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Comparison of global sensitivity analysis methods for urban scale building stock energy models

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The aim of applying global sensitivity analysis methods (GSA) at simulation models is to characterise the impact that changes in the model input parameters have on the model output. GSA is a diagnostic tool that can guide model calibration and validation, support the prioritisation of efforts for uncertainty reduction or help with model-based decision-making (Pichery C., 2014 [1]; Song *et al*., 2015 [2]; Sarrazin *et al*., 2016 [3]).

As available processing power has increased, GSA has been steadily more utilised among building energy modellers, especially at individual building level (Tian, 2013 [4]). At building stock level, however, GSA has only scarcely been used (Fennell *et al*., 2019 [5]). Yet, several stock models are being used for decision and policy making. Even fewer studies investigated the performance of GSA at stock level (*e.g*., Cheng *et al*., 2011 [6]; Ascione *et al*., 2017 [7]), which leaves a huge gap in application at scale.

No model can be considered as a perfect representation of the world around us. All models inevitably contain uncertainty (Refsgaard *et al*., 2004 [8]). The gaps in our knowledge are bridged by assumptions, probability distributions, expert opinion, best guesses and a variety of other techniques (Gorris & Yoe, 2014 [9]). At small scale, modellers can generally rely on detailed high-quality data and less (critical) assumptions need to be made. At stock level, fewer and less detailed input parameters are generally available and the quality of the data is not always guaranteed. Furthermore, the complex physical energy equations (typically used at small scale building energy models) have to be simplified and generalised due to input parameter shortage and/or to allow for acceptable model computation times.

Hence, due to the high computation times necessary to perform a reliable GSA at scale and input data absence and/or shortage or a lack of GSA knowledge, researchers performing GSA also often limit the SA scope and/or computation time of their study by reducing the building stock size (*i.e*., the number of buildings in the stock) used for building stock model GSA as well as the number of model evaluations. The consequences of such constraints are a possibly increased uncertainty in the model output results and a reduction in GSA quality since convergence might not be reached.

Therefore, this study aims to broaden the knowledge of global sensitivity analysis application on building stock level by application of the Sobol' SA (Sobol', 1990 [10]), the Morris [11] method and DGSM [12] at an internally developed bottom-up building stock model (Delghust, 2015 [13]; Delghust *et al*., 2015 [14] [15]), based on ISO 13790 (ISO, 2007 [16]). The study will elaborate further on the required stock size, comparison of the model output of the three methods and to-be-expected uncertainty ranges for the model output and SA indices. Additionally, in order to confirm the robustness of SA results, the study will further check and elaborate on model convergence criteria.

The study is part of the IEA EBC Annex 70 on Building Energy Epidemiology (IEA EBC, 2017 [17]), where a group of research teams participated in a co-ordinated investigation to take existing GSA methods and apply them to their distinct stock models and datasets in a first attempt to quantify added value of GSA for building stock modelling. Through this process the teams aimed to examine:

- The challenges of defining input parameter uncertainties for large-scale BES models and collecting appropriate data.
- The applicability of different SA techniques in terms of robustness of results, quality assurance and computational cost.
- Key drivers of uncertainty in the models.

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