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On Fault-Tolerant Control Systems: A Novel Reconfigurable and Adaptive Solution for Industrial Machines

JORGE RODRIGUEZ-GUERRA[1], (Member, IEEE), CARLOS CALLEJA[1], ANA MARIA MACARULLA[2],(Member, IEEE), ARON PUJANA[1], IKER ELORZA[1], AND MIKEL RAMOS[3], (Member, IEEE)

[1]Ikerlan Technology Research Centre, 20500 Arrasate, Spain
[2]Department of Informatics, Electronic and Communication Technology, University of Deusto, 48007 Bilbao, Spain
[3]Fagor Arrasate S. Coop., 20500 Arrasate, Spain

Corresponding author: Jorge Rodriguez-Guerra (jorge.rodriguez@ikerlan.es)

ABSTRACT Fault-Tolerant Controllers (FTCs) modify system behaviour to overcome faults without human interaction. These control algorithms, when based on active approach, detect, quantify and isolate the faults during Fault Detection and Isolation (FDI) phase. Afterwards, during Control Re-design (CR) phase, the controller is reconfigured and adapted to the faulty situation. This last phase has been approached by a wide variety of algorithms, being Adaptive Controllers (ACs) the ones studied in this paper. Despite their potentiality to overcome faults, industrial manufacturing systems demand robustness and flexibility levels hardly achievable by these algorithms. On this context, the paper proposes to upgrade them introducing novel Digital-Twin (DT) models to increase its flexibility and Anti-Windup (AW) techniques to improve their robustness. These novelties reach their maximum potential when FDI and CR phases merge to generate a novel FTC platform based on a Bank of Controllers (BC), improving the fault avoidance process as controller gains are switched to the ones that recover the machine more efficiently.

INDEX TERMS Virtual manufacturing, fault tolerant systems, adaptive control, digital systems.

I. INTRODUCTION

Industry behaves as a living entity, continuously evolving their manufacturing processes to decrease production times without reducing product quality. This search has lead to improve the manufacturing cycles, introducing novel techniques to maintain the machine working despite the appearance of faults [1], [2]. Due to this tendency, industrial systems have increased their productivity avoiding downtime periods.

Predictive maintenance brought the first step into this direction [3]. This technique estimates the machine break down, scheduling a maintenance before this drawback occurs to avoid the inner cost of a malfunctioning tool without stopping periodically the production cycle. Despite control designers are able to anticipate the fault emergence with high precision, their unpredictable nature makes the inversion effortless when they appear earlier than expected.

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Fault-Tolerant Control (FTC) has been postulated as a solution to avoid these troubles, as they prepare the controller to surpass the fault and keep the system working without decreasing the product quality [4]. Control designers have a wide trajectory implementing one of its approaches, the Passive Fault-Tolerant Control (PFTC) [5], [6], nonetheless these controllers lack the flexibility needed to avoid different faults, specially when they have a wide harm-grade. Opposite to that tendency, Active Fault-Tolerant Control (AFTC) approach [7]–[9] offers a versatile environment as they are designed to detect, grade and isolate the fault source in a first instance during the Fault Detection and Isolation (FDI) phase and, afterwards, modify the control law to overtake the fault during Control Re-design (CR) phase without stopping the system.

The AFTC approach presented on this paper sought a robust control algorithm prepared to work in industrial conditions and flexible enough to be adapted when the manufacturing cycle conditions vary. To accomplish both properties, we propose a novel methodology based on Advanced

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Process Control (APC). On the one hand, FDI phase has been improved introducing Neural-Nets (NNs) into the detection, grading and isolation mechanism. On the other hand, CR phase has been upgraded with Adaptive Controllers (ACs) in order to modify dynamically the controller response.

ACs have multiple approaches, being the Model Reference Adaptive Control (MRAC) the one implemented in this paper. This algorithm improves conventional PID controllers introducing into the control loop three major improvements: an adjustable controller, a model reference and an adaptation mechanism. The study developed for the first one sought to acquire compatibility between the previous control designs and the new techniques, while the second one substitutes the mathematical equations used as the reference model with a Digital-Twin (DT), replicating the machine behaviour. Lastly, MIT and Lyapunov adaptive rules [10]–[13] have been analysed and improved introducing an Anti-Windup (AW) mechanism capable of adjusting the reference signal to the new saturation in the faulty system.

The control techniques used in the adaptive rules increase the overall robustness of industrial system, while the DT implemented in the reference model brings MRACs with a flexible platform prepared to modify these controllers attending to the production cycle requirements. Despite these benefits, the adaptation mechanism reduces its efficiency when the fault harm-grade increases [14]–[16], [19]. Integrating a Bank of Controllers (BCs) structure in the CR phase allows to overcome a wider number of faults, as the information provided during FDI phase is used to pick the most efficient adaptive gains to get over the fault.

This MRACs are suited for industrial applications, such us hydraulic-presses, vacuum pumps and conveyor belts, as the enhances have been designed to be compatible with this type of environment [20]. The presented novel methodology is explained on Section II through an analysis of the BCs, showing the improvements introduced in FDI and CR phases. In addition, Section II-B provides information about the DT, AC rules and new AW techniques designed to overcome the faults. Section III continues with the study showing how the novel methodology is implemented in an industrial press, testing its performance against three faults. Finally, on Section IV the conclusions drawn from the paper are presented.

II. NOVEL FAULT-TOLERANT CONTROL METHODOLOGY

Systems are altered constantly due to internal and external factors, as there are a wide variety of sources that modify their behaviour positively or negatively. Changes paired with this last road degrade system performance and are called faults. They modify the machine behaviour, whose functioning will be determined by the harm-grade taken in its components. The paper sought to find a methodology prepared to avoid faults independently of the damage taken by the machine.

Fault-Tolerant Controllers, specially when they are based on the active approach, are prepared to deal with these uncertainties and avoid the faults without stopping the system.

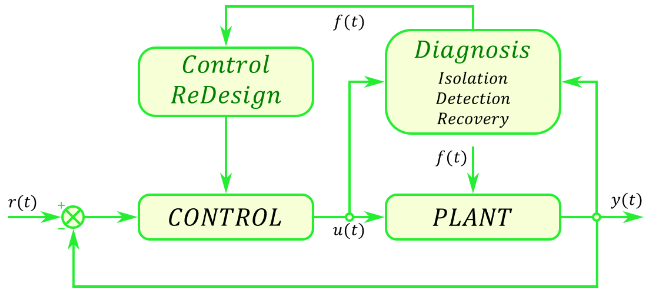

FIGURE 1. Architecture followed in the active fault-tolerant control platform designed on the paper.

These controllers handle them introducing a two step process, first faults are identified with a Fault-Detection and Isolation mechanism and, afterwards, during Control Re-design, the controller is adapted to surpass them. On the paper, we propose a novel methodology for this approach based on a Neural-Net trained to detect, grade and isolate the fault source and Adaptive Controllers to reduce the fault effect $f(t)$ on the system implemented through Fig. 1 schematic. This mechanism gathered the fault information who is exported afterwards into the Control Re-design phase

Despite the fact that this approach manages most of the faults, when their harm-grade increases, the AC become less efficient. To overcome this problem the AFTC has been upgraded through a Bank of Controllers. Adding this feature enables an individualized study of each fault, as the FDI mechanism select the best AC gains to surpass them. When both techniques are mixed, a novel methodology is born to avoid faults even for high harmful grades. On Section II-A the FDI mechanism is explained while Section II-B shows the novel features used on CR phase, while in Section III-B the technical improvements used on CR phase are shown.

A. FAULT DETECTION AND ISOLATION

There are several harm-grades in industrial machines, from soft faults that are corrected by the controller to more severe ones in which the production has to be stopped. Between both extremes, there are faults that affect the system negatively but are avoidable modifying the control loop. This paper focuses on this kind of faults, that it is to say, the novel methodology pursue to recover the system from faults that degrade system behaviour while it keeps the machine working avoiding its spread. In AFTC approach, faults are classified into four categories attending to their source:

- **Component:** Comprehends faults in the physical pieces compounding the machine. They are linked with malfunctions appearing in actuators or sensors, such us noise, disconnection or offsets in the signals.
- **Plant:** Modifications in internal factors. The machine behaviour suffers variations due to mechanical degradation on its components.
- **Communication:** Readings from the plant or the control loop are corrupted giving wrong information about the system performance. They represent a discordance between controller and machine signals.

- **Controller:** The control loop behaviour gets degraded, leading the system to instability. They are related with controller malfunctions or wrong user commands.

Traditionally, faults are identified through mathematical methods due to the lack of information [17]. Nonetheless, during FDI phase, an alternative detection mechanism based on Neural-Nets is used. Introducing this Artificial Intelligence (AI) algorithm brings a powerful tool prepared to detect the fault, discriminates its source and grades its harm even when there are uncertainties about how the system is affected [18]. The NN is trained through a fault database created replicating the undesired behaviour in a Hardware in the Loop (HiL) platform [21]–[23]. This process is divided into three stages, as Fig. 2 shows:

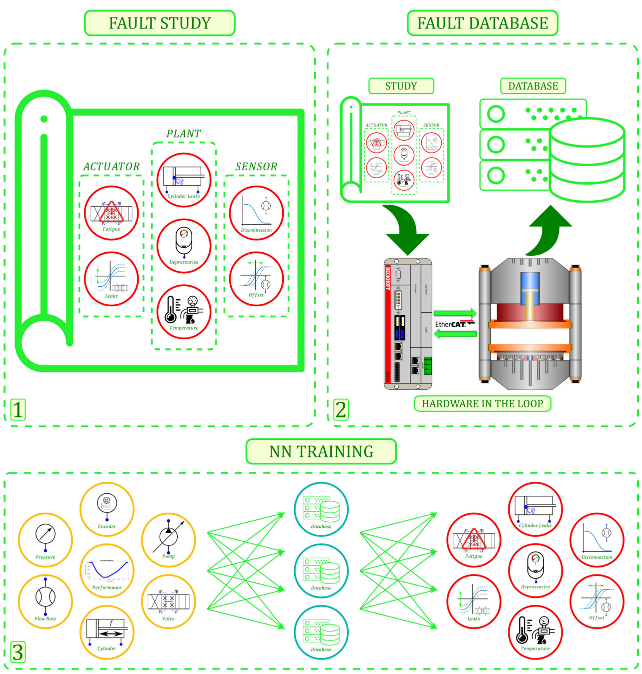

FIGURE 2. Process followed during fault detection and isolation phase.

- **Fault Study:** Before the faults are simulated in the HiL platform, each component is studied to determine if they are prone to fail, pointing their tolerance to faults and how their performance gets affected.
- **Fault Database:** On the HiL platform, the fault conditions from the previous study are replicated in each component. The machine behaviour under this faulty circumstances is measured and stored to generate a fault database.
- **NN Training:** Using the information stored from the previous stage, the NN is trained to identify and grade faults with the measures brought by machine sensors.

B. CONTROL RE-DESIGN

If the fault is understood as a new system behaviour, Control Re-design stage sought to modify the controller in such a way that keeps the machine working replicating the initial performance. In the literature, [3], there are multiple approaches for the CR stage, being Model Reference Adaptive Controllers the ones implemented on this paper. Its structure, as Fig. 3 shows, is compounded of three elements, the adjustable controller (initial control algorithm), the adaptation mechanism (rules followed to adapt controller gains) and the model reference (closed loop system behaviour), in addition to the plant.

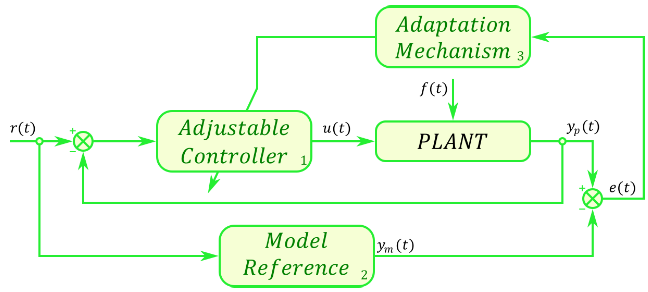

FIGURE 3. Model reference adaptive control common loop structure.

Each one has been studied and improved to make them suitable for the novel methodology presented:

1) ADJUSTABLE CONTROLLER

The novel methodology sought to introduce MRACs benefits to overcome faults in industrial controllers. Conventional PID controllers are upgraded in such a way that their old gains remain identical but the output signal is modified by the new control loop (Fig. 4). In addition, the novel features have to be commissioned without stopping the manufacturing cycle.

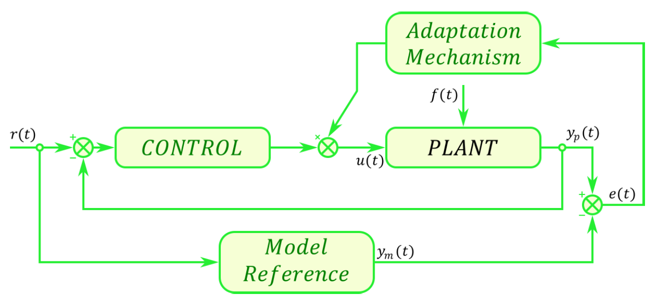

FIGURE 4. Conventional PID control modified to introduce MRAC adaptive gains.

To accomplish both objectives, HiL platforms play a crucial role, as they offer a harmless environment to study the MRAC loop effect in the PID controller without affecting the real machine nominal behaviour as the test is done in a secure and isolated environment [37], [38].

2) MODEL REFERENCE

MRAC's model reference represents the system nominal behaviour in closed loop. On FTC methodology, the model reference is used to compare the machine behaviour without faults against the response obtained in the plant. This error is integrated to adapt the controller gains searching to minimize the difference between both responses. Conventional approaches have used mathematical models to describe the plant closed loop response, nonetheless, in the methodology presented a new strategy based on Digital-Twins is proposed.

The DT is created through a library prepared to replicate the behaviour of industrial components in a process that resembles how an operator would construct the machine. Fig. 5 represents the assembling process, summarized in the following three steps:

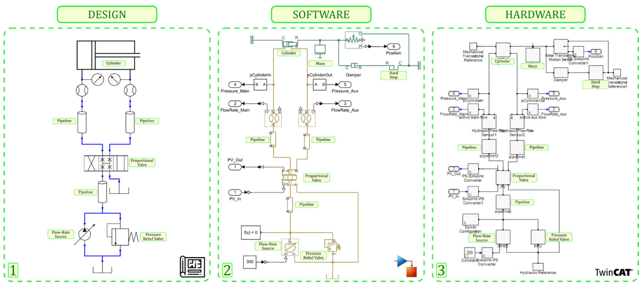

FIGURE 5. Graphical representation of the Digital-Twin creation stages.

- **Designing process:** Initially, operators design the blueprints to configure the machine components placement. These schematics reproduce the final distribution of each component, parametrizing them with the information extracted from data-sheets.
- **Software platform:** Afterwards, a DT model is generated in Simulink®. The components are connected following schematic information ensuring the virtual machine has an identical distribution as the real system. Each component has been parametrized browsing manufacturer specifications from data-sheets. The DT performance is compared against the responses obtained in the machine.
- **Hardware platform:** When the model has been validated in the software environment, it is exported into TwinCAT 3, Beckhoff native hardware programming platform. During this final validation, a virtual commissioning process is set up as the DT model is simulated in Real-Time and communicated through a deterministic protocol with the controller.

This process creates Digital-Twin modules reflecting the real behaviour of systems with high accuracy as the designing process replicates the conditions followed in the industry to build the machine [21]. In addition, the library has been designed to parametrize the components with information brought by data-sheets, replicating in the virtual environment an identical component as the one used in the industry.

DT replicates the real machine characteristic with high accuracy, reproducing the same effects that the system has in the industrial plant. Introducing these improvements brought MRACs with the flexibility required in manufacturing systems, as the DT is adapted automatically to variations in the production cycle. Independently of the new commands,

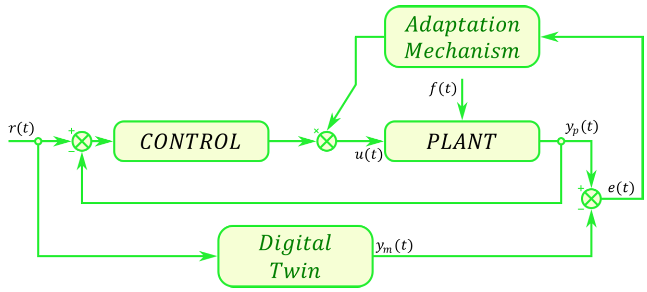

FIGURE 6. Conventional PID control modified to introduce MRAC adaptive gains.

the DT will behave as the real system, but without the drawback of being affected by faults. Control designers have an adaptive model that expands the possibilities for conventional MRACs (Fig. 6), as variations in the production cycles are reflected on the model, who will behave actively to surpass it, as Section II-B.3 shows.

3) ADAPTATION MECHANISM

This type of ACs overcomes the fault varying controller gains to adapt the system new behaviour to the old performance [26], [27], that is to say, the adaptation mechanism is based on studying the tracking error e between the plant output y_p and the reference model output y_m:

$$e(t) = y_p(t) - y_m(t) \tag{1}$$

MRAC objective is to reduce the tracking error between model and system response modifying control gains to cancel the new fault dynamics [24], [25]. This ensures, for any reference, that the system tracking error tends to zero. In a common structure, the process output is defined by the plant g_p and the controller output signal u:

$$Y_p(s) = G_p(s)U(s) = \frac{b}{s+a}U(s) \tag{2}$$

where a and b are plant dynamics. The reference model represents system behaviour in closed loop g_m, so its equation is defined by:

$$Y_m(s) = G_m(s)R(s) = \frac{b_m}{s+a_m}R(s) \tag{3}$$

The tracking error is obtained from the difference between both equations, that is to say, the objective is that the process dynamics:

$$\dot{y}_p(t) + ay_p(t) = bu(t) \tag{4}$$

match the desired reference r dynamics:

$$\dot{y}_m(t) + a_m y_m(t) = b_m r(t) \tag{5}$$

which is achieved when the control law is adapted by two variable gains θ_1 and θ_2:

$$u(t) = r(t)\theta_1 - y_p(t)\theta_2 \tag{6}$$

When this equation is inserted into the previous ones the following expression is obtained:

$$\dot{y}_p(t) + a y_p(t) = b(r(t)\theta_1 - y_p(t)\theta_2) \tag{7}$$
$$\dot{y}_p(t) + (a + b\theta_2) y_p(t) = b\theta_1 r(t) \tag{8}$$

being able to define both gains as:

$$\theta_1 = \frac{b_m}{b} \tag{9}$$
$$\theta_2 = \frac{a_m - a}{b} \tag{10}$$

These gains are considered the adaptive parameters and are the ones that modify the controller to reach a null error. Fig. 7 shows the behaviour of MRAC systems, proving the earlier assumptions, the error between the expected output and the real one tends to zero. The time to reach this value varies attending to the system, as it is linked with the number of iterations in the productive cycle, faster cycles reach the null value earlier than slower ones, providing that the adaptive gains are tuned accordingly to the speed.

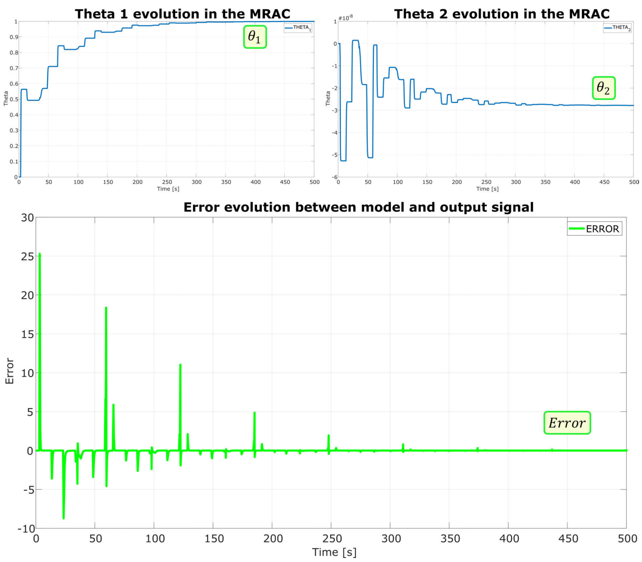

FIGURE 7. **MRAC objectives: Acquire controller gain stability (top) while minimizing the error (bottom).**

As a summary, ACs combine system information obtained during the offline design to modify the control law online. This approach allows the controllers to adapt their dynamics to the new situation reaching the optimal performance despite the appearance of faults. The adaptation laws are based in the following approaches [28], [29]:

- **Sensitivity Methods:** Parameters are estimated by a cost function based on the partial derivative of the signal multiplied by the error. *Massachusetts Institute of Technology* (MIT) rules are the common approach for this type of laws [30], [31].
- **Positivity Design:** In this case, a stability problem is formulated and solved by a differential equation. The transfer function reduces the error comparing the system output signal against the one obtained from a model. Afterwards, a Lyapunov function (V) is set out in such a way that its first derivative ($\dot{V}$) is negative, accomplishing the system stability [32], [33].

The derivative law analysis gives a new adaptation control loop, which is represented in Fig. 8.

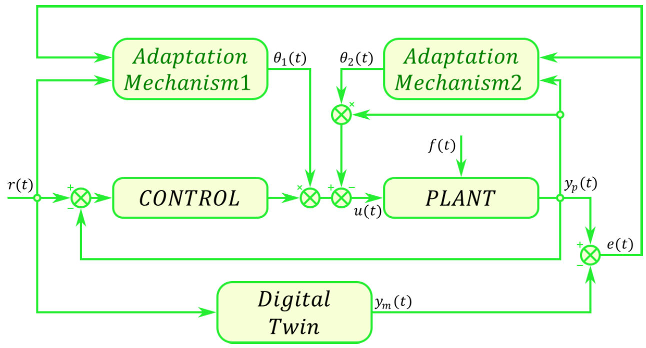

FIGURE 8. **MRAC schematic modified for MIT and Lyapunov adaptive rules.**

a: MIT RULE

In the MIT Rule [34], the adaptive gains θ_1 and θ_2 are obtained through a cost function $J(\theta)$. This equation is based on the tracking error square, whose minimum value is obtained when the first derivative is null. The equation is developed to determine the adaptive gains who are defined through the tracking error, its first derivative and an update law α:

$$J(\theta_1, \theta_2) = \frac{e^2}{2} \tag{11}$$
$$\frac{d}{dt}\theta = -\alpha \frac{\partial}{\partial \theta} J \tag{12}$$
$$\frac{d}{dt}\theta = -\alpha e \frac{\partial}{\partial \theta} e(\theta) \tag{13}$$

This function is introduced in the process to obtain the relation between plant output and reference:

$$\dot{Y}_p(s) + aY_p(s) = bU(s) \tag{14}$$
$$\dot{Y}_p(s) + aY_p(s) = b\left(R(s)\theta_1 - Y_p(s)\theta_2\right) \tag{15}$$
$$Y_p(s) = \frac{b\theta_1}{s + a + b\theta_2} R(s) \tag{16}$$

The sensitivity equation is obtained deriving the previous expression (Eq. 1) for θ_1:

$$\frac{\partial J}{\partial \theta_1} = e \frac{\partial e}{\partial \theta_1} \tag{17}$$
$$\frac{\partial e}{\partial \theta_1} = \frac{\partial}{\partial \theta_1}\left(Y_p(s) - Y_m(s)\right) \tag{18}$$
$$= \frac{\partial}{\partial \theta_1}\left(\frac{b\theta_1}{s + a + b\theta_2} R(s)\right) \tag{19}$$
$$= \frac{b}{s + a + b\theta_2} R(s) \tag{20}$$

and similarly for θ_2:

$$\frac{\partial J}{\partial \theta_2} = e\frac{\partial e}{\partial \theta_2} \tag{21}$$

$$\frac{\partial e}{\partial \theta_2} = \frac{\partial}{\partial \theta_2}\left(Y_p(s) - Y_m(s)\right) \tag{22}$$

$$= \frac{\partial}{\partial \theta_2}\left(\frac{b\theta_1}{s+a+b\theta_2}R(s)\right) \tag{23}$$

$$= -\frac{b}{s+a+b\theta_2}Y_p(s) \tag{24}$$

As the objective is achieve the *Perfect Model Following*, these equations are rewritten in terms of the plant model:

$$\frac{d}{dt}Y_p(s) + (a+b\theta_2)\,Y_m(s) = b\theta_1 R(s) \tag{25}$$

$$\frac{d}{dt}Y_m(s) + a_m Y_m(s) = b_m R(s) \tag{26}$$

$$b_m = b\theta_1 \tag{27}$$

$$a_m = a + b\theta_2 \tag{28}$$

Giving the following expressions:

$$\frac{d}{d\theta_1}e = \frac{b}{s+a_m}R(s) = \frac{b}{a_m}\frac{a_m}{s+a_m}R(s) \tag{29}$$

$$\frac{d}{d\theta_2}e = -\frac{b}{s+a_m}Y_p(s) = -\frac{b}{a_m}\frac{a_m}{s+a_m}Y_p(s) \tag{30}$$

The adaptation law is obtained when both expressions are introduced into the previous equations:

$$\frac{d}{dt}\theta_1 = -\alpha_1 e\frac{b}{a_m}\frac{a_m}{s+a_m}R(s) = -\gamma_1 e\frac{a_m}{s+a_m}R(s) \tag{31}$$

$$\frac{d}{dt}\theta_2 = \alpha_2 e\frac{b}{a_m}\frac{a_m}{s+a_m}Y_p(s) = \gamma_2 e\frac{a_m}{s+a_m}Y_p(s) \tag{32}$$

As both equations show, adaptive gains in MIT Rule case depend on an update law γ, the model behaviour, the error e and the reference R or the plant output Y_p.

b: LYAPUNOV RULE

Lyapunov rules [35] follow a similar schematic as the one defined for the MIT rules, but in these case it is necessary to define a Lyapunov function V to minimize:

$$V = \frac{1}{2}\gamma e^2 + \frac{1}{2b}\left(b\theta_1 - b_m\right)^2 + \frac{1}{2b}\left(b\theta_2 + a - a_m\right)^2 \tag{33}$$

whose derivative is:

$$\dot{V} = \gamma e\dot{e} + \dot{\theta}_1\left(b\theta_1 - b_m\right) + \dot{\theta}_2\left(b\theta_2 + a - a_m\right) \tag{34}$$

The model and plant equations are inserted onto the previous expression:

$$\dot{y}_p(t) = -ay_p(t) + b\left(r(t)\theta_1 - y_p(t)\theta_2\right) \tag{35}$$

$$\dot{y}_m(t) = -a_m y_m(t) + b_m r(t) \tag{36}$$

obtaining:

$$\dot{V} = \gamma e\left(\dot{y}_p(t) - \dot{y}_m(t)\right) + \dot{\theta}_1\left(b\theta_1 - b_m\right) + \dot{\theta}_2\left(b\theta_2 + a - a_m\right) \tag{37}$$

$$= -\gamma a_m e^2 + \left(\gamma e r(t) + \dot{\theta}_1\right)\left(b\theta_1 - b_m\right) \tag{38}$$

$$+ \ldots\ldots + \left(-\gamma e y_p(t) + \theta_2\right)\left(b\theta_2 + a - a_m\right) \tag{39}$$

Re-adjusting the terms and following a similar schematic as the one shown during MIT rule, the adaptive gains obtained are:

$$\frac{d}{dt}\theta_1 = -\gamma_1 e r(t) \tag{40}$$

$$\frac{d}{dt}\theta_2 = \gamma_2 e y_p(t) \tag{41}$$

Similarly as the MIT Rule case, in the Lyapunov Rule, the adaptive gains depend on an update law γ, the error e and the reference $r(t)$ or the plant output $y_p(t)$. In this case, they do not take into account the model behaviour.

c: IMPROVEMENTS

The rules presented previously modify the controller to avoid the fault. Nonetheless, as faults alter the plant behaviour, actuator saturation values are also modified and consigns that were achievable by the faultless system become unreachable. This effect is avoided in a conventional design through an Anti-Windup, but this mechanism is not directly replicable for ACs, as both, integration and adaptive process are stopped [36]. To solve this drawback, this paper proposes a new AW technique based on the DT to reflect the optimal behaviour of the faulty plant.

This technique adapts the model response to the mechanical limits of the faulty system varying the reference. An additional adaptive loop is introduced in the DT to modify the model reference signal attending to the new saturation limits, as Fig. 9 shows:

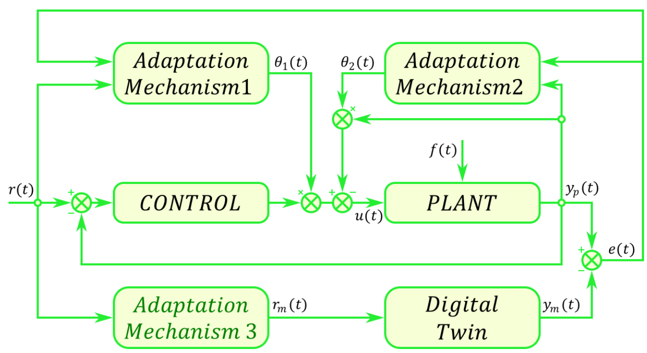

FIGURE 9. **Conventional PID control modified to introduce MRAC adaptive gains.**

If the system is described by the following equation when it is saturated $Y_{p_{sat}}(s)$:

$$Y_{p_{sat}}(s) = G_p(s)U_{sat}(s) = G_p(s)\left(U(s) + \Delta U\right) \tag{42}$$

where u_{sat} is the controller signal saturated. The AW mechanism has to mitigate the effect of ΔU. The maximum controller signal is determined by the new behaviour in the real system, so the additional adaptive loop sought to reduce the error e_u between the controller output in the model u_m and in the plant u_p:

$$\Delta u = e_u(t) = u_p(t) - u_m(t) \tag{43}$$

This additional adaptive loop varies the controller output signal in the model through an adaptive gain:

$$\frac{d}{dt}\theta_3 = \gamma_3 e_u r(t) \tag{44}$$

As the equations shown, the methodology benefits from the DT to create an adaptable AW and reducing the effect of saturated signals in the plant actuators. This ensures the MRAC robustness, as system tends to acquire the optimal behaviour dynamically modifying the reference model avoiding faults independently of their harm-grade.

III. REAL CASE STUDY

When system behaviour changes due to variations in the environment conditions or the adverse effect of an unknown parameter, ACs modify controller gains adapting them to the new situation. This characteristic makes them really attractive in Fault-Tolerant Control field, as they overcome the fault re-designing dynamically controller gains. Despite these benefits, they lack the flexibility needed in industrial environment. Production cycles are modified regularly attending to the article characteristics they are currently manufacturing. The Fault-Tolerant Controller sought to discriminate changes in the production cycle from faults, varying controller gains for this last case.

Section II has explained the novel methodology introduced into FTCs to improve their performance against a wider range of faults. To accomplish this objective, the control loop is introduced into a Bank of Controllers that modifies the adaptive process picking up the best gains in regards to each fault case (Fig. 10).

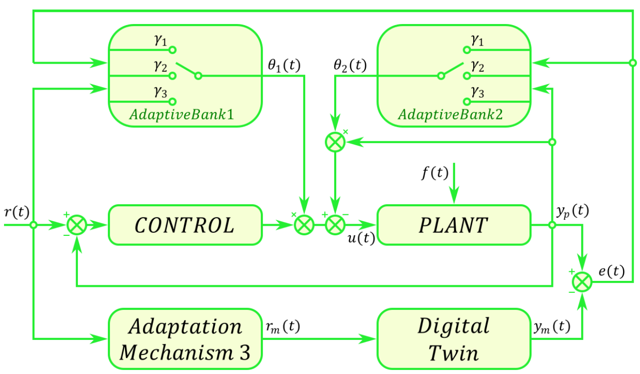

FIGURE 10. Control loop modified to include an adaptive bank of controllers.

Introducing BCs concept allows to treat each fault independently, without modifying the control loop, as they have their own adaptive gains keeping the rules identical. The novel methodology has been tested in a hydraulic-press to acknowledge its potentiality, who is compounded of a hydraulic-actuator performing a cyclical movement to displace a load from an upper position to a bottom one.

The hydraulic-press used as the test system corresponds with the Digital-Twin of an existing industrial machine controlled through a conventional PID. Before introducing the novel methodology for MRAC, the Digital-Twin has been tested replicating the working conditions of the industrial system. During this experiments, the position in both situations has been compared, showing the similarities between both responses, ensuring the model has been created correctly [21].

When a fault arises on the system, this behaviour gets compromised, starting a recovery process divided into four stages summarized on the following points (Fig. 11):

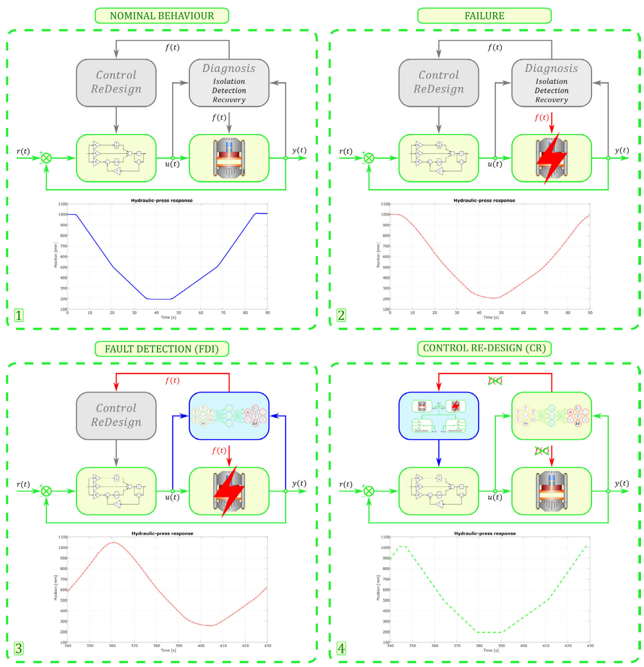

FIGURE 11. Stages followed on the fault recovery process.

- **Nominal Behaviour:** The hydraulic-press performs its cycle controlled by the PID. This stage represents system performance without faults.
- **Failure:** When a fault appears on the plant, system behaviours gets compromised and stops working properly.
- **Fault Detection and Isolation (FDI):** The mechanism detects the fault, grades the harm produced into the system and isolates the affected component.
- **Control Re-design (CR):** With the information gathered during FDI phase, BCs switch the adaptive rule to overcome the fault more efficiently. The optimization process compares the response obtained from the real system against its digital counterpart, adapting the controller gains until the fault effect disappears.

The hydraulic-press performs a continuous cycle starting from the upper part, where they rest, to the bottom, where they mould the piece, as Fig. 12 shows. When faults arise in the system, this cycle gets compromised and the machine stops working properly. The fault is dealt by the conventional PID, nonetheless when the harm-grade is high this controller can not recover the machine, spreading the fault and performing

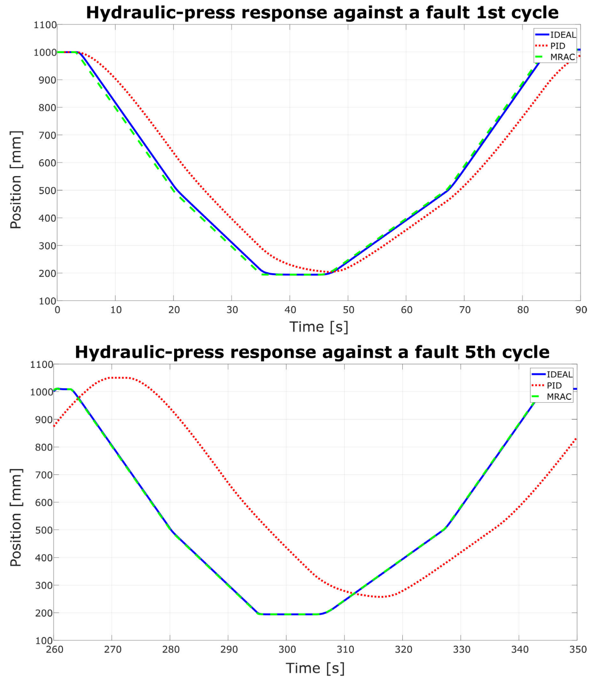

FIGURE 12. **Hydraulic-press cycle when a fault arises in one of its components. Initial performance (top) against its evolution (bottom).**

an erroneous cycle. When the system is under this situation, the novel FTC methodology analyses the fault, detects its source and select the optimal adaptive gains to overcome it automatically in order to recover the nominal behaviour.

During Section III-A the system is tested under faults from different origins to verify the effectiveness of the methodology. In addition, more details about how the BCs performance are given, showing the selection process followed to pick up the best gains for each fault case. Finally, on Section III-B the hydraulic-press is struck against multiple faults with diverse harming grades.

A. FAULTY SCENARIO

Components react to faults in unexpected ways, making difficult to determine how the machine behaves under the effect of these drawbacks. The novel methodology presented minimizes this lack of information during the FDI phase, as Section II-A has exposed. The NN detects the faulty component comparing the current hydraulic-press response against the previously analysed fault cases.

The analysis has brought more than thirty-five faults that affect negatively the system without compromising completely its stability. All of them have been studied, obtaining the adaptive gains that reduce the harming effect most effectively, nonetheless, in this paper, only three faults are going to be developed, two for the component, discerning between actuator and sensor, and one for the plant.

This distribution has been selected due to the fact that communication and controller faults are out of the scope for the novel methodology presented. MRACs are not prepared to

TABLE 1. **Description of the faults analysed in the case study divided attending to their source.**

SOURCE	FAULT	DESCRIPTION
Actuator	Mechanical Fatigue	Degraded performance in the proportional valve opening due to mechanical fatigue.
Plant	Internal Leaks	Hydraulic leaks between the cylinder chambers.
Sensor	Position	Variations in the measures obtained from the position sensor

modify the response if there are looses or delays in the communication channels. Similarly, when there is an instability in the control loop, the MRAC structure would not be able to recover automatically from it, being necessary to reboot the controller. Table 1 resumes their characteristics.

Despite that only three faults are shown, the control design process has been identical for the rest of the cases. The controllers are designed following the MRAC modified with the novelties presented in this paper and tested under similar conditions as they would have during CR phase. The experiments carried out on this stage keep the similar control loop, varying the adaptive gains to the ones that avoid the fault more efficiently.

Initially the MRAC is introduced into the PID control following the schematic of Fig. 4, testing its performance in the HiL platform. Fig. 13 shows the system behaviour after the new control loops are introduced in the machine, appreciating the identical response between the older technique against the new one. Despite the accuracy between both signals, the MRAC controller has a transitory stage until the adaptive gains reach the optimal value.

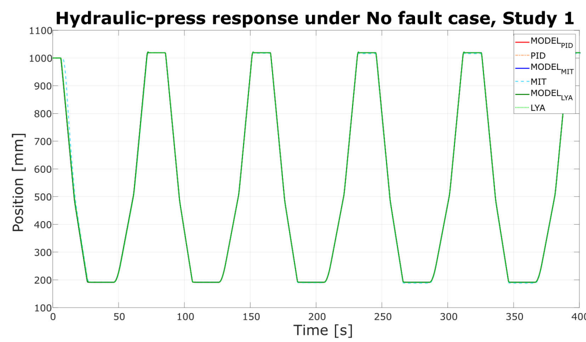

FIGURE 13. **Responses obtained when the machine is upgraded with the MRAC.**

Fig. 13 shows how the hydraulic-press nominal performance is not affected by the improvements brought to the MRAC control loop. On the following study, the system is going to be tested against the faults commented on Section 1, comparing the responses obtained for the PID, the MIT and the Lyapunov rules against their optimal behaviour (without fault). Both rules have their own set of adaptive gains, which have been designed trying to minimize the output error between the model (faultless behaviour) against the plant response (faulty behaviour).

In addition to the mentioned study, an extra one has been done varying the hydraulic-speed to reach the mechanical limits and test the AW technique. Finally, as the fault harm-grade affects negatively the performance, each controller has been tested when the fault is in a 10% or a 90% of their aggressiveness.

Fig. 14 and Fig. 15 shows the response obtained in the press when is subjected to a *Mechanical Fatigue* fault. The system remains unaffected when the fault is below a 10%, but suffers a high degradation when the fault grade increase. The second figure mentioned as when the fault is at a 90% value, the PID starts to deviate more from the original behaviour on each iteration.

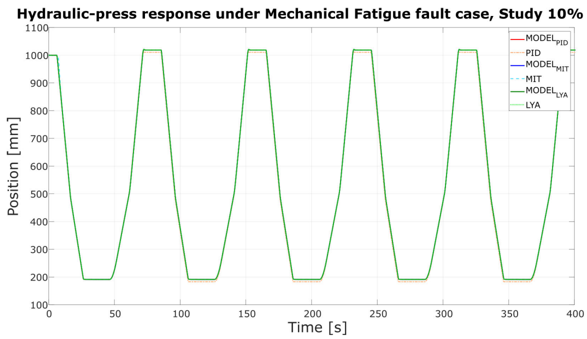

FIGURE 14. Position of the hydraulic-press under *Mechanical Fatigue* fault, performance against a 10% fault.

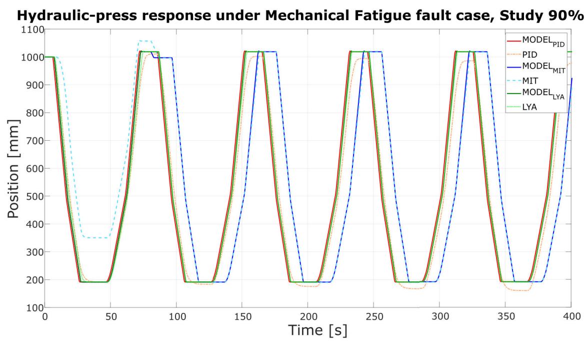

FIGURE 15. Position of the hydraulic-press under *Mechanical Fatigue* fault, performance against a 90% fault.

The maximum separation and the Root Mean Square Error (RMSE) are studied on Fig. 16, comparing the maximum separation (tracking error $e(t)$) between the ideal behaviour against the faulty response. ACs have less separation and RMSE values rather than their nominal PID counterparts. In addition, is observed how the error between model and real system performance is reduced until reach a null value.

Table 2 shows the numerical values extracted from Fig. 16 on the first cycle and on the tenth one. During these iterations, ACs recover completely the system for soft faults and reduce

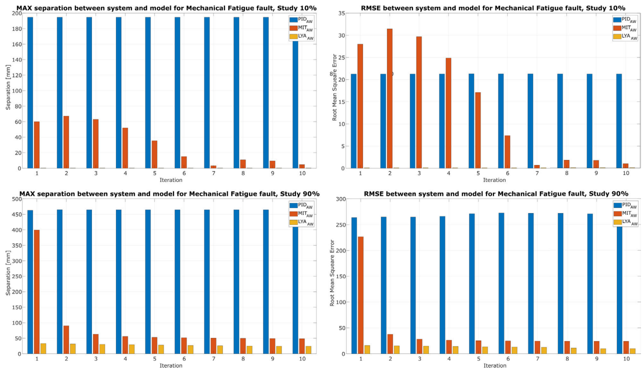

FIGURE 16. Maximum separation and RMSE between the real system and the model in a *Mechanical Fatigue* fault.

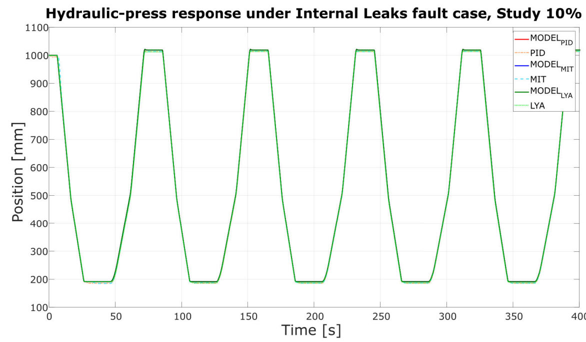

FIGURE 17. Position of the hydraulic-press under *Internal Leaks* fault, performance against a 10% fault.

the maximum separation between both signals. For this fault, MIT and Lyapunov rules recover the nominal performance nullifying the error after finishing the CR phase.

TABLE 2. Maximum separation and RMSE between the desired signal and the AC for *Mechanical Fatigue*.

$FAULT$	$MechanicalFatigue$					
$VALUE$	10%					
$CONTROL$	PID		MIT		LYA	
$CYCLE$	1^{st}	10^{th}	1^{st}	10^{th}	1^{st}	10^{th}
MAX	14.58	14.58	0.35	0.35	0.238	0.236
$RMSE$	9.041	9.04	0.13	0.11	0.072	0.067
$VALUE$	90%					
$CONTROL$	PID		MIT		LYA	
$CYCLE$	1^{st}	10^{th}	1^{st}	10^{th}	1^{st}	10^{th}
MAX	152.86	134.12	39.63	30.85	47.04	30.63
$RMSE$	68.10	67.80	10.39	7.59	12.18	6.91

The *Internal Leaks* fault is more aggressive than the previous one as Fig. 17 and Fig. 18 show. When the fault is soft, the controllers requires around ten cycles to stabilize, but when its harm-grade increases, only the Lyapunov rule AC recovers the system.

Following a similar schematic as Fig. 16, Fig. 19 represents the maximum separation and the RMSE between model and

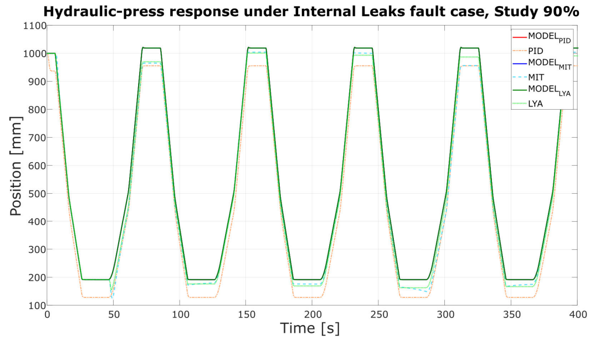

FIGURE 18. Position of the hydraulic-press under ***Internal Leaks*** fault, performance against a 90% fault.

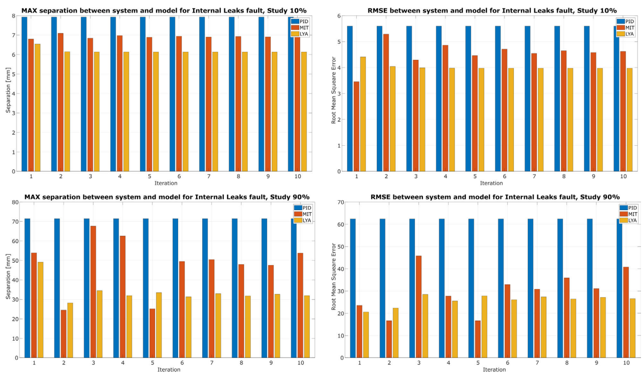

FIGURE 19. Maximum separation and RMSE between the real system and the model in a ***Internal Leaks*** fault.

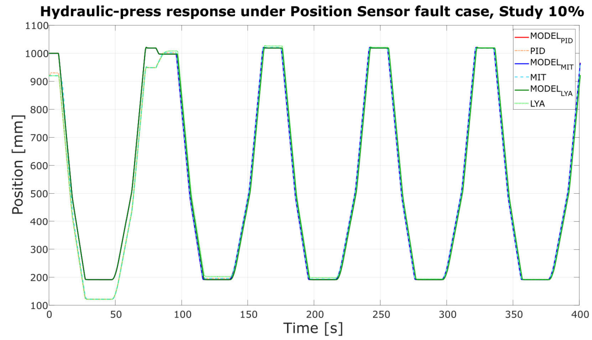

FIGURE 20. Position of the hydraulic-press under ***Position Sensor*** fault, performance against a 10% fault.

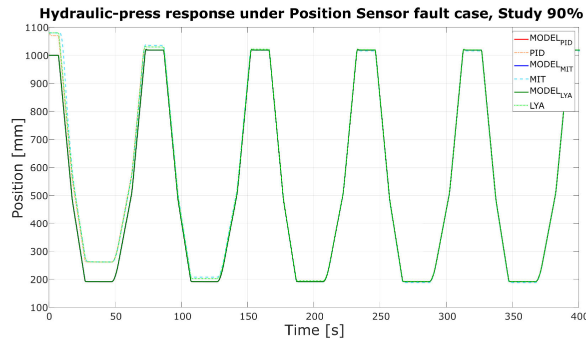

FIGURE 21. Position of the hydraulic-press under ***Position Sensor*** fault, performance against a 90% fault.

real system. On this case, the error is higher in the initial cycle and going down while the number of cycles increases.

The previous assumption is corroborated with the empirical data extracted from Table 3. ACs designed following Lyapunov rule reduce the adverse effect more consistently than their MIT rule counterpart, despite the fact that both need multiple iterations to make the error null.

TABLE 3. Maximum separation and mean squared error between the desired signal and the AC for ***Internal Leaks***.

$FAULT$	$Internal Leaks$					
$VALUE$	10%					
$CONTROL$	PID		MIT		LYA	
$CYCLE$	1^{st}	10^{th}	1^{st}	10^{th}	1^{st}	10^{th}
MAX	7.92	7.92	6.79	6.92	6.54	6.13
$RMSE$	5.60	5.60	3.46	4.62	4.41	3.98
$VALUE$	90%					
$CONTROL$	PID		MIT		LYA	
$CYCLE$	1^{st}	10^{th}	1^{st}	10^{th}	1^{st}	10^{th}
MAX	71.43	71.43	53.92	53.77	49.14	31.98
$RMSE$	62.42	62.42	23.57	40.79	20.62	26.61

In *Position Sensor* faults (Fig. 20 and 21), ACs perform a similar behaviour as the real system. This factor occurs due to the fact that PIDs are designed to avoid disturbances in the plant output signal, which is correspondent with the fault case studied, offset variations in the sensor.

ACs improve the controller response when a fault arises on the system, nonetheless, the PID was initially designed to avoid this undesired performance in the sensors, being able to recover the system even without the novel methodology, as Fig. 22 shows.

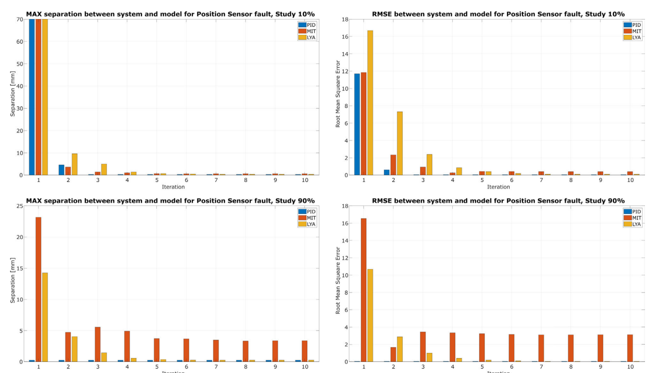

FIGURE 22. Maximum separation and RMSE between the real system and the model in a ***Position Sensor*** fault.

Fig. 20 and 21 empirical results are gathered in Table 4. In this case, PID controller is capable of recover the system nominal performance in a similar way as the ACs based on Lyapunov rules. For this type of faults, adaptive controller

TABLE 4. Maximum separation and RMSE between the desired signal and the AC for *Position Sensor*.

$FAULT$	$PositionSensor$					
$VALUE$	10%					
$CONTROL$	PID		MIT		LYA	
$CYCLE$	1^{st}	10^{th}	1^{st}	10^{th}	1^{st}	10^{th}
MAX	69.98	0.24	69.97	0.57	69.96	0.30
$RMSE$	11.70	0.036	11.86	0.381	16.69	0.08
$VALUE$	90%					
$CONTROL$	PID		MIT		LYA	
$CYCLE$	1^{st}	10^{th}	1^{st}	10^{th}	1^{st}	10^{th}
MAX	0.236	0.236	23.16	3.38	14.25	0.24
$RMSE$	0.03	0.03	16.54	3.12	10.68	0.03

are not strictly necessary, however, they offer a more robust controller than the PID.

The study continues modifying the hydraulic-press velocity to reach the maximum and minimum valve opening, reproducing a change in the productive cycle to displace more loads in less time. This new velocity creates an over-damping in the hydraulic-press movement, as it needs more trajectory to slow down. Despite the fact that in nominal conditions the machine reaches the new set points, when it is affected by a *Mechanical Fatigue* fault the controller gets saturated and unable to perform the configured cycle.

The PID controller tries to perform the fast cycle, nonetheless, the fault makes impossible to reach the desired velocity, generating a great discordance between the ideal plant response and the real one. ACs improve the hydraulic-press performance as the reference signal is modified attending to the new mechanical limits. The machine is slowed down by the Anti-Windup technique, ensuring that the adaptive gains work under nominal conditions. Fig. 23 shows the hydraulic-press evolution, from the first cycle to the tenth one.

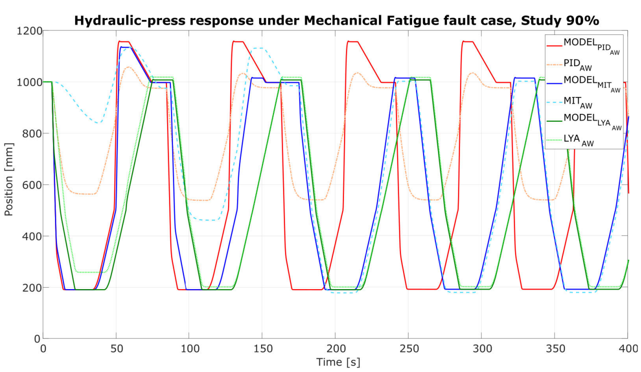

FIGURE 23. Position of the hydraulic-press under *Mechanical Fatigue* fault when the system is saturated.

Similar as the behaviour shown for the system without AW techniques, include them improves the controller performance, who after some iterations is capable of reducing the error practically to zero, as Fig. 24 shows.

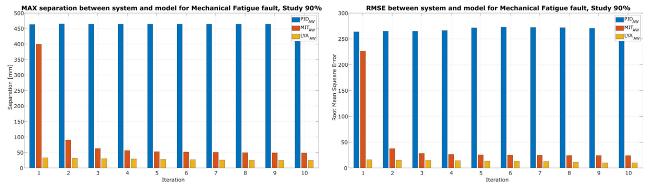

FIGURE 24. Maximum separation and RMSE between the real system and the model in a *Mechanical Fatigue* fault when the system is saturated.

TABLE 5. Maximum separation and mean squared error between the desired signal and the AC for *Mechanical Fatigue* when the hydraulic-press movement is saturated.

$FAULT$	$PositionSensor$					
$VALUE$	90%					
$CONTROL$	PID_{AW}		MIT_{AW}		LYA_{AW}	
$CYCLE$	1^{st}	10^{th}	1^{st}	10^{th}	1^{st}	10^{th}
MAX	194.66	194.66	60.03	4.60	0.23	0.23
$RMSE$	21.25	21.27	28.00	0.96	0.0674	0.0699

Table 5 shows empirically the maximum separation and the mean squared error when the hydraulic-press is saturated. Despite the fact that the machine has been slowed down, the response obtained in the real system is practically identical to the one dictated by the model after ten cycles. This fact corroborates the assumptions made on Section II, as the new controllers maintain the manufacturing flexibility (the production cycle varies attending to new consigns) while they keep the system robust (when a fault arises ACs keep the machine inside the range of its mechanical limits).

The study realized reflects the improvements obtained in the system performance including ACs instead of conventional PID controllers, as they keep the hydraulic-press working under nominal circumstances despite faults. Nonetheless, both rules achieve different levels of similarity between the model signal and the real system. The whole study (thirty five faults) has corroborated how Lyapunov rules tend to behave better than their MIT counterpart, however, there are cases in which this last ones are able to recover the system more efficiently, as they reach global minimums instead of local ones. The conclusion drown from the study is that each fault case requires their own set of update laws to behave correctly, a fact that is increased if it is taken into account the high disparity of faults and harm-grades. Taking into account this considerations, the controller has been improved with a BCs prepared to switch the update laws to the ones that avoid faults in the most effective way.

B. SYSTEM PERFORMANCE

The paper has improved the current methodology introducing novel techniques into CR phase. These advantages

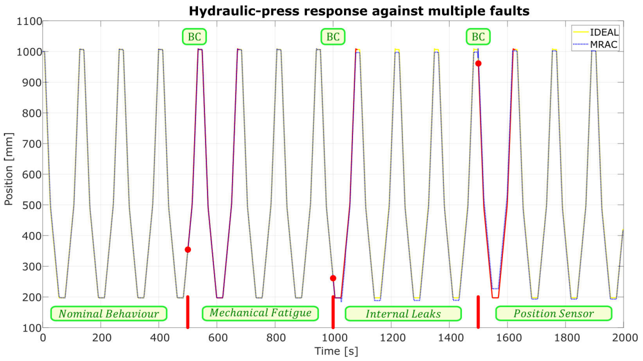

FIGURE 25. Hydraulic-press behaviour under the effect of three faults.

maintain the hydraulic-press working despite the faults. For example, Fig. 25 shows the machine behaviour across two thousand seconds. During this time, the machine is affected by three different faults. Initially the system works under nominal behaviour, suffering from mechanical fatigue in the actuators after the first five hundred seconds. Afterwards, internal chambers in the cylinder start exchanging flow rate between them for another five hundred seconds. Finally, the position sensor broke giving false measures.

During each stage the system is attacked by one fault, but the AC responds to them modifying the controller to continue performing the hydraulic-press cycle. These new control techniques keep the system working despite the apparition of different faults without the drawbacks of stopping it. In addition to these experiments, the system has been tested against changes in the parameters and loads suffering from the same fault, showing how the recovery is independently to these variations (Fig. 26).

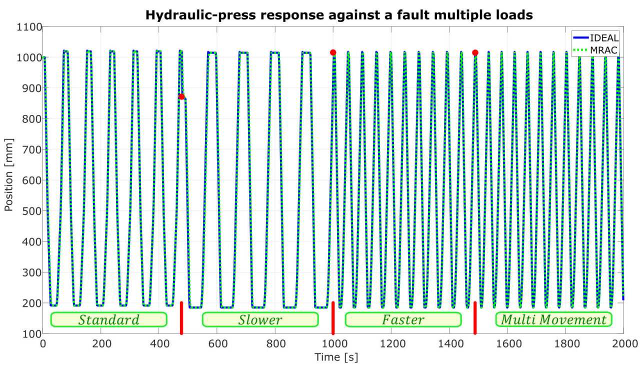

FIGURE 26. Hydraulic-press behaviour under the effect of an identical fault varying the loads.

When the system is under the effect of multiple faults simultaneously, the NN detects the most harmful one, modifying the BCs according to this drawback. The potential of this novel features is increased when in addition to modify the adaptive gains, the initial PID parameters are also adjusted. Nonetheless, this rises the commissioning costs and the current methodology has been designed to be compatible with the older controllers installed in the machine, attending to the fact that despite the PID is not optimized to the fault, the MRAC would adapt the controller signal to recover the nominal behaviour without harming the machine.

IV. CONCLUSION

Faults affect negatively the system performance, making them produce less quality articles and putting at risk operators life. Traditional controllers require to stop the machine in this adverse conditions, but the novel methodology presented in the paper maintains industrial machines working, recovering them from faults. These techniques offer a fault solution based on a two phases process that avoids these drawbacks by the use of Artificial Intelligence algorithms. During FDI phase, faults are detected, graded and isolated dynamically with a NN trained with the machine faulty behaviour. The databased used for the training replicates machine harm conditions under a HiL platform.

CR phase modifies the PID controller introducing ACs into it, which are tested in a HiL platform without affecting the original machine. From the catalogue of ACs, MRACs are the ones implemented, as they search for the minimal error between plant output and reference model. A DT has been created to replicate the system behaviour, bringing an interactive model adaptable to reproduce the productive cycle in a virtual environment. In addition, the traditional MIT and Lyapunov rules have been upgraded with AW techniques prepared to avoid dangerous positions when the machine is under the effect of faults. Both improvements provide the FTC with a flexible platform and create a robust technique to reduce the effect of faults in industrial machines.

These improvements increase the overall performance of traditional FTCs, nonetheless, to ensure that the new techniques are suitable for industrial machines, a BCs is introduced to switch the ACs gains to the one that overcomes the detected fault more efficiently. This last set-up provides a FTC prepared to overcome a wide variety of faults independently of their harm-grade. All the improvements and novel techniques introduced into the conventional MRAC designs have upgraded its capabilities and prepare them to be used in industrial environment.

The novel methodology presented is suited to maintain a machine working independently of harmful effects on their components, nonetheless, it does not take into account the performance of other systems in the productive cycle. Further research is going to be done in this field generating a methodology that also reduces the energy consumption when the system is under the fault effect taking into account the performance of other devices in the manufacturing plant.

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JORGE RODRIGUEZ-GUERRA (Member, IEEE) was born in Logroño, Spain. He received the B.Sc. degree in engineering for industrial electronic and automation and the M.Sc. degree in industrial engineering from the Polytechnic School of La Rioja, Logroño, in 2015 and 2017, respectively. He is currently pursuing the Ph.D. degree with the Control and Monitoring Department, Ikerlan.

His work is geared toward the development of advanced controllers and particularly in the field of virtual commissioning, fault-tolerant control, and adaptive control.

CARLOS CALLEJA received the B.Sc. degree in electronics from the University of Mondragon, Spain, in 2003, the M.Sc. degree from the National Polytechnic Institute of Grenoble, Grenoble, France, in 2009, and the Ph.D. degree from the University of Mondragon, in 2013. In 2009, he joined the Control and Monitoring Department, Ikerlan, where he is currently a Researcher. His main field of research is the advanced control of machines and drives.

ANA MARIA MACARULLA (Member, IEEE) was born in Pamplona, Spain. She received the master's degree in electrical engineering and the Ph.D. degree in automatic control from the Tecnun-University of Navarra, in 1996.

She developed her doctoral research in CEIT, San Sebastián, Spain, when finished she was a Lecturer with the University of the Basque Country, for two years. Since 1999, she has been an Associate Professor with the Engineering Faculty, University of Deusto. Her work is geared toward the development of advanced controllers and particularly in the field of predictive and adaptive control. She is currently focused her research on using advanced modeling and control technologies in order to improve the efficiency of the processes and to minimize the impact of contaminant spills. She is also working toward the use of artificial intelligence in environmental engineering design.

ARON PUJANA was born in Amorebieta-Etxano, Bizkaia. He received the bachelor's degree in physic sciences from the Science Faculty, UPV/EHU, in 2001, and the master's degree in advanced studies, in 2008.

In 2001, he joined the Control and Automatic Department, Ikerlan, where he is currently a Senior Researcher. His master's degree focused on modeling and controlling an actuator device based on pneumatic muscles. This work was co-directed by the prestigious Dr. S. D. Bencomo, from the Department of Informatics and Automatic, UNED University. Since his early beginning as a Researcher, his work is geared toward the fields of modeling complex systems, virtual prototyping, and designing advanced control techniques. He is the author or coauthor of more than 20 articles and conferences related with the subjects of modeling and controlling mechatronic systems. On the last years, his focus has changed to the sector of renewable energies and design of advanced controllers for hydraulic actuators.

IKER ELORZA received the Mechanical Engineering degree from the University of the Basque Country, Spain, and the University of Bristol, U.K., and the Ph.D. degree from the University of Bristol. He is currently a Researcher with the Control and Monitoring Department, Ikerlan. His research is focused on modeling and control of industrial machinery.

MIKEL RAMOS (Member, IEEE) was born in Vitoria-Gasteiz, in 1995. He received the B.Sc. degree in engineering for renewable energies and the M.Sc. degree in control, automation and robotics engineering from the Science Faculty, UPV/EHU, in 2017 and 2019, respectively. In 2019, he joined the KONIKER Team of electronic researchers, a part of Fagor Arrasate S. Coop., where he currently practices. His research has been focused on fault-tolerant-control.