Machine Learning to Densify IAM Scenario Ensembles for Policy Insight: A Proposal

Georgia Ray, Joeri Rogelj, Rossella Arcucci
Imperial College London

Problem Statement

Integrated Assessment Models (IAMs) link climate and economic systems to project how human activity shapes temperature outcomes [1]. However, different IAM modelling groups have biases, assumptions, and therefore outputs for the same scenario inputs [2]. This uncertainty accurately represents the uncertainty of the future, but it can be challenging for policy makers.

The AR6 Scenario Explorer and Database aggregates models and their different scenario inputs forcomparison in a centralized location. However, even this aggregation is:

- not a statistical sample of all potential futures
- sparsely populated
- computationally inefficient to mutate

Ongoing Work & Future Directions

Evidence of variability in other variables based on constraints on an individual variable (see *Figure 2*) indicates a learned represenation of the interdependency implicit in this high-dimensional scenario output space. Additionally, a precision of 80% is achieved, with 80% of real scenarios constrained near to the prescibed constraints falling within accepted ranges.

However, problems with consistency as have plagued other researchers who have generated scenarios [3] persist. The failure on sum checking (see *Figure 3*) for a vast majority of the generated scenarios, indicates the custom loss function is not working as expected, an area we will continue to explore.

If perfected, the proposed output would have several use cases:

(1) more efficient down-scaling of global climate targets for both state and non-state actors; an long-called for improvement on the sectoral decarbonisation approach [4]

(2) an exploration space for multi-agent reinforcement learning, an increasingly popular approach for actioning IAMs [5, 6]

(3) an increased ability to embed equity considerations as IAM constraints

References

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[2] Dekker, et al., Identifying energy model fingerprints in mitigation scenarios. Nature Energy 2023 8:12, 8:1395–1404, 11 2023. ISSN 2058-7546. doi: 10.1038/s41560-023-01399-1. URL https://www.nature.com/articles/s41560-023-01399-1.
[3] Li et al., Using deep learning to generate key variables in global mitigation scenarios. Nature Climate Change 2025, pages 1–9, 6 2025. ISSN 1758-6798. doi: 10.1038/s41558-025-02352-8. URL https://www.nature.com/articles/s41558-025-02352-8.
[4] Krabbe et al., Aligning corporate greenhouse-gas emissions targets with climate goals. Nature Climate Change, 5:1057–1060, 12 2015. ISSN 17586798. doi: 10.1038/NCLIMATE2770;TECHMETA=129;SUBJMETA=106,66,682,694,703,704,706;KWRD=BUSINESS,CLIMATE-CHANGE+MITIGATION. URL https://www.nature.com/articles/nclimate2770.
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Proposed Solution

A smooth output function over the solution space, providing densification within existing scenarios while maintaining uncertainty recognitions through non-deterministic ranges.

Current exploration is considering the use of a transformer-based scenario generator (See *Figure 1*), a more traditional statistical copula, and imputation via machine learning.

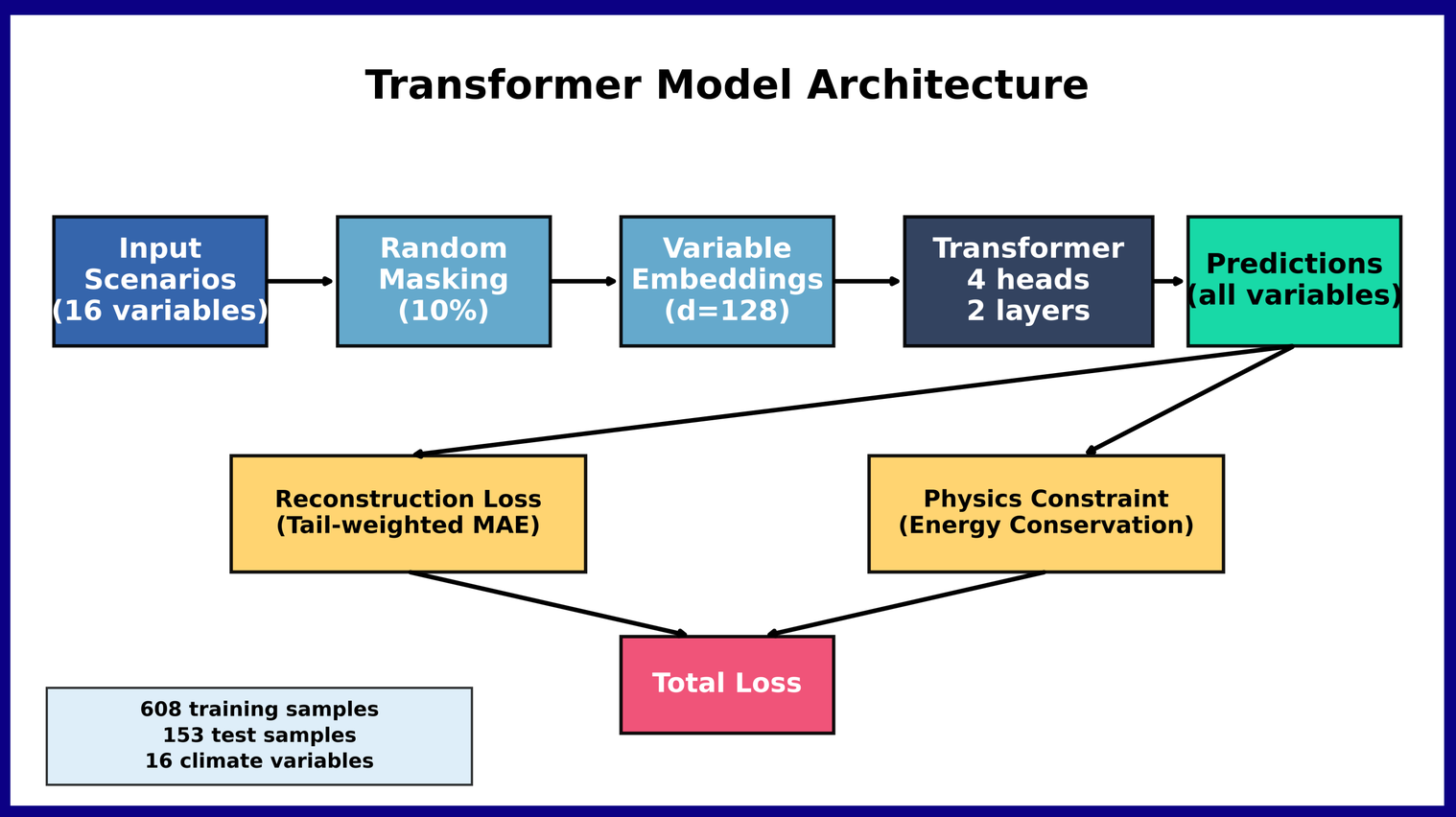

Figure 1. Early attempt at transformer architecture including custom loss function

Preliminary Results

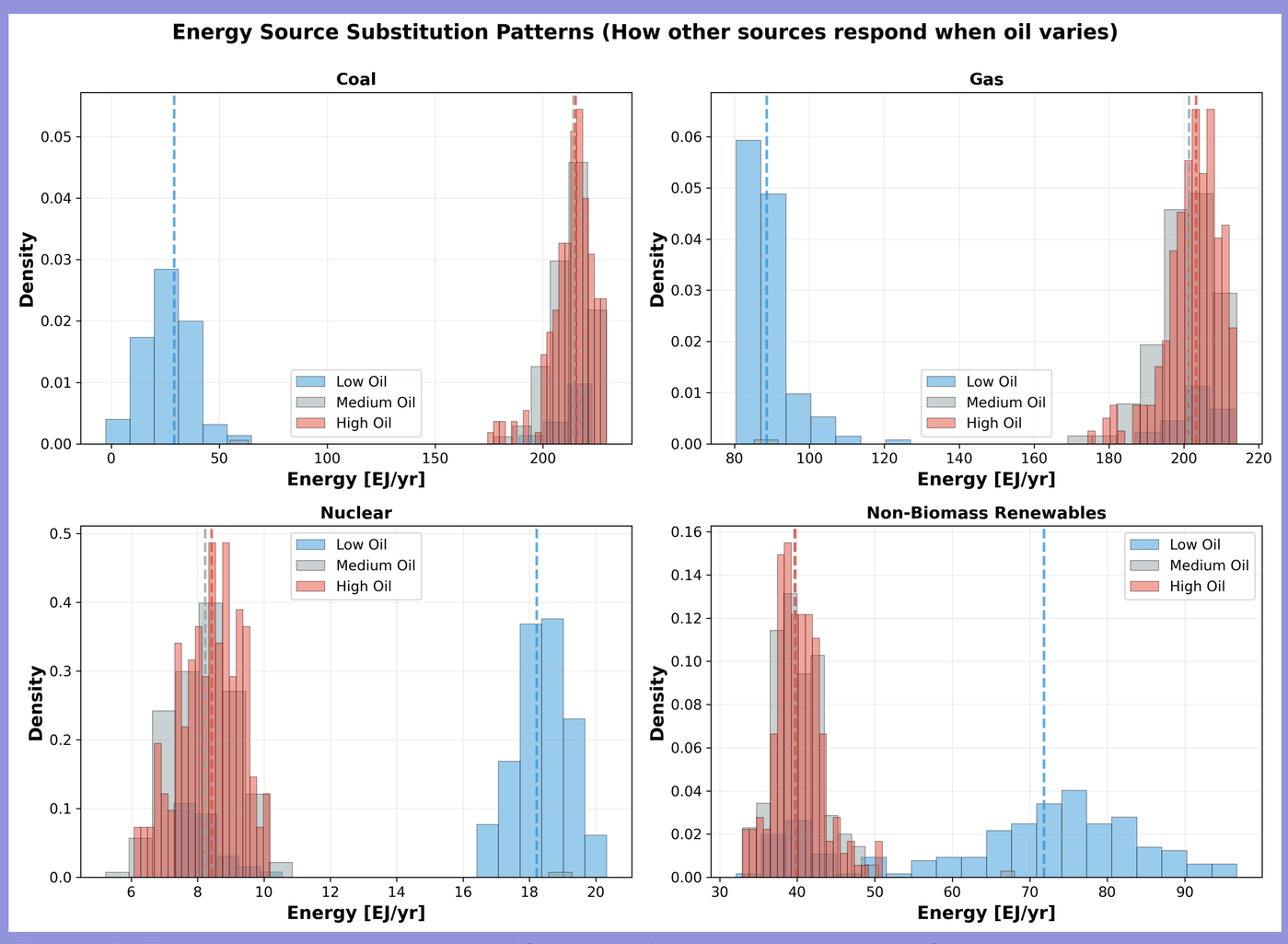

Figure 2. The changes in other variables based on constraints to oil; represented via percentile designations of low, medium, and high (25, 50, 75)

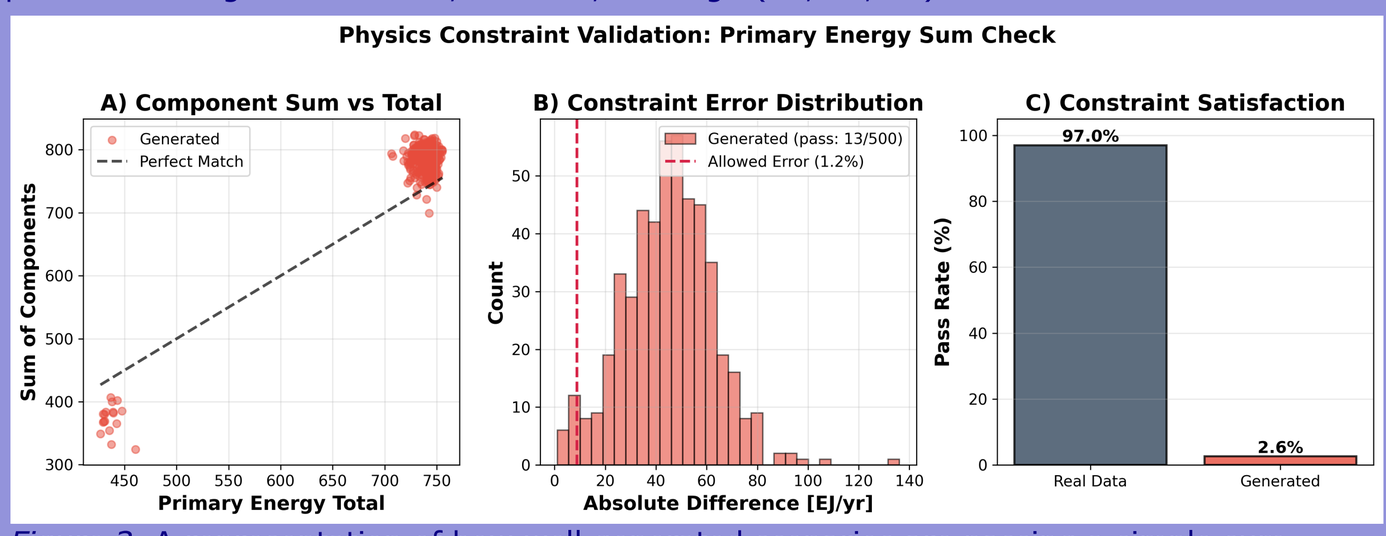

Figure 3. A representation of how well generated scenarios are passing a simple sum check; poor performance is aligned with other generative attempts and a direction for ongoing work