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WATERFLEX Exploratory Research Project: version 1

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Abstract

Water is needed for energy. For instance, hydropower is the technology that generates more electricity worldwide after the fossil-fuelled power plants and its production depends on water availability and variability. Additionally, thermal power plants need water for cooling and thus generate electricity. On the other hand, energy is also needed for water. Given the increase of additional hydropower potential worldwide in the coming years, the high dependence of electricity generation with fossil-fuelled power plants, and the implications of the climate change, relevant international organisations have paid attention to the water-energy nexus (or more explicitly within a power system context, the water-power nexus). The Joint Research Centre of the European Commission, the United States Department of Energy, the Institute for Advanced Sustainability Studies, the Midwest Energy Research Consortium and the Water Council, or the Organisation for Economic Co-operation and Development, among others, have raised awareness about this nexus and its analysis as an integrated system. In order to properly analyse such linkages between the power and water sectors, there is a need for appropriate modelling frameworks and mathematical approaches.

This report comprises the water-constrained models in electric power systems developed within the WATERFLEX Exploratory Research Project of the European Commission's Joint Research Centre in order to analyse the water-power interactions. All these models are deemed modules of the Dispa-SET modelling tool.

The version 1 of the medium-term hydrothermal coordination module is presented with some modelling extensions, namely the incorporation of transmission network constraints, water demands, and ecological flows. Another salient feature of this version of Dispa-SET is the modelling of the stochastic medium-term hydrothermal coordination problem. The stochastic problem is solved by using an efficient scenario-based decomposition technique, the so-called Progressive Hedging algorithm. This technique is an Augmented-Lagrangian-based decomposition method that decomposes the original problem into smaller subproblems per scenario. The Progressive Hedging algorithm has multiple advantages:

- It is easy parallelizable due to its inherent structure.
- It provides solution stability and better computational performance compared to Benders-like decomposition techniques (node-based decomposition).
- It scales better for large-scale stochastic programming problems.
- It has been widely used in the technical literature, thus demonstrating its efficiency.

Its implementation has been carried out through the PySP software package which is part of the Coopr open-source Python repository for optimisation.

This report also describes the cooling-related constraints included in the unit commitment and dispatch module of Dispa-SET. The cooling-related constraints encompass limitations on allowable maximum water withdrawals of thermal power plants and modelling of the power produced in terms of the river water temperature of the power plant inlet. Limitations on thermal releases or water withdrawals could be imposed due to physical or policy reasons.

Finally, an offline and decoupled modelling framework is presented to link such modules with the rainfall-runoff hydrological LISFLOOD model. This modelling framework is able to accurately capture the water-power interactions. Some challenges and barriers to properly address the water-power nexus are also highlighted in the report.

1 Introduction

1.1 Motivation

Electricity generation worldwide is one of the major activities utilising freshwater resources due to hydropower generation and cooling of thermal power plants.

Hydropower is a mature technology which provides multiple benefits to the power system (black start capability, spinning reserve, back-up and reserve with quick start and shutdown capabilities, frequency response, flexibility, or reactive power compensation) [1]. Hydropower supplies 16.3 % of the world's electricity followed by nuclear power and other renewable technologies [1]. Apart from hydropower production, their associated reservoirs or dams can be used for water management of a wide variety of purposes such as water supply, flood control, irrigation, navigation, recreation activities, fish breeding or aquiculture, among others [2], as can be seen in Figure 1. The distribution for purposes of freshwater is uneven and highly depends on the availability and variability of freshwater. According to ICOLD (International Commission on Large Dams) database which contains 58 519 registered dams ([1]) around the world, irrigation is the most common purpose of both single-purpose and multipurpose dams, as shown in Figure 2. Moreover, hydropower production is the second largest use of single-purpose dams followed by water supply, whereas multipurpose dams are used more often for flood control and water supply than for hydropower production. However, hydropower production is still far from fossil-fuel power plants' production (67.2 % of the world's electricity), according to the International Energy Agency (IEA) [1].

Regarding the thermal power plants, the largest amount of freshwater withdrawals for cooling can be found in North America and Europe representing 86 % of the global water withdrawals [3], while the water used for cooling represents 43 % of the European Union's water demand [3], [4].

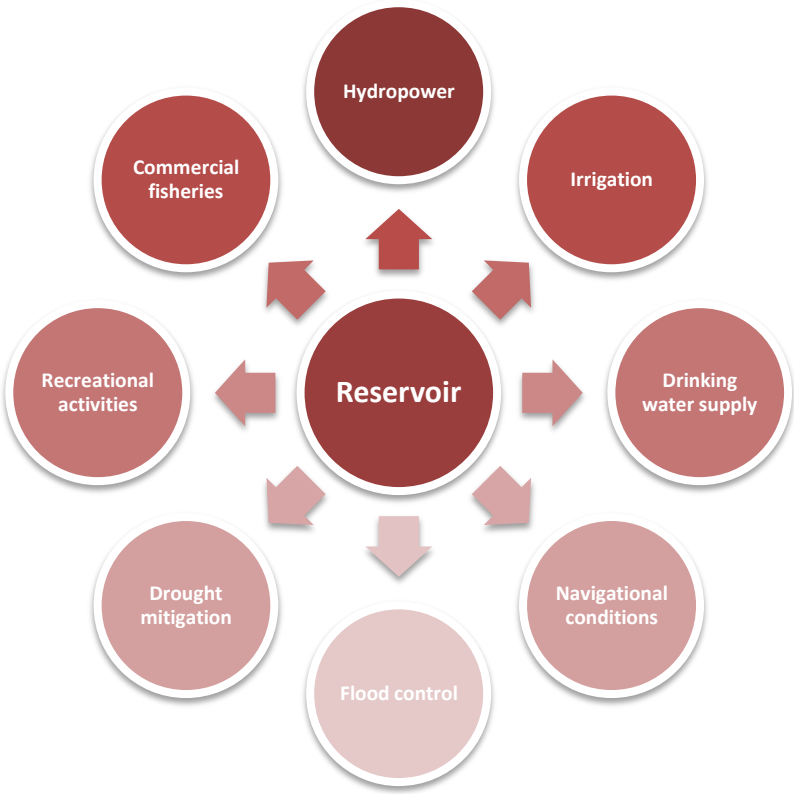
On the other hand, the water sector needs electricity for abstraction, treatment, desalination, transport, or irrigation purposes. Thus, the power system is involved in a new paradigm of water for energy and energy for water, which would be further exacerbated in the coming years due to an increase of additional hydropower potential worldwide [1], the indispensable use of thermal power plants, and the implications of the climate change.

From a power system perspective, due to water shortages or high river water temperatures, '*the number of days with a reduced useable capacity is projected to increase in Europe and USA*' according to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) [5]. In fact, water impacts on European power systems have recurrently occurred in the last years and they led to monetary losses, power curtailments, temporary shutdowns, demand restrictions, and ultimately increased wear and tear of the power plants ([6] and references therein). On the other hand, the operation of the power system may impact on the quantity and quality of the water resources.

Therefore, the water-power link – which has been recently analysed by Pereira-Cardenal *et al.* [7] and Bertoni *et al.* [8] – needs to be further explored in order to propose reasonable and realistic policy measures about water withdrawals and thermal pollution. Those analyses call for appropriate power system models in both the mid- and short-term.

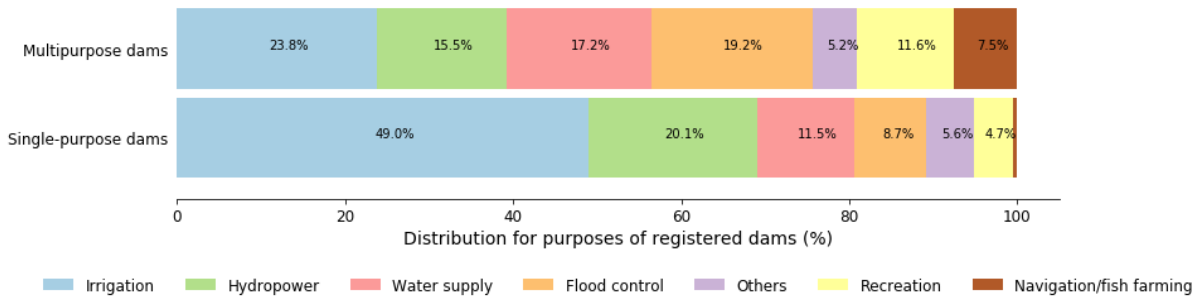
([1]) ICOLD contains only large dams, which are defined as dams with a height of 15 metres or greater from lowest foundation to crest or a dam between 5 metres and 15 metres impounding more than 3 million cubic metres (See http://www.icold-cigb.org/GB/world_register/general_synthesis.asp).

Figure 1. Purposes of reservoirs.



Source: JRC 2017.

Figure 2. Distribution for purposes of registered dams.



Source: ICOLD.

1.2 Literature review

As part of the WATERFLEX exploratory research project carried out at the European Commission's Joint Research Centre, this report is focused on 1) the recent developments of the Dispa-SET Medium-Term Hydrothermal Coordination (Dispa-SET MTHC) module (i.e. some amendments to the deterministic problem and the implementation of the stochastic module); and 2) the implementation of cooling-related constraints for thermal power plants in the Dispa-SET Unit Commitment and Dispatch (Dispa-SET UCD) module. Therefore, this section provides a brief overview of three topics:

— The medium-term hydrothermal coordination problem.

— The progressive hedging algorithm whose popularity has been increased in the last years for solving large-scale stochastic problems.

— Cooling-related constraints in electric power systems.

1.2.1 Medium-term hydrothermal coordination

There is a large body of technical literature on the hydrothermal coordination problem including the short-, mid-, and long-terms. However, this work is focused on the medium-term hydrothermal coordination (MTHC) problem [7], [9]–[22], which is a power system tool used for operation planning of hydropower reservoirs and thermal power plants driven by the minimization of the expected system-wide generation costs over a given planning horizon (in the mid-term). Typically, the planning horizon ranges from 1 year to several years with daily, weekly, or monthly time steps. In the MTHC problem, the degree of detail of hydropower reservoirs is greater than in short-term operation problems at expense of clustering the remaining power plants. Moreover, it takes usually into account uncertainties of water inflows or demand, among others. All in all, the MTHC problem can be characterised as a large-scale, nonlinear, and nonconvex optimisation.

The MTHC problem can be solved from two perspectives: 1) the extensive form (also known as deterministic equivalent) or 2) the stochastic form. The deterministic MTHC problem basically assumes fixed water inflows and can be formulated by linear programming, nonlinear programming, or mixed-integer linear programming, depending on the modelling assumptions of hydro- and thermal-related technical features. The deterministic problem could be useful to perform a scenario analysis based on representative time periods, e.g. years. On the other hand, stochastic programming is more valuable when these models are used in production. In this case, the inherent uncertainty of different variables affects real-time operational decisions.

Table 1 collects a summary of references addressing the stochastic MTHC problem. The second and third columns of Table 1 show the respective solution techniques applied to tackle such complex problem and information about the case study. Several solutions techniques have been proposed: stochastic dynamic programming (SDP) [7]; stochastic dual dynamic programming (SDDP) [7], [10], [11], [15], [17]; benders' decomposition (BD) [9], [21], [22]; progressive hedging (PH) [16], [18], [20]; nonlinear programming (NP) [19]; interior point methods (IPMs) [12], [13]; semidefinite programming [14]; or other kind of algorithms or decompositions [18], [22]. Regarding the case studies, both Brazilian and Spanish systems have typically been suitable targets for applying these techniques on the corresponding MTHC problems due to the high share of hydropower production in their respective generation mixes.

Traditionally, dynamic programming have been applied to reservoir operations [23] and SDP has been used to solve the MTHC problem, e.g. in [7]. However, computational difficulties are associated with dynamic programming techniques when solving large-scale instances. The state variables need to be discretized and the computational requirements exponentially increase when the number of state variables increases. This is known as the '*curse of dimensionality*' and it could limit its application to systems with a reduced number of reservoirs. Therefore, as suggested by Pereira and Pinto [9], it '*becomes necessary to develop methods able to approximate the solution of the operating problem with a reasonable computational cost*'.

Decomposition techniques are therefore required to overcome the '*curse of dimensionality*' for solving large-scale multistage stochastic hydrothermal problems. Benders' decomposition [24] has been applied to this planning problem in [9], [21], [22]. Benders-like algorithms decompose the problem by stage or time period and thus allowing for parallelization of the corresponding subproblems. In addition, the SDDP method proposed by Pereira [10] and Pereira and Pinto [11], which is based on Benders' decomposition, makes it possible to optimise multi-reservoir systems. SDDP has been widely used in the open literature [7], [10], [11], [15], [17]. However, unlike dynamic programming techniques, SDDP relies on the approximation of the expected cost-to-go functions of SDP by convex functions [10], which may remove some of the advantages of dynamic programming.

Other techniques have been applied to solve the MTHC problem. Medina *et al.* [12], [13] proposed the use of IPMs that seek the optimal solution through the interior of the

feasible region rather than the vertices of such region, as done by simplex methods. IPMs outperform simplex decomposition-based methods when solving large-scale hydrothermal coordination problems [12], [13]. Along the same lines, Fuentes-Loyola and Quintana [14] applied semidefinite programming to the convex medium-term hydrothermal coordination problem. Semidefinite programming is a technique that can efficiently solve convex problems in polynomial time. However, convexification of the problem may show some mismatches in the integer variables that should be corrected by a heuristic method [14]. Linear programming [18] or NP [19] have been directly applied to solve the MTHC by using commercial solvers.

Table 1. Model characterisation, solution method, and case study for selected references (in chronological order) addressing medium-term hydrothermal coordination problems.

Reference	Method(s)	Case study
Pereira and Pinto [9]	Benders' decomposition	Southeast and south regions of the Brazilian system
Pereira [10] Pereira and Pinto [11]	Stochastic dual dynamic programming	Southeast and south regions of the Brazilian system.
Medina *et al.* [12]	Interior-point methods	Spanish system up to 30 thermal power plants and 30 hydropower plants
Medina *et al.* [13]	Clipping-off interior-point algorithm	Spanish system up to 25 thermal power plants and 12 cascaded hydro plants
Fuentes-Loyola and Quintana [14]	Semidefinite programming	Spanish system up to 60 thermal power plants and 32 hydropower plants
Tilmant and Kelman [15]	Stochastic dual dynamic programming	Turkish case study. 20 stages and time horizon of 60 months
Santos *et al.* [16]	Progressive hedging	Brazilian system
Gjelsvik *et al.* [17]	Stochastic dual dynamic programming	-
Gonçalves *et al.* [18]	Linear programming Nested decomposition Progressive hedging	Brazilian system
Ramos *et al.* [19]	Nonlinear programming	Spanish system with up to 118 thermal power plants, 56 hydropower plants and 2 pumped storage hydro
Gonçalves *et al.* [20]	Classical and alternative progressive hedging	Brazilian system. 1440 scenarios
Gonçalves *et al.* [21]	Benders' decomposition Augmented Lagrangian-based decomposition	-
Pereira-Cardenal [7]	Stochastic dynamic programming Stochastic dual dynamic programming	Iberian Peninsula
Ennes and Diniz [22]	Linear programming Benders' decomposition	System up to 43 units, 8 periods and 128 scenarios

Source: JRC 2017.

Lagrangian relaxation techniques have also been proposed in the literature but they often lead to primal infeasible solutions [12]. However, decomposition frameworks based on Augmented Lagrangian (AL) make it promising for multistage stochastic linear programs [18] since AL methods obtain a feasible primal solution. PH is an AL-based decomposition technique which is currently becoming more popular to solve stochastic programming problems [25] since it can be parallelized with minimum amount of communication between each instance. Unlike BD, PH decomposes the original problem into smaller subproblems by scenario through relaxation of the non-anticipativity constraints. Then the optimal solution is found by penalising iteratively constraints violations. It has been successfully applied in [16], [18], [20], [22]. According to [18], it is also more stable than the Nested Decomposition (a Benders-like decomposition), allowing for good solutions with less computational time; and it may scale better for large-scale systems.

Also, there are some statistical approaches (external sampling based) such as sample average approximation (SAA) [26], [27] which can be used when the stochastic problem is too large to be solved by exact solution techniques. However, the approach of random generation of scenarios is computationally intractable for solving multistage stochastic programs because of the exponential growth of the number of scenarios when increasing the number of stages [27].

1.2.2 Progressive Hedging algorithm

Rockafellar and Wets [25] pioneered the PH algorithm to cope with stochastic programming problems. As mentioned in the previous subsection, PH is an AL-based decomposition technique that decomposes the original stochastic problem into smaller subproblems by scenario. The major advantages is the easy parallelization of all subproblems, the solution stability and its better computational performance compared to Benders-like decomposition techniques, and its better scalability for large-scale instances [18].

Since this algorithm was rigorously proved by Rockafellar and Wets [25], it has been applied to a wide variety of mathematical problems (see Table 2). Mulvey and Vladimirou [28] apply PH to solve stochastic generalized networks and different internal tactics were evaluated to improve algorithmic performance. Stochasticity can be found in many elements of an optimisation problem. In [29], PH was used to determine the optimal operation of a heat storage tank connected to a Combined Heat and Power (CHP) plant by assuming uncertainty attached to the future power production.

Within power systems, uncertainty can be found in different modelling parameters such as water inflows, electricity prices, or power demand, to name a few. PH was used to solve hydrothermal scheduling problems in the short-term [30] and in the mid-term [16], [18], [20], [21]; unit commitment [31]–[34]; or multistage investment problems [35], [36]. Gil and Araya [30] analysed the computational performance of PH in short-term operational problems and concluded that parallelism and the potential use of high-performance computing would be suitable alternatives to reduce simulation times. The previously discussed references [16], [18], [20], [21] take into account uncertainty on water inflows. Reliability unit commitment problems have also been solved by PH [31], [32], but the stochastic parameter was assumed to be demand and renewable generation in [31] and generator outages in [32]. PH was also used to solve stochastic unit commitment problems [33], [34]. Ryan *et al.* [33] considered demand and renewable uncertainty and demonstrated tractability for solving modest-scale systems with large number of scenarios. Ordouris *et al.* [34] took into account wind power uncertainty and tested different hedging and internal strategies to compare PH's computational performance. Finally, stochasticity can also (and need to) be modelled in investment problems [35], [36]. Munoz and Watson [35] implemented a simple generation investment planning problem considering load, wind, solar and hydro power uncertainty, whereas Liu *et al.* [36] modelled large-scale uncertainties such as changes in investment costs and generating-fuel prices.

To the authors' knowledge, the PH algorithm was first implemented as a part of a software package in 2012 [37] (PySP software package). The software package PySP is part of the Coopr open-source Python repository for optimisation, and the latter is distributed as part of IBM's COIN-OR repository.

Table 2. Mathematical problems solved by using the Progressive Hedging algorithm.

Problem	References
Medium-term hydrothermal coordination problem	Santos *et al.* [16] Gonçalves et al. [18], [20], [21]
Multistage stochastic investment planning	Munoz and Watson [35] Liu *et al.* [36]
Reliability unit commitment	Gu *et al.* [31] Li *et al.* [32]
Resource allocation problem	Watson and Woodruff [38]
Stochastic generalized networks	Mulvey and Vladimirou [28]
Stochastic heat storage problem	Palsson and Ravn [29]
Short-term hydrothermal scheduling	Gil and Araya [30]
Stochastic unit commitment	Ryan *et al.* [33] Ordoudis *et al.* [34]

Source: JRC 2017.

1.2.3 Cooling-related constraints on power system problems

Recently, the vulnerability of thermal power plants to climate change have been assessed in the technical literature either in US and Europe [4] or only within the European Union [39]–[41]. Reference [4] analysed the effects of high river water temperatures or reduced river flows on electricity production as a consequence of climate change and it concluded that thermal power plants in southeastern Europe and US will be greatly impacted by changing climatological conditions. In addition, they highlighted that power plants with once-through cooling will be even more impacted by low river flows or high water temperatures. In [39], the water stress within the European Union is analysed on a river basin scale by 2030. Similar studies to [4] are shown at site-specific (Krümmel nuclear power plant) [40] or country scale (Germany) [41]. However, there is a lack of detailed representation of the power system, which may lead to distorted results when quantifying the water-power linkage on the electricity sector.

On the other hand, the number of thermal power plants with once-through cooling (OTB, OTF and OTS) ([2]) represents 43 % of all European thermal power plants, as can be seen in Figure 3 ([3]). In addition, water used for cooling represents 43 % of the European Union's water demand [3], [4]. Moreover, the current studies about the water-power nexus have stressed that potential aspects of the water-power nexus need further attention, e.g. '*the impact of reduced river discharge on cooling of thermal power plants*', as suggested in [7]. Therefore, given these information and the conclusions from [4] and [39], there is a need for modelling cooling systems of thermal power plants in power system problems.

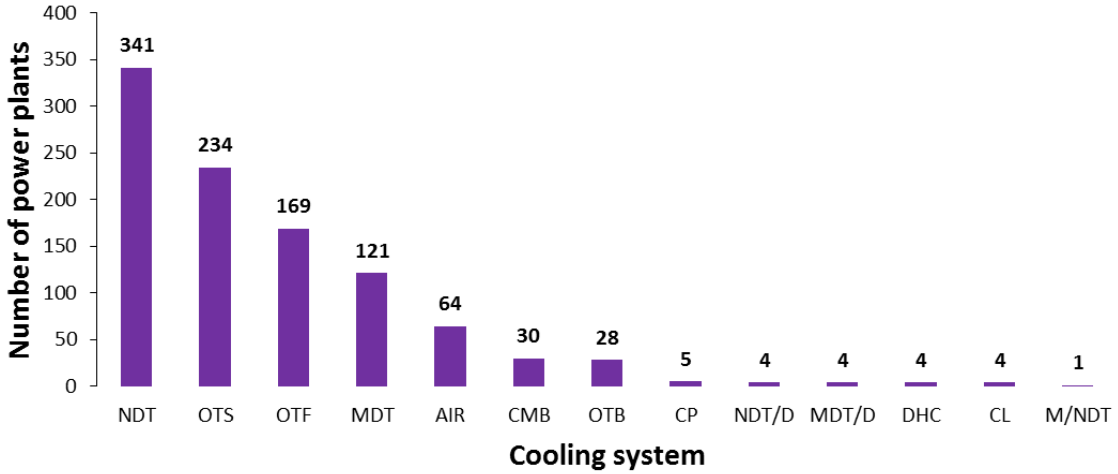
([2]) According to Platts, OTB, OTF, and OTS refer to once-through cooling using brackish water, fresh water, and saline water, respectively.

([3]) This figure accounts for gas, hard, lignite, nuclear and oil power plants of 36 European countries from Platts [46].

Few references have accounted for cooling- and policy-related constraints on thermal power plants in a unit commitment or economic dispatch problem [8], [42], [43]. Zhao *et al.* [43] integrated the operation of cooling systems of gas-fired power plants into the unit commitment problem. They included both the dependence of gas-fired power plants' efficiency with the inlet air temperature and costs of cooling systems (mainly operating and maintenance cost when running a cooling system).

Within a water-energy nexus approach, the implementation of cooling-related constraints has been addressed recently. Bertoni *et al.* [8] implemented the thermal cooling water consumption constraint in its economic-dispatch-based model. This constraint is an adaptation of the cooling-related constraint proposed in [44], which relates the maximum permissible temperature rise of the water, the available capacity, and the maximum permissible withdrawal of fresh water. This constraint is suitable for thermal power plants with once-through cooling technologies, which are more sensitive to river water temperature changes. Finally, Gjorgiev and Sansavini [42] conducted a water-energy study at a river basin scale with an upstream hydropower plant with reservoir and a downstream thermal power plant. Two different cooling designs were analysed for the thermal power plant, namely once-through and wet tower cooling. In this study, they proposed the incorporation of cooling- and policy-related constraints such as constraints on water thermal pollution and on water withdrawals/consumptions. The former constraints are in line with the regulation policy for salmonid waters as defined by the European Fish Directive ([4]), whereas the latter ones impose bounds on the allowable water consumed for cooling purposes.

Figure 3. Number of power plants for each cooling system at European level.



Source: Platts.

1.3 Challenges for the water-power nexus' assessment

In this report, we describe the power system models as well as the methodology to analyse the water-power nexus (or water-electricity nexus). However, such assessment is highly complex due to several barriers and challenges [45]. In subsections 1.3.1-1.3.3, we briefly discuss each of the challenges faced during the WATERFLEX exploratory research project; and subsection 1.3.4 summarises additional barriers and challenges identified by Khan *et al.* [45].

([4]) Directive 2006/44/EC of the European Parliament and of the Council of 6 September 2006 on the quality of fresh waters needing protection or improvement in order to support fish life.

1.3.1 Data collection

The analysis of the water-power nexus depends on data availability ([5]). For instance, power plant characteristics, hydro-related information, water uses and demands or river water temperature time series are needed for performing such analysis. Also, the more disaggregated the data are, the more accurate the results will be. Therefore, there is a need for real and accurate data with high temporal and spatial resolution in power systems.

Power system data can be found in the following sources:

— National databases which may not contain easy-to-find accessible information.

— Commercial databases such as Platts [46] with third-party use policies.

— The transparency platform from ENTSO-E ([6]), which contains aggregated data but only from 2014 onwards (in European countries).

Water-related data can be found, e.g. in ICOLD ([7]) or GRanD ([8]) databases. However, lack of data in critical locations is a common occurrence. Therefore, this time-consuming task could make it difficult to analyse the water-power nexus and thus data mining is one of the major challenges to a great extent when it comes to the water-power nexus' assessment.

1.3.2 Degree of model aggregation

Identification of suitable temporal and spatial scales is highly important in order to produce sound results. Fine temporal and spatial scales could help identify water stress or excessive water withdrawal periods and locations with a high resolution, but data mining may be time-consuming and the computational complexity for solving detailed mathematical problems may exploit. On the other hand, coarse temporal and spatial resolution could limit the assessment of the water-power nexus, and thus overlooking some important metrics, e.g. at generating units' level. Therefore, special attention should be paid to the degree of model aggregation and the objectives of the water-power nexus' assessment should be clearly identified a priori.

In line with model aggregation, system boundaries pose challenges from computational and technical perspectives. A wide scope with high resolution could lead to slow convergence or even problem intractability. National scopes (or even continental scopes) would be suitable targets for assessing the water-power nexus. A global scope would be more relevant for a water-energy analysis and a local scope would not capture the operation and planning activities of the power system. Finally, the power and water sectors are often managed in different jurisdictions, e.g. the power system can be operated on a country-level basis, whereas the water system is managed at catchment level.

1.3.3 Computational complexity

Related to data availability and model aggregation, one should pay also attention to the computational complexity of the proposed mathematical models. The trade-off between model complexity and accuracy is an everlasting debate in power systems. This trade-off depends on what research question(s) should be answered and how deep the analysis should be performed.

For the water-power nexus' assessment, hydropower modelling and cooling-related modelling on thermal power plants are essential to analyse the water-power interactions. However, hydropower economic modelling is a complicated problem itself due to its

([5]) A full list of required data can be found in [55].
([6]) https://transparency.entsoe.eu/
([7]) http://www.icold-cigb.net/GB/icold/icold.asp
([8]) http://www.gwsp.org/products/grand-database.html

inherent complexity, which can be aggravated when it comes to multipurpose hydro reservoirs.

Uncertainty characterisation is used for modelling unforeseeable information such as water inflows, demand, or renewable profiles, rendering large-scale stochastic programming problems. Thus, the computational complexity is expected to grow as the possible realizations or scenarios increase, which may lead to slow convergence when solving large-scale instances. Then, it is crucial to appropriately reduce this number of scenarios with scenario reduction techniques.

1.3.4 Other challenges and barriers

Khan *et al.* [45] thoroughly reviewed the integrated water and energy models and identified some barriers or challenges to address such integrated model. The authors also proposed some recommendations to overcome water-energy issues in terms of both each individual sector and integration modelling. For a quick reference, we list below the challenges and barriers identified by Khan *et al.* [45] for an integrated assessment of the water-energy nexus, which can be also extended to the water-power nexus.

- Traditionally independent and isolated sector management.
- Distinct spatial, temporal and physical characteristics.
- Complementary data availability requirements.
- Degree of model aggregation and generalization.
- Complexity of multipurpose reservoir topology and management.
- Collaboration of expertise and research groups.
- Tracking changes in infrastructure and technological aspects.
- Uncertainty of energy and water futures.

1.4 Aim

The objective of the WATERFLEX Exploratory Research Project is to assess the potential of hydropower as a source of flexibility to the European power system, as well as analysing the water-energy nexus against the background of the EU initiatives towards a low-carbon energy system. Within this context, the aim of this report is to present:

- The recent developments of the Dispa-SET MTHC module.
- The cooling-related constraints included in the Dispa-SET UCD module.
- An off-line methodology to analyse the water and power interactions in the electric power systems.

1.5 Layout

The structure of the report is organised as follows:

- Chapter 2 describes the Dispa-SET MTHC module including both its deterministic and stochastic versions.
- Chapter 3 explains how the Dispa-SET UCD module is extended to a water-constrained unit commitment.
- Chapter 4 gives an overview of the proposed methodology to analyse water-power interactions in electric power systems.
- Conclusions are drawn in Chapter 5.

2 Dispa-SET medium-term hydrothermal coordination module

The Dispa-SET MTHC module is explained in the next sections. The main notation used throughout Chapter 2 can be found in Section 2.1. A compact formulation of the MTHC problem is presented in Section 2.2. Finally, sections 2.3 and 2.4 provide the mathematical description and implementation details for the deterministic and stochastic versions of the MTHC problem.

2.1 Notation

The main notation used throughout this Chapter is listed in Table 3.

Table 3. Main notation.

A. Indices	
h	Index of time periods
j	Auxiliary index of time periods
l	Index of transmission lines
n	Index of nodes
u	Index of units
B. Sets	
H	Set of time periods
L	Set of transmission lines
N	Set of nodes
U	Set of units
Ω_{hydro}	Set of hydro units
Ω_u	Set of upstream reservoirs of plant u
C. Parameters	
c_u	Variable cost (k€/GWh)
d_{hn}^{E}	Electricity demand at node n and period h (GW)
d_{hu}^{EF}	Environmental flow satisfied at period h by hydro reservoir u (m^3/s)
d_{hu}^{W}	Water demand satisfied at period h by hydro reservoir u (m^3/s)
f^1	Conversion factor to convert m^3/s into hm^3
f^2	Conversion factor to convert m^3/s into GWh
$FLOW_l^{max}$	Transmission line capacity (GW)
g	Gravitational constant (m/s^2)
G_u^{max}	Maximum generation level (GW)
$head_u$	Nominal head (m)
m_{un}	Unit-node connection map (m_{un} = 1 if unit u is located at node n, 0 otherwise)
m_{nl}	Line-node connection map (m_{nl} = -1 if node n is the origin node of line l, m_{nl} = 1 if node n is the destination node of line l, 0 otherwise)
N_H	Number of time periods
q_{hu}	Natural inflow (m^3/s)
RES_u^0	Initial water content (hm^3)
RES_u^{max}	Maximum water content (hm^3)
RES_u^{min}	Minimum water content (hm^3)
x_l	Reactance of transmission line l (Ω)
Δt	Time step (h)

ρ	Water density (kg/m^3)
τ_u	Water transport delay
η_u	Roundtrip pumping efficiency
D. Variables	
CH_{hu}	Water charge (m^3/s)
$COST$	Objective function value (k€)
DIS_{hu}	Water discharge (m^3/s)
$FLOW_{hl}$	Energy flow (GWh)
G_{hu}	Generation (GWh)
$PUMP_{hu}$	Pumped energy (GWh)
RES_{hu}	Reservoir level or water content (hm^3)
$SPILL_{hu}$	Water spillage (m^3/s)
W_{hu}	Water value (€/hm^3)
$THETA_{hn}$	Voltage phase angle (rad)

Source: JRC 2017.

2.2 Compact formulation

The MTHC module of Dispa-SET can be mathematically expressed as:

Minimise $C^M(x^M)$ (1a)

subject to:

$$f^M(x^M, y^M) = 0 : (\lambda^M) \quad (1b)$$

$$g^M(x^M, y^M) \leq 0 \quad (1c)$$

$$x^M, y^M \geq 0, \quad (1d)$$

where $C^M(\cdot)$ is the generation cost function, x^M is the vector of continuous variables in energy units, $f^M(\cdot)$ is the function involving all equality constraints, y^M is the vector of continuous variables in water units, λ^M is the vector of dual variables or Lagrange multipliers associated with the equality constraints, and $g^M(\cdot)$ is the function involving all inequality constraints associated with the mid-term.

2.3 Deterministic medium-term hydrothermal coordination problem

The deterministic problem can be formulated as the following mathematical program:

$$COST = \sum_{h \in H} \sum_{u \in U} c_u G_{hu} \quad (2a)$$

subject to:

$$\sum_{u \in U} (m_{un} G_{hu} - m_{un} PUMP_{hu}) + \sum_{l \in L} m_{nl} FLOW_{hl} = d^E_{hn}; \forall h \in H, \forall n \in N \quad (2b)$$

$$RES_{hu} - RES_{h-1,u} =$$

$$f^1\left(q_{hu} + \eta_u CH_{hu} - DIS_{hu} - d_{hu}^W - SPILL_{hu} + \sum_{j\in\Omega_u}\left(DIS_{h-\tau_u,j} + SPILL_{h-\tau_u,j}\right)\right) : (W_{hu}); \quad \forall u \in \Omega_{hydro}, \forall h \in H \tag{2c}$$

$$FLOW_{hl} = \frac{1}{x_l}\left(\sum_{n\in N} m_{nl} THETA_{hn}\right); \forall h \in H, \forall l \in L \tag{2d}$$

$$THETA_{hn} = 0; \forall h \in H \text{ and } n = 1 \tag{2e}$$

$$G_{hu} = DIS_{hu} f^2 head_u; \forall u \in \Omega_{hydro}, \forall h \in H \tag{2f}$$

$$PUMP_{hu} = CH_{hu} f^2 head_u; \forall u \in \Omega_{hydro}, \forall h \in H \tag{2g}$$

$$DIS_{hu} + SPILL_{hu} \geq d_{hu}^{EF}; \forall u \in \Omega_{hydro}, \forall h \in H \tag{2h}$$

$$-FLOW_l^{max}\Delta t \leq FLOW_{hl} \leq FLOW_l^{max}\Delta t;\ \forall h \in H, \forall l \in L \tag{2i}$$

$$RES_u^{min} \leq RES_{hu} \leq RES_u^{max}; \forall u \in \Omega_{hydro}, \forall h \in H \tag{2j}$$

$$RES_{N_H,u} = RES_u^0;\ \forall u \in \Omega_{hydro} \tag{2k}$$

$$0 \leq G_{hu} \leq G_u^{max}\Delta t; \forall u \in U, \forall h \in H \tag{2l}$$

$$SPILL_{hu} \geq 0; \forall u \in \Omega_{hydro}, \forall h \in H. \tag{2m}$$

The objective function (2a) is identical to (1a) and represents the total cost of operating the power system during the whole simulation period and is expressed as the sum of the variable costs of the generating units.

The set of constraints (1b) encompass the equality constraints (2b)-(2g). The energy and water balance are respectively enforced in (2b) and (2c). The energy balance (2b) takes into account the energy produced by thermal, hydro, and renewable units as well as the energy flows so that the energy demand is satisfied for all time periods and nodes. The water balance (or continuity equation) (2c) is enforced for each hydropower plant and each time period and accounts for the difference on the water volume of each reservoir, its natural inflow, the energy pumped (if any), the water release (production and spillage), and the water release from upstream reservoirs. The dual variables W_{hu} associated with these constraints represent the water value of each hydropower plant for each time period. Note that, to convert m^3/s into hm^3, the factor f^1 is equal to $0.0036\,\Delta t$.

By using a dc load flow model [47], the power flow can be written in terms of the voltage phase angles as in equation (2d) and equation (2e) sets at 0 the voltage phase angle at the slack bus of node 1. The last equality constraints are related to the water-energy conversion for hydropower discharges and pumped power, i.e. equations (2f) and (2g). A simple conversion unit approach is adopted by means of the conversion factor $f^2 = g\rho\Delta t/10^9$ to convert m^3/s into GWh.

The set of inequality constraints (1c) correspond to constraints (2h)-(2l). Constraint (2h) imposes the ecological flows that must be satisfied for each hydro reservoir and time period. The lower and upper bounds on energy flows and reservoir levels are imposed in (2i) and (2j), respectively. The border condition is enforced in (2k). Generation bounds on generation energy are set in (2l) for each power plant and time period.

Finally, the non-negativity of the water spillage is enforced in (2m), which correspond to constraints (1d). Needless to say, the water spillage could be easily bounded by minimum and maximum limits representing regulations in force aimed at protecting the fauna and flora of the water channel.

This problem is thus characterised as a large-scale linear program and is solved by using the solver GLPK [48] in Pyomo [49], [50]. The formulated model is fully compatible with proprietary solver like CPLEX [51], GUROBI [52] which are preferred for larger problems.

2.4 Stochastic medium-term hydrothermal coordination problem

The stochastic MTHC problem is solved by using the PH decomposition technique. The uncertainty parameter is assumed to be the net inflow for each hydro reservoir. Therefore, encoding a scenario tree is required by the PH algorithm. Subection 2.4.1 describes the scenario tree generation whereas subsection 2.4.2 provides an overview of the PH algorithm.

2.4.1 Scenario tree generation

A scenario tree is made up to nodes and stages. Each stage comprises of nodes which are linked to the nodes of the next time stages via edges based on a given probability.

For this purpose, it is necessary to use proper scenario generation and reduction methods in order to capture all possible realizations of the stochastic time series with the minimum information [53], [54]. As a scenario generation method, we used the Gauss-Markov model that was described in [55] using the statistical moments of available historical annual realizations.

In order to reduce all the developed scenarios and encode them into a scenario tree, we selected the neural gas method. It is a simple algorithm for finding the optimal data representation based on feature vectors. This algorithm has been successfully used for the hydro-thermal coordination problem in [56], [57]. It can be considered as a generalization of the k-means algorithm. The difference is that every vector assigned to the closest class with a high weight and to other classes with smaller weights. After an iteration, the mean of a class is replaced by the weighted average of all assigned vectors. It is called neural gas because the way that the algorithm tries to find the optimal data representation resembles the movement of a gas diffusing into space.

The first step is to describe the desired structure of the scenario tree. There are many ways to describe this tree but one way that is convenient for this purpose is by means of a scenario tree nodal partition matrix. In this representation, this matrix has $[N_S \text{ x } N_\Omega]$ dimensions wherein N_S is the number of stages and N_Ω is the number of scenarios. Each value in the matrix represents the unique name of the node. As a result one single column shows which nodes are used at each stage. In order to decide how many branches we should use for each time stage, we have used the coefficient of variance (CV) as a metric, i.e. the ratio of standard deviation to the mean: the higher the coefficient of variance, the more branches this node would have.

After the definition of the tree structure, the neural gas algorithm works based on the following steps:

- **Step 1**

  Random initialization of tree based on given structure.

- **Step 2**

  Weight by Euclidean distance order.

- **Step 3**

  Node adjustment.

- **Step 4**

Repeat steps 2 and 3 for desired number of iterations. The weights decay exponentially with the increasing distance-rank of the classes.

— **Step 5**

Compute probabilities of scenarios by assigning a realization to each computed node per time step.

The results of this data structure is encoded as a graph using the *networkx* package [58].

Examples of a generated tree according to this method can be found below.

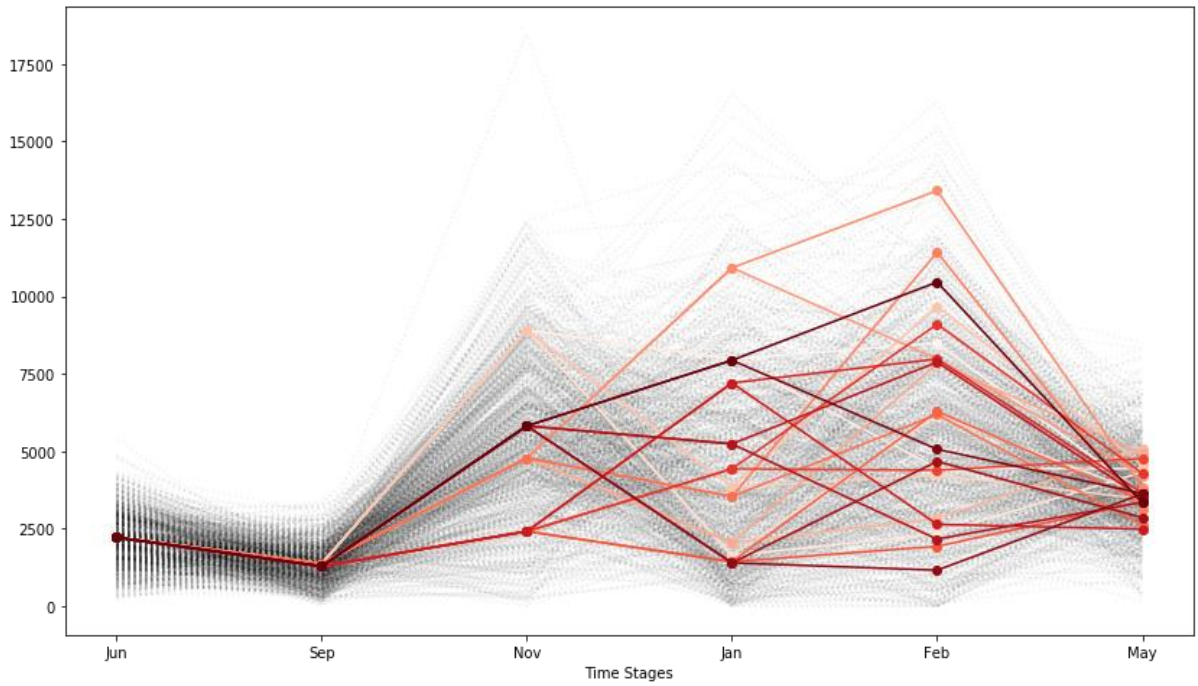
The following nodal partition matrix was used for this case:

$$NP = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 3 & 3 & 3 & 3 & 3 & 3 & 3 & 3 & 3 & 3 & 3 & 3 \\ 4 & 4 & 4 & 4 & 4 & 4 & 5 & 5 & 5 & 5 & 5 & 5 & 6 & 6 & 6 & 6 & 6 & 6 & 7 & 7 & 7 & 7 & 7 & 7 \\ 8 & 8 & 9 & 9 & 10 & 10 & 11 & 11 & 12 & 12 & 13 & 13 & 14 & 14 & 15 & 15 & 16 & 16 & 17 & 17 & 18 & 18 & 19 & 19 \\ 20 & 21 & 22 & 23 & 24 & 25 & 26 & 27 & 28 & 29 & 30 & 31 & 32 & 33 & 34 & 35 & 36 & 37 & 38 & 39 & 40 & 41 & 42 & 43 \\ 44 & 45 & 46 & 47 & 48 & 49 & 50 & 51 & 52 & 53 & 54 & 55 & 56 & 57 & 58 & 59 & 60 & 61 & 62 & 63 & 64 & 65 & 66 & 67 \end{bmatrix}$$

As discussed before the number of rows correspond to the stages (in this case N_S=6) and the number of columns correspond to the number of generated scenarios (in this case N_Ω=24). Each value in this matrix corresponds to a unique node identifier.

Figure 4 shows the values of the generated scenario tree. Figure 5 shows the unique nodes of the generated scenario tree and the edges show the transition probability from one node to the next one.

Figure 4. Values of generated scenario tree imposed on possible realizations.



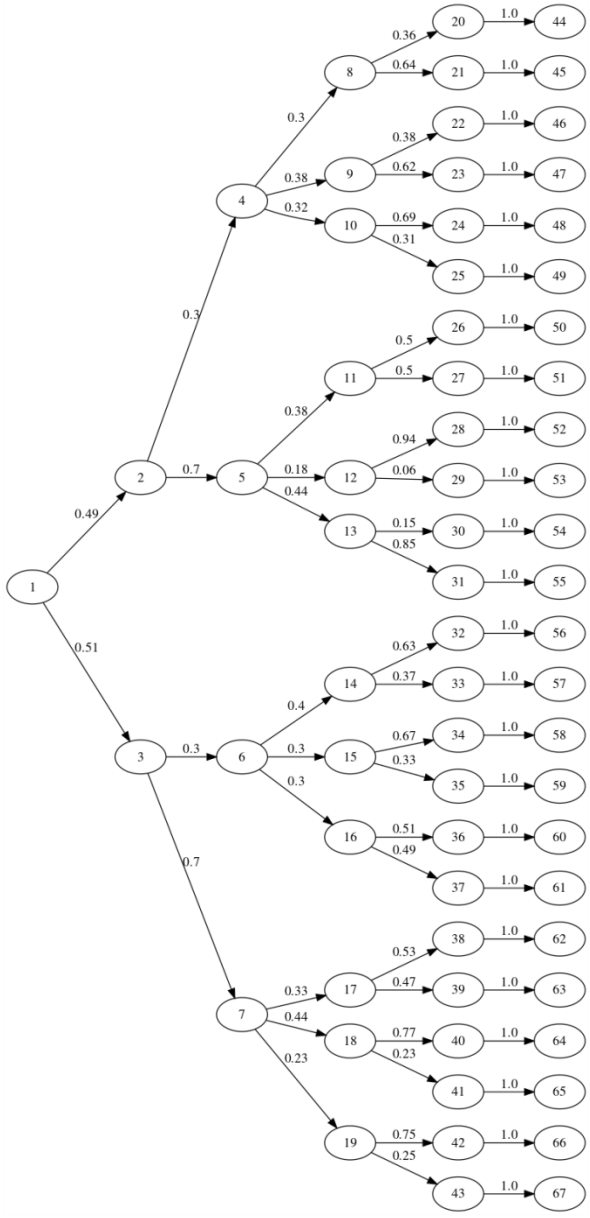
Source: JRC 2017.

PySP [37] uses the abovementioned scenario tree as an input. Then it creates one model object per network leaf (scenario) and solves all models in parallel based on the algorithm described in the next subsection. The non-anticipativity constraints are indicated by means of the variables that should remain the same at each stage for all scenarios. In our case, the hydro discharge is a non-anticipativity constraint.

After the solution of this problem, all decision variables are given per scenario, i.e. we have N_Ω and not one decision variable vectors. These show how the decision variables would be for a given realization of each scenario. However, the decisions on each stage

are made without knowing the realization but based on given probabilities of each scenario evolution.

Figure 5. Nodal structure of a six-stage scenario tree. The values on the edges correspond to the transition probabilities.



Source: JRC 2017.

2.4.2 Overview of the Progressive Hedging algorithm

Given the scenario tree of the uncertainty parameter(s), the deterministic equivalent of a stochastic optimisation problem can be rewritten in two different ways: 1) implicitly when the problem is written in terms of nodes and 2) explicitly when the mathematical problem is written in terms of scenarios [21]. Following a similar notation as defined in [36], the compact formulation of the explicit deterministic equivalent can be expressed as follows:

$$\text{Minimise} \sum_{\omega \in \Omega} \pi_{\omega} \sum_{s \in S} C^{M}_{\omega,s}\left(z_{\omega,s}\right) \tag{3a}$$

subject to:

$$f_{\omega,s}^{M}\left(z_{\omega,s}, z_{\omega,s-1}\right) = 0 : \left(\lambda_{\omega,s}^{M}\right);\ \forall\omega \in \Omega, \forall s \in S \tag{3b}$$

$$g_{\omega,s}^{M}\left(z_{\omega,s}\right) \leq 0;\ \forall\omega \in \Omega, \forall s \in S \tag{3c}$$

$$z_{\omega,s} = z_{\omega',s};\ \forall\omega \in \Omega, \omega' \in \overline{\Omega}_s, \forall s \in S \tag{3d}$$

$$z_{\omega,s} \geq 0, \forall\omega \in \Omega,\ \forall s \in S, \tag{3e}$$

where ω is the index for scenarios, Ω is the set of scenarios, π_ω is the probability of scenario ω, s is the index for stages, S is the set of stages, $C_{\omega,s}^{M}(\cdot)$ is the expected system-wide generation cost function, $z_{\omega,s}$ is the vector of continuous variables, $f_{\omega,s}^{M}(\cdot)$ is the function involving all equality constraints per scenario ω and stage s, $\lambda_{\omega,s}^{M}$ is the vector of dual variables or Lagrange multipliers associated with the equality constraints for each scenario ω and stage s, $g_{\omega,s}^{M}(\cdot)$ is the function involving all inequality constraints associated with the mid-term for each scenario ω and stage s, ω' is an auxiliary index for scenarios, and $\overline{\Omega}_s$ is the set of scenarios that are indistinguishable from scenario ω.

Constraint (3a) is the minimisation of the expected system-wide generation cost in the mid-term over the set of scenarios and stages. Constraints (3b) and (3c) define all the technical constraints of the stochastic MTHC problem, which may model inter-temporal relationships between continuous variables. Constraints (3d) are the non-anticipativity constraints. Finally, constraints (3e) impose the nonnegativity of the continuous variables.

Problem (3) is characterised as a large-scale multistage stochastic program, which can be parallelizable due to its inherent structure based on scenarios. Therefore, the PH algorithm, which is a scenario-based decomposition technique, is suitable to solve such problem.

PH decomposes the original problem (3) into smaller subproblems per scenario, wherein the non-anticipativity constraints are relaxed. The relaxed subproblems are:

$$\left\{\text{Minimise} \sum_{\omega\in\Omega} \pi_\omega \sum_{s\in S} \left(C_{\omega,s}^{M}\left(z_{\omega,s}\right) + m_{\omega,s} z_{\omega,s} + \frac{\rho}{2}\left\|z_{\omega,s} - \bar{z}_s\right\|^2\right)\right. \tag{4a}$$

subject to:

$$f_{\omega,s}^{M}\left(z_{\omega,s}, z_{\omega,s-1}\right) = 0;\ \forall s \in S \tag{4b}$$

$$g_{\omega,s}^{M}\left(z_{\omega,s}\right) \leq 0;\ \forall s \in S \tag{4c}$$

$$\left. z_{\omega,s} \geq 0, \forall s \in S \qquad \right\} \forall\omega \in \Omega, \tag{4d}$$

where $m_{\omega,s}$ is the Lagrange multiplier used in the PH algorithm, ρ ([9]) is a penalty factor that should be greater than 0, and $\overline{z}_s$ is the probability-weighted average of $z_{\omega,s}$.

Constraint (4a) is the objective function of each relaxed subproblem and includes two penalisations: 1) the second term is penalised based on a Lagrange multiplier $m_{\omega,s}$, and 2) the third term penalises the deviation of the scenario solutions $z_{\omega,s}$ from the average values $\overline{z}_s$ by using a penalty factor $\rho > 0$. Constraints (4b)-(4d) define the feasibility space for each stage s.

([9]) Note that the symbol 'ρ' has a different meaning in this subsection than in the rest of the report.

Based on [34], [36], we briefly explain the steps of the PH algorithm:

— **Step 1: Initialization**

Let us assume the iteration counter $\nu = 0$. First, problem (4) is solved for all $\omega \in \Omega$ while assuming no penalty terms. Then, a set of decision variables $z_{\omega,s}^{(\nu)}$ is obtained.

— **Step 2: Computation of parameters**

The aggregated decision variables and the Lagrange multipliers used in the PH algorithm can be computed for the first iteration as follows:

$$\bar{z}_s^{(\nu)} = \frac{\sum_{\omega' \in \bar{\Omega}_s} \pi_{\omega'} z_{\omega',s}^{(\nu)}}{\sum_{\omega' \in \bar{\Omega}_s} \pi_{\omega'}};\ \forall s \in S \tag{5}$$

$$m_{\omega,s}^{(\nu)} = \rho\left(z_{\omega,s}^{(\nu)} - \bar{z}_s^{(\nu)}\right);\ \forall \omega \in \Omega, \forall s \in S \tag{6}$$

— **Step 3: Iteration $\nu > 0$**

The following steps should be done until satisfying the stopping criteria:

- Iteration update: $\nu \leftarrow \nu + 1$
- Problem (4) should be solved for all $\omega \in \Omega$ in order to obtain the set of decision variables $z_{\omega,s}^{(\nu)}$.
- Parameters' update:

$$\bar{z}_s^{(\nu)} \leftarrow \frac{\sum_{\omega' \in \bar{\Omega}_s} \pi_{\omega'} z_{\omega',s}^{(\nu)}}{\sum_{\omega' \in \bar{\Omega}_s} \pi_{\omega'}};\ \forall s \in S \tag{7}$$

$$m_{\omega,s}^{(\nu)} \leftarrow m_{\omega,s}^{(\nu-1)} + \rho\left(z_{\omega,s}^{(\nu)} - \bar{z}_s^{(\nu)}\right);\ \forall \omega \in \Omega, \forall s \in S \tag{8}$$

- Computation of the gap $\sum_{\omega \in \Omega} \pi_\omega \left\| z_{\omega,s}^{(\nu)} - \bar{z}_s^{(\nu)} \right\|$

— **Step 4: Stopping criteria**

The PH algorithm terminates when the gap is below a pre-specified threshold ϵ. Otherwise, go to step 3.

3 Dispa-SET unit commitment and dispatch module

3.1 Compact formulation

The Dispa-SET UCD model is fully explained in [59]. Similar to the Dispa-SET MTHC module, this model can mathematically be written as:

Minimise $C^D(x^D)$ (9a)

subject to:

$f^D(x^D) = 0 : (\lambda^D)$ (9b)

$g^D(x^D, z^D, y^{M*}) \leq 0$ (9c)

$x^D \geq 0; z^D \in \{0,1\}$ (9d)

where $C^D(\cdot)$ is the system-wide generation cost function, x^D is the vector of continuous dispatching variables, $f^D(\cdot)$ is the function involving all equality constraints, λ^D is the vector of dual variables or Lagrange multipliers associated with the equality constraints, $g^D(\cdot)$ is the function involving all inequality constraints, z^D is the vector of binary commitment variables, and y^{M*} is a given vector of continuous variables in energy units which is the output from the mid-term planning problem.

The unit commitment problem is driven by the system-wide generation cost minimisation (9a), which includes variable and fixed production costs of generating units, start-up and shutdown costs, ramp-up and ramp-down-related costs, and penalisations on some constraints to ensure feasibility.

The unit commitment problem must satisfy technical constraints to provide feasible dispatch and commitment decisions on generating units, i.e. the on/off statuses and the corresponding power productions. The technical constraints that are or may be considered in the Dispa-SET UCD are listed below.

- Nodal power balance per period.
- Power balance in storage units.
- The transmission network, which is represented by a pipeline model, typically used in transport problems.
- Power flow capacity limits.
- Inter-temporal constraints on thermal generators such as ramp-rate constraints or minimum up and down time constraints.
- Storage-related constraints.
- Emission limits.
- Curtailment and load shedding limits.
- Integrality constraints for modelling the on/off statuses of generating units.
- Heating and cooling related constraints.
- Cooling-related constraints for thermal power plants, which are fully explained in the next section.

Due to the binary nature of the commitment decisions, this model is characterised as a large-scale mixed-integer linear program that can be solved by using CPLEX [51] under GAMS [60].

3.2 Cooling-related constraints

The unit commitment model has been modified to incorporate two sets of cooling- and policy-related constraints modelling 1) the maximum allowable water withdrawn for thermal power plants, and 2) the effect of river water temperature for cooling of thermal power plants with once-through cooling systems. These constraints may lead to curtailable power output of the thermal power plant or even its shutdown under certain environmental conditions and/or stringent policy measures.

3.2.1 Water withdrawal constraints

Policies on water withdrawals may be imposed for thermal power plants because of two reasons: 1) there is no enough water in the main stream of the river, or 2) there are large withdrawals which can affect the ecosystem in river waters. Currently, there are no unified policies on water withdrawals or consumptions and the regulations are site-dependent and mostly imposed by local authorities [42].

The water withdrawal limit is imposed in constraint (10) for each thermal power plant $u \in U^t$ and for each time period $t \in T$, where U^t is the set of thermal power plants and T is the set of time periods. The water withdrawn can be computed as the product of the power output $p_{t,u}$ and the water withdrawal factor F_u^{ww} and is limited by the maximum allowable water withdrawn $\overline{F}_{t,u}^{ww}$. This value may be given in drought time periods due to either physical limitations or environmental policy measures.

$$p_{t,u} \cdot F_u^{ww} \leq \overline{F}_{t,u}^{ww}; \forall u \in U^t, \forall t \in T \tag{10}$$

As can be seen in (10), the power output can be curtailed if $\overline{F}_{t,u}^{ww}/F_u^{ww}$ is below the nameplate capacity of the power plant or the power plant can be shut down if $\overline{F}_{t,u}^{ww}/F_u^{ww}$ is less than its minimum power output. This could be used for vulnerability analyses of cooling-constrained power plants since it caps their maximum capacity. However, a more sophisticated constraint based on the water stress index could be added to the unit commitment model to account for the water withdrawal.

As defined in [6], the water stress index can be computed as the water withdrawn ($p_{t,u} \cdot F_u^{ww}$) divided by the water runoff ($RO_{t,u}$). This index varies between 0 if the plant is not stressed at all and 1 if all the water available is used for cooling. The computation of this index would be of highly importance in future power systems in order to maximise the societal welfare or minimise the net costs of both power and water sectors. Bearing in mind the definition of the water stress index, the following constraint could be imposed:

$$\frac{p_{t,u} \cdot F_u^{ww}}{RO_{t,u}} \leq \overline{WSI}_u; \forall u \in U^t, \forall t \in T \tag{11}$$

Constraint (11) sets a maximum water stress index per power plant and time period based on the water runoff.

3.2.2 Thermal release constraints

On the other hand, the aquatic life could be harmed when the water for once-through cooling is returned to the main stream of the river, which may affect to the water flow and may increase the water temperature (also known as thermal pollution). Thermal pollution has been regulated through the European Fish Directive ([10]) because it has been a concern in many countries, however few papers address these policy constraints in electric operational problems [8], [42], [43]. The European Fish Directive imposes that:

([10]) Directive 2006/44/EC of the European Parliament and of the Council of 6 September 2006 on the quality of fresh waters needing protection or improvement in order to support fish life.

— The temperature measured downstream of a point of thermal discharge must not exceed the unaffected temperature by more than 1.5 °C for salmonid waters (3 °C for cyprinid waters).

— Thermal discharges must not cause the temperature downstream of the point of thermal discharge to exceed 21.5 °C for salmonid waters (28 °C for cyprinid waters).

In addition, according to the European Environment Agency, the critical limit for the intake of cooling water is 23 °C [61]. This limit however could be exceeded if the relevant authorities allow for it. Therefore, nowadays there exists certain flexibility when applying limiting thermal pollution.

The effect of river water temperature for cooling thermal power plants with once-through cooling technology is modelled by constraints (12) and (13).

$$p_{t,u} \leq v_{t,u}\overline{P}_{t,u}^{wc}; \forall u \in U^t, \forall t \in T \tag{12}$$

$$v_{t,u} = 0 \; if \; \overline{P}_{t,u}^{wc} < \underline{P}_u^g; \forall u \in U^t, \forall t \in T \tag{13}$$

where $v_{t,u}$ is the on/off status of power plant u in time period t, $\overline{P}_{t,u}^{wc}$ is the water-constrained capacity of power plant u in time period t, and $\underline{P}_u^g$ is the minimum power output of power plant u. Note that $\overline{P}_{t,u}^{wc}$ can be computed as follows:

$$\overline{P}_{t,u}^{wc} = \begin{cases} \dfrac{\overline{P}_{t,u}^{g} \cdot F_u^{ww} \cdot \rho \cdot c \cdot \Delta T_{t,u}}{\Gamma \cdot 3.6 \cdot 10^6} & if \quad T_{t,u}^{in} \neq 0 \\ \overline{P}_{t,u}^{g} & if \quad T_{t,u}^{in} = 0 \end{cases}; \forall u \in U^t, \forall t \in T \tag{14}$$

$$\Delta T_{t,u} = \begin{cases} 0 & if \quad T_{t,u}^{in} \geq T_{tu}^{limit} \\ T_{tu}^{limit} - T_{t,u}^{in} & if \quad T_{t,u}^{in} < T_{tu}^{limit} \end{cases}; \forall u \in U^t, \forall t \in T \tag{15}$$

where ρ is the water density, c is the specific heat capacity, $\Delta T_{t,u}$ is the river water temperature difference, Γ is a correction factor, $T_{t,u}^{in}$ is the river water temperature in the power plant inlet, and T_{tu}^{limit} is the river water temperature limit.

Constraint (12) sets a cap on the maximum capacity depending on the river water temperature, whereas constraint (13) models the shutdown of the power plant provided the water-constrained cap on the maximum capacity is less than its minimum power output. This cap is computed according to equation (14) and depends on the maximum water withdrawal ($\overline{P}_{t,u}^{g} \cdot F_u^{ww}$) and the river water temperature difference. For implementation purposes, if the inlet water temperature is set to 0 Kelvin degrees, then the water-constrained cap is equal to the nameplate capacity, and thus no limitation is imposed. Finally, as can be observed, if the inlet water temperature is less than the temperature limit, the efficiency of the power plant may be reduced and may generate less electricity; otherwise if $T_{t,u}^{in} \geq T_{tu}^{limit}$, the power plant will be shut down.

4 Methodology

The proposed framework to address water-power nexus studies is presented in Figure 6. In this figure, we can see that both modules of Dispa-SET are linked to the rainfall-runoff hydrological LISFLOOD model [62] in an off-line mode. The steps are explained next:

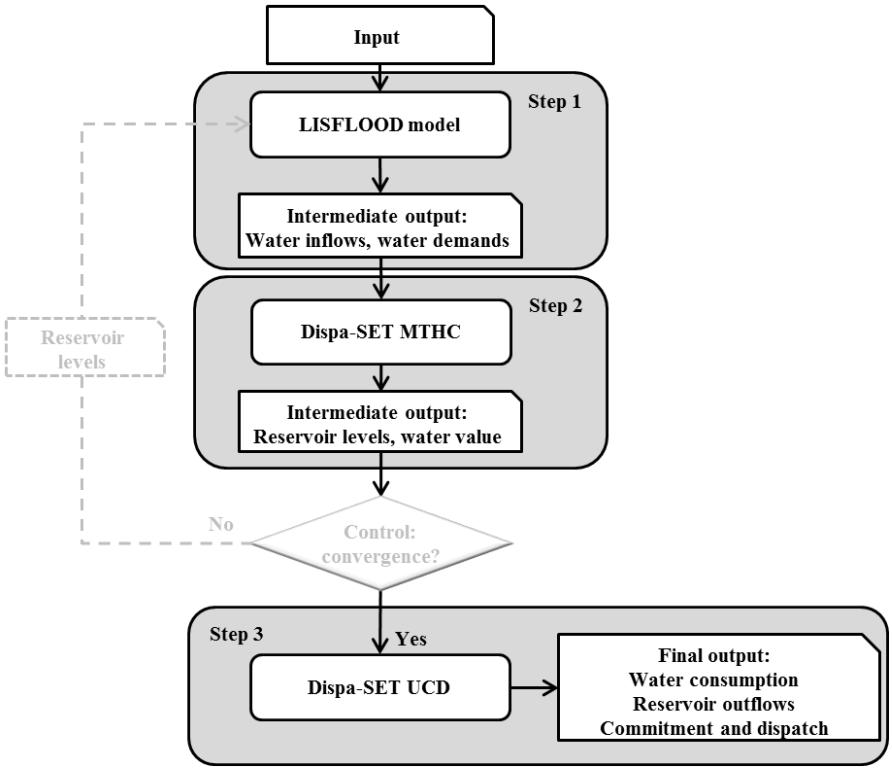
— **Step 1:** LISFLOOD is solved to feed water inflows and water demands into the Dispa-SET model, which would impose constraints on hydropower plants and water-constrained limitations in thermal power plants.

— **Step 2:** Dispa-SET MTHC model runs at daily, weekly or monthly time steps during one or several years in order to provide the management of water resources in the mid-term, i.e. the reservoir levels from the dams are passed on to shorter-term problems. As mentioned earlier, water values for hydropower sources are an outcome of this model.

— **Step 3:** Dispa-SET UCD model runs at hourly time steps during a target year and the following results can be obtained: 1) the power schedule and dispatch, 2) water-related outcomes (e.g. water withdrawn and consumed by power plants), and 3) economic results (prices and costs).

Note that ideally Dispa-SET MTHC and LISFLOOD should be run iteratively until reaching a stable solution. The stopping criteria may be based on the reservoir levels so that a set of adequate and optimised levels is derived. However, this issue should be further investigated and the methodology is non-iterative.

Figure 6. Interactions between LISFLOOD, Dispa-SET MTHC, and Dispa-SET UCD models.



Source: JRC 2017.

5 Conclusion

Within the WATERFLEX exploratory research project of the European Commission's Joint Research Centre, this report describes the main developments of the Dispa-SET medium-term hydrothermal coordination module, the incorporation of the cooling-related constraints of thermal power plants into the Dispa-SET unit commitment and dispatch module, and an off-line methodology to analyse the water and power interactions in electric power systems.

In the Dispa-SET medium-term hydrothermal coordination module, the optimisation horizon can range from 1 year to several years. The model can run in two different modes: deterministic or stochastic. The model includes hydro-specific features such as:

- The continuity equation in water units.
- Bounds on water release, spillage, and reservoir levels.
- The consideration of the hydraulic network.
- Water demands.
- Ecological flows.

From the power system point of view, the model takes into account generation constraints, transmission network constraints, and power balance. Unlike the previous version, the deterministic mode includes water demands or ecological flows as well as multiple nodes in the transmission network. The deterministic problem is thus characterised as a linear programming problem which can be directly solved with solvers for linear programming such as GLPK or CPLEX.

Another salient feature of this version of Dispa-SET is the modelling of the stochastic medium-term hydrothermal coordination module, which is characterised as a linear stochastic program. The stochastic problem is solved by using an efficient scenario-based decomposition technique, the so-called Progressive Hedging algorithm. This technique is an Augmented-Lagrangian-based decomposition method that decomposes the original problem into smaller subproblems per scenario. Its implementation has been carried out through the PySP software, part of the Coopr open-source Python repository for optimisation, which embeds the progressive hedging algorithm.

Moreover, the report includes how Dispa-SET unit commitment and dispatch module is modified to model cooling- and policy-related constraints on water withdrawals or cooling constraints of thermal power plants with once-through cooling systems.

Finally, a decoupled and off-line methodology is proposed to analyse the water-power interactions in electric power systems by means of Dispa-SET, which needs data from the rainfall-runoff hydrological LISFLOOD model. This framework allows for scenario-based or stochastic assessments of the water-power linkage in current or future hydro-dominant power systems. The main challenges for assessing those linkages are also briefly discussed and include data collection, degree of model aggregation and computational complexity of models.

Several areas of interest for future work are suggested next:

- Modelling the water head effect of hydro reservoirs. This water head effect is represented by the Hill chart and links the water discharge, the reservoir level, and the power production. This effect is highly nonlinear and a precise model would be needed to accurately represent the Hill chart. Although a simple linear model could be adopted, the lack of publicly available data is a barrier to model this feature.
- Modelling of pumped-hydro generating units in the medium-term optimisation problem by using various load levels per time period.
- Incorporation of uncertainty features besides inflows such as demand or generation capacity.

— Water-power-food-environment nexus' assessments call for joint modelling of irrigation and power. One possibility is to couple LISFLOOD and Dispa-SET models; however this task could be challenging due to the underlying assumptions of each model. Another possibility is the incorporation of explicit and simple irrigation models into the medium-term hydrothermal coordination problem.

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List of abbreviations and definitions

AIR	Air (dry) main condenser cooling – Platts' definition
AL	Augmented Lagrangian
BD	Benders' Decomposition
CL	Cooling Lake or cooling pond – Platts' definition
CMB	Combination cooling system (once-though with helper cooling tower or other device) – Platts' definition
CP	Cooling Pond – Platts' definition
CPLEX	Commercial optimisation solver
Dispa-SET UCD	Unit Commitment and Dispatch model
Dispa-SET MTHC	Medium-Term Hydrothermal Coordination model
ENTSO-E	European Network of Transmission System Operators for Electricity
EU	European Union
GAMS	General Algebraic Modelling System: commercial high-level modelling software for mathematical optimisation
GRanD	Global Reservoir and Dam Database
GUROBI	Commercial optimisation solver
ICOLD	International Commission on Large Dams
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
IPM	Interior Point Method
JRC	Joint Research Centre
LISFLOOD	Rainfall-runoff hydrological model
MDT	Mechanical Draft cooling Tower, also known as induced draft cooling tower – Platts' definition
M/NDT	Mechanical and Natural Draft cooling Towers – Platts' definition
NDT	Natural Draft cooling Tower – Platts' definition
NDT/D	Dry type or indirect system Natural Draft cooling Tower – Platts' definition
NP	Nonlinear Programming
OTB	Once through cooling using Brackish water – Platts' definition
OTF	Once through cooling using Fresh water – Platts' definition
OTS	Once through cooling using Daline water – Platts' definition
PH	Progressive Hedging
PySP	An open-source software package of generic and customisable stochastic programming solvers
SAA	Sample Average Approximation
SDP	Stochastic Dynamic Programming
SDDP	Stochastic Dual Dynamic Programming

USA	United States of America
WATERFLEX	Exploratory research project
WEPP	The UDI World Electric Power Plants Data Base is a comprehensive, global inventory of electric power generating units

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