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Hydropower optimization

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Abstract : Energy generation has always been a major stake in our economy and is all the more so with the increase in energy demand all over the world. In that context, hydroelectricity is considered one of the most important renewable energy sources. Hydropower optimization is a rich field that has been studied since hydropower dams exist. The major challenge in hydropower optimization is to use the available water to produce energy as efficiently as possible, since it is almost impossible to vary the physical installations once in place. Many challenges arise: uncertainty in the inflows, prices, outages, size of the problems, hydrological constraints, physical characteristics of the turbines and the power plants, and recently, the climate change context that tends to add complexity to the resolution, given that history does not repeat itself and the addition of extreme weather episodes. This paper intends to introduce the reader to the basic concepts of hydropower and present a survey of the field from an optimization point of view. The aim is to better understand the methodologies currently used, in order to assess if it is possible to shift or focus research in areas that may improve the current approaches.

Keywords: Energy production, hydropower optimization, management of hydropower systems, long-term optimization, medium-term optimization, short-term optimization, unit commitment

1 Introduction

In the last decades, substantial efforts have been made in order to direct the energy production towards more clean and renewable sources for the energy production to be sustainable [71]. Hydropower is one of the main sources used to produce electricity in a clean and renewable way. As of 2019 [62], renewable energy is made up of 60% hydropower and it accounts for 15.9% of the world's electricity production. Generating hydropower is about using dams and other types of diversion structures in order to harness flowing water to create energy. In Canada, 67.6% of the energy is generated by hydropower plants [63]. Many provinces, such as Quebec, rely on hydropower to produce their energy. Although a huge cost is associated with the construction of hydropower plants and ecological imprints are unavoidable, hydropower plants use the energy generated by water to produce energy without air pollutant emissions. Once in place, it is necessary to design decision making tools that help manage efficiently the hydropower systems. Optimization has been used for many decades to help decision makers operate hydropower systems.

A hydropower system is composed of power plants, which are composed of turbines. Power produced by a power plant depends on the physical characteristics of the turbines in place. There are three types of hydropower plants: *run-of-river*, *pumped storage* and *with dams*. The energy produced by the first mainly depends on the flow of the river, as there is little water storage whereas the second and the third are influenced by both the water stored in the reservoir and the flow of the water. Hydropower production functions are nonlinear and non-convex, which adds difficulty when modelling the objective function of an optimization model. Minimal operational constraints to meet are water balance, energy demand, bounds on variables, more precisely water discharges and reservoir volumes, recreational constraints, and so forth. Hydropower optimization deals with determining the reservoir volumes, water discharges and units in function for each period of a given planning horizon. Given the complexity of the problem and the size of the state space, it is impossible to model all of the constraints and specifics of the problem into a single problem. To achieve this goal, multiple optimization models are used: long-term, medium-term, short-term and real-time dispatch models. Their output, as well as their planning horizon differ, but ultimately, all of the models are used to manage efficiently a hydropower system. On an operational basis, long-term models are left out as they are used when major modifications occur in the hydropower system: turbine replacement, turbine outage for a long period or major changes in the operation of the system, for example. Medium-term optimization addresses determining the reservoir targets, more precisely the water volumes in the reservoirs and the water flows for each time step and power plant. Short-term optimization aims at determining the reservoir volumes, turbines operating and unit water discharges. Real-time models deal with the exact unit commitment, specifically the optimal water flow in each turbine, given a power to produce (or water to dispatch) and a given forebay elevation.

Optimization models which contain uncertainty are treated as stochastic, as deterministic optimization is used when all of the parameters in the optimization model are considered to be known at the time of taking a decision. In hydropower optimization, uncertainty arises mainly in demand, turbine outages and inflows in the reservoirs. In a deregulated market, where the energy is bought and sold every day, energy prices are also a source of uncertainty.

The goal of this survey is to introduce the field of hydropower optimization and to present the different methods that are widely used in the field. The paper is organized as follows. Section 2 presents the basic concepts and definitions that are necessary to understand any paper dedicated to hydropower optimization. Section 3 details energy production and technical considerations. Section 4 explains the different horizons on which the optimization is carried out, namely the long-, medium- and short-term horizons. The current solution methodologies as well as their limitations are exposed. Finally, Section 5 presents some concluding remarks.

2 Concepts and definitions

This section presents the basic concepts that are related to a hydropower system. The different components of the system are defined as well as the different types of dams and markets.

2.1 Hydropower system

A hydropower system consists of single or multiple power plants which are composed of single or multiple turbines. Figure 1 presents different configurations for hydropower systems. Reservoirs are represented with triangles and powerhouses with rectangles. In this figure, the system is said to be cascaded, which means that the reservoirs and the power plants follow a linear river without any diversions. As one can observe, reservoirs may or may not be coupled to powerhouses and powerhouses do not require to be coupled to a reservoir. Diversions may occur at any point in the system and it could be possible to have 2 powerhouses in parallel, for example. All the configurations are correct, as they must represent the physical hydropower system.

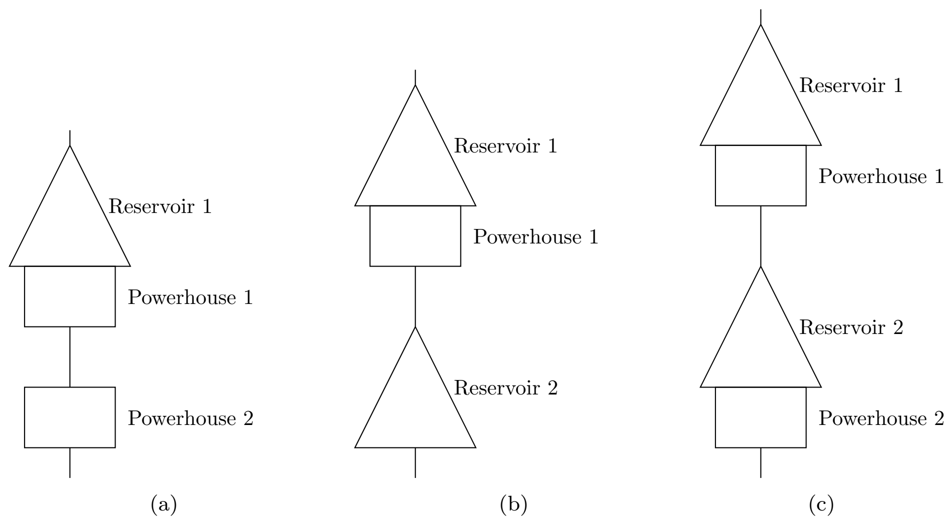

Figure 1: (a) One reservoir, two powerhouses (b) Two reservoirs, one powerhouse (c) Two reservoirs, two powerhouses

Hydropower optimization is a broad field and the following list, shown in Table 1, which is not exhaustive, gathers the basic terms commonly found in the literature.

Table 1: Common terms in the field of hydropower optimization

Capacity factor (net)	The ratio of the net electricity generated, for the time considered, to the energy that could have been generated at continuous full-power operation during the same period.
Dispatch	The operation of a generating unit within a power system at a designated output level.
Drawdown season	Time of the year with low inflows.
Efficiency	The percentage obtained by dividing the actual power or energy by the theoretical power or energy. It represents how well the hydropower plant converts the potential energy of water into electrical energy.
Energy	Power production over a period of time. Units are usually MWh or GWh.
Energy arbitrage	The action of purchasing (storing) energy when electricity prices are low, and selling (discharging) it when electricity prices are high.
Filling season	Time of the year when the reservoirs refill, typically following heavy rain or snowmelts.
Flexibility	The ability of the power system to respond to variations in supply and/or demand.
Flow	The volume of water, expressed as cubic feet or cubic meters per second, passing a point in a given amount of time.
Generator	A device that converts the rotational energy from a turbine to electrical energy.
Gross water head	The vertical variation in elevation, expressed in feet or meters, between the head (reservoir) water level and the tailwater (downstream) level.

Net water head	The gross head minus the energy losses in the penstock.
Peak power plant	A plant that is generally known to operate only when there is a high demand of electricity.
Penstock	A closed conduit or pipe that is used to conduct water from the reservoir to the powerhouse.
Power	Typically measured in kW, MW or GW, it represent the rate at which electrical energy is transferred in an electrical circuit per unit of time.
Powerhouse (powerplant)	The structure that houses the generators, turbines and/or pumps.
Ramping capability	The ability of a power station to change its output over time.
Ramping rate	Refers to the increase or reduction of the output per minute and is usually expressed by megawatts per minute (MW/min) [95].
Reservoir	A large natural or artificial lake used as a water supply.
Spillage	Every powerplant has a spillage capacity. Water is said to be spilled around the powerhouse, therefore the turbines do not treat this water. Spillage is mostly used when inflows are high and reservoirs are full, or during snowmelts to make space for the incoming water.
Turbine	A machine used to produce power. Water flows on the pales of the turbine, which in turn rotates the turbine and generates power.
Water value	Corresponds to the future expected revenue/production from a given volume of water.

2.2 Watershed

Hydropower systems are located on watersheds. Basically, the output of a watershed is a reservoir, and the water located on the area covered by the watershed, which comes from water streams, rainfall and snowmelts, eventually becomes available to the reservoir. Watersheds cover large territories and the modelling of this area is very important for the management of the hydropower system since natural inflows in the reservoirs are to be considered in the optimization models. As this is related to the field of hydrology, and optimization is a user of such values, this paper will not detail calculations and modelling leading to natural inflow predictions, represented with i in Figure 2. One can observe two reservoirs with two power plants in a cascaded fashion. Each reservoir has a natural inflow adding to the reservoir volume and water is released from the reservoir through its different turbines or spillway.

From an optimization point of view, water balance constraints are mandatory when modelling a hydropower optimization problem, since water conservation is to be respected. Such constraints are expressed in Equation (1) for a period t, and index of plants are dropped for clarity.

$$s_{t+1} = s_t - \sigma(q_t - w_t + i_t + q_t^u + w_t^u),\ \forall t \in T, \tag{1}$$

where s is the volume of stored water in the reservoir, q is the water flow, w is the water spilled, i are the water inflows, σ is a conversion factor from water flow to volume and u is the upstream plant.

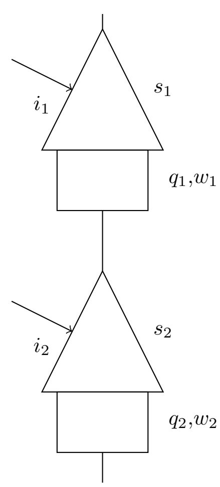

Figure 2: Water conservation constraints

2.3 Different types of power plants

The complexity of a hydropower system depends, among other things, on the number of power plants it contains, on the number of turbines each plant has but also on the topology of the system [82]. In what follows, the three types of power plants are presented.

Dam

Impoundment or dam facilities are probably the most common type of hydropower plants. They are part of large hydropower systems and use dams in order to store water in reservoirs. When released, the water flows from the reservoirs into turbines causing the latter to spin. This spinning activates a generator that produces electricity. Water may be released either to meet specific electricity demands or to maintain a certain level in the reservoirs. Such a facility is presented in Figure 3.

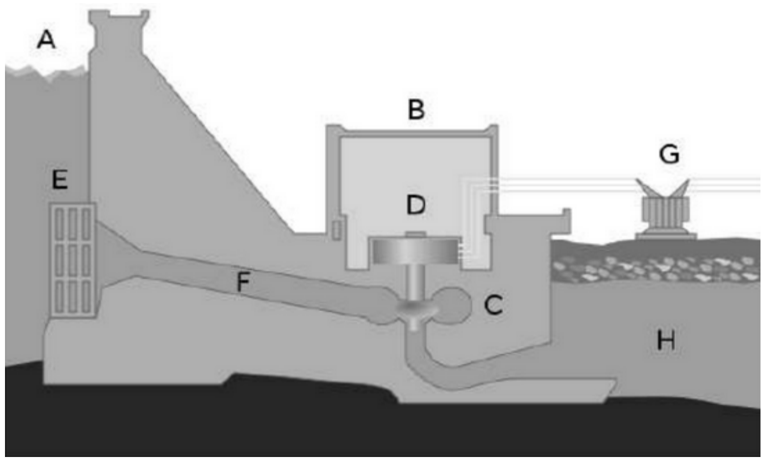

Figure 3: Transversal view of an impoundment hydropower plant. Adapted with permission by "Hydroelectric dam" by Tomia, 2008. Image under licence GFDL and CC-BY-2.5.

Run-of-river

This type of plant does not involve using a dam. Instead, it channels the power of the running water of a river through a canal or a penstock. In other words, the powerhouse sits directly on the river. This type of plant is characterized by a rather high spillage rate, as most of the water may not be directed to the penstock.

Pumped storage

This type of plant acts like some kind of battery by storing electricity for later use. When the electricity demand is low, it pumps water uphill to a reservoir at a higher elevation from a reservoir at a lower elevation. When the demand in electricity increases, it releases the water pumped in the higher reservoir into the lower reservoir through turbines in order to generate electricity. When the two reservoirs (upstream and downstream of the plant) are not connected to naturally flowing sources of water, this type of plant is referred to as a *closed-loop pumped storage* plant. A pumped storage plant could be viewed on Figure 3 by adding a pipe from H to A.

2.4 Different types of markets

The way a hydropower system is managed and/or optimized depends on the type of market it evolves in. The two types of markets are presented in what follows.

Regulated markets

This type of market can be found in Quebec, Canada. The prices of electricity are fixed by a governmental company which is the main producer of hydroelectricity. All the other producers are subject to these prices in all their purchasing and selling transactions. In this context, one aims at maximizing the produced energy. There are different ways of doing so depending on the horizon of the optimization as detailed in Section 3. Typically, in this type of market, the energy prices are not considered in the optimization model.

Deregulated markets
Typically found in Europe and the United States of America and some Canadian provinces, this type of market is characterized by the fact that the government has no power over the prices of hydroelectricity and by the presence of a high competition between the different producers. These producers bid for contracts in a regulatory framework. The liberalization of hydropower was established to cope with the complexity of generating systems but also to induce low costs and maintain high reliability [61]. In this context, one aims at minimizing costs and/or maximizing profits. There exist many methods that are used to approximate hourly prices. For example, the work in [64] in which the authors develop a model capable of approximating hourly prices in the context of larger time steps (weeks or months). Their model proved to be efficient as it provided prices with an error of less than 1% when compared to the exact values in a test case. In these markets, the operations follow several stages of transaction : *day-ahead*, *intra-day* and *real-time electricity markets*, for further details, see [79]. Other examples of studies in deregulated markets can be found in [24, 94].

3 Energy production and technical considerations

Managing a hydropower system comes down to determining, for every moment in time, which turbine to use and their level of production. To do so, it is necessary to model the energy production of the power plant and its turbines. This section presents the energy production functions and technical considerations when modelling a hydropower optimization problem.

3.1 Energy production

Figure 3 depicts a dam hydropower plant. The powerhouse (B) contains a turbine (C) and a generator (D). The water goes from the upstream reservoir (A) to the downstream river (H) through the penstock (F), passing by the powerhouse (B). The flow of water through the pales of a turbine (C) generates electricity which is then transferred from the generator (D) to its final destination through cables (G). The water that passes through the penstock (F) is used to generate power, but water could also be released from the reservoir directly to the downstream river, without passing through the turbines. This water is said to be spilled, as it is not used for production, but rather to avoid an overflow of the reservoir.

Energy produced by a single turbine is a nonlinear function which depends on potential energy and kinetic energy which in turn involves the water storage and the water release [101]. The potential energy is given by the net water head whereas the kinetic energy is given by the water flowing through the turbine.

The power produced P (kW) by a single turbine [93] is given by:

$$P = \eta(Q_{turb}) \times g \times Q_{turb} \times h_{net}(Q_{tot}), \tag{2}$$

where η is the efficiency of the turbine, g is the gravitational acceleration constant in m/s^2, Q_{turb} is the unit water discharge in m^3/s and Q_{tot} the total water discharge and h_{net} the net water head in m.

The gross water head h_{gross} is the difference between the forebay elevation e_f, as shown by (A) in Figure 3 and the tailrace elevation e_t, as shown by (H):

$$h_{gross}(Q_{tot}) = e_f - e_t(Q_{tot}). \tag{3}$$

The net water head is given by:

$$h_{net}(Q_{tot}) = h_{gross}(Q_{tot}) - \phi(Q_{tot}), \tag{4}$$

where $\phi(\cdot)$ is a function representing the energy losses caused by friction of the water in the penstock represented by (F) in Figure 3.

The power produced by a single turbine is a function that depends on unit water discharge and total water discharge at the power plant. Objective functions usually involves energy, since it represents the power produced over time.

The energy produced by a turbine over a period of time length t is given by:

$$E = \sum_{t \in T} P_t \times \delta_t, \tag{5}$$

where δ_t is the length of period t.

3.2 Hydropower function approximations

The types of approximations of the hydropower production functions typically characterize the optimization models. Approximations may be linear, meaning that the net water head is neglected and therefore the hydropower production function depends only on the water flow. Run-of-river plants are often represented with linear production functions. Continuous nonlinear models are easier to solve than nonlinear integer models, also linear models are easier to solve than their nonlinear counterparts, therefore nonlinear production functions are often linearized [7].

Typical representations of hydropower production functions usually involve [15]: polynomial approximations, splines [76] and tangent planes [83]. An example of a polynomial representation is presented in Figure 4. The hydropower production function is given for a net water head. As a reminder, production functions are nonlinear, therefore, for different water heads, the power produced for a certain amount of water discharge varies. Turbines have a maximal amount of water they can process. When this limit is reached, water needs to be spilled, therefore causing the power production to reduce since the water head decreases.

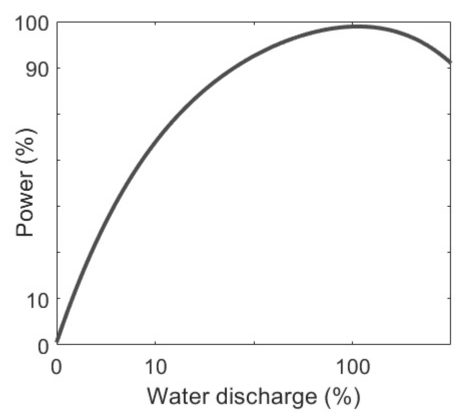

Figure 4: Hydropower production function for a given water head

Given the topology of the system and the different constraints, the problem needs to be carefully modelled, depending on different factors: precision and execution time, for example.

3.3 Technical considerations

Other considerations are important when modelling a hydropower optimization problem and are presented in what follows.

3.3.1 Turbine efficiency

Since power produced by a single turbine is a nonlinear function which depends on water flow and the net water head, and since turbines are mechanical equipment that wear out differently given the number of their working hours, each turbine has a different efficiency. Therefore, for the same values of water flow and net water head, turbines will produce a different power output.

Also, turbines have maximal water flow limits. When this limit is reached, water needs to be spilled, causing the power production to decrease. Increasing the water flow does not mean increasing the power production. Each turbine has a Hill Curve, which represents efficiency as a function of water head and flow.

3.3.2 Startups and shutdowns

Turbines require to be started or stopped in order to follow the production plan. Useless starts and shutdowns may cause premature wear out of the turbines, therefore, the optimization models should limit the unnecessary starts and shutdowns in order to preserve the normal life-cycle of the equipment.

3.4 Modelling and solving

Different modelling and solving techniques for hydropower systems are presented in more details in Section 4. However, there are a few common challenges that arise whenever one attempts to design an optimization tool to manage a hydropower system. First, the complexity of the problem to model is directly correlated with the number of plants it contains and how the latter are connected. Indeed, large numbers of plants significantly add to the complexity, as does the number of connections between the plants [92]. On some levels of solving, the same applies for the number of turbines in the different plants.

As mentioned before, some parameters in a hydropower system are subject to uncertainty. Whereas this mainly concerns the inflows, in some contexts, this also applies to the prices. This adds to the complexity of the model to design and influences the type of plants and/or strategy to use in the hydropower system. For example, variations in the prices on the short-term level may redirect the management of the hydropower system towards using more pumped storage plants and/or investing in larger reservoirs when possible [92].

As for any system that produces renewable energy, it is demanded that hydropower systems are flexible and fast-responding, mainly to be able to satisfy peak demands, especially when the resources are scarce. To be able to achieve such flexibility and fast response, it is important to have a correct and accurate modelling in order to completely grasp all the aspects and factors that intervene in the studied hydropower system. An efficient management of a hydropower system allows, among other things, the operating of that system at capacity limits when this is required (for example in case of peak demands). As detailed in Section 4, different horizons allow to split the whole managing problems into different sub-problems subject to various horizons, each one being focused on a specific aspect of the optimization.

A hydropower system is subject to many constraints, some of which are meant to reduce its environmental impact on the ecosystem it is located in [48, 67, 88]. A typical example of these constraints is the one that limits the volume of water that can be stored in reservoirs which reduces the ability of a power plant to respond to peak demands [32]. Usually, the constraints can be classified into three categories: technical, strategic and operational constraints [70]. Technical constraints are related to the structural properties of the plant such as the maximum and minimum flow through the turbines for example [32]. Strategic constraints on the other hand are about more long-term guidelines such as the water value curves [32], for example while operational constraints are tied to the functioning of the plant such as assigning other priority uses to the reservoirs and other environmental constraints [16, 49].

As previously mentioned, a lot of different parameters need to be considered when managing a multi-reservoir hydropower system. This induces high dimensional problems that are quite challenging [96].

4 Different solving horizons

Many papers deal with the different aspects of managing a hydropower system. Many case studies are considered, mainly in Canada, Norway, China and Brazil.

As hydropower systems are complex to manage, different levels of optimization models are used to solve the problem. Typically, three levels of optimization are used: long-term, medium-term and short-term. Such models are presented in Figure 5. Their horizon as well as their outputs are shown.

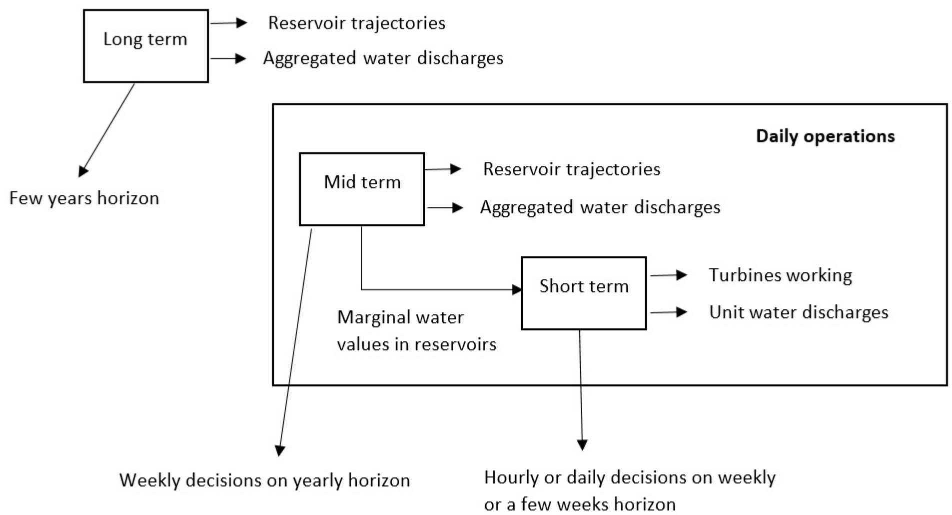

Figure 5: Different optimization levels

The long-term optimization models are used less often than their medium-term and short-term counterparts. They are applied over planning horizons of one to several years. The medium-term models are used more frequently and propose weekly solutions over one-year horizons. They usually aim at maximizing the water value. The short-term optimization models are used to construct daily solutions over a horizon of several weeks. Finally, the unit-commitment models are used when a total amount of power or flow is to be divided between the turbines. In what follows, the three types of models are presented and a thorough literature review is conducted.

4.1 Long-term optimization

Long-term hydropower scheduling problems are a complex class of optimization problems. The inherent difficulty of these problems is mainly due to the large number of parameters and variables to consider, the non-linearity of the production function, the operational interconnection between the plants of a same system and lastly to the long-term horizon to be analyzed [99].

Models for long-term optimization, sometimes referred to as power market simulation models, are used to schedule the hydropower production, to forecast prices (when applicable), to plan expansions and lastly to analyze the power systems [92]. They are also used when the hydropower system is meant to undergo a significant structural modification. Such cases occur for example when a new power plant is to be built, when a power plant or a turbine is planned to be unavailable for a long time for maintenance purposes or, on rarer occasions, when a power plant is scheduled to be shut down. The long-term models usually have a planning horizon of one year or more. This type of model also provides boundary conditions for medium-term and short-term scheduling models.

Long-term optimization models are mainly stochastic and often involve simplifying assumptions and approximations such as aggregations in order to reach acceptable computational time. This is typically used when modelling large hydropower systems [92]. However, later on the solving process, a disaggregation routine is applied to make sure that the decisions of the aggregated model are valid on the real system. It also ensures that the simplifications such as the unrealistic flexibility brought about by the aggregation do not pose any problem on the feasibility of the solution.

Although it is sometimes necessary to use aggregation to tackle very large problems within a reasonable computational time, it is worth mentioning that this could lead to non-optimal solutions and thus a non-optimal utilization of resources or wrong investment choices [92]. A summary of the main approaches applied for solving the long-term hydropower optimization problem are presented in Table 2. Many long-term optimization models use Stochastic Dynamic Programming (SDP) [24, 94] and Stochastic Dual Dynamic Programming (SDDP) [6, 30, 56, 57, 69].

Table 2: Classification of the long-term hydropower optimization papers

Main topic	References
Forecasts	[54, 99]
Stochastic Dynamic Programming	[24, 94]
Stochastic Dual Dynamic Programming	[6, 30, 56, 57, 69]
Fuzziness-based	[99]
Metaheuristics	[36, 53, 81, 91, 97]
Parallel solution methods	[52]
Scenario-trees and fans	[37, 38, 92]
Multi-objective	[42, 100]
Hybrid systems	[92]
Day-ahead electricity markets	[32]
Optimal carryover storage	[86, 101]
Environmental concerns	[11, 35, 87]
Artificial intelligence	[13, 44]
Flood control	[11]
Multiple Markets	[55]

Some methods were designed almost specifically for large-scale problems as an alternative to dynamic programming-based methods such as the work of Carpentier et al. [11]. The authors adapt the progressive hedging algorithm to the long-term hydropower optimization problem since it provided promising results on shorter horizons. The proposed method solves scenario sub-problems by using a deterministic model ; this will then provide an input for a stochastic optimization model. The progressive hedging algorithm in used in a highly uncertain decision environments since the authors attempt to tackle a problem of spring flood management in a watershed in Quebec, Canada. After a series of tests, the authors conclude to the effectiveness and robustness of the method as well as the importance of using a variable penalty parameter.

In hydropower optimization and in particular in its long-term variant, it is very important to have a good idea of what to expect in terms of inflows, electricity demands, etc. In that context, many studies deal with forecasting systems that provide values for the parameters that are subject to uncertainty to the optimization model. In [54], the authors design a long-term climate informed forecasting system of hydro-energy inflow and test it on the Brazilian hydropower system which consists of more than 70 hydropower reservoirs. A statistical model that allows to forecast streamflows on the long-term horizon in order to maximize the efficiency and the produced energy is designed. The goal is to improve the Brazilian streamflow forecasts, which is non-reliable. The predictors used are the NINO3 index [22] and the main modes of the tropical Pacific thermocline structure. The experiments demonstrated the efficiency of the proposed model.

In [92], a hydro-thermal system which combines plants containing both hydro and heat turbines is studied. Two optimization models developed at SINTEF Energy Research are considered, both are used for forecasting and planning in electricity markets. The authors compare a power market simulation model operatively used in the Nordic power market with a new prototype that is expected to give better utilization in systems with large shares of hydro power. The models are compared with regards to hydropower scheduling, market prices and socio-economic surplus. The first model [73] alternates between two phases: computing the water value and taking production decisions. If these decisions are satisfying, it stops, otherwise, it adjusts its parameters and starts all over again. The new model, namely SOVN, is based on scenario fans [37, 38], where each node of subsequent stages in the scenario fan is a two-stage stochastic linear program (LP) which is solved using Benders decomposition [78]. The experiments on a fictitious system of 4 market areas shows that both models have good utilization and flexibility rates but it is the SOVN model that allows for a more optimal use of water with a higher hydropower production and less spillage but also lower prices [92].

In [32], the author studies the long-term optimization of reservoir operation with minimum flows and maximum ramping rates in the context of price-taker peak hydropower plants that sell energy in day-ahead electricity markets. The author developed several long-term optimization models for hydropeaking and presents sensitivity analysis for the effects of minimum flow and maximum ramping rate on economical and operational aspects of the peak power plant. The study shows that the presence of these two constraints increases the spillage volume but decreases the number of start-ups and shutdowns. It also shows that the minimum flows increases the water value but decreases the generated energy while the maximum ramping rates increases the number of plant operating hours but reduces the revenue and the water value.

In [86], the authors propose a long-term optimal operation model that aims to find the optimal carryover storage to balance carryover utilities in a context of a low forecast accuracy and complex hydrological, hydraulic and electric connections between the different reservoirs of a hydropower system. In the model, the carryovers storages are controlled dynamically in cascaded hydropower reservoirs. The proposed model limits the effect of prior knowledge by expressing the carryover utility in terms of energy potential rather than storage. When tested in the Ylong river basin, the proposed model shows results superior to those of conventional optimization tools.

In [101], the authors study the application of the marginal utility principle in long-term hydropower scheduling, the aim being to determine the optimal carryover storage between periods in one-, two- and multi-period cases by investigating the marginal cost and the marginal return. The approach tackles the issue of being unable to decrease the marginal return in the context of hydropower optimization. The conclusions point to saving as much carry-over storage as possible subject to the capacity and environmental flow constraints. These guideline principles are confirmed after a series of tests on the case study of the Three Gorges reservoir.

In [99], the authors study one one main concerns of hydropower optimization which is the uncertainty of the inflows [81]. An annual inflow forecasting model in an open-loop feedback control operational policy is proposed. Based on a fuzzy inference system, it provides inflow values for a deterministic model that takes into consideration the water head as a nonlinear function of storage, discharge and spillage. The quality of the forecasts induces good quality solutions when the model is tested on a multi-reservoir system. The experiments show that the solutions are characterized by low levels of spillage and higher levels of productivity [99].

Another recent trend in optimizing hydropower systems on the long term is the use of metaheuristics. In [97], the authors aim to construct a long-term schedule that maximizes the benefits. A gradient-based Harmony search algorithm is used to optimize a cascaded hydropower system in the Jinsha river. Dynamic adjustments and a random gradient strategy to improve the basic version of the harmony search algorithm are made. The results on Jinsha river basin highlights the effectiveness of the method on the long-term horizon. In [36], the authors study a small hydropower plant (SHP) located at Himreen Lake. A particle swarm optimization coupled with the firefly algorithm are used to get a stable power production and minimize the utility loss. In [91], the authors study a large cascade hydropower stations in the Jinsha River in China which represents a considerable source of hydropower in the country. The authors adapt a multi-population ant colony with continuous domain for the resolution of the long-term optimization of said hydropower system. Both a Gaussian group selection strategy and a circulatory solution correction strategy are used in order to prevent premature convergence, enhance search ability but also to handle outflows and output constraints. The superiority of the proposed method compared to those of the literature was proven by a series of numerical experiments on the Jinsha River. In [53], the authors presented an adaptive artificial bee colony algorithm designed to solve the long-term dispatch of cascaded hydropower systems. A novel probabilistic method to enhance the search ability of the algorithm is proposed. The algorithm showed its superiority when compared to the literature and tested on the system Three Gorges in China.

Some studies even used parallelism to improve the computing capability of the methods. Such an example can be found in [52] where the authors designed a multi-core parallel particle swarm optimization algorithm. The increase in computational efficiency allowed to tackle problems of much larger sizes that often arise in Chinese hydropower systems. The algorithm showed great potential for a future application in larger systems as it was characterized by fast running times and low implementation costs.

Other recent studies use artificial intelligence-inspired methods to solve the hydropower optimization problem but also forecast energy demands. In [44], the authors develop a teaching-learning-based method to solve the long-term hydropower optimization problem in Turkey ; the method used is that of artificial neural networks. That method is later successively hybridized with a backpropagation routine and a metaheuristic known as the bee colony algorithm. The model considers the gross domestic product, the population, the import, and the export as variables and proves to perform well on the case study that was Turkey. In [13], authors use feedforward and recurrent neural networks to forecast energy inflows. The issue of over-fitting is avoided by using and optimal weight estimate procedure which also reduces the training time of the algorithms. The authors were able to outperforms classical stochastic models with regards to forecasts accuracy.

Some latest studies have focused on the environmental aspect of optimizing hydropower systems. In [87], the authors assess the ecological and contamination risks on the long-term of polluted sediments with heavy metals in a small hydropower cascade. The study highlight how in dams, sedimentation affects the degree of toxicity of the water and how this issues arises particularly in small-scale hydropower plants whose number seems to be increasing rapidly. Some others consider the effect of climate change and non-stationarity. In [35], the authors study that aspect in the context of deterministic and stochastic optimization. Seasonal and intra-annual variability of the inflows are considered in three models : the one-time step sampling stochastic dynamic programming (SSDP), the long-term deterministic dynamic programming (LT-DDP) and the long-term sampling stochastic dynamic programming (LT-SSDP). After performing a study in the Manicouagan water system in Canada, the predictions is that, with the climate change, there will be an increase in the water inflows with an increase in the uncertainty. The stochastic optimization model with two-steps was the best to handle non-stationarity among the three designed.

Lastly, it is worth highlighting that all the studies presented above are about mono-objective problems where the goal is either to maximize the produced energy, minimize the cost, etc. However, and despite the complex nature of hydropower optimization problems, some recent studies dealt with a multi-objective version.

In [81], the authors developed an ant colony optimization framework for the so-called environmental flow management alternatives. The latter include releases, wetland regulators, etc. To tackle the variability of inflows, a multi-objective optimization was used within an adaptive framework, while the forecasts were obtained using artificial neural networks. The efficiency of the model was assessed by testing it on a 89km section of River Murray in South Australia. The results show an improvement when compared to approaches that were previously used and induce a more efficient management of water resources.

The work of Zhang et al. [100] may be cited. In that study, the authors extended the classical long-term hydropower optimization problem to include the environment's ecological aspect and constraints. To solve the extended problem, a multiobjective adaptive differential evolution with chaotic neuron network is used. The algorithm involves an adaptive crossover as well as a mutation operator based on a chaotic neuron operation whose purpose is to avoid premature convergence and control the population's diversity. The method is tested on both theoretic benchmarks and real-life cascade systems and proves to provide good quality trade-off solution that optimize both objectives which are the maximization of the total power produced and the minimization of the ecological lack and overflow water volume subject to the basic reservoir constraints.

Another example is the work of Hu et al. [42] where the authors design an adaptive multi-objective particle swarm optimization based on decomposition and dominance. The considered objectives are once again the maximization of the produced energy with the minimization of the ecological flow. An improved logistic map is used to initialize the population then a Tchebycheff decomposition is used to select the best individuals. The non-dominated solutions are stored in a dedicated archive where a routine of crowding distance and an elitist learning strategy are applied to maintain a certain level of diversity. A trade-off between the exploitation and exploration abilities of the method is achieved by using an adaptive flight parameter based on Pareto entropy. After a series of tests on the Three Gorges cascade system, the authors concluded that the newly designed method achieves faster convergence and a better diversity than four other methods from the literature in less time.

In more complex settings, a hydropower system may have to provide energy to multiple markets. For example, the work of Luo et al. [55] in which the authors propose a novel optimization model where the model seeks to maximize the overall profits of a hydropower system on the long-term horizon in a context where the demand that has to be satisfied comes from multiple (local and external) markets. The authors use the copula function to describe the correlation of stochastic prices between multiple markets then generate scenarios based on that function's fitting. These scenarios are then reduced and clustered to reduce the problem's complexity. The optimization model is tested on the Wu river hydropower system and achieves a rather substantial increase in the income when compared to the conventional scheduling model.

4.2 Medium-term optimization

As previously mentioned, the medium-term optimization models usually aim at maximizing the water value and provide weekly solutions over one-year horizons. As opposed to some short-term models, they consider the uncertainty on several parameters such as the inflows. Some of the most famous methods used to solve medium-term optimization models belong to the dynamic programming family; a few are briefly described hereafter. A larger summary of the main approaches used to solve the medium-term hydropower optimization problem are presented in Table 3.

Table 3: Classification of the medium-term hydropower optimization papers

Main topic	References
Forecasts	[12, 28, 77, 80]
Stochastic Dynamic Programming	[39, 72, 102]
Sampling Stochastic Dynamic Programming	[39, 46]
Stochastic Dual Dynamic Programming	[40, 74]
Parallel solution methods	[43]
Hybrid systems	[29]
Environmental concerns	[3, 28]
Flood control	[26, 27, 28]
Multiple Markets	[40]
Non-linear programming	[76]
Mixed integer programming	[34, 39]
Linear approximations	[51]
Dis-aggregation models	[68]
Chance-constrained programming	[29, 103]

Stochastic dynamic programming (SDP) [102] is an efficient algorithm to solve medium-term models, but it is better suited for small systems containing few reservoirs, since it requires discretizing the state variables, the decision variables, as well as the random variables, leading to an optimization problem that is too big to solve. Sampling stochastic dynamic programming (SSDP) [46] is interesting as the uncertainty of the inflows is represented by different scenarios, and transition probabilities between stages are calculated for every possibility to move from one scenario to the other. Again, one of the drawbacks of this method is the size of the optimization problem to solve, but compared to SDP, where each scenario is blind to the other, SSDP has the advantage that scenarios are related. Stochastic dual dynamic programming (SDDP) [74] allows to overcome the dimensionality problem as the uncertain inflows do not require to be discretized. This algorithm is an optimization-simulation approach, which first does a backward optimization pass, followed by a forward simulation. The two steps are repeated until convergence, more precisely until the upper bound on the solution is statistically acceptable to the expected upper bound. Instead of discretizing the inflows, a periodic auto-regressive model is used to generate inflows and to calculate the parameters of the approximation of the cost-to-go function, during the backward pass. The forward optimization simulates the operating policy and allows to validate the parameters of the cost-to-go function. Short-term stochastic models, on the other hand, are too complex to be solved with SDP, SSDP or SDDP algorithms. Hydropower production functions are nonlinear and non-convex, turbines have different efficiencies and discontinuous operating zones and uncertain inflows add to the dimension of the problem [83]. Nonlinear formulations [76], as well as mixed integer programming [34] or linear approximations [51] are usually solved to find a solution to the problem.

Some early studies on medium-term hydropower optimization date back to the beginning of the 1980s, such as the work of Pereira et al. [68]. In that study, the authors develop a monthly streamflow model for the Brazilian hydropower system. The model includes several features such as the non-parametric generation of monthly flows and is mainly based on dis-aggregating annual values into monthly ones. In order to assess the model suitability, the authors test it on a real case study from the Brazilian hydropower network and compare it with a multivariate monthly auto-regressive model. The results show a rather substantial increase in revenues that reaches up to a billion US$.

In [103], the authors design solution methods based on chance-constrained programming and dynamic control. The Chance-constrained model takes into consideration the so-called hydrological parameters. The uncertain inflows are modelled by a simple discrete-time Markov chain then are used within an SDP frame in order to obtain a solution. Then, a dynamic control model is used to improve the dispatching decisions. The latter takes as input short-term and long-term forecasts. The newly designed methods are then compared to a deterministic dynamic programming on the test case of Xiluodu hydro plant in China. The results show that the best method depends on the quality of the forecasts. If the forecast deviation is rather large, one should use chance-constrained programming. Otherwise, especially when the distribution of the latter is close to normal, one should use the dynamic control model.

In [40], the authors develop a medium-term model that takes into consideration the uncertainty of inflows, reserve capacities and energy prices as well as the variability of the head. Hydropower producers can gain additional profits by participating in several markets and not restrict to the energy market only. In order for this goal to be achieved, hydropower systems need to be modelled with a higher level of detail. The authors apply an SDDP-based algorithm to solve the problem at hand which is non-convex. The experiments show the accuracy of the scheduling results when using strengthened Benders cuts to represent the expected future profit function. A method to visualize the shape and non-convexity of the expected future profit is also provided.

In [72], the authors used an SDP-based solutions method and provide a novel optimization model that allows to compute the water value which is one of the most important outputs of a medium-term hydropower optimization model. One-day decision stages over a horizon of one year are considered. The model manages sales of both energy and frequency restoration reserves (FRR) [31]. The novelty of the solutions method lies in the consideration of a producer's price-making ability in the FRR market. Once the water value is obtained, it is injected in a 100-year scenario in order to simulate the day-ahead scheduling of a given power plant. When comparing the new model with the one where the price-making ability of a producer is ignored, an increase in the profit is observed, although modest but also and most importantly a significant reduction in the water spillage which is an important aspect to consider especially in cases where the reservoirs of the hydropower system at hand are used to control floods.

In [39], the authors consider hydropower systems with capacity reserves and study the impacts of detailed modelling. Indeed, as previously mentioned, hydropower systems are subject to the variability of inflows and water volumes and the latest years have seen an increasing demand for reserve capacities in order to ensure the stable operation of the power grid associated with the considered hydropower systems. Thus, producers started to take interest in optimizing both their produced energy along with the capacity. In that context, more detailed modelling is required. The model in [39] consists of two parts, namely a strategy and a simulator part. The first is based on a combination of SDP and SDDP where variables and functional relationships are linear. The former provides a profit-to-go function that is used in an Mixed Integer Program (MIP)-based simulator. After a series of tests on a Norwegian water course, the authors noted that the simulator allows to obtain more viable results although providing expected profits that were 40% lower than those of the model that combines both the strategy and simulator parts.

In [43], the main aim of the authors is to design a method that is more computing time-effective, especially for large hydropower systems. In that context, medium and long-term models are considered and a method implemented by using topological parallel computing is designed. The efficiency of the proposed approach is validated on a test case watershed located in the Southwest of China.

Other studies focused on finding the best way to obtain viable and reliable forecasts. Indeed, they are an important aspect to consider when managing a hydropower system since they influence the power generation, the water supply as well as the flood control policies [77]. Also, they are subject to several exterior parameters that may put to the test the efficiency of prediction models [77]. The work of Sowiński [80], where the author develops a forecasting method base on an Adaptive Neuro-Fuzzy Inference System (ANFIS) may be cited. This method is used to obtain both short-term forecasts and structures of electricity generation which allows to analyze the energy mix. Indeed, the data used is taken from the Energy Market Agency in Poland and includes several energy sources such as thermal, hydropower and wind. The presented model uses time series characterized by periodic variability which allows to predict the main structure of the generated electricity in a medium-term horizon.

Another example is the work of Sibtain et al. [77]. In that study, the authors attempt to design a robust model that could get around the challenge imposed by the nonlinear dynamics of the climatic factors. The model's streamflow prediction's reliability and accuracy are enhanced thanks to the three-stage hybridization of an integrated improved complete ensemble empirical mode decomposition with additive noise (ICEEMDAN), a variational mode decomposition (VMD), and a long short-term memory (LSTM) neural networks. As a case study, monthly data series of streamflow are used, as well as temperature and precipitation in the Swat River watershed which is located in Pakistan. The obtained results showed the efficiency of the proposed model as it provided good quality results that vouch for its applicability in obtaining monthly streamflow predictions.

Lastly, the authors of Chu et al. [12] study the runoff forecasting in the Yellow River headwaters region. Both large-scale and local-scale climatic factors are considered in order to design an approach that is more reliable than what already exists in the literature. The models are built based on multiple linear regression, radial basis function neural networks and support vector regression. These models are then weighted in a Bayesian model averaging-based multi-model whose performance is then compared with the individual models. The results on the selected test case showed the superiority of the fourth model as well as the importance of including climatic factors. The best model proved to provide reliable medium and long-term runoff forecasts.

In more complex settings, some studies deal with electric systems combining wind, hydro and thermal energy sources. In [29], the authors study a wind-hydro-thermal system where both the energy generation and the maintenance are handled. A chance-constrained programming formulation is used to model the uncertainty of the wind, the inflows, the electricity demands, etc. Then, the formulations are converted into their deterministic equivalents in order to reduce the computational complexity. After solving two test cases with a MILP using the CPLEX solver, the authors conclude to the effectiveness of an electrical system combining multiple energy sources in comparison with more conventional systems.

4.2.1 Risk assessment and environmental issues

As for any system subject to uncertainty, managing a hydropower system involves a large uncertainty component that becomes more important when there are economic and/or environmental stakes. Many papers have attempted to assess the risks related to given hydropower systems across the globe.

The work of Ajroon et al. in [3] is interesting. The authors study the economic impacts of building the Grand Ethiopian Renaissance Dam (GERD) on both Ethiopia and the neighbouring countries as well as those who have a share in the Nile River. This study is conducted in a context where neighbouring countries expressed concerns as to the effects of such a dam on their respective use of the Nile River. In order to assess the hydrological and economic risks, the authors used a stochastic hydro-economic model of the entire Nile River to analyze various development and management scenarios. The authors came to the conclusion that if the countries involved agreed to cooperative management, they would all benefit from increased revenues and power productivity.

In [28], Gauvin et al. attempt to find a solution that maximizes the generated power while minimizing flood risks. A variable water head is considered and the non-convexity it introduces is tackled with a multi-stage stochastic programming model. In addition to that, the authors present a novel inflow representation which is both non-linear but also considers serial correlations. To asses the quality of the method, the authors apply it on a real test case. The results show the improvements brought by the proposed methods both energy and flood-control-wise with the small drawback that it results in lower final volumes. In [26], the same group of authors present a novel formulation for the risk averse stochastic reservoir management problem. After defining a risk measure associated with floods and droughts, a multi-stage model that aims at minimizing the latter is designed. A series of experiments conducted on a basin in Western Quebec, Canada shows the performance and robustness of the stochastic program in addition to its flexibility in terms of integrating new constraints compared to existing models. In [27], the authors present another multi-stage stochastic model that is based on enhanced existing linear time series models. The proposed enhancement consists in considering heteroscedasticity and the objective is still the minimization of the risks of floods. Using techniques borrowed from robust optimization and combining them with affine decision rules allowed the authors to design a tractable convex program, which is quite the achievement considering the inherent complexity of the problem at hand. Both the simulations and tests on real systems allowed to prove the effectiveness of the proposed approach.

4.3 Short-term optimization

Short-term optimization is concerned with finding the optimal values of the unit water discharges and reservoir volumes to maximize the energy production, minimize costs, or maximize profits, to name a few examples. In the literature, most of the problems are considered deterministic since the forecasts are updated frequently. Recently, stochastic models for short-term have been investigated. This section presents methods for deterministic and stochastic models. Usual constraints for these models are water balance and energy demand, plus bounds on the different optimization variables, which are usually the water discharges and reservoir volumes. A summary of the main approaches used to solve the short-term hydropower optimization problem are presented in Table 4.

4.3.1 Deterministic

Popular methods to formulate and solve short-term optimization problems are dynamic programming, integer programming and Lagrangian relaxation.

Dynamic programming is a widely used method that allows to solve the problem into multiple sub-problems in order to build the optimal solution using recursion. A dynamic programming algorithm consists of steps, the different sub-problems and the possible states of the system which are related to the decision variables.

Table 4: Classification of the short-term hydropower optimization papers

Main topic	References
Fuzziness-based methods	[98]
Artificial intelligence	[4]
Metaheuristics	[25]
Hybrid systems	[18, 20, 58, 59]
Environmental concerns	[75, 89]
Scenario trees	[18, 83]
Mixed integer programming	[8, 14, 17, 19, 20, 21]
Lagrangian relaxation	[20]
Literature review	[1, 47, 84, 85, 90]
Deregulated markets	[1, 2, 5, 19]

In [14], the authors present a novel mixed-integer formulation for the short-term unit-commitment problem. The aim is to maximize the produced energy on all the periods and use information from the efficiency curves of the turbines. Each turbine may have a different efficiency curve, so the authors study the different pairs of maximum efficiency points of water discharge and the power produced at maximum storage over all possible configurations of active turbines. For practical purposes, the model also aims at reducing the number of start-ups of turbines in order to prevent premature wear. The method is tested on a real test case located in Quebec, Canada. The experimental study on instances with two powerhouses of five turbines each shows the improvements brought by the newly designed model compared to historical decisions.

In [47], Kong et al. present a recent literature review that focused on the short-term hydro scheduling problem. The authors highlighted the frequent use of aggregation between the different units in the various studies present in the literature. However, the increasing need for precision and accuracy in solution models calls for a more detailed modelling which relies on the individual representation of units in order to capture better the shapes of energy and capacity functions. Furthermore, the authors present a detailed classification of the approaches so far applied to the short term unit-based hydropower optimization problem. The various issues and dilemma in the choice of objective functions that may occur when modelling such a problem are explored in order to better guide any researcher and/or practitioner that would face them.

The unit-commitment problem is one that is closely related to the short-term hydropower general problem and one that has drawn a lot of attention in the last years ; one reason may be the increasing demand in electricity demand and the ever-growing need for renewable resources on one hand, and for evermore efficient solution methods on the other hand. This problem is known to be difficult, non-convex but also high-dimensional in terms of decision variables. Over the years, many variants have been studied and various solution methods have been proposed among which some of the most efficient are based on mathematical programs. In [85], Taktak and D'Ambrosio present a literature review on the mathematical programming approaches for its deterministic version. The different variants, constraints, objectives and solution mathematical-programming based models and solution methods are exposed.

One seminal study in the field of hydropower optimization focused on an isolated plant [17]. In that work, Finardi and da Silva designed a non-linear mixed integer mathematical program to solve the unit commitment problem in a deterministic setting. The solution technique is based on branch-and-bound and projected gradient methods. The approach takes into account a target of water discharge volume and also forbidden operation zones. Another recent study [8] in a multi-unit environment attempts to linearize the production function by means of a logarithmic aggregated convex combination while tackling the intricacies of adapting this technique to a mixed-integer mathematical program. The first step, in which the identical units are aggregated, provides initial values for the gross head while in the second step, the latter is used to solve a disaggregated model and find the optimal dispatch values. In order to assess the quality of the approach, the authors test it on a case study derived from a Brazilian basin involving two types of units. The experiments allow to demonstrate the performance and efficiency of the newly designed method.

Furthermore, some recent studies deal with hybrid systems combining multiple energy sources. One example is the work of Ming et al. [59] in which the authors studied a large-scale energy production station combining hydropower with photovoltaic power. The two energy sources are said to complement each other but on the down side, one needs to note that photovoltaic power is rather volatile which generates more uncertainty on the hydropower section demand to be met. To tackle this rather complex problem, a stochastic hydro unit commitment model that considers the uncertainty on the photovoltaic power forecasts is designed. The objective function of the model aims at minimizing the hydro plant's water consumption when there are external constraints load-wise on the system. To solve the proposed model, a two-layer nested optimization framework is designed ; the aforementioned framework consists of a cuckoo search algorithm and load dispatching schemes based on dynamic programming routines. To assess the quality of the solution method, the authors test on a real hydro-photovoltaic plant located in China. After comparing the actual operation with a deterministic scenario that ignores photovoltaic forecasts errors and a stochastic scenario that takes them into consideration, the authors came to the conclusion that the new method provided the best results. The method allowed to provide robust results but also reduced the problem's dimensionality thus inducing faster running times.

Some studies involved the adaptation of a Lagrangian relaxation along with some other mathematical programming techniques, such as the work of Finardi et al. [20]. The authors deal with a hybrid system involving both hydro and thermal energies. In order to tackle this large-scale problem and be able to model it with the adequate precision, a nonlinear model solved by Lagrangian relaxation with sequential quadratic programming is used. The authors also consider many different variables such as the hydraulic losses, the turbine efficiencies as well as forbidden zones of operation. This aims at avoiding unwanted events such as vibrations and low efficiency operations. Three different decomposition techniques are considered and the approach is tested on a real test-case derived from a hydro-thermal system located in Brazil.

The unit-commitment problem is also addressed in the case of deregulated market, for example the work of Finardi and Scuzziato [19]. The authors deal with a unit-commitment and loading problem in the context of day-ahead operations in plants with multiple turbines. The model takes into consideration multiple constraints including those related to the technical operation of turbines. A new nonlinear mixed-integer mathematical model is proposed in order to solve the problem optimally, which they do using two-phase dual-decomposition-based approach. To assess the quality of the method, it is tested on real cases derived from the Brazilian hydropower system.

4.3.2 Stochastic

Stochastic models are used to solve problems which have one or many uncertain components. Managing a hydropower system involves many uncertain parameters such as the water inflows, the energy demand, the temperatures and other meteorological variables [23]. Although these parameters are considered deterministic on some short decision horizons, there are many benefits to considering stochastic versions of hydropower systems in terms of accuracy and robustness [5].

Many stochastic techniques have been adapted to solve hydropower optimization problems through the years. These methods all have a common practical upper limit on the number of reservoirs/plants they can handle within a reasonable computational time [92]. The work of Fleten and Kristoffersen [21] presents a multi-stage mixed-integer linear stochastic program to deal with a short-term hydropower optimization problem subject to the uncertainty of prices and production-based constraints. The authors aim to reach a compromise between optimizing current profits and expected future profits. The quality of the model is then assessed by experimental studies on a test case derived from a Norwegian hydropower producer. Other stochastic models rely on the modelling of scenario trees. For example the work of Séguin et al. [83] where the authors consider the unit-commitment and loading problems with uncertain inflows. A scenario tree is used to model a set of scenarios too large for them to be considered individually. The scenario tree is then used in a two-phase multistage stochastic model and tested on a real test case derived from a basin in Canada. Experiments show the adequacy of the model and its potential for application on larger-scale instances. In a more recent work [18], Finardi et al. study the resolution of a non-convex unit-commitment problem in a regulated environment. In order to tackle the increase in the problem size induced by both the need for discretization and the non-convexity of the problem, the authors use multi-level scenario trees. The approach deals at each level with a particular aspect of the problem ; first the commitment of units, then the minimization of the operational cost. The two levels are coordinated using a variant of Benders decomposition. For testing purposes, the authors use several cases derived from a Brazilian watershed ; the results are claimed to be promising and to induce a more efficient management of the considered resources.

As previously mentioned, one of the latest trends in solving hydropower optimization problems is the use of metaheuristics and the short-term version is no exception, such as the work of Fu et al. [25] where the authors adapt an immune algorithm-based particle swarm optimization algorithm for the scheduling of cascaded reservoirs on a short-term horizon. To do so, the authors include an immune information processing mechanism within a particle swarm optimization framework. The modelling considers the high-dimensional, dynamic, nonlinear and stochastic aspects of the multi-reservoir version of the problem with an objective function aiming to maximize the energy production. The computational experiments on a hydropower system derived from the Qingjiang River show the ability of the newly designed method to achieve a better global optimization within shorter times than those of the conventional operation method.

In the search of evermore accurate forecasting techniques, especially for larger systems and those with a strong emphasis on flood control, other Artificial Intelligence-based methods are adapted for the short-term hydropower optimization problem. In [4], the authors develop a precipitation forecast model based on the use of Deep Neural Networks which extrapolates Cloud-Top Brightness temperature. The output of the latter becomes an input for a rainfall retrieval algorithm which generates forecasts for up to 6 hours. The proposed method uses a Long Short-Term Memory (LSTM) [10, 33] and the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) [41, 45] and is applied on three hydropower systems in the United States of America. The forecasts that are obtained are claimed to indicate better quality statistics than those obtained from previous methods like Rapid Refresh [50] and show a good potential of application in larger systems but also in different climate areas.

Short-term models are no exception to the consideration of environmental constraints especially with increase of laws and regulations that aim to reduce the negative effects of any form of human activity on the environment, especially in the context of an ever-growing demand but also ever-changing climate conditions. This requires advanced techniques for predicting, among other parameters, the stream flows but also advanced and precise optimization methods [75]. In that field of research, one of the aspect that is more and more studied in the literature is that of flood-control ; it aims at improving the quality and accuracy of developed models and approaches while respecting the environmental constraints. In [89], the authors include the long-term water supply objectives into a Guide Curve and use a Model Predictive Control-based approach on a short-term horizon in order to reduce extreme floods. Furthermore, the authors propose a new time-dependent Guide Curve derived from and Implicit Stochastic Optimization approach. The approach is tested on the Yuvacik Dam Reservoir which is located in Turkey. The results show the effectiveness of the method in mitigating floods while allowing to meet the requirements in term of water supply.

Another example is the work of Schwanenberg et al. [75]. The authors present a framework for the short-term operation and optimization of reservoirs with a consideration for flood control for a Brazilian company and focus on the Três Marias hydropower reservoir. A forecast horizon of up to 15 days and predictions based on the MGB model (Modelo de Grandes Bacias) [65, 66] as well as predictions from the ECMWF (European Centre for Medium-range Weather Forecasts) [9, 60] are used. Scenario trees are then used to model the set of forecasts and become the input of a multi-stage stochastic optimization process. The authors also highlight the advantages of using such a method compared to the usual deterministic models in short-term optimization, especially in the context of flood control which requires more robust methods.

As it is the case for the medium-term version of the problem, fuzziness-based methods are also recently explored in the context of the short-term problem, as in the work of Yuan et al. [98]. The study addresses one of the most important issues in short-term hydropower problems which is the minimization of the start-ups and switches of turbines. Indeed, when too frequent, the latter may cause premature wear of the turbines which leads to a high increase in maintenance costs. The authors define the error in power load as a random fuzzy variable and analyze its distribution before integrating it in a short-term hydropower scheduling model. The model ensures that the demand of power grids is met and later assess the quality of the model on a test case derived from the Qing River Basin in China. The obtained results vouch for the efficiency and adequacy of the newly developed approach.

Some studies focus on energy systems that involve more than one way of generating the energy, for example the work of Matevosyan and Söder [58]. The authors study an energy system combining hydropower and wind power. The authors propose a day-ahead planning algorithm that accounts for the uncertainty of the different parameters involved. The water and wind installations may be owned by different utilities and the goal is to reduce wind energy curtailment for the water power is supposed to have the highest priority, especially during congestion situations. The algorithm should enforce that all the transmissions constraints are met. Also, the impact from the coordinate planning is later assessed with an evaluation algorithm on the long-term horizon. Tests are then conducted on a real case study ; results show the accuracy of the coordinated model as well as its ability to reduce wind power curtailments.

In Tahanan et al. [84], the authors provide a literature review on the large-scale unit-commitment problem where the aim is to optimize the production schedule while considering uncertainty as well as various system constraints. One of the major challenges to be faced is the need to design a rather fast solution method for an inherently difficult problem in a context where the large-scale aspect makes it only more difficult, especially considering the uncertainty on the inflows. The authors survey the contributions for the deterministic version of the problem with a focus on mathematical programming techniques that are more easily adapted to the uncertain context of the problem at hand. Then, the authors survey existing methods for the stochastic version of the problem. One can notice the increasing interest of the research community has for hydropower optimization problems in general and the unit-commitment short-term problem in particular. Indeed, in [90], van Ackooij et al. published an updated literature review in which the authors updated the work from [84] with more than 170 recent references. For further details on the unit-based short-term hydropower problem, see [47].

Furthermore, other studies on the unit commitment problem deal with problems encountered in deregulated markets. The studied problem in [2] lies in a context where hydropower producers need to bid their production. They aim at maximizing their profits and therefore seek to offer energy at marginal costs. In the field of hydropower optimization, if water could have been stored for future utilization, it incurs an opportunity cost that is used to determine marginal costs. Of course, these costs are affected by the uncertainty on both inflows and future prices. The authors present a bidding model that uses information from the optimal production schedule generated by a stochastic model. Furthermore, in order to meet the market operator requirements, an heuristic method is developed to reduce the size of the bid matrix. The quality of the approach is assessed on a case study which demonstrated that, while not guaranteeing the preservation of optimal bid curves, the method performed well with only marginal deviations between the optimized and reduced bid matrices. Another paper presented a literature review in the more general context of short-term hydropower optimization with the additional consideration of multi-market settings [1]. In that paper Aasgard et al. aim to survey the solution methods that exist for the main parts that compose a hydropower optimization problem in the context of deregulated markets, namely, mathematical programming, electricity price forecasting and scenario generation. The authors point out the benefits that could be brought by a multi-market environment in terms of flexibility and stability for hydropower producers and also highlight the aspects and open questions that have not yet been addressed in the literature. In [5], Belsnes et al. present a new model for a short-term hydropower optimization problem where the uncertainty on both inflows and prices is considered. The authors aim at highlighting the advantages of considering stochastic versions rather than deterministic ones in the field of hydropower optimization. In order to do so, the authors solve a series of stochastic linear programs and compare its results to deterministic solutions. The efficiency of the approach is assessed on a group of real test cases derived from Norwegian basins. In addition to improving the quality of solutions, the proposed approach has the advantage of reducing the spillage which is a desirable feature in hydropower systems.

5 Conclusion

Nowadays, the field of energy production presents many challenges one of which is switching progressively to renewable energy sources considering the scarce and finite characters of the current mainstream *fossil* energies. In that context, one of the main renewable sources of energy is water. Laws and regulations as well as its inherent complexity make the hydropower optimization problem one that is difficult to solve, no matter what is the solving horizon (long, medium or short-term). Solving this problem comes down to finding the most efficient way of using the available water resources in order to either maximize the produced energy or maximize the revenue with different constraints such as the conservation of water or meeting a given demand.

In this paper, a general overview of this problem is presented from the definition of the basic concepts to the problem description and the main categories of solution methods. An analysis of the literature shows that the way of handling the problem is different from one solving horizon to the other and various types of methods have been adapted for its resolution from mathematical programs to various version of the dynamic programming method and even metaheuristics and fuzziness-based methods.

Recent tendencies involve improving the accuracy of forecasting models and the adaptation of artificial-intelligence-based methods which would allow handling larger systems. Indeed, in the highly competitive environment of energy production, it is of utmost importance to find evermore efficient solution methods that are capable of handling larger-size systems especially considering the fact that the resources are renewable but not infinite at a given point in time.

Another recent trend is the study of multi-objective problems. Indeed, these problems are especially important in the context of environmental constraints such as flood control. Finally, some studies focus on hybrid systems involving more than one renewable energy source and including, in addition to hydropower, wind, thermal or photovoltaic energy. The latter are more and more needed, particularly in areas with a high energy demand.

Another aspect noted is that the problems are solved separately and independently on various horizons by groups of people who have different focuses and views on the problem. It would be of interest to study a larger model by fusing two solving horizons and see what impact it would have on the quality of the obtained solutions.

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