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# Robust Staged Development of Water Supply Systems

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**Abstract**

This paper presents a new methodology for optimal staged development of water supply systems that ensures robust and sustainable solutions. This problem is formulated as a multi-objective optimisation problem under uncertainty with objectives being the minimisation of average present value of intervention costs and greenhouse gas emissions, and the maximisation of supply robustness. The above methodology was validated and demonstrated on southern portion of the regional water supply system of Adelaide. The results obtained illustrate the importance of identifying optimal staged solutions to ensure robustness and sustainability of water supply into uncertain long-term future.


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*Keywords:* Staged development; water resource management; optimization; robustness; uncertainty; sustainability; climate change.

## 1. Introduction

Existing water supply systems are under increasing pressure to deliver water in a robust and sustainable manner under uncertain climate variability and change and increasing urbanisation resulting in worsening long-term supply demand balance if 'business as usual' is continued into the future. At the same time, an increasing number of different types of intervention options are now available, but all are typically costly and require substantial lead times for implementation. Therefore, selecting and staging these intervention options in an optimal way over a long-term planning horizon is a key challenge for water utilities around the world.

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This paper presents a new approach for robust staged development of water supply systems (i.e. water resources management) under uncertainty. A number of similar approaches have been developed recently [1,2]. The key difference in the approach presented here is uncertainty is incorporated in the long term sequencing process by utilizing metamodels to reduce computational effort.

The paper is organised as follows. The new methodology is presented in section 2, followed by application to a case study in section 3. The conclusions obtained based on the case study results are summarised in section 4.

## 2. Methodology

The long-term regional water supply (i.e. water resources management) problem is formulated here as a multi-objective optimization problem under uncertainty. The objectives are as follows: (a) the minimisation of the average present value (PV) of intervention costs; (b) the minimisation of the average present value (PV) of greenhouse gas (GHG) emissions; and (c) the maximisation of supply robustness. The uncertain variables are rainfall, per capita water consumption, population growth and discount rate Supply robustness is defined as the probability that water supply reliability (i.e. likelihood of water being fully supplied) and vulnerability (measured by supply/demand deficit) are simultaneously above and below pre-specified thresholds, respectively. The decision variables are the implementation stages and the sizes of some of the intervention options. The above problem is solved by using the NSGA-II optimisation method [3]linked to a WaterCress (Water-Community Resource Evaluation and Simulation System)simulation model [4]. Uncertain variables are sampled using the Latin Hypercube sampling (LHS) method. Computational efficiency is increased by using Artificial Neural Network (ANN) surrogate or metamodels, trained to calculate values of the objectives mentioned above. A multilayer perceptron (MLP) ANN architecture is used here.

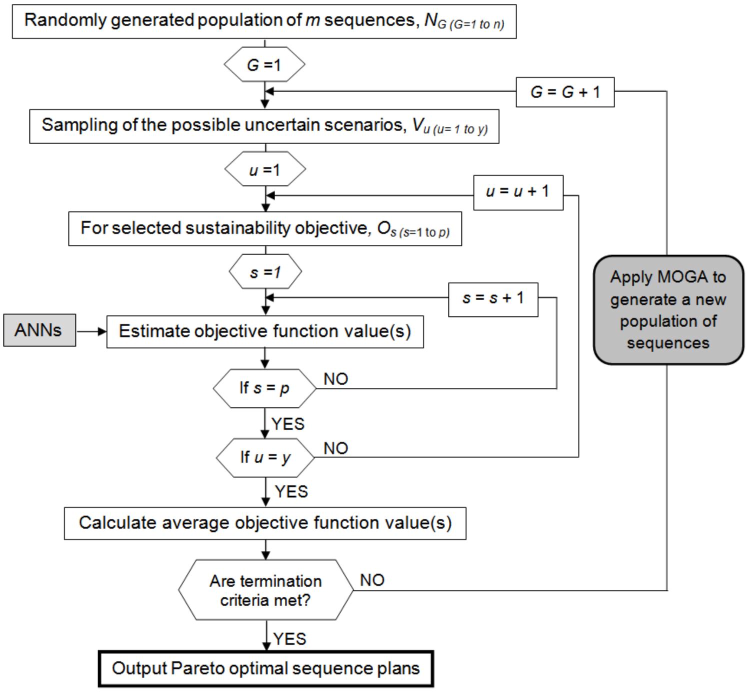


Fig. 1. Optimal sequencing process

The ANN model inputs include i) the timing to implement the potential water supply sources; ii) the capacity of the rainwater tanks, if implemented; iii) per capita demand; iv) population; v) discount rate and vi) climate change factor. Separate, single output ANN models are developed to estimate cost, GHG emissions, reliability and vulnerability.

As per the procedure outlined in Fig. 1, initially m sets of random values of the decision variables are generated, resulting in m random sequence plans (i.e. staged intervention strategies defined over a pre-specified planning horizon). These sequence plans are then assessed with y combinations of uncertain scenarios sampled with the selected uncertain variables (i.e., per capita demand, population, discount rate and climate change factor). Then, objective function values (i.e., cost, GHG emissions, and robustness) are estimated for each of the uncertain scenarios for each of the sequences in the population with the aid of the ANN metamodels.

## 3. Case Study

The above approach was applied to the southern portion of Adelaide water supply system (WSS) in South Australia. The system is currently supplied by three reservoirs – Myponga, Mount Bold and Happy Valley (see Fig. 2). Mount Bold and Myponga reservoirs receive water from local catchments, and Mount Bold also receives water pumped from the River Murray via the Murray Bridge to Onkaparinga pipeline. Other potential water supply sources include a desalination plant, various stormwater harvesting (SWH) schemes, and household rainwater tanks [5]. A 100 year planning horizon is subdivided into ten stages of equal duration (10 years each) for the purpose of sequencing the potential water supply sources.

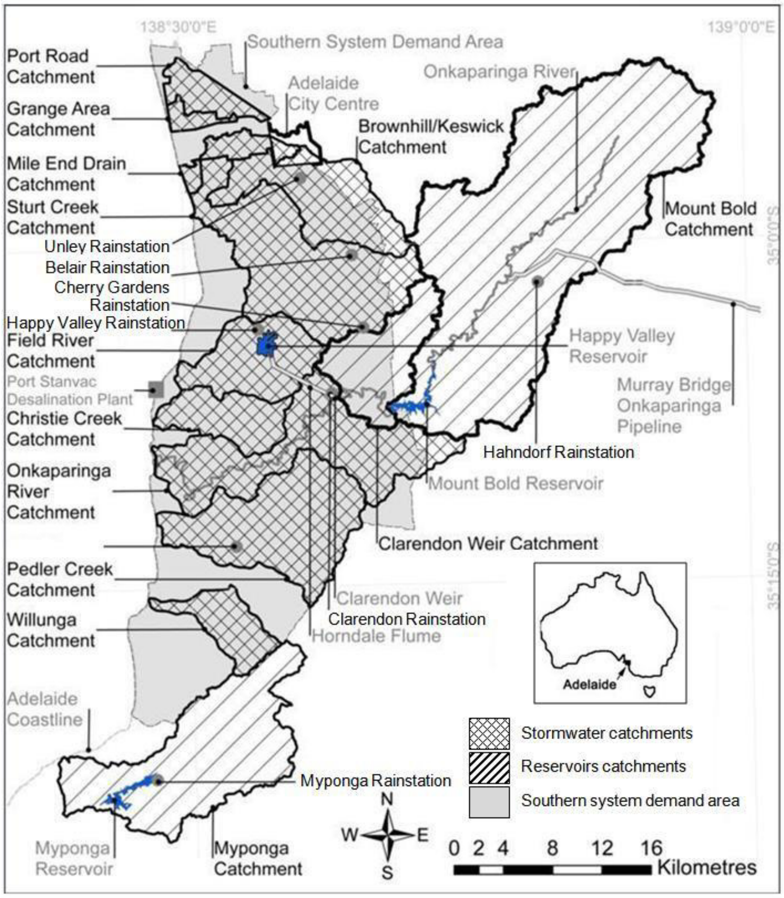


Fig. 2. Southern part of the Adelaide water supply system

In order to develop the ANN metamodels, m=3000 combinations of the input variables, including the sizes and timing of the implementation of the potential water supply sources, as well as values of the uncertain variables, such as per capita demand, population, discount rate and climate change factor, are generated with the aid of LHS. Next, these datasets are used in the calculation of objective function values, including cost, GHG emissions, and robustness. In order to achieve this, the annual supply from each potential water supply sources is determined using a simulation model, which is WaterCress [4] in this instance.

The resulting 3000 input/output datasets with the computed objective function values are then used to develop the ANN models. Prior to developing the ANNs, the available datasets are divided into training, testing and validating subsets as follows [6]: 60% of the available data are used for training, 20% are used for testing and 20% are used for validation. For the cost and GHG data, the systematic method is used for this purpose, as the data are relatively uniformly distributed. In contrast, the self-organizing map based stratified sampling using the proportional allocation rule (SBSS-P) is used to split the datasets used to develop the ANNs for reliability and vulnerability, as the distribution of these data is highly skewed [7].

The optimal intervention sequencing process is formulated using nine decision variables, as summarised in Table 1. These variables correspond to the decision stage at which a particular option is implemented, ranging from 0 (i.e. the option is not implemented over the planning horizon) to 10 (i.e. the option is implemented at stage 10). However, in addition to a decision variable for timing, rainwater tanks also have a decision variable corresponding to rainwater tank capacity, ranging from 1 to 10kL.

Table 1.Case study decision variables

| Decision variable | Descriptions | Lower limit | Upper limit |
|---|---|---|---|
| 1 | 50GL desalination plant implementation stage | 0 | 10 |
| 2 | 100GL desalination plant implementation stage | 0 | 10 |
| 3 | 50GL desalination plant expansion implementation stage | 0 | 10 |
| 4 | Household rainwater tank implementation stage | 0 | 10 |
| 5 | Household rainwater tank size (kL) | 1 | 10 |
| 6 | Brownhill & Keswick Creek SWH scheme implementation stage | 0 | 10 |
| 7 | Sturt River SWH scheme implementation stage | 0 | 10 |
| 8 | Field River SWH harvesting scheme implementation stage | 0 | 10 |
| 9 | Pedler Creek SWH harvesting scheme implementation stage | 0 | 10 |

The optimal tradeoffs between the average PV of costs and average PV of GHG emissions and system robustness is presented in Fig. 3 and the corresponding optimal sequence plans are shown in Table 2. As it can be seen from this table, for sequence plans with lower average PV of cost and GHG emissions (sequence plans 1 and 4), the 50GL desalination and the expansion are implemented later in the planning horizon, resulting in lower system robustness due to demand shortfalls during the early stages of the planning horizon.

In contrast, for the sequence plan with the highest system robustness (sequence plan 24), the 50GL desalination and the 100GL desalination are implemented at the first and second stage of the planning horizon, which results in a greater PV of cost and GHG emissions, but the substantial supply from the desalination plant is able to demands under the most critical conditions (i.e., high demand, high population growth and higher climate change impact conditions).

The training, testing and validating all ANNs prior to optimisation took approximately 220 hours. The NSGA-II optimisation run (population size of 200 stopped after 250 generations) where ANNs were used instead of the WaterCress model took only 20 minutes to complete. The computational time required to solve the same optimisation problem by using the WaterCress model is prohibitively large and hence this was not attempted (it takes 72 hours just to solve a similar deterministic optimisation problem. i.e. without considering uncertainty).

Table 2. Implementation stage of selected water supply sources for each optimal sequence plan and corresponding average PVs of cost and GHG emissions and robustness

| | Decision stage at which to implement water supply options (1 = 2010, 2 = 2020, etc) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sequence plan | 50GL desalination | 100GL desalination | 50GL desalination expansion | Household rainwater tank [size] | Brownhill & Keswick Creek SWH | Sturt River SWH scheme | Field River SWH scheme | Pedler Creek SWH scheme | Average PV of cost ($ million) | Average PV of GHG ($MtCO_2$-e) | Average robustness |
| 1 | 9 | 0 | 10 | 10 [5kL] | 0 | 9 | 0 | 0 | 1323.45 | 21.29 | 0.06 |
| 2 | 9 | 0 | 10 | 10 [1kL] | 0 | 9 | 0 | 0 | 1324.24 | 21.05 | 0.11 |
| 3 | 10 | 8 | 0 | 10 [1kL] | 0 | 8 | 0 | 0 | 1380.27 | 22.09 | 0.17 |
| 4 | 9 | 0 | 10 | 10 [1kL] | 0 | 4 | 0 | 6 | 1383.72 | 20.92 | 0.11 |
| 5 | 10 | 8 | 0 | 10 [1kL] | 0 | 7 | 0 | 9 | 1385.32 | 22.07 | 0.17 |
| 6 | 9 | 7 | 10 | 10 [1kL] | 0 | 9 | 0 | 0 | 1463.56 | 23.93 | 0.22 |
| 7 | 10 | 6 | 0 | 10 [1kL] | 0 | 4 | 5 | 0 | 1594.53 | 24.19 | 0.28 |
| 8 | 10 | 6 | 0 | 10 [1kL] | 0 | 4 | 4 | 6 | 1608.12 | 24.22 | 0.33 |
| 9 | 10 | 5 | 0 | 10 [1kL] | 0 | 9 | 0 | 0 | 1660.75 | 25.08 | 0.39 |
| 10 | 10 | 6 | 0 | 10 [1kL] | 0 | 3 | 7 | 4 | 1664.46 | 24.10 | 0.28 |
| 11 | 10 | 5 | 0 | 10 [1kL] | 0 | 7 | 0 | 9 | 1670.74 | 25.06 | 0.39 |
| 12 | 9 | 8 | 10 | 10 [1kL] | 1 | 6 | 1 | 2 | 1674.20 | 23.33 | 0.22 |
| 13 | 10 | 6 | 0 | 10 [1kL] | 0 | 1 | 7 | 9 | 1834.82 | 24.08 | 0.28 |
| 14 | 10 | 3 | 0 | 10 [1kL] | 4 | 7 | 0 | 9 | 2380.99 | 27.35 | 0.44 |
| 15 | 10 | 3 | 0 | 10 [1kL] | 4 | 7 | 0 | 9 | 2380.99 | 27.35 | 0.44 |
| 16 | 1 | 9 | 0 | 10 [1kL] | 3 | 4 | 0 | 7 | 3386.61 | 26.78 | 0.44 |
| 17 | 1 | 7 | 6 | 8 [1kL] | 1 | 9 | 5 | 0 | 3601.45 | 32.11 | 0.50 |
| 18 | 1 | 5 | 6 | 10 [1kL] | 1 | 4 | 2 | 2 | 3882.05 | 32.71 | 0.56 |
| 19 | 8 | 1 | 9 | 10 [1kL] | 0 | 7 | 0 | 9 | 4184.67 | 30.87 | 0.56 |
| 20 | 1 | 3 | 0 | 10 [1kL] | 1 | 1 | 1 | 2 | 4491.45 | 31.53 | 0.67 |
| 21 | 1 | 3 | 8 | 10 [1kL] | 1 | 1 | 2 | 2 | 4526.16 | 32.82 | 0.72 |
| 22 | 6 | 1 | 0 | 10 [4kL] | 1 | 1 | 2 | 2 | 4568.38 | 31.34 | 0.61 |
| 23 | 5 | 1 | 0 | 10 [4kL] | 1 | 1 | 2 | 2 | 4639.79 | 31.71 | 0.72 |
| 24 | 1 | 2 | 6 | 10 [1kL] | 1 | 1 | 2 | 2 | 5179.53 | 34.70 | 0.78 |

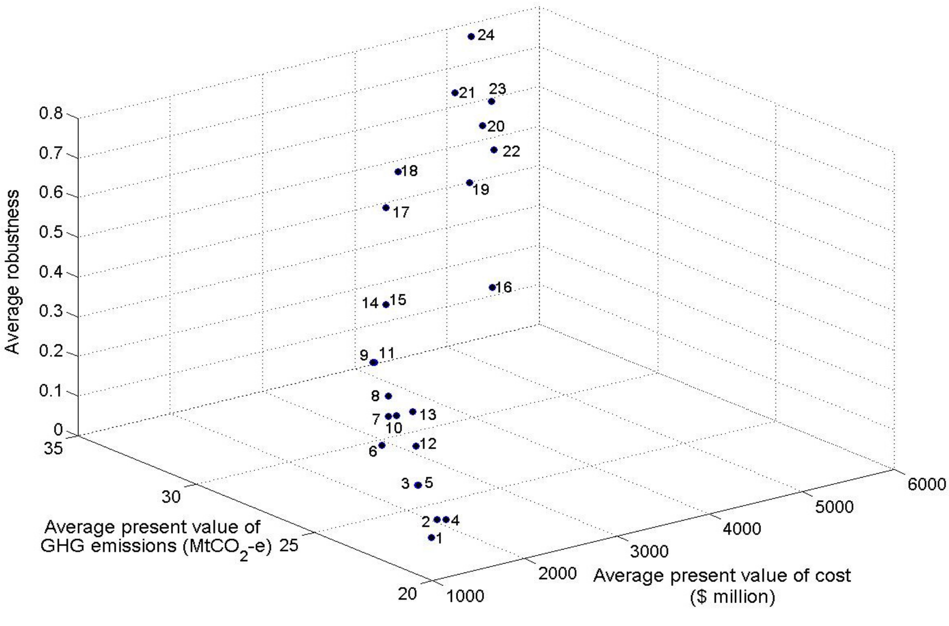


Fig. 3. Optimal tradeoffs between the average present value of costs and GHG emissions and system robustness

## 4. Summary and Conclusions

This paper presents a new methodology for optimal staged development of water supply systems that ensures identification of robust and sustainable solutions. This problem is formulated as a multi-objective optimisation problem under uncertainty with objectives being the minimisation of average present value of intervention costs, the minimisation of average present value of greenhouse gas emission costs and the maximisation of supply robustness. The uncertain variables are rainfall, per capita water consumption, population count and discount rate. The supply robustness is defined as the probability that water supply reliability (i.e. likelihood of water being fully supplied) and vulnerability (measured by supply/demand deficit) are simultaneously above and below respective, pre-specified thresholds.

The case study results obtained demonstrate the value of the proposed approach in being able to cater to the sequencing of urban water sources while taking account of alternative sources of water, multiple, competing objectives and extended planning timeframes, which is able to assist water resources managers to identify intervention sequences that are least sensitive to changes in various possible future conditions. Furthermore, the approach suggested here allows long term plans to be reviewed and re-optimized at regular intervals to take account of changes in circumstances and the availability of new data and information. Finally, the results obtained illustrate the importance of identifying optimal staged solutions to ensure robustness and sustainability of water supply into an uncertain long-term future.

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