CMN 2017

Congress on Numerical Methods in Engineering

July 3 - 5, Valencia, Spain

Edited by: Irene Arias, Jesús María Blanco, Stephane Clain, Paulo Flores, Paulo Lourenço, Juan José Ródenas and Manuel Tur

Congress on Numerical Methods in Engineering

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WATER POLLUTION MANAGEMENT WITH EVOLUTIONARY MULTI-OBJECTIVE OPTIMISATION AND PREFERENCES

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Keywords: Water distribution systems, multi-objective optimisation, evolutionary multi-objective optimisation.

Abstract

Dealing with real world engineering problems, often comes with facing multiple and conflicting objectives and requirements. Water distributions systems (WDS) are not exempt from this: while cost and hydraulic performance are usually conflicting objectives, several requirements related with environmental issues in water sources might be in conflict as well. Commonly, optimisation statements are defined in order to address the WDS design and/or management. Multi-objective optimisation can handle such conflicting objectives, by means of a simultaneous optimisation of the design objectives. At the end of such process, a potential set of solutions, the Pareto front, are calculated. In such a set of solutions, there is not a best solution, but a preferable solution. In this paper, we will apply a multi-objective optimisation process with preferences in order to deal with a water pollution management constrained problem with 6 design objectives. With the provided example, it will be shown the usefulness of such tools for decision making and trade-off analysis for WDS management.

1 INTRODUCTION

Dealing with real world engineering problems often comes with facing multiple and conflicting objectives and requirements. Water distributions systems (WDS) are not exempt from this: while cost and hydraulic performance are usually conflicting objectives, several requirements related with environmental issues in water sources might be in conflict as well. Commonly, optimisation statements are defined in order to address the WDS design and/or management. Nevertheless, such problems become difficult since, besides their multi-objective conflicting nature, the optimisation problem might be non-linear (due to head-loss relationships for example) and/or discrete combinatorial (due to standardization of pipe parameters) [1].
Multi-objective optimisation can handle such an issue, by means of a simultaneous optimisation of the design objectives. At the end of this process, a potential set of solutions, the Pareto front, are calculated. In this set of solutions, there is not *a best solution*, but a *preferable solution*. This meaning that several solutions are calculated, with different trade-off between conflicting objectives and the engineer will select among them the most preferable for the problem at hand.
In this paper, we will apply a multi-objective optimisation process with preferences [2] in order to deal with a water pollution management constrained problem [3] with 6 design objectives. Such design objectives are related with maximising dissolved oxygen concentration at three locations while minimizing financial costs. With the provided example, it will be shown the usefulness of such tools for decision making and trade-off analysis for WDS management.
The remainder of this paper is as follows:in Section 2 a brief background on multi-objective optimisation is given. In Section 3 the case study is presented and in Section 4 its results are presented. Finally, some conclusions are given.

2 BACKGROUND

As referred in [4], a multiobjective problem (MOP) with m objectives, can be stated as follows:

$$\min_{\boldsymbol{x}} \boldsymbol{J}(\boldsymbol{x}) = [J_1(\boldsymbol{x}), \dots, J_m(\boldsymbol{x})] \tag{1}$$

subject to:

$$\boldsymbol{K}(\boldsymbol{x}) \leq 0 \tag{2}$$
$$\boldsymbol{L}(\boldsymbol{x}) = 0 \tag{3}$$
$$\underline{x_i} \leq x_i \leq \overline{x_i}, i = [1, \dots, n] \tag{4}$$

where $\boldsymbol{x} = [x_1, x_2, \dots, x_n]$ is defined as the decision vector with $\dim(\boldsymbol{x}) = n$; $\boldsymbol{J}(\boldsymbol{x})$ as the objective vector and $\boldsymbol{K}(\boldsymbol{x})$, $\boldsymbol{L}(\boldsymbol{x})$ as the inequality and equality constraint vectors respectively; $\underline{x_i}, \overline{x_i}$ are the lower and the upper bounds in the decision space.
It has been noticed that there is not a single solution in MOPs, because there is not generally a better solution in all the objectives. Therefore, a set of solutions, the Pareto set, is defined. Each

solution in the Pareto set defines an objective vector in the Pareto front (see Figure 1). All the solutions in the Pareto front are a set of Pareto optimal and non-dominated solutions:

Pareto optimality [4]: An objective vector $\boldsymbol{J}(\boldsymbol{x}^1)$ is Pareto optimal if there is not another objective vector $\boldsymbol{J}(\boldsymbol{x}^2)$ such that $J_i(\boldsymbol{x}^2) \leq J_i(\boldsymbol{x}^1)$ for all $i \in [1, 2, \ldots, m]$ and $J_j(\boldsymbol{x}^2) < J_j(\boldsymbol{x}^1)$ for at least one j, $j \in [1, 2, \ldots, m]$.

Dominance: An objective vector $\boldsymbol{J}(\boldsymbol{x}^1)$ is dominated by another objective vector $\boldsymbol{J}(\boldsymbol{x}^2)$ iff $J_i(\boldsymbol{x}^2) \leq J_i(\boldsymbol{x}^1)$ for all $i \in [1, 2, \ldots, m]$ and $J_j(\boldsymbol{x}^2) < J_j(\boldsymbol{x}^1)$ for at least one j, $j \in [1, 2, \ldots, m]$. This is denoted as $\boldsymbol{J(x_2)} \preceq \boldsymbol{J(x_1)}$.

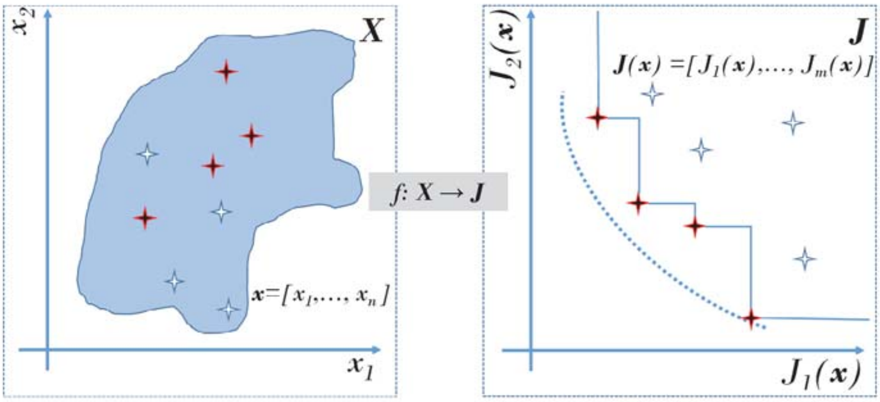

Figure 1: Pareto optimality and dominance concepts for a min-mim problem. Dark solutions is the subset of non-dominanted solutions which approximates a Pareto front (right) and a Pareto set (left). Remainder solutios are dominated solutions, because it is possible to find at least one solution with better values in all design objectives.

To successfully implement the multiobjective optimisation approach, three fundamental steps are required: the MOP definition, the multiobjective optimization (MOO) process and the multicriteria decision making (MCDM) stage. This integral and holistic process will be denoted hereafter as a multiobjective optimisation design (MOOD) procedure [5].

Multiobjective problem statement: design objectives definition, decision variables and their bounds, constraints for feasibility or suitability.

Multiobjective optimisation process: Pareto front approximation via an algorithm.

Multicriteria decision making: analysis of the approximated Pareto front, tradeoff analysis between design alternatives and final selection according to a set of preferences.

Next, we will use this MOOD procedure in a pollution management constrained problem.

3 CASE STUDY

Case study is based on the hypothetical condensed example of the bow river valley, as presented in [3]. It deals with the pollution problem due to a cannery industry (Pierce-Hall Cannery), to two sources of municipal waste (named Bowville and Plymton), with an a park in the middle (Robin State Park). Water quality is evaluated via dissolved oxygen concentration (DO). Waste content is measured with the biochemical oxygen demanding material (BOD) which is separated into carbonaceous and nitrogenous material (BODc and BODn respectively).

3.1 MOP definition

The MOP under consideration has 6 design objectives:

$J_1(\boldsymbol{x})$ **:** DO level at Bowville [mg/l] (maximise).

$J_2(\boldsymbol{x})$ **:** DO level at Robin State Park [mg/l] (maximise).

$J_3(\boldsymbol{x})$ **:** DO level at Plymton [mg/l] (maximise).

$J_4(\boldsymbol{x})$ **:** Return on equity [%] (maximise).

$J_5(\boldsymbol{x})$ **:** Tax increment (Bowville) (minimise).

$J_6(\boldsymbol{x})$ **:** Tax increment (Plymton) (minimise).

Additionally the DO at the state line $G_1(\boldsymbol{x})$ [mg/l] is considered. Decision variables $\boldsymbol{x} = [x_1, x_2, x_3]$ are the treatment levels of water discharge at the Pierce-Hall cannery, at Bowville and a Plymton respectively. The constrained MOP for optimisation is as follows:

$$\min_{\boldsymbol{x}} \boldsymbol{J}(\boldsymbol{x}) = [-J_1(\boldsymbol{x}), -J_2(\boldsymbol{x}), -J_3(\boldsymbol{x}), -J_4(\boldsymbol{x}), J_5(\boldsymbol{x}), J_6(\boldsymbol{x})] \tag{5}$$

subject to

$$\begin{aligned} G_1(\boldsymbol{x}) &\geq 3.5 & (6)\\ 0.3 \leq x_1 &\leq 1.0 & (7)\\ 0.3 \leq x_2 &\leq 1.0 & (8)\\ 0.3 \leq x_3 &\leq 1.0 & (9) \end{aligned}$$

where

$$\begin{aligned} J_1(\boldsymbol{x}) &= 4.75 + 2.27(x_1 - 0.3) & (10)\\ J_2(\boldsymbol{x}) &= 2.0 + 0.524(x_1 - 0.3) + 2.79(x_2 - 0.3) + \\ &\quad 0.882(w_1 - 0.3) + 2.65(w_2 - 0.3) & (11)\\ J_3(\boldsymbol{x}) &= 5.1 + 0.177(x_1 - 0.3) + 0.978(x_2 - 0.3) + \\ &\quad 0.216(w_1 - 0.3) + 0.768(w_2 - 0.3) & (12) \end{aligned}$$

$$J_4(\boldsymbol{x}) = 7.5 - 0.012\left(\frac{59}{1.09 - x_1^2} - 59\right) \tag{13}$$

$$J_5(\boldsymbol{x}) = 0.0018\left(\frac{532}{1.09 - x_2^2} - 532\right) \tag{14}$$

$$J_6(\boldsymbol{x}) = 0.0025\left(\frac{450}{1.09 - x_3^2} - 450\right) \tag{15}$$

$$\begin{aligned} G_1(\boldsymbol{x}) = {} & 1.0 + 0.0332(x_1 - 0.3) + 0.0186(x_2 - 0.3) + 3.34(x_3 - 0.3) + \\ & 0.0204(w_1 - 0.3) + 0.778(w_2 - 0.3) + 2.62(w_3 - 0.3) \end{aligned} \tag{16}$$

$$w_i = \frac{0.39}{1.39 - x_i^2}, i \in [1, 2, 3] \tag{17}$$

Table 1: Preference matrix $\mathfrak{m}$ for MOP statement. Five preference ranges have been defined: highly desirable (HD), desirable (D), tolerable (T) undesirable (U) and highly undesirable (HU).

Preference Matrix						
	← HD	→← D	→← T	→← U	→← HU	→
Objective	J_i^0	J_i^1	J_i^2	J_i^3	J_i^4	J_i^5
$-J_1(\boldsymbol{x})$ [mg/l]	-9	-8	-6	-4	-1	0.0
$-J_2(\boldsymbol{x})$ [mg/l]	-9	-8	-6	-4	-1	0.0
$-J_3(\boldsymbol{x})$ [mg/l]	-9	-8	-6	-4	-1	0.0
$-J_4(\boldsymbol{x})$ [$]	-9	-8	-6	-4.5	-1	0.0
$J_5(\boldsymbol{x})$ [%]	0	1	2	3	8	10
$J_6(\boldsymbol{x})$ [%]	1	1	2	3	8	10
$-G_1(\boldsymbol{x})$ [mg/l]	-6	-5	-4	-3.5	-2	-1

3.2 Methods for MOO and MCDM

The sp-MODEII algorithm [2] will be used , which is an evolutionary algorithm for multi-objective optimization which uses the preference matrix $\mathfrak{m}$ provided in Table 1 to evolve the population to the pertinent region of the Pareto front. For visualization, level diagrams are used [6, 7, 8], due to their capabilities to depict m-dimensional information [9].

4 ANALYSIS

Pareto front and set approximations using minimal information from preference matrix $\mathfrak{m}$ are depicted in Figures 2 and 3 respectively. Only those design alternatives which dominate the tolerable vector $T = [-4, -4, -4.5, 3, 3, -3.5]$ are used for such approximations. A total of 784 solutions are calculated. In Figures 4 and 5 the same problem is filtered and limited to 60 solutions (ten times the number of design objectives) using all the information provided by the preference matrix $\mathfrak{m}$. In such approximations, it is easier to perform a decision making analysis; furthermore, such analysis will focus on the most pertinent region of the objective space for the designer.

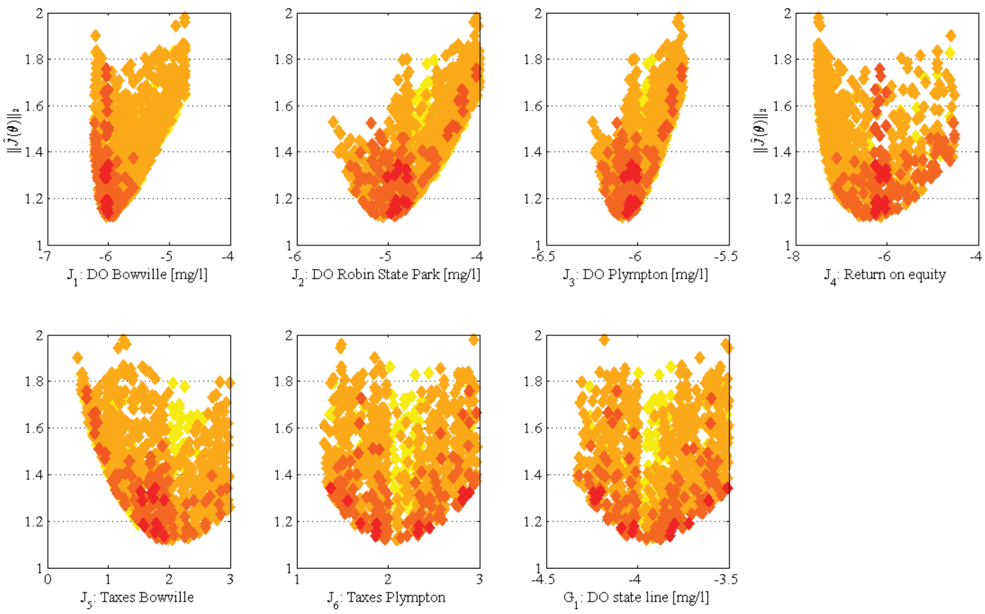

Figure 2: Pareto front approximation. The darker the solution, the mot preferable according to the Preference Matrix.

It can be noticed that, while there is certain degree of flexibility for decision variables x_1, x_3, for x_2 the recommended value practically lies in $x_2 \approx 0.84$. The expected return of equity, in agreement with the requirements for pollution control, is in the range $J_4(\boldsymbol{x}) \approx [-6.3, -6.0]$ [%] .

This allows to have a better understanding of the achievable trade-off of the MOP. If additional tools are required in order to support the decision making, methodologies as Topsis [10] or Promethee [11] could be used.

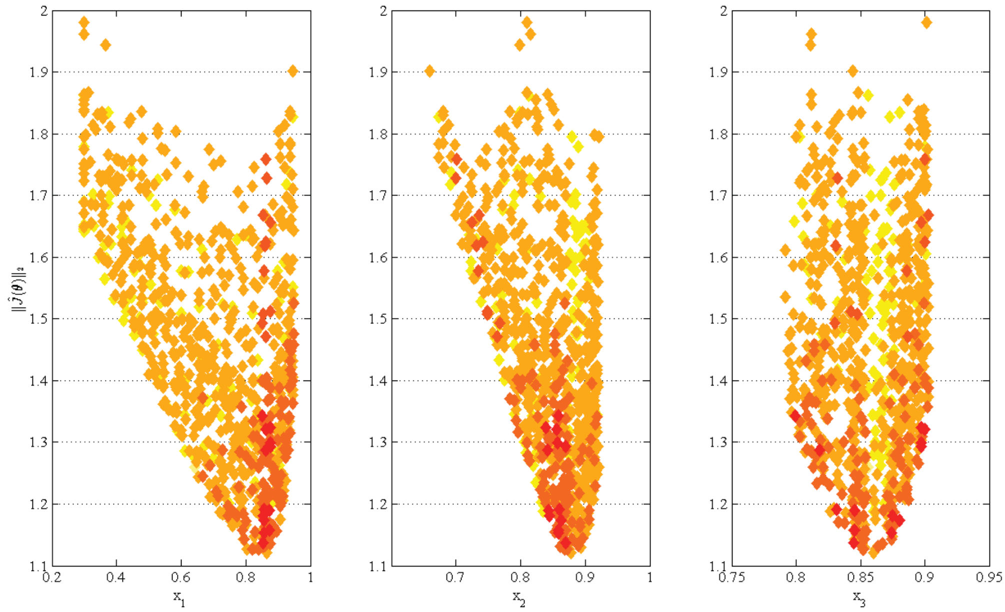

Figure 3: Pareto set approximation. The darker the solution, the mot preferable according to the Preference Matrix.

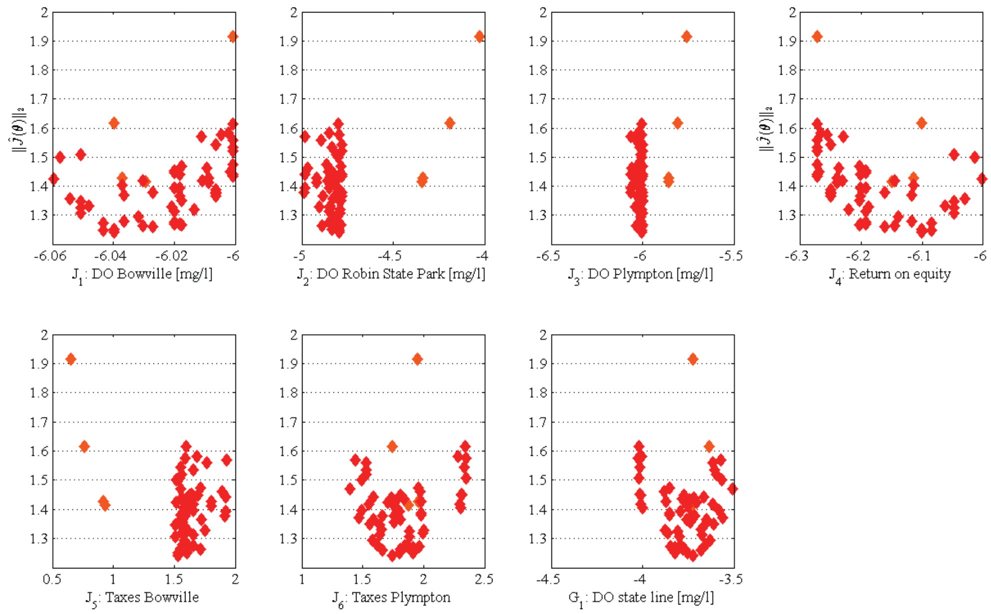

Figure 4: Pareto front approximation filtered with preference matrix $\mathfrak{m}$.

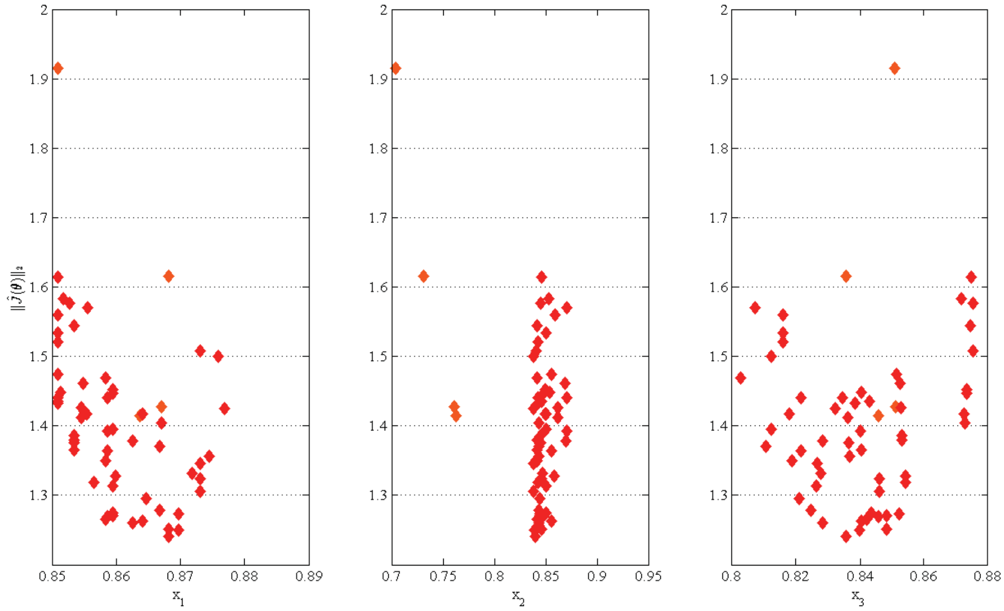

Figure 5: Pareto set approximation filtered with preference matrix $\mathfrak{m}$.

5 CONCLUSIONS

In this paper we applied a multi-objective optimisation process with preferences in order to deal with a water pollution management constrained problem with 6 design objectives. Such design objectives are related with maximising dissolved oxygen concentration at three locations while minimizing financial costs.

Two approaches were compared. The first of them, with minimal information about preferences. With such information, a Pareto front with several solutions was approximated. This could overwhelm the decision maker in the decision making step. The second approach, using more information about preferences, in order to filter the Pareto front in a more manageable set of solutions. Further work will focus on developing new tools for visualization and decision making for such instances.

ACKNOWLEDGEMENTS

First author would like to acknowledge the National Council of Scientific and Technological Development of Brazil (CNPq) for providing funding through the grant PQ-2/304066/2016-8. The second author acknowledges SEMNI for providing registration fees for this conference.

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