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Grid-Connected Hydrokinetic Energy Conversion System Using Back-to-Back Converters: A Model Predictive Control Approach

Karolina Nowak^{1*}, Tomasz Wrobel², Julia Mazur¹

Abstract

The integration of hydrokinetic turbine (HKT) systems relies heavily on power converters, which enable precise control of turbine rotational speed to regulate active power delivered to the grid while providing reactive power compensation. This paper introduces an advanced model predictive control (MPC) strategy designed for maximum power point tracking and output frequency regulation in an HKT system interfaced through a back-to-back converter. The setup comprises a horizontal propeller turbine, a permanent magnet synchronous generator, a rectifier, and an inverter. The proposed control scheme was implemented in MATLAB and validated via simulations, with performance assessed through the system's state variables. A comparison with a conventional proportional-integral (PI) control method demonstrates that MPC delivers superior transient performance and shorter settling times for high-efficiency operation, while remaining straightforward to implement. Specifically, the MPC controller exhibited a settling time that was 4 times faster than that of the PI controller.

Keywords Hydrokinetic turbine, HKT+VSC with MPC control, River and estuaries turbine control, Model predictive control

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Introduction

Global warming has caused considerable environmental damage, largely driven by human activities. Consequently, all nations now share the responsibility to curb their carbon footprints and greenhouse gas emissions [1] while advancing the global energy transition. Over recent decades, renewable energy sources have attracted increasing attention due to their clean, sustainable, and environmentally benign characteristics [2]. Technologies such as photovoltaic, wind, and hydroelectric power are widely viewed as essential solutions. Nevertheless, solar and wind power face a key limitation stemming from the intermittent availability of their primary resources [3].

Motivation

Hydroelectric power occupies a leading role in worldwide electricity production [4]. This generation method benefits from the consistent availability of water, offering excellent energy storage potential and flexible dispatch capabilities [5]. Large-scale hydroelectric facilities are typically employed for high-capacity output (exceeding 10 MW), whereas small hydropower plants (SHPs) better serve smaller communities. With ratings below 10 MW and no dam requirements, they are well-suited to regions with limited energy needs [6]. However, this approach depends on the presence of waterfalls. It

entails substantial installation costs, making it less feasible in low-relief areas, sparsely populated zones, and regions facing socioeconomic challenges—locations where rural households frequently lack adequate access to education, infrastructure, and information [4]. Notably, although one-third of the world's population remains without electricity, many such communities have access to flowing rivers. Small, isolated settlements generally need power only for basic purposes such as lighting, cooling, and communication [7]. In areas with little elevation change, however, traditional SHPs become impractical.

A highly promising option for electricity generation in low- or zero-head locations is hydrokinetic power. This technology is known under several terms, including Marine Current Turbine [8], ultra-low head hydraulic turbine [9], free-flow/stream turbine [10], or hydraulic turbine in current [11]. Hydrokinetic turbines produce electricity without requiring dams, water diversions, or large-scale civil works typical of conventional hydropower installations [12]. Moreover, they exert only minimal effects on the surrounding ecosystem's flora and fauna. These systems are generally small-scale, with capacities in the range of a few hundred kVA [13]. Compared to wind or solar generation, hydrokinetic energy offers greater long-term predictability—particularly under tidal regimes—and more consistent availability in river environments [14].

Since 2017, hydrokinetic turbine (HKT) technology has experienced considerable progress and is currently advancing through phases of innovation, research, development, and supportive public policies, especially in rural electrification initiatives [15]. Nevertheless, as highlighted in [14], widespread adoption faces obstacles, including limited public awareness of its benefits, insufficient real-world performance data, and the technology's relative immaturity, particularly in river and estuarine settings. In Colombia, hydrokinetic turbine applications remain at an early stage, with limited research and deployments. Notable initiatives have occurred in Neiva [16] and Medellín [17], while the Chocó department has seen no comparable projects to date.

The main objective in controlling a hydrokinetic turbine is to maximize energy capture while reducing mechanical wear and optimizing overall system behavior. This encompasses system stabilization, enhanced transient dynamics, improved steady-state performance, and reliable operation within acceptable bounds for maintenance, safety, and functionality [18].

State of the art

When considering control strategies for hydrokinetic turbines (HKT), the fundamental aims are system stabilization, superior dynamic performance, enhanced steady-state behavior, and effective implementation of maximum power tracking control (MPTC) [19]. In particular, maximum power point tracking (MPPT) represents a well-established and thoroughly investigated topic in the wind energy field, as documented in [20–23]. In contrast, equivalent studies applied to hydrokinetic energy conversion remain comparatively sparse.

Within the relatively small body of literature on this subject, several comprehensive review papers provide important background [4, 14], while other publications analyze the technical difficulties inherent to HKT installations [19]. A limited number of works also evaluate practical implementation aspects, such as technology benchmarking and alternative power regulation methods. One particularly relevant contribution appears in [24], where the authors constructed models to directly compare hydrokinetic and wind-based generation. Their findings indicated that hydrokinetic systems offer markedly lower costs than small wind installations and focused on developing appropriate control frameworks to secure acceptable dynamic response and steady-state accuracy via maximum power tracking techniques.

A variety of power regulation schemes have been reported in the literature. Examples include the combination of Disturb & Observe MPPT with PI-based voltage control for stand-alone operation [25], Power Signal Feedback MPPT using look-up tables paired with linearized PI regulation [26], and Field-Oriented Control incorporating PI controllers whose gains are optimized via a biogeography-based algorithm tailored for grid-connected operation [18]. It should be noted, however, that most of these techniques were originally designed for DC architectures.

For grid-interfaced AC configurations, one approach described in [3] combines MPPT with impedance-based control to regulate the HKT system's output voltage. Although the publication briefly surveys hydrokinetic turbine classifications, the turbine itself is represented solely by a C_p curve extracted from a simple one-dimensional look-up table, without any in-depth hydrodynamic modeling. On the inverter side, the strategy employs conventional PWM with phase-locked loop synchronization and standard linear PI regulators. In a similar vein, the work reported in [2] introduces a regulation method for a cross-flow hydraulic turbine operating in grid-tied mode. By directly modulating the generator's q-axis current, the scheme bypasses the need for an internal speed control loop. That study, however, modeled the turbine using only a constant C_p value to estimate extractable power rather than a detailed dynamic representation, relied on a linearized mechanical torque expression, and implemented control through conventional PI controllers formulated via transfer functions.

A critical observation is that although the aforementioned techniques employ MPPT algorithms (whether look-up table-based or extremum-seeking), their reliance on linearized models arranged in cascaded structures and on classical P, I, or PI regulators limits reliable operation to narrow deviations around a single operating condition. Large disturbances or substantial changes in operating conditions can push the system outside the linear region, leading to degraded performance or even instability. This limitation underscores the value of more sophisticated nonlinear control methods—such as model predictive control (MPC)—which can natively handle multivariable, nonlinear dynamics while maintaining reasonable implementation complexity.

Accordingly, the objective of the current research is to develop an integrated control architecture for simultaneous power and voltage regulation using a nonlinear model predictive control (MPC) framework. This model-based methodology leverages a full-state-space representation to deliver a unified multivariable solution that accommodates wider variations in river current velocity.

Contribution and scope

The key original contributions of the present paper can be summarized as follows:

- Development of a comprehensive mathematical model that describes an HKT system in grid-connected operation, explicitly accounting for the nonlinear characteristics of the hydrokinetic turbine, the permanent magnet synchronous generator (PMSG), the DC/DC stage, and the grid-side inverter.
- Design of a nonlinear MPC algorithm utilizing the multiple-shooting approach together with dedicated numerical optimization solvers, applied across multiple prediction horizons; performance is systematically contrasted with that of a standard PI controller.
- Implementation of a simplified single-step-ahead MPC variant intended to minimize computational burden, with corresponding evaluation of its effectiveness.

The scope of this work is confined to the performance assessment of the proposed MPC strategy within a grid-connected HKT configuration. Analysis is restricted to the evolution of key state variables and to direct comparison against classical PI control. Only changes in river flow speed are considered; no formal stability analysis is conducted.

Unified Model for HKT System

From both architectural and functional viewpoints, an HKT system closely parallels a wind energy conversion system. The most significant distinction arises from the fact that water has a density approximately 800 times that of air, which, in turn, leads to substantially slower rotational speeds for hydrokinetic rotors compared with wind rotors [27]. **Figure 1** depicts the general layout of a grid-connected HKT installation, comprising a horizontal-axis hydrokinetic turbine, a permanent-

magnet synchronous generator (PMSG), a controlled rectifier, and a grid-tied inverter. The mathematical representation of each subsystem is introduced in the subsections below:

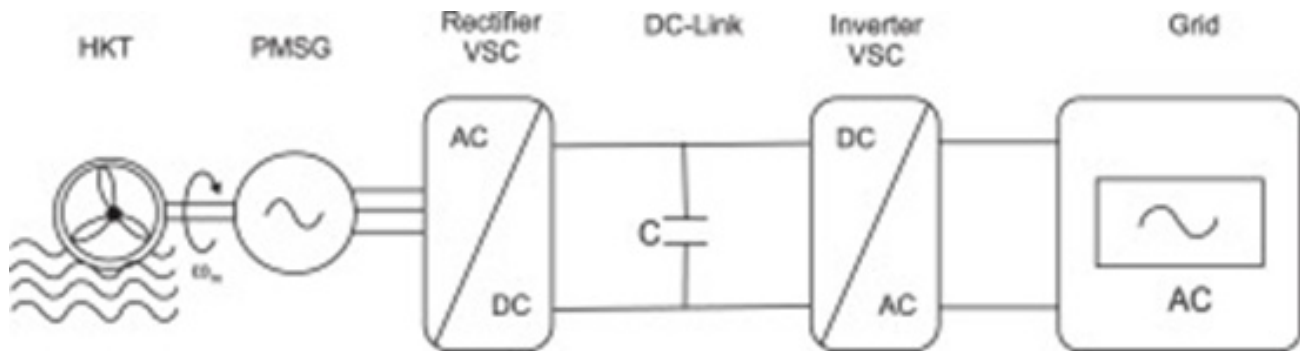


Figure 1. Schematic representation of an HKT system.

HKT turbine model

A hydrokinetic turbine (HKT) captures kinetic energy from the moving water and transforms it into mechanical rotational energy at its shaft. The mechanical power extracted and the corresponding torque are expressed as follows [24]:

$$P_m = \frac{1}{2} \rho \pi r^2 C_p v^3, \quad (1)$$

$$T_m = \frac{P_m}{\omega_m}, \quad (2)$$

Where C_p denotes the power coefficient of the turbine—a parameter influenced by turbine design, blade count, and other factors—and varies as a function of the tip speed ratio (λ).

For this study, the selected HKT is based on the model described in [24], with its power coefficient given by the expression:

$$\begin{aligned} \frac{1}{\lambda_i} &= \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{1 + \beta^2}, \\ l &= \frac{1}{\lambda_i}, \\ C_p(\lambda, l, \beta) &= c_1 (c_2 l - c_3 \beta - c_4) e^{-c_5 l} + c_6 \lambda. \end{aligned} \quad (3)$$

Meanwhile, the turbine's rotational speed is also tied to λ and is determined using:

$$\omega_m = \frac{v_r \lambda}{r}. \quad (4)$$

The core principle of the turbine control approach is to identify the tip speed ratio λ that yields the highest possible power coefficient, thereby maximizing the turbine's mechanical power output. By setting $\beta = 0$ in Eq. 3, the optimal tip speed ratio λ_{opt} can be found. This simplification results in maximum values for both the power coefficient (C_{pmax}) and the mechanical power (P_{mmax}), both of which depend on the river flow velocity, as shown in Figure 2.

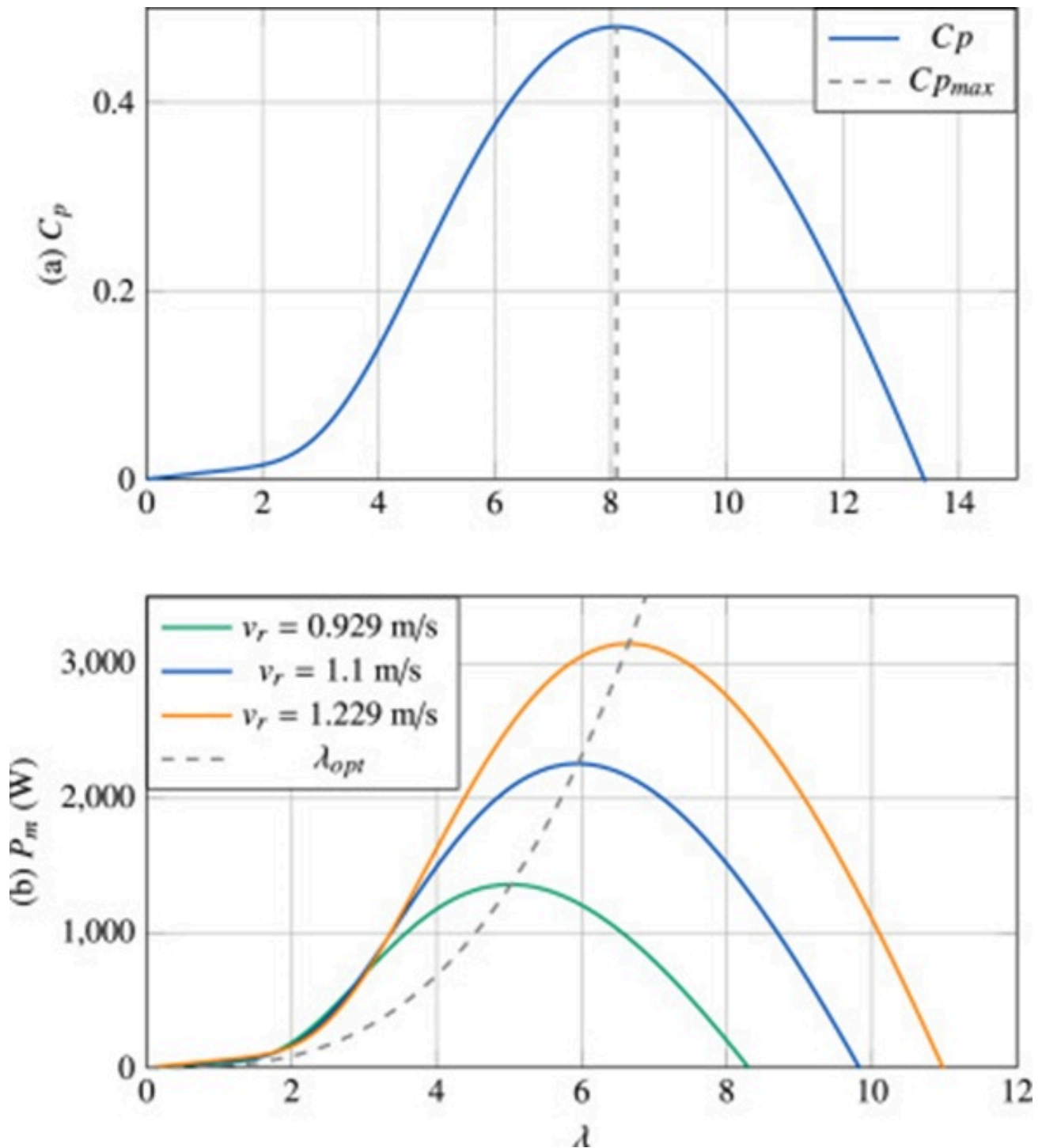


Figure 2. Power coefficient and mechanical power as a function of tip speed ratio: (a) Power coefficient, and (b) Mechanical power.

PMSG model

In an HKT system, the electrical generator is a permanent-magnet synchronous generator (PMSG) that converts mechanical rotational energy into electrical power. For mathematical modeling, the PMSG is commonly analyzed in the dq stationary reference frame. This transformation is accomplished via the Park transform, a standard technique for

converting three-phase machine variables into a direct-quadrature (dq) coordinate system [28]. In this dq frame, the voltage equations of the PMSG are expressed as [29]:

$$\begin{aligned}\frac{di_{gd}}{dt} &= \frac{1}{L_{sd}}(v_{gd} - r_s i_{gd} + \omega_e L_{sq} i_{gq}), \\ \frac{di_{gq}}{dt} &= \frac{1}{L_{sq}}(v_{gq} - \omega_e L_{sd} i_{gd} - r_s i_{gq} - \omega_e \psi_{pm}).\end{aligned}\quad (5)$$

The electromagnetic torque developed by the generator is given by [30]:

$$T_e = \frac{3P}{2}(\psi_{pm} i_{gq} - (L_d - L_q) i_{gd} i_{gq}). \quad (6)$$

In **Eq. 6**, the first component represents the mutual (or alignment) torque, produced by the interaction between the permanent magnets and the stator currents. The second component is the reluctance torque, which stems from the rotor's magnetic saliency [25].

The rotational dynamics of the electromechanical system are governed by the angular acceleration of the generator shaft, described by [31]:

$$\frac{d\omega_m}{dt} = \frac{1}{J}(T_m - T_e - \xi(\omega_m - \omega_{m0})). \quad (7)$$

Additionally, the relationship between the mechanical angular frequency of the generator and the electrical frequency is provided by [32]:

$$\omega_e = P\omega_m. \quad (8)$$

AC-DC rectifier model

The controlled rectifier converts the PMSG's alternating current (AC) output into a regulated direct current (DC) voltage. Its output voltage is determined according to [33]:

$$\begin{aligned}v_{gd} &= v_{dc} m_{gd}, \\ v_{gq} &= v_{dc} m_{gq}.\end{aligned}\quad (9)$$

DC-AC inverter model

The DC/AC inverter transforms the smoothed DC voltage from the DC-link capacitor into an alternating current suitable for grid connection. Its dynamic behavior is modeled using Kirchhoff's current and voltage laws applied to both the DC-link and grid sides, incorporating the Park transform and **Eq. 9**, leading to:

$$\begin{aligned}
 \frac{di_{rd}}{dt} &= \frac{1}{L}(-r_r i_{rd} + \omega_e L i_{rq} + v_{rd} - v_d^n), \\
 \frac{di_{rq}}{dt} &= \frac{1}{L}(-\omega_e L i_{rd} - r_r i_{rq} + v_{rq} - v_q^n), \\
 \frac{v_{dc}}{dt} &= \frac{1}{C}(m_{gd} i_{gd} + m_{gq} i_{gq} - m_{rd} i_{rd} - m_{rq} i_{rq}), \\
 v_{rd} &= v_{dc} m_{rd}, \\
 v_{rq} &= v_{dc} m_{rq}.
 \end{aligned} \quad (10)$$

Fully model of the HKT system

The overall behavior of the HKT system depicted in **Figure 1** arises from the combined dynamics of the hydrokinetic turbine, PMSG, mechanical shaft, rectifier, and inverter. These interactions form a nonlinear dynamic system, which can be represented as:

$$\dot{x} = f(x) + g(x)u, \quad (11)$$

where $x = [x_f, \omega_m, i_{gd}, i_{gq}, i_{rd}, i_{rq}, v_{dc}]^\top$, $u = [m_{gd}, m_{gq}, m_{rd}, m_{rq}]^\top$, and

$$f(x) = \begin{bmatrix} \frac{1}{\tau}(p_m - x_f) \\ \frac{1}{J}(\tau_m - \tau_e - \xi(\omega_m - \omega_b)) \\ \frac{1}{L_{sd}}(-r_s i_{gd} + x_{sq} i_{gq}), \\ \frac{1}{L_{sq}}(-x_{sd} i_{gd} - r_s i_{gq} - \omega_e \psi_{pm}) \\ \frac{1}{L}(-r_r i_{rd} - \omega_e L i_{rq} - v_d^n) \\ \frac{1}{L}(-\omega_e L i_{rd} - r_r i_{rq} - v_q^n) \\ 0 \end{bmatrix}, \quad (12)$$

$$g(x) = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \frac{v_{dc}}{L_{sd}} & 0 & 0 & 0 \\ 0 & \frac{v_{dc}}{L_{sq}} & 0 & 0 \\ 0 & 0 & \frac{v_{dc}}{L} & 0 \\ 0 & 0 & 0 & \frac{v_{dc}}{L} \\ \frac{i_{gd}}{C} & \frac{i_{gq}}{C} & -\frac{i_{rd}}{C} & -\frac{i_{rq}}{C} \end{bmatrix}. \quad (13)$$

This nonlinear system **Eq. 11** is discretized for digital implementation using the fourth-order Runge–Kutta method, resulting in:

$$x^+ = x + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4)\Delta t, \quad (14)$$

Where x^+ represents the state vector at the next time step $t+1$, x is the state vector at the current time t , Δt denotes the sampling period for control, and

$$\begin{cases} k_1 = f(x, u), \\ k_2 = f\left(x + \frac{1}{2}\Delta t k_1, u\right), \\ k_3 = f\left(x + \frac{1}{2}\Delta t k_2, u\right), \\ k_4 = f\left(x + \frac{1}{2}\Delta t k_3, u\right). \end{cases} \quad (15)$$

Target state and input trajectories of the HKT system

The reference states and input trajectories are determined based on the measured river flow velocity, v_r , [34] at each sampling instant. This enables the hydrokinetic turbine to operate at an estimated optimal mechanical angular speed ω_{opt} , delivering maximum estimated mechanical power P_{mmax} . In contrast, electrical power is generated at the corresponding optimal electrical frequency ω_{eopt} , computed from [Eqs. 1, 4 and 8](#).

To maximize the efficiency of the HKT system, it is essential to ensure optimal transfer of the electromagnetic torque produced by the generator and to extract the highest possible active electrical power. This is accomplished by enforcing $\bar{i}_{gd}=0$ in [Eq. 6](#) and by minimizing i_{rq} through the setting $\bar{i}_{rq}=-Q_{ref}/v_{nd}$, with the reactive power reference set to $Q_{ref}=0$.

Following these calculations, the target state vector $\bar{x} = [\bar{x}_f, \bar{\omega}_m, \bar{i}_{gd}, \bar{i}_{gq}, \bar{i}_{rd}, \bar{i}_{rq}, \bar{v}_{dc}]^T$ and the reference control input vector $\bar{u} = [\bar{m}_{gd}, \bar{m}_{gq}, \bar{m}_{rd}, \bar{m}_{rq}]^T$ are obtained and defined as follows:

$$\begin{aligned} \bar{x}_f &= P_{mmax}, \\ \bar{\omega}_m &= \omega_{mopt}, \\ \bar{i}_{gd} &= 0, \\ \bar{i}_{gq} &= \frac{2T_{mmax}}{3P\psi_{pm}}, \\ \bar{i}_{rd} &= \sqrt{\left(\frac{v_d^n}{2r_s}\right)^2 + \frac{\bar{v}_{dc}(\bar{m}_{gd}\bar{i}_{gq} + \bar{m}_{gq}\bar{i}_{gd})}{r_s}} - \bar{i}_{rq} - \frac{v_d^n}{2r_s}, \\ \bar{i}_{rq} &= -\frac{Q_{ref}}{v_d^n}, \\ \bar{v}_{dc} &= V_{dc}, \end{aligned} \quad (16)$$

and

$$\begin{aligned}
 \bar{m}_{gd} &= -\frac{\omega_{e_{opt}} L_{sq} \bar{i}_{gq}}{\bar{v}_{dc}}, \\
 \bar{m}_{gq} &= \frac{r_s \bar{i}_{gq} + \omega_e \psi_{pm}}{\bar{v}_{dc}}, \\
 \bar{m}_{rd} &= \frac{v_d^n + r_s \bar{i}_{rq} - \omega_{e_{opt}} L_{sq} \bar{i}_{rq}}{\bar{v}_{dc}}, \\
 \bar{m}_{rq} &= \frac{\omega_{e_{opt}} L_{sq} \bar{i}_{rd} + r_s \bar{i}_{rq}}{\bar{v}_{dc}}.
 \end{aligned} \quad (17)$$

Model-Predictive Control

Model predictive control (MPC) has a well-established history in control engineering and remains one of the most actively researched and applied techniques in both industry and academia. The method uses the system's mathematical model, along with constraints and specified optimization goals, to predict future behavior and compute the optimal sequence of control actions. By forecasting the system's evolution over defined prediction horizons, MPC selects control inputs that best satisfy the optimization objective while respecting all imposed constraints, thereby reducing the effects of disturbances and model uncertainties.

The MPC algorithm operates in a receding-horizon manner: at each time step, it solves a finite-horizon optimal control problem that minimizes a cost function (typically based on tracking error) subject to the system dynamics and constraints. **Figure 3** provides a schematic overview of the procedure. The process begins with acquiring the current system measurement. An optimization problem is then formulated and solved to determine the control sequence that minimizes the deviation between predicted states and desired references over the prediction horizon. Only the first control action from this sequence is applied to the system, after which the horizon is shifted forward, new measurements are obtained, and the procedure repeats until the system reaches the target operating condition.

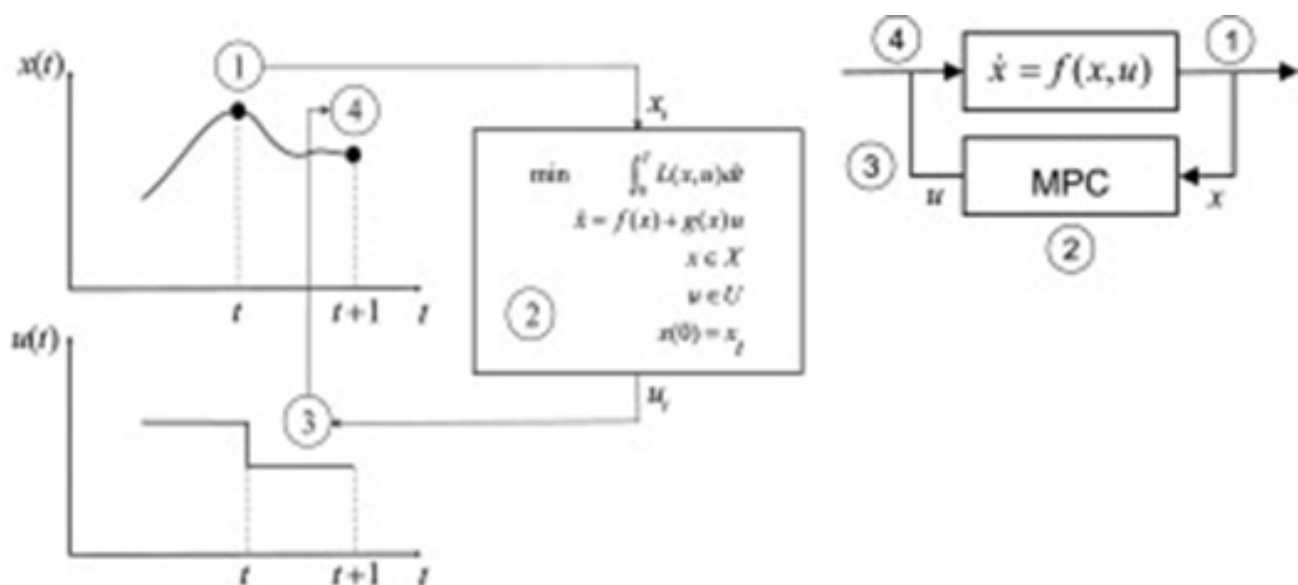


Figure 3. Schematic representation of a model-predictive control.

The cost function is typically formulated as a quadratic function of the tracking error. At the same time, the constraints include the discretized dynamic model, initial conditions, and bounds on both states and control inputs.

In the present work, the optimization task is addressed as follows: the continuous-time model is first discretized using either the Euler method or the fourth-order Runge–Kutta integration scheme. The resulting nonlinear program is then solved using the open-source framework CasADi, specifically designed for nonlinear optimization [35]. The implementation adopts the multiple-shooting approach, which, despite introducing a larger number of decision variables, offers greater simplicity in handling constraints derived from the discretized dynamics and naturally accommodates inequality constraints [36].

The MPC strategy can be expressed formally as an optimal control problem in the following manner:

$$\begin{aligned}
 & \min \quad \frac{1}{2} (x^+ - \bar{x})^\top Q (x^+ - \bar{x}) + \frac{1}{2} (u - \bar{u})^\top R (u - \bar{u}) \\
 & \text{s.t.} \quad (14), (15) \\
 & \quad x \in \mathcal{X} \\
 & \quad u_{\min} \leq u \leq u_{\max} \\
 & \quad x(0) = x_t, \\
 & \quad \text{where } Q \succeq 0 \text{ and } R \succ 0.
 \end{aligned} \tag{18}$$

Due to the nonlinear nature of both the objective function and the constraints given in Eqs. 14 and 15, the formulation in Eq. 18 constitutes a nonlinear optimization problem.

The HKT System, Results, and Analysis

To assess the effectiveness of the proposed MPC controller when applied to the hydrokinetic turbine (HKT) system, simulations were conducted under the grid-connected configuration shown in Figure 4.

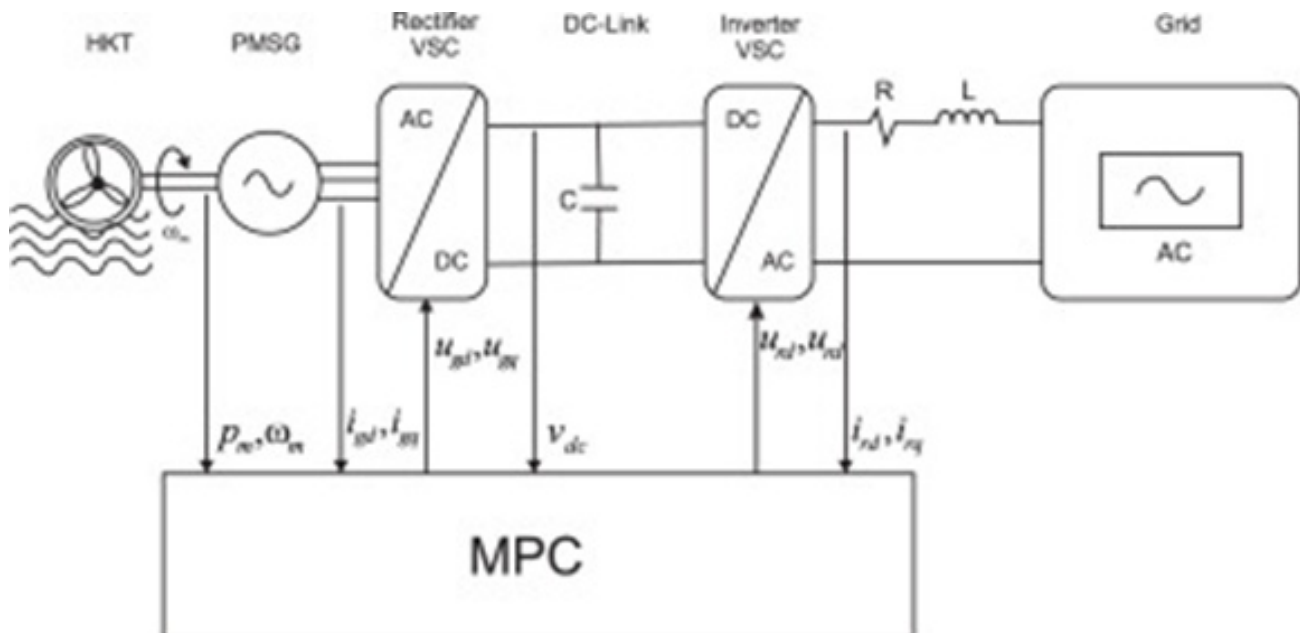


Figure 4. MPC controller for the HKT system.

This setup evaluates the controller's capability to drive the key state variables (p_m , ω_m , i_{gd} , i_{gq} , i_{id} , i_{iq} , v_{dc}) to their respective reference values in the shortest possible time. All simulations were carried out in MATLAB. The system

dynamics were discretized via the fourth-order Runge–Kutta method, and the optimization problems were solved using the CasADi toolbox.

A fixed sampling time of $\Delta t = 0.1$ ms was used for the MPC implementation. Different prediction horizons h were evaluated to examine the resulting closed-loop behavior of the state variables under MPC action. Step changes in river velocity were applied at times $\text{trc1} = 0.1$ s and $\text{trc2} = 0.2$ s, corresponding to velocities $v_{r1} = 1.229$ m/s and $v_{r2} = 0.929$ m/s, respectively, as depicted in **Figure 5**.

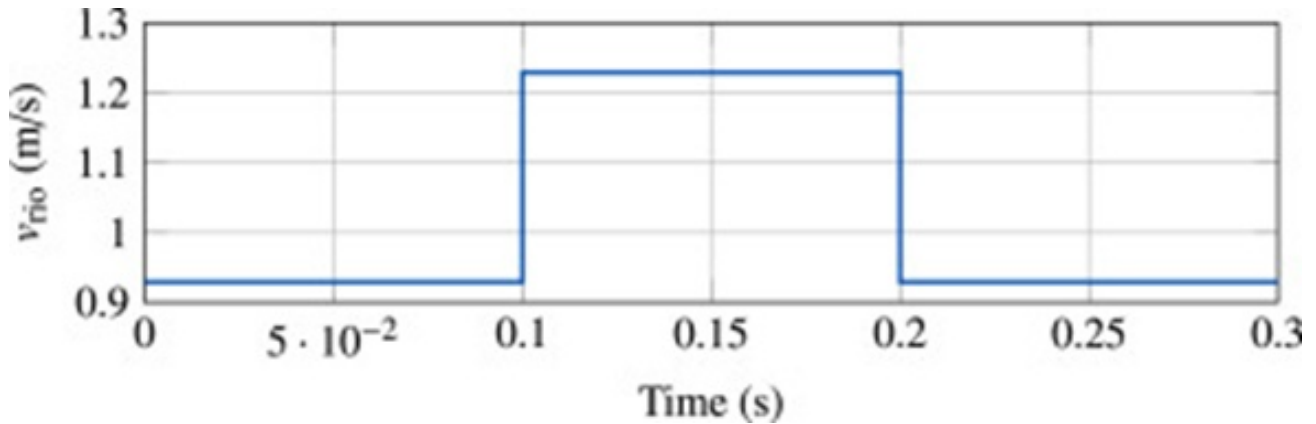


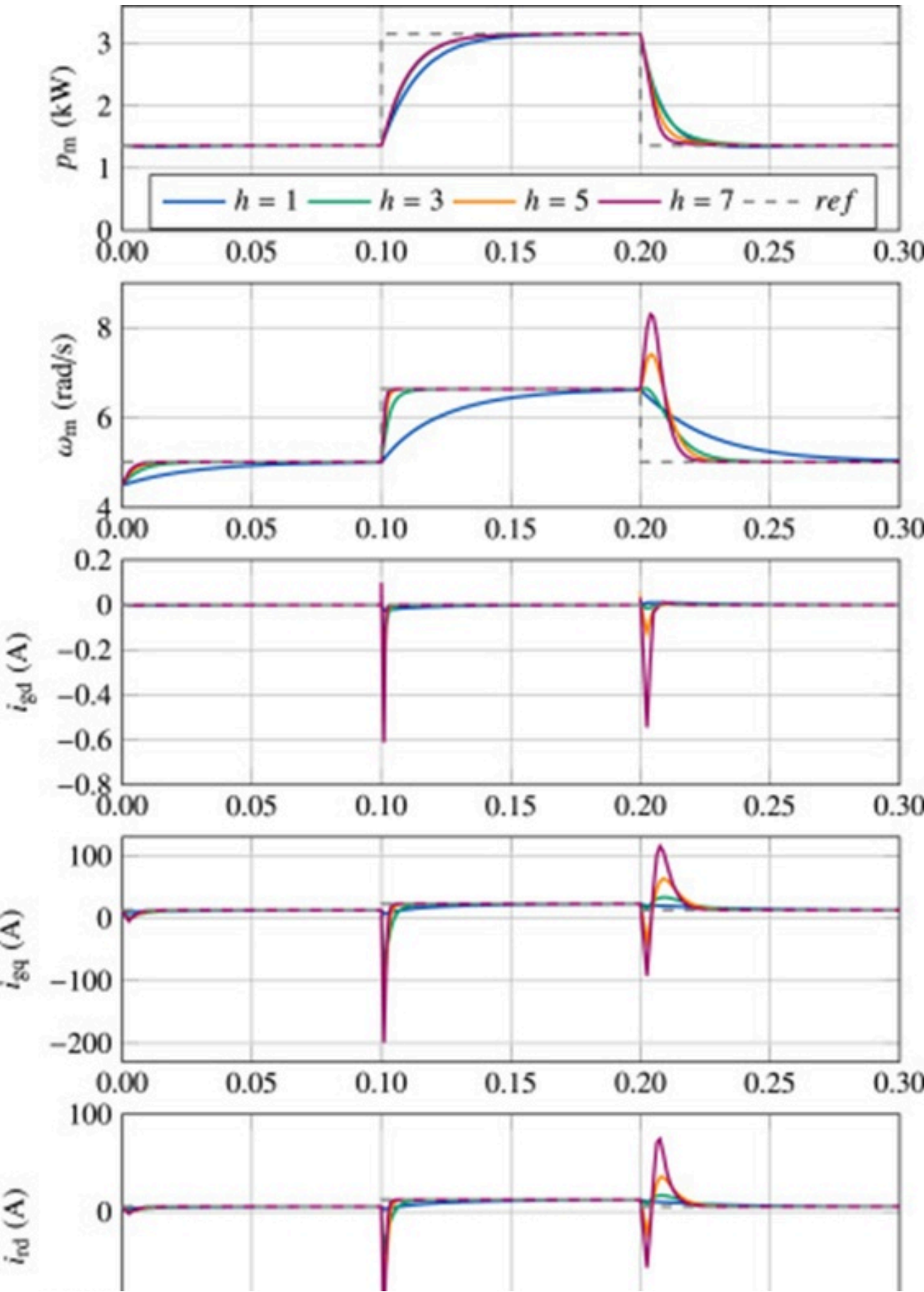
Figure 5. Changes in river speed.

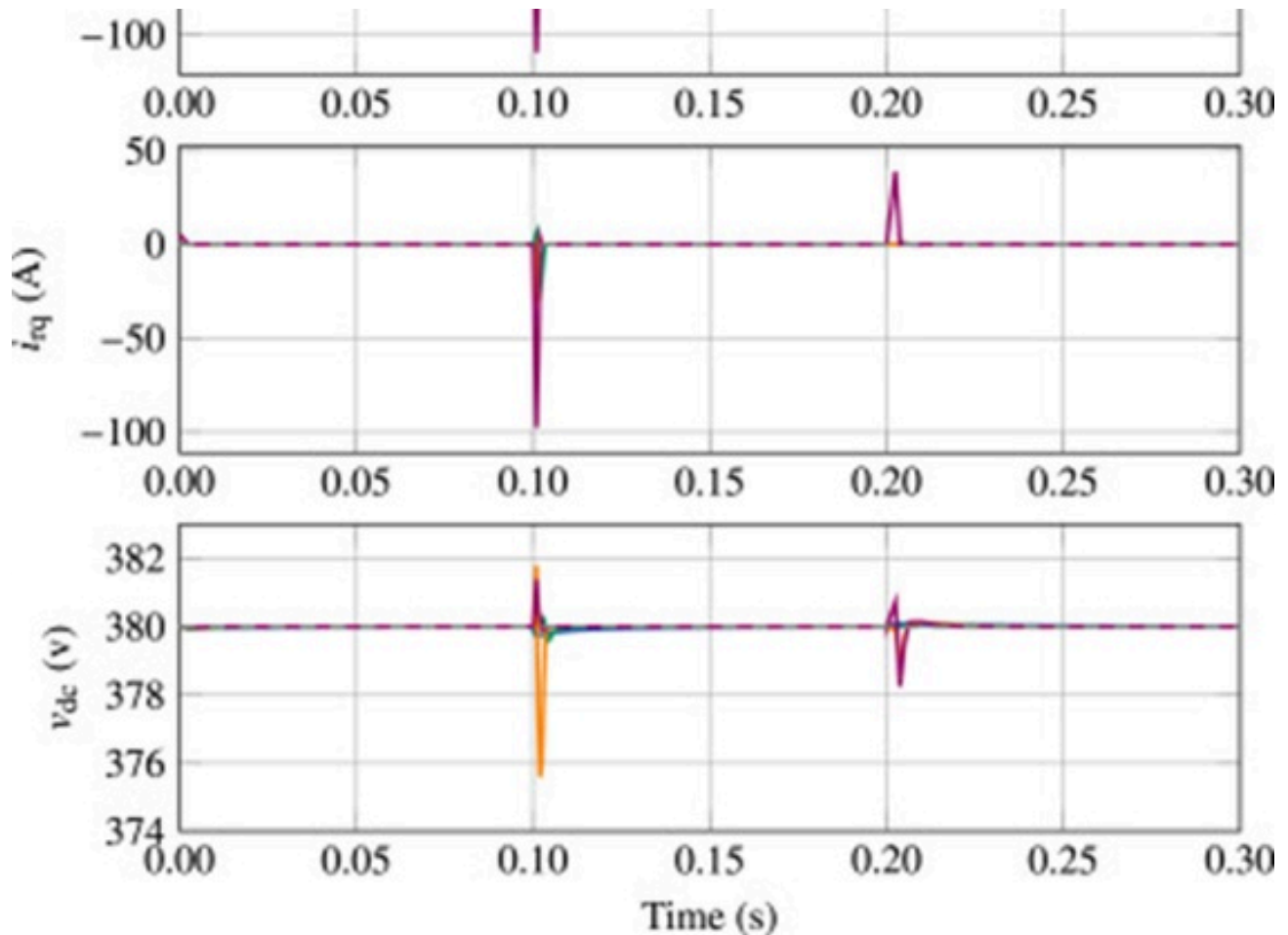
Furthermore, the weighting matrices Q and R are adjusted through iterative trial-and-error simulations to achieve the targeted reference tracking and desired dynamic waveforms for the state variables. The optimal tuning is reached when

$$Q = \text{diag} \left\{ Q_{x_{pmh}}, Q_{x_{wmh}}, Q_{x_{igd_h}}, Q_{x_{igq_h}}, Q_{x_{ird_h}}, Q_{x_{irg_h}}, Q_{x_{vdc_h}} \right\}. \quad (19)$$

MPC performance with CasADi

The proposed MPC strategy employs the CasADi framework to assess the feasibility and computational behavior of the optimization problem across various prediction horizons ($h = 1, 2, 3, 5$, and 7). **Figure 6** illustrates the closed-loop responses of the key state variables for the different prediction horizons.





- The behavior of the d-axis grid current i_{rd} closely resembles that of i_{gq} , with settling times of $ts_1 = 0.2 \mu s$, $ts_2 = 0.12 s$, and $ts_3 = 0.23 s$ for $h = 3, 5$, and 7 . The primary distinction lies in the overshoot magnitudes: i_{rd} exhibits smaller excursions (ranging from -100 at $t_{ch1} = 0.1 s$ to $+100$ at $t_{ch2} = 0.2 s$) compared with i_{gq} (ranging from -200 at $t_{ch1} = 0.1 s$ to $+200$ at $t_{ch2} = 0.2 s$).
- For the q-axis grid current i_{rq} , the controller achieves the references at $ts_1 = 0.1 \mu s$, $ts_2 = 0.11 s$, and $ts_3 = 0.21 s$ for horizons $h = 1, 3, 5$, and 7 . However, at $h = 7$, the signal displays a noticeably larger overshoot than at $h = 1, 3$, and 5 .
- Regarding the DC-link voltage v_{dc} , horizons $h = 3, 5$, and 7 produce settling times of $ts_1 = 0.1 \mu s$, $ts_2 = 0.11 s$, and $ts_3 = 0.21 s$. For $h = 1$ the settling times are $ts_1 = 0.1 \mu s$, $ts_2 = 0.13 s$, and $ts_3 = 0.21 s$. Longer horizons result in increased overshoot amplitudes, with the maximum overshoots occurring at $h = 5$ during the first change ($t_{ch1} = 0.1 s$) and at $h = 7$ during the second change ($t_{ch2} = 0.2 s$).

Overall, for settling times around $ts_1 = 0.02 s$, $ts_2 = 0.15 s$, and $ts_3 = 0.23 s$, stable operation of all state variables is achieved with prediction horizons $h = 3, 5$, and 7 . In contrast, when $h = 1$, the system stabilizes later, at approximately $ts_1 = 0.05 s$, $ts_2 = 0.17 s$, and $ts_3 = 0.27 s$, introducing a delay of roughly $0.03 s$ in settling time compared with the longer horizons. As the prediction horizon increases, the closed-loop response becomes more underdamped, producing larger overshoots while still converging to the desired references without loss of stability. The case $h = 1$ yields fewer oscillations and smaller overshoots. Moreover, the controller adjusts the electrical quantities (i_{gd} , i_{gq} , i_{rd} , i_{rq} , v_{dc}) more rapidly than the mechanical quantities (p_m and ω_m), demonstrating that the power converters proactively regulate the electrical variables to enable the turbine's mechanical states to follow their references effectively.

In addition, two critical implementation aspects must be evaluated when deploying MPC with CasADi: the optimization time (the duration required to solve the optimal control problem at each step) and the total simulation time (the cumulative time needed to discretize the model and perform all optimizations). For real-time applicability, both values must remain well below the controller’s sampling period to guarantee that a feasible solution is computed before the next measurement update.

Table 1 summarizes the optimization time (Top) and simulation time (Tsim) for the MPC controller across the different prediction horizons tested. The data clearly indicate that shorter prediction horizons result in substantially reduced optimization and simulation times. Consequently, selecting $h = 1$ provides the fastest execution, with $T_{op} = 0.3074$ s and $T_{sim} = 46.98$ s.

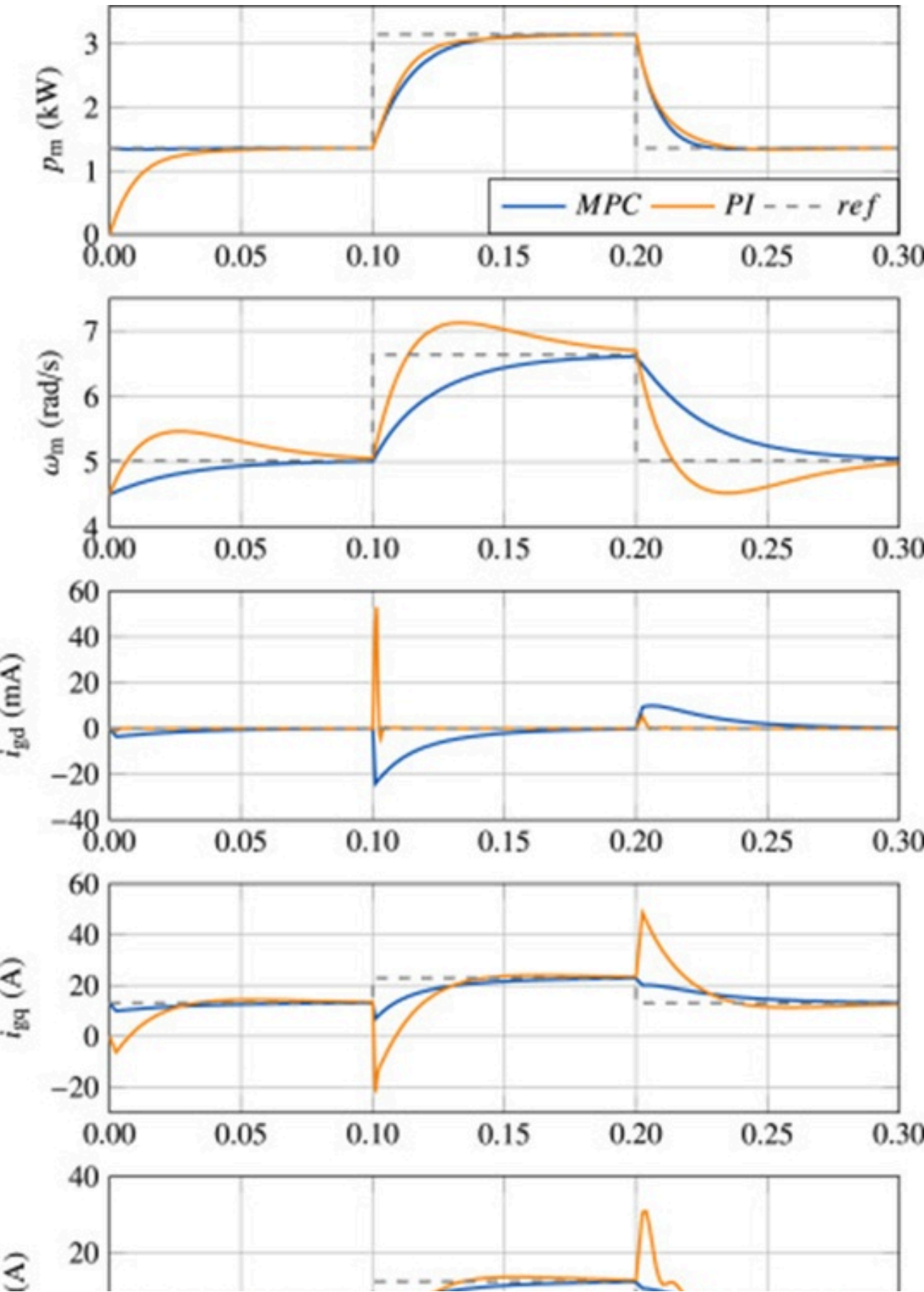
Table 1. MPC method performance for different prediction horizons.

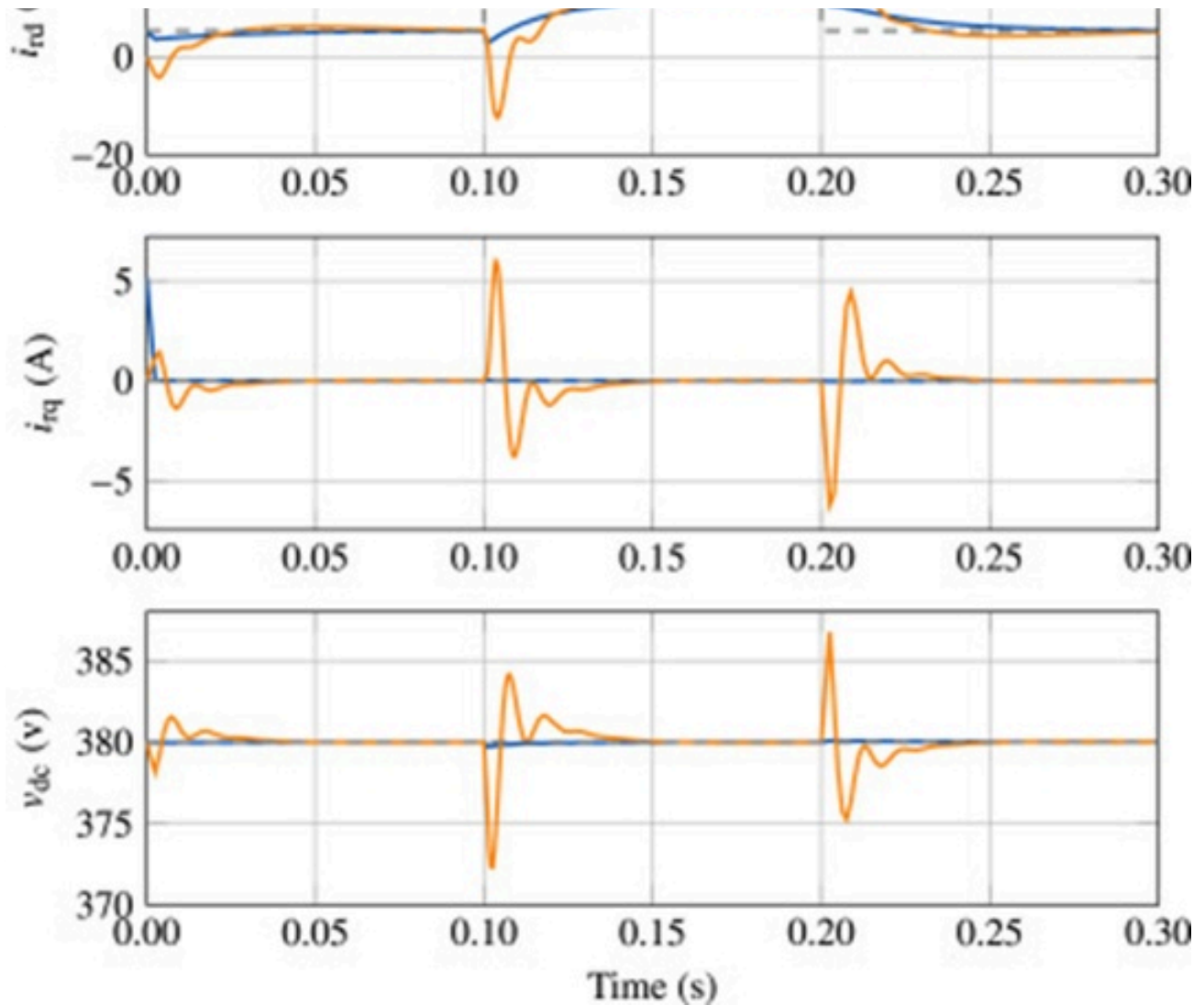
Prediction Horizon [steps]	MPC Optimization Time [s]	PI Simulation Time [s]	MPC Simulation Time [s]
1	0.3074	46.9791	32.1677
2	0.2344	63.4206	32.1677
3	0.3457	83.8509	32.1677
5	0.5247	116.5954	32.1677
7	0.7658	169.8734	32.1677

Furthermore, a side-by-side evaluation of computational demand—measured by total simulation duration—reveals that the MPC controller requires roughly 1.46 times the processing effort of its PI counterpart. The primary reason lies in the iterative solution of the finite-horizon optimal control problem inherent to MPC. At first glance, this higher resource consumption might suggest that MPC is less practical than the well-established PI technique. A detailed head-to-head performance analysis of both controllers is therefore presented in the following section to better assess the real-world merits of the MPC approach.

MPC method vs. conventional control

After establishing that the MPC strategy performs reliably across a range of prediction horizons in grid-tied operation, the focus now shifts to a comparative study between single-step MPC ($h = 1$) and classical PI control. The outcomes of this benchmark are displayed in **Figure 7**.





0.27 s. By contrast, the PI response is characterized by sustained oscillations before finally settling at $ts1_{PI} = 0.07$ s, $ts2_{PI} = 0.18$ s, and $ts3_{PI} = 0.28$ s. These traces highlight two clear MPC advantages: quicker convergence and complete suppression of the oscillatory ringing that plagues the PI controller. Overshoot amplitudes are likewise smaller under MPC, reinforcing its superior damping properties in this channel.

- For the q-axis grid current i_{rq} , the MPC controller achieves the reference value extremely rapidly under initial conditions, settling in $ts1_{MPC} = 0.01$ s. During the river velocity step changes applied at $t_{ch1} = 0.1$ s and $t_{ch2} = 0.2$ s, MPC tracks the new references virtually instantly, with settling times of $ts2_{MPC} = 0.1$ s and $ts3_{MPC} = 0.2$ s. By comparison, the PI controller settles at $ts1_{PI} = 0.04$ s, $ts2_{PI} = 0.15$ s, and $ts3_{PI} = 0.25$ s. These results clearly show that MPC reacts much more swiftly than PI and completely suppresses the oscillatory behavior PI exhibits as it approaches the setpoints. In terms of peak deviation, MPC outperforms PI by producing noticeable overshoots only during the startup phase and eliminating them during subsequent velocity disturbances.

- For the DC-link voltage v_{dc} , MPC converges to the steady-state references almost immediately in all scenarios: $ts1_{MPC} = 0.1$ μ s from initial conditions, $ts2_{MPC} = 0.1$ s after the first change, and $ts3_{MPC} = 0.2$ s after the second change. In stark contrast, the PI controller requires $ts1_{PI} = 0.04$ s, $ts2_{PI} = 0.15$ s, and $ts3_{PI} = 0.25$ s to reach the same targets. This highlights MPC's markedly faster response and its ability to avoid the persistent oscillations generated by the PI regulator during reference tracking. Moreover, MPC exhibits superior overshoot performance, generating virtually no peak

excursions under either initial conditions or during river-speed variations, whereas PI consistently produces noticeable overshoots.

Controller performance was further quantified using integral-based error metrics, specifically the Square Error Time Index (SETI) and the Absolute Error Time Index (AETI), defined as follows:

$$SETI = \int t_{sim} 0t'(\Delta x)^2 dt', AETI = \int t_{sim} 0t'|\Delta x| dt', \quad (20)$$

Where Δx represents the tracking error between each state variable x and its corresponding reference value.

Numerical evaluation of these indices reveals that, for the input currents ig_d and ir_d , the SETI values achieved by the MPC controller are 73.81×10^6 and 25.85×10^6 , respectively, compared with 383.48 and 113.41 for the PI controller. As summarized in **Table 2**, the SETI figures for MPC are dramatically lower than those for PI, demonstrating substantially more accurate reference tracking and a much smaller accumulated squared error over the simulation period. The AETI indices follow the same pattern, reinforcing MPC's clear advantage in minimizing overall tracking deviation.

Table 2. Performance indices comparison of MPC and PI controllers.

Metric	SETI (1×10 ⁶)	AETI (1×10 ⁶)
Control	igq	ird
MPC	73.81	25.85
PI	383.48	113.41
Metric	max{ts} (μs)	
Control	igq	
MPC	0.26	
PI	0.29	
Metric	max{%OS} (%)	
Control	igq	
MPC	−152.8	
PI	−352.3	

It should be emphasized that, for a fair comparison in this section, the MPC controller parameters (specifically the weighting matrices Q and R) were re-tuned for the single-step prediction horizon $h = 1$. This adjustment was essential to reduce the computational effort required during the optimization phase.

Conclusion

The present work introduced an advanced model predictive control (MPC) strategy tailored for maximum power point tracking (MPPT) of the hydrokinetic turbine and precise regulation of the output voltage in a grid-connected hydrokinetic turbine (HKT) system. A complete nonlinear model was developed encompassing the hydrokinetic turbine, permanent magnet synchronous generator (PMSG), AC/DC rectifier, and DC/AC inverter. The resulting nonlinear optimal control problem was formulated and solved efficiently with the CasADi optimization framework. Extensive simulations were conducted across multiple prediction horizons, and a detailed benchmark was performed against a classical proportional-

integral (PI) controller using key performance indicators, including settling time, overshoot magnitude, and integral error criteria such as ITSE and ITAE. The proposed MPC approach consistently outperformed the conventional PI method. The main findings of this investigation are summarized below:

- Incorporation of the full nonlinear dynamics of the integrated HKT system posed significant challenges during tuning of the MPC weighting matrices Q and R . The pronounced instability of the open-loop plant—driven primarily by the strong nonlinearity of the turbine characteristic (embodied in the C_p and P_m curves)—frequently caused the optimization problem to become infeasible under certain initial conditions or large river-velocity disturbances.
- The MPC controller delivered robust and satisfactory closed-loop performance across a range of prediction horizons. However, extending the horizon beyond one step did not yield meaningful improvement in either transient or steady-state behavior. Consequently, tuning the controller with a single-step prediction horizon ($h = 1$) proved sufficient to achieve effective and reliable system regulation.
- Longer prediction horizons provided negligible enhancement in overall control quality while substantially increasing the computational complexity and solution time of the optimization task. Adopting a horizon of one therefore represents the most practical choice, as it minimizes the real-time processing demand of the MPC implementation without sacrificing performance.
- The MPC strategy clearly surpassed the traditional PI controller in overall effectiveness. Regarding settling time, MPC exhibited substantially quicker convergence for the DC-link voltage v_{dc} and the q-axis grid current i_{rq} . In contrast, the performance gap was negligible for the remaining variables (p_m , ω_m , i_{gd} , i_{gq} , i_{rd}). In terms of overshoot and oscillation suppression, MPC achieved markedly lower peak deviations and damping of transient ringing across all state variables when compared with PI, demonstrating particularly strong robustness against river velocity variations for v_{dc} and i_{rq} . Quantitative evaluation using the SETI and AETI indices further confirmed MPC's superiority, as it consistently produced lower accumulated error values than PI for both the direct- and quadrature-axis currents (i_{dq} and i_{rd}), even in the presence of river speed disturbances.
- The electrical state variables displayed significantly faster dynamic behavior than their mechanical counterparts, which respond more slowly. The MPC controller successfully accommodated this disparity by simultaneously regulating both the fast electrical and the slower mechanical quantities within a unified multivariable framework.

Nomenclature

λ_{opt} : Optimal tip speed ratio

ω_e : Angular electrical frequency of the PMSG (rad/s)

ω_m : Mechanical angular frequency of turbine(rad/s)

ω_{m0} : Nominal angular frequency of turbine (rad/s)

ρ : Water density (kg/m³)

ξ : Damping coefficient of the shaft PMSG (Ns/m)

AETI: Absolute error time index

C : DC-link capacitor (F)

$c_i \in i=1, \dots, 6$: Turbine coefficients

C_p : Power coefficient

i_{gd} , i_{gq} : Current at stator terminals on dq-axes (A)

i_{rd} , i_{rq} : Inverter currents in the dq frame (A)

J : Total system inertia (kgm²)

L : Grid side inductance (H)

L_{sd} , L_{sq} : Inductances in the stator on the dq-axes (H)

m_{gd} , m_{gq} : Modulation indices of the converter in the dq frame

OS: Overshoot index (%)

P : Number of pole pairs

P_m : Mechanical power of the turbine (W)

Q_{ref} : Reference reactive power injected into the grid (VA)

r : Turbine radius (m)

r_s : Stator resistance (Ω)

r_r : Network side resistance (Ω)

SETI: Square error time index

T_e : Mechanical torque of the PMSG (Nm)

T_m : Electromechanical torque of the PMSG (Nm)

T_s : Settling time index (s)

v : River speed (m/s)

v_{nd} , v_{nq} : Grid voltage in the dq frame (V)

v_{dc} : Voltage at DC-link capacitor terminals (V)

v_{gd} , v_{gq} : Voltage at stator terminals of PMSG on dq-axes (V)

v_{rd} , v_{rq} : AC side voltage of the inverter VSC in the dq frame

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Conflict of interest

The authors declare the following financial interests/personal relationships, which may be considered potential competing interests: Jhon Ronald Terreros Barreto reports that financial support was provided by Diego Luis Córdoba Technological University of Chocó. Jhon Ronald Terreros Barreto reports that financial support was provided by the Colombian Ministry of Science, Technology, and Innovation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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