Supporting Information - Human-in-the-loop MGA to generate energy system design options matching stakeholder needs

Francesco Lombardi[1] *, Stefan Pfenninger[1]

1 TU Delft, Faculty of Technology, Policy and Management, Department of Engineering Systems and Services, Delft, Netherlands

* Correspondence: flombardi@tudelft.nl

Supporting Methods

Metrics to assess alignment with high-level preferences

Synthetic high-level preferences	Assessment metric	Computation logic	Units
Low import dependency	Import dependency rate	Ratio of electricity and hydrogen imports over total primary energy supply	non-dimensional
Limited wind concentration	Capacity-adjusted wind power share	Linear combination of the highest share of wind power capacity in any model region and the ratio between total deployed wind capacity and the maximum deployed across the original option space	non-dimensional
Limited new infrastructure	Overall capacity deployment	Total new electricity generation, storage, transmission and electrolysis capacity deployed	GW
Limited central planning	Degree of deployment of centralised technologies	One's complement to the weighted sum of capacity deployment for key technologies (the same as those considered for the *Yearly rate of infrastructure deployment*) normalised to their cumulative deployed capacity. The weights indicate qualitatively the extent to which a given technology's deployment can be driven by decentral initiatives. Solar roof-mounted has a decentral weight of 1; battery, wind onshore and solar open-field have a decentral weight of 0.5; all other technologies have a null decentral weight.	non-dimensional
Low hydrogen use	Deployment of electrolysers	Deployed electrolysis capacity	GW

Table A. Summary of metrics used to assess the performance of a given system design option with respect to the assumed synthetic high-level preferences.

Methods to assign weights in the SPORES MGA algorithm

In section 2.1.2 of the main text, we state that we further differentiate the N=45 system design options generated in each of the M=(5+1) parallel runs of the MGA-HITL workflow by adopting different MGA weights (w_{ij} in Equation 3). More precisely, we split these N=45 design options into three parallel batches of N=15 designs each, in which we adopt alternatively *integer*, *relative-deployment* or *evolving-average* weighting methods. These were introduced in prior work [2], and are here reported for convenience.

The *integer* weight-assignment method is reported in Equation S1. We apply it to location-technology decision variables (x_{ij}) rather than to system-wide technology variables only, thereby making it spatially explicit. The weight is summed to the weight obtained in the preceding iteration (w_{ij}^{n-1}), as it happens for all the other methods below.

$$w_{ij}^{n} = w_{ij}^{n-1} + k_{ij}, \;\; with\ k_{ij} = \begin{cases} 100,\ if\ x_{ij}^{cap,n} > c \\ 0,\ if\ x_{ij}^{cap,n} \leq c \end{cases} \tag{S1}$$

where c is a threshold defined to avoid very marginal deployments of capacity receiving a weight, which may lead to almost all decision variables receiving a non-zero weight. The weight is set to 100 based on the internal unit scaling of our model and in line with previous work [2].

The *relative-deployment* method, which we devised with a focus on spatial diversity in previous work [1], is outlined in Equation S2.

$$w_{ij}^{n} = w_{ij}^{n-1} + \frac{x_{ij}^{cap,n}}{x_{ij,max}^{cap}} \tag{S2}$$

where $x_{ij,max}^{cap}$ is the maximum potential for deployment of a given location-technology decision variable at that location.

Finally, the *evolving-average* method is illustrated in Equation S3. This method retains a more explicit memory of past iterations. It calculates, for each location-technology decision variable, its (absolute) distance from the average capacity deployed for that variable across all previously found feasible solutions ($\overline{x_{ij}}^{cap,n-1}$). Such a distance is continuously updated after each iteration. The weight is the inverse of the absolute distance; if the distance is small, the weight is high; vice versa, if the distance is large, the weight is small. The work where we first introduced this method showed that it provides a stronger push for technological diversity compared to the others [2].

$$\begin{cases} w_{ij}^{n} = \left(\left| \frac{\overline{x_{ij}}^{cap,n-1} - x_{ij}^{cap,n}}{\overline{x_{ij}}^{cap,n-1}} \right| \right)^{-1} \\ \overline{x_{ij}}^{cap,n-1} = \frac{\sum_{n=1}^{n-1} x_{ij}^{cap,n}}{n-1} \end{cases} \tag{S3}$$

References

1. Lombardi F, Pickering B, Colombo E, Pfenninger S. Policy Decision Support for Renewables Deployment through Spatially Explicit Practically Optimal Alternatives. Joule. 2020;4(10):2185–2207. doi:10.1016/j.joule.2020.08.002.

2. Lombardi F, Pickering B, Pfenninger S. What is redundant and what is not? Computational trade-offs in modelling to generate alternatives for energy infrastructure deployment. Applied Energy. 2023;339:121002. doi:10.1016/j.apenergy.2023.121002.