Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 49-32 (2016) 124–128

Industrial Application of Multi-criterial Decision Support to improve the Resource Efficiency ⋆

Daniel Ackerschott * Benedikt Beisheim ** Stefan Krämer ** Sebastian Engell *

* *Technische Universität Dortmund, Emil-Figge-Straße 70, 44227 Dortmund, Germany (e-mail: daniel.ackerschott@bci.tu-dortmund.de)*
** *INEOS Köln GmbH, Alte Straße 201, 50769 Köln, Germany*

Abstract: The high complexity of integrated processing plants makes it a hard problem for managers and operators to find the best operational strategy. And it becomes even more difficult when they have to deal with more than one criterion for optimality because trade-offs between conflicting goals have to be taken into account. Usually optimisation problems are set-up with a single objective function, where several criteria are compressed into one figure by weighting factors. Thus, the result is a single number without any leeway in decision making. In contrast, multi-criterial optimisation reveals the room for manoeuvre. Since the plant personnel have to balance several requirements in order to run the plant in an "optimal" fashion, we propose to use multi-criterial optimisation to assist them in their daily decisions.
A prototypical tool was developed and the approach is applied to a real-world problem; a Butadiene plant in combination with cooling towers. The Butadiene plant consists of distillation columns and consumes a solvent, heating steam and cooling water, the cooling towers consume electric power. Thus, the criteria for the optimisation are the minimisation of these utilities. As they are interchangeable to some extent, conflicting goals appear naturally and the multi-criterial optimisation reveals the important interdependencies.

Keywords: Decision Support Systems, Multiobjective Optimisation, Genetic Algorithms, Chemical Industry

1. INTRODUCTION

The foundation for decision support systems was laid in the 1960s and the domain evolved strongly in the following decade (Shim et al., 2002). In the 1970s the combination of decision support systems and multi-criterial optimisation (MCDSS) gained attention in the research community (Korhonen et al., 1992). The reason is that many real world problems involve the optimisation of several, often competing, objectives (Fonseca and Fleming, 1993). With the standard approach to integrate these criteria in a single objective function using weighting factors (e.g. money), the view on the problem becomes quite narrow, the optimisation will provide only one solution, considering it to be the best achievable performance. In contrast, multi-criterial optimisation leads to a set of points that depict the inherent flexibility of the system and provide insight into the problem for the decision maker.

A general optimisation problem involving more than one objective (vectorial optimisation) can be defined as shown in (1). The aim is the simultaneous minimisation of the vector function y in M dimensions under inequality and equality constraints (g and h) as well as lower and upper bounds on the decision variables x.

$$\begin{array}{lll} min & y = (f_1(x), f_2(x), \dots, f_M(x))^T, & \\ s.t. & g_j(x) \geq 0, & j = 1, 2, \dots, J, \\ & h_k(x) = 0, & k = 1, 2, \dots, K, \\ & x_i^L \leq x_i \leq x_i^U, & i = 1, 2, \dots, N. \end{array} \quad (1)$$

There might be one solution that outperforms all other and thus would be the truly optimal solution. But in many real-life problems the objectives are competing and improvements in one criterion lead to deteriorations of other objectives. Therefore, it is reasonable to generate a set of solutions that represents good compromises.

Related to this set, there is the basic concept of Pareto-optimal solutions. These points in the multidimensional solution space are characterised by the fact that no improvement in one criterion is possible without the degradation of at least one other objective. Since these optima are better or as good as all other feasible points, they are called dominant. A solution y dominates another solution y^* ($y \prec y^*$) iff it is equally good (or better) in all and really better in at least one criterion as shown in (2). The aggregation of all Pareto-optimal solutions forms the Pareto frontier, which depicts the trade-offs between the objectives and reveals important interdependencies.

⋆ The research leading to these results was done within the project MORE (Real-time Monitoring and Optimization of Resource Efficiency in Integrated Processing Plants). The project has received funding from the European Unions Seventh Framework Programme for research, technological development and demonstration under grant agreement No 604068.

10.1016/j.ifacol.2016.12.201

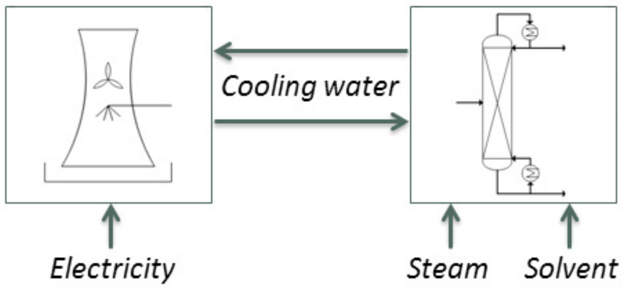

Fig. 1. Scheme of the combined models

$$y \prec y^* : \forall i \in 1,\dots,M : y_i \leq y_i^* \wedge \\ \exists j \in 1,\dots,M : y_j < y_j^* \quad (2)$$

2. DESCRIPTION OF THE CASE STUDY

As a case study the combination of a cooling tower and a Butadiene plant (shown in Fig. 1) has been investigated. The optimisation goal is the reduction of the resource utilisation, while maintaining the production rate and product quality. In the Butadiene plant, a complex distillation process separates a mixture of raw C4 chemicals in order to produce Butadiene as the main product. The two models are connected via the stream of cooling water that is provided by the cooling towers and is used in the Butadiene plant in several condensers. Its temperature strongly influences the overall performance of the distillation columns. The Butadiene plant also is a consumer of steam (on three different pressure levels) and of a solvent which is necessary to perform the separation task. The cooling towers consume electricity to power the fans. Due to the interconnections among and within the plants, all three resources (electricity, steam, and solvent) are partly interchangeable. The same holds for the three steam headers used in the Butadiene plant, since the distillation duty can be shifted (slightly) between the columns.

For the cooling towers a mixed-integer non-linear problem formulation was set-up that incorporates an external software package for the calculation of the thermodynamics. In this model electricity is the only resource applied, whereas the ambient air temperature and humidity are seen as disturbances. The simulation uses a reference state of the towers as the starting point and calculates the difference to this under the consideration of changes in terms of the incoming water and the environmental conditions. Details can be found in Beisheim et al. (2015) and MORE Project (2015).

The Butadiene plant model is derived from an MPC solution, which comprises two similar plants that run in parallel, as a linear gain model (cf. (3)). The state of the plant is denoted by y, the inputs to the plant are x and A represents the gain matrix. For all variables upper and lower bounds are specified. A new state is calculated as the old state plus the gain matrix multiplied with the difference in inputs at two points. As external disturbances the ambient air temperature and the cooling water temperature influence the state of the plant.

$$\Delta y = A \Delta x \quad (3)$$

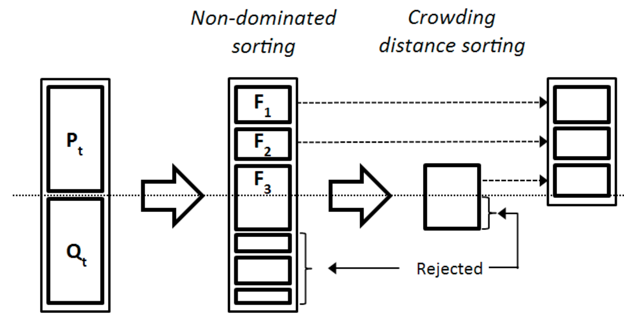

Fig. 2. Scheme of the NSGA-II algorithm (Deb et al., 2002)

3. MULTI-CRITERIAL OPTIMISATION

The multi-criterial optimisation is done by an evolutionary algorithm (EA), which is a variant of the NSGA-II algorithm (Deb et al., 2002) as implemented in MATLABs Global Optimization Toolbox. An evolutionary algorithm was chosen because of its applicability to a wide range of problems. Especially when mixed-integer nonlinear problem formulations (MINLP) which are not convex, have to be solved, evolutionary algorithms show a good performance in terms of finding near-optimal solutions. Furthermore, due to the fact that the cooling tower model contains an external software (blackbox) only derivative-free approaches are suitable to find good solutions.

The NSGA-II type algorithm is well suited for multi-dimensional optimisation, since it fulfils the requirements of elitism and a wide spread of the solutions along the Pareto front. The elitism is useful to keep good candidate solutions “alive” along the computation and therefore to ensure that good optima are not lost. The spreading ensures that the solutions will not focus on a small elite, hence stay in a narrow region, but the set of solutions will provide the full picture.

The algorithm solves the optimisation problem by a two-stage sorting and selection of candidate solutions (cf. Fig. 2). After the evaluation of one generation (P_t), a set of offspring (Q_t) is generated by standard operations in EA (tournament selection, recombination, and mutation). Both sets, the parents and the offspring, are merged and ranked by their non-domination level (F_i). A high quality of a solution denotes a low number of candidates that dominates it. Solutions with the highest level dominate all other candidates (except those at the same level).

The next generation is formed by the selection of the best non-dominated solutions. When a non-domination level cannot be transferred completely, due to the size limitation per generation, the crowding distance of every solution at this level is checked. The crowding distance describes the average distance of one solution to its nearest neighbour solutions, so, how crowded the surrounding is. To preserve a wide spread along the Pareto front it is favourable to have large distances between solutions. Again, the best solutions are selected to complete the new generation.

4. DECISION SUPPORT

Multi-criterial decision support systems classically assist managerial decision, but the described approach will be