# Energy Efficient Control and Fault Detection for HVAC Systems

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DIPARTIMENTO
DI INGEGNERIA
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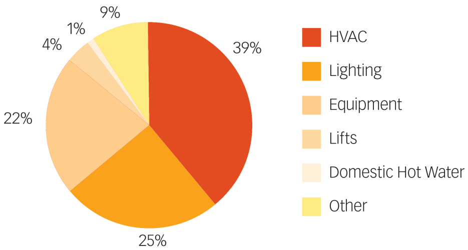
# Heating, Ventilation and Air Conditioning (HVAC)

- HVAC systems ensure safe and healthy conditions in the environments of medium and large buildings
- Control, optimisation and maintenance procedures are fundamental in HVAC systems to guarantee people comfort and energy efficient solutions

Typical energy consumption breakdown
in an office building

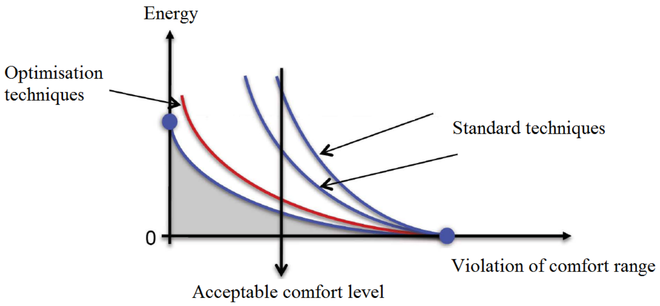



# Part I

# Energy Efficient Control of Ice Thermal Energy Storage Systems

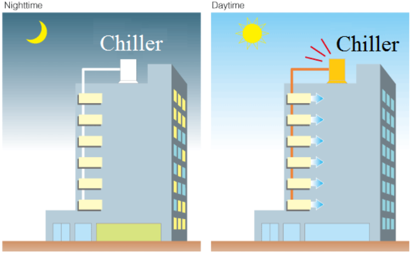
# Why Thermal Energy Storage (TES)?

- Energy efficiency politics encourage the adoption of different time slots of energy price
- TES technology can be adopted to store energy when its cost is low and exploit it when the price increases
- Optimisation techniques can find the right trade-off between energy efficiency and people thermal comfort

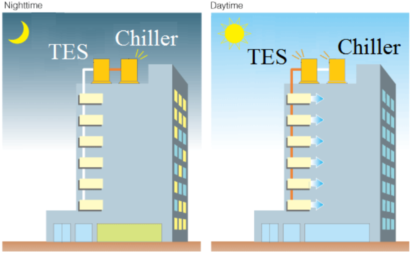


# Conventional Cooling vs TES

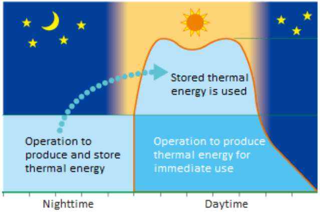
Conventional cooling



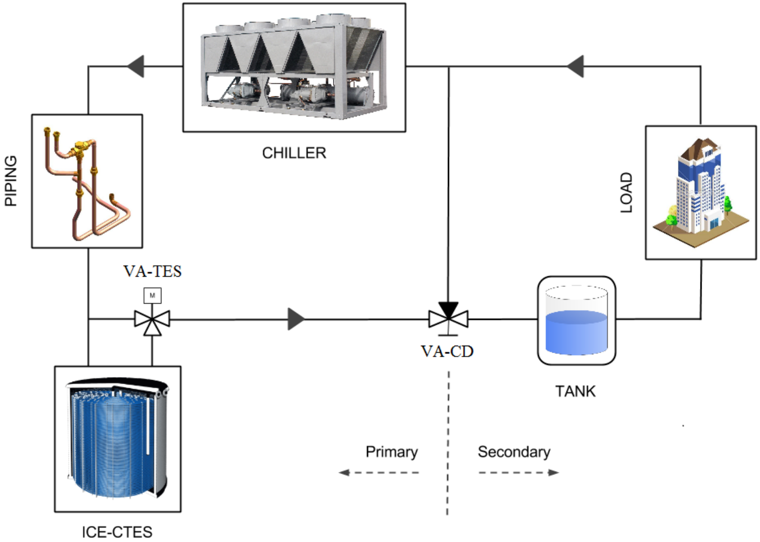

Cooling with thermal storage




Operation of cooling with thermal storage



# HVAC System with Ice-Cold TES



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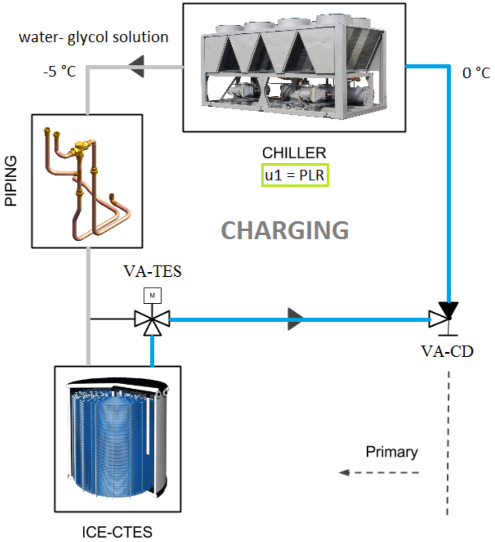
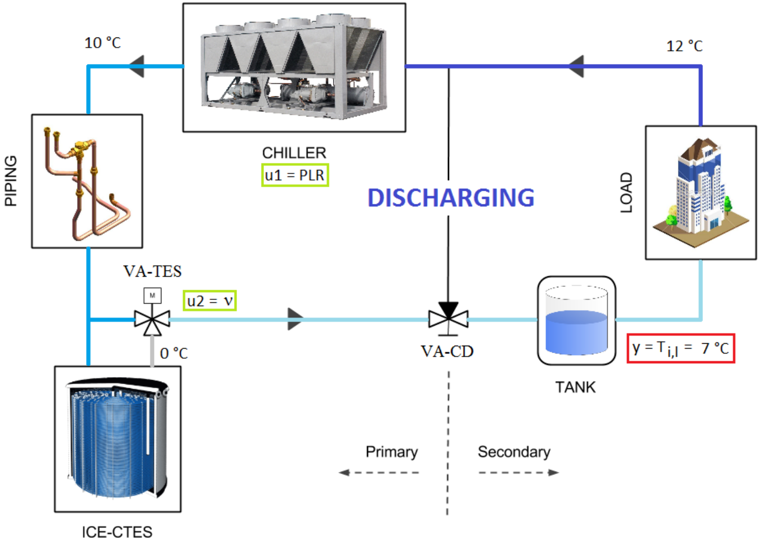
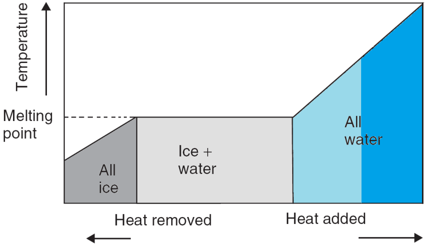
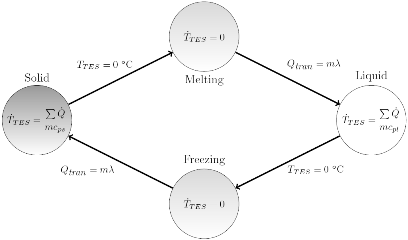


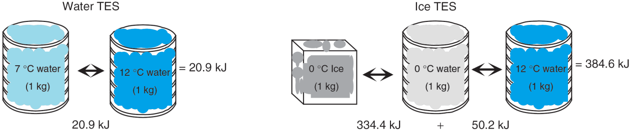
# HVAC System with Ice-Cold TES



# Ice-CTES Model

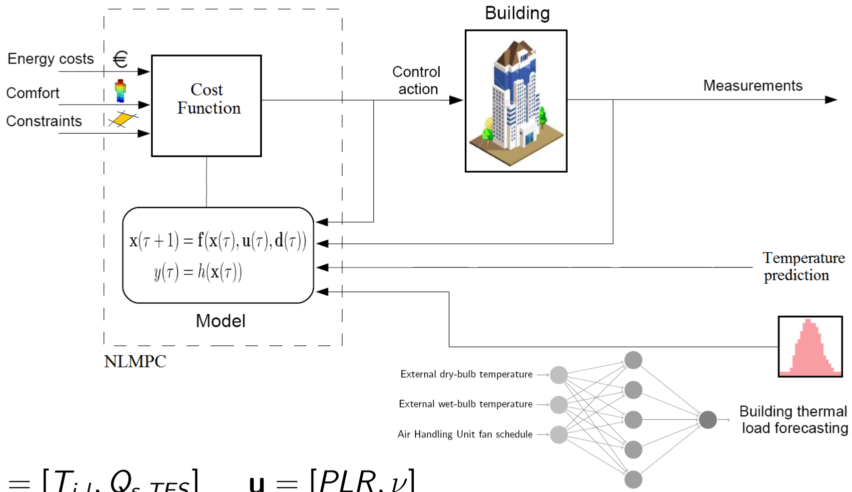



- Ice storage has a much higher capacity with respect to water storage, due to the heat that can be exchanged during the latent phases
- The ice-CTES is modelled as a heat exchanger: it exchanges heat with the water coming from the chiller and with the external environment (energy dissipation)

# Non-Linear Model Predictive Control (NLMPC)




ANN-based model

$$\mathbf{x} = [T_{i,l}, Q_{s,TES}] \qquad \mathbf{u} = [PLR, \nu]$$

$$y = [T_{i,l}] \qquad \mathbf{d} = [\text{Load}, T_{air}]$$

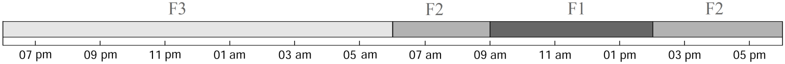
# NLMPC Formulation

## Constrained finite time optimal control problem

$$\text{find} \qquad \underset{\bar{\mathbf{u}}}{\arg\min} \sum_{\tau=t}^{t+T_p} \mathcal{C}(\tau)\dot{Q}_{e,ch}(\tau)\Delta\tau + \alpha \left|\bar{y}(\tau) - \bar{r}(\tau)\right|^2$$

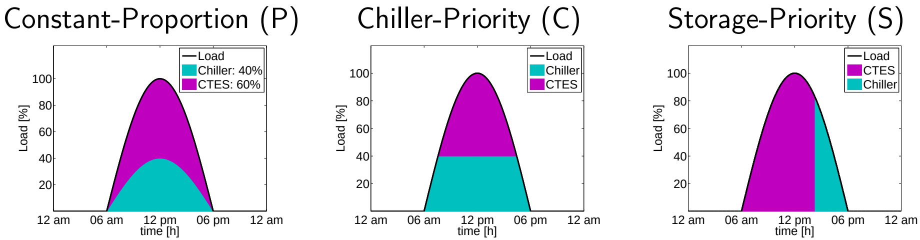
subject to: system dynamics, constraints, initial conditions

- $\mathcal{C}$: price of electric energy (F1>F2>F3)




- $\dot{Q}_{e,ch}$: chiller electric power consumption
- $\bar{y}$: inlet load-side water temperature
- $\bar{r} = 7\,[^\circ C]$: inlet load-side water temperature setpoint

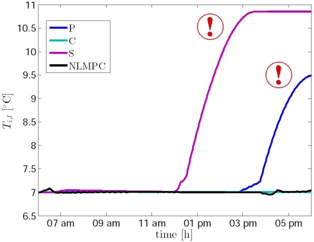
# Discharging: Conventional Strategies



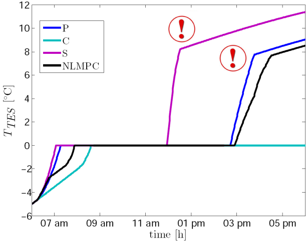

- Constant-Proportion: the storage and the chiller meet a constant fraction of the cooling load
- Chiller-Priority Control: chiller runs to satisfy cooling load up to its maximum capacity while the storage provides the remaining cooling power
- Storage-Priority Control: chiller provides cooling power only after the complete discharging of the storage

# Discharging Example: Conventional and NLMPC

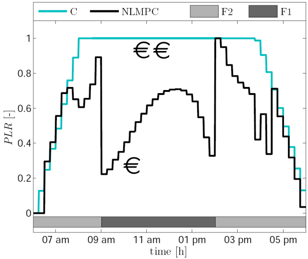
Inlet load-side water temperature



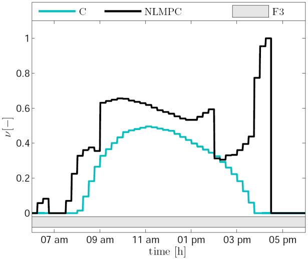

TES temperature




Normalised chiller power




VA-TES valve opening



# Conclusions and Future Works

## Conclusions

- Optimisation techniques are crucial in order to efficiently manage TES systems
- A HVAC system with ice-CTES is developed in a simulation environment
- Conventional control strategies and a non-linear MPC approach are compared
- Non-linear MPC provides the lower energy cost, satisfying cooling demand

## Future Works

- Comparison with different plant structures (e.g. chiller/storage in parallel configuration)
- Design of optimisation techniques for both charging and discharging operations

# Publications

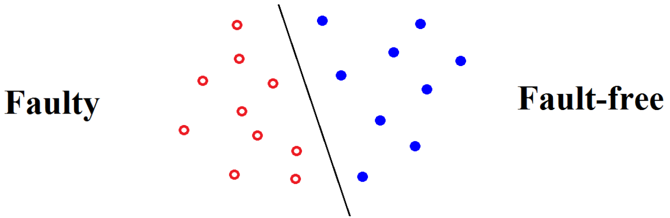
- A. Beghi, L. Cecchinato, M. Rampazzo, and F. Simmini. Load Forecasting for the Efficient Energy Management of HVAC Systems. In *IEEE International Conference on Sustainable Energy Technologies (ICSET)*, 2010
- A. Beghi, L. Cecchinato, M. Rampazzo, and F. Simmini. Modeling and Control of HVAC Systems with Ice Cold Thermal Energy Storage. In *IEEE 52nd Annual Conference on Decision and Control (CDC)*, 2013
- A. Beghi, L. Cecchinato, M. Rampazzo, and F. Simmini. Energy efficient control of HVAC systems with ice cold thermal energy storage. *Journal of Process Control*, 24(6):773-781, 2014

# Part II

# Fault Detection in HVAC Systems

# FDD and Classification

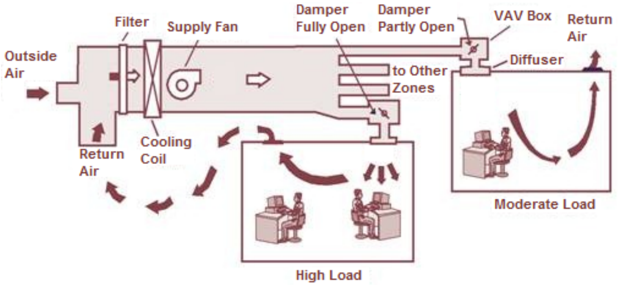
- Different faults may occur in HVAC systems, which can cause discomfort and waste of energy
- Cost-effective Fault Detection and Diagnosis (FDD) methods can ensure an increase in system reliability and overall efficiency
- Binary classification methods are developed: data are labelled with faulty or fault-free conditions
- To perform data-based FDD either real data from actual HVAC plants are available or artificial data from models are needed



1. Fault Detection and Diagnosis for VAVAC Systems

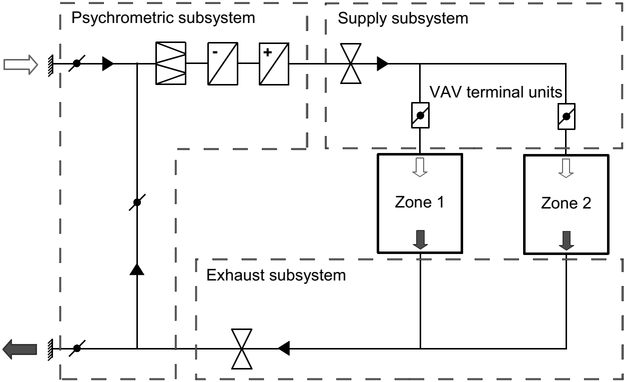
2. Fault Detection for Chiller Systems

# VAVAC Systems




- Variable Air Volume Air Conditioning (VAVAC) systems ensure satisfactory comfort levels for the occupants with high energy efficiency
- The supplied air is kept at a constant temperature while internal temperatures are controlled by varying the air mass flow rate in the zones

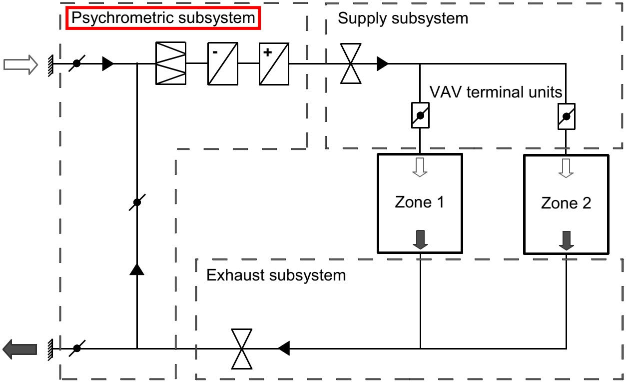
# VAVAC System: Two-Zone, Single-Duct



# VAVAC System: Two-Zone, Single-Duct

## Psychrometric subsystem

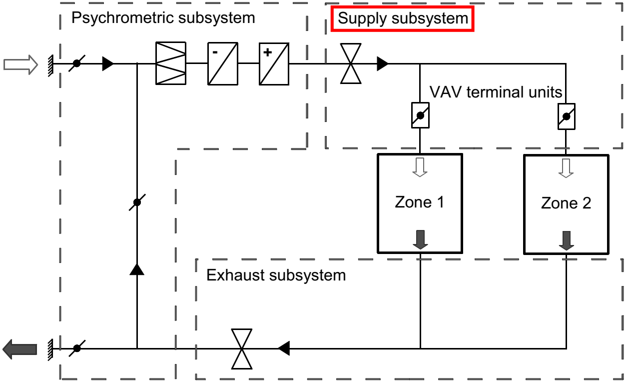
- chilled water
- air filter
- cooling coil
- fresh, recirculation and exhaust air dampers



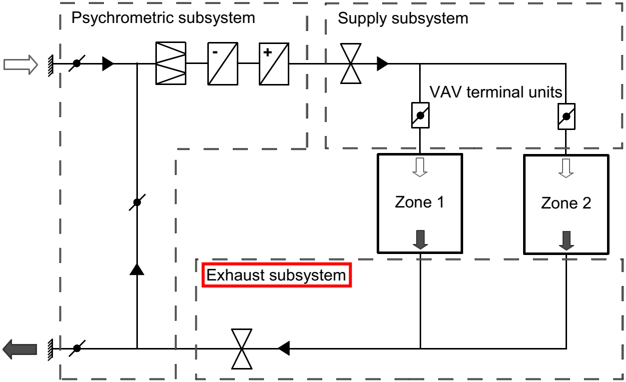
# VAVAC System: Two-Zone, Single-Duct

## Supply subsystem

- variable-duty supply fan
- network of air distribution ducts
- VAV terminal units
- air terminal devices



# VAVAC System: Two-Zone, Single-Duct




**Exhaust subsystem**

- return air fan
- return air ducts

# Model: States, Inputs and Disturbances

| | |
|---|---|
| $x_1 = T_{z,1}$ | air temperature of 1st zone [$^\circ$C] |
| $x_2 = T_{z,2}$ | air temperature of 2nd zone [$^\circ$C] |
| $x_3 = T_{sa}$ | supply cold air temperature [$^\circ$C] |
| $x_4 = T_{wo}$ | outlet water temperature of cooling coil [$^\circ$C] |
| $u_1 = \dot{m}_{a,1}$ | air mass flow rate of 1st zone [$\mathrm{kgs}^{-1}$] |
| $u_2 = \dot{m}_{a,2}$ | air mass flow rate of 2nd zone [$\mathrm{kgs}^{-1}$] |
| $u_3 = \dot{m}_w$ | chilled water mass flow rate [$\mathrm{kgs}^{-1}$] |
| $d_1 = \dot{Q}_1$ | internal and external heat gains of 1st zone [W] |
| $d_2 = \dot{Q}_2$ | internal and external heat gains of 2nd zone [W] |
| $d_3 = T_{ext}$ | external air temperature [$^\circ$C] |

# VAVAC Non-Linear Model and Control

$$
\begin{aligned}
\dot{x}_1 &= a_1 u_1 (x_3 - x_1) + a_2 d_1 + a_3 (d_3 - x_1) \\
\dot{x}_2 &= b_1 u_2 (x_3 - x_2) + b_2 d_2 + b_3 (d_3 - x_2) \\
\dot{x}_3 &= \left[ \frac{C_{pw}}{C_{pa}} \frac{u_3}{u_1 + u_2} (T_{wi} - x_4) + \left( r \frac{x_1 u_1 + x_2 u_2}{u_1 + u_2} + (1 - r) d_3 - x_3 \right) \right] \\
&\quad \cdot \frac{(UA)_c}{M_c C_{pc}} \\
\dot{x}_4 &= \left[ C_{pw} u_3 (T_{wi} - x_4) + C_{pa} (u_1 + u_2) \left( r \frac{x_1 u_1 + x_2 u_2}{u_1 + u_2} + (1 - r) d_3 \right. \right. \\
&\quad \left. \left. - x_3 \right) \right] \cdot \frac{1}{(M_c C_{pc})}
\end{aligned}
$$

$$
y_1 = x_1 \,, \quad y_2 = x_2 \,, \quad y_3 = x_3
$$

# The Direct Feedback Linearisation (DFL) Control

Consider the class of controllable non-linear plants:

$$y^{(n)} + a_{n-1}y^{(n-1)} + \ldots + a_1 y^{(1)} + a_0 y = f(y^{(n-1)}, \ldots, y^{(1)}, y, u)$$

## Theorem

*If* $\frac{\partial f}{\partial u}\Big|_{y_0} \neq 0$*, there exists a function* $g$ *and a new input* $v$ *in a neighbourhood of* $(y_0^{(n-1)}, \ldots, y_0^{(1)}, y_0)$ *such that:*

$$u = g(y^{(n-1)}, \ldots, y^{(1)}, y, v)$$

$$y^{(n)} + a_{n-1}y^{(n-1)} + \ldots + a_1 y^{(1)} + a_0 y = v = f(y^{(n-1)}, \ldots, y^{(1)}, y, u)$$

# Direct Feedback Linearisation Scheme

## New inputs

$$\begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} := \begin{bmatrix} \dot{y}_1 \\ \dot{y}_2 \\ \dot{y}_3 \end{bmatrix}$$

## Control signals

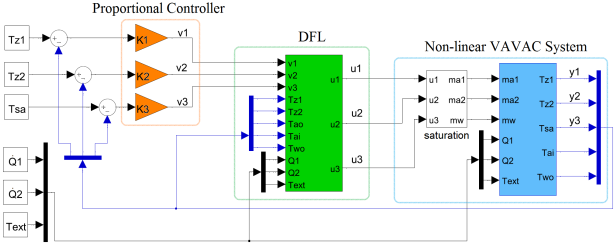
$$u_1 = \frac{v_1 - a_2 d_1 - a_3(d_3 - x_1)}{a_1(x_3 - x_1)}$$

$$u_2 = \frac{v_2 - b_2 d_2 - b_3(d_3 - x_2)}{b_1(x_3 - x_2)}$$

$$u_3 = \left[\frac{M_c C_{pc}}{(UA)_c} v_3 - \left(r\frac{x_1 u_1 + x_2 u_2}{u_1 + u_2} + (1 - r)d_3 - x_3\right)\right] \frac{C_{pa}(u_1 + u_2)}{C_{pw}(T_{wi} - x_4)}$$

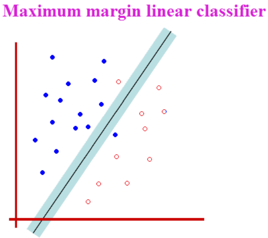
## Proportional controller

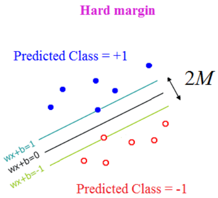
$$\begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} = \begin{bmatrix} k_1(y_{1,set} - y_1) \\ k_2(y_{2,set} - y_2) \\ k_3(y_{3,set} - y_3) \end{bmatrix}$$

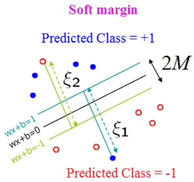


# Support Vector Machines

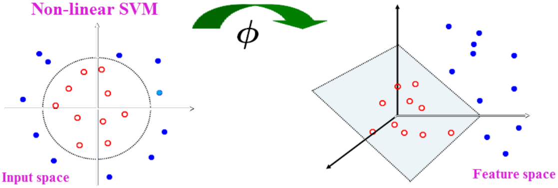
- Support Vector Machines (SVMs) perform classification by linearly separating data in two categories with maximum margin




$\{\xi_i\}$: slack variables



# SVMs Learning

## Objective function

$$\arg\min_{\mathbf{w},b} \frac{1}{2}||\mathbf{w}||^2 + C\sum_{i=1}^{n}\xi_i$$

subject to:

$$\xi_i \geq 0 \quad \mu_i f(\mathbf{x}_i) \geq 1 - \xi_i \quad \forall i$$

with

$$f(\mathbf{x}_i) = \mathbf{w}^T\phi(\mathbf{x}_i) + b$$

## Decision function

$$G(\mathbf{x}_i) = \operatorname{sign} f(\mathbf{x}_i)$$

## SVMs data and parameters

- $\{\mathbf{x}_i\}$: training samples
- $\{\mu_i\}$: training labels
  - fault-free condition: 1
  - faulty condition: -1
- $\{\xi_i\}$: slack variables
- $\mathbf{w}$, $b$: hyperplane parameters
- $\phi$: transformation function
- $C$: trade-off coefficient

## Kernel function

$$k(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T\phi(\mathbf{x}_j) = \exp\left(\frac{-||\mathbf{x}_i - \mathbf{x}_j||^2}{2\sigma}\right)$$

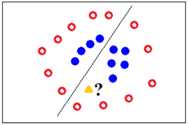
# SVMs Parameters Tuning

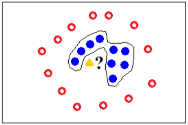
- SVMs performances depend on the setting of the parameters $C$ and $\sigma$
- The right trade-off between generalisation and representation performances is achieved by minimising the FDD error:

$$\arg\min_{C,\sigma} \frac{1}{n} \sum_{i=1}^{n} \mathcal{H}(-\mu_i f(\mathbf{x}_i))$$

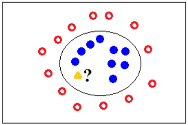
- $\mathcal{H}$ is the Heaviside step function

too simple





too complex

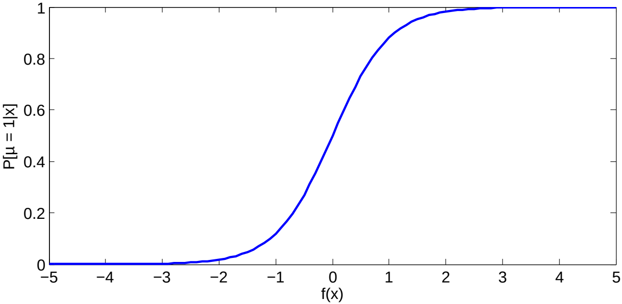


trade-off

# Posterior Probability

- Standard SVMs do not produce a posterior probability
- Platt's method, that maps the output of SVMs into a probability with a sigmoid function shape, is used:

$$P[\mu = 1|\mathbf{x}] \approx P_{A,B}(f) := \frac{1}{1 + \exp(Af(\mathbf{x}) + B)}$$



# SVMs Training and Validation

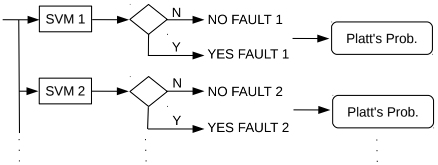
## Stationary normal/faulty data

- States
  - Supply cold air temperature
  - Air temperatures of the zones
  - Outlet water temperature of cooling coil
- Manipulated variables
  - Air mass flow rates in the zones
  - Chilled water mass flow rate
- Disturbances
  - Heat gains in the zones
  - External air temperature
- Other data
  - Recirculated air temperature
  - Mixed air temperature

## Faults and Affected Parameters

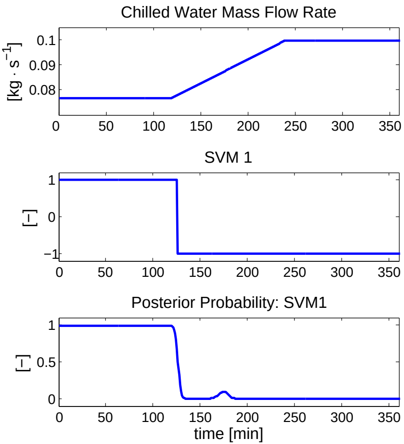
| Faults | Affected Parameters | SVM |
|---|---|---|
| stuck chilled water valve | chilled water mass flow rate | 1 |
| stuck damper zone 1 | air mass flow rate zone 1 | 2 |
| stuck damper zone 2 | air mass flow rate zone 2 | 3 |
| sensor zone 1 | temperature sensor offset zone 1 | 4 |
| sensor zone 2 | temperature sensor offset zone 2 | 5 |
| stuck recirculation damper | percentage of air recirculation | 6 |

## FDD structure

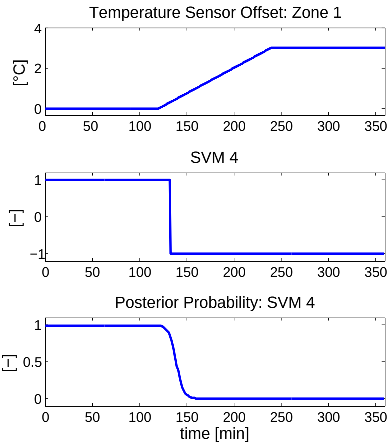


# FDD Examples

## Stuck Chilled Water Valve (+30%)




## Temperature Sensor Offset (+3°C).



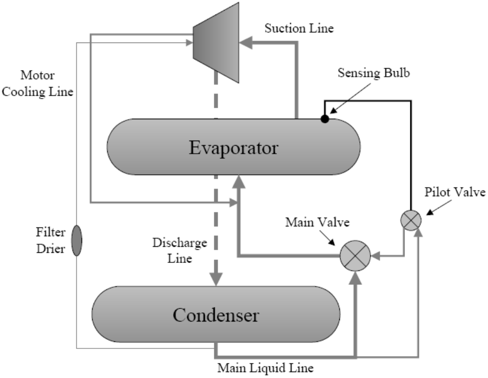
# ASHRAE Research Project 1043-RP

- In the 90s the American Society of Heating, Refrigerating and Air Conditioning Engineers (ASHRAE) performed experimental tests on a 316-kW centrifugal water-cooled chiller in order to produce a database of measurements in both normal and different faulty conditions
- The faulty conditions were tested at four levels of severity

| Fault Type with Symbol | Normal Operation | SL1 | SL2 | SL3 | SL4 |
|---|---|---|---|---|---|
| Reduced condenser water flow (fwc) | 264-270 gpm | 234-250 gpm | 209-219 gpm | 187-190 gpm | 159-166 gpm |
| Reduced evaporator water flow (fwe) | 214-216 gpm | 194-196 gpm | 175-177 gpm | 155-156 gpm | 137-141 gpm |
| Refrigerant leak (rl) | 300 Ibs | 270 lbs | 240 lbs | 210 lbs | 180 lbs |
| Refrigerant overcharge (ro) | 300 lbs | 330 lbs | 360 lbs | 390 lbs | 420 lbs |
| Excess oil (eo) | 22 lbs | 25 lbs | 29 lbs | 33 lbs | 37 lbs |
| Condenser fouling (cf) | 164 tubes | 144 tubes | 131 tubes | 115 tubes | 90 tubes |
| Non-condensables in refrigerant (nc) | 0% N | 1.0% N | 1.7% N | 2.4% N | 5.7% N |

# Features Selection

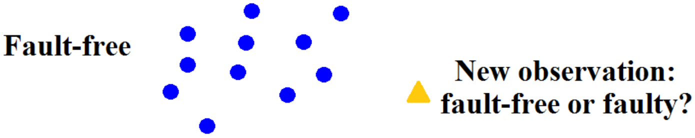
- A steady-state detector is employed in order to select the measurements in stationary conditions
- 15 characteristic features are deduced from the steady-state data using simple arithmetic operations




| Characteristic Features |
| --- |
| Evaporator Water Temperature Difference |
| Condenser Water Temperature Difference |
| Calculated Condenser Heat Rejection Rate |
| Calculated Evaporator Cooling Rate |
| Refrigerant Suction Superheat Temperature |
| Refrigerant Discharge Superheat Temperature |
| Liquid-line Refrigerant Subcooling from Condenser |
| Compressor Power |
| Calculated Compressor Efficiency |
| Evaporator Approach Temperature |
| Condenser Approach Temperature |
| Oil Feed minus Oil Vent Pressure |
| Oil in Sump minus Oil Feed Temperature |
| Pressure of Refrigerant in Evaporator |
| Pressure of Refrigerant in Condenser |

# Fault and Novelty Detection

- Fault detection can be seen as a novelty detection problem in which the faults are seen as novelties, i.e. events that have not been observed in the past
- A one-class classifier is developed to tackle the novelty detection problem: only data of one class (i.e. fault-free) are considered labeled and are used in the training phase
- Fault diagnosis can not be performed, since faulty data are not used during the training phase



# One-Class Support Vector Machines (OCSVMs)

- OCSVMs may be viewed as standard two-class SVMs where all the training data lie in the first class and only the origin is taken as member of the second class:

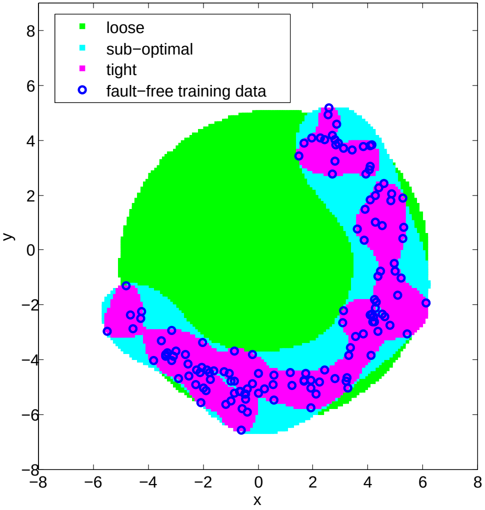
$$\underset{\mathbf{w},\xi,\rho}{\arg\min}\ \frac{1}{2}\|\mathbf{w}\|^2 + \frac{1}{\nu n}\sum_{i=1}^{n}\xi_i - \rho$$

$$\text{subject to} \quad \begin{cases} \langle \mathbf{w}, \Phi(\mathbf{x}_i)\rangle \geq \rho - \xi_i \\ \xi_i \geq 0 \end{cases}$$

- $\rho$ is the offset of the hyperplane in the feature space
- Since a radial basis function is used as kernel, an appropriate value for the Gaussian parameter $\sigma$ is required: the *tightness detecting* algorithm is used to choose $\sigma$

# *Tightness Detecting* Algorithm: Example

- The magenta boundaries are considered tight, enhancing representation properties
- The green boundaries are considered loose, enhancing generalisation properties
- The cyan boundaries are considered sub-optimal, i.e. neither loose nor tight, and they are the output result of the *tightness detecting* algorithm



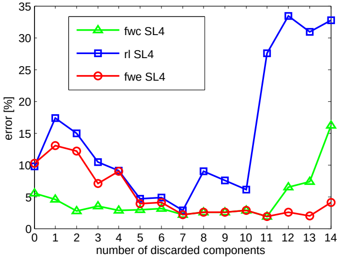
# Experimental Settings

- Principal component analysis is applied on the $d = 15$ characteristic features in fault-free behaviour, thus concentrating most of the variability in the first principal components
- The principal components $\{\mathbf{p}_j\}$ of the fault-free data are fed to the one-class classifier in order to characterize the correct behaviour of the system
- Different classifiers are computed by changing the training input space:
  - Input spaces $\{U_i\}$ with $U_i = [\mathbf{p}_{i+1} \dots \mathbf{p}_d]$, for $i = 0, \dots, d-1$
  - Input spaces $\{V_i\}$ with $V_i = [\mathbf{p}_1 \dots \mathbf{p}_{d-i}]$, for $i = 0, \dots, d-1$
- The computed classifiers are tested on new data in fault-free and faulty conditions

# Classifiers Error Rates with Different Input Spaces

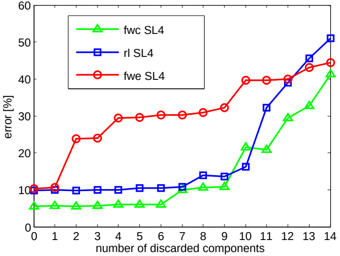
## Classifier input: $\{U_i\}$

The abscissa represents the number of discarded principal components, from the **first** to the **last** one. The minimum error is never achieved with the first components included




## Classifier input: $\{V_i\}$

The abscissa represents the number of discarded principal components, from the **last** to the **first** one. The error increases as the number of discarded components is augmented




- If the **first** seven principal components are discarded the lower classification error rate is obtained

# Faults and Principal Components

- First principal components are not informative in a novelty detection perspective
- First components exhibit normal variability due to changes in operating points and they contain information that does not change when an anomaly occurs
- They add useless information and complexity to the one-class classification problem, concealing the interesting changes associated to novelties
- Last principal components are strongly informative for novelty detection

# Classification Performances

## Positive and negative data

- Positive data: in fault-free conditions
- Negative data: in faulty conditions

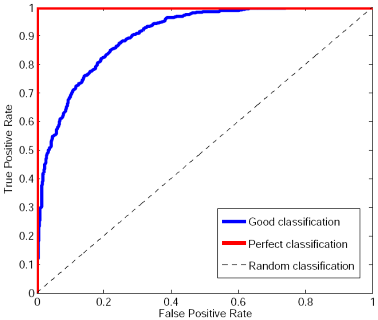
## Classification results for positives and negatives

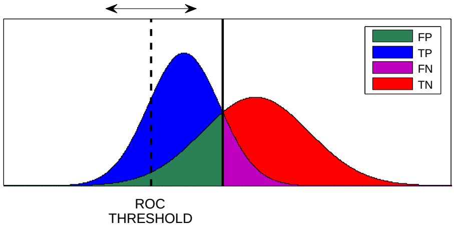
- True Positives (TP)
- False Positives (FP)
- True Negatives (TN)
- False Negatives (FN)

## Classification parameters

- True Positive Rate $= \frac{TP}{TP+FN}$
- True Negative Rate $= \frac{TN}{FP+TN}$
- Positive Predictive Value $= \frac{TP}{TP+FP}$
- Negative Predictive Value $= \frac{TN}{TN+FN}$
- False Positive Rate $= \frac{FP}{TN+FP}$
- False Negative Rate $= \frac{FN}{TP+FN}$

# Classification Performances: ROC Analysis

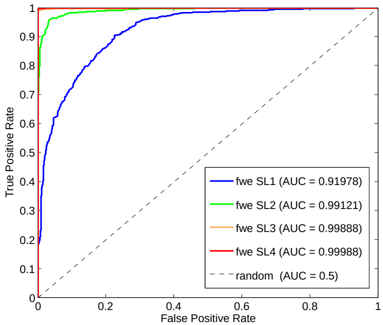


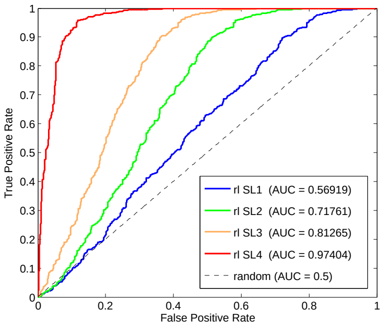

- A Receiver Operating Characteristic (ROC) curve is created by plotting the True Positive Rate and the False Positive Rate, for a range of different thresholds
- The corresponding Area Under the ROC Curve (AUC) is an indicator of the classifier performances

# ROC Analysis: Examples

## Reduced evaporator water flow




## Refrigerant leak




- All the ROC curves are above the diagonal representing a good classification result (better than random classification) and the classification score increases quickly as the severity level raises

# Conclusions and Future Works

## Conclusions

- HVAC systems maintenance and energy efficiency can be increased by adopting fault detection methods
- A two-zone, single-duct VAVAC system model is developed
- Two-class classification methods are used in order to detect and diagnose the simulated faults in the VAVAC model
- A novelty detection approach is used to identify anomalous situations in chiller systems with the help of a one-class classifier
- The one-class classification is shown to be effective in the detection of the most common faults affecting chiller systems

## Future Works

- Automatic faults labelling methods for novelty detection
- Multi-fault algorithms

# Publications


- A. Beghi, L. Cecchinato, L. Corso, M. Rampazzo, and F. Simmini. Process History-Based Fault Detection and Diagnosis for VAVAC Systems. In *IEEE International Conference on Control Applications (CCA), Part of the IEEE Multi-Conference on Systems and Control (MSC)*, 2013
- A. Beghi, L. Cecchinato, C. Corazzol, M. Rampazzo, F. Simmini, and G.A. Susto. A One-Class SVM Based Tool for Machine Learning Novelty Detection in HVAC Chiller Systems. In *19th IFAC World Congress*, 2014

Thank you for your attention!

# Energy Efficient Control and Fault Detection for HVAC Systems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