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Bi-objective optimization of a water network via benchmarking

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ABSTRACT

This paper presents an approach to water system retrofitting by estimating both the economic and environmental impacts of a water network structure, using bi-objective optimization. The environmental impact is evaluated via benchmarking. By using benchmarking, the decision maker can have an insight, not only into the environmental impacts of certain designs belonging to Pareto optimal solutions, but also into the competitiveness of the design within a particular production sector. The economic criterion used is the total cost of the water network involving the freshwater cost, wastewater treatment cost, and the annual investment costs of storage tank, piping, and local treatment unit installation. A mixed-integer nonlinear programming (MINLP) model is used for water re-use and regeneration re-use within batch and semi-continuous processes. The Pareto fronts are generated using the classic and adaptive weighted-sum methods. The proposed approach was applied to an industrial case study within a brewery. The results obtained show that the benchmark could not be reached by process integration within the packaging area, therefore investment is needed regarding new technologies that lower freshwater consumption. Within the production area, however, the freshwater consumption could be reduced below the benchmark by water re-use and regeneration re-use, meaning that the brewery could achieve better performance than its competitors.

1. Introduction

Over the past decade, industries have begun to show more interest in minimizing the negative environmental impacts of designs, as a result of increasing environmental control costs and more demanding environmental regulations. In general, process design and optimization problems are based on economic objectives, such as capital investment, net present value, operating costs, and the payback period. Water network synthesis is being used in order to minimize the flow rate and cost of freshwater in the water supply systems of industrial plants by maximizing water reuse and regeneration re-use. The minimization of freshwater consumption in total water networks is mainly addressed by using the following two approaches: the graphical approach (Liu et al., 2009; Ng and Foo, 2009), and mathematically-based optimization approaches that can be sequential procedures (Liu et al., 2009) or simultaneous approaches, such as superstructure-based mathematical programming (Tan et al., 2009; Ahmetović and Grossmann, 2011) or genetic algorithms (Tudor and Lavric, 2010). The environmental aspect of water networks has recently become very important in design and optimization, in an effort to enhance their environmental performances. Process flow diagram (PFD)-based life cycle assessment (LCA) was used by Lim and Park (2007) to evaluate the environmental impacts of water networks. Ku-Pineda and Tan (2006) proposed a sustainable process index for the optimization of water networks. In order to minimize the total annualized cost and environmental impacts, Erol and Thoming (2005) applied multi-objective optimization. Finding an optimal solution that satisfies both the economic and environmental objective functions is often difficult within multi-objective optimization. Also, different environmental objectives may be conflicting or competing, and improving one may worsen the others. The central point of bi-objective optimization is to reveal the trade-offs between these two kinds of objectives.

1.1. Bi-objective optimization

In the real world, many engineering problems are multi-objective, for example maximizing profit with the desire of minimizing freshwater and/or energy consumption, minimizing cost with the requirement of maximizing safety etc. Multi-objective minimization of two objectives attempts to determine the

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trade-off curve (Pareto frontier) between the objectives, so that at any point on the curve the value of one objective cannot be decreased without increasing the other. Mathematically, the trade-off analysis can be defined as a vector nonlinear optimization problem with constraints. Each point on the trade-off curve is a solution of the multi-objective optimization (MOO) problem. A decision maker selects the final solution from among the Pareto points on the basis of additional requirements, which may be subjective. Therefore, it is desirable to have a sufficient number of well-spread Pareto points to represent the entire Pareto frontier at minimum computational cost. However, in the case of real design problems, the decision maker can only take into consideration only a few possible solutions. On the other hand, the decision maker can actively take part in the multi-objective optimization via an interactive approach based on iterative improvement of the identified best compromise alternative. This procedure terminates when the decision maker is fully satisfied with the offered best trade-off solution, Castelletti et al. (2010). In general, optimization methods can be split into two principal categories: classic methods based on deterministic approaches, and evolutionary algorithms based on stochastic algorithms (Ehrgott, 2005). In the classic methods, optimization is often reduced to the minimization of an aggregated objective function. In contrast, evolutionary methods consider all the objective functions in the optimization, simultaneously. The weighed-sum method is the simplest multi-objective optimization method, and has been widely applied. In general, a bi-objective mimization problem can be represented as follows:

$$
\begin{aligned}
&\text{Min} \quad f_1(\mathbf{x})\\
&Min \quad f_2(\mathbf{x})\\
&s.t. \quad \mathbf{g}(\mathbf{x}) \le 0\\
&\qquad\ \ \mathbf{h}(\mathbf{x}) = 0\\
&\mathbf{x} = [x_1 \ldots x_n]^T\\
&\mathbf{g} = [g_1(\mathbf{x}) \ldots g_{m_1}(\mathbf{x})]^T\\
&\mathbf{h} = [h_1(\mathbf{x}) \ldots h_{m_2}(\mathbf{x})]^T
\end{aligned}
\tag{1}
$$

where $f_j(\mathbf{x})$ is the vector objective function ($j = 1,2$), $\mathbf{x}$ is a vector of the decision variables, $\mathbf{g}$ and $\mathbf{h}$ are the inequality and equality constraints vectors. The weighted-sum method converts the bi-objective minimization problem into a scalar one by constructing a weighted sum of both objectives:

$$
\begin{aligned}
&Min \quad f(\mathbf{x}) = w_1 \cdot f_1(\mathbf{x}) + w_2 \cdot f_2(\mathbf{x})\\
&s.t. \qquad\qquad \mathbf{g}(\mathbf{x}) \le 0\\
&\qquad\qquad\quad\ \ \mathbf{h}(\mathbf{x}) = 0\\
&\mathbf{x} = [x_1 \ldots x_n]^T\\
&\mathbf{g} = [g_1(\mathbf{x}) \ldots g_{m_1}(\mathbf{x})]^T\\
&\mathbf{h} = [h_1(\mathbf{x}) \ldots h_{m_2}(\mathbf{x})]^T
\end{aligned}
\tag{2}
$$

where w_j is the weight of the objective function j. The main point of the problem here is to attach weights to each of the objectives. The weights do not necessarily represent the relative importance of the objectives or allow trade-offs between the objectives to be expressed. Although it is extensively used, the weighted-sum method has several disadvantages. First, even though there are many methods for determining the weights, a satisfactory a priori selection of weights does not necessarily guarantee an acceptable final solution for the decision maker. In fact, weights must be the functions of the original objectives not the constants, in order to accurately mimic the preference function by the weighted sum method (Messac, 1996). The second problem is that it is impossible to obtain points on non-convex portions of the Pareto frontier. The theoretical reasons for this shortcoming were given by Das and Dennis (1997) and Messac et al. (2000). The final difficulty with the weighted sum method is that even distribution of Pareto optimal points and an accurate, complete representation of the Pareto optimal set cannot be ensured by consistent and continuous variation of the weights. This was confirmed by Das and Dennis (1997), as well as that the spread of the points strongly depends on the relative scaling of the objectives. Kim and Weck (2005) proposed an adaptive weighted-sum method to ensure even distribution of a whole Pareto front. This method is focused on unexplored regions of the Pareto front by changing the weights adaptively and specifying additional inequality constraints. The optimal solutions are well-distributed when applying the adaptive weighted-sum method. The solutions within the non-convex regions are also identified, while the non-Pareto optimal solutions are neglected. Other classic methods able to provide even distribution of the Pareto front are the Normal-Boundary Intersection (Das and Dennis, 1998; Shukla and Deb, 2007; Messac et al., 2003), the Normal Constraint Method (Messac et al., 2003; Messac and Mattson, 2004), and the Physical Programming Method (Messac, 1996; Messac and Mattson, 2002).

1.2. Environmental impact assessment

There are several methodologies for the environmental assessments of products and processes (Herva et al., 2011). Life cycle assessment (LCA) and life cycle costing (LCC) methods are useful tools for evaluating the environmental burdens and economic costs during the life cycle (Azapagic and Clift, 1999; Lim and Park, 2007). The eco-efficiency of systems and processes can be improved by reducing environmental burdens and economic costs, while increasing profits and benefits. The Eco-Indicator 95, developed for the product LCA purposes (Goedkoop, 1995), uses nine environmental indices for assessment. The weighting factor of each index is determined based on the "distance-to-target" concept for the importance of each impact category, and has a value of between 2.5 and 100. The Eco-Indicator 95 is one of the more widely applied LCA approaches. The method of Minimizing Environmental Impact (MEIM) (Stefanis et al., 1995) uses principles of the LCA within a chemical process optimization framework. MEIM defines the process boundaries and waste emissions, quantifies the environmental impacts via defined metrics, and incorporates these metrics into the process design and optimization. The Waste Reduction (WAR) algorithm, developed by the U.S. Environmental Protection Agency (Hilaly and Sikdar, 1994), focused on identification of the existing and the generation of the potential environmental impacts within chemical processes. Shadiya et al. (2012) used WAR for evaluating the environmental impact of the modified acrylonitrile process obtained by multi-objective optimization linked with process simulation. The sustainable process index (SPI) was developed by Narodoslawsky and Krotscheck (2004) as a tool for evaluating industrial processes. Based on the LCA, it uses the mass and energy balances of the processes. The references used are the natural concentrations of substances within the compartments of the atmosphere, groundwater, and soil. Ku-Pineda and Tan (2006) applied the SPI for the optimization of water networks. A carbon footprint is a subset of the ecological footprints, which measures the total amount of carbon dioxide (CO_2) and methane (CH_4) emissions of a defined system (Qi and Chang, 2012). An overview of various footprints as indicators of sustainable development is given in Čuček et al. (2012). Composite footprints combining two or more individual footprints could also be assessed.

This paper applies bi-objective optimization in order to explore the trade-offs between the economic and environmental impacts during water network retrofits. An environmental sustainability index based on benchmarking is proposed in order to evaluate the environmental impact of the water network, while the total cost is