Additive Internal Model Control

Fernando Morgado Dias, Ana Antunes and Alexandre Manuel Mota

Abstract— In this article a new control strategy is proposed: Additive Internal Model Control. This control strategy is based in two existing strategies: Additive Feedforward Control and Internal Model Control.
Internal Model Control is composed of an inverse model connected in series with the plant and a forward model connected in parallel with the plant, this structure allows the error feedback to reflect the effect of disturbance and plant mismodelling resulting in a robust control loop.
Additive Feedforward Control consists of introducing an extra controller into an existing loop with the purpose of improving the quality of the control action.
This new controller introduced is a feedforward controller, which performs better than the existing controller. In the proposed strategy, Additive Internal Model Control, the new controller added to the control loop is an Internal Model Controller.
The new control strategy is tested in a temperature control loop of a reduced scale prototype kiln resulting in improved performance compared to Additive Feedforward Control.
The models used to implement both the control strategies are built with feedforward neural networks.

Index Terms— Feedforward Neural Networks, Additive Feedforward Control, Additive Internal Model Control, Internal Model Control and Measurement Noise.

I. Introduction

In this article a new control strategy is proposed: Additive Internal Model Control. This control strategy is based in the principle of Additive Feedforward Control (AFC): improving an existing control loop.
AFC can lead to the removal of the existing controller leaving a Direct Inverse Control loop. This kind of loop is the simplest control solution but is unable to guarantee null steady state error.
To guarantee that the loop, after the removal of the existing controller, is capable of a better performance, this new control strategy is based on adding one Internal Model Controller. This will improve both steady state and transitory performance.

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To achieve this goal, instead of adding a simple inverse model to the existing loop as in AFC, a complete IMC loop is added.

II. Additive Feedforward Control

Additive Feedforward Control is a known strategy [1], [2], [3] whose principle is quite simple: add to an existing (but not satisfactory functioning) controller an additional inverse process controller. The existing controller might be or not a feedback controller. The principle of AFC can be illustrated with the block diagram of figure 1.
The AFC strategy offers the following important advantages [1]:

- Data collecting can be done using the existing closed loop: avoiding plant stopping for data collection and allowing the access to good quality data.
- There is no need for opening the existing control loop neither during training nor during the introduction of the additive controller.

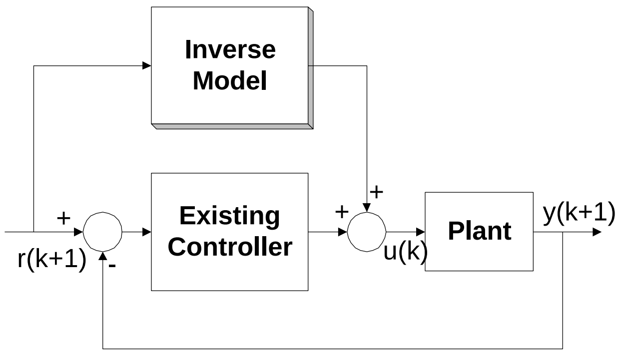

Fig. 1. Additive Feed Forward Control block diagram.

Taking into account the mentioned advantages, AFC can also allow the removal of the existing controller.
If the existing controller is removed, the remaining loop will be a simple direct inverse controller that though better than the existing controller doesn't perform as good as a feedback controller [3].
With this perspective, the proposal of the present work is to use the idea of AFC, keeping its advantages while improving the quality of the control action, by replacing the feedforward controller to be introduced by a feedback controller. The feedback controller chosen is an Internal Model Controller (IMC).

A. *Mixed Feedforward and Feedback in AFC Controllers.*

In [1] a distinction is made between the pure and mixed additive feedforward control. The adjective pure is used when AFC is implemented using a model, which does not receive information from the plant (see block diagram in figure 2), by opposition the mixed adjective is applied when the model used receives feedback information from the output of the plant.

The AFC implemented in the present work is of the mixed feedforward and feedback control type (see block diagram in figure 3), as the one presented in [1].

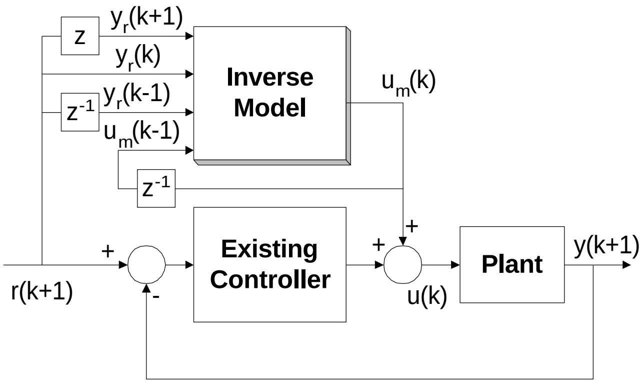

Fig. 2. Pure Additive Feed Forward Control block diagram. Example for a second order inverse model.

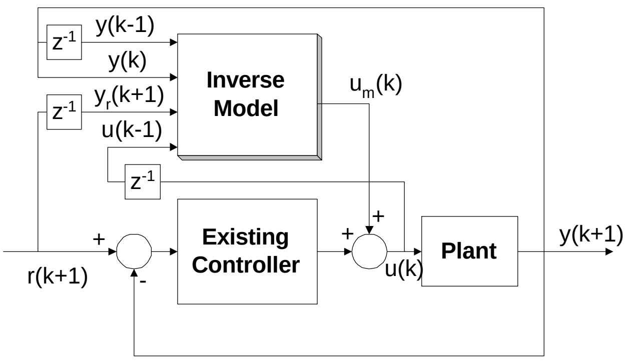

Fig. 3. Mixed Additive Feed Forward Control block diagram. Example for a second order inverse model.

III. INTERNAL MODEL CONTROL

Internal Model Control is a structure composed of an inverse and a direct model of the plant that allows the error feedback to reflect the effect of disturbance and plant mismodelling.

It can be shown [3] that for this structure a good match between forward and inverse models is enough to have good control and that disturbance's influence is also reduced.

The basic IMC structure can be seen in figure 4.

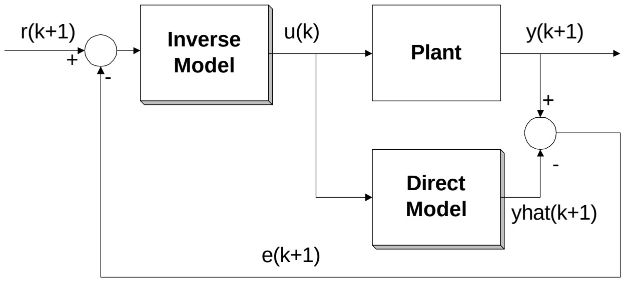

Fig. 4. Structure for Internal Model Control.

A. *Adapting IMC to use Neural Models.*

The basic IMC structure needs some refinements to work properly with neural networks [4], while the AFC can be used in a straightforward way.

The good match between forward and inverse models, referred above translates to having the forward model output's fedback to the input of the inverse and direct model instead of the outputs of the plant. This means that the inverse model will implement the following equation:

$$u(k) = g\begin{bmatrix} r(k+1), yhat(k),..., yhat(k-n_y+1) \\ u(k-t_d),...,u(k-n_u-t_d+1) \end{bmatrix} \quad (1)$$

instead of:

$$u(k) = g\begin{bmatrix} r(k+1), y(k),..., y(k-n_y+1) \\ u(k-t_d),...,u(k-n_u-t_d+1) \end{bmatrix} \quad (2)$$

Where n_y is the number of previous output samples used, n_u is number of previous control signal samples used and t_d is the time delay of the system. The block diagram of the resulting control loop can be seen in figure 6.

This matching between the models would normally point out to specialized training, though in the present work the better results where achieved with normal training as depicted in figure 5.

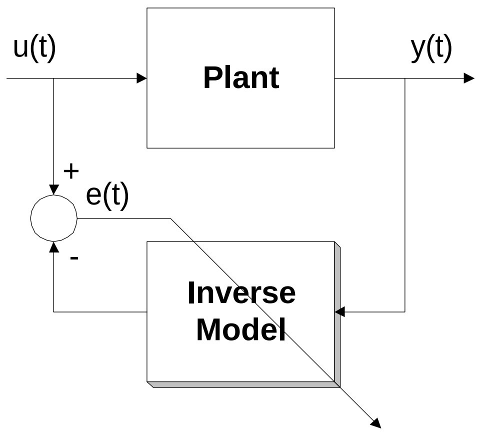

Fig. 5. Structure for training the inverse model.

IV. ADDITIVE INTERNAL MODEL CONTROL

In the two previous sections Additive Feedforward Control and Internal Model Control have been shortly presented. In the present section Additive Internal Model Control will be introduced.

Additive Feedforward Control introduces in the control loop an additional controller in the form of an inverse model performing a simple correction of the poor performance of the existing controller. This inverse model introduced in the loop along with the plant completes a Direct Inverse Control strategy.

The DIC strategy usually under performs feedback strategies [2][3] and this type of control could in principle be replaced by a feedback controller.

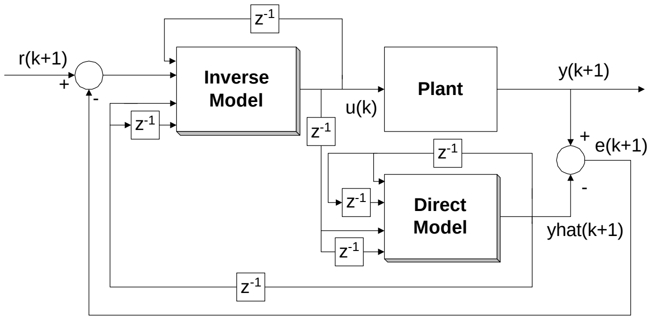

Figure 6- Internal Model Control structure with detail of the implementation of inverse and direct model for second order models.

This analysis led to conjugation of IMC and AFC resulting in the block diagram of figure 7, which was named Additive Internal Model Control because of the two loops which were used to create it.

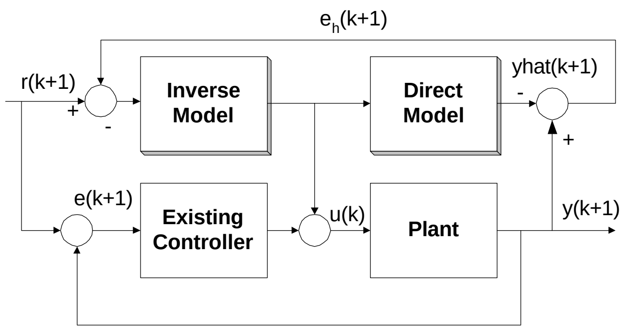

Fig. 7. Structure for Additive Internal Model Control.

The existing controller and the plant constitute the initial loop while the inverse model, direct model and plant constitute an IMC loop. Both are feedback loops but their feedback signal is different. The initial loop's input is the error between output and reference and the IMC's feedback is the error between the plant and the direct model.

This structure keeps the advantages of AFC and makes it safer to remove the existing controller since the remaining loop will still be a feedback loop.

V. THE PLANT

The plant used to test AIMC is a reduced scale prototype kiln. The complete system is composed of a kiln, electronics for signal conditioning, power electronics module, cooling system and a Data Logger from Hewlett Packard HP34970A to interface with a Personal Computer (PC).

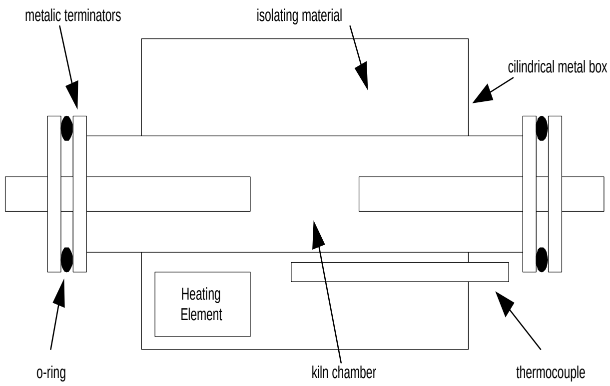

Fig. 8. Schematic view of the kiln.

Details about the kiln can be seen in figure 8 and the connections between the modules can be seen in figure 9.

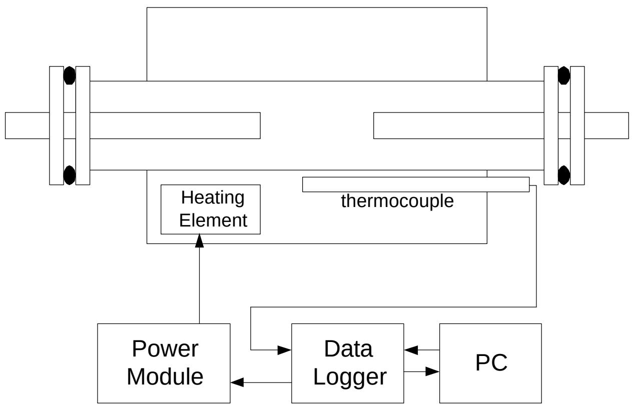

Fig. 9. Block diagram of the system.

The kiln is a cylindrical metal box of steal which is completely closed, filled with an isolating material up to the kiln chamber. The kiln chamber is limited by the metallic terminators and o-rings.

The heating element is an electrical resistor that is driven by the power module.

The Data Logger acts as an interface to the PC where the controller is implemented using MATLAB. Through the Data Logger bi-directional information is passed: control signal in real-time supplied by the controller and temperature data for the controller. The temperature data is obtained using a thermocouple.

The power module receives a voltage signal from the controller implemented in the PC, which ranges from 0 to 4.095V and converts this signal in a power signal ranging from 0 to 220V.

The signal conversion is implemented using a sawtooth wave generated by a set of three modules: zero-crossing detector, binary 8 bit counter and D/A converter. The sawtooth signal is then compared with the input signal generating a PWM type signal.

The PWM signal is applied to a power amplifier stage that produces the output signal. The signal used to heat the kiln produced this way is not continuos, but since the kiln has integrator behavior this does not affect the functioning.

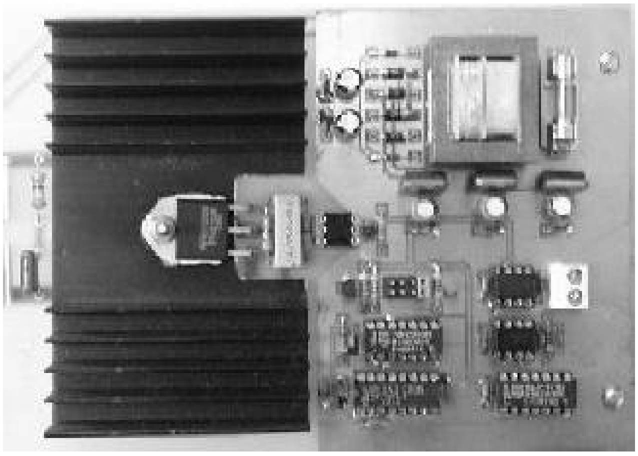

Fig. 10. Picture of the power module.

The actual implementation of this module can be seen in figure 10 and a block diagram of the power module processing can be seen in figure 11.

The operating range of the kiln under normal conditions is between 750ºC and 1000ºC. A picture of the kiln and electronics can be seen in figure 12.

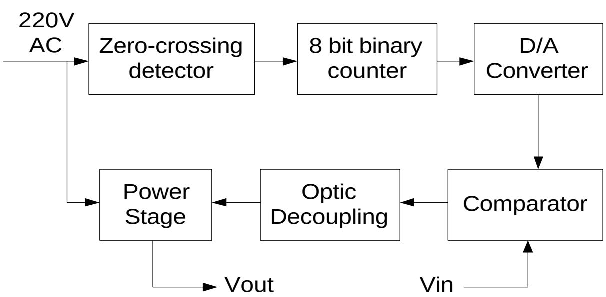

Fig. 9. Block diagram of the power module.

VI. IDENTIFICATION

Direct and inverse models were identified using Feedforward Neural Networks (FNNs) and Auto-Regressive with eXogenous inputs (ARX) architectures.

A sampling period of 30 seconds was used and because of the measurement noise all the data was filtered using a simple first order filter with multiple iterations. Care was taken to avoid phase distortion and to choose appropriate cut-off frequency.

Training was performed off-line using the Levenberg-Marquardt algorithm because of its fastest convergence. After identifying the order of system with the lipschit function [5] [9], different architectures regarding the hidden layer were tested and the best results were obtained using four neurons on the hidden layer of the direct model and five neurons on the inverse model. Both models have a linear output neuron and hyperbolic tangents as activation functions in the hidden layer.

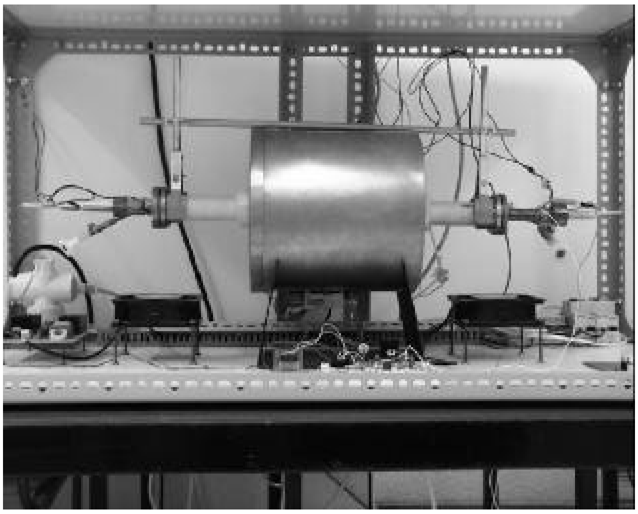

Fig. 12. Picture of the kiln and electronics.

One common problem that arises during training is overtraining or overfitting. This corresponds to having the FNN modelling not only the features of the system but to an undesirable extent also the noise [9].

The overtraining problem has been an open topic for discussion motivating the proposal of several techniques like Regularization [10], Early stopping [11] and pruning - Optimal Brain Damage [12] and Optimal Brain Surgeon [13]. In the present work both models were trained using early stopping.

For more details on the implementation of the models please refer to [2], [3] or [7].

When the quality of the models was considered to be "good", the models were used for inverse control simulation and later used in the control strategies presented in the next section.

During the identification and control tasks the NNSYSID [5] and NNCTRL [6] toolboxes for MATLAB were used.

VII. THE REAL TIME CONTROL ACTION

In this section the results obtained with AFC and AIMC are presented and compared, some of the signals obtained are also analysed in order to extract conclusions about the way AIMC works.

Figure 13 shows the results obtained with AFC. The existing controller used is a PI tuned manually (the parameters are Ki=0.5, Ti=0.5 and Kp=0.5) without particular optimisation.

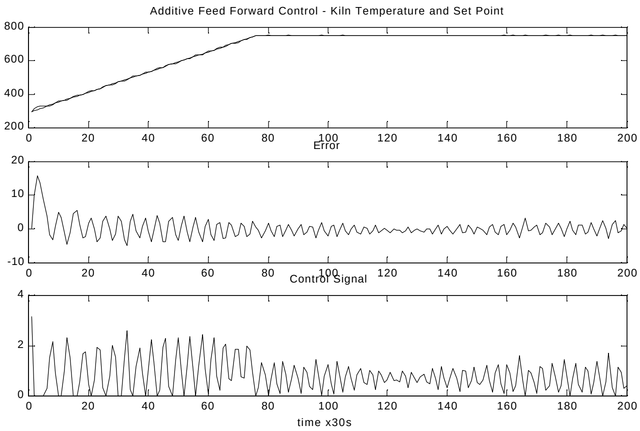

Fig. 13. Kiln temperature control using Additive Feedforward Control.

In figure 14 the results obtained with AIMC are presented.

The same existing controller is used up to sample 200, afterwards the existing controller is suppressed leaving the IMC loop to work alone. As it can be seen at this point there is no disturbance being caused by the removal of the existing controller.

The removal of the existing controller could not be performed this easily with AFC since, as can be seen from the results presented in [2], the remaining loop would not be free of steady state error and could perform worst than the AFC.

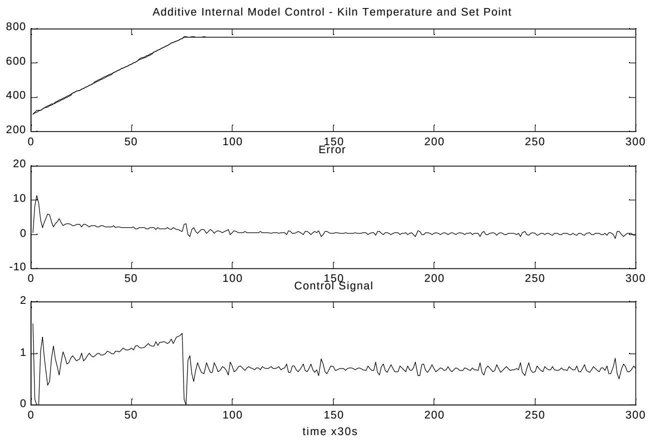

Fig. 14. Kiln temperature control using Additive Internal Model Control.

To further investigate the quality of AIMC a different reference has been used to control the same system. The results obtained can be seen in figure 15.

The proposal of a loop composed of two feedback loops might cause some disbelief and in order to establish how the two controllers work together figure 16 shows a detail of both control signal. Note however that the control signals are shown unscaled and that before being applied to the kiln they are added and limited to the power module range, which is 0 to 4V DC.

The control signal coming from the neural network is plotted with a solid line, while the control signal coming from the PI controller is plotted with a dashed line.

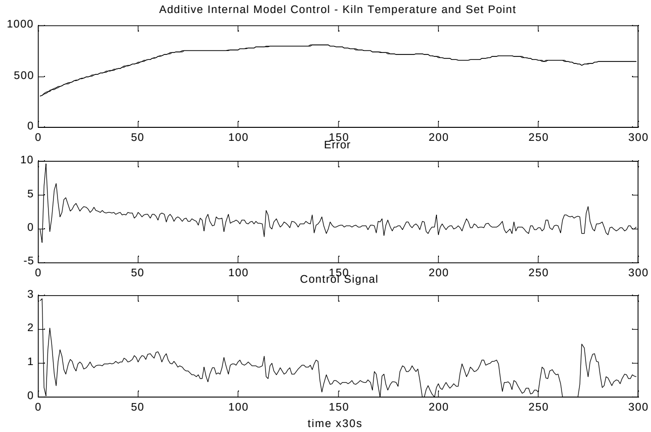

Fig. 15. Kiln temperature control using Additive Internal Model Control with a different reference.

As it can be seen the contribution of the existing controller, being based on the error signal, is very small. After the 200th sample the PI controller is removed.

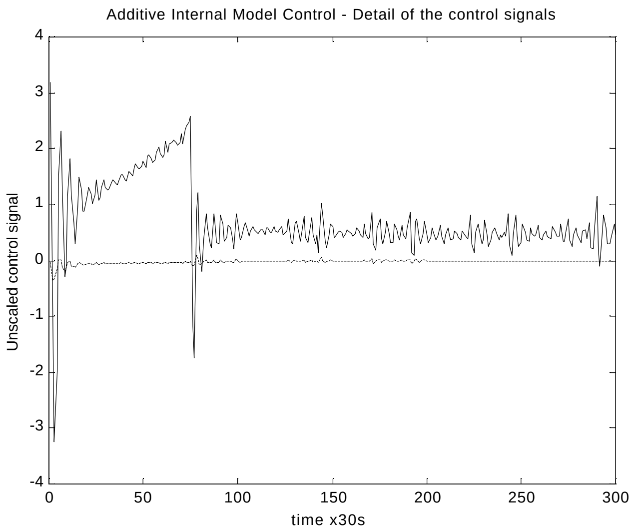

Fig. 16. Detail of the control signals produced by the two controllers. The solid line shows the signal produced by the

neural network controller and the dashed line shows the signal produced by the PI controller.

In table 1 the results obtained are summarized in terms of Mean Square Error (MSE).

CONTROL TYPE	MSE 200 SAMPLES	MSE SAMPLES 80 TO 200
AFC (Fig.11)	6.70	1.56
AIMC (Fig.12)	4.10	0.44
AIMC (Fig.13)	3.70	0.87

Table 1. Mean Square Error for the examples presented.

To complete the information presented in table 1, it can be added that the MSE obtained in the 100 samples after the removal of the existing controller is of 0.13, while in the previous 100 samples is 0.30. This additional information confirms that the existing controller is no longer needed.
The results in table 1 show the advantage of AIMC over AFC while using the same model and the same reference:

- An improvement of 39% over the 200 samples.
- An improvement of 72% after the initial rising phase.

VIII. Conclusions

A new control strategy has been proposed based in two existing strategies: Additive Feedforward Control and Internal Model Control.
The new control strategy, Additive Internal Model Control, is meant to be used in the same situations where AFC can be used: improving an existing but not satisfactory functioning controller, while extending the feature of replacing the existing controller since the remaining loop is a stable feedback IMC.
The proposed strategy was tested in a kiln temperature control loop where the results presented confirm the advantage over AFC and the feature of replacing the existing controller.
From the results presented, it can be stated that:

- The AIMC control strategy shows an improvement of 39% using the same model and the same reference, over the 200 samples.
- The two different references tested show the good performance of the AIMC loop.

It should be noted that the functioning of this strategy is based in the fact that the two control loops feedback different signals.

IX. References

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