

## Article

# Generalized Predictive Control with Added Zeros and Poles in Its Augmented Model for Power Electronics Applications

Raymundo Cordero , Matheus Caramalac  and Wisam Ali 

Faculty of Engineering, Architecture and Urbanism and Geography, Federal University of Mato Grosso do Sul, Campo Grande 79070-900, Brazil; mattcaramalac@gmail.com (M.C.); wisamemhmd@gmail.com (W.A.)

\* Correspondence: raymundo.garcia@ufms.br

**Abstract:** Generalized predictive control (GPC) became one of the most popular and useful control strategies for academic and industry applications. An augmented model is applied to predict the future plant responses. This augmented model can be designed to embed the model of the plant reference, allowing its tracking by the controller according to the internal model principle (IMP). On the other hand, the performance of many controllers can be improved by adding zeros and poles in their structures (e.g., lead and lag compensators). However, according to the authors' research, adding arbitrary poles or zeros to the GPC augmented model has not been explored yet. This paper presents a simple methodology to add arbitrary zeros and poles in the GPC augmented model. A new augmented model state variable is defined. The control law of the proposed approach embeds zeros and poles when zero-pole cancellation is avoided. Simulation results (considering a LCL filter controlled by a single-phase inverter of 500 W and a polynomial reference tracking controller) and experimental tests (using a third-order linear plant controlled by a resonant controller) prove that the proposed approach improves the transient response of different kinds of predictive tracking controllers applied to control different plants (including power electronics applications), without affecting the steady-state tracking capabilities of the control systems.

**Keywords:** augmented model; generalized predictive control; poles; power electronics; zeros



**Citation:** Cordero, R.; Caramalac, M.; Ali, W. Generalized Predictive Control with Added Zeros and Poles in Its Augmented Model for Power Electronics Applications. *Energies* **2024**, *17*, 6037. <https://doi.org/10.3390/en17236037>

Academic Editor: Ahmed Abu-Siada

Received: 6 November 2024

Revised: 22 November 2024

Accepted: 28 November 2024

Published: 1 December 2024



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## 1. Introduction

Recently, predictive control has become a powerful tool in different applications, such as power systems [1–3], inverters/converters [4–7], motor drives [8–10], electric vehicles [11–13], photovoltaic systems [14,15], energy storage systems [16,17], uninterrupted power supplies [18,19], robotics [20,21], microgrids [22,23], and others [24,25]. Among the various types of existing predictive controllers, Generalized Predictive Control (GPC) is a popular control strategy due to its fast response, robustness, capability to consider restrictions, and simple mathematical structure [26,27]. GPC consists of the estimation of the future control actions that minimizes a cost function defined in terms of the plant future response. An augmented model is used in GPC to predict the plant response based on the state variables and a set of future control actions. The response to be predicted can include the plant output, the tracking error, or any useful signal to be controlled. The control performance in GPC is typically measured through a cost function that depends on the predicted response, the state variables, and the set of future actions. An optimization procedure allows the future control actions to minimize this cost function.

On the other hand, internal model principle (IMP) is commonly used to guarantee asymptotic tracking of a reference [28]. Let  $R$  be the model (e.g., Laplace or Z transform) of the reference. IMP states that, if the model of the controller or the plant embeds the reference model  $R$  without having a zero-pole cancellation problem, then the plant output will track the reference. For example, the Laplace transform of a step reference is  $R(s) = \frac{1}{s}$ ,

while the transfer function of a proportional-integral regulator is  $C(s) = k_p + \frac{k_i}{s} = \frac{k_p s + k_i}{s}$ . Observe that  $C(s) = (k_p s + k_i)R(s)$ . Therefore, if there is no zero-pole cancellation between the controller and the plant, a PI regulator can be used for the tracking of step references. IMP can also be applied to other time-varying references. Furthermore, IMP states that the closed-loop plant can reject a perturbation if the controller embeds the model of that perturbation. Augmented prediction models that embed the poles of polynomial and sinusoidal signals were proposed in the literature [29,30]. Predictive controllers can improve the response speed, the stability, and robustness of power electronics applications [31]. Hence, the development of new kinds of predictive controllers is necessary to improve the performance of power electronics devices.

The addition of lead and/or lag compensators can improve the transient and the steady-state response of the closed-loop control system [32–34]. For example, adding zeros and poles in repetitive controllers enhances the reference tracking and disturbance rejection of periodic exogenous signals [34]. Additionally, adding zeros to a resonant controller may improve the system stability [35]. Lead and lag compensators typically have a zero and a pole, and various techniques can be applied to define the parameters of lead and lag compensators (e.g., root locus, Bode diagram, etc.).

Usually, GPC augmented models can be designed to include the poles of the reference to be tracked or the perturbation to be rejected, as explained in [29,30]. These approaches describe methodologies to add poles to the augmented model, but do not describe how to arbitrarily add zeros to the augmented model. Hence, those approaches cannot be applied to add lead or lag compensators to a GPC control system. Similar to other control approaches, adding zeros in the GPC augmented model may improve the closed-loop control performance. However, according to the authors' research, no methodology to add arbitrary zeros (and poles) to the GPC augmented model was proposed in the literature.

This work describes a methodology to add arbitrary zeros and poles into an GPC augmented model to improve the closed-loop transient response by incorporating a lead or lag compensator into a GPC algorithm (previously defined to track a reference). A discrete-time space-state model of a lead/lag compensator with an arbitrary zero and pole was designed to be integrated with the augmented model of a GPC algorithm. Thus, a new augmented model that embed an arbitrary zero and pole is created. It is proved that both the proposed augmented model and the control law embed the desired zeros and poles, provided that zero-pole cancellation is avoided. The proposed approach can be applied together with strategies presented in [29,30] to track a required reference. The mathematical analysis was conducted considering Single Input Single Output (SISO) plants. Some important power electronics devices, such as buck converters and boost converters of LCL filters, can be modeled as SISO plants. The main contributions presented in this research are:

- The proposed methodology for designing the augmented model with arbitrary zeros and poles can be used in the development of new predictive controllers.
- The proposed approach adds zeros in the GPC control law, improving the transient response of the plant. According to the authors' research, this is the first time a method to add zeros to the GPC control law is proposed in the literature.
- The proposed approach can be applied to different plants or references.

The tuning of the GPC parameters is not straightforward. Different algorithms (e.g., genetic algorithms) were proposed to set the GPC parameters [36,37]. These techniques can be used to select the adequate zeros and poles to improve the transient response of the closed-loop system.

The remainder of the paper is organized as follows: Section 2 describes the mathematical structure of a generalized predictive control. The proposed approach, based on the addition of arbitrary zeros and poles into a GPC augmented model (considering that there is no zero-pole cancellation problem), is explained in Section 3. Simulations and experimental results, shown in Section 4, demonstrate that the proposed approach is able to

improve the transient response of control systems and can be applied in power electronics applications (e.g., resonant controllers). Finally, conclusions are outlined.

In this work,  $I_n$  denotes a  $n \times n$  identity matrix,  $O_n$  is a  $n \times 1$  vector composed of zeros, and  $Z\{\}$  denotes the Z-transform.

## 2. Theoretical Foundations

### 2.1. Generalized Predictive Control

A discrete-time Single-Input Single-Output (SISO) of a plant  $G_p[z]$  with order  $n$  can be represented as follows:

$$x_d[k+1] = A_d x_d[k] + B_d u_d[k], \quad (1)$$

$$y[k] = C_d x_d[k], \quad (2)$$

where  $A_d$ ,  $B_d$ , and  $C_d$  are  $n \times n$ ,  $n \times 1$ , and  $1 \times n$  matrices, respectively, while  $x_d[k]$ ,  $u_d[k]$ , and  $y[k]$  are the state vector, the input, and the output of the plant, respectively. Equation (3) describes the discrete-time transfer function of the plant  $G_p[z]$ :

$$G_p(z) = C_d(zI_n - A_d)^{-1}B_d. \quad (3)$$

Let  $r(k)$  be the discrete reference with Z-transform  $R(z)$ :

$$Z\{r[k]\} = R(z) = \frac{N(z)}{D(z)}, \quad (4)$$

where  $N(z)$  and  $D(z)$  are coprime (they do not have common roots). Equation (5) defines the tracking error  $e[k]$ :

$$\begin{aligned} e[k] &= r[k] - y[k] \\ &= r[k] - Cx[k]. \end{aligned} \quad (5)$$

A space-state augmented model, with order  $w$ , is usually applied in GPC to estimate the plant response:

$$\underline{x}[k+1] = \underline{A}\underline{x}[k] + \underline{B}\underline{u}[k], \quad (6)$$

$$\underline{y}[k] = \underline{C}\underline{x}[k], \quad (7)$$

where  $\underline{x}[k]$  is the  $w \times 1$  augmented model state vector,  $\underline{y}[k]$  is the desired response to be predicted, and  $\underline{u}[k]$  is the augmented model control action whose future values defines the future responses. The matrices  $\underline{A}$ ,  $\underline{B}$ , and  $\underline{C}$  have dimensions of  $w \times w$ ,  $w \times 1$ , and  $1 \times w$ , respectively, and depend on  $A_d$ ,  $B_d$ , and  $C_d$ . Table 1 shows the signals and matrices of the augmented model for the polynomial and sinusoidal tracking predictive controllers proposed in [29,30], where  $\gamma$  is defined in (A4).

Let us define  $Y$  and  $U$  as the vector of the future responses ( $y[k+1]$ ,  $y[k+2]$ , ...,  $y[k+n_p]$ ) and the vector of future control actions ( $u[k]$ ,  $u[k+1]$ , ...,  $u[k+n_c-1]$ ), respectively:

$$Y = \begin{bmatrix} y[k+1] & y[k+2] & \dots & y[k+n_p] \end{bmatrix}^T, \quad (8)$$

$$U = \begin{bmatrix} u[k] & u[k+1] & \dots & u[k+n_c-1] \end{bmatrix}^T, \quad (9)$$

where  $n_p$  and  $n_c$  are, respectively, the sizes of the prediction and control windows, with  $n_c \leq n_p$ . The vector of predicted responses can be estimated as follows [38]:

$$Y = F\underline{x}[k] + \Phi U, \quad (10)$$

where

$$F = \begin{bmatrix} \underline{\mathcal{C}}\underline{\mathcal{A}} \\ \underline{\mathcal{C}}\underline{\mathcal{A}}^2 \\ \underline{\mathcal{C}}\underline{\mathcal{A}}^3 \\ \vdots \\ \underline{\mathcal{C}}\underline{\mathcal{A}}^{n_p} \end{bmatrix}, \quad (11)$$

$$\Phi = \begin{bmatrix} \underline{\mathcal{C}}\underline{\mathcal{B}} & 0 & 0 & \dots & 0 \\ \underline{\mathcal{C}}\underline{\mathcal{A}}\underline{\mathcal{B}} & \underline{\mathcal{C}}\underline{\mathcal{B}} & 0 & \dots & 0 \\ \underline{\mathcal{C}}\underline{\mathcal{A}}^2\underline{\mathcal{B}} & \underline{\mathcal{C}}\underline{\mathcal{A}}\underline{\mathcal{B}} & \underline{\mathcal{C}}\underline{\mathcal{B}} & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \underline{\mathcal{C}}\underline{\mathcal{A}}^{n_p-1}\underline{\mathcal{B}} & \underline{\mathcal{C}}\underline{\mathcal{A}}^{n_p-2}\underline{\mathcal{B}} & \underline{\mathcal{C}}\underline{\mathcal{A}}^{n_p-3}\underline{\mathcal{B}} & \dots & \underline{\mathcal{C}}\underline{\mathcal{A}}^{n_p-n_c}\underline{\mathcal{B}} \end{bmatrix}. \quad (12)$$

**Table 1.** Matrices of an augmented model used in GPC.

| Matrix             | GPC for Polynomial Reference Tracking                                                                                                                                                                       | GPC for Sinusoidal Reference Tracking                                                                                     |
|--------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------|
| $\underline{x}[k]$ | $\begin{bmatrix} e(k) \\ \nabla^1 e(k) \\ \vdots \\ \nabla^{m-1} e(k) \\ x[k] \\ \nabla^m u_d[k] \end{bmatrix}$                                                                                             | $\begin{bmatrix} x[k-3] - \gamma x[k-2] + \gamma x[k-1] - x[k] \\ e[k-2] \\ e[k-1] \\ e[k] \end{bmatrix}$                 |
| $\underline{u}[k]$ | $u_d[k]$                                                                                                                                                                                                    | $u_d[k-3] - \gamma u_d[k-2] + \gamma u_d[k-1] - u_d[k]$                                                                   |
| $\underline{y}[k]$ | $e[k]$                                                                                                                                                                                                      | $e[k]$                                                                                                                    |
| $\underline{A}$    | $\begin{bmatrix} 1 & 1 & \dots & 1 & -C_d A_d \\ 0 & 1 & \dots & 1 & -C_d A_d \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & -C_d A_d \\ O_n & O_n & \dots & O_n & A_d \end{bmatrix}$ | $\begin{bmatrix} A_d & O_n & O_n & O_n \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ C_d A_d & 1 & -\gamma & \gamma \end{bmatrix}$ |
| $\underline{B}$    | $\begin{bmatrix} -C_d B_d \\ -C_d B_d \\ \vdots \\ -C_d B_d \\ B_d \end{bmatrix}$                                                                                                                           | $\begin{bmatrix} B_d \\ 0 \\ 0 \\ C_d B_d \end{bmatrix}$                                                                  |
| $\underline{C}$    | $[1 \quad O_{m-1}^T \quad O_n^T]$                                                                                                                                                                           | $[O_n^T \quad 0 \quad 0 \quad 1]$                                                                                         |

The definition of  $\gamma$  and the operator  $\nabla$  are explained in the Appendix A.

It will be assumed, from now on, that the response to be predicted in GPC is the tracking error, i.e.,  $y[k] = e[k]$ . The cost function in (13) is used to evaluate the performance of the predictive controller based on the future errors  $e[k+1]$ ,  $e[k+2]$ , ...,  $e[k+n_p]$ :

$$J = Y^T Y + U^T R_w U, \quad R_w = r_w I_c, \quad (13)$$

where  $I_c$  is an  $n_c \times n_c$  identity matrix, while  $r_w$  is a tuning parameter—the greater the value of  $r_w$ , the more important is the minimization of the magnitude of  $U$  in the solution. The optimal solution  $U_{op}$  for  $J$  makes  $\frac{\partial J}{\partial U} = 0$ . Substituting (10) into (13), and after some mathematical manipulations, the optimal solution of  $J$  is [38]:

$$U_{op} = -(\Phi^T \Phi + R_w)^{-1} \Phi^T F \underline{x}[k]. \quad (14)$$

The receding horizon control strategy states that only the first element of  $U_{op}$  in (14), i.e.,  $\underline{u}[k]$ , is used to calculate the plant input (control law). Therefore, according to (14):

$$\begin{aligned}\underline{u}[k] &= \underbrace{[1 \ 0 \ \dots \ 0]}_{N_c \text{ elements}} U_{op} \\ &= \underbrace{-[1 \ 0 \ \dots \ 0](\Phi^T \Phi + R_w)^{-1} \Phi^T F}_{K_r} \underline{x}[k],\end{aligned}\quad (15)$$

The plant input  $u[k]$  can be obtained from (15) and the definition of  $\underline{u}[k]$  in the augmented model. For example, (16) defines the plant input for sinusoidal reference tracking used in [29]:

$$u_d[k] = u_d[k-3] - \gamma u_d[k-2] + \gamma u_d[k-1] - \underline{u}[k]. \quad (16)$$

## 2.2. Augmented Model and Internal Model Principle

Let  $R(z)$  be the Z-transform of the reference, while  $G(z)$  and  $C(z)$  are the transfer functions of the plant and the controller, respectively. The internal model principle (IMP) states that, if the  $G(z)C(z)$  embeds the poles of  $R(z)$ , then the output will asymptotically track the reference [28].

IMP can be used to analyze the tracking capability of a predictive controller based on space-state augmented model. The transfer function of the augmented model in (6) and (7) is  $G_m(z)$ :

$$G_m(z) = \underline{C}(zI_w - \underline{A})^{-1} \underline{B}, \quad (17)$$

where  $I_w$  is an identity matrix with the same size of  $\underline{A}$ . It is proved in [29,30] that:

$$G_m(z) = M(z)R(z)G_p(z), \quad (18)$$

where it is assumed that there is no zero-pole cancellation between  $M(z)$ ,  $R(z)$ , and  $G_p(z)$ . Equation (18) states that the augmented model contains the poles of the reference  $R(z)$ . Thus, the GPC based on that augmented model will track the reference.

## 2.3. Lead and Lag Compensator

The continuous-time lead and lag compensator have the following structure:

$$C(s) = k_0 \frac{s - s_z}{s - s_p}, \quad (19)$$

where  $k_0$  is a gain and  $s_z$  and  $s_p$  are the zero and the pole of the compensator, respectively. In a lag compensator  $|s_p| < |s_z|$ , while  $|s_z| < |s_p|$  in a lead compensator. The lead compensator can be used to improve the transient response, while the lag compensator, is usually applied to improve the steady-state response. Applying discretization techniques (e.g., Euler discretization) to (19), this compensator can be discretized as follows:

$$C(z) = k_1 \frac{z - z_0}{z - p_0}. \quad (20)$$

## 3. Proposed GPC with Arbitrary Zero and Pole in Its Augmented Model

### 3.1. Proposed Augmented Model and Control Law

Let  $C(z) = \frac{z - z_0}{z - p_0}$  be a first-order compensator, similarly to (20), being  $k_1 = 1$ , with input  $v[k]$  and output  $y_d[k]$ . This compensator can be expressed through the following space-state model:

$$g[k+1] = p_0 g[k] + (p_0 - z_0)v[k], \quad (21)$$

$$y_c[k] = 1g[k] + 1v[k]. \quad (22)$$

This paper proposes integrating the augmented model in (6) and (7) with the space-state model in (21) and (22). Making  $y_c[k] = \underline{u}[k]$  in (22) yields:

$$\underline{u}[k] = g[k] + v[k]. \quad (23)$$

Replacing (23) into (6) yields:

$$\begin{aligned} \underline{x}[k+1] &= \underline{A}x[k] + \underline{B}(g[k] + v[k]) \\ &= [\underline{A} \quad \underline{B}] \begin{bmatrix} x[k] \\ g[k] \end{bmatrix} + \underline{B}v[k]. \end{aligned} \quad (24)$$

Furthermore, (21) can be rewritten as follows:

$$g[k+1] = [O_w^T \quad p_0] \begin{bmatrix} x[k] \\ g[k] \end{bmatrix} + (p_0 - z_0)v[k], \quad (25)$$

where  $O_w$  is a  $w \times 1$  vector of zeros, with  $\underline{A}$  being a  $w \times w$  matrix. A new augmented model can be created by integrating (7), (24), and (25):

$$\underbrace{\begin{bmatrix} x[k+1] \\ g[k+1] \end{bmatrix}}_{\chi[k+1]} = \underbrace{\begin{bmatrix} \underline{A} & \underline{B} \\ O_w^T & p_0 \end{bmatrix}}_{\hat{A}} \underbrace{\begin{bmatrix} x[k] \\ g[k] \end{bmatrix}}_{\chi[k]} + \underbrace{\begin{bmatrix} \underline{B} \\ p_0 - z_0 \end{bmatrix}}_{\hat{B}} v[k] \quad (26)$$

$$\text{Output: } \underline{y}[k] = \underbrace{\begin{bmatrix} \underline{C} & 0 \end{bmatrix}}_{\hat{C}} \underbrace{\begin{bmatrix} x[k] \\ g[k] \end{bmatrix}}_{\chi[k]}, \quad (27)$$

where  $\chi[k]$  is the new augmented model state vector, while  $\hat{A}$ ,  $\hat{B}$ , and  $\hat{C}$  are the new augmented model matrices. Observe that the output of the proposed augmented model in (27) is equal to the original output in (7). Considering that the tracking error is the desired plant response to be predicted ( $\underline{y}[k] = e[k]$ ), similarly to (10), the vector  $E$  with the future errors can be predicted as follows:

$$E = F_0\chi[k] + \Phi_0V, \quad (28)$$

where

$$E = [e[k+1] \quad e[k+2] \quad \dots \quad e[k+n_p]]^T, \quad (29)$$

$$V = [v[k] \quad v[k+1] \quad \dots \quad v[k+n_c-1]]^T, \quad (30)$$

$$F_0 = \begin{bmatrix} \hat{C}\hat{A} \\ \hat{C}\hat{A}^2 \\ \hat{C}\hat{A}^3 \\ \vdots \\ \hat{C}\hat{A}^{n_p} \end{bmatrix}, \quad (31)$$

$$\Phi_0 = \begin{bmatrix} \hat{C}\hat{B} & 0 & 0 & \dots & 0 \\ \hat{C}\hat{A}\hat{B} & \hat{C}\hat{B} & 0 & \dots & 0 \\ \hat{C}\hat{A}^2\hat{B} & \hat{C}\hat{A}\hat{B} & \hat{C}\hat{B} & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \hat{C}\hat{A}^{n_p-1}\hat{B} & \hat{C}\hat{A}^{n_p-2}\hat{B} & \hat{C}\hat{A}^{n_p-3}\hat{B} & \dots & \hat{C}\hat{A}^{n_p-n_c}\hat{B} \end{bmatrix}. \quad (32)$$

Replacing  $\underline{x}[k]$ ,  $Y$ ,  $U$ ,  $F$ , and  $\Phi$  by  $\chi[k]$ ,  $E$ ,  $V$ ,  $F_0$ , and  $\Phi_0$ , respectively, into (13)–(15) yields:

$$J = E^T E + V^T R_w V, \quad (33)$$

$$V_{op} = K_{zp} \chi[k], \quad K_{zp} = -(\Phi_0^T \Phi_0 + R_w)^{-1} \Phi_0^T F_0, \quad (34)$$

$$v_{op}[k] = [1 \ 0 \ \dots \ 0] V_{op}. \quad (35)$$

Equation (34) indicates the value of the future control actions that minimize the cost function in (33), while  $v_{op}[k]$  (35) is the first element of that optimized solution (based on receding horizon method).

The proposed solution  $v_{op}[k]$  defined in (35) is used in (21) and (23) to get the plant input (the control law):

$$g[k+1] = p_0 g[k] + (p_0 - z_0) v_{op}[k], \quad (36)$$

$$\underline{u}[k] = g[k] + v_{op}[k]. \quad (37)$$

To implement (36), it is possible to consider that  $g[0] = 0$  (null initial condition). The input plant  $u[k]$  is deduced from (37) and the definition of  $\underline{u}[k]$  (for example, see (16)).

### 3.2. Analysis of the Proposed Augmented Model

The discrete transfer function of the proposed augmented model in (26) and (27) is:

$$G_a(z) = \hat{C}(zI_h - \hat{A})^{-1} \hat{B}, \quad (38)$$

where  $I_h$  is a identity matrix which has the same size of  $\hat{A}$ . Using block matrix algebra and the definitions of  $\hat{A}$ ,  $\hat{B}$ , and  $\hat{C}$ ,  $G_p(z)$  can be expressed as follows:

$$\begin{aligned} G_a(z) &= [\underline{C} \ 0] \left( z \begin{bmatrix} I_w & 0 \\ O_w^T & 1 \end{bmatrix} - \begin{bmatrix} \underline{A} & \underline{B} \\ O_w^T & p_0 \end{bmatrix} \right)^{-1} \begin{bmatrix} \underline{B} \\ p_0 - z_0 \end{bmatrix} \\ &= [\underline{C} \ 0] \begin{bmatrix} zI_w - \underline{A} & -\underline{B} \\ O_w^T & z - p_0 \end{bmatrix}^{-1} \begin{bmatrix} \underline{B} \\ p_0 - z_0 \end{bmatrix}. \end{aligned} \quad (39)$$

Let  $\Gamma = \begin{bmatrix} M & N \\ O & T \end{bmatrix}$ , where  $M$  and  $T$  are square, nonsingular matrices and  $O$  is a matrix composed of zeros with adequate dimensions. Block matrix algebra states that  $\Gamma^{-1} = \begin{bmatrix} M^{-1} & -M^{-1}NT^{-1} \\ O & T^{-1} \end{bmatrix}$  [39]. Applying this property into (39) yields:

$$\begin{aligned} G_a(z) &= [\underline{C} \ 0] \begin{bmatrix} (zI_w - \underline{A})^{-1} & (zI_w - \underline{A})^{-1} \underline{B} (z - p_0)^{-1} \\ O_w^T & (z - p_0)^{-1} \end{bmatrix} \begin{bmatrix} \underline{B} \\ p_0 - z_0 \end{bmatrix} \\ &= [\underline{C} (zI_w - \underline{A})^{-1} \quad \underline{C} (zI_w - \underline{A})^{-1} \underline{B} (z - p_0)^{-1}] \begin{bmatrix} \underline{B} \\ p_0 - z_0 \end{bmatrix} \\ &= \underline{C} (zI_w - \underline{A})^{-1} \underline{B} + \underline{C} (zI_w - \underline{A})^{-1} \underline{B} \frac{p_0 - z_0}{z - p_0} \\ &= \underline{C} (zI_w - \underline{A})^{-1} \underline{B} \left( 1 + \frac{p_0 - z_0}{z - p_0} \right) \\ &= \underline{C} (zI_w - \underline{A})^{-1} \underline{B} \left( \frac{z - z_0}{z - p_0} \right). \end{aligned} \quad (40)$$

Replacing (17) and (18) into (40) yields:

$$G_a(z) = M(z) R(z) G_p(z) \frac{z - z_0}{z - p_0}. \quad (41)$$

On the other hand, the transfer function between  $\underline{u}[k]$  and  $v_{op}[k]$  can be obtained through the application of Z-transform into (36) and (37):

$$\frac{Z\{\underline{u}[k]\}}{Z\{v_{op}[k]\}} = \frac{z - z_0}{z - p_0}. \quad (42)$$

Using (42), the transfer function between the plant input  $u[k]$  and the GPC control action  $v_{op}[k]$  can be expressed as follows:

$$\frac{Z\{u_d[k]\}}{Z\{v_{op}[k]\}} = \left( \frac{Z\{u_d[k]\}}{Z\{\underline{u}[k]\}} \right) \left( \frac{Z\{\underline{u}[k]\}}{Z\{v_{op}[k]\}} \right) = \frac{Z\{u_d[k]\}}{Z\{\underline{u}[k]\}} \left( \frac{z - z_0}{z - p_0} \right). \quad (43)$$

In [29,30], it is proved that the GPC augmented model can be designed for the transfer function  $\frac{Z\{u[k]\}}{Z\{\underline{u}[k]\}}$  to embed the Z-transform of the reference. Therefore, the proposed controller satisfy the IMP and also embeds the pole  $p_0$  and the zero  $z_0$ .

Equation (41) shows that the proposed augmented model embeds the poles of the reference  $r[k]$ , the plant transfer function  $G_p(z)$ , a pole in  $z = p_0$ , and a zero in  $z = z_0$ . Furthermore, Equation (43) proves that the control law embeds the desired zeros/poles and the model of the reference. As a result, the control law will have the advantages of using a lead or lag compensator. To avoid a zero-pole cancellation problem,  $z_0$  must be different to the poles of  $M(z)$ ,  $R(z)$ , and  $G_p(z)$ , while  $p_0$  must be different to the zeros of the aforementioned transfer functions. If those requirements are satisfied, the proposed approach can be used together with the augmented models of the polynomial or the sinusoidal tracking control systems defined in Table 1.

#### 4. Results

In order to test the advantages of the proposed approach, simulations and experimental tests were performed:

- Simulation tests: control of the output current of a LCL filter connected to a grid. This application is useful to connect photovoltaic systems to a grid.
- Experimental tests: application of a GPC-based resonant controller to control a third-order plant.

##### 4.1. Simulation Tests

Simulations were performed in MATLAB R2016a. An LCL filter used to connect a single-phase inverter (maximum power of 500 W) to a grid was used as a plant to perform tests. The filter is modeled through the transfer function  $G(s) = \frac{3.436 \times 10^{12}}{s^3 + 5.488 \times 10^9 s}$ , as indicated in [40], which was discretized considering  $t_s = 5 \times 10^{-5}$  s, with the inverter switching frequency being  $f_{sw} = 20$  kHz. Thus, the discrete model of the LCL filter is represented by (1) and (2), being:

$$A_d = \begin{bmatrix} 0.8879 & 0.1121 & 0.0048 \\ 1.7338 & -0.7338 & -0.0742 \\ -3.5992 & 3.5992 & -0.8460 \end{bmatrix}, \quad B_d = \begin{bmatrix} 0.0310 \\ 0.0358 \\ 0.1121 \end{bmatrix}, \quad x_d[k] = \begin{bmatrix} x_1[k] \\ x_2[k] \\ x_3[k] \end{bmatrix}, \quad C_d = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix}, \quad (44)$$

where  $x_1[k]$ ,  $x_2[k]$ , and  $x_3[k]$  are the current in the input inductance, the current in the output inductance (the filter output current) and the capacitor voltage of the filter, respectively. Thus, the plant output to be controlled is the output current  $y[k] = C_d x_d[k] = x_2[k]$ .

The polynomial reference tracking predictive controller (named as Poly-GPC) described in [40] was used as the main technique to control the output current of the LCL filter. Its parameters are  $n_p = 70$ ,  $n_c = 2$ ,  $r_w = 0.001$ . The proposed methodology was applied to add three different sets of zeros and poles to the augmented model of the aforementioned controller. Thus, three different configurations were created:

- Configuration 1:  $n_p = 70$ ,  $n_c = 2$ ,  $r_w = 0.001$ ,  $p_0 = 0.00001$ ,  $z_0 = 0.55$ ;
- Configuration 2:  $n_p = 70$ ,  $n_c = 2$ ,  $r_w = 0.001$ ,  $p_0 = 0.0$ ,  $z_0 = 0.4$ ;
- Configuration 3:  $n_p = 70$ ,  $n_c = 2$ ,  $r_w = 0.001$ ,  $p_0 = 0.001$ ,  $z_0 = 0.05$ .

Figure 1 shows the filter current reference and the tracking error for the proposal in [40], while Figures 2–4 show the results for the three different configurations of the proposed predictive controller. In each test, the reference, which frequency equals to 60 Hz, is composed of two sectors:

- Sector 1: from 0 s to 1 s.
- Sector 2: from 1 s to 2 s.

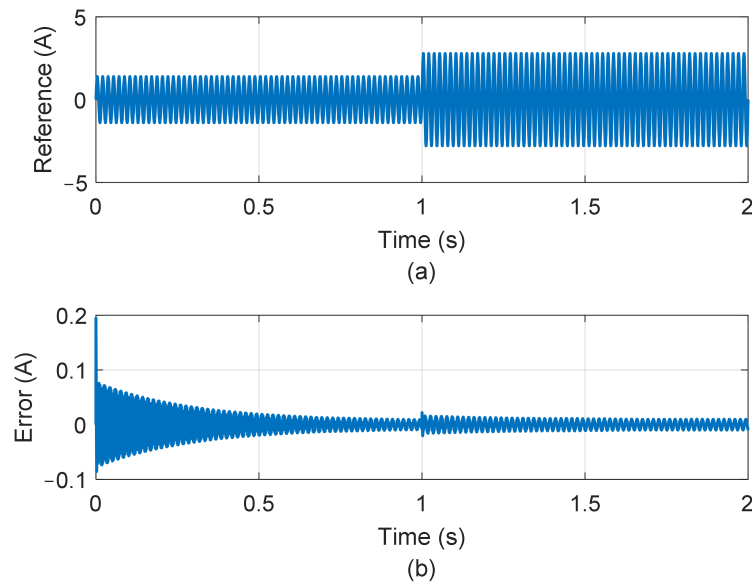


**Figure 1.** Simulation results for Poly-GPC strategy in [40]: (a) current reference of the LCL filter output current and (b) tracking error.

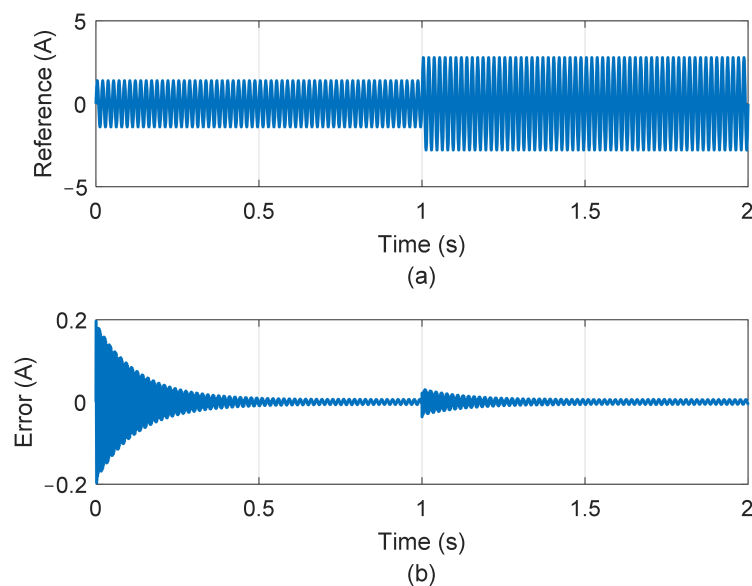


**Figure 2.** Simulation results for configuration 1 of the proposed controller: (a) current reference of the LCL filter output current and (b) tracking error.

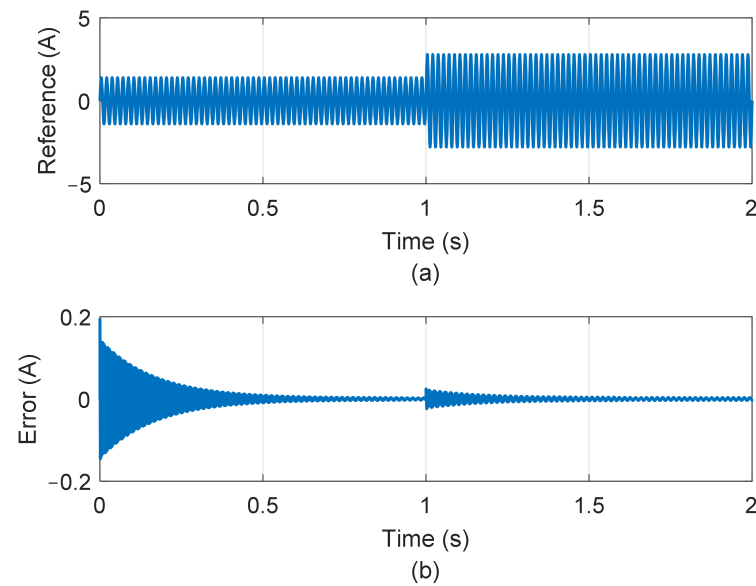


**Figure 3.** Simulation results for configuration 2 of the proposed controller: (a) current reference of the LCL filter output current and (b) tracking error.

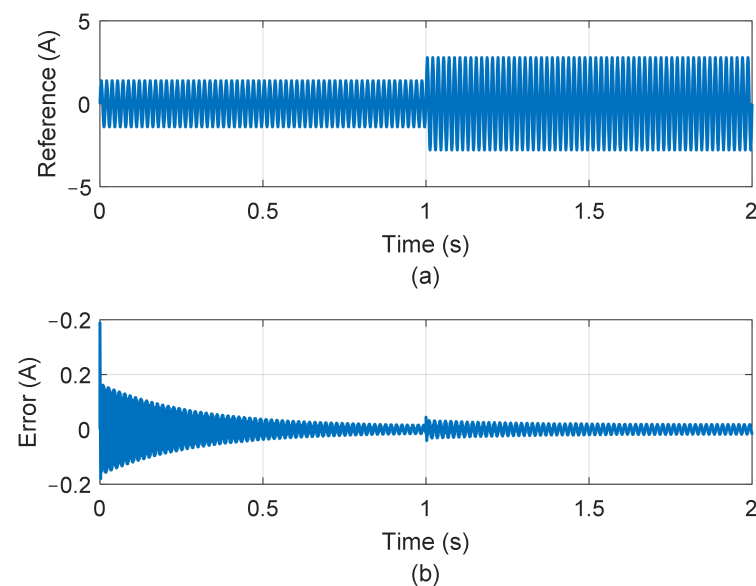


**Figure 4.** Simulation results for configuration 3 of the proposed controller: (a) current reference of the LCL filter output current and (b) tracking error.

Table 2 shows the root mean square error in steady-state conditions (RMSE-ss) of the tracking error and the settling time for each configuration and reference sector. This table indicates the following results:

- First sector: the addition of zeros and poles reduces the steady-state error ripple and settling time, improving the accuracy of the LCL filter control. The errors oscillations for configurations 1 and 2 in the first sector of the reference have a greater amplitude than the error for the PolyGPC in [40] and configuration 3. However, the value of RMSE-ss for configuration 3 is higher than the other two configurations.
- Second sector: the settling time for all tests are similar. However, the steady-state RMSE-ss for the proposed approach is always lower than the RMSE-ss for the conventional Poly-GPC.

The addition the zeros and poles in the augmented model reduced the RMSE-ss. In general, configuration 3 had better performance than the approach in [40]. The dynamic of

the proposed controller depends on the values of  $z_0$  and  $p_0$  (and the GPC parameters). The selection of the values of  $p_0$  and  $z_0$  are as difficult as the setting of  $n_p$ ,  $n_c$ , and  $r_w$ . A genetic algorithm could be used to select those parameters [36].

**Table 2.** RMSE and settling time obtained in the simulation tests, for each reference sector.

| Test             | RMSE-ss<br>Sector 1 (A) | Settling Time<br>Sector 1 (s) | RMSE-ss<br>Sector 2 (A) | Settling Time<br>Sector 2 (s) |
|------------------|-------------------------|-------------------------------|-------------------------|-------------------------------|
| Poly-GPC in [40] | 0.0071                  | 0.80                          | 0.0071                  | 0.21                          |
| Proposed-conf. 1 | 0.0044                  | 0.50                          | 0.0041                  | 0.25                          |
| Proposed-conf. 2 | 0.0027                  | 0.65                          | 0.0025                  | 0.27                          |
| Proposed-conf. 3 | 0.0063                  | 0.60                          | 0.0064                  | 0.25                          |

The voltage drop in the LCL filter was the same in all simulation tests: 4.8 V and 4.6 V for the Sectors 1 and 2 of the reference, respectively.

Table 3 shows the active and reactive power obtained in the simulation tests. The active power in each test is practically equal. However, the reactive power (which, in an ideal case, should be zero, allowing the system to operate with unitary power factor and transfer the maximum active power to the grid) is lower for the proposed approach, especially for the configuration 1. As a result, the proposed controller allows operating with higher power factor.

On the other hand, Table 4 shows the total harmonic distortion (THD) of the filter voltage and currents (the state variables of the filter model), where  $x_1[k]$ ,  $x_2[k]$ , and  $x_3[k]$  are the current in the input inductance, the current in the output inductance (the filter output current) and the capacitor voltage of the filter, respectively. The THD for the three configurations of the proposed approach were practically equals. Observe that the THD of the filter output current ( $x_2[k]$ ) for the proposed approach is lower than the THD obtained without using arbitrary zeros and poles.

**Table 3.** Active and reactive output power in the simulation tests, for each reference sector.

| Test             | Active Power<br>Sector 1 (W) | Active Power<br>Sector 2 (VAR) | Reactive Power<br>Sector 1 (W) | Reactive Power<br>Sector 2 (VAR) |
|------------------|------------------------------|--------------------------------|--------------------------------|----------------------------------|
| Poly-GPC in [40] | 125.56                       | 250.92                         | −0.20                          | −0.43                            |
| Proposed-conf. 1 | 125.62                       | 250.93                         | −0.11                          | −0.09                            |
| Proposed-conf. 2 | 125.40                       | 250.79                         | 0.16                           | 0.17                             |
| Proposed-conf. 3 | 125.58                       | 251.05                         | −0.14                          | −0.37                            |

**Table 4.** THD of the filter voltages and current in the simulation tests, for each reference sector.

| Test                 | $x_1[k]$<br>Sector 1 | $x_1[k]$<br>Sector 2 | $x_2[k]$<br>Sector 1 | $x_2[k]$<br>Sector 2 | $x_3[k]$<br>Sector 1 | $x_3[k]$<br>Sector 2 |
|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Poly-GPC in [40]     | 20%                  | 10%                  | 2.30%                | 1.10%                | 0.35%                | 0.34%                |
| Proposed (all cases) | 20%                  | 10%                  | 1.80%                | 0.90%                | 0.34%                | 0.34%                |

Note:  $x_1[k]$ : filter input current,  $x_2[k]$ : filter output current,  $x_3[k]$ : filter capacitor voltage.

#### 4.2. Experimental Results

The proposed methodology to add zeros and poles to a GPC system was used to create a resonant controller capable to control the output of a plant with transfer function  $G(s) = \frac{1.418 \times 10^6 s + 3.637 \times 10^8}{s^3 + 2179s^2 + 2.273 \times 10^6 s + 7.274 \times 10^8}$ . This plant can be discretized and represented through the discrete-time plant in (1) and (2), considering:

$$A_d = \begin{bmatrix} 0.413 & 0.454 & 0 \\ -0.240 & 0.788 & 0 \\ -0.437 & 0.422 & 0.774 \end{bmatrix}, \quad B_d = \begin{bmatrix} 0.1331 \\ 0.4528 \\ 0.1273 \end{bmatrix}, \quad C_d = [0 \ 0 \ 1], \quad t_s = 0.5 \text{ ms}. \quad (45)$$

The proposed approach was implemented using the GPC-based resonant controller described in [29], considering  $n_p = 5$ ,  $n_c = 2$ , and  $r_w = 0.001$ , but adding the pole  $p_0 = -0.375$  and the zero  $z_0 = 0.947$  to the augmented model. The proposed controller was implemented in the DSP Dspace DS1104. Figure 5 shows the experimental setup.

Figure 6 shows the sinusoidal reference used in the experimental tests, which has a frequency of 50 Hz. Many resonant controllers are designed to track a sinusoidal reference with fixed frequency (50 Hz in this case). The amplitude of this reference changes according to a step signal, allowing the capture of characteristics of the transient response (peak error, settling time, etc.) of the proposed predictive controller. This amplitude variation can model, for example, an increment in the required RMS voltage value of a motor. Besides, the analog output of the Dspace DS1104, used to generate the control law, has a maximum amplitude of 10 V. Thus, to test the robustness of the proposed approach, the maximum amplitude of the reference was selected in order to create a saturation of the control law during the variations of the reference amplitude (the control law, without the saturation effect, would have a maximum amplitude higher than 10 V).

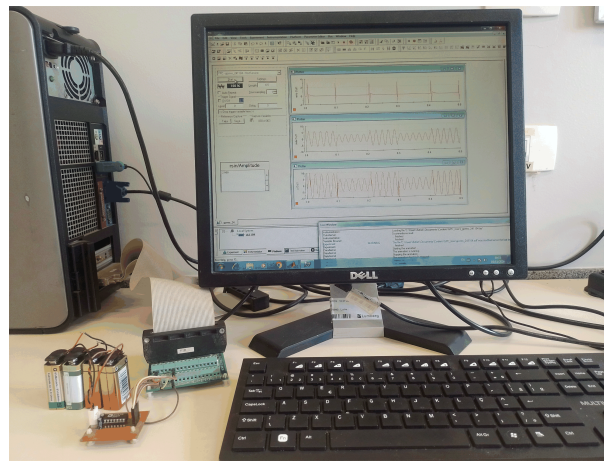


**Figure 5.** Experimental setup for testing resonant controllers.

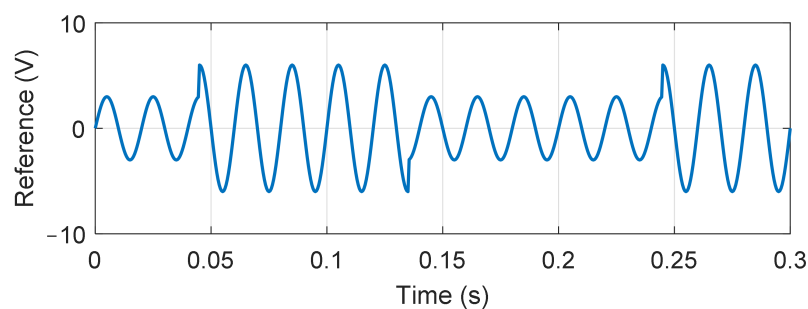


**Figure 6.** Sinusoidal reference for the experimental test.

Figures 7 and 8 show the experimental results for both the GPC-based resonant controller described in [29] and the proposed approach. Both controllers have steady-state errors that tend to zero. However, the proposed approach presents better transient responses (lower error peaks and oscillations) when the reference amplitude changes. Table 5 shows the peak error and the settling time for the first and second variation in the reference amplitude that appears in Figure 6 (the third variation is a repetition of the first one). These results show that adding a zero (and a pole) in the GPC-based resonant controller can improve the control performance.

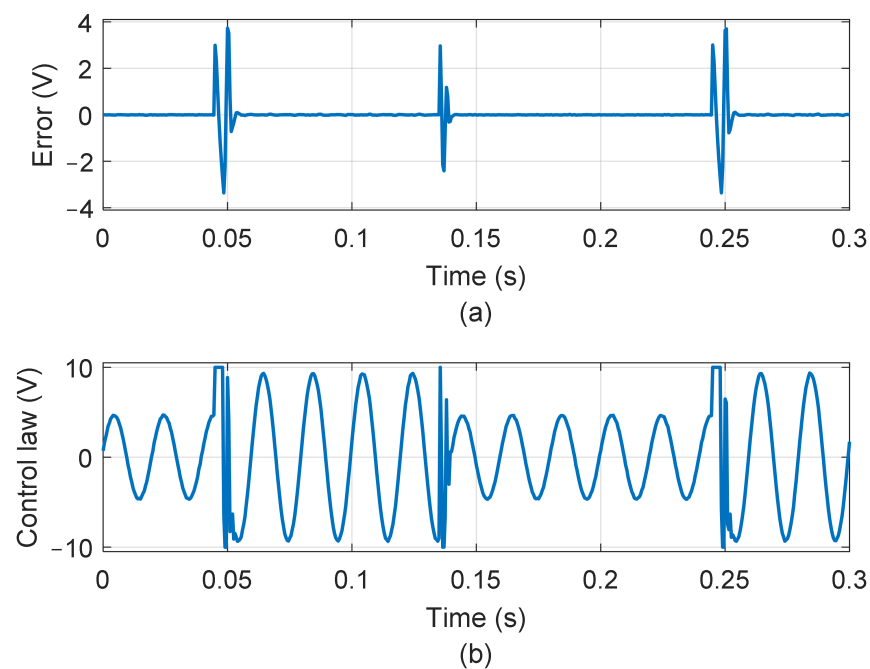


**Figure 7.** Experimental results for the resonant control in [29] without adding zeros. (a) Tracking error. (b) Control law.

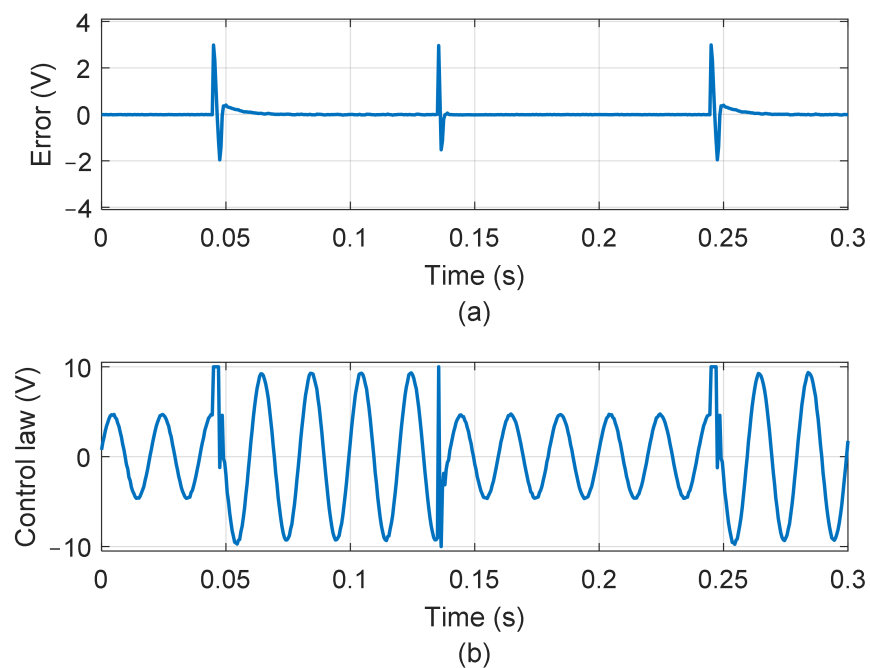


**Figure 8.** Experimental results for the proposed approach. (a) Tracking error. (b) Control law.

**Table 5.** Experimental results for resonant controllers.

| Test               | Error Peak (V) | Settling Time First Variation (s) | Settling Time Second Variation (s) |
|--------------------|----------------|-----------------------------------|------------------------------------|
| Controller in [29] | 3.73           | 0.0105                            | 0.005                              |
| Proposed approach  | 2.98           | 0.0105                            | 0.003                              |

## 5. Discussion

Simulation and experimental results show that the proposed approach, based on the addition of zeros and poles in the augmented model, improves the transient response

without affecting the tracking capability of the closed-loop system. Equation (41) explains these characteristics of the proposed predictive controller.

Assuming that there is no cancellation among the zeros and poles of  $M(z)$ ,  $R(z)$ ,  $G_p(z)$ , and  $\frac{z-z_0}{z-p_0}$ , Equation (41) proves that the proposed augmented model embeds the Z-transform of the reference  $R(z)$ , the transfer function of the plant  $G_p(z)$ , the zero at  $z = z_0$ , and the pole at  $z = p_0$ , independent of the structures of the reference and the plant. The aforementioned equation also proves that the proposed augmented model satisfies IMP, as the augmented model contains the poles and zeros of the plant and the reference Z-transform. The proposed approach only adds zeros and poles to the augmented model. Thus, the proposed control law embeds the zeros, poles, and the model of the reference, as shown in (43).

As a result, the proposed approach can be applied to different linear (or linearized) plants of any order (i.e., to different applications) if the closed-loop system is stable and zero-pole cancellation is avoided. Therefore, the following requirements must be satisfied for the application of the proposed approach:

- The plant must be controllable;
- The selected values of  $p_0$  and  $z_0$  must avoid a zero-pole cancellation with the poles and zeros of  $G_m(z) = M(z)R(z)G_p(z)$ ;
- Replacing (35) into (26) yields  $\chi[k+1] = (\hat{A} - \hat{B}K_{zp})\chi[k]$ ; therefore, to guarantee stability, the gain  $K_{zp}$  must be selected such that the eigenvalues of  $\hat{A} - \hat{B}K_{zp}$  are located inside of the unit circle in the complex plane.

## 6. Conclusions

This paper presents a methodology to add arbitrary zeros and poles to a GPC augmented model to improve the transient and steady-state responses of plants used in power electronics applications controlled through GPC (e.g., the control of an LCL filter or in the development of resonant controllers). Simulation and experimental results show the advantages of adding zeros and poles in the GPC augmented model. Simulation results show that the proposed approach reduces the THD of the filter output current and improves the system power factor. These facts prove that the proposed controller can be used to design improved power electronics applications. The closed-loop response can be regulated through the selection of the GPC parameters ( $n_p$ ,  $n_c$ ,  $r_w$ ) and the added zeros and poles ( $z_0$ ,  $p_0$ ). The addition of zeros and poles in the augmented model can enhance the prediction accuracy of the plant responses. For example, the zeros and poles can be selected to act as a filter that attenuates the effect of noise in the prediction. An improved prediction model can also be used in other applications that require this type of information, such as the prediction of pollutant emissions [41] or market behavior [42] and the flexible management of energy sources in power systems [43], among others. A heuristic algorithm (e.g., a genetic algorithm) can be used to select those parameters. Application of the proposed approach for Multiple Input Multiple Output (MIMO) plants requires more mathematical analysis. As future work, experimental validation of the proposed approach in MIMO plants will be performed.

**Author Contributions:** Conceptualization, R.C. and W.A.; methodology, R.C.; validation, R.C.; writing, reviewing, and editing the initial version of the manuscript, R.C. and M.C. All authors have read and agreed to the published version of the manuscript.

**Funding:** This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior—Brasil (CAPES)—Finance Code 001.

**Data Availability Statement:** The raw data supporting the conclusions of this article will be made available by the authors on request.

**Acknowledgments:** The authors want to thank the Federal University of Mato Grosso do Sul, CNPQ (Conselho Nacional de Desenvolvimento Científico e Tecnológico) and CAPES (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior) for their support of this research.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

|            |                                                               |
|------------|---------------------------------------------------------------|
| GPC        | Generalized Predictive Control                                |
| IMP        | Internal Model Principle                                      |
| MPC        | Model Predictive Control                                      |
| THD        | Total Harmonic Distortion                                     |
| RMSE       | Root Mean Square Error                                        |
| $J$        | Cost function                                                 |
| $k$        | Discrete instant of time                                      |
| $K_{zp}$   | GPC gain for the proposed controller                          |
| $t$        | Continuous time                                               |
| $t_s$      | Sampling time                                                 |
| $\gamma$   | Term that depends on $\Omega$ . $\gamma = 2 \cos(\Omega) - 1$ |
| $\omega_0$ | Angular frequency (rad/s)                                     |
| $\Omega$   | Discrete-time angular frequency (rad/sample)                  |

## Appendix A. Preliminaries

The first-order backward difference of the signal  $d[k]$  is:

$$\nabla d[k] = \nabla^1 d[k] = d[k] - d[k-1]. \quad (A1)$$

Based on (A1), the  $m$ -order backward difference of the signal  $d[k]$  is recursively defined as follows:

$$\nabla^m d[k] = \nabla^{m-1} d[k] - \nabla^{m-1} d[k-1]. \quad (A2)$$

Let  $r(t) = m_0 \sin(\omega_0 t)$  be a continuous-time sinusoidal signal with amplitude  $m_0$  and frequency  $\omega_0$ . The discrete-time reference ( $r[k]$ ) can be obtained by making  $t = t_s k$ , with  $t_s$  being the sampling period. The discrete frequency  $\Omega$  is defined as follows:

$$\Omega = t_s \omega_0. \quad (A3)$$

Let us define  $\gamma$  as follows:

$$\gamma = 2 \cos(\Omega) - 1. \quad (A4)$$

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