Resource Adequacy in the 2030s

Spotlight: Exploring approaches and metrics to assess resource adequacy in a fully decarbonised power system

May 2024

ESO

Introduction

We published our first study assessing resource adequacy in the 2030s with AFRY in December 2022. This study considered the potential risks to resource adequacy for a fully decarbonised power system and how different portfolios of resources could provide adequate electricity supplies, when over 80% of annual electricity generation could be from weather-dependent resources.[1]

Since then we have engaged with stakeholders through round-table debates and bilateral discussions, and have convened a small expert advisory group to help us further develop this work with a new Net Zero Adequacy Modelling team in the ESO.

We are already working to produce our next study assessing resource adequacy in the 2030s, building on the study we did with AFRY. We currently expect this to be published by September 2024.

Ahead of the next study, we also wanted to explore a few areas of interest through a set of shorter 'spotlights'. This one, exploring the approaches and metrics we use to assess resource adequacy, represents the first of these.

We expect further spotlights to follow in the coming months, focussing on our assumptions for the next study and the role of demand-side response in resource adequacy. The panel on the right-hand side sets out the timeline of our activities in this area.

Our study with AFRY found that new approaches and metrics would be needed to assess resource adequacy for a fully decarbonised power system as existing metrics such as loss of load expectation (LOLE) would not be sufficient on their own.

We want to use this spotlight to introduce some new ideas on this, which we intend to incorporate in our next study. We recognise that some of these ideas can be more complex, and so by introducing them now, we hope that this will help stakeholders start to become more familiar with them.

In this spotlight we review the findings from our previous study and present a comparison of some of the alternative adequacy metrics. We then set out an illustrative example showing how an alternative approach that considers expected energy unserved (EEU) for individual weather years ('weather-conditional EEU') can provide deeper understanding of the potential resource adequacy risks.

We should emphasise that this spotlight is not designed to indicate or recommend any decisions on existing policy. This includes the current reliability standard, which is set by Government. The purpose of this spotlight is to explore additional approaches and metrics which can help us to better understand future adequacy risks in a fully decarbonised power system.

As ever, we invite feedback and welcome engagement with stakeholders. The best way to contact the team or main author is by email at:
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Timeline of ESO activities on resource adequacy in the 2030s

Dec 2022	First study assessing resource adequacy in the 2030s published with AFRY
Mar 2023	Stakeholder engagement including round-table debates and bilateral discussions
Jul 2023	Published an update reflecting themes from stakeholder engagement and set out our intention for the next study, a set of spotlights and establishing an expert advisory group
May 2024	Spotlight exploring new approaches and metrics published
May/Jun 2024	Spotlights exploring the role of demand-side response (DSR) in adequacy and the technology assumptions for our next study
Sep 2024	Next ESO study assessing resource adequacy in the 2030s

1 For example, see the ESO's Future Energy Scenarios (FES) https://www.nationalgrideso.com/future-energy/future-energy-scenarios-fes

Recap: why we need new approaches and metrics for resource adequacy

Our previous study with AFRY showed that the GB power system is expected to evolve from one where tight periods are relatively short to one where they could be much longer, even though the loss of load expectation (LOLE) of the system remains broadly similar. This means that the inherent risk profile of the system is changing but the key metric to assess resource adequacy is not. In addition, LOLE does not reveal information on what is causing these periods or how many consumers could be affected. While LOLE remains an important metric, it is insufficient on its own to assess resource adequacy risks.

Our study assessing resource adequacy in the 2030s with AFRY found that the GB power system will be more susceptible to events that have a lower likelihood of occurring but will have a greater impact if they materialise. This is particularly evident from longer-duration weather events becoming increasingly dominant in driving stress periods, for a similar LOLE value. This is reflected in Figure 1, which is reproduced from that study.

While LOLE remains a useful metric to assess resource adequacy, it is not sufficient on its own to characterise a system where the risk is increasingly driven by events that occur less frequently. For example, in many years, weather conditions are more benign and so we would not expect any tight periods on the GB power system. Occasionally in other years, there could be weather patterns that lead to more prolonged loss of load periods that are more challenging.

LOLE is a summary metric that considers an average across all of these conditions. It does not reveal information about lower likelihood, high impact events which are driving load loss. For example, we cannot see which particular events or weather years are driving loss of load and the metric itself is sensitive to the choice of weather years considered. In addition, LOLE on its own cannot fully assess the impact of load loss on consumers, as it does not provide any information on the unserved energy or how many consumers could be affected. Finally, different (sensible) strategies on deploying limited duration resources such as batteries can lead to different LOLE values for the same event.

It is increasingly apparent that new approaches and metrics will be needed for resource adequacy, potentially considered alongside existing metrics like LOLE. The next slide considers some of these options.

	Year	Distribution of length of hours with unserved energy (hours)										Mean length of load los periods (hours)
		<2	2-3	4-5	6-9	10-14	15-22	23-30	31-40	41-50	>50	
'Consumer Transformation' (reference)	2025	3	26	19	0	3	0	0	0	0	0	4
	2028	2	24	9	1	5	0	0	0	0	0	4
	2030	3	20	8	4	2	0	0	0	0	0	4
	2033	8	12	5	6	2	0	0	0	0	0	4
	2035	3	8	4	5	6	1	0	0	0	0	6
	2038	7	12	5	5	4	2	0	1	0	0	6
	2040	2	16	8	2	3	2	0	1	0	0	6
'Gas CCS, H2 and battery storage'	2025	3	26	19	0	3	0	0	0	0	0	4
	2028	1	27	6	3	3	0	0	0	0	0	4
	2030	3	13	2	2	5	0	0	0	0	0	5
	2033	7	14	11	14	1	3	4	0	1	0	7
	2035	6	10	9	10	2	6	3	0	1	0	8
	2038	5	12	8	7	4	4	0	0	1	0	7
	2040	2	8	2	4	2	1	1	0	0	0	6
'Nuclear, H2 and battery storage'	2025	3	26	19	0	3	0	0	0	0	0	4
	2028	1	27	6	3	3	0	0	0	0	0	4
	2030	3	13	2	2	5	0	0	0	0	0	5
	2033	8	18	12	11	2	5	4	0	0	0	7
	2035	7	11	7	14	5	5	3	0	2	0	9
	2038	7	8	7	8	4	5	1	0	1	0	8
	2040	5	10	9	5	2	4	1	0	1	0	7
'H2 and battery storage'	2025	3	26	19	0	3	0	0	0	0	0	4
	2028	6	27	6	4	2	0	0	0	0	0	4
	2030	5	20	8	5	2	0	0	0	0	0	4
	2033	2	18	6	10	2	2	0	0	0	0	5
	2035	9	12	3	8	6	2	0	0	0	0	6
	2038	1	11	5	5	3	3	0	0	0	0	6
	2040	3	3	1	3	3	2	0	0	0	0	7

Figure 1: table showing how the GB power system is expected to evolve from one where loss of load periods are shorter, to one where they could be much longer but less frequent. This was found for different portfolios of resources and a broadly constant LOLE of around 1 hour per year. See our study assessing resource adequacy in the 2030s for further details.

Potential options to assess resource adequacy

Table 1 presents some potential metrics to assess resource adequacy. Some options are familiar and already widely used, while others are less familiar. It is possible that future resource adequacy assessments need to consider a combination of these through a multi-metric approach – a conclusion also supported in a recent study by the Energy Systems Integration Group.

Metric	Description	Advantages	Disadvantages
De-rated margin	The amount of expected available capacity above peak demand for the year	• Simple approach that is easy to understand for a wide audience	• Does not reflect risk of more complex systems with higher penetrations of variable and flexible resources, in which tight periods occur more frequently outside times of peak demand
Loss of load expectation (LOLE)	The average number of hours with loss of load in a year	• Considers tight periods that may occur outside times of peak demand • Indicates the potential duration of loss of load events • Can provide greater insight on loss of load events by conditioning on specific weather years • Already widely used in resource adequacy	• Does not indicate the impact of loss of load events • Does not provide sufficient information on low likelihood, high impact events • Results are sensitive to assumptions on flexible resources like storage
Expected Energy Unserved (EEU)	The average volume of unserved energy in a year	• Indicates potential severity and cost of loss of load events, particularly when combined with LOLE • Can provide greater insight on loss of load events by conditioning on specific weather years • Results are less sensitive to assumptions on flexible resources like storage • Already widely used in resource adequacy	• Does not provide sufficient information on low likelihood, high impact events
Duration, depth and frequency of loss of load events	Average / maximum / distributions of the duration, depth and frequency of loss of load events	• Potentially provides more information on the nature and impact of loss of load events, including low likelihood, high impact events, especially if assessing the distributions	• Results are sensitive to assumptions on flexible resources like storage • Potential for ambiguity as a single event could lead to more than one separate period of load loss occurring close together
Hourly loss of load probability	The number of hours in a year in which the loss of load probability for that hour exceeds a threshold	• Indicates the risk of a shortfall in any given hour • Might be more intuitive for market participants as it aligns with near real-time market information available in GB	• Potentially similar to LOLE
The [95th] percentile of unserved energy or loss of load hours	The level of unserved energy or loss of load hours that has a [1-in-20] chance of being exceeded	• Provides information on low likelihood, high impact events • Provides information on the variability of outcomes	• Requires a lot of simulations (e.g. weather years, outage patterns) for a confident estimate • Less familiar and intuitive for a wider audience
Conditional value at risk (CVAR) of unserved energy or loss of load hours	The expectation of unserved energy or loss of load hours above a defined percentile (e.g. 95th)	• Provides information on the probability distribution of low likelihood, high impact events	• Requires a lot of simulations (e.g. weather years, outage patterns) for a confident estimate • Less familiar and intuitive for a wider audience
Modelling specific scenarios or events of interest	Assessing resource adequacy under a set of specifically chosen scenarios	• Allows scenarios of greater interest to be explicitly considered in resource adequacy assessments	• Outcomes are wholly dependent on the choice of scenarios modelled, which may have inherent biases and not be exhaustive

Table 1: advantages and disadvantages of some of the potential metrics to assess resource adequacy

Illustrative example: Weather-conditional EEU (1)

Summary metrics such as LOLE and EEU are useful in assessing resource adequacy over many weather years. It is often the case that weather events from a small number of years are responsible for driving potential loss of load. Assessing LOLE and EEU for individual weather years – "*weather-conditional LOLE and EEU*" – can provide insight into which specific years are of most interest for resource adequacy.

Our study assessing resource adequacy in the 2030s with AFRY showed that weather patterns will be the dominant driver of stress periods in a fully decarbonised power system. The ESO currently has access to 34 years of historic weather covering the period 1985 – 2018 in our pan-European market model (PLEXOS).

In representing the importance of weather and system stress periods, it can be helpful to assess resource adequacy conditional on:

1. More challenging weather years
2. More typical or average weather years

Different mixes of generation, interconnection and storage, together with different demand profiles, could lead to portfolios that are susceptible to different risks. Therefore, whether particular weather years are more challenging or average in their nature will somewhat depend on the resources available in the system being studied. This approach should help pave the way for deeper analysis on how weather drives system stress events and should be of benefit to policy-makers, system operators, energy market participants and consumers.

We can illustrate this with an example. We have modelled a system with LOLE and EEU values of 1.7 hours and 2.9 GWh per year, respectively, when considering all weather years. Figure 2 shows the EEU conditional on each historic weather year. It shows clearly how weather from a small number of years drives loss of load that dominate the contributions to the LOLE and EEU values. For example, if this system were to experience weather based on that of 2010, the LOLE and EEU values would be 19 hours and 54 GWh, respectively – much higher than the values reported considering all years. (A weather year in these illustrations runs from 1st October of that year until 30th September of the following year).

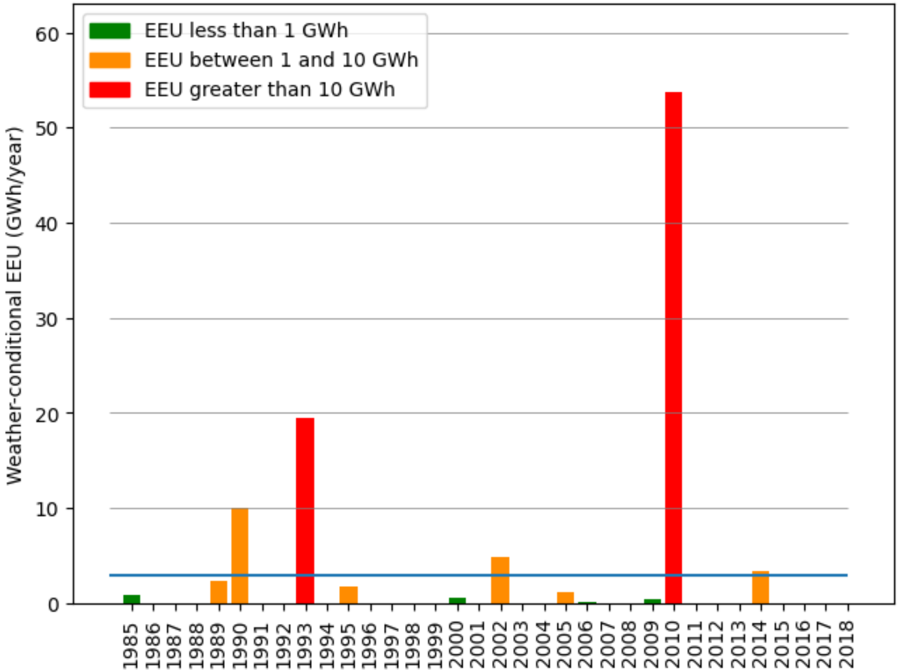

Figure 2: Weather-conditional EEU for a system with LOLE and EEU values of 1.7 hours and 2.9 GWh, respectively. The simulations considered the system operating in 2023/24 with different historic weather years and 10 different generator outage patterns. Weather year 2010 dominates the EEU and is responsible for around half of all unserved energy in this system.

Illustrative example: Weather-conditional EEU (2)

Weather-conditional metrics such as LOLE and EEU provide more insight compared with LOLE and EEU calculated over all weather years. We can seek even deeper understanding by visualising the underlying distributions and calculating percentiles which are also conditioned on weather years.

This illustrative example has already shown that conditioning on particular weather years can provide more insight on how weather drives system stress periods than the LOLE or EEU summary statistics that include all weather years.

We can get an even deeper understanding through visualisation of the underlying distributions. Figure 3 shows a scatter plot of loss of load hours versus energy unserved for 150 simulations, all conditional on weather year 2010. It also shows histograms of the distributions of loss of load hours and energy unserved.

Calculating percentiles (e.g. 95th) which are conditioned on weather years can provide a useful summary statistic on the range of possible outcomes.

The scatter plot shows the results of all 150 simulations and shows that the variability in outcomes is still large even when using a single historic weather year, providing valuable insight to stakeholders on the potential adequacy risks. The colours estimate an upper bound on the number of hours individual consumers may be disconnected for. In this particular case, the estimated weather-conditional LOLE and EEU are 18 hours and 36 GWh per year, respectively, and indicated by the black cross. The 95th percentile of these variables are 27 hours and 81 GWh per year, represented by the dotted lines.

We note that generally a larger number of data points than 150 is needed to confidently estimate a 95th percentile. The numbers reported here are only to illustrate the use of weather-conditional percentiles as an additional metric and the further insight that they could bring on the variability of outcomes.

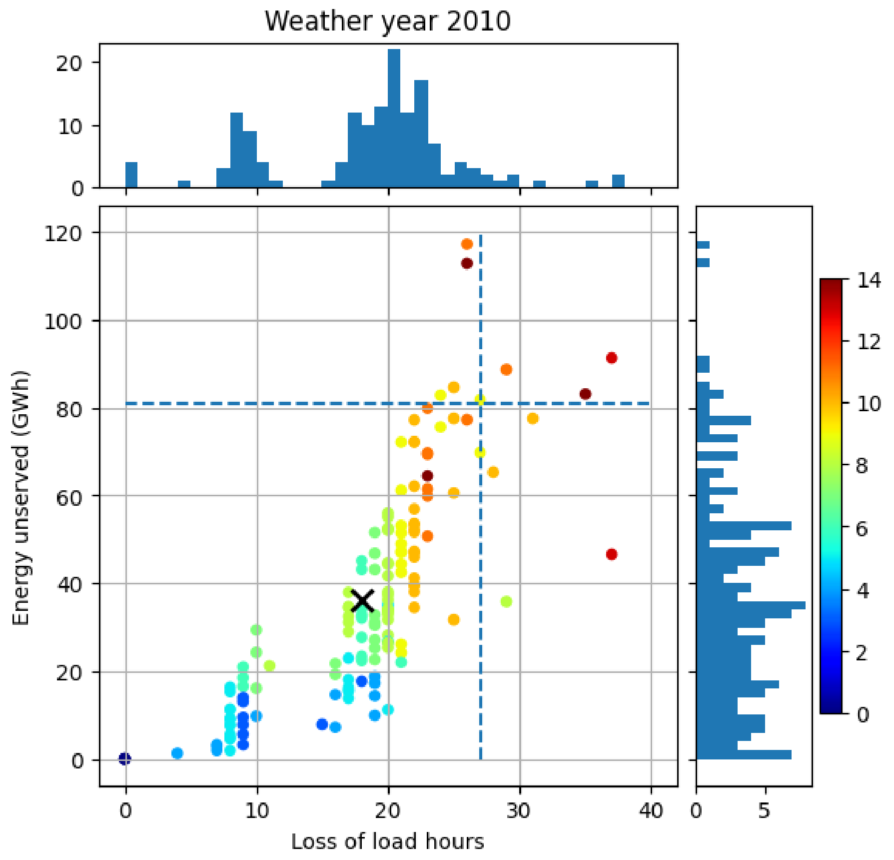

Figure 3: Loss of load hours versus unserved energy from 150 simulations, all conditional on weather year 2010. Histograms show the distributions of both variables. The colours estimate an upper bound on the number of hours individual consumers may be disconnected for. The dotted lines represent the 95th percentiles and the black cross represents the expectation.

Illustrative example: Weather-conditional loss of load probability

Using a multi-metric approach helps identify specific events that drive potential loss of load. In this illustrative example, the loss of load probability for each hour of the year indicates the periods where risk of load loss is highest. Understanding resource adequacy risks in this way provides critical information to stakeholders and allows mitigations to be explored.

While the weather-conditional LOLE and EEU approach provides greater insight than the simple summary metrics, it still does not tell us the events in that year that are driving load loss and when the periods of greatest risk are.

We can seek to consider this by calculating the loss of load probability for each hour of the year to identify when load loss might occur. We have done this for the same illustrative example on the previous slide, still using weather year 2010, and shown the results in Figure 4.

Figure 4 shows that the weather conditions in mid to late December are the dominant driver of potential load loss in this example, with the loss of load probability close to or exceeding around 80% in two periods. In this case, the weather conditions were exceptionally cold and coincided with low wind too. December 2010 remains the UK’s coldest December on record.[1]

This example clearly shows that delving deeper beyond the summary statistics of LOLE and EEU, as well as the weather-conditional LOLE and EEU, can provide greater insight to stakeholders and allow mitigations to be explored.

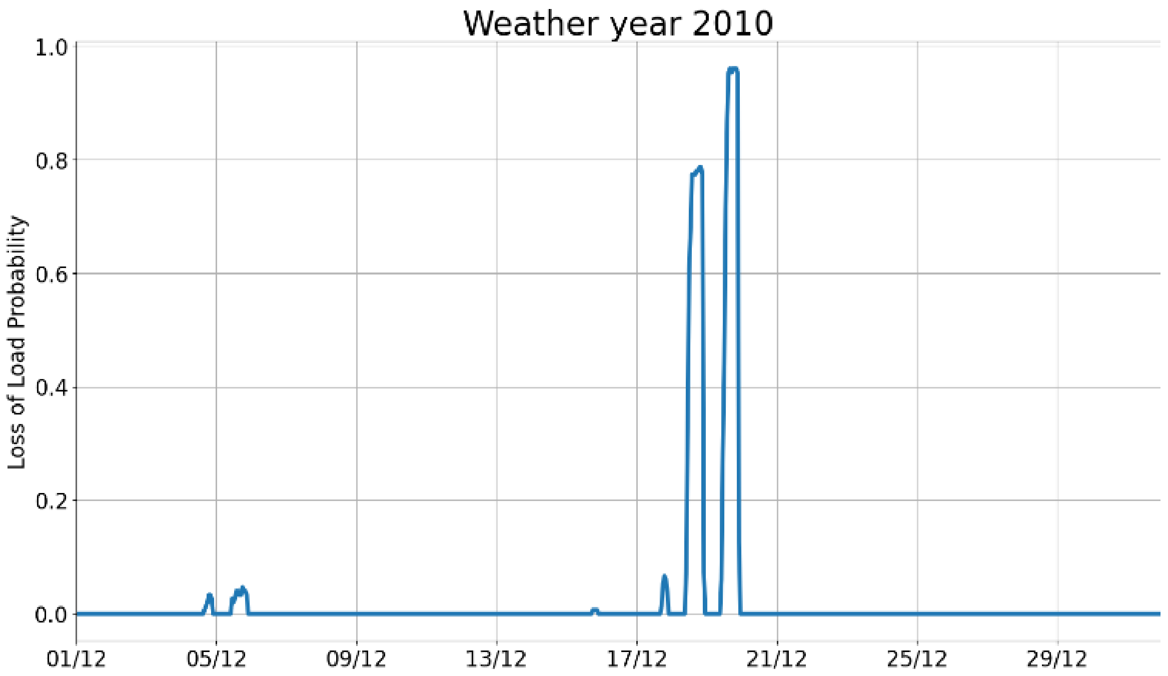

Figure 4: Loss of load probability for each hour in December from 150 simulations, all conditional on weather year 2010. This shows that weather conditions in mid to late December are the main driver of potential load loss in this example.

1 For example, see https://blog.metoffice.gov.uk/2022/12/30/cold-december-concludes-warmest-year-on-record-for-uk/