Current Sustainable/Renewable Energy Reports (2020) 7:94–99
https://doi.org/10.1007/s40518-020-00152-6

Challenges in the Management of Hydroelectric Generation in Power System Operations

Álvaro Lorca [1,2,3] · Marcel Favereau [1,2] · Daniel Olivares [1,3]

Published online: 9 June 2020

Abstract

Purpose of Review The management of hydroelectric generation in the context of power system operations has been a difficult and important problem since the inception of power systems more than a century ago; however, various current developments are leading to important new associated challenges and opportunities: massive integration of variable renewable energy and other disruptive technologies, climate change effects on the availability of hydro inflows, and also new efficient techniques for optimization under uncertainty.

Recent Findings Multistage stochastic optimization and stochastic dual dynamic programming are currently the dominant techniques for hydroelectric generation scheduling problems; however, there are many recent extensions and improvements on such techniques, and alternative approaches are being developed with significant potential for future concrete applications from power system operators and policy makers.

Summary In this context, this paper presents a literature review on hydroelectric generation scheduling models, and a discussion on the critical challenges, open research questions, and future lines of research associated to this problem.

Keywords Energy planning · Hydroelectric power · Optimization under uncertainty · Power system operations · Renewable energy

Introduction

Managing the power production from hydroelectric resources is a challenging task that requires properly balancing operational costs and electricity shortage risks throughout time. Whenever hydroelectric generators produce power, this moves water downstream from a reservoir, which renders the availability from hydro power production to be reduced in the near future. In other words, operators need to continuously analyze if water should be employed for power production at that time or kept stored for future production. This difficult decision depends critically on the structure of the power system (generation mix, transmission capacities, etc.) and also on future hydro inflows into the water network, which are highly uncertain.

In order to account for hydro inflow uncertainty, the management of hydroelectric generation relies on stochastic optimization models that represent the operation of the power system over a given planning horizon (e.g., a few weeks, months, or even years), considering uncertainty on the hydro inflows over such horizon, in order to represent the power production from all generators throughout time, in such a way that the water kept stored in reservoirs throughout time ensures a cost-effective operation over the entire horizon.

In this context, the purpose of this paper is to provide an updated literature review on the problem of hydroelectric generation in the context of power system operations and a critical discussion of the most pressing associated challenges and potentially promising research lines. In what follows, "Literature Review" presents such literature review, "Discussion" such discussion, and "Conclusion" concludes.

This article is part of the Topical Collection on *Regional Renewable Energy*

✉ Álvaro Lorca
alvarolorca@uc.cl

1 OCM-Lab at the Department of Electrical Engineering, Pontificia Universidad Católica de Chile, Santiago, Chile

2 Department of Industrial and Systems Engineering, Pontificia Universidad Católica de Chile, Santiago, Chile

3 UC Energy Research Center, Pontificia Universidad Católica de Chile, Santiago, Chile

Literature Review

The problem of hydroelectric generation has been modeled through multistage stochastic programming (MSP). In an MSP, there is a stochastic process that represents uncertain factors (e.g., hydro inflows and/or other factors), and decisions are made throughout time in such a way that expected costs (or some other metric) are minimized [1]. Every time a decision is made, it need to take into account the potential realizations from uncertainty that comes afterwards. Further, large-scale linear MSPs can be solved using the *stochastic dual dynamic programming* (SDDP) algorithm, a method first proposed by Pereira and Pinto [2••], which is based on a nested and iterative application of Benders decomposition [3], possibly exploiting various assumptions in the problem formulation. SDDP was developed for hydropower scheduling in hydropower dominated systems such as Brazil [4, 5] or Norway [6, 7] and has been used both under short and long time horizons [8, 9]. This method is based on two critical assumptions: (i) a finite number of uncertainty realizations (or *scenarios*) and (ii) that the random data process is stagewise independent. Based on this, the algorithm employs cutting-plane approximations of expected future costs (or cost-to-go functions) in a nested form and randomly draws samples from the distribution of the uncertainty data process to iteratively solve an approximation of the problem under a given scenario tree (in what are called *forward* steps of the algorithm), and then iteratively add Benders cuts to each cost-to-go function to improve their approximation of future expected costs (in what are called *backward* steps of the algorithm).

With the purpose of improving the risk-management capabilities of MSPs, various authors have worked on including risk-averse objective functions in SDDP-based algorithms [10–13]. Further, according to Rudloff et al. [14], time inconsistency induces sub-optimality, and an inconsistency gap can measure it; thus, a risk-averse approach based on CVaR (conditional value at risk) with time consistency was proposed. Through the use of SDDP, in the work of Brigatto et al. [15], the results of Rudloff et al. [14] were extended, along with a methodology proposed to evaluate the sub-optimality gap when considering inconsistent policies as a result of ignoring Kirchhoff voltage laws and the "$n-k$" security criterion. It was also showed that these inconsistent policies might exhibit system vulnerabilities and distort market signals.

Both stopping condition and convergence analysis are among the most relevant issues regarding SDDP [8, 16], especially in risk-averse formulations [17]. Thus, for a hydroelectric operation planning problem, Brandi et al. [18] developed a convergence criterion, where including a CVaR does not hind the convergence analysis and whose results yield improvements in the SDDP algorithm and the effectiveness of the convergence criterion. In this context, a very relevant associated difficulty is that the algorithm does not guarantee convergence under non-convexities. As an example, one of the main assumptions of SDDP is the stagewise independence of the uncertainty parameters, thus, including intertemporal dependence needs to be carefully addressed to avoid possible non-convexities arising from the representation of the stochastic processes involved (due to the need of auxiliary variables for representing such process). For example, it has been shown that autoregressive processes are a form of capturing intertemporal dependencies that can keep the convexity of the problem [19, 20].

On the other hand, the SDDiP (stochastic dual dynamic integer programming) method proposed by Zou et al. [21••] allows solving MSPs with integer variables by approximating all state variables through binary variables. The main difference with SDDP lies in the description of the expected cost-to-go function: cutting planes (Benders cuts) are used in SDDP, while Lagrangian and strengthened Benders cuts are used in SDDiP. A key property of this algorithm is that it significantly extends the capability of representing non-convex expressions, as in the case of the work done by Hjelmeland et al. [22], where SDDiP was applied for a medium-term hydropower scheduling problem with a non-convex function for the relation between water discharge and power production. This is an important type of non-convexity, which is poorly approximated under an assumption of linearity; in particular, the authors show an important overestimation of reserve capacity sales when these non-convexities are ignored.

It should also be noted that important contributions have been made in the development of open-source and readily implementable SDDP/SDDiP libraries. Dowson and Kapelevich [23••] developed SDDP.jl, an open-source Julia library for solving linear MSP problems using SDDP. Further, Ding et al. [19••] developed MSPPy, a Python/Gurobi package to solve linear MSPs and integer MSPs through algorithms based on SDDP and SDDiP.

An alternative method to solve MSPs is approximate dynamic programming (ADP). In the work of Asamov et al. [24••], it was demonstrated that for the problem of grid-level energy storage, the use of piecewise linear value function approximations for future operational costs provides similar performance to those obtained with SDDP, although there are no guarantees of optimality. On the other hand, Löhndorf and Minner [25] propose the use of an ADP approach that combines the policy iteration method with a least-squares policy evaluation to approximate the value function in a model of optimal bidding strategy for renewable power generation with storage. Further, through the approximate stochastic dual dynamic programming (ADDP) approach proposed by Löhndorf et al. [26], the work of Löhndorf and Minner [25] was extended to allow to model systems with a higher number of units, and hence, a higher number of decision variables for each stage. ADDP combines ideas from SDDP with ADP by approximating the value function through multidimensional Benders cuts. In turn, Salas and Powell [27•] present an ADP algorithm based on separable, piecewise linear value function approximation to obtain near-optimal control policies in stochastic energy storage problems, where the proposed method linearly scales with the number of storage devices.

In recent years, another approach that has gained popularity for solving MSPs is the use of linear decision rules (LDR). LDR produces an approximation of linear MSPs by restricting that each stage decisions are a linear (or affine) function of the uncertain parameters, and under certain assumptions, an explicit linear model can be formulated. In Gauvin et al. [28••], a multistage multi-reservoir model based on LDR was proposed, where various relevant aspects were explicitly modeled (e.g., water delays). The objective was to minimize the flood risk through a CVaR risk functional, and the obtained results confirmed the value of the use of LDR by obtaining implementable policies and maintaining the model tractability. Based on this work and using LDR, in Gauvin et al. [29•], a nonlinear time series (ARIMA) was introduced along with variable water head. Due to the non-convexity of the time series, the authors used a successive linear programming (SLP) algorithm in a rolling horizon framework. Compared to his previous work [28••], the nonlinear representation of water inflow improved flood management. Beyond the direct use of LDR for MSP, Bodur and Luedtke [30••] introduce a new approach called two-stage LDR, where there are two advantages over static LDR: it works with slight assumptions (relatively complete resource), and it provides better bounds and policies through approximating MSPs by traditional two-stage stochastic optimization problems that can be solved with Benders decomposition. Although two types of problems are analyzed by the authors (inventory planning and capacity expansion planning), it would be interesting to test this approach in other contexts.

Besides stochastic optimization approaches, there are various other areas of optimization under uncertainty that could potentially play an important role in the management of hydroelectric generation. In particular, the area of distributionally robust optimization (DRO) has received a growing attention in recent years [31–33]. The overall idea of DRO is that expected costs are minimized under the selection of a worst-case distribution within a given set of probabilistic distributions (typically called *ambiguity set*). This provides the decisions obtained with a guarantee that they are less affected by potentially biased or poorly representative data. In this context, Huang et al. [34••] developed risk-averse multistage hydrothermal planning model using a convex combination between expected costs and CVaR under an ambiguity set constructed using an ℓ_∞ distance metric between the scenario weights of different probability distributions. A similar approach is found in the work of Philpott et al. [35], where a distance ℓ_2 is used to define the ambiguity set, and a novel algorithm that extends the SDDP is derived to solve DRO problems, which converges almost surely to an optimal policy.

Due to the stochastic nature of the problem of hydroelectric generation scheduling, it is of upmost importance to have an adequate representation of the uncertainty involved. The use of historical data for modeling the future realizations of uncertainty is the most commonly performed practice, and in the literature there is a wide range of streamflow forecasting methods that are generally time series (such as autoregressive models), artificial intelligence methods (such as neural networks or support vector machines), and also hybrids between the previous two [36]. Regarding time series approaches, for hydro inflows there is important research on vector autoregressive (VAR) models [17, 37], periodic autoregressive (PAR) models [5, 38, 39], and geometric periodic autoregressive (GPAR) models [20], among others. The final model choice is entirely dependent on the problem to be addressed and the historical behavior of the uncertainty factors. For instance, according to Lohmann et al. [40••], models such as AR, ARMA (autoregressive moving average), and ARIMA (autoregressive integrated moving average) are generally used to model annual forecasts [41] because they assume stationarity, while for those with greater temporal granularity (which need to incorporate seasonal aspects) models such as periodic ARMA (PARMA) or PAR are typically used [42]. In particular, in Lohmann et al. [40••] the modeling of a SPAR (spatial PAR) is proposed to consider spatial correlations of reservoir water inflows on a monthly scale. In turn, it has been shown that autoregressive models are highly efficient methods, as in the case of Dashti et al. [37], where it was found that modeling the uncertainty associated with water inflow was more accurate by a VAR instead of a simpler polyhedral set based on historical data, in the context of a robust optimization model. Although hydro affluents can be considered as the most significant uncertainty sources, there are other sources of interest. Regarding solar, wind, and electricity demand, considerable research work has been carried out to consider them in short-term problems [43–45].

Regarding unexpected contingencies, contingency constraints can be added to operational models, e.g., the $n-1$ or $n-k$ criteria. In the work of Street et al. [46], the "$n-k$" criterion is considered, where operational decisions are such that they can cope with up to k components removed from the network due to contingencies, while Brigatto et al. [15] considers an $n-1$ criterion.

Discussion

This section presents a discussion about various important current challenges in the management of hydroelectric generation scheduling.

Flexibility Representation in Cases of Deep Variable Renewable Energy Integration

Wind and solar power represent variable renewable energy sources that are increasingly being integrated in many power systems across the globe due to their cost-effectiveness and important sustainability contributions; however, their integration requires power systems to adequately compensate their variability with flexible energy sources that can quickly adapt to varying power injection requirements. In this context, hydroelectric resources can play an important role in providing such flexibility and thus contributing to the massive adoption of variable renewable energy. This raises an important challenge in terms of correctly representing the flexibility that the different energy sources can provide, in hydroelectric generation scheduling problems. In particular, to model flexibility in a more precise form, such problems need to be adapted by incorporating more detailed representations of the operational dynamics of the system, including for example the consideration of hourly granularities through representative days [47]. Further, associated flexibility challenges are to properly represent the reserves that each generator can provide, the role of short-term storage units (batteries, concentrated solar power, hydro run-of-river, and pumped storage), and unit commitment aspects (start-up costs, minimum up and down times, etc.).

Improved Hydro Inflow Uncertainty Modeling and the Effects of Climate Change

Hydroelectric generation scheduling depends critically on how hydro inflow uncertainty is modeled. If the uncertainty representation employed is closer to the real phenomena it is reasonable to expect that better water storage decisions will be carried out throughout time. However, not all uncertainty models will lead to efficient optimization model formulations. Thus, it is important to strike the right balance between the complexity of the uncertainty model employed, and the accuracy with which all other relevant phenomena are represented in a hydroelectric generation scheduling model. An interesting development in this context is the use of Markov chains estimated with clustering techniques and employed in SDDP approaches [19, 20]. This could be a promising method to capture relevant uncertain hydro inflow dynamics. Further, it is a good question if new DRO and robust optimization models can be developed, with alternative representations of uncertainty in hydroelectric generation scheduling models. Moreover, it is important to take into account the fact that historic data for hydro inflows might be significantly biased as compared to what is expected from future hydro inflows, due to climate change effects [48, 49]. In fact, many countries are currently experiencing droughts without precedent in historic records (see, e.g., the Chilean case in Garreaud et al. [50]).

Incorporating Other Sources of Uncertainty and the Concept of Resilience

Another important challenge in hydroelectric generation scheduling is incorporating other sources of uncertainty into the models, beyond uncertainty only in hydro inflows. Some uncertain factors, such as fuel prices, play a role in a similar time span as hydro inflows. In such factors, the hourly uncertainty is not relevant, but weekly or monthly uncertainty is very relevant. Thus, similar methods can be employed, or adapted, to include such uncertainties into the model. However, other sources of uncertainty present a very different nature and can be difficult to represent in hydro scheduling models. For example, wind and solar power present a significant hourly (and even intra-hourly) variability. This again connects to the concept of flexibility representation and remains an open challenge. Further, another very relevant source of short-term uncertainty is that of failure contingencies in generation and transmission assets, which remains an area where some efforts have been carried out [46] but where many questions are open, in terms of how this affects hydro scheduling. Finally, in the near future some other sources of uncertainty might become relevant for hydro scheduling; for example, many countries are adopting demand response mechanisms, which can create uncertainty in terms of the flexibility provision capabilities of demand response assets.

Handling Difficult Non-convexities

Finally another important challenging problem in hydroelectric generation scheduling models is capturing relevant non-convexities. For example, the relation between water discharge and power production is typically highly non-convex [22]. Other relevant non-convex relations are how filtrations in reservoirs can depend on the level of water stored, certain regulatory constraints (e.g., water consumption from farms in the proximities of the water network [51]), and also many aspects related to thermal generators (start-up costs, minimum up and down times, etc.). A particular method, discussed above, which presents a significant potential for addressing such non-convexities is SDDIP [21••]. It remains an open challenge to see if SDDIP or other methods can be successfully employed to capture such non-convexities efficiently in large-scale instances.

Conclusion

This paper has presented a literature review and discussion of challenges on the management of hydroelectric generation in the context of power system operations. Multistage stochastic optimization as a modeling framework and stochastic dual dynamic programming as an algorithm are currently the dominant techniques to handle such problem; however, this paper has reviewed many improvements on SDDP and alternative approaches with significant potential for future concrete applications from power system operators and policy makers. Further, some important challenges and open research questions are associated to flexibility and variable renewable energy, hydro uncertainty modeling and climate change effects, the inclusion of other relevant uncertainties, and efficiently capturing difficult non-convexities.

Funding Information This research was partially supported by CONICYT/FONDECYT/11170423 and CONICYT-PFCHA/National Doctorate Program/2019-21190693.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

References

Papers of particular interest, published recently, have been highlighted as:
• Of importance
•• Of major importance

1. Shapiro A, Dentcheva D, Ruszczyński A. Lectures on stochastic programming. Lectures on Stochastic Programming. Society for Industrial and Applied Mathematics; 2009. https://doi.org/10.1137/1.9780898718751.
2.•• Pereira MVF, Pinto LMVG. Multi-stage stochastic optimization applied to energy planning. Math Program. 1991;52(1–3):359–75. https://doi.org/10.1007/BF01582895.
3. Benders JF. Partitioning procedures for solving mixed-variables programming problems. Numer Math. 1962;4(1):238–52. https://doi.org/10.1007/BF01386316.
4. Pereira MVF. Optimal stochastic operations scheduling of large hydroelectric systems. Int J Electr Power Energy Syst. 1989;11(3):161–9. https://doi.org/10.1016/0142-0615(89)90025-2.
5. Maceira MEP, Damázio JM. USE of the PAR(p) model in the stochastic dual dynamic programming optimization scheme used in the operation planning of the Brazilian hydropower system. Probability Eng Inform Sci. 2006;20(1):143–56. https://doi.org/10.1017/S0269964806060098.
6. Røtting TA, Gjelsvik A. Stochastic dual dynamic programming for seasonal scheduling in the norwegian power system. IEEE Trans Power Syst. 1992;7(1):273–9. https://doi.org/10.1109/59.141714.
7. Mo B, Gjelsvik A, Grundt A. Integrated risk management of hydro power scheduling and contract management. IEEE Trans Power Syst. 2001;16(2):216–21. https://doi.org/10.1109/59.918289.
8. Homem-De-Mello T, De Matos VL, Finardi EC. Sampling strategies and stopping criteria for stochastic dual dynamic programming: a case study in long-term hydrothermal scheduling. Energy Syst. 2011;2(1):1–31. https://doi.org/10.1007/s12667-011-0024-y.
9. Bezerra B, Veiga A, Barroso LA, Pereira M. Assessment of parameter uncertainty in autoregressive streamflow models for stochastic long-term hydrothermal scheduling. In: IEEE Power and Energy Society General Meeting 2012. https://doi.org/10.1109/PESGM.2012.6345322.
10. Philpott AB, De Matos VL. Dynamic sampling algorithms for multi-stage stochastic programs with risk aversion. Eur J Oper Res. 2012;218(2):470–83. https://doi.org/10.1016/j.ejor.2011.10.056.
11. Philpott A, De Matos V, Finardi E. On solving multistage stochastic programs with coherent risk measures. Oper Res. 2013;61(4):957–70. https://doi.org/10.1287/opre.2013.1175.
12.•• Homem-De-Mello T, Pagnoncelli BK. Risk aversion in multistage stochastic programming: a modeling and algorithmic perspective. Eur J Oper Res. 2016;249(1):188–99. https://doi.org/10.1016/j.ejor.2015.05.048.
13. Shapiro A, Tekaya W, Soares MP, Da Costa JP. Worst-case-expectation approach to optimization under uncertainty. Oper Res. 2013;61(6):1435–49. https://doi.org/10.1287/opre.2013.1229.
14. Rudloff B, Street A, Valladão DM. Time consistency and risk averse dynamic decision models: definition, interpretation and practical consequences. Eur J Oper Res. 2014;234(3):743–50. https://doi.org/10.1016/j.ejor.2013.11.037.
15. Brigatto A, Street A, Valladão DM. Assessing the cost of time-inconsistent operation policies in hydrothermal power systems. IEEE Trans Power Syst. 2016;32(6):4541–50. https://doi.org/10.1109/TPWRS.2017.2672204.
16. Shapiro A. Analysis of stochastic dual dynamic programming method. Eur J Oper Res. 2011;209:63–72. https://doi.org/10.1016/j.ejor.2010.08.007.
17. Shapiro A, Tekaya W, Da Costa JP, Soares MP. Risk neutral and risk averse stochastic dual dynamic programming method. Eur J Oper Res. 2013;224(2):375–91. https://doi.org/10.1016/j.ejor.2012.08.022.
18. Brandi RBDS, Marcato ALM, Dias BH, Ramos TP, Junior ICDS. A convergence criterion for stochastic dual dynamic programming: application to the long-term operation planning problem. IEEE Trans Power Syst. 2018;33(4):3678–90. https://doi.org/10.1109/TPWRS.2017.2787462.
19.•• Ding L, Ahmed S, Shapiro A. A Python package for multi-stage stochastic programming. Optimization Online. 2019:1–42.
20. Löhndorf N, Shapiro A. Modeling time-dependent randomness in stochastic dual dynamic programming. Eur J Oper Res. 2019;273(2):650–61. https://doi.org/10.1016/j.ejor.2018.08.001.
21.•• Zou J, Ahmed S, Sun XA. Stochastic dual dynamic integer programming. Math Program. 2019;175(1–2):461–502. https://doi.org/10.1007/s10107-018-1249-5.
22. Hjelmeland MN, Zou J, Helseth A, Ahmed S. Nonconvex medium-term hydropower scheduling by stochastic dual dynamic integer programming. IEEE Transact Sustain Energy. 2019;10(1):481–90. https://doi.org/10.1109/TSTE.2018.2805164.
23.•• Dowson O, Kapelevich L. SDDP.jl: a Julia package for stochastic dual dynamic programming. Optimization Online. 2017.
24.•• Asamov T, Salas DF, Powell WB. SDDP vs. ADP: the effect of dimensionality in multistage stochastic optimization for grid level energy storage. 2016.
25. Löhndorf N, Minner S. Optimal day-ahead trading and storage of renewable energies—an approximate dynamic programming approach. Energy Syst. 2010;1(1):61–77. https://doi.org/10.1007/s12667-009-0007-4.
26. Löhndorf N, Wozabal D, Minner S. Optimizing trading decisions for hydro storage systems using approximate dual dynamic

programming. Oper Res. 2013;61(4):810–23. https://doi.org/10.1287/opre.2013.1182.
27.• Salas DF, Powell WB. Benchmarking a scalable approximate dynamic programming algorithm for stochastic control of grid-level energy storage. INFORMS J Comput. 2018;30(1):106–23. https://doi.org/10.1287/ijoc.2017.0768.
28.•• Gauvin C, Delage E, Gendreau M. Decision rule approximations for the risk averse reservoir management problem. Eur J Oper Res. 2017;261(1):317–36. https://doi.org/10.1016/j.ejor.2017.01.044.
29.• Gauvin C, Delage E, Gendreau M. A successive linear programming algorithm with non-linear time series for the reservoir management problem. Comput Manag Sci. 2018;15(1):55–86. https://doi.org/10.1007/s10287-017-0295-4.
30.•• Bodur M, Luedtke JR. Two-stage linear decision rules for multistage stochastic programming. Math Program. 2018. https://doi.org/10.1007/s10107-018-1339-4.
31. Delage E, Ye Y. Distributionally robust optimization under moment uncertainty with application to data-driven problems. Oper Res. 2010;58(3):595–612. https://doi.org/10.1287/opre.1090.0741.
32. Ben-Tal A, Den Hertog D, De Waegenaere A, Melenberg B, Rennen G. Robust solutions of optimization problems affected by uncertain probabilities. Manag Sci. 2013;59(2):341–57. https://doi.org/10.1287/mnsc.1120.1641.
33. Mohajerin Esfahani P, Kuhn D. Data-driven distributionally robust optimization using the Wasserstein metric: performance guarantees and tractable reformulations. Math Program. 2018;171(1–2):115–66. https://doi.org/10.1007/s10107-017-1172-1.
34.•• Huang J, Zhou K, Guan Y. A study of distributionally robust multistage stochastic optimization. 2017.
35. Philpott A, De Matos V, Kapelevich L. Distributionally robust SDDP. Comput Manag Sci. 2018;15:431–54. https://doi.org/10.1007/s10287-018-0314-0.
36. Zhang Z, Zhang Q, Singh VP. Univariate streamflow forecasting using commonly used data-driven models: literature review and case study. Hydrol Sci J. 2018;63(7):1091–111. https://doi.org/10.1080/02626667.2018.1469756.
37. Dashti H, Conejo AJ, Jiang R, Wang J. Weekly two-stage robust generation scheduling for hydrothermal power systems. IEEE Trans Power Syst. 2016;31(6):4554–64. https://doi.org/10.1109/TPWRS.2015.2510628.
38. Bezerra B, Veiga Á, Barroso LA, Pereira M. Stochastic long-term hydrothermal scheduling with parameter uncertainty in autoregressive streamflow models. IEEE Trans Power Syst. 2017:1. https://doi.org/10.1109/TPWRS.2016.2572722.
39. Castro Souza R, Luí A, Marcato M, Dias BH, Luiz F, Oliveira C. Optimal operation of hydrothermal systems with hydrological scenario generation through bootstrap and periodic autoregressive models. Eur J Oper Res. 2012;222:606–15. https://doi.org/10.1016/j.ejor.2012.05.020.
40.•• Lohmann T, Hering AS, Rebennack S. Spatio-temporal hydro forecasting of multireservoir inflows for hydro-thermal scheduling. Eur J Oper Res. 2016;255(1):243–58. https://doi.org/10.1016/j.ejor.2016.05.011.
41. Yurekli K, Kurunc A, Ozturk F. Application of linear stochastic models to monthly flow data of Kelkit stream. Ecol Model. 2005;183(1):67–75. https://doi.org/10.1016/j.ecolmodel.2004.08.001.
42. Mondal MS, Wasimi SA. Generating and forecasting monthly flows of the Ganges river with PAR model. J Hydrol. 2006;323(1–4):41–56. https://doi.org/10.1016/j.jhydrol.2005.08.015.
43. Lorca Á, Sun XA, Litvinov E, Zheng T. Multistage adaptive robust optimization for the unit commitment problem. Oper Res. 2016;64(1):32–51. https://doi.org/10.1287/opre.2015.1456.
44. Lorca Á, Sun XA. Adaptive robust optimization with dynamic uncertainty sets for multi-period economic dispatch under significant wind. IEEE Trans Power Syst. 2015;30(4):1702–13. https://doi.org/10.1109/TPWRS.2014.2357714.
45. Bertsimas D, Litvinov E, Sun XA, Zhao J, Zheng T. Adaptive robust optimization for the security constrained unit commitment problem. IEEE Trans Power Syst. 2013;28(1):52–63. https://doi.org/10.1109/TPWRS.2012.2205021.
46. Street A, Brigatto A, Valladão DM. Co-optimization of energy and ancillary services for hydrothermal operation planning under a general security criterion. IEEE Trans Power Syst. 2017;32(6):4914–23. https://doi.org/10.1109/TPWRS.2017.2672555.
47. Maluenda B, Negrete-Pincetic M, Olivares DE, Lorca Á. Expansion planning under uncertainty for hydrothermal systems with variable resources. Int J Electr Power Energy Syst. 2018;103:644–51. https://doi.org/10.1016/j.ijepes.2018.06.008.
48. Vicuna S, Maurer EP, Joyce B, Dracup JA, Purkey D. The sensitivity of California water resources to climate change scenarios. J Am Water Resour Assoc. 2007;43(2):482–98. https://doi.org/10.1111/j.1752-1688.2007.00038.x.
49. Vicuna S, Leonardson R, Hanemann MW, Dale LL, Dracup JA. Climate change impacts on high elevation hydropower generation in California's Sierra Nevada: a case study in the Upper American River. Clim Chang. 2008;87(1):123–37. https://doi.org/10.1007/s10584-007-9365-x.
50. Garreaud RD, Boisier JP, Rondanelli R, Montecinos A, Sepúlveda HH, Veloso-Aguila D. The Central Chile Mega Drought (2010–2018): a climate dynamics perspective. Int J Climatol. 2019. https://doi.org/10.1002/joc.6219.
51. Pereira-Bonvallet E, Püschel-Løvengreen S, Matus M, Moreno R. Optimizing hydrothermal scheduling with non-convex irrigation constraints: case on the Chilean electricity system. In: Energy Procedia. Elsevier Ltd; 2016. p. 132–40. https://doi.org/10.1016/j.egypro.2015.12.342.