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IEEE-IJCNN, May 12-17, Honolulu, HI, 2002.

Adaptive Neural Model-Based Predictive Control of a Solar Power Plant

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***Abstract*–This paper describes the application of a non-linear adaptive constrained model-based predictive control scheme to the distributed collector field of a solar power plant at the Plataforma Solar de Almería (Spain). This methodology exploits the intrinsic non-linear modelling capabilities of non-linear state-space neural networks and their online training by means of an unscented Kalman filter. Tests on the ACUREX field illustrate the great engineering potential of the proposed control strategy.**

***Index Terms*–Solar power plant; state-space neural networks; online training; constrained model-based predictive control; dual unscented Kalman filter.**

I. INTRODUCTION

In a solar thermal power plant (SPP) solar radiation is used to heat a working fluid as it circulates through the receivers. The heated fluid may then be used to generate high-pressure superheated steam to feed a conventional turbine/generator system for producing electricity or heating water for industrial use, just to name a few applications. Thus, using solar energy to produce industrial process heat, not only conserves non-renewable energy sources but also reduces anthropogenic gas emissions.

One drawback of solar energy, apart from its intermittency, is that the sun's direct beam radiation at the earth's surface is profoundly influenced by climate conditions, such as clouds and fog, and atmospheric turbidity, not to mention the fact that it changes considerably throughout the daylight. In such a scenario, maximising the usage of available energy, while maintaining desired operating conditions for the heat consumer process, should be a primary concern of the control policy. The main control prerequisite in a SPP is to maintain the outlet temperature of the heat transfer fluid at a prescribed value by suitably manipulating its flow rate through the receivers. Since the SPP dynamics depends mainly on the working fluid flow rate and beam radiation at the mirror aperture varies throughout the daylight and additionally it is subject to the mentioned atmospheric disturbances, substantial variations in the SPP dynamics (*e.g.* the response rate and the time delay) will occur.

For dealing with this inherent feature of the plant, several control schemes have been proposed and implemented on real SPPs. Using a linear indirect adaptive control scheme Rubio *et al* [1] have reported the implementation of a self-tuning PI controller based on a pole placement approach, whereas Camacho and Berenguel [2] implemented an input constrained model predictive control strategy combined with a robust identification methodology. Also in a predictive control framework, a number of other control schemes have successfully been applied to real SPPs (see *e.g.* [3]–[5]). Using a different methodology by combining intelligent techniques with conventional control methodologies, Henriques *et al* [6] have proposed a control strategy based on a fuzzy logic switching of PID controllers.

In the past few years the development of artificial neural networks (NN) methodologies have been receiving a great deal of attention in a variety of scientific fields, owing to the approximation capabilities of multi-layer networks [7]. Neural modelling is one of their applications in the mathematical approximation theory realm with relevance to the control field [8]–[10]. In this context, Sørensen *et al* [11] reported a neural input-output black-box model in a generalised predictive control framework, while Gil *et al* [12] have described an implementation of a neural model-based predictive control methodology that provides zero static offsets by incorporating a pre-filter in the control loop. In a different approach the same authors propose to carry out an online NN weights adaptation [13] in order to eliminate the model/plant mismatch responsible for steady state deviations from set points.

Fig. 1. The distributed solar collector field at PSA.

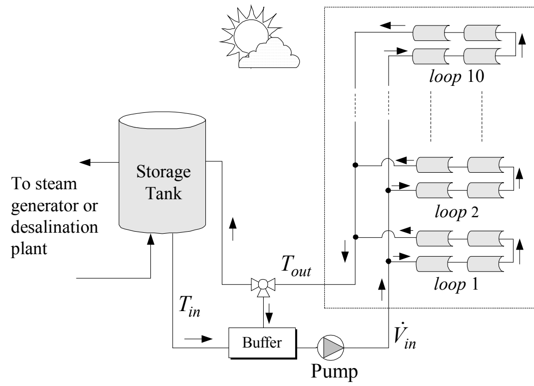


Fig. 2. Distributed solar collector field schematics.

In the present work this direction was followed in developing an adaptive constrained model-based predictive control scheme to the distributed solar collector (DSC) field of a solar thermal power plant at the Plataforma Solar de Almería. The methodology consist in an online NN weights adaptation and state estimation methodology by means of a dual unscented Kalman filter (DUKF) within a model-based predictive control framework.

The paper is organized as follows: Section 2 gives a short description of the DSC field. Section 3 focuses on the state space neural network architecture and training. In Section 4 the model based predictive control problem is covered. Section 5 presents experimental results obtained on the PSA's ACUREX field and Section 6 provides some concluding remarks.

II. THE SOLAR THERMAL POWER PLANT

The ACUREX distributed solar collector field is part of the Plataforma Solar de Almería (PSA), Fig. 1. It is a center for testing thermal solar energy applications, located on the desert of Tabernas, in south of Spain. The DSC field consists of 480 parabolic trough collectors arranged in 20 rows aligned on a West-East axis and forming 10 independent loops as depicted in Fig. 2. Every solar collector has a linear parabolic-shaped reflector that focuses the sun's beam radiation on a linear absorber tube located at the focus of the parabola. Each of the loops is 172 *m* long, with an active part of 142 *m*, while the reflective area of the mirrors is around 264.4 m^2.

The heat transfer fluid used to transport the thermal energy is the Santotherm 55, which is a synthetic oil with a maximum film temperature of 318 °*C* and an autoignition temperature of 357°*C*. The thermal oil is heated as it circulates through the absorber tube before entering the top of the storage tank. The colder inlet oil is extracted form the bottom of the tank. A three way valve located at the field outlet enables the oil recycling (by-passing the storage tank) until its outlet temperature is high enough to be sent to the storage tank. The thermal energy storage in the tank can be subsequently used to produce electrical energy in a conventional steam turbine/generator or in the solar desalination plant operation.

The DSC field is provided as well with a sun tracking system, which causes the solar collector to revolve around an axis parallel to the receiver in order to follow the yearly variation of the sun's declination.

III. NEURAL NETWORKS MODELLING

Consider a deterministic discrete-time non-linear system having the general form:

$$\begin{aligned} x(k+1) &= f(x(k), u(k), k) \\ y(k) &= h(x(k), k) \end{aligned} \tag{1}$$

where $f : \Re^n \times \Re^m \times \Re \to \Re^n$ and $h : \Re^n \times \Re \to \Re^p$ are non-linear functions, assumed to be smooth; $u(k) \in \Re^m$, $x(k) \in \Re^n$ and $y(k) \in \Re^p$ are, respectively, the input vector, the state vector and the output vector, at a discrete time k.

The aim in NN modelling is to find a parameterised structure that emulates the non-linear mappings $f(\cdot)$ and $h(\cdot)$.

A. The Architecture for the DSC Field

The DSC non-linear model is obtained by training, in a supervised way, a non-linear state space neural network comprising 3 layers of neurons, Fig. 3. Both the input and the output layers incorporate one neuron, corresponding to the same number of inputs and outputs, while the number of neurons in the hidden layer was chosen as 2 by means of a trade-off between the generalisation performance and the training error. This NN architecture is of recurrent type consisting of a feedforward main body where signals are propagate forward from the input neuron to the hidden units and from this layer to the output neuron to produce the network output. Additionally, within the hidden layer are allowed time-delayed (q^{-1}) feedback connections.

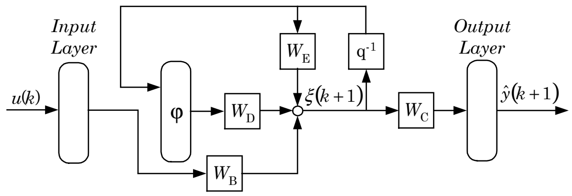


Fig. 3. State-space neural network block diagram.

Such a structure for φ as a hyperbolic tangent function can be described in the state space form by the following equations:

$$\begin{aligned} \xi(k+1) &= W_D \tanh(\xi(k)) + W_E\, \xi(k) + W_B\, u(k); \quad \xi(0) = \xi_0 \\ \hat{y}(k) &= W_C\, \xi(k) \end{aligned} \tag{2}$$

where $\xi(k) \in \Re^{Nn}$ denotes the network internal hyperstate, $\hat{y}(k) \in \Re^{No}$ is the network output, $u(k) \in \Re^{Ni}$ is the external input; Ni, Nn and No are, respectively, the number of neurons in the input layer, hidden layer and output layer. The synaptic weights between neurons, namely, W_B, W_C, W_D and W_E are real-valued matrices with appropriate dimensions.

B. *Training*

A number of methods for training neural networks have been proposed for either offline parameters estimation or real-time adaptation (see *e.g.* [14] [15] [16] [17] and the many references therein). These algorithms fall basically into two different categories: gradient based methods and second order methods. Since gradient based methods are slow and ineffective at finding a good solution they should be avoided when training recurrent neural networks.

In the present work the PSA's DSC field identification is carried out in two levels. First, a parameterisation is obtained for the selected topology by training the neural network on a batch mode, following an online estimation of weights in order to get rid of any model/plant mismatch due to the quality of the offline training set or the time variant nature of some plant's parameters such as the oil thermal capacity or the global coefficient of thermal losses, just to name a few.

In the offline NN training, the Levenberg-Marquardt algorithm is applied in minimising a cost-function given by the sum of square errors. The model parameters updating law is given by:

$$w^{i+1} = w^i - \left(\widetilde{\mathcal{H}} + \lambda \mathbf{I}\right)^{-1} \nabla J\left(w^i\right) \tag{3}$$

where w is the model parameters vector; $\widetilde{\mathcal{H}}$ denotes the approximation of the Hessian matrix; $\nabla J\left(w^i\right)$ is the cost-function gradient, $\lambda \in \Re^+$ is the Marquardt factor; $\mathbf{I}$ is an identity matrix of appropriate dimensions. By means of the Marquardt factor, this algorithm provides a compromise between the speed of convergence of the Newton's method and the guarantee of convergence of steepest descent algorithm.

Regarding the online weights adjusting, the present work follows the dual Kalman filter approach based on the unscented transformation [18]. Like all Kalman filter based algorithms, in the DUKF approach both states and parameters of a given dynamical system are computed simultaneously in two stages: i) in the time update one step-ahead predictions for the estimates are computed; ii) in the measurement update a correction is provided to these estimates on the basis of current noisy measurement. The dual filter equations are given by:

Weights estimation

Time update:

$$\begin{aligned} \Omega(k \mid k-1) &= \Omega(k-1 \mid k-1) \\ \mathrm{P}_{ww}(k \mid k-1) &= \mu^{-1}\, \mathrm{P}_{ww}(k-1 \mid k-1) \\ \mathcal{Z}^w(k \mid k-1) &= h\left(\hat{x}(k-1 \mid k-1), \Omega(k \mid k-1), k\right) \\ \hat{z}_w(k \mid k-1) &= \textstyle\sum_{i=0}^{2Nw} \Gamma_i^w \mathcal{Z}_i^w(k \mid k-1) \end{aligned} \tag{4}$$

Measurement update:

$$\begin{aligned} P_{\nu\nu}^w(k \mid k-1) &= \textstyle\sum_{i=0}^{2Nw} \Big\{ \Gamma_i^w \left[\mathcal{Z}_i^w(k \mid k-1) - \hat{z}_w(k \mid k-1)\right] \\ &\qquad \left[\mathcal{Z}_i^w(k \mid k-1) - \hat{z}_w(k \mid k-1)\right]^T \Big\} + R \\ P_{wz_w}(k \mid k-1) &= \textstyle\sum_{i=0}^{2Nw} \Big\{ \Gamma_i^w \left[\Omega_i(k \mid k-1) - \hat{w}(k \mid k-1)\right] \\ &\qquad \left[\mathcal{Z}_i^w(k \mid k-1) - \hat{z}(k \mid k-1)\right]^T \Big\} \\ \mathcal{K}^w(k) &= \mathrm{P}_{wz_w}(k \mid k-1)\left(P_{\nu\nu}^w(k \mid k-1)\right)^{-1} \\ \hat{w}(k \mid k) &= \hat{w}(k \mid k-1) + \mathcal{K}^w(k)\left[z(k) - \hat{z}(k \mid k-1)\right] \\ \mathrm{P}_{ww}(k \mid k) &= \mathrm{P}_{ww}(k \mid k-1) - \mathcal{K}^w(k) \mathrm{P}_{\nu\nu}^w(k \mid k-1) \mathcal{K}^w(k)^T \end{aligned} \tag{5}$$

States estimation

Time update:

$$\begin{aligned} \mathcal{X}(k \mid k-1) &= f\big(\mathcal{X}(k-1 \mid k-1), u(k-1 \mid k-1), \\ &\qquad w(k-1 \mid k-1), k\big) \\ \hat{x}(k \mid k-1) &= \textstyle\sum_{i=0}^{2Nn} \Gamma_i^x \mathcal{X}_i(k \mid k-1) \end{aligned} \tag{6}$$

$$\mathrm{P}_{xx}(k \mid k-1) = \sum_{i=0}^{2Nn} \Gamma_i^x \left[\mathcal{X}_i(k \mid k-1) - \hat{x}(k \mid k-1)\right]$$
$$\mathcal{Z}^x(k \mid k-1) = h(\mathcal{X}(k \mid k-1), w(k-1 \mid k-1), k)$$
$$\hat{z}_x(k \mid k-1) = \sum_{i=0}^{2Nn} \Gamma_i^x \mathcal{Z}_i^x(k \mid k-1)$$

Measurement update:

$$\begin{aligned} P_{\nu\nu}^x(k \mid k-1) &= \sum_{i=0}^{2Nn} \Big\{ \Gamma_i^x \left[\mathcal{Z}_i^x(k \mid k-1) - \hat{z}_x(k \mid k-1)\right] \\ &\qquad \left[\mathcal{Z}_i^x(k \mid k-1) - \hat{z}_x(k \mid k-1)\right]^T \Big\} + R \\ P_{xz_x}(k \mid k-1) &= \sum_{i=0}^{2Nn} \Big\{ \Gamma_i^x \left[\mathcal{X}(k \mid k-1) - \hat{x}(k \mid k-1)\right] \\ &\qquad \left[\mathcal{Z}_i^x(k \mid k-1) - \hat{z}_x(k \mid k-1)\right]^T \Big\} \\ \mathcal{K}^x(k) &= \mathrm{P}_{xz_x}(k \mid k-1)\left(P_{\nu\nu}^x(k \mid k-1)\right)^{-1} \\ \hat{x}(k \mid k) &= \hat{x}(k \mid k-1) + \mathcal{K}^x(k)\left[z(k) - \hat{z}(k \mid k-1)\right] \\ \mathrm{P}_{xx}(k \mid k) &= \mathrm{P}_{xx}(k \mid k-1) - \mathcal{K}^x(k)\mathrm{P}_{\nu\nu}^x(k \mid k-1)\mathcal{K}^x(k)^T \end{aligned} \tag{7}$$

where μ denotes the forgetting factor, Ω the sigma points matrix of *w*, Γ the corresponding weight vector, $\mathcal{K}$ the Kalman gain and $\mathcal{X}$ the sigma points matrix of *x*.

IV. MODEL-BASED PREDICTIVE CONTROL

Model-based predictive control is a discrete-time technique for which an explicit dynamic model of the plant is used to predict the system's outputs over a finite prediction horizon P when control actions are manipulated over a finite control horizon *M*. At time step *k*, the optimiser computes an open-loop control action sequence in such a way that the predicted output follows a pre-specified reference while taking into account possible hard and soft constraints. Only the current control action $u(k \mid k)$ is actually fed to the plant over time $[k, k+1)$. Next, the prediction and control horizons are shifted ahead by one step and a new optimisation problem is solved.

Let a first order Taylor expansion of (2) be given as:

$$\begin{aligned} x(k+1) &= \Phi x(k) + \Xi u(k) + \mathrm{E} \\ y(k) &= \mathrm{H} x(k) \end{aligned} \tag{8}$$

where $\Phi \in \Re^{Nn \times Nn}$, $\Xi \in \Re^{Nn \times Ni}$ and $\mathrm{H} \in \Re^{No \times Nn}$ denote, the state, the input and the output matrices, respectively; $\mathrm{E} \in \Re^{Nn}$ is the first term of the Taylor series expansion.

The constrained open-loop optimisation problem can be stated as follows:

$$\begin{aligned} \min_u J = \min_u \Big\{ &\sum_{i=1}^{P} \| y(k+i \mid k) - r(k+i) \|_{\mathcal{Q}_i}^2 \\ &+ \sum_{i=0}^{P-1} \| u(k+i \mid k) \|_{\mathcal{R}_i}^2 + \sum_{i=0}^{M-1} \| \Delta u(k+i \mid k) \|_{\mathcal{S}_i}^2 \Big\} \end{aligned} \tag{9}$$

subject to the system dynamics (8) and to the following constraint inequalities:

$$\begin{aligned} y_{\min} \le y(k+i|k) \le y_{\max}, \ & i = 1,..,P, \ k \ge 0 \\ u_{\min} \le u(k+i|k) \le u_{\max}, \ & i = 0,..,P-1, \ k \ge 0 \\ \left| \Delta u(k+i|k) \right| \le \Delta u_{\max}, \ & i = 0,..,M-1, \ k \ge 0 \\ \left| \Delta u(k+i|k) \right| = 0, \ & i = M,..,P-1, \ k \ge 0 \end{aligned} \tag{10}$$

with $\mathcal{Q}_i \in \Re^{No \times No}$, $\mathcal{R}_i \in \Re^{Ni \times Ni}$, $\mathcal{S}_i \in \Re^{Ni \times Ni}$; $\Delta u \in \Re^{Ni}$ is the control action moves and $r(k) \in \Re^{No}$ the reference vector.

As a result of the optimisation problem convexity, the open-loop optimal control problem can be rewritten as a quadratic programming problem (11).

$$\begin{aligned} &\textit{minimise} && J(\Delta\tilde{u}) = h^T \Delta\tilde{u} + \frac{1}{2} \Delta\tilde{u}^T \mathcal{H} \, \Delta\tilde{u} \\ &\textit{Subject to} && A^T \Delta\tilde{u} \le b \end{aligned} \tag{11}$$

where $A \in \Re^{(Ni \cdot M) \times (4Ni \cdot M + 2No \cdot P)}$, $b \in \Re^{(4Ni \cdot M + 2No \cdot P)}$; $\Delta\tilde{u} \in \Re^{Ni \cdot M}$ denotes the extended control moves over the control horizon. The cost function gradient $h \in \Re^{Ni \cdot M}$ and Hessian $\mathcal{H} \in \Re^{(Ni \cdot M) \times (Ni \cdot M)}$ expressions can be found in [12].

V. DSC FIELD CONTROL TEST

The proposed adaptive constrained non-linear MPC scheme was tested on the Plataforma Solar de Almería DSC field on 13 September 2001. In order to maintain (or drive) the outlet oil temperature at a pre-specified level despite variations in the sun's beam radiation and in inlet oil temperature, the control system manipulates the thermal oil flow rate pumped to the solar collector field.

Given the complexity and memory requirements of this approach it was considered to run the online identification and states estimation, as well as the open loop optimisation routines, in a separate computer, a laptop computer in the case. Thus, these routines were able to be implemented in MATLAB 5.3 taking advantage of its programming flexibility and using the optimisation toolbox for solving in real-time the required open loop constrained quadratic optimisation problem.

This laptop computer was then connected with the ACUREX field computer (a Pentium PC with DOS operating system) via a RS232 communication system providing the means for the exchange of data. In this framework the ACUREX PC provides the DSC field data to the laptop computer where a new control action will be evaluated. Next, this new oil flow rate value is sent to the laptop's COM and read by the ACUREX field PC which forwards it to the pump PI remote controller.

Communication routines for "synchronisation", "sending" and "reading" have been implemented in both C code for the ACUREX software package and in MATLAB to be called within the main control program, being used in this case the Real Time Toolbox from HUMUSOFT.

The training data set considered for offline adaptation of the NN weights has been collected from the plant on 8 June 2001 and the Levenberg-Marquardt algorithm used in minimising the error cost-function. Due to lack of space it is merely mentioned that the neural predictor for the cross validation data performs in a satisfactory way.

With respect to the constrained open-loop optimal control problem (11) the prediction horizon and the control horizon were chosen as $P = 7$ and $M = 1$ time steps, the sampling time was set to 15 seconds, while the cost functional weight matrices were chosen as:

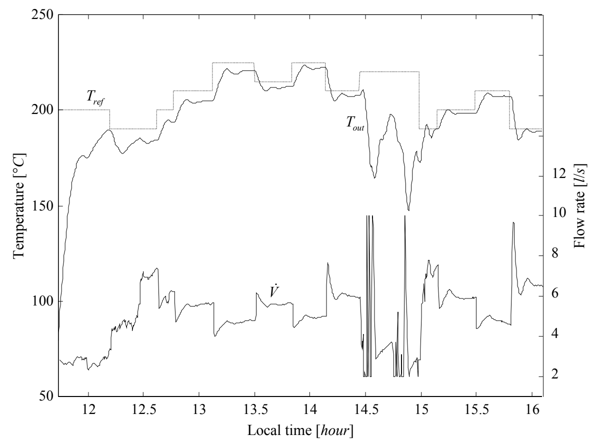
$$
\begin{aligned}
\mathcal{Q}_i &= \begin{cases} 10, & i = 1, \ldots, P-1 \\ 100, & i = P \end{cases} \\
\mathcal{R}_i &= 10^{-5}, \quad i = 0, \ldots, P-1 \\
\mathcal{S}_i &= 10^{-5}, \quad i = 0, \ldots, M-1
\end{aligned}
\tag{12}
$$

For safety reasons while solving the open loop optimisation problem, constraints were imposed in both the oil flow rate, which should be within 2 ls^{-1} and 10 ls^{-1} and the outlet oil temperature which is limited to 300°*C*. Additionally, the oil flow rate (control action) moves were constrained to 0.1 ls^{-1} in order to enable a smoother pump operation, thus rendering a controller not much aggressive.

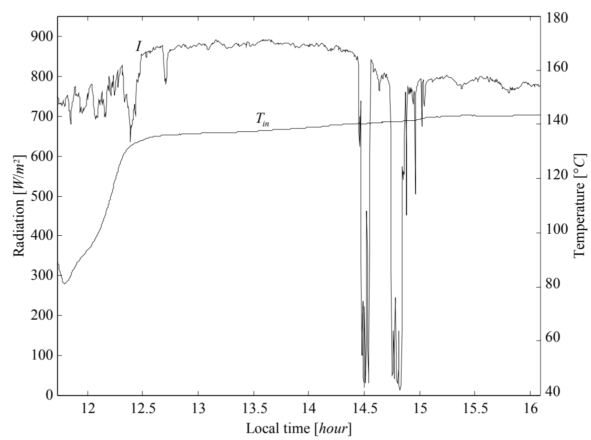
Concerning the dual unscented Kalman filter, the most relevant configuration parameters were chosen as follows:

$$
\begin{aligned}
P_{xx}(0) &= \mathbf{I}_{Nn} \\
P_{ww}(0) &= 10^{-6}\mathbf{I}_{Nw} \\
R &= 10^{-3}\mathbf{I}_{No} \\
Q &= 10^{-3}\mathbf{I}_{Nn} \\
\mu &= 0.9999
\end{aligned}
\tag{13}
$$

Figures 4.a) and b) depict the outlet oil temperature (T_{out}), set point (T_{ref}), oil flow rate through each DSC loop ($\dot{V}$), the inlet oil temperature (T_{in}) and the solar radiation (I) during the control tests on this particular day.



a)



b)

Fig. 4. ACUREX field test on 13 September 2001: a) set point, outlet oil temperature and oil flow rate; b) solar radiation and inlet oil temperature.

As can be inferred from the above plots, the adaptive MPC scheme provides a very interesting dynamic response of the outlet oil temperature, being the control system quite stable in all the operating points. An exception occurs for $t \in (14.5, 15)$ *hour*, when the radiation felt down abruptly due to passing clouds. However, despite the satisfactory controller performance, static offset errors are not entirely removed. They are manly due to the model/plant mismatch not completely compensated by the online identification. The reason why this happens is related to the small gain adaptation of the model parameters as a result of a small initial covariance matrix. Yet, it is also perceptible that, as time goes by, since the modelling errors are becoming less significant by means of an online identification, which results in decreasing static deviations from the set points. Possibly, static offsets would be entirely eradicated in the course of time.

VI. CONCLUSIONS

In this paper an adaptive constrained model-based predictive control scheme is applied to the distributed collector field of a solar power plant at the Plataforma Solar de Almería. The black-box model is derived by means of a state-space neural network and the real-time training and states estimation is based on a dual unscented Kalman filter. Experimental results on a particular day, shows the validity of the proposed control scheme.

ACKNOWLEDGEMENTS

This work was partially supported by POSI–*Programa Operacional da Sociedade de Informação* of Portuguese Fundação para a Ciência e Tecnologia and by the European Union's FEDER and PRAXIS XXI ALCINE Projects. The experiments were carried out within the "Access to Research Infrastructures Action of the Improving Human Potential Program" supported by the European Community. The authors wish to express their gratitude to the PSA staff.

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