Comfort control in buildings using solar energy

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UNED – Departamento de Informática y Automática 5 de mayo de 2015



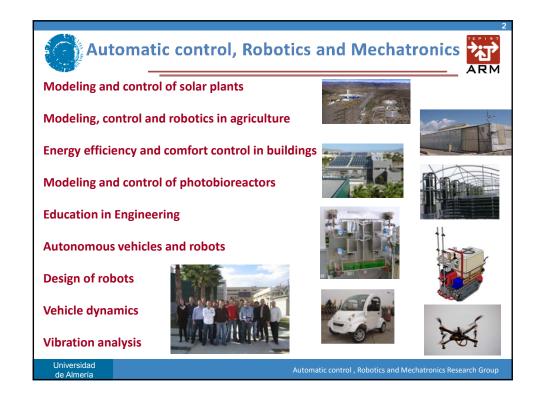


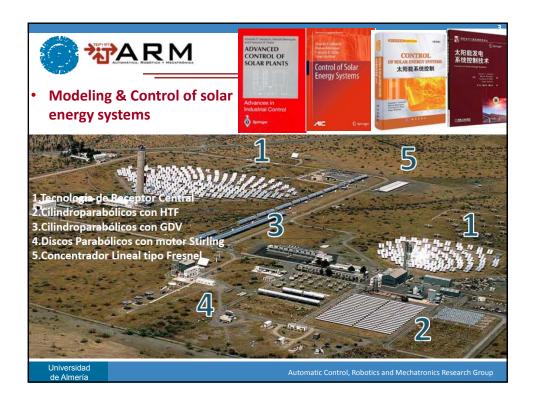
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Departamento de Informática - Universidad de Almería

People involved: María del Mar Castilla, Domingo Álvarez, Francisco Rodríguez, Julio Normey-Rico, Manuel Pasamontes, José Luis Guzmán, Manuel Pérez, Ricardo Silva

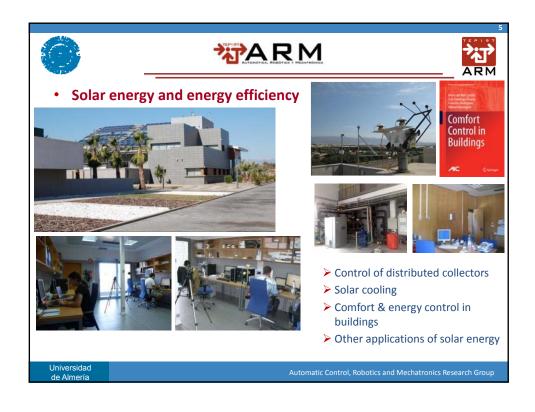
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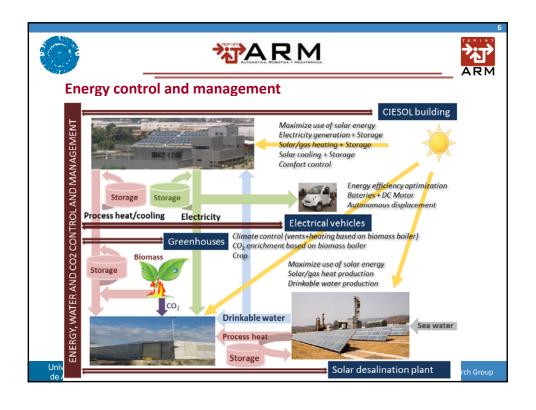
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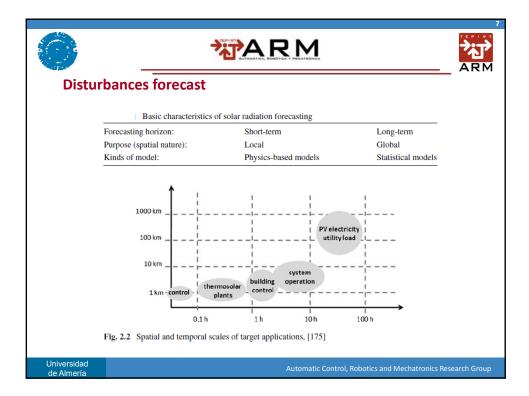


















Ingredients: Solar energy is a disturbance and the main source of energy Short-term forecast (15 minutes) useful for predictive control

A. Pawlowski, J.L. Guzmán, M. Berenguel, F. Rodríguez, J. Sánchez. Application of time-series methods to disturbance estimation in predictive control problems. International Symposium on Industrial Electronics ISIE'10, 409-414, Bari, Italy, 2010.

- A. Discrete Kalman Filter
- B. Discrete Kalman Filter with Data Fusion
- C. Exponentially Weighted Moving Average
- D. Double Exponential Smoothing

 z_k measurement

 S_k unadjusted forecast

 b_k estimated trend

 γ smoothing parameter for trend (0,1)

btained via α smoothing parameter for data (0,1)

NIST. (2006) Engineering statistics handbook. [Online]. Available:

 $S_k = \alpha z_k + (1 - \alpha)(S_{k-1} + b_{k-1})$

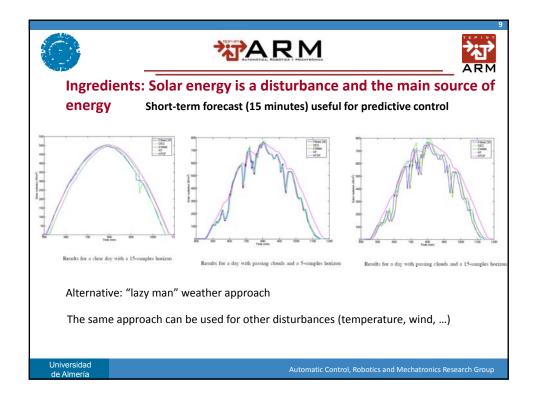
$$b_k = \gamma (S_k - S_{k-1}) + (1 - \gamma)b_{k-1}$$

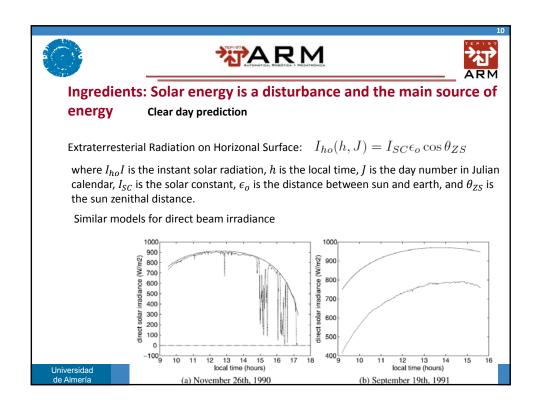
The one-period-ahead forecast is given by:

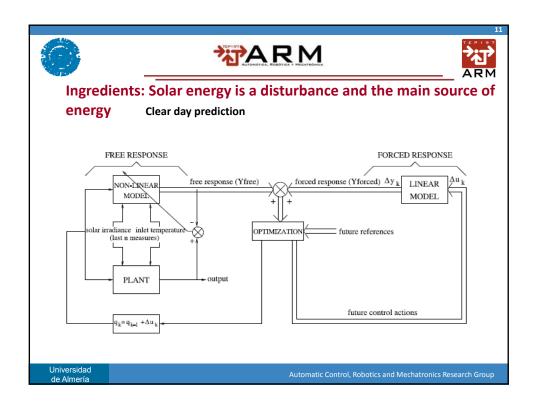
$$\hat{x}_{k+1} = S_k + b_k$$

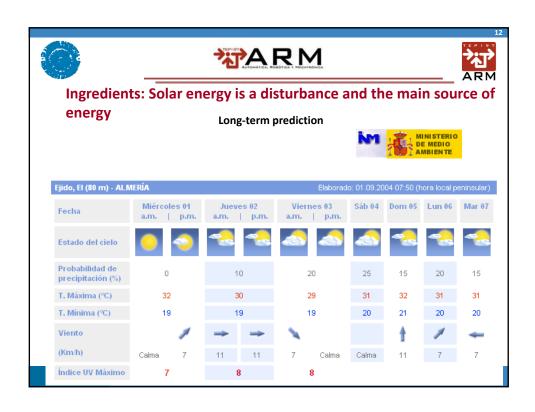
The m-periods-ahead forecast is given by:

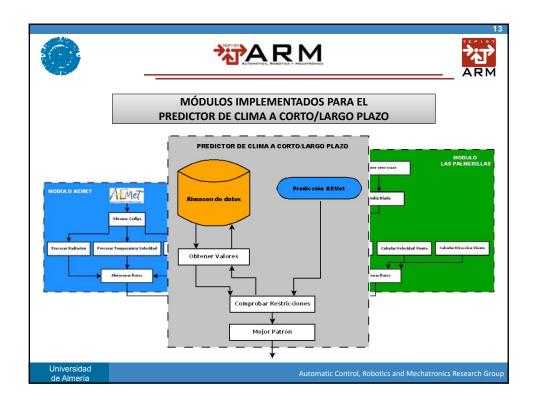
$$\hat{x}_{k+m} = S_k + mb_k$$

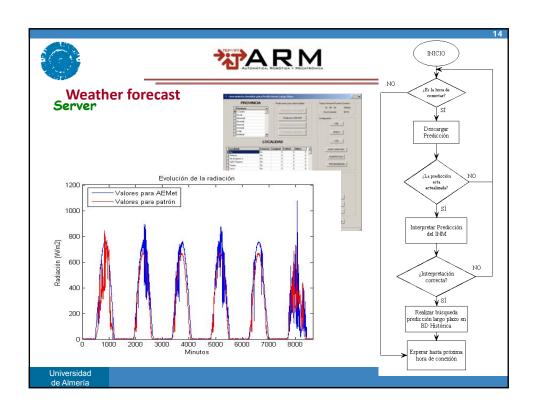


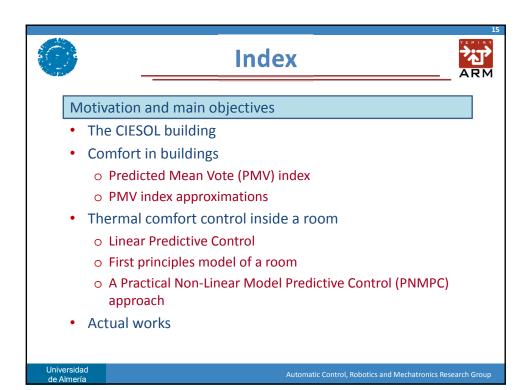


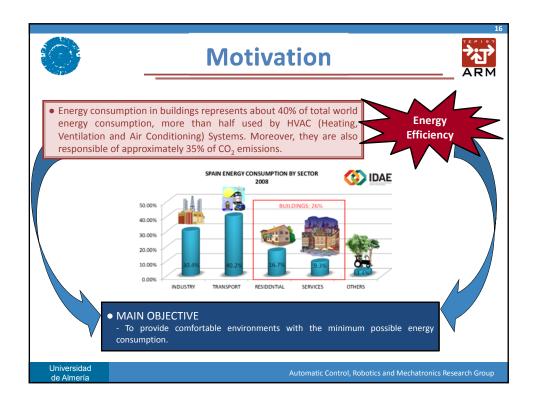


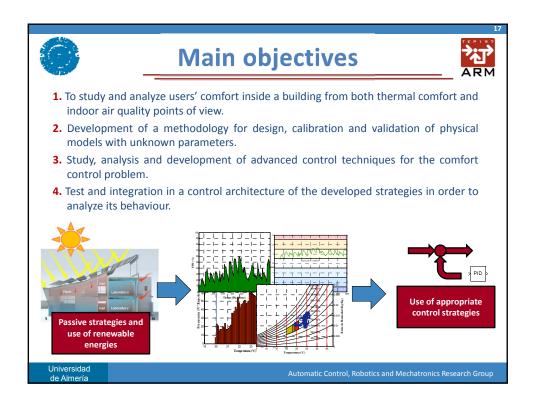
















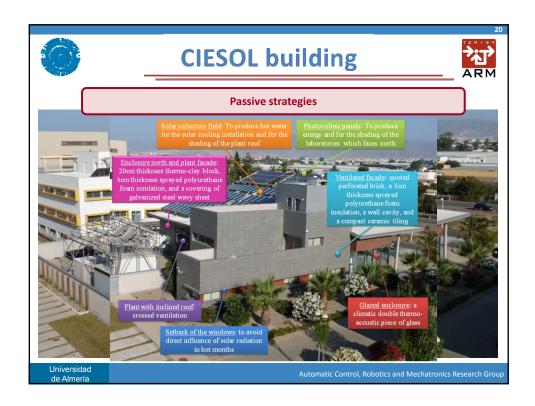
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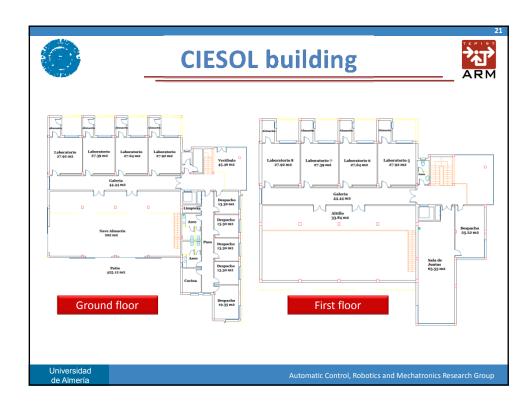


Motivation and main objectives

- The CIESOL building
- Comfort in buildings
 - o Predicted Mean Vote (PMV) index
 - o PMV index approximations
- Thermal comfort control inside a room
 - o Linear Predictive Control
 - o First principles model of a room
 - A Practical Non-Linear Model Predictive Control (PNMPC) approach
- Actual works

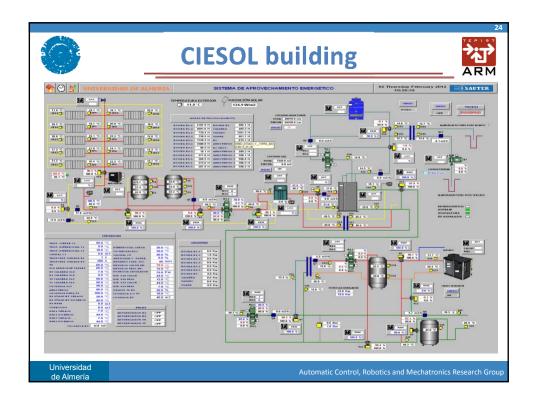
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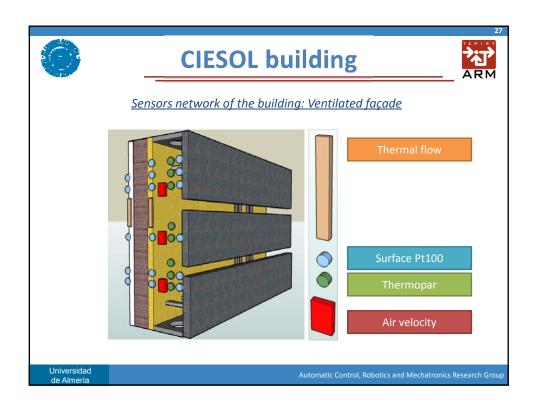












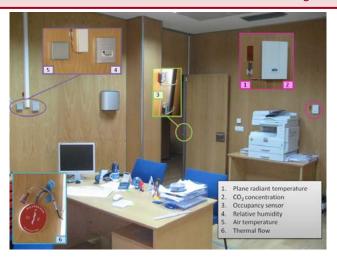




CIESOL building



Sensors network. A characteristic room of the building



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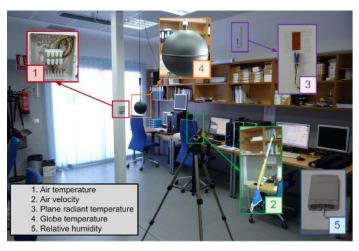
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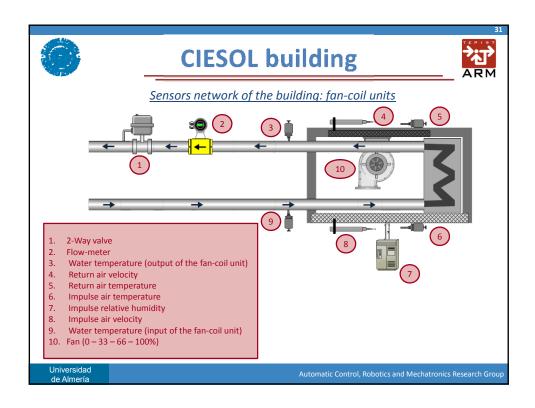
CIESOL building



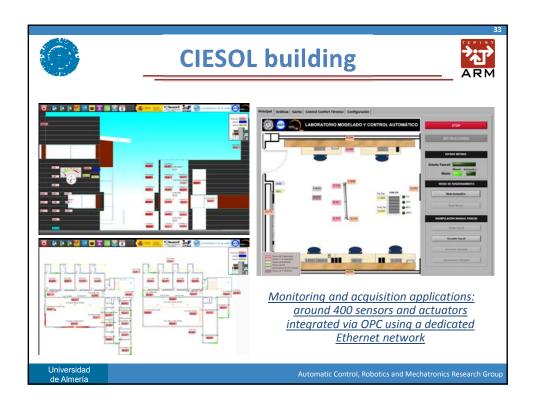
Sensors network of the building: Representative rooms of the building

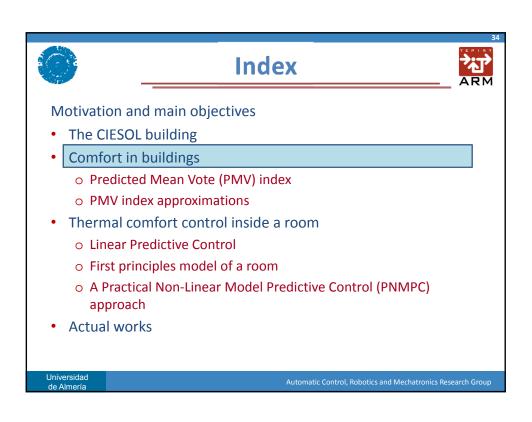


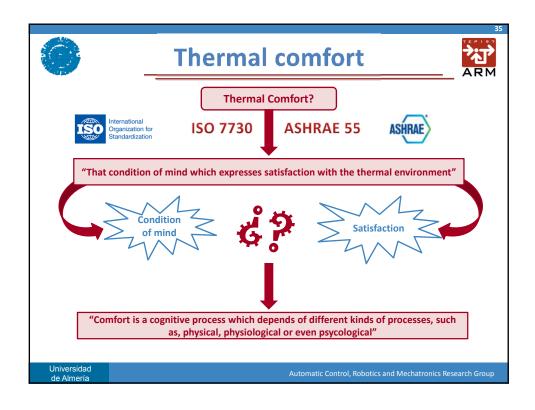
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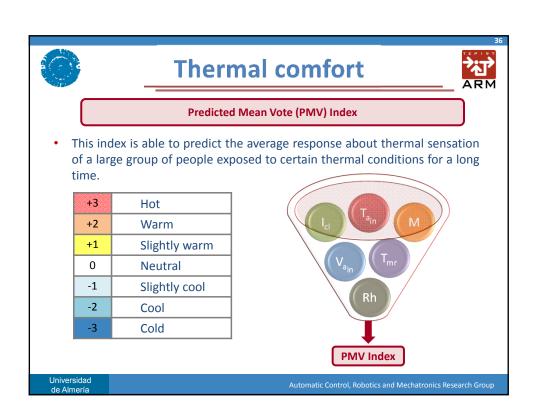


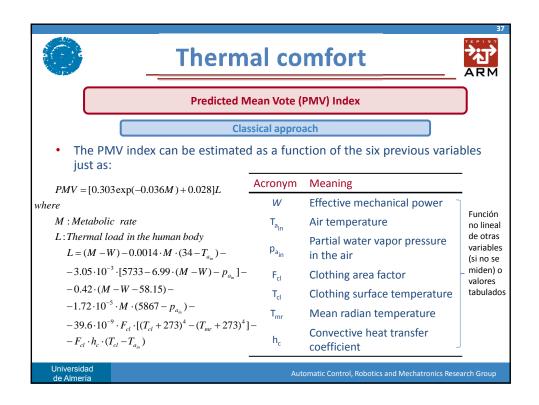


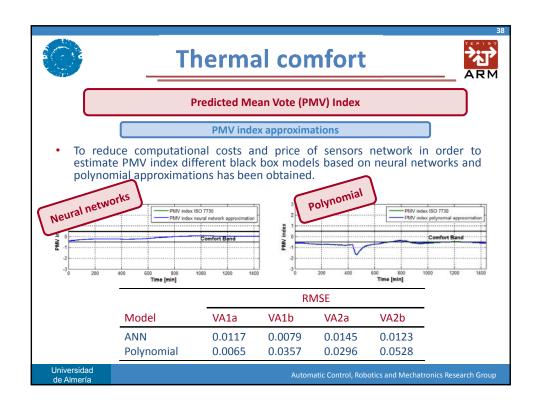


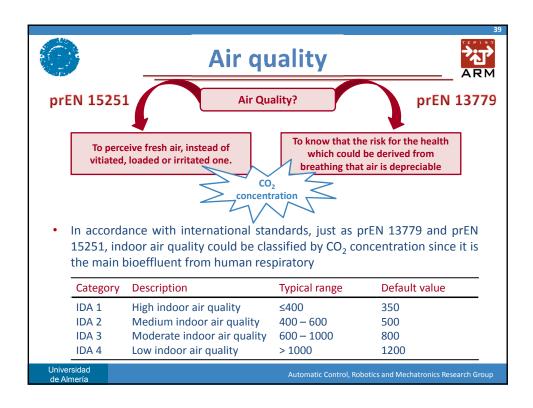


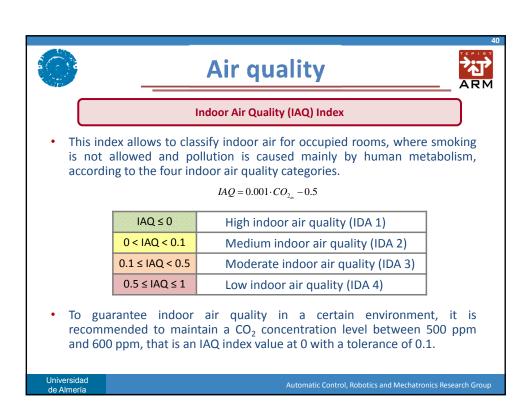














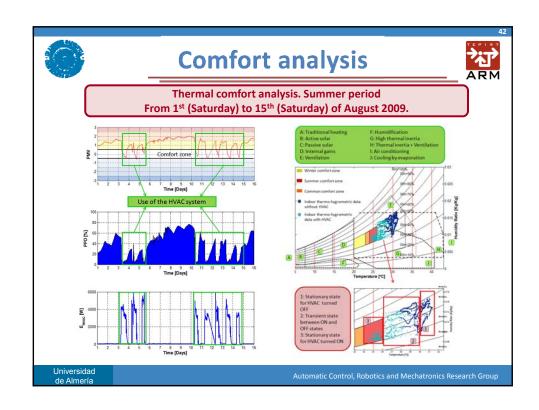
Comfort analysis

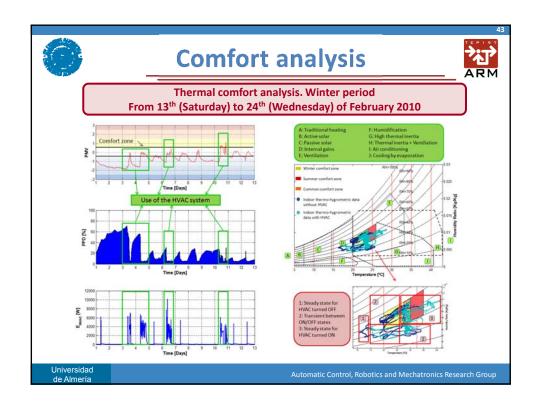


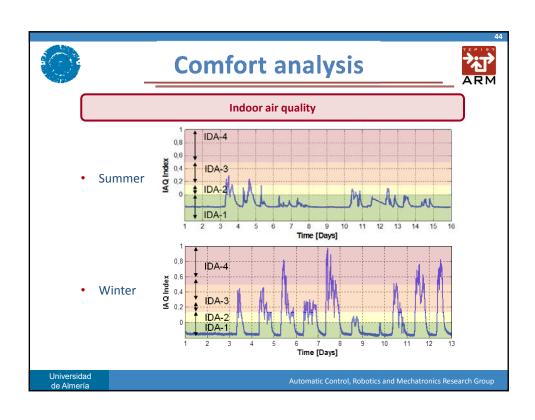
- The main objective of this study is to evaluate the performance of the passive bioclimatic strategies of the CDdI-CIESOL-ARFRISOL building without the use of any control strategy.
- As the building does not have a fixed work schedule, the following assumptions has been established:
 - o Saturdays and Sundays are considered periods of non occupation, that is, the building is supposed to be empty.
 - o Within the occupation periods (from Monday to Friday) it is established a night time period that comprise from 21:00 PM to 07:00 AM.

Almería characteristic climate	Summer	Winter	Autumn
Maximum mean air temperature [ºC]	30.7	17.7	20.4
Minimum mean air temperature [ºC]	22	8.8	12.0
Mean relative humidity [%]	65	68	70
Average precipitation days [-]	0	3	3
Mean monthly sunshine hours [-]	312	191	187

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Comfort analysis



Main conclusions of the comfort analysis

- For both summer and winter periods, it is necessary the use of a HVAC system to cool in summer, and to heat in winter.
- The existence of a significant percentage of data outside the comfort zone during summer and winter periods allows to consider two hypothesis which are not strictly exclusive:
 - $\circ\quad$ Insufficiency of manual control that was implemented in the HVAC system.
 - o Existence of subjective factors in the evaluation of both thermal comfort and indoor air quality.
- As a function of this comfort analysis, it has reached the conclusion that it was
 necessary to develop a specific control system which allows to maintain
 environmental conditions of the building inside a comfort zone for the user
 minimising, at the same time, energy consumption.

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Indoor climate model of a room

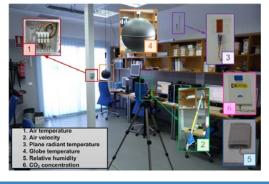


Models allow to obtain important information about systems, and thus, they represent a key factor in order to design control strategies and solve optimization problems.

A typical CDdI-CIESOL-ARFRISOL office room

- <u>Room location</u>: second floor of the building.
- Total volume: 4.96 x 5.53 x 2.8 m³
- North orientation
- Number of windows: 1
- Window surface: 2.15 x 2.09 m²
- Window location: north wall
- Actuators:
 - o Window opening/closing system
 - o Shading opening/closing system
 - o HVAC fan power
 - o HVAC water flow valve

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Indoor climate model of a room



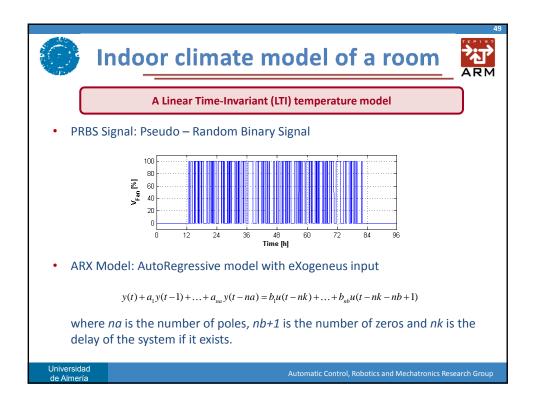
A Linear Time-Invariant (LTI) temperature model

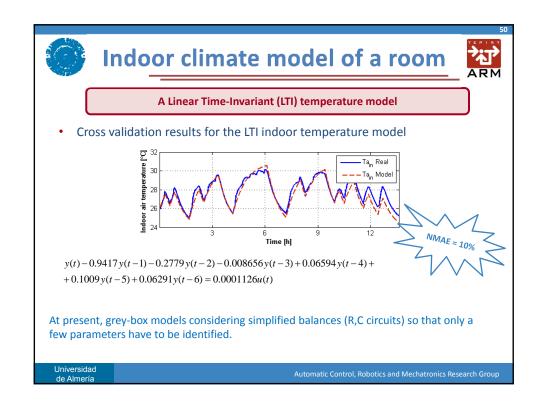
Assumptions:

- The state variable of the system is the indoor air temperature.
- There exist only one element which interact with the indoor air temperature: the external air.
- As control variable, it was supposed that there was only one actuator available, the fancoil
 unit, which allows to control indoor air temperature by means of its fan velocity.
- It is considered that all the variables of the process are homogenously distributed.



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Indoor climate model of a room

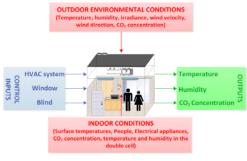


A first principles model of a room

 The first principles model of a room is composed of three submodels which describe the indoor air temperature, the indoor air relative humidity and the indoor CO₂ concentration dynamic behaviour. Hence, it can be represented by a system of differential equations given by:

$$\frac{dX}{dt} = f(X, U, D, V, C, t) \text{ with } X(t_i) = X_i$$

where X, U, D, V and C are vectors of the state variables, control inputs variables, disturbances, system variables and system constants, respectively, t is the time, X_i is the known initial state at the initial time t_i , and f is a nonlinear function based on mass and heat transfer balances.



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Indoor climate model of a room

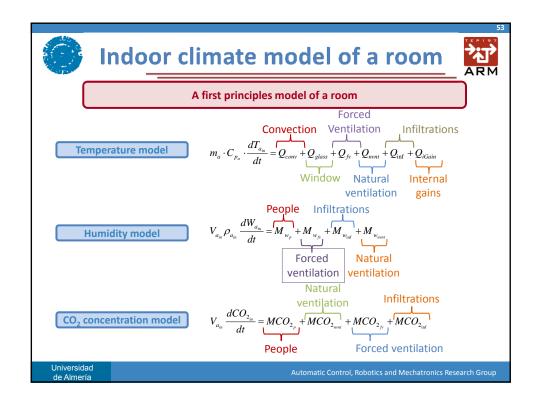


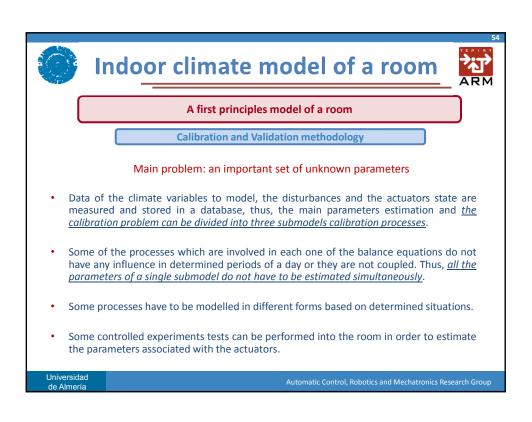
A first principles model of a room

Assumptions:

- It is supposed that the room is composed by seven elements: indoor air, walls, windows, shading system, HVAC system, people and electrical appliances.
- The state variables of the model are: indoor air temperature, indoor relative humidity and CO₂ concentration.
- The <u>control inputs</u> of the system are: the natural ventilation, expressed as a function of the window opening, the blind, and the forced ventilation by means of a fancoil unit.
- The <u>disturbance inputs</u> of the system are: the outside air temperature, humidity and CO₂ concentration, wind speed and its direction, direct, diffuse and reflected irradiance, the plane radiant temperatures of all surfaces of the room, indoor air velocity, number of people inside the room and the electrical appliances that are connected at each moment.
- The physical characteristics of the different elements (walls, windows, etc.) such as density or specific heat are considered constant. However, the physical characteristics of the air inside the room are estimated as a function of indoor air temperature.

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Indoor climate model of a room



A first principles model of a room

Calibration and Validation methodology

- The proposed methodology consists of a two steps calibration process:
 - o First step. To determine a search space by means of an iterative search by performing single experimental tests for each one of the involved processes.
 - Second step. To obtain the final value for each one of the unknown parameters by means of genetic algorithms.

$$J(x) = \min \sum_{i=1}^{N} |x(i) - \hat{x}(i, \Psi)|^{2} =$$

$$= \min \sum_{i=1}^{N} \sum_{k=1}^{3} |x_{k}(i) - \hat{x}_{k}(i, \Psi)|^{2}$$

where N is the number of samples and k is the number of models which are going to be calibrated.

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Indoor climate model of a room

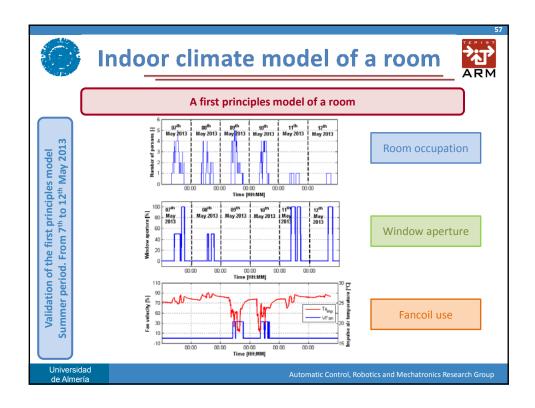


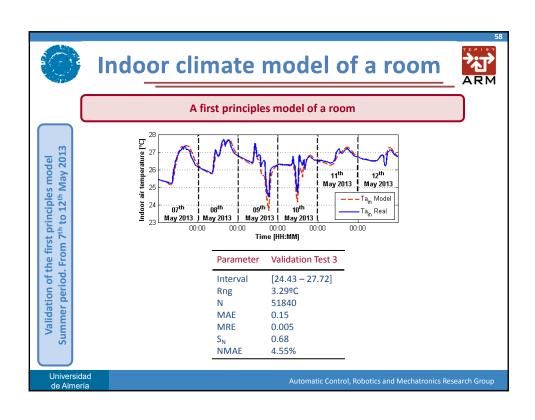
A first principles model of a room

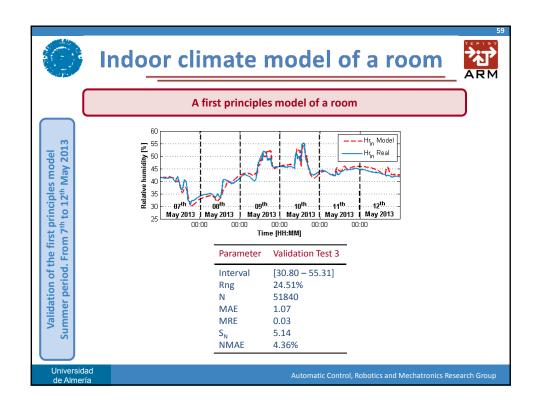
Calibration and Validation methodology

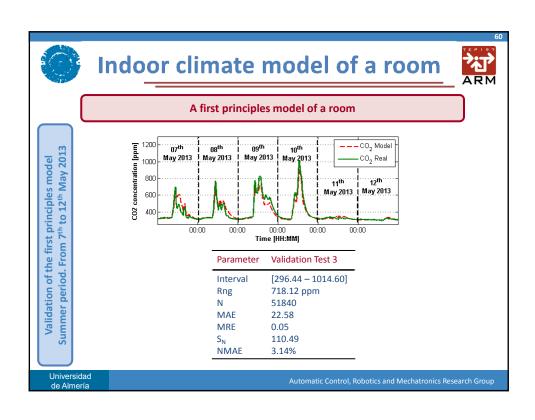
- Test 1. Empty room and blind closed (5).
- Test 2. Empty room and blind open (1).
- Test 3. Empty room and blind in several positions (6).
- Test 4. Empty room and using forced ventilation (1).
- Test 5. Empty room and using natural ventilation (1).
- Test 6. Occupied room (1).
- Test 7. Occupied room and using natural ventilation (2).
- Test 8. Validation of the selected unknown parameters (10).

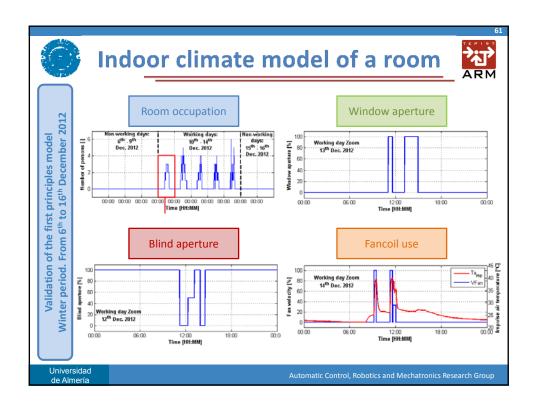
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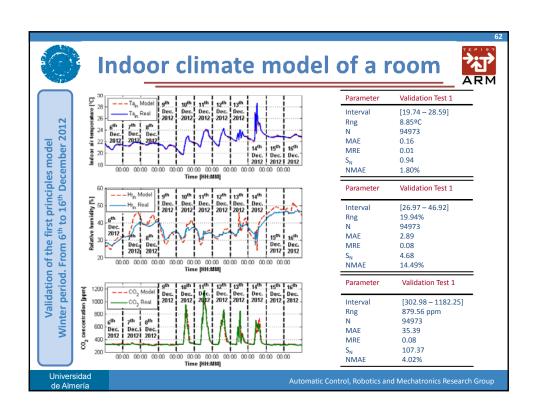










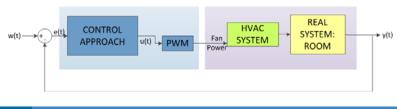




Linear controllers for users' thermal comfort



- Main objective. To obtain a high thermal comfort level taking energy costs into account.
- To do that, it has been considered that there is only one actuator available inside the CDdI-CIESOL-ARFRISOL building in order to control thermal comfort, the HVAC system.
- Two different approaches are presented:
 - o A hierarchical predictive control strategy.
 - o A classical Model Predictive Control (MPC) strategy.



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Thermal comfort control inside a room



Generalized Predictive Control Algorithm

Controller Auto-Regressive Integrated Moving-Average (CARIMA)

$$\begin{split} A(z^{-1})y(t) &= z^{-d}B(z^{-1})u(t-1) + C(z^{-1})\frac{e(t)}{\Delta} & \quad A(z^{-1}) = 1 + a_1z^{-1} + a_2z^{-2} + \ldots + a_{na}z^{-na} \\ B(z^{-1}) &= b_0 + b_1z^{-1} + b_2z^{-2} + \ldots + b_{nb}z^{-nb} \\ \Delta &= 1 - z^{-1} & \quad C(z^{-1}) = 1 + c_1z^{-1} + c_2z^{-2} + \ldots + c_{nc}z^{-nc} \end{split}$$

Quadratic Cost Function

$$J = \sum_{j=N_1}^{N_2} \delta(j) [\hat{y}(t+j \mid t) - w(t+j)]^2 + \sum_{j=1}^{N_u} \lambda(j) [\triangle u(t+j-1)]^2$$

- D.W. Clarke, C. Mohtadi and P.S. Tufts. Generalized predictive control I. The basic algorithm. Automatica, 23, 137-148, 1987
- o E.F. Camacho, C. Bordóns. Model Predictive Control. Springer, 2012.
- o One of the most popular MPC algorithm in both industry and academy.

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Thermal comfort control inside a room



Generalized Predictive Control Algorithm

Obtaining the GPC Control Law

• The predicted outputs, $\hat{y}(t+k/t)$, are calculated using the prediction model $(C(z^1)=1)$:

$$A(z^{-1})y(t) = z^{-d}B(z^{-1})u(t-1) + C(z^{-1})\frac{e(t)}{\Delta} \qquad \qquad \mathbf{y} = \underbrace{\mathbf{G}\mathbf{u}}_{\text{forced response}} + \underbrace{\mathbf{f}}_{\text{free response}} + \underbrace{\mathbf{f}}_{\text{free response}}$$

o Substitute the compact prediction values in the cost function, J.

$$J = \sum_{j=N_1}^{N_2} \delta(j) [\hat{y}(t+j\mid t) - w(t+j)]^2 + \sum_{j=1}^{N_u} \lambda(j) [\triangle u(t+j-1)]^2 \qquad \qquad J = \left(\mathbf{G}\mathbf{u} + \mathbf{f} - \mathbf{w}\right)^\top \left(\mathbf{G}\mathbf{u} + \mathbf{f} - \mathbf{w}\right) + \lambda \mathbf{u}^\top \mathbf{u}$$

o Minimize J with respect to Δu where an analytical solution is obtained for the unconstrained case:

$$\mathbf{u} = -\mathbf{H}^{-1}\mathbf{b} = (\mathbf{G}^{\mathsf{T}}\mathbf{G} + \lambda \mathbf{I})^{-1}\mathbf{G}^{\mathsf{T}}(\mathbf{w} - \mathbf{f})$$
 \longrightarrow $u(t) = u(t-1) + \mathbf{K}(\mathbf{w} - \mathbf{f})$

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Thermal comfort control inside a room



Generalized Predictive Control Algorithm

Obtaining the GPC Control Law (future predictions):

 $\mathbf{y} = \underbrace{\mathbf{G}\mathbf{u}}_{ ext{forced response}} + \underbrace{\mathbf{f}}_{ ext{free response}}$

The prediction outputs, y(t+j), must be obtained for $j \ge N_1$ and $j \le N_2$. The horizons can be set as $N_1 = d+1$, $N_2 = d+N$, $N_u = N$. Thus, N-ahead predictions will be used in the optimization process.

The predictions could be done just from the CARIMA model:

$$\hat{y}(t+d+j|t) = (1-a_1)\hat{y}(t+d+j-1|t) +$$

$$+(a_1-a_2)\hat{y}(t+d+j-2|t) + \dots + a_{na}\hat{y}(t+d+j-n_a-1|t) +$$

$$+b_0\Delta u(t+j-1) + \dots + b_{nb}\Delta u(t+j-n_nb-1)$$

This is really done using a Diophantine Equation.

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Thermal comfort control inside a room



Generalized Predictive Control Algorithm

Dealing with constraints:

Typical Quadratic Programming (QP) Problem:

$$J = rac{1}{2} \mathbf{u}^T \mathbf{H} \mathbf{u} + \mathbf{b}^T \mathbf{u} + \mathbf{f}_0$$
 $J = rac{1}{2} \mathbf{x}^T \mathbf{H} \mathbf{x} + \mathbf{f}^T \mathbf{x}$ $\mathbf{R} \mathbf{u} \leq \mathbf{c}$ $\mathbf{R} \mathbf{x} \leq \mathbf{c}$ $\mathbf{E} \mathbf{u} = \mathbf{g}$ $\mathbf{E} \mathbf{x} = \mathbf{g}$

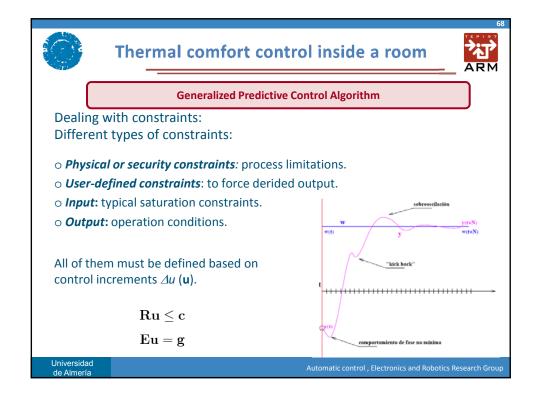
Minimization of a quadratic function with linear constraints. Example: **quadprog** function of *Matlab*.

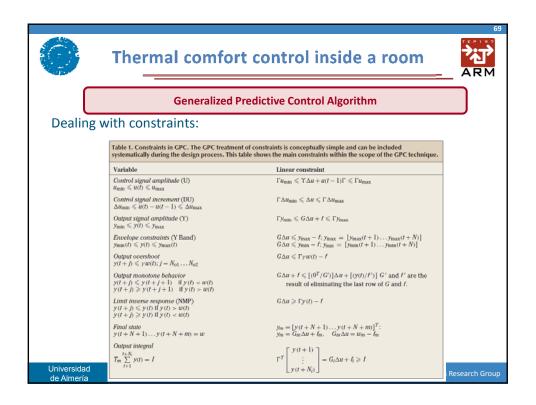
QUADPROG Quadratic programming.
 X = QUADPROG(H,f,A,b) attempts to solve the quadratic programming problem:

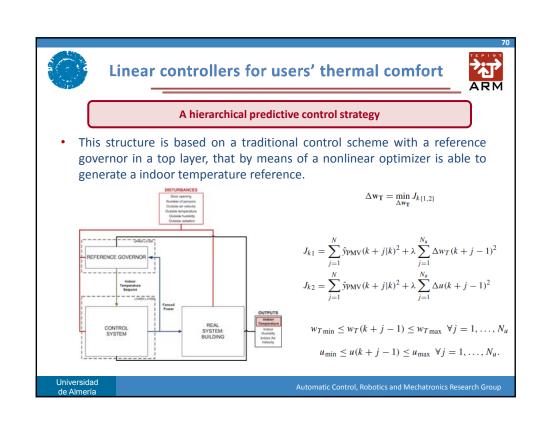
min 0.5*x'*H*x + f'*x subject to: A*x <= b x

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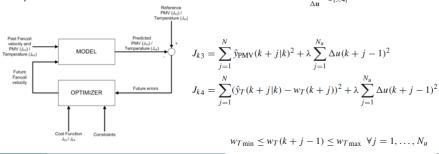


Linear controllers for users' thermal comfort



A classical MPC strategy

• This technique uses a model of the system to make predictions of the future outputs. They are included inside a cost function which establishes a relationship between the close loop behaviour of the system and the control effort. This cost function is minimized taking into account the constraints of the problem. Finally. a receding horizon strategy is implemented. $\Delta \mathbf{u} = \min_{\mathbf{n}} J_{k[3,4]}$



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 $u_{\min} \le u(k+j-1) \le u_{\max} \ \forall j=1,\ldots,N_u.$



Linear controllers for users' thermal comfort

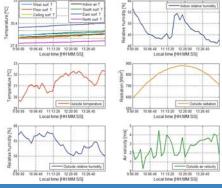


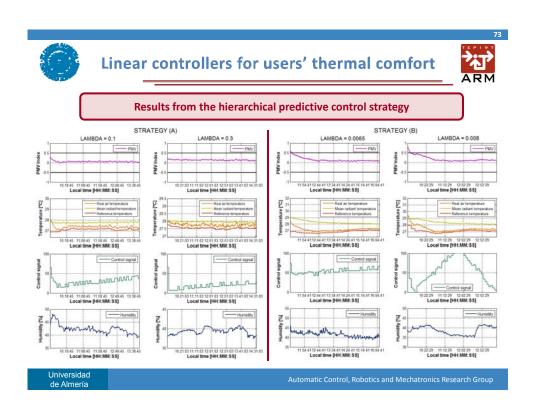
Selection of weighting coefficients for the cost functions

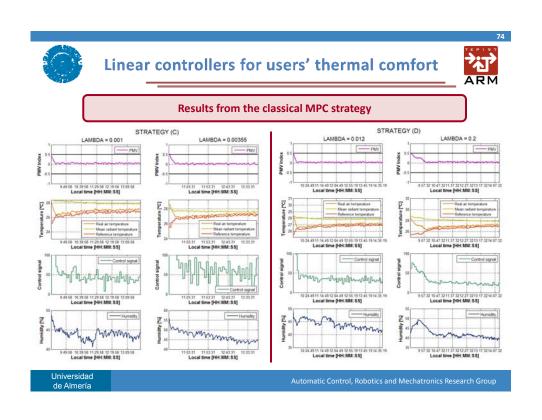
It is almost impossible to find different days with identical conditions, since these variables are non controllable. Thus, a typical day for the analyzed period has been chosen to compare different strategies through simulations.

Strategy	Lambda (λ)	ISE Criterion
(A): J _{k1}	0.1 0.3	20.01 33.46
(B): J _{k2}	0.0065 0.008	27.29 33.37
(C): J _{k3}	0.001 0.00355	19.77 33.53
(D): J _{k4}	0.012 0.2	27.83 58.53

 $ISE = \int_0^\infty e(t)^2 dt$









Linear controllers for users' thermal comfort



Results

- A comparison among different strategies have been performed as a function of several indexes:
 - o Index 1: Mean number of changes per hour [-].
 - o Index 2: Percentage of total time in which the HVAC system is connected [%].
 - o Index 3: Average energy consumption per hour [W].

Strategy	Lambda (λ)	ISE Criterion	Index 1	Index 2	Index 3
(A): J _{k1}	0.1	20.01	30	30.13	40
	0.3	33.46	62	18.20	24
(B): J _{k2}	0.0065	27.29	58	42.50	56
	0.008	33.37	84	37.74	50
(C): J _{k3}	0.001	19.77	42	42.14	55
	0.00355	33.53	35	29.39	39
(D): J _{k4}	0.012	27.83	47	33.26	44
	0.2	58.53	57	41.61	55

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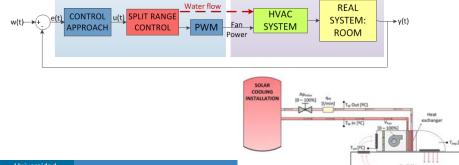
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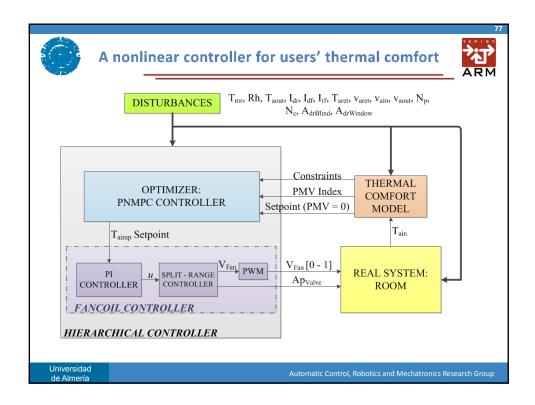
A nonlinear controller for users' thermal comfort



- Main objective. To obtain a high thermal comfort level trying to reduce energy consumption.
- Main differences of this approach with the linear control approaches:
 - o The use of a nonlinear first principles model which accurately reflects the dynamics of the room climate and takes into account the main disturbances.
 - It has been considered that the HVAC system has two degrees of freedom, the fancoil power and the water flow.



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A nonlinear controller for users' thermal comfort



Optimization layer: A nonlinear MPC approach

• In general, MPC control algorithms, as Generalized Predictive Control (GPC), are applied to linear systems that are characterized by the use of a predicted output data vector, $\hat{\mathbf{Y}}$, throughout a prediction horizon, N, as a function of a vector which contains changes in the control action, Δu:

$$\hat{Y} = F + G \cdot \Delta u$$

where the system free response vector, \mathbf{F} , and the matrix \mathbf{G} are estimated by means of different methods depending of the selected algorithm.

 In this case, the PNMPC strategy is used to compute both F and G from the nonlinear model explained previously.

$$\hat{Y} = F + G_{PNMPC} \cdot \Delta u$$

$$F = f(y_p, \Delta u_p, \Delta v_p) \qquad G_{PNMPC} = \frac{\partial \hat{Y}}{\partial \Delta u}$$

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Thermal comfort control inside a room



A Practical Non-Linear Model Predictive Control (PNMPC) approach

$$\hat{Y} = F + G_{PNMPC} \cdot \Delta u$$

$$F = f(y_p, \Delta u_p, \Delta v_p) \qquad G_{PNMPC} = \frac{\partial \hat{Y}}{\partial \Delta u}$$

$$\mathbf{G} = \begin{bmatrix} \frac{\partial \widetilde{y}(k+1)}{\partial \Delta u(k)} & 0 & \dots & 0 \\ \frac{\partial \widetilde{y}(k+2)}{\partial \Delta u(k)} & \frac{\partial \widetilde{y}(k+2)}{\partial \Delta u(k+1)} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \widetilde{y}(k+N_2)}{\partial \Delta u(k)} & \frac{\partial \widetilde{y}(k+N_2)}{\partial \Delta u(k+1)} & \dots & \frac{\partial \widetilde{y}(k+N_2)}{\partial \Delta u(k+N_u-1)} \end{bmatrix}$$



Thermal comfort control inside a room



A Practical Non-Linear Model Predictive Control (PNMPC) approach

- The control law is obtained using techniques similar to the used in classical MPC algorithms. $\hat{Y} = F + G_{PNMPC} \cdot \Delta u$
 - o Cost function

$$F = f(y_p, \Delta u_p, \Delta v_p) \qquad G_{PNMPC} = \frac{\partial \hat{Y}}{\partial \Delta u}$$

$$J = \sum_{j=1}^{N} \delta(j) \left[\hat{Y}(k+j|k) - w(k+j|k) \right]^{2} + \sum_{j=1}^{N_{u}} \lambda(j) \left[u(k+j-1) \right]^{2}$$

o Constraints

$$\Delta u_{\min} \leq \Delta u(k+j\mid k) \leq \Delta u_{\max} \qquad \forall j=0,\cdots,N_u-1$$

$$u_{\min} \le u(k+j|k) \le u_{\max}$$
 $\forall j = 0, \dots, N_u - 1$

$$\hat{Y}_{\min} \le \hat{Y}(k+j|k) \le \hat{Y}_{\max}$$
 $\forall j = 0, \dots, N-1$



Thermal comfort control inside a room



A Practical Non-Linear Model Predictive Control (PNMPC) approach

- To estimate F and G_{PNMPC} at each sample time it is necessary to use the following algorithm:
 - o 1. Obtain $\hat{\mathbf{Y}}^0$ vector with a length of *N*. To do that, it is necessary to execute the model using past inputs, outputs and measurable disturbances, and with $\Delta \mathbf{u} = [0\ 0\ ...\ 0]^T$.

$$\hat{\mathbf{Y}}^0 = \mathbf{F}$$

o 2. Estimate the first column of the G_{PNMPC} matrix. The model has to be executed using past inputs, outputs and measurable disturbances, and, in this case, with $\Delta u = [\epsilon \ 0 \ ... \ 0]^T$ where ϵ is a very small value, such as, u(k-1)/1000.

$$\mathbf{G}_{\text{PNMPC}}(:,1) = (\mathbf{\hat{Y}^1} - \mathbf{\hat{Y}^0}) \; / \; \epsilon$$

o 3. Estimate the second column of the G_{PNMPC} matrix. The model has to be executed using past inputs, outputs and measurable disturbances, and, in this case, with $\Delta u = [0 \epsilon ... 0]^T$.

$$\mathbf{G}_{\mathsf{PNMPC}}(:,2) = (\hat{\mathbf{Y}}^2 - \hat{\mathbf{Y}}^0) / \epsilon$$

• 4. Continue with the remainder columns of $\mathbf{G}_{\mathsf{PNMPC}}$ matrix until the last column where \mathbf{Y}^{Nu} vector is obtained executing the model with past inputs and outputs, and with $\mathbf{\Delta u} = [0\ 0\ ...\ \epsilon]^\mathsf{T}$ where Nu is the control horizon.

$$\mathbf{G}_{\mathsf{PNMPC}}(:,Nu) = (\hat{\mathbf{Y}}^{\mathsf{Nu}} - \hat{\mathbf{Y}}^{\mathsf{0}}) / \varepsilon$$

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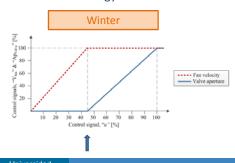


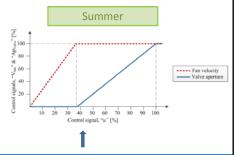
A nonlinear controller for users' thermal comfort



Control layer: Fancoil MISO Controller

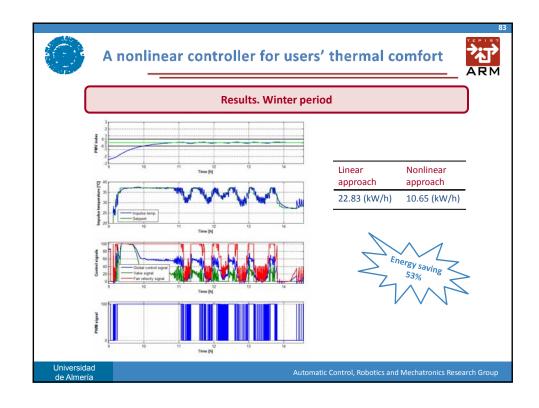
- The fancoil unit available in the CDdI-CIESOL-ARFRISOL building allows to change the impulse air temperature by the regulation of the water flow through it, and/or the return air velocity.
- To do that, a discrete PI with antiwindup combined with a split-range control strategy has been used.

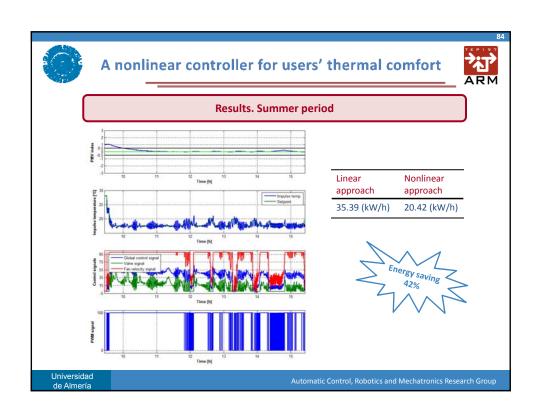


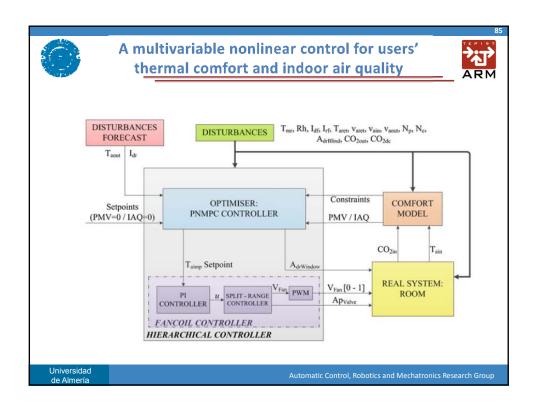


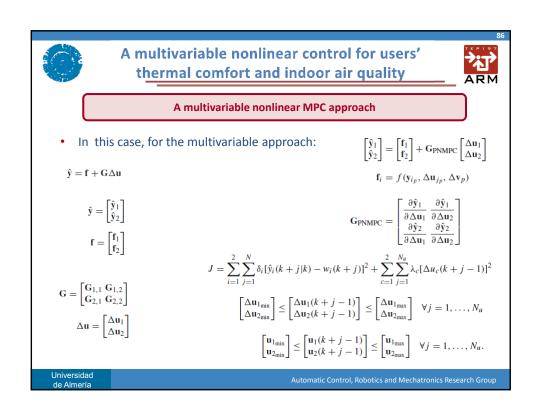
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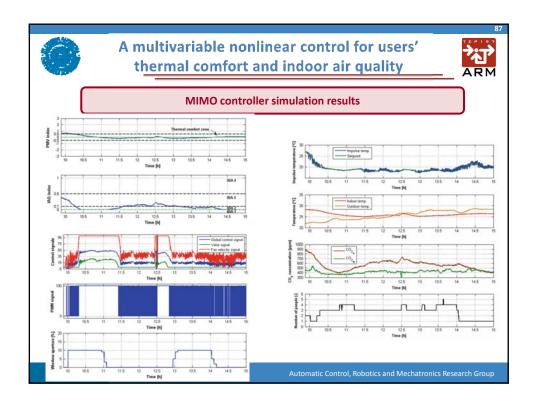
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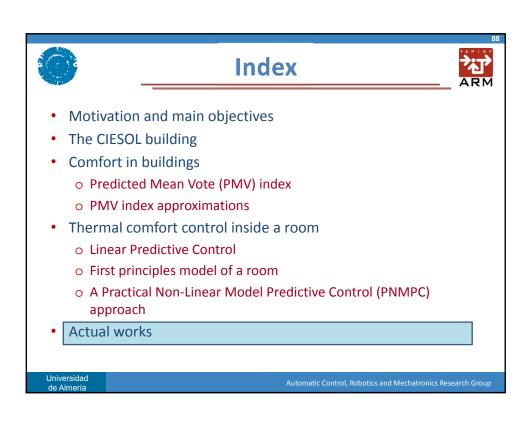


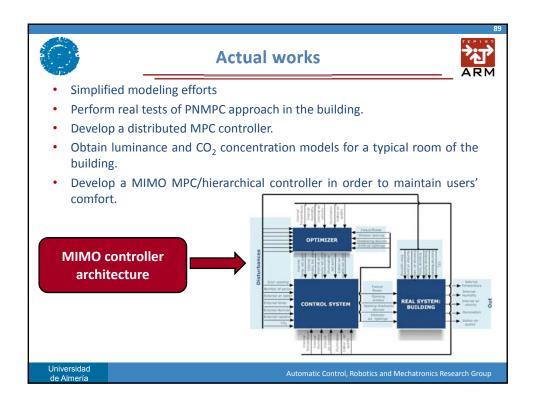


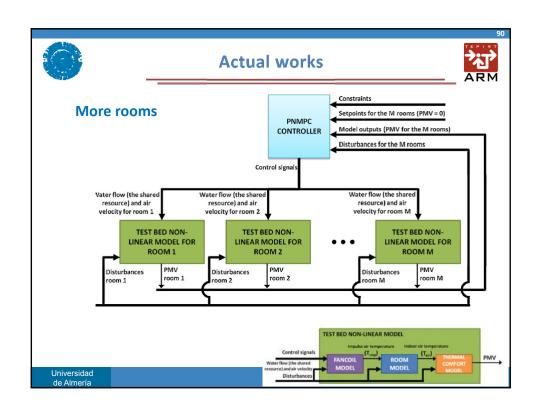














Actual works



More rooms

$$\sum_{i=1}^{M} u_i(t+j|t) \le a, \quad \forall j=1,\dots,N$$

$$\sum_{i=1}^{M} \dot{q}_{w_i} \le 60 \text{ 1/min},$$

$$N_i = 10 \quad N_{u_i} = 4$$

$$P(k): \min \quad J(\Delta \mathbf{u}) = \frac{1}{2} \Delta \mathbf{u}^T \mathbf{H} \Delta \mathbf{u} + \mathbf{b}^T \Delta \mathbf{u} + f_0$$

$$\text{s.to}: \mathbf{A}\mathbf{u} \le \mathbf{a}$$

$$\Delta \mathbf{u}_{\min} \le \Delta \mathbf{u} \le \Delta \mathbf{u}_{\max}$$

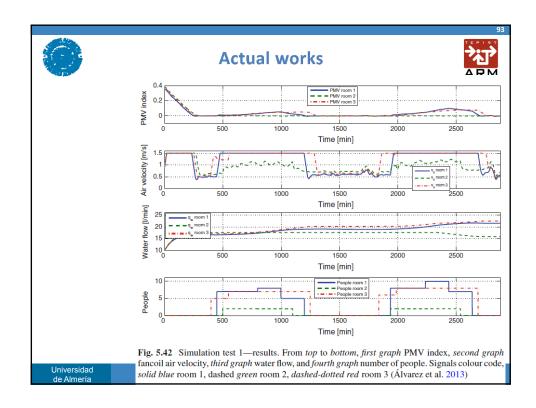
$$\mathbf{u}_{\min} \le \mathbf{u} \le \mathbf{u}_{\max}$$

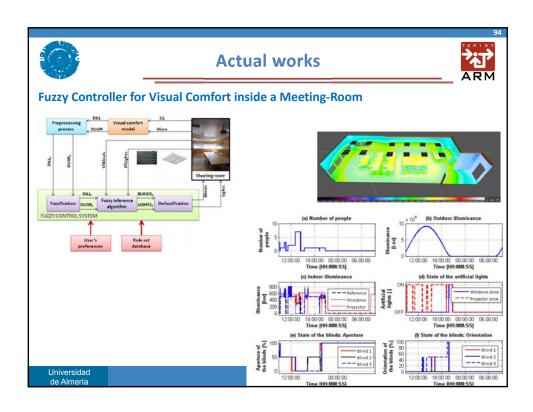
$$\hat{\mathbf{y}}_{\min} \le \hat{\mathbf{y}} \le \hat{\mathbf{y}}_{\max}$$

$$-0.1 \text{ 1/min} \le \Delta V_{\text{Fan}_i} \le 0.1 \text{ 1/min}$$

$$4\lambda v_i = \lambda_{q_i}$$

Actual works Time [min] Time [min] Time [min] Fig. 5.41 Boundary conditions in the simulations. From top to bottom, first graph radiant temperatures (North, South, East, West, ceiling and ground), second graph indoor air velocity and indoor air humidity, and third graph direct solar irradiation (Álvarez et al. 2013)







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