Real-time building design space exploration using two-sample Kolmogorov Smirnov tests to rank inputs according to multiple outputs

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1 Background

Building design is challenged by ever-increasing requirements towards energy demand, building costs, indoor climate, and sustainability. The industry seeks methods to support the multi-actor decision-making during the early design stage, which is characterized by an enormous design space that is difficult to model, and explore. To tackle this issue, we propose to: a) describe the variability of design parameters using uniform distributions, b) model the design space by a Monte Carlo analysis using quasi-random sampling, and c) explore the simulation results using Monte Carlo Filtering [1]. An interactive parallel coordinate plot (PCP) combined with histograms allows for real-time exploration of the simulations results by the multiple stakeholders (e.g. building owner, architects, and engineers).

Early building design typically involves many design parameters and multiple, opposing objectives (outputs). Thus, there is a need for Factor Fixing [2] of the least significant parameters prior to multi-actor meetings. Still, the PCP may contain an overwhelming number of coordinates that makes it difficult to immediately see which coordinates have been affected by a certain filter /criterion (figure 1). This study aims to see if SA using two-sample Kolmogorov-Smirnov test (KS-2-SA) can be applied to meet these challenges. KS-2-SA seems relevant since the MCF (or Factor Mapping) splits the simulations into *behavioral* and *non-behavioral* realizations [2] and MCF can be applied to models with multiple outputs (and inputs).

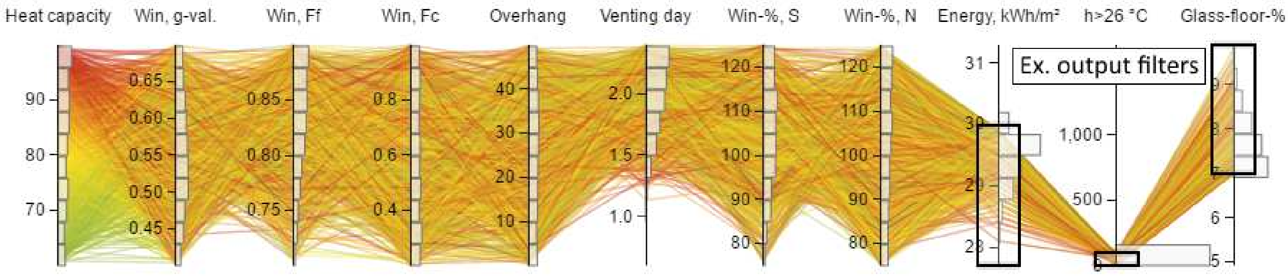

Figure 1: PCP shows input/output relationships while histograms show input/output distributions. Filters have been applied to output coordinates.

2 Methods

First, we consider sensitivity related to a single output (*Glass-floor-%* [1]). Suppose that we have performed N QMC realizations of the model output. The latter is split in J = 10 subsamples of equal probability (i.e. each subsample is approximately of size N/J). For each subsample, MCF compares the behavioral input sample (that produced realizations of the output in the current subsample) with the non-behavioral input sample (the complementary subsample). This comparison is carried out with the two-sample Kolomogorov-Smirnov statistics D_{ij}, j=1,…, J and i=1,…,d with d standing for the number of input parameters (1). For each input, an average of this statistic over the number of subsamples is computed (2). We test this approach by using different sizes of subsamples J (10, 4, and 2) and different sample sizes N (200, 2.000, and 5.000).

(1) $SA_{ks2,ij} = \dfrac{D_{ij}}{\sum_i D_{ij}}$ (2) $\overline{SA}_{ks2,i} = \dfrac{1}{J}\sum_j SA_{ks2,ij}$

As a test, we first investigate how sensitivity measures from KS-2-SA compares with other sensitivity analysis methods, i.e. Pearson's R, Spearman's ρ, SRC, SRRC, Morris, and SDP (state dependent parameter SA) [3]. To compare the SA techniques, we convert the sensitivity measures into percentages (despite that Morris provides a measure for the total sensitivity whereas SRC and others estimate sensitivity from first order effects only). Secondly, we try to extend this method (of removing subsamples) to three outputs in order to enable Factor Fixing and Factor Prioritization, i.e. rank inputs in the PCP according to their influence on the three outputs simultaneously.

For this case study, we use a shoebox shaped residential building with 3.000 m² floor area. A quasi-steady state simulation model based on ISO 13790 is used to evaluate energy demand and thermal comfort (measured as the number of hours in the years during which the mean temperature exceeds 26 °C). Daylight availability is assessed by the *Glass-floor-%*. Uniform input distributions are assigned to important design variables and the

[1] The variable *Glass-floor-%* describes the amount of glazing in the building's facades measured as the percentage of glazing area per heated floor area.

combination of these constitute our “design space”. This design space is represented by up to 5.000 Monte Carlo simulations (samples) using Sobol’s (LP_τ) low discrepancy sequences.

3 Findings

To evaluate the significance sample size N and subsample size J, we consider the “user-defined” output *Glass-floor-%*, which only depends on three variables: *Window frame factor*, *Window-%, South*, and *Window-%, North*. Thus, the remaining five variable inputs have no influence. To validate the results, we compare with the sensitivity percentages obtained from SRC. From figure 2.A, it seems that using subsample size of two is the best approach since the SA measures for the non-influential inputs are close to zero and to SRC measures. Figure 2.B shows how the sensitivity measure seems to improve with increasing sampling size N.

To compare different SA methods, we choose the least linear output *h>26°C* which has a $R^2_{SRC} = 0.729$ whereas *Energy demand* and *Glass-floor-%* have values of 0.988 and 0.996. Figure 2.C shows that the sensitivity measures from KS-2 are similar to those obtained from other methods. Only the SDP approach does not match the others.

Finally, we estimate sensitivity with respect to all three variables using KS-2. We added 7 variables – all with small variations. Each output distribution is split into two subsamples which results in 8 combinations of filtering. The added variables are correctly identified as having little influence (figure 2.D). The most important inputs are: 1) *Venting day*; 2) *Win-%, S*; 3) *Win, g-value*; and 4) *Win, Ff*. Indeed, the histograms for these coordinates on figure 1 seem to be affected the most by the applied filters, i.e. their behavioral distributions are the “least” uniform on figure 1.

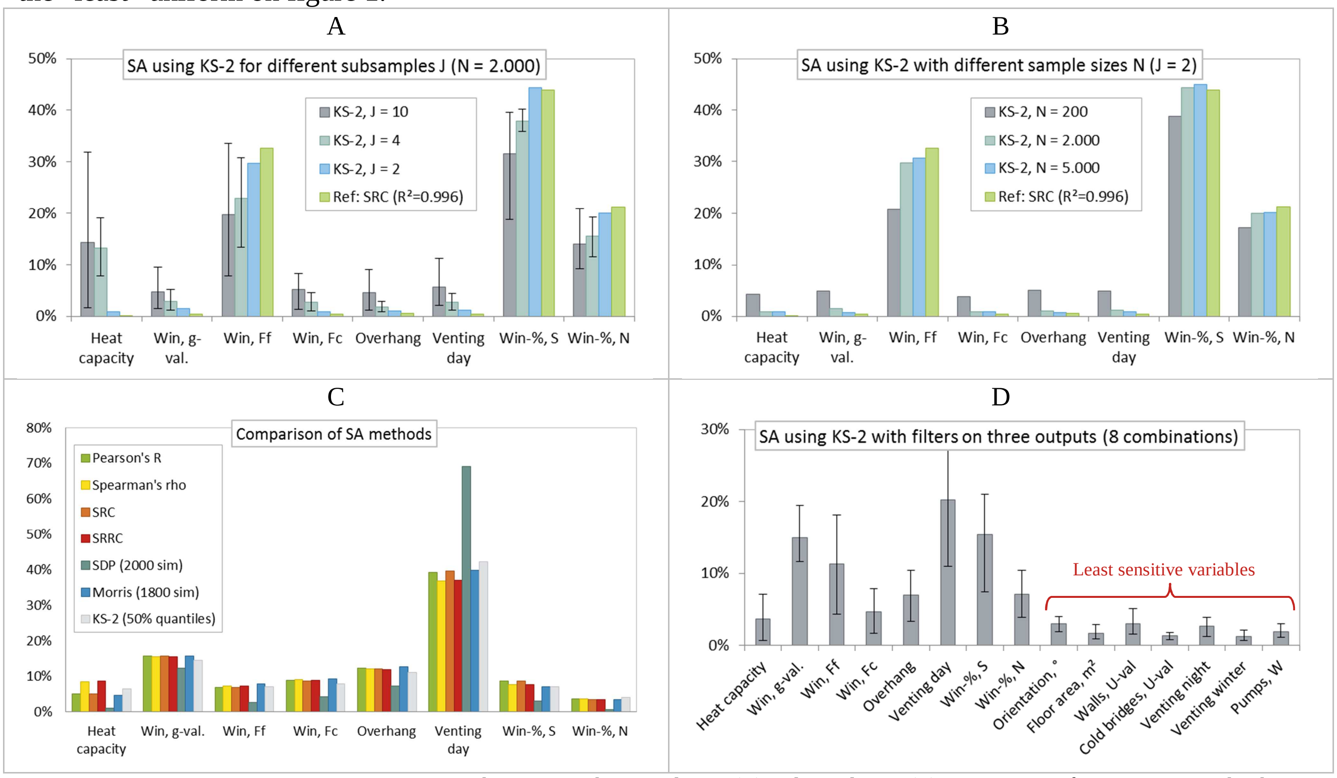

Figure 2: Comparing KS-2-test sensitivity measures when varying the quantile size (A) and sample size (B). Comparison of KS-2-test SA with other sensitivity measures based on 5.000 simulations (C). Ranking of inputs due to the combined sensitivity on 3 outputs (D).

4 Conclusion

KS-2 SA enables ranking (FP) and Factor Fixing of inputs with respect to multiple outputs. In future work, we will try to apply KS-2 SA together with PCP in real-time (Factor Mapping) so that the users immediately see which coordinates have been affected by the filtering.

5 References

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