IMPROVING EFFICIENCY OF GREENHOUSE HEATING SYSTEMS USING MODEL PREDICTIVE CONTROL

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Abstract: This article presents a comparison of commercial and model based predictive control strategies aimed at optimizing efficiency of classical heating systems used in greenhouse temperature control. Two kind of heating systems are considered: aerial pipes with hot water and air-fan heaters. By using simple linearized models of the system around the predefined setpoints and a generalized predictive control strategy, the performance is improved without requiring modifications in the heating systems. The main strength of this paper lies in the fact that the MPC algorithm has been tested in a greenhouse.

Keywords: Temperature control, Agriculture, Generalized predictive control, Cascade control, feedforward control

1. INTRODUCTION

Temperature control in greenhouses is a practical problem of considerable interest and economic significance since the primary objective of greenhouses is to produce agricultural products outside the cultivation season, representing the fuel-based heating costs the 30% of the overall operational costs in the greenhouse industry. Generally, greenhouses are heated by hot water that circulates in pipes or by hot air that is distributed by ducts. In (Baille and von Elsner, 1988), six types of heating systems were presented and discussed: (1) heat exchangers in the soil, (2) heat exchangers laid directly on the ground, (3) aerial pipes near the ground or benches, (4) fan heater units, (5) roof heating systems, (6) a combination of two of these. This paper presents the application of Model Predictive Control (MPC) strategies to types (3) and (4). Regulating air temperature in the greenhouse is important for both vegetative growth and fruiting. To determine heating requirements, it is essential to know the minimum temperature requirements for the crop, the lowest outdoor temperature that might be expected, and the surface area of the greenhouse. Heat loss also will be affected by wind and site exposure. Due to the favourable weather conditions in the Mediterranean areas, the required energy to provide adequate temperature integrals to the crop during daylight is provided by the Sun. Moreover, during the day the problem is to avoid large values of the temperature and thus natural and forced ventilation are used. During the night, the temperature setpoints are lower and while the temperature remains over these, the heating is not used. The most widely used heating systems in Mediterranean greenhouses are based on hot air, distributed in the greenhouse via perforated polyethylene ducts (Teitel *et al.*, 1999). Recently, there has been a growing trend to install hot-water pipe systems in new greenhouses.

Several authors have used different greenhouse heating climate control strategies (mainly by aerial pipes). In (Udink ten Cate, 1983), several PI control structures were tested and compared to model reference adaptive control in a Venlo greenhouse with tomato crop, showing good steady-state behaviour but large overshoots without optimizing efficiency. In (Davis and Hooper, 1991), a cascaded

PI control is introduced and tested in a Venlo greenhouse improving the results obtained with classical PI control. In (Young and Chotai, 2001) a PIP control scheme is used with a model of a Venlo greenhouse, while Tantau and co-workers (Tantau, 1985; Tantau, 1993; El Ghoumari *et al*., 2002) used feedforward controllers and extended linearized predictive controllers obtaining also acceptable results. In (Boaventura *et al.*, 1997; Coelho *et al.*, 2002) used both PID and GPC controllers in a tunnel greenhouse in Portugal, obtaining better results with the GPC approach, accordingly with the results of (Nielsen and Madsen, 1996) in cold climates. The most relevant experiences with receding horizon optimal controllers have been reported by van Straten and co-workers (van Straten *et al.,* 1999; van Straten *et al.*, 2000; van Straten *et al.*, 2002; Tap *et al.*, 1996a; Tap *et al.*, 1996b; Tap, 2000), demonstrating the feasibility and features of this kind of control technique in a Venlo greenhouse in the Netherlands. Seginer and co-workers (Gutman *et al*., 1993; Ioslovich *et al.*, 1996) studied different techniques using linear programming and Pontryagin's principle to minimize heating costs. In (Rodriguez *et al.*, 2003) the integration of heating within a hierarchical crop production control scheme is treated. Many authors only report results in simulation. Gain scheduling control algorithms are explained in (Kamp and Timmerman, 1996), without providing any experimental results. Decentraliced MPC controllers have been tested under simulation by (Kyriannakis *et al.*, 2002), while (Piñon *et al*., 2002) used several MPC control schemes, including embedded feedback linearization and robust control. In (Alessandri *et al*., 1994) neural network based predictive controllers and optimal controllers are used to cope with the temperature control problems. As seen before, many authors have selected MPC techniques for heating control purposes. There are some reasons which may justify the use of a MPC scheme when controlling greenhouse heating, as the problem is not only related with a classical regulatory-disturbance rejection control loop, but also to the costs associated to the control actions (fuel consumption). In this sense, the use of a cost function as that used by MPC algorithms helps the costs associated to the control actions to be taken into account. Although the delay time in this kind of applications is of the same order of the dominant time constant of the system, it influences the consumption. Moreover, although many control strategies can cope with the disturbance rejection problem (mainly changes in outside temperature and wind speed), MPC approaches offer a natural way to deal with feedforward control. System constraints can be taken into account in the design and optimisation process.

The paper is organized as follows: section 2 presents a brief description of the greenhouses used to perform the experiences. Section 3 outlines the applied control techniques. Section 4 shows some illustrative experimental results. Finally, section 5 presents the conclusions.

2. MATERIALS AND METHODS

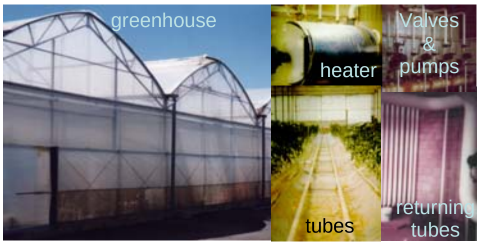
2.1 Greenhouses

Two greenhouses have been used in the experiences shown in this paper. The first one has two symmetric curved slopes roof (gothic roof) and five North-South oriented naves with dimensions 7.5x40 m (1500 m^2). Different sensors where installed to measure inside air temperature and humidity, inside global and PAR radiation and CO_2 concentration. Also, a meteorological outside station has been installed with the same previous sensors plus wind direction and speed sensors, and a resistive rain sensor. The installed control actuators (figure 1(*a*)) consist of vents, a shade screen, and a hot water pipe heating system, composed by a boiler, a burner, mixing valves, pumps, and heating pipes. The power of the heating system is 2000000 Kcal using a constant water temperature of 80ºC. The main steel pipe has 8.2 cm of diameter and the secondary one 5.9 cm. A 2.5 HP pump is used to produce 25 m^{3}h^{-1} of water flow. The position of the vents, screens and heating valves, and the status of the pumps and burner are measured. The sample and control time is 1 min.

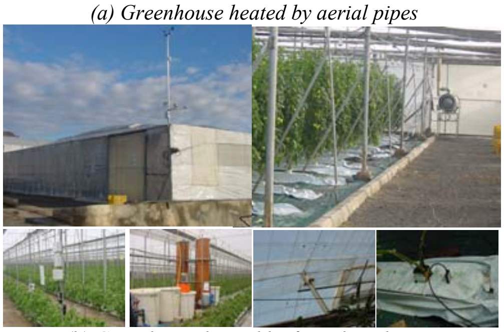
The second one is a plastic cover greenhouse of 38.7 m length, 23.2 m width and height from 2.8 m to 4.4 m). It is composed by automated zenital and lateral vents, the first ones with a maximum aperture angle of 45º and the last ones with dimensions 37 m length, and 1.2 m aperture. A forced-air heating system RGA 95 KW has been used for heating purposes (figure 1(*b*)), with stainless steel body, including chimney, thermostat controlled environment by relays and a 500 l Polyethylene diesel oil deposit. The installed sensors are: soil temperature both at 40 cm and 3 cm depth, soil cover temperature, temperature and relative humidity of the air (1.5 m over the soil), leaves temperatures (4 sensors), plastic cover temperature (4 sensors), air velocity inside the greenhouse, inside CO_2, crop substrate temperature, and global and PAR radiation. A meteorological station is also installed at the outside measuring temperature, relative humidity, rain, wind speed and direction, and global and PAR radiation.

2.2 Heating by aerial pipes

The pipes heated by hot water circulating though them, transmit heat to the air by convection, producing an increase in the greenhouse inside temperature. Then, the control problem consists in calculating the required temperature of the water within the pipes to meet inside air setpoint requirements. In order to perform this task, the system has one three way valve to mix the water of the boiler (constant temperature) with the water returning from the greenhouse in a cascade structure (figure 2), where the temperature measurement is acquired near the boiler. The actuators have constraints as the water temperature through the pipes is lower than the water temperature in the boiler and higher than that of the greenhouse air.



(a) Greenhouse heated by aerial pipes



(b) Greenhouse heated by forced-air heaters

Fig. 1.Greenhouses used in the experiences

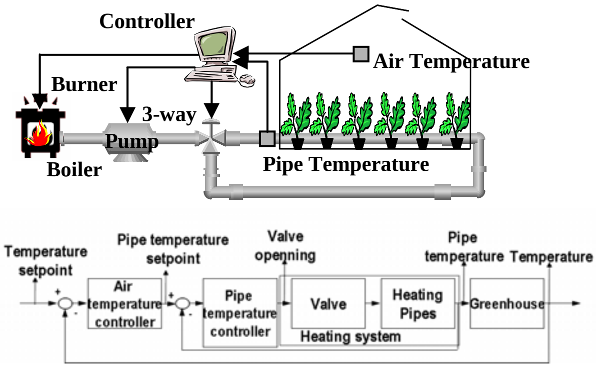


Fig. 2. Schematic diagram of the aerial pipes heating system and control blocks

2.3 Heating by forced-air heaters

The system is composed by an indirect combustion hot air generator using a heat exchanger to separate exhaust gases from hot air that is introduced in the greenhouse (figure 3). The system incorporates three units: a combustion chamber supplied with fuel oil, the heat exchanger and a fan to extract the exhaust gases throughout a chimney. The efficiency is between 80 and 90%.

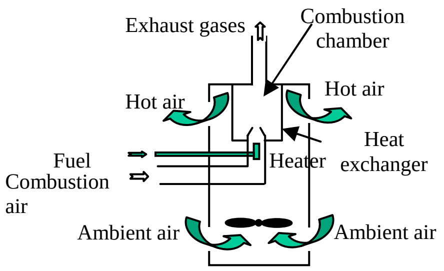


Fig. 3. Schematic diagram of the air heating system

3. CONTROL ALGORITHMS

3.1 Commercial and classical control algorithms

Commercial hot water heating systems are usually controlled by proportional or cascaded PI+parallel feedforward controllers to cope with outlet disturbances (mainly outside temperature and wind speed) like those shown in figure 2, while on/off control with dead/zone is used in forced-air heaters. Commercially available control algorithms have been described in horticultural engineering textbooks (e.g., Kamp and Timmerman, 1996). Although this system is nonlinear (Rodríguez, 2002), it can be linearized when operating around a setpoint for control purposes, as a first order system with a delay between 7 and 11 min, a time constant between 7 and 13 min, and a static gain between 0.07 and 0.1 for this installation. The same conclusions can be obtained when linearizing a model of the system obtained from physical principles (Rodríguez, 2002). Notice that disturbances affect the heating performance. During the night, the greenhouse looses heat through the cover (conduction/convection), depending on the outside temperature and wind speed. Thus, ideally the controller must take into account the outside climatic conditions to calculate the water temperature in the pipes. Transfer functions can also be found relating these disturbances to changes in inside air temperature, to be used for feedforward control purposes. In other cases, a feedforward term based on first principles models can also be used (Rodríguez *et al*., 2001).

3.2 Model based predictive control schemes

In this work, a Generalized Predictive Control (GPC) control approach has been used (Clarke *et al*., 1987). Using a model of the process at each sampling instant, the future outputs are predicted for a given horizon ($\hat{y}(t+k|t)$, $k=1...N$) and substituted within an objective function to compute the future controls ($u(t+k|t)$, $k=0...N-1$), while taking process constraints into account. Following the receding horizon approach, the first control signal calculated is implemented, then the horizon is moved ahead, and the procedure is repeated in the next sampling instant as the new output is known (all the sequences are updated). A CARIMA model (Clarke *et al.*, 1987) has been used obtained from transfer functions relating greenhouse temperature to changes in heating and disturbances (mainly outside temperature and mean wind speed) when operating around a particular setpoint. Both empirical transfer functions and obtained by linearization of a nonlinear climate model (Rodríguez, 2002) have been used. The classical GPC cost function has been implemented and constraints have been taken into account (Guzmán *et al*., 2004).

$$J = E\{\sum_{j=N_1}^{N_2}\delta(j)[\hat{y}(t+j\,|\,t)-w(t+j)]^2+\sum_{j=1}^{N_u}\lambda(j)[\Delta u(t+j-1)]^2\} \quad (1)$$

In this cost function, where $E\{.\}$ is the mathematical expectation, $\hat{y}(t+j|t)$ is an optimal system output prediction sequence performed with data known up to instant t, $\Delta u(t+j-1)$ is a sequence of future control increments, obtained from cost function minimization, N_1 and N_2 are the minimum and maximum prediction horizons, N_u is the control horizon, and $\lambda(j)$ and $\delta(j)$ are weighting sequences that penalize the future tracking and control efforts, respectively, along the horizons (here δ equals 1 and λ is a user-chosen constant). The reference trajectory $w(t+j)$ can be the setpoint itself or a smooth approximation from the present value of output $y(t)$ to the setpoint, usually implemented as a first order filter. If no constraints are taken into account, as the model is linear and the optimization criterion is quadratic, an explicit solution can be found. Otherwise, a quadratic programming (QP) optimization algorithm is used.

For controlling the forced-air heaters, due to the discrete nature of the actuator, two possible ways of implementation have been considered, providing very similar results: a branch and bound strategy previously used by the authors within the control of photobioreactors framework (Berenguel et al., 2004) and a PWM approximation in which the activation of the actuator is done between 4 min (1%) and 10 min (100%) using a control time of 1 min. When the tracking error is negative the control is switched off. Figure 4 shows the basic MPC strategy taking into account the discrete nature of the control signal in this problem. The predictions along the prediction horizon using possible input values in the control horizon are used to evaluate the following objective function:

$$J = \sum_{j=N_1}^{N_2} \left[\hat{y}(t+j|t) - w(t+j) \right]^2 + \sum_{j=1}^{N_u} \lambda(j) [u(t+j-1)]^2 \qquad (2)$$

$y_{min} \le y \le y_{max}$; $u \in \{u_{min}, u_{max}\}=\{0,1\}$; $\Delta u \in \{\Delta u_{min}, \Delta u_{max}\}=\{0,1\}$; $\{0,1\}$:{off, on}

Those future input values (and associated predictions) minimising the cost function are selected and only $u(t)$ is implemented at the current sampling time. In this case, the values of the control actions have been used (weighted by the control effort weighting factor λ) as they are related with the costs associated to fuel consumption. Figure 4 illustrates the basic idea of this technique for the control space discretized into two alternatives (on-off control) and lower prediction horizon $N_1=2$.

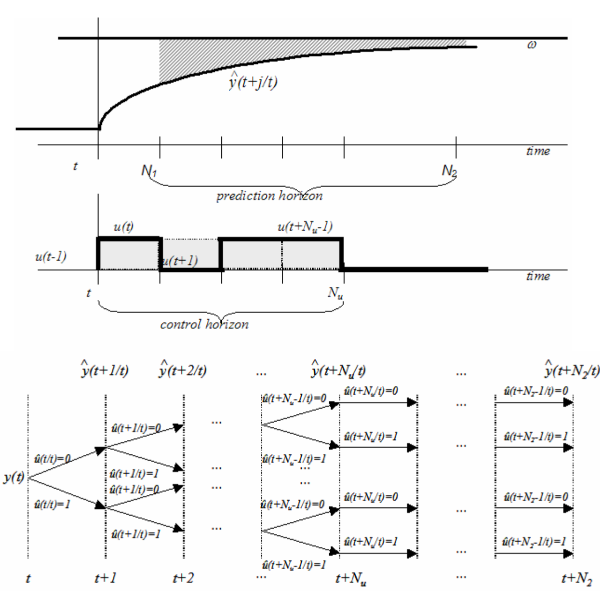


Fig. 4. Branch-and-bound GPC.

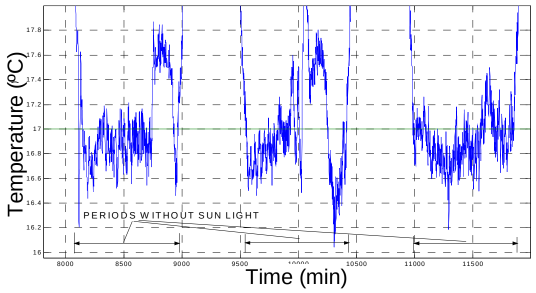
4. EXPERIMENTAL RESULTS

4.1. Heating by aerial pipes

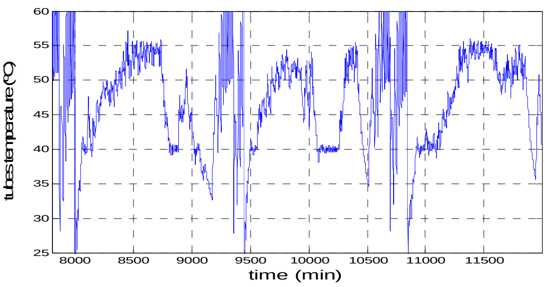
Figure 5 shows the results when controlling the greenhouse using the control scheme in figure 2, saturating the pipes temperatures at a maximum of 55ºC during three nights. Two kind of linearized models have been used to design the controllers: a first order linear model relating inside temperature with heating has been obtained for an operating point defined by heating status (setpoint) and outside disturbances (temperature and wind speed levels), thus no explicit models of the disturbances have been considered. In a second stage, approximated linear models of how disturbances affect the inside temperature have been obtained using least-squares identification over a set of data. In both cases acceptable results have been obtained when the linearized models have been used to design the controllers. The tuning of the master controller has been done using open loop Ziegler-Nichols rules around an operating point of 17ºC, with a mean wind speed of 6 ms^{-1} and with an outlet mean temperature of 11ºC (typical in this zone from December to February). A proportional gain of 12.8 and an integral time of 300 min have been obtained. The same procedure has been used to tune the slave controller. As seen in the figure, the results are quite acceptable as in this case the actuator is continuous and the control scheme is appropriate for this kind of application, although it should be desirable to diminish the variance of the temperature signal. A classical constrained GPC strategy has been also implemented to calculate the desired temperature of the water pumped through the pipes using the same linear models. The parameters of the GPC are: N_1=11, N_2=30, N_u=30 (min), δ=1 and λ=0.001. The sampling time is 1 min and the control signal has been saturated to 55ºC. The unknown outside conditions over the prediction horizon have been considered constant and equal to the actual measured value. Other different controller configurations have been tested obtaining similar results. Figure 6 presents illustrative results during four nights (the last one leading to actuator saturation). As is to be expected, the differences between both techniques are not quite considerable, although the predictive nature of the GPC algorithm and the fact that the constraints surpassing can be anticipated produce slightly better results that can help to save energy.

4.2. Heating by forced air heaters

In this case, the tuning knobs of the GPC algorithms were selected taking into account the characteristic dynamics of the system (static gain 0.04ºC%$^{-1}$, time constant of about 15 min, representative delay of 2 min and settling time of 30 min): N_1=3, N_2=30 and N_u=30. After several simulations and real tests, the selected values are: N_2=10 and N_u=6, as no improvements are observed when increasing these values. The value of N_2 is a trade-off between tracking characteristics and number of activations of the controller. As in the previous case, two kind of implementations have been done, one without explicitly taking into account disturbances (then the model is only valid for a range of operating conditions) and other including the linear models of the disturbances within the GPC framework. In this last case, again the unknown outside conditions over the prediction horizon have been considered constant and equal to the actual measured value.

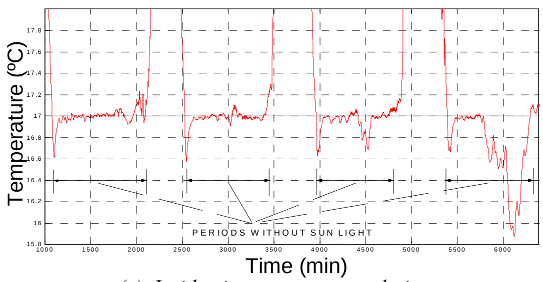


(a) Inside air temperature evolution

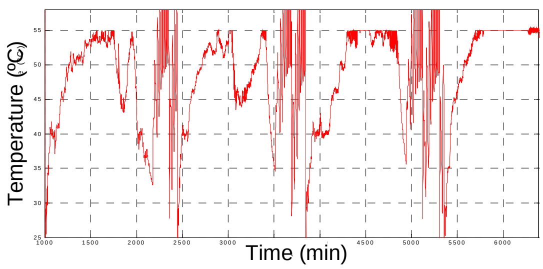


(b) Pipes temperature evolution

Fig. 5. Results under heating pipes cascade control



(a) Inside air temperature evolution



(b) Pipes temperature evolution

Fig. 6. Results under heating pipes GPC control

Figure 7 shows a typical profile of the control using an on/off controller with dead zone of ±0.5 and sample time of 10 min. Many tests have been performed modifying the activation time till the minimum allowed by the vendor (4 min) and similar results have been obtained regarding number of commutations and activation times. Figure 8 shows representative results of the performance of the GPC-PWM controller (similar to those of the branch-and-bound algorithms). This controller helps to achieve about 20% of saving in fuel consumption, although it has been observed that, even using different tuning knobs in the GPC algorithm and different sample times and dead-zones in the on/off control, the GPC controller produces more commutations and less consumption than the on/off controller, the number of commutations being within the ranges recommended by the supplier. As an example, during a typical night the number of minutes during which the heating system is on with the on/off control is 221 min (11.27 € cost), while with the GPC controller is 164 min (8.36 € cost). There might also be effects on the crop, but not evident on the relatively short time scales used here.

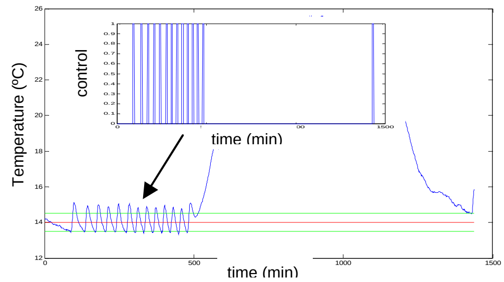
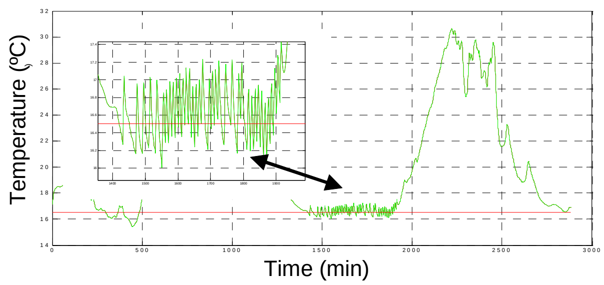
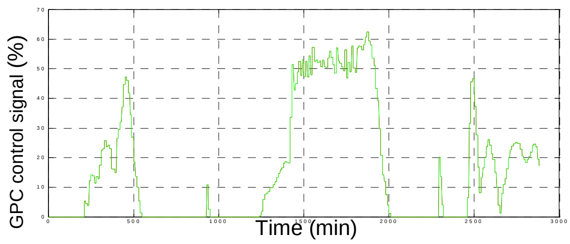


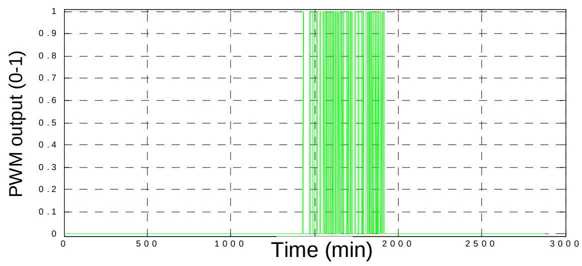
Fig. 7. On/off control with dead zone



(a) Inside air temperature evolution



(b) Continuous control signal



(c) Discrete control signal

Fig. 8. Results using the PWM GPC

It is common textbook knowledge that almost any control scheme will do better than an on-off control scheme. So, the comparison of MPC with an on-off controller may not be very convincing (despite decades of research, this point has not yet been fully accepted in horticultural industry, e.g. forced air heaters still have on-off control, today). The effects of outdoor weather conditions such as outdoor temperature and wind speed have a relatively low frequency behaviour and a simple well tuned PI-algorithm could in principle do the job equally well. For instance, in figure 9, a comparison between the responses of a PI-PWM+antiwindup controller and that of a GPC-PWM controller without incorporating models of the disturbances are shown using a validated nonlinear model of the greenhouse (Rodríguez, 2002). As can be seen, at the beginning of the night the GPC controller anticipates the control action, while at the end of the night the control signals are similar in the case of PI and GPC controllers, and thus the operating costs. This is an expected result as the PI and the GPC are based on the same model and no input or output constraints are violated, although in this case the λ parameter tuning modulates the tradeoff between costs and tracking. The advantages of GPC are more evident when reliable system and disturbance models are used and the operating conditions are such that minimum inside temperature constraints are violated.

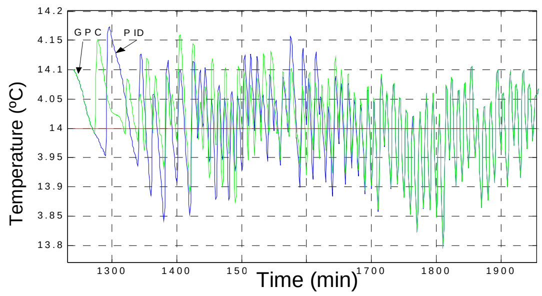


Fig. 9. Comparing PWM GPC and PI

5. CONCLUSIONS

The application of classical and GPC techniques to control greenhouse heating has been treated in this paper in order to analyze and compare the economical savings that can be achieved when compared to classical control techniques.

6. ACKNOWLEDGEMENTS

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