A Comparison Analysis of Adaptive Control Techniques Applied over Coupled DC Motors under Disturbances

Santiago Pulgarín-Correa, Sebastián López-Blandón, Eduardo Giraldo

***Abstract*—In this paper, a novel approach to the automatic control of a DC motor has been presented through the application of advanced identification and adaptive control techniques. A combination of online and offline identification methods, including least squares and projection algorithms, has been explored to establish accurate models for the motor. Based on these identified models, PID and generalized polynomial integral-acting controllers have been specifically tailored and implemented. A distinctive feature of this work is the integration of adaptive control strategies with these controllers. The adaptive framework has enabled the controllers to autonomously adjust in response to varying DC motor conditions, thereby ensuring robust performance across different operating scenarios. The efficacy of the proposed methodology has been rigorously evaluated through comprehensive simulations and practical experiments on a physical DC motor setup. Utilizing an Arduino Due and an H-bridge for motor control, disturbances have been assessed by coupling an additional motor to the main setup. This approach has facilitated a thorough comparison of disturbance responses across all implemented models and controllers. In summary, a novel methodology combining advanced identification techniques with adaptive control strategies has been contributed by this research, demonstrating significant advancements in the automatic control of DC motors under varying operational conditions.**

***Index Terms*—Adaptive control, DC motor, Identification techniques, Arduino**

I. Introduction

DC motors have been commonly utilized for extended operational periods due to their favorable internal and external properties as well as their control characteristics [1],[2]. Their linearity has made them suitable for various speed control applications; however, nonlinear behavior has been exhibited under unstable conditions and in the presence of disturbances. In the control of dynamic systems like DC motors, model-based techniques have been extensively employed for designing feedback controllers to maintain desired motor positions [3],[4]. Nevertheless, discrepancies have inevitably arisen between developed mathematical models and actual plants due to uncertainties in system parameters, unmodeled dynamics, nonlinearities, external disturbances, and measurement noise. Thus, the challenge has lain in designing identification and control systems capable of handling these uncertainties to implement robust and efficient control systems.

The modeling of physical plants has been acknowledged as having played a crucial role in the design and control of automated systems, as noted in [5]. In many cases, an accurate representation of system dynamics through parameter identification has been required to be achieved using parametric models. Elementary identification methods may have proven inadequate, necessitating the use of advanced techniques such as optimization or model fitting methods. Despite this, manual model implementations have often been described in the literature, even in critical applications such as navigation bridge simulator design. While human expertise has been relied upon, this interactive approach has been found to be laborious and time-consuming. Therefore, the exploration of advanced parameter identification methods has been deemed essential to improve system representation accuracy and enhance feedback controller design. Initially, the problem of parameter identification has been formulated and studied within the framework of general systems theory, with the aim of applying it to solve control system reference problems [6],[7],[8]. Sufficient knowledge of mathematical models of controlled or stabilized objects has been deemed necessary for the synthesis of adaptive and optimized control laws.

According to [9], identification algorithms have been categorized into two main groups: online and offline identification. Offline identification has involved the determination of a system model using a batch of measured data available at all stages of the procedure. In experimental studies, parameter identification has often been performed during the post-processing of obtained data, requiring careful analysis to ensure accuracy and reliability. In contrast, online identification has entailed simultaneous measurement and identification processes, albeit with some temporal separation, necessitating precise synchronization to achieve accurate model parameter identification.

In [10], a didactic plant has been implemented for learning control techniques, with potential plant changes considered during mathematical modeling. Various methods for identifying DC motor plants have been employed, such as online identification using least squares, as proposed in [11]. Control systems for managing motor position, speed, and torque have been categorized into three main groups [12]: classical systems (P, PI, PD, PID) [13], modern systems (adaptive, sliding mode, etc.) [14], and intelligent systems

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Santiago Pulgarín-Correa is an undergraduate student in Electrical Engineering at Universidad Tecnológica de Pereira, Pereira, Colombia. Research Group in Automatic Control. E-mail: santiago.pulgarin@utp.edu.co.

Sebastián López-Blandón is an undergraduate student in Electrical Engineering at Universidad Tecnológica de Pereira, Pereira, Colombia. Research Group in Automatic Control. E-mail: sebastian.lopez3@utp.edu.co.

Eduardo Giraldo is a Full Professor at the Department of Electrical Engineering, Universidad Tecnológica de Pereira, Pereira, Colombia. Research group in Automatic Control. E-mail: egiraldos@utp.edu.co.

(neural networks, fuzzy controllers, etc.). In [15], a general form of adaptive control for multivariable systems, including identification and polynomial control, has been presented. In [16], adaptive control of an induction motor based on indirect field-oriented control has been presented and validated through simulation and a real prototype.

In [17], a discrete sliding mode-based control algorithm, termed ”Position-Braking Tracking Control (PBTC),” has been developed to enhance position-tracking performance for low-frequency trajectories in a permanent magnet DC servo motor application. With the estimation of plant values, discrete controllers have been found necessary, as proposed in [18]. Specifically, PID controllers for second-order plants and more general controllers, such as generalized polynomial controllers with integral action, have been considered. Methods for simultaneous estimation and control have been suggested for DC motor position control [19]. The evaluation of the proposed controllers and identification methods has been conducted to highlight superior controller performance under both normal and disturbed conditions. In [20], model-based control of a buck converter has been presented, with the system identified as a second-order discrete model using a PID controller, as well as other state space controllers, which have been successfully validated over a real prototype [21],[22],[23],[24].

In this paper, an innovative methodology for the automatic control of DC motors has been introduced, featuring cutting-edge identification and adaptive control techniques. State-of-the-art algorithms have been integrated into this novel approach to redefine how DC motor control is achieved, advancing both the precision and adaptability of the control systems. The main contribution of this study has been the enhancement of control system performance against external disturbances through the use of adaptive control techniques and their validation by using open-source Arduino microcontrollers and low cost DC motors. The proposed adaptive control techniques are evaluated in simulation and over a real workbench with two coupled DC motors. In addition, a comparison analysis of the proposed techniques is presented. The paper has been structured as follows: Section II has presented identification model methods and control techniques, outlining structures designed for online and offline identification, PID controllers, and integral action polynomial controllers. Section III has showcased evaluation results of the proposed controllers in simulations and real-time DC motor experiments under external disturbances. Finally, conclusions have been drawn.

II. Materials and Methods

In this work are proposed several combinations between identification methods and discrete controllers in order to evaluate adaptive control approaches over two coupled DC motors by using open-source Arduino microcontrollers.

A. Discrete controllers

1) PID Controller: This version of the PID controller is used for second-order systems. This controller has integral action and therefore the closed-loop system will have zero steady-state error. The equation of the controller is defined as follows:

$$C(z) = \frac{c_0 z^2 + c_1 z + c_2}{(z + c_3)(z - 1)} \quad (1)$$

being c_i, with $i = 1, \ldots, 4$ the controller coefficients.

2) Generalized polynomial controller with integral action: This polynomial controller can be used for systems of any order. In this case, the equation will be given for a second-order system:

$$C(z) = \left(\frac{1}{z-1}\right) \frac{p_1 z^2 + p_2 z + p_3}{z^3 + l_1 z^2 + l_2 z + l_3} \quad (2)$$

being p_i and l_i, with $i = 1, \ldots, 3$ the controller coefficients.

B. System identification

System identification is the process of obtaining a mathematical model from the input and output data of a dynamic system [25]. Offline and online identification are two common approaches to system identification.

1) Offline identification: Offline identification involves the use of historical data to build a mathematical model. In this approach, system input and output data are collected over time, and the identification algorithms are used to fit the parameters of the mathematical model [26].

For least squares, the input-output data measurements are organized as $y = A\theta$, being y is the system's outputs, A the inputs and outputs of the system at a previous time, and θ the parameters that describe the system dynamics. A general description of this data arrangement can be expressed as follows:

$$y[k] = -\sum_{j=1}^{n} a_j y[k-j] + \sum_{j=1}^{m} b_j u[k-j] \quad (3)$$

For a second-order system it would be simplified as follows:

$$y[k] = \begin{bmatrix} -y[k-1] & -y[k-2] & u[k-1] & u[k-2] \end{bmatrix} \underbrace{\begin{bmatrix} a_1 \\ a_2 \\ b_1 \\ b_2 \end{bmatrix}}_{\theta} \quad (4)$$

being θ the vector that holds the parameters of the system for the whole measured dataset.

2) Online identification: In this work an online identification is proposed to achieve a good performance of the controllers regardless of the disturbance applied to the system.

3) Online projection algorithms: Projection algorithms are a common technique for online identification used for linear and nonlinear systems. The identification is performed by applying the following equation recursively:

$$\theta[k] = \theta[k-1] + \frac{\phi[k-1]}{\phi^T[k-1]\phi[k-1]} (y[k] - \phi^T[k-1]\theta[k-1]) \quad (5)$$

being $\theta[k]$ the systems parameters identified at time instant k.

4) Online Least Squares: Least squares algorithms are another common technique for online identification, as described in [27]. This approach involves minimizing the sum of squared errors between the system output and the mathematical model output. The model parameters are recursively adjusted to minimize the difference between the system output and the model output. To this end, the identification of θ is performed by applying recursively the following equation:

$$\theta[k] = \theta[k-1] + \frac{p[k-1]\phi[k-1]}{1+\phi^T[k-1]P[k-1]\phi[k-1]} (y[k] - \phi^T[k-1]\theta[k-1]) \tag{6}$$

where θ holds the parameters of the system to be identified. The matrix P is computed recursively by applying the following equation:

$$P[k] = P[k-1] - \frac{P[k-1]\phi[k-1]\phi^T[k-1]P[k-1]}{1+\phi^T[k-1]P[k-1]\phi[k-1]} \tag{7}$$

C. Controllers design

The design of the controllers is performed by defining the closed-loop characteristic polynomial $p_{LC}(z)$ according to a desired polynomial $p_D(z)$. In this case, a second order system defined as follows is considered:

$$H(z) = \frac{b_1 z + b_2}{z^2 + a_1 z + a_2} \tag{8}$$

By considering the closed-loop polynomial $p_{LC}(z)$ the desired polynomial is defined as follows:

$$p_D(z) = z^4 + \alpha_1 z^3 + \alpha_2 z^2 + \alpha_3 z + \alpha_4$$

being α the desired coefficients for the closed-loop dynamics. By comparing the polynomials $p_{LC}(z) = p_D(z)$, the following set of equations is obtained for the PID controller of (1) in matrix form:

$$\begin{bmatrix} b_0 & 0 & 0 & 1 \\ b_1 & b_0 & 0 & a_1-1 \\ 0 & b_1 & b_0 & a_2-a_1 \\ 0 & 0 & b_1 & -a_2 \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \\ c_2 \\ c_3 \end{bmatrix} = \begin{bmatrix} \alpha_1+1-a_1 \\ \alpha_2+a_1-a_2 \\ \alpha_3+a_2 \\ \alpha_4 \end{bmatrix} \tag{9}$$

where is worth noting that the parameters a_1, a_2, b_1 and b_2 are computed at each time instant, and therefore (9) must be solved at each time instant as well.

The implementation of the polynomial controller with integral action is perform in a similar way to the PID controller. In this case, the desired polynomial is defined as follows:

$$p_D(z) = z^6 + \alpha_1 z^5 + \alpha_2 z^4 + \alpha_3 z^3 + \alpha_4 z^2 + \alpha_5 z + \alpha_6$$

By comparing the polynomials $p_{LC}(z) = p_D(z)$, the following set of equations is obtained for the polynomial controller of (2) in matrix form:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_1-1 & 1 & 0 & 0 & 0 & 0 \\ a_2-a_1 & a_1-1 & 1 & b_0 & 0 & 0 \\ -a_2 & a_2-a_1 & a_1 & b_1 & b_0 & 0 \\ 0 & -a_2 & a_2-a_1 & 0 & b_1 & b_0 \\ 0 & 0 & -a_2 & 0 & 0 & b_1 \end{bmatrix} \begin{bmatrix} l_1 \\ l_2 \\ l_3 \\ p_1 \\ p_2 \\ p_3 \end{bmatrix} = \begin{bmatrix} \alpha_1+1-a_1 \\ \alpha_2+a_1-a_2 \\ \alpha_3+a_2 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \end{bmatrix} \tag{10}$$

where the parameters a_1, a_2, b_1 and b_2 are also computed at each time instant, and therefore (9) must be solved at each time instant.

III. Result and Discussion

An Arduino DUE is used for the evaluation of the proposed approach, which is connected to the DC motor position sensor that has an encoder with 2000 pulses per revolution. The motor, which has a maximum supply voltage of 12 V DC, requires power that the Arduino cannot deliver. Therefore, an H bridge is used to change the rotation of the motor and to add a different power supply. The connection diagram is shown in Fig. 1. The system is identified and controlled in real time by using a sampling time pf 0.010 seconds.

Very low-cost elements were employed for the actual implementation of advanced control techniques in conjunction with different identification techniques. In Fig. 2, the components used for implementing control without disturbance are depicted, along with the elements used to connect the two motors via coupling. One motor serves as the controlled motor, while the other motor acts as the disturbance source in the system.

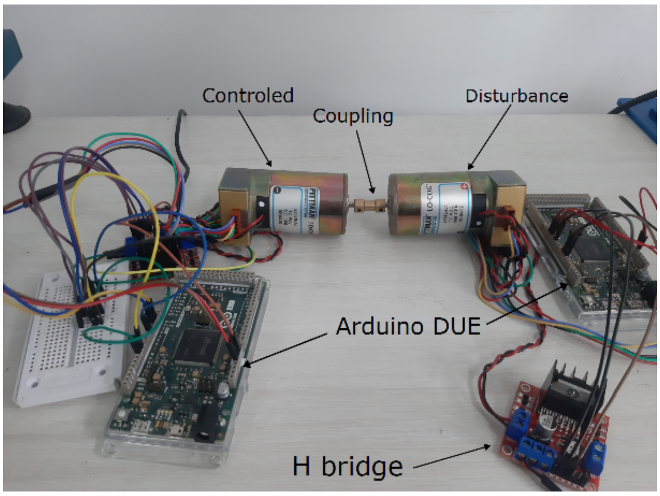

Fig. 2. Real implementation of the coupled DC motors.

When implementing the offline identification using least squares to find the plant dynamics approximating a plant of order 2, the following constants and discrete transfer functions were obtained.

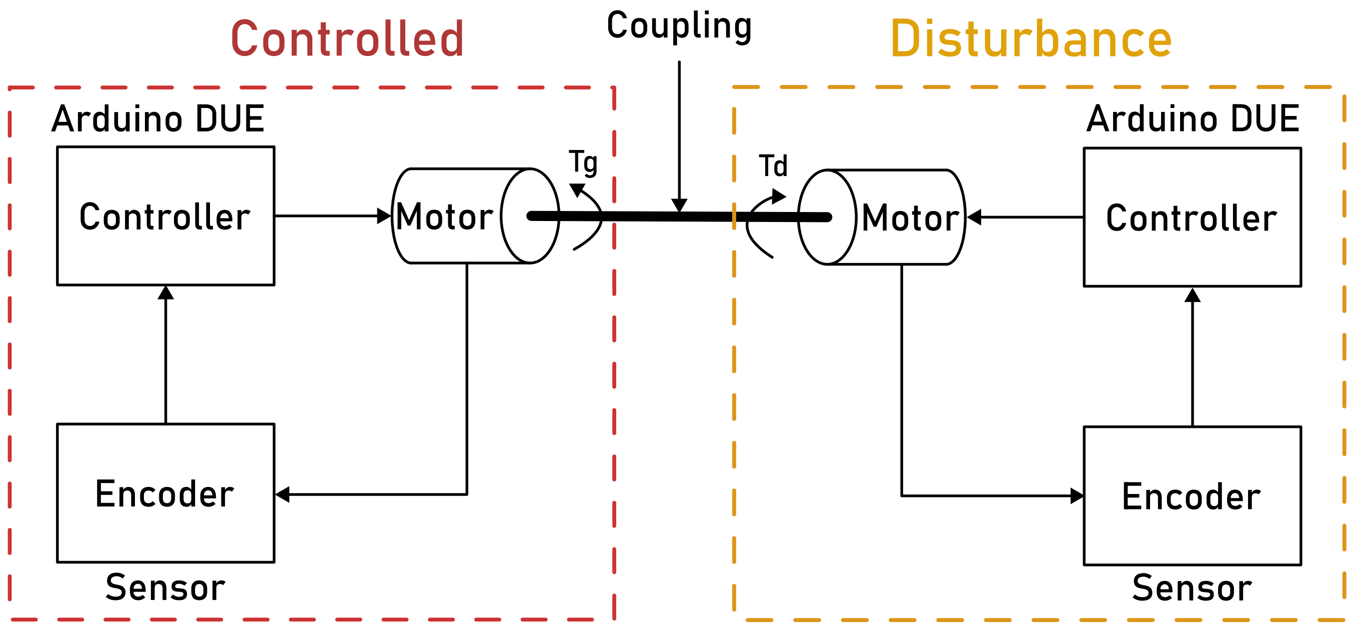

Fig. 1. Schematic diagram of the proposed approach.

$$\theta = \begin{bmatrix} a_1 \\ a_2 \\ b_0 \\ b_1 \end{bmatrix} = \begin{bmatrix} -1.7856 \\ 0.7734 \\ 0.1129 \\ 0.1181 \end{bmatrix} \tag{11}$$

$$H(z) = \frac{b_0 z + b_1}{z^2 + a_1 z + a_2} = \frac{0.1129z + 0.1181}{z^2 - 1.7856z + 0.7734} \tag{12}$$

To get an approximation of the mean square error, the following expression is used:

$$J = ||b - A\theta||_2^2 = (b - A\theta)^T (b - A\theta) = 1207.9 \tag{13}$$

The discrete transfer function found in (12) using offline least squares identification behaves very similarly than the real system, as shown in Fig. 3. In Fig. 3 a simulation under the same input is performed by considering the estimated offline parameters.

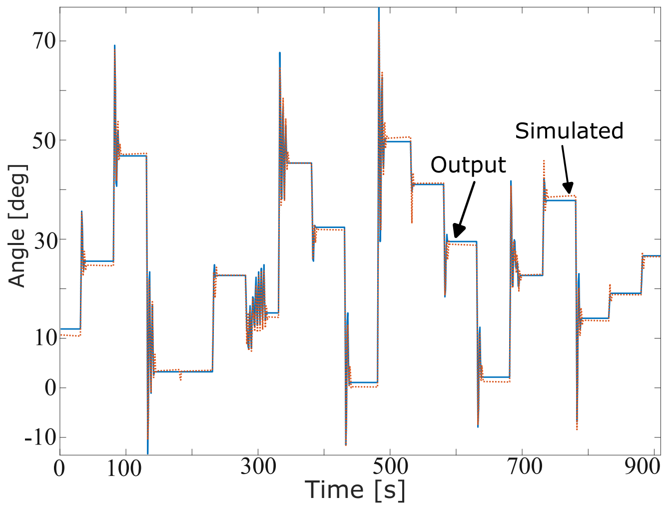

Fig. 3. Estimated output and system output.

The simulation and offline identification plots are so over-plotted that they are not noticeable, which means that the identified transfer function correctly models the changes generated by the input u.

The constants of the closed-loop transfer function of the PID controller are:

$$\begin{aligned} c_0 &= 16.7927 \\ c_1 &= -18.2875 \\ c_2 &= 5.8234 \\ c_3 &= 0.8890 \end{aligned}$$

by considering that α coefficients are chosen as zero, resulting in a closed-loop system with dead beat dynamics.

The closed-loop response of the PID controller of (12) based on the offline identification is implemented in the Arduino DUE microcontroller, and the reference tracking performance is shown in Fig. 4.

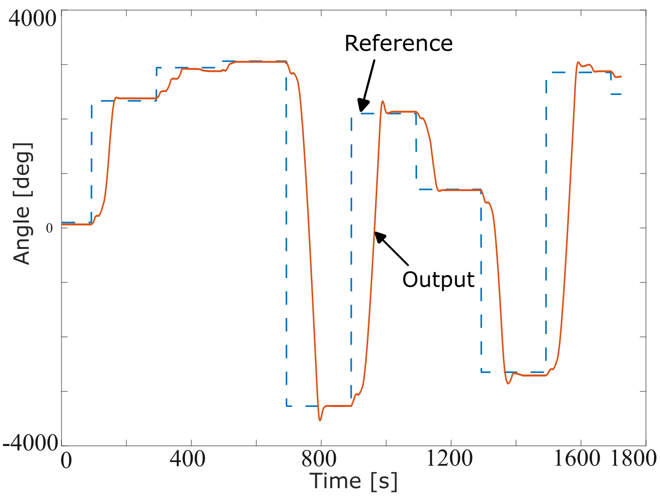

Fig. 4. Offline PID controller.

Figure 4 shows the behavior of the offline PID controller, by considering a reference signal that varies in step values. In Fig. 4 can be seen how the output signal manages to reach the reference after 100 seconds and stabilizes near the reference, and remaining with some small errors that fail to eliminate due to the dead point that has the engine, which behaves as a non-linearity just at this point.

For the polynomial controller it follows that, when solving the system (10), the following constants are obtained:

$$l_1 = 2.7856$$
$$l_2 = 6.7476$$
$$l_3 = 4.7394$$
$$p_1 = 68.1916$$
$$p_2 = -88.2116$$
$$p_3 = 31.0445$$

The closed-loop response of the polynomial controller of the equation (13) is implemented in the Arduino DUE microcontroller, and the reference tracking performance is shown in Fig. 5.

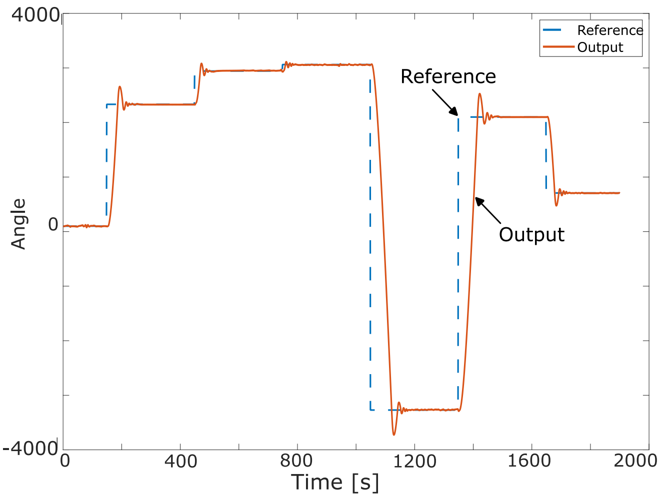

Fig. 5. Generalized polynomial controller with offline integral action.

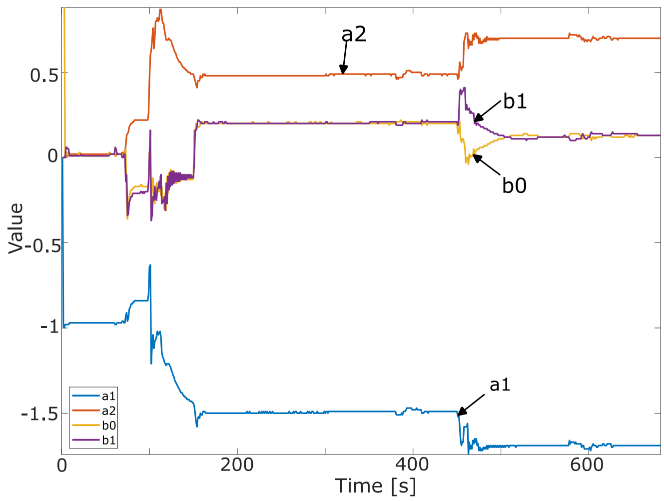

Fig. 6. Estimation of values by projection algorithm projection algorithm.

Figure 5 is the graph representing the generalized polynomial controller with integral action with offline identification. There it can be seen that the output reaches the reference with a bit of overshoot, however this quickly returns to the reference and stays there stable until the reference changes.

The online identification of the plant is performed in this case using the equation (5) of the projection algorithm to estimate the real-time values of the plant in addition to the fact that we would also be monitoring changes or disturbances of the identified plant at the same time.

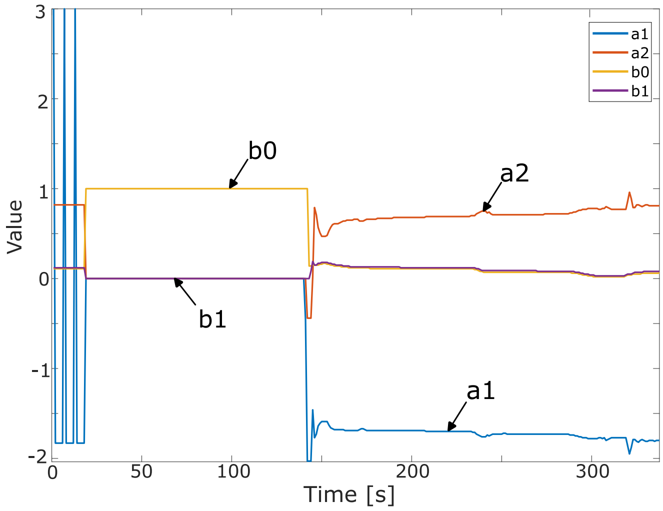

Fig. 7. Least squares value estimation.

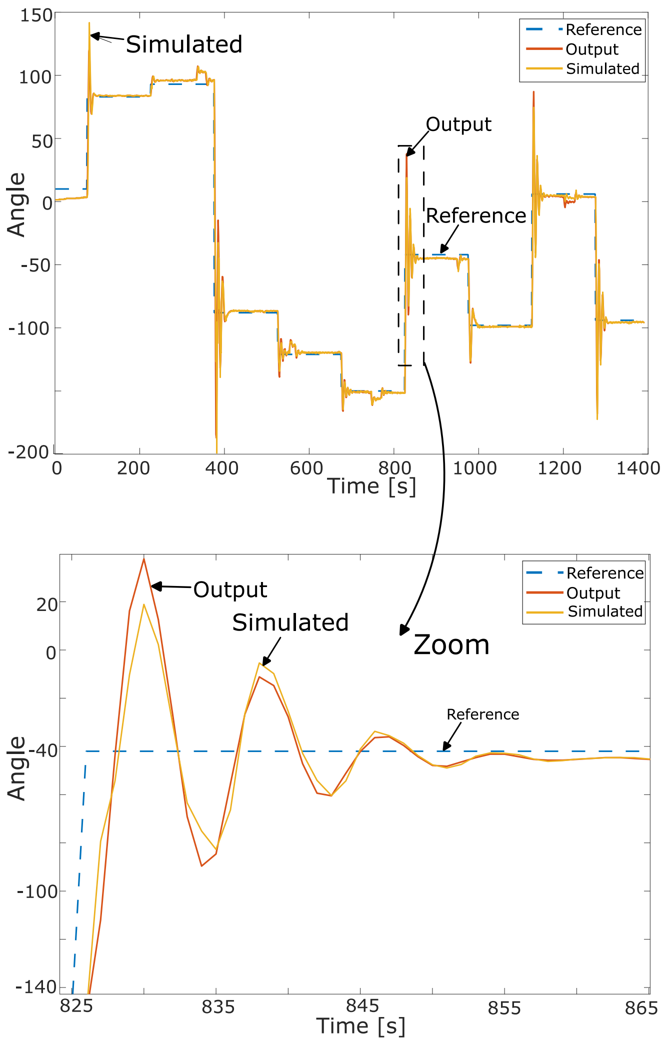

Fig. 8. PID Controller based on online identification.

The constants of the adaptive line identification are shown in Fig. 6, where an initial disturbance is made for the projection algorithm to estimate the parameters of the function in differences, these variables change over time because the plant can change due to different circumstances of the plant itself.

The variables estimated using this projection algorithm need many iterations to converge to a value that represents the system's dynamics. This makes the identification very slow and the initial controller will not be as good.

Figure 7 shows the graph of the variables obtained using the least squares method, with this method it can be seen that the response is faster because it reaches the parameter values in a shorter time than with the projection algorithm.

The problem with this algorithm is that if the P matrix becomes zero, the estimation values do not change even if the system is disturbed. To solve this problem, what is proposed is to reset the values of the P matrix so that the system re-estimates and identifies the dynamics of the system again.

In the same way as the PID control with offline identification in Fig. 4, a PID controller with online identification in Fig. 8 was implemented to evaluate the behavior of this form of identification.

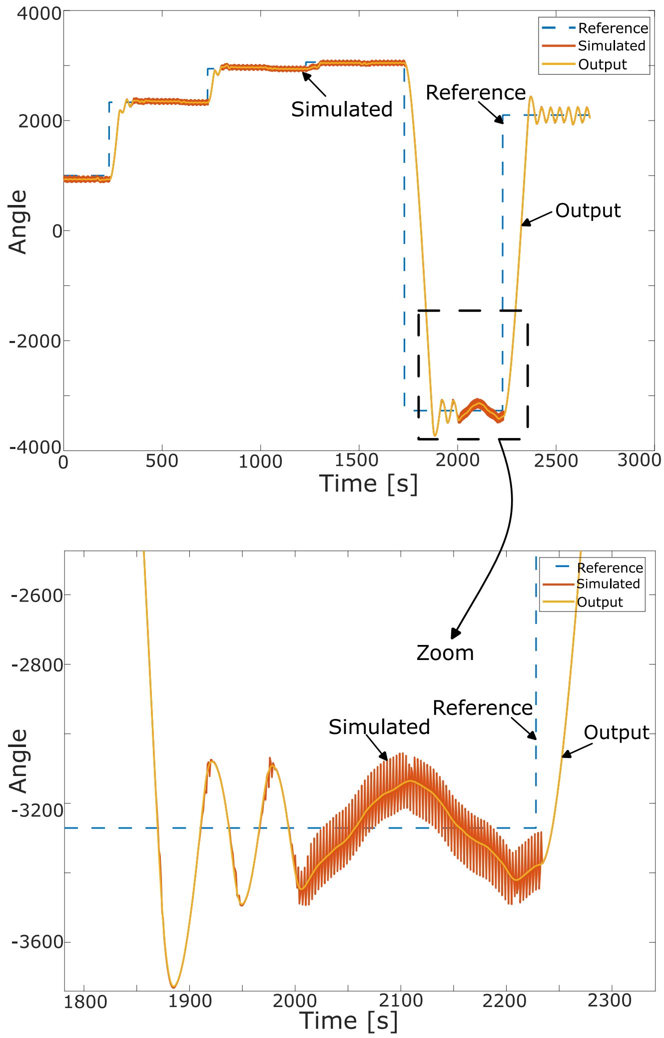

Fig. 9. Generalized polynomial controller with line integral action with online identification.

In Fig. 8 we see that there are some overshoot peaks coming out due to the projection algorithm as it tries to approximate a nonlinear system to a linear one, however, it can also be seen that the reaction time of the controller makes the system follow the reference faster.

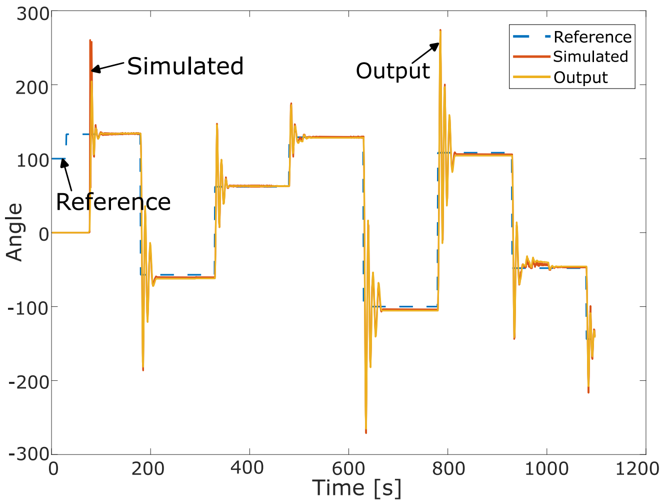

Fig. 10. PID Controller with online least squares.

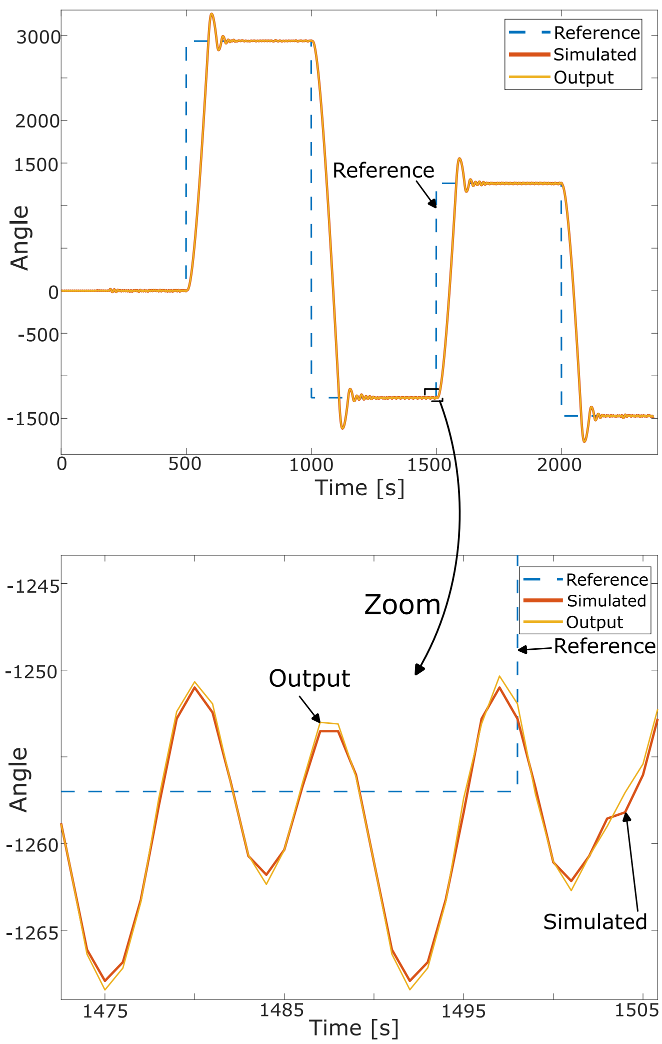

Fig. 11. Generalized polynomial controller with online least squares

When the system is implemented, it is possible to see the response of the estimated system, which is modeled by differential equations and compared with the response of the real system. This visual analysis allows to verify if the estimation of the system is good or not.

After having the PID controller working we change the controller in this case the generalized polynomial with integral action. The solution of the system of equations, given by (10), is solved by using a LU decomposition, which reduces the number of operations needed to solve the system. This reduced the computational load of the Arduino, which has to compute the identification and controller design every 0.01 seconds.

Using this polynomial controller, the closed-loop response of Fig. 9 is obtained.

It is worth noting that, while the system estimated the parameters by using the projection algorithm, several oscillations are shown in the closed-loop response when the reference is reached. This makes the motor direction changes very fast, so the actuator used to switch much faster and therefore generating a higher heat dissipation.

A more efficient identification method will be used to estimate the values of the difference equation much faster. To this end, the online least squares identification algorithm is used, as described in (6) and (7). This identification algorithm is used by considering the PID and the polynomial controller.

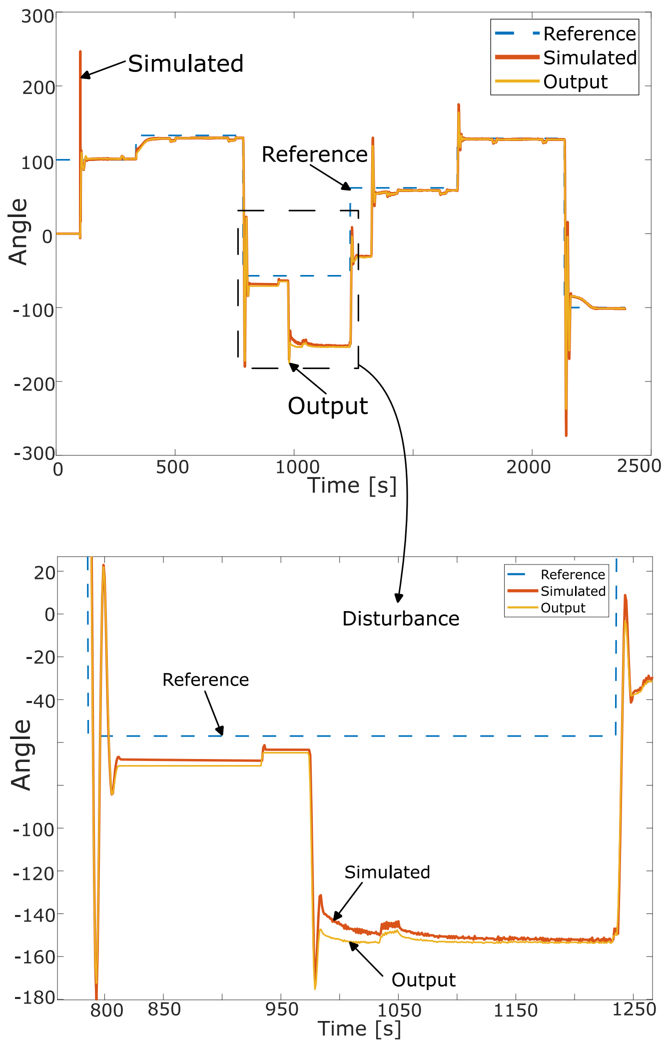

Fig. 12. PID controller with online least square identification under a disturbance.

For the online identification using least squares for the generalized polynomial and PID controllers, a better system response is seen when using the generalized polynomial compared to the PID controller, as shown in Fig. 10, which has a lot of oscillation and does not stabilize quickly, on the contrary in Fig. 11 it has a small overshoot and then stabilizes at the desired reference.

The estimation of the values is so good with the least squares method that in Fig. 10 and Fig. 11 the two graphs overlap and are not easily visualized, so in Fig. 11 an approach is made to notice which is the simulated and which is the real one.

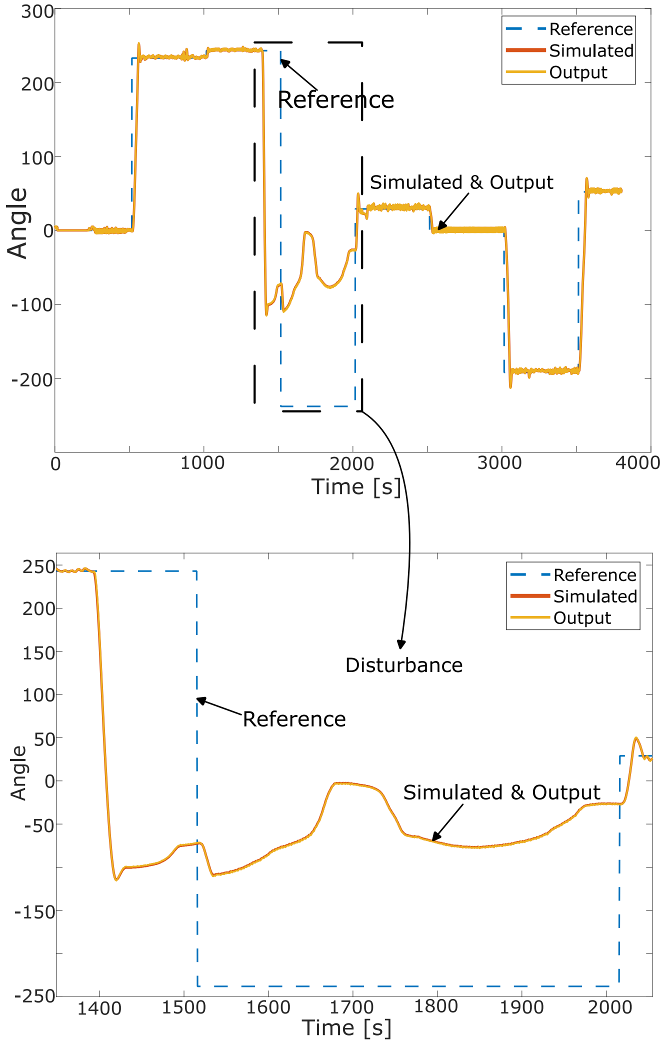

Fig. 13. Polynomial controller with online least square identification under a disturbance.

To evaluate the controllers and estimators to additive disturbances in the system and check their performance, for this we used another motor with the same characteristics using the same H-bridge and another Arduino DUE that fulfills the function of adding a disturbance in torque one of the disturbances difficult to control. In this case, the motor that generates the disturbance will do it for 3.5 s and then leave the controlled motor free to reach its reference, the case where we are interested in checking this disturbance is in the online identifiers.

For the Fig. 12 the disturbance for the identification by least squares and the PID controller is being checked, the disturbance entered in the time of 9.8 seconds and the disturbance was maintained until the 13. 3 seconds of simulation, this time the controlled engine deviated from the reference about 90 degrees but remained in that position and did not let the engine with the disturbance make it deviate more from the reference, after the disturbance the engine reaches the reference without any problem.

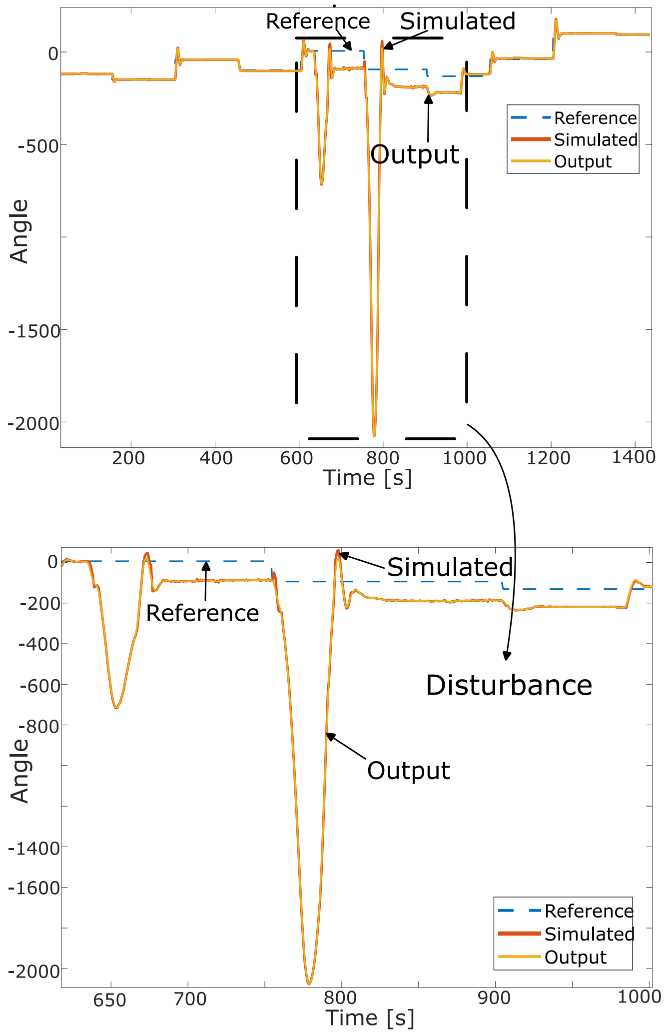

Fig. 14. PID controller with online projection identification under a disturbance.

Now the disturbance is applied to the same previous identifier, and the controller is changed to the generalized polynomial. In this case, as can be observed in Fig. 13, the disturbance is initiated at 14 seconds, and at 17.5 seconds, it is disconnected. The controlled motor attempts to reach the reference, but later changes its reference and eventually achieves it. The disturbance causes the controlled motor to deviate from the reference by almost 350 degrees, surpassing the intended deviation of 300 degrees.

The identification is switched to the projection algorithm, and the first controller tested for performance is the PID controller, as depicted in Fig. 14. In this case, the disturbance begins at 6.2 seconds and concludes at 9.7 seconds. The system experiences multiple overshoots as it attempts to estimate and control the disturbance. Due to the projection algorithm requiring numerous iterations to converge, the disturbances are highly noticeable.

In the case of Fig. 16, the disturbance in torque for the polynomial with in-line identification by the projection method resulted in the output being moved away from the reference, resulting in a substantial error of approximately 2700 degrees. This disturbance could not be effectively countered by this controller with this identification method, demonstrating inefficiency compared to expectations.

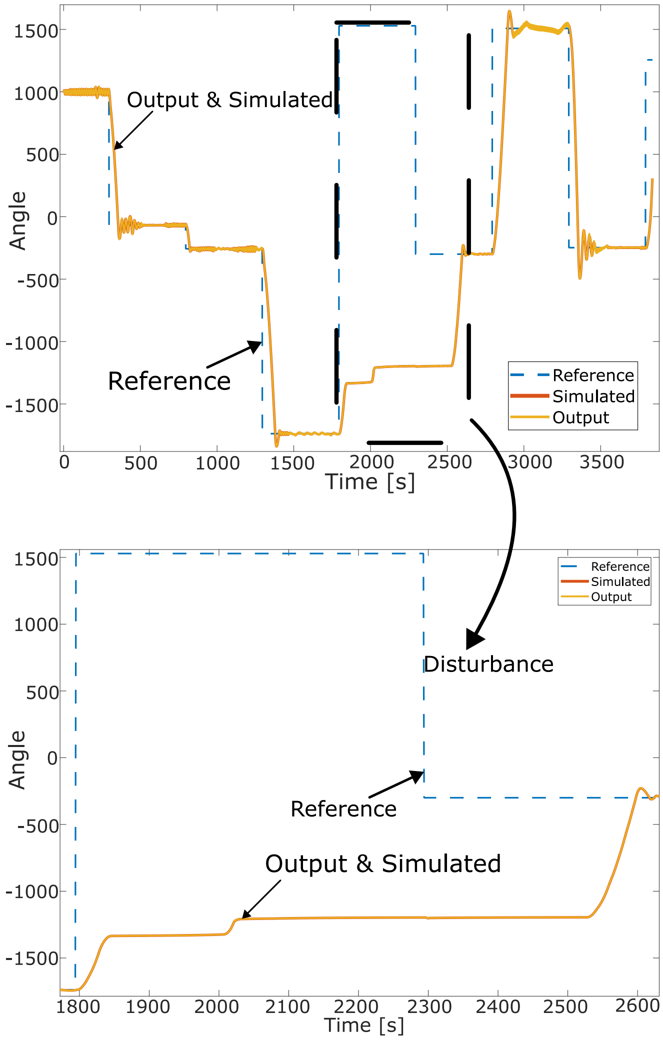

Fig. 15. Polynomial controller with online projection identification under a disturbance

Since no arrangement between identifier and controller proved effective against torque disturbances, a hybrid method is proposed where the two identification methods are combined. This hybrid method incorporates the strengths of each: least squares identification for its high-speed convergence and the projection algorithm for its robustness.

The Hybrid method is tested in Fig. 16 without disturbances to evaluate its performance against reference changes and tracking.

In Fig. 16, a hybrid identification is implemented with the PID controller. Initially, there is time for identification and calculation of control constants to achieve the reference, resulting in decreasing oscillations over time. However, a steady-state error is observed in the system, attributed to the motor's dead zone and the resolution limitations of the encoder sensor.

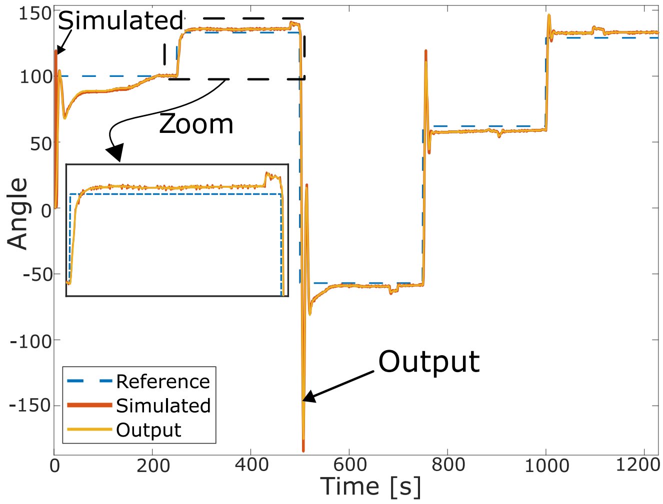

Fig. 16. Hybrid identification with the PID controller.

Unlike Fig. 16, in Fig. 17 where a generalized polynomial control is utilized and the hybrid identification was conducted swiftly, focusing on reference tracking.

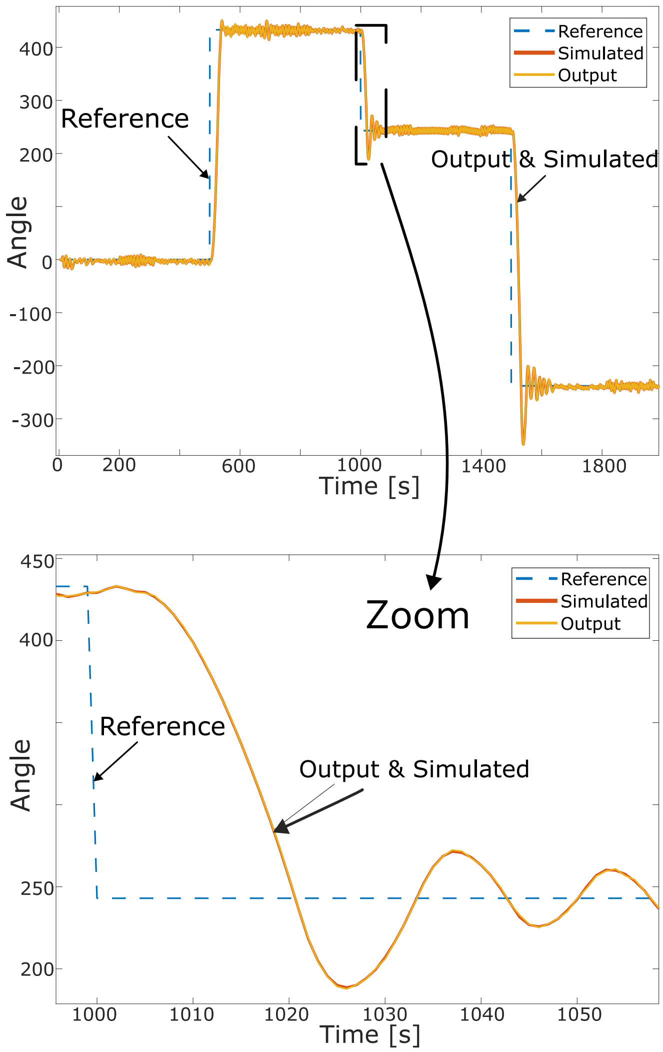

Fig. 17. Hybrid identification with the polynomial controller.

In this case, oscillations are observed as the system attempts to reach the reference and compensate for the motor's dead zone.

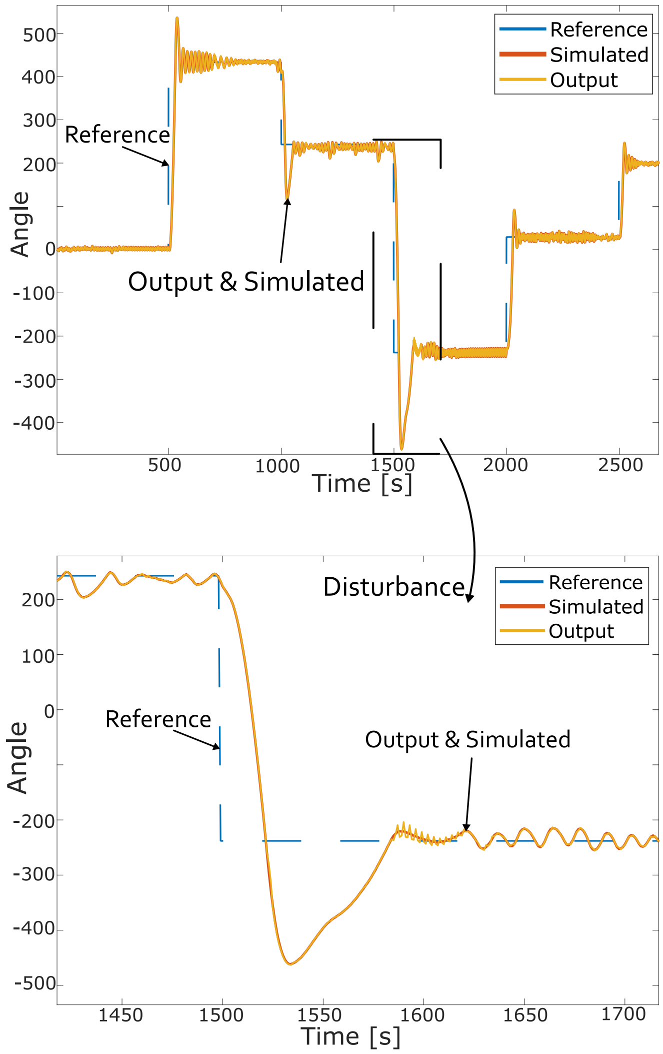

Fig. 18. Hybrid identification control polynomial with disturbance.

Regarding the identification, it can be noted that the approximation is very close, making it difficult to distinguish between simulated and actual data.

The performance of the disturbance in the proposed identification system is now being evaluated under these conditions, as depicted in Fig. 18 and Fig. 19.

The first controller evaluated with disturbance and hybrid identification was the polynomial control, as depicted in Fig. 18. When the disturbance occurs, the system momentarily deviates from the reference but manages to bring the output back to the reference with increased oscillation, influenced by the motor's response to the disturbance. This behavior represents an improvement compared to previous observations.

Finally, the hybrid identification is utilized in conjunction with the PID controller in Fig. 19. In this case, the torque disturbance manages to cause the output of the controlled system to deviate, resulting in a steady-state error. However, this error is expected to be less than with previous controllers and with fewer oscillations compared to Fig. 18.

IV. Conclusion

In this work, a comparison analysis of several control and identification techniques is conducted. The performance of each control and identification method is evaluated using two coupled DC motors.

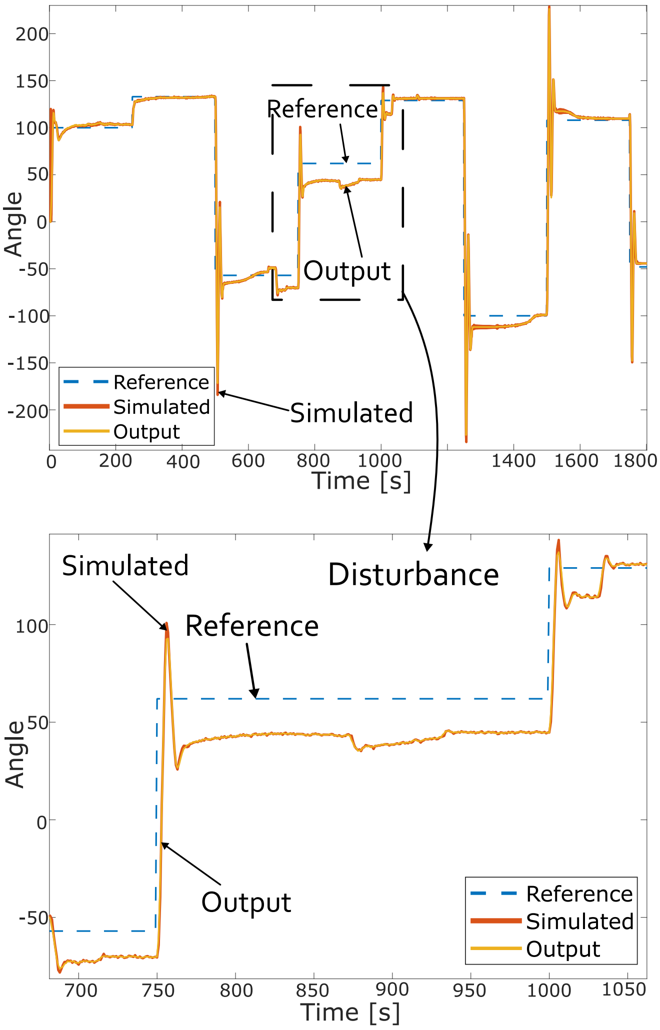

Fig. 19. Hybrid identification with the PID controller under a disturbance.

An angular position tracking control task is implemented on one motor, while a torque disturbance is induced in the coupled motor. The hybrid identification methods, in conjunction with the PID controller, exhibited the best performance against disturbances compared to state-of-the-art methods. Furthermore, it is observed that the evaluation of these complex adaptive controllers is carried out on a low-cost Arduino-based platform. It is noteworthy that the motor model is successfully identified using the identification methods, rendering the proposed approach suitable for implementation in both simulated and real prototypes, even under nonlinear, unstable, or disturbed conditions.

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