Visualising risk in generating capacity adequacy studies using clustering and prototypes

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Abstract—Generating capacity adequacy studies play a significant role in long term capacity planning. Risks of capacity deficits are usually reported in the form of one or more average quantities, which cannot fully convey the nature of the risks being faced. Chronological Monte Carlo simulations may be used to construct comprehensive multi-dimensional risk profiles, but such profiles tend to be difficult to interpret. This paper proposes the use of a clustering method to partition the risk profile into clusters of similar outcomes with associated probabilities. The results are presented in accessible tabular form, and prototypical scenarios can be analysed in detail to provide further insight.

Index Terms—generating capacity adequacy, Monte Carlo simulations, risk measures, clustering methods

I. INTRODUCTION

Generating capacity adequacy studies are an important tool for quantifying the ability of a power system to supply power to connected loads. The resulting risk assessments are used in the short and medium term to anticipate potential capacity deficits and to prepare corrective measures. In the longer term they are used to guide capacity planning. The latter is increasingly relevant in many markets as governments and regulators contemplate capacity payments to incentivise investments in generators that will see very infrequent use in renewable-dominated generation systems.

The Great Britain system has a capacity adequacy reliability standard that is set at a loss-of-load expectation (LOLE) of 3 hours/year. This reliability standard also drives the aggregate capacity targets for the Capacity Market [1]. Annual security of supply studies are carried out by the transmission system operator (National Grid) [2] and the regulator (Ofgem) [3], which report their results in terms of LOLE or additionally as expected energy unserved (EEU, also known as EUE/EENS).

The drawbacks to using average values such as LOLE or EUE to represent the risk of generating capacity shortages are well-recognised [4]. Because expectation values do not distinguish between relatively likely minor events and rare major events, such risk measures cannot accurately convey the range of possible outcomes and their likelihood of occurrence. For example, the historically dominant standard of a LOLE equal to 0.1 day/year is often summarised as “1 day in 10 years”, but it could arise equally from 10-day-long events with a recurrence time of 100 years. This shortcoming can be

addressed by replacing average risk measures by distributions that illustrate the range of possible impacts and their likelihood of occurrence in the period of interest (see e.g. [4]). However, when multiple aspects of capacity adequacy are studied, this results in multidimensional risk profiles that are hard to interpret by the untrained eye.

In this paper we present a method to condense the information contained in multidimensional risk profiles into an accessible tabular form. Annualised risk measurements from Monte Carlo simulations are partitioned into clusters with similar outcomes. The cluster probabilities and the cluster-averaged risk measurements provide a summary view of the range of simulation outcomes. Moreover, the cluster medoids represent prototypical scenarios that may provide insight into ‘typical’ system behaviour within each cluster. These tools can be used to understand implications of current reliability standards, and may help to guide their future evolution.

II. GENERATION CAPACITY ADEQUACY MODELS

Generation capacity adequacy studies determine the ability of the generators in a system to supply the load on the system. Disregarding transmission constraints, a probabilistic description of the system’s adequacy consists of two processes: $l(t)$, representing the load on the system, and $g(t)$, which characterises the available generating capacity. Capacity adequacy studies are concerned with the statistical properties of the capacity margin $g(t) - l(t)$.

Within this paper we consider two common generating capacity adequacy models. The first is the IEEE Reliability Test System (RTS-96), which is studied in a three area configuration with 96 generators [5]. The second is RTS-96HW [6], a variant that introduces variability of renewable resources. This model replaces a 350 MW coal power plant by 1526 MW of wind power capacity. The model also defines three annual availability curves for hydropower and wind power, which are independently selected at the start of each year.

Both models use the deterministic load profile $l(t)$ defined in [5]. It has annual periodicity and near-periodicity on a weekly and daily basis. As this load model is specified in weeks, we will henceforth take a year to be 364 days (52 weeks), resulting in a 8736-valued hourly load profile. For

the construction of wind and hydropower profiles in the RTS-96HW model, August is assumed to have 30 days. Generator outages are modelled as independent two-state Markov models with type-dependent failure and repair rates.

III. QUANTIFYING RISKS

Risk measures are used to distill the most relevant information from the capacity margin process $g(t) - l(t)$ into a set of numbers that capture various qualities of the process, such as the propensity, frequency and duration of capacity deficits. Furthermore, distributions of risk measures are more insightful than simple averages [4]. In line with the annual periodicity of the load profile and business/policy cycles we measure risks on an annual basis (starting on January 1st), using the measures

aLOLT: annual loss-of-load time,

aUE: annual unserved energy,

aLOLC: annual loss-of-load count.

Formally, these may be defined as

$$\text{aLOLT} = \int_{0h}^{8736h} \mathbb{I}_{l(t) > g(t)} dt, \quad (1a)$$

$$\text{aUE} = \int_{0h}^{8736h} [l(t) - g(t)]^+ dt, \quad (1b)$$

$$\text{aLOLC} = \int_{0h}^{8736h} \delta_{-\rightarrow+}[l(t) - g(t)] dt. \quad (1c)$$

Here, $\mathbb{I}_s$ is the indicator that returns 1 if statement s is true and 0 otherwise; $[f(t)]^+$ returns the positive part of $f(t)$; $\delta_{-\rightarrow+}[f(t)]$ assigns a unit measure to times at which $f(t)$ crosses zero from below. Note that aLOLT, aUE and aLOLC are random variables due to the random nature of the generating capacity process $g(t)$. The expectation values of these variables are the common risk measures LOLP ($\times 8736$ hours), EUE/EEU/EENS and LOLF, respectively.

In this paper risks will be analysed by means of chronological Monte Carlo simulations. Whereas efficient convolution methods or state-space sampling methods may be used for the estimation of average risk measures such as LOLP, EUE or LOLF, the annualised risk measures in (1) relate properties of $l(t) - g(t)$ at instants up to one year apart, thus necessitating the analysis of time series. This is straightforward using chronological simulations, which have the added advantage that they scale well to more complex model systems.

Monte Carlo simulations are run for N independent years, and the evolution of the capacity margin $g(t) - l(t)$ for each year i is summarised by the triplet

$$r_i = (\text{aLOLT}_i, \text{aUE}_i, \text{aLOLC}_i). \quad (2)$$

Collectively, the points r_i for the years $i = 1, \dots, N$ form an empirical *risk profile* in three dimensions. Understanding the annualised risk due to capacity shortages requires understanding the shape and density of this profile in three dimensions, including dependencies between the different risk measurements for the same year. The scatter matrix shown in Figure 1 visualises these dependencies. Note that years without capacity shortages (i.e. the overwhelming majority with $r_i = \vec{0}$) are suppressed in this image.

IV. CLUSTERING AND VISUALISATION

The scatter matrix representation in Figure 1 gives a comprehensive view of the risk profile, but it suffers from two drawbacks. First, interpreting three-dimensional probability distributions by means of its lower-dimensional projections requires substantial familiarity with these concepts. Second, due to the large variations in point density in the scatter plots it is not easy to get a quantitative grasp of the relations between different parts of the graph. Therefore, there is no intuitive mapping from the graph to the likelihood of occurrence of events of a certain severity.

We propose to address these shortcomings by using a clustering method to partition the point cloud that makes up the risk profile into a manageable number of clusters, each of which contains points with similar outcomes. Note that clustering is used strictly to summarise results; there is no prior expectation that the observations actually form distinct clusters in feature space.

A. Clustering method

As a first step, the clustering should reflect the dichotomy between years in which generation deficits did or did not occur. Therefore, the first cluster is defined to consist of all sampled years in which no generation deficits occurred ($r_i = \vec{0}$).

The remaining points are partitioned using a k -medoids algorithm [7]. The algorithm selects k out of N points as cluster centres and assigns each of the remaining points to the cluster defined by the nearest centre. The *medoids* (also known as representative points or prototypes) are the points that minimise the total sum of distances to the nearest medoid:

$$\min_{i_1, \dots, i_k} \sum_{c=1}^k \sum_{j \in \mathcal{C}_c} d(i_c, j) \quad (3)$$

Here c is the cluster index and i_c the year-index of the associated medoid. The set $\mathcal{C}_c$ contains the indices of all points in cluster c , and the function $d(i, j)$ is the distance between two points with indices i and j .

Two considerations affect our choice of distance function. The first is how the different coordinates of each point should be combined given their different magnitudes, dimensions and types (real-valued time and energy, ordinal event count). We address this by establishing a natural scale for each coordinate, computed as its average value over the years in which a generation shortfall occurred. For a coordinate Q this is denoted by $\overline{Q}_{>0}$; the measured quantities Q_i are divided by $\overline{Q}_{>0}$ when the distance is computed. We note that this choice is nearly equivalent to the standardisation procedure using the mean absolute deviation proposed in [7, chapter 1], because of the exceedingly large number of zero-impact years in capacity adequacy studies and the non-negativity of the Q_i .

The second consideration is the desired sensitivity to outliers, which can be controlled using the power of the distance function. The Euclidean distance is robust against outliers, but results in positioning all medoids close to the origin, where the density of points is highest. Empirically, a good balance

Fig. 1. Scatter matrix of the risk measurements for the IEEE RTS-96 model; $N = 100,000$ simulations; years with $r_i = \vec{0}$ are suppressed. Panels on the diagonal show log-scale histograms of each of the three risk measures, and off-diagonal panels depict pairwise scatter plots. Panels on the lower left also show the result of a 5-medoid cluster analysis, with large dots indicating the position of the medoids, and colours indicating cluster membership.

was obtained using the *squared* Euclidean distance function, which leads to a better spread of medoids. The implemented distance function is thus

$$d(i, j) = \left(\frac{\text{aLOLT}_i - \text{aLOLT}_j}{\text{aLOLT}_{>0}} \right)^2 + \left(\frac{\text{aUE}_i - \text{aUE}_j}{\text{aUE}_{>0}} \right)^2 + \left(\frac{\text{aLOLC}_i - \text{aLOLC}_j}{\text{aLOLC}_{>0}} \right)^2. \quad (4)$$

Let N_c be the number of points assigned to cluster c . The estimated probability of encountering an outcome of the type present in cluster c is therefore $\Pr(c) \approx N_c/N$. For small probabilities, this is most intuitively expressed as a 1-in-(1/ $\Pr(c)$)-years statistic. The risk measures associated with this cluster can be summarised by the mean, minimum and maximum

values of each measure. This compact representation is used in Tables I and II. If desired, a further reduction could be obtained by only reporting mean values for each cluster.

B. Prototypes

The analysis so far has been concerned exclusively with the triplet of risk measures aLOLT, aUE and aLOLC. It is worth emphasising that their values only *summarise* the annual trace of the process $l(t) - g(t)$, and further insight may be gained by studying individual simulation runs in more detail.

The clustering method defined above provides a natural method to select representative traces that display a variety of capacity shortage scenarios. The medoids that are computed as part of the k-medoids algorithm are representative prototypes

TABLE I
CLUSTERED RISK MEASUREMENTS USING 5-MEDOID CLUSTERING; IEEE RTS-96 (3 AREAS), $N = 100,000$ SIMULATION YEARS

cluster	probability	aLOLT (h)		aUE (MWh)		aLOLF (occ)	
		mean	[min, max]	mean	[min, max]	mean	[min, max]
no events	96.8%	0	[0, 0]	0	[0, 0]	0	[0, 0]
1	1 in 46.2	2.08	$[2.47 \times 10^{-3}, 5.00]$	188	[0.0471, 718]	1.08	[1, 3]
2	1 in 149	5.08	[1.95, 10.0]	816	[92.3, 1754]	2.05	[1, 5]
3	1 in 382	10.7	[5.80, 17.9]	2110	[902, 4037]	3.32	[1, 8]
4	1 in 1300	19.7	[11.0, 30.0]	5000	[3237, 7379]	4.45	[1, 9]
5	1 in 3450	30.7	[19.0, 50.3]	10800	[7772, 16942]	4.90	[3, 10]
average	-	LOLP $\times$ 8736 h/yr = 0.131(3) h/yr		EUE = 22.0(9) MWh/yr		LOLF = 0.0508(11) occ/yr	

TABLE II
CLUSTERED RISK MEASUREMENTS USING 5-MEDOID CLUSTERING; RTS-96HW, $N = 100,000$ SIMULATION YEARS

cluster	probability	aLOLT (h)		aUE (MWh)		aLOLF (occ)	
		mean	[min, max]	mean	[min, max]	mean	[min, max]
no events	93.5%	0	[0,0]	0	[0,0]	0	[0,0]
1	1 in 24.8	2.20	$[1.05 \times 10^{-4}, 5.34]$	207	$[8.08 \times 10^{-4}, 994]$	1.14	[1,3]
2	1 in 62.5	6.31	[2.73, 12.4]	982	[47.3, 2885]	2.44	[1,6]
3	1 in 154	14.3	[6.84, 26.7]	3020	[1054, 5809]	4.04	[1,9]
4	1 in 442	26.7	[13.0, 45.1]	7560	[4471, 13074]	5.75	[1, 13]
5	1 in 2380	46.3	[28.0, 73.7]	18900	[12101, 55464]	7.45	[4, 14]
average	-	LOLP $\times$ 8736 h/yr = 0.362(7) h/yr		EUE = 68.6(20) MWh/yr		LOLF = 0.1273(19) occ/yr	

of their respective clusters, so their simulation traces are certain to illustrate certain characteristics of each cluster. These traces may therefore be used to visualise the nature of the capacity shortages associated with each cluster.

It is only known at the end of the clustering analysis which points are the medoids. For a long simulation run it may be prohibitive in terms of memory requirements to store full time traces for all potential medoids. If this is the case, an alternative approach is to store the random seed for each simulated year alongside the risk measurements. When the medoids have been identified, their full traces can be recomputed by re-initialising the pseudo-random number generator with the appropriate seed. Because the number of medoids is much smaller than the total number of simulated years the computational impact of this recomputation is negligible.

V. RESULTS

Generating capacity adequacy studies have been performed using the IEEE RTS-96 (3 area) and RTS-96HW models. In both cases, $N = 100,000$ independent years were simulated using event-driven chronological Monte Carlo simulations. The studies were implemented in Mathematica 10, and k -medoid clustering was performed using the built-in Partitioning Around Medoids algorithm; $k = 5$ was selected to provide a balance of detail and brevity.

Figure 1 depicts the relations between risk measures for the IEEE RTS-96 system, showing only years where capacity deficits occurred. Histograms for each measure are shown on the diagonal; the off-axis diagrams show that the annual loss-of-load time (aLOLT) and energy (aUE) measurements are strongly correlated with each other, whereas the number of

events in each year (aLOLC) show a weaker dependence. The panels on the bottom left show the results of 5-medoid clustering performed on this data set. It can be seen that the medoids and their clusters form a sequence of decreasing density (i.e. probability) and increasing impact.

These results are reflected in Table I, which shows the clusters along with the no-event cluster in order of decreasing likelihood of occurrence. No-event years are by far the most likely to occur (96.8%), and the clusters represent events with empirical probabilities ranging from 1-in-46.2 years down to 1-in-3450 years. For comparison, the simple LOLP, EUE and LOLF measures, which can be computed as weighted averages of the rows above, are shown on the bottom row.

Figure 2 shows the load and generating capacity traces corresponding to the prototypes of each of the five clusters. For each prototype the risk measurements are reported, followed by the annual traces (centre column). Because the generating capacity deficit events for these traces all occurred during high load levels in December, that month is magnified in the rightmost column. It can be seen that in all cases the capacity deficit events are part of a single macroscopic event that spans multiple days, with recurrent negative margins occurring for each load peak.

The same analysis was performed for the RTS-96HW model, which includes a stochastic selection of hydropower and wind power traces for each simulated year. Only the tabular form of the cluster results is shown, in Table II. The results are qualitatively similar to those for the IEEE RTS-96 model shown in Table I, but the risk measures have higher magnitudes. Capacity deficits are also more likely to occur, in 6.5% of years compared to 3.2%.

Fig. 2. Generating capacity (orange) and load (blue) traces for the RTS-96 risk prototypes shown in Figure 1. December profiles are magnified on the right.

VI. SUMMARY AND DISCUSSION

We have proposed a method for accurately and concisely presenting the results of generating capacity adequacy studies. Chronological Monte Carlo simulations were used to construct a multidimensional risk profile, and a k -medoid method was employed to partition simulation results into clusters with similar outcomes. The risk measures for each cluster were presented in tabular form, listing a range of possible impacts and their likelihood of occurrence. In particular, such a table highlights the probability of shortfall-free years, and separates the more frequent minor events from major, but rare, events. Furthermore, the clustering method identifies prototypical realisations that may be used to illustrate the nature of the risks in each cluster.

These visualisation tools may be used to communicate complex risk profiles to non-specialists. For example, they can help convey to regulators and the public the true distribution of risks associated with the use of a 3 hours/year LOLE standard. On longer time scales, such insights can inform the debate regarding desirable properties of future reliability standards.

In this paper we have considered only basic generating capacity adequacy models, but the approach is equally applicable to more complex capacity adequacy models, which may feature time-dependent dynamics through storage facilities or load-dependent failures. Similarly, the clustering approach

may be used for other applications that result in multi-dimensional representations of risk.

Finally, we note that the method as presented here may be refined in a number of ways. Possible improvements of the method include automatic selection of the number of clusters, and further studies on suitable distance metrics.

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