Systemic approach for the capacity expansion of multisource water-supply systems under uncertainty

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Abstract

Increased demand, reduced supply or the imposition of new regulations might evince the physical limitations of the current infrastructure of a water supply system and force structural intervention. The problem consists of determining capacity expansion solutions for multisource water supply systems from a long-term perspective, with some representation of the uncertainty that can be involved and the risk-averse behavior of the decision-makers. The systemic approach proposed includes a detailed simulation of physical processes, such as the water storage in surface reservoirs, the groundwater flow in aquifers and the water transport, with explicit representation of water quality. Water quality is a crucial element in multisource systems as the quality of the source water often varies. Different capacity expansion solutions can be obtained that explicitly balance the trade-offs between the gains in system performance and the cost of the solution. The application of the systemic approach developed for the western Algarve multi-municipal water supply system in Portugal shows that can deal with a real world case study.

Keywords: water supply; capacity expansion; optimization under uncertainty

Introduction

Water supply systems are subjected to a great many situations over their lifetime. In general, when water managers are faced with an inadequate performance by a water system they first seek ways to improve management strategies of the current infrastructure (Hsu et al. 2008). However, an increase in water demand, a decrease in the water supply or the imposition of new regulation might evince the physical limitations of the current infrastructure. Structural level interventions to expand the capacity of water supply systems include either the expansion of available infrastructure (e.g., new water source) or the rehabilitation of what is in place (e.g., replacement of pipes to reduce losses). Capacity expansion decisions should be taken from a long term perspective and consider how the systems will operate in an uncertain environment.

The seminal works of Beale (1955) and Dantzig (1955) introduced a proactive systemic approach based on the use of scenarios that explicitly took some knowledge about uncertainty during the operating period into account in planning models, aimed to find solutions less sensitive to the model data. Scenarios are discrete points of the uncertain parameter space set with a given probability. Many studies have been done in this field since those two seminal works. More recently, Mulvey et al. (1995) gave a new impetus to the scenario planning models by formulating an approach called robust optimization, which aimed to capture some of the risk-averse behavior of the decision makers. Specific metrics were introduced by Mulvey et al. (1995) to capture the notion of risk in scenario planning models. In addition, Mulvey et al. (1995) use weighted terms to evaluate the trade-offs between conflicting goals. Later, Ben-Tal and Nemirovski (1999) proposed a robust optimization approach that avoids the need to specify discrete scenarios with a given probability which was and used later by Housh et al. (2011). More recently, Monte Carlo simulation methods have been used to explore a variety of uncertainties in multiobjective problems and to find robust solutions (e.g., Kasprzyk et al. 2009, 2015; Steinschneider et al. 2015). The systemic approach proposed here is inspired by the scenario-based robust optimization field that began with Mulvey et al. (1995).

Recent research papers on scenario-based planning models addressing different uncertain factors and supporting decision-making about water supply infrastructure for multisource systems are described in Rosenberg and Lund (2009), Ray et al. (2012), Kang and Lansey (2013; 2014), Matrosov et al. (2013), Cai et al. (2015) and Lan et al. (2015). Although the above scenario planning models do consider robust optimization, climate change scenarios or a multistage planning problem, they either do not represent water quality or only handle it implicitly (e.g., low quality water with high treatment costs). The study presented here extends the design of water supply infrastructure for large scale multisource systems under uncertainty by describing the water transport with explicit representation of water quality. Water quality can be a crucial element when waters from different sources are used, in particular when the water is for drinking purposes. Two research papers describing scenario planning models for large-scale water supply systems, which address uncertainty and explicitly include water quality, are described in Housh et al. (2013a; 2013b) but the focus is long term management, not water supply infrastructure planning.

The modeling approach we describe has been developed to support capacity expansion solutions (i.e., expansion solutions) for multisource water supply systems at a specific time, taking a long term perspective and with an explicit representation of water quality. A distinction is made between the structural and operating decisions. Uncertainty, risk aversion and conflicting goals are also represented as in the scenario-based robust optimization approach introduced initially by Mulvey et al. (1995). Different capacity expansion solutions can be obtained and offered to the decision makers dealing with the trade-offs between two conflicting goals: system robustness and solution cost. The case study selected for demonstration covers a single stage infrastructure planning problem well, but the systemic approach presented here can be extended to a multistage planning problem in which the capacity expansion could take place over time, in multiple periods.

The remainder of this paper is organized as follows. The next section describes the systemic approach developed. That section is followed by one that sets out an application to a real based problem. The paper ends with a summary of its main conclusions. Additional details about the work presented here can be found in Vieira (2014).

Systemic approach

General description

The systemic approach presented here for the determination of capacity expansion solutions for multisource water supply systems results from the formulation of and connection between two decision models (designated as the operating model and the strategic model) in a coherent framework for addressing structural and operating decisions, uncertainty, risk and conflicting goals.

One expansion solution is defined by making one or more investments in water supply new or rehabilitated infrastructure at a specific time. Such structural decisions must be taken from a long-term perspective and considering the way the operation (e.g., abstractions from the water sources, pumping volumes, water allocation to users) will be performed over the project lifetime. During its operation, the system’s performance will be influenced by a variety of situations that might occur, depending on the behavior of a number of uncertain factors. As has long been recognized, failure to incorporate uncertainty in the planning process may result in solutions that do not meet needs in the immediate future, solutions that will become obsolete in the short/medium term or solutions that turn out to be oversized. The solutions sought are expected to perform well under a set of possible future situations (called scenarios).

In the subsections that follow describing the operating model, the strategic model and the solution method that ensures also the interconnection between the two decision models, Y is the vector describing the capacity expansion solutions, X_s is the vector describing the operating decision variables and S is the set of scenarios ($s \in S$). Vector Y is composed of binary elements (i.e., $Y \in \{0, 1\}$) and is 1 if it represents the development of one investment option (e.g., setting a new water source or rehabilitating a set of pipes to reduce losses), and 0 otherwise. The investment options to be made in the capacity expansion of a water system at a specific time are represented by the elements of Y whose value is 1 ($y = 1$). Each vector X_s is composed of non-negative elements (i.e., $X_s \geq 0$) representing the operating decisions (e.g., volume of withdrawals from each water source, the operation of the treatment and pumping facilities and the allocation of water from each source to demand centers) in scenario s. The operating decisions are discretized in monthly periods t over an operational planning time horizon T ($t \in T$).

Operating model

The operating model (*OM*) is used to obtain optimal operating decisions for each scenario. It adapts the optimization model developed by Vieira et al. (2011) to the capacity expansion problem handled here. The application of the operating model depends on the representation of each expansion solution as a flow network composed of arcs (A) and nodes (N). The arcs represent pipes and channels. The nodes are categorized as: supply nodes (N_S) representing water sources; demand nodes (N_D) representing urban areas, cities or principal urban reservoirs, and transshipment nodes (N_T), without supply or demand, representing water treatment plants, pumping stations and other components where pipes/channels join together or originate. Water quality is explicitly represented in the description of the water transport using the multicommodity network flow approach (Yang et al. 2000). Under this approach water from a different source, or simply of a different quality, is regarded as a separate commodity $k \in K$ sharing a common distribution system. The network flows are represented by the variable $x^k_{pq,t,s}$ which represents a non-negative flow of a water type identified by the index k in the network arc (p,q) from node p to node q in period t in scenario s. Fig. 1 represents a simple system with two water sources (source nodes: 1 and 2), one junction point (transshipment node: p), two demand areas (demand nodes: 3 and 4) and two multicommodity flows. Water leaving nodes 1 and 2 is identified by index $k = 1$ and $k = 2$, respectively.

Major constraints

The major constraints of the operating model include the simulation of the water storage in surface reservoirs; the groundwater flow at aquifers, and the water transport in the distribution network with explicit representation of water quality, as explained next. On the other hand, simple inequality constraints imposing minimum and maximum flows $x^k_{pq,t,s}$ (Fig. 1) can be included to model the abstraction from other types of water source (e.g., water transfer systems or desalination plants).

1. Water storage in surface reservoirs – Water balances in the source nodes representing surface reservoirs are used to model changes in the water storage:

$$S_{p,t,s} = S_{p,t-1,s} + \sum INF_{p,t,s} - \sum LOS_{p,t,s} - \sum OUTF_{p,t,s}\,,\ \ p \in N_{S_R},\ \ t \in T,\ \ s \in S \qquad (1)$$

where N_{S_R} = set of surface reservoir nodes ($N_{S_R} \subset N_S$) and $S_{p,t,s}$ = storage at reservoir p in the end of period t in scenario s. The other terms represent the sum of inflows ($INF_{p,t,s}$ – e.g., natural inflows, water transfers from other reservoirs), the sum of water losses ($LOS_{p,t,s}$ – e.g., evaporation, infiltration) and the sum of withdrawals and discharges ($OUTF_{p,t,s}$). This last sum is able to include different terms as follows:

$$\sum OUTF_{p,t,s} = R_{V_{p,t,s}} + R_{F_{p,t,s}} + R_{T_{p,t,s}} + DN_{p,t,s} + DE_{p,t,s}, \quad p \in N_{S_R}, \ t \in T, \ s \in S \tag{2}$$

where $R_{V_{p,t,s}}$ = withdrawals for the multisource water supply system (decision variable), $R_{F_{p,t,s}}$ = fixed withdrawals for other uses, $R_{T_{p,t,s}}$ = water transfers between reservoirs, $DN_{p,t,s}$ = discharges for downstream ecosystem maintenance that act as an environmental constraint, and $DE_{p,t,s}$ = spills to remain within storage capacity. The natural inflows, the fixed withdrawals and the discharges for ecosystem maintenance define the input data in the water balance given by Eqs. (1) and (2). All other terms are calculated as the model is solved. A simple water balance guarantees the continuity between the withdrawals $R_{V_{p,t,s}}$ from Eq. (2) and one specific water flow in the multicommodity network:

$$R_{V_{p,t,s}} = \sum_{q:(p,q)\in A} x^{k^p}_{pq,t,s}, \quad p \in N_{S_R}, \ t \in T, \ s \in S \tag{3}$$

where k^p = multicommodity water flow leaving node p ($k^p \in K$).

2. Groundwater flow at aquifers – Distributed parameter simulation models are incorporated in the model constraints by means of the matrix response approach proposed by Maddock (1972) and since used by many others in decision models (see review by Harou and Lund 2008). The piezometric levels are calculated at selected locations with simple expressions that are able to reproduce the effect of multiple abstractions:

$$h_{i_p,t,s} = h0_{i_p,t,s} - \sum_{w_p\in W_p} \sum_{j=1}^{t} \beta_{i_p,w_p,t-j+1} VG_{w_p,j}, \quad i_p \in I, \ t \in T, \ s \in S \tag{4}$$

where I = set of locations for piezometric level control, W_p = set of wells in aquifer p, $h_{i_p,t,s}$ = piezometric level at location i_p at the end of period t in scenario s,

$h0_{i_p,t,s}$ = piezometric level at location i_p at the end of period t in scenario s in the absence of any withdrawals from the set of wells W_p, $\beta_{i_p,w_p,t-j+1}$ = drawdown at location i_p in period t owing to a unit pumping at well w_p in period j, and $VG_{w_p,j}$ = volume of withdrawals for the multisource water supply system at well w_p in period j (decision variable). The variables $\beta_{i_p,w_p,t-j+1}$ and $h0_{i_p,t,s}$ in Eq. (4) are data calculated prior to the optimization with the distributed parameter groundwater simulation flow model of aquifer p. Variables $\beta_{i_p,w_p,t-j+1}$ represent the response of the aquifer to a unit pumping of water at any location. The piezometric levels $h0_{i_p,t,s}$ are calculated from an initial piezometric surface, each scenario $s \in S$ of distributed recharge and one volume of fixed pressures (e.g., withdrawals for other uses) in each $t \in T$. Water balances similar to Eq. (3) guarantee the continuity between each $VG_{w_p,j}$ and one specific multicommodity water flow. Minimum piezometric levels at i_p are included to prevent problems related to the overexploitation of groundwater resources.

3. Water transport in the distribution network – Two sets of constraints are used to model the water flows in the distribution network, with explicit representation of the water quality:

$$\sum_{q:(p,q)\in A} x^k_{pq,t,s} - \sum_{q:(q,p)\in A} x^k_{qp,t,s} = b^k_{p,t,s}, \;\; p \in N, \;\; k \in K, \;\; t \in T, \;\; s \in S \tag{5}$$

$$\frac{x^k_{pq,t,s}}{\sum_{k\in K} x^k_{pq,t,s}} = \frac{x^k_{pr,t,s}}{\sum_{k\in K} x^k_{pr,t,s}}, \quad \text{for all } (p,q)\,,(p,r) \in A, \;\; k \in K, \;\; t \in T, \;\; s \in S \tag{6}$$

Constraint (5) ensures the individual continuity of the $k \in K$ water flows at any network node p and $b^k_{p,t,s}$ = sink/source term of water type k at node p in period t in scenario s. Constraint (5) reduces to $\sum_{q:(p,q)\in A} x^k_{pq,t,s} = b^k_{p,t,s}$ in source nodes (N_S) and to $-\sum_{q:(q,p)\in A} x^k_{qp,t,s} = b^k_{p,t,s}$ in demand nodes (N_D). Constraint (6) models a perfect mixing condition by requiring that all outgoing flows from each node have the same volumetric blending ratio of each multicommodity flow $k \in K$. This hypothesis can be justified for planning purposes with timescales of one month (Yang et al. 2000), and the water quality is specified in terms of volumetric blending ratios. Inequality constraints are also included to limit the flows in each arc for describing properly the water distribution infrastructure.

The water allocated to each demand node p in period t and scenario s ($C_{p,t,s}$) is equal to the sum of all $k \in K$ inflows [Eq. (7)] and is upper-bounded by the demand [Eq. (8)]:

$$C_{p,t,s} = \sum_{q:(q,p)\in A} \sum_{k\in K} x^k_{qp,t,s}, \quad p \in N_D,\ t \in T,\ s \in S \tag{7}$$

$$C_{p,t,s} \le D_{p,t,s}, \quad p \in N_D,\ t \in T,\ s \in S \tag{8}$$

Objective function

The main objectives of the water utilities during the operation are represented in the objective function to be minimized that includes the variable operating costs and a set of penalty functions:

$$z_{OM,s} = VOC_s + PEN_{Def,s} + PEN_{TMix,s} + PEN_{DE,s} \tag{9}$$

The variable operating costs (*VOC*) includes all costs that depend on the quantity of water supplied. The penalty functions minimize deviations from the objectives to satisfy the demand (*Def*) and to deliver water of the appropriate quality (*TMix*). The last term is not an operating objective but it is included to prevent unnecessary excess discharges from reservoirs (*DE*). The three penalty functions included in Eq. (9) can be written as follows:

$$PEN_{Def,s} = \sum_{t\in T}\sum_{p\in N_D} Wgt_{Def} \times \frac{\left(D_{p,t,s} - C_{p,t,s}\right)^2}{D_{p,t,s}} \tag{10}$$

$$PEN_{TMix,s} = \sum_{t\in T}\sum_{p\in N_D}\sum_{k^-\in K^-} Wgt_{TMix^{k^-}} \times \left\{\max\left[\left(\frac{\sum_{q:(q,p)\in A} x^{k^-}_{qp,t,s}}{C_{p,t,s}} - TMix^{k^-}\right), 0\right]\right\}^2 \tag{11}$$

$$PEN_{DE,s} = \sum_{t\in T}\sum_{p\in N_{S_R}} Wgt_{DE} \times DE_{p,t,s} \tag{12}$$

The first term of Eqs. (10)-(12) is a weight factor (*Wgt*) to be selected by the analysts to prioritize the objectives in each situation. Water allocated cannot exceed the demand [Eq. (8)] and any deficit at a demand node – i.e., $D_{p,t,s} - C_{p,t,s} > 0$ – is penalized in relation to the value of the demand [Eq. (10)]. In Eq. (11), the set $K^- \subset K$ defines the set of multicommodity flows subjected to the control of the volumetric blending ratios. The “max” function ensures that blending of water type k^- is penalized only above the volumetric blending ratio objective $TMix^{k^-}$. The penalty functions given by Eqs. (10) and (11) are quadratic so that greater deviations from the objectives of satisfying the demand and delivering water of the appropriate quality are more heavily penalized. Excess discharges ($DE_{p,t,s}$) in Eq. (12) are also included in the water balance defined by Eqs. (1)-(2). These discharges must be included in the water balance to keep storage within reservoir capacity if necessary. Without Eq. (12), unnecessary excess discharges could be suggested from the solution of the operating model when VOC are minimized, and $PEN_{Def,s} = 0$ and $PEN_{TMix,s} = 0$ (i.e., demand and water quality requirements are satisfied in all time periods, respectively).

Condensed formulation

The condensed formulation of the operating model can be written as follows:

$$\underset{X_s}{\text{Min}}\ z_{OM,s} = f_s(A_s,X_s) \tag{13}$$

$$\text{subject to (s.t):}\ g_{m,s}(B_s,X_s) = 0 \qquad m \in M \tag{14}$$

$$X_s \geq 0 \tag{15}$$

where $f_s()$ is equivalent to Eq. (9), $g_{m,s}()$ includes Eqs. (1)-(8), A_s and B_s are generic vectors of parameters and X_s, as already described, defines the operating decisions to be optimized. All X_s can be written as individual or combined network flows $x^k_{pq,t,s}$ as illustrated in Eqs. (3) and (7).

Strategic model

The strategic model (*SM*) is defined by an objective function integrating two metrics – the performance index and the normalized solution cost. The description of these two metrics is followed by the complete definition of the objective function; and the condensed formulation of the strategic model using the notation previously introduced, where Y is the vector describing the capacity expansion solutions and X_s is the vector describing the operating decision in each scenario s. As detailed in the description of the solution method, the strategic model is used at each iteration to evaluate one capacity expansion solution, assuming optimized operating decisions for all scenarios. Thus, the value of all the metrics and the objective function of the strategic model are calculated with one vector Y and one set of vectors X_s for all scenarios $s \in S$.

Performance index

Indexes (or indices) aggregate in one single value the information given by a set of performance criteria (or indicators). McMahon et al. (2006) claim that the use of indexes is not a major issue in the context of a single reservoir system but it could be useful for the comparison of several systems. As stated by Sandoval-Solis et al. (2011), indexes can be a valuable tool for evaluating and comparing the performance of water systems and water management policies if they are built in a meaningful manner. For example, Cai et al. (2002), Tsai et al. (2009) and Ray et al. (2014) have previously extended the use of individual performance criteria or aggregated metrics in water supply related problems handled by decision models.

The performance index (*PI*) developed to evaluate the expansion solutions includes three performance criteria, namely, two (*Rel* and *Vul*) about water quantity and one (*VBld*) about water quality. *Rel* (from reliability) and *Vul* (from vulnerability) are related to the quantity of water supplied and embody the general characteristics proposed for these indicators by Hashimoto et al. (1982). *VBld* is the water quality criterion. The non-inclusion of a performance criterion representing the system's resilience in the *PI* might be questionable in issues related to sustainability. But Kjeldsen and Rosbjerg (2004) and McMahon et al. (2006) conclude that resilience and vulnerability tend to show a strong correlation. If we accept this relation, then only one of these criteria should be included in an aggregated performance index so that redundant information is not included. McMahon et al. (2006) claim that vulnerability is more tangible because it quantifies the water shortage.

Reliability is computed from the optimal operation in each scenario $s \in S$ for each expansion solution tested during the solution process as follows:

$$Rel_s = \frac{\sum_{t \in T} C_{t,s}}{\sum_{t \in T} D_{t,s}} \tag{16}$$

where $C_{t,s} = \sum_{p \in N_D} C_{p,t,s}$ and $D_{t,s} = \sum_{p \in N_D} D_{p,t,s}$ [see Eqs. (7) and (8)]. As defined in Eq. (16), *Rel* is also named as the volumetric reliability and returns the average ratio between the water supplied and the water demand.

The vulnerability refers to the magnitude of the deficits from the operation of the water systems. Kundzewicz and Kindler (1995) and Kjeldsen and Rosbjerg (2004) agree that vulnerability metrics based on average deficits are not appropriate after non-monotonic behavior was observed when demand increased. The results from both studies suggest that maximum deficit values appear to be better for obtaining vulnerability metrics with monotonic behavior. Here, the vulnerability in each scenario *s* is defined by the maximum ratio between total deficit and total demand in all time periods:

$$Vul_s = \max_{t \in T} \left(\frac{D_{t,s} - C_{t,s}}{D_{t,s}} \right) \tag{17}$$

as $D_{t,s}$ and $C_{t,s}$ as defined in Eq. (16).

The water quality criterion is to some extent similar to the function formulated for penalizing failures in the supply of water with the appropriate quality in the operating model [PEN_{TMix} – Eq. (11)]. The value of the $VBld_s$ is aggregated and corresponds to the highest positive deviation of the volumetric water blend $k^- \in K^-$ from $TMix^{k^-}$ in all demand nodes *p* and time periods *t*:

$$VBld_s = \max_{p \in NN_D,\, t \in T, k^- \in K^-} \left[\left(\frac{\sum_{q:(q,p) \in A} x_{qp,t,s}^{k^-}}{C_{p,t,s}} - TMix^{k^-} \right), 0 \right] \tag{18}$$

By minimizing $VBld_s$, the highest deviations should be mitigated as far as possible, given all other factors involved.

Finally, the value of the performance index is calculated as the simple average of the three performance criteria:

$$PI_s = \frac{Rel_s + (1 - Vul_s) + (1 - VBld_s)}{3} \tag{19}$$

This aggregation method represents an equal weight given to each performance criterion. An additive aggregation method can be more useful than a multiplicative aggregation method. In the latter method it suffices that any of the criteria are zero so that the index would be zero no matter what the values of the other criteria. But multiplicative aggregation methods capture any deterioration in the performance criteria more easily (e.g., McMahon et al. 2006; Sandoval-Solis et al. 2011). The terms $(1 - Vul_s)$ and $(1 - VBld_s)$ are used in Eq. (19) so that the objective of the solution process is to maximize Rel_s and to minimize Vul_s and $VBld_s$. The value of the PI_s is a non-negative number, being 1 or smaller than one.

Normalized solution cost

Water system implementation costs (or total cost) can be categorized as construction costs and operating costs (including maintenance). Here, the operating costs are divided into fixed costs and variable costs according to the quantity of water supplied. Personnel, cleaning, monitoring, security, taxes and licenses are usually fixed costs. Chemicals, electricity and replacement of equipment are usually variable costs.

Each expansion solution is evaluated reporting the total cost to the “present” at a certain discount rate. The construction costs and the fixed operating costs depend on the infrastructure alone, thus making them independent from the system’s operation. If the construction costs for the capacity expansion of the water supply systems are concentrated in the initial stage of the project lifetime, the present total cost (*PC*) of any expansion solution can be written as follows:

$$PC = CC + \sum_{yr \in NYL} \left[\frac{FOC_{yr}}{(1+a)^{yr}} \right] + \sum_{s \in S} p_s \left[\sum_{yr \in NYL} \left[\frac{\overline{AVOC_s}}{(1+a)^{yr}} \right] \right] \tag{20}$$

where NYL = project lifetime in years, CC = construction costs, FOC_{yr} = fixed operating costs in year yr, $\overline{AVOC_s}$ = average annual variable operating costs in scenario s and a = discount rate.

The $\overline{AVOC_s}$ are related to the variable operating costs VOC_s included in Eq. (9) as follows:

$$\overline{AVOC_s} = \frac{VOC_s}{NT} \times 12 \tag{21}$$

The $\overline{AVOC_s}$ are annual, given that VOC_s are spread over NT months ($t=1,\ldots,NT$).

In the objective function of the strategic model (see next subsection), the present total cost of each expansion solution is divided by the value of the present total cost of one specific capacity expansion solution called *Sup*:

$$EI = \frac{PC}{PC_{Sup}} \tag{22}$$

Eq. (22) normalizes the solution cost. The value of the PI_s given by Eq. (19) is one or smaller. The value of the normalized solution cost *EI* will also be no more than one if the solution *Sup* has the highest present total cost of all the capacity expansion solutions. PC_{Sup} is calculated before the solution of the expansion problem in one single iteration of the solution process described next.

Objective function

The expansion solutions are evaluated by an objective function that should be maximized. Its formulation was inspired by the work of Mulvey et al. (1995) in the field of robust optimization. The formulation of the objective function is as follows:

$$z_{SM} = \sum_{s \in S} p_s PI_s - \varphi \sum_{s \in S} p_s \left(PI_s - \sum_{s \in S} p_s PI_s \right)^2 - \omega EI \tag{23}$$

where p_s is the probability of scenario s and, φ and ω are weights to be selected. The best solutions correspond to those that for each pair of values φ and ω maximize the value of z_{SM}. The first term is the expected system performance (given by the performance index) in all scenarios. The second term is the variance of the system performance, weighted by the parameter φ. These first two terms of Eq. (23) define the system robustness (that corresponds to the solution robustness in the original mean-variance formulation of Mulvey et al. 1995). Naturally, the decision makers aim to maximize the expected outcome and minimize the variance of that outcome. A high variance means that the outcome is greatly in doubt. Large values of φ reduce the chance of solutions being selected that show low system performance in some scenarios. Given the outcome variance as a measure for risk, we are seeking to maximize the expected system performance for a given level of risk after setting φ. The third term penalizes the solution costs, weighted by the parameter ω. Lower cost solutions are expected for larger values of ω. The possibility of obtaining trade-offs between system robustness and solution costs by modifying φ and ω approximates the systemic approach developed from a multiobjective approach.

Condensed formulation

The condensed formulation of the strategic model can be written as follows:

$$\underset{X_1,\ldots,X_{NS},Y}{\text{Max}}\; z_{SM} = F(E_1,\ldots,E_{NS},X_1,\ldots,X_{NS},Y) \tag{24}$$

where $F()$ is equivalent to Eq. (23), X_s and Y are the variables representing the operating decisions and the capacity expansion solutions, E_s are generic vectors of parameters for each scenario $s \in S$ and NS is the number of scenarios in set S.

Solution method – SA-NLP

The solution method developed to solve the capacity expansion problem is a hybrid method that combines modern heuristics with classic nonlinear programming. Other hybrid solution methods have been developed for complex problems in the water sector (Heidari and Ranjithan 1998; Cai et al. 2002; Ejeta and Mays 2002; Reis et al. 2005; Tu et al. 2005; Afshar et al. 2008, 2010).

The solution method briefly presented next combines a simulated annealing algorithm with solving a series of nonlinear optimization problems (SA-NLP method). As depicted in Fig. 2, the process begins with the random generation of an expansion solution, Y^f. The operating model is solved with the constraints and the parameters being unequivocally defined only after fixing the expansion solution with Y^f, individually for each scenario $s \in S$. The solution of the operating model for each scenario s is identified by X_s^*. The value of $F()$ is calculated as function of Y^f and X_s^*. A stop criterion included in the simulated annealing algorithm determines either the end of the solution process or if a new expansion solution should be generated.

Case study: Capacity expansion of the Western Algarve multi-municipal water supply system

Introduction

In the 1990s, two multisource-regional systems were designed to guarantee the urban water supply to the Algarve region (Portugal). The systems are known as the Western and the Eastern Multi-municipal Water Supply Systems (in short, WMWSS and EMWSS) from their geographic location and intervention area.

This case study deals only with the WMWSS, where there is a potential deficit from the supply side. The current sources of the WMWSS include two big surface water reservoirs (Odelouca and Bravura) and two groups of wells for pumping groundwater (Vale da Vila group in the Querença-Silves aquifer and Almádena group in the Almádena-Odiáxere aquifer). The potential deficit arises from the environmental impact assessment procedure of the Odelouca reservoir, which found that the size of this (principal) water source of the WMWSS would diminish from 196 million m^3 to 132 million m^3 (-33% in storage capacity). A report drafted for the water utility that manages the WMWSS (Águas do Algarve – AdA) and already bearing the smaller size of the Odelouca reservoir in mind concluded there would be difficulties meeting the estimated demand of 74.7 million m^3 for the year 2025 (Hidroprojecto and Ambio 2005).

We set out to show the ability and usefulness of the modeling framework by applying it to the planning of a capacity expansion of the WMWSS given the estimated demand for the year 2025. The most relevant input data for this application are the list of the investment options for the capacity expansion of the WMWSS, the multicommodity network and the planning objectives in system operation, the cost factors and the hydrologic scenarios. The implementation of the SA-NLP method is briefly described before the discussed of results.

Input data

Investment options

Hidroprojecto and Ambio (2005) identified for AdA a set of investment options for the capacity expansion of the WMWSS that includes two water transfers from neighborhood systems – one from the Santa Clara reservoir system (this system has a significant surplus of water) and the other from the EMWSS (with the construction of a new surface reservoir in this system) – and one seawater desalination plant with three possible design sizes for the reverse osmosis system (250 L/s, 500 L/s or 750 L/s).

Vieira (2014) added to the previous investment options the rehabilitation of six groups of wells, all located in the Querença-Silves aquifer. Additionally, as the groundwater is naturally hard, Vieira (2014) considered for all groups of wells (current and rehabilitated) the possibility of installing nanofiltration systems for softening groundwater with a water recovery rate (i.e., ratio of permeate flow rate to feed flow rate) of 85% (from Gorenflo et al. 2003). In total, 589 824 different capacity expansion solutions resulted from all the possible combinations (one or more) of the investment options listed in Table 1.

The maximum flows indicated in Table 1 depend solely on the pumping and treatment systems installed/to be installed, whereas the maximum firm quantities also depend on the limits set by the authorities. For example, the total pumping capacity of the Vale da Vila wells group as a current source is 984 L/s, but AdA can in any case extract more than 13 million m^3/yr, as defined by the authorities. The maximum flow and the maximum firm quantity indicated in Table 1 for this wells group under the investment option H4.O1 (837 L/s and 11.05 million m^3/yr, respectively) result from combining the total pumping capacity, the annual limit imposed by the authorities and the water recovery rate set for the nanofiltration system (85%). In the investment option H4.O2, the maximum flow is determined by the capacity of the nanofiltration system to be installed (350 L/s). This figure corresponds to the 11.05 million m^3 distributed uniformly over one year.

Multicommodity network and system operation

The network flow is shown in Fig. 3. Supply nodes represent the surface reservoirs (Odelouca and Bravura), the aquifers in which the groups of wells are located (Querença-Silves and Almádena-Odiáxere), the two possible water transfers (from the Santa Clara reservoir system and the EMWSS) and the sea-water desalination plant. The transshipment nodes represent the two water treatment plants (WTP) of the WMWSS (Alcantarilha WTP in TT1 Fontaínhas WTP in TT2), pipe junctions and origins (TT3-TT10) and, as detailed next, artificial nodes for modeling groundwater softening (TT11-TT17). The demand nodes (D1-D10) represent different urban areas of western Algarve. The connections of the investment options with the WMWSS were defined as suggested by Hidroprojecto and Ambio (2005) and AdA (personal information).

Two multicommodity network flows ($k \in K$) were used to distinguish between soft water ($k = 1$) and hard water ($k = 2$). Water quality control implies setting a maximum hard water volumetric blending goal $TMix^{k=2}$ in Eqs. (11) and (18). Below this target, the $PEN_{TMix,s}$ [Eq. (11)] and the $VBld_s$ [Eq. (18)] must be zero. The target for this case study was set after Campinas et al. (2001) had concluded in a research work done for AdA that a volumetric blend of hard groundwater below 25% (i.e., $TMix^{k=2} = 0.25$) would prevent significant variations in drinking water quality when mixed with soft water.

Throughout the solution process the constraints and the parameters of the operating model are unequivocally defined at each iteration and for each scenario only after one expansion solution with the vector Y^f is fixed (see also Fig. 2). For example, the water balances to be applied to the artificial nodes TT11-TT17 in Fig. 3 are defined only after fixing Y^f. These artificial nodes were introduced specifically to model the softening of hard groundwater by modifying a multicommodity flow $x^k_{pq,t,s}$ of type $k = 2$ into $k = 1$. In a clear example, Eq. (25) reproduces the water balances that could be applied to the artificial node TT13 (i.e., one of the two artificial nodes that could receive groundwater from a wells group included in the current sources of the WMWSS). Only one of the two water balances described next is considered in the constraints of the operating model after the expansion solution with Y^f has been fixed for the current iteration:

$$\begin{cases} x^2_{(\mathrm{A1,TT13}),t,s} = x^2_{(\mathrm{TT13,TT1}),t,s}, & y^f_{\mathrm{H4.O1}} = 0 \wedge y^f_{\mathrm{H4.O2}} = 0 \\ 0.85 \times x^2_{(\mathrm{A1,TT13}),t,s} = x^1_{(\mathrm{TT13,TT1}),t,s}, & y^f_{\mathrm{H4.O1}} = 1 \vee y^f_{\mathrm{H4.O2}} = 1 \end{cases} \quad t \in T, s \in S \qquad (25)$$

where 0.85 = water recovery rate of the nanofiltration systems (see the introduction to the case study). When $y^f_{\mathrm{H4.O1}} = 0$ and $y^f_{\mathrm{H4.O2}} = 0$ ($y^f \in Y^f$), this reproduces an expansion solution in which the groundwater (naturally hard) withdrawn from the Vale da Vila wells group would continue to be used without installing nanofiltration systems to soften the groundwater. The expression $x^2_{(\mathrm{A1,TT13}),t,s} = x^2_{(\mathrm{TT13,TT1}),t,s}$ ensures continuity between the withdrawals at the aquifer and the hard water flows in the multicommodity network. When $y^f_{\mathrm{H4.O1}} = 1$ or $y^f_{\mathrm{H4.O2}} = 1$, this reproduces an expansion solution that includes the installation of nanofiltration systems for the Vale da Vila wells group. The expression $0.85 \times x^2_{(\mathrm{A1,TT13}),t,s} = x^1_{(\mathrm{TT13,TT1}),t,s}$ reproduces the softening of the groundwater with the water recovery rate of 85%. An additional constraint ensures that soft water is never withdrawn from the Vale da Vila wells group:

$$x^{1}_{(\mathrm{A1,TT13}),t,s} = 0 \quad t \in T, s \in S \tag{26}$$

In the operation of the WMWSS and without constraints of water availability at the sources, the demand should be fully met, water with the appropriate blend supplied, and the operating costs minimized. With reduced water availability at the sources, initial deficits should be prevented by relaxing the water blending standards (i.e., <25% of hard water). Deficits should be avoided unless no more water could be obtained from the WMWSS sources.

Cost factors

Table 1 includes the cost factors of each water source. Pumping costs in the distribution network were also included when necessary. All the variable operating costs were calculated as a function of a unit operating cost factor associated with the total flow in each arc of the multicommodity network.

The total cost in Eq. (20) was determined assuming a 25-year project lifetime and a discount rate of 3%. In Eq. (22), the total cost is normalized by the value of the total cost of one specific capacity expansion solution designated as *Sup*. Here, the *Sup* solution was set as the one with the highest fixed costs (construction + operating) in Table 1, and thus includes the selection of investment options H1, H2, H3.O3, H4.O2, H5.O2, H6.O3, H7.O3, …, and H10.O3).

Hydrologic scenarios

For this demonstration, ten hydrologic five-year period scenarios were used to capture the uncertainty and impact of extreme events associated with reservoir inflows (Odelouca and Bravura) and aquifer recharges (Querença-Silves and Almádena-Odiáxere). The scenarios corresponded to a five-year data block sampled from a 55-year record (October 1951 – September 2006) of monthly precipitation figures, turned into reservoir inflows using the

Temez hydrological model (Temez 1977), and into aquifer recharges using average recharge rates that depend on the hydrogeological formations.

The scenarios were sampled from a multivariate time series using the semi-random method applied by Watkins and McKinney (1999) to a scenario planning model. Watkins and McKinney (1999) sampled ten scenarios from a long multivariate time series. Two scenarios were chosen specifically and the other eight were selected randomly using the moving-blocks bootstrap method (Vogel and Shallcross 1996) with partial block overlap.

In this case study, one of the ten scenarios (October 2001 – September 2006, 2001-2006 below) was chosen specifically so that the serious drought in the Algarve in 2004 and 2005 would have to be included. The other nine scenarios were selected randomly using the moving-blocks bootstrap method. The average annual reservoir inflows and aquifer recharge in the 10 scenarios selected (141.6 hm^3/yr and 107.2 hm^3/yr, respectively) are close to the average values of the multivariate time series (130.6 hm^3/yr and 104.8 hm^3/yr, respectively). The same degree of probability was given to all scenarios (i.e., $p_s = 0.1$). It might be argued that this could reproduce a high level of risk aversion in decision making as the high degree of probability given to the scenario that includes the serious drought in the Algarve in 2004 and 2005 reproduces a situation in which the importance given to that scenario is higher than that related directly to how often it occurs.

Implementation of the SA-NLP method

The SA-NLP method was implemented by connecting the simulated annealing algorithm proposed by Cunha (1999) and programmed in C++ to GAMS/MINOS. Two Application Programming Interfaces (APIs) were used to solve the operating model in GAMS/MINOS from an executable file and in parallel programming for the 10 scenarios selected (Barney

2012; GAMS Development Corporation 2012). The capacity expansion solutions were found in fewer than 15 000 iterations using a personal computer with an Intel Core i7 processor running at 3.07 GHz and 12 GB RAM memory in tens of hours.

Results and discussion

The expansion solutions presented next were obtained with the operation of the WMWSS optimized in each scenario from an annual management perspective and an interannual management perspective of the water resources. An annual management perspective allows a year-by-year analysis of the results obtained in each scenario, and therefore there is an opportunity for a more detailed discussion if the results are meaningful and as expected. An interannual management perspective enhances an integrated water resources management, and the results obtained are discussed from a decision-making standpoint.

Annual management

The expansion solutions presented in Table 2 were obtained for constant weight $\varphi = 1$ and for weight $\omega = 0.1, 0.5, 1, 5$ and 10. As shown in Fig. 4, the solutions for higher values of ω (the same solution was found for $\omega = 5$ and 10) have lower costs – construction costs (CC) and present total cost (PC) are defined in Eq. (20) – as this weight corresponds to a penalization of costs. But there is also a trade-off from Fig. 4. The least cost solutions have limited gains in system robustness, as represented by smaller increases in the expected value of the performance index [first term of Eq. (23): $\overline{PI_s} = \sum_{s=1}^{NS} p_s PI_s$] and/or lower decreases in its variance [second term of Eq. (23): $\operatorname{Var} PI_s = \sum_{s=1}^{NS} p_s (PI_s - \overline{PI_s})^2$]. Furthermore, all the metrics computed lie in the region defined by the values for two specific solutions – the $\varnothing$ solution (the “do nothing” solution that keeps the current sources) and the *Sup* solution (see cost factors subsection). These results support the hypothesis that solution ∅ and solution *Sup* should be those of minimum and maximum robustness, respectively.

The results are analyzed in greater detail after Fig. 5 is explained. This figure shows the variation of (besides $\overline{PI_s}$ already in Fig. 4) the expected value of the three criteria included in the performance index, $\overline{Rel_s}$, $\overline{Vul_s}$ and $\overline{VBld_s}$, as well as the worst values of the performance index and the three criteria in all scenarios. Given the mathematical formulation of the performance index, the worst values are represented by minimum ($[PI_s]_{\mathrm{m}} = \min_{s \in S} PI_s$ and $[Rel_s]_{\mathrm{m}} = \min_{s \in S} Rel_s$) and maximum ($[Vul_s]^{\mathrm{M}} = \max_{s \in S} Vul_s$ and $[VBld_s]^{\mathrm{M}} = \max_{s \in S} VBld_s$) values.

$\overline{PI_s}$ and the $[PI_s]_{\mathrm{m}}$ show a monotonically increasing behavior as the weight ω was decreased. As can be inferred from Fig. 5, the modifications of $\overline{PI_s}$ and the $[PI_s]_{\mathrm{m}}$ from solution ∅ to the expansion solution obtained with ($\varphi = 1$ and) $\omega = 5$ or 10 are closely related to the positive evolution of the water quality criterion ($\overline{VBld_s}$ and $[VBld_s]^{\mathrm{M}}$) to the zero value, which is sufficient to offset the lower reliability ($\overline{Rel_s}$ and $[Rel_s]_{\mathrm{m}}$). The expansion solution found with $\omega = 5$ or 10 is the installation of nanofiltration systems for the two groups of wells included in the current sources of the WMWSS (Vale da Vila and Almádena). With the installation of the nanofiltration systems all the water distributed from either a surface water or groundwater source would be soft. Thus, the $VBld_s$ has to be zero since the volumetric blend of hard water is also always zero. In this case study, the $VBld_s$ was different from zero with volumetric blending ratios of hard waters above 25%.

But the installation of the nanofiltration systems in each wells group decreases the maximum flow and the firm quantity (Table 1). The permeate flow rate corresponds to 85% of the feed water and influences the quantity of water that can be supplied. Reliability Rel_s represents the ratio between the total water supplied and the total water demand in each scenario s [Eq.

(16)]. In solution ∅ and in the expansion solution found with $\omega = 5$ or 10, the critical value of the reliability between all scenarios is associated with the 2001-2006 scenario. In both cases, the demand is fully satisfied in the first year of that scenario, but in the expansion solution found with $\omega = 5$ or 10 the groundwater is not used initially. The variable operating costs of the Vale da Vila and Almádena wells groups with the installation of the nanofiltration systems are higher than the costs associated with the water abstraction and treatment from the Odelouca and Bravura reservoirs (Table 1). The operating costs are minimized by supplying almost all water from the Odelouca reservoir. The Bravura reservoir is used only when the demand exceeds the drinking water production capacity of the Alcantarilha WTP. The intensive use of the Odelouca reservoir in the first hydrologic year is directly related to the first deficits in the second hydrologic year in the expansion solution obtained with $\omega = 5$ or 10. The Odelouca reservoir reaches the dead storage level at end of the second year and the maximum contribution of all the other sources is not sufficient to prevent deficits in the WMWSS that year. The deficits increase in the third and the fourth hydrologic years, and these years coincide with the drought in 2004 and 2005. The deficits built up in the third and fourth years are higher in the expansion solution obtained with weights $\omega = 5$ or 10 (52.4%) than in solution ∅ (47.8%). In these years, the total contribution of surface water from the Odelouca and the Bravura reservoirs is nearly the same in the two cases, but the contribution of the groundwater sources in the expansion solution obtained with weights $\omega = 5$ or 10 is less due to the installation of the nanofiltration systems in the Vale da Vila and Almádena wells groups. In both cases, the demand is fully satisfied in the fifth hydrologic year, which is the wet year of 2005-2006.

The average value of vulnerability ($\overline{Vul_s}$) is higher in the expansion solution found with $\omega = 5$ or 10 than in the ∅ solution. This represents, on average, higher maximum deficits in the expansion solution found with $\omega = 5$ or 10. But the worst value of vulnerability ($[Vul_s]^{M}$) is higher in solution ∅. A detailed analysis of the results showed that $[Vul_s]^{M}$ is not associated with the same scenario in the two expansion solutions. In solution ∅, the worst value of vulnerability is associated with the 2001-2006 scenario, whereas in the expansion solution found with $\omega = 5$ or 10 the same performance criterion is associated with another scenario (1995-2000), selected randomly for this case study. The 1995-2000 scenario includes two less severe droughts but with a slight interval between them.

The solutions obtained with ($\varphi = 1$ and) $\omega = 0.5$ and 1 are fairly similar (Table 2). The positive trend of all metrics in Fig. 5, except for the water quality criterion that was already at its best value, is mainly due to selecting the water transfer from the Santa Clara reservoir system. The selection of municipal wells with nanofiltration systems for softening groundwater does not change the system performance significantly. In any of the two expansion solutions, the maximum deficits are still greater than 50%, as indicated by $[Vul_s]^{M}$. In both cases, this critical vulnerability value occurs in the fourth year of the 2001-2006 scenario. In that period, all water sources are exhausted: the Odelouca reservoir reaches the dead storage level; the withdrawals from the Bravura reservoir are maximum; the water transfer from the Santa Clara reservoir system is totally exploited, and minimum piezometric levels are reached in certain locations in the Querença-Silves and Almádena-Odiáxere aquifers, preventing additional withdrawals.

The system performance increases as additional investments are selected in the expansion solution found with ($\varphi = 1$ and) $\omega = 0.1$. But even if the capacity expansion of the WMWSS is maximized with the *Sup* solution, the worst vulnerability value was high, approximately 20% (Fig. 5). This value was obtained in the fourth year of the 2001-2006 scenario, after a very intensive use of the Odelouca reservoir in the first three years, as this water source has the lowest variable operating costs of all the soft and/or surface water sources (Table 1). The Odelouca reservoir becomes totally exhausted in the fourth year of the scenario 2001-2006 and, as in the solutions described in the previous paragraph, it is not enough to satisfy the demand, even with the maximum contribution of all the other sources. These results make it clear that very intensive use of the Odelouca reservoir in the short term will always have strong implications for the performance of the WMWSS if droughts are not appropriately anticipated, unlike of the implementation of an interannual water management scheme.

Interannual management

Table 3, Fig. 6 and Fig. 7 summarize the results for constant $\varphi = 1$ and for $\omega = 0.1, 0.5, 1, 5$ and 10, with a five-year interannual management perspective of the water resources.

The expansion solutions found with the three highest values of the weight balancing the cost (i.e., $\omega = 1, 5$ and 10) result from incorporating the municipal group of wells in the WMWSS and installing nanofiltration systems for softening groundwater. The solutions cost less but they have less impact on system performance. This lower impact mostly derives from the fact that, apart from the Almádena wells group, all the other groups of wells are located in the Querença-Silves aquifer (Table 1). The withdrawals from the Querença-Silves aquifer were too often limited by model constraints that were activated by minimum piezometric levels at selected locations. In addition, the rehabilitation of groups of wells may not be sufficient to reverse decreases in the maximum flows and/or total firm quantity from the installation of nanofiltration systems in the group of wells of Vale da Vila and/or Almádena-Odiáxere.

The same expansion solution was found with $\omega = 0.1$ and 0.5. The results show a robust system associated with an initial investment of 28.3 million euros (M€) for the water transfer from the Santa Clara reservoir system. There are no deficits in any scenario (given that $[Rel_s]_{\mathrm{m}} = 1$ or $[Vul_s]^{\mathrm{M}} = 0$) and the maximum volumetric blending ratio of hard groundwaters is only 1.7% higher than the volumetric blending ratio target of 25%. ($[VBld_s]^{\mathrm{M}} = 0.017$ or 1.7%).

Table 4 shows the minimum, average and maximum contribution of each water source for this expansion solution. There is a significant difference between the minimum and maximum contribution of the Odelouca reservoir, and the use of the water transfer from the Santa Clara reservoir system is limited. The water transfer is reduced since it is possible to avoid deficits and guarantee the water quality, for lower operating costs, mainly using the Odelouca reservoir. However, it does not seem to be sustainable to achieve a substantial investment in infrastructure for such a reduced use. Herman et al. (2015) explain how a sensitivity analysis can provide decision-relevant information following optimization. In this regard, Table 4 also summarizes the results obtained by a sensitivity analysis, considering the same expansion solution and optimizing the system's operation with an additional constraint that imposes the use of 80% of the capacity of the water transfer in any time period. The introduction of such constraint leads to a more regular and less uncertain use not only of the water transfer from the Santa Clara reservoir system but also from the Odelouca reservoir, with no significant impact on the solution cost and system performance. The total solution cost rises by less than 4 M€ (from 194.58 M€ to 198.31 M€).

To sum up, the results presented here indicate that achieving more significant improvements in the performance of the WMWSS involves investment in supply-side options, as well as the adoption of an interannual management perspective,. Demand-side options (e.g., loss reduction investment and/or wastewater reuse for non-potable urban uses) were not considered in this case study. Nevertheless, it is quite unlikely that expansion solutions including only demand-side options would be robust solutions.

But even if other investment options and sources of uncertainty (e.g., demand or cost factors) are not considered, it will be always complex arriving at a final decision on how to expand the capacity of the WMWSS. As stated by Watkins and McKinney (1999), if the decision maker plans for higher risk aversion to extreme events such as droughts, and if they do not occur it can be argued that huge sums of money have been misspent. Instead, if planning is done for the more frequent conditions the investment may not be enough to limit the negative impacts of droughts to an acceptable level. The expansion solutions identified here can be examined in more detail in subsequent studies before a final decision is made. A post-analysis could also estimate the level of confidence in the capacity expansion solutions generated here. Mak et al. (1999) show that minimizing the value of a stochastic scenario-based optimization model using NS randomly sampled scenarios is expected to be a lower bound on the true (unknown) solution value, and this bound monotonically increases as NS increased. They suggest a two-step Monte Carlo approach to estimate the level of confidence in the derived solutions, using a larger set of scenarios. Another development would be to adapt the approach of Kasprzyk et al. (2009) to test the capacity solutions generated in extremely unlikely scenarios, under increasing hydrologic uncertainty from the hypothesis of non-stationary conditions.

Finally, a multistage infrastructure planning problem could be developed from the systemic approach presented here. However, the case study selected for demonstration purposes addresses a single stage infrastructure planning problem very nicely. The capacity expansion of the WMWSS is motivated by a potential deficit from the supply side and the natural variability in precipitation that raises difficulties in meeting the projected demand within a water utility's planning horizon. A multistage infrastructure planning problem would be more suitable for dealing with longer time horizons, increased demand or time-varying system uncertainties stemming from global climate change projections.

Conclusions

The systemic approach presented in this paper was developed to support capacity expansion solutions for multisource water supply systems under uncertainty, with explicit representation of water quality. It included the formulation of and connection between two decision models (called the operating model and the strategic model) in a coherent framework for addressing structural and operating decisions, uncertainty, risk and conflicting goals. The uncertain parameter space is discretized into a finite number of realizations that represent future states called scenarios. The operating model is used to obtain optimal operating decisions for each scenario after fixing one capacity expansion solution. Water quality is explicitly represented as it can be a crucial element when waters from different sources are used, in particular when the water is used for drinking. The capacity expansion solutions are evaluated in the strategic model and the operation is deemed optimized for all scenarios through two specific metrics that address the system's performance and solution costs. Two weighted terms are included in the objective function so that trade-offs between the expected system performance in all scenarios, the variance of that same system performance as a measure for risk and the costs can be evaluated.

To demonstrate its utility, the proposed approach was applied to a real-world case study in Portugal, considering future projected demand. The problem is perhaps so complex that only by means of such an approach could a final decision be taken by the decision makers. However, it has served to demonstrate the ability of the approach to generate a restricted set of capacity expansion solutions that can be examined in more detail in subsequent studies.

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Table 1 Summary of the current sources (CS) and the investment options (IO) of the WMWSS (*CC* – Construction costs, *FOC* – Fixed operating costs, *VOC* – Variable operating costs)

Water source		Investment ID	Availability		Costs		
			Max. flow (L/s)	Firm quantity ($\times 10^6$ m^3/yr)	*CC* ($\times 10^6$ €)	*FOC* ($\times 10^3$ €/yr)	*VOC* (€/m^3)
CS	Odelouca reservoir	--	3000	257.20	NA	NA	0.106
	Bravura reservoir	--	280	6.00	NA	NA	0.190
	Vale da Vila wells group	--	984	13.00	NA	NA	0.090
	Almádena wells group	--	110	3.47	NA	NA	0.023
IO	Water transfer						
	Santa Clara reservoir system	H1	650	20.00	28.31	443.3	0.122
	EMWSS	H2	780	18.42	35.45	348.1	0.113
	Seawater desalination plant	H3.O1	250	7.88	23.03	1152.8	0.266
		H3.O2	500	15.77	41.60	2004.7	0.263
		H3.O3	750	23.65	56.37	2847.7	0.261
	Installation of nanofiltration systems (NFS) in current wells group						
	Vale da Vila wells group (in Querença-Silves aquifer)	H4.O1	350	11.05	6.67	135.1	0.137
		H4.O2	837	11.05	16.14	202.1	0.133
	Almádena wells group (in Almádena-Odiáxere aquifer)	H5.O1	51	1.61	1.09	34.2	0.140
		H5.O2	94	2.95	1.96	39.7	0.137
	Rehabilitation of wells group						
	Paderne wells group (in Querença-Silves aquifer)						
	Local disinfection	H6.O1	231	7.27	1.41	100.0	0.037
	Installation of NFS	H6.O2	98	3.09	3.37	112.6	0.150
		H6.O3	196	6.18	5.35	148.3	0.147
	Torrinha wells group (in Querença-Silves aquifer)						
	Local disinfection	H7.O1	100	3.15	0.18	16.4	0.023
	Installation of NFS	H7.O2	42	1.34	1.03	44.0	0.141
		H7.O3	85	2.68	1.89	54.3	0.137
	Marco wells group (in Querença-Silves aquifer)						
	Local disinfection	H8.O1	207	6.53	0.73	56.9	0.029
	Installation of NFS	H8.O2	88	2.78	2.48	79.0	0.143
		H8.O3	176	5.55	4.26	104.5	0.140
	Ferrarias wells group (in Querença-Silves aquifer)						
	Local disinfection	H9.O1	59	1.86	0.12	9.7	0.023
	Installation of NFS	H9.O2	25	0.79	0.62	36.3	0.145
		H9.O3	50	1.58	1.13	43.1	0.140
	Medeiros wells group (in Querença-Silves aquifer)						
	Local disinfection	H10.O1	80	2.52	0.17	12.9	0.023
	Installation of NFS	H10.O2	34	1.07	0.85	40.0	0.145
		H10.O3	68	2.14	1.54	48.7	0.138

Table 2 Expansion solutions obtained for $\varphi = 1$ and $\omega = 0.1, 0.5, 1, 5$ and 10 for an annual management perspective of the water resources

Weight φ	Weight ω	Investment options selected	Changes in relation to Solution ∅	
			Maximum flow (L/s)	Firm quantity (× 10^{6} m^{3}/y)
1	10	H4.O1, H5.O1	-692.7	-3.81
	5	H4.O1, H5.O1	-692.7	-3.81
	1	H1, H4.O1, H5.O1, H7.O3, H9.O2, H10.O3	+83.9	+20.18
	0,5	H1, H4.O1, H5.O2, H7.O3, H9.O3, H10.O3	+101.3	+20.73
	0,1	H1, H2, H4.O2, H5.O2, H7.O3, H9.O3, H10.O2	+1621.4	+41.80

Table 3 Expansion solutions obtained for $\varphi = 1$ and $\omega = 0.1, 0.5, 1, 5$ and 10 for a five-year interannual management perspective of the water resources

Weight φ	Weight ω	Investment options selected	Changes in relation to Solution ∅	
			Maximum flow (L/s)	Firm quantity (× 10^{6} m^{3}/y)
1	10	H5.O2, H7.O7, H10.O1	+163.3	-5.15
	5	H4.O1, H5.O1, H10.O1	-612.7	-1.29
	1	H4.O1, H5.O1, H7.O3, H9.O3, H10.O1	-520.1	+1.63
	0,5	H1	+650.0	+20.00
	0,1	H1	+650.0	+20.00

Table 4 Minimum, average and maximum contributions of the waters sources with the capacity expansion of the WMWSS via the Santa Clara reservoir system for a five-year interannual management perspective of the water resources

Water sources		Optimization (φ = 1 and ω = 0.1 or 0.5)			Sensitivity analysis		
		Contributions from each source to the WMWSS (×10^{6} m^{3}/yr)					
		Min.	Aver.	Max.	Min.	Aver.	Max.
Current sources	Odelouca reservoir	35.32	55.42	60.80	35.32	43.14	45.22
	Bravura reservoir	1.18	1.81	6.00	1.14	1.84	6.00
	Vale da Vila wells group	11.09	12.90	13.00	11.07	12.90	13.00
	Almádena wells group	0.03	0.23	0.39	0.14	0.23	0.38
Investment option	Santa Clara reservoir system (water transfer)	0	4.29	20.00	16.00	16.58	20.00

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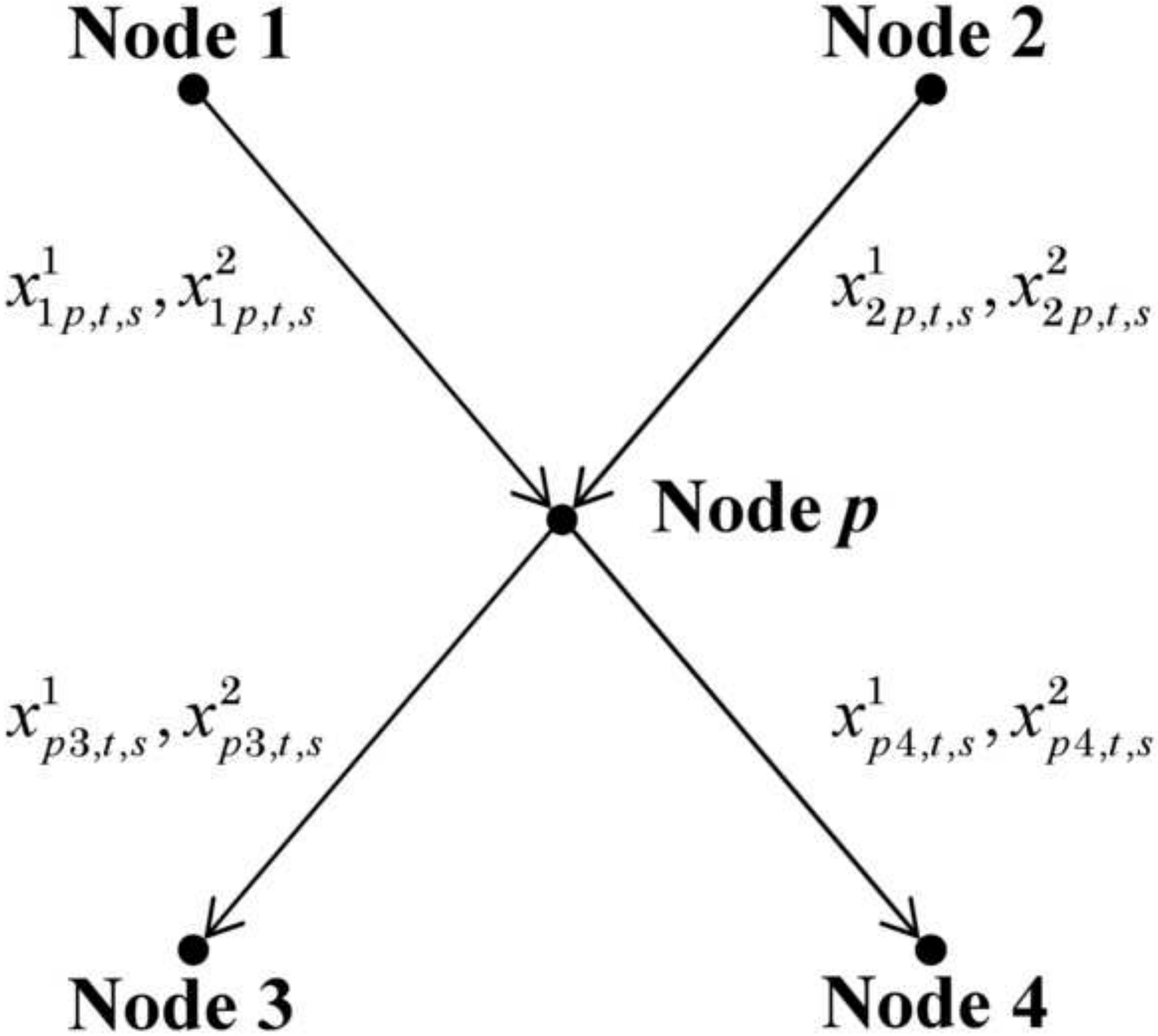
Fig.1



Node 1
Node 2
$x^1_{1p,t,s}, x^2_{1p,t,s}$
$x^1_{2p,t,s}, x^2_{2p,t,s}$
Node *p*
$x^1_{p3,t,s}, x^2_{p3,t,s}$
$x^1_{p4,t,s}, x^2_{p4,t,s}$
Node 3
Node 4

Fig.2

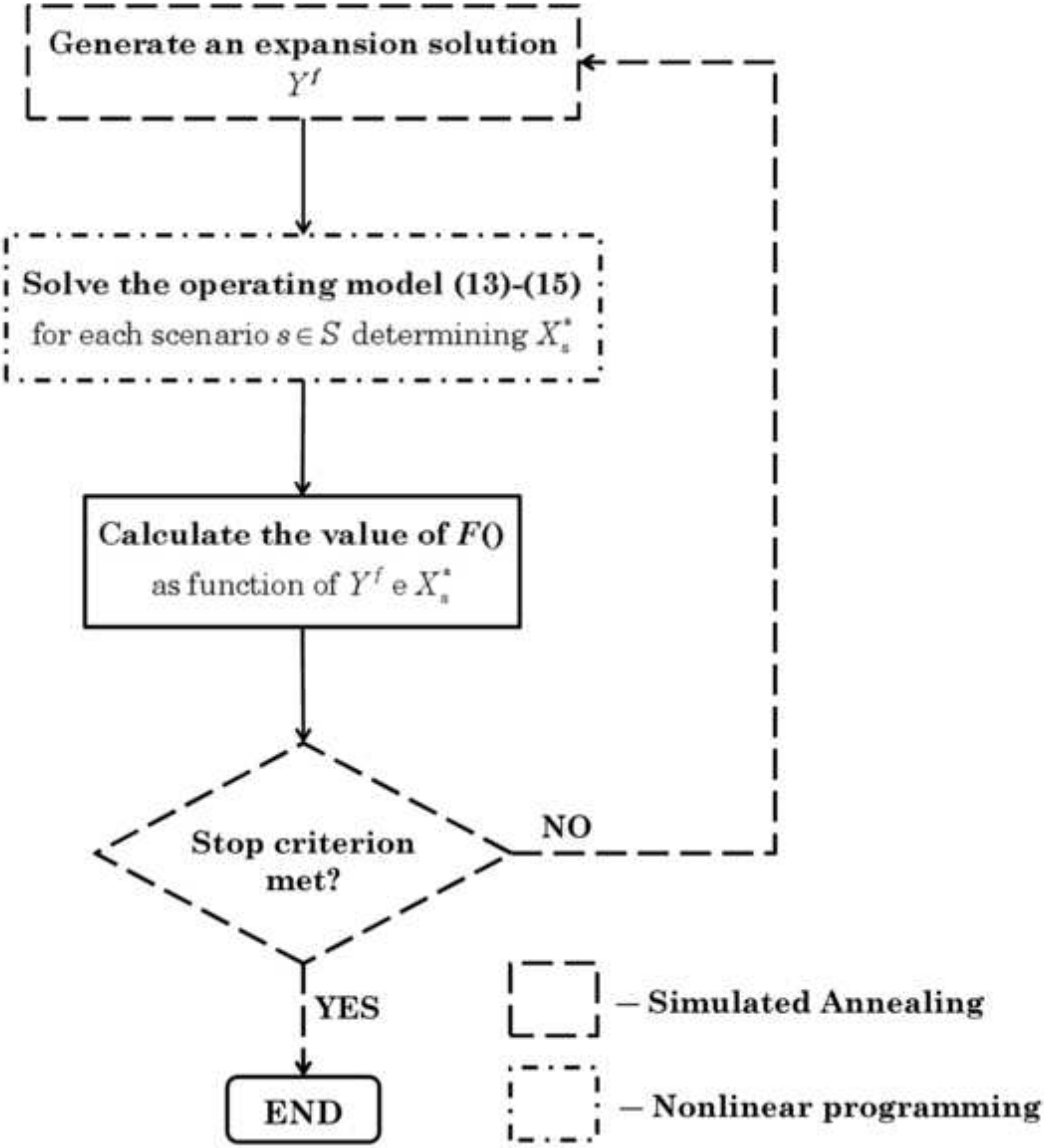

Generate an expansion solution
Y^f
Solve the operating model (13)-(15)
for each scenario $s \in S$ determining X_s^*
Calculate the value of $F()$
as function of Y^f e X_s^*
Stop criterion met?
NO
YES
END
– Simulated Annealing
– Nonlinear programming

Fig.3

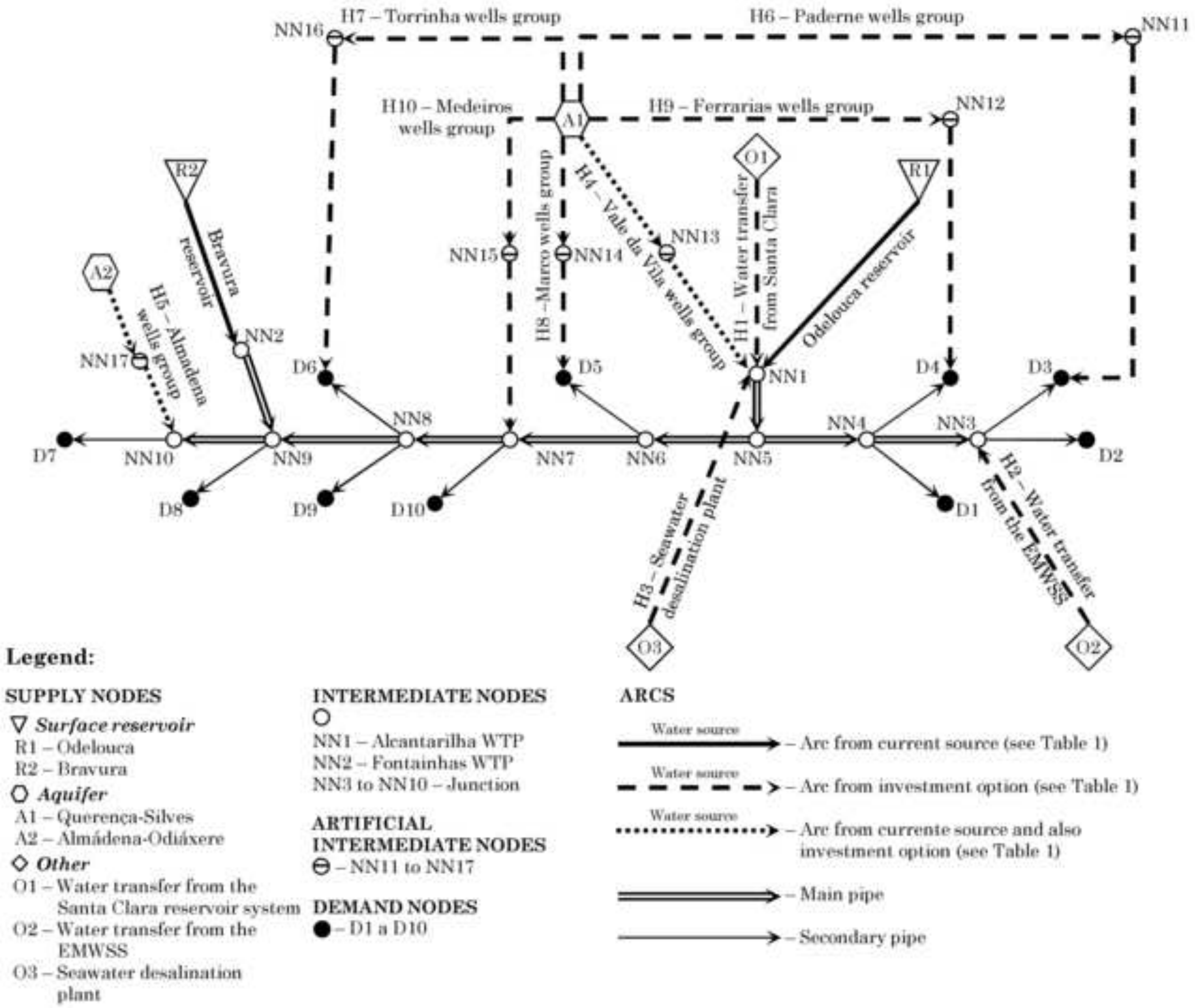
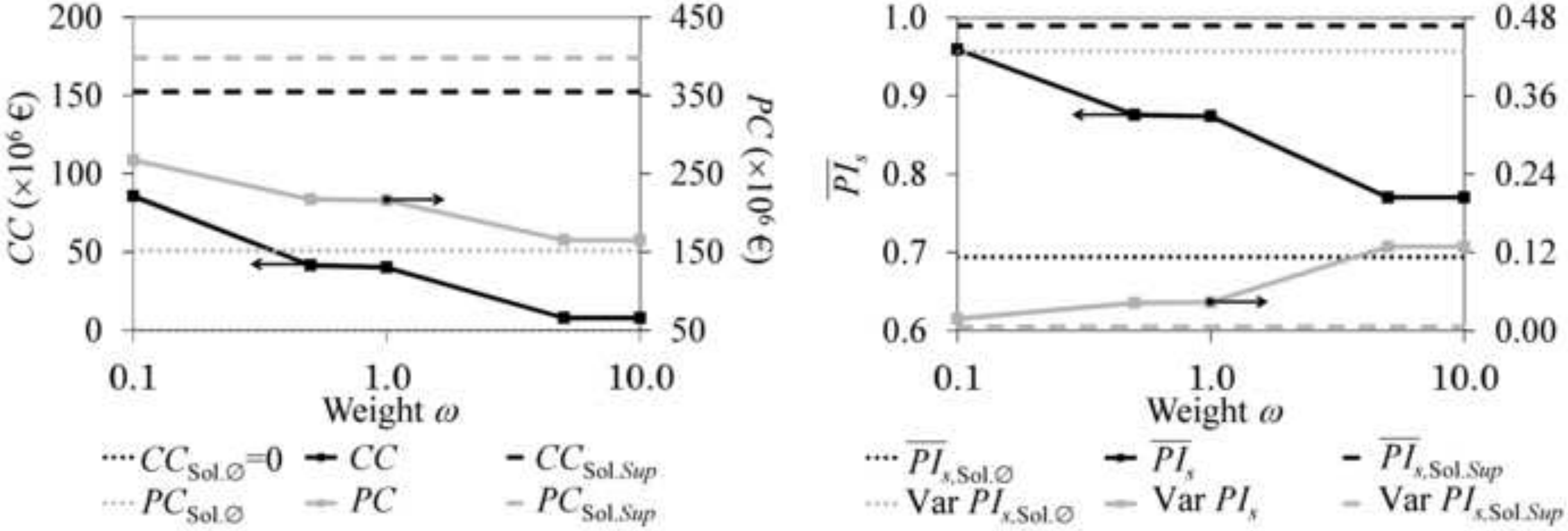

NN16
H7 – Torrinha wells group
H6 – Paderne wells group
NN11
H10 – Medeiros wells group
A1
H9 – Ferrarias wells group
NN12
O1
R2
R1
H8 – Marco wells group
H4 – Vale da Vila wells group
NN13
H1 – Water transfer from Santa Clara
Bravura reservoir
NN15
NN14
A2
H5 – Almadena wells group
Odelouca reservoir
NN2
NN17
D6
D5
NN1
D4
D3
NN8
NN4
NN3
D7
NN10
NN9
NN7
NN6
NN5
D2
D8
D9
D10
D1
H3 – Seawater desalination plant
H2 – Water transfer from the EMWSS
O3
O2
Legend:
SUPPLY NODES
▽ Surface reservoir
R1 – Odelouca
R2 – Bravura
⬡ Aquifer
A1 – Querença-Silves
A2 – Almádena-Odiáxere
◇ Other
O1 – Water transfer from the Santa Clara reservoir system
O2 – Water transfer from the EMWSS
O3 – Seawater desalination plant
INTERMEDIATE NODES
○
NN1 – Alcantarilha WTP
NN2 – Fontainhas WTP
NN3 to NN10 – Junction
ARTIFICIAL INTERMEDIATE NODES
⊖ – NN11 to NN17
DEMAND NODES
● – D1 a D10
ARCS
Water source
– Arc from current source (see Table 1)
Water source
– Arc from investment option (see Table 1)
Water source
– Arc from currente source and also investment option (see Table 1)
– Main pipe
– Secondary pipe

Fig.4



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PC (×10⁶ €)
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Weight ω
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CC_Sol.Sup
PC_Sol.∅
PC
PC_Sol.Sup
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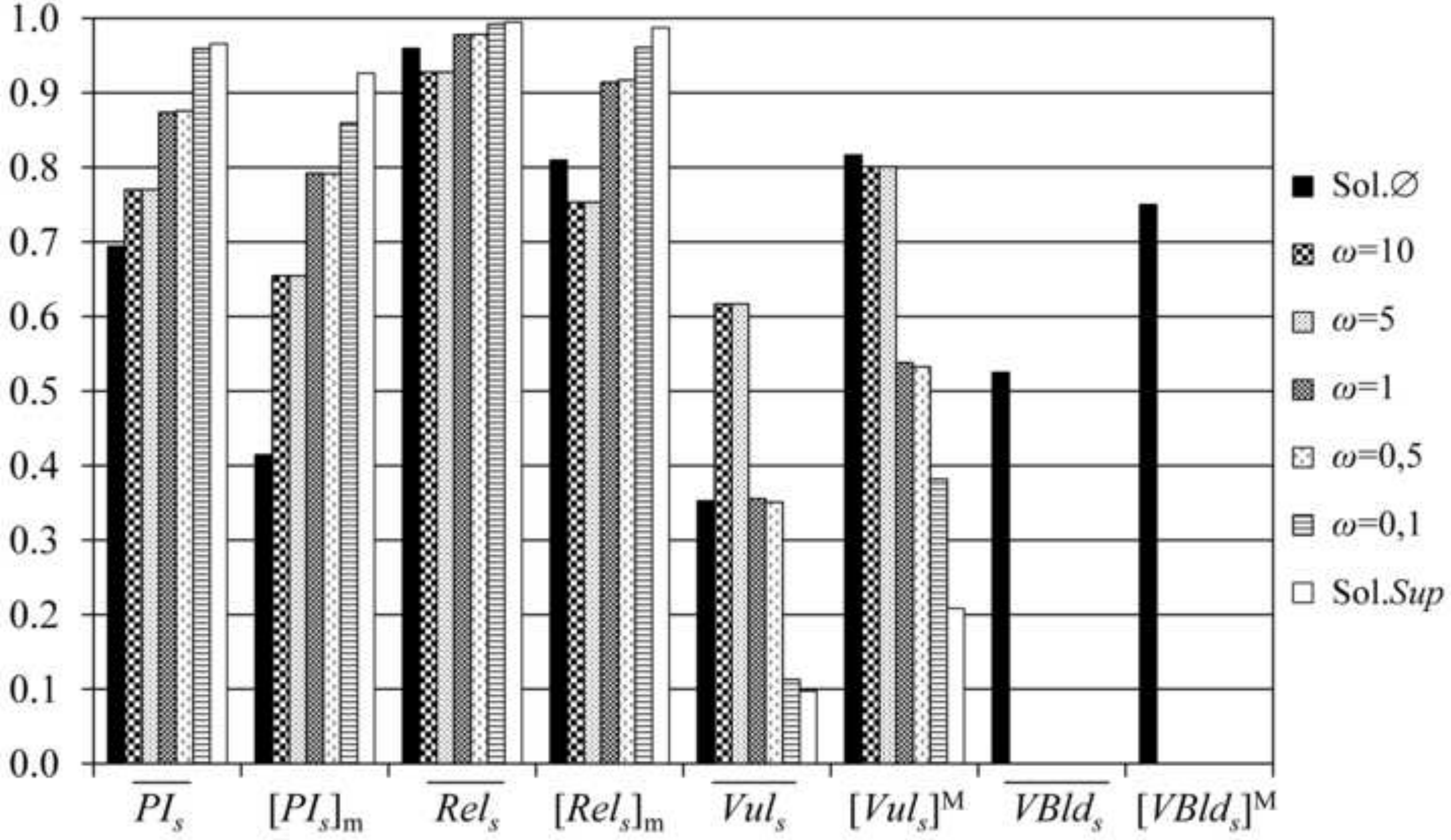
0.8
0.7
0.6
0.48
0.36
0.24
0.12
0.00
PI_s
Var PI_s
0.1
1.0
10.0
Weight ω
PI_s,Sol.∅
PI_s
PI_s,Sol.Sup
Var PI_s,Sol.∅
Var PI_s
Var PI_s,Sol.Sup

Fig.7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$\overline{Rel_s}$
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$\overline{Vul_s}$
$[Vul_s]^M$
$\overline{VBld_s}$
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Sol.∅
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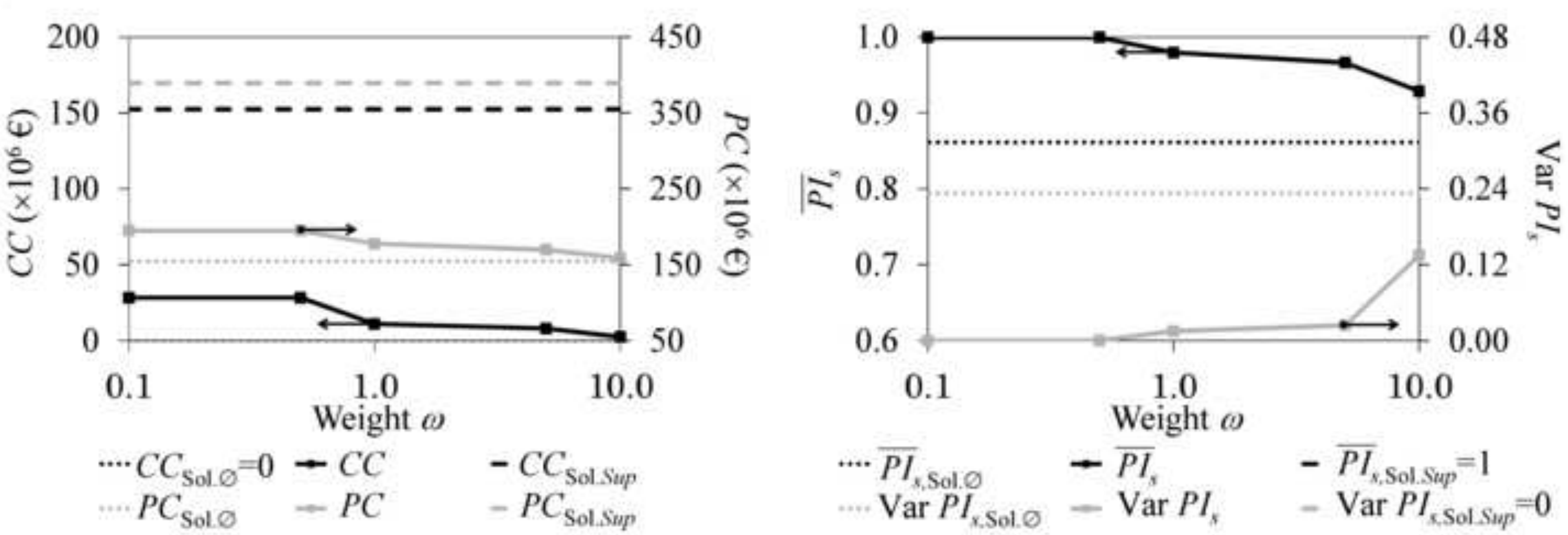
ω=5
ω=1
ω=0,5
ω=0,1
Sol.*Sup*

Fig.6


200
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CC (×10⁶ €)
PC (×10⁶ €)
0.1
1.0
10.0
Weight ω
$CC_{\mathrm{Sol.}\varnothing}$=0
CC
$CC_{\mathrm{Sol.}Sup}$
$PC_{\mathrm{Sol.}\varnothing}$
PC
$PC_{\mathrm{Sol.}Sup}$
1.0
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$\overline{PI_s}$
Var PI_s
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1.0
10.0
Weight ω
$\overline{PI}_{s,\mathrm{Sol.}\varnothing}$
$\overline{PI}_s$
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Var PI_s
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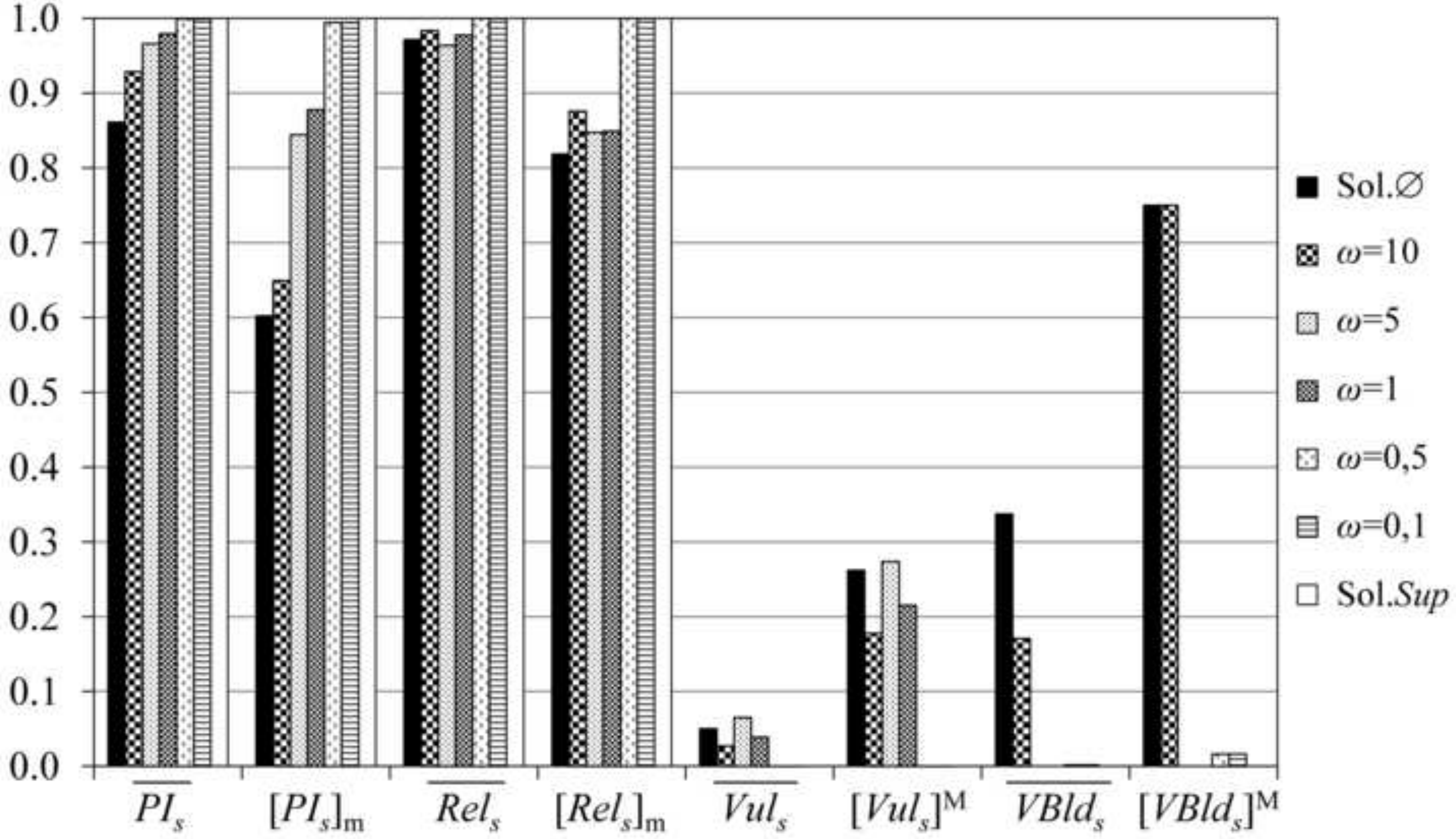
Fig.7



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$[PI_s]_m$
$\overline{Rel_s}$
$[Rel_s]_m$
$\overline{Vul_s}$
$[Vul_s]^M$
$\overline{VBld_s}$
$[VBld_s]^M$
Sol.∅
ω=10
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ω=1
ω=0,5
ω=0,1
Sol.Sup