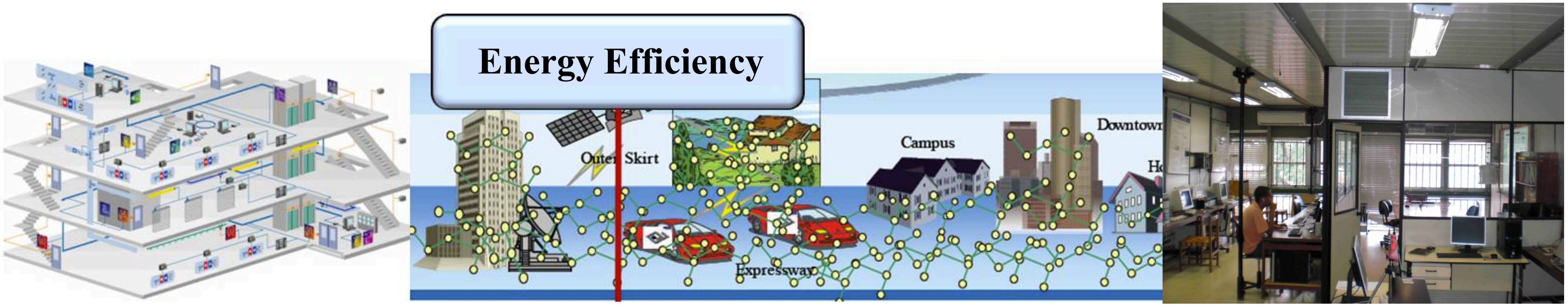
MCTIC/CNPq/UnB - Brasília Living Labs

Simulation and Dynamic Models

Energy Efficiency in Buildings



Adolfo Bauchspiess

Brasília, July 3rd, 2020

Thermal Modelling of an Office Room

Meeting Room
LARA/ENE/FT

Urban Energy Efficiency ⟶ Building's EE ⟶ Room's EE

60% to 70% of the energy demand in buildings is HVAC

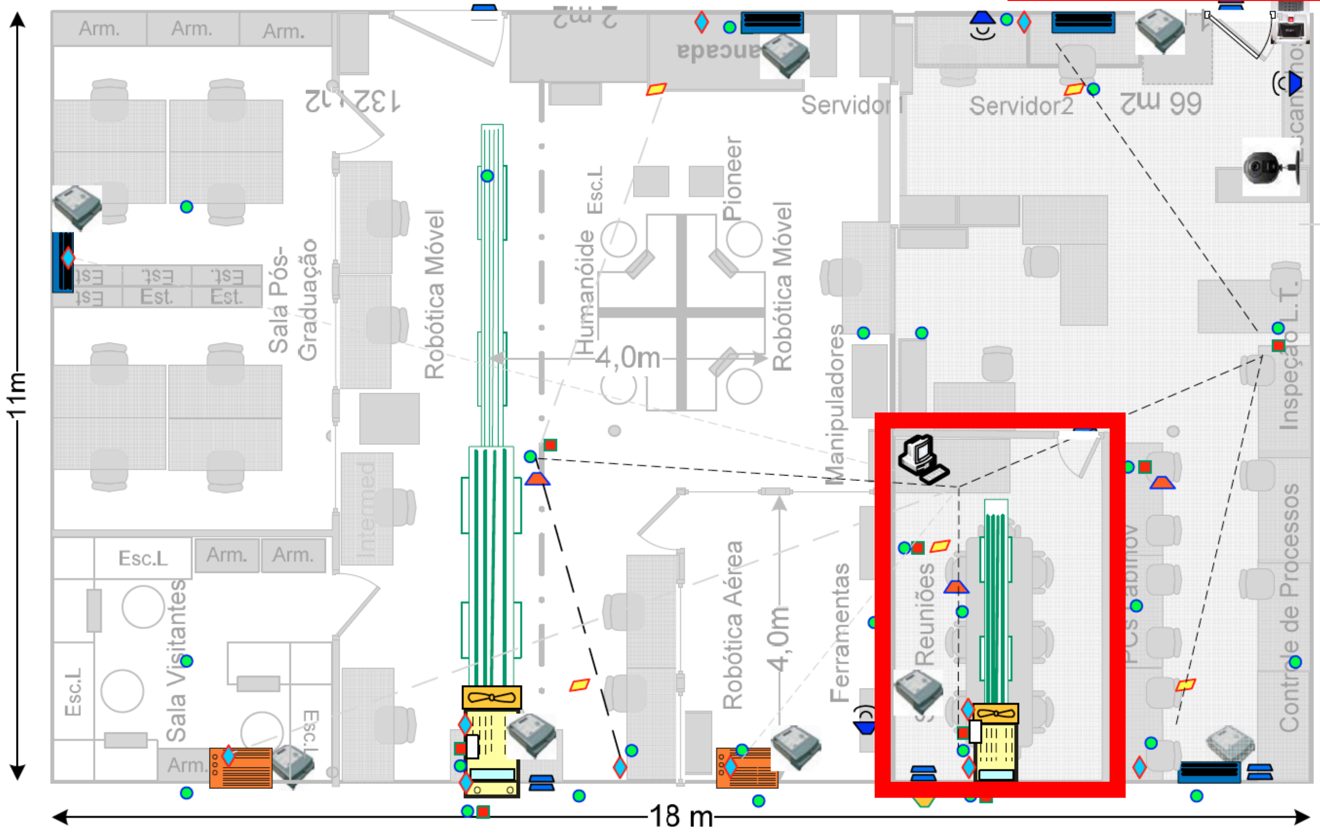
- In Brasília, despite the favorable climatic zone, cooling is necessary, at many days a year (> 50%).
  - Thermal Comfort (TC) ➪ Ergonomics ➪ Productivity
  - Energy Efficiency (EE)
  - Installation Cost (IC) + Operation Cost (OC)

- Starting with a "raw" meeting room. Technological solutions to enhance EE:
  - Natural Ventilation, Blinders - EE ⇡ CT ⇣ CI+ CO+
  - IoT sensors - EE ⇢ CT ⇢ CI- CO+ ⇢ (waste awareness)
  - Split window air conditioner - EE ⇣ CT ⇡ CI- CO-
  - Evaporative cooling - EE ⇡ CT ⇢ CI- CO+ ⇢ (not all year sufficient)
  - Hybrid air-conditioning - EE ⇡ CT ⇡ CI-- CO++
  - Occupancy estimation - EE ⇡⇡ CT ⇡ CI- CO+++

Thermal Modelling of an Office Room

- Sensor de Temperatura
- Sensor de Umidade
- Anemômetro
- Sensor Radiação Térmica Média
- Piranômetro
- Atuador Ar Cond.
- Detector de Presença
- Detector Porta/Janela aberta
- Ar Condicionado de Janela
- Ar Condicionado Split
- Ar Condicionado Evaporativo
- Medidor de Energia
- Camera de Vigilância
- Controle de Acesso
- Supervisório

Sala de reuniões
LARA/ENE/FT



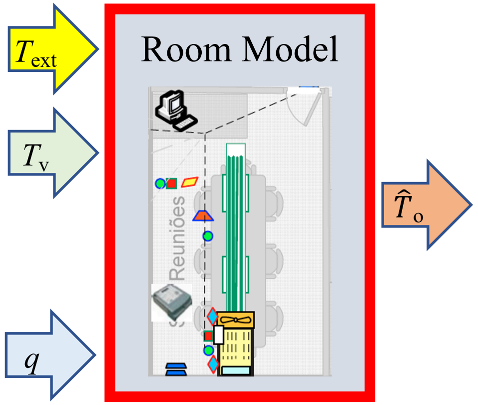
LARA – Lab. Automação e Robótica SG11/UnB

Thermal Modelling of an Office Room

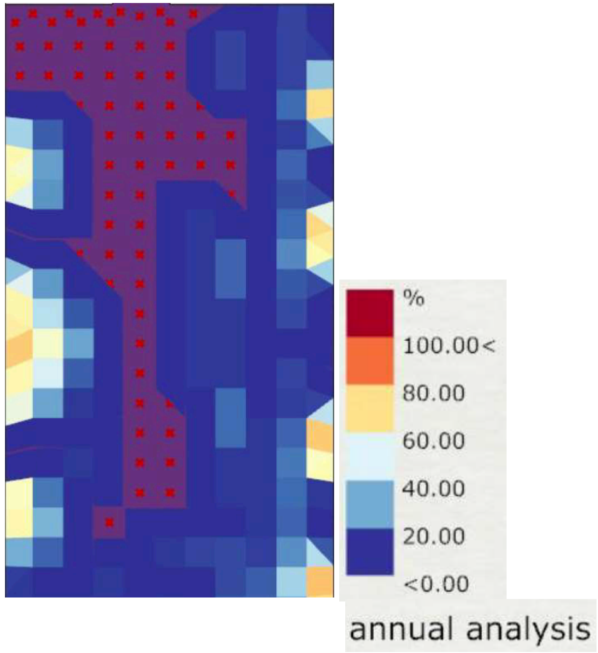
A) The "most precise" model: CFD – Computational Fluid Dynamics

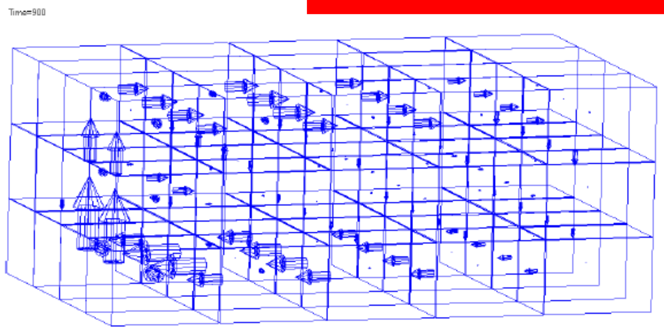
Heat flow trough the walls, floor and ceil.

Partial Differential Equations



$\hat{T}_o = f\,(T_o, q, T_v, T_{ext})$





Conservation of mass, momentum and thermal energy equations for a steady, 2-D, incompressible, laminar flow with no energy generation and negligible body forces are given as:

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} = 0 \qquad \rho\left(u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y}\right) = -\frac{\partial p}{\partial x} + \mu\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right)$$

$$\rho\left(u\frac{\partial v}{\partial x} + v\frac{\partial v}{\partial y}\right) = -\frac{\partial p}{\partial y} + \mu\left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2}\right)$$

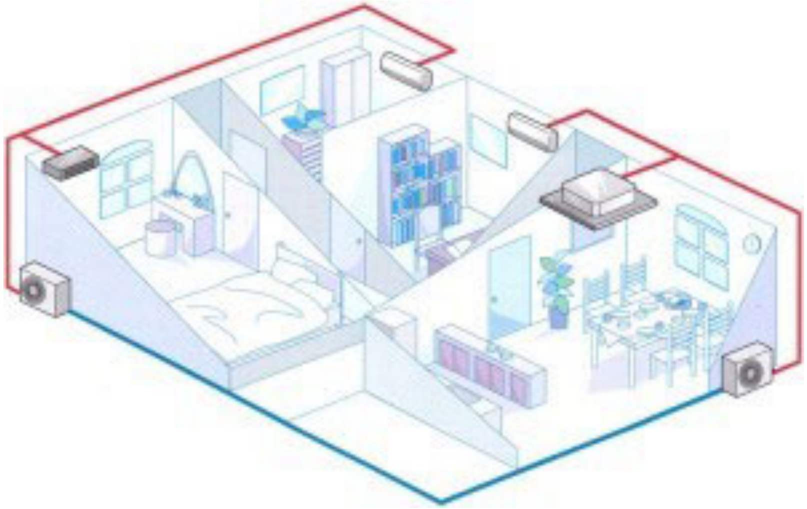
$$\rho c_p\left(u\frac{\partial T}{\partial x} + v\frac{\partial T}{\partial y}\right) = \frac{\partial}{\partial x}\left(k\frac{\partial T}{\partial x}\right) + \frac{\partial}{\partial y}\left(k\frac{\partial T}{\partial y}\right) + \mu\Phi \qquad \mu\Phi = \mu\left\{\left(\frac{\partial u}{\partial y} + \frac{\partial v}{\partial x}\right)^2 + 2\left[\left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial v}{\partial y}\right)^2\right]\right\}$$

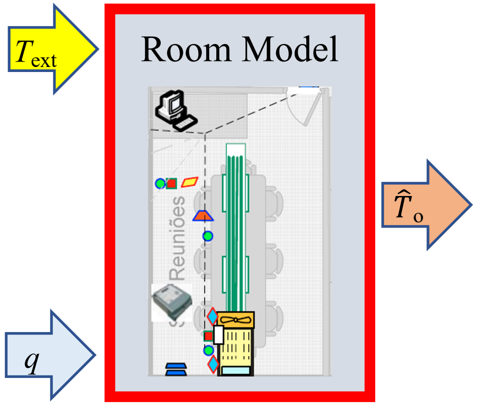
Finite Elements Simulation, e.g. Fluent

Thermal Modelling of an Office Room

B) Static Model

- Area of the Room
- Windows
- Sun side
- Occupancy





$$\hat{T}_o = f(T_o, q, T_v, T_{ext})$$

Estimate for the worst case scenario

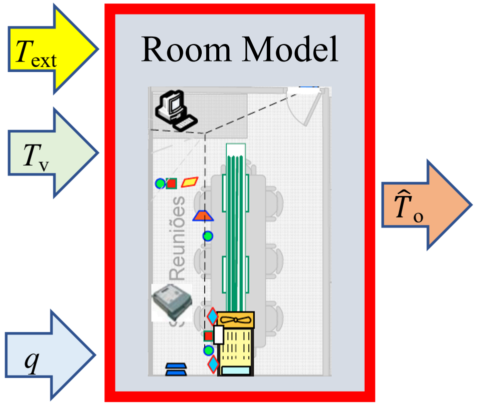
Sol à tarde ou o dia todo	Sol de manhã	Tamanho do ambiente
Até 7.500 BTU's	Até 7.500 BTU's	Até 10 m²
10.000 BTU's	7.500 BTU's	12 m²
10.000 BTU's	10.000 BTU's	15 m²
12.000 BTU's	12.000 BTU's	20 m²
15.000 BTU's	12.000 BTU's	25 m²
18.000 BTU's	15.000 BTU's	30 m²

Companies use environment characteristics to recomend an air conditioning device (BTU's)

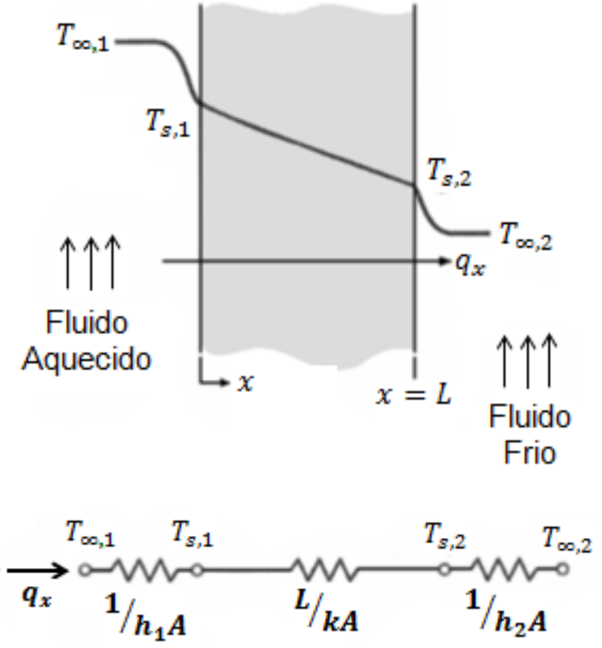
Thermal Modelling of an Office Room

C) Dynamic Model (lumped parameters)

Room, walls, floor and ceil
store energy ⟶ time constants

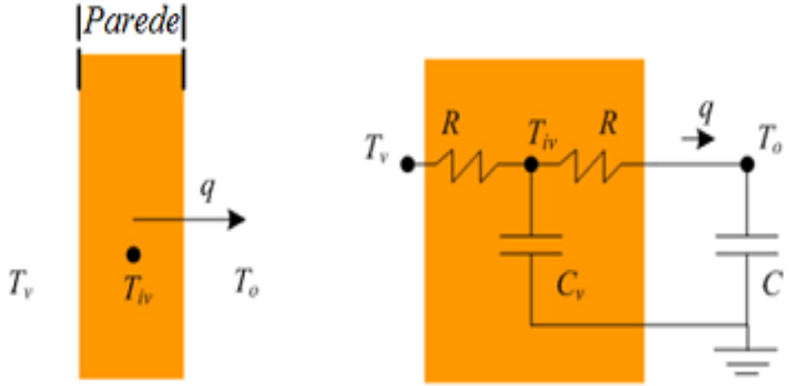


$\hat{T}_o = f(T_o, q, T_v, T_{ext})$



LTI model ⟶ Transfer Function

Thermal flow simplifications:



Wall analog Model

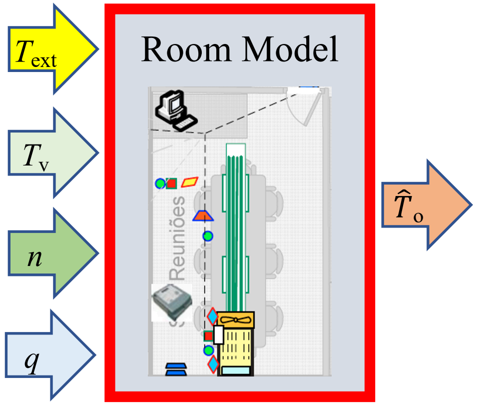
2RC Electrical Analogy
Ordinary Dif. Equations
LTI model ⟶ Transfer Function

Thermal Modelling of an Office Room

C) Dynamic Model (parameters R, C, Cv)

How to obtain the parameters?

C.1) Calculate by materials used, areas, volumes.



$\hat{T}_o = f(T_o, q, T_v, T_{ext})$

Very hard job! ⟶ Simplifications ⟶ Poor approximation

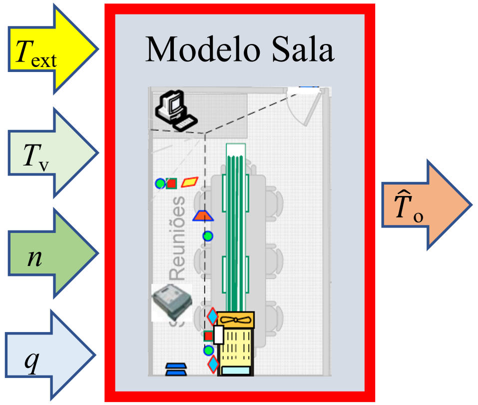
- Many different, non-homogeneous materials employed
- Medium characteristics can presente hight variance (e.g., thermal conductivity of the roof)

Estimate by averaged simplified construction elements

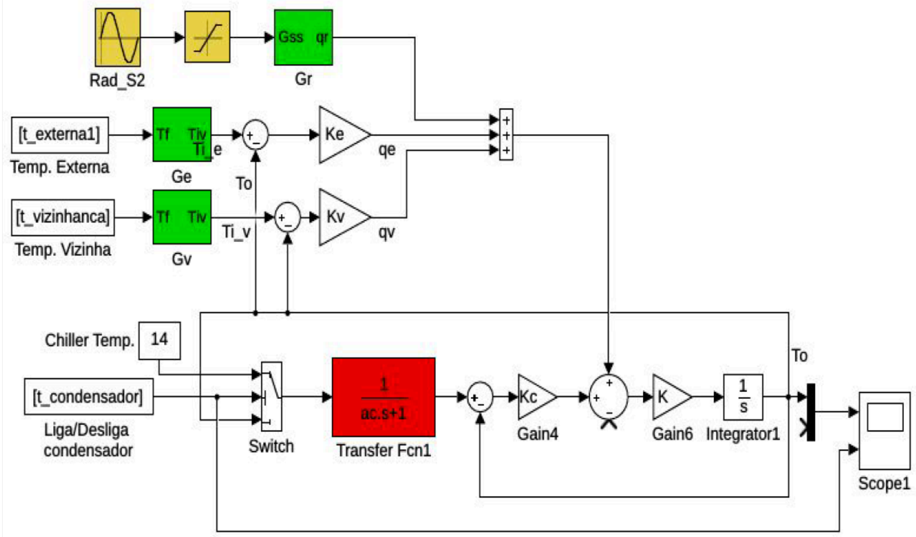
Thermal Modelling of an Office Room

C) Dynamic Model (parameters R, C, Cv)

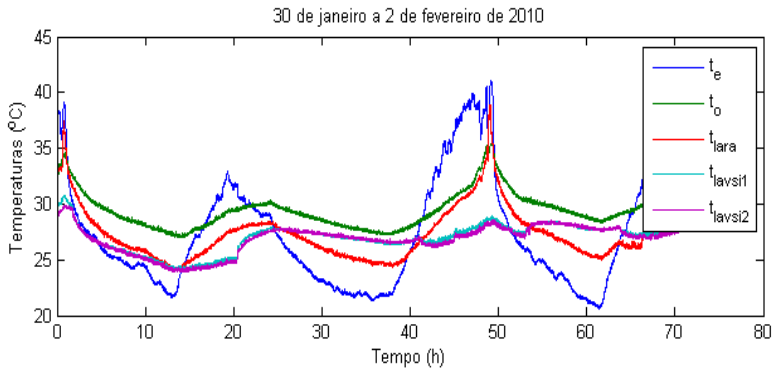
C.2) Access parameters by Identification, from experiments.

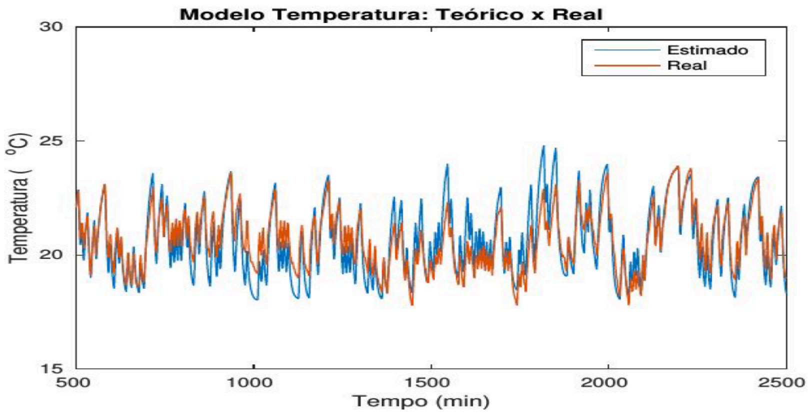


$\hat{T}_o = f(T_o, q, T_v, T_{ext})$



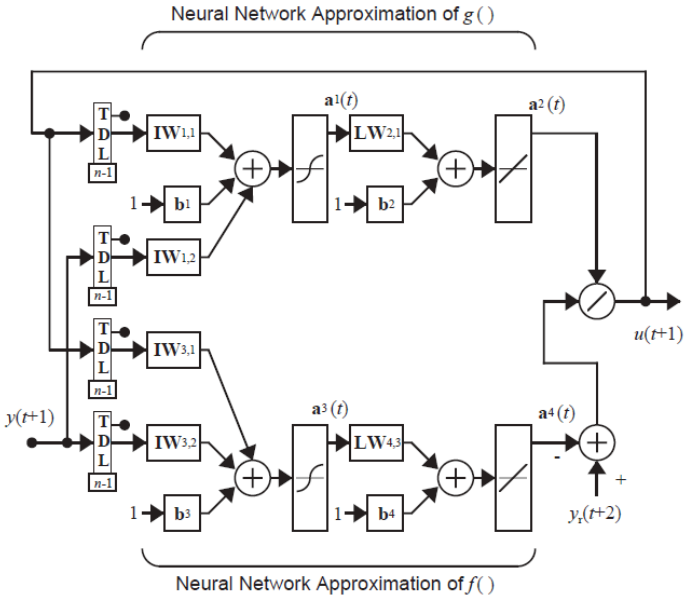
Required *a priori* Knowledge :
- order, which inputs matter, disturbances,...

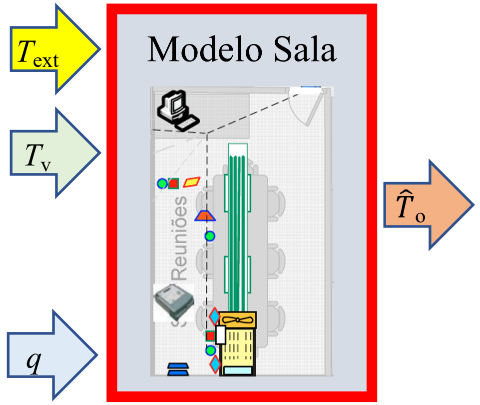




Thermal Modelling of an Office Room

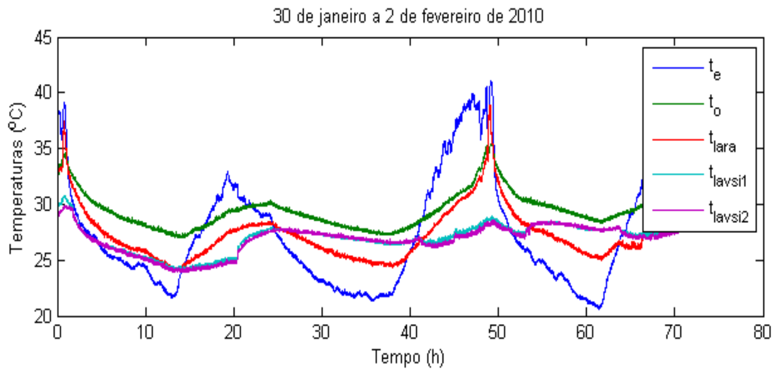
D) NARMA-L2 ANN

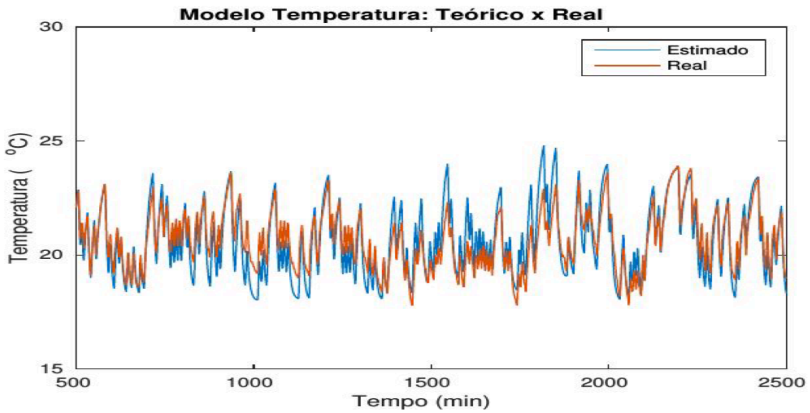




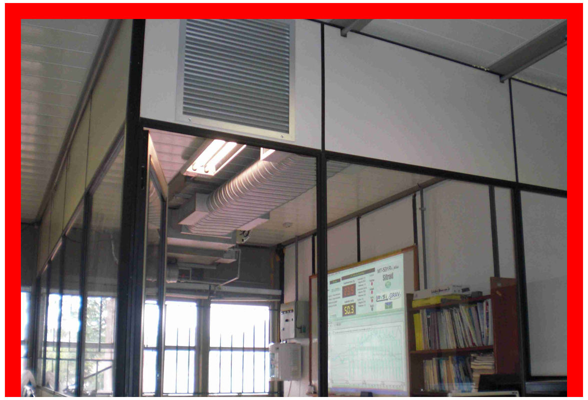
$\hat{T}_o = f(T_o, q, T_v, T_{ext})$

ANN (Non-Linear Map)
with TDLs (Time Delay Lines - memory)
is trained with signals,
until the MODEL has learned ($\hat{T} \sim T$).

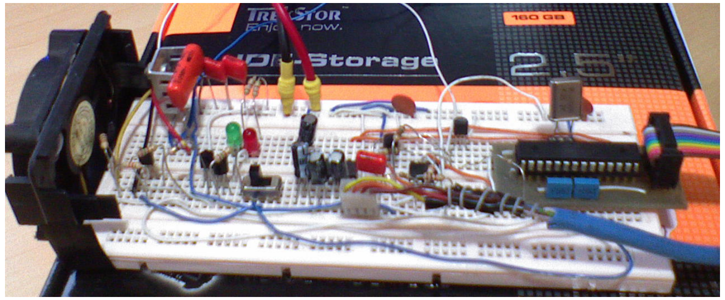


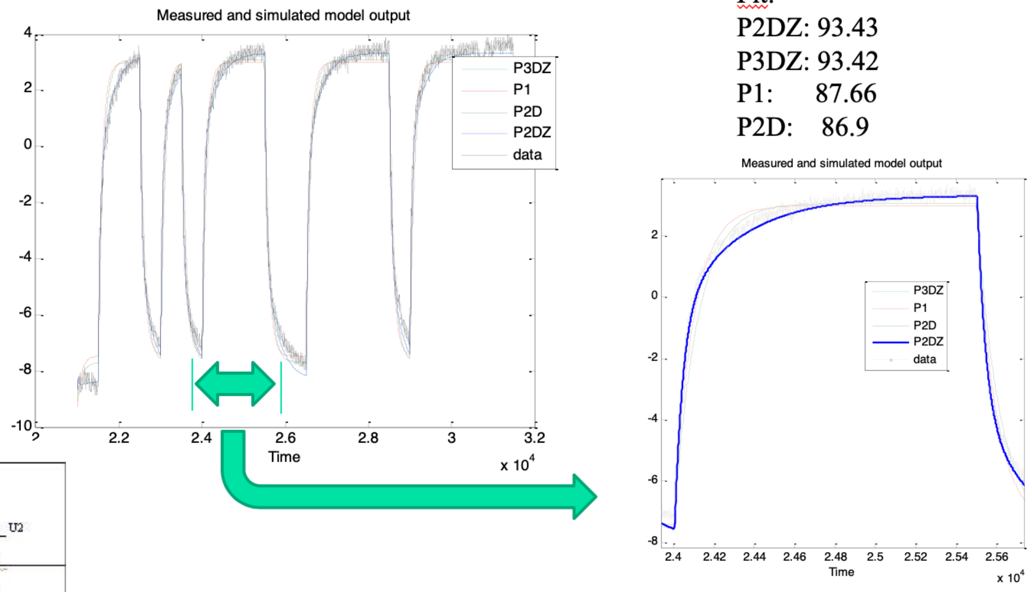


Thermal Modelling of an Office Room

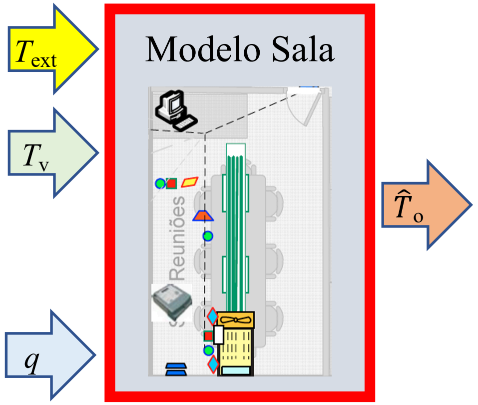


F) Small Scale Analogon

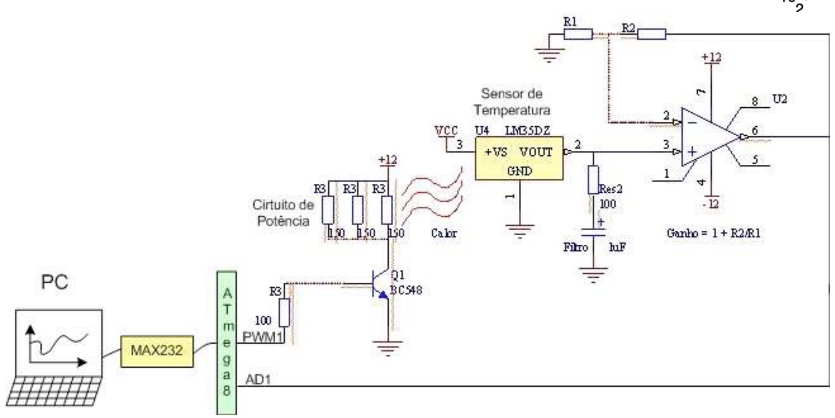




Fit:
P2DZ: 93.43
P3DZ: 93.42
P1: 87.66
P2D: 86.9



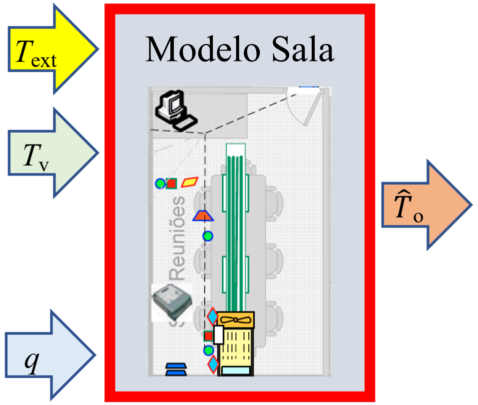
$$\hat{T}_o = f(T_o, q, T_v, T_{ext})$$



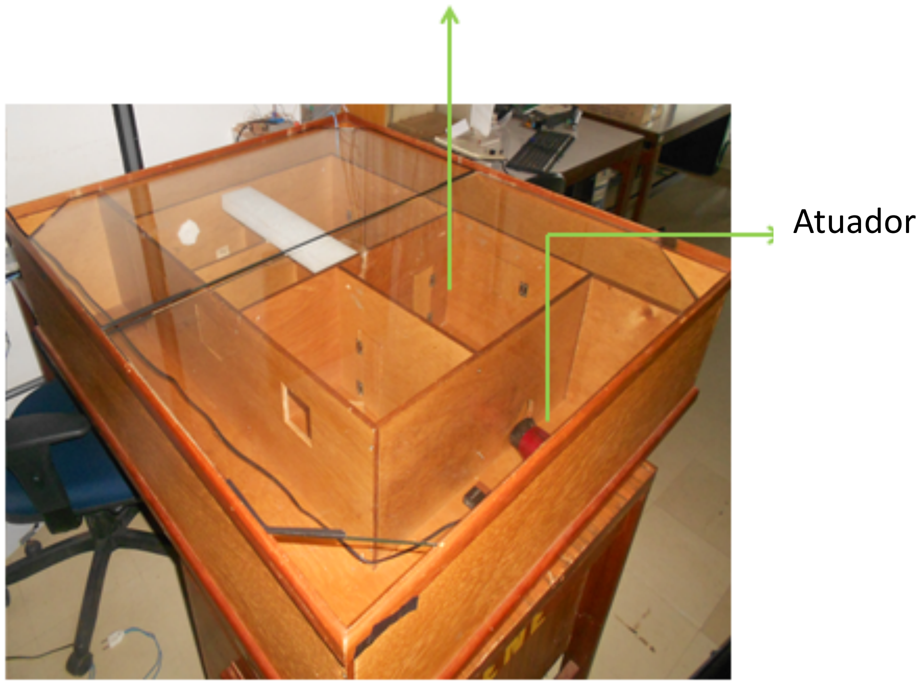
- Same process nature.
- Allows save experimentation.
- Fast evaluation of algorithms efficiency.

Thermal Modelling of an Office Room

G) "Maquete" – small scale building replica



$$\hat{T}_o = f\,(T_o, q, T_v, T_{ext})$$



Permite simular salas vizinhas e temperatura externa.

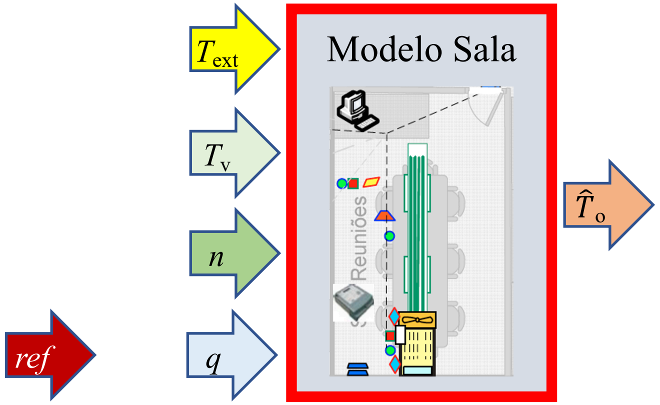
"Análogo invertido" - o ar condicionado é substituído por um secador de cabelos.

Mesmos sinais, permitem avaliar a eficácia de algoritmos.

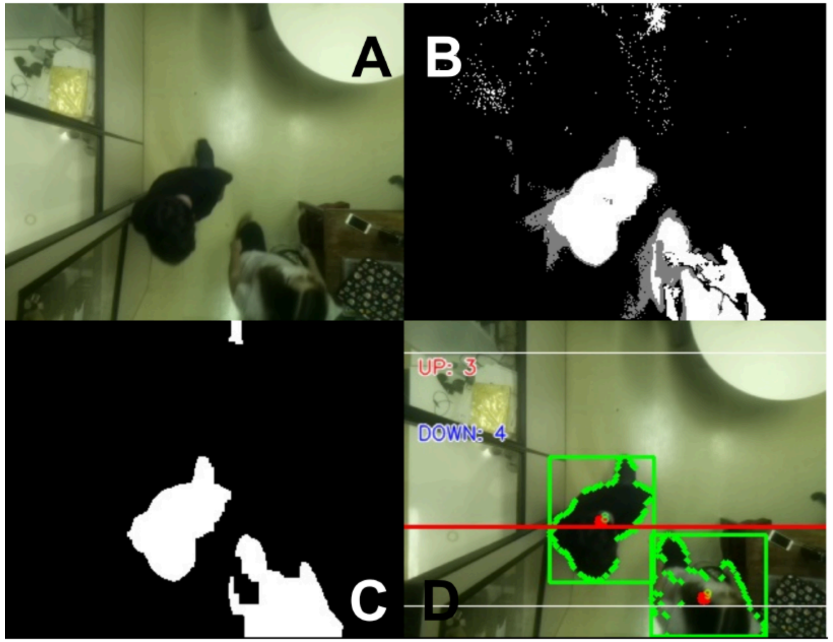
Thermal Modelling of an Office Room

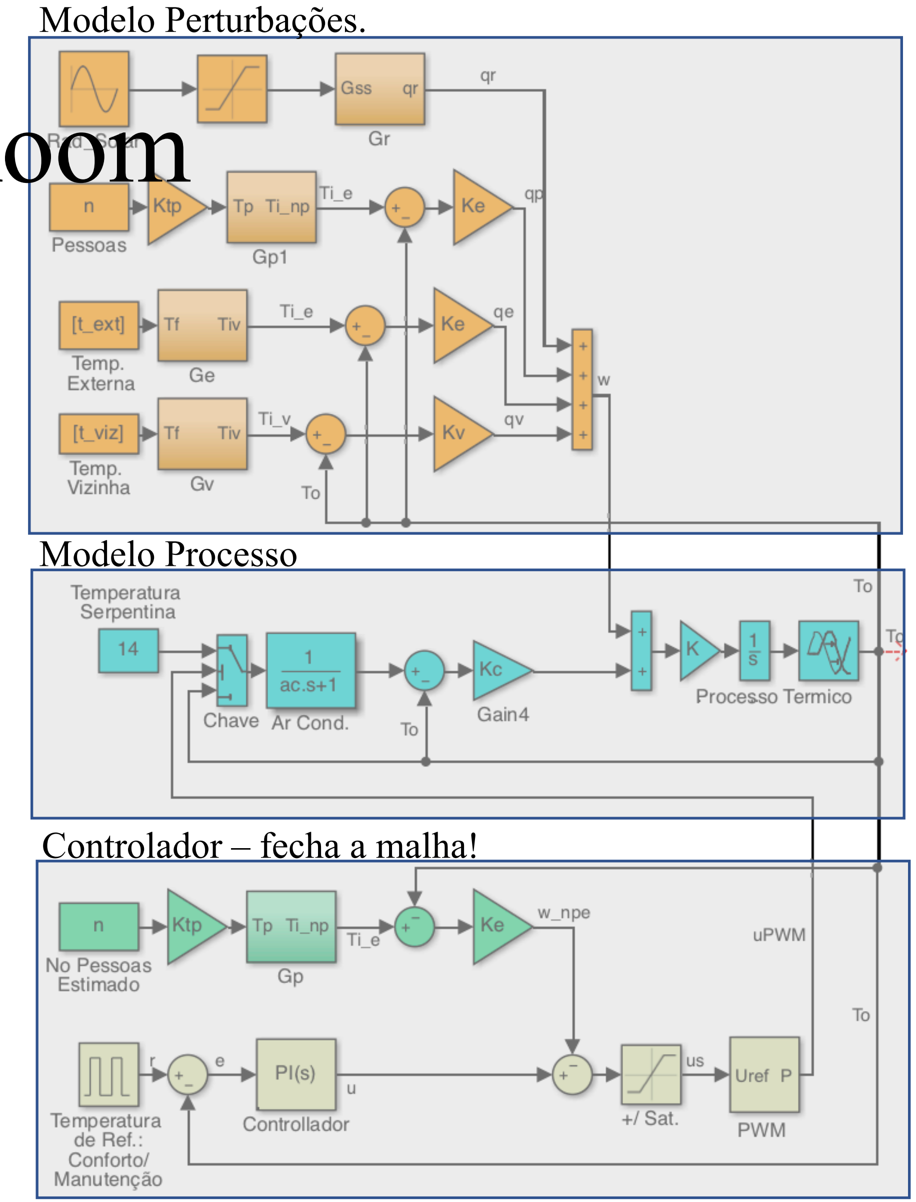
G) Living Lab - Validação Human-in-the loop

A estimativa de ocupação (estimativa de carga térmica) é considerada no algoritmo.



$$\hat{T}_o = f(T_o, q, T_v, T_{ext})$$





Thermal Modelling of an Office Room

G) Living Lab

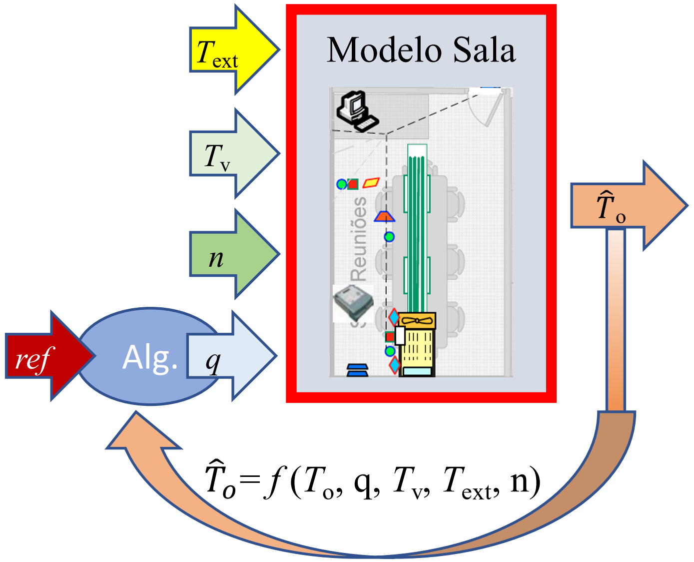
A estimativa de ocupação (estimativa de carga térmica) é considerada no algoritmo.

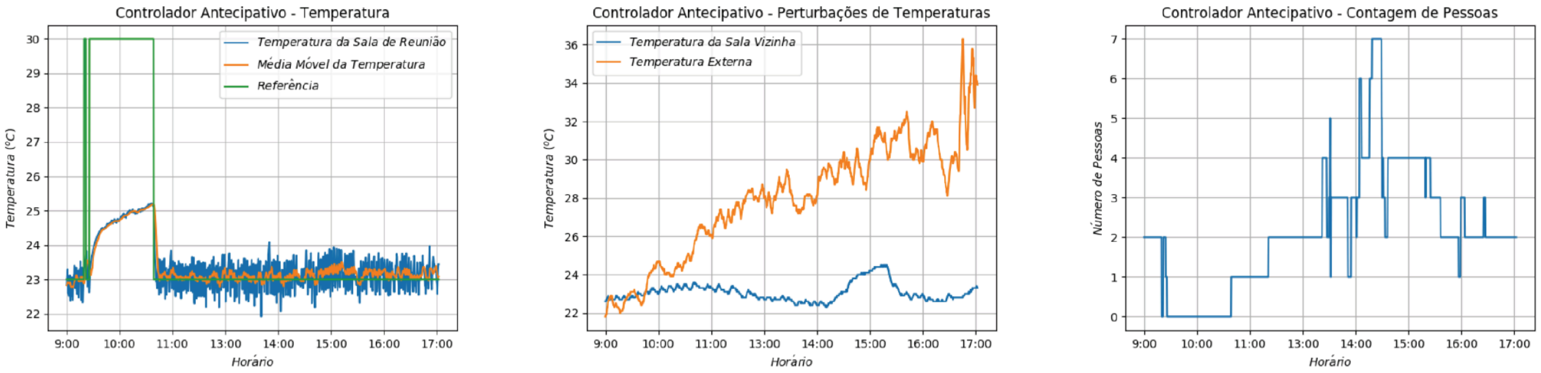
Tabela 1. Comparação Controladores.

Controlador	kWh	IBT	RMSE
Liga-Desliga	7,92	8,63	0,42
PI	6,16	2,70	0,42
Antecipativo referência fixa	6,00	6,06	0,35
Antecipativo referência variável	5,81	8,71	0,37

Tabela 2. Melhoria do Antecipativo.

Referência fixa	Erro	Energia
Liga-Desliga	16,66%	24,24%
PI	16,66%	2,6%
Referência variável	**Erro**	**Energia**
Liga-Desliga	11,90%	26,64%
PI	11,90%	5,8%

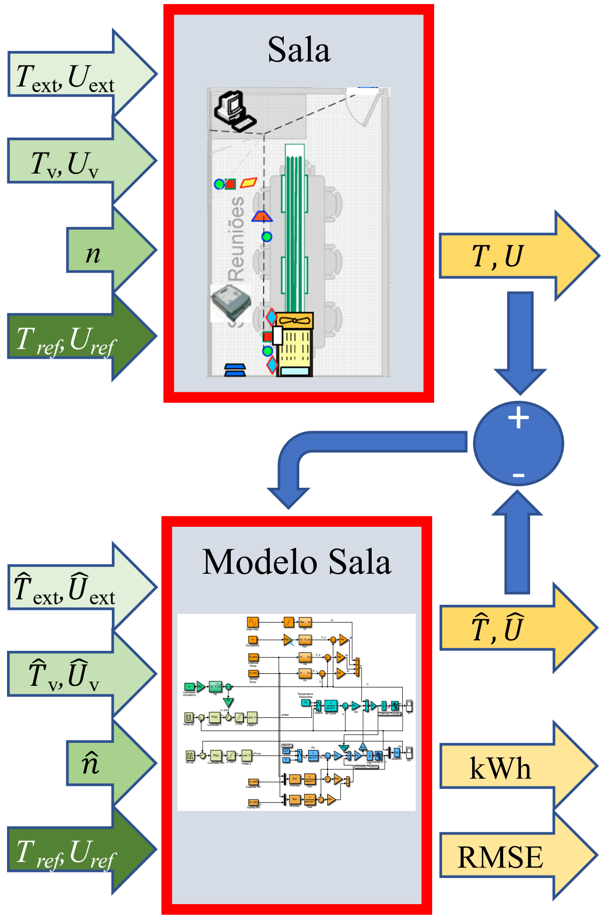




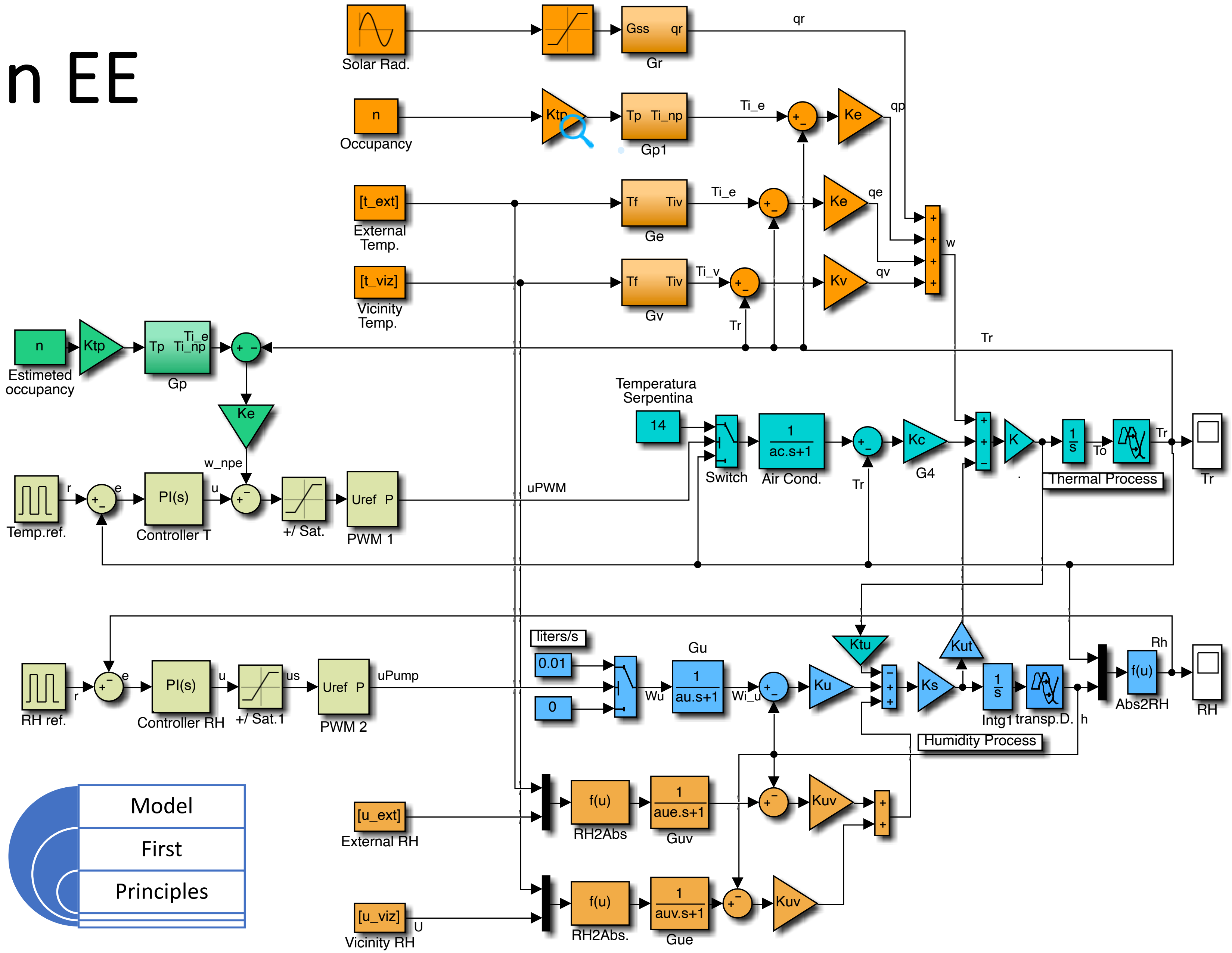
(a) Temperatura da sala de reuniões. (b) Temperatura externa e da sala Vizinha. (c) Número de pessoas.

Figura 11. Controlador antecipativo (considerando mudança na referência para sala vazia). Medido em 16/11/18.

Room EE Dig. Twin EE

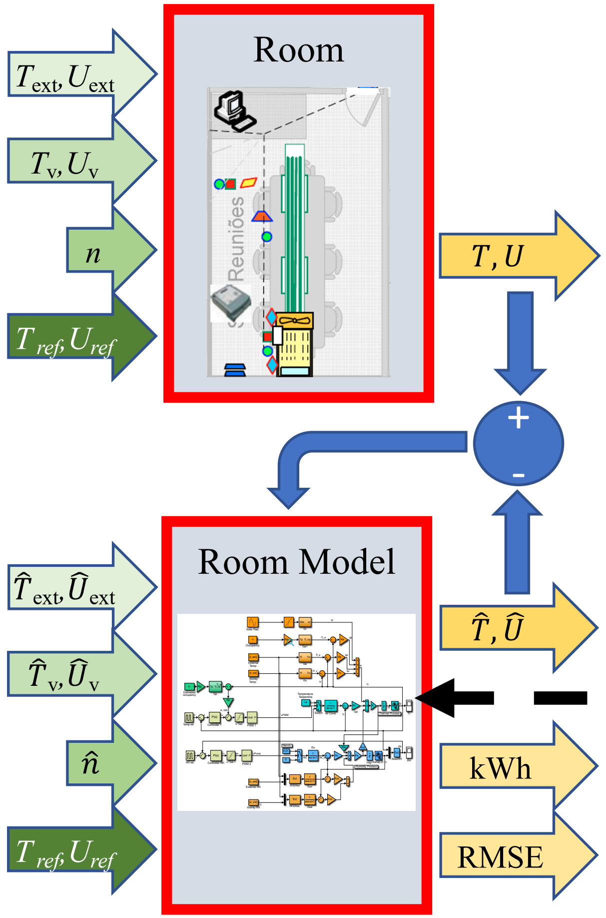


$$[\hat{T}_o, \hat{U}] = f(T, U, Tref, Uref, \hat{T}_v, \hat{T}_{ext}, \hat{U}_v, \hat{U}_{ext}, \hat{n})$$

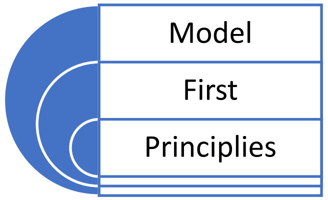


Model
First
Principles

Dig. Twin Model Updating



$[\hat{T}_o, \hat{U}] = f(T, U, Tref, Uref, \hat{T}_v, \hat{T}_{ext}, \hat{U}_v, \hat{U}_{ext}, \hat{n})$

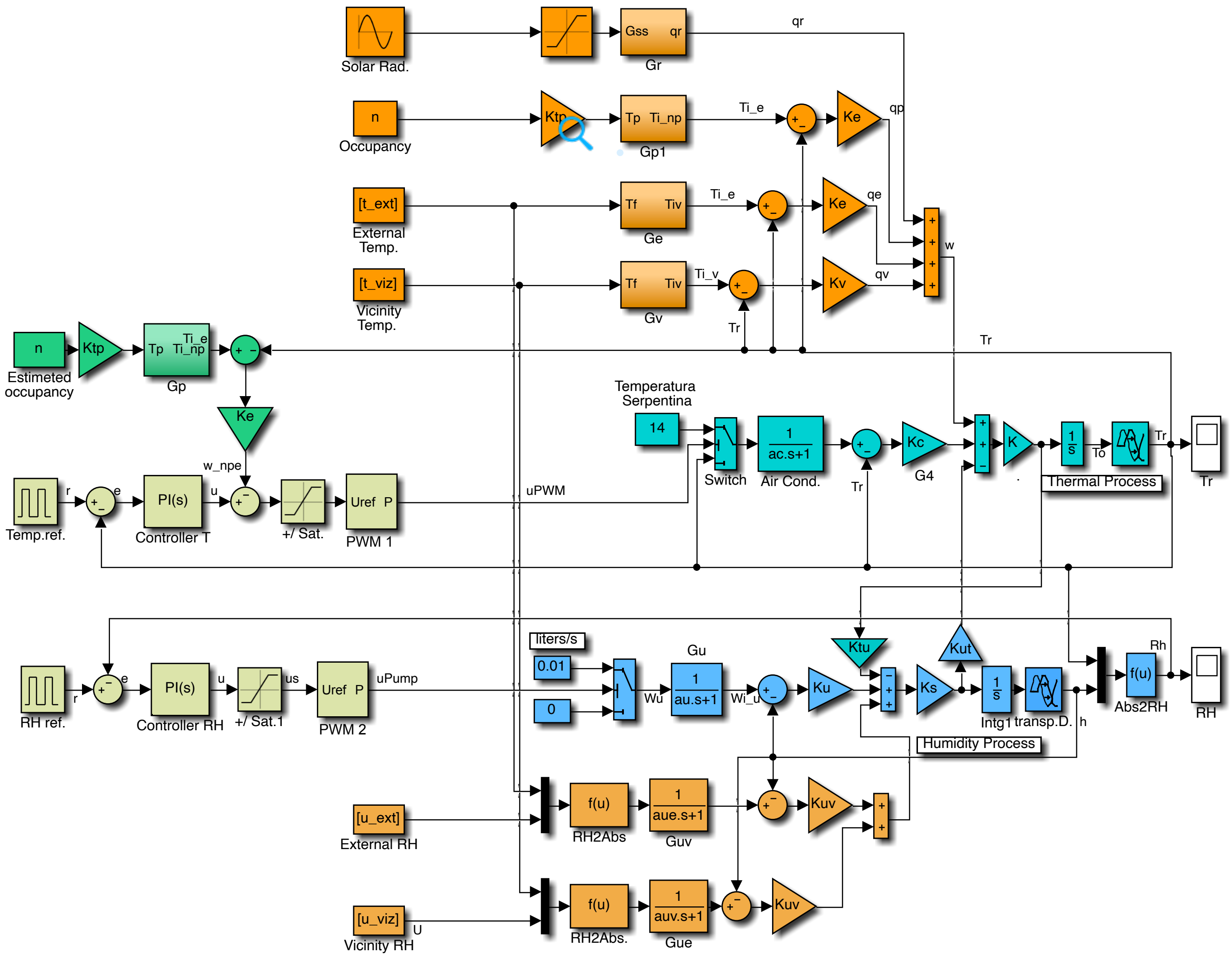


$q = K(T_2 - T_1)$

Thermal Convection

Conduction

q_v, q_c, ... explicit !!



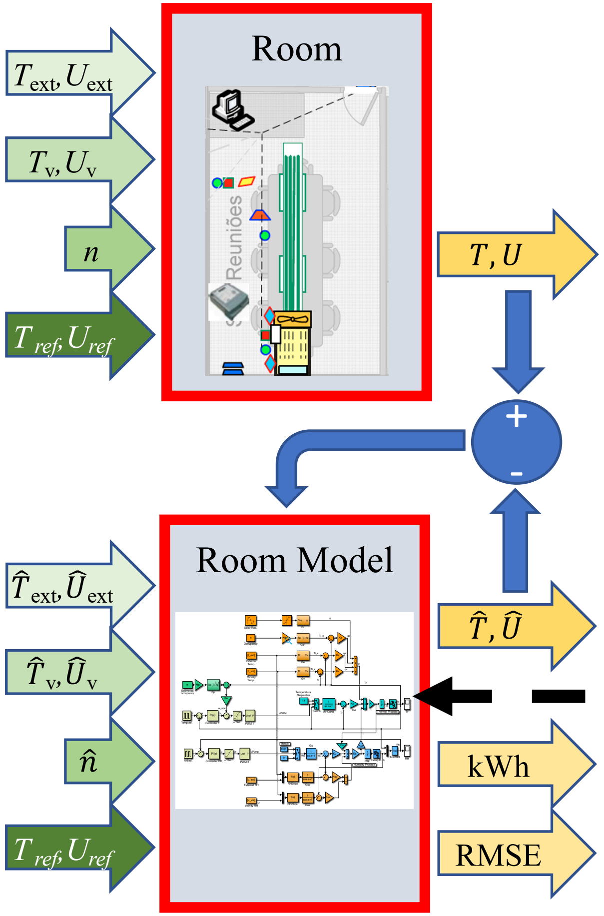
Model Structure: Fixed, Grey-Box First-Principles

Model Parameters: $K, K_c, K_u, K_v, a_c, a_u$ ... (25!)

→ Batch seasonal Identificaton

→ **Recursive** on-line Identificaton

Twins - SD Surrogates



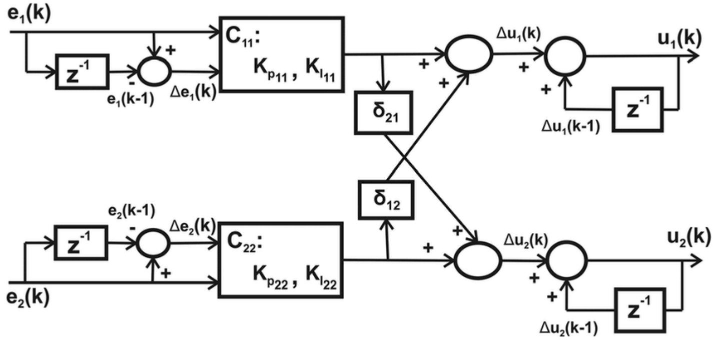
$[\hat{T}_o, \hat{U}] = f(T, U, Tref, Uref, \hat{T}_v, \hat{T}_{ext}, \hat{U}_v, \hat{U}_{ext}, \hat{n})$

Model:
First
Principles

- ✓ Very good fit
- ✓ Insight knowledge (struct. policy)

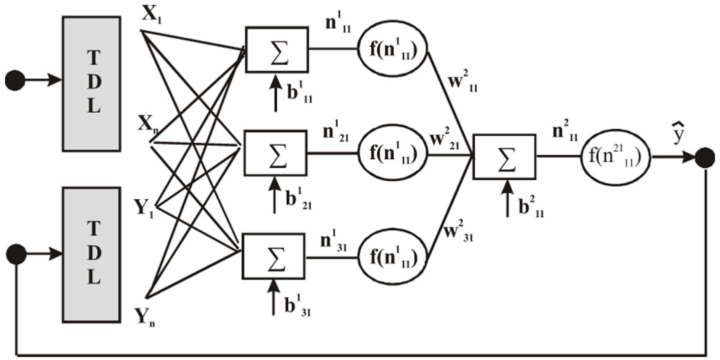
Model:
Black-Box
Identification

- ✓ Best fit
- • no insight (I/O model) (no struct. policy clue)



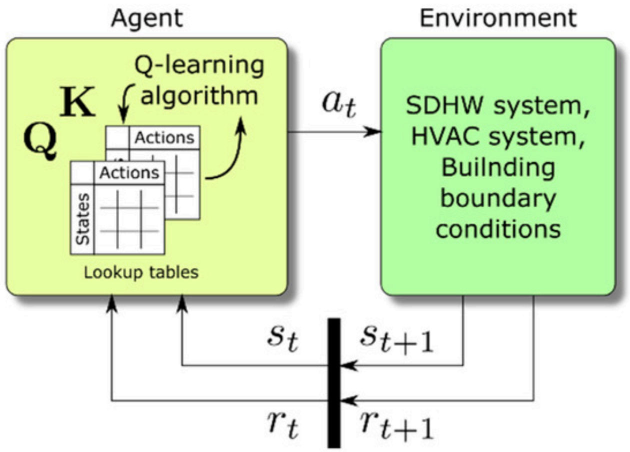
Model:
Neural Network
TDL dynamics

- ✓ Good fit, generalization
- • no insight (no struct.)

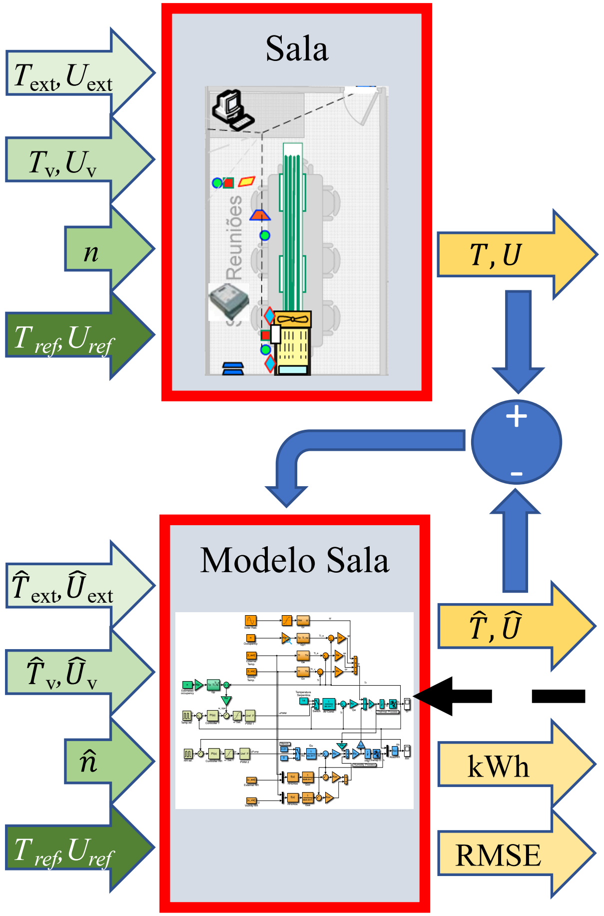


Model:
Reinforcement
Learning

- • Poor fit
- ✓ Finds the solution (target) (no struct.)



Twins - HD surrogates



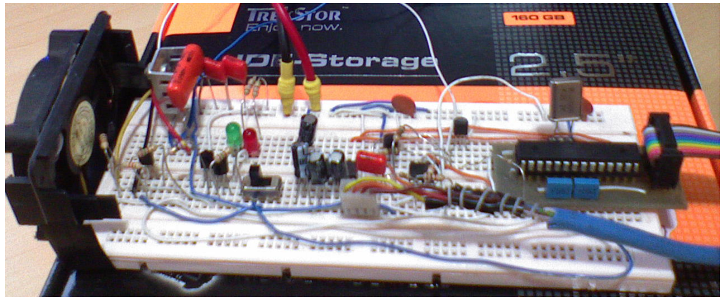
$[\hat{T}_o, \hat{U}] = f(T, U, Tref, Uref, \hat{T}_v, \hat{T}_{ext}, \hat{U}_v, \hat{U}_{ext}, \hat{n})$

SD - Models:
First
Principles

- ✓ Fast, save,
  can run exhaustive scenarios
- *You simulate what you modelled!*

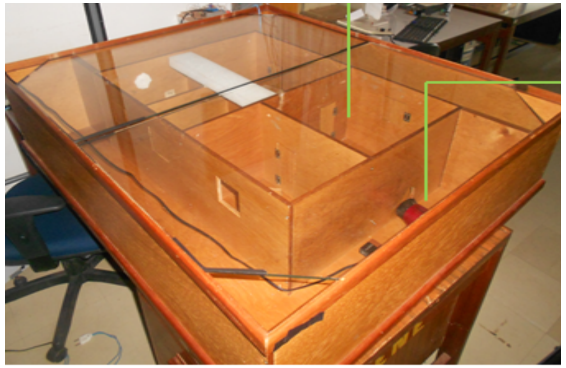
Model:
Small-scale
Analogon

- ✓ Cheap, fast, save
- Test only main factors (no struct. policy clue)



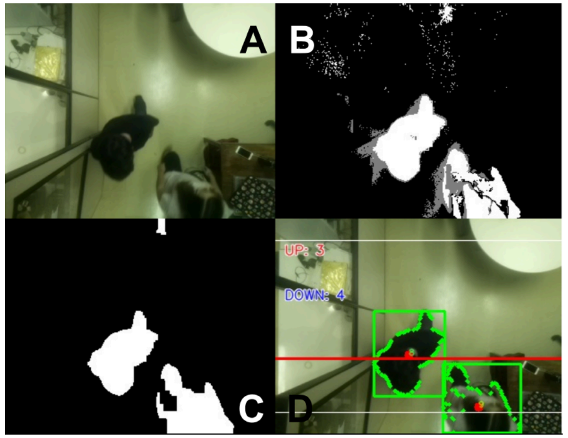
Model:
Small-scale
Building Replica

- ✓ Cheap, fast, save
- Artificial environment (struct. policy clue)



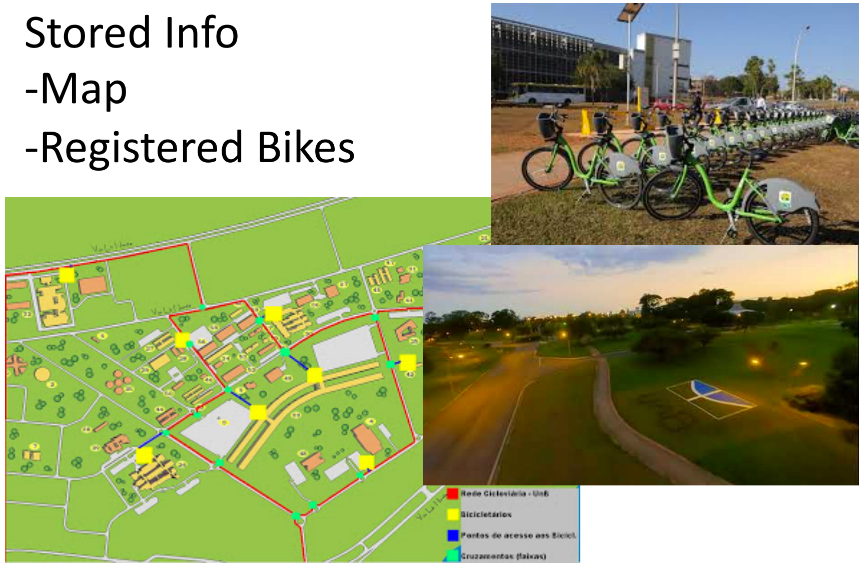
Model:
Living
Lab

- ✓ Real world, insight, save
- Can't excite all situations (struct. policy)



Bike ways

Stored Info
-Map
-Registered Bikes



Trajectories $(x,y,z,\emptyset,t)$

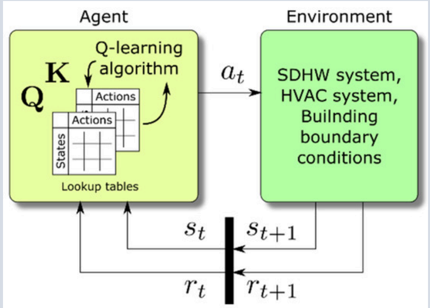
Bike ways

$Im(k)$

+
-

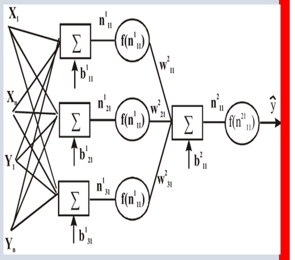
$Im(k)$

Bike ways Model



$\hat{C}$hange

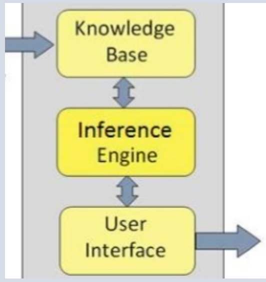
Deep Neural Network



$\hat{P}$attern Recognition

-*Hole*
-*Near FT Block F*
-Coord. (*23*N,*300*W)

Expert System

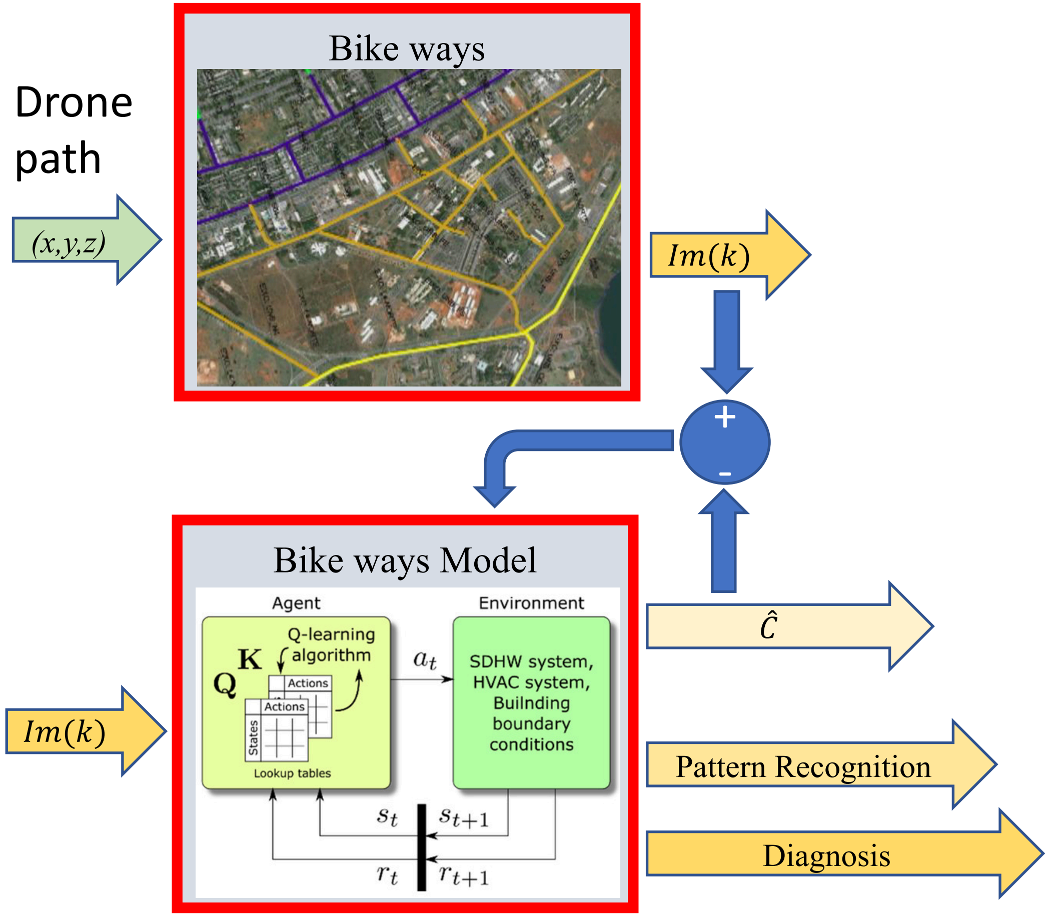


- $\hat{D}$iagnosis
- Recommended actions at (x,y)

-*Urgent*
-*Send Maintainance*

$[\hat{C},\hat{P},\hat{D}]=f\,(Im(k), Im(k\text{-}1),\ldots$ *Map, Rule Base, Inference Engine*)

ChangeNet as Twin

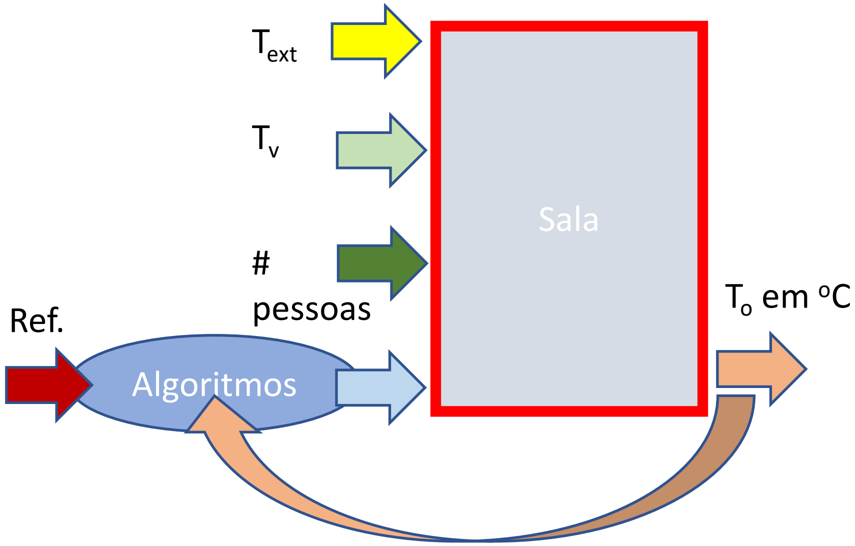


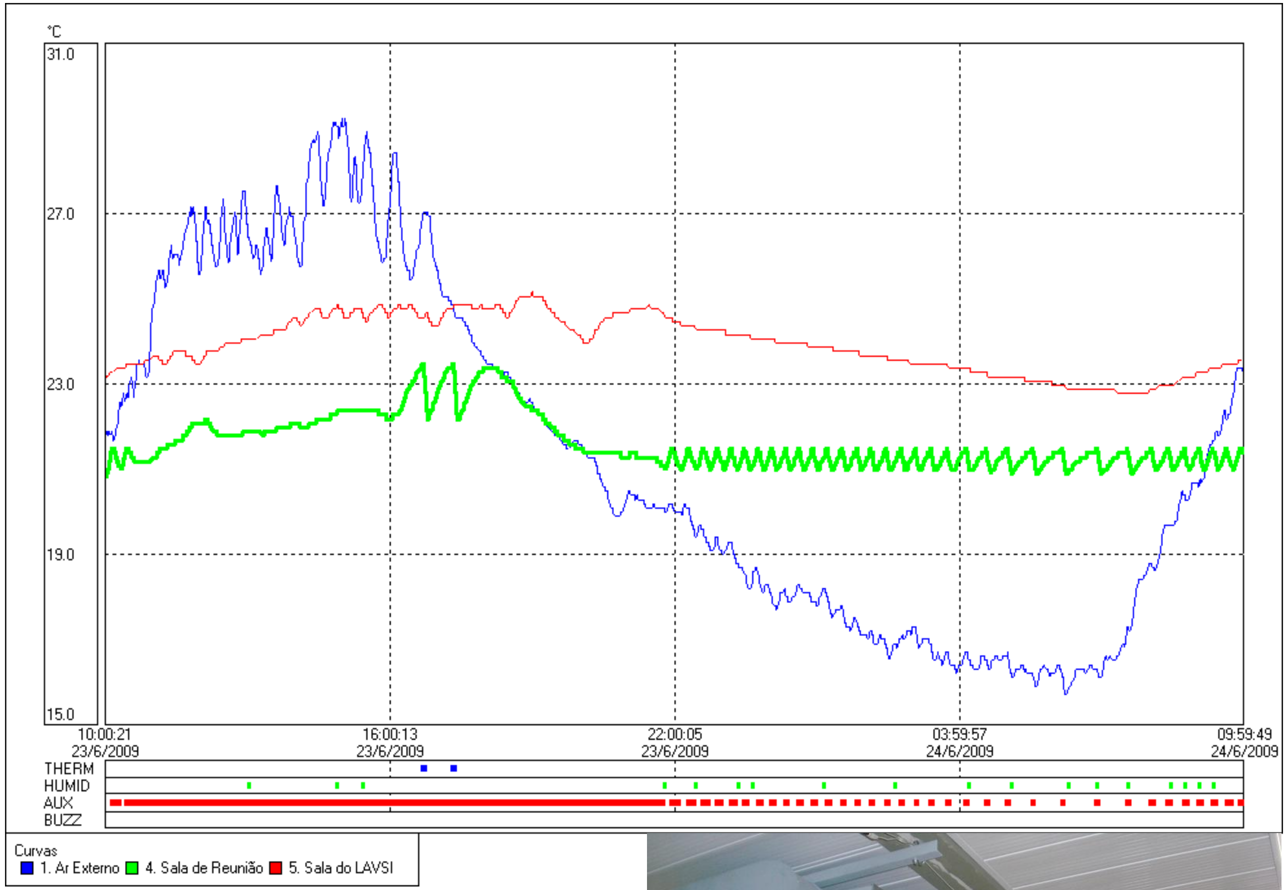
$[\hat{C}, \hat{P}, \hat{D},] = f$(Im(k), Im(k-1), Map, Inference Engine, Rule Basis)

Test Image Reference Image ChangeNet Ground Truth

EE Efficiency
→ Hybrid cooling

H) Evaporative cooling has very cheap operation costs





The conventional compressor is only used when the Evaporative cooling is not sufficient
Energy saving ~70%!!

Damper & Water reservoir.