water

MDPI

Article

Water Resource Systems Analysis for Water Scarcity Management: The Thames Water Case Study

Mark Morley [1] and Dragan Savić [1,2,*]

[1] KWR Water Research Institute, 3433 PE Nieuwegein, The Netherlands; mark.morley@kwrwater.nl
[2] Centre for Water Systems, College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter EX4 4QF, UK
* Correspondence: dragan.savic@kwrwater.nl or d.savic@exeter.ac.uk

Received: 17 May 2020; Accepted: 18 June 2020; Published: 20 June 2020

Abstract: Optimisation tools are a practical solution to problems involving the complex and interdependent constituents of water resource systems and offer the opportunity to engage with practitioners as an integral part of the optimisation process. A multiobjective genetic algorithm is employed in conjunction with a detailed water resource model to optimise the "Lower Thames Control Diagram", a set of control curves subject to a large number of constraints. The Diagram is used to regulate abstraction of water for the public drinking water supply for London, UK, and to maintain downstream environmental and navigational flows. The optimisation is undertaken with the aim of increasing the amount of water that can be supplied (deployable output) through solely operational changes. A significant improvement of 33 Ml/day (1% or £59.4 million of equivalent investment in alternative resources) of deployable output was achieved through the optimisation, improving the performance of the system whilst maintaining the level of service constraints without negatively impacting on the amount of water released downstream. A further 0.2% (£11.9 million equivalent) was found to be realisable through an additional low-cost intervention. A more realistic comparison of solutions indicated even larger savings for the utility, as the baseline solution did not satisfy the basic problem constraints. The optimised configuration of the Lower Thames Control Diagram was adopted by the water utility and the environmental regulators and is currently in use.

Keywords: water resource modelling; multiobjective optimisation; river abstraction

1. Introduction

The field of systems analysis has often been associated with the advent of operations research during and after the Second World War, while its application to water resource systems advanced more significantly from around the 1970s, when computers became widely available [1]. The parallel development in computational hydraulics and hydrology, which was also stimulated by the advent of modern information and communication technology, led to the emergence of the aligned discipline of hydroinformatics in the 1990s [2]. Both systems analysis and hydroinformatics embrace not only technological issues, such as scientific methods and the application of data, models and decision support tools, but also much wider questions of the role of the discipline in addressing societal challenges [2]. Water security, resilience, governance and ethical issues are just a few of those societal challenges that are also affected by growing climate, population and uncertainty concerns. The complexity of water issues, often involving incomplete, contradictory and changing requirements, together with the involvement of stakeholders holding multiple and opposing views, give water challenges a "wicked" (ill-defined) character [3,4]. The wicked nature of water resource challenges also meant that a multitude of methods for optimising the planning and management of water resources developed over the years [5,6] were not fully adopted in practice [7].

One of the challenges most often encountered in water resource systems planning and management is how to define operating rules for multiple sources requiring an integrated vision, thus accounting for interrelations and interdependencies among complex system components [5–8]. The widespread reporting of the use of simulation and optimisation methods shows that systems analysis tools are being used in practice [8,9]. However, despite this vast wealth of literature, publications reporting on practical applications of such tools, their impact and the experiences of analysts and clients are rare.

Each water service provider in England and Wales must produce a water resources management plan (WRMP), which is updated every five years. Such plans aim to ensure "sufficient supply of water to meet the anticipated demands of its customers over a minimum 25-year planning period, even under conditions where water supplies are stressed" [10]. This paper presents a case study in which systems analysis tools were used to develop a constituent of a WRMP for a water service provider, Thames Water, considering the complexities and requirements of such a plan. An optimisation tool was developed to redesign a key component of the water management strategy for the River Thames in such a way as to maximise the capacity of the system to supply drinking water whilst ensuring the maintenance of strict environmental criteria regarding the quantity of water left in the river as it flows into its tidal reach.

2. Materials and Methods

Thames Water abstracts water from the lower reaches of the River Thames for the purpose of public water supply via a number of large reservoirs to the west of London. Transfers are also made to reservoirs in the Lea Valley found to the northeast of London. Left unconstrained, these abstractions could have a deleterious effect on the downstream environment. Accordingly, these are undertaken in agreement with the English Environment Agency (EA) environmental regulator, under Section 20 of the Water Resources Act 1991 [11]. This agreement describes the Lower Thames Control Diagram (LTCD), which is used to control the level of abstraction permitted as a function of current reservoir storage. Thames Water seeks to optimise the LTCD, with a view to maximising the deployable output of the system as a whole. Deployable output is considered to be the maximum output capacity (i.e., demand that could be supplied) of one or more commissioned water sources that can achieve a prescribed level of service as constrained by factors such as, inter alia, hydrological yield, licence constraints and treatment and transport and pumping capacity.

In addition, a second optimisation scenario was evisaged in which aggregate could be extracted from an existing reservoir to facilitate additional storage capacity for the system. This was to be run as a separate analysis to determine what impact such a change would have on the deployable output of the system as a whole.

2.1. Lower Thames Control Diagram

The LTCD controls abstraction principally by defining a target environmental and navigational flow that must reach the tidal reaches of the Thames at Teddington Lock: the Teddington target flow (TTF). The TTF matrix is illustrated in Figure 1 where each month/operating band has a minimum flow target.

As can be seen, when reservoir storage is full, Thames Water are obligated to ensure that a minimum of 800 Ml/day is discharged into the tidal reach. This figure diminishes as reservoir storage becomes lower, with the constraints becoming more relaxed in the late spring and early summer months.

The solid lines on the LTCD represent the points at which the various demand-saving measures, agreed with the environmental (EA) and economic (Ofwat) regulators and outlined in the appropriate act and statutory instruments [11,12], are implemented:

- Level 1: intensive media campaign.
- Level 2: sprinkler/unattended hosepipe ban and enhanced media campaign.
- Level 3: temporary use ban, ordinary drought order (non-essential use ban).
- Level 4: emergency drought order (e.g., standpipes and rota cuts).

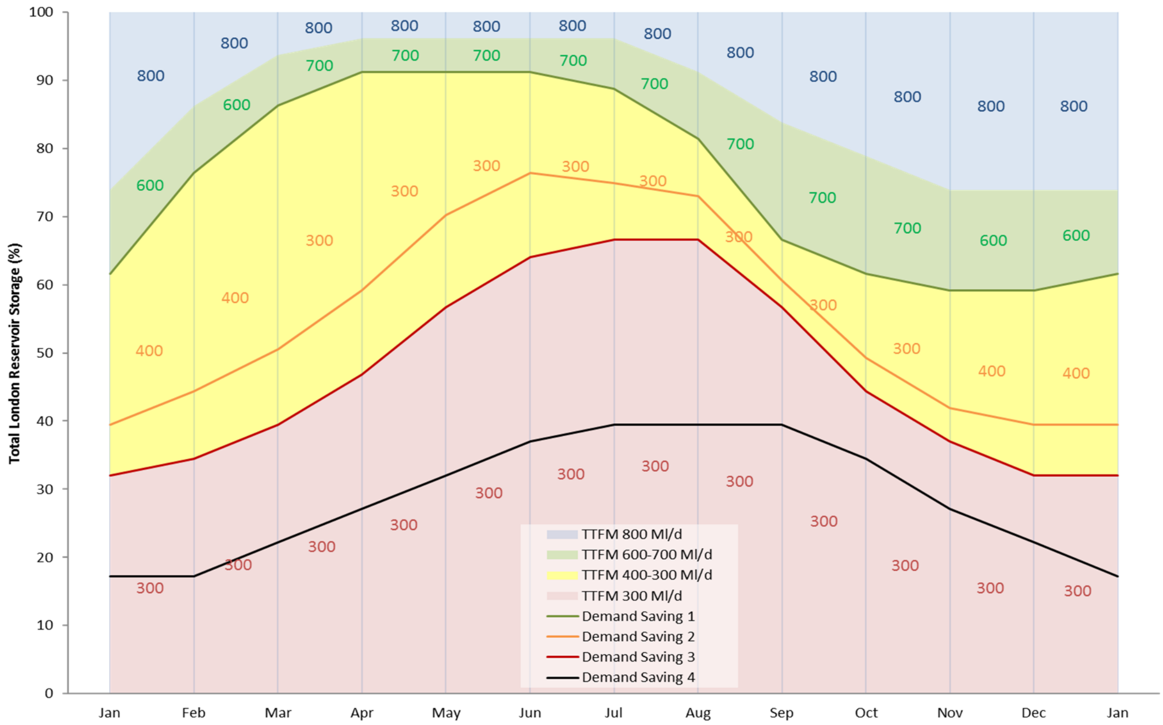

Figure 1. The Lower Thames Control Diagram (LTCD).

In addition, the "crossing" of these demand-saving lines also triggers the implementation of further schemes, such as transfers of water from neighbouring water resource zones and the use of the Thames Gateway desalination plant at Beckton [13].

For the purposes of this analysis, the existing LTCD [14], which dates back to 1980 and was last updated in 1997, is considered to give a deployable output of 2285 Ml/day. The shape of the curves was derived by iteratively applying a water resource model over the historical draw-down record and adjusting the profiles to account for violations of the level of service constraints.

2.2. Constraints

The deployable output (DO) is defined as being the maximum demand that the system can supply whilst meeting the terms of the level of service. The level of service criteria, measured over a time horizon of 100 years, agreed with the regulator for the system are:

- Level 1 events should occur at a frequency of no more than 1 in 5 years.
- Level 2 events should occur at a frequency of no more than 1 in 10 years.
- Level 3 events should occur at a frequency of no more than 1 in 20 years.
- Level 4 events are considered unacceptable and thus any solution must not allow such an event.

The permitted occurrence of Level 2 and Level 3 events is complicated by the impact of the Flood and Water Management Act 2010 [15], which stipulates that there should be periods of 14 and 56 days of public consultation, respectively, in advance of these measures being implemented. Accordingly, it is required that 14 days elapse between a Level 1 and a Level 2 event starting, and 56 days between the start of Level 2 and Level 3 events. The existing LTCD DO of 2285 Ml/day did not consider these additional constraints. As at present, the lines defining the implementation of the demand-saving levels were to be considered coincident with the boundaries between the respective TTF bands.

Further constraints were agreed with the environmental regulator for the production of the new LTCD, which included ensuring that the boundary between the TTF800 and TTF600-700 bands (coloured blue and green, respectively, in Figure 1) should be no higher than its current implementation. In addition, the definition of the Level 4 curve is changed to represent 30 days of storage at the prevailing DO and thus this line will represent a greater storage capacity for higher demand scenarios; the revised form of the Level 4 curve for the baseline scenario is shown as the horizontal line in Figure 2.

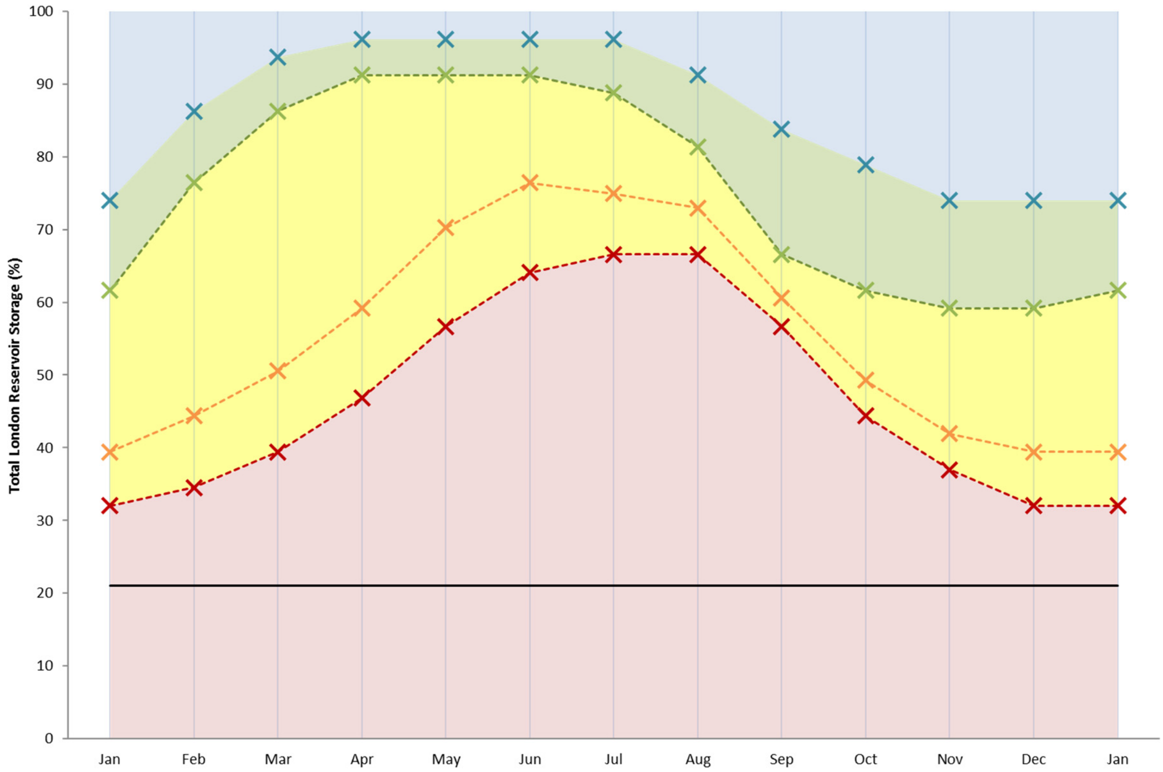

Figure 2. Annotated LTCD showing the 48 decision variables needed to define its shape.

The addition of each of these constraints increases the complexity of the problem to such an extent that it is difficult to imagine an efficient mechanism for deriving a workable solution, let alone a good one, without the use of optimisation tools.

2.3. Aquator Model

As part of this research project, an Aquator [16] water resources model was made of the whole Thames Water resource and supply area. Aquator is widely used in the UK water industry and has been used as a platform for a software application: AquatorGA [17]. This optimisation tool has been used in a number of projects in which it acts as a controller for the Aquator modelling package. The Aquator model simulates the daily operation of the system, applying the rules and constraints of the LTCD. Uncertainty in future inflows is accommodated by running the model for a given present-day DO against historic inflow data from 1920 to 2010. These inflows could be substituted by stochastically generated ensembles, if required. The model is executed by the optimisation algorithm repeatedly for a given DO and curve profile combination and is used to determine whether the combination (a) is feasible, and (b) meets the constraints of the maximum number of level of service events that occur in each category over the 90-year time horizon. The model is able to operate in two modes: a simplified cut-down model, for the purposes of optimisation, and a full mode, for validating the results as a post-process, which takes approximately three times longer to run. Tests showed that the differences in the accuracy of the two modes of the model were of the order of 1 or 2 Ml/day. Even so, the cut-down model required around 1 h to run for the historic inflow data.

2.4. Genetic Algorithm Optimisation

Genetic algorithms (GAs) are a powerful optimisation technique which can be applied to a wide variety of problems without any prerequisite knowledge of the problem domain. They perform a directed search of the decision space, which also contains a stochastic component, based on the "survival of the fittest" principle. The methodology takes advantage of the simulation model, i.e., Aquator in this case, ensuring that each potential solution is tested using a realistic representation of the water resource system being analysed. The most important advantage of GA over any other optimisation techniques is its flexibility in simulating different decision variables, objectives and constraints, due to the fact that any potential solution can be assessed directly in the model without the need for the derivation of specific mathematical properties (e.g., linearity) or expressions (e.g., derivatives), which present the main drawbacks to classic optimisation methods. A multiobjective GA [18] that can easily handle multiple constraints was used as part of the AquatorGA software.

Two objectives were specified for the production of the new LTCD: to maximise the deployable output of the system and to minimise the complexity of the produced curves in order to make them acceptable to practitioners by reducing their jaggedness. Although this latter objective is, strictly speaking, not a genuine operational requirement, this objective was included as a result of the discussions with the client and consideration of the practicability of the implementation of the solution. Past applications of the AquatorGA software demonstrated that practitioners find it easier to relate to and explain control rules and curves when they are presented as smooth curves rather than more jagged ones, even though these may be perfectly valid solutions and represent mathematically "better" results.

The shape of the LTCD is represented by 48 decision variables representing the monthly values for each of the four profile curves, as shown in Figure 2. Each variable was defined with a nominal precision of 1 decimal place and was permitted to vary between the level of the Level 4 line and the current boundary between the TTF800 and TTF600-700 bands. In order to accommodate the curve complexity objective, each of the 48 curve shape decision variables was coupled with a Boolean decision variable, which determined whether the point was considered as part of the curve or not. In this way, by "switching off" the curve points, the optimisation can easily simplify the shape of the curves.

One further decision variable was used to define the requested DO for the solution, hence the unusual situation where the DO was both an objective a decision variable. This approach was adopted because the total demand on the system was, along with the curve profile shapes, an input value submitted to the Aquator simulation model. The long run-times of the Aquator model meant that it was important that the number of infeasible solutions evaluated was minimised. To this end, once a feasible set of profiles had been identified, the DO decision variable was gradually increased in subsequent generations in order to determine the maximum valid DO for the combination of curve profiles specified. This was achieved by dynamically constraining the allowed range of the DO decision variable. If a feasible solution was subsequently found to have a valid higher DO, then the minimum value of the DO decision variable for this solution would be set to the new high DO. Similarly, if the evaluation of a higher DO proved not to be feasible, then the maximum value of the DO would be pegged to that higher value, so that higher values could no longer considered for that solution. Over time, the population of solutions gradually migrated to their true DO values. "Immature" solutions whose maximum DO has yet to be determined were protected from being removed from the population.

The combination of decision variables and constraints gives rise to a solution space consisting of 48 curve shape decisions, each of which can take on 1000 different values (0–100% at 1 decimal place = 1000^{48} options) plus 48 boolean decisions (2^{48} options) plus a single integral decision variable representing DO which is allowed to vary between 1800 and 2350 Ml/day (550 options), which gives $1000^{48} \times 2^{48} \times 550 = 1.5 \times 10^{161}$ possible solutions to the problem. The use of a genetic algorithm allowed this huge space to be efficiently sampled and evaluated, using of the order of 120,000 solutions. Nevertheless, with each solution taking around 1 h to simulate on a high-specification PC (2015), it was necessary to employ some form of parallelisation in order to reduce the optimisation run-times to a manageable length. To this end, the AquatorGA software used in this optimisation included a distributed-processing system in order to militate against the extended run-times that are a common issue when optimising evolution algorithms applied to hydroinformatics problems. The software employs the industry standard message passing interface (MPI) protocol to execute many Aquator simulation models in parallel. This system permits the concurrent evaluation of a large number of potential solutions either on local processors or to other computers on a local area network.

For the purposes of this optimisation, the software was deployed across a cluster of five workstations, each equipped with two Intel Xeon E5645 CPU packages, which comprise six cores running at 2.4 GHz for a total of 60 processor cores. In addition, this hardware architecture can take advantage of hyper-threading technology, which improves the performance of identical threads running on multiple cores by around 10–20%. Accordingly, the run-time of the optimisation model was reduced, in total, from around 13 years to around 3 weeks when deployed to 120 virtual processor cores.

3. Results

A multiple objective optimisation produces a gamut of results distributed between the competing objectives. This allows the end user to select a solution which meets their requirements, rather than being presented with a single solution. This optimisation resulted in a trade-off between the maximum DO of the system versus the complexity of the profile curves obtained. Figure 3 illustrates the least complex profile curve set from the optimisation results, in which the curves are collapsed to two straight lines and a greatly simplified upper band shape. This solution demonstrates a DO of 2144 Ml/day.

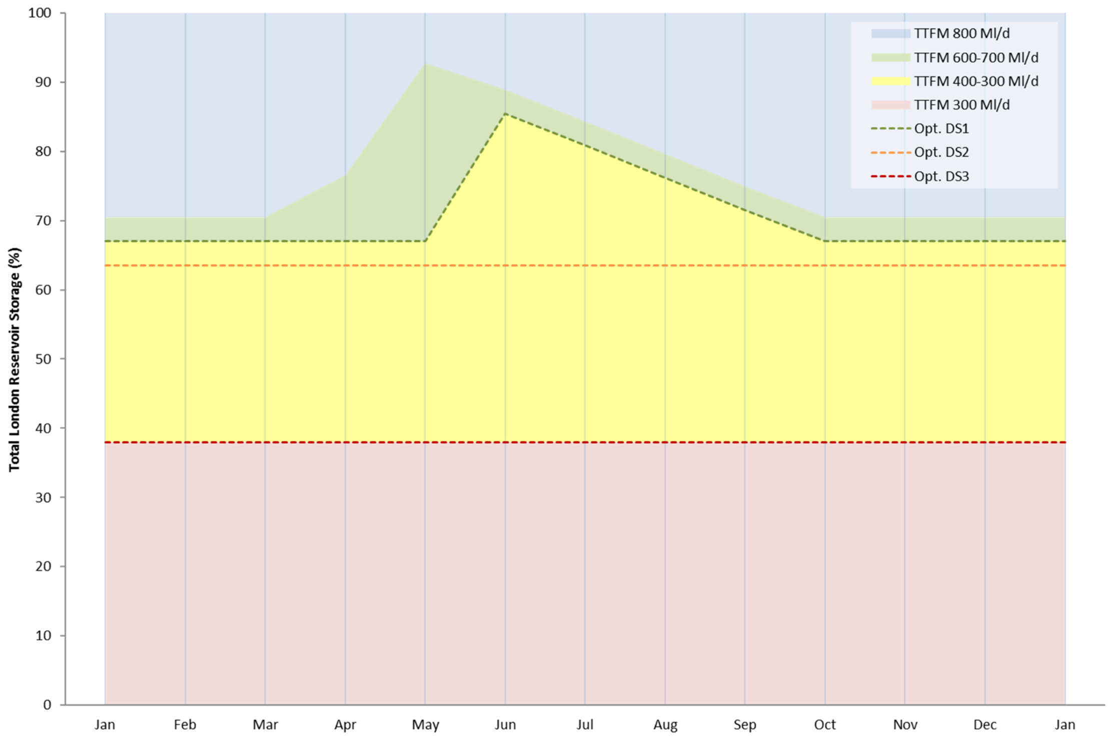

Figure 3. The simplest solution obtained for the LTCD which results in DO of 2144 Ml/day.

The highest DO/most complex curve result can be seen in Figure 4. This solution represents a DO for the system of 2308 Ml/day. It is interesting to note that the overall shape of the profile curves obtained is very similar to that of the original LTCD.

A second scenario was considered in which the total storage capacity of the London system was expanded by approximately 3% (6000 Ml) through the dredging (removal) from the reservoir of aggregate which had accumulated over time. The optimisation was rerun to take account of the increased storage and the flexibility this might add to the operation of the system. This result is seen in Figure 5.

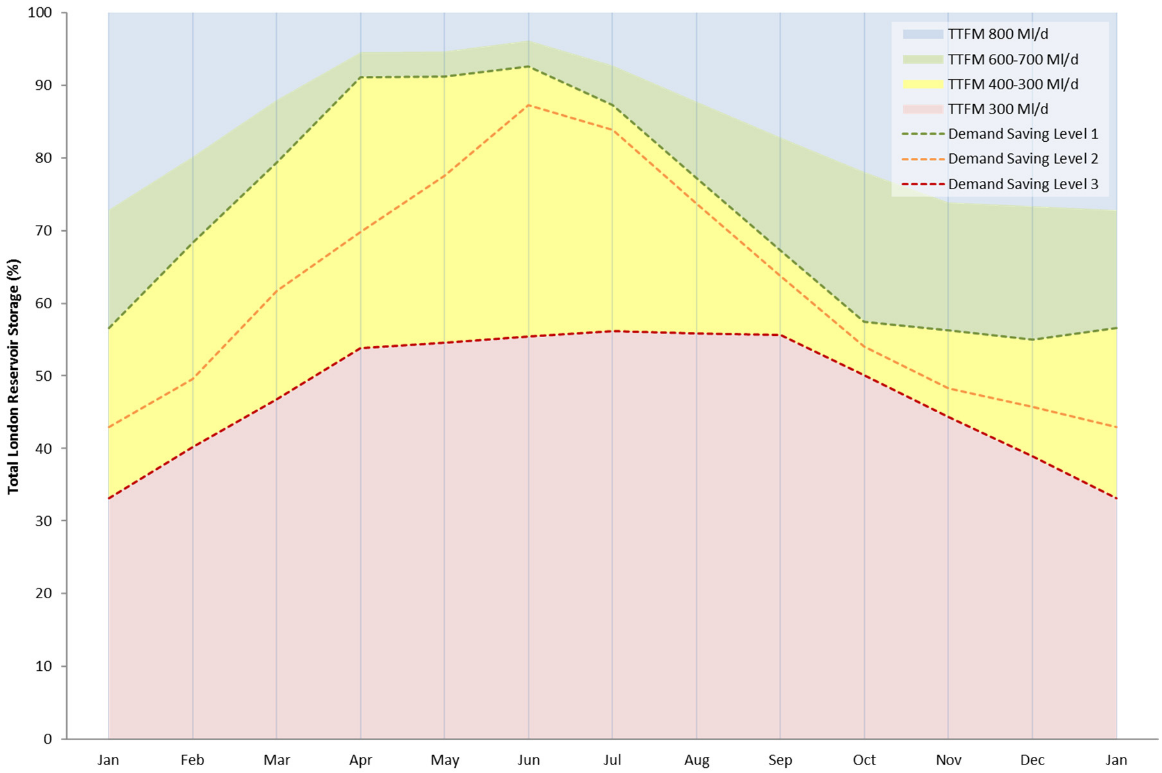

Figure 4. The most complex solution obtained for the LTCD which results in DO of 2308 Ml/day.

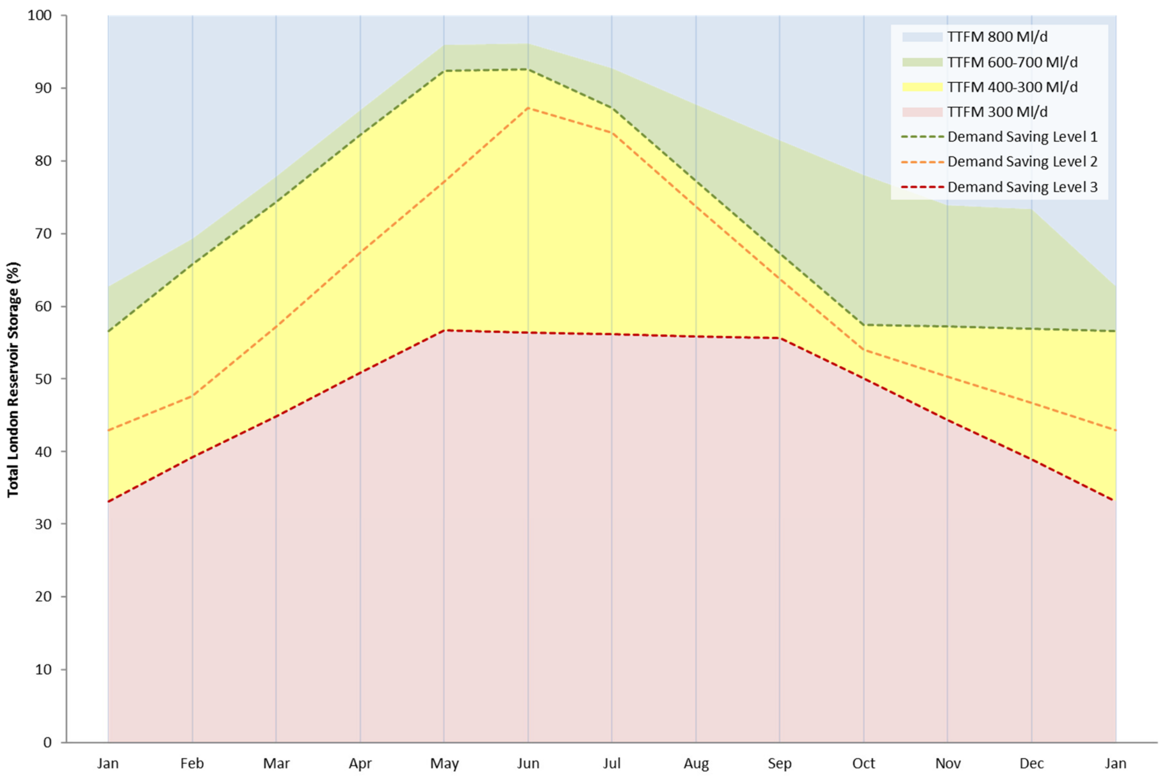

Figure 5. The most complex solution obtained for the LTCD with expanded storage of 6 Ml, which results in DO of 2335 Ml/day.

As shown, a small increase in total storage results in a slightly different shape of LTCD, but one which results in DO of 2335 Ml/day.

4. Discussion

The application of a GA optimisation tool to the Lower Thames Control Diagram resulted in the realisation of a significant increase of around 1% (33 Ml/day) in the deployable output of the London Water Resource Zone. The optimised LTCD for the scenario in which storage had not been increased (2308 Ml/day) was adopted by Thames Water, approved for use by the environmental regulator in late 2016 and continues to be in use to date [19]. However, it is interesting to note that the baseline solution (Table 1) did not satisfy the key constraints, which made it not valid for implementation, but also not easily comparable with the optimised solutions. If, for example, the simple optimised solution is used as a baseline, the realistic improvement in DO afforded by the selected optimised (complex) solution or the optimised solution with the increased storage amounts to an increase of 164 Ml/day (7.6%) and 191 Ml/day (8.9%), respectively. Considering also that London is in a drought-prone area and that Thames Water invested £270 million [20] in a desalination plant (Beckton) with a nominal capacity of 150 Ml/day that began operating in 2011, the selected solution would save the utility almost £60 million in equivalent capital expenditure. The two more realistic increases in DO would result in savings of £295 and £344 million, respectively.

Table 1. Summary of LTCD optimisation results.

LTCD Version	Deployable Output (Ml/day)	% Change
Baseline	2285 [1]	n/a
Optimised: simple)	2144	−6.2%
Optimised: complex	2308	1.0%
Optimised: increased storage	2335	1.2%

[1] Baseline LTCD does not respect the constraints for Level 2/Level 3 events relating to public consultation lead-times. If these constraints are considered, the DO is some 200 Ml/day lower.

Table 1 summarises the results obtained for the LTCD optimisation:

The use of an optimisation tool, particularly one with such long run-times, afforded a good opportunity for incorporating feedback from the client into the optimisation whilst it was still ongoing. One requirement that emerged during the optimisation was that each of the bands representing the different Teddington target flows should be present in the final solution. Early results saw the GA collapsing the 600–700 Ml/day band out of existence, something that was thought unlikely to satisfy the regulator. Accordingly, a minimum storage percentage for each band was incorporated into the optimisation while it was running.

The environmental objective for this study is embodied in the Teddington target flow matrix, detailing how much water must remain in the river at Teddington Lock. The key influence on this matrix was the maintenance of levels for the purposes of fisheries, particularly for Atlantic salmon [21] returning to the river to spawn. There is also a lesser component for the maintainance of navigation. In the absence of a numerical model or criteria to allow the comparison of potential solutions for this objective, it is not possible to undertake Pareto or qualitative multi-criteria analysis to compare solutions [22] which would allow further investigation of conflicts and synergies in policy choices. In lieu of such a possibility, the target flow matrix is applied as a hard constraint in the optimisation model, such that the status quo must be met or exceeded, with no way of quantifying what benefit any excess water might accrue for the environmental objective.

5. Conclusions

Optimal operational policies should, as in this case, be formulated as a multi-objective problem, i.e., one with more than one objective. In this way, instead of a single optimal solution, this approach leads to multiple solutions: a set of efficient or non-dominated solutions, also known as Pareto-optimal solutions, that represent the optimal trade-off curve between the objectives. Each solution is optimal in that it can only be improved for one objective, at the expense of another. The Pareto set gives a decision maker more flexibility in the selection of a suitable alternative. Each solution along the front is considered to be equally optimal. In this instance, the second objective (curve complexity) is largely a cosmetic consideration; however, it was one that was strongly valued by those in the water company. For each of the two optimisations undertaken, eight candidate solutions were presented to the client for their final selection.

The existence of a group of solutions, rather than a single one, offers additional advantages from the engineering point of view, such as increased sensitivity analysis possibilities and selection according to priorities, such as the attitude of the practitioner toward risk. It is possible to extend the application of this approach to water resources management, such that further objectives might be considered, including differential costs for supply sources, assessing infrastructure options to achieve a given DO, maximising different level of service requirements (or conversely, minimising water shortages), etc.

Author Contributions: Conceptualization, M.M. and D.S.; methodology, M.M.; software, M.M.; validation, M.M. and D.S.; formal analysis, D.S.; investigation, M.M.; resources, D.S.; data curation, M.M.; writing—original draft preparation, M.M. and D.S.; writing—review and editing, M.M. and D.S.; visualization, M.M.; supervision, D.S.; project administration, M.M.; funding acquisition, D.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: The authors would like to express their gratitude to Kevin Mountain of Thames Water Utilities Ltd. and Chris Green, Will Clark and Peter Edgely for their longstanding collaboration in optimising water resource models with Aquator.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Brown, C.M.; Lund, J.R.; Cai, X.; Reed, P.M.; Zagona, E.A.; Ostfeld, A.; Hall, J.; Characklis, G.W.; Yu, W.; Brekke, L. The future of water resources systems analysis: Toward a scientific framework for sustainable water management. *Water Resour. Res.* **2015**, *51*, 6110–6124. [CrossRef]
2. Vojinović, Z.; Abbott, M.B. Twenty-five years of hydroinformatics. *Water* **2017**, *9*, 59. [CrossRef]
3. Freeman, D.M. Wicked water problems: Sociology and local water organizations in addressing water resources policy. *J. Am. Water Resour. Assoc.* **2000**, *36*, 483–491. [CrossRef]
4. Reed, P.M.; Kasprzyk, J. Water resources management: The myth, the wicked, and the future. *J. Water Resour. Plan. Manag.* **2009**, *135*, 411–413. [CrossRef]
5. Simonović, S.P. Reservoir systems analysis: Closing gap between theory and practice. *J. Water Resour. Plan. Manag.* **1992**, *118*, 262–280. [CrossRef]
6. Labadie, J.W. Optimal operation of multireservoir systems: State-of-the-art review. *J. Water Resour. Plan. Manag.* **2004**, *130*, 93–111. [CrossRef]
7. Quinn, J.D.; Reed, P.M.; Giuliani, M.; Castelletti, A. What is controlling our control rules? Opening the black box of multireservoir operating policies using time-varying sensitivity analysis. *Water Resour. Res.* **2019**, *55*, 5962–5984. [CrossRef]
8. Macian-Sorribes, H.; Pulido-Velazquez, M. Inferring efficient operating rules in multireservoir water resource systems: A review. *Wiley Interdiscip. Rev. Water* **2020**, *7*, e1400. [CrossRef]
9. Loucks, D.P. Managing water as a critical component of a changing world. *Water Resour. Manag.* **2017**, *31*, 2905–2916. [CrossRef]
10. Water UK. *Water Resources Long Term Planning Framework (2015–2065)*; Water: London, UK, 2016.
11. Water Resources Act. 1991. Available online: http://www.legislation.gov.uk/ukpga/1991/57/contents (accessed on 15 May 2020).
12. The Water Use (Temporary Bans) Order. 2010. Available online: http://www.legislation.gov.uk/uksi/2010/2231/contents/made (accessed on 15 May 2020).
13. Thames Gateway Water Treatment Works. Available online: https://www.thameswater.co.uk/help-and-advice/water-quality/where-our-water-comes-from/thames-gateway-water-treatment-works (accessed on 15 May 2020).
14. Thames Water. *Water Resources Management Plan. 2015–2040*; Thames Water Utilities Ltd.: Reading, UK, 2014.

15. Flood and Water Management Act. 2010. Available online: http://www.legislation.gov.uk/ukpga/2010/29/contents (accessed on 15 May 2020).
16. Hydro-Logic Aquator. 2020. Available online: https://hydro-int.com/en-gb/products/hydro-logic-aquator (accessed on 15 May 2020).
17. Vamvakeridou-Lyroudia, L.S.; Morley, M.S.; Bicik., J.; Green, C.; Smith, M.; Savić, D.A. AquatorGA: Integrated Optimisation for Reservoir Operation using Multiobjective Genetic Algorithms. In *Integrated Water Systems: Proceedings 10th International Conference Computing and Control for the Water Industry*; Boxall, J., Maksimović, Č., Eds.; Taylor & Francis: Sheffield, UK, 2010; pp. 493–500.
18. Deb, K.; Tiwari, S. Omni-Optimizer: A Generic Evolutionary Algorithm for Single and Multi-Objective Optimization. *Eur. J. Oper. Res.* **2008**, *185*, 1062–1087. [CrossRef]
19. Thames Water. *Water Resources Management Plan. 2019. Section 4: Current and Future Water Supply—April 2020*; Thames Water Utilities Ltd.: Reading, UK, 2019; p. 47.
20. Loftus, A.; March, H. Financializing desalination: Rethinking the returns of big infrastructure. *Int. J. Urban Reg. Res.* **2016**, *40*, 46–61. [CrossRef]
21. Hughes, S.N.; Willis, D.J. The fish communities of the River Thames: Status, pressures and management. In *Management and Ecology of River Fisheries*; Cowx, I.G., Ed.; Wiley-Blackwell: Oxford, UK, 2008; pp. 55–70.
22. van der Voorn, T.; Svenfelt, A.; Bjornberg, K.E.; Faure, E.; Milestad, R. Envisioning carbon-free land use futures for Sweden: A scenario study on conflicts and synergies between environmental policy goals. *Reg. Environ. Chang.* **2020**, *20*, 1–10. [CrossRef]