# Experience of a Predictive Adaptive Controller on Pilot and Industrial Plants with Transport Phenomena

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*Abstract:* **The existing experience on using MUSMAR, a predictive adaptive controller, on industrial and large scale pilot plants with transport phenomena is discussed. The processes to control have been selected because their dynamics depends not only on time, but also on space, being therefore described by partial differential equations, and implying increase difficulties for the controller. Case studies on an industrial boiler, an arc-welding machine, a distributed collector solar field and a water distribution canal are used to illustrate the main difficulties and the corresponding solutions when using MUSMAR. These include plant model uncertainty and start-up adaptation transients, large and uncertain plant i/o transport delay, existence of un-modelled dynamics, closed-loop response shaping and constraints. The emphasis of the presentation is on the practical impact of the theoretical properties of the MUSMAR algorithm and on their illustration by means of actual experiments on the real processes mentioned above.**

**Keywords:** Adaptive control, predictive control, control applications, transport processes.

## I. INTRODUCTION

Although model predictive control (MPC) is now recognized as a major tool to solve many difficult control problems, uncertainty in plant knowledge is still a major issue. To tackle this, an approach to embed adaption in MPC is considered in this paper. It relies on the concept of *redundancy* and consists in the separate estimation of the predictive models describing plant dynamics according to the MUSMAR algorithm. As such, if there is a mismatch between model assumptions and reality, its effects are not amplified as there should be the case when estimating just one of the predictors and computing the other from it.

The MUSMAR algorithm is not new and there is rich bibliography on it. The contribution of this paper consists in presenting a number of experimental examples, developed in industrial or industrial scale pilot plants, to illustrate the effectiveness of the approach as well as the major difficulties. A new extension of the basic MUSMAR algorithm, based on an exponential weight modification of the underlying cost is also presented.

The paper is organized as follows. After this introduction, the main features related to the MUSMAR controller are reviewed in section II. The new algorithm version is presented in the appendix. Section III presents experimental case studies and section IV draws conclusion.

## II. MUSMAR PREDICTIVE ADAPTIVE CONTROLLER

MUSMAR (Multistep Multivariable Adaptive Regulator) [1] is a data driven algorithm designed for the adaptive regulation of linear ARMAX plants that combines the following features:

- Optimization of a receding horizon quadratic cost;

- Assumption of a constant feedback over the prediction horizon;

- Minimization of the cost based on a set of predictive models for both plant input and output signals;

- Separate estimation of the predictors directly from the data (and not just estimation of the one-step ahead predictor together with extrapolation to find the other predictors);

These features, and in particular the *redundancy* introduced by the separate estimation of the predictors, yield the following properties [2]:

- Robustness with respect to the exact value of the plant i/o transport delay;

- Capability of locally minimizing an underlying quadratic cost, even in the presence of plant un-modelled dynamics;

- Capability to converge to the correct minimum in the presence of colored noise and $C$ polynomial with non-positive real characteristics;

- Capability of tackling moderate plant non-linearities

Although the algorithm relies on a set of multiple predictive models, these are not used one at each time, *e. g.* depending on the operating conditions, or as in Switched Multiple Model Adaptive Control. Instead, these models are combined together at each sampling time to yield the controller gains. Adaptation results from the continuous identification of the model parameters. Since the closed loop admits models such that the residual is orthogonal to subspace generated by plant i/o data [3, 4], Recursive Least Squares (RLS) are used as identifiers. A common regressor to all predictive models requires only one Riccati equation, thereby implying a small computational load that does not grow with the prediction horizon [1]. In [1] it is shown that MUSMAR is equivalent to a bank of parallel self-tuners, each one tuned to a different value of plant delay and with different weights. If the actual plant delay is bigger than the delay assumed for a given self-tuning channel, then the corresponding weight will be zero and this explains the robustness properties with respect to uncertainty in delay.

### A. MUSMAR extensions

The basic regulation version has been extended to solve several problems. The extensions include:

- Detection of plant changes to embody fault tolerant characteristics [5].

- Dual modification to tackle adaptation transients [6];

- Observer polynomial modification to enhance stability robustness [7]

- Inclusion of feed-forward from accessible disturbances [7, 4];

- Integral effect [8];

- Cascade control [9];

- Constraints in the mean-value of the variables [10, 11];

- Solution of the exact infinite horizon underlying control problem in the presence of colored noise [12].

### B. Convergence properties

There are no global stability results for MUSMAR. It has been proved that the only possible convergence points are the local minima of the underlying cost, constrained to the chosen regressor structure (thereby allowing the existence of un-modelled plant dynamics) [2]. This result is proved using the so called "ODE method" for analyzing stochastic systems. Furthermore, close to a local minimum of the underlying cost $J$, the vector of controller gains $F$ is updated by

$$F_{new} \approx F_{old} - \gamma [\triangledown^2 J]^{-1} \triangledown J$$

where $\gamma > 0$ is a scalar gain, $\triangledown J$ denotes the gradient and $\triangledown^2 J$ denotes the hessian matrix of $J$ with respect to $F$.

A synthetic example is presented to illustrate the result, as well as to highlight the importance of using multiple predictive models. Consider the PLANT described by the ARMAX model

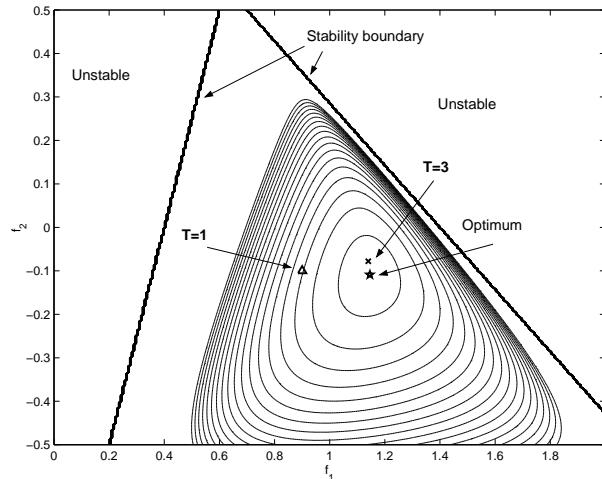$$y(t + 1) + 0.98y(t) - 0.5y(t - 1) = u(t) + e(t + 1) - 0.7e(t)$$

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Figure 1: Quadratic cost level curves as a function of controller gains and MUSMAR convergence points with different horizons $T$.

where $y$ is the output, $u$ is the manipulated variable and $e$ is a white noise sequence of unit variance. This plant is to be regulated with a controller having the structure

$$u(t) = f_1 y(t) + f_2 u(t-1)$$

where $f_1$ and $f_2$ area gains to be tuned. Remark that the structure selected for the controller implies the existence of un-modelled dynamics. Furthermore, the plant is open-loop unstable. Fig. 1 shows the level curves of the cost constrained to the chosen controller structure. The optimum is marked, as well as the convergence points of MUSMAR with just one predictor ($T = 1$) and with three predictors ($T = 3$). The higher number of predictors yields a clearly better approximation to the optimum.

### C. Simulation experience

A rich simulation experience is available for MUSMAR. This includes synthetic "difficult" examples to test convergence and stability properties [2] as well as the test of physical plants such as robot arms [1, 5], water distribution canals or hypnosis level in anaesthesia [13].

## III. INDUSTRIAL APPLICATIONS

Besides many tests in small scale laboratory plants (such as air heaters [5], tanks, pneumatic systems or ser-vomechanisms, there is a significant experience on large-scale or industrial plants. These include arc welding [8], distributed collector solar fields [7, 9, 6] and industrial boilers [14].

### A. Supersteam steam temperature

Fig. 2 shows a result obtained in the control of superheated steam temperature in a thermoelectric plant with co-generation, where a cascade of PIDs is compared with MUSMAR (time interval between A and C). MUSMAR is a tool for finding local minima of the linear stochastic cost. Considering the main motivation in the example of fig. 2, in which the fluctuations of superheated steam temperature are to be modelled from a stochastic point of view, their variance being directly related with economic performance, MUSMAR appears naturally as an appropriate tool. Indeed, reducing the fluctuations allows to increase the set-point and this corresponds to an economic reward.

### A. Arc welding

A schematic view of the experimental set-up used for the arc welding control example is shown in fig. 3. The objective of the arc welding control example is to lay a seam of soldier over a metallic piece, such that the rate of cooling (which determines the mechanical properties of the seam) is kept constant. The manipulated variable is the welding voltage. Further details and examples on the use of MUSMAR, as well as references on other types of approach may be found in [8]. The dynamic behavior of the weld bead centerline temperature is modelled by
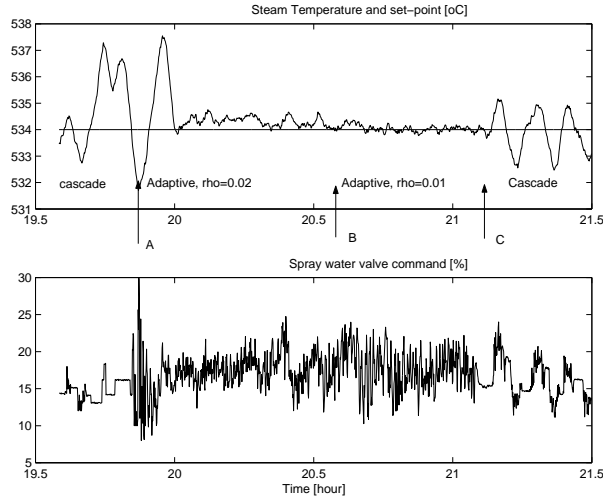
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Figure 2: Superheated steam temperature control, together with a constant set-point of $534^oC$ (above) and the manipulated variable (spray water valve position in [%] – below) in an industrial boiler, controlled with MUSMAR.
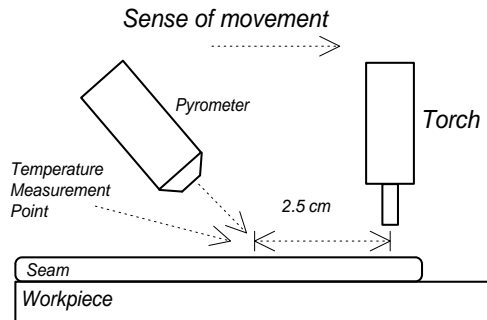


Figure 3: Trailing centerline temperature measurement set-up.

a set of energy conservation equations describing the energy accumulation in the bead and in the workpiece. The dynamics is actually complex, being affected by various effects, including reflection of heat waves depending on the geometry of the pieces to weld. It may be shown [8] that it is impossible for a fixed gain controller to meet a robust stability specification, a fact naturally leading to an adaptive control approach.

The sampling frequency was chosen as $F_s = 3\,Hz$, the forgetting factor is $\lambda = 0.98$, the prediction horizon is $T = 10$ and the weight on the input penalty is $\rho = 500$. Results obtained on a $12\,mm$ piece show that MUSMAR is able to stabilize the plant yielding an acceptable performance. These are shown on fig. 4. In this example the value of $\rho$ has the value $\rho = 2000$ in order to reduce excessive control action. In order to cancel the tracking offset, a parallel integrator has been inserted.

### A.   Distributed colector solar field

Cascade control is a classical structure in process control. It explores the situation in which the system to be controlled can be split in two series subsystems $P_1$ and $P_2$ with the dominant time constant of $P_1$ being much faster than the dominant time constant of $P_2$. Two controllers $C_1$ and $C_2$ are connected such that the manipulated variable of $C_2$, $u_2$, is the set-point of $C_1$, thus forming two nested loops. Furthermore, in a computer control framework, again exploring the difference between the dominant time constants of $P_1$ and $P_2$, these subsystems are sampled at different rates $h_1$ and $h_2$, with $h_2 > h_1$. In this example, experimental results are presented on the application of a cascade control structure to the oil outlet temperature in a distributed collector solar field. Both loops of the cascade employ MUSMAR. The use of MUSMAR together with the above mentioned multi-rate sampling scheme provides an alternative way of controlling this plant which is particularly effective in the outer loop where a long, time varying, pure delay is present. The plant to be controlled consists of a distributed solar
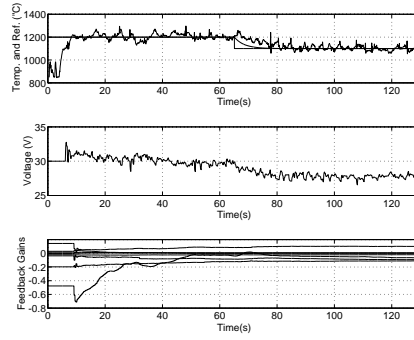
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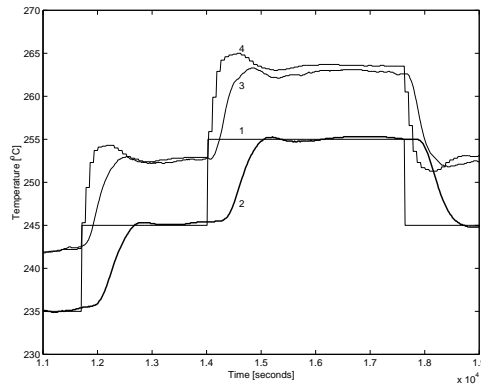Figure 4: Arc welding: Experimental results with MUSMAR on a $12\,mm$ plate.



Figure 5: Solar field: Temperature control using the MUSMAR multi-rate cascade algorithm.

collector field (manufactured from ACUREX) which is part of Plataforma Solar de Almeria, located in the south of Spain. The field is made of 480 cylindric collectors of parabolic type, which concentrate the solar radiation in a metallic pipe located along their focus. The metallic pipe contains a fluid (oil) which serves as an energy storage medium. The collectors are organized in 10 parallel loops placed along an east-west axis and are provided of a sun elevation tracking mechanism. The oil to be heated is extracted from the bottom of a storage tank and is pumped through the collector loops. At the other end, the outlet of the loops is collected in a passive pipe and brought back to the storage tank, where it enters at the top. The passive pipe introduces a long delay. The oil pump is provided with a local controller so that it can be assumed that oil flow is the manipulated variable, ranging from $2l/s$ to $9l/s$. The main process variable is the temperature of the oil entering the storage tank. In a cascade control framework, the average of the temperatures at the outlet of the loops is taken as the intermediate variable. In this way, the dynamics is decomposed in two parts: The dynamics of the collector loops, which relate the oil flow to $\overline{T}$; and the dynamics of the pipe connecting the outlet of the loops with the inlet of the storage tank, which relates the temperatures in both points. The former corresponds to the faster time constant (with a value of about 3 minutes). The latter corresponds to the slower time constant (in this case a pure delay of about 9 minutes in series with a time constant of about 2 minutes). With cascade control, the problems of rejecting disturbances in both subsystems are split apart.

Fig. 5 shows experimental results obtained with cascade multi-rate MUSMAR control. In this experiment both $T_1$ and $T_2$ (the prediction horizons on both MUSMAR controllers in fig.5) were made equal to 15 samples. This value was found from previous experiments and simulation to be adequate. The sampling intervals were $h_1 = 15\,sec$, $h_2 = 60\,sec$. When $h_2$ increases, the pure delay in $P_2$, measured in number of samples, decreases. The orders were set equal in both controllers and given by $n_i = 3$, $m_i = 2$. The control weight $\rho_i$ is set equal to 0.001 in both controllers and the variance of the dither noise was 0.01. The pure delay is apparent in fig. 5, where the heat loss in the pipe connecting the outlet of the collector loops to the storage tank is also seen. The outer loop controller adjusts the set-point of the inner loop, such that $y_1$ is high enough to compensate for the thermal losses in the pipe and let the temperature at the inlet of the tank be equal to the set-point.
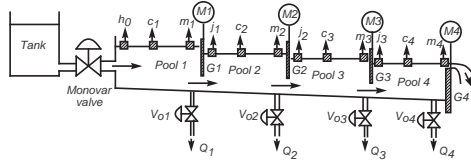
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Figure 6: Water distribution canal. Schematic view of the pilot installation.
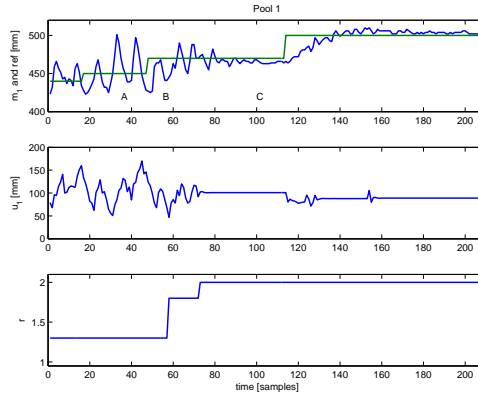


Figure 7: Water distribution canal. Level control of one pool.

## A.  *Water distribution canal*

This case study is concerned with the application of MUSMAR to pool level control at the experimental water distribution canal of Núcleo de Hidráulica e Controlo de Canais (NuHCC) of Universidade de Évora, Portugal. Fig. 6 shows a schematic view of the canal. The process variable to be controlled is the pool level immediately upstream to the gate ($m$, expressed in $mm$). The manipulated variable is the gate level command ($u$, expressed in $mm$). The disturbances are the flow (that may be influenced by the other gates or by the *MONOVAR* valve) and the water outlet takes at the side of the canal.

Fig. 7 shows the results obtained with one pool when the basis of the weight of the exponential weight is increased, forcing the closed-loop poles to be constrained to a circle of radius that is the inverse of this parameter.

## II.  CONCLUSIONS

This paper shows experimental exemples of application of the MUSMAR controller. This algorithm is very effective as a tuner in the presence of stochastic disturbances and *a priori* unknown plants. This is illustrated in particular by the superheated steam temperature and arc welding examples. Non-zero mean accessible disturbances may be rejected including feedforward terms in the algorithm. MUSMAR proves however difficulties in the presence of "hard" constraints. In many cases of practical interest, these may be avoided by conveniently shapping the closed-loop response, as done by the exponential weight modification illustrated in relation to the water distribution canal example, or by including on-line weight adjustment. As expected from its underlying predictive control law, MUSMAR tackles well plant input/output transport delays, as shown in the distributed collector solar field example.

## APPENDIX I – MUSMAR ALGORITHM

The MUSMAR algorithm modified to include an exponential weight and feedforward from accessible disturbances reads as follows:

At the beginning of each sampling interval $t$ (discrete time), recursively perform the following steps:

**1.**Sample plant output, $y(t)$ and compute the tracking error $\tilde{y}$, with respect to the desired set-point $y^*(t)$, by:

$$\tilde{y}(t) = y^*(t) - y(t) \tag{1}$$

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**2.** Using Recursive Least Squares (RLS), update the estimates of the parameters $\theta_j$, $\psi_j$, $\mu_{j-1}$ and $\phi_{j-1}$ in the following set of predictive models:

$$\tilde{y}(t+j) \approx \theta_j u(t) + \psi'_j s(t) \tag{2}$$

$$u(t+j-1) \approx \mu_{j-1} u(t) + \phi'_{j-1} s(t) \tag{3}$$

$$j = 1, \ldots, T$$

where $\approx$ denotes equality in least squares sense and $s(t)$ is a sufficient statistic for computing the control, hereafter referred as the pseudo-state, given by

$$s(t) = [\tilde{y}(t) \ \ldots \ \tilde{y}(t-n+1) \ u(t-1) \ \ldots \ u(t-m)$$

$$w_1(t) \ \ldots \ w_1(t-n_{w1}) \ \ldots \ w_N(t) \ \ldots \ w_N(t-n_{wN}) \ 1]' \tag{4}$$

where the $w_i$ are samples of auxiliary variables such as intermediate process variables or accessible disturbances. Since, at time $t$, $\tilde{y}(t+j)$ and $u(t+j)$ are not available for $j \geq 1$, for the purpose of estimating the parameters, the variables in (2,3) are delayed in block of $T$ samples. The estimation equations are thus,

$$K(t) = \frac{P(t-1)\varphi(t-T)}{1 + \varphi'(t-T)P(t-1)\varphi(t-T)[1-\beta(t)]} \tag{5}$$

$$P(t) = [I - K(t)\varphi'(t-T)(1-\beta(t))]P(t-1) \tag{6}$$

and, for $j = 1, \ldots, T$:

$$\hat{\Theta}_j(t) = \hat{\Theta}_j(t-1) + K(t)[y(t-T+j) - \hat{\Theta}_j(t-T)'\varphi(t-T)] \tag{7}$$

for $j = 1, \ldots, T-1$:

$$\hat{\Omega}_j(t) = \hat{\Omega}_j(t-1) + K(t)[u(t-T+j) - \hat{\Omega}_j(t-T)'\varphi(t-T)] \tag{8}$$

In these equations, $\hat{\Theta}_j$ represents the estimate of the parameter vector of the output predictors, given at each discrete time and for each predictor $j$ by

$$\hat{\Theta}_j = [\theta_j \ \psi'_j]'$$

and $\varphi(t-T)$ represents the regressor, common to all predictors, given by

$$\varphi(t-T) = [u(t-T) \ s'(t-T)]'$$

Similarly, $\hat{\Omega}_j$ represents the estimate of the parameter vector of the input predictors, given at each discrete time and for each predictor $j$ by

$$\hat{\Omega}_j = [\mu_j \ \phi'_j]'$$

Note that, since the regressor $\varphi(t-T)$ is common to all the predictive models, the Kalman gain update (5) and the covariance matrix update (6) are also common to all the predictors and need to be performed only once per time iteration. This greatly reduces the computational load.

The variable $\beta(t)$ denotes the quantity of information discarded in each iteration, being given according to a directional forgetting [**?**] scheme by

$$\beta(t) = 1 - \lambda + \frac{1-\lambda}{\varphi'(t-T)P(t-1)\varphi(t-T)}$$

where $\lambda$ is a constant to be chosen between 0 (complete forgetting) and 1 (no forgetting) which determines the rate of forgetting in the direction of incoming information. In practice, a factorized version is used to implement eq. (5).

**3.** Apply to the plant the control given by

$$u(t) = f's(t) + \eta(t) \tag{9}$$

where $\eta$ is a white dither noise of small amplitude and $f$ is the vector of controller gains, computed from the estimates of the predictive models by

$$f = -\frac{1}{\alpha}\left(\sum_{j=1}^{T}(\frac{1}{r})^{2j}\theta_j\psi_j + \rho\sum_{j=1}^{T-1}(\frac{1}{r})^{2j}\mu_j\phi_j\right) \tag{10}$$

with the normalization factor $\alpha$ given by

$$\alpha = \sum_{j=1}^{T}(\frac{1}{r})^{2j}\theta_j^2 + \rho\left(1 + \sum_{j=1}^{T-1}(\frac{1}{r})^{2j}\mu_j^2\right) \tag{11}$$

Here, $r$ is thed inverse of the basis of the exponential weight. In other words, $r$ is the radius of the circle to which the closed-loop poles are confined by the algorithm.

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