Generating scenarios algorithmically

One of the significant problems with scenario generation is the sentiment that scenarios are simply an individual's or group's guess as to future states of the world. This makes scenario-based risk management a guessing game, albeit one that might carry the weight of experts. Another issue with scenarios, especially in applications to stress testing of portfolios, is that one cannot know whether a scenario stresses a portfolio until after the fact. In this paper we show how to systematize the generation of scenarios so as to enable them to be generated completely automatically, without any prior assumptions on the underlying probability distributions. The only inputs required are the future macro events, financial or otherwise, that trigger the request for forward looking scenario analysis. Our methodology has one other important feature in that we can show that in a significant number of cases it guarantees the generation of spanning set of scenarios. That is, the worst and best scenarios are guaranteed to be in the generated set. More importantly, it minimizes the bias introduced when humans design scenarios. We conclude by showing a detailed example of a proof of concept of our algorithmics approach to scenario generation in the context of power distribution planning in California

In December 2015 the Financial Stability Board of the G20 established the industry–led Task Force on Financial Disclosure (TCFD). Its goal was to find a way for governments, businesses, banks and others to measure their financial risk with respect to climate change. This task force has met on numerous occasions over the years and has produced a number of reports and a framework for how participants should go about measuring these risks. The stated objective was to establish a methodology that: 'would enable stakeholders to better understand the concentrations of carbon-related assets in the financial sector and the financial system's exposures to climate-related risks'.

On one thing the participants agreed – that the measurement of such risks would require the generation of credible forward-looking scenarios that would encompass future risks and upside for each of the participants.[1] Even as recently as April 2018 at a meeting held in New York[2] there was still no agreement as to how these scenarios should be generated. The Governor of the French Central Bank, François Villeroy de Galhau, expressed the problem of mapping nonfinancial scenarios into financial ones clearly at the recent European Systemic Risk Board Panel meeting on Sustainability saying: 'we still do not know how to take nonfinancial scenarios and convert them into financial variables'.[3]

Organizations Face 3 Key Challenges in Disclosing Climate Risk.
Mercer, July 2018

Organizations face a broad array of scenarios. These include, for example, systematic scenario models (such as CO_2 emission trajectories for various temperature scenarios) or event-based scenarios (that is, carbon pricing or storms and hurricane events). Predicted outcomes vary widely across even the most authoritative models. As one company noted, 'In some sense, the process involves a lot of very educated guesswork, but not everyone guesses in the same way'.

The primary goal of this paper is to present a unique, complete, consistent algorithmic framework for generating and using these scenarios, to stress test and calculate risk of an organization under radical uncertainty – climate change is but one example. Other examples are pandemics and cyber risk and our algorithm applies equally well to those situations.

[1] *https://www.fsb-tcfd.org/publications/final-recommendations-report/TCFD.*
[2] *TCFD Conference on Scenarios, May 1, 2018, New York.*
[3] *Excerpt from the Third Annual ESRB Conference Panel Discussion on Sustainability (1 minute): https://youtu.be/00J8tQeyfZc.*

Scenario generation

One of the significant problems with scenario generation is the sentiment that scenarios are simply a group or an individual's guesses as to future states of the world. A method that is widely used in stress-testing financial markets is to shock key inputs using some form of expert judgement. This makes scenario-based risk management a guessing game, albeit one that might carry the weight of experts. Another issue with scenarios, especially in applications to stress testing of portfolios, is that one cannot know whether a scenario stresses a portfolio until after the fact.

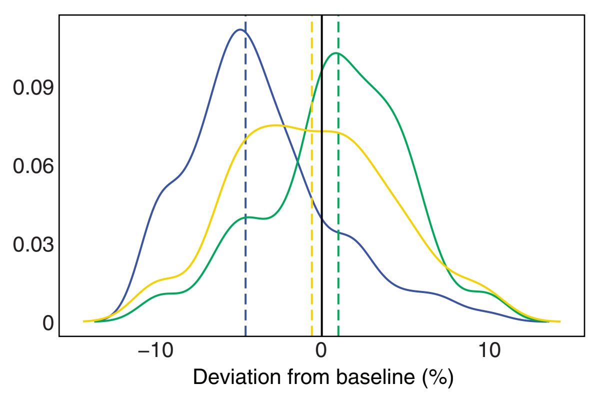
The holy grail is to be able to have a machine generate scenarios completely automatically, with as little bias from humans as possible. On the other hand, valuable intelligence and sentiment regarding the future rests with the experts who are very involved or care deeply about the event that is about to unfold and it needs to be accounted for. These scenarios need to 'span' the range of possible future states and, in the case of financial applications, stress the portfolios they will encounter without a priori knowledge of the positions of securities in the portfolios (the definition of a spanning set in this case).

Imagine if we could **automate** scenario generation; **span** the range of possible future events; find the '**black swans**'; understand the risk of '**white elephants**' and account for a full range of market sentiment. In this paper we describe such a method. The inputs that are required are estimates of the future uncertainty in the individual risk factors that govern the situation. The outputs of our algorithm are the multifactor scenarios that are so difficult to generate directly. So, where do we get the future uncertainty inputs from? We need primarily forward-looking information which is often in the heads, discussions, papers and presentations of the individuals most concerned about the factor or factors that are relevant.

We propose to get these estimates in a number of ways, all of which are relevant. The key is that they have to embody the full range of uncertainty in the factors. One way is polling, another is using Machine Learning to extract this information from the things they write, the discussions they have and their presentations. Either way, we represent the future uncertainty of a factor by its distribution of possible values, based on trusted sources, at some future point in time (the horizon). A key input to computing scenarios on combinations of climate related factors, or any other radically uncertain variables, is the individual distributions of possible values for each of the factors at some designated future point in time (the horizon). Where would we get this information from? For example, how could one generate the distribution of sea level in Southern Florida in 2030? Or, the distribution of Category 5 Hurricanes in the Atlantic in 2030 for that matter. Or, the effect on the Euro conditional on the outcome of these factors? Certainly, historical information would be a source but on its own would be seriously inadequate.

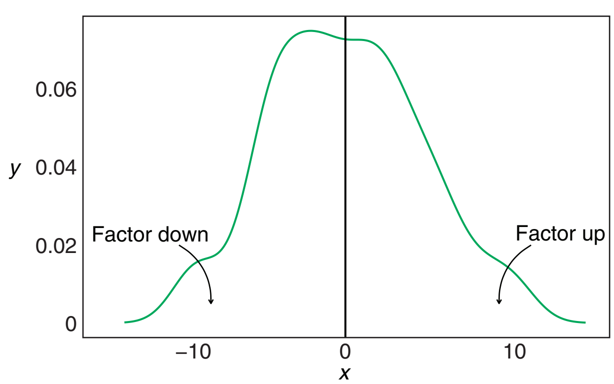
The one source that has been neglected - but that could give us useful, forward-looking information - is the ***collective wisdom*** of the people worldwide who are experts and otherwise involved in understanding and influencing the future values of these factors. If we could extract their views on the subject, we would obtain a distribution of possible outcomes that would span the range of possibilities. Moreover, if we collected this information carefully, it would have both sides of the forecast – the general consensus and the naysayers. In essence we are looking for a discrete set of possible scenarios for combinations of these factors, so that ***the precise nature of these distributions is less important than their ability to capture extremes***.

1 The distributions of values for the factors 1, 2, 3 at the horizon



These distributions give us estimates of four critical values which are needed to be able to develop scenarios which combine all factors that are material to the issue at hand. Namely, the possible range of Upside and Downside movements in the factors and their likelihood of occurrence (see figure 2).

2 Useful information embodied in the forward distribution



By combining the information in the forward distributions with scenario trees we can get both scenarios for the combinations of factors as well as estimates of the likelihood of these scenarios occurring. The four values – up and down ranges for the factors as well the likelihoods of the up and down movements are all we need to complete the data required to evaluate the tree (see figures 1 and 2). These extremes as well as the seemingly odd combinations (some of which humans would probably neglect) are likely to 'span' the range of possible outcomes for the scenario space. Since we are primarily interested in extremes, both on the upside and downside ('White Elephants' and Black Swans') this method may be an efficient way to find them. Indeed, we prove it is.

Whereas we have shown this using collective wisdom, there are clearly many ways of achieving the end goal, that is, deriving the distributions for the factors at the horizon. The quality of the scenarios we develop will hinge on how well we can estimate these distributions. Since in many cases we are dealing with radical uncertainty, these distributions are unknowable.[4] The best we can do is estimate them periodically and improve our judgement over time.

We now have all the ingredients to define an Algorithmic framework for stress testing/risk management in a climate change setting. But first, we need some theory.

What do we mean by a 'spanning set' of scenarios?

Definition 1 (A spanning set of scenarios) Let $f = \{f_1, f_2, f_3, \dots, f_n\}$ be a finite set of random variables (risk factors) and let $V(f)$ be a real valued function. An instance of f, $f^i = \{f_1^i, f_2^i, f_3^i, \dots, f_n^i\}$ is defined as a scenario.

Define $V^i = \sum_j V_j(f_j^i)$ is the value of the portfolio being measured under scenario i.

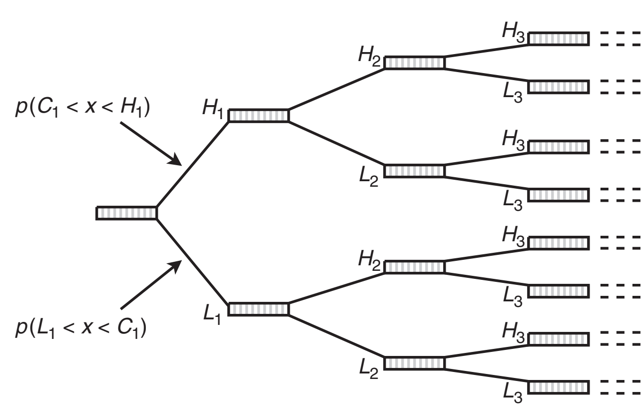
A set of scenarios is defined to be a **spanning set** if it contains the maximum and minimum values of V^i for any valid choice of f^i.

We show later how, under certain circumstances, the scenario algorithm we will propose generates a spanning set.

Automating the generation of scenarios

The factors $f_1, f_2, f_3, \dots, f_n$ may or may not be independent. One convenient way to represent the possible states of the world at some future point (the horizon) would be to use a scenario tree. A simple version is the binary tree shown in figure 1. In this example there are 3 factors each of whom only exhibit two states, higher (H), with probability $p(H)$, or lower (L) with probability $p(L)$.

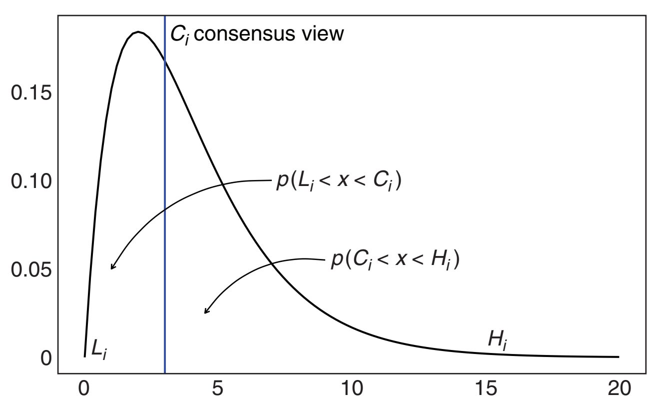
3 A scenario tree



[4] *Radical Uncertainty, John Kay and Mervyn King, Norton and Company (2020).*

Now imagine we know the forward distribution, $D_i(f_i)$, $i = (1, 2, \dots, n)$, of each factor at the horizon. This distribution embodies the uncertainty inherent in the factor and is the key data that we need to operate our algorithm. Now also assume there exists some known consensus forecast for the factor at the horizon. The distribution of the ith factor is said to be **coherent** if L_i is lower than the consensus forecast, C_i, and H_i is higher than the consensus forecast. For coherent factors, $p(C_i < x < H_i)$ is the likelihood of an upward movement in the ith factor, and $p(L_i < x < C_i)$ is the likelihood of a downward movement in the ith factor.

4 The forward distribution of a coherent risk factor



Naturally, there are more complex trees and possibly networks that could be used when analyzing a given situation. We use a binary tree because of its simplicity but also since it is able to capture the extreme scenarios, we wish to use for stress testing. The discussions below would apply to more complex trees as well.

So where could we get the values for L_i, H_i and their associated likelihoods $p(L_i)$, $p(U_i H_i)$?

Imagine we could estimate the frequency distribution of each factor at the horizon. Then one possible choice for H_i would be the upper extreme of the distribution and L_i would be the lower extreme. The extremes may be chosen in a number of ways, for example H_i could be set to the 99th percentile of the distribution.

Why would we want L_i and H_i to be the extremes? The extremes hopefully allow us to generate a Spanning Set of scenarios. We show later that this is the case under certain, reasonable assumptions.

Steps for algorithmic scenario generation

1. Identify macro factors affecting the issue being analyzed.
2. Generate a scenario tree for these factors.[5]
3. Generate the forward distributions for each factor at the horizon.
4. Identify the extreme values and the corresponding likelihoods for each factor.
5. A scenario is a path in the tree, its likelihood is the product of the likelihoods along the path and the value associated with scenario is the sum of the values along the path.

There is clearly much detail and many options behind each one of these steps. We discuss these below.

[5] *The ordering will be important if there are dependencies between factors.*

■ **Identify macro factors affecting the issue being analyzed.** This is usually the domain of experts. It can, however, also be done automatically using machine learning. The question that it answers is: 'What are the combination of material macro factors that affect the value being measured'. For example, if we were analyzing a possible future strategy for a Californian electricity distributor, macro factors might be the world temperature rise, electrical load in the future, precipitation and so on. If we were looking at Brexit and its effect on a fund, the factors might be the value of pound, various financial indices, the deal reached with the EU, etc. If we were analyzing a pandemic, the factors might be the lockdown period and its effects of the economy. The factors are often a mixture of financial and non-financial ones. Importantly, the algorithm handles arbitrary combinations of both.

■ **Generate a scenario tree for these factors.** For this paper we will restrict the analysis to trees, which does put some constraints on the types of dependence among factors that we can handle. Within this restriction we can handle situations where the dependence between factors follows some order. In this case the likelihoods on the arcs will be conditioned on the factors that came before them in the tree. Clearly, if the factors are independent the tree represents all possible permutations and combinations of the factors. The tree is no longer a necessary representation but simply useful as a visual representation. In an extremely uncertain situation, correlations may become meaningless and the tree is as good an approximation as anything.

■ **Generate forward-frequency distributions at the horizon.** This is the essential ingredient of the method, its power and to which it is most sensitive. As can be seen from the algorithm, we do not truly need the entire distribution. We only use extreme values and the likelihoods of upward and downward movements. The four numbers extracted from the distributions are enough to populate the tree for evaluation purposes. Still, when we have the entire distribution it could be useful for deciding if an extreme value might be an outlier that should be excluded.

In many situations facing us the history is scant, not very informative or nonexistent, making the estimation of the future distributions of factors a difficult task. Good examples might be the analysis of the risk climate change will have on corporations, governments and institutions; the risks inherent in reusable launch vehicles for space applications; the risks of the outcome of a referendum (eg, Brexit); cyber risk, pandemic risk, etc. It is in these situations that the usually accepted measures do not work well.

A source that could overcome these difficulties is the sentiment of the large numbers of people who influence the outcome of such future events or whose intuition could help where data is missing. The most important aspect of the forward estimation of factor values is that it spans the range of possible outcomes and that it contains values that might go against the general consensus. A single forecast is dangerous in such situations but the range of expectations that is observable could be very useful. Think of Brexit where the vast majority of people predicted a NO vote, but the YES vote prevailed. There were a small minority of people predicting NO and their view should always be taken into account in a risk assessment.

So, how do we obtain this data?

One possibility is to poll a large number of people who are knowledgeable or otherwise engaged in the future values of the factor in question. Another is to use machine learning and AI to extract these sentiments from a broad base of information on the subject. Yet a third is to use historical proxies wherever appropriate. We suggest that an optimal situation would be to use combinations of all of the above.

Identify the extreme values and corresponding probabilities for each factor. A key challenge is to eliminate spurious numbers (noise) from this estimation. These might occur when nonsensical answers are obtained from a poll or other means. There is a fine line however, between crazy values and those that estimate true extreme situations from trusted sources. Certainly, elimination of events that have never happened before in recorded history will not necessarily be a good criterion for elimination. We use expert judgement to remove genuine outliers. An example of this, in a recent poll we conducted, was some respondents predicted a value of 0 for the S&P 500. Clearly this is nonsensical, so we eliminated it. Things are not always so black and white but a close look at the extremes can eliminate impossible outcomes or outcomes that lack any theoretical basis. Clearly, this is often more art than science and can introduce some bias if it is not done carefully.

THEOREM 1 (Algorithmic scenario generation) *Assume* $f = \{f_1, f_2, f_3, \dots, f_n\}$ *is a set of independent factors whose distributions are known at some horizon. Also, let each factor* f_j *be a random variable whose frequency distribution at the horizon is* D_j. *Let* f_j^i, f_j^i *in* F_j, *be the i th realization of* f_j *at the horizon and* $f^i = \{f_1^i, f_2^i, f_3^i, \dots, f_n^i\}$. *We refer to* f^i *as the i th scenario. Now define* $V^i = V(f^i)$ *the value associated with some institution, under the i th scenario, at the horizon. Let* S *be the set of all feasible scenarios. Furthermore, assume that* V *is a monotone function of each of* $f_1, f_2, f_3, \dots, f_n$. *Then the set of scenarios,* S, *is a spanning set.*

PROOF In our algorithm, the scenarios are chosen to be all the permutations of $f_1^i, f_2^i, f_3^i, \dots, f_n^i$ with f_j^i given by the maximum and minimum values of the estimated factor distribution for the up and down move at the node. Given the monotonicity and independence assumptions, at each node we could choose the value that maximizes the gain in $V(f)$, which could be either the lower or higher end of the factor distribution and hence, by following the path of maximum gain, we will arrive at the path(scenario) that yields the overall maximum gain. In a similar fashion we can generate the maximum loss. Hence the paths in the scenario tree are a spanning set of scenarios. □

Discussion regarding the assumptions of the theorem. Many financial portfolios, in fact the vast majority of investment portfolios, are constructed with products that are linear and exhibit the monotone property required by the theorem. Also, many climate risk-factors such as temperature also exhibit this monotone property over the long run – higher temperatures imply more drought, stronger storms, etc which ultimately translate into higher costs. The assumption of independence might also be acceptable if the horizon is far away. In the immediate term the factors are likely to be correlated but far less so as time passes or under extreme uncertainty. Still this assumption is the more difficult one to live with. Probably the most powerful argument for not using correlations is that in extremely risky situations the correlations diverge rapidly away from their long-term norms.

It might also be possible to use this result when monotonicity cannot be assumed. By restricting its use to a local approximation to V where the assumptions hold.

The initial event and the resulting financial shocks. To illustrate the methodology, we describe a complete end-to-end automatic scenario generation process that is based on 'the wisdom of the trusted experts' using a simple polling mechanism to obtain the information we need.

It starts with an event (eg, the French Election, Brexit, a 2 degree warming by 2050, etc), financial or non-financial that could have an effect on the financial markets. There may be possible sub events of interest (eg, a list of possible candidates who are eligible to win, sea level rise in various cities, etc). We can use experts studying the event to decide on the macro factors that could be affected by each possible sub-event (eg, various indices, spreads, GDP, etc). In practice we propose that trusted experts in the field, coupled with machine learning and artificial intelligence engines be used to ascertain what macro financial factors are important to consider. We believe that this is a function that could be executed well by machines guided by human experts. Once we have these factors, we can poll a large independent sample of actors in the financial markets for their opinions on the possible effect of the event on these factor movements over the time horizon in question. The result is a frequency distribution for each macro-factor. This gives us the likelihood of an upward movement in factor i over the time horizon that has been chosen. Similarly, we can obtain the likelihood of a downward movement in the i th factor. In addition, we get the range of possible up and downside moves for the i th factor. This proves to be all we need to generate a spanning set of scenarios.

In lieu of this poll, depending on the data available, we could also run artificial intelligence engines to derive these frequency distributions or do a combination of trusted experts and polls

Example: measuring climate risk

The problem of how to measure the financial risk of a climate change regime, such as 'a 2° world', may be disaggregated into two distinct phases.

Phase A. Identifying the macro factors that are material to the risk of the institution. Generation of a scenario tree that reflects the possible future paths that these factors might take between now and the planning horizon, conditioned on a 2° world (for example).[6] Generating possible future values for these factors at the horizon. Generating scenarios on combinations of these factors.[7]

Phase B. Relating the macro scenarios to scenarios on the micro factors that affect a particular organization for each sector and in each geography in which it operates (ie, translating a scenario made up of macro climate risk factors, financial and nonfinancial, into the value effect it would have on an institution).

To make this concrete, let us take a real example.[8]

It concerns the CAISO organization, in charge of distribution of electricity in California. CAISO is concerned about the unknown effects of climate change, coupled with possible transitions occurring in transportation and the generation of electricity, may have on their planning and ability to deliver electricity efficiently and securely. They are considering joining their grid with other Western utilities to be able to construct a resilient grid, make more effective use of renewables and handle the possible growth of electric vehicles (EVs).

The factors that influence their strategy have been identified as: the average temperature in California in 2050 (to account for all the unknowns that

[6] *This shows how for TCFD, we can obtain consistent estimates linking transition risk scenarios and physical risk scenarios.*

[7] *Dembo R, October 2018: http://www.caiso.com/Documents/Session1-RonDembo-MeasuringFinancialRiskOfClimateChange.pdf.*

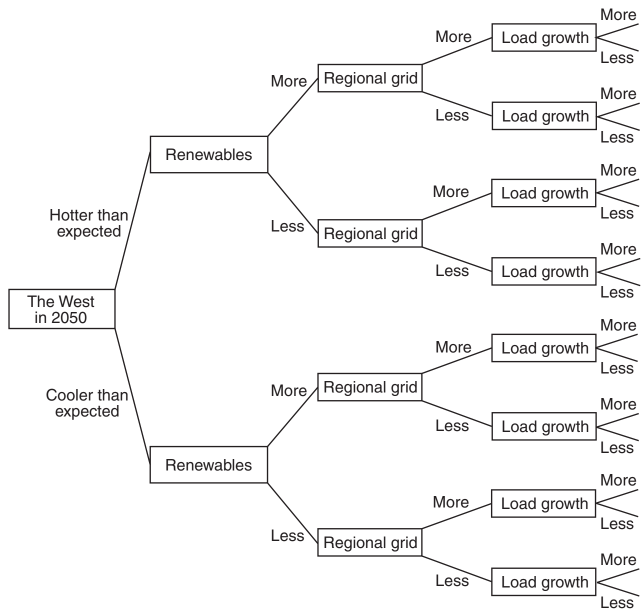
[8] *In the interest of simplifying this presentation, the example is a highly simplified version of their true issues but captures the essence of the decision-making process. We would like to acknowledge the assistance of CAISO management, Joanne Serina and Mark Rothleder for their help with the creation of this tree.*

might result from climate change such as higher temperatures, increased frequency and higher severity of droughts, wildfires, etc), whether renewable targets will be reached; the ability to form a regional grid with other western states; and the load growth.

They start by defining a 'scenario tree' that shows the different possible paths these factors might take between now and 2050, their planning horizon. (See figure 5.)

Note that their decision involves a mixture of climate change factors as well as factors that influence their business that are not caused by climate change.

5 CAISO'S scenario tree (key: more = more than expected)



The paths in this tree are the scenarios of the combined factors that need to be accounted for in their strategic planning pilot.

Figure 6 shows a single scenario and its expression in English terms.

In order to evaluate this tree, we need four values for each factor, the possible upside and downside values for each factor and their likelihoods.

CAISO now takes a poll of its members (see appendix 1) or uses a machine learning algorithm to estimate the frequency distributions of each of these factors as at 2050, as discussed previously. With these distributions, data in this tree can be estimated and the possible scenarios that need to be examined by CAISO can now be determined.

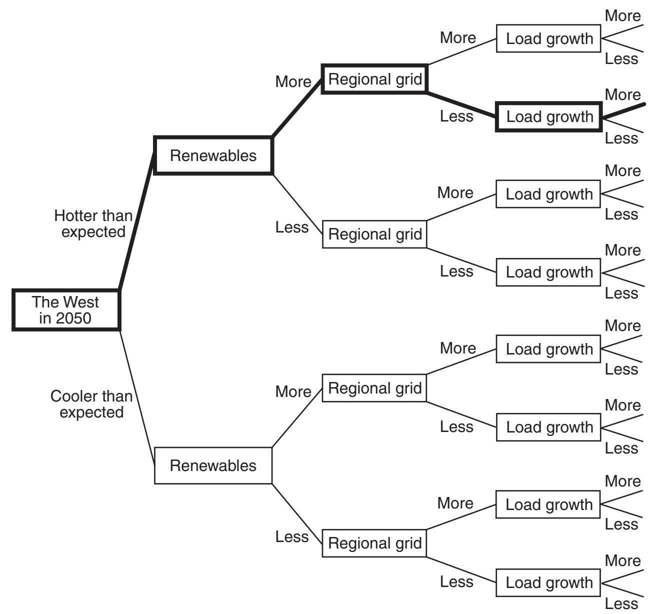
This completes Phase A. Note that Phase A could apply to any Californian utility, there is nothing specific to CAISO.

Phase B is specific to CAISO. That is, given (for the example in figure 6):

> By 2050 California's average temperature will have risen more than expected. The growth of renewable energy generation is more than was predicted the regional grid has not materialized as much as was expected. Load growth by contrast is more than was expected.

What will the optimal strategy for CAISO be going forward? This analysis needs to be done for each possible scenario. As time passes and the data gets better and better, scenarios will improve, and the strategy chosen today will

6 A single scenario (key: more = more than expected)



By 2050 California's average temperature will have risen more than expected. The growth of renewable energy generation is more than was predicted and the regional grid has not materialized as much as was expected. Load growth by contrast is more than was expected

evolve. CAISO could, of course, choose to ignore this particular scenario (ie, bet that it will never occur and remain unhedged to its consequences should it or something close to it occur). Or, it could hedge its bets with respect to the outcomes that this portfolio implies. This is their business decision.

In order to then compute the actual gains or losses to the organization we need to translate the scenarios developed in Phase A into actual gains or losses for the organization. Whereas Phase A is generic to all organizations (they might differ by not having exposure to some of the macro financial risk factors) It is this second phase, Phase B, that will be **unique** to each and every organization. It will depend on the organization's strategic direction as well as the physical location of its operations (see figure 7).

This decomposition of the problem allows for comparison amongst a diverse group of organizations. The macro risk factors computed in Phase A are common to all organizations, but each organization is subject to the forces of only a subset of macro factors. In this way, one set of scenarios may be generated for all participants in Phase A and resulting specific valuation scenarios are then computed by each and every organization. **This also justifies diverse organizations collaborating in Phase A**. This allows for a level of consistency in the measurement of risk and accommodates the diversity that is found across the participants. Naturally, the risk factors will be different for different geographies and different sectors of the economy. So, this exercise needs to be done separately for each geography and each sector within that geography.

Note that in the example of CAISO, the factors they consider contain factors both relevant to transitional risk and physical risk.[9] The procedure

[9] *https://www.fsb-tcfd.org/publications/final-recommendations-report/TCFD.*

used to develop scenarios applies equally to both. The TCFD decomposition into Physical and Transition risks is potentially problematic. It could lead to two sets of scenarios (potentially inconsistent) being generated – one for transition Risk and another for physical risk.

We propose linking transition risk and physical risk by designing scenario trees that integrate both risks. Typically, this would take the form of physical risk factors conditioned on a transition scenario.

So, for a particular horizon one may have both physical and transition risks, but the scenarios generated would need to be consistent. Also, the physical and transition risks would both be part of the total risk. Therefore, we do not see a need for the distinction set out by TCFD.

Algorithm for climate stress testing a corporation, bank, state, city or country

For a given horizon (eg, 2050) and given climate regime (eg, A 2°C World in 2100):

Phase A: developing the combined factor scenarios

- Step 1 Identify the macro factors that affect the institution in question;
- Step 2 Generate the distributions of possible values for these risk factors at the horizon
- Step 3 Generate a set of scenarios on the combinations of macro climate risk factors

Phase B: determining the impact of the scenarios developed in Phase A

- Step 4 Identify all the micro financial effects on the business that are impacted by all the macro climate risk factors
- Step 5 Value the financial effect on the company using the, macro to micro, climate conversion for each scenario using the analysis in Step 4
- Step 6 Develop a strategy based on the results of Steps 4 and 5

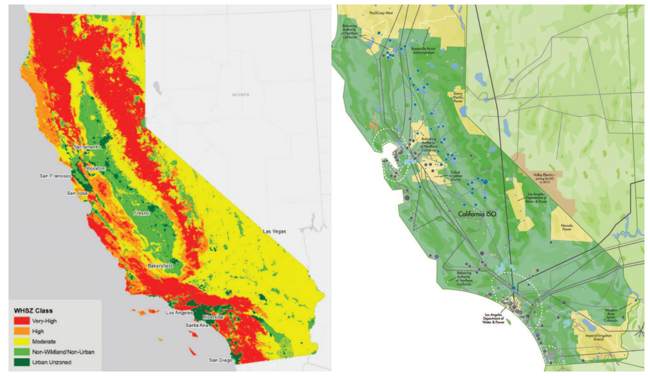
Phase B in the CAISO case would consist of identifying all of CAISO's generating sources, transmission lines, and other infrastructure necessary to supply California with electricity, excluding the electricity generated by individuals or companies not under CAISO's jurisdiction. It would also involve mapping this to the possible scenarios for fires in California under different IPCC transition scenarios.

The data on climate scenarios that are generated by CAISO on combinations of temperatures, fires, drought, etc are then mapped onto this infrastructure data to get estimates of the costs or benefits that would result for each and every scenario (an example is given in figure 7).

Fires will threaten transmission lines; sea level rise will compromise coastal grid infrastructure; higher temperatures will increase demand and decrease supply; Droughts will decrease hydro availability and so on.

Management would then use these scenarios as a basis for discussions with its Board to explain its decisions around the strategy that is proposed going forward.

7 The electricity infrastructure in California mapped to the possibility of future wildfires



Source CAISO and IPCC Transition Scenario RPC8.5 (IPCC, 2014: Summary for Policymakers. In Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Edenhofer O., R Pichs-Madruga, Y Sokona, E Farahani, S Kadner, K Seyboth, A Adler, I Baum, S Brunner, P Eickemeier, B Kriemann, J Savolainen, S Schlömer, C von Stechow, T Zwickel and JC Minx (eds). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.)

This process would be repeated at least once a year or whenever there is an event that results in a material change in the factors that have been used.

Conclusions

This paper provides an algorithm for generation scenarios on combinations of multiple risk factors that in many cases will yield a Spanning Set of scenarios. It is particularly useful in the case of decision making under radical uncertainty. The scenarios that are generated may be combinations of political, non-financial and financial factors. This is particularly valuable when stress testing in pandemics or for climate change risk, where many factors of different types may need to be considered as part of a scenario.

For TCFD analysis we are able to show how to generate scenarios that combine transition risks and physical risks. Also, we show how a single set of consistent scenarios may be produced for stress testing across heterogeneous markets with companies in many different sectors. ■

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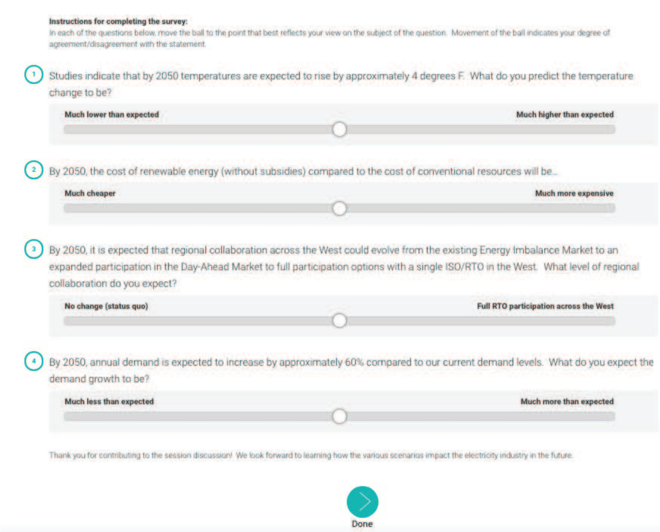
Appendix 1: CAISO example poll[10]

8 The CAISO poll


Instructions for completing the survey:
In each of the questions below, move the ball to the point that best reflects your view on the subject of the question. Movement of the ball indicates your degree of agreement/disagreement with the statement.

1. Studies indicate that by 2050 temperatures are expected to rise by approximately 4 degrees F. What do you predict the temperature change to be?
Much lower than expected — **Much higher than expected**

2. By 2050, the cost of renewable energy (without subsidies) compared to the cost of conventional resources will be...
Much cheaper — **Much more expensive**

3. By 2050, it is expected that regional collaboration across the West could evolve from the existing Energy Imbalance Market to an expanded participation in the Day-Ahead Market to full participation options with a single ISO/RTO in the West. What level of regional collaboration do you expect?
No change (status quo) — **Full RTO participation across the West**

4. By 2050, annual demand is expected to increase by approximately 60% compared to our current demand levels. What do you expect the demand growth to be?
Much less than expected — **Much more than expected**

Thank you for contributing to the session discussion! We look forward to learning how the various scenarios impact the electricity industry in the future.

Done

This survey is not meant to be a definitive analysis of CAISO's future risk. Its purpose is to demonstrate the method on a simplified problem. In particular, since the results from this survey (shown in appendix 2) implicitly assume the higher temperature branch, we would also need to do a similar poll for the lower temperature branch in the scenario tree. This is because the conditional probability distributions for the factors, renewables, regionalization and load growth will almost certainly be different for each major branch of the tree.

As was mentioned in the text of this paper, its purpose was to show how the algorithm for generating scenarios operates and not to presume that our example was a complete analysis for CAISO.

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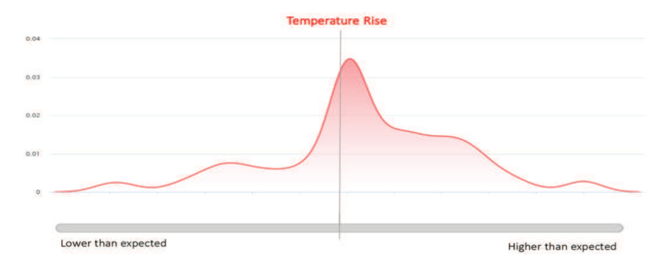
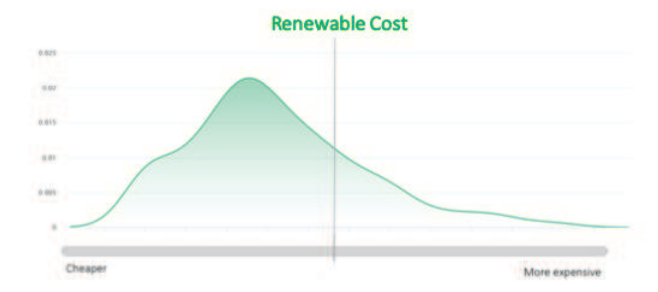
[10] *We would like to thank the organizers of the CAISO 2018 Stakeholder Symposium, especially Joanne Serina and Mark Rothleder, for their cooperation in this exercise and for conducting this poll with CAISO's stakeholders. Approximately 25% of the 1,000 attendees responded to the poll.*

Appendix 2: results of the CAISO poll

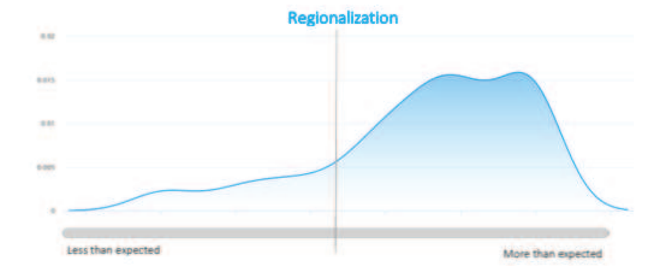
9 Studies indicate that by 2050 temperatures are expected to rise by approximately 4 degrees F. What do you predict the temperature change to be?



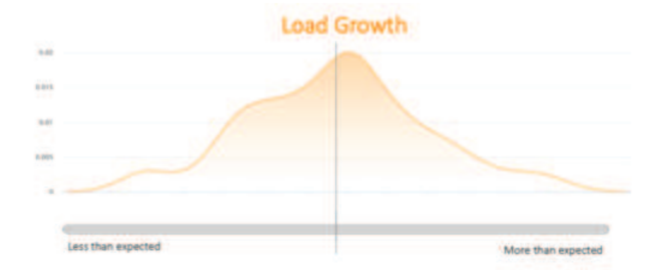
10 By 2050, the cost of renewable energy (without subsidies) compared to the cost of conventional resources will be …



11 By 2050, it is expected that regional collaboration across the West could evolve from the existing Energy Imbalance Market to an expanded participation in the Day-Ahead Market to full participation options with a single ISO/RTO in the West. What level of regional collaboration do you expect?

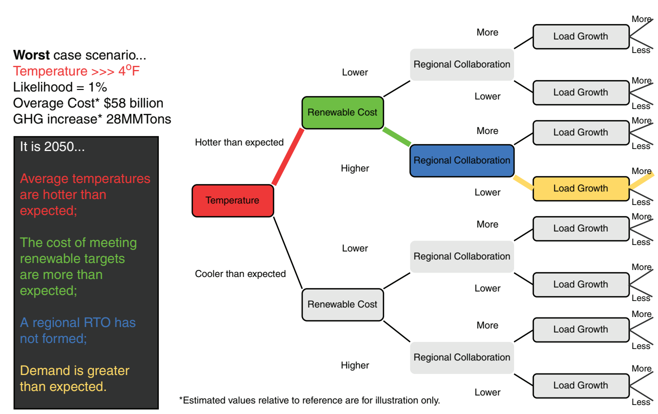


12 By 2050, annual demand is expected to increase by approximately 60% compared to our current demand levels. What do you expect the load growth to be?



Appendix 3: the CAISO representative scenario tree (worst case scenario)

13 Worst case scenario



These results are not meant to be a definitive analysis of CAISO's future risk. They are meant to demonstrate the algorithm on a simplified problem.