Predictive management approach for the coordination of wind and water-based power supplies

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Abstract

This paper addresses the coordinated operation between wind farms and reservoir hydropower plants in networks with weak transmission capacity. The joint operation of the energy sources is captured by a Virtual Power Plant (VPP) representation. With the aim of maximising renewable energy penetration while ensuring a suitable VPP integration, a supervisory controller for the energy dispatch layer is proposed. To deal with the variable nature of both resources, the controller has been designed into a model predictive control framework including mixed-integer quadratic programming (given the hybrid considered model) for solving the related optimisation problem, and complementary techniques as constraints softening and time-varying weighting. The results indicate that the predictive control approach achieves a better Independent System Operator (ISO) reference tracking that, together with reservoir management, are the most important factors to ensure a suitable VPP incorporation to the main grid. As a case study, a sub-network of the Argentinian power system is tackled. The controller performance is quantitatively and qualitatively assessed under uncertain conditions and compared with other approaches over a nine-year period. By means of the proposed power management policy, the ISO's effort to balance the sub-network is reduced 56% with regard to other approaches without any water spillage.

Keywords: Wind energy integration, Power management policy, Virtual power plant, Mixed-integer quadratic programming, Hydropower, Predictive control

1. Introduction

As more renewable energies (REs) are installed, new requirements arise to achieve high wind energy penetration. The most important issues are the variable wind resource [1], congestion in the transmission [2] and distribution systems [3], technical and legal regulations for RE dispatch policies [4], and grid fault ride through capabilities [5]. Additionally, fast RE integration represents a big challenge from the system control and energy management viewpoints [6].

High wind resource areas are often far from load centres with weak transmission infrastructure connecting them [7]. Improving the transmission capacity is a time-and-money-consuming task due to planning, delays and investment [8]. Therefore, a coordinated operation (CO) between complementary generation systems should be the first option to achieve a better use of the transmission capacity, avoiding wind energy spillage [9]. In such a way, priority transmission use could be given to WFs when there is a considerable amount of resource and give it back when there is not, reaching better wind energy integration. Among others, hydro-energy systems have been widely combined with wind energy to improve its lack of storage and intermittency.

Pumped hydro storage (PHS) systems are the most common in this kind of associations, ranging from traditional water pumping in isolated areas [10], to most recent implementations where water is stored in a built-in reservoir inside the wind tower structure [11]. An insight and review of current trends are presented in [12]. Furthermore, the impacts on hydro-turbines due to the integration of hybrid RE in PHS systems can be assessed by the model proposed in [13].

Complementary operation with existing hydropower plants (HPPs) seems to be an effective alternative to deal with limited transmission capacity requiring little investment [14]. Following the classification addressed in [15], conventional HPPs can be broadly divided into run-of-river (ROR) plants either with or without a small reservoir; and large reservoir plants where water can be stored from wet to dry seasons. On the one hand, ROR power plants are suitable for low power compensation, as they are mainly base-load providers with a limited storage capacity. Thus, this type of hydroelectricity is a small-scale compensator due to the typical low heads and the constraining factor of the upstream reservoir size [16]. In [17], a substantial contribution to the energy policy formulation of Nepal has been made based on the country's ROR plants potential. On the other hand, together with their fast regulation speed, large reservoir HPPs have higher storage capacity, making them the best option to compensate for high power production and frequency imbalances. See for instance [18], where Norwegian

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Nomenclature

Variables

P_a	available wind turbine power [MW]
v	wind speed [m/s]
P_{a-WF}	available WF power [MW]
P_{d-WF}	WF dispatched power [MW]
P_{h_i}	i-th hydro-turbine power [MW]
H	height difference between upstream and downstream at the dam [m]
Q_t	individual volume flow rate [m^3/s]
P_H	total HPP output power [MW]
ℓ	reservoir level [m.a.s.l.]
Q_{in}	total volume flow rate [m^3/s]
P_{gen}	generated power [MW]
$P_{VPP-dem}$	VPP demanded power [MW]
P_{L_i}	i-th load of the VPP [MW]
P_{CP}	required power at the CP [MW]
P_{dem}	total demanded power [MW]
s	set of level threshold
P_{spi-WF}	wind power spillage [MW]
P_{bal}	power balance [MW]
γ_k	upper band weight
V	reservoir volume [Hm^3]
u_{ℓ_n}	n-th hydro turbine on/off state
M	constraint condition matrix

Parameters

$P_{MPPT,\max}$	maximum power point tracking along wind turbine curve section [MW]
P_{rated}	rated wind turbine power [MW]
v_{ci}	cut-in wind speed [m/s]
v_r	rated wind speed [m/s]
v_{co}	cut-out wind speed [m/s]
N	number of wind turbines
ρ_w	water density [$\mathrm{kg/m}^3$]
g	gravitational acceleration [$\mathrm{m/s}^2$]
η_H	hydro efficiency
n	number of HPP turbines
Δt	sampling interval [s]
N_s	hours of simulation
$P_{h_{i,max}}/P_{h_{i,min}}$	i-th maximum/minimum hydro-turbine power [MW]
$\Delta P_{H_{max}}/\Delta P_{H_{min}}$	maximum/minimum HPP output variation [MW]
ΔP_{WF}	WF power output variation [MW]
$P_{CP,\max}$	maximum transmissible power at the connection point [MW]
$\ell_{\text{upp}}/\ell_{\text{low}}$	upper/low threshold [m.a.s.l.]
r	number of the VPP loads
$\ell_{\max}/\ell_{\min}$	maximum/minimum reservoir level [m.a.s.l.]
H_p	predictive horizon [hours]
H_u	control horizon [hours]
γ_i	i-th cost objectives weight
$V_{\max}/V_{\min}$	maximum/minimum reservoir volume [Hm^3]
σ	standard deviation

reservoir HPPs are proposed to balance large shares of RE in the Central-West European power system. In [19], the RE planning in Brazil is studied, emphasising the importance of hydro and wind energies seasonal complement. Furthermore, in [20] the wind market in power systems with large reservoir HPPs like in Sweden is assessed. The results show that the dispatch flexibility of HPPs mitigates wind power drops in contrast to markets that are dominated by thermal power plants.

Recently, power system decentralization is suggested to improve distributed RE integration providing flexibility against varying grid conditions [21]. The role of microgrids and virtual power plants (VPPs) is essential to cope with this new challenge. Microgrids are small-scale oriented solutions [22], while VPPs are defined as a coordinated and flexible aggregation of distributed energy resources (DERs) participating in the energy market as a conventional large-scale power plant. In this way, technical VPPs provide a structural solution to merge neighbouring electrical energy systems for grids redesigning in response to the rapid REs growth [23] [24]. An illustrative VPP representation is depicted in Fig. 1. Likewise, clustering is another way to achieve a system decentralization. In [25] the clustering of hydropower cascades with wind and solar generation results in another effective alternative to integrate distributed RE.

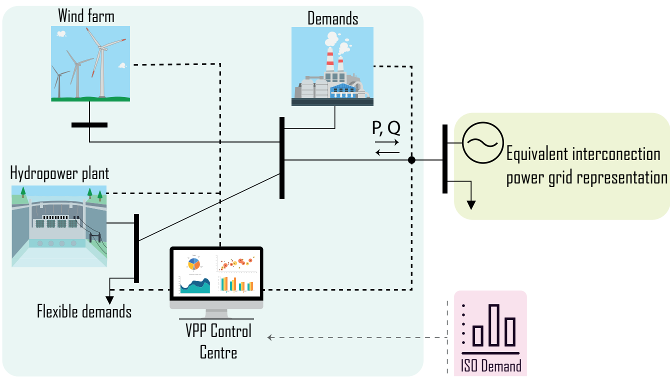

Fig. 1: Characterisation of a power sub-network as a VPP.

An extensive amount of works in energy management for the hydro-wind coordinated dispatch can be found in the literature. However, there is a lack of long-term dispatch policies for the joint operation of large reservoir HPPs and WFs working in a VPP scheme. The research in the topic covers primarily PHS systems or ROR HPPs combined with RE systems, whilst the research on large reservoir HPPs is not oriented to the CO procedure with WFs. Therefore, this paper fills this gap by making use of the well-known Model Predictive Control (MPC) strategy for supervising the hourly power dispatch procedure. The research was originally conceived to give a solution to a real problem with a limited transmission system capacity. In general, HPPs management are based on heuristic methods attending to the different objectives, as downstream irrigation, floods, among others. This is why a first contribution was made in this field by means of a heuristic control based on independent system operator (ISO) procedures [26]. Nevertheless, as the system model gets complex, the rules-based methods exposed their drawbacks to incorporate additional features. Anyway, their main disadvantage is the non-optimal solution they would provide. This can be overcome by using advanced methods such as MPC that indeed deals with optimisation problems. MPC provides an excellent tool to incorporate demand, renewable generation, and forecasts and hence future system behaviour can be optimally evaluated. In this way, the feedback mechanism allows facing uncertainties and disturbances in these variables. Furthermore, physical constraints are easily handled by this sort of control.

The novelty and main contribution of this paper lies in a proposal for the joint coordination of large reservoir HPPs and WFs aiming to work as a VPP in a weak transmission system. The proposed long-term dispatch management policy is addressed by means of an MPC strategy including complementary techniques such as constraints softening and time-varying weighting for the controller tuning. In this proposed approach, the reservoir has the main role to compensate for the wind imbalances/spillages. Particularly, this work focuses on the active power control considering the reservoir and power system restrictions. The goal is to maximise the penetration of wind energy, meeting load energy demand while an adequate reservoir level is kept. Since reservoir dynamics are slower than the hourly power dispatch objective, the reservoir level control is relaxed, provided that its level is kept within a specific seasonal band. Furthermore, to consider the minimum/maximum HPPs dispatchable power values, individual hydro-turbines on/off states are included into the model, yielding a mixed-integer quadratic programming (MIQP) problem. Finally, the modelling of the transmission system capacity between the VPP and the main grid gives a greater degree of realism that quite often is neglected.

A sub-network connected to the main Argentinian grid is taken as a case study. The energy system comprises an existing large reservoir HPP without pumping capacity (516 MW) and a projected WF (200 MW) to be connected about 250 km away from the HPP to the same transmission system. So far, the sub-network exchange energy capacity is not enough to handle both generation at rated.

2. Notation and methods

2.1. Notation

Throughout this paper, $\mathbb{R}$, $\mathbb{R}^n$ and $\mathbb{R}_{\geq 0}$ denote the field of real numbers, the set of column real vectors of length n and the set of non-negative real numbers. Moreover, $\mathbb{Z}_{\geq 0}$ denotes the set of non-negative integer numbers, $\mathbb{Z}_{\geq c} := \{x \in \mathbb{Z}_{\geq 0} \mid x \geq c\}$ for some $c \in \mathbb{Z}_{\geq 0}$ and $\mathbb{Z}_{[c_1,c_2]} := \{x \in \mathbb{Z}_{\geq 0} \mid c_1 \leq x \leq c_2\}$ for some c_1, $c_2 \in \mathbb{Z}_{\geq 0}$. By superscript $^\top$ transposition is denoted, and $diag(x)$ is the diagonal matrix of the vector x. The identity matrix of size $n \times n$ is denoted by I_n, $\mathbf{1}_n$ is the column vector with n unitary entries, and $0_{n\times l}$ is the matrix of null entries and dimension $n \times l$. Additionally, $||\cdot||$ and $||\cdot||_p$ denotes the Euclidean and the p-norm of a vector, respectively. For discrete-time systems, $k \in \mathbb{Z}_{\geq 0}$ denotes discrete time and is used in a subscript format. Moreover, in the discrete-time notation of the MPC controller, $x_{k+j|k}$ refers to the prediction at time k of the value that will take x at time $k+j$, where $j \in \mathbb{Z}_{\geq 0}$, i.e., in the argument $k+j|k$, the first element $k+j$ denotes prediction, whereas the second element k denotes current simulation instant. Finally, $\hat{x}$ denotes the presence of uncertainty in the sequence x.

2.2. Methods

The power dispatch framework and the wind-hydro power system model are presented in this section.

2.2.1. Power Dispatch Framework

The VPP concept is related to a group of DERs including generating units, flexible loads, and storage systems coupled in a single entity, and usually connected to the transmission system in a single node [27]. A VPP is meant to coordinate the production and consumption of its components aiming to maximise their performance [28]. Consequently, the VPP scheme could enhance DERs operation and integration improving capacity, flexibility and controllability to make system management and support activities cost effective or technically feasible [29]. Furthermore, payment mechanisms such as the one addressed in [30] can be accomplished to promote DERs to join VPPs by scoring rules and incentives based on accurate predictions. Likewise, the contribution of the VPP to the system management can be accomplished by its direct interaction in the wholesale market [31]. In Fig. 1, a regional power subsystem is masked (and seen by the ISO) as a single generator connected to the transmission system. From the market and ISO viewpoints, the VPP acts as a unique power plant receiving power setpoints for the connection point (CP). Any deviations from these setpoints are supposed to be informed to the ISO. Thus, the VPP framework is used to maximise the RE penetration, either prioritising the WFs power injection when there is enough wind resource or using the reservoirs otherwise.

Nowadays, large reservoirs HPPs energy have their cost associated mainly with the reservoirs seasonal management rather than to the cost associated with energy production. This results from the fact that other HPPs purposes such as avoiding downstream flooding and irrigation programming plans have a higher priority than energy generation. Accordingly, economic competition between large HPPs and WFs is not an adequate criterion to evaluate the power programming policy, and therefore, economic objectives are not explicitly reflected in this power dispatch framework.

Heuristic controllers have been the first algorithms used for HPP management. These rules-based strategies are still used by many system operators who capitalise on the empirical knowledge of the plant. The ad-hoc nature of these controllers reflects the intrinsic reduced portability of the approach. Also, as the system becomes more complex, the controller has to include more rules, which increases the degree of detail to be added in the algorithm. On the other hand, the MPC strategy is able to handle a lot of variables, constraints and control/management objectives, as it is proved by its acceptance in process industry [32].

According to the strategy described above, the power dispatch management policy of the VPP is based on the following considerations:

1. Priority dispatch is given to WFs as long as it leads neither to water spillage nor non-configurable HPPs output power.
2. HPPs reservoir levels are maintained between operable limits defined in accordance with seasonal requirements.
3. Two weeks with an hourly time step is taken into account for the proposed rolling power dispatch scheduling. This methodology is followed by many ISOs for both the weekly power scheduling and hourly remuneration computation [33].
4. The P_{bal} indicates if either the intended reference sent by the ISO can be met hourly or if more/less energy could be delivered by the VPP.

2.2.2. WF Model

The classical wind turbine operation is considered to obtain the available wind energy. This feature can be summarised for every time instant k as

$$P_{a,k} = \begin{cases} P_{MPPT,\max} & v_{ci} \leq v < v_r, \\ P_{\text{rated}} & v_r \leq v < v_{co}, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

Without loss of generality, the P_{a-WF} is modelled assuming each turbine produces the same power, i.e.,

$$P_{a-WF,k} = N\, P_{a,k}. \tag{2}$$

In order to implement the MPC strategy, the WF is modelled as the difference equation

$$u_{WF,k} = u_{WF,k-1} + \Delta u_{WF,k}, \tag{3}$$

where $u_{WF,k}$ is $P_{d-WF,k}$ and $\Delta u_{WF,k}$ is the variation from the previous dispatched power ($\Delta P_{d-WF,k}$). An active power control (APC) of each turbine is assumed in this paper instead of a start-stop approach. The APC technique consists in derating the wind turbines to accomplish a power setpoint [34]. Based on this assumption, $\Delta u_{WF,k}$ can be set to any value to achieve a desired $u_{WF,k}$ provided the following condition holds:

$$P_{d-WF,k} \leq P_{a-WF,k}. \tag{4}$$

2.2.3. HPP model

A hydro-turbine power can be expressed as

$$P_{h,k} = \zeta_H\, H_k\, Q_{t,k}, \tag{5}$$

where $\zeta_H = \rho_w\, g\, \eta_H$ and H_k model the variable head at the turbine admission [35]. The total HPP output power can be expressed as the sum of each hydro-turbine of the plant, i.e.,

$$P_{H,k} = \sum_{i=1}^{n} P_{h_i,k}, \tag{6}$$

The reservoir level is described by a Multiple Input Single Output (MISO) model, where the output is the water volume stored in the reservoir, the inputs are the power dispatch at each hydro-turbine and the incoming flow is the perturbation. The reservoir level (ℓ) and volume (V) are related by a known static function $\ell = f(V)$ [36]. Therefore, any of them will be used when referring to the water stored in the reservoir. Volume will be preferably used in modelling, while level will be used for management issues since it is more intuitive. Hence,

$$V_{k+1} = V_k + \Delta t\, \left(Q_{in,k} - \frac{P_{H,k}}{\zeta_H H_k} \right). \tag{7}$$

The state-space realisation of (7) can be written as

$$x_{h,k+1} = A\, x_{h,k} + B_k\, u_{h,k} + B_p\, d_k, \tag{8a}$$

$$y_k = C\, x_{h,k}, \tag{8b}$$

$$A = C = 1,\;\; B_k = -\Delta t/(\zeta_H H_k)\, \mathbf{1}_n^\top,\;\; B_p = \Delta t, \tag{9}$$

where $x_{h,k}$ is $V_{\forall k}$, $u_{h,k}$ is a vector with individual dispatchable P_{h_i}, d_k is Q_{in} and B_k is a time-varying vector. Notice that (8) includes a discrete-time equation for the dispatched power of each hydro-turbine. Each of these turbines operates between a minimum and a maximum output power. For this reason, P_H results in a non-continuous range. Therefore, restrictions on each hydro-turbine generated power are included in the proposal. This differs from the procedure followed in (3) for the WF power, where a continuous range of output power can be assumed due to APC control. The augmented state vector to express the model in terms of Δu can be formulated as [32]

$$\varphi_k = \begin{bmatrix} x_{h,k} \\ u_{h,k-1} \end{bmatrix}. \tag{10}$$

Finally, the complete HPP model is given by

$$\begin{bmatrix} x_{h,k+1} \\ u_{h,k} \end{bmatrix} = \begin{bmatrix} A & B_k \\ 0_{n\times 1} & I_n \end{bmatrix} \begin{bmatrix} x_{h,k} \\ u_{h,k-1} \end{bmatrix} + \begin{bmatrix} B_k \\ I_n \end{bmatrix} \Delta u_{h,k} + \begin{bmatrix} B_p \\ 0_{n\times 1} \end{bmatrix} d_k, \tag{11a}$$

$$y_k = C_1 \begin{bmatrix} x_{h,k} \\ u_{h,k-1} \end{bmatrix}, \tag{11b}$$

where $u_{h,k-1}$ and $\Delta u_{h,k}$ are the dispatched hydro-turbines power in a previous time step k and the variation of each turbine power between $k-1$ and k, respectively. Notice that C_1 is the identity matrix I_{n+1}.

2.2.4. VPP Model and Constraints

The dynamics of the whole system, merging both hydro and WF models, can be represented in state-space form as

$$x_{k+1} = A_{e,k}\, x_k + B_{1,k}\, \Delta u_k + B_2\, d_k, \tag{12a}$$

$$y_k = C_e\, x_k, \tag{12b}$$

where

$$A_{e,k} = \left[\begin{array}{c|cc} A & B_k & 0 \\ \hline 0_{n+1\times 1} & I_{n+1} & \end{array}\right], \; B_{1,k} = \begin{bmatrix} B_k & 0 \\ & I_{n+1} \end{bmatrix}, \tag{13a}$$

$$B_2 = \begin{bmatrix} B_p \\ 0_{n+1\times 1} \end{bmatrix}, \; C_e = I_{n+2}, \tag{13b}$$

$$x_k = \begin{bmatrix} \mathcal{V}_k & P_{h_{1,k-1}} & \dots & P_{h_{n,k-1}} & P_{d-WF_{k-1}} \end{bmatrix}^\top, \tag{14a}$$

$$\Delta u_k = \begin{bmatrix} \Delta P_{h_{1,k}} & \dots & \Delta P_{h_{n,k}} & \Delta P_{d-WF_k} \end{bmatrix}^\top. \tag{14b}$$

The state and input constraints can be written in compact form as

$$x_k \in \mathbb{X} := \{x \in \mathbb{R}^{n_x} | x_k \in [\underline{x}, \overline{x}], \forall k \in \mathbb{Z}_{\geq 0}\}, \tag{15a}$$

$$\Delta u_k \in \mathbb{U} := \{\Delta u \in \mathbb{R}^{n_u} | u_k \in [\underline{\Delta u}, \overline{\Delta u}], \forall k \in \mathbb{Z}_{\geq 0}\}, \tag{15b}$$

where n_x and n_u are the number of states and decision variables, respectively; $\underline{x} \in \mathbb{R}^{n_x}$ ($\underline{\Delta u} \in \mathbb{R}^{n_u}$) and $\overline{x} \in \mathbb{R}^{n_x}$ ($\overline{\Delta u} \in \mathbb{R}^{n_u}$) are minimum and maximum admissible vectors of the states (decision variables), respectively. Moreover,

$$\overline{x} = \begin{bmatrix} \mathcal{V}_{\max} & P_{h_{1,max}} & \dots & P_{h_{n,max}} & P_{a-WF,k} \end{bmatrix}^\top, \tag{16a}$$

$$\underline{x} = \begin{bmatrix} \mathcal{V}_{\min} & P_{h_{1,min}} & \dots & P_{h_{n,min}} & 0 \end{bmatrix}^\top, \tag{16b}$$

and

$$\overline{\Delta u} = \Delta P_{H_{\max}}, \tag{17a}$$

$$\underline{\Delta u} = \Delta P_{H_{\min}}, \tag{17b}$$

as ΔP_{WF_k} is not constrained.

The on/off hydro-turbines states can be modelled including n logical variables $u_{\ell_1,k}, \dots, u_{\ell_n,k} \in \{0,1\}^n$, yielding the optimisation problem into an MIQP problem. This feature allows considering the hierarchical structure of the power dispatch process. In this way, on/off hydro turbine status is settled by upper-dispatch layers and communicated to lower-dispatch layers. The resulting constraint condition including the logical states can be represented as

$$M\underline{x} \leq x_k \leq M\overline{x}, \tag{18}$$

with

$$M = diag(1, u_{\ell_1,k}, \dots, u_{\ell_n,k}, 1). \tag{19}$$

Although the transmission system constraint is not included in the VPP model (12)-(19), the maximum hourly exchanged power at the CP can be modelled as the sum of generated and demanded power for all k as

$$P_{gen,k} - P_{VPP-dem,k} \leq P_{CP_{\max}}, \tag{20}$$

where $P_{VPP-dem,k} = \sum_{i=1}^{r} P_{L_i,k}$.

3. Proposed energy management system

The proposal is an energy management system based on a predictive control for the hourly power dispatch. It is assessed in the framework of a coordinated dispatch policy for the operation of both hydro and wind energy in a VPP scheme.

As it is mentioned above, the reservoir has the main role in compensating for the wind variability. In large reservoir HPPs, the dam level is operated according to pre-fixed thresholds that create different operable bands for long-term management. As the reservoir level gets closer to the minimum/maximum levels, measures must be taken to return the level to a non-penalised *free level* band. Thus, the reservoir level is usually split into three operable bands (defined by two level thresholds $\ell_{\text{low}}/\ell_{\text{upp}}$) and two forbidden bands beyond both $\ell_{\min}$ and $\ell_{\max}$. Therefore, the classical management bands are defined as

- **Band** Z_0 (forbidden): below $\ell_{\min}$.
- **Band** Z_1 (penalised): above $\ell_{\min}$ but below ℓ_{low}.
- **Band** Z_2 (non-penalised band): between ℓ_{low} and a seasonal ℓ_{upp}.
- **Band** Z_3 (penalised): between ℓ_{upp} and $\ell_{\max}$.
- **Band** Z_4 (forbidden): above $\ell_{\max}$.

Regarding the management targets, as mentioned in Section 2, the general goal of the proposal is to increase RE penetration by means of a predictive control strategy. The proposed operation policy of the VPP can be summarised as follows. The delivered power is set to meet the power setpoint imposed to the VPP at the CP while the reservoir level is being operated in a non-penalised level band. The total power demand is fulfilled with as much wind energy as possible and completed with hydroelectric energy. Deviations from the non-penalised band to another band are gradually penalised to meet the reservoir operation targets. This penalty could result in a minor/major HPP power dispatch in order to keep the target level. If this situation is accompanied by low wind speed, a re-dispatch over the power setpoint could be required. Accordingly, the control task can be formulated as a multi-objective cost function optimisation problem. The particular goals are stated as follows:

1. To track the power demand profile (internal and at the CP).
2. To provide a smart integration and harnessing of wind energy.
3. To guarantee the suitable reservoir management throughout the year, maintaining the level mostly in a non-penalised level.

These objectives can be quantitatively expressed by the costs defined for all time steps k as follows:

$$f_1(x_k, P_{L_i,k}, P_{CP,k}) := \|P_{gen,k} - P_{dem,k}\|_1 = \|P_{bal,k}\|_1, \tag{21a}$$

$$f_2(x_k, P_{a-WF,k}) := \|P_{a-WF,k} - P_{d-WF,k}\|_1 = \|P_{spi-WF,k}\|_1, \tag{21b}$$

$$f_3(x_k, s_k) := \begin{cases} (\ell_k - \ell_{\text{low},k})^\top (\ell_k - \ell_{\text{low},k}) & \text{if } \ell_k \leq \ell_{\text{low,k}} \\ (\ell_{\text{upp},k} - \ell_k)^\top (\ell_{\text{upp},k} - \ell_k) & \text{if } \ell_k \geq \ell_{\text{upp,k}} \\ 0 & \text{otherwise.} \end{cases} \tag{21c}$$

The first objective $f_1(x_k, P_{L_i,k}, P_{CP,k}) \in \mathbb{R}_{\geq 0}$, for all k and $i \in [1, r]$, is a performance index that penalises the demand tracking deviation. Besides, P_{dem} is the total demanded power including $P_{VPP-dem}$, P_{CP} and lines losses. The second objective, $f_2(x_k, P_{a-WF,k}) \in \mathbb{R}_{\geq 0}$, represents the harnessing of the available wind energy at time step k, aiming its maximisation. The last objective $f_3(x_k, s_k) \in \mathbb{R}_{\geq 0}$, for all k, represents the penalty to reservoir level band deviations mentioned above. This objective allows the level constraints to be slightly relaxed, provided the cost associated to this relaxation keeps lower than the others defined cost functions. This objective penalises the amount of water volume going below $\ell_{\text{low},k}$ and above $\ell_{\text{upp},k}$. Note that this band objective is a piecewise continuous function, but it can be redefined as $f_3(\xi_{j,k}, x_k, s_k) := \sum_{j=1}^{2} \xi_{j,k}^T \xi_{j,k}$ accompanied with two additional convex softening constraints,

$$\ell_{\text{low},k} - \ell_k \leq \xi_{1,k}, \tag{22a}$$

$$\ell_k - \ell_{\text{upp},k} \leq \xi_{2,k}, \tag{22b}$$

and $\xi_{j,k} \in \mathbb{R}_{\geq 0}$, for all $j \in \{1, 2\}$. Then, the performance indicator in (21c) can be reformulated as

$$f_3(x_k, \xi_{j,k}, s_{i,k}) = \|\xi_{1,k}\|^2 + \gamma_k \|\xi_{2,k}\|^2, \tag{23}$$

where γ_k is a time-varying weight that increases the cost in the most critical upper band. The proposal includes this variable weight which is tuned depending on the shape of ℓ_{upp} and is based on the knowledge of the reservoir management and its current and historical information.

Assumption. It is assumed in the prediction model that the inflow water to the reservoir, safety thresholds, requested power demand, losses and P_{a-WF} are known/estimated for a given future time horizon $H_p \in \mathbb{Z}_{\geq 1}$ and a control horizon $H_u \in \mathbb{Z}_{\geq 1}$, with $H_u \leq H_p$. According to this idea, the sequences are defined as $\hat{\mathbf{Q}}_{in,k} = \{\hat{Q}_{in,i}\}_{i \in \mathbb{Z}_{[k,k+H_p-1]}}$, $\mathbf{s}_k = \{s_i\}_{i \in \mathbb{Z}_{[k,k+H_p-1]}}$, $\hat{\mathbf{P}}_{L_i,k} = \{\hat{P}_{L_i,j}\}_{j \in \mathbb{Z}_{[k,k+H_u-1]}}$, $\hat{\mathbf{P}}_{CP,k} = \{\hat{P}_{CP,i}\}_{i \in \mathbb{Z}_{[k,k+H_u-1]}}$ and $\mathbf{P}_{a-WF,k} = \{P_{a-WF,i}\}_{i \in \mathbb{Z}_{[k,k+H_u-1]}}$, respectively. ■

The MPC strategy is based on the explicit use of a dynamical model to predict the state of a system in future time instants along H_p while determining the control inputs along H_u. The set of future control signals is calculated by solving a finite-time optimisation problem with a given cost function merging the control objectives and satisfying the physical and operational constraints. Only the control signal calculated for the first time instant k along H_p is applied to the system. The procedure is repeated in a receding horizon control fashion [32]. Therefore, for a given H_p and a given sequence of available wind power, water inflow, power demands and the set of level thresholds, denoted respectively as $\mathbf{P}_{a-WF,k}$, $\hat{\mathbf{Q}}_{in,k}$, $\hat{\mathbf{P}}_{L_i,k}$, $\hat{\mathbf{P}}_{CP,k}$ and $\mathbf{s}_k$, the MPC controller results from the minimisation of the following cost function $V(k, x_k, \boldsymbol{\xi}_{j,k})$ at each time instant k:

$$\min_{\mathbf{u}_k, \boldsymbol{\xi}_{j,k}} V(k, x_k, \boldsymbol{\xi}_{j,k}) := \sum_{i=0}^{H_p-1} \gamma_3 f_3(k+i, x_{k+i|k}, \xi_{j,k+i|k}) + \tag{24a}$$

$$+ \sum_{i=0}^{H_u-1} \gamma_1 f_1(k+i, x_{k+i|k}) + \sum_{i=0}^{H_u-1} \gamma_2 f_2(k+i, x_{k+i|k}),$$

subject to

$$\hat{x}_{k+i+1|k} = \begin{bmatrix} A_{e,k} & B_{1,k} & B_2 \end{bmatrix} \begin{bmatrix} \hat{x}_{k+i|k} \\ \Delta u_{k+i|k} \\ \hat{d}_{k+i} \end{bmatrix}, \quad \forall i \in \mathbb{Z}_{[0,H_p-1]} \tag{24b}$$

$$\hat{x}_{k+i|k} \in \mathbb{X}, \quad \forall i \in \mathbb{Z}_{[1,H_p]} \tag{24c}$$

$$\Delta u_{k+i|k} \in \mathbb{U}, \quad \forall i \in \mathbb{Z}_{[0,H_u-1]} \tag{24d}$$

$$\xi_{1,k+i|k} \geq s_{k+i} - \hat{x}_{k+i|k}, \quad \forall i \in \mathbb{Z}_{[1,H_p]} \tag{24e}$$

$$\xi_{2,k+i|k} \geq \hat{x}_{k+i|k} - s_{k+i}, \quad \forall i \in \mathbb{Z}_{[1,H_p]} \tag{24f}$$

$$\xi_{1,k+i|k} \geq 0, \quad \forall i \in \mathbb{Z}_{[1,H_p]} \tag{24g}$$

$$\xi_{2,k+i|k} \geq 0, \quad \forall i \in \mathbb{Z}_{[1,H_p]} \tag{24h}$$

$$\Delta u_{k+i|k} = u_{k+i|k} - u_{k+i-1|k}, \quad \forall i \in \mathbb{Z}_{[0,H_u-1]} \tag{24i}$$

$$\hat{x}_{k|k} = x_k, \quad u_{k-1|k} = u_{k-1}, \tag{24j}$$

with decision variables $\boldsymbol{\Delta u}_k = \{\Delta u_{k+i|k}\}_{i \in \mathbb{Z}_{[0,H_u-1]}}$ and $\boldsymbol{\xi}_{j,k} = \{\xi_{j,k+i|k}\}_{i \in \mathbb{Z}_{[1,H_p]}}$.

The proposed method is summarized in Algorithm 1.

Algorithm 1 Predictive control-based dispatch procedure

VPP's management agent/operator share information with ISO and set k = 0.
for each k
    ISO provides $\hat{P}_{CP,k} \in [1, H_u]$
    Update s_k, v_k and H_k
    Compute $A_{e,k}$ and $B_{1,k}$
    Evaluate WF resource $\rightarrow P_{a-WF,k} \in [1, H_u]$
    Estimate VPP's loads $\rightarrow \hat{P}_{VPP-dem,k} \in [1, H_u]$
    Receive HPP inflow forecast $\rightarrow \hat{Q}_{in,k} \in [1, H_p]$
    Compute the optimal $[P_{d-WF,k}, P_{H,k}]$ and $M \in [1, H_p]$
    Calculate $\hat{\ell}_k \in [1, H_p]$
    VPP Agent share $P_{gen,k}$ with ISO
end for

In order to assess the performance of the proposed control strategy, four key performance indicators (KPIs) are computed.

Power Demand Supply KPI. This indicator represents the amount of yearly net energy balance between the generated and demanded energy. The KPI is calculated as

$$\text{KPI}_\text{S} := \sum_{k=1}^{N_s} \left| P_{dem,k} - P_{gen,k} \right|. \tag{25}$$

Wind farm Integration KPI. This performance indicator gives the percentage of available wind power harnessed in each period. This KPI is defined as

$$\text{KPI}_\text{I} := \frac{\sum_{k=1}^{N_s} P_{d-WF,k}}{\sum_{k=1}^{N_s} P_{a-WF,k}} \times 100\%, \tag{26}$$

Lower Safety Threshold KPI. This indicator represents the average amount of level deviation towards the penalised band

Z_1. This KPI is computed as

$$\mathrm{KPI}_{\ell_{\mathrm{low}}} := \frac{1}{N_s}\sum_{k=1}^{N_s} |\xi_{1,k}|. \tag{27}$$

Upper Safety Threshold KPI. This indicator represents the average amount of level deviation from ℓ_{upp} and is defined as

$$\mathrm{KPI}_{\ell_{\mathrm{upp}}} := \frac{1}{N_s}\sum_{k=1}^{N_s} |\xi_{2,k}|. \tag{28}$$

Ideally, threshold KPIs should have a low value, meaning that the reservoir level throughout the year is kept/operated mainly in the non-penalised band. However, in real operation, the threshold levels are surpassed since the reservoir management is also subject to various factors such as forecast, historical data, drought, irrigation, frequency control, among others.

4. Case study: description of Futaleufú power system

In this section, the system under study including power system location, natural resources and the key problem is addressed.

4.1. The 330 kV power system and Futaleufú HPP

The power system is located in Patagonian region. On the Southern Andes is placed the hydroelectric power station *Futaleufú*, located at 43°07′45″S 71°37′48″W. This is the main generation source of the area being its main purpose to avoid downstream floods and to feed an aluminium plant in Puerto Madryn city, 550 km to the east of the main station by a double 330 kV transmission line. Likewise, it supplies surrounding villages. A WF is to be installed and connected to this line probably at half distance of both ends (43°05′23″S 68°41′19″W). The location of the HPP and the WF are shown in Fig. 2. Up to this moment, prior to the WF installation, no overload in any transmission system element is present.

The single-line diagram of the addressed power system with real operating values (power, voltage, loads, transformers, etc.) is shown in Fig. 3. The main loads of the system are Puerto Madryn city (P_{L_2}) and the aluminium company (P_{L_3}) with a joint peak load of 100 MW ($\widehat{P}_{L_2} + \widehat{P}_{L_3}$); and surrounding villages near Futaleufú with a peak consumption of 22 MW ($\widehat{P}_{L_1}$). Fig. 4 shows the busbars normalised demands for a typical day according to the national ISO reports [37]. A load profile (P_{CP}) is established as a power balance reference required by the ISO at the CP, which means exporting/importing energy from the area to the argentine interconnection system (SADI, from the Spanish acronym).

The Futaleufú complex has four Francis turbines, two with a rated power of 118 MW and two recently re-powered up to 140 MW. The reservoir has a storage capacity of 5,700 Hm^3, covering an area of 9,200 ha. The dam has a height of 120 m reaching 500 m.a.s.l.. At the top, it has a length of 600 m by 10 m wide. The minimum and maximum reservoir levels are 465 and 495 m.a.s.l., respectively [36]. The relationship between m.a.s.l. and volume at the reservoir is shown in Fig. 5.

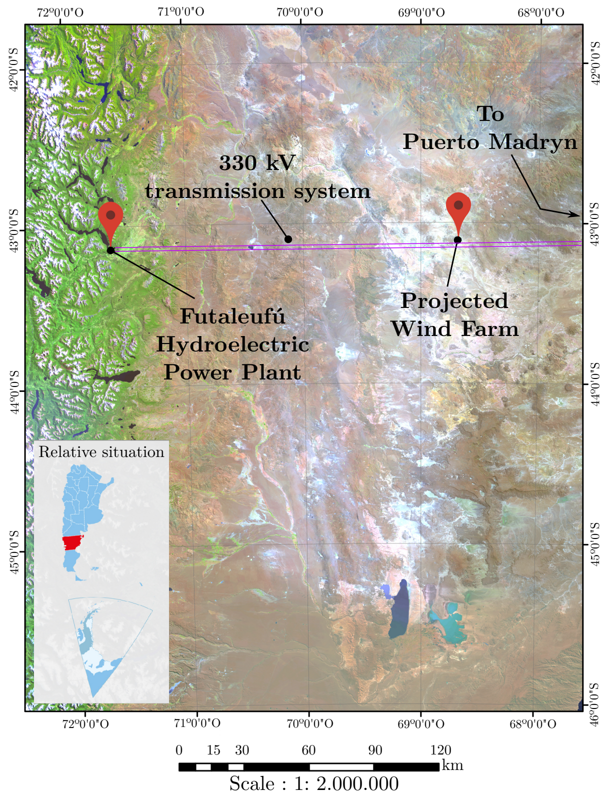

Fig. 2: Geographical location of the HPP and the projected WF.

4.2. Reservoir Management Criteria

Table 1 shows the dam management threshold levels along the year [36]. In this way, based on the real HPP operational levels, five bands are established to take into account the VPP scheme introduced in Section 3. The reservoir management bands are outlined in Fig. 6. Z_0 and Z_4 are forbidden operation bands, due to a possible emptying (Z_0) or crowning (Z_4) of the dam. Moreover, Z_1 is a safe band limit due to its proximity to Z_0. Like Z_1, Z_3 is a gradual guard band that prevents from operating near dangerous levels in case of unexpected floods. Thereby, the reservoir level is desired to be kept within the *free level* band Z_2.

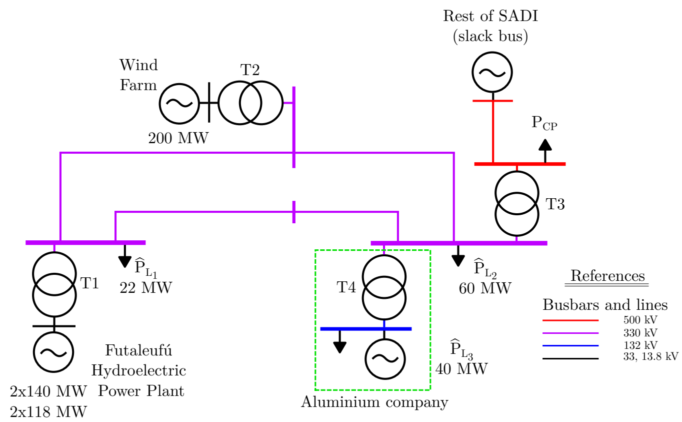

Fig. 3: Futaleufú power system model.

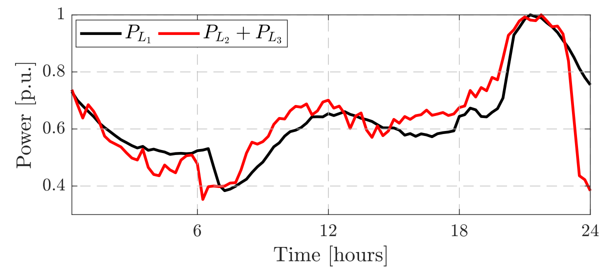

Fig. 4: Hourly active power pattern demand at Futaleufú and Puerto Madryn 330 kV busbars in per unit (p.u.) [37].

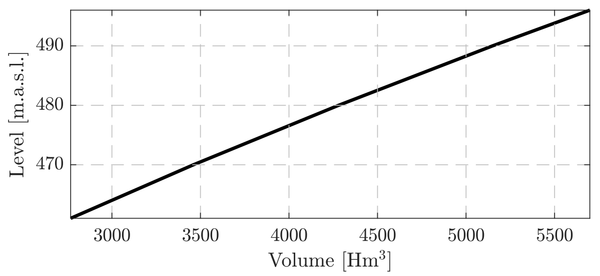

Fig. 5: Relationship between m.a.s.l. and volume at the reservoir [36].

4.3. Wind resource and WF

Wind speed at the location of the WF has an annual average of 9 m/s and a standard deviation of 4 m/s, which is an important amount of resource. The designed rated power of the WF is 200 MW and will be connected to the northern 330 kV line at 254 km from Futaleufú HPP.

4.4. Key problem – Restriction in the transmission system

With the new WF inclusion into the system, the importing/exporting area transformer T3 (rated power of about 450 MW) will be insufficient to handle both generations at rated. As the 330kV system is unique in the country, it is not economically viable to replace T3 for the moment. Thus, the CP maximum transmissible power is limited by T3 resulting $P_{CP_{\max}} = P_{T3_{\max}}$. This technical restriction encourages the design of alternative management solutions.

5. Results and discussion

This section presents the simulation results obtained with the proposed MPC controller. For comparative purposes, two heuristic control algorithms are also evaluated. Furthermore,

Table 1: Lower and upper threshold operation levels of the dam at the beginning of each period [m.a.s.l.] [38].

Periods	Threshold levels	
	ℓ_{low}	ℓ_{upp}
Jan - Apr	472.00	494.00
May - Oct	472.00	490.95
Nov - Dec	472.00	492.50

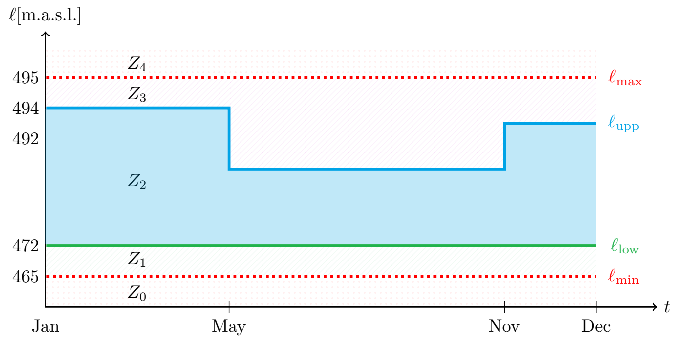

Fig. 6: Reservoir management bands throughout the year.

the MPC controller was assessed under uncertainties to show the robustness of the control proposal.

The numerical assessment was based on real time-series data over nine years with an hourly time step. Hydro and power system data were provided by the hydroelectric company (Hidroeléctrica Futaleufú) and by the Argentinian Wholesale Electricity Market Management Company (CAMMESA, from the Spanish acronym). The wind power profile also corresponds to real measured data at WF location. Aleatory maintenance support was assumed and applied to the WF, taking into account two consecutive days per turbine and per year. Transmission system losses were established with power flows through PSS®E [39]. Average losses from Futaleufú busbar to the CP and from CP to Puerto Madryn busbar were set to 2.3 % and 3.7 %, respectively. Furthermore, the system loads of Fig. 4 and the ISO reference defined above were set in accordance with [26].

The H_p was set to 336 hours (two weeks) and the H_u to 24 hours, according to considerations in Section 2. Cost function weights in (24a) were set to $\gamma_1 = 4$, $\gamma_2 = 1$ and $\gamma_3 = 0.05$, which have been obtained through exhaustive simulations and trial-and-error procedure. The function weight γ in (23) varies in accordance with ℓ_{upp} evolution. The value was set to $\gamma = 3$ between Jan-May and Nov-Dec; and $\gamma = 1.5$ between May-Nov. The simulation has been carried out using the MIQP solver GUROBI and YALMIP environment [40].

Three dispatch policies were assessed, two of them are based on heuristic algorithms. The first one is essentially a seasonally on/off control (O-C) specifically developed in [41] for the power sub-network addressed here as case study. The second one applies the Heuristic Controller (H-C) proposed in [26]. The last one implements the predictive management dispatch policy presented in Section 3 which includes a VPP scheme. The predictive control proposal is assessed under two scenarios. The first scenario (S1) assuming perfect knowledge of the input signals, and the second one (S2) considering disturbances. Although other hybrid dispatch approaches are found in the literature, they focus on systems including PHS or ROR technologies, so a quantitative performance comparison with these approaches cannot be done.

- Dispatch policies based on Heuristic Algorithms:
  - H-C approach: For the sake of comparison, the re-

Table 2: Scheduled turbines to be disconnected during high hydro season [41].

Weeks	1-12	13	14	15	16-30	31	32-52
Disconnected turbines	0	5	6	4	7	4	0

sulting power at the CP obtained with this approach was set as the ISO reference P_{CP} for all the simulated approaches. For further insight about this heuristic approach, and its improvement over traditional approaches, the reader can refer to [26].

  - O-C approach: Priority dispatch is given to the HPP, thus requiring wind spillage when high mean wind speed matches high water inflow. Therefore, wind energy spillage is stipulated according to Table 2 [41].

- Dispatch policy based on the predictive control approach:
  - S1: This scenario applies the proposal stated in Section 3 assuming variables Q_{in} and P_{dem} are known over both H_p and H_u.
  - S2: In this scenario the control proposal is addressed using the real available data to give to $Q_{in,k}$ and $P_{dem,k}$ time series their stochastic properties. Uncertainty in P_{a-WF} is out of the scope of this paper. In the case of considering the wind power generation forecast, readers are recommended to read [42]. The forecasted $\hat{\mathbf{Q}}_{in,k}$ was constructed by using historical data presented in Fig. 7. Each hourly forecasted value over H_p is a normal random number following a Gaussian distribution based on the registered daily mean and standard deviation. On the other hand, each $\hat{\mathbf{P}}_{CP,k}$ and $\hat{\mathbf{P}}_{L_i,k}$ forecasted value was built by normal random numbers using each hourly requested value as the mean. With regards to σ, a linear increment is implemented as the predicted value is further away from the moment in which the forecast is done. Based on the analysis of each forecasted load, an initial σ of 0.5 MW and final σ of 1.5 MW were set for each $\hat{\mathbf{P}}_{L_i,k}$ while the initial and final σ for $\hat{\mathbf{P}}_{CP,k}$ were set as 1 and 7 MW, respectively. Fig. 8 shows the load forecasted done for the first hour of $\hat{\mathbf{P}}_{CP,k}$ at 1-Jan-2008. It can be seen that the first forecasted hour has a 99.73 % confidence range of 6 MW against the final forecasted hour with an range of 42 MW.

Fig. 9 shows the operation performance of predictive and heuristic assessments, including from top to bottom: ℓ, P_{bal}, P_H and P_{spi-WF}. For a better understanding, P_{bal}, P_H and P_{spi-WF} were weekly averaged in this figure. It is important to note that a positive P_{bal} means a surplus of power that the VPP is able and recommended to generate (to accomplish reservoir levels). Likewise, a negative P_{bal} means less available power than the requested to the VPP. The controllers performance are quantified by each KPI in Table 3. In addition, the last row indicates

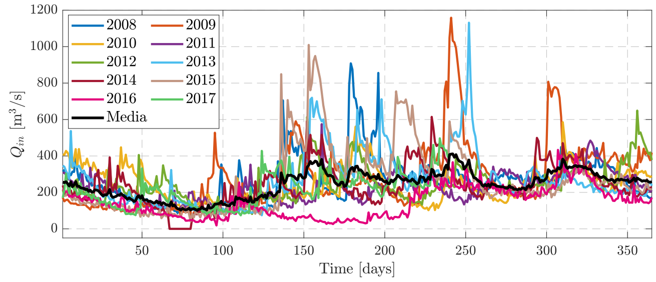

Fig. 7: Historical Q_{in} at the Futaleufú's reservoir for each year (colours) and mean (black).

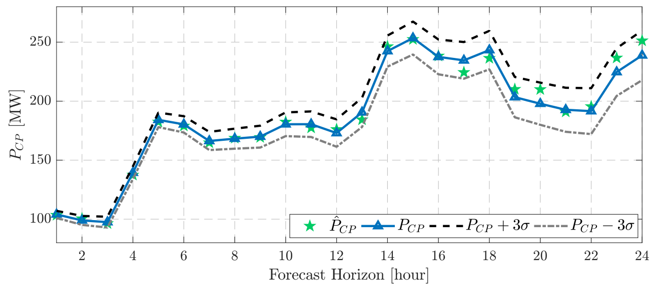

Fig. 8: Forecasted P_{CP} for 1-Jan-08 01:00. Real requested power for each hour (upward-triangle-blue), forecasted value for each hour done in that hour (pentagram-green) and upper (dashed-black) and lower (dash-dot-grey) 3σ distance.

the performance indexes for the whole nine years assessed period. First and foremost, it can be seen from Fig. 9 that the reservoir level in any approach follows a similar shape due to the fact that they supply the same loads. Besides, no significant differences are established for the total low-level threshold KPI.

It can be seen from Fig. 9 that the preventive wind energy spillage carried out by the O-C overloads the HPP generation, degrading the reservoir management. This overload causes a low reservoir level leading to a drop in HPP head (H) and thus much more water flow is needed for power production. As ℓ draws closer to ℓ_{low}, power balance is also notably degraded resulting in a minimum HPP dispatch. In view of this, the O-C approach does not seem a suitable option to increase RE integration in a coordinated dispatch scheme.

Beyond the limitation of the heuristic algorithms in terms of resource forecasts and horizons evaluation, the H-C maintains a suitable VPP operation, especially with regard to power balance in contrast to the O-C. However, ℓ shape decreases as in the O-C thereby yielding an increase in $KPI_{\ell_{low}}$ during the dry year 2016. As a result, the HPP generates at minimum levels increasing power imbalances. In addition, as it is shown in Fig. 9, the highest averaged wind energy spillage is observed during 2010, although the largest KPI_I is achieved for the whole period.

Unlike the heuristic algorithms, which are unable to anticipate the system behaviour, the proposed MPC controller achieves a significant improvements in terms of VPP management.

The dispatch policy accomplished by the MPC controller

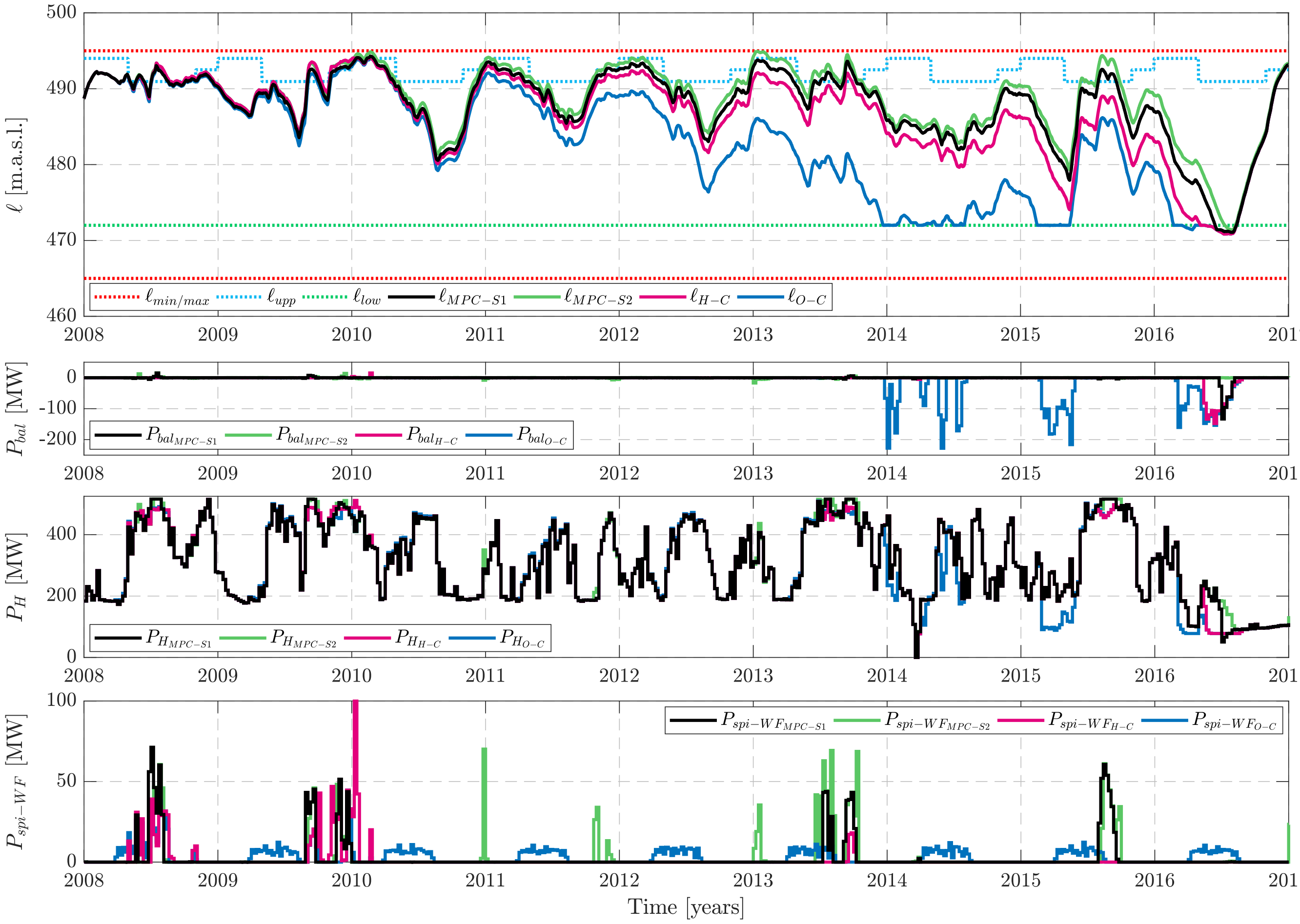

Fig. 9: O-C (blue), H-C (magenta), MPC-S1 (black) and MPC-S2 (green) nine year simulation. **1st:** Reservoir levels, minimum and maximum levels (dotted-red), upper threshold (dotted-sky blue) and lower threshold (dotted-green). **2nd:** Weekly average balance between generated and demanded power. **3rd:** Weekly average HPP dispatch. **4th:** Weekly average wind power spillage.

Table 3: Key performance indicators for each controller and each evaluated year.

Year	$KPI_{\ell_{upp}}$ [m.a.s.l.]				$KPI_{\ell_{low}}$ [m.a.s.l.]				KPI_S [GWh]				KPI_I [%]			
	O-C	H-C	MPC-S1	MPC-S2	O-C	H-C	MPC-S1	MPC-S2	O-C	H-C	MPC-S1	MPC-S2	O-C	H-C	MPC-S1	MPC-S2
2008	0,15	0,26	0,18	0,24	0,00	0,00	0,00	0,00	0,22	0,00	6,24	20,81	95,46	94,16	93,47	94,72
2009	0,07	0,33	0,13	0,28	0,00	0,00	0,00	0,00	0,80	0,01	5,80	20,63	97,04	93,52	93,62	92,95
2010	0,00	0,00	0,02	0,10	0,00	0,00	0,00	0,00	0,77	3,49	0,81	17,19	99,95	96,26	100,00	98,49
2011	0,00	0,00	0,01	0,11	0,00	0,00	0,00	0,00	0,08	0,00	0,48	18,33	100,00	100,00	100,00	98,38
2012	0,00	0,00	0,00	0,04	0,00	0,00	0,00	0,00	0,64	0,00	0,64	16,54	100,00	100,00	100,00	99,83
2013	0,00	0,03	0,20	0,56	0,00	0,00	0,00	0,00	52,79	0,00	4,53	20,72	100,00	99,15	94,38	88,34
2014	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	232,31	1,52	2,12	14,62	100,00	100,00	99,95	99,92
2015	0,00	0,00	0,12	0,42	0,00	0,00	0,00	0,00	270,18	0,34	2,01	12,45	100,00	100,00	94,13	94,01
2016	0,01	0,01	0,01	0,02	0,19	0,16	0,11	0,03	341,86	198,11	67,00	14,49	100,00	100,00	99,97	99,45
Total	0,03	0,07	0,08	0,20	0,02	0,02	0,01	0,00	899,65	203,47	89,64	155,79	96,55	98,12	97,28	96,24

in S1 (hereinafter called MPC-S1) improves the power balance and reservoir management by wind spillage mainly in accordance with above-expected volume inflow (see for instance 2008, 2009, 2013 and 2015 in Fig. 7). The increase in ℓ does not immediately mean low-performance reservoir management, on the contrary, this is in fact preferred instead of a drained reservoir as in the O-C. As mentioned above, a lower ℓ implies less *balancing resource* and lower H. The MPC-S1 significantly outperforms the assessed rule-based algorithms w.r.t the most important control goal, i.e., the accumulated power balance. When comparing H-C and MPC-S1, the accumulated power imbalance is 127% higher for the H-C. This mismatch corresponds to an hourly discrepancy of 1.14 MW for the MPC-S1 against 2.58 MW for the H-C. In fact, this hourly distribution allows observing an increase of more than twice the effort required by the ISO to close the hourly power balance in the area. In terms of wind energy integration, a difference of about 0.84 % is observed in favour of the H-C mainly due to the wind spillage carried out during 2013 and 2015 by MPC-S1. In return, this spillage serves to improve P_{bal}.

An average annual power imbalance of about 17 GWh is obtained when the MPC controller is assessed under S2, hereinafter called MPC-S2. This is mainly due to a best performance during 2016 (dry year). The improve is achieved without risk of water spillage as it can be seen from Fig. 9, where HPP maximum capacity is still available during high ℓ periods. In view of this, minor-additional wind spillage events are needed, such as those by the end of 2010, 2011 and at the beginning of 2013. Nevertheless, even under uncertain conditions, the MPC controller shows no significant differences between S1 and S2.

To conclude, the MPC approach achieves a better reservoir management (without water spillage), benefiting from the softening constraints and the time-varying tuning, as well as a significant improvement in demand supply, which in turn achieves a smaller dispatch power discrepancy. In return, a small reduction in WF penetration is expected.

6. Conclusions

This paper has proposed the design of a predictive control approach for the power management policy of an energy system comprising wind and hydro sources. The benefits of using a multi-objective model predictive control with softening constraints and variable weighting under a virtual power plant (VPP) framework have been demonstrated by means of a case study in Argentina. The proposal has been assessed using real data over an interval of nine years, which have been provided by the involved agents. Furthermore, a comparison with other approaches is done. It is shown that, because of the nature of both resources, coordination by a predictive control structure leads to a significant improvement of the overall energy efficiency against previous approaches, including the classical seasonal wind energy spillage. Considerable improvement in the independent system operator reference tracking and transmission system capacity harnessing is achieved with the proposed controller. A power mismatch reduction of 56% is obtained at the expense of a 0.84% decrease in wind farm penetration, likewise the predictive controller is less susceptible to uncertainties. Moreover, reservoir level management is improved, keeping it mostly in safe level bands and without water spillage, due to both the soft constraints and the variable weighting implementations. Thus, this approach allows a better joint operation and natural resources exploitation, with the possibility of incorporating the forecast in the dispatch procedure. In addition, the presented dispatch policy and model can be applied to any other location to assess the suitability/development of wind farms in the neighbourhood of large-conventional hydropower plants (HPPs).

Since existing HPPs reduces the additional investment needed to compensate for renewable energy (RE) variations, the operation policies that involve both generations could support dispatch policymakers to modernise and include the coordinated operation in the future dispatch procedures. In this way, the large reservoir HPPs priorities could be modified to include, after floods and irrigation, the joint operation with REs whenever possible in the framework of new RE integration policies. To this end, the VPP structure presented here could also enhance the vision of the system operator by a more summarised model of a region.

Future work will include the impact of the RE forecast, adaptive tuning law of the weighting parameters in the cost function, and an additional upper supervisory predictive control layer for longer time steps within a hierarchical structure. Also, the power flow restrictions will be modelled to better characterise the system topology including voltage magnitudes and phase angle values.

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