parametrically to gain insights in impacts on stakeholders and identification of any dominant strategies. The models proposed in this paper can be calibrated and validated using insurance and re-insurance policies and other risk transfer agreements by contracts, any insights gained from regulations and rulemaking practices, accepted practices in other industries, such as commercial nuclear power, and ligation and court decisions. A full review of this subject is beyond the paper's scope, although it was illustrated by Ayyub and Parker (2009) that was further developed by Ayyub et al. (2016) and Shao, et al. (2017), HSE (1992 and 2023), TRB (2018), and Charness et al. (2013). The paper additionally recommends and proposes the use of formal expert-opinion elicitation methods to calibrate underlying parameters using input from specialists and stakeholders based on related practices, and markets including option pricing, insurance, reinsurance, and investment decisions in a structured and formal setting (Ayyub 2014, and Ayyub 2002, and Ayyub and Klir 2006).

CONCLUSION

Electric and gas investor-owned utilities operate in a regulated environment, and are key contributors to community wellbeing and resilience. Decisions associated utilities and communities entail significant risks requiring a special attention to risk tolerances and attitudes. This paper sets context, defines key terms, and develops an innovative approach for methodically reflecting risk tolerance and attitude in informing risk management decisions by offering flexibility to account for preferences by stakeholders in a structured manner. The paper proposes the use of risk aversion amplification factors in economic and tradeoff studies for utilities and communities in a method easily implementable in existing practices. It enables consistency, transparency and adaptability to existing decision-making cultures of utilities and communities, and associated policy- and rule-making practices. It offers a strong basis to tie to markets, such insurance, bonds and policy, for calibration. The method is illustrated in the context of wildfire risk management, and it provides a proposed way forward, including calibration and validation approaches.

ACKNOWLEDGEMENTS AND DISCLAIMER

The authors acknowledge the guidance of R. Ito and A. Mani, contributions of T. Brown and A. Tzamaras, and reviews by A. Maranghides and Dr. S. W. Gibert. The financial support of PG&E, NIST, and BMA Engineering, Inc. is acknowledged. Statements in the paper are those of the authors and do not represent views of sponsors nor a consensus that the method constitutes the best practice. The information in the paper shall not be used without securing competent advice with respect to its suitability for any general or specific application, and assuming all liability arising from such use. The opinions, recommendations, findings, and conclusions do not necessarily reflect the views or policies of NIST or the United States Government.

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