ADAPTIVE PREDICTIVE CONTROLLER APPLIED TO AN OPEN WATER CANAL

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Abstract: This paper concerns to the application of adaptive control to a large scale water canal experimental plant. Water canals are complex spatially distributed systems which aim at distributing water either for irrigating, or domestic, or industrial purposes. In this paper a predictive adaptive control algorithm (MUSMAR) is applied to a large scale experimental water canal prototype. The experimental facilities with a fully instrumented canal, a PLC network and a SCADA system, are briefly described. This paper describes the developed software module and the MUSMAR control algorithm. Finaly, Some experimental results obtained in the experimental water canal, are presented.

1 INTRODUCTION

Water distributing systems are increasingly important as fresh water scarcity is becoming a critical issue in many places worldwide. In this increasing water scarcity situation an efficient management of water canals, minimising water losses, is an obviously important issue. Nevertheless, this management task brings conflicting goals - minimise water loss *vs.* Quality of Service. On one side, users demand more and more flexibility on water withdrawing from canals. On the other side, the use of the traditional pre-scheduled water turns may attain a very low level of water losses but at cost of users QoS. Thus, modern water canals with advanced control techniques may have and an important role on the management of these conflicting goals.

Two strategies of upstream automatic control are applied: local upstream control and distant upstream control. Local control is the most practical way to introduce automatic control on existing canals, since every equipment can be concentrated an one place. Nevertheless, distance upstream control as well as remote supervision are promising approaches.

Adaptive control techniques are most suited to situations where the dynamic behaviour is unknown or slowly changing. Nevertheless, the adaptive predictive algorithm MUSMAR has also shown to cope well with incomplete order modelling and minor nonlinearities. Thus MUSMAR has been tested and successfully applied in several experimental processes ranging from distributed solar power plants (Coito et al., 1997)(Rato et al., 1997) to Internet traffic control (Costa et al., 2002).

This control approach is implemented through a developed software package that communicates to the supervisory control and data acquisition (SCADA) system which is connected to a programmable logic controller(PLC) network.

2 WATER CANAL DESCRIPTION

The experimental water canal used in this work is at the NuHCC (Núcleo de Hidráulica e Controlo de Canais) of the University of Évora, Fig. 1.

The canal has a trapezoidal cross section geometry, and is constituted by four pools of roughly 40 m each, resulting in a 145 m long instrumented canal, plus a traditional water canal which completes a closed water circuit. The canal inlet water flow is defined by an electrical controlled MONOVAR valve. The flow along the four pools may be controlled by three sluice gates and there is a water off-take up-

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Figure 1: Experimental water canal at the University of Évora.

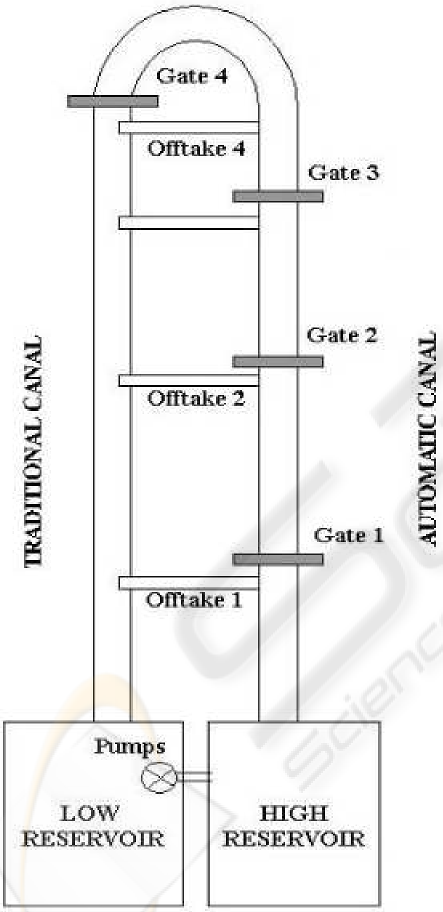

Figure 2: Schematic diagram of the experimental water canal at the University of Évora.

stream of each gate. This off-take is equipped with a flow meter and an electrical butterfly valve and discharges into the traditional return canal. Concerning sensors, there are three float and counter-weight level sensors in stilling wells for each pool - one at each end and one in the middle of the pool. Figure 2 shows a schematic diagram of the experimental plant. This facility is described in more detail in (Ratinho et al., 2002).

It should be noted that the dynamic behaviour of this type of plant is modelled by the Saint-Venant equations which are nonlinear partial differential equations which can be linearised for small variations around stationary values. Thus, this plant belongs to a class of distributed parameter plants with transport phenomena, such as highway traffic, distributed solar plants, and boiler circuits of thermal power plants that have been studied with success in the scope of advanced control algorithms, as adaptive and predictive control techniques(Silva et al., 2003; Marques and Silva, 2005).

2.1 Data Acquisition and Supervision System

The experimental plant is equipped with a network of 6 PLCs. Five local PLCs (one for each sluice gate or inlet valve) and one central master PLC. The data acquisition and analog-to-digital conversion are performed locally at each PLC. These are interconnected by a MODBUS network to the master PLC, which communicates to the SCADA computer by a serial port RS232 interface.

The SCADA system is build over the WIZCON environment, and presents a user friendly graphical interface to command the process as well as to observe the evolution of measured variables over time. The SCADA also has a DDE interface which allows the communications between the SCADA and external applications.

This system is described in more detail in (Almeida et al., 2002).

2.2 Control Algorithm Software Package

Due to the complexity of MUSMAR algorithm, it is impracticable to implement local control directly in the local PLCs. Moreover, although the SCADA may implement a predefined set of controllers, it has little support to develop general algorithms. Thus a software package was developed in C language in order to extend the control capabilities of the SCADA system and implement the MUSMAR algorithm has an external process.

Once the SCADA system has a Dynamic Data Exchange(DDE) communication interface, this was the chosen process of interaction between the external process (the controller) and the SCADA system.

The initialisation, reading and writing of the variables which define the state of the process can be performed through the following functions

```
DDEInit("WIZCON", "GATE")
DDERequest(char var[])
DDEPoke(char []var, char []valor)
```

These functions define the basic application programming interface (API).

However, while the reading needs usually just one call to DDERequest(), to define a command into the actuators, several calls of DDEPoke(...) are usually necessary, stating the control mode of one or more (cascade) loops, and defining the variable value.

Thus, we have defined a two layer API: the base API (dde-base.c) which communicates to the SCADA through DDE and defines DDERequest(...) and DDEPoke(...); and a second layer with a more user friendly API (scada-api.c).

This second layer defines a set of 55 functions to read and write in or from each of the plant sensors and actuators. The API implementation for the case of a sluice gate is presented above.

Sluice Gates Api Implementation

We consider in the following, the case of gate API to gate number 1, which is connected to PLC2. The sluice gate control mode is defined by the tag "MODE_MATIC_A2", which can take values from 1 to 4 corresponding to direct control of the actuator; local control of sluice gate position; local control of upstream level; and local control of downstream level. When MODE_MATIC_A2 is set to 1 it is possible to command the gate directly with three commands: open, close, and stop.

If the gate is closing and the desired option is to completely open the gate it is necessary to set MODE_MATIC_A2=1 to set the direct control mode; then an order to inhibit the closing command, MATIC_CLOSE_OUT_A2=0, and only then should be sent the order to open the gate MATIC_OPEN_OUT_A2=1, as shown below.

```
void open_gate_1(){
  DDEPoke("MODE_MATIC_A2", "1");
  DDEPoke("MATIC_CLOSE_OUT_A2", "0");
  DDEPoke("MATIC_OPEN_OUT_A2", "1");
}
```

Similar procedures are developed to interact with other actuators.

Api Definition

In the API definition is listed below, "N" stands for the number of the PLC that controls the device.

```
void open_gate_N()
void close_gate_N()
float level_gate_N()
void set_level_gate_N(int level)
void close_monovar()
void open_monovar()
void set_in_flow(int flow)
void set_monovar_level(float level)
float flow_monovar_in()
float level_monovar()
float flow_valve_gN()
float level_valve_gN()
void close_valve_gN()
void open_valve_gN()
void set_valve_flow_gn(float flow)
void set_valve_level_g1(float level)
int level_upstream_canal()
int level_middle_gN()
int level_upstream_gN()
int level_downstream_gN()
```

Other Package Functions

Along with the API, the developed package provides also: a simple command line; a text oriented output interface; data logging; and a timing function. These are functions that may be naturally adapted to the experiment to be performed.

Development Environment

This package was developed in a MinGw environment. This is a set of free open-source tools for the Windows operating system, and includes among others: a port of the *GCC* compiler, a *bourne shell* compatible environment (MSYS) and a $make file$ utility.

3 MUSMAR ADAPTIVE PREDICTIVE CONTROLLER

In this paper, experimental results are presented on the application of MUSMAR, a predictive adaptive control algorithm for which there is evidence of robustness against plant unmodelled dynamics(Mosca et al., 1989), and have been tested in large number of experimental plants.

At the beginning of each sampling interval, recursively perform the following steps: **1.** Sample the process output at time t, compute the tracking error. **2.** Using Recursive Least Squares, update the estimates of the parameters in a set of predictive models. **3.** Apply to the plant the control given by

$$u(t) = F's(t) + \eta(t) \qquad (1)$$

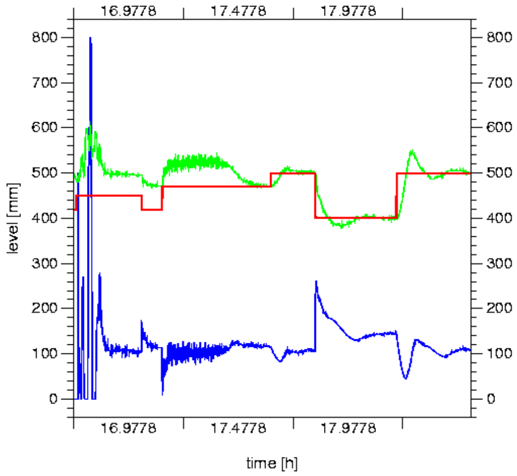

Figure 3: Experimental results. Local upstream control. Water level (mm), reference (mm), gate position (mm), time (h).

where η is a white dither noise of small amplitude, such that and F is the vector of controller gains, computed from the estimates of the corresponding predictive models by the optimization of a cost function across a predefined horizon T.

An integral effect has been also considered in parallel with MUSMAR. This algorithm has been implemented in C and linked with the software package presented above. A detailed description of MUSMAR is presented in (Mosca et al., 1989).

4 EXPERIMENTAL RESULTS

The following results were obtained at the experimental canal with MUSMAR controller in January 2007.

In the experiment the control structure is a local upstream one. The sampling time was set to 5 s, the controlled variable is the level upstream of gate 2, the manipulated variable is the position of gate 2. The inlet flow of the canal was locally controlled to 35 l/s, off-take valves were closed and gate 1, 3, and 4 were opened.

Experimental results are shown in Fig.3. After the startup the gains converge and the algorithm follows the reference, although with a significant static error. At instant $17,2$ the integral gain was set to 0.05 eliminating the static error.

5 CONCLUSIONS

An adaptive predictive control algorithm and an API software package were implemented, and tested in an experimental process plant. The results show the applicability of advanced control algorithms in the context of water canal systems. Instrumented canal plants with centralised control and supervision are essential to the application of complex control algorithms, which are impractical to implement on local PLCs. As future work the inclusion of a priori information (loading initial gains and initial covariance matrix) is a promising step as it has been observed in other applications to be an important issue in order to apply the MUSMAR algorithm in production environment.

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