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Discussions

Interactive comment on "Multi-objective parameter optimization of common land model using adaptive surrogate modelling" *by* W. Gong et al.

Anonymous Referee #2

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This paper presents an application of an efficient parameter optimisation technique developed by the authors. As the method is recently published and parts of it have already been presented elsewhere, the paper's contribution lies in the analysis of different surrogate model construction methods with respect to their application to multi-objective optimisation of a land surface model. To a certain extent, the paper achieves this aim. There are however a number of improvements that I would expect to see before publication as a final paper.

The most important improvements required are:

1. Acknowledgement and literature review of existing surrogate-based optimisation techniques

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Interactive Discussion

Discussion Paper

2. Discussion of the generality of the conclusions and assumptions underlying the results obtained

3. Clarification of some points which are not sufficiently well presented

4. Editing of typos, editing of language and filling in of placeholders

e.g. 'Artificial Neural Network (ANN) (REF) is a time-hornored marchine learning method comparing to the former four' p6736, L3

While the paper is already of interest, these changes would improve the quality of the manuscript and give the reader a clearer impression of the context and utility of the method proposed by the authors.

More detailed discussion follows:

1. Acknowledgement and literature review of existing surrogate-based optimisation techniques (dating back to at least 2001)

Given that the paper aims to promote the use of the author's new adaptive surrogate model based optimisation (ASMO) strategy (p6718 L25), I would expect to see acknowledgement and a brief overview of existing surrogate-based optimisation techniques within the main text, even if the author's have mentioned this literature in other papers/journals.

The paper appears to contain only one other reference to existing surrogate-based optimisation techniques: Song, X., Zhan, C., and Xia, J.: Integration of a statistical emulator approach with the SCE-UA method for parameter optimization of a hydrological model, Chinese Sci. Bull., 57, 3397–3403, 2012. p6729, L18 Appendix A1 'MARS method can be used as parameter screening method (Gan et al., 2014; Li et al., 2013; Shahsavani et al., 2010), and also surrogate modeling method (Razavi et al., 2012; Song et al., 2012; Zhan et al., 2013).'

A quick search for the terms "surrogate optimization" brings up at least the following

references, dating back to at least 2001 and including several reviews, a book and open-source implementations.

Ong, YewSoon, P B Nair, A J Keane, and K W Wong. 2005. "Surrogate-Assisted Evolutionary Optimization Frameworks for High-Fidelity Engineering Design Problems." In Knowledge Incorporation in Evolutionary Computation SE - 15, edited by Yaochu Jin, 167:307–31. Studies in Fuzziness and Soft Computing. Springer Berlin Heidelberg. doi:10.1007/978-3-540-44511-1_15.

Koziel, Slawomir, and Leifur Leifsson, eds. 2013. Surrogate-Based Modeling and Optimization. New York, NY: Springer New York. doi:10.1007/978-1-4614-7551-4.

Forrester, Alexander I.J., and Andy J. Keane. 2009. "Recent Advances in Surrogate-Based Optimization." Progress in Aerospace Sciences 45 (1-3): 50–79. doi:10.1016/j.paerosci.2008.11.001.

Jin, Yaochu. 2011. "Surrogate-Assisted Evolutionary Computation: Recent Advances and Future Challenges." Swarm and Evolutionary Computation 1 (2): 61–70. doi:10.1016/j.swevo.2011.05.001.

Jones, Donald R. 2001. "A Taxonomy of Global Optimization Methods Based on Response Surfaces." Journal of Global Optimization 21 (4). Kluwer Academic Publishers: 345–83. doi:10.1023/A:1012771025575.

Queipo, Nestor V., Raphael T. Haftka, Wei Shyy, Tushar Goel, Rajkumar Vaidyanathan, and P. Kevin Tucker. 2005. "Surrogate-Based Analysis and Optimization." Progress in Aerospace Sciences 41 (1): 1–28. doi:10.1016/j.paerosci.2005.02.001.

Zhou, Aimin, Bo-Yang Qu, Hui Li, Shi-Zheng Zhao, Ponnuthurai Nagaratnam Suganthan, and Qingfu Zhang. 2011. "Multiobjective Evolutionary Algorithms: A Survey of the State of the Art." Swarm and Evolutionary Computation 1 (1): 32–49. doi:10.1016/j.swevo.2011.03.001.

http://www.mathworks.com/matlabcentral/fileexchange/38530-surrogate-model-

optimization-toolbox

Optimisation methods that aim to provide satisfactory solutions given a limited computational budget should also be mentioned, in light of the comment that "Such parameter set might not be the true global optimum, but it is the "not bad" solution that is cheap enough we can afford." (P6725, L23) e.g. Tolson, B. A., and C. A. Shoemaker (2007), Dynamically dimensioned search algorithm for computationally efficient watershed model calibration, Water Resour. Res., 43, W01413, doi:10.1029/2005WR004723.

2. Discussion of the generality of the conclusions and assumptions underlying the results obtained

The application uses 40 parameters (p6719 L11) of a single land surface model (CoLM) applied to a single column case study (p6716, L17). It concludes (p6716 L19-22) that: "The result indicated that this framework can achieve optimal parameter set using totally 411 model runs, and worth to be extended to other large complex dynamic models, such as regional land surface models, atmospheric models and climate models."

This seems like a big jump given that doing so might involve:

- scalability of the technique to more parameters

- suitability of the response surface of the "other large complex dynamic models" to be fit by the surrogate technique

- suitability of the runtime of these larger models (411 may still be prohibitively large?)

- case-specific requirements as to how close it is necessary to be to the optimal value
- given that the result is not actually optimal, but rather 'similar with the one gotten from SCE method using more than 1000 model runs' (p6728, L12)

- availability of software that can be used with those larger models - given that software availability is not discussed at all

- varying impacts of considering only sensitive parameters, where insensitive parame-

ters may have significant interactions with sensitive parameters

- effect of stochasticity in sampling points to build and adapt the surrogate

...

At the very least, it would be useful for the paper to try to explain the factors affecting performance of the method, and its corresponding limitations.

3. Clarification of some points which are not sufficiently well presented

- p6716 the paper refers to the framework alternatively as a "uncertainty qualification framework" and "uncertainty quantification framework". In any case it is unclear how uncertainty is addressed at all, given that the result is a single set of optimal parameters corresponding to a single weighted objective function of multiple outputs.

- Discussion of the sufficient number of points should recognise the statistical fact that error commonly continues to decrease as sample size increases and that the sufficient number of points therefore depends on the required error for a particular purpose. It therefore seems misleading to say that: 'error becomes stable' p6721, L28 'elbow points' p6722, L5

It may also be of interest to mention that the absolute error in the surrogate's estimate of the objective function is less important than the ability of the surrogate to capture the relative value of the objective function across parameter space.

Loshchilov, Ilya, Marc Schoenauer, and Michèle Sebag. 2010. "Comparison-Based Optimizers Need Comparison-Based Surrogates", September. Springer-Verlag, 364–73. http://dl.acm.org/citation.cfm?id=1885031.1885071.

- The paper combines multiple objectives using weights. It states: "assign more weight to the objective function output, if that output is simulated more poorly as compared to other outputs" (p6724, L26) Clarification is needed to the effect that the weighting is calculated based on performance of the default parameters, i.e. outputs that need

more improvement are emphasised.

Otherwise I would expect that poor performance might be an indicator of error in data or model structure, in which case it is customary to assign weight inversely proportional to the error. The reference cited (Liu et al. 2005) divides each objective function by its performance with the default parameters, which appears to have the opposite effect - of giving less weight to poorly performing outputs?

4. Editing of typos, editing of language and filling in of placeholders

There are sufficiently many improvements necessary that the manuscript should be thoroughly reviewed in full. This includes but is not limited to pages 6716, 6718, 6723-6728, 6730-6733, 6736

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