# Chapter 247

## Design, Simulation and Performance Analysis of Parametric Estimation Algorithms Applied to Model Reference Adaptive Control

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**ABSTRACT**
This article performed the design, simulation, and performance analysis between two parametric estimation algorithms, the Gradient Method (GM) and the Recursive Least Squares Method (RLSM), both applied to the Model Reference Adaptive Control (MRAC) system. The study of design techniques and control analysis, as well as the comparison of the methods presented here, enhance the ability of the designer to deal with practical problems effectively. The main contribution of the article was to apply and clarify the advantages of the methods presented. Thus, the specific objectives were: $(i)$ identify the plant to be controlled; $(ii)$ discretize the plan *(iii)* build the control law; $(iv)$ implement the identification algorithm; and $(v)$ analyze the simulated results. Based on numerical simulations, we analyzed the performance of each algorithm and its respective advantages and characteristics. The RLSM has an excellent transient regime, but its computational cost was high. The GM has the slowest accommodation time and has low computational demand when compared to the RLSM. By taking into account the characteristics of each algorithm and having prior knowledge about the plant you want to control, such previous information helps you choose the algorithm, thus enhancing the better performance of the control system.

**Keywords:** Recursive Least Squares Method (RLSM), Gradient Method (GM), Model Reference Adaptive Control (MRAC), Comparison of Paramétric Methods.

## 1 INTRODUCTION

Adaptive control emerged in the 50s, in the area of automation processes and aviation. Over the past few decades, this type of control strategy has stood out and motivated applications in time-varying models. The reason for the advancement of adaptive control was to develop control systems that could adapt to changes in process dynamics (ÅSTRÖM; WITTENMARK, 2008).

There is a class of adaptive controlers that makes use of parametric and real-time (online) estimation methods. Thus, from the estimation of parameters, these controllers use the estimated values in the control law to adjust the gains of the controller or regulator, whose purpose is to meet the performance criteria pre-established by the designer (LANDAU *et al*., 2011).

When considering this context, the area of adaptive control research is booming. Thus, it is important to understand methods of estimation of parameters and states of dynamical systems as well as their adaptations and extensions, related to the area of mathematical modeling and control systems (AGUIRRE, 2007) (ROSSINI; MARTINS; SILVA GONCALVES; GIESBRECHT, 2018) (ROSSINI, 2020) (ROSSINI; OLIVEIRA; GIESBRECHT, 2021) (TAKEMOTO; ROSSINI; CORRÊA, 2022). Using dynamic systems identification techniques, allow you to describe the dynamics of the process with little or no prior knowledge about the plant (ROSSINI, 2020).

The Model Reference Adaptive Control (MRAC) system can be characterized as indirect or direct and with normalized or non-normalized adaptive law. The MRAC is a flexible control strategy, allowing to couple of different methods of parameter estimation, as well as different control laws (CANHAN; BROLIN; ROSSINI, 2022a) (CANHAN; BROLIN; ROSSINI, 2022b) (COLDEBELLA; BROLIN; ROSSINI, 2022a) (COLDEBELLA; BROLIN; ROSSINI, 2022b). In the indirect MRAC, the plant parameters are estimated in real-time, and from this estimation the gains of the controller are computed. In direct MRAC, which is addressed in this work, the gains of the controller are estimated from the error signal between the plant and model outputs. In this work, the adaptive laws were composed of the Gradient Method (GM) and Recursive Least Squares Method (RLSM) (IANNOU, 1996).

The MRAC strategy with direct structure was applied to a second-order plant with a relative degree equal to two. For the MRAC system, it became necessary to design a controller with periodic earnings updates. From the output signal of the plant and the model, the respective signals are composed, thus producing an error signal. Then, the controller's earnings are computed and updated. The goal of MRAC is to make the parameters converge to values that lead the response of the plant to become equal to the response of the reference model (JACOMÉ, 2013) (PAULO, 2015).

The article is organized as follows: The Section on Materials and Methods tried to demonstrate the concept of MRAC through a block diagram, describe the law of control and present the methods of parametric estimation; in the Section Results and Discussions, the responses generated from each algorithm are presented, as well as a comparison between the two estimation methods; and the Conclusion Section, the characteristics observed in the closed-loop control system were reported.

## 2 MATERIALS AND METHODS

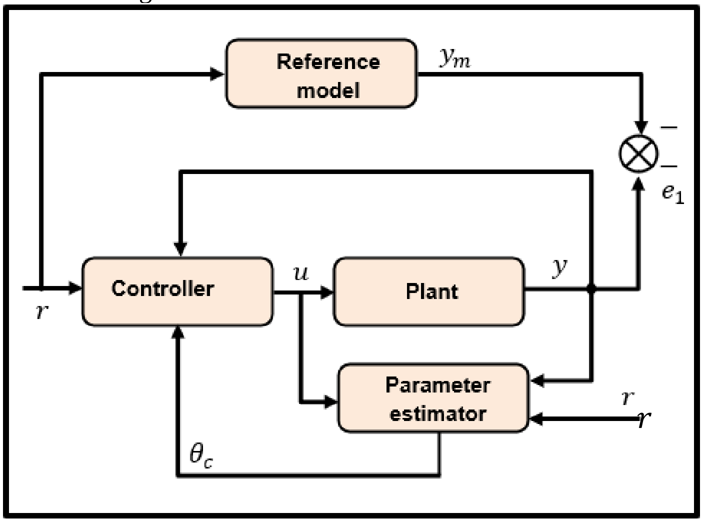
Model Reference Adaptive Control (MRAC) is one of the main approaches in the field of adaptive control. Figure 1 illustrates the MRAC scheme, in which the reference model is chosen to generate a trajectory, which the plant output must follow, for a given reference signal, expressed by:

$$e_1 = y_p - y_m \tag{1}$$

where $y_p$ and $y_m$ are the plant and model output signals, respectively. The error sign $e_1$, shown in Equation (1) represents how much the plant has deviated from the desired trajectory.

Based on this error, Equation (1), the gains of the controller are adapted with the aid of a parameter estimator. Thus, it is desired that the error is null or as close to zero as possible (IANNOU, 1996) (CANHAN; BROLIN; ROSSINI, 2022a) (CANHAN; BROLIN; ROSSINI, 2022b) (COLDEBELLA; BROLIN; ROSSINI, 2022a) (COLDEBELLA; BROLIN; ROSSINI, 2022b).

Figure 1 - Basic structure of a direct MRAC




Source: (CANHAN; BROLIN; ROSSINI, 2022b).

ORDER PLAN WITH ARBITRARY RELATIVE DEGREE $n$

Iannou (1996) described a Single Input Single Output (SISO), Linear Time Invariant (LTI) plant, represented by the equations of state and output, expressed respectively as:

$$\dot{x}_p = A_p x_p + B_p u_p$$

$$y_p = C_p^T x_p + D_p u_p \quad (2)$$

Being $x_p \in \mathbb{R}^n$ is the vector of plant states, $u_p \in \mathbb{R}^m$ the input signal of the plant and $y_p \in \mathbb{R}^p$ the output vector of the plant, in addition to the matrices, $A_p \in \mathbb{R}^{n \times n}$ of transition of states of the system, $B_p \in \mathbb{R}^{n \times m}$ is the input matrix, $C_p^T \in \mathbb{R}^{p \times n}$ is the output of the system and $Dp \in \mathbb{R}^{p \times m}$ is the direct transmission matrix (ROSSINI, 2020).

Iannou (1996) shows that the transfer function of the plant is given by:

$$y_p = G_p(s)u_p \tag{3}$$

where $G_p(s)$ is the transfer function, which can be expanded as follows:

$$G_p(s) = k_p \frac{Z_p(s)}{D_p(s)} \tag{4}$$

being $Z_p$ a monic polynomial and Hurwitz, and $k_p$ is the gain of the transfer function. The relative degree is the difference in the order of the degree of the polynomial $D_p(s)$ minus the order of the degree of the polynomial $Z_p(s)$. In this work, the relative degree of the plant to implement the algorithm is equal to 2, $n^* = n_p - m_p = 2$

Iannou (1996), showed that the reference model has the same characteristics as the plant and is represented by equations of states:

$$\begin{aligned} \dot{x}_m &= A_m x_m + B_m r \\ y_m &= C_m^T x_m \end{aligned} \tag{5}$$

being $x_m \in \mathbb{R}^n$ is the vector of plant states, $u_m \in \mathbb{R}^m$ the input signal of the plant and $y_m \in \mathbb{R}^p$ the output vector of the plant, in addition to the matrices, $A_m \in \mathbb{R}^{n \times n}$ of transition of states of the system, $B_m \in \mathbb{R}^{n \times m}$ is the input matrix, $C_m^T \in \mathbb{R}^{p \times n}$ is the output of the system and $D_m \in \mathbb{R}^{p \times m}$ is the direct transmission matrix (ROSSINI, 2020).

According to Iannou (1996), the reference model must have the same relative degree and the same characteristics of the plant, in this work the relative degree is $n^* = 2$. The model transfer function is given by:

$$y_m = W_m(s)r \tag{6}$$

$W_m(s)$ is expressed in the form:

$$Q_m(s) = k_m \frac{Z_m(s)}{D_m(s)} \quad (7)$$

DISCRETIZATION

The discretizations of the plant and the reference model were made with the *Zero Order Hold* (ZOH).

Analogical-digital (A/D) conversion is a two-step process. In an A/D converter, the analog signal is converted into a sampled signal and then converted into a binary sequence, the digital signal. The sampling rate shall be at least twice the signal passing range. This minimum sampling frequency is called the *Nyquist sampling rate.* To model digital systems, one must obtain a mathematical representation of the sampler and insurer process (NISE, 2013).

The mathematical model for the sampler is given by:

$$f_{Tw}^*(t) = f(t)s(t)$$

$$f_{Tw}^*(t) = T_w \sum_{k=-\infty}^{\infty} f(kT)\delta(t-kT) \quad (8)$$

Sampling can be considered the product of the waveform in the time domain to be sampled, $f(t)$, with a sampling function, $s(t)$. If $s(t)$ is a sequence of pulses of width $T_w$, constant amplitude and uniform rate, the sampled output, $f_{Tw}^*(t)$ , will consist of a sequence of part of $f(t)$ at regular intervals. In Equation (8), the term $\delta(t-kT)$ constitutes in Dirac delta functions. With this, the result of sampling with rectangular pulses can be considered as a series of delta functions where their areas are the product of the width of the rectangular pulse with the amplitude of the sampled waveform, or $T_w\, f(kT)$ (NISE, 2013).

For Nise (2013), the zero-order insurer produces a stepped approximation for $f(t)$. Thus, the output of the insurer is a sequence of stepped functions whose amplitude is $f(t)$ at the sampling instant, $f(kT)$. Since a single impulse from the sampler produces a step during the sampling interval, the Laplace transform of this step, $G_h(s)$, which is the impulse response of the zero-order insurer, is the transfer function of the zero-order insurer. When using an impulse at the zero instant, the transform of the resultant step starting at $t = 0$ and ending at $t = T$, expressed by:

$$G_h(s) = \frac{1 - e^{-Ts}}{s} \quad (9)$$

In a physical system, samples of the input waveform as a function of time, $f(kT)$, are held during the sampling interval. It can be verified from Equation (9) that the insurance circuit integrates the input and maintains its value throughout the sampling interval. As the area of the delta function that comes from the sampler is $f(kT)$, by integrating the ideal sampled waveform and obtaining the same result as for the physical system (NISE, 2013).

## 3 CONTROL LAW

Silveira (2018) described when considering that a plant $G_p(s)$, Eq. (4), of order and relative degree, a control law described as $n^* = 2$

$$u_p = \theta^T \varphi \tag{10}$$

where $\varphi = [\varphi_1^T, \varphi_2^T, y_p, r]^T$ and $\theta = [\theta_1^T, \theta_2^T, \theta_3, c_0]^T$ where $\varphi_1^T$ and $\varphi_2^T$ vectors that make up the state reconstitution filters, $y_p$ the plant output signal and $r$ the reference signal; $\theta_1^T, \theta_2^T, \theta_3, c_0$ gain vectors.

State-reconstitution filters can be represented in the discrete-time domain as:

$$\varphi_1(k) = (I + \bar{F}T)\varphi_1(k-1) + gTu_p(k-1) \tag{11}$$

$$\varphi_2(k) = (I + \bar{F}T)\varphi_2(k-1) + gTu_p(k-1) \tag{12}$$

STANDARDIZATION OF ADAPTIVE LAWS

According to Silveira (2018) to solve the problem of divergence of adaptive laws when the reference signal is excessively high, the normalization technique should be used. Normalization divides the law of adaptation by a quadratic function $m^2$. This signal $m^2$ acts as a brake that prevents the divergence of the estimated parameters. The solution often given by:

$$m^2 = 1 + \varphi^T \varphi \tag{13}$$

The use of a normalization signal, in addition to contributing to the convergence of the adaptive law, also improves the robustness of the controller in the face of plant uncertainties.

## GRADIENT METHOD – GM

Iannou (1996) described a parametric model in discrete time:

$$z(k) = \theta^{*T}\psi(\mathrm{k}) \tag{14}$$

being $\theta^*$ a vector of unknown parameters of order $n$, and $z \in \mathcal{R}^n$ is known for every instant $k = 1, 2, 3,..$ of the estimation of the error $e(k)$ is obtained by:

$$\hat{z} = \theta^T(k-1)\,\psi(k)$$

$$e(k) = \frac{z(k) - \hat{z}(k)}{m^2(k)} \tag{15}$$

the estimation of the error $e(k)$ at time $k$ depends on the previous estimate of $\theta^*$, that is, at time $\theta(k-1)$, because $\theta(k)$ is then generated from $e(k)$.

The adaptive law is given by:

$$\theta(k) = \theta(k-1) - \Gamma\psi(k-1)e(k-1)sgn(p^*) \tag{16}$$

being $\Gamma$ is a fixed gain, $\psi$ is a regressor vector, $e(k)$ the error between the estimated answer and the actual response and the absolute value $sgn(p^*) = sgn(K_p/K_m)$.

## RECURSIVE LEAST SQUARES METHOD – RLSM

According to Åström (2008) in this method, the unknown parameters of a mathematical model must be chosen in such a way that the sum of the squares of their differences must be minimal. The normalized algorithm presented by Iannosun (1996) is formed by a covariance matrix, expressed by:

$$\dot{P} = \frac{-P\zeta\zeta^T P}{m^2} \tag{17}$$

Equation (17) can be implemented in digital form as:

$$P(k) = P(k-1) - T\frac{P(k-1)\zeta(k-1)\zeta(k-1)^{T}P(k-1)}{m^{2}(k-1)} \quad (18)$$

and the estimation of the parameters:

$$\theta(k) = \theta(k-1) - \frac{P(k-1)sgn(p^{*})\zeta(k-1)e(k-1)}{m^{2}(k-1)} \quad (19)$$

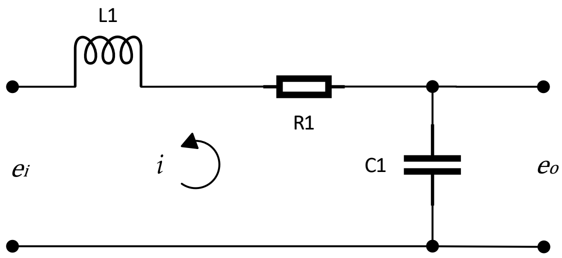
being $\zeta(k)$ a regressive vector and $e(k)$ is the error between the estimated response and the actual response and the absolute value $sgn(p^{*}) = sgn(K_p/K_m)$.

## 4 RESULTS AND DISCUSSIONS

For the present work, a direct MRAC algorithm was developed, where its performance was compared when using the RLSM and GM estimators (CANHAN; BROLIN; ROSSINI, 2022a) (CANHAN; BROLIN; ROSSINI, 2022b) (COLDEBELLA; BROLIN; ROSSINI, 2022a) (COLDEBELLA; BROLIN; ROSSINI, 2022b).

For the analysis of the algorithms, the transfer functions of the plant and the reference model used in this work were based on an LRC circuit presented in Figure 2:

Figure 2 – LRC Circuit.




Source: Adapted from Ogata (1995).

According to Ogata (1995), the circuit consists of an inductor $L_1$ (henry), a resistor $R_1$ (ohm) and a capacitor $C_1$ (farad), $i$ the current of the circuit, $e_i$ the input of the circuit and $e_o$ the output of the circuit. According to Ogata (1995) to find the transfer function of this plant one must apply the law of Kirchhoff voltages in the circuit. When it is considered to $e_i$ be the input and to be the $e_o$ output, thus, the transfer function of the circuit will be:

$$\frac{E_o(s)}{E_i(s)} = \frac{1}{LCs^2 + RCs + 1} \tag{20}$$

Equation (20) in the form of state space is given by:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{1}{LC} & -\frac{R}{L} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{LC} \end{bmatrix} u$$

$$y = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \tag{21}$$

For the reference model, we used a model, observable and controllable, which has a peak time of 0.2s (seconds), a damping factor of 0.69, an overshoot of 5%, an accommodation time of 0.3s (seconds) and an ascent time of 0.1s (second). Having this data, the transfer function can be described as:

$$Q_m(s) = \frac{471.1}{s^2 + 29.96s + 471.1} \tag{22}$$

For the development of the RLSM algorithm, a square wave was used as a reference signal. The transfer function for the plant and the reference model are shown in Equations (20) and (22), respectively. This method has an optimal transient regime, due to its covariance matrix being updated with each recursion. The covariance matrix must be initialized with sufficiently high values, because the higher the value, the faster the convergence, however extremely high values can lead to numerical divergence.

Figure 3 shows the output of the plant together with the reference model, where the capacity of this method can be seen. The plant follows the reference model with an error very close to zero. With each update, the accommodation time of the plant signal is 3 s (s seconds), a peak time of 0.2 s (seconds) and an overshoot of 1.2%.

The error between the plant output signal and the reference model output signal is relatively small. Thus, to have a better visualization of the two signs the image is enlarged to the place indicated in Figure 3 and presented in Figure 4.

Figure 3 - Outputs of the RLSM estimator.

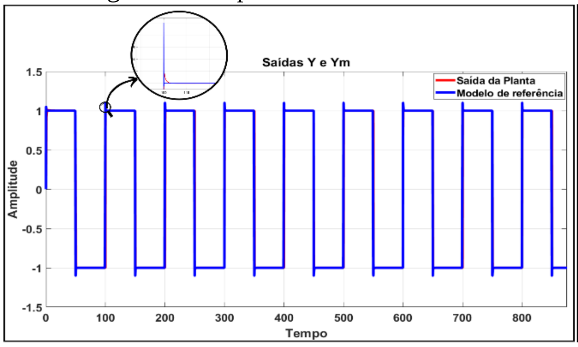



Figure 4 – Outputs RLSM Identifier Extended.

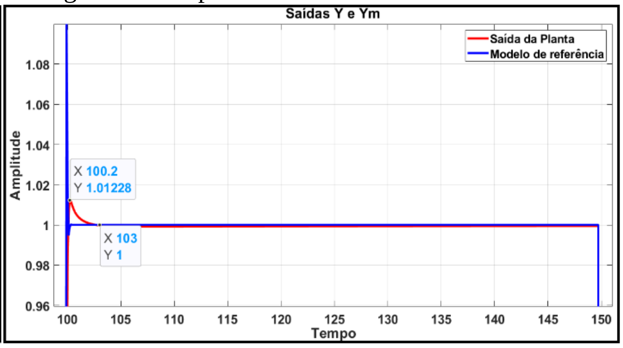



Figure 5 illustrates the update of the error for the RLSM. In the first instant, the error is high, with the amplitude 100%, with a peak value 1. However, in the first update of the error, in 50 s, with 0.27 peak, this error drops considerably. Also, it is noted that in 50 s the amplitude is greater about the next update because the error between the plant and the reference model is more or. From 150 s the error update has a smaller amplitude, with 0.18 peak, and with each new update, the error is adjusted to get close to zero, thus confirming the convergence of the plant with the reference model.

Figure 5 – Update of the error for RLSM.

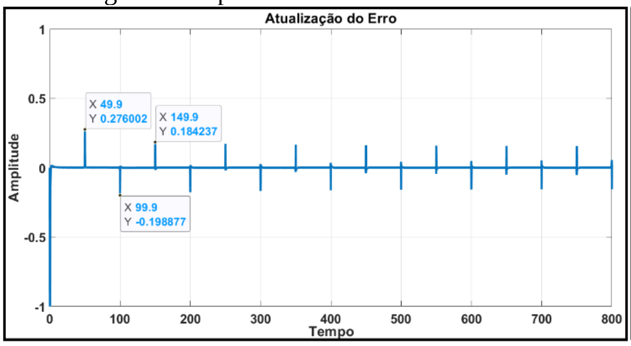



Figure 6 – Mean Squared Error for RLSM.

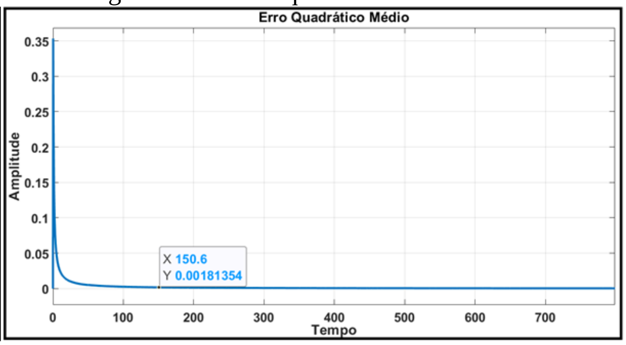



Figure 6 shows the Mean Squared Error (MSE), and it was noted that the error tends to zero quickly. In 150 s, the error is negligible and therefore the efficiency of the algorithm was observed.

For a better analysis of the data, Table 1 presents the values used for the reference model and the values obtained by the behavior of the plant against the RLSM.

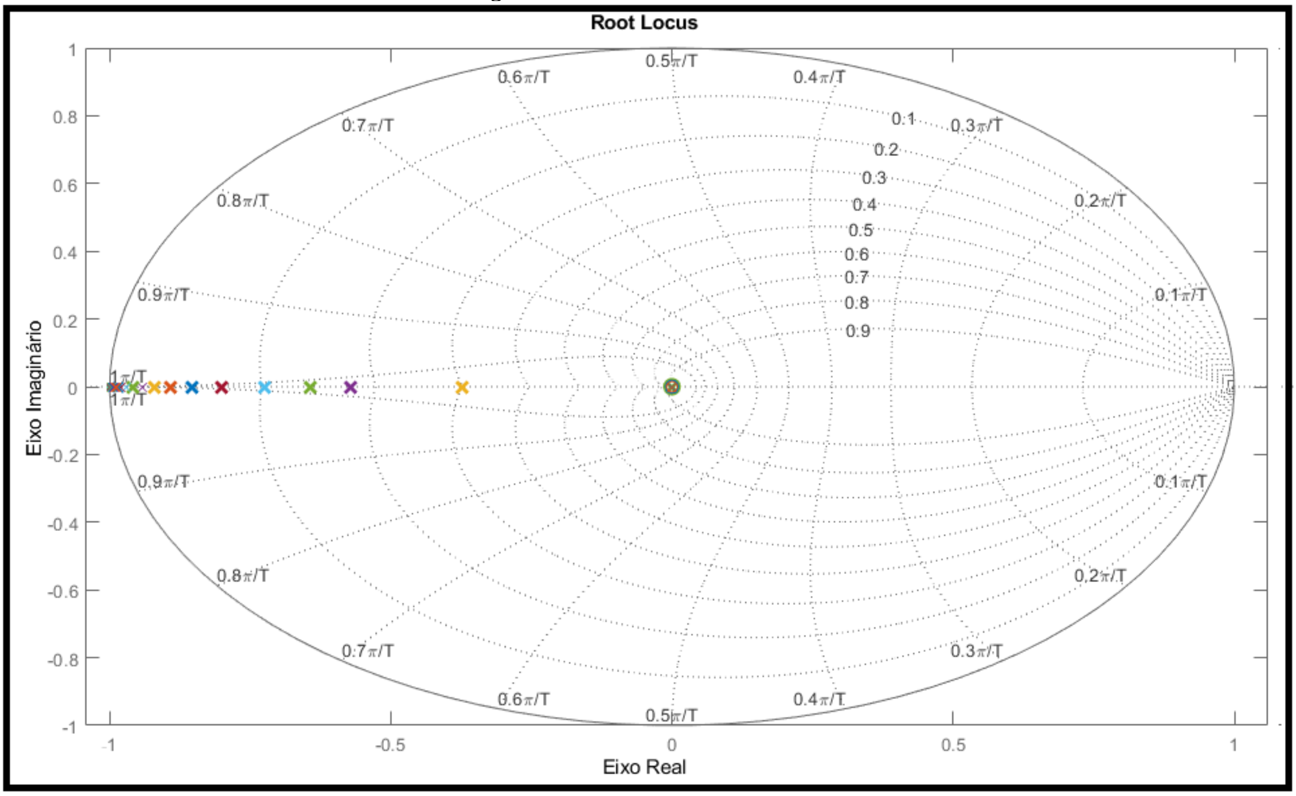
Table 1 – Values for the Reference Model and the MMRQ.

| | *Peak Weather(s)* | *Accommodation(s)* | *Overshoot (%)* | *Sampling(s)* | *Adaptation(s)* | *Gain ($P_0$)* |
|---|---|---|---|---|---|---|
| **Model** | 0.2 | 0.3 | 5 | 0.1 | - | - |
| **RLSM** | 0.2 | 3 | 1.2 | 0.1 | 150 | 10 |

According to Nise (2013), the geometric place of the roots is a representation of the poles in the closed mesh as a parameter of the system undergoes variation. The place of roots was used for analysis and design for stability and transient response. The geometric place of the roots can be used to describe, qualitatively, the performance of a system as various parameters are changed.

Figure 7 shows the geometric place of the roots for the RLSM. In the figure one can observe the pole and the zero of the plant near the center of the unitary circle, as the process undergoes variations the poles are relocated to the left, tending to the value of in the $-1$ real axis. The reason why the poles do not have an imaginary part is that the chosen plant also does not have an imaginary part.

Figure 7 – Root Locus for RLSM.




For the development of the GM algorithm, a square wave was also used as a reference signal and the plan and reference model were presented in Equations (20) and (22), respectively. This method has a slower transient regime than RLSM, but is efficient when the controller gains are close to the real ones. The algorithm diverges if it has a very high gain. Because it has a fixed gain with this, it does not need to update this constant, it has a low computational cost when compared to RLSM.

Figure 8 shows the plant output together with the reference model. Like GM, the output signal from the plant tracks the output signal of the reference model with an error close to zero. With each update, the signal accommodation time is 3 s, the peak time is 0.2 s, and an overshoot of 3.25%.

Due to the error between the output signal of the plant and the signal of the reference model tends to zero, so to have a better visualization of the two signs the image is enlarged from the location indicated in Figure 8 and presented in Figure 9.

Figure 8 - GM estimator outputs.

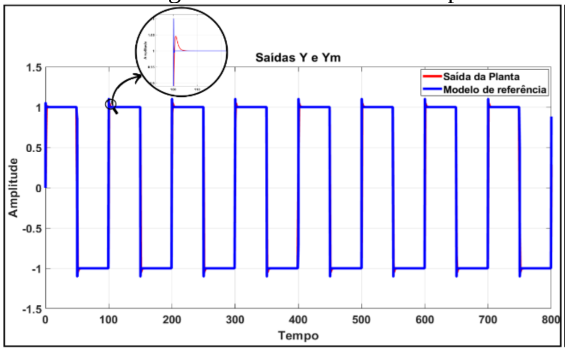



Figure 9 – Outputs Identifier GM Extended.

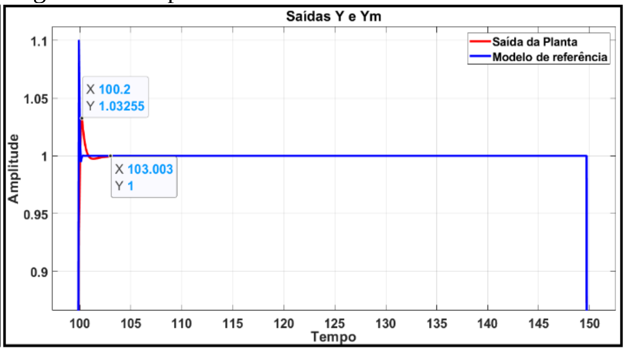



Figure 10 shows the update of the error for the GM. In the first instant, the error is less than the RLSM, with 105% of the total or peak amplitude $-1.05$. Onall,  in the following updates, there was a low decrease in the error with the RLSM. In the first update of the error, in 50 s, there is a peak of 0.29, an error higher than the RLSM at the same instant. It is also worth noting that in 50 s the amplitude is greater about the next update because the error between the plant and the reference model is greater. With each update, the error is adjusted to get closer to zero. Thus, the convergence of the plant with the reference model is confirmed.

Figure 11 shows the Mean Squared Error (MQE), which requires a longer time for the error to be equivalent to the RLSM, in 255 seconds.

Figure 10 – Error update for GM.

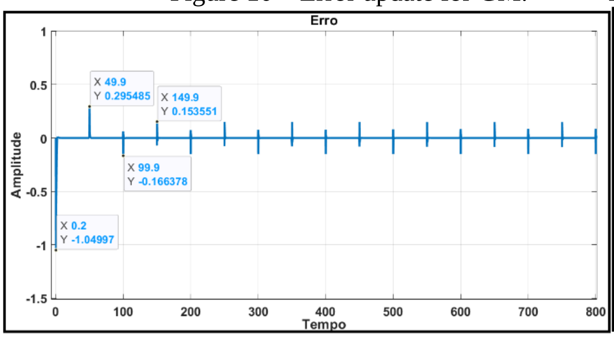
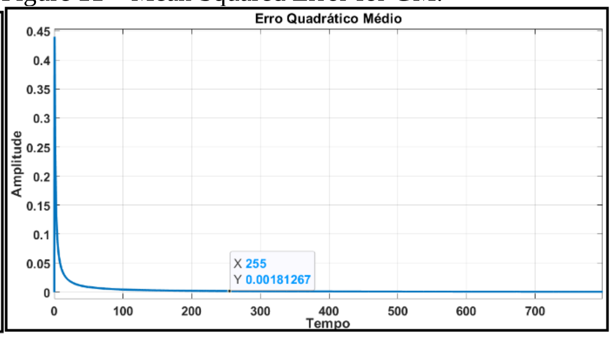



Figure 11 – Mean Squared Error for GM.



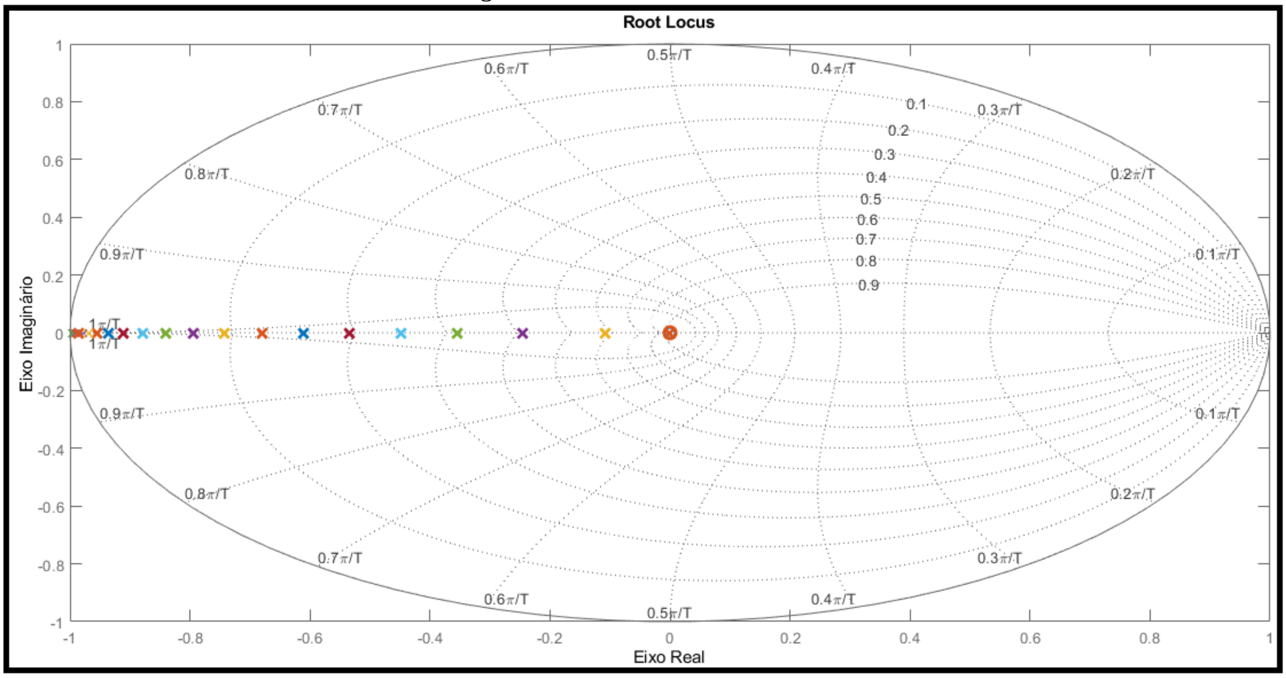

For a better analysis of the data, Table 2 presents the values used for the reference model and the values obtained by the behavior of the plant against the RLSM. Table 2, note that in the Adaptation colun the time required for the plant to get closer to zero was 255 seconds.

*Table 2* – **Values for the Reference Model and for the GM.**

| | *Peak Weather(s)* | *Accommodation(s)* | *Overshoot (%)* | *Sampling(s)* | *Adaptation(s)* | *Gain (Γ)* |
|---|---|---|---|---|---|---|
| **Model** | 0.2 | 0.3 | 5 | 0.1 | - | - |
| **GM** | 0.2 | 3 | 3.25 | 0.1 | 255 | 3 |

Figure 12 shows the geometric place of the roots for the GM. As with RLSM, one can notice the pole and zero of the plant near the center of the unit circle. Confirm the process undergoes variations the poles are relocated to the left, tending to the $-1$ real axis. The reason why the poles do not have an imaginary part is that the chosen plant also does not have an imaginary part.

Figure 12 –Root Locus for RLSM.




## 5 CONCLUSION

In this work a comparative study was carried out between two parametric estimation methods applied to direct MRAC, RLSM, and GM, thus analyzing the closed mesh performance of each algorithm when applied to the same plant and reference model.

The results obtained are very attractive since each estimation method has its particular performance characteristic. GM has its gains close to the true gains and lowers the processing demand. The RLSM has greater numerical stability but has a much higher computational cost than the GM presented. It is up to the designer to decide the best option to use.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