Applied Energy 310 (2022) 118510

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Short-term hydropower optimization driven by innovative time-adapting econometric model

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ARTICLE INFO

Keywords:
Hydropower generation
Short-term hydropower optimization
Electricity prices forecast
Time-adapting econometric models
Storage reservoir management

ABSTRACT

The ongoing transformation of the electricity market has reshaped the hydropower production paradigm for storage reservoir systems, with a shift from strategies oriented towards maximizing regional energy production to strategies aimed at the revenue maximization of individual systems. Indeed, hydropower producers bid their energy production scheduling 1 day in advance, attempting to align the operational plan with hours where the expected electricity prices are higher. As a result, the accuracy of 1-day ahead prices forecasts has started to play a key role in the short-term optimization of storage reservoir systems. This paper aims to contribute to the topic by presenting a comparative assessment of revenues provided by short-term optimizations driven by two econometric models. Both models are autoregressive time-adapting hourly forecasting models, which exploit the information provided by past values of electricity prices, with one model, referred to as Autoarimax, additionally considering exogenous variables related to electricity demand and production. The benefit of using the innovative Autoarimax model is exemplified in two selected hydropower systems with different storage capacities. The enhanced accuracy of electricity prices forecasting is not constant across the year due to the large uncertainties characterizing the electricity market. Our results also show that the adoption of Autoarimax leads to larger revenues with respect to the use of a standard model, increases that depend strongly on the hydropower system characteristics. Our results may be beneficial for hydropower companies to enhance the expected revenues from storage hydropower systems, especially those characterized by large storage capacity.

1. Introduction

Hydropower generation is an important human action affecting the water-energy nexus, representing about 15% of the world's electricity generation [1]. Due to the high amounts of precipitation and potential energy, hydropower generation in the Alpine regions is even more important as electric energy production largely exceeds the regional demand [2]. Among Renewable Energy Sources (RES), hydropower is also typically considered one of the cleanest power-generating sources [3].

Hydropower generation depends on the location, as well as on the type of hydropower system. Run-of-the-river systems are directly influenced by streamflow regimes, whilst storage hydropower systems can both adopt different management strategies to match electricity market dynamics and ensure energy balance and stability to national power grid networks [4,5]. In particular, due to their flexibility, storage hydropower systems can cover possible mismatches between energy demand and production and thus guarantee the needed voltage levels and frequencies across the power grid [4]. These peculiar characteristics identify storage hydropower systems as fundamental actors in electricity production, able both to provide large amounts of clean energy and to support the integration of other renewable energy sources, such as wind or solar, which are intermittent because of their intrinsic dependency on climate conditions [6]. Storage hydropower systems thus operate as "virtual batteries" with stored water acting as the "charge" [7,8]: during high solar or wind generation, the reservoir system accumulates water; this water is then used for production when wind and solar energy generation is low (or even absent) or to meet fluctuating electricity demands.

The introduction of deregulated electricity markets to several nations entailed new challenges for hydroelectricity producers and water

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https://doi.org/10.1016/j.apenergy.2021.118510
Received 20 May 2021; Received in revised form 29 December 2021; Accepted 30 December 2021
Available online 1 February 2022

resources managers [9]. In particular, the ongoing process of market liberalization induced a change in the hydropower production paradigm, which has shifted from the maximization of the regional energy production to the revenue maximization of individual systems [10, 11]. The resulting competition between all energy suppliers introduced some peculiar effects: (i) electricity prices fluctuate at hourly and/or sub-hourly time scales [12]; (ii) hydropower producers, as well as all the other market participants, bid their energy production in advance and then are forced to schedule their operation plans according to the taken commitments [10,13]; and (iii) electricity prices are unknown during the bidding process [12,13]. Except for a few examples worldwide, in most electricity markets the main auction is represented by the so called "1-day ahead market", where day-ahead electricity prices are determined for each hour of the following day, by the intersection of the aggregated curves of demand and supply [14,15]. Besides the 1-day ahead market, there are several intra-day markets used by the suppliers to modify the production schedule resulting from the 1-day market. Furthermore, other balancing markets take place where the Transmission System Operator (TSO) may modify the production plans to meet electricity grid balance requirements [10,16,17].

While the transformation of the electricity market led to a non-significant alteration in energy production from run-of-the-river plants [18], on the contrary, electricity prices became the main driver for the management of storage hydropower systems, which indeed have the flexibility and the capability to align electricity production with the hours in which the forecasted prices are higher [19]. In this context, a prominent role is played by the electricity production optimization process, which should rely on the identification of a 1-day ahead plan for scheduling water releases (i.e., 1-day-ahead production plan), aiming at maximizing the expected revenue. Specifically, the object of this optimization process is to maximize the revenue of a single day of production by exploiting the use of forecasts for inflows and 1-day ahead electricity prices [20,21].

Optimization of hydropower generation is indeed a complex problem requiring the accurate prediction of electricity prices and water availability under given installation, management and regulatory constraints (i.e., maximum capacity of the penstock channel, minimum and maximum regulation levels in the reservoirs, respect of environmental flows, etc.). Furthermore, the optimization problem is highly non-linear and affected by both hydrological and econometric uncertainties [22]. The comprehension of the mutual interaction between these sources of uncertainty remains largely unquantified in the existing literature and, in particular, limited attention has been given to the investigation of the role played by electricity prices forecast accuracy [11]. A vast majority of the literature has hitherto paid attention either to optimizing short-term electricity production, thus neglecting the role of electricity prices [23], or to analysing short-term forecasting errors of hydrological inflows to storage systems [24–26].

A limited number of papers have studied short-term hydropower optimization by explicitly considering forecasts of electricity prices. In these works, forecast prices are replaced by real prices [e.g. 27] or are generated statistically using the recorded time series of electricity prices [28]. These approaches suffer, however, from important limitations: relying only on actual prices ignores the econometric uncertainties and, more generally, neglects the forecast challenge. Few exceptions are represented by the works of Fleten and Kristoffersen [13] and De Ladurantaye et al. [10], which adopt stochastic optimization autoregressive models in order to model day-ahead electricity prices. However, both works limit their attention to single electricity prices forecast model and the optimization problem is presented with reference to a few individual days, thus not considering the limitations imposed by the seasonal management of storage reservoirs. To the best of the authors' knowledge, no studies investigated the effect of the accuracy of short-term econometric forecasts on the resulting hydropower optimization by also considering the constraints imposed by the seasonal management of storage reservoirs.

In order to overcome the aforementioned limitations, in this work we try to answer the ensuing research questions: (i) what is the revenue gain provided by using accurate forecasts of electricity prices in short-term optimization of storage hydropower systems?; (ii) how do electricity market dynamics affect econometric-driven optimizations in different periods of the year? (iii) how do reservoir characteristics affect such optimizations?

Specifically, two econometric models for 1-day ahead hourly prices forecasting have been considered, both belonging to the class of "adaptive autoregressive" models. Autoregressive models have been widely used in electricity price forecasting given the econometric features of the data such as mean reversion and autocorrelation [29]. These models employ past values of electricity prices and a non-linear combination of the forecasted errors [30]. The first model, hereafter referred to as the "Benchmark", is a model that exploits econometric properties of the electricity prices augmented with dummy variables (i.e., an independent variable which takes the value 0 or 1 in order to consider or omit categorical data, respectively) to account for seasonal and weekly patterns of electricity prices in a deterministic fashion. The second model, referred to as "Autoarimax" [31], extends the specification of the Benchmark model with fundamental time-varying exogenous variables related to electricity demand and production, such as 1-day ahead hourly forecasts of demand, production from renewable energy and fossil sources, and the physical flow of electricity from neighbouring areas. Recent works by Gianfreda and Grossi [32] and Gianfreda et al. [33] show how important are these fundamental variables for predicting Italian (regional) prices. Both models automatically select the relevance of the different variables by using a time-adaptive minimization criterion, i.e., the coefficients of the autoregressive models are updated for each hour of the forecast day on the basis of information belonging to a preceding time window of fixed length (2 years in our specific case). The Autoarimax approach has been shown to produce accurate 1-day ahead predictions of northern Italian zonal electricity prices by taking advantage of hourly forecasts for demand and production variables, including RES [31]. Furthermore, our work also provides interesting indications into whether more accurate and statistically superior models can offer economic gains in the framework of hydropower optimization.

In order to study the effects of different storage capacities, as well as of seasonal reservoir dynamics, on hydropower revenue, the optimization is performed with reference to two hydropower systems located in the upper part of the Adige river basin (south-eastern Alps). Specifically we selected two systems with significantly different regulation capacities in order to investigate their capability of adjusting the daily pattern of turbined water discharges according to the forecasts provided by the two aforementioned econometric models. Econometric driven optimizations are then evaluated for both reservoirs and span an entire chronological year (i.e., by solving 365 independent optimization problems for each reservoir and econometric model). With the intention of preventing the addition of unnecessary complexity and of filtering out other sources of uncertainty, we considered the following assumptions: the reservoirs' inflows are simulated by a distributed hydrological model and thus considered as exact and not affected by forecasting errors; mid-term management of the storage reservoirs is imposed on the basis of historical simulations provided by a regional hydropower systems model.

The paper is organized as follows: Section 2 illustrates the framework adopted for the assessment of econometric driven short-term hydropower optimization; Section 3 presents the case studies and the set-up of the modelling framework; In Section 4, the econometric driven optimization outcomes are described; and finally, Section 5 discusses the main results followed by Section 6 where conclusions are drawn.

2. Methods

The methodological approach developed in this study for assessing short-term optimization driven by a suite of econometric models is detailed in the subsections that follow.

2.1. Formulation of the short-term hydropower optimization problem

Following the approach proposed by Azizipour et al. [34], the short-term optimization problem for the generic 1-day ahead forecast d can be mathematically defined as:

$$\begin{cases} R_d^M = max\left(\sum_{t=1}^{24} W_{d,t}^M P_{d,t}^M\right); & \text{(a)} \\ W_{d,t}^M = g\eta H_{d,t}^M Q_{d,t}^{Turb,M} & \forall t \in [1,24];\ \text{(b)} \\ V_{d,t}^M = V_{d,t-1}^M + \left(Q_{d,t}^{in} - Q_{d,t}^{Turb,M} - Q_{d,t}^{min}\right)\Delta t & \forall t \in [1,24];\ \text{(c)} \\ H_{d,t}^M = h_{d,t}^M - z_{PP}; & \forall t \in [1,24];\ \text{(d)} \end{cases} \tag{1}$$

where the subscript t, with $t \in [1,24]$, indicates the tth hour of the selected optimization day d and the superscript M refers to the econometric model adopted; the term R_d^M represents the daily aggregated forecasted revenue generated by the hydropower system; $W_{d,t}^M$ and $P_{d,t}^M$ are the power generated by the hydropower plant and the electricity price at a given hour t, respectively; g is the gravity acceleration; η is the efficiency of the hydropower unit; $H_{d,t}^M$ is the hydraulic head at hour t computed according to Eq. (1)(d) as the difference between the reservoir water elevation at hour t ($h_{d,t}^M$), estimated by means of a specific volume-elevation reservoir function, and the elevation of the turbine nozzle z_{PP} at the plant connected to the reservoir through the penstock of the hydropower system; $Q_{d,t}^{Turb,M}$ are the hourly turbined water discharges; $V_{d,t}^M$ is the hourly water volume stored in the reservoir; $Q_{d,t}^{in}$ is the hourly reservoir water inflow; $Q_{d,t}^{min}$ is the Minimum Ecological Flow imposed at the reservoir; and Δt is the hourly modelling time step. We underline how forecasted inflows $Q_{d,t}^{in}$ and forecasted electricity prices $P_{d,t}^M$ represent the independent variables of the problem, while the hourly turbined water discharges $Q_{d,t}^{Turb,M}$ represent the decision variables computed by means of the optimization algorithm described in Section 2.4.

The short-term hydropower optimization problem depicted in Eq. (1) is subject to both hard and soft constraints [26,35,36]. The hard constraints are conditions for the variables of the problem that must be satisfied by any feasible solution, while soft constraints are requirements that the optimization algorithm tries to satisfy, although they can be violated without causing an interruption in the optimization process [37].

Hard constraints considered in this work read as follow:

$$\begin{cases} V_{min} \le V_{d,t}^M \le V_{max} & \forall t \in [1,24];\ \text{(a)} \\ 0 \le Q_{d,t}^{Turb,M} \le Q_{max}^{Turb} & \forall t \in [1,24];\ \text{(b)} \end{cases} \tag{2}$$

where Eq. (2)(a) represents the constraint for reservoir volume, bounded to vary between a minimum V_{min} and a maximum storage, V_{max}, and Eq. (2)(b) imposes a limit on the maximum value of turbined water discharge Q_{max}^{Turb} that the diversion channel connecting the reservoir and the hydropower plant can convey.

Soft constraints are defined as follows:

$$\Delta t \sum_{t=1}^{24} Q_{d,t}^{Turb,M} \le \begin{cases} 24\Delta t \overline{Q}_d^{Turb} & \text{if} \quad V_{min} \le V_{d,0}^M + \Delta t \sum_{t=1}^{24}\left(Q_{d,t}^{in} - \overline{Q}_d^{Turb}\right) \le V_{max}; & \text{(a)} \\ \Delta t \sum_{t=1}^{24} Q_{d,t}^{in} + V_{d,0}^M - V_{min} & \text{if} \quad V_{d,0}^M + \Delta t \sum_{t=1}^{24}\left(Q_{d,t}^{in} - \overline{Q}_d^{Turb}\right) < V_{min}; & \text{(b)} \\ \Delta t \sum_{t=1}^{24} Q_{d,t}^{in} & \text{if} \quad V_{d,0}^M + \Delta t \sum_{t=1}^{24}\left(Q_{d,t}^{in} - \overline{Q}_d^{Turb}\right) > V_{max}; & \text{(c)} \end{cases} \tag{3}$$

where Eq. (3)(a) expresses the upper bound, $24\Delta t\overline{Q}_d^{Turb}$, for the daily turbined water volume $\Delta t \sum_{t=1}^{24} Q_{d,t}^{Turb,M}$, introduced in order to guarantee the accomplishment of a realistic seasonal pattern of reservoir dynamics and simultaneously to avoid unrealistic emptying of the reservoir, with $V_{d,0}^M$ being the initial reservoir volume of day d; Eq. (3)(b) imposes that the daily turbined water volume does not exceed the daily incoming streamflow in the cases in which the minimum water volume V_{min} is reached; and Eq. (3)(c) softens the upper limit of the daily turbine water volume in the case in which V_{max} is reached and overflow may occur. We remark how the 3 conditions in Eq. (3) are determined for a given day on the basis of the mass balance Eq. (1)(c) and they are mutually exclusive. The term $\overline{Q}_d^{Turb}$ has been computed on the basis of historical simulations provided by a regional hydropower systems model as described in Section 2.3.

The volume obtained at the end of the optimization of a given day d, $V_{d,24}$, represents the initial volume of the reservoir for the optimization conducted in the ensuing day $d+1$, $V_{d+1,0}$. Finally, it has to be noticed that the system of Eqs. (1) refers to a single daily optimization problem within a set of 365 sequential optimizations conducted during a reference year of simulations.

2.2. Econometric models

Autoregressive models have been widely used in electricity price forecasting given the mean-reverting nature of market fundamentals, the highly repetitive nature of electricity auctions and also the increased market integration, see for example [29,38–40]. Following the definition of econometric versus fundamental types of modelling in the seminal review paper of Weron [9], we considered two types of autoregressive models for forecasting 1-day ahead hourly electricity prices. The first one, labelled Benchmark, is an econometric model that exploits econometric properties of the historical hourly data prices with a set of dummy variables to account for seasonality. The second model, labelled Autoarimax, extends the previous specification by employing market fundamental time-varying variables relative to electricity demand and supply. For example, Gianfreda and Grossi [32] and Gianfreda et al. [33] show how important are these fundamental drivers for predicting Italian (regional) prices. Specifically, the northern area is characterized by a varied, flexible generation mix, with a large role of hydropower and a growing role of solar, and conventional thermal generation (principally gas) covering the remaining portion. This zone is also connected with four foreign countries. Indeed, because of the relevant interconnection capacity between foreign countries and northern Italy, it is possible to import electricity at a lower price. Accordingly, we included an additional variable, termed weighted imports, using prices in interconnected countries and in the central northern Italian zone weighted by the cross-border physical flows thus accounting for the different areas generating portfolio. Therefore, in the Autoarimax formulation we considered forecasts of demand, forecasts of RES (hydropower, solar and wind) and fossil production (gas and CO_2), and the weighted imports. Autoarimax model thus includes fundamental information on electricity demand and supply, but also market features, such as imports of electricity from neighbouring areas. Therefore, the model applies exogenous stochastic variables to predict hourly electricity prices.

The Benchmark model can be written as:

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)\left(1 - L^1\right)^f \left(P_{d,t}^R - \mu_{d,t}\right) = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right)\varepsilon_{d,t} \quad \varepsilon_{d,t} \sim \mathcal{N}\left(0, \sigma^2\right); \tag{4}$$

$$\mu_{d,t} = \mu + \psi_1 D_d^1 + \cdots + \psi_{11} D_d^{11} + \gamma Weekend_d + \xi Monday_d;$$

where $P_{d,t}^R$ is the t-hourly electricity price observed on day d, L^k is the generic kth lag operator defined as $L^k P_{d,t}^R = P_{d-k,t}^R$, and f is the first-differencing parameter which allows to model the price itself ($f = 0$) or the first-order difference of the price ($f = 1$). The parameters p and q represent the autoregressive and moving average orders, respectively.

The error term at time t, $\varepsilon_{d,t}$, is assumed to follow a Normal conditional distribution with mean 0 and finite constant variance σ^2. D_d^k for $k = 1,\dots,11$ are dummies for months (excluding December), $Weekend_d$ is a dummy for weekends and holidays, $Monday_d$ is a dummy for Mondays, and ψ_k, ξ and γ are their coefficients, respectively. This last set of dummy variables accounts for deterministic seasonal and weekly patterns. The coefficients ϕ_i, θ_j, $i = 1,\dots,p$, $j = 1,\dots,q$, $p = q = 7$ (max order of lags), μ, f, ψ_j, ξ and γ are selected and estimated iteratively over time, that is lags and dummies are selected, and their coefficients are re-estimated when a new forecast is produced.

The Autoarimax model extends the benchmark specification in Eq. (5) with a vector $\mathbf{x}_{d,t}$ of exogenous regressors in the following way:

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)\left(1-L^1\right)^f\left(P_{d,t}^R-\mu_{d,t}\right) = \left(1+\sum_{j=1}^{q}\theta_j L^j\right)\varepsilon_{d,t} \quad \varepsilon_{d,t}\sim\mathcal{N}\left(0,\sigma^2\right); \tag{5}$$

$$\mu_{d,t} = \mu+\psi_1 D_d^1+\cdots+\psi_{11}D_d^{11}+\gamma Weekend_d+\xi Monday_d+\lambda'\cdot\mathbf{x}_{d,t};$$

where $\mathbf{x}_{d,t}$ includes hourly forecasts of demands, wind and solar PV generation, weighted imports, natural gas, CO_2 prices, and hydropower generation, and λ is the vector containing the associated coefficients that need to be estimated iteratively in addition to those already present in Eq. (4).

Specifically, we compared the two models in terms of forecast accuracy of the electricity zonal prices predicted over individual hours; i.e. each hourly forecast is modelled separately by using past values of prices and drivers available for the same hour. We assumed that market operators submit their bids on day $d-1$ for the ensuing day d, on the basis of hourly price forecasts simulated for day d. These latter forecasts are obtained by considering fuel prices available on day $d-1$; the forecasted values for RES and zonal demand available on day $d-1$; the hydropower generation and weighted imports observed on day $d-1$ for hours $1-10$ and their realized values observed at hour 10 as a proxy for the electricity prices of hours $11-24$, as suggested in [41] and [42]. Because all information is available or reconstructed before 11 a.m. of day $d-1$ (i.e. before the market closure when traders must submit their offers), we are indeed able to forecast all the 24 h for the ensuing day d by employing a simple prediction process on the basis of the time-adaptive autoregressive models calibrated for the set of 24 h belonging to day d. Therefore, at 11 a.m. of day $d-1$ our models predict the electricity prices for all the 24 h on day d, $P_{d,t}^M$, $t = 1,\dots,24$.

The estimation process for both models is based on a maximum likelihood estimator and it is executed using the R software using the function "auto.arima" in the "forecast" library [43]. In particular, we use the first 730 days of our dataset (i.e. from 1/1/2016 to 31/12/2017) for the in-sample coefficients estimation, and then the first out-of-sample predictions are performed independently for the 24 price values of 1/1/2018. Thereafter, the window is rolled one day ahead with further estimation and forecasts obtained for 2/1/2018, and so forth, until the last day in the simulation period.

2.3. Hydrological modelling

The hydrological modelling component adopted in this work feeds the optimization algorithm with the hourly time series of inflows at the selected storage reservoirs, $Q_{d,t}^{in}$. Inflows have been computed using the ICHYMOD hydrological model [Integrated Catchment-scale Hydrological Model, see, 44,45]. This choice is corroborated by two important characteristics of ICHYMOD. Firstly, ICHYMOD is easily applicable due to the limited requirements of input meteorological forcing. In particular the model relies solely on precipitation and temperature data, information easily retrievable from weather stations located in the case study region [44]. Secondly, ICHYMOD is particularly suitable for applications in mountainous catchments, where hydropower reservoirs are typically located [46], by exploiting the use of accurate and reliable modules for snow accumulation and melt dynamics [47–49]. ICHYMOD is also equipped with the GLUE (Generalized Likelihood Uncertainty Estimation Beven and Binley [50]) calibration method, which allows for the set of parameters that maximizes a given objective function between observed and simulated water discharges to be identified. As is customary in hydrological simulations, we used the Nash–Sutcliffe index [NSE 51] as an efficiency metric.

2.4. Optimization algorithm

In this work, the Speed-constrained Multi-objective Particle Swarm Optimization algorithm (SMPSO) has been adopted as the optimization algorithm [52]. The SMPSO is a more sophisticated variant of the classic PSO (Particle Swarm Optimization, Kennedy and Eberhart [53] and Majone et al. [54]). Compared to PSO, SMPSO is characterized by a velocity constraint mechanism, which is designed to prevent the so-called 'swarm explosion' [55], that is an inconsistent movement of the particles when the velocities are high. SMPSO thus implements a limitation on the maximum velocity of the particles that allows for a more effective search of the optimal solution. Moreover, the algorithm is equipped with an external archive to store the solutions that are non-dominated and also a polynomial mutation is applied to perturbate particle locations and further enhance the exploration of the hyperspace.

In the implementation of the optimization algorithm, particular attention has been given to avoid the identification of local optima, which can produce solutions that are far from the absolute optimum. Specifically, convergence of the optimization algorithm for each simulation day d has been ensured by implementing the approach proposed by Do et al. [56] and Zanfei et al. [57], in which multiple runs of the same optimization problem (i.e., one for each day and for each econometric scenario considered, see Section 2.2) are performed in order to generate a set of possible solutions. Therefore, a solution is identified for each econometric scenario by selecting the one providing the highest revenue for each day. A comprehensive explanation of the SMPSO algorithm is provided in Appendix.

2.5. Econometric and optimization performance metrics

In order to analyse the performance of the optimizations conducted using the two identified econometric models (See Section 2.2), a reference optimization problem has been introduced. This solution, hereafter referred to as "Real", is obtained by solving 20 runs of the optimization problem described in Section 2.1 for each day d by using the real electricity prices $P_{d,t}^R$ as the input. The obtained solutions thus represent the best possible economic scenario, in which perfect 1 day-ahead foresight is assumed and the hourly distribution of the turbined water discharges (i.e., $Q_{t,d}^{Turb,R}$) attempts to perfectly match the electricity price dynamics given the installation constraints of the storage reservoirs (see Fig. 1a). In doing so, the optimization problem driven by real electricity prices provides the maximum revenue obtainable in a given simulation day, R_d^R, which reads as:

$$R_d^R = \sum_{t=1}^{24} W_{d,t}^R P_{d,t}^R \tag{6}$$

On the contrary, actual daily revenues obtained using the two different econometric forecasting models are computed considering the optimized production plan (i.e., $Q_{d,t}^{Turb,M}$ in Eq. (1)(b)) and the real electricity prices for day d, which actually represent the realized market price value obtained in the 1-day ahead electricity market. Actual revenues can then be computed as follows:

$$R_d^{M*} = \sum_{t=1}^{24} W_{d,t}^M P_{d,t}^R; \tag{7}$$

where $W_{d,t}^{M}$ are the hourly powers generated by the plant computed according to the optimization process driven by the $M-th$ econometric model (Eq. (1)(a)). Notice that the actual revenue, $R_d^{M^*}$, obtained after the bidding as driven by the Benchmark (Model = B) and the Autoarimax (Model = A) econometric models (see Fig. 1b and c, respectively), differs from R_d^M, which represents the daily revenue value maximized during the optimization process. Actual revenues are compared with the reference optimization by means of the percentage ratio metric Φ_d^M, which can be expressed as follows:

$$\Phi_d^M = \frac{R_d^{M^*}}{R_d^R} \cdot 100 \tag{8}$$

For the sake of completeness, we also introduced a metric to assess electricity price forecasting accuracy. The metric expresses the relative change of hourly forecast prices $P_{d,t}^M$, at hour t and for a given day d, with respect to the real hourly prices $P_{d,t}^R$, and can be expressed as follows:

$$\Delta P_{t,d}^M = \left| 1 - \frac{P_{t,t}^M}{P_{d,t}^R} \right| \cdot 100 \tag{9}$$

3. Case study

The comparative assessment between optimizations conducted using the Autoarimax and Benchmark econometric models has been performed with reference to the storage reservoirs of Vernago and Monguelfo, both located in the south-eastern Alps (see Fig. 2). Water stored in the reservoir of Vernago is used in the Naturno hydropower plant, while water stored in the reservoir of Monguelfo is utilized in the power plant of Brunico. Both power plants deliver the produced electricity to the northern Italian power grid and operate in the northern Italian electricity market.

The drainage basins of the two reservoirs (69 km^2 and 430 km^2 for Vernago and Monguelfo, respectively, see Table 1) are located in the Adige river basin, an Alpine watershed in north-eastern Italy. The Adige is the second longest Italian river, and its watershed hosts the presence of a dense network of man-made channels, reservoirs and plants associated to intense hydropower exploitation [58–61]. Both the Vernago and Monguelfo drainage basins are characterized by a typical snow-dominated streamflow regime with water discharges varying significantly across seasons [62–65]. High flows occur typically in late spring due to snow melt and in the autumn triggered by moist air flows blowing from the Mediterranean area [49,66,67].

Both reservoirs are managed according to their regulation capacity, with different operating policies resembling the hydrological regime of the related watersheds. In particular, Vernago has a storage capacity of about $37.79 \cdot 10^6$ m^3 and is managed following a seasonal regulation: a minimum level is typically maintained at the beginning of the snow melt season (end of April), while a maximum level is normally reached at the end of the summer season (end of September). Volume regulation aims to refill the reservoir volume during high flow period (late spring and summer) and maximize the hydropower production during low flow period (i.e., late autumn and winter) when electricity prices are usually higher because of heating demand [68]. On the contrary, due to its limited storage capacity (about $6.45 \cdot 10^6$ m^3), the Monguelfo reservoir follows a multi-weekly regulation. Scheduling of the production is typically performed during the winter season only, when the incoming flow rate is limited and comparable with the storage capacity of the reservoir. During high flow periods (late spring and summer), Monguelfo behaves like a run-of-the-river power plant because inflows largely exceed maximum penstock capacity. An overview of the main characteristics of the two reservoirs and of the connected hydropower plants is presented in Table 1.

Table 1
Main characteristics of the Monguelfo and Vernago storage reservoirs and of the associated hydropower plants.

	Unit	Monguelfo	Vernago
Hydropower station name		Brunico	Naturno
Gauging station name		Rienza	Gerstgras
Contributing area	[km^2]	430.00	69.00
Reservoir V_{min}	[m$^3 \cdot 1e^3$]	0.00	2.84
Reservoir V_{max}	[m$^3 \cdot 1e^3$]	6.44	40.64
Mean hydraulic head	[m]	200.00	1135.00
Penstock capacity	[m^3/s]	22.00	13.7
Maximum regulation level	[m]	1055.00	1689.50
Minimum regulation level	[m]	1026.70	1637.65

3.1. Set-up of the modelling framework

In this work, the year 2018 has been selected as the reference period for econometric driven optimization. Since the econometric models are calibrated on two-year data, 2016 and 2017 data are then used to produce the first forecast for 1 January, 2018 and so on for the following days. Anticipating the investigation period to pre-2018 would imply calibrating models on data from before 2016. However, the year 2015 presented a large-scale deployment of intermittent renewables in Italy, which caused substantial modifications in the electricity market, henceforth denoted with a higher degree of uncertainty in electricity demand and supply, and consequently we prefer to exclude all the years before 2016 as suitable for the optimization assessment [69].

The hourly northern Italy zonal electricity prices[1] have been extracted from the Italian system operator GME (Gestore dei Mercati Energetici), while the European Network of Transmission System Operators — Electricity (ENTSO-E) [70] has provided the day-ahead hourly load forecasts, used as a proxy for local electricity demand, and the day-ahead hourly forecasts of RES generation. We remark that ENTSO-E and GME data are public available without fees and as described in Section 2.2 market participants can access them before submit theirs bids before 11 a.m. on day d-1 for day d. For fossil production, to account for the marginal costs of conventional thermal generation, we use the costs of conventional thermal generation: the Dutch TTF natural gas prices (for delivery over the next month) and the EEX-EU CO_2 emissions E/EUA prices in euros, all collected from Datastream [71]. We assume the same hourly price in the 24 h of the day for thermal generation. Furthermore, the following data have been collected in order to take into account neighbouring markets: hourly day-ahead prices observed in Austria, France, Switzerland, Slovenia, and in central northern Italy; actual hourly electricity physical flows into the northern Italy electricity zone. Though we tested both physical and market flows during the development of the econometric model, in the end we opted for using physical flows because they were superior in terms of electricity price forecast accuracy.

[1] The Italian electricity market is structured into geographical and foreign virtual zones. The geographical zones represent a portion of the national grid delimited by bottlenecks in transmission capacity, and these are northern Italy, central-northern Italy, central-southern Italy, southern Italy, Calabria, Sicily, and Sardinia. The foreign virtual zones are points of interconnection with neighbouring countries. This paper considers northern Italy because it covers the Alpine region where the investigated storage reservoirs are located. The foreign virtual zones are France, Switzerland, Austria, and Slovenia. Each geographical and virtual zone yields an hourly (clearing) price, obtained from an implicit bidding mechanism in which pairs of quantities (in MWh) and prices (in €/MWh) are considered by accounting for the market splitting in case of congestions. Therefore, in the same hour, zonal prices in contiguous market zones can differ depending on transmission bottlenecks. The zonal prices concur to generate the single national price (or *prezzo unico nazionale*, PUN), that is the average of zonal day-ahead prices weighted for total purchases, net of purchases for pumped-storage units, and purchases by neighbouring zones.

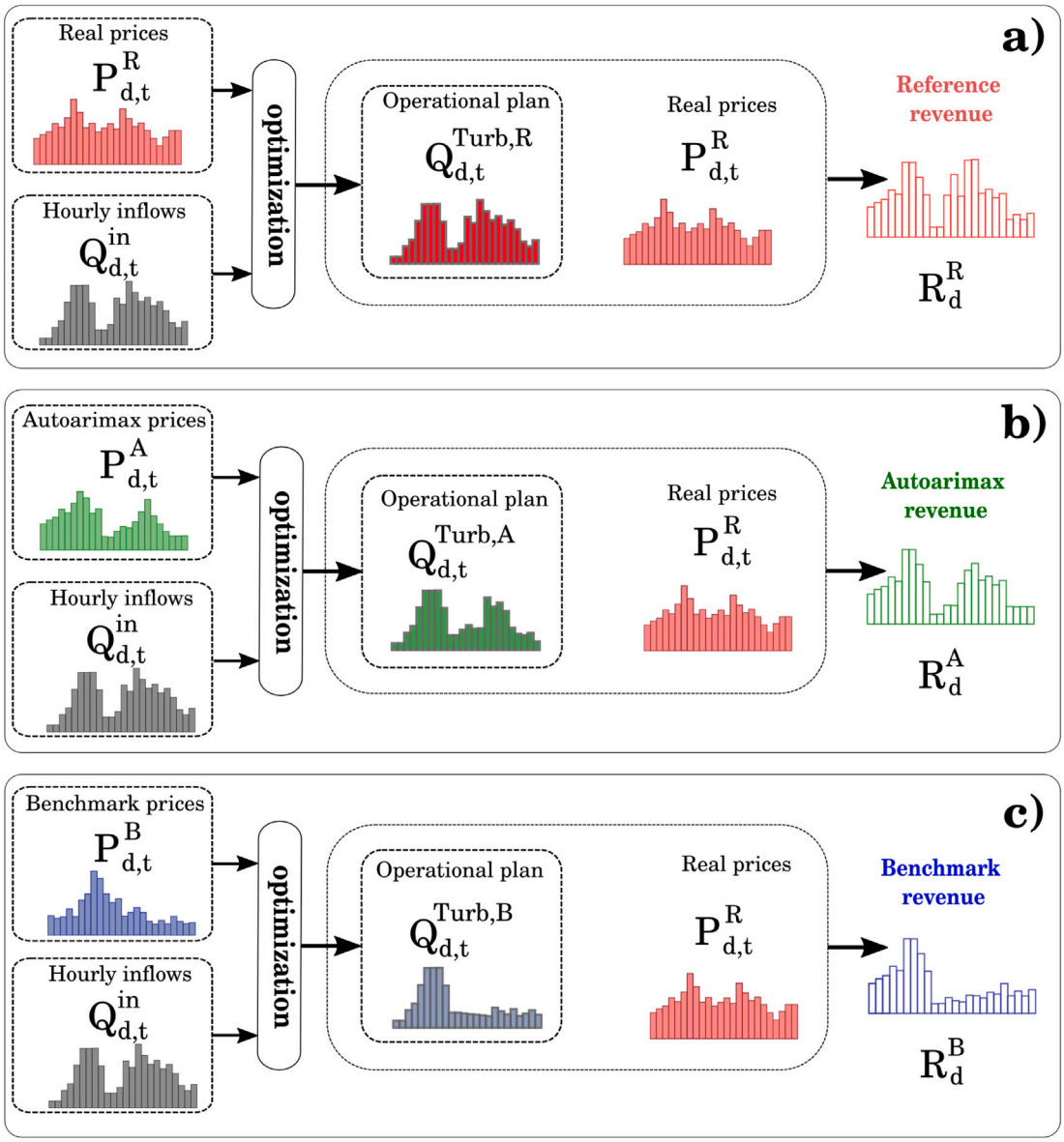

Fig. 1. Scheme representing the procedure adopted to compute hydropower revenue for a given day d driven by (a) real electricity prices $P^{R}_{d,t}$, (b) Autoarimax forecasted electricity prices $P^{A}_{d,t}$ and (c) Benchmark forecasted electricity prices $P^{B}_{d,t}$. The term $Q^{in}_{d,t}$ represents the hourly inflow to a reservoir in the day d; $Q^{Turb,R}_{d,t}$, $Q^{Turb,A}_{d,t}$ and $Q^{Turb,B}_{d,t}$ represent the optimized daily operational plans (i.e., hourly turbined water discharges) as driven by real, Autoarimax and Benchmark electricity prices, respectively; and R^{R}_{d}, R^{A}_{d} and R^{B}_{d} are the associated revenues.

The ICHYMOD hydrological model has been used to compute the hourly time series of inflows $Q^{in}_{d,t}$ for the two selected reservoirs during the year 2018. In particular, the calibration of ICHYMOD for the Vernago drainage basin has been performed using the streamflow data of the Gerstgras gauging station during the period 1 October 2018–30 September 2019; in the case of Monguelfo, the data from 1 October 1994 to 30 July 1998 retrieved from the Rienza gauging station have been used (see Fig. 2). According to the classification provided by Moriasi et al. [72], calibrations can be considered as very good and satisfactory with NSE = 0.90 and NSE = 0.61 for the Vernago and Monguelfo drainage basins, respectively. Afterwards, the parameterizations obtained for the ICHYMOD hydrological model during calibration have been used to simulate hourly inflows to the reservoirs during the year 2018.

The daily upper bounds of turbined water discharge $\overline{Q}^{Turb}_{d}$ (which implicitly represent a limitation for the water volume that can be turbined in a given day) have been obtained from [61], where the hydrological model HYPERstreamHS [61,73] has been presented and used to simulate historical time series of water releases from the reservoirs in the investigated study region, i.e., the entire Adige river basin. HYPERstreamHS is indeed a hydrological model embedding modules for simulating the presence of infrastructures, such as reservoirs and diversion channels. Historical operational rules of storage reservoirs present in the Adige river basin have been inferred from regional electricity production data that is publicly available from the Italian Energy Services Manager [74]. In this work, the simulated time series of daily simulated turbined flows at the Vernago and Monguelfo reservoirs during the period 1989–2013, retrieved from [61], have been averaged to provide the daily targets of water releases over the year $\overline{Q}^{Turb}_{d}$.

For the sake of completeness, the parameters adopted in the optimizations conducted with the SMPSO algorithm are also reported. Specifically, the swarm size and the so-called archive size are both set equal to 1000, the mutation probability is equal to 25%, and the

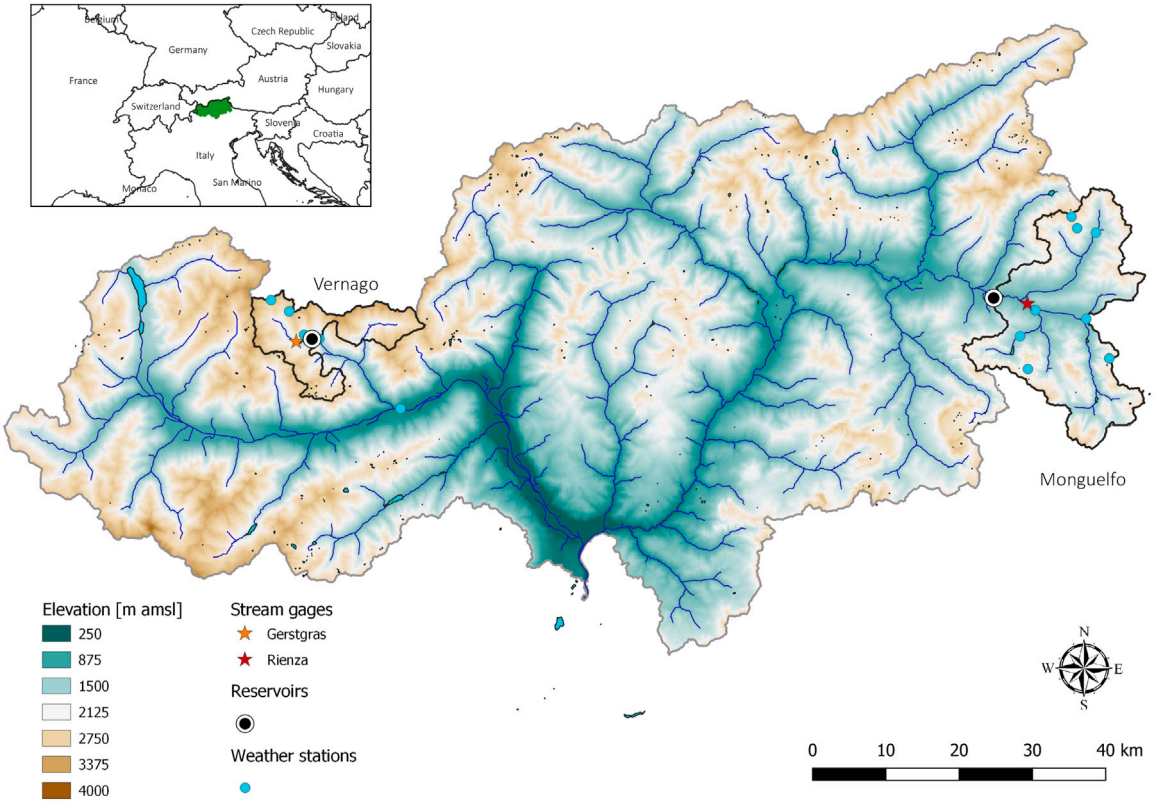

Fig. 2. Location of the Vernago and Monguelfo storage reservoirs with their associated drainage basins (black line) within the South-Tyrol region (northern Italy). Locations of weather stations and stream gages stations used as input data for hydrological modelling is also presented. The inset shows the geographic location of the South-Tyrol region within the Alpine region.

max number of generations is fixed at 10 000. For additional details concerning SMPSO algorithm parameters, please refer to [52].

4. Results

4.1. Electricity prices forecasting

The relative change (expressed as percentage) of hourly forecasted electricity prices for the Autoarimax and Benchmark econometric models with respect to the real electricity prices is presented in Fig. 3a. The relative changes are presented as an average of all the 365 daily forecasts performed during 2018, with the corresponding hourly averages of real prices highlighted in Fig. 3b. The Autoarimax model provides better forecasting performances with respect to the Benchmark model, with an overall average relative change of 9.38%, a value that is lower than the 10.21% obtained with the Benchmark model (see the dashed lines in Fig. 3a).

A visual inspection of Fig. 3a shows that the maximum average differences between the two econometric forecast models are located in the hours when the maximum deviance from the real prices also occurs: at the beginning of the first price ramp-up (i.e. 3*rd*-4*th* hours); at the 8th hour, in correspondence with the first peak of electricity prices (see Fig. 3b); and at the 14th hour, at the beginning of the second price ramp-up. Price ramp-ups are associated with higher price volatility and market uncertainty, therefore informative regressors, such as the ones applied in the Autoarimax, can increase forecast accuracy and substantially reduce forecast errors. It is worth noticing that during the price recession phase after the evening price peak (from 19th to 23th hour), both models present a similar forecast accuracy. We attribute this result to two reasons: (i) the forecasting accuracy of RES, electricity demand and electricity import flows employed in the Autoarimax model decrease across the day [75], reducing its predictability

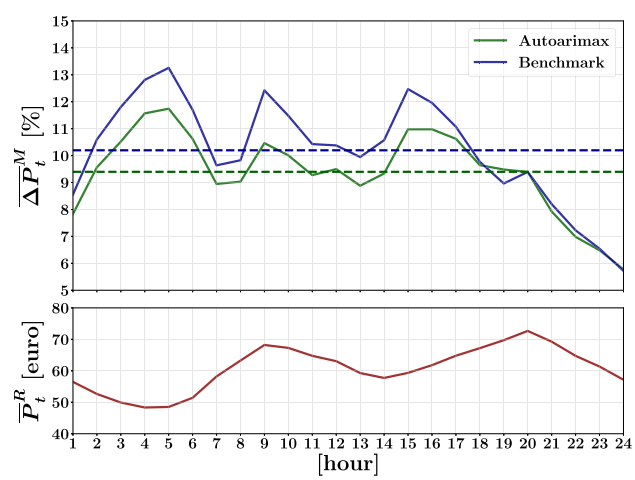

Fig. 3. (a) Average percentage relative change $\overline{\Delta P}_t^M$ of hourly forecasted electricity prices for both the Autoarimax and Benchmark econometric models; and (b) hourly averages of real electricity prices $\overline{P}_t^R$. The overbar notation indicates that the average has been performed over all the 365 forecasts conducted during 2018. Dashed lines indicate the overall relative change of both models.

power; and (ii) there is an intrinsic and time-varying electricity price uncertainty. This increases with the forecasting time and its cause is still being debated in the econometric literature.

4.2. Real prices driven optimizations

Results of daily optimizations driven by real electricity prices (i.e., the reference optimization) are presented in Fig. 4 with reference to

the two investigated storage reservoirs of Monguelfo (left column) and Vernago (right column) during the year 2018. The upper bounds of the daily turbined water discharges from the two reservoirs (subplots 4a,b) are presented as yellow lines and represent the historical seasonal pattern of releases as obtained by the simulations performed by Avesani et al. [61] by using the hydropower production module embedded in the HYPERstreamHS model (see Section 3.1). Furthermore, Fig. 4 presents the time series of daily inflows to the reservoirs as simulated by ICHYMOD hydrological model (blue lines in subplots 4a,b) and the time evolution of reservoir water volumes (subplots 4c,d). Finally, revenues obtained by solving the daily optimization problems driven by real electricity prices are presented as red lines in subplots 4e,f.

Indeed, a strong connection between water inflow and turbined water discharge is observed at Monguelfo (Fig. 4a) as a consequence of the multi-weekly regulation capacity of the reservoir. High inflow rates fill the reservoir rapidly (few days) resulting in prolonged periods in which maximum turbined water discharge is released (see the plateaus of turbined flows in Fig. 4a). As a consequence, in these periods the reservoir water volume remains at the maximum value V_{max} (see Fig. 4c). On the contrary, in periods of low inflows the reservoir water volume rapidly dwindles to the minimum storage capacity (V_{min} in Fig. 4c) with turbined discharges equalling the inflows. These reservoir dynamics exert a strong control on optimized daily revenues, which present significant seasonal variations resembling those of the incoming flows (see Fig. 4e).

The strong correlation between incoming flows and reservoir water volumes is lost for Vernago due to its larger storage capacity (see Fig. 4b,d). In this case, a prolonged filling phase is observed, which lasts from late April to early September (Fig. 4.d). In the remaining periods of the year, when low inflows typically occur, the water stored in the reservoir gradually decreases to reach its minimum level by the end of March. As a consequence, the seasonal pattern of turbined water discharges is much smoother with respect to the Monguelfo case and it does not resemble that of the incoming flows. Similarly, the optimized daily revenues do not present abrupt variations with a seasonal pattern that is well correlated with the time series of both reservoir volumes and turbined water discharges (Fig. 4f).

For sake of completeness, Fig. 5 exhibits as an example the results of the optimization process at Vernago reservoir driven by real prices in two consecutive days: 6–7 April 2018. As expected, the hourly operational plan for both days is perfectly aligned with the pattern of electricity prices, with turbined flows (red vertical bars in Fig. 5a) scheduled in the hours where the prices are higher. Coherently, power at the hydropower plant is generated in the hours where turbined flows are scheduled (Fig. 5b). No significant differences are observed in the power generated at individual hours as a consequence of the limited water level oscillation occurring at Vernago ($\simeq 0.5$ m), which we remind is a reservoir presenting a significant storage capacity.

4.3. Econometric forecasts driven optimizations

The forecast performances of the Autoarimax and Benchmark econometric models are assessed here in terms of actual daily revenue values (see Eq. (7)), as compared to reference revenues obtained using real prices as input to the optimization problem. In particular, we consider the differences in the percentage ratio metric as introduced in Eq. (8).

Average monthly percentage ratios, Φ_m^M, for the two econometric models are illustrated in Fig. 6a and c for the Monguelfo and Vernago reservoirs, respectively. Φ_m^M is always larger than 82% for all months and for both models, thus indicating a satisfactory performance of both econometric models in reproducing the reference revenues. This is confirmed by the values of annual average percentage ratios (dashed lines in Fig. 6a and c), which approach about 95% for the two econometric models in both the investigated reservoirs. At the monthly time scale, the use of Autoarimax forecasts leads to a revenue increase at Vernago up to 2.31% with respect to the case in which Benchmark forecasts are used in the optimizations. This maximum gain decreases to 1.31% at Monguelfo. For both hydropower systems, the maximum gain is registered in April.

Peculiar differences are indeed observed at the two reservoirs. At Monguelfo, optimizations driven by the forecasts of the two econometric models indeed provide similar performances in terms of revenues. The average monthly percentage ratios approach 100% (i.e., almost equalling the maximum reference value) in three months (May, September and November), while during the remainder of the year they exhibit larger differences from the reference revenue with maximum deviations observed, for both econometric models, in February and March. On the other hand, monthly percentage ratios obtained at Vernago show an attenuated seasonal variability, though associated with larger dissimilarities between monthly values of the Φ_m^A and Φ_m^B, which are particularly evident in the spring season (see April and May in Fig. 6c).

The Empirical Cumulative Distribution Functions (ECDFs) of daily revenue percentage ratios, Φ_d^M, at the Monguelfo and Vernago reservoirs are illustrated in Fig. 6b,d with reference to both econometric models. In agreement with the monthly behaviour, the two ECDFs at Monguelfo are almost overlapping, with both Φ_d^A and Φ_d^B exhibiting values of daily percentage ratios larger than 98% in nearly 25% percent of the simulated days (i.e., the three aforementioned months). At Vernago, the two ECDFs present uni-modal behaviour (i.e., smaller differences between the revenues obtained in the different days), though larger deviations between Φ_d^A and Φ_d^B are indeed observed (see 0–0.2 probability interval in 6d).

This last result is particularly relevant since it highlights that optimized revenues differ not only as a consequence of the different accuracies of the two forecasting econometric models but are also strongly influenced by reservoir characteristics. This aspect will be further discussed in Section 5.2.

5. Discussion

5.1. Temporal dynamics of electricity prices forecasting

Results presented in Section 4.1 highlighted that the forecasting accuracy of the two econometric models changes significantly across the year. Electricity prices are indeed determined by an equilibrium between time-varying factors affecting both electricity supply and demand. These factors include seasonal variations in electricity demand and seasonal variations in meteorological forcing, which in turn affect RES generation, and variations in the temporal availability of electricity flows from surrounding regions [76]. Some of these features are indeed particularly relevant for the northern Italian zone market: the peaks in electricity demand occur in summer and in winter in correspondence with consumption peaks for heating and cooling, respectively [77,78]; electricity supplies from solar and wind generation have a strong seasonal component correlated with seasonal variations of meteorological forcing [79,80]. Additional insights about the Italian electricity market can also be found in [81–83].

The temporal dynamics of electricity prices in the northern Italian zone are indeed highly variable, as illustrated in Fig. 7a, where observed daily average prices during the year 2018 are presented. Electricity prices are higher between February and March and from September to November, when solar generation is typically lower, while the prices dwindle during spring and summer seasons. This is in agreement with the seasonality patterns identified in [78] by means of Fourier Transform (FT) analysis applied to the electricity price time series of the northern Italian zone market during the 2005–2015 period. Volatility of electricity prices (i.e., fluctuations in prices over a given time period) are presented in Fig. 7b as a measure of price uncertainty in the electricity market. Here we assumed that volatility can be estimated by calculating the standard deviation (SD) of the hourly observed prices over a moving time window of 7 days centred around the investigated day d. Indeed, periods with large volatility are

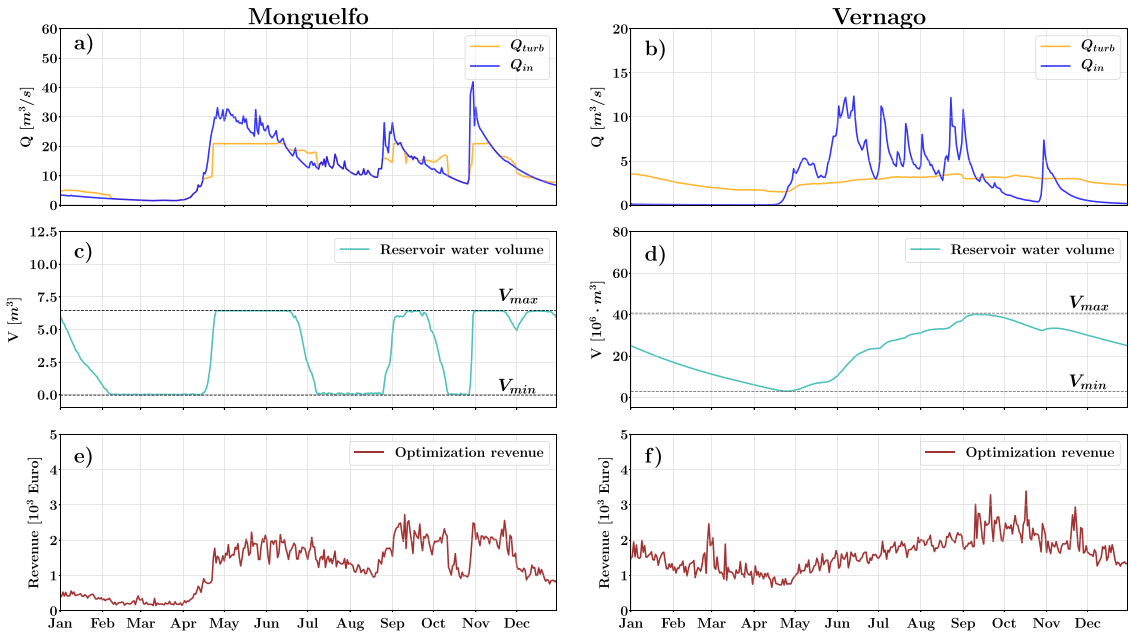

Fig. 4. Temporal evolution of real price-driven optimizations at the Monguelfo (left column) and Vernago (right column) reservoirs during the year 2018: (a) and (b) water inflows and turbined water discharges; (c) and (d) reservoir water volumes; (e) and (f) daily revenues provided by the optimization algorithm.

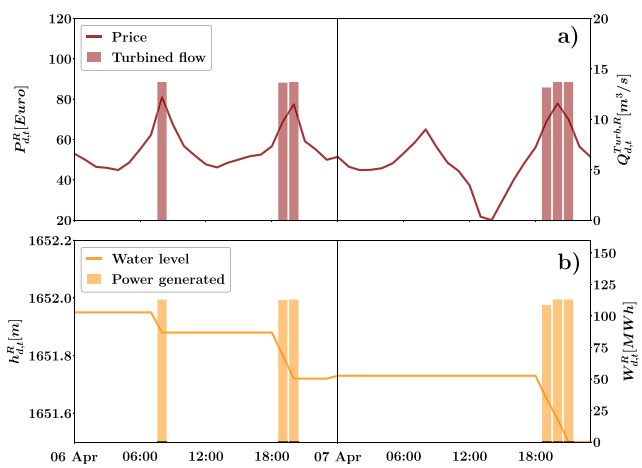

Fig. 5. Example of hydropower optimizations conducted at Vernago reservoir driven by real prices in two consecutive days: 6–7 April 2018: (a) electricity prices and turbined flows; (b) water level in the reservoir and power generated at the connected hydropower plant.

those also characterized by relatively high daily electricity prices (see Fig. 7a,b). This uncertainty in the electricity market can be attributed to seasonal unbalances in supply and demand, as previously discussed, but also to short-term effects, such as unpredictable changes in electricity demand, RES generation or the physical flow of electricity from neighbouring areas. The latter can be particularly relevant at certain hours of the day and is affected by bottlenecks in the transmission grid, which further add uncertainties into market dynamics [84–86].

The seasonal dissimilarities between the Autoarimax and Benchmark models in reproducing real prices (see Section 4.1) can thus be interpreted in terms of the different capabilities of the two econometric models in considering the dependence of the market from the aforementioned time-varying factors relative to electricity supply and demand. The superior performance of the Autoarimax model is also in line with the recent findings of [75], where the comparison between several autoregressive models have been performed with reference to the time window 1/1/2017 to 31/12/2018 for the northern Italian zone market.

The temporal evolution of the forecasting accuracy of the two adopted econometric models is further investigated in Fig. 8 with reference to the entire year of 2018. Average monthly relative changes with respect to real prices, Φ^M_m, are larger for both models in the first half of the year (subplot a) with maximum deviations observed in March and April and minimum deviations in August and October. The difference in the performances between the two model is not constant throughout the entire year, with the largest relative differences being observed in March and April and from August to October. The maximum difference is registered in March, with the Autoarimax being more accurate than the Benchmark by about 2.84%. Notably, the Autoarimax outperforms the Benchmark in the months with both high prices and volatility (see Fig. 7). In other words, the Autoarimax model is capable of better handling uncertainties in the electricity market with respect to the Benchmark model due to the adoption of exogenous variables related to electricity supply and demand. On the contrary, the Autoarimax and Benchmark models present similar accuracy in May and June. These months are indeed characterized by lower volatility of electricity prices and thus a predominant role in the time-adapting calibration of the two autoregressive models is played by the information provided directly in the time series of past prices (see Eqs. (4)–(5)) without the need to rely on exogenous regressors. The average annual difference in the forecasting accuracy between the two models is about 0.80% in favour of Autoarimax (see dashed lines in 8a).

The difference in accuracies between the Autoarimax and Benchmark forecasts is confirmed by a visual inspection of Fig. 8b, where the ECDF of the differences in the daily relative change between the two models, ΔP^A_d - ΔP^B_d, is presented. We notice how positive values of such differences indicate better daily accuracy of the Autoarimax model ($\Delta P^A_d < \Delta P^B_d$). Two important considerations can be drawn: (i) the Autoarimax model outperforms the Benchmark in 60% of days (right side of the plot); and (ii) when the Autoarimax model provides better performances, the relative difference (ΔP^B_d - ΔP^A_d) reaches values up to nearly 30%, while in the opposite case (when the Benchmark model provides better performances) the maximum relative difference in ΔP^B_d - ΔP^A_d reduces to 15% (considering the modulus of the difference). The presence of days where the Benchmark model is more accurate can

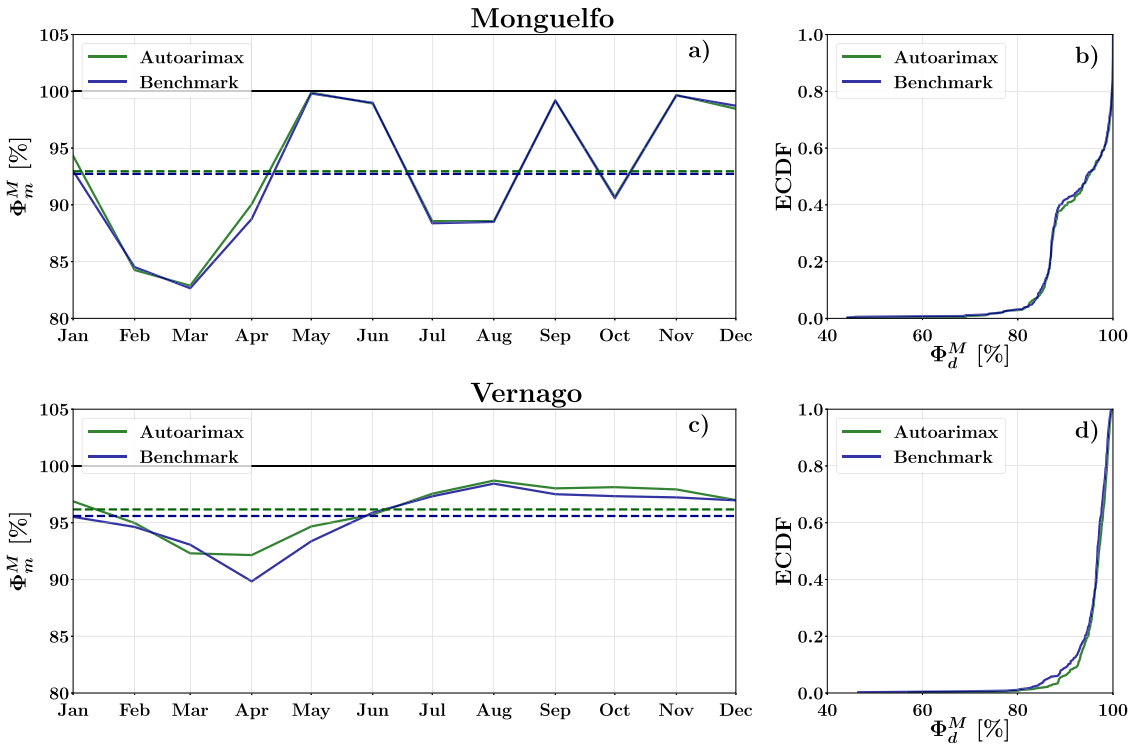

Fig. 6. Revenue percentage ratios for optimizations driven by Autoarimax (green lines) and Benchmark (blue lines) econometric forecasts: (a) monthly average percentage ratios and (b) ECDFs of daily percentage ratios at the Monguelfo reservoir, respectively; (c) and (d) same as (a) and (b) but with reference to the Vernago reservoir. Annual average percentage ratios are also presented as dashed lines.

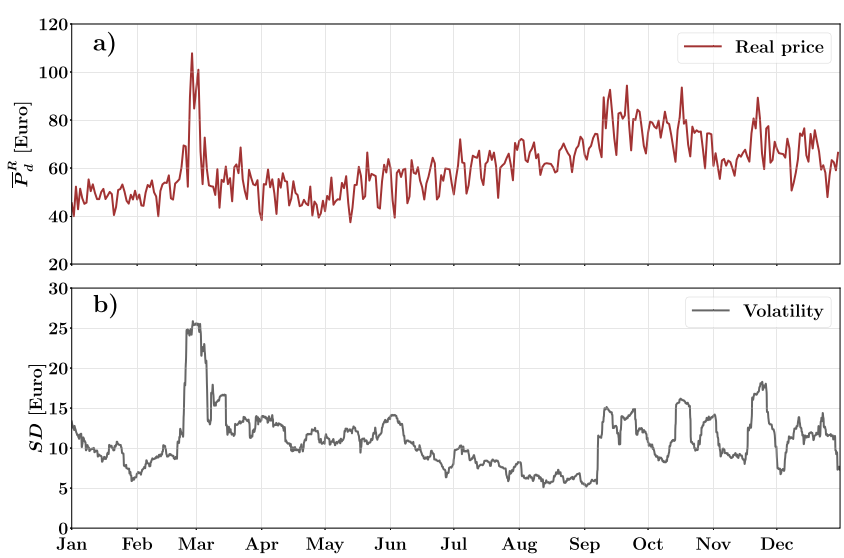

Fig. 7. Real price dynamics in the year 2018: (a) daily average prices; and (b) price volatility defined as the standard deviation (SD) of the hourly prices over a moving time window of 7 days centred around the investigated day d.

be attributed to overfitting problems in periods where the information provided by exogenous variables may be redundant and thus create collinearity issues between the various predictors [87–89].

The daily difference in forecasting accuracy between the two econometric models is highlighted in Fig. 8c, which illustrates the evolution over the year of ΔP_d^B - ΔP_d^A. Notice that the grey area highlights the region of the plot where ΔP_d^B - ΔP_d^A is positive, i.e., where the relative deviation of Autoarimax forecasts from observed prices is lower than that of the Benchmark. In accordance with the results shown in Fig. 8a, the maximum daily differences in ΔP_d^B - ΔP_d^A are observed in March and April and, albeit with smaller values, from mid-July to December. In the period from August to October, the Autoarimax outperforms the Benchmark model in almost all the simulation days, although with values of ΔP_d^B - ΔP_d^A that are smaller than those recorded from March to May.

5.2. Impact of electricity prices modelling accuracy on hydropower optimization

Results presented in Section 4.3 showed that reservoir characteristics and their associated water storage dynamics play a major role in controlling the expected revenues as provided by optimization process.

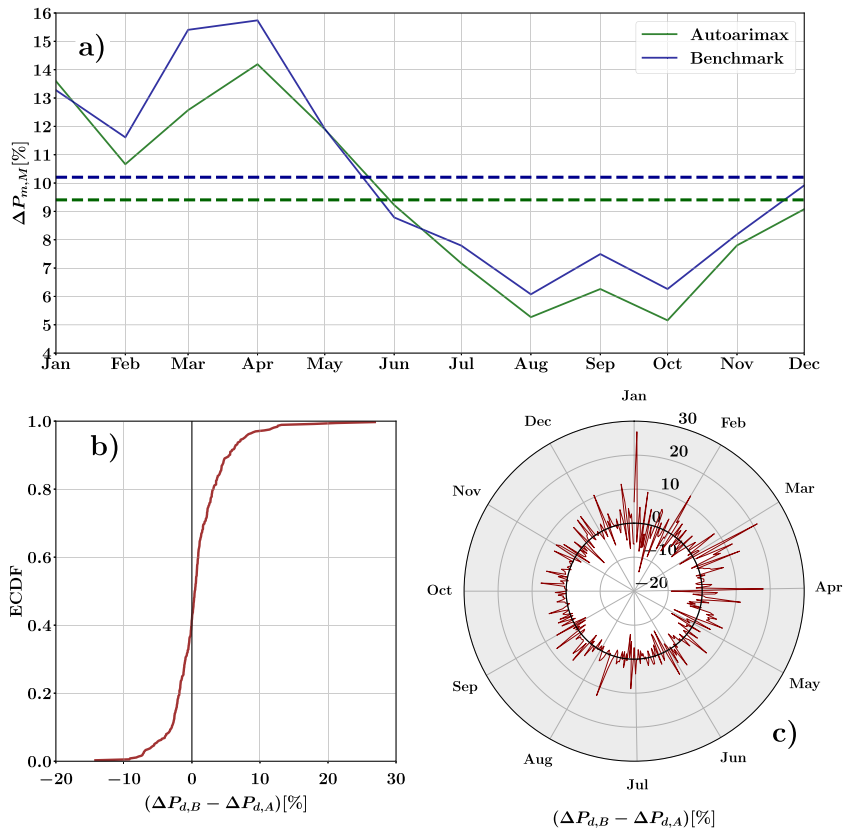

Fig. 8. Temporal evolution of the forecasting accuracy. (a) Mean monthly change with respect to observations for the Autoarimax (green line) and the Benchmark (blue line) econometric models. The average annual deviation is also presented as dashed lines. (b) ECDF of the differences in the daily relative change between the two econometric models; and (c) daily difference of the relative changes with respects to observations. The grey area illustrates the region of the plot where ΔP_d^B - ΔP_d^A is positive, i.e., where the Autoarimax provides more accurate forecasts with respect to Benchmark.

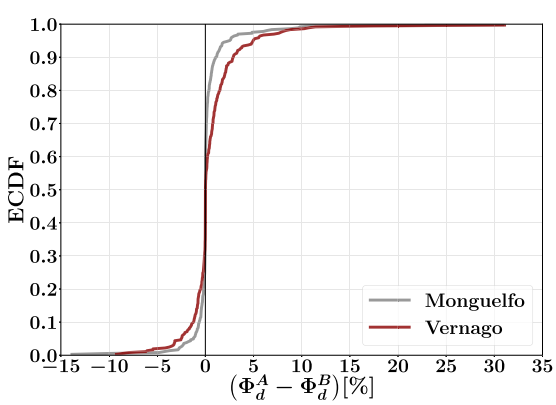

Fig. 9. ECDF of the differences in the daily percentage ratios, $\Phi_d^A - \Phi_d^B$, between Autoarimax and Benchmark driven optimizations for Monguelfo (grey line) and Vernago (red line) reservoirs, respectively.

Indeed, large storage reservoir hydropower systems have the capability to adjust their energy production (i.e., to modulate the time allocation of turbined water discharges) according to the forecasts of the electricity prices and thus are able to increase expected revenues by taking full advantage of the improved accuracy provided by innovative econometric models. These systems are indeed flexible [following the definition provided by 90] and are less subject to limitations imposed by reservoir size and water availability.

This result is further confirmed by the analysis presented in Fig. 9, where the ECDFs of the difference between the actual revenues (as described by the difference in the percentage ratios metric, $\Phi_d^A - \Phi_d^B$, see Eq. (8)), obtained by using the forecasts provided by the two different econometric models in the optimization, are presented for both the Monguelfo and Vernago reservoirs, respectively. We notice how positive values of such differences indicate larger actual revenues obtained from the use of the Autoarimax forecasts ($\Phi_d^A > \Phi_d^B$). At Monguelfo (low storage capacity), Autoarimax driven optimizations provide larger daily revenues with respect to the Benchmark model ($\Phi_d^A > \Phi_d^B$) in about 30% of the simulation days (0.7–1.0 probability interval in 9). In another 50% of the days (0.2–0.7 probability interval) both econometric forecasts lead to the same performance in term of actual daily revenue ($\Phi_d^A \simeq \Phi_d^B$), while in the remaining 20% of the days the Benchmark driven optimizations lead to larger revenues than the Autoarimax counterpart. The differences in the actual revenues are indeed amplified at the Vernago reservoir (high storage capacity). The number of days when the Autoarimax driven optimizations guarantee larger revenues with respect to the Benchmark increases significantly up to 50% of the total (from the 30% at Monguelfo). In addition, the number of days where the forecasts of two econometric models lead to similar revenues reduces to 30%, from the 50% in the case of Monguelfo.

These different responses can indeed be ascribed to the different characteristics of both storage reservoirs and associated hydropower plants, namely: reservoir capacity and the ratio between inflows and maximum turbined water discharge that can be conveyed to the plant. When inflows are larger than the penstock capacity and the storage size is limited (i.e., the Monguelfo case), the reservoirs fill rapidly and the maximum turbined water discharge is released constantly. On the contrary, in low flow periods the Monguelfo reservoir operates the closest to the minimum storage capacity and the amount of water available for optimization is strongly reduced (see Fig. 4a,c). We note that since

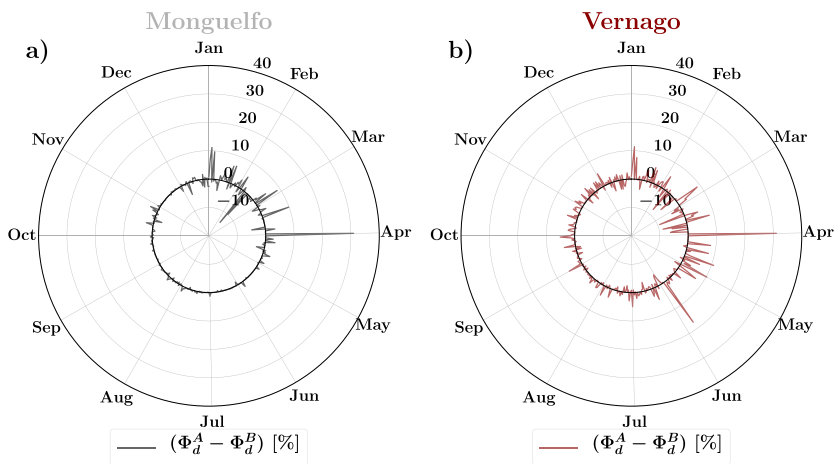

Fig. 10. Daily difference in percentage ratios between Autoarimax and Benchmark driven optimizations at the (a) Monguelfo and (b) Vernago reservoirs, respectively.

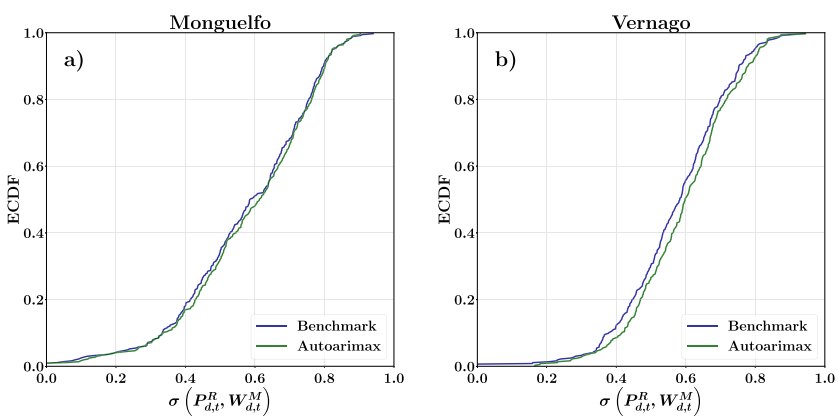

Fig. 11. ECDF of correlation coefficient day-per-day on the 24 h between real prices $P_{d,t}^R$ and power generated by the hydropower plant according to econometric driven optimization $W_{d,t}^M$ with $M = A$ for the Autoarimax driven optimization and $M = B$ for the Benchmark driven optimization: (a) at the Monguelfo reservoir; (b) at Vernago reservoir.

the soft and hard constraints imposed in the optimization algorithm are the same for all the daily optimization problems solved at the two reservoirs, the time evolution of daily turbined water discharges, inflows and storage volumes depicted in Fig. 4 is representative of all the investigated electricity prices models (i.e., Autoarimax, Benchmark and Real prices). The limited flexibility of the Monguelfo reservoir thus curbs the possibility to take full advantage of the superior performance of the Autoarimax econometric model. This occurrence is not present at Vernago, where the larger storage capacity leads to significantly larger daily actual revenues obtained using the forecasts provided by the Autoarimax model (see the right side of Fig. 9).

Daily differences in actual revenue obtained using the forecasts of the two econometric models are also highlighted in Fig. 10, which illustrates the evolution over the year of $\Phi_d^A - \Phi_d^B$ for both reservoirs. Consistently with the previous considerations, prolonged periods where the actual revenues are substantially equivalent between the two models are observed at Monguelfo (see the limited oscillations of $\Phi_d^A - \Phi_d^B$ from May to December in Fig. 10a), which are aligned with periods in which the storage capacity is generally either at maximum or minimum storage capacity. Indeed, the limited storage capacity of Monguelfo dampens the effects of the improved accuracy of Autoarimax forecasts. Positive values of $\Phi_d^A - \Phi_d^B$ are observed at Vernago throughout the entire year (Fig. 10b), thus indicating that reservoir dynamics are not representing a limiting factor in the exploitation within the optimization of the improved accuracy provided by the Autoarimax model. Consistently with the improved electricity prices forecasting accuracy provided by the Autoarimax model, the largest differences in percentage ratios ($\Phi_d^A - \Phi_d^B$) are observed for both reservoirs during the period from January to April, with maximum daily deviations reaching about 31% at the end of March for both reservoirs. Though limited in the magnitude, positive deviations in the percentage ratios between the Autoarimax and Benchmark are generally observed at Vernago during the period June to December.

The difference in flexibility for the investigated storage reservoirs is further highlighted in Fig. 11, where we show the ECDFs of the correlation coefficient $\sigma(P_{d,t}^R, W_{d,t}^M)$ between the real prices $P_{d,t}^R$ observed at a given day d and power generated $W_{d,t}^M$ in the same day as provided by the Autoarimax (M=A) and Benchmark (M=B) driven optimizations. Namely, $\sigma(P_{d,t}^R, W_{d,t}^M)$ indicates the capacity of the reservoir to align the daily operational plan with respect to real prices. In other words, higher values of $\sigma(P_{d,t}^R, W_{d,t}^M)$ thereby denote a better capacity of the hydropower system to generate electricity when real prices are higher. Visual inspection of Fig. 11a shows that the two ECDFs at Monguelfo are very similar, thus confirming that the limited capacity of the reservoir is not able to fully exploit the higher accuracy of the Autoarimax model. On the contrary, at Vernago there is an evident amplification of the difference between the ECDFs of the correlation coefficients, which is a clear indication that the reservoir, thanks to its higher flexibility, is able to substantially increase the actual revenues as a consequence of the improved accuracy of the price forecasts.

Reservoir characteristics and the presence of hard and soft constraints thus lead to a non-linear relationship between the improved econometric model accuracy provided by the Autoarimax, which is the same for the two investigated reservoirs, and actual revenues.

The presence of small storage capacity, as in the case of Monguelfo, thus represents an important limiting factor for reservoir operations, since the system does not have enough degrees of freedom to align electricity production to the improved forecasts provided by innovative econometric models.

6. Conclusion

In this paper, we have evaluated the effects of the improved forecasting accuracy of innovative econometric models on short-term hydropower revenue optimizations. The analysis is conducted with reference to the 1 day-ahead electricity market by employing two different autoregressive and time-adapting models, namely Autoarimax and Benchmark. We considered 365 daily independent optimizations driven by the different econometric models bounded by hard and soft constraints mimicking the seasonal management of storage reservoirs in the Alpine region. Finally, the analyses considered two storage hydropower systems of different sizes.

Our results highlight that 1 day-ahead hydropower optimizations driven by Autoarimax forecasts can substantially increase actual revenues with respect to the adoption of a more standard autoregressive model, such as the Benchmark. However, these increases depend on two main factors: (i) the improved forecasting accuracy of the innovative econometric model, which, however, varies significantly over the year; and (ii) reservoir characteristics and storage capacity.

The different time-varying performance of the Autoarimax model with respect to the Benchmark is linked to the role played by the exogenous variables embedded in the econometric model, which include factors affecting both electricity supply and demand. The added valued of the information provided by these variables is indeed not constant over time and across hours of the day. Autoarimax forecasts are generally more accurate than their Benchmark counterparts, though the increased accuracy is more evident in some periods of the year and certain times of the day. Autoarimax outperforms the Benchmark model when the electricity price and its volatility are typically higher, while in periods characterized by relatively low volatility, the Benchmark model provides better performance, albeit to a lesser extent, with respect to the Autoarimax. This is a clear indication that the Autoarimax model is more capable of handling uncertainties in the electricity market with respect to the Benchmark model due to the adoption of exogenous variables related to electricity supply and demand. This result also suggests the possibility of using an ensemble of econometric forecasts to drive the optimizations, in order to account for the documented model uncertainty.

Reservoirs with low storage capacity (i.e., Monguelfo) indeed work like run-of-the-river plants during most of the year. In this case, the improved econometric model accuracy of the Autoarimax model is not transformed directly into a substantial increase in the actual revenues resulting from the optimization process. On the contrary, hydropower systems characterized by large storage capacity (i.e., Vernago) are able to better exploit the advantage of more accurate forecasts and thus provide a larger increase in actual revenues.

Reservoir characteristics and the presence of constraints in the optimization process leads to a non-linear transformation of the improved econometric model accuracy provided by the Autoarimax, which is the same for the two investigated reservoirs, and actual revenues. The presence of small storage capacity, as in the case of Monguelfo, thus represents an important limiting factor for reservoir operations, since the system does not have enough freedom to align energy production with the improved forecasts provided by innovative econometric models. This also indicates a significant dependence of the temporal evolution of the actual revenues on the characteristics of the hydropower system, thereby calling for plant-specific analyses to evaluate the benefit of using more accurate econometric models in the optimization of storage reservoir systems.

Our results may also provide useful indications to hydropower companies to enhance their expected revenues from storage hydropower systems, especially those characterized by large storage capacity, by considering the use of innovative econometric models capable of dealing with the large uncertainties associated with the electricity market.

CRediT authorship contribution statement

Diego Avesani: Writing – original draft, Investigation, Software, Visualization, Funding acquisition. **Ariele Zanfei:** Investigation, Software, Data curation. **Nicola Di Marco:** Investigation, Software, Visualization, Data curation. **Andrea Galletti:** Software Data curation. **Francesco Ravazzolo:** Writing – review & editing, Methodology, Supervision, Funding acquisition. **Maurizio Righetti:** Supervision, Funding acquisition. **Bruno Majone:** Writing – review & editing, Conceptualization, Methodology, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research received financial support from the "Seasonal Hydrological-Econometric forecasting for hydropower optimization (SHE)" project funded within the call for projects "Research Südtirol/ Alto Adige" 2019 Autonomous Province of Bozen/Bolzano – South Tyrol. This research was also supported by the Italian Ministry of Education, University and Research (MIUR) under the Departments of Excellence, grant L.232/2016. Streamflow and meteorological data were provided by the Hydrographic Office of the Autonomous Province of Bolzano (www.provincia.bz.it/hydro)

Appendix. The SMPSO algorithm

The SMPSO is a more sophisticated variant of the classic PSO algorithm that is designed to handle multi and single objective problems. PSO is an iterative method belonging to the swarm intelligence category, which is based on the exploration of the space of parameters by N particles, called bees. Particles locations are first randomly initialized and then iteratively updated in the search of the optimal solution. The location updating procedure usually involves three steps: particle initialization, the calculation of velocities and the update of the positions and of the archive (i.e., the memory of all locations visited by the whole collection of particles). Formally, each ith particle is located in a position $\vec{z}_i\,(t)$ at a time step t. Then, the position $\vec{z}_i\,(t+1)$ is updated by adding the velocity $\vec{v}_i\,(t+1)$ of the particle to its previous location according to the following equations:

$$\vec{z}_i\,(t+1) = \vec{z}_i\,(t) + \vec{v}_i\,(t+1); \tag{A.1}$$

$$\vec{v}_i\,(t+1) = \chi[w\,\vec{v}_i\,(t) + C_1\phi_1(x_{p,i} - \vec{z}_i\,(t)) + C_2\phi_2(x_{g,i} - \vec{z}_i\,(t))]; \tag{A.2}$$

where the coefficient w is the inertial weight, which controls the particle memory (i.e. how the previous velocity affects the actual one), the variables ϕ_1 and ϕ_2 are two uniformly distributed random numbers between 0 and 1 that weight the particle best position ($x_{p,i}$) and the global best ($x_{g,i}$), C_1 and C_2 are uniformly distributed random numbers between 1.5 and 2.5, and χ is a constriction factor. Differently from PSO, SMPSO implements the constriction factor χ to limit the particles velocities thus allowing a more effective search of the optimal solution:

$$\chi = \frac{2}{2 - \psi - \sqrt{\psi^2 - 4\psi}}; \tag{A.3}$$

where the coefficient ψ is expressed as:

$$\psi = \begin{cases} C_1 + C_2 & \text{if} \quad C_1 + C_2 > 4 \ \text{(a)} \\ 4 & \text{if} \quad C_1 + C_2 \leq 4 \ \text{(b)} \end{cases} \tag{A.4}$$

SMPSO algorithm also includes an additional constriction mechanism to further bound the jth component of the velocity $v_{i,j}$ associated to each particle i, with $i = 1, \ldots, N$, $j = 1, \ldots, N_p$, and N_p being the dimension of the parameter space. The constraint is applied as follows:

$$v_{i,j}(t) = \begin{cases} \delta_j & \text{if} \quad v_{i,j}(t) > \delta_j; \quad \text{(a)} \\ -\delta_j & \text{if} \quad v_{i,j}(t) \leq -\delta_j; \quad \text{(b)} \\ v_{i,j}(t) & \quad otherwise; \quad \text{(c)} \end{cases} \tag{A.5}$$

where the term δ_j is expressed as:

$$\delta_j = \frac{upper\_limit_j - lower\_limit_j}{2} \tag{A.6}$$

This latter mechanism verifies if the velocities may lead to particle positions (calculated on the basis of Eqs. (A.1) and (A.2)) outside the bounds of the parameters space, as identified by the lower ($lower\_limit_j$) and upper ($upper\_limit_j$) limits of each dimension j. If this occurs, the velocities are limited according Eq. (A.5).

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