REAL-TIME CONTROL OF A LABORATORY HEAT EXCHANGER USING THE PARTICLE SWARM OPTIMISATION ALGORITHM

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ABSTRACT

In the past decade, evolutionary based algorithms have been a popular research theme in many disciplinary areas like control systems. Although, due to the computational load required, this type of algorithms usually are applied off-line. In this paper, a stochastic search algorithm known as particle swarm is used as an optimisation tool for on-line control of a custom made laboratory thermodynamic system.

Keywords: Real-Time Control, Model Predictive Control, Particle Swarm Optimisation Algorithm.

1. INTRODUCTION

In this work, a model predictive controller is applied to regulate the air temperature of a thermodynamic laboratory process. This type of control strategy have become very popular since the 80's [1] and, comparing to other control algorithm, has the advantage of providing the system with the ability to react before any deviations in the controlled variable takes place. This anticipatory behaviour of the controller is achieved by using a model of the process in order to predict the system response in view of a given set of future control actions. The control values to be injected in the system for a specific time horizon are usually computed by minimizing a quadratic cost function of the form [2]:

$$J = \lambda_1 \sum_{j=a}^{b} [\varepsilon(k+j\,|\,k)]^2 + \lambda_2 \sum_{j=1}^{c} [\Delta u(k+j-1)]^2 \tag{1}$$

were,

$$\varepsilon(k+j\,|\,k) = \hat{y}(k+j\,|\,k) - w(k+j) \tag{2}$$

In the above formulae, $\Delta u(k+j-1)$ represents the control effort, λ_1 and λ_2 are weights for each expression component, c characterize the control horizon and the constants a and b represent the instant limits in which it is desirable that the output follows the reference. $\varepsilon(k+j\,|\,k)$ is the prediction error between the future trajectory $w(k+j)$ and the predicted output $\hat{y}(k+j\,|\,k)$.

Usually the cost function J must be minimized regarding a set of design and physical constraints. It is common to consider magnitude and rate constraints for the control actions and level constraints for the output signal.

Discarding the problems associated to model fitting, the predictive control resumes the minimisation of a function subject to constraints. Due to the nature of this function, the controller states are obtained by iterative numerical procedures. These function minimisation strategies can be based in either deterministic or stochastic search methods. However, since the search space defined by the restricted cost function is, generally, very complex, non-linear and non-convex, stochastic search algorithms seems suitable for this application.

2. THE PARTICLE SWARM OPTIMISATION ALGORITHM

In real-time control, any control algorithm must be fast enough to run completely between sample instants. In this context, the application of a given control strategy depends on the sampling frequency, on the computational power of the hardware and on the complexity of the control algorithm. The model predictive control is, by himself, a computational heavy algorithm. The computational load depends on several factors like the prediction horizon, the complexity of the model and the performance of the search algorithm.

Among the fastest stochastic search algorithms is the particle swarm optimisation algorithm (PSO). This search strategy has a decade of existence and was firstly proposed by Kennedy and Eberhart [3]. Since then several works have been published on this subject concerning his mathematical proprieties, or application in a specific problem like greenhouse environment control [4].

Conceptually, the PSO is an algorithm based on the social behaviour of groups of organisms such as herds, schools and flocks. As an evolutionary technique the PSO is a population based algorithm, formed by a set of particles, which represent a potential solution for a given problem. Each particle moves through a *n*-dimensional search space with an associated position vector $X_i(t)=\{x_{i1}(t),x_{i2}(t),\ldots,x_{in}(t)\}$ and velocity vector $V_i(t)=\{v_{i1}(t),v_{i2}(t),\ldots,v_{in}(t)\}$ for the current *i* particle and evolutionary iteration *t*.

The original PSO model integrates two types of knowledge acquisition by a particle: through it's own experience and from social sharing from other population members. The former was termed cognition-only model and the latest social-only model (Kennedy, 1997). The behaviour of each particle is based on these two types of knowledge and their current position regarding the search. In this context, the behaviour of particle *i* in the search space is governed by the following two equations:

$$v_{id}(t+1)=\omega(t)\cdot v_{id}(t)+\varphi_1.\left[p_{id}(t)-x_{id}(t)\right]+\varphi_2.\left[p_{gd}(t)-x_{id}(t)\right] \tag{3}$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \tag{4}$$

in which *d* represents the dimension index, $1\le d\le n$, $p_{id}(t)$ represents the best previous position of particle *i* in the current iteration *t*, $p_{gd}(t)$ represents the global best in the current iteration for a pre-defined neighbourhood type. Parameter φ_1 is known as the cognitive constant and φ_2 as the social constant, that represent uniformly distributed random numbers generated in a pre-defined interval. The $\omega(t)$ variable represents the inertia weight and his value affects the type of search. A large ω value will direct the PSO for a global search while a small ω will direct the PSO for a local search. In order to make a global search in the early run and more local in the end, the inertia weight can be made to vary linearly from a larger value to a smaller one.

In each iteration the velocity of the particles is bounded by a maximum value V_{max}. The value of this constraint is intimately connected with the maximum "jump" each particle can make. The value selected for V_{max} should not be too high to avoid oscillations, or too low to avoid search traps. Additionally the particle's position should be, if necessary, relocated to a point inside the defined search space.

2. EXPERIMENTAL SETUP

In order to apply the addressed control strategy in a real physical system, a thermodynamic process was built. The plant is composed by a PVC tube with an inner diameter of 63 mm and a length of 60 cm. Additionally two actuators, a fan and a heating resistor grid, was embedded in the tube. Air is forced to circulate by a fan through a pipe and is heated at its inlet by the electric heater. The purpose of this system is to control the air temperature in a specific spot of the tube. In order to do that three temperature sensors have been installed. One to measure the temperature of the heating element, one to measure the environment temperature and the other installed at ten centimetres away from the tube outlet.

The proposed system has two degrees of freedom, i.e. it is possible to manipulate the mass of air at room temperature entering the tube by regulating the fan speed and the heat produced by the resistor by controlling the mean power applied to this element. A diagram of the building blocks of the process and a picture of its final aspect are illustrated in the following figures.

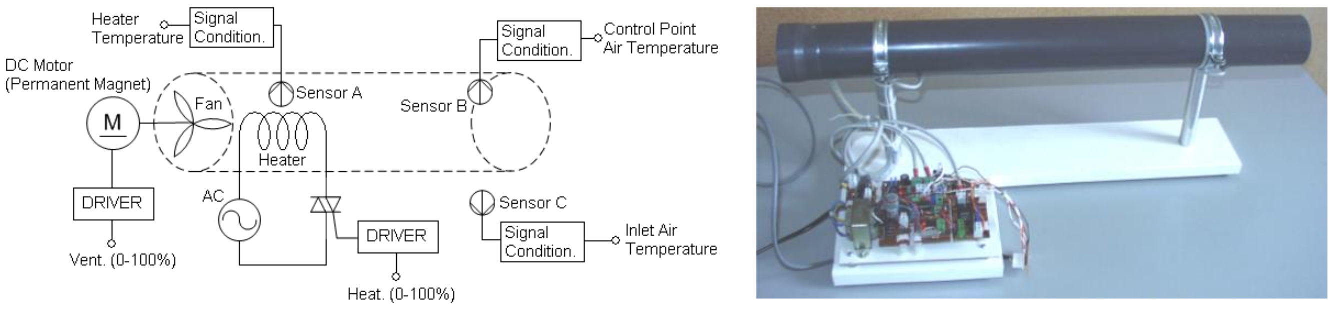


Figure 1: Block diagram of the process to be controlled (left) and picture of the process's final aspect (right)

The control and measured signals are manipulated in a PC compatible digital computer with a Pentium II processor running at 450 MHz. The communication between the plant and the computer was handled by a custom made ISA bus data acquisition card with an 8 bit resolution. Due to the time constants involved in the process, a 1Hz sampling frequency was found suitable.

3. SYSTEM MODEL

Regardless of the system's two degrees of freedom, in this work the air flow rate is kept constant. Hence the system input is a voltage that controls the mean power applied to the heater and the output is the outlet air temperature. In order to use a MPC control strategy a model of the plant is required. For that propose, a preliminary system identification process was carried out using as an input signal a random in amplitude and period excitation signal.

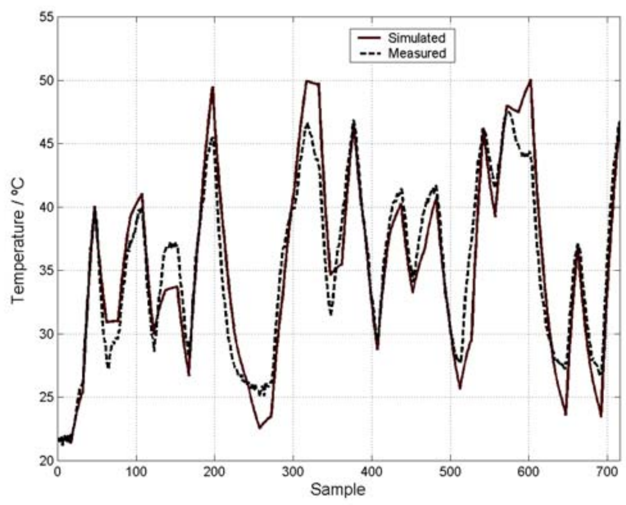


Figure 2: Open-Loop simulation of the ARX plant model under validation data.

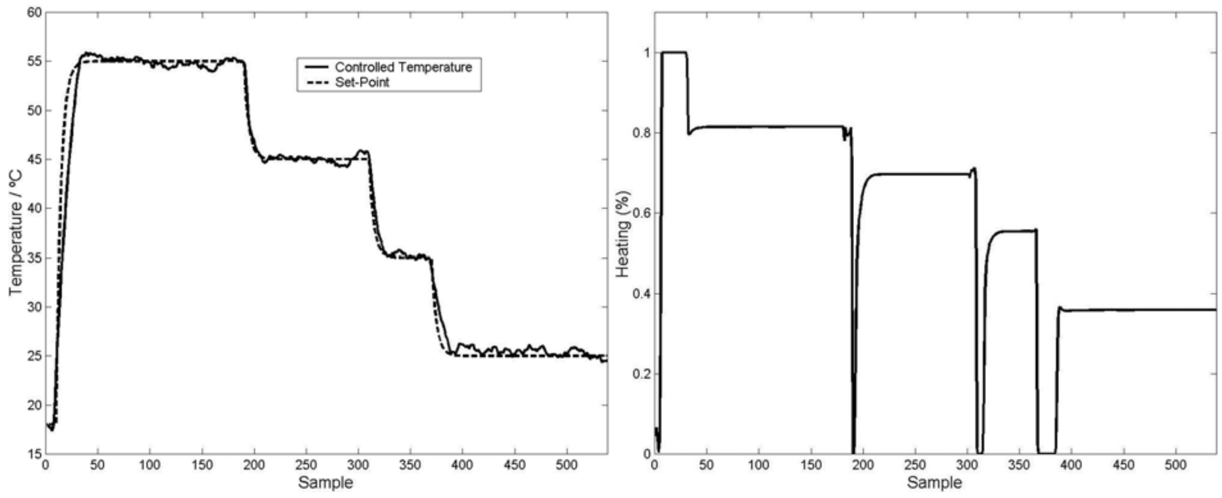
Considering that the outdoor temperature and ventilation rate is approximately constant, the model that has been found sufficiently accurate in order to model the dynamic behaviour of the plant was:

$$T_{pipe}\left[kT\right]=0.9579\cdot T_{pipe}\left[\left(k-1\right)T\right]-0.194\cdot Heat^{2}\left[\left(k-1\right)T\right]+2.1684\cdot Heat^{2}\left[\left(k-2\right)T\right]+0.749 \qquad (6)$$

where T_{pipe} is the outlet air temperature, $Heat$ is the relative voltage applied to the phase control hardware that drives the heater and T is the sampling period. As one can see, the model incorporates not the $Heat$ variable but his square. This is because the relation between the heat generated and the applied voltage has a quadratic proportionality as stated by the well known Jules law. Although the model seems non-linear it is still linear in the parameters. Hence the values of the model coefficients were obtained using the least squares method. In figure 2, the open-loop simulation results for the proposed model under validation data are presented.

4. EXPERIMENTAL RESULTS

In the following figure, the controller performance regarding the set-point accuracy and the control signal of the heater is shown.



Those results were accomplished using a fifty particles PSO algorithm evolved during two hundred generations. In this experiment the prediction horizon and the control horizon was set to ten steps ahead and the weight factors λ_1 and λ_2 was set to 0,6 and 0,4 respectively.

5. CONCLUSION

In this paper, the preliminary results of real-time control on a physical plant using the particle swarm optimisation algorithm have been presented. From the results obtained one is able to conclude that this tool has real practical use outside the simulation environment. Indeed, evolutionary algorithms great potential it’s their ability to evolve a set of possible solutions in a highly sophisticated multimodal search space with large number of discontinuities. Moreover its application in multiobjective problems allied to automatic decision mechanisms can be of great interest in applications outside the computer environment. With an obsolete computer one has shown that it is possible to use this kind of evolutionary search tool in practical real-time control applications.

8. REFERENCES

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