ICT for Building Design: Energy Modelling and Characterization

POLITECNICO
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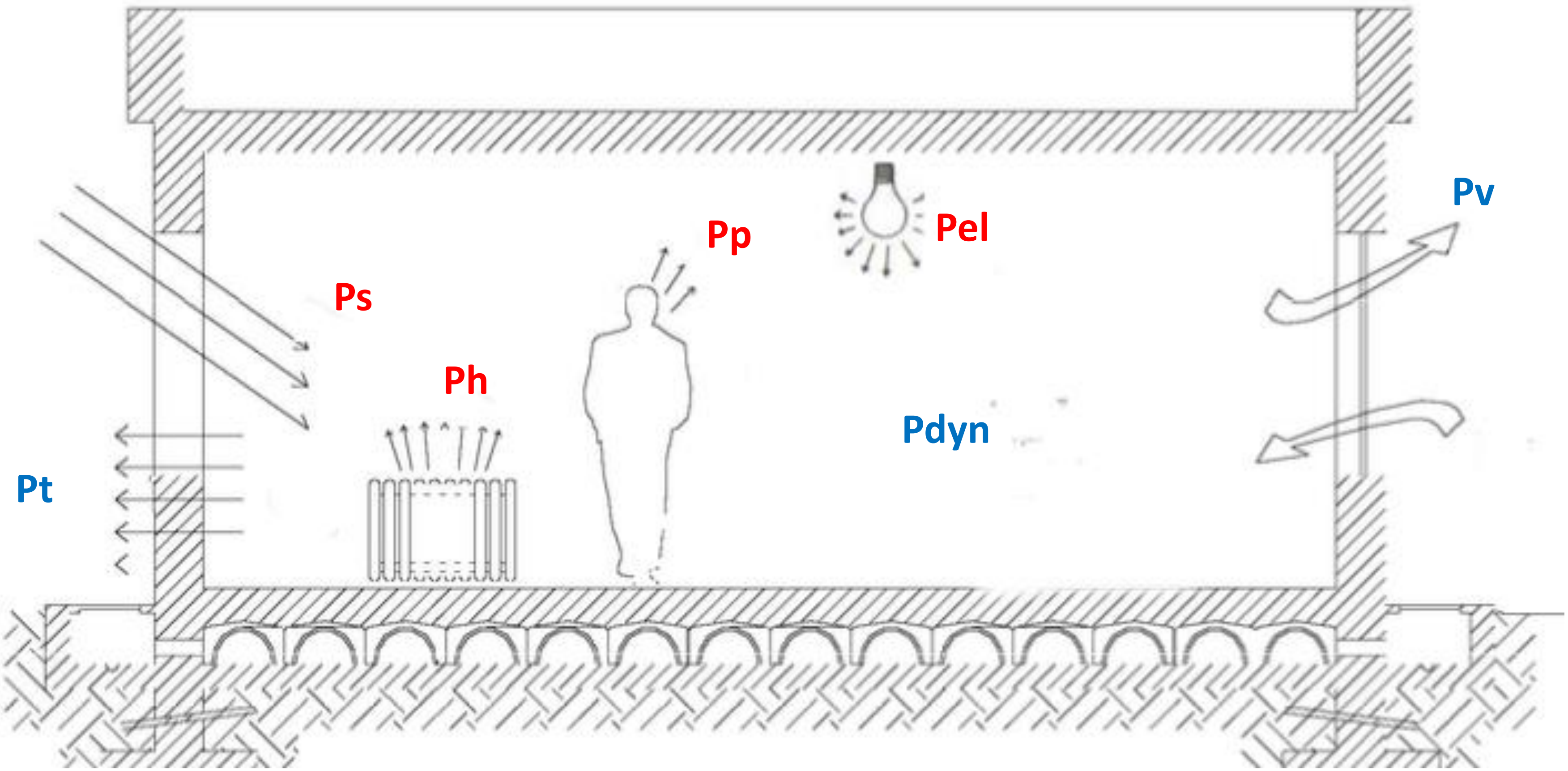
Ploss = Psup

Energy Balance single zone



Ploss = Psup

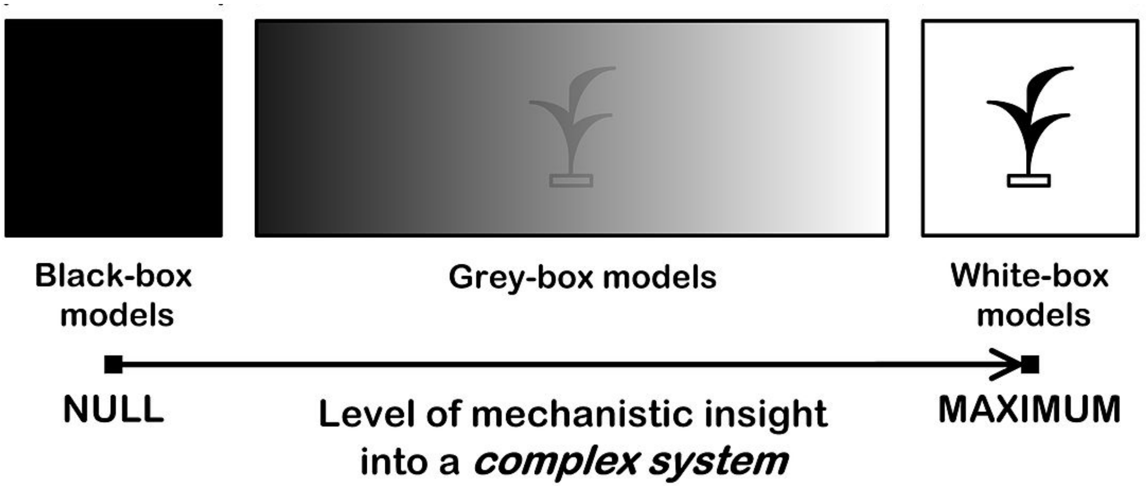
$$P_{sup} = P_h + P_p + \alpha P_{el} + P_{sol}$$

$$P_{loss} = P_v + P_t + P_{dyn}$$

$$P_v + P_t + P_{dyn} = P_h + P_p + \alpha P_{el} + P_{sol} + P_{hw}$$

- White box
- Black box
- Grey Box

- White box
- Black box
- Grey Box



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- Linear models are used to capture macro characteristics of buildings
- Non-Linear models are used for both macro characteristics and dynamics characterization (e.g. temperature envelopes)

Which models should be used in an energy consumption prediction framework?

Which models should be used in an energy consumption prediction framework?

A rule of thumb: if enough building knowledge is available to describe the set of heat transmission, heat storage and heat flux, and the corresponding parameters with physical significance, then these can be described by fundamental physical principles.

Type	Example	Application
Static linear equations	$q = L(T - T_a) - A_s I + \varepsilon$ $\dot{q}_{21} = h\,A \cdot (T_2 - T_1)$	Transmission through component

q : Power (W); L: Coefficient of static losses (W/°C); $T_2 - T_1$: Difference between indoor and outdoor temperature (°C); A_s : Equivalent surface (m^2); I : Solar energy received by a vertical wall (W/m^2), ε : Depends by the state of variables measured at the beginning and end of the period observational (W).

$\dot{q}_{21}$: Heat transfer coefficient (W) $T_2 - T_1$: Difference between the boundary and ambient temperature (°C); h: Convective heat transfer coefficient (W/m$^2\cdot$°C) and A: heat transfer area of the surface (m^2).

Type	Example	Application
Static nonlinear equations	$\dot{q}_{21} = \varepsilon \cdot \sigma \cdot A \cdot (T_2^4 - T_1^4)$	Building simulation radiation exchange (walls and ceilings)

$\dot{q}_{21}$: Emitted heat transfer rate (W); ε : Surface emissivity; σ : Stefan-Boltzmann constant (5.669×10^{-8} m^{2}K^4) A: Radiation surface.

Type	Example	Application
Dynamic linear equation Ordinary differential equation	$C \cdot \frac{dT}{dt} = U \cdot (T - T_a)$ Heat storage	Passive/active Energy storage

C : Thermal capacity (J/°C)

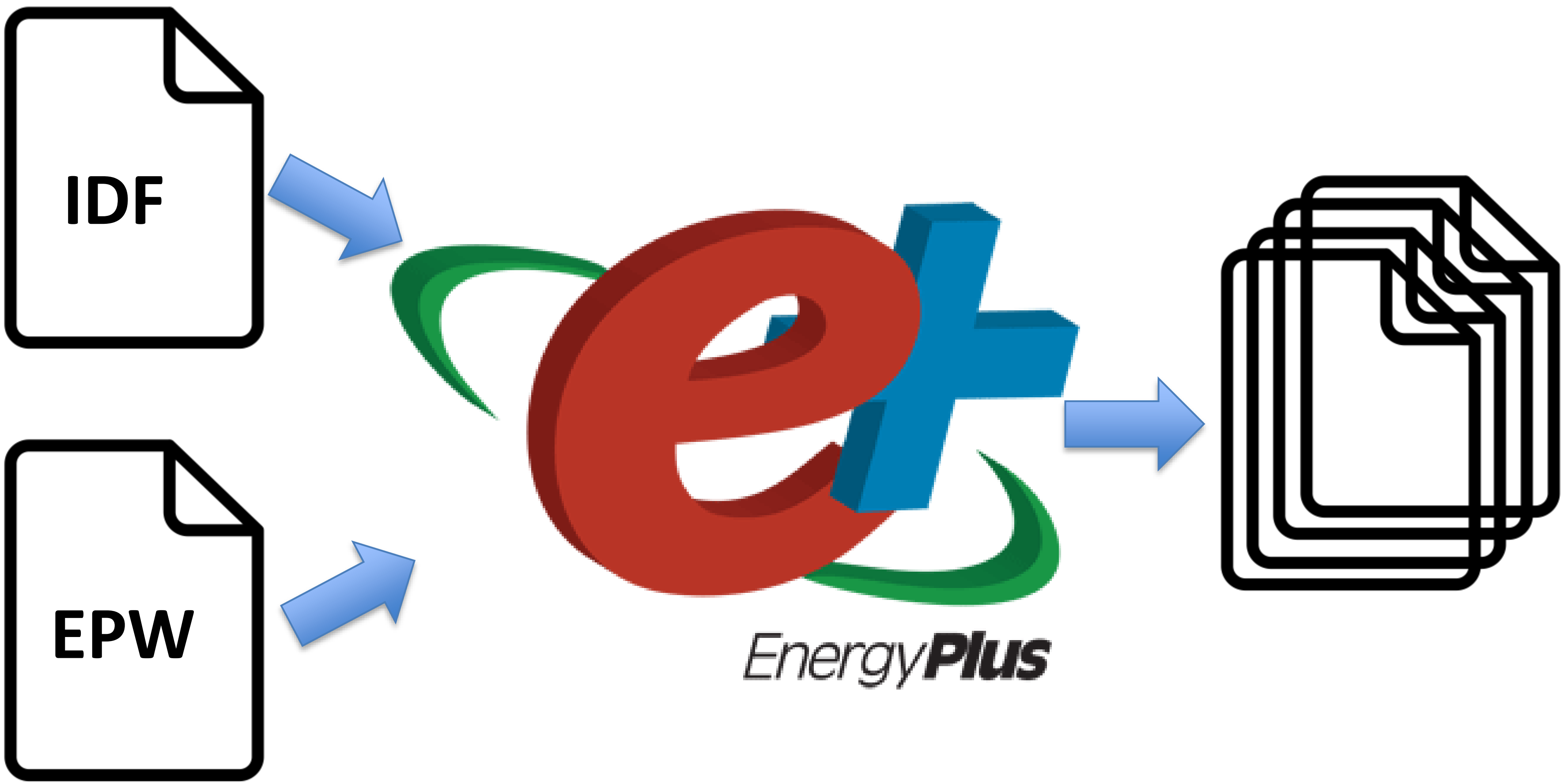
Type	Example	Application
Dynamic linear equation Partial linear	$\frac{\partial}{\partial t} u(x,t) = a \frac{\partial^2}{\partial t^2} u(x,t)$ Heat conduction equation	Dynamic heat flux

$u(x,t)$: Temperature at position x and time (t) and a: Thermal conductivity (W m$^{-1}\cdot$°C)

The complexity of white-box modeling depends mainly on the chosen precision levels of the known phe-nomena associated with the building system to be modeled.

The parameters of white-box models have physical significance (e.g. thermal conductivities of certain materials)

Fundamental physical principles are used, there are always errors associated with random variables that are not represented in the known parameters (e.g. window openings and air exchange rates in natural ventilation)


IDF
EPW
EnergyPlus

Black Box Models

Type of model	Model structure	Parameter estimation	Example
	Static		
Linearly	Linear function	Linear regression (Least Squares method)	Energy signature of weekly values
Nonlinear	Polynomials Any nonlinear function	Linear regression (Least Squares Method) Iterative process, Levenberg Marquardt	Pump curve
	Dynamic		
Linearly	Transfer functions models (ARMA, ARMAX, etc.)	Linear regression (least square method), an iterative procedure	Heat flow through a plane wall
Nonlinear	Neural Networks (sigmoid, wavelet, radial basis networks)	Damped Gauss-Newton backpropagation	Arbitrary non-linear systems
	Polynomials (Wiener /Hammerstein model, Volterra model)	Linear regression (least squares method)	Linear system with static nonlinearities at the input or output (control element with saturation behavior)

In the black-box, the parameters are generally adjusted automatically. This automatic adjustment of calibration of black-box parameters provides the greatest benefit over white-box models.

However, a disadvantage is their implicit relationship with physical fundamental principles. Indeed, black-box model identification is found to be inconsistent with physical reality when applied under hard conditions (little building system data)

Therefore, black-box models are mainly used for error detection, but not for the optimization. Their advantage is the rapid and automated identification of outputs of thermal energy building consumption. With respect to the model internal structure of black-box models it can be static and dynamic, linear and nonlinear models, just as the white-box models.

Grey-box models are therefore mixed or transitional forms of white-box and black-box models.

Definition 1 (type of parameters)
Grey-box parameters are both empirical and have a physical significance.

Grey-box models

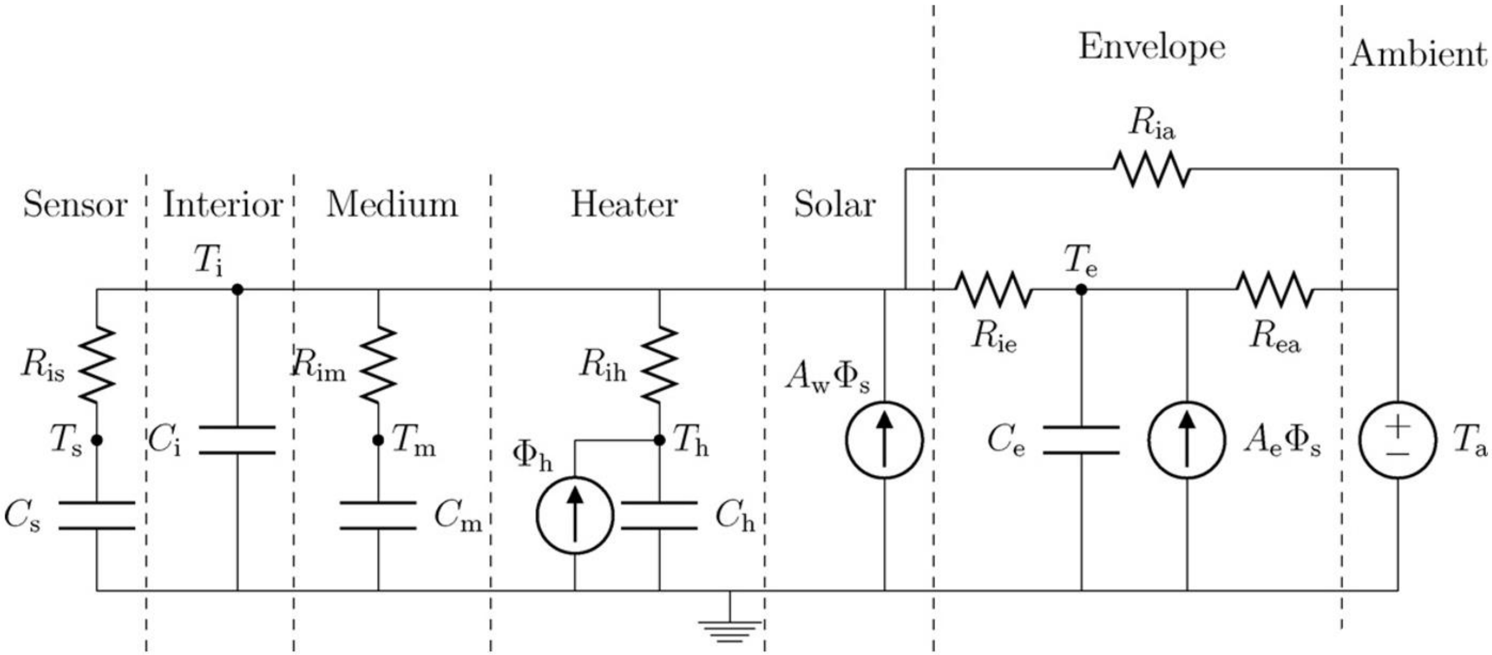
Definition 2 (determination of the parameters)
Grey-box models are characterized by the fact that all their parameters or a part of them are determined on the basis of measured data of real system

Comparison of Modelling Approaches

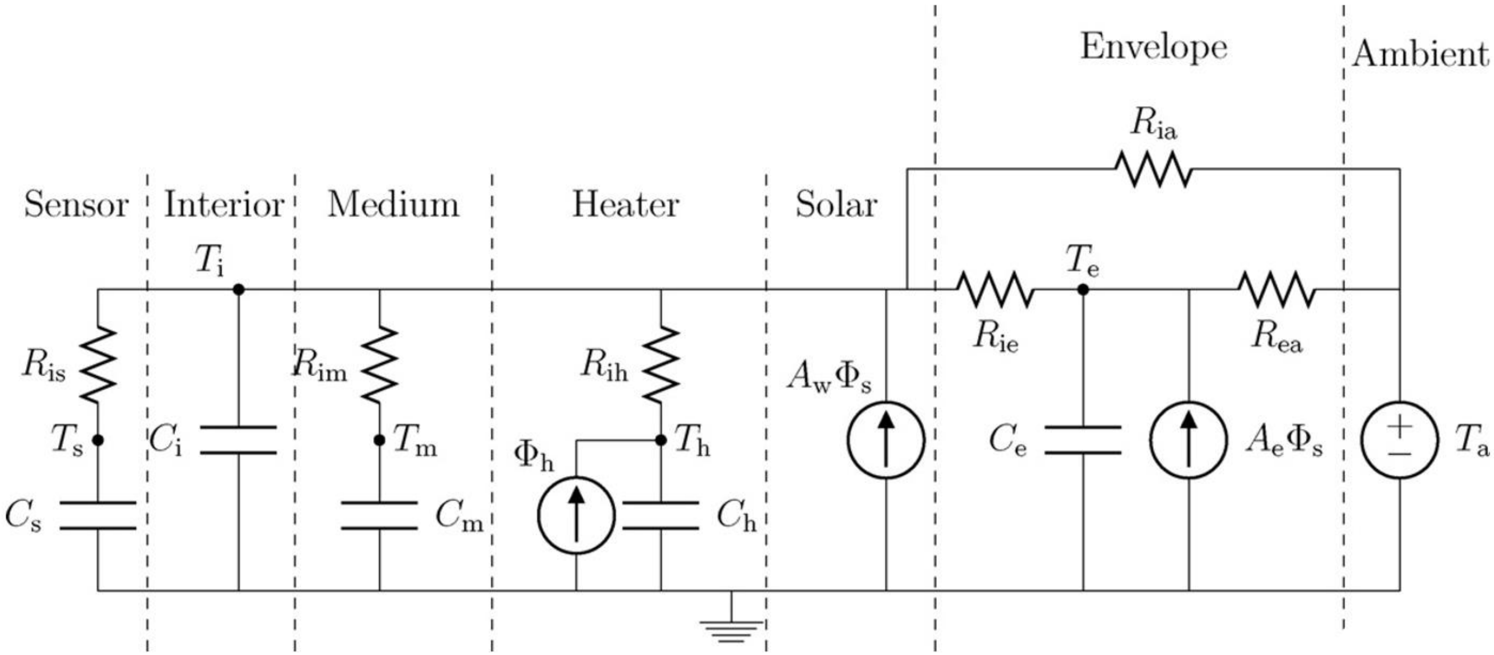
	White-Box	Grey-Box	Black-Box
Internal structure of the model	+	0	−
Number of parameters Source of error	−	0	+
Formulation of the model	+ −	+ 0	+
Processing speed	+ 0	+ 0	+
Required training data	+	0 −	−
Calibration effort	+ −	+ −	+
Extrapolation	+	0	−
Suitable for optimization	+	0	−
Parameters physical meaning	+	+ −	−
Formulation system equations	+ −	+ 0	+

(+) Advantages
(−) Drawbacks
(0) Not available

A possible Grey Box model can be build from the RC representation of the heating dynamic of a building



Lumped Thermal Model 6R5C



$$dT_s = \frac{1}{R_{is}C_s}(T_i - T_s)dt$$

$$dT_i = \frac{1}{R_{is}C_i}(T_s - T_i)dt + \frac{1}{R_{im}C_i}(T_m - T_i)dt + \frac{1}{R_{ih}C_i}(T_h - T_i)$$

$$\frac{1}{R_{ie}C_i}(T_e - T_i)dt + \frac{1}{R_{ia}C_i}(T_a - T_i)dt + \frac{1}{C_i}A_w\Phi_s dt$$

$$dT_h = \frac{1}{R_{ih}C_h}(T_i - T_h)dt + \frac{1}{C_h}\Phi_h dt$$

$$dT_m = \frac{1}{R_{im}C_m}(T_i - T_m)dt$$

$$dT_e = \frac{1}{R_{ie}C_e}(T_i - T_e)dt + \frac{1}{R_{ea}C_e}(T_a - T_e)dt + \frac{1}{C_e}A_e\Phi_s dt$$

As described in Annex B of the International Standard EN ISO 15603:2008, the Energy Signature is an evaluation method in which energy consumption is correlated with climatic variables aimed at representing the actual energy behaviour of the building

The energy signature method (Fels, 1986; Hammarsten, 1987) is either of single or multivariate type. The single-variate model depends on temperatures while multi-variate versions commonly add solar irradiation as the second regressor variable.

When using the energy signature method it is common to measure the energy use in the building and plot the observations in a power versus temperature difference graph.

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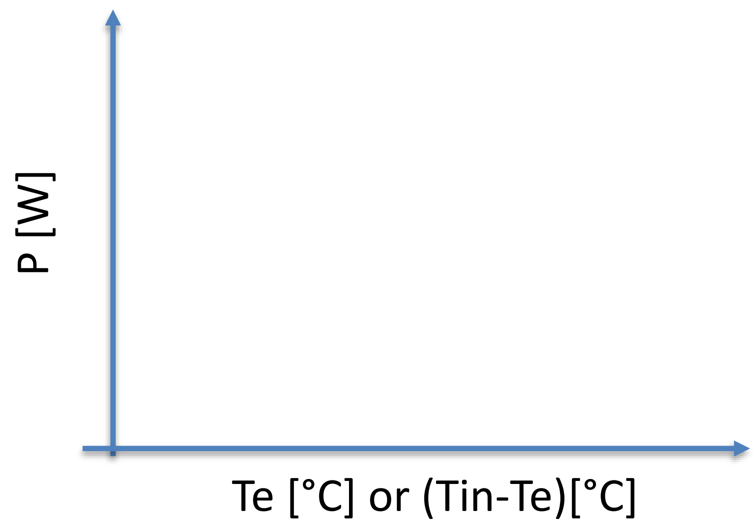

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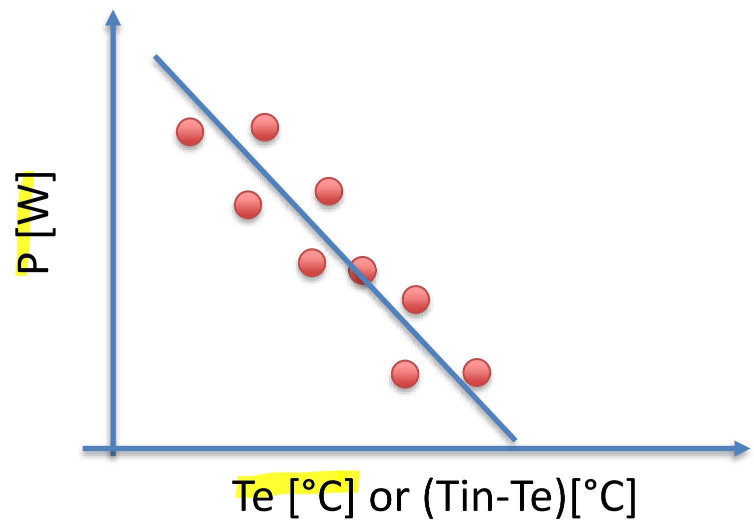


$$P_v + P_t + P_{dyn} = P_h + P_p + \alpha P_{el} + P_{sol}$$

With high frequency data we see all non linear effects of the building heating dynamics

Hourly or sub−hourly data is affected by environmental variables and intrinsic characteristics of the components (for example, thermal capacity).

Daily mean data provides detailed information but could be influenced by any climatic variables and requires a “heavy” monitoring activity;

Weekly mean data provides a good approximation of the energy behaviour of a building by mediating any anomalous climatic conditions and requiring a "light" monitoring.

Monthly mean data can be used for a very simplified assessment, for example to compare the consumption of different years. These data give little information on the building behaviour.

$$\cancelto{\sim 0}{Pv} + Pt + \cancelto{0}{Pdyn} = Ph + \cancelto{0}{Pp} + \cancelto{0}{\alpha Pel} + \cancelto{0}{Psol}$$

$$\underbrace{\cancel{Pv}}_{\sim 0} + Pt + \underbrace{\cancel{Pdyn}}_{0} = Ph + \underbrace{\cancel{Pp}}_{0} + \alpha \underbrace{\cancel{Pel}}_{0} + \underbrace{\cancel{Psol}}_{0}$$

Psup = Ploss

Energy signature

$$\cancelto{\sim 0}{Pv} + Pt + \cancelto{0}{Pdyn} = Ph + \cancelto{0}{Pp} + \alpha \cancelto{0}{Pel} + \cancelto{0}{Psol}$$

Psup = Ploss

Psup = K (Ti-Te)

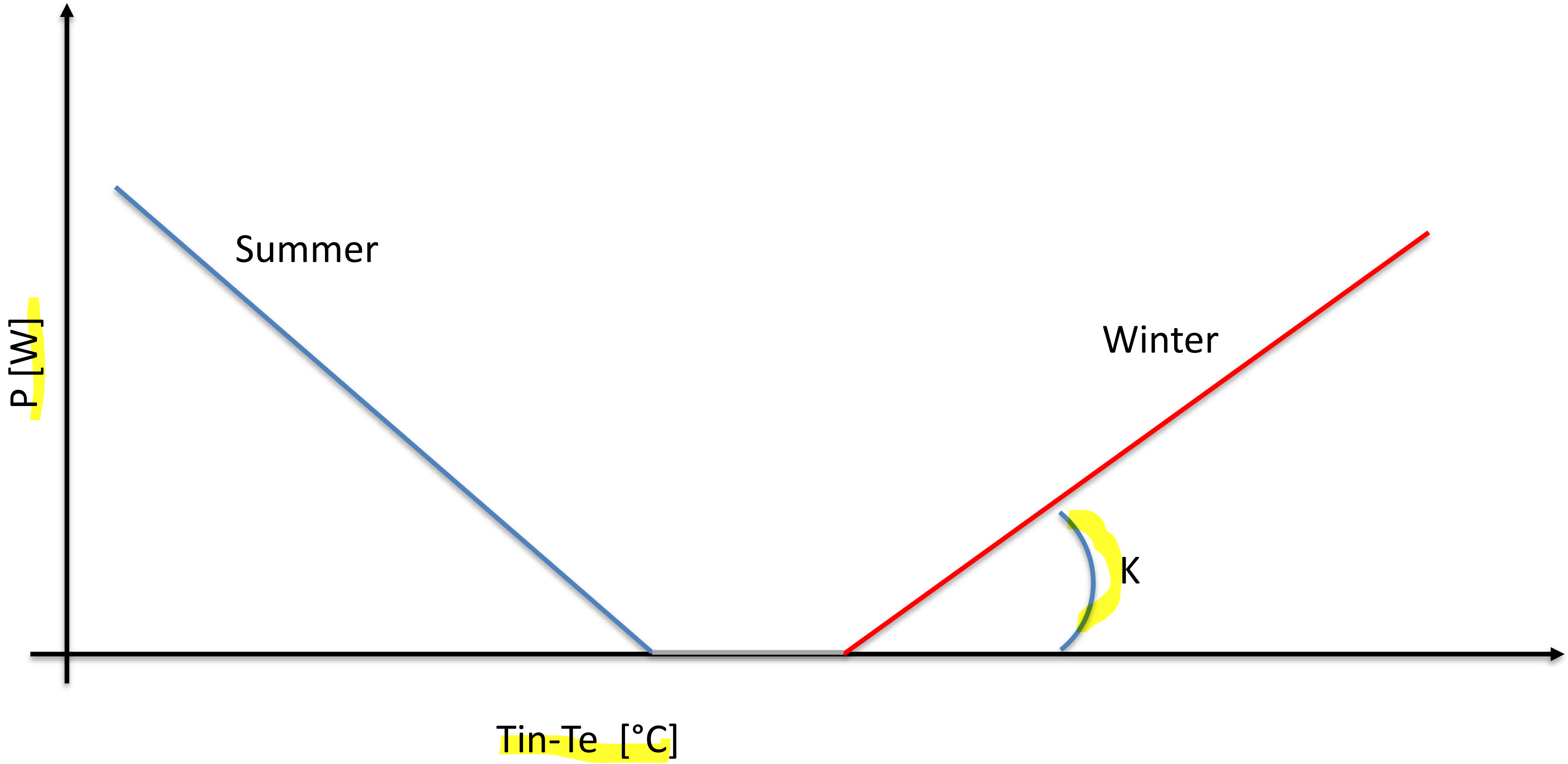
Energy signature

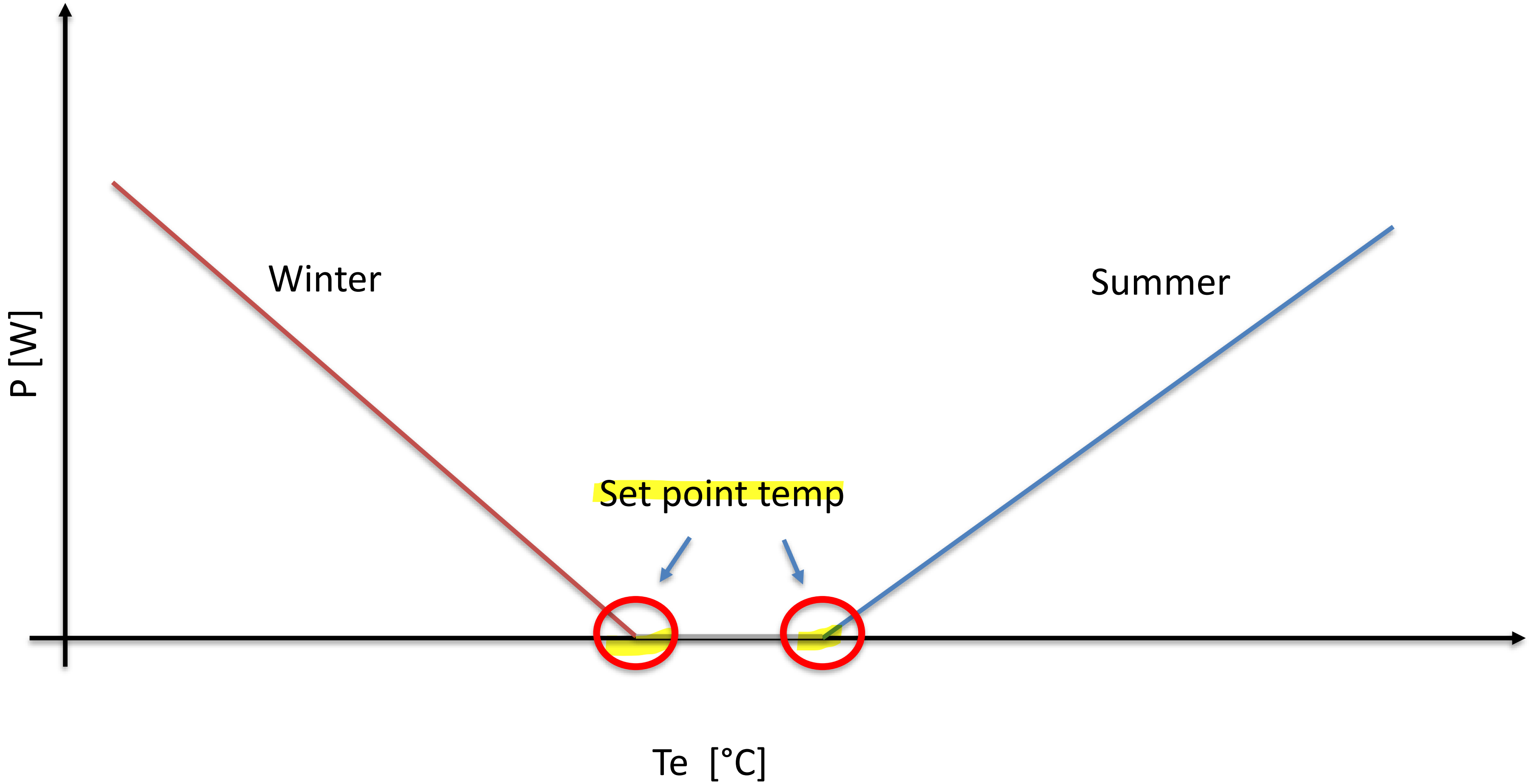
$$\cancelto{\sim 0}{Pv} + Pt + \cancelto{0}{Pdyn} = Ph + \cancelto{0}{Pp} + \alpha \cancelto{0}{Pel} + \cancelto{0}{Psol}$$

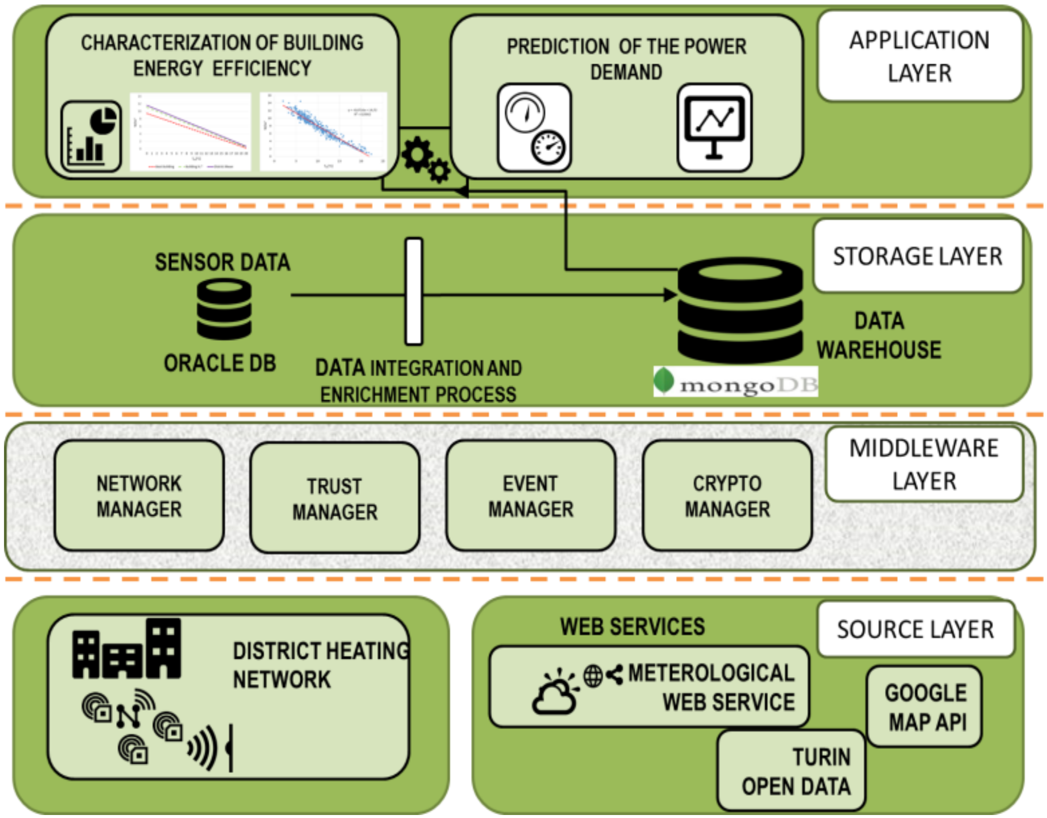
Psup = Ploss

Psup = K (Ti-Te)

The therm K represents the Heat loss factor [W/°K]


Summer
Winter
P [W]
K
Tin-Te [°C]


P [W]
Winter
Summer
Set point temp
Te [°C]

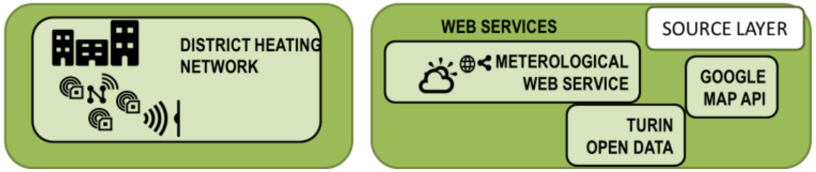


Analyzes the collected data through a MapReduce algorithm and provides feedbacks to the users

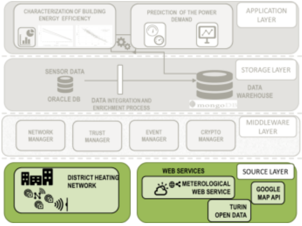
Integrates and enriches data and stores them into a distributed non-relational database.

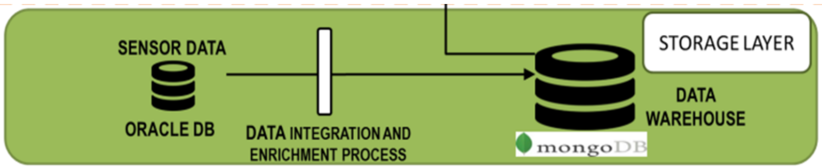
Provides encrypted communications across heterogeneous data sources

Includes objects providing data to the system.



- **Smart meters** installed into buildings
  - *instantaneous power, cumulative energy consumption, water flows and temperatures, indoor temperature,…*
  - *data forwarded to the Storage Layer every 5 minutes*
- **Weather Underground web service** (more than 20 PWS in Turin)
  - *Historical weather information: air temperature, relative humidity, precipitation level, wind speed and sea level atmospheric pressure*
- **Google Maps APIs** for addresses geocoding

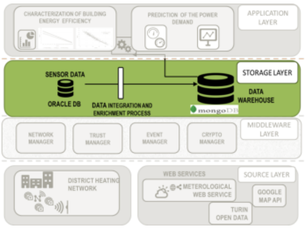




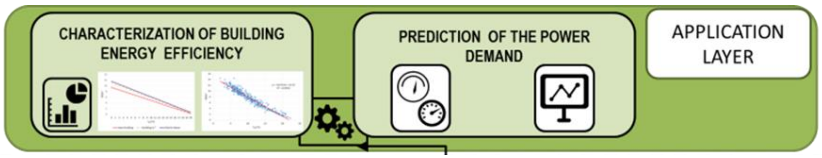
1. Process data collected by smart meters and store them in an **Oracle relational database**

2. **Enrich data** with contextual and topological features

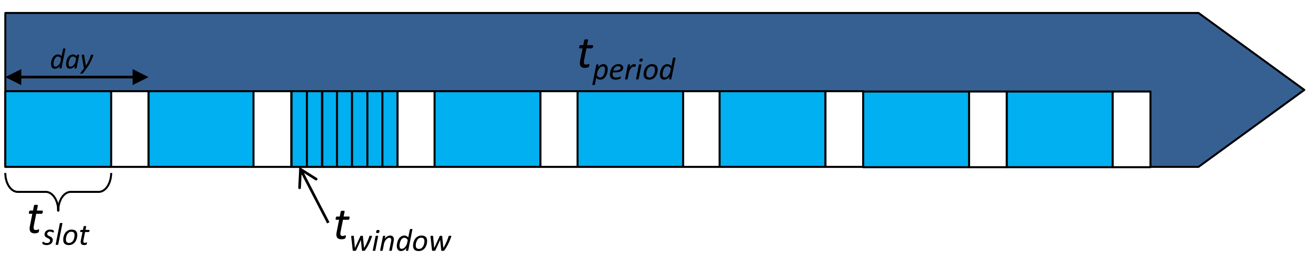
3. Store enriched data into a non-relational distributed database (**MongoDB**)

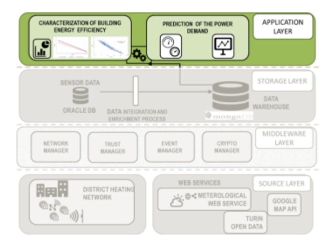


Application layer



- Provide different services to users (like energy signature analysis) to **evaluate building efficiency** and forecast the future power demand
  - variable data range (t_{period}) and in specific day time slots (t_{slot})
  - power consumption per unit of volume vs $T_{in} - T_{out}$
    - *Samples aggregated (mean values) at different granularity levels (t_{window})*





Energy efficiency indicators: comparative KPIs

- ***Intra-building KPI*** compares latest observations with past energy demand in the same conditions
  - outdoor temperature (T_{ex}) and indoor temperature (T_{in})

- ***Inter-building KPI*** ranks the overall building performance with respect to nearby and similarly characterized buildings
  - spatial co-location, building size, usage patterns (residential, office, public building,…)

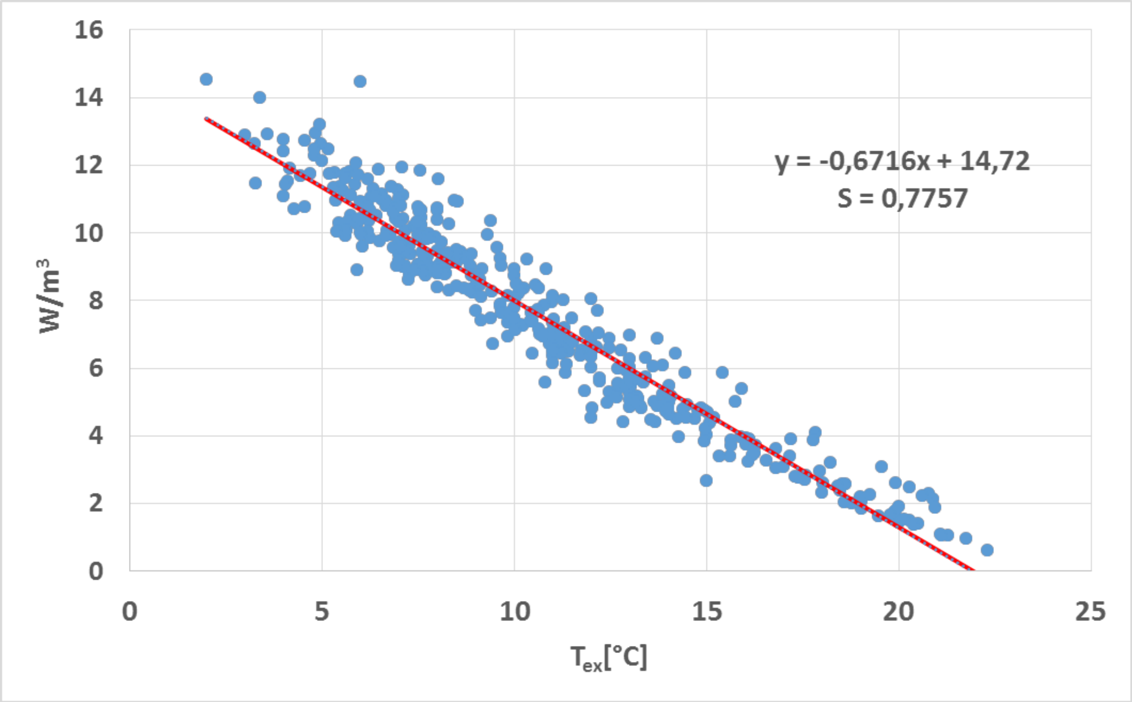
Heat loss coefficient estimated through a **MapReduce algorithm**

- The algorithm is executed for each building
- The **Map** function distributes data among computing nodes (shards)
- The **Reduce** function receives a portion of the data and computes summations over all the records of the same building (parallel section)
- A **Finalize** function uses the aggregated output of the Reduce phase to compute the *total heat loss coefficient* and the *Energy Signature equation*

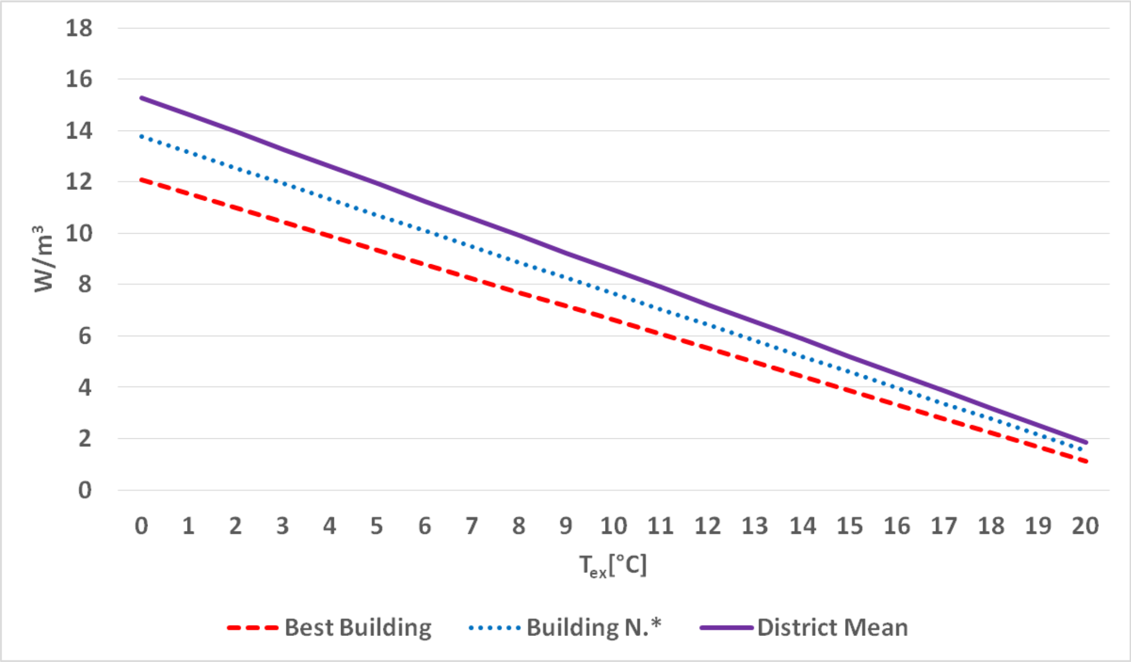
- Experiments on real data collected
  - *From 4,000 smart meters in Turin (Italy)*
  - *Over a three years (2012-2014) period*
  - *With samples every 5 minutes*
- Size of the database in MongoDB : ~ 300 GB

- <u>Three addressed issues</u>
  - the characterization of energy signatures
  - the sensitivity and robustness of the method
  - the horizontal scalability of the analytic system wrt the number of nodes

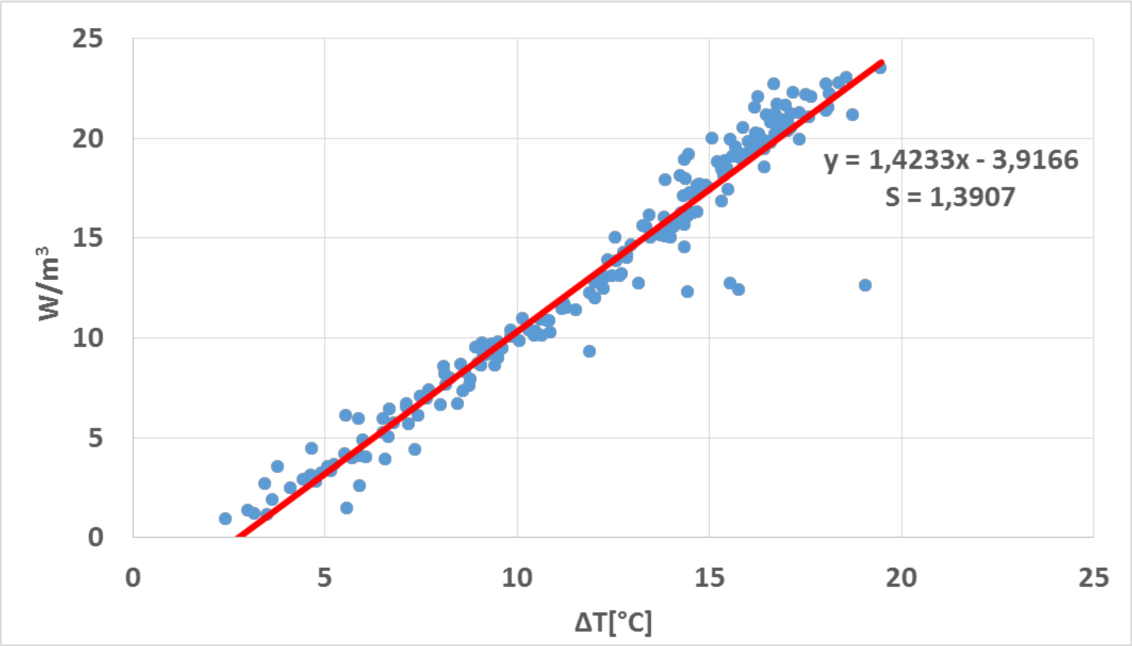
Single residential building (*scatter plot*)



Compared residential buildings (*linear regression*)



School building (*scatter plot*)



Standard error of regression

$$S = \sqrt{\frac{1}{(n-2)}\left[\sum (y-\bar{y})^2 - \frac{[\sum (x-\bar{x})(y-\bar{y})]^2}{\sum (x-\bar{x})^2}\right]}$$

		Best Building		Building N.*		District Mean
t_{window}	t_{slot}	K_{tot}	S	K_{tot}	S	K_{tot}
Weekly	6:00am-10:00pm	0.46	0.35	0.53	0.47	0.55
Weekly	5:00-7:00pm	0.51	0.67	0.72	0.55	0.74
Weekly	5:00-9:00pm	0.54	0.57	0.68	0.68	0.68
Daily	6:00am-10:00pm	0.46	0.64	0.53	0.55	0.54
Daily	5:00-7:00pm	0.53	1.02	0.72	0.90	0.73
Daily	5:00-9:00pm	0.55	0.62	0.67	0.77	0.67
Hourly	6:00am-10:00pm	0.36	4.61	0.49	7.41	0.51
Hourly	5:00-7:00pm	0.52	1.16	0.71	0.88	0.73
Hourly	5:00-9:00pm	0.53	1.11	0.64	2.38	0.64

Overall, the longer the t_{window} the more accurate the linear regression

What is a Typical Meteorological Year (TMY)?

A typical meteorological year (TMY) is a set of meteorological data with data values for every hour in a year for a given geographical location. The data are selected from hourly data in a longer time period (normally 10 years or more). For each month in the year the data have been selected from the year that was considered most "typical" for that month.

How it is calculated?

The solar radiation data used for the TMY have been calculated from satellite data by the CM SAF collaboration (www.cmsaf.eu). All other data have been taken from the ECMWF ERA-interim reanalysis (www.ecmwf.int). Air temperature data have been corrected for elevation. The selection of the months for the TMY is done using the method described in the international Standard ISO 15927-4. The selection is done based on air temperature, global horizontal irradiance and relative humidity.

What can it be used for?

TMY data are used in many fields to perform calculations that need meteorological data, and where a calculation involving many years would be too time-consuming. One example is the EnergyPlus software for calculating the energy performance of buildings. You can choose output in the EPW format needed for EnergyPlus or a generic CSV format.

What are the main columns of EPW file?

- *Dry Bulb Temperature [°C]*
- *Dew Point Temperature [°C]*
- *Relative Humidity [%]*
- *Atmospheric Station Pressure [Pa]*
- *Global Horizontal Radiation [Wh/m2]*
- *Direct Normal Radiation [Wh/m2]*
- *Diffuse Horizontal Radiation [Wh/m2]*
- *Wind Direction [° deg]*
- *Wind Speed [m/s]*

Where can we find Meteorological data?

Many web site offers meterological data such as:

Weather undergound

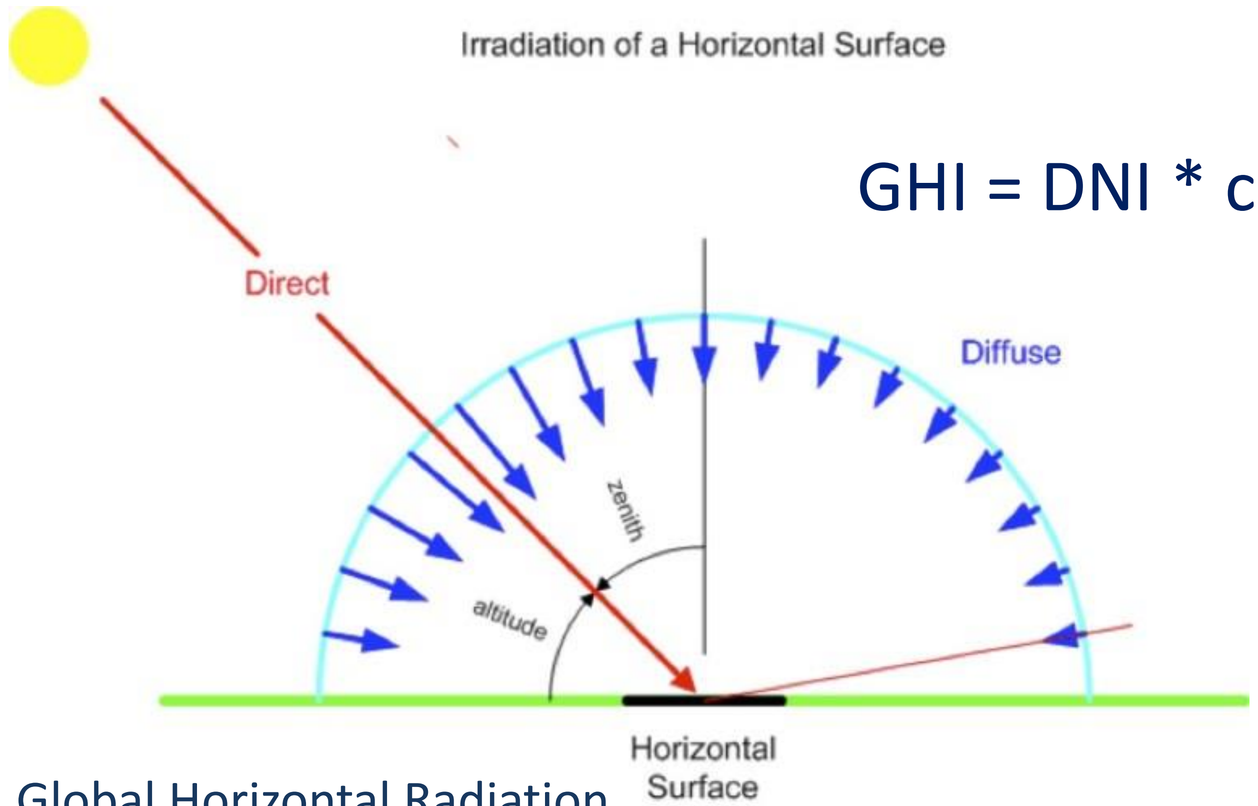
Open weather maps

Dark Sky

Meterological Data

https://www.wunderground.com/dashboard/pws/IPIEMONT220

https://www.wunderground.com/dashboard/pws/IPIEMONT220/graph/2020-11-3/2020-11-3/daily



$$GHI = DNI * \cos(\Theta_z) + DHI + RI$$

GHI Global Horizontal Radiation

DNI Direct Normal Incident Radiation

DHI Diffuse Horizontal Incident Radiation

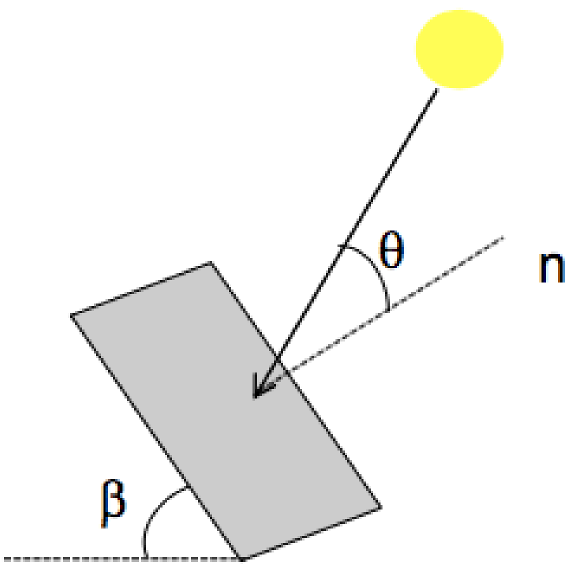
RI Reflected radiation

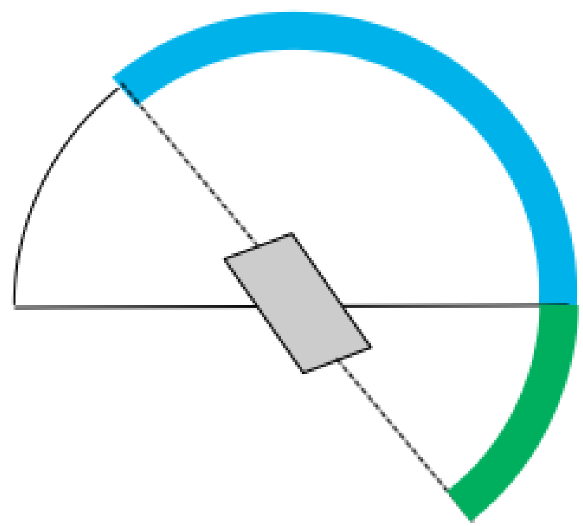
Θ_z Zenith Angle

Solar Radiation

$$G = G_{bn}\cos\theta + G_{dh}F_{sc} + \rho G_{th}\left(1 - F_{sc}\right)$$

Direct **Diffuse** **Reflected**





$$F_{sc} = \frac{1+\cos\beta}{2}$$

$$F_{st} = \frac{1-\cos\beta}{2} = 1 - F_{sc}$$

Solar Radiation Decomposition models are data driven model that can be used to estimate DHI from GHI.

They use the clearness index k_t as predictor and the diffuse fraction k_d.

k_t is the ratio between global radiation and extraterrestrial radiation both on a horizontal pelane.

k_d is the ration between DHI and GHI

Erbs Decomposition Model

This model was developed from data collected at five stations in the USA at latitudes between 31° and 42° N.

$$k_d = 1 - 0.09k_t : (k_t < 0.22)$$

$$k_d = 0.9511 - 0.1604k_t + 4.388k_t^2 - 16.638k_t^3 + 12.336k_t^4 : (0.22 < k_t \leq 0.8)$$

$$k_d = 0.165 : (k_t > 0.8)$$

Reindl et al. Decomposition Model 1

This model was developed from data collected at five stations in the USA and Europe.

$$k_d = 1.02 - 0.248k_t : (k_t \leq 0.3)$$

$$k_d = 1.45 - 1.67k_t : (0.3 < k_t < 0.78)$$

$$k_d = 0.147 : (k_t \geq 0.78)$$

Orgill and Hollands Decomposition Model

This model was developed from data collected in Toronto, Canada

$$k_d = 1 - 0.24k_t : (k_t < 0.35)$$

$$k_d = 1.577 - 1.84k_t : (0.35 \leq k_t < 0.75)$$

$$k_d = 0.177 : (k_t > 0.75)$$

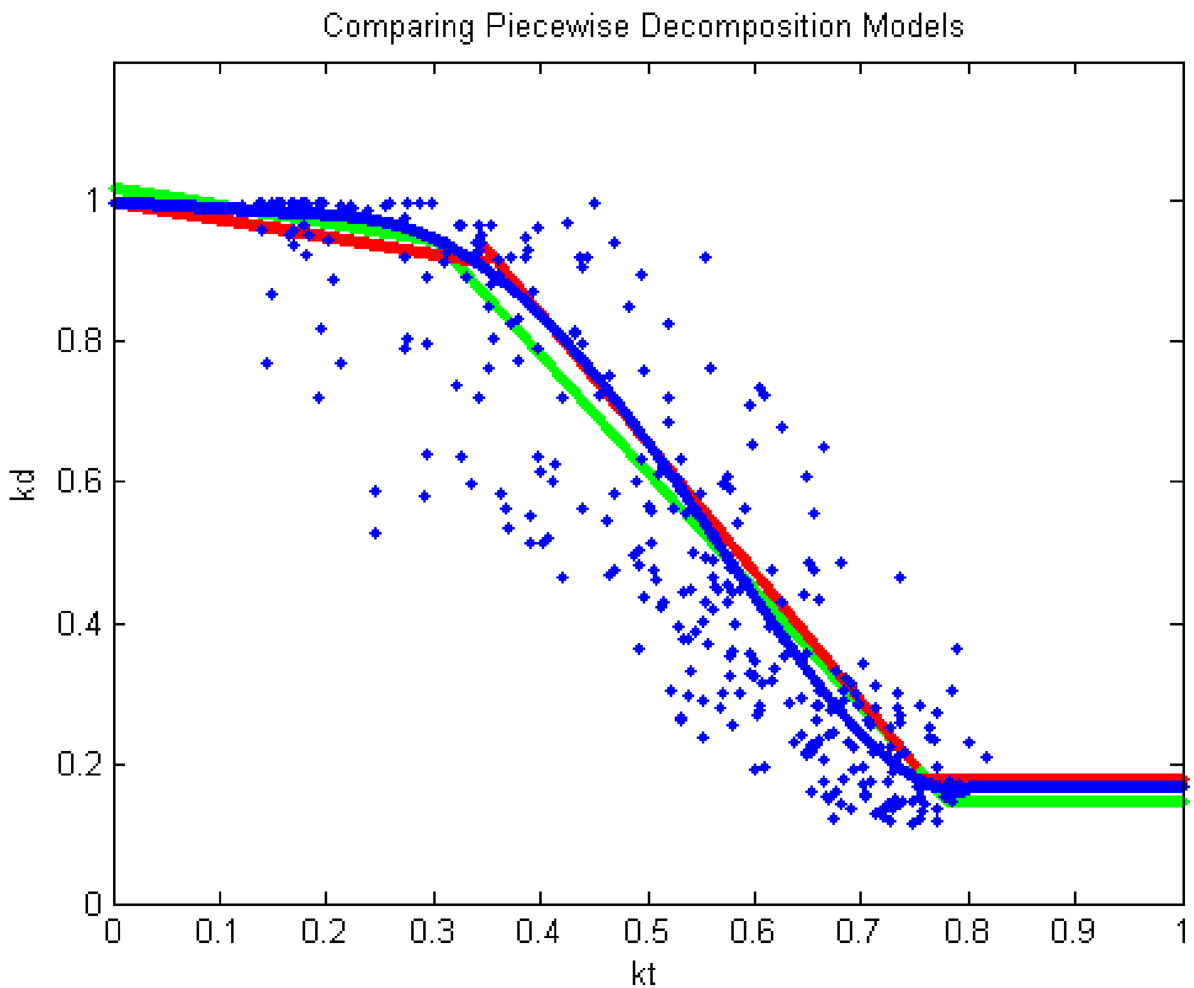


Figure compares three piecewise decomposition models. (Blue = Erbs, Red = Orgill and Hollands, and Green= Reindl et al. Model 1). The blue data points are hourly averaged measurements from Florida for September 2013.