Reducing the Dead Zone Time Effect of Actuators in Sensor-Based Agricultural Sprayers under S-shaped Functions Gain Scheduling Management of a Generalized Predictive Control (GPC) Strategy

Deniver R. Schutz*,†,Vilma A. Oliveira†, Paulo E. Cruvinel*

*Embrapa Instrumentation
Brazilian Agricultural Research Corporation, São Carlos, SP, Brazil
† Department of Electrical and Computer Engineering
São Carlos School of Engineering
University of São Paulo, São Carlos, SP, Brazil
Email: deniver@usp.br, voliveira@usp.br, paulo.cruvinel@embrapa.br

***Abstract*—This paper presents a study on the relationship between sensors, control systems and actuators for agricultural spraying. Sensors associated with appropriate control systems can be used to support decision-making processes for nozzles in relation to the correct application of pesticides. In such a context, results related to a comparison were evaluated considering not only an adaptive generalized predictive control based on both fuzzy and sigmoid-based strategies for scheduling management but also the enhancement of the dead zone management improving actuators performance in relation to the nozzles stitching's processes. These systems involving sensors, controllers and switching are essential for the automation of agricultural sprayers, especially for those that work with variable rate application, in management based on precision agriculture. A Sigmoid-based Generalized Predictive Control (SGPC) is proposed for flow rate regulation in agricultural pesticide sprayers. Evaluated against conventional Fuzzy Logic-based GPC (FGPC), the SGPC shows reduced Integral Absolute Error (IAE) and faster rise time despite higher overshoot in certain scenarios. Results indicate enhanced tracking accuracy and dynamic response compared to traditional fuzzy logic approaches. This framework demonstrates potential for improving precision in agricultural spraying systems. Such results can be valuable for the current machinery agricultural industry, which needs to improve productivity and quality gains and reduce negative externalities in favor of food security and sustainability.**

Keywords-Agricultural sensors; Agriculture actuators; Predictive controller; Agricultural sprayers; Precision agriculture.

I. Introduction

Pesticide application using agricultural sprayers is traditionally performed at a constant rate (liters per hectare), independent of the spatial variability in pest and disease density into a crop field. This approach often leads to inefficiencies, as it does not account for localized needs, potentially resulting in over-application or even an under-application of chemicals [1].

Considering precision agriculture applications, the Variable Rate Application (VRA) systems leverage prescription maps, sensor data, and real-time actuator adjustments to tailor pesticide application rates based on the specific spatial distribution of pests and diseases across one crop agricultural field. By dynamically controlling flow rate and pressure, VRA enhances precision and reduces losses, aligning with the principles of precision agriculture [2].

Effective control of flow rate and pressure in agricultural spraying systems is critical for multiple reasons. Accurate flow regulation ensures that the correct amount of pesticide can be applied, reducing production costs and minimizing environmental impact. Similarly, precise pressure control improves spray quality by optimizing droplet size and distribution, which directly influences the effectiveness of the application. In addition, together with these factors, one may find a way to contribute to minimizing resource losses, enhancing application efficiency, and promoting sustainable farming practices [3].

The reliability of instruments responsible for monitoring flow and pressure, such as flowmeters and pressure sensors, as well as that regulating system performance, such as proportional valves, is critical. Malfunctions in these components can lead to significant errors in pesticide application, including either over-application, which increases costs and environmental risks, or under-application, which compromises pest control. Such inaccuracies not only jeopardize crop health but also can raise the risk of contaminating neighboring ecosystems due to drift or runoff [1].

From the perspective of automatic control, the performance of a spraying system can be evaluated based on parameters such as overshoot, steady-state error, rise time, and settling time. Issues such as overshoot and a high positive steady-state error are associated with overapplication, a phenomenon in which the applied volume exceeds the desired rate. This leads to waste of inputs, increased operational costs, and negative environmental impacts. On the other hand, an elevated rise time combined with a negative steady-state error can result in underapplication, compromising the effectiveness of phytosanitary treatments and negatively affecting crop development [4] [5].

In fact, the regulation of flow rate and pressure in agricultural sprayers are predominantly achieved using the Proportional-Integral-Derivative (PID) controllers. However, actuator control valves are inherently nonlinear systems, which can impair the performance of linear controllers, such as PID or even a Generalized Predictive Control (GPC) in regulating application rates [6]–[8].

On the other hand, advanced control strategies, such as those leveraging adaptive algorithms, can further enhance sprayer system reliability and adaptability to varying field conditions. Recent works have explored the use of Artificial Neural Networks (ANNs) to introduce non-nonlinearities into GPC strategies. For instance, [9] and [10] investigate ANNs for modeling the dynamic behaviors and adapting to changing conditions and disturbances. However, the use of ANNs can be challenging due to the extensive data requirements for training.

In [11], an adaptive GPC controller is introduced, discrete-time fuzzy model with parameter estimation. Additionally, in [12], where a predictor error approach based on the recursive least squares method is proposed for microclimatic control in a fan-ventilated tunnel greenhouse. In [5], results are presented utilizing fuzzy logic for scheduling the parameters λ and δ of the GPC controller.

In this paper, a study is presented replacing a fuzzy logic based GPC by a sigmoid function to simplify gain scheduling and reduce the time processing required for the adaptive parameters. Additionally, the stability analysis is presented. Finally, a sensitivity function analysis is also conducted to determine boundary values for λ and δ to satisfy robustness conditions against noise and disturbances.

In this work, following the introduction, Section II presents a preliminary study of the main components of the Generalized Predictive Controller (GPC). Section III introduces an S-shaped function to implement gain-scheduling of the GPC parameters λ and δ, aiming to reduce the influence of dead zones. Section IV provides a discussion of the simulation results obtained using MATLAB®. Finally, conclusions and future research directions are outlined in Section V.

II. Preliminaries

A model-based GPC is defined by its capability to anticipate the future behavior of dynamic systems through mathematical modeling. This is achieved by computing an optimal control sequence that minimizes a predefined objective function. The GPC framework employs a receding horizon approach, also referred to as a sliding horizon, where the control horizon is continuously updated as the system evolves. In this strategy, only the first element of the computed control sequence is implemented at each time step [13] [14].

The prediction of future outputs relies on the system model, meaning that the accuracy of the model directly influences the precision of the predictions. More specifically, the closer the predicted output is to the actual system response, the more effective the control strategy becomes. At each time step k, the predicted output sequence $\overrightarrow{y}(k)$ is computed based on the past input increments $\Delta\overleftarrow{u}(k-2)$, past output sequence $\overleftarrow{y}(k-1)$, and future control increments $\Delta\overrightarrow{u}(k-1)$. The control signals and their respective increments are determined over a predefined control horizon to ensure that the plant output closely follows the desired reference trajectory $\overrightarrow{r}(k-1)$.

The control law in GPC is derived by minimizing a quadratic cost function [14]. For Single-Input Single-Output (SISO) systems, this cost function is formulated as:

$$J(\Delta u, r, y) = \sum_{k=1}^{N_p} \delta \|(\overrightarrow{r}(k) - \overrightarrow{y}(k))\|_2^2 + \sum_{k=1}^{N_c} \lambda \|\Delta\overrightarrow{u}(k-1)\|_2^2 \tag{1}$$

where J represents the cost function, N_p is the prediction horizon, and N_c is the control horizon. The parameters $\delta > 0$ and $\lambda > 0$ are weightings associated with the error sequence $\overrightarrow{e}(k) = \overrightarrow{r}(k) - \overrightarrow{y}(k)$ and the future control increment sequence $\Delta\overrightarrow{u}(k-1)$, respectively. The tuning process of parameters λ and δ, including their impact on the control law, is detailed in Section III.

Using this cost function, the control law for the GPC is formulated as follows:

$$\Delta u(k) = P_r \overrightarrow{r}(k) - D_k \Delta\overleftarrow{u}(k-2) - N_k \overleftarrow{y}(k-1) \tag{2}$$

where $P_r = E_1^T \left(\delta H^T H + \lambda I\right)^{-1} \delta H^T$, $D_k = P_r P$, and $N_k = P_r Q$. The matrix $E_1^T = \begin{bmatrix} I & 0 & \cdots & 0 \end{bmatrix}$ ensures that only the first control increment $\Delta u(k)$ from the computed control sequence $\Delta \underset{\rightarrow}{u}(k)$ is applied to the system input. To reduce computational effort and operational costs, the control law in (2) can be simplified by limiting the calculations to the control horizon:

$$\Delta u(k) = -E_1^T S^{-1} a \tag{3}$$

where $S = \delta H_1^T H_1 + \lambda I$ with $H_1 = H(1:N_P, 1:N_c)$ with $H = C_A^{-1} C_b \in \mathbb{R}^{N_p \times N_p}$, and $a = X[\Delta\overleftarrow{u}(k-2)\ \overleftarrow{y}(k-1)\ \overrightarrow{r}(k)]^T$ with $X = \begin{bmatrix} \delta H_1^T P & \delta H_1^T Q & -\delta H_1^T L \end{bmatrix}$ with $L = \begin{bmatrix} 1 & 1 & \cdots & 1 \end{bmatrix}^T$, $P = C_A^{-1} H_b \in \mathbb{R}^{N_p \times n_b}$ and $Q = -C_A^{-1} H_A \in \mathbb{R}^{N_p \times n_a}$, the matrices $C_b \in \mathbb{R}^{N_p \times N_p}$, $H_b \in \mathbb{R}^{N_p \times n_b}$, $H_A \in \mathbb{R}^{N_p \times n_a}$ and $C_A \in \mathbb{R}^{N_p \times N_p}$ are obtained through the polynomials $\tilde{A}(z)$ and $B(z)$ from the Controlled Auto-regressive Integrated Moving Average (CARIMA) model and Toeplitz and Hankel matrices as described in [15].

This formulation ensures that the control action is efficiently computed while maintaining the desired tracking performance.

Given the plant transfer function $G(z) = \frac{b(z)}{a(z)}$, the closed-loop characteristic polynomial, is expressed as:

$$P_c(z) = D_k(z)\Delta a + b N_k(z) \tag{4}$$

Considering the loop transfer function $G(z)\phi(z)$, where $\phi(z) = \frac{N_k(z)}{D_k(z)\Delta}$, the sensitivity functions to noise and disturbances are given as follows [14]:

$$S_d = \frac{\phi(z)}{1 + G(z)\phi(z)} = -\frac{a N_k(z)}{P_c(z)} \tag{5}$$

$$S_n = \frac{1}{1 + G(z)\phi(z)} = \frac{a D_k(z)\Delta}{P_c(z)} \tag{6}$$

These sensitivity functions characterize the system's response to external perturbations and uncertainties, playing a crucial role in the robustness analysis of the control strategy.

The stability of the constrained GPC can be established through Theorem 1 and Corollary 1.1, which utilize the method of Lagrange multipliers. These theoretical foundations provide a rigorous framework for ensuring stability while accounting for system constraints, thereby enhancing the robustness and reliability of the control strategy in practical applications [5].

***Theorem** 1:* Let matrices C and r_t be as in [5]. Assume that there exists an optimal minimization solution that satisfies the Karush-Kuhn-Tucker (KKT) conditions along an infinite trajectory for given weightings λ and δ . The optimum constrained cost function of the GPC at the k-th instant given by:

$$\begin{aligned} J(k) = \min_{\Delta u(k+i), i=0,1,\cdots} & \sum_{i=1}^{\infty} \delta(e(k+i))^2 \\ & + \sum_{i=1}^{N_c} \lambda(\Delta u(k+i-1))^2 \\ \text{subject to} \quad & C\Delta \overrightarrow{u}(k-1) \leq r_t \end{aligned} \tag{7}$$

is a monotonic decreasing function.

***Corollary** 1.1:* Let S and a be defined as in (3). The constrained GPC is stable if there exists an optimal solution that satisfies the KKT conditions such that the control law can be written as:

$$\begin{bmatrix} S & C^T \\ C & 0 \end{bmatrix} \begin{bmatrix} \Delta \overrightarrow{u}(k-1) \\ \overrightarrow{\phi}(k) \end{bmatrix} = \begin{bmatrix} -a \\ r_t \end{bmatrix}. \tag{8}$$

III. S-shaped function based GPC Strategy

The developed S-shaped function based GPC strategy incorporates a gain scheduling stage for the cost weighting parameter λ, to update the matrix of the standard GPC. The configuration of the proposed GPC approach is illustrated in Figure 1, where a sigmoid output is used to adjust the S matrix of the GPC.

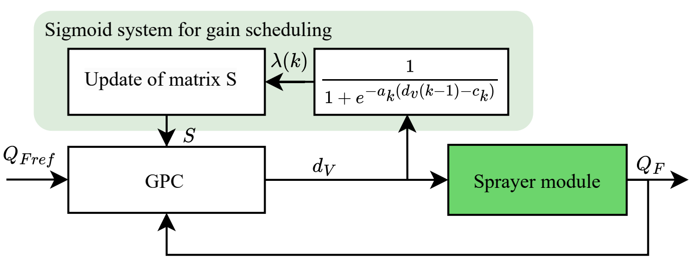

Figure 1. Adaptive GPC with λ scheduling via a sigmoid function, based on the last control signal dv.

The proposed sigmoid-based GPC is formulated as the following optimization problem:

$$\min_{\Delta u(k+i), i=0,1,\cdots} J(\Delta u, r, y) =$$

$$\sum_{i=1}^{N_p} \delta \|\overrightarrow{r}(k) - \overrightarrow{y}(k)\|_2^2 + \sum_{i=1}^{N_c} \hat{\lambda}(k) \|\Delta \overrightarrow{u}(k-1)\|_2^2 \tag{9}$$

subject to

$$C\Delta \overrightarrow{u}(k-1) \leq r_t$$

$$\forall \ \lambda(k) = \lambda_{min} + (\lambda_{max} - \lambda_{min}) \cdot f(u(k-1))$$

where λ_{max} and λ_{min} are predefined bound values for the estimates of λ established by the designer to enhance the controller's efficiency in handling nonlinearities, mainly in the dead-zone region. The function $f(u(k-1))$ represents the output of a sigmoid function, resulting values between zero and one that span the range between λ_{min} and λ_{max}, depending on the previous control input

The control strategy is implemented in conjunction with an S-shaped function known as the sigmoid function, a commonly used activation function in neural networks. The sigmoid function ensures continuity and differentiability of the system, particularly around the dead zone region, enabling smooth transitions and improved adaptability in system behavior [16]. The sigmoid function is described as:

$$f(d_v(k-1), a_k, c_k) = \frac{1}{1 + e^{-a_k(d_v(k-1)-c_k)}} \tag{10}$$

where the parameter a_k determines the inclination or spread of the transition region, while c_k specifies the midpoint of the sigmoid region.

Figure 2 illustrates the sigmoid function with varying slopes (a_k), demonstrating how the slope influences the transition between states. Smaller values of a_k result in a smoother transition (broader curves), while larger values of a_k produce a sharper transition (narrower curves). The midpoint of the sigmoid function is chosen to be around ± 20 in order to encompass the dead zone at small values of $\lambda(k)$.

The general idea of the sigmoid S-shaped function based GPC is that smaller values of $\lambda(k)$ should be adopted for the dead zone regions, causing larger control variations $\Delta u(k)$. This is because, in such cases, the ideal scenario is $\delta > \lambda(k)$, which results in larger control variations $\Delta u(k)$, driving the control signal d_v away from the dead zone. Outside the dead zone, larger values of $\lambda(k)$ stabilize the system by reducing unnecessary control activity.

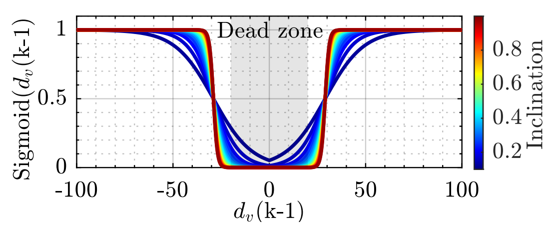

Figure 2. Proposed sigmoid S-shaped function with different inclinations.

The reason for keeping one weighting gain fixed while modifying only the other, instead of adjusting both gains simultaneously, is simplifying the system design. This simplification arises from the fact that the control signal $\Delta u(k)$ varies depending on the ratio $\frac{\lambda}{\delta}$:

- When $\delta > \lambda(k)$, the emphasis is on minimizing the tracking error, promoting aggressive control actions.
- When $\delta \leq \lambda(k)$, the ontrol effort is penalized more heavily, leading to smoother but potentially slower responses.

Fixing one parameter and dynamically adjusting the other, the complexity of tuning both parameters is reduced, while still achieving the desired balance between tracking performance and control effort.

Copyright (c) IARIA, 2025. ISBN: 978-1-68558-273-9

A. Stability analysis of constrained GPC with variable λ gain

The stability of the constrained GPC with a variable $\lambda(k)$ weighting gain is ensured through the careful design of the cost function and the dynamic adjustment of $\lambda(k)$. By exploiting the properties of the sigmoid function and bounding $\lambda(k)$ within predefined limits, the controller achieves a balanced trade-off between tracking performance and control effort. The stability analysis can be accomplished by Theorem 1 e Corollary 1.1 proposed in [5] for the constrained GPC, extended to the case of varying $\lambda(k)$.

Since the optimization problem involves minimizing a quadratic cost function (7), if matrix S is positive definite, the problem is convex, ensuring a global minimum solution. Since λ interferes with the main diagonal of the matrix S, to guarantee that the variation of $\lambda(k)$ does not affect the positive definiteness of S, $\lambda(k)$ is treated as a parametric uncertainty. Specifically, λ_{min} must be greater than zero, and λ_{max} must be less than a design-specified value, where the range between λ_{min} and λ_{max} is known to be stable and robust. Consequently, as long as S remains positive definite, the problem remains convex with a global minimum solution, and the stability is guaranteed.

B. Sensitivity analysis

To illustrate the effects of varying λ and δ on the robustness of the system, sensitivity analyzes were conducted, as depicted in Figures 3 and 4. These analyzes provide insights into how these parameters influence the system's ability to handle noise and disturbances. The agricultural spraying system model is considered to be described by the discrete ARMAX model obtained using 14 spray nozzles of the model 422SFC11005-ARAG and a sampling period of 300 ms:

$$A(z)y(t) = B(z)u(t) \tag{11}$$

where

$$\begin{aligned} A(z) &= 1 - 14.67 \cdot 10^{-2} z^{-1} + 24.52 \cdot 10^{-2} z^{-2} \\ &+ 22.22 \cdot 10^{-2} z^{-3}, \\ B(z) &= 0.277 \cdot 10^{-2} z^{-3} + 19.54 \cdot 10^{-5} z^{-4} \end{aligned}$$

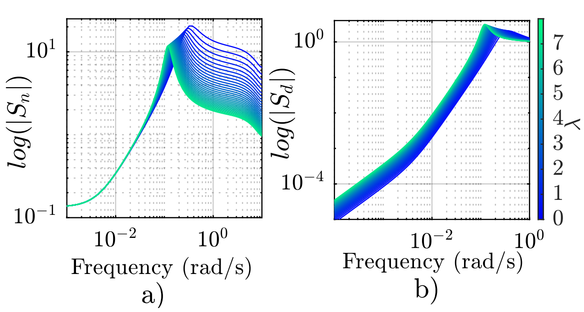

Figure 3. Sensitivity analysis curves for noise a) and disturbance b) with variable λ.

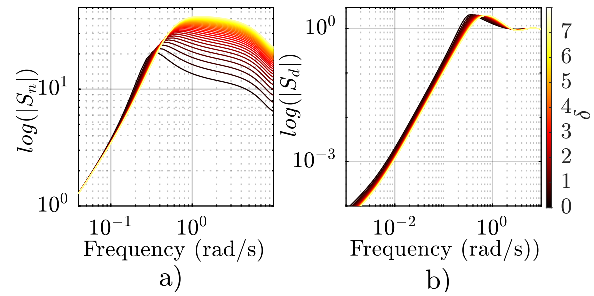

Figure 4. Sensitivity analysis curves for noise a) and disturbance b) with variable δ.

Figures 3 and 4 analyze the effects of varying λ and δ on system robustness, revealing a trade-off between noise suppression and disturbance rejection. In Figure 3, with δ held constant ($\delta = 1$) and λ varied within $0 < \lambda \leq 8$, higher values of λ reduce the amplitude of the noise sensitivity function (S_n) at high frequencies, enhancing robustness against high-frequency noise by penalizing abrupt control signal variations and promoting smoother actions. However, this comes at the expense of increased sensitivity to low-frequency disturbances, as indicated by the rise in the disturbance sensitivity function (S_d). Conversely, Figure 4 examines the impact of varying δ while keeping λ fixed ($\lambda = 1$) within $0 < \delta \leq 8$. Smaller δ increases S_n at high frequencies, reducing noise robustness due to more aggressive control adjustments that amplify high-frequency components, whereas larger δ improves robustness to low-frequency disturbances by decreasing S_d, though it may increase susceptibility to high-frequency noise. Together, these results highlight the opposing roles of λ and δ and the need for careful parameter tuning to balance performance across different operating conditions.

The opposing behaviors of λ and δ highlight the necessity for careful tuning to strike an optimal balance between noise suppression and disturbance rejection. Furthermore, system nonlinearities can introduce regions where λ and δ become inefficient for specific tuning scenarios, complicating the parameter adjustment process. This emphasizes the importance of considering gain scheduling for these parameters to address such limitations and ensure robust performance across varying operating conditions.

IV. Results and Discussions

A simulation was conducted in MATLAB® to evaluate the regulation of a proportional valve in a sprayer module. The performance of the proposed sigmoid-based GPC is compared with that of the conventional GPC and fuzzy-based GPC controllers. The block diagram of the sprayer system is presented in Figure 5. The proportional valve actuator consists of a Direct Current motor and an H-bridge with gain K_{pH}, including a saturation block to limit the piston angle between $\theta_v = 0$ and 94.2 rad. The flow rate Q_F and pressure P_S depend on the proportional valve's fluidic resistance K_{VP}, the total equivalent fluidic resistance K_{Teq}, and the pump flow Q_B.

Parameters α_0, α_1, and β define the valve's fluidic resistance curve, obtained experimentally. The parameters of the sprayer system were identified and are described in detail in [8], with the key parameters summarized in Table I.

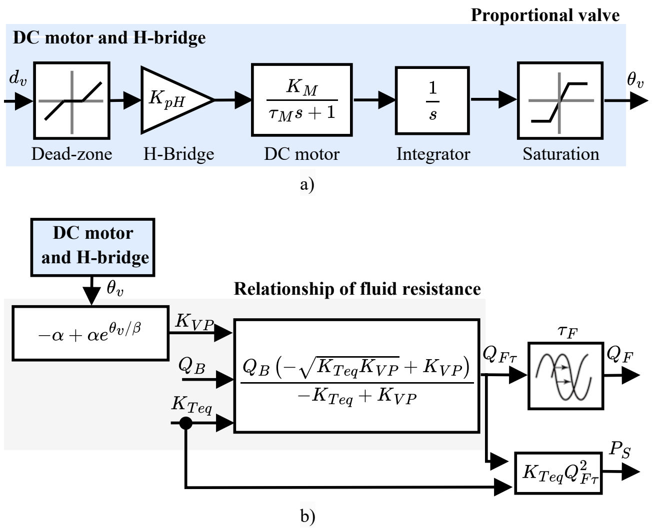

Figure 5. Block diagram of the sprayer module. Adapted from [15].

The standard GPC was tuned to minimize overshoot, achieve a faster response time, and ensure accurate predictions, with parameters set as $N_c = 4$, $N_p = 20$, $\lambda = 1$, and $\delta = 5$. For the fuzzy GPC and Sigmoid GPC designs, the same prediction and control horizons (N_p and N_c) were used. However, δ and λ were dynamically adjusted: λ was scheduled according to the fuzzy system proposed in [5], and the Sigmoid function described in Section III was employed for adaptive weighting, using $c_k = 16$, $a_k = 0.4$, $\lambda_{min} = 0$ and $\lambda_{max} = 5$.

TABLE I
PARAMETERS OF SPRAYER MODULE [8].

Parameter	Value
α	2.8110^{-6}
β	6.53
K_M	1.10 rad/V
T_M	5.0010^{-2}
K_{pH}	0.12
τ_F	0.6 s
Q_B	40 l/min
K_{Teq} (CH0.5)	5.71 kPa/(l/min)^2
K_{Teq} (CH01)	1.91 kPa/(l/min)^2
K_{Teq} (CH03)	0.97 kPa/(l/min)^2
K_{Teq} (CH06)	0.48 kPa/(l/min)^2

The simulations were repeated for each controller using two bars, each equipped with seven MagnoJet® nozzles. Constraints on the control input were handled using the Accelerated Dual Gradient-Projection Method (GPAD for short), with the input restricted to $-100 < dv(k) < 100$ due to limitations in the duty cycle of the Pulse Width Modulation (PWM) signal. A step variation was used as the reference signal using four different spray nozzles. This type of reference was chosen to approximate the problem to a real-world scenario, based on pesticide prescription maps. The simulation results are presented in Figure 6 from a) to d) for the M063/1 CH6, M061 CH3, M059 CH1, and M059/1 CH0.5 nozzles, in this sequence. The GPAD method [17] is used for handling constraints in the controllers.

For most simulations, the sigmoid based GPC controller exhibits a shorter rise time and lower steady-state error. However, for the CH0.5 nozzle in Figure 6 d), the sigmoid based GPC controller showed oscillations around the dead zone in the interval between 10 and 22 seconds. Table II provides a numerical comparative analysis of the Integral Absolute Error (IAE), Overshoot (OS), and rise time for the simulations conducted with the four nozzles.

TABLE II
PERFORMANCE OF THE CONTROLLERS WITH DIFFERENT NOZZLES

Controller	IAE (l/min)	OS (l/min)	Rise time (s)
CH06			
GPC	2.11	0.51	11.1
SGPC	1.61	0.62	8.4
FGPC	1.96	0.51	8.6
CH03			
GPC	2.22	0.6	11.4
SGPC	1.73	0.51	8.4
FGPC	2.00	2.00	9.9
CH01			
GPC	2.22	0.6	11.4
SGPC	2.00	0.61	8.5
FGPC	2.17	0.51	9.9
CH0.5			
GPC	2.48	0.2	12.7
SGPC	2.18	2.4	9.6
FGPC	2.31	0.1	11.1

The analysis of Table II reveals that the Sigmoid-based GPC (SGPC) generally outperforms the standard GPC and Fuzzy GPC (FGPC) in terms of IAE and rise time across most nozzle configurations. For instance, with the CH06 nozzle, SGPC achieves a 23.7% and 7.1% reduction in IAE compared to GPC and FGPC and a slightly faster rise time (8.4 s vs. 11.1 s and 8.6s). Similarly, for CH01, SGPC reduces IAE by 10.8% compared to GPC, while maintaining a comparable rise time. However, overshoot varies significantly: SGPC exhibits higher OS in some cases, such as CH05, where it reaches 2.4 l/min, contrasting sharply with FGPC's 0.1 l/min. This suggests a trade-off between error minimization and transient response smoothness.

Across all nozzles, FGPC demonstrates moderate performance, balancing IAE and OS but often failing to match the IAE reductions achieved by SGPC. For example, in CH03, FGPC shows a high OS of 2.0 l/min, indicating potential instability or excessive control effort despite reducing IAE by 10.4% compared to GPC. Overall, SGPC emerges as the most effective controller for minimizing IAE and rise time, achieving improvements of up to 23.7% in IAE, though its higher OS in certain scenarios may require further tuning to optimize robustness.

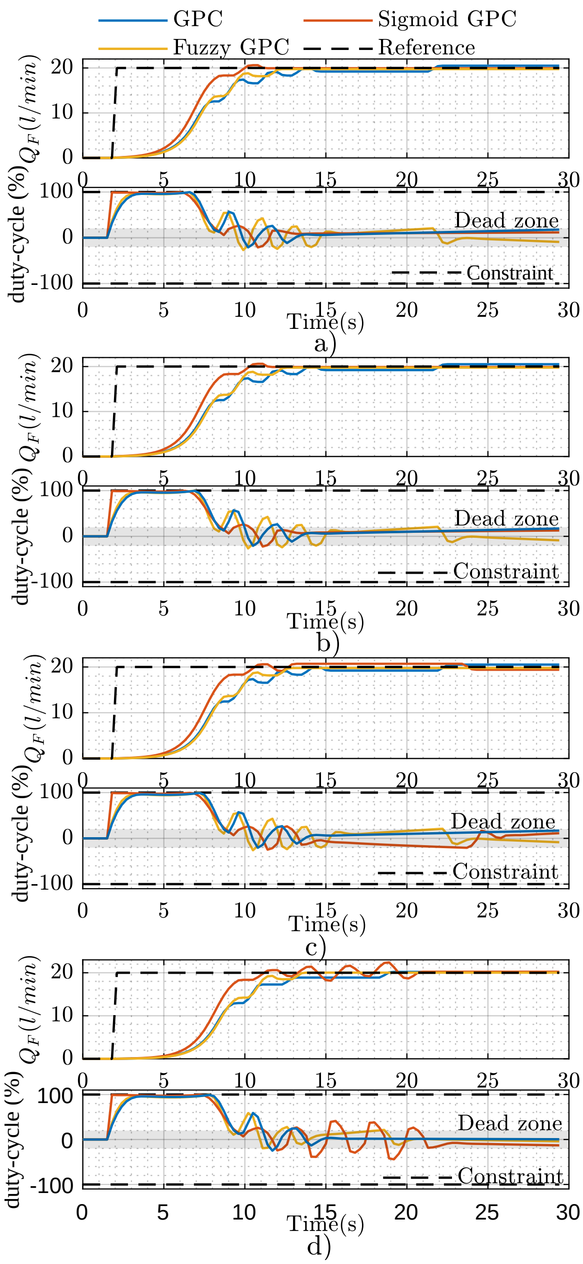

Figure 6. Step response to MagnoJet ® nozzles.

V. CONCLUSION AND FUTURE WORK

In this paper, the performance of GPC, fuzzy-based GPC, and a sigmoid-based GPC controller for regulating flow rate in agricultural sprayers is discussed and compared. The simulation results demonstrate the feasibility of using the sigmoid function to schedule the GPC parameter λ, enhancing system response and addressing dead zone nonlinearities.

The incorporation of the sigmoid function enables the inclusion of bounds for the GPC parameters in the stability analysis, as discussed. Furthermore, the sensitivity analysis provides insights into determining the bounds of the sigmoid-based GPC parameters while considering the system's response to noise and disturbances. The results confirm the practical effectiveness of the sigmoid-based GPC in agricultural sprayers, reducing actuator wear and minimizing application errors caused by abrupt reference changes.

For future research, an embedded programmable sigmoid-based GPC is proposed for real-time processing. The sigmoid S-shape function simplifies the embedded implementation of adaptive systems, requiring minimal code and reducing processing time compared to fuzzy logic, which often depends on lookup-table searches or surface inference methods. This method is promising for real-time applications in resource-constrained environments.

ACKNOWLEDGMENTS

This research was supported by the Brazilian Agricultural Research Corporation (Embrapa Instrumentation, under grant SEG, Process 11.14.09.001.05.06.001 Development of advanced automated models, tools and instruments for precision agricultural spraying), the National Counsel of Technological and Scientific Development (CNPq, under grant 88887.703189/2022-00) and São Paulo Research Foundation (FAPESP, under grant 2023/06759-0).

REFERENCES

[1] E. A. Straw, E. Kelly, and D. A. Stanley, "Self-reported assessment of compliance with pesticide rules," *Ecotoxicology and Environmental Safety*, vol. 254, 2023.

[2] E.-C. Oerke, R. Gerhards, G. Menz, and R. A. Sikora, *Precision crop protection - the challenge and use of heterogeneity*. Boon: Springer, 2010, vol. 5.

[3] M. Grella et al., "Field assessment of a pulse width modulation (pwm) spray system applying different spray volumes: duty cycle and forward speed effects on vines spray coverage," *Precision Agriculture*, vol. 23, no. 1, pp. 219–252, 2022.

[4] P. Wang, A. Saiful Hanif, S.-H. Yu, C.-G. Lee, Y. Ho Kang, D.-H. Lee, and X. Han, "Development of an autonomous drone spraying control system based on the coefficient of variation of spray distribution," *Computers and Electronics in Agriculture*, vol. 227, p. 109529, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169924009207

[5] D. R. Schutz, H. V. Mercaldi, E. A. Peñaloza, L. J. Silva, V. A. Oliveira, and P. E. Cruvinel, "Advanced embedded generalized predictive controller based on fuzzy gain scheduling for agricultural sprayers with dead zone nonlinearities," *Journal of Process Control*, vol. 135, no. 103164, pp. 1–11, 2024.

[6] Y. Shi, A. Liang, H. Yuan, C. Zhang, and J. Li, "Modeling and simulation for a variable sprayer rate system," *Computer and Computing Technologies in Agriculture II*, vol. 1, no. 293, p. 573–584, 2009.

[7] A. E. Aissaoui, F. Lebeau, L. Elbahir, M. F. Destain, and K. Houmy, "A feasibility study of developing direct injection spraying technology for small scale farms," in *2nd international conference on agricultural engineering, Synergy in the Technical Development of Agriculture and Food Industry*. Godollo, Hungary, 2011, pp. 9–15.

[8] K. R. Felizardo, H. V. Mercaldi, V. A. Oliveira, P. E. Cruvinel, and B. L. Steward, "Modeling and model validation of a chemical injection sprayer system," *Applied Engineering in Agriculture*, vol. 32, no. 3, pp. 285–297, 2016.

[9] Q. Zhao, Q. Liu, N. Cao, F. Guan, S. Wang, and H. Wang, "Stepped generalized predictive control of test tank temperature based on back-propagation neural network," *Alexandria Engineering Journal*, vol. 60, no. 1, pp. 357–364, 2021.

[10] S. Xie, Y. Xie, T. Huang, W. Gui, and C. Yang, "Generalized predictive control for industrial processes based on neuron adaptive splitting and merging RBF neural network," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 2, pp. 1192–1202, 2018.

[11] J. Mendes, R. Araújo, and F. Souza, “Adaptive fuzzy generalized predictive control based on discrete-time TS fuzzy model,” in *2010 IEEE 15th Conference on Emerging Technologies & Factory Automation (ETFA 2010)*. IEEE, 2010, pp. 1–8.

[12] S. F. Ramezani, E. Vafa, M. Fakhroleslam, and M. Shahrokhi, “Adaptive predictive control of a fan-ventilated tunnel greenhouse with evaporative cooling,” *Journal of Process Control*, vol. 129, 2023.

[13] E. F. Camacho and C. Bordons, *Model predictive control*. London: Springer Science & Business Media, 2013.

[14] J. A. Rossiter, *Model-based predictive control: a practical approach*. Washington, D.C.: CRC press, 2003.

[15] D. R. Schutz, H. V. Mercaldi, E. A. Penaloza, V. A. Oliveira, and P. E. Cruvinel, “An intelligent fuzzy-GPC control for agricultural sprayers: comparison between GPC and PID fuzzy controllers,” in *15th APCA International Conference on Automatic Control and Soft Computing, July 6-8, 2022, Caparica, Portugal*. Springer, 2022, pp. 272–284.

[16] L. J. R. Silva, M. V. R. Campos, B. M. Zilli, T. A. Fagundes, R. V. A. Neves, R. Q. Machado, and V. A. Oliveira, “A sigmoid-weighted-consensus for balancing multiple battery energy storage systems,” *IEEE Transactions on Industrial Electronics*, 2024.

[17] V. B. Peccin, D. M. Lima, R. C. C. Flesch, and J. E. Normey-Rico, “Fast generalized predictive control based on accelerated dual gradient projection method,” *IFAC-PapersOnLine*, vol. 52, no. 1, pp. 480–485, 2019.

 ISBN: 978-1-68558-273-9