Effective Visualisation of the High-Dimensional Pareto-Optimal Solutions

Maizura Mokhtar, Ian Hunt
School of Engineering & the Built Environment
Edinburgh Napier University, Merchiston Campus
Edinburgh EH14 5JH, United Kingdom
m.mokhtar@napier.ac.uk

Stephen Burns, Dave Ross
SRUC Research Division, Scotland's Rural College (SRUC)
Midlothian EH25 9RG, United Kingdom
(Stephen.Burns,Dave.Ross)@sruc.ac.uk

ABSTRACT

Visualising the Pareto-optimal solutions and their objectives can be challenging, more so when the number of objectives is large. The paper proposed the combined use of clustering and parallel coordinates plots to visualise the Pareto-optimal solutions. The trade-off surface is first segmented using a clustering algorithm, and parallel coordinates plots are then used to visualise the resulting set of Pareto-optimal designs. The paper described the analysis from the waste heat recovery system optimisation commonly found in the food and drinks process industries, comprising of a desuperheater coupled to a hot water reservoir. The system was parameterised, considering typical objectives, and MOEA was used to approximate the Pareto-optimal designs. The proposed visualisation was used to better understand the sensitivity of the system's parameters and their trade-offs, providing another source of information for prospective installations. *Original publication: M. Mokhtar, S. Burns, D. Ross, and I. Hunt, Exploring Multi-Objective Trade-Offs in the Design Space of a Waste Heat Recovery System, Applied Energy, Elsevier, Vol. 195, 1 June 2017, Pages 114-124*

CCS CONCEPTS

•Applied computing → Industry and manufacturing; Multi-criterion optimization and decision-making; *Command and control;*

KEYWORDS

Visualisation; Parallel coordinates; Multi-objective optimisation; Waste heat recovery

ACM Reference format:
Maizura Mokhtar, Ian Hunt and Stephen Burns, Dave Ross. 2017. Effective Visualisation of the High-Dimensional Pareto-Optimal Solutions. In *Proceedings of GECCO '17 Companion, Berlin, Germany, July 15-19, 2017,* 2 pages.
DOI: http://dx.doi.org/10.1145/3067695.3084377

1 INTRODUCTION

There is a growing interest in the use of Multi and Many Objectives Optimisation Algorithm, more so for the use of Multi and Many Objectives Evolutionary Algorithms (MaOEA). The key benefits of using MaOEA is that a set of Pareto-optimal solutions is approximated. However, when the number of objectives are large ($n > 3$), visualising the results of the Pareto becomes a challenge. More so when one wishes to convey both the trade-off information between the solutions, whereby, not only will the objectives have to be visualised, but there is a need to visualise both the solutions and their objective values together, in order for the trade-off information to be conveyed most efficiently.

To aid in the analysis of the results from high-dimensional multi-objective optimisation, and to identify a reduced set of representative designs, the paper has proposed an alternative method of visualising the Pareto-optimal solutions. The solutions are first clustered into k-number of clusters, either in the design space or the parameter space, to identify the degree of commonality between the solutions. For each cluster identified, parallel coordinate plots [1] are used to visualise the Pareto-optimal solutions. The correlation between a solution and its objective values in a specific cluster are identified by the common colour used in both plots. This method of visualisation can therefore reduce the number of figures (and tables) to depict the results significantly, down to $2k$ figures.

2 MULTI-OBJECTIVE OPTIMISATION

For the waste heat recovery system optimisation presented in the paper, the objectives that were considered for the optimisation are:

(1) to minimise the need for back-up energy when the heat captured by the WHRS is insufficient to meet demand,
(2) to maximise the overall savings when using the WHRS, i.e. the difference in the external energy usage with and without the WHRS installation,
(3) to minimise the temperature difference when the demanded temperature was not met,
(4) to minimise the temperature difference when the HWR water temperature exceeds the demand,
(5) to minimise the exceeding mass of water in the HWR from its maximum limit of $m_{wt_{max}}$, when the water is replenished from the mains,
(6) to minimise the waste heat not captured.

The parameters of the WHRS to be optimised are:

(1) $m_{wt_{max}}$: the maximum mass of water in the HWR, i.e. the capacity of the HWR,
(2) $m_{wt_{min}}$: the minimum mass of water that must be met when the hot water is demanded, also known as the depth of discharge (DoD),
(3) T_{mx}: the maximum temperature level of the HWR,
(4) $P_{b_{max}}$: the maximum power of the back-up heater,

GECCO '17 Companion, Berlin, Germany

DOI: http://dx.doi.org/10.1145/3067695.3084377

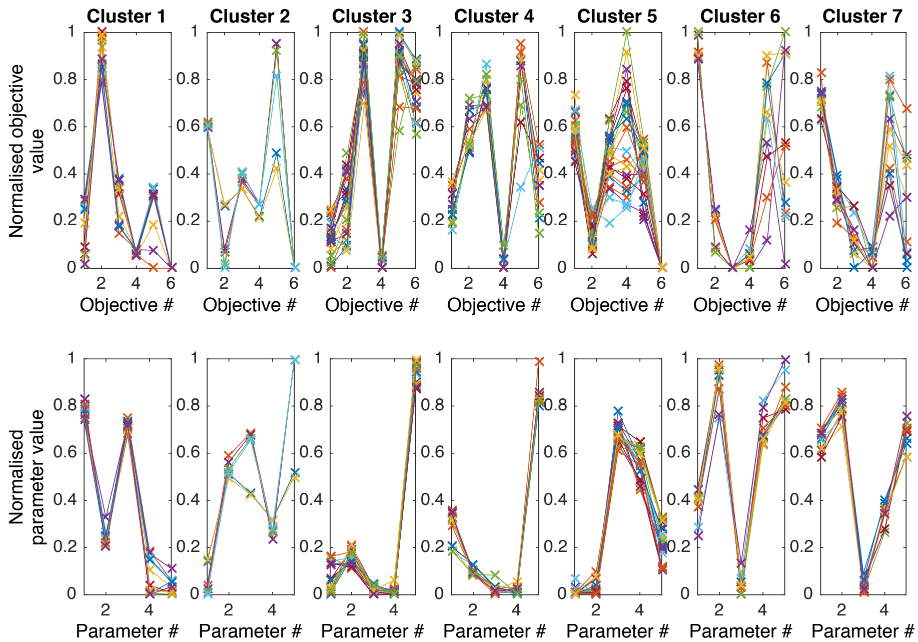

Figure 1: Parallel coordinate plots showing clusters of solutions in the Pareto set. Each solution in a cluster is indicated by a different coloured line.

(5) $\dot{m}_{wd_{max}}$: the maximum mass flow rate of the water entering the desuperheater (DSH).

Figure 1 depicts the Pareto-optimal solutions approximated and their objective values. To avoid clutter, the y-axes are not shown for each dimension; rather, all values are normalised and scaled to the interval [0, 1], allowing the use of a shared y-axis. The limits used in the normalisation for each objective and parameter are detailed in the paper. The correlation between a solution and its objectives values in a specific cluster is distinguishable by the common colour used in both plots. Typically, a company would prefer that a small HWR is to be installed. If a small tank (parameter 1) is preferable with small running cost (external energy used, objective 1), a solution is available from the Pareto-optimal set (clusters 3 and 4). The solutions however comes at the expense of the amount of waste heat recovered (objective 5), and in turn, in the amount of savings achieved (objective 2), if one was to compare these clusters with that of cluster 1, consisting of solutions with larger tank sizes. This similar observation was made in [2], whereby, if payback period was a priority, the solution will come at the expense of its efficiency and effectiveness of the waste heat recovery. If a small tank is, however, required, solutions in cluster 4 provide a better investment in comparison to those in cluster 3. The proposed visualisation method has aid in conducting this trade-off analysis.

3 CONCLUSION

The paper shows how a multiobjective evolutionary algorithm (MOEA) in concert with multidimensional visualisation methods can be used to explore the design space of a waste heat recovery system (WHRS), which recovers waste heat to provide hot water stored in a hot water reservoir (HWR). Multi-objective approaches explicitly identify solutions with different trade-offs, providing a broader view of possible design choices. This is particularly important when optimisation objectives are mutually exclusive, common in a number of the engineering systems. The MOEA, first, finds the Pareto-optimal solutions. Clustering is then used to partition the Pareto-optimal solutions into a smalller number of representative trade-off solutions that could be considered by potential installers, with the parallel coordinate plots used to visualise the solutions. The combination of the two therefore eased in the trade-offs analysis between the solutions. In the case study presented, if one was to prioritise the minimisation of cost through the installation of a small HWR, this may impact on the effectiveness and efficiency of the WHRS in recovering waste heat, and in turn the savings achieved. This trade-off is made obvious when the Pareto-optimal solutions and their objectives were displayed using the proposed visualisation methods.

ACKNOWLEDGMENT

This work was supported by Innovate UK (project no. 101995) and the Engineering and Physical Sciences Research Council (EP/M507180/1).

REFERENCES

[1] A. Inselberg. 1997. Multidimensional detective. In *Information Visualization, 1997. Proceedings., IEEE Symposium on.* 100–107.

[2] Chuan Zhang, Li Zhou, Pulkit Chhabra, Sushant S. Garud, Kevin Aditya, Alessandro Romagnoli, Gabriele Comodi, Fabio Dal Magro, Antonella Meneghetti, and Markus Kraft. 2016. A novel methodology for the design of waste heat recovery network in eco-industrial park using techno-economic analysis and multi-objective optimization. *Applied Energy* 184 (2016), 88 – 102.