Written evidence submitted by Dr. Daniel Donaldson, Professor Ian Dobson, and Arslan Ahmad in response to OFGEM ED3 Sector Specific Methodology Consultation

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This response is submitted by Dr. Daniel Donaldson, Assistant Professor of Electrical Power Systems and Deputy Head of the Resilient Systems and Climate Action Research Group at the University of Birmingham (UK), Professor Ian Dobson, Sandbulte Professor of Electrical and Computer Engineering at Iowa State University (USA) and Arslan Ahmad, postgraduate researcher, at Iowa State University (USA). We collaborate with distribution network operators across the world to support the evaluation and enhancement of distribution network resilience. Our reason for submitting this evidence is to provide perspective from our previous research in response to two of the questions laid out in the area of Climate Resilience.

OFGEM Q92. "What are your reflections on the stress testing methodological framework for the first phase (see Climate resilience stress testing methodological framework annex)? Does it align with your expectations of the responsibilities of a DNO and current capabilities? Can you foresee any support or changes that might improve its effectiveness? Do you have any views on priorities for future phases of work?"

Response: The stress testing methodological framework for Phase A laid out in the climate resilience stress testing methodological framework Annex provides a foundation to build upon in future phases. The methodology strikes a balance between feasibility and comprehensiveness. We would offer the following perspectives on aspects that could be beneficial for each step in future phases of work:

Step 1: For the evidence gathering, it would be useful to further align the hazards of focus with the quantitative data from historical outage records as well as projections of how threats might evolve in the future climate.

Step 2: The Phase A vulnerability analysis centres around extreme events. However, fragility curves typically reflect an average response in relationship to a specific weather parameter. It would be useful to clarify how fragility curves will be produced to capture these extremes. Section 6.3 also acknowledges the potential for factors such as location, topology, type, age, condition and operation of assets to affect fault probabilities. Understanding the magnitude of these limitations is important for future phases of work.

Our prior work[1] demonstrated fragility curves differ regionally for wind related faults, with impacts varying seasonally and with wind direction. Furthermore, the current proposed method of using fragility curves does not account for interactions between hazards or the factors mentioned in Section 6.3. Given these limitations, a move from fragility curves to other more advanced methods of predictive analytics would be useful for future phases of the work[2].

Step 3: We do not have feedback on step 3.

[1] Daniel L Donaldson et al. "Enhancing power distribution network operational resilience to extreme wind events". In: *Meteorological Applications* 30.2 (2023), e2127. DOI: https://doi.org/10.1002/met.2127.

[2] Daniel L Donaldson and Saif Al-Omairi. *Informing standards for electricity distribution network resilience: Insight from IEEE Distribution Resiliency Guide and Metrics.* University of Birmingham, 2025. DOI: https://doi.org/10.25500/epapers.bham.00004399.

Step 4: We offer a further data-driven approach for consideration to support the aims of Step 4 (valuation and resilience options). This approach is a method termed "rerunning history"[3][4]. This method takes the recorded historical event data and reruns this history with the effects of proposed investment included to quantify the effect that the mitigations would have had if they had been implemented in the past. The rerunning history method can be used with the Climate resilience stress testing methodological framework to quantify the historical benefits of a candidate investment. This method can be applied to infrastructure investments to withstand higher wind speeds, investments to improve the event restoration, and others listed in Appendix 2 of the ED3 SSMC Climate resilience stress testing methodological framework Annex.

While this method does not predict the future, it has distinct advantages of realism and simplicity. In communicating the benefits of a proposed resilience investment to the public, the historical rerun directly relates to the lived experience of the public. Especially for particular large events, historical rerun can be more persuasive than benefits that are simulated for predicted events at some indeterminate time in the future. Overall this approach quantifies the benefits and costs of mitigating vulnerabilities, thereby enabling more informed decision-making for maintaining existing levels of climate resilience.

Step 5: We do not have feedback on step 5.

OFGEM Q97: "Do you have any views on the proposed CRMI Framework (Climate Resilience Metrics and Indicators (CRMI) Annex)? Do the CRMI Framework objectives and attributes reflect what's needed to measure climate resilience? Are there specific metrics or indicators we should consider?"

In addition to the metrics already considered in the CRMI Annex, we would like to suggest an additional metric for consideration: Annual Log Cost Resilience Index (ALCRI). ALCRI is a practical way to calculate customer risk using data that is already collected by utilities. ALCRI is computed by taking a yearly sum of the logarithms of past large weather event costs, where large event cost is the total customer minutes lost in the large event multiplied by the VoLL and normalized by the number of customers served by the DNO.

Tracking the cost of distribution system power outages shows that most outages are small and do not cost much, but a few are massive, such as those caused by a major storms, and are very expensive[5]. The costs of these high impact low frequency events can be thousands of times greater than the more common ones. Due to this huge variability in costs, if we try to calculate the average cost of large events over time, the result is erratic whenever one of the most extreme rare events occurs. For example, computing event cost as total event CML times VoLL while including large events gives erratic results. The usual average does not converge, and does not give a meaningful value that is representative of the large event risk[6]. It is similar to trying to find the average wealth in a room that includes a billionaire; the billionaire's wealth makes the average misleading. This is where the ALCRI metric can be beneficial. It focuses on the large events and uses a logarithmic transformation to handle these massive variations to obtain a stable and practical measure of the risk to customers from large blackouts.

[3] Arslan Ahmad and Ian Dobson. "Towards using utility data to quantify how investments would have increased the wind resilience of distribution systems". In: *IEEE Transactions on Power Systems* 39.4 (2024), pp. 5956–5968. DOI: https://doi.org/10.1109/TPWRS.2023.3342729.

[4] Arslan Ahmad and Ian Dobson. "Quantifying distribution system resilience from utility data: large event risk and benefits of investments". In: *IET Generation, Transmission & Distribution* 19.1 (2025), e70179. DOI: https://doi.org/10.1049/gtd2.70179.

[5] Arslan Ahmad and Ian Dobson. "Logarithmic Resilience Risk Metrics That Address the Huge Variations in Blackout Cost". In: *IEEE Transactions on Power Systems* 40.6 (2025), pp. 5507–5510. DOI: https://doi.org/10.1109/TPWRS.2025.3612225.

[6] Ibid.