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How to approach energy efficiency projects: understanding the energy consumption patterns

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Outline

- Treatment of the *data* gathered from individual consumers and their aggregations – load *patterns* and load *duration curves*
- Interactions among energy vectors in *multi-generation* applications
- Representation of residential load aggregations – *probabilistic* aspects
- Load pattern-based categorisation of electricity consumers – *clustering* applications
- Aggregation of loads with *thermostatic* control – load diversity, energy payback and cold load pickup
- Data representation with loads and local generation – *net metering* and effects of *data averaging* on the energy calculations

DATA

GATHERING

(power measurement, load patterns, load duration curve, utilization of the electrical energy)

Representation of the load in a specified period of analysis

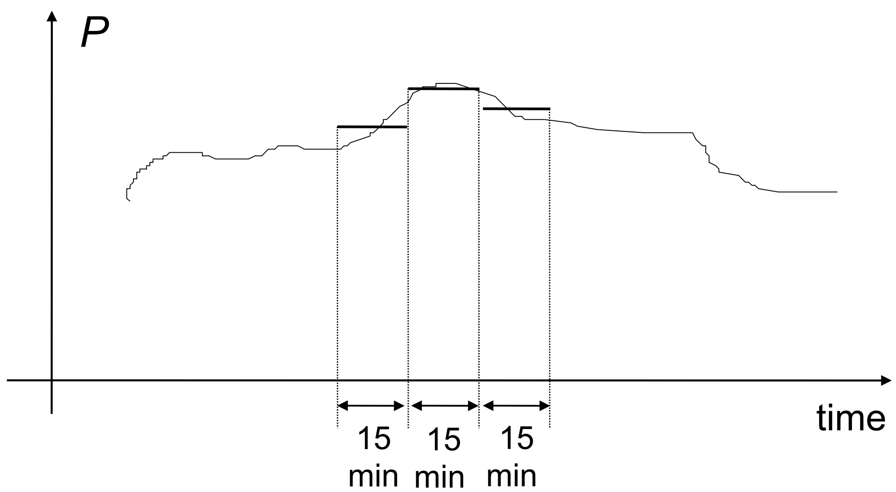
Load pattern:

- time evolution of the (active and/or reactive) *power*, determined by suitable measurements in a given analysis period (e.g., one month)
- but… power is an *instantaneous* quantity, thus it is not measurable
- the *average power* is determined by measuring an *energy* in a specified time interval (e.g., 15 minutes, 1 hour,...) and dividing by the duration of the time interval
- the *maximum power value* obtained in the analysis period is usually stored to be used for tariff purposes

Power measurement

(average) *power evaluation* in a specified time interval:

- load pattern obtained from energy measurements at regular rate (e.g., each quarter of hour)
- the power obtained is assumed to be constant for the whole time interval to which it is referred
- the lower the rate, the better the representation of the actual evolution of the instantaneous power demand
- however, very fast rates use huge amount of memory and are not always necessary

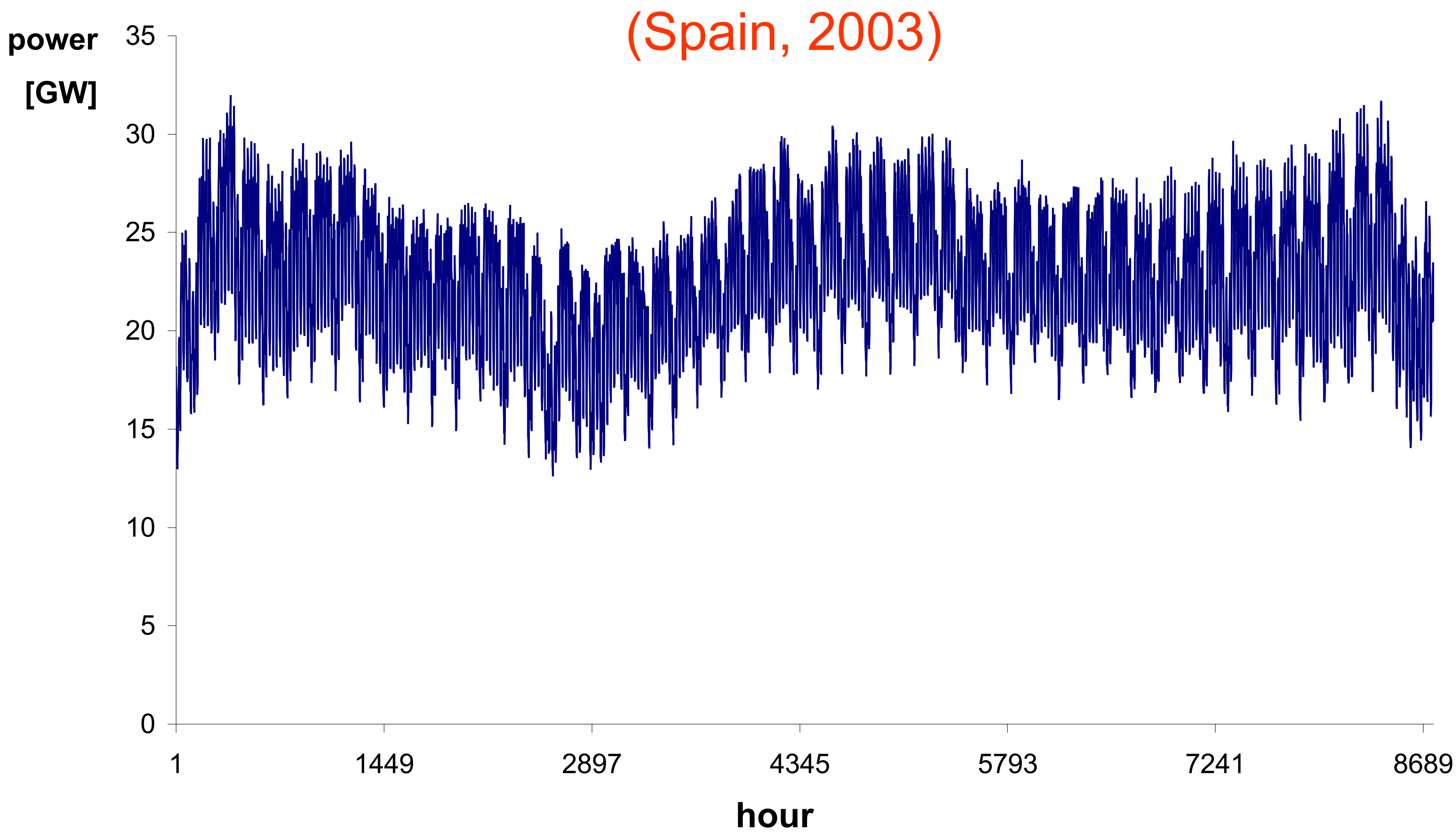


Load duration curve

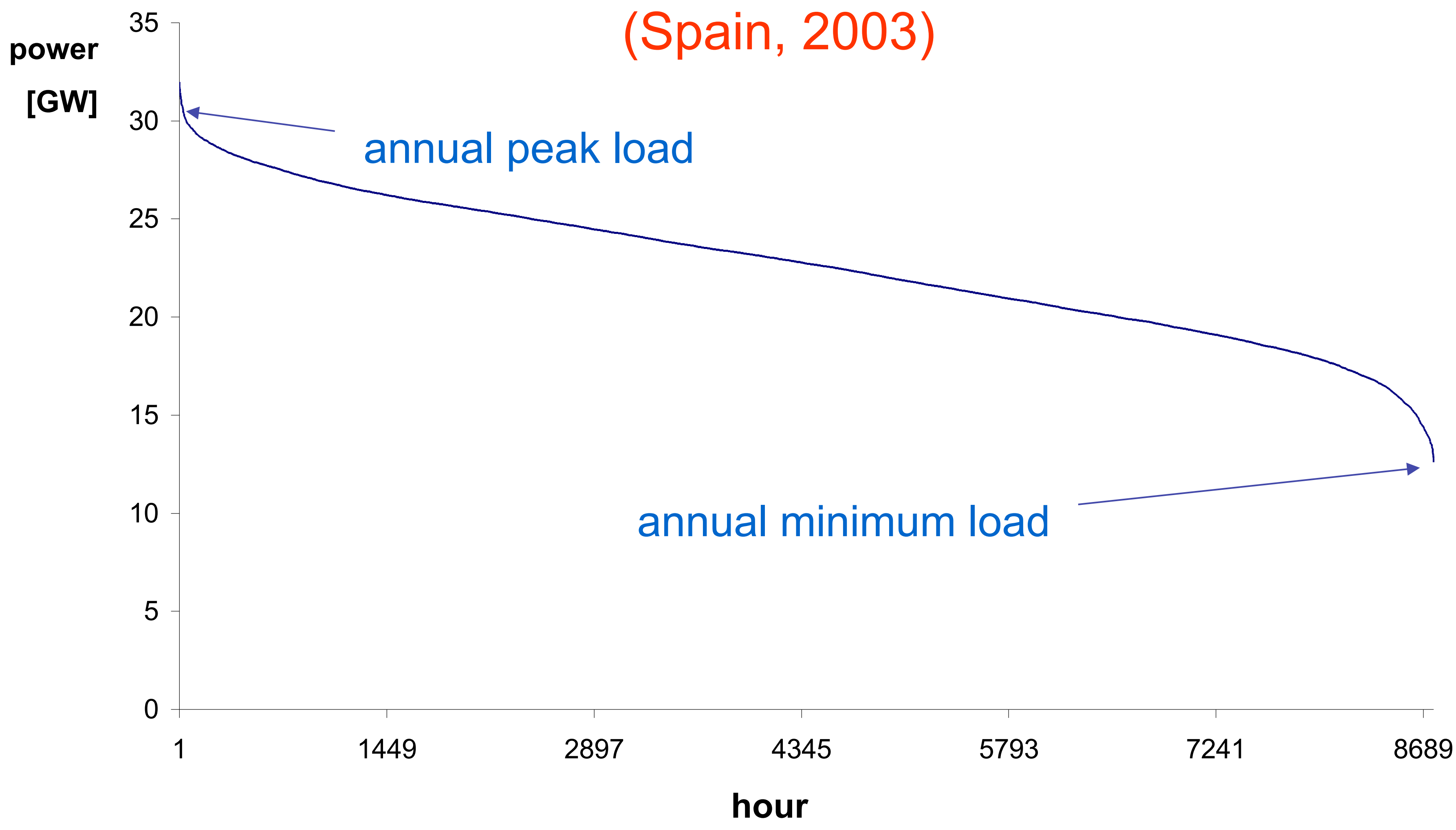
Load Duration Curve (LDC):

- built starting from the *load pattern* by reordering the average power values in the *descending order*
- for each power value, it represents the *duration* for which the power has been *reached* or *exceeded*
- over the *peak power* the duration is *null*
- the duration for the *minimum power* is the whole analysis period

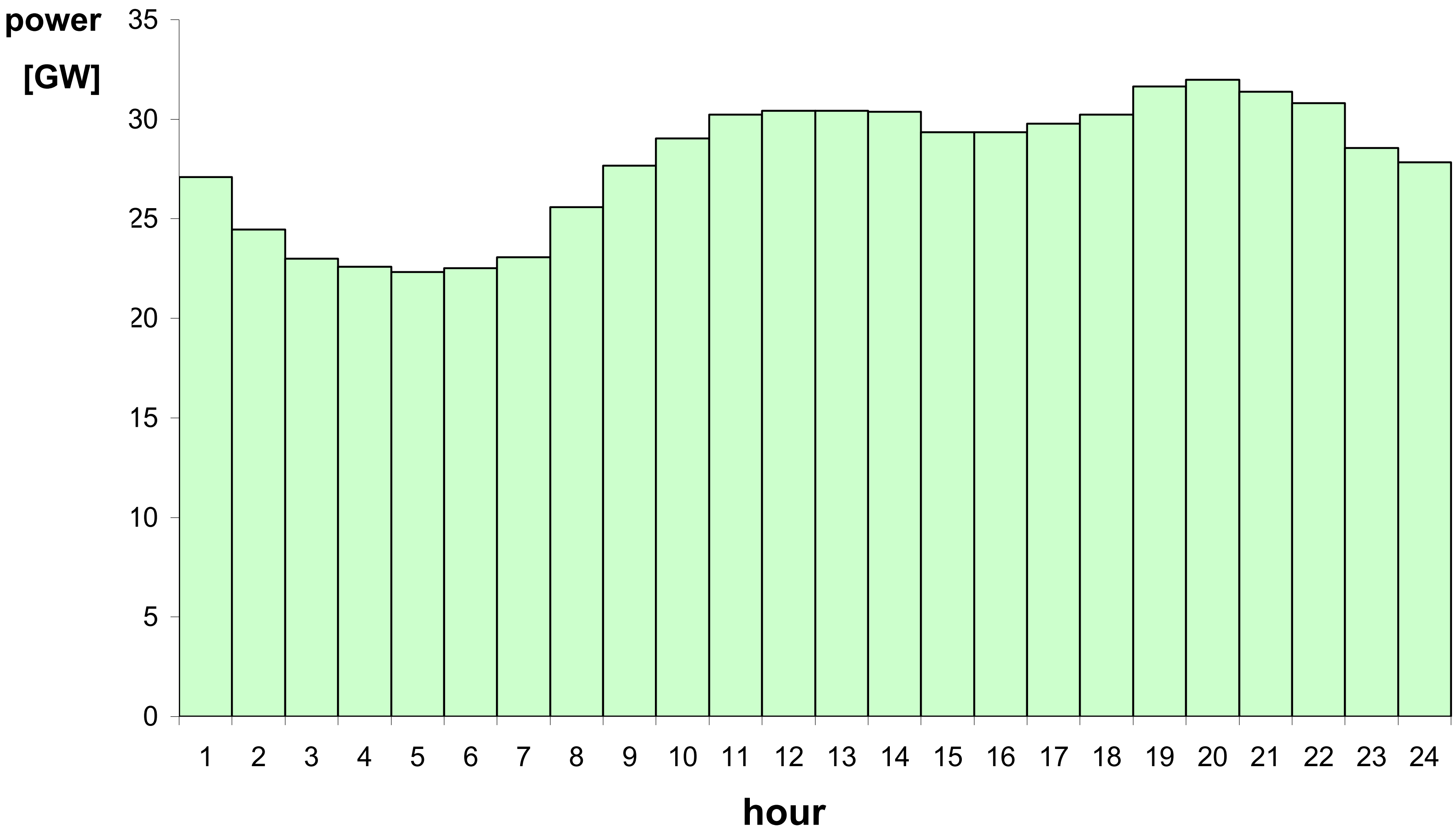
Annual load pattern



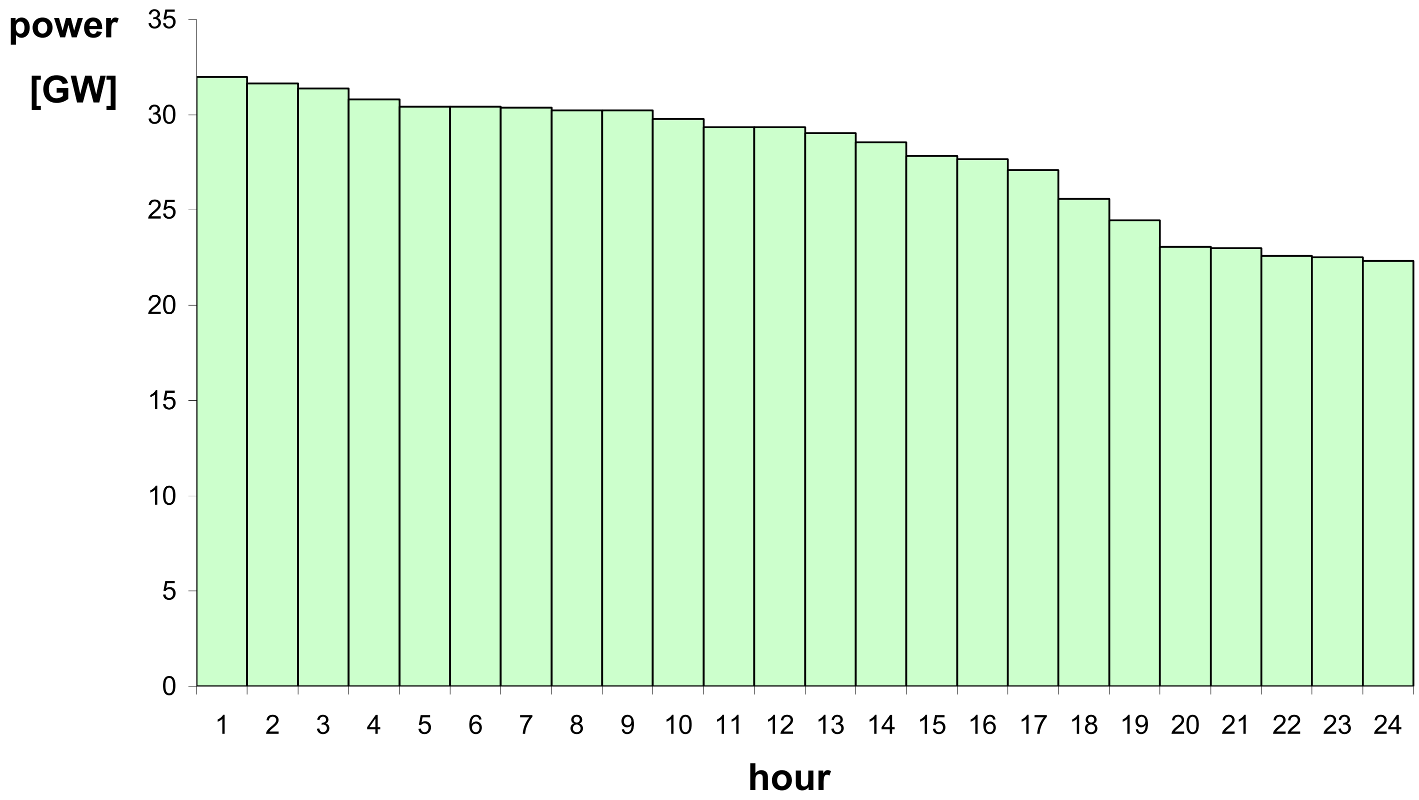
Annual Load Duration Curve



Hourly load pattern



Hourly Load Duration Curve

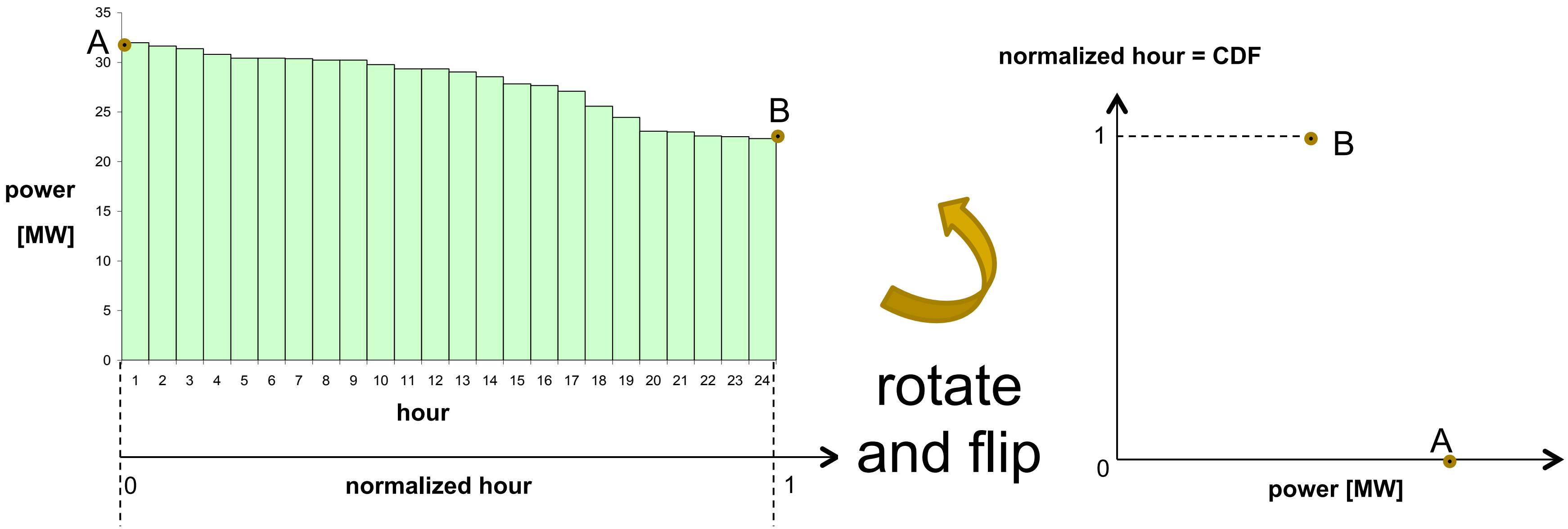


Starting from a load pattern represented by a set of power values, the *LDC* is simply built by in reordering the power values in descending order

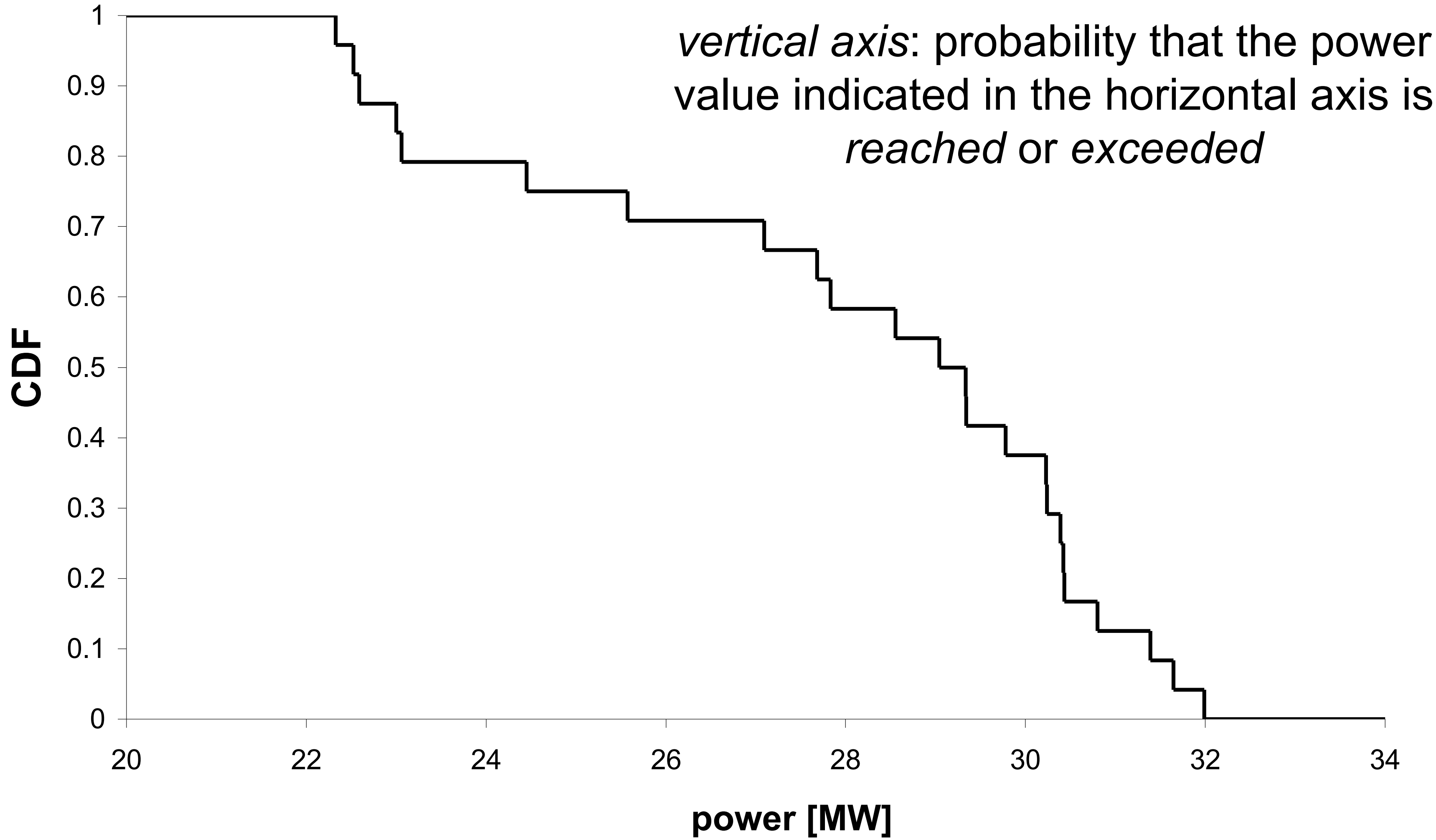
Probabilistic load model

Cumulative Distribution Function (*CDF*) of the load:

- Obtained from the *duration curve* of the hourly load power (in discrete form) by *exchanging* the horizontal and vertical axes and substituting the values on the time axis with the relative duration referred to the total time interval of analysis



Cumulative curve (CDF) of the load power

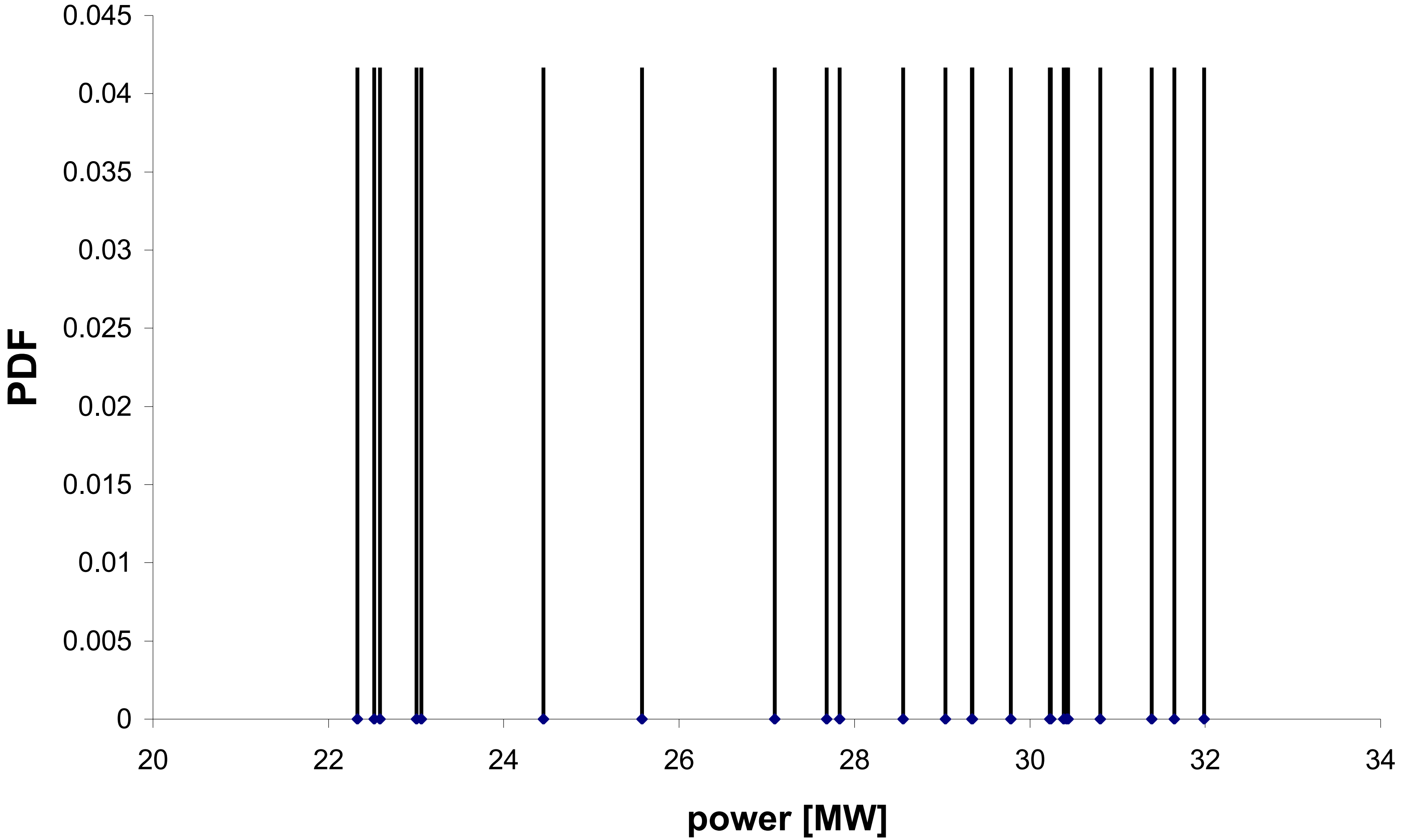


Probabilistic density function (PDF)

Probability Density Function (*PDF*) of the load:

- Formally representing the *derivative* of the CDF with respect to the load power
- With CDF represented in *discrete* form, is formed by a number of *Dirac pulses*, each one located at a step of the CDF and with amplitude (area) equal to the one of the corresponding step
- If the duration curve of the hourly power is constructed on the basis of the *hourly peak power* values (with N_h steps), the PDF is composed of N_h *equal size samples*, each one of amplitude equal to $1/N_h$

Probability density (PDF) of the load power



Data resolution

A relevant aspect is the *resolution* with which the information is gathered and represented

Two types of *resolution* can be identified, the combined effect of which determines the data representation effectiveness

For *time series* data:

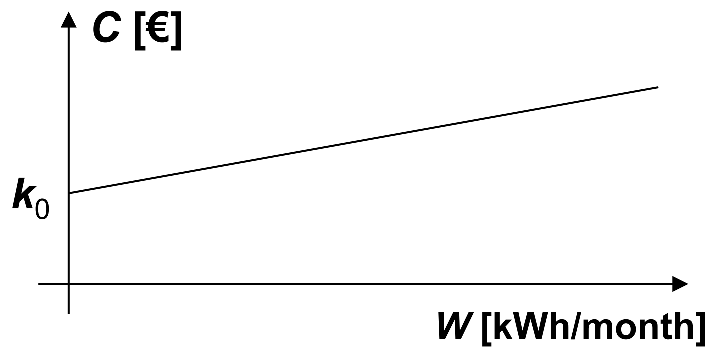
- *vertical* resolution: refers to the *discretization step* and depends on the *number of digits/bits* of the output
- *horizontal* resolution: refers to the *time* axis and depends on the *data averaging time step*
  - increasing the *averaging time steps* make the patterns *smoother*
  - however, in this smoothing process, information on relatively *fast variations* are not preserved

Utilization of the electrical energy

- The electricity tariffs are defined by using *three terms*
- Given the reference power P (kW), the energy consumption W (kWh) and the coefficients c_0 [€], c_P [€/kW] e c_W [€/kWh], the amount of the tariff C is expressed as $C = c_0 + c_P P + c_W W$
- Putting into evidence the energy W, the tariffs can be represented on the amount/energy plane as

$$C = k_0 + c_W W$$

where $k_0 = c_0 + c_p P$



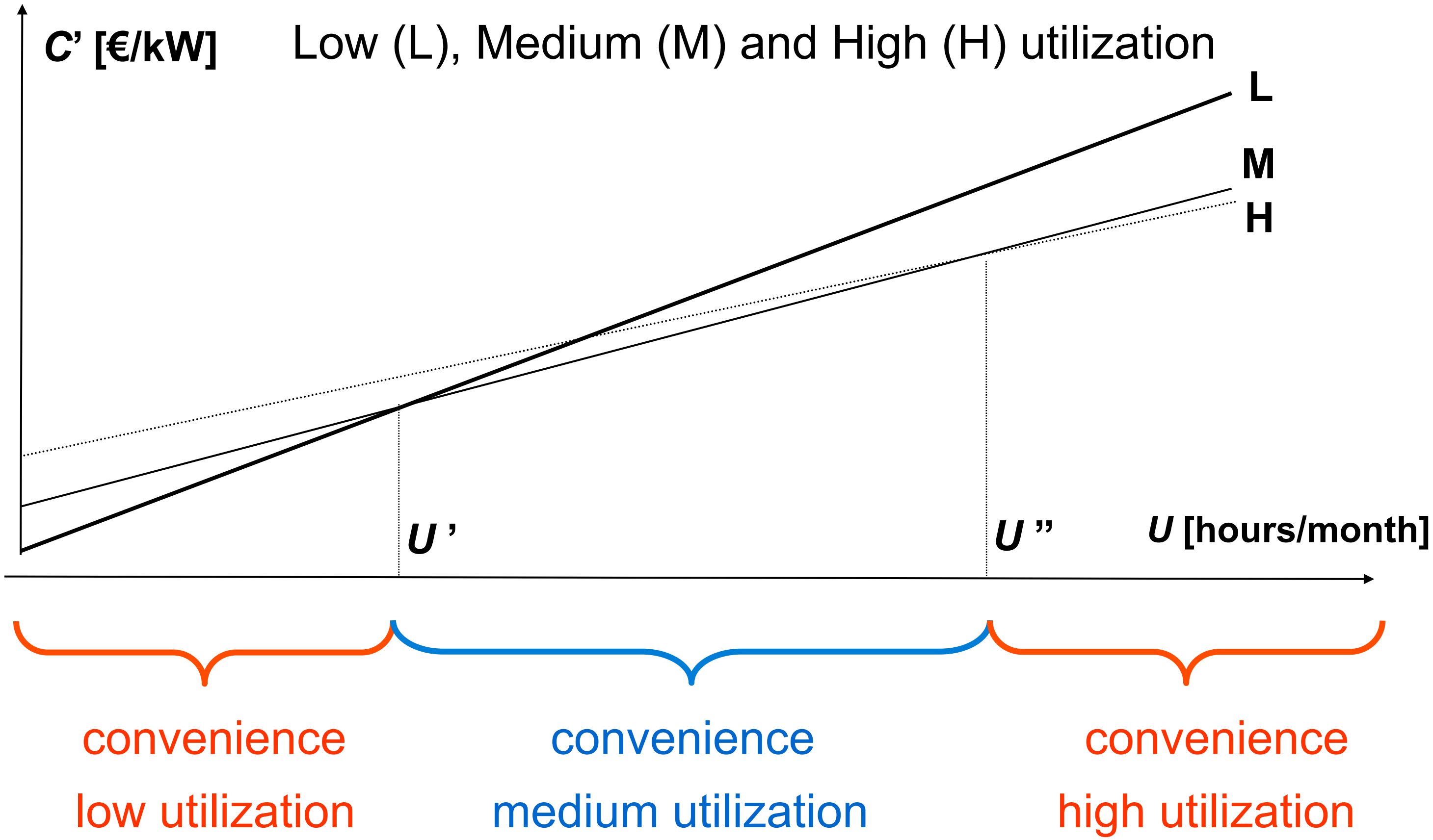
- By dividing the two terms by P:

$$C' = k + c_W U$$

- The *utilization U* [hours/year] is defined as the ratio between the energy consumption W and the reference power P
- Practically, U represents the *number of hours equivalent* to a *continuous* use of the power P to provide the total energy W

Utilization of the electrical energy

- The intersections between the lines determine the *convenience* regions
- Declaring the *right utilization* is convenient for both user and supplier



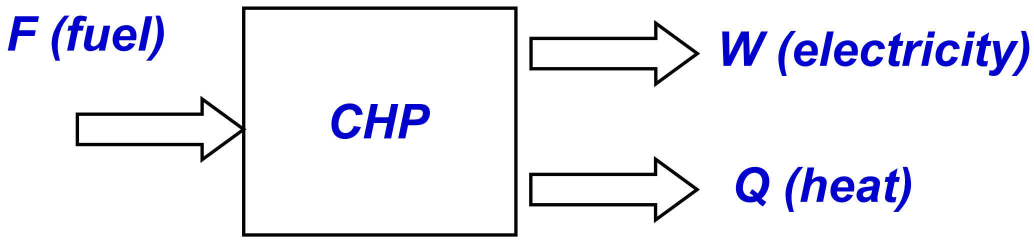
MULTI-GENERATION

APPLICATIONS

(energy patterns,
lambda analysis,
impact of cooling equipment)

Cogeneration

- *Simultaneous* production of electricity and heat from one fuel source (*cogeneration*) may provide significant *energy efficiency* improvements with respect to *separate production* serving the *same energy outputs*
- Black-box model representation of ***CHP*** (Combined Heat and Power)



- *Parameters*:
  - electrical efficiency $\eta_W = W/F$
  - thermal efficiency $\eta_Q = Q/F$
  - cogeneration ratio $\lambda = Q/W$

P.Mancarella and G.Chicco, Distributed multi-generation systems: energy models and analyses (ISBN: 978-1-60456-688-8), Nova Science Publishers, New York, 2009.

Energy efficiency indicator: Primary Energy Saving (*PES*)

- Definition:

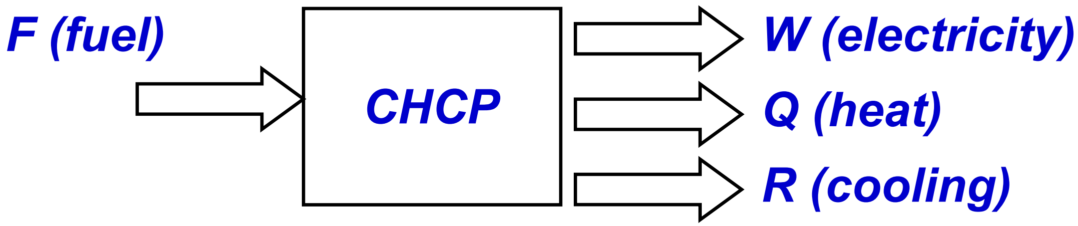
$$PES = \frac{F^{SP} - F}{F^{SP}} = 1 - \frac{F}{\frac{W}{\eta_e^{SP}} + \frac{Q}{\eta_t^{SP}}}$$

$$\boxed{\begin{array}{c}\textbf{convenient if} \\ \boldsymbol{PES > 0}\end{array}}$$

- η_e^{SP} electrical efficiency of the *reference electricity production* system
- η_t^{SP} thermal efficiency of the reference *boiler*
- *Conventional* evaluation of the energy saving for a cogenerator producing the *same* quantities of *useful energy* (electricity W and heat Q) by using the fuel F, with respect to the *separate production* (SP) requiring F^{SP} kWh_t of fuel
- The reference efficiency values are defined by the *regulatory bodies*

Trigeneration efficiency

- Similar improvements for *multi-generation* applications
- Example for *trigeneration* (or Combined Heating Cooling and Power – CHCP) serving electricity, heating and cooling loads



- Trigeneration Primary Energy Saving (*TPES*)

$$TPES = \frac{F^{PS} - F}{F^{PS}} = 1 - \frac{F}{\dfrac{W}{\eta_e^{PS}} + \dfrac{Q}{\eta_t^{PS}} + \dfrac{R}{\eta_e^{PS}\,COP^{PS}}}$$

convenient if

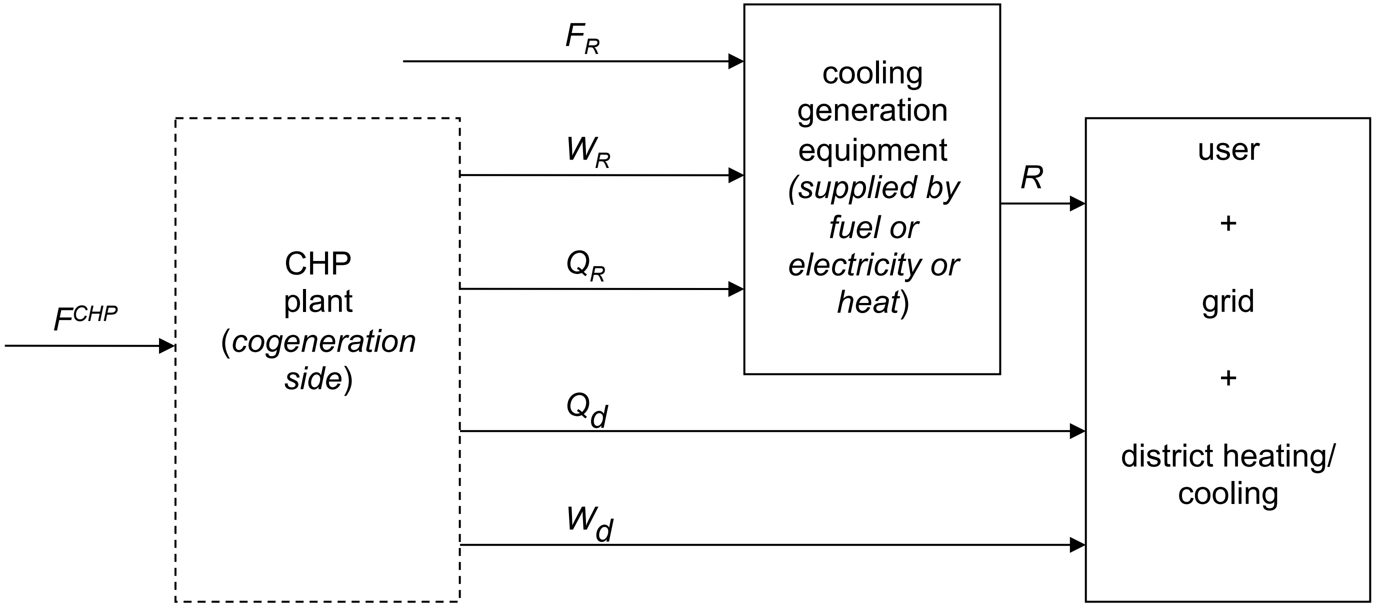
***TPES* > 0**

COP^{PS} *Coefficient of Performance* of a chiller supplied by ***electricity*** (*reference* for *separate production* of cooling energy)
R ***useful*** cooling energy (kWh_c)

G.Chicco and P.Mancarella, Trigeneration Primary Energy Saving Evaluation for Energy Planning and Policy Development, Energy Policy, Vol. 35, No.12, 2007, pp. 6132–6144

Trigeneration plant scheme

- Different cooling generation equipment can be used, supplied by either electricity or heat from the cogenerator, or directly by fuel
- The cooling production through different cooling generation equipment impacts on the "load" seen at the cogeneration side



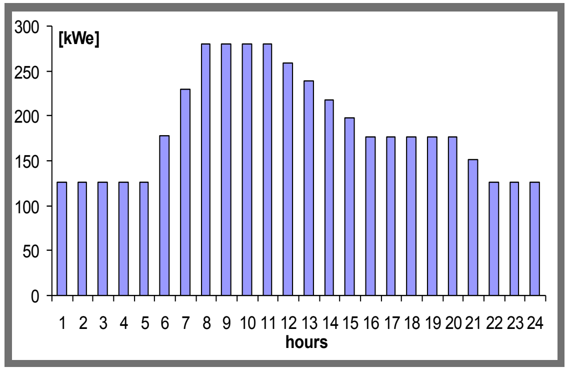
G.Chicco and P.Mancarella, A unified model for energy and environmental performance assessment of natural gas-fueled poly-generation systems, Energy Conversion and Management, Vol. 49, No.8, August 2008, 2069-2077

Effect of using different cooling generators

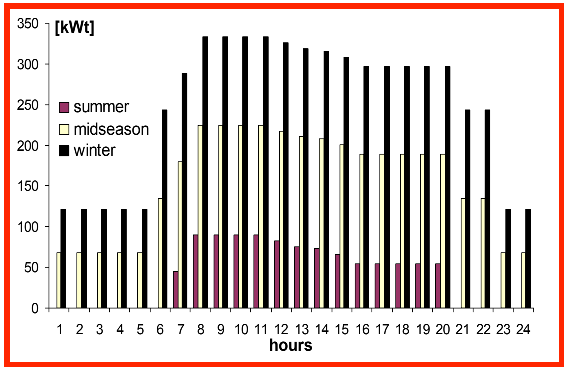
- Electric chiller (supplied by electricity): *electrical* CHP load increase
- Absorption chiller (supplied by heat): *thermal* CHP load increase
- Refrigeration group supplied by gas: *no* CHP load increase
- Extension of the cogeneration ratio: introduction of a *trigeneration demand-related cogeneration ratio*, in which the thermal and electrical load include the corresponding effect of supplying the cooling demand

$$\lambda_d^{tot} = \frac{Q_d^{tot}}{W_d^{tot}} = \frac{Q_d + Q_R}{W_d + W_R}$$

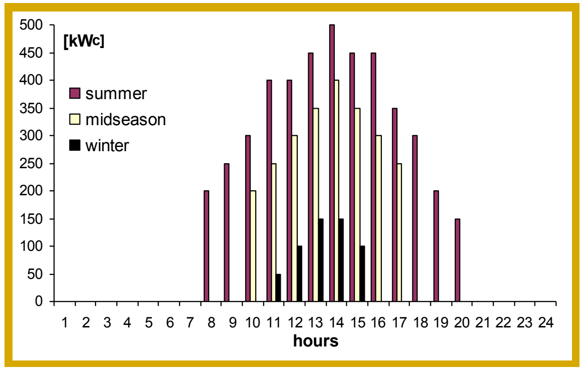
Case study example: hospital site



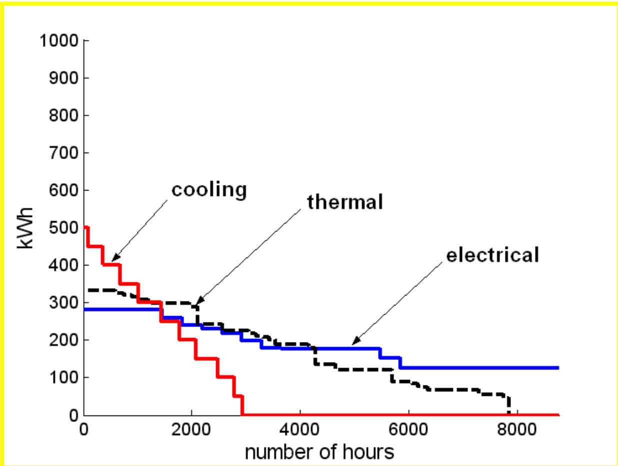
electrical load



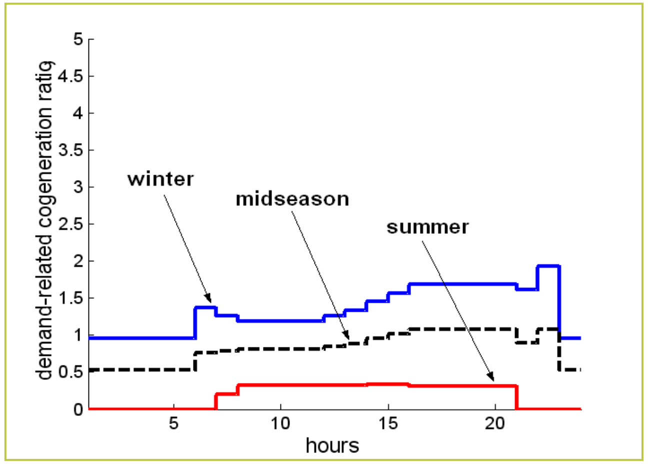
thermal load



cooling load



load duration curves



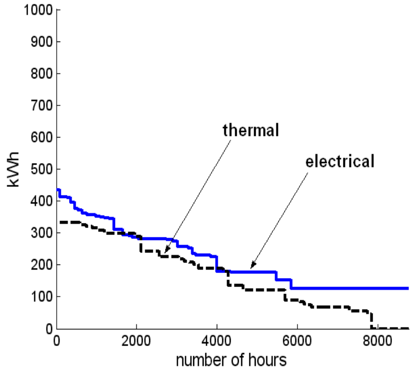
user's lambda (λ_d)

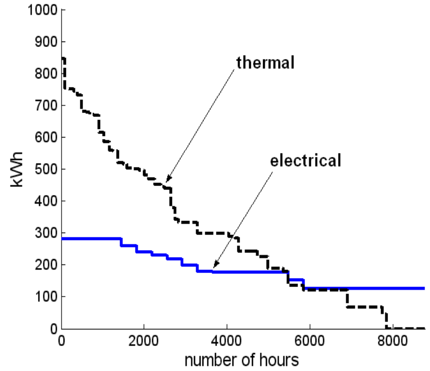
Impact of the cooling side

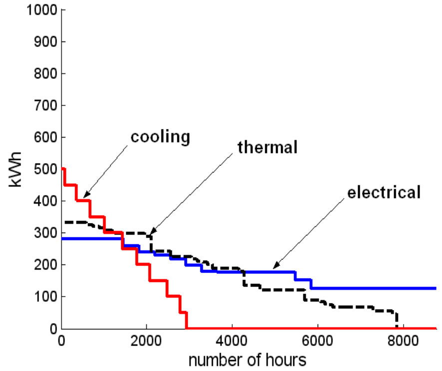
- Different impacts depending on how the chiller is *supplied*

Electricity supplied chiller | **Heat supplied absorption chiller** | **Gas-supplied chiller**

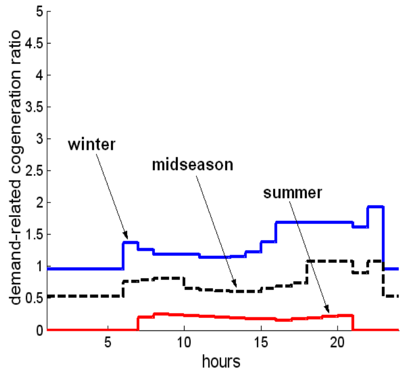
load duration curves

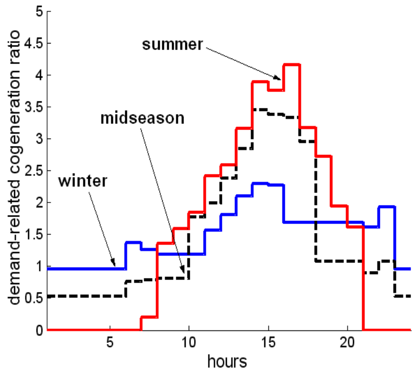


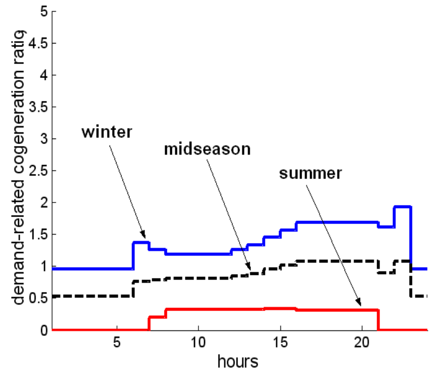




user's lambda







CATEGORIZATION OF THE

ELECTRICAL LOAD PATTERNS

(consumer categories,
individual and aggregate patterns,
active and reactive power patterns,
load profiles)

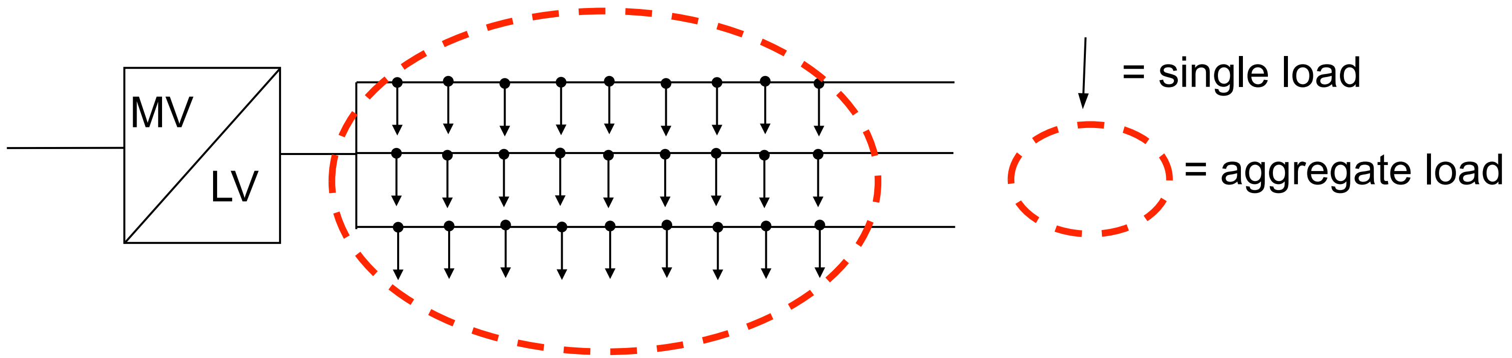
Macro-categories of users

Macro-categorization based on the *energy use*:

- *residential* users
- *industrial* users
- users of the *tertiary sector*
- *other* users (e.g., lighting, traction, etc.)

Each user may exhibit a *variable* load pattern, depending on the type of use of the energy

In several cases the distribution system does not supply each residential user individually, but supplies an *aggregate load*



Load aggregation

For a *residential area*:

- the consumption may vary in function of the *number* of persons in the family, of the *activity* of the persons and of their *lifestyle*
- the *characterization* of the residential consumption by taking into account the possible load pattern of the electrical appliances would require a *statistical analysis* based on the various aspects affecting the energy use in the family
- fortunately, the aggregated load pattern for a *significant number* of residential customers (e.g., 20-100) connected to the same feeder or substation can be forecast in a relatively easy way
- the different behavior of the single customers (families) leads to an *overall daily evolution* of the total load with some regularities

Other users:

- large industrial and tertiary users are supplied *individually*
- It is possible to define the *load patterns* for the single loads

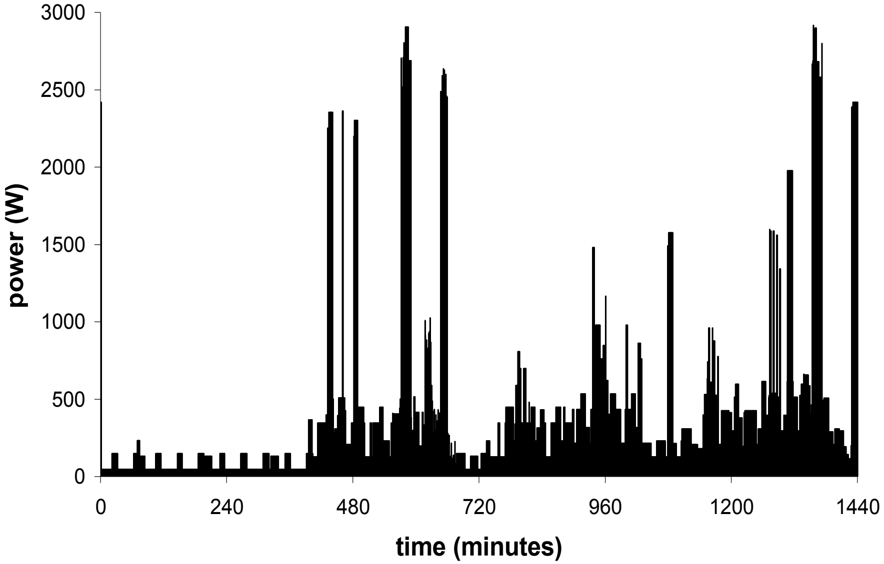
Residential load patterns

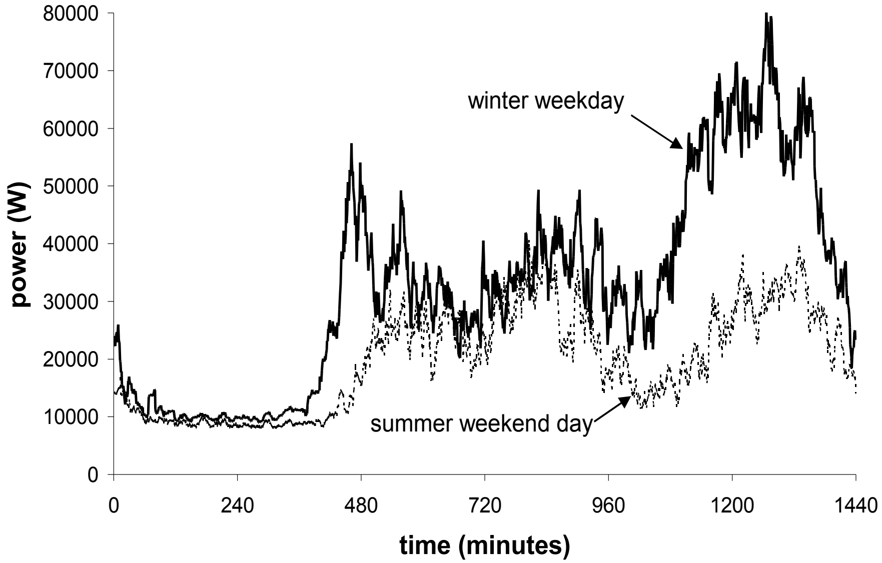
- *Detailed representation* of the residential load patterns is a key issue for dealing with studies on electricity markets and distributed generation
- Drawing *single-customer* residential load patterns is difficult, because of:
  - high dependence on *non-electrical* aspects (family composition, age, lifestyle...)
  - *irregular* usage of the appliances
  - presence of load pattern peaks of *short duration*, mainly dependent on a few high-power appliances
- The main interest is on *aggregating* the load patterns of residential customers, with some *key questions*:
  - how load pattern uncertainty depends on the *number* of customers ?
  - is load pattern *uncertainty* variable with the hour of the day ?

E.Carpaneto and G.Chicco, Probabilistic characterisation of the aggregated residential load patterns, *IET Generation, Transmission and Distribution* , Vol. 2, No. 3, May 2008, 373–382

Individual and aggregate load patterns

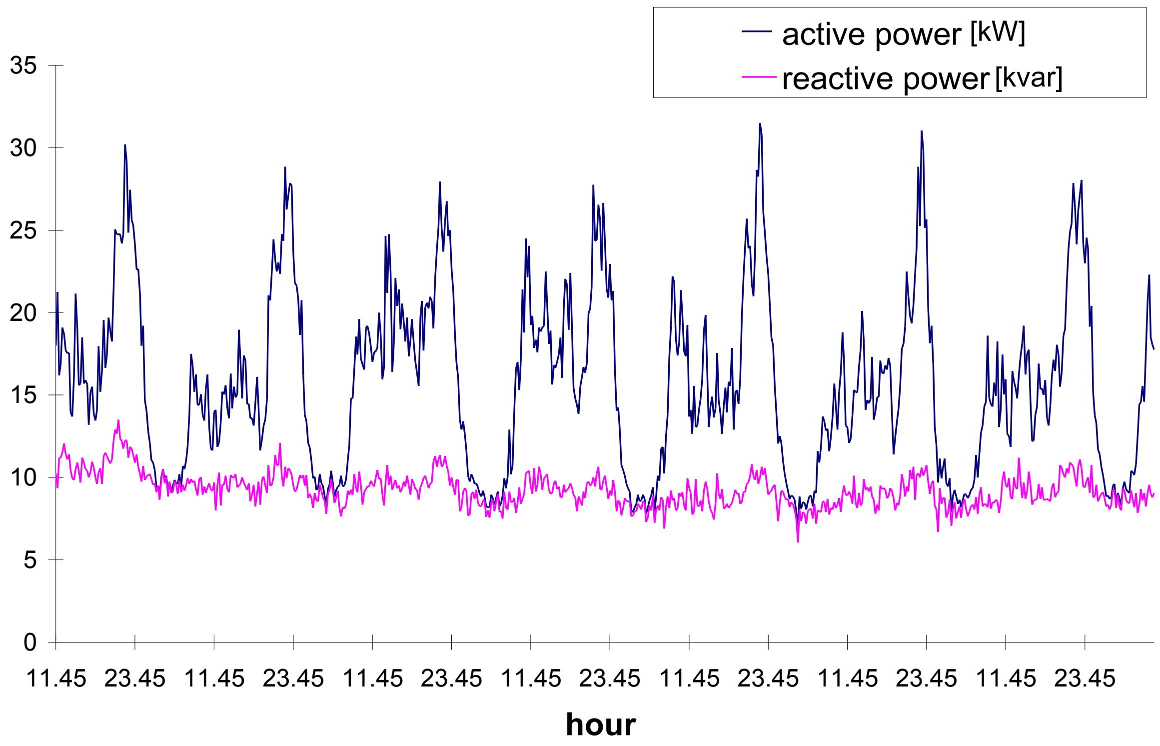
- *Typical* load patterns with:
  - *single customer*: large consumption peaks at *poorly predictable* time moments
  - *customer aggregation*: relatively smooth consumption pattern, with “smoothness” depending on the number of customers





Aggregate residential load

Composition	Number of users	reference power [kW]
Residential load	80	237.5
General services of the buildings	8	50
Other	--	--



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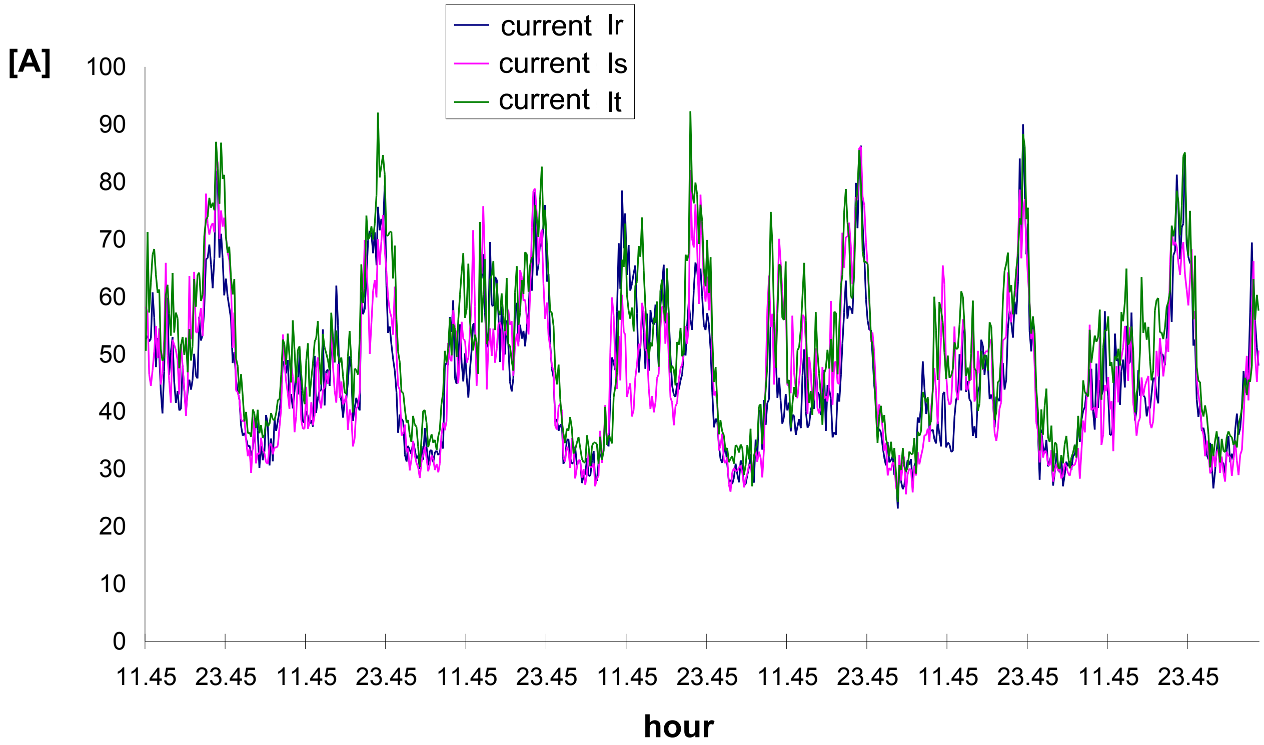


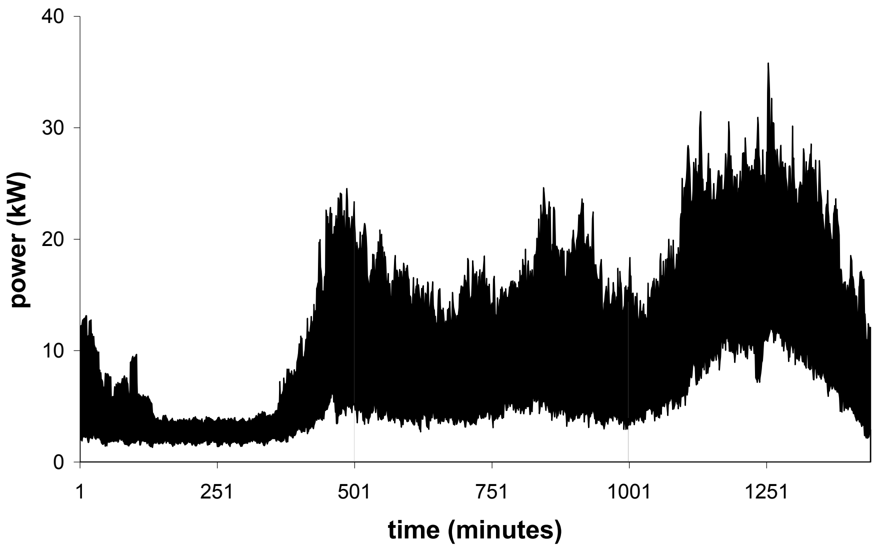
Analysis on extra-urban customers

- Analysis considering a *number* of customers (families) variable from 10 to 300
- 3 kW reference (contract) power for every customer
- Specific results:
  - variation of mean value and standard deviation of the aggregated demand for different numbers of customers
  - ranges of variation of the load power for different time instants and for various numbers of customers

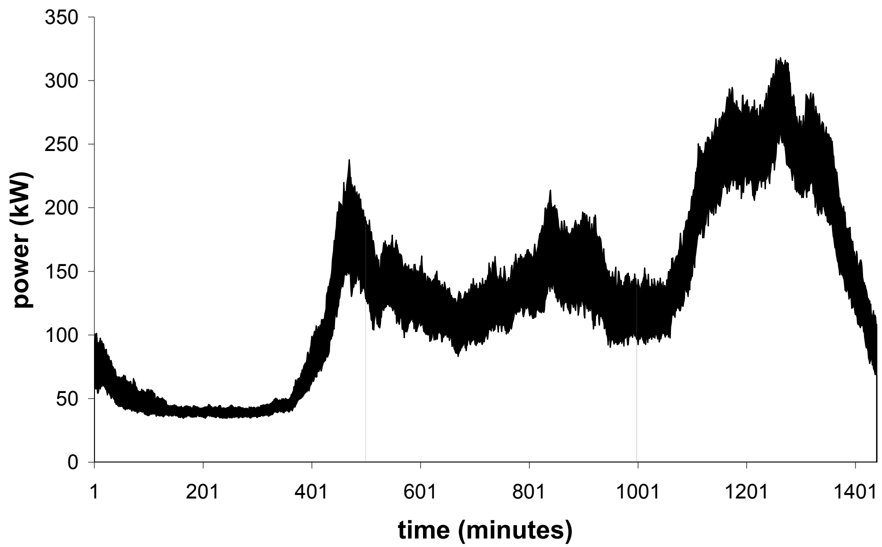
A. Cagni, E. Carpaneto, G. Chicco and R. Napoli, Characterisation of the aggregated load patterns for extra-urban residential customer groups, *Proc. IEEE Melecon 2004* , Dubrovnik, Croatia, May 12-15, 2004, Vol.3, pp. 951-954

Ranges of variation of the load power

- The *relative ranges of variation* highly depend on the number of customers *N*
- *Low numbers* of customers are related to higher uncertainties
- Results for *extra-urban aggregate customers* in a winter weekday



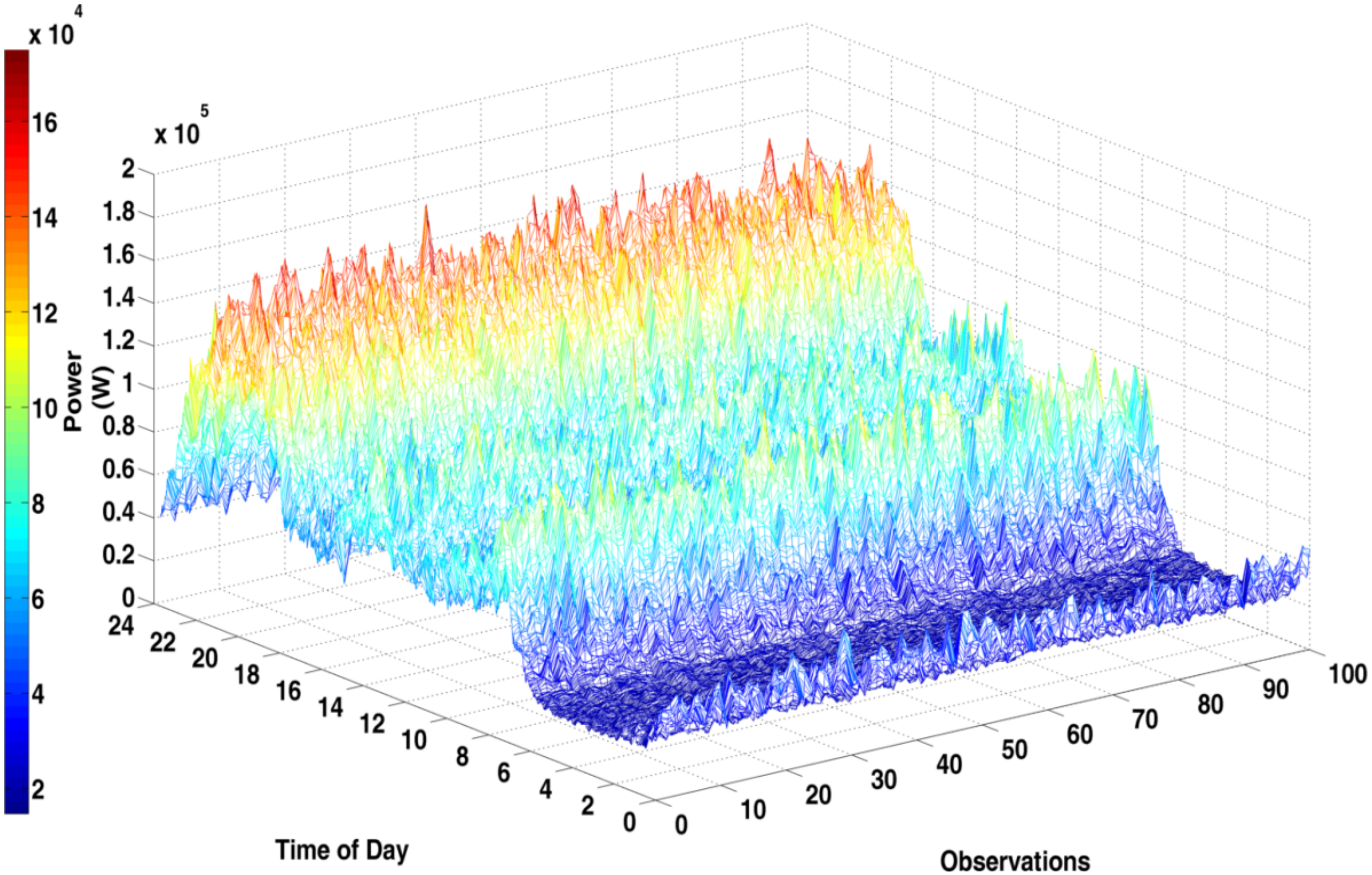
***N* = 20**



***N* = 300**

Evolution in time of the aggregate demand

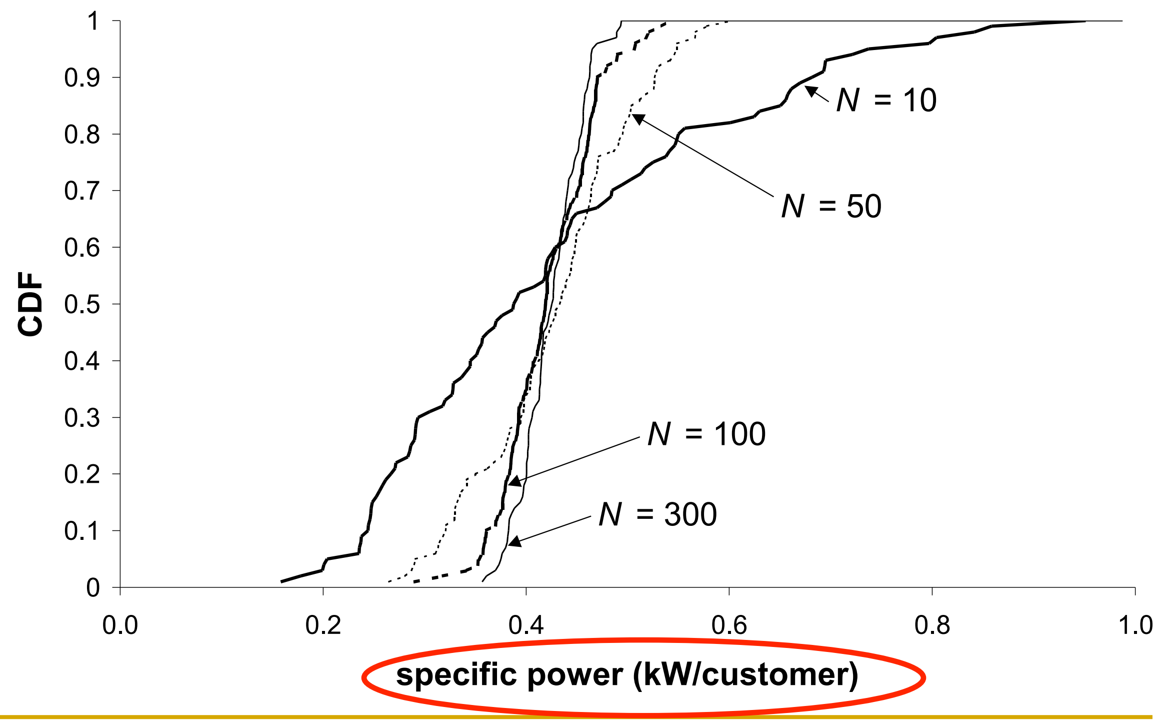
- Time evolution (in minutes) of the aggregated demand for 150 houses and sampling interval of 1 min (100 Monte Carlo observations)



Cumulative Distribution Functions (CDFs)

- The CDFs quantitatively represent how the load power variation depends on hour and number of customers
  - for a given hour, the *mean value* for different numbers of customers is nearly *similar*

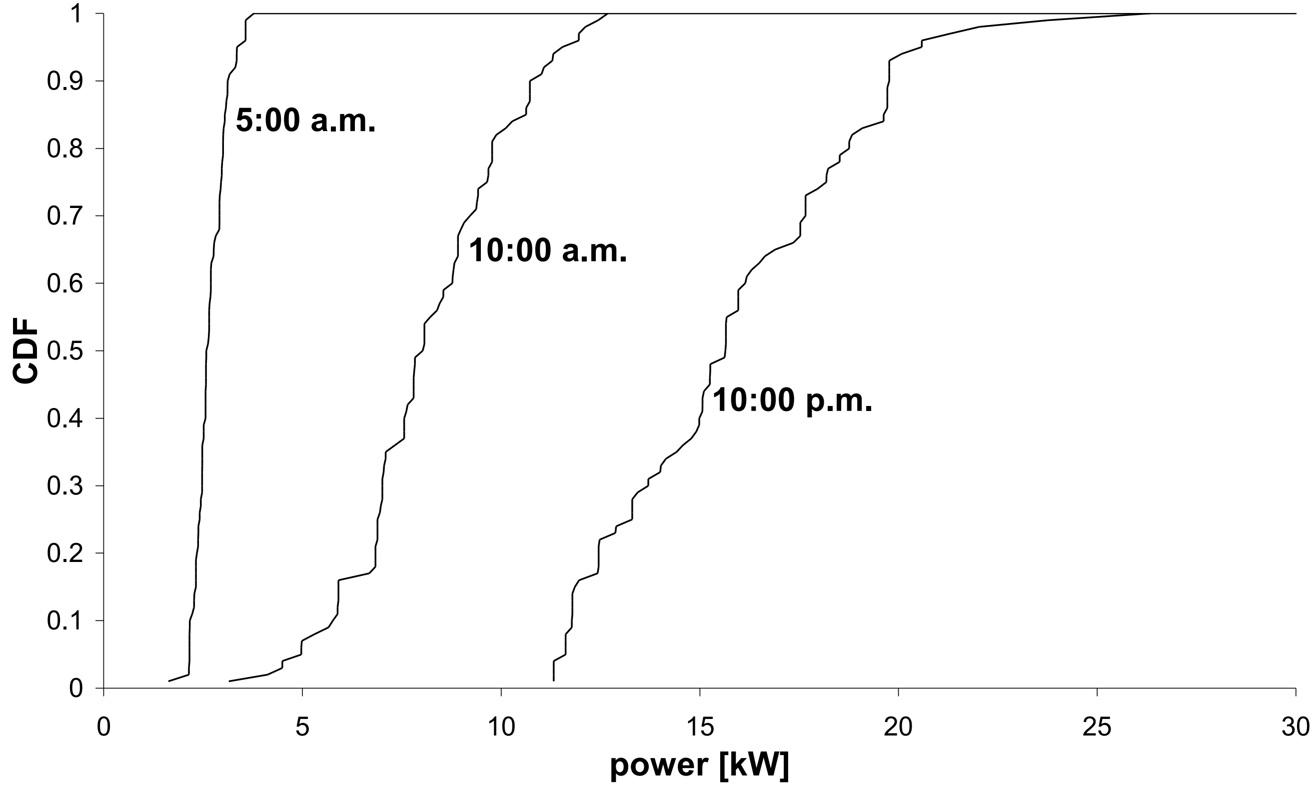
hour 10 a.m.



Cumulative Distribution Functions (CDFs)

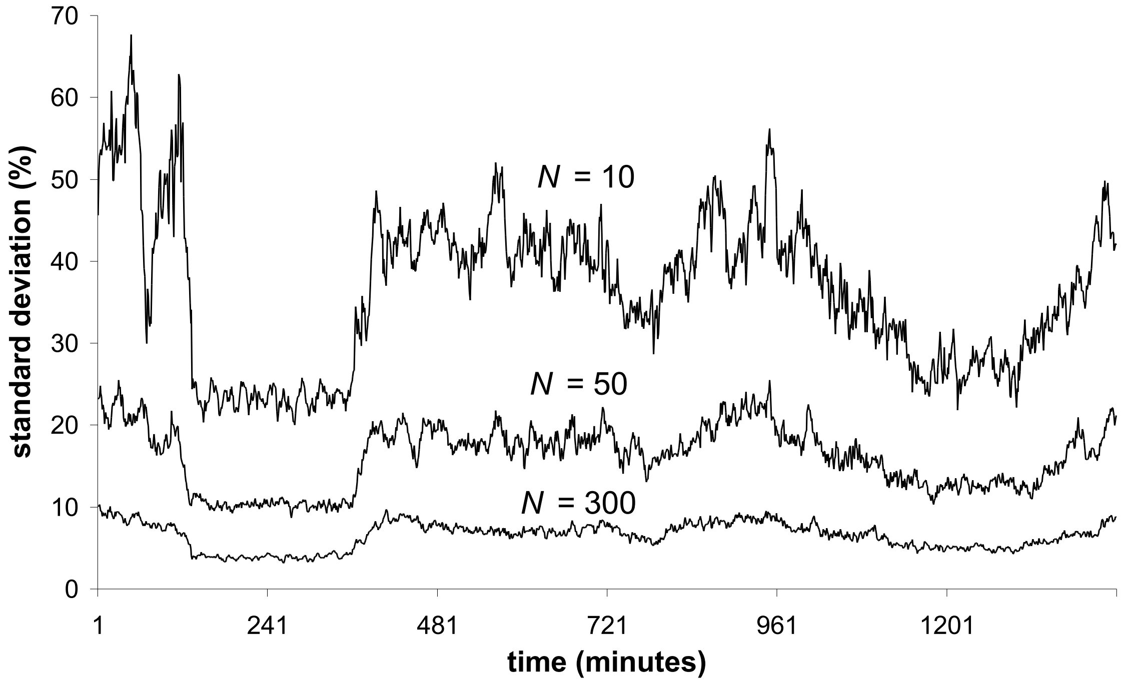
- For a *given number* of customers, the mean value and the standard deviation highly depend on the hour

***N* = 20**



Evolution of the standard deviation

- Quantitative evaluation of the evolution of the standard deviation w.r.t. time and number of customers
  - standard deviations in *per cent* of the corresponding *mean* value
  - lower values represent more easily *predictable* consumption during night (low consumption) and evening (high consumption)



Useful probability distributions

- Is it possible to represent aggregate load pattern data with a *known* probability distribution?
- Goodness-of-fit tests compare the empirical data to different probability distributions, e.g.:
  - two *one-parameter* distributions (Exponential and Rayleigh)
  - five *two-parameter* distributions (Gamma, Gumbel, Log-normal, Normal and Weibull), computing the two parameters on the basis of the average value and the standard deviation of the empirical data
  - the *three-parameter* Beta distribution, with parameters a and b computed on the basis of the average value and the standard deviation of the data, and the third parameter c set to the maximum value of the data sample
- The *Kolmogorov-Smirnov* (KS) statistical test is used as an example

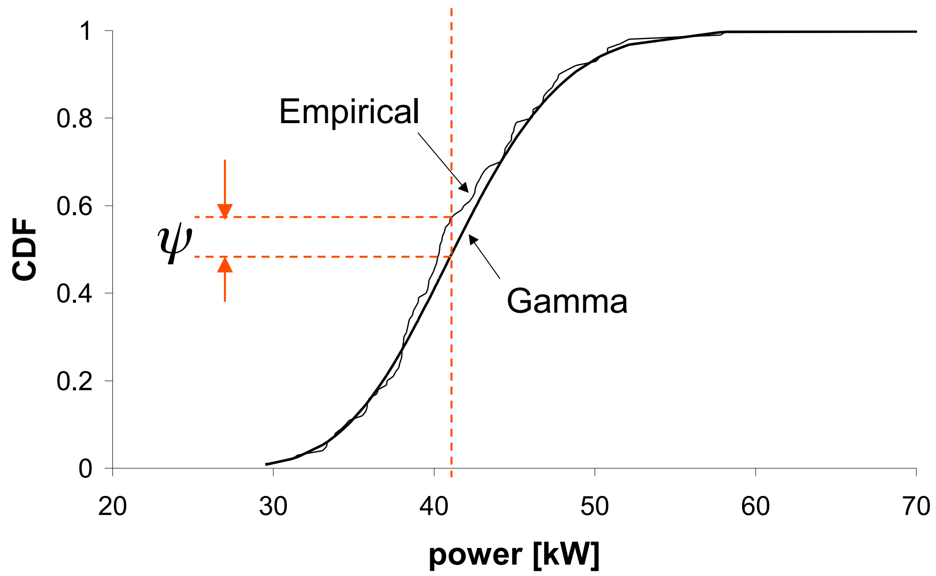
E.Carpaneto and G.Chicco, Probabilistic characterisation of the aggregated residential load patterns, IET Generation, Transmission and Distribution, Vol. 2, No. 3, May 2008, pp. 373–382

Probability distributions

name	PDF $f(P)$	CDF $F(P)$	*parameter limits*
Beta	$\dfrac{\Gamma(a+b)\,P^{a-1}(c-P)^{b-1}}{\Gamma(a)\Gamma(b)\,c^{a+b-1}}$	$\dfrac{\int_0^{P/c} x^{a-1}(1-x)^{b-1}dx}{\int_0^1 x^{a-1}(1-x)^{b-1}dx}$ = Beta incomplete($P/c,a,b$)	$0 \le P \le c$ $a > 0$ $b > 0$
Exponential	$\dfrac{1}{b}e^{-\left(\frac{P}{b}\right)}$	$1-e^{-\left(\frac{P}{b}\right)}$	$P \ge 0$ $b > 0$
Gamma	$\dfrac{P^{a-1}}{b^a\,\Gamma(a)}e^{-\left(\frac{P}{b}\right)}$	$\int_0^P \dfrac{x^{a-1}}{b^a\Gamma(a)}e^{\frac{-x}{b}}dx$ = Gamma incomplete(P/b)	$P \ge 0$ $a > 0$ $b > 0$
Gumbel	$\dfrac{1}{b}e^{\left(\frac{a-P}{b}\right)}e^{-e^{\left(\frac{a-P}{b}\right)}}$	$1-e^{-e^{\left(\frac{a-P}{b}\right)}}$	$-\infty \le P \le \infty$ $b > 0$
Log-normal	$\dfrac{e^{-\frac{(\ln P-b)^2}{2a^2}}}{a\,P\sqrt{2\pi}}$	$\dfrac{1}{2}\left(1+erf\left(\dfrac{\ln P-b}{a\sqrt{2}}\right)\right)$	$P \ge 0$ $a > 0$
Normal	$\dfrac{e^{-\frac{(P-\mu)^2}{2\sigma^2}}}{\sigma\sqrt{2\pi}}$	$\dfrac{1}{2}\left(1-erf\left(\dfrac{P-\mu}{\sigma\sqrt{2}}\right)\right)$	$-\infty \le P \le \infty$ $\sigma > 0$
Rayleigh	$\dfrac{2P}{b^2}e^{-\left(\frac{P}{b}\right)^2}$	$1-e^{-\left(\frac{P}{b}\right)^2}$	$P \ge 0$ $b > 0$
Weibull	$\dfrac{a\,P^{a-1}}{b^a}e^{-\left(\frac{P}{b}\right)^a}$	$1-e^{-\left(\frac{P}{b}\right)^a}$	$P \ge 0$ $a > 0$ $b > 0$

The KS statistical test

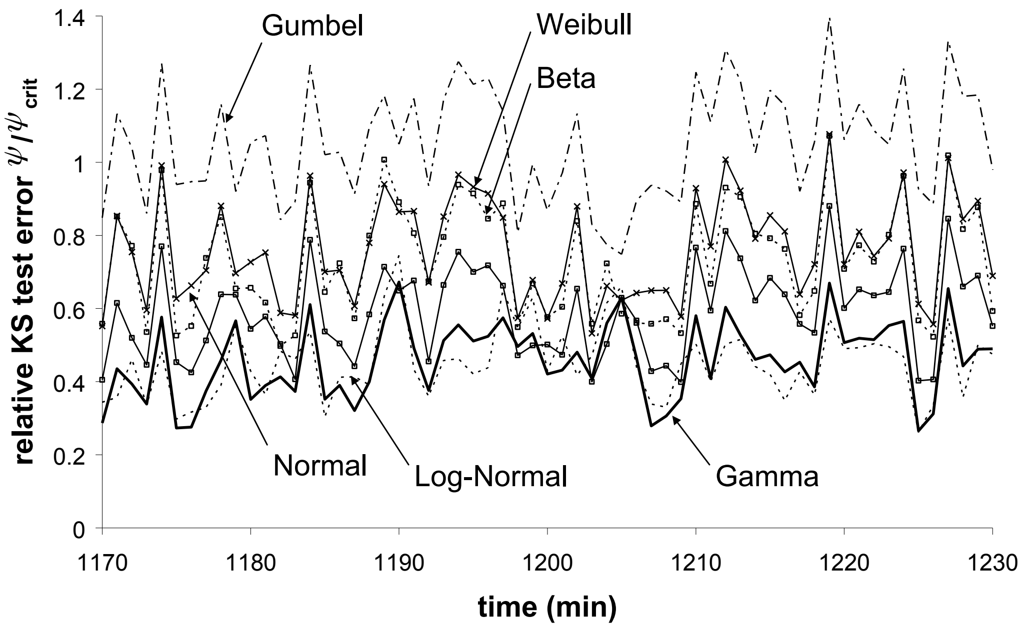
- The KS test is based on the calculation of the *error* ψ, given by the *maximum vertical mismatch* between the Empirical CDF (ECDF) obtained by the set of data under analysis and the CDF of the probability distribution under test
- The error ψ is compared to a *critical value* ψ_{crit}
- The KS test is *successful* if $\psi \leq \psi_{crit}$



Results of the statistical tests

- KS test results generalised with various CDFs during the day
- The *relative KS test error* has been defined as the ratio between the observed value ψ and the critical value ψ_{crit} of the KS test
- Relative KS test errors computed at every minute for 24 hours (1440 time intervals for each CDF) with significance level 5%

- Zoom: hours 19:30÷20:30, winter working day (N = 20)
- Log-normal and Gamma CDFs exhibiting the best goodness-of-fit
- The relative KS test errors for Exponential and Rayleigh CDFs (not shown) are much higher



Results of the statistical test

- Attention focused on the Gamma probability distribution:

$$f(t)=\frac{t^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)}e^{-\frac{t}{\beta}}$$

  - defined only for *positive values*
  - *straightforward calculation* of the Gamma parameters $\alpha = \mu^2/\sigma^2$ and $\beta = \sigma^2/\mu$ from *mean value* μ and *standard deviation* σ
  - the *simplicity* of this calculation makes the Gamma probability distribution particularly interesting for representing the aggregate residential load

Comments

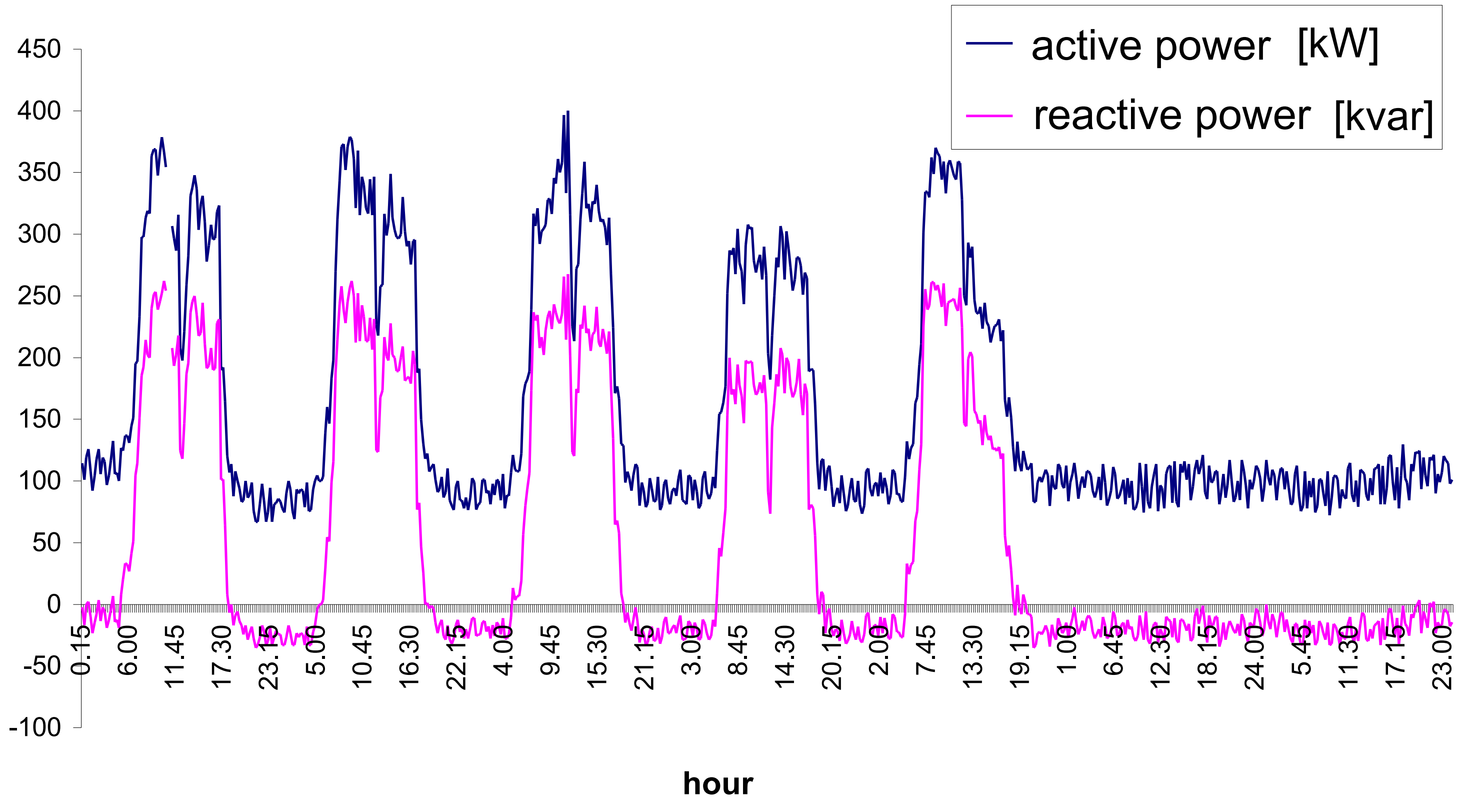
- Residential load pattern characterisation requires a *comprehensive approach* with data gathering, validation and Monte Carlo simulation
- Quantitative evaluations of the *time-dependent* load power uncertainty for small numbers of residential customers is obtained
- The load power distribution at given time instants can be satisfactorily represented by a *Gamma probability distribution* with parameters easily computed from data mean value and standard deviation
- The results obtained are useful for *probabilistic characterisation* of residential customers in the evolving scenario of the electricity markets and in the presence of distributed generation

Industrial load

reference power [kW]
400

rated voltage [kV]
6.3

utilization
medium

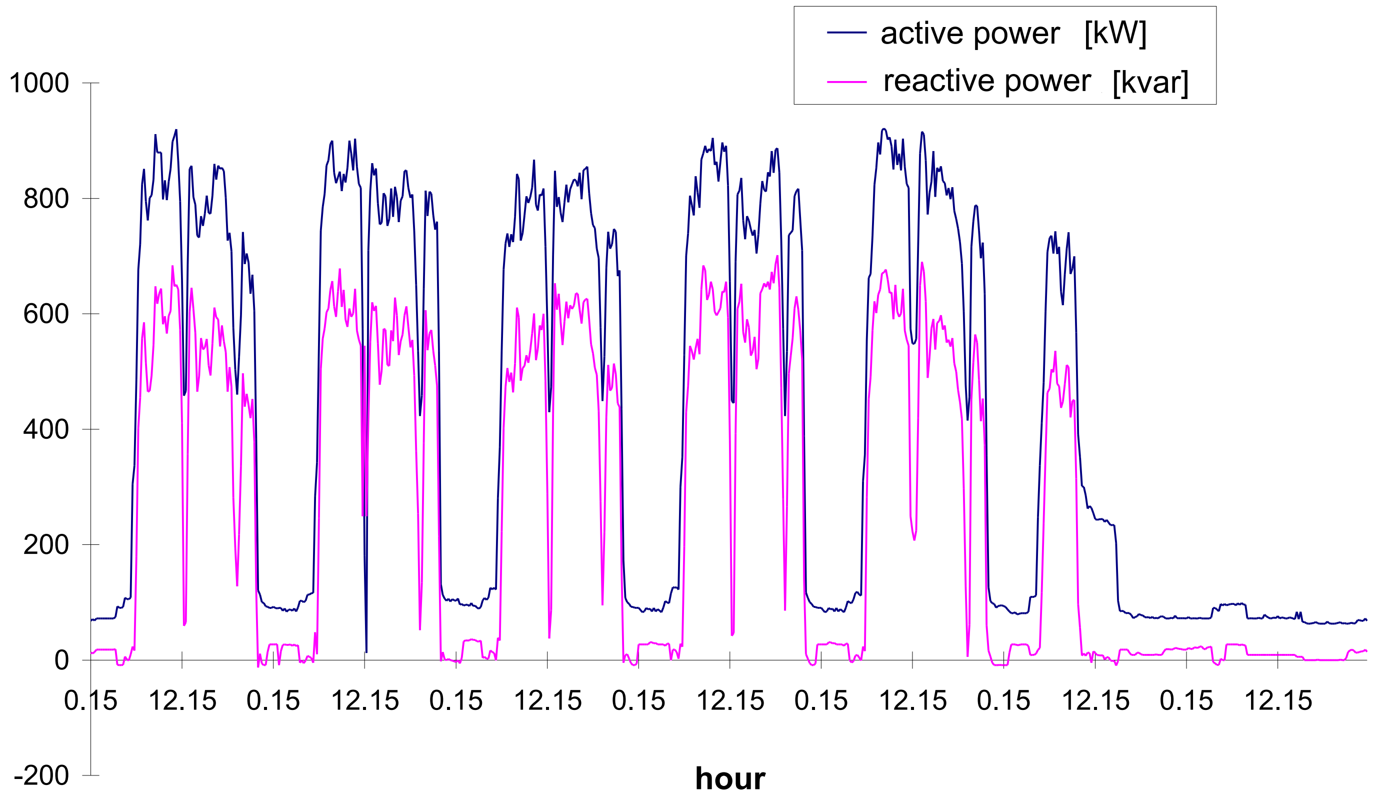


Industrial load

reference power [kW]
1000

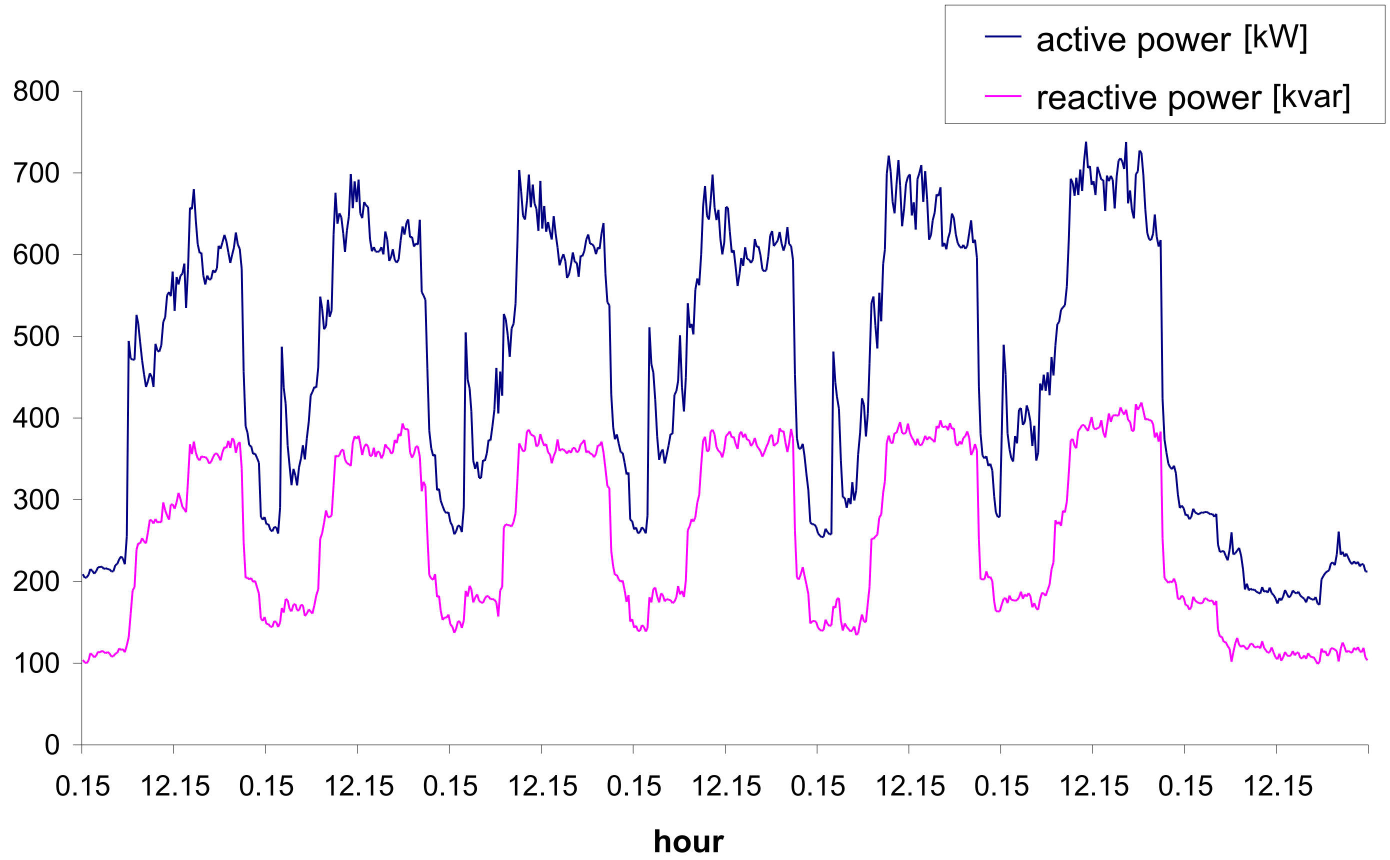
rated voltage [kV]
27

utilization
high



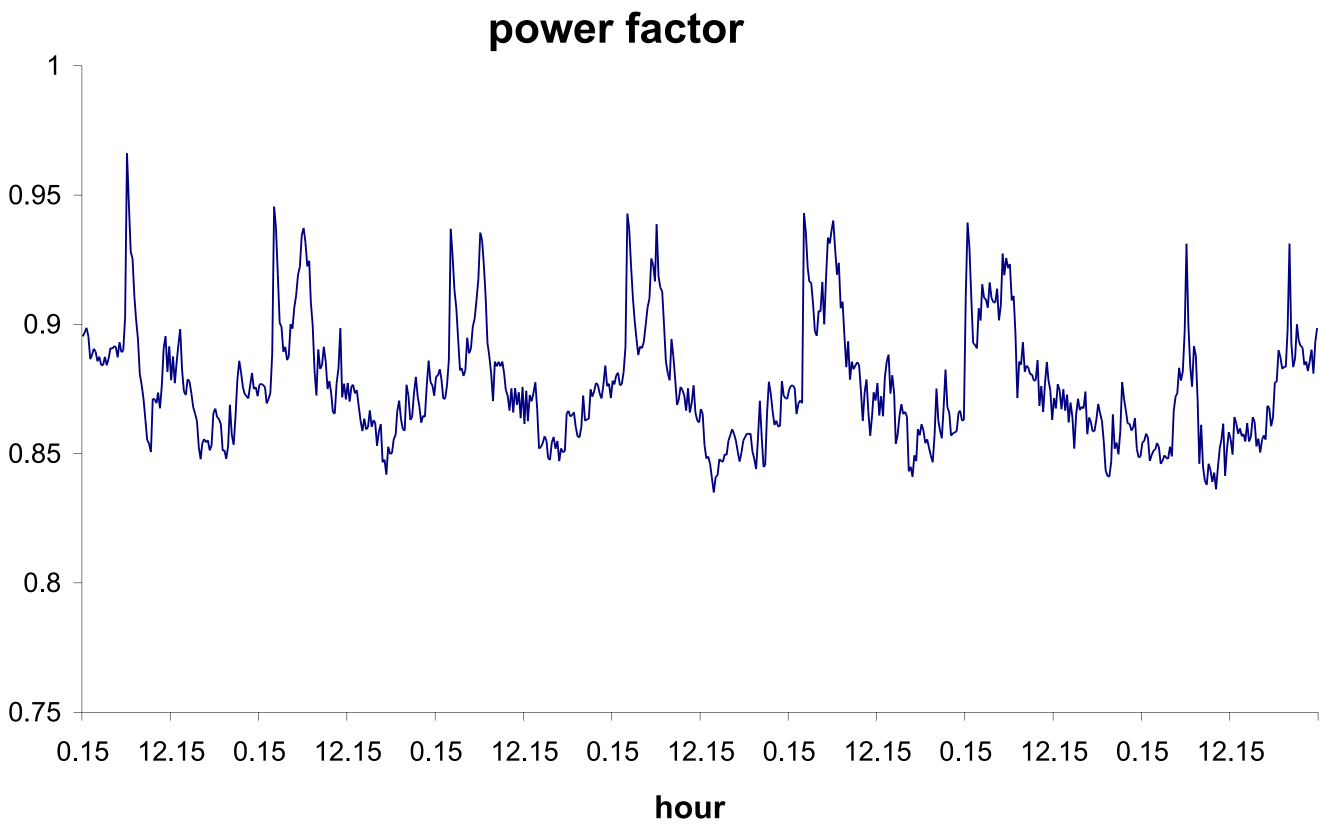
Consumer of the tertiary sector

reference power [kW]	rated voltage [kV]	utilization
800	6.3	high



Consumer of the tertiary sector

reference power [kW]	rated voltage [kV]	utilization
800	6.3	high

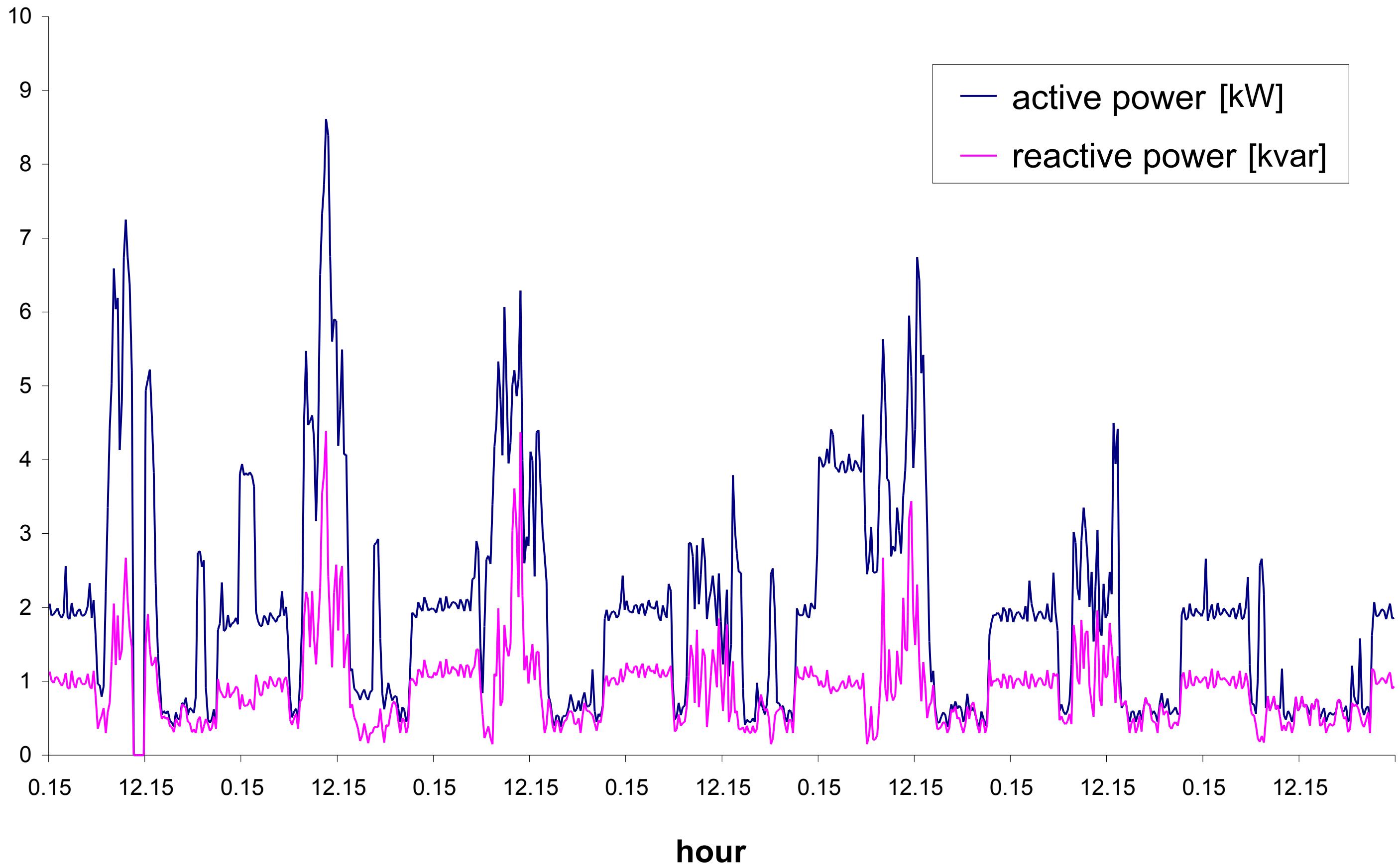


Consumer of the tertiary sector

reference power [kW] 15

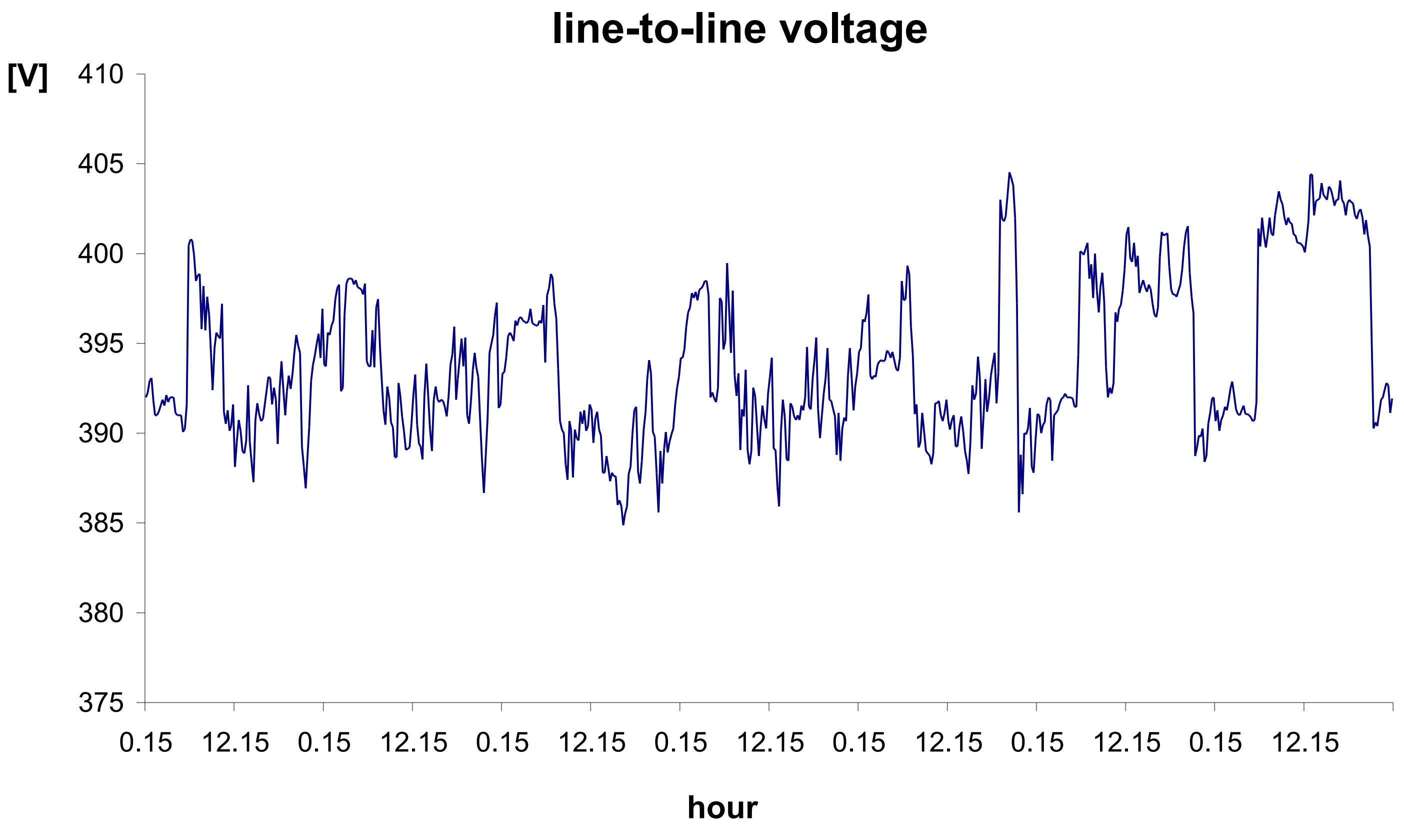
rated voltage [V] 400

utilization medium



Consumer of the tertiary sector

reference power [kW]	rated voltage [V]	utilization
15	400	medium



Load patterns

Residential users:

- Load pattern with significant portion of *base power* due to the *diversity* among the aggregation of similar loads (e.g., refrigerators) although each of them has cycling (intermittent) operation
- higher consumption during the day (with concentration of the activities) and lower (but non-zero) at night

Industrial users:

- typical patterns with two peaks due to the working activity in the morning and in the afternoon and to the lunch pause
- energy request reduced during the night

Tertiary users:

- *medium-small users* (e.g., small commercial activities and offices): load profile similar to the industrial one
- *large users* (e.g., shopping malls and large offices): single peak during the day due to continuing working period, and non-negligible demand at night, with services in continuous operation (e.g., refrigerators and lighting)

Load profiles

After the introduction of the competitive electricity market, the energy suppliers may *new degrees of freedom* to formulate new tariff structures

The knowledge of the *electrical load evolution* is essential for the definition of the time-variable tariffs

From detailed analysis carried out on specific load categories, the load patterns representative of load aggregations (*load profiles*) are extracted

The load profiles are *normalized* with respect to the peak of the load pattern, to facilitate their use with different load aggregations

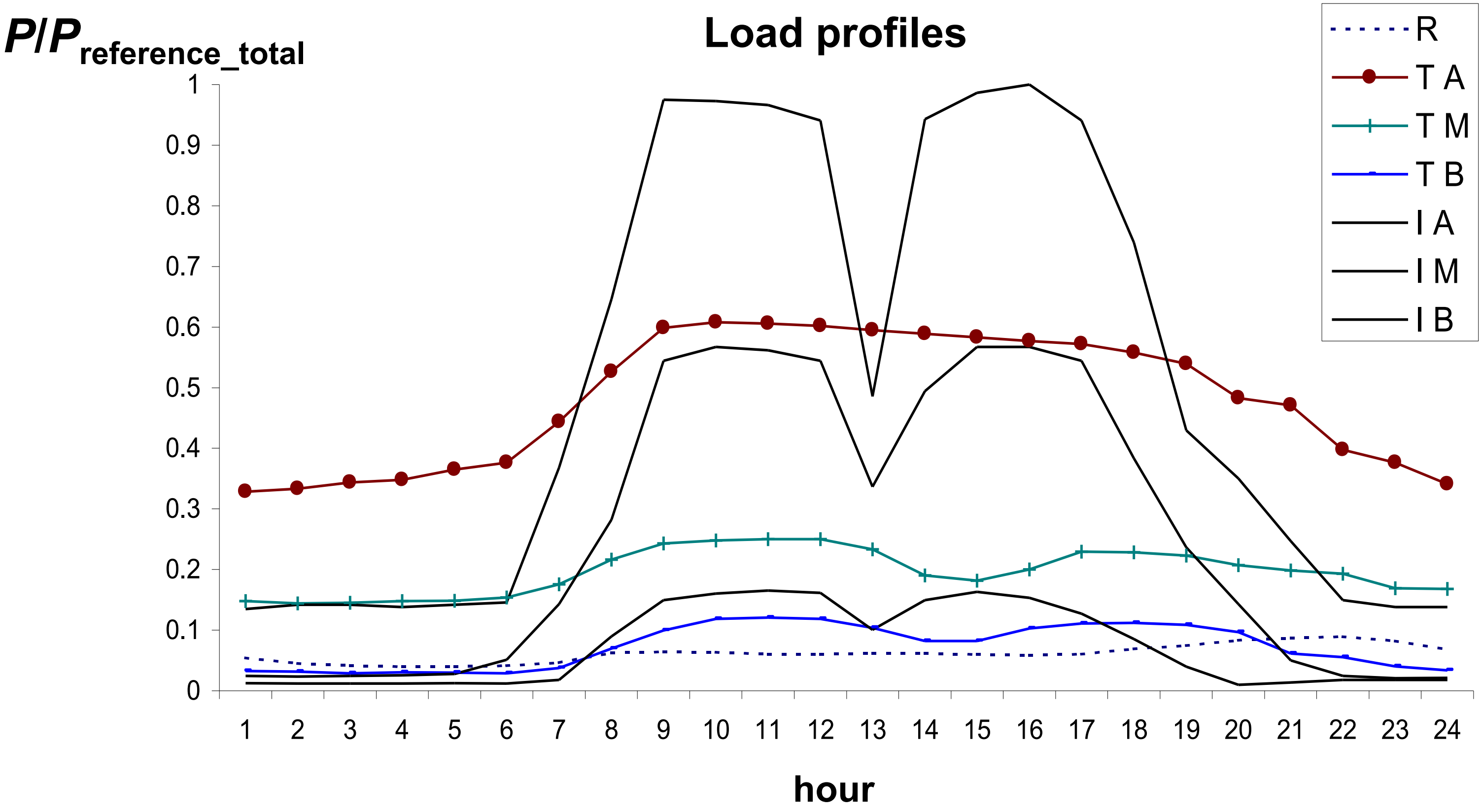
The load profiles are used to *forecast* the evolution of the consumption at the HV/MV or MV/LV substation level

This information allow for identifying *criticality* and *periodicity* (weekly, monthly or seasonal) of the consumption oscillations

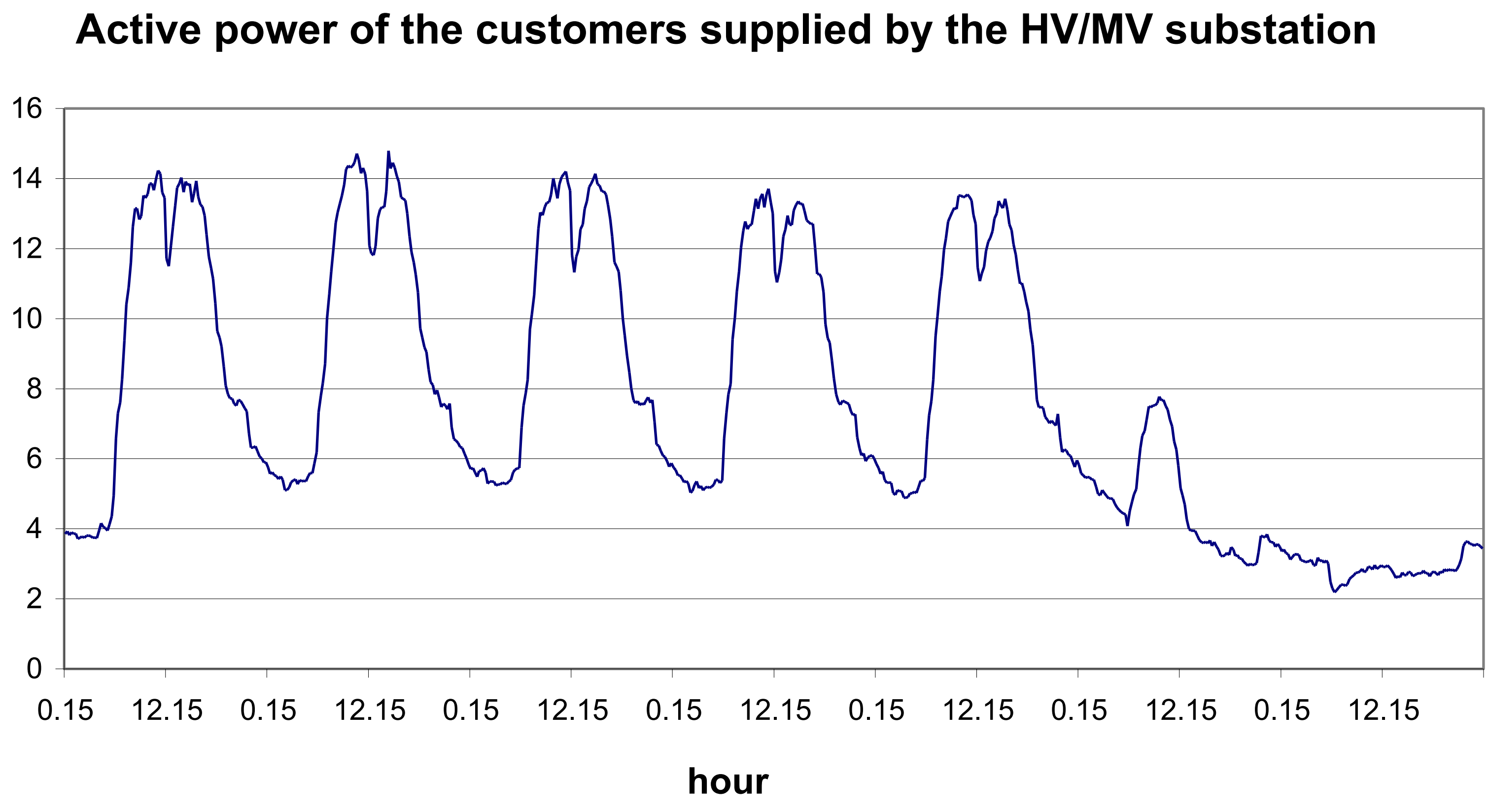
Normalized load profiles

R = residential
I = industrial
T = tertiary

A = high utilization
M = medium utilization
B = low utilization

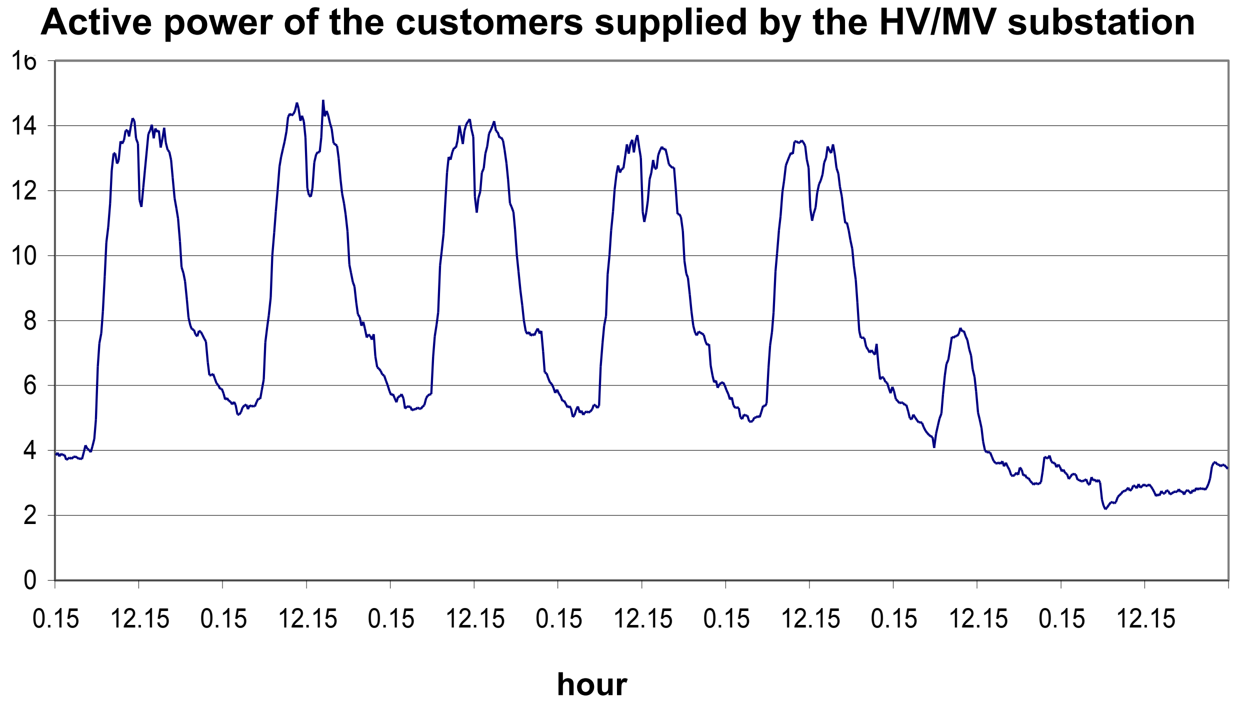


HV/MV substation

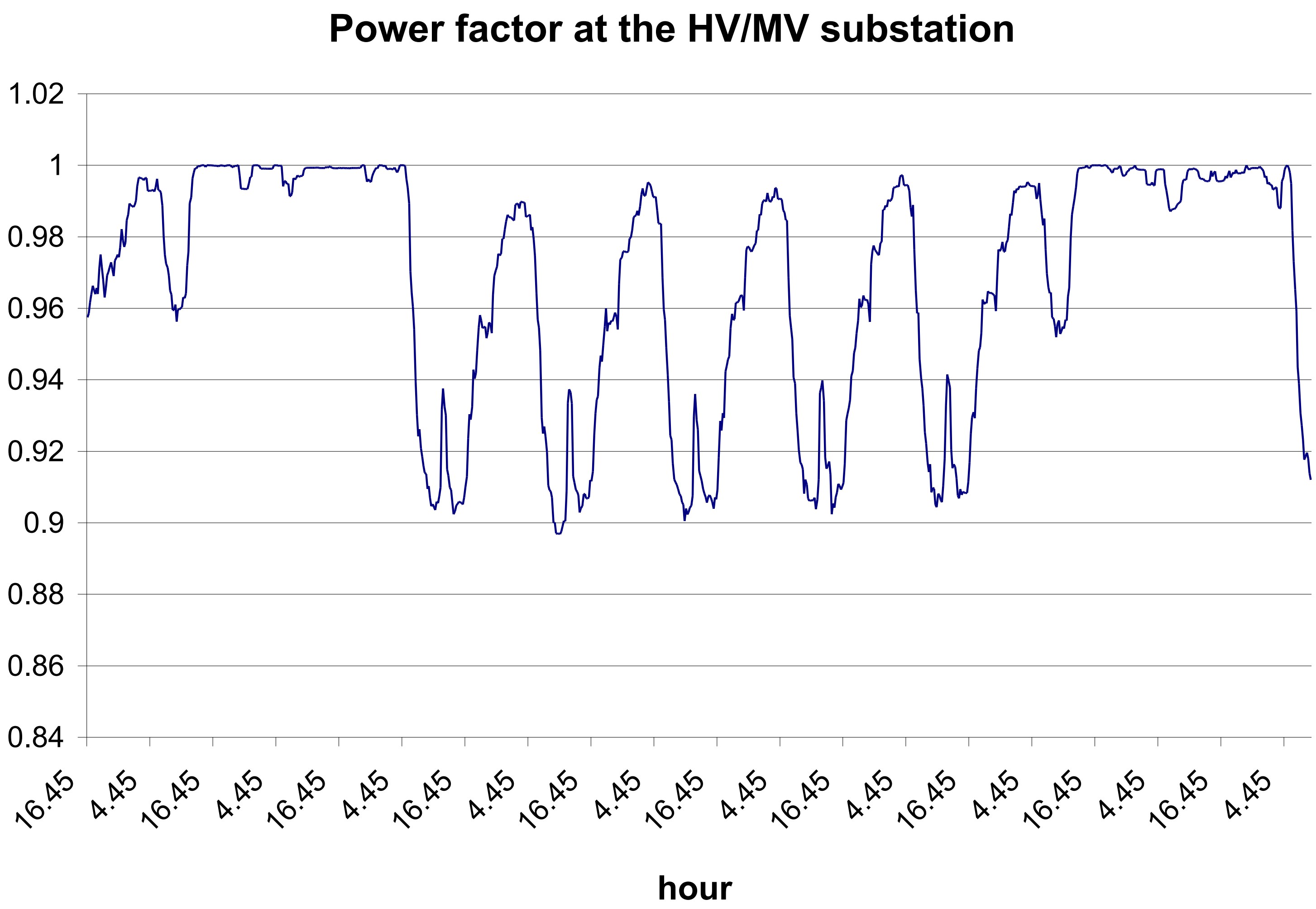


HV/MV substation

- *Which types* of loads form the overall demand of the HV/MV substation?



HV/MV substation



CUSTOMER

GROUPING

(load pattern shape-based grouping, clustering techniques)

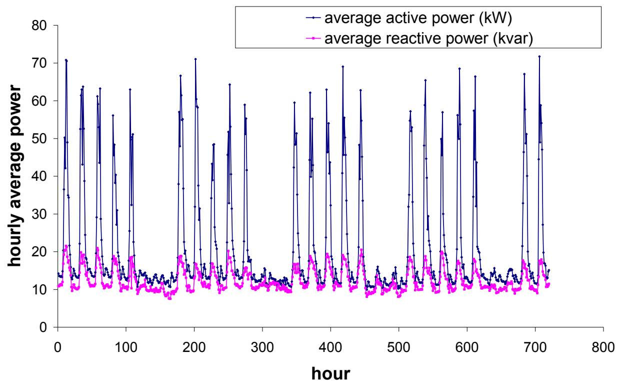
Customer grouping

- Within a given *macro-category* (e.g., industrial, commercial, …), there is a great diversity among the load patterns of the customers belonging to the same *type of activity* or associated to the same *commercial code*
- Customer partitioning based on the type of activity and on commercial codes are *not efficient* for representing the specific aspects of the electricity consumption
- A categorization based on the *shape* of the load patterns is much more useful for different purposes:
  - Group customers with *similar electrical behaviour*
  - Identify similar behaviour in different *time periods*
  - Formulate *tariff options* dedicated to each group
  - Study the possible interactions among *different energy sources*

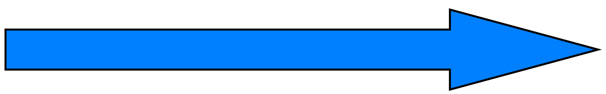
G.Chicco, R.Napoli, P.Postolache, M.Scutariu and C.Toader, Customer Characterization Options for Improving the Tariff Offer, IEEE Transactions on Power Systems, Vol.18, No.1, February 2003, pp.381-387

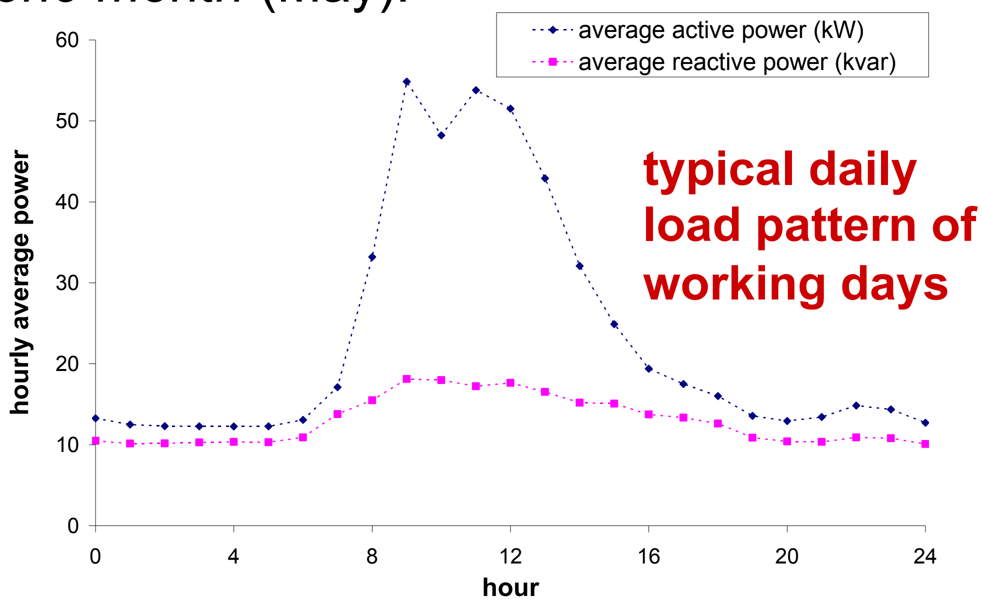
Load patterns for clustering

- *Clustering* techniques are used to form the customer groups
- Data are taken from the same *loading conditions*, that is, comparable periods in terms of type of day (weekday/weekend) and season
- Typical patterns are built (after detecting and eliminating *bad data)* by *averaging* the load data monitored during a period of observation
- Example from data gathered in *one month* (May):



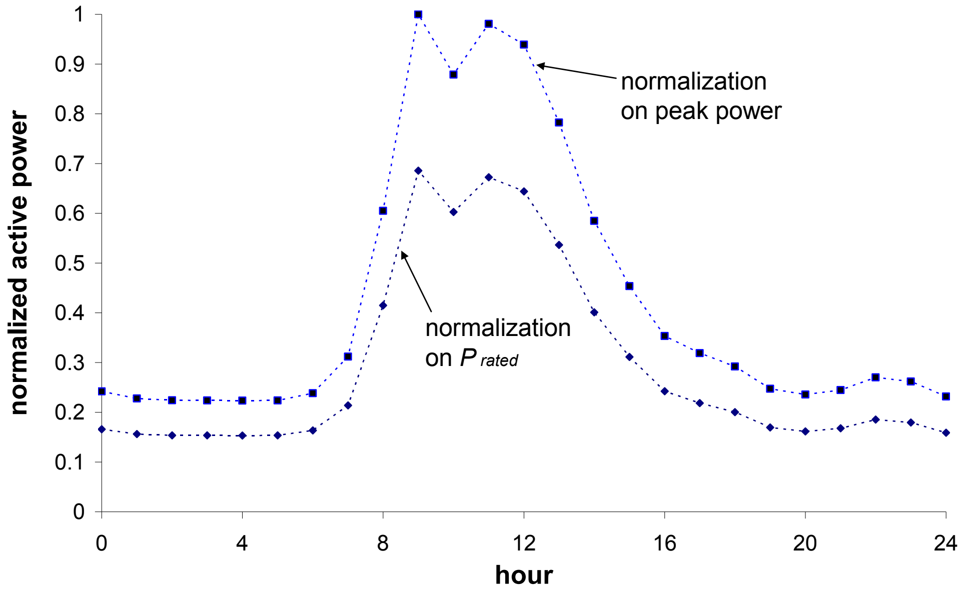
averaging the 22 working days





Representative load pattern

- The typical daily load pattern is then *represented* by using *normalized* values, in the vector $\mathbf{p}^{(i)}$ for customer $i=1,\ldots,N$
- Two types of representations can be considered, leading to different values for the *reference power* used for normalization:
  - the *rated power* (e.g.: $P_{ref} = P_{rated}$ = 80 kW)
  - the *maximum point* of the pattern (P_{ref} = 54.86 kW), using a *representative load pattern* (**RLP**), dividing each point of the pattern by the reference power (all RLP values belong to [0,1])



G.Chicco, R.Napoli, F.Piglione, M.Scutariu, P.Postolache and C.Toader, Emergent Electricity Customer Classification, IEE Proceedings Generation Transmission and Distribution, Vol.152, No.2, March 2005, pp.164–172

Load pattern categorisation

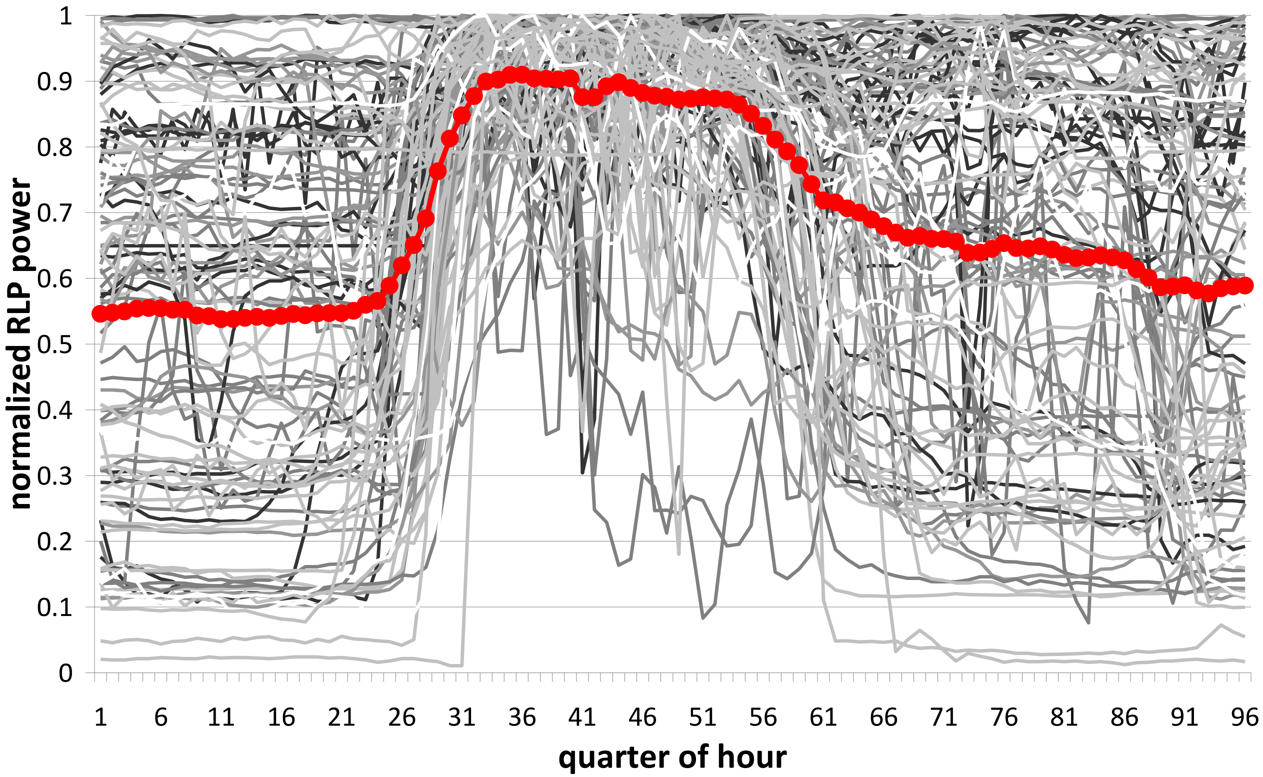
- *Each* customer is represented by its RLP
- The set of RLPs is used to define a number of *customer classes* according to a specified *shape-based* criterion
- The formation of the customer classes is assisted by the use of suitable *clustering* techniques (many techniques are available and can be compared through appropriate *validity indices*)
- The result of the clustering process is the *aggregation* of load patterns having similar characteristics
- The *customer classes* are then obtained by recognizing the properties of the customers with RLPs in the same cluster
- Each customer class is then represented by its characteristic pattern called *load profile*

G. Chicco, Overview and performance assessment of the clustering methods for electrical load pattern grouping, Energy, Vol. 42, No. 1, June 2012, pp. 68–80

Load pattern data example

Dataset with 234 non-residential RLPs

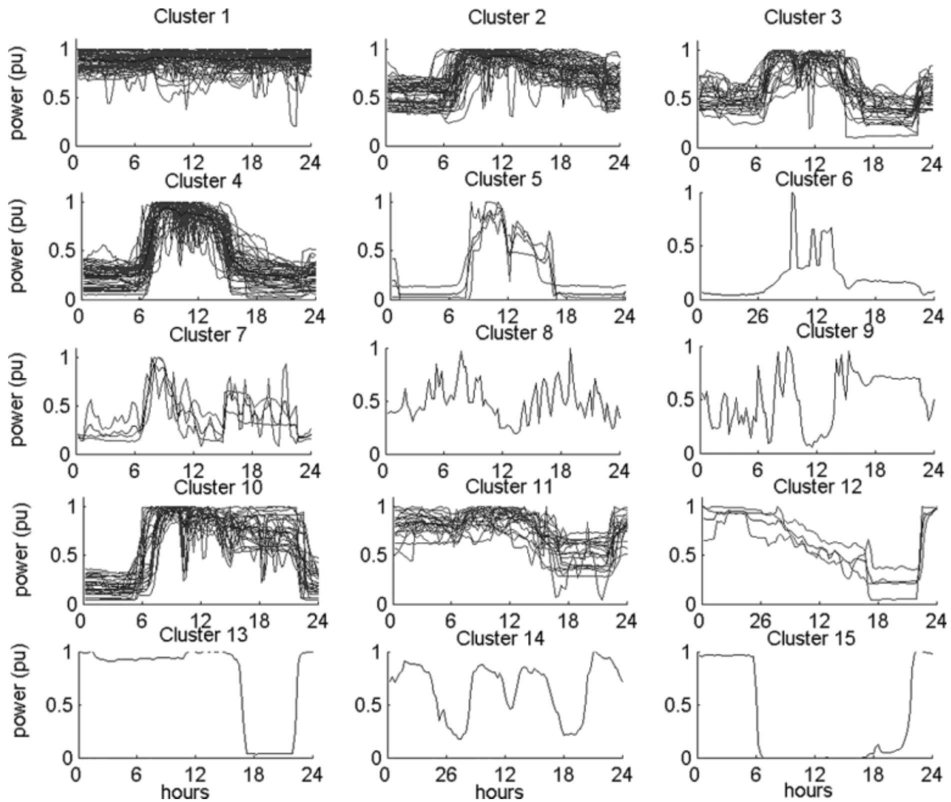
The red line represents the overall average (or *pooled scatter*)



G. Chicco, O.-M. Ionel and R. Porumb, Electrical Load Pattern Grouping Based on Centroid Model with Ant Colony Clustering, IEEE Transactions on Power Systems, Vol. 28, No. 2, May 2013, pp.1706–1715

Clustering results

- *Clustering* groups the customers according with the load pattern *shape*
- Example with *modified follow the leader* clustering



uncommon patterns are identified as *outliers*

G.Chicco, R.Napoli and F.Piglione, Comparison among Clustering Techniques for Electricity Customer Classification, IEEE Transactions on Power Systems, Volume 21, No.2, May 2006, pp.933–940

AGGREGATION OF LOADS

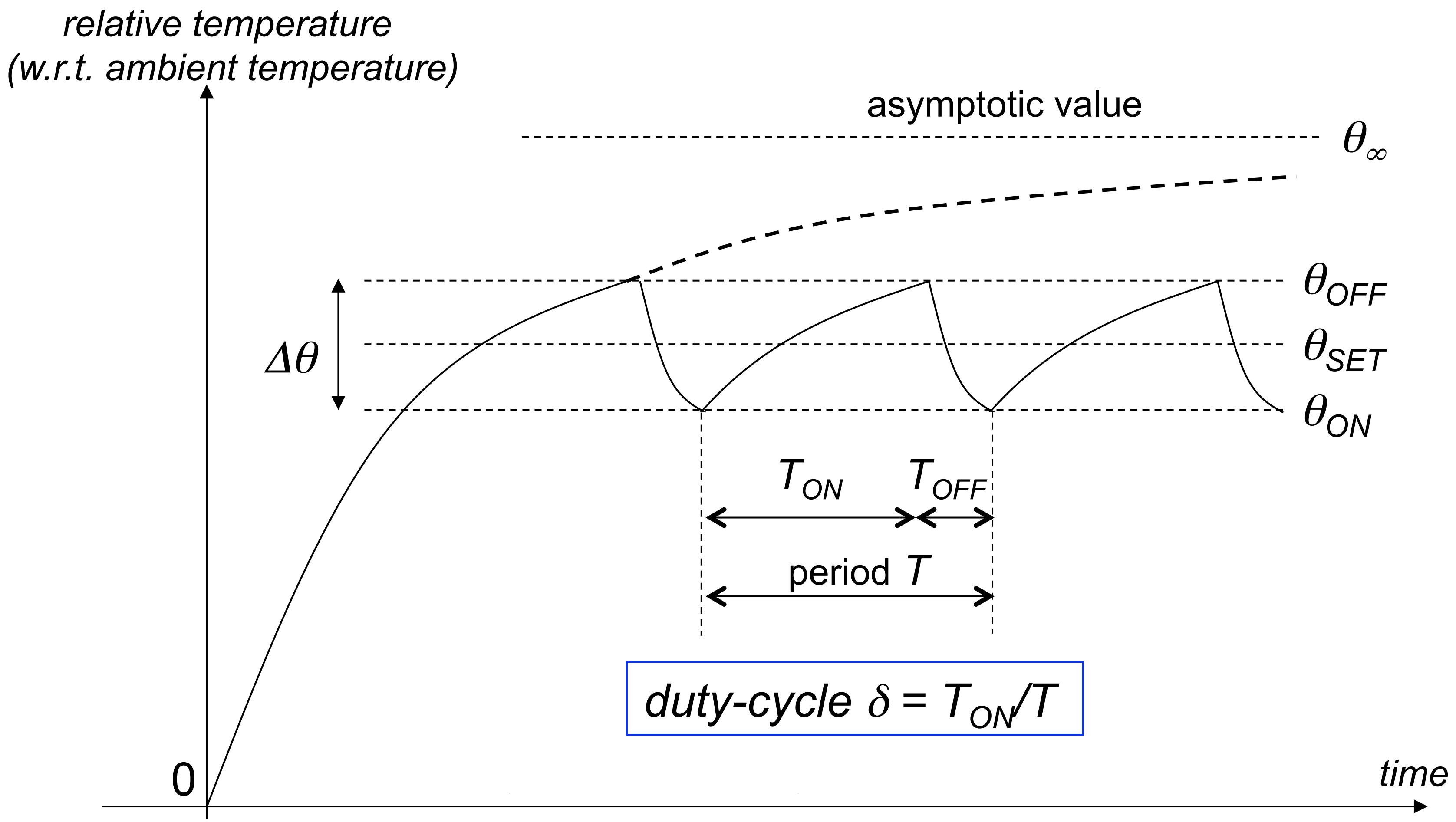
WITH

THERMOSTATIC CONTROL

(load diversity, cold load pickup, energy payback)

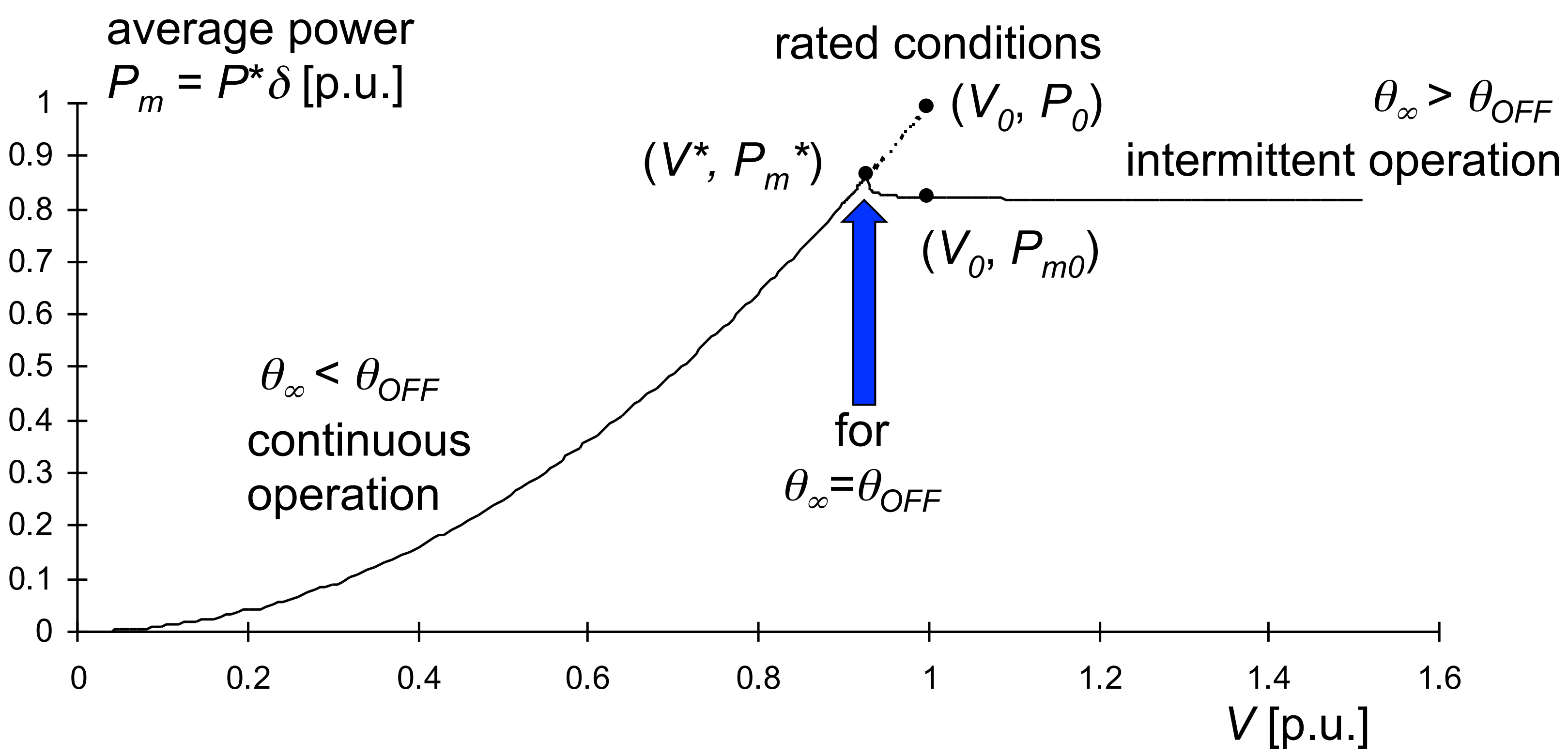
Temperature range for thermostat control

- *Heating load* (for *cooling load* the temperature is reverted)



Static characteristic of a single load controlled by a thermostat

- Details on *continuous operation* (CO) branch and *intermittent operation* (IO) branch

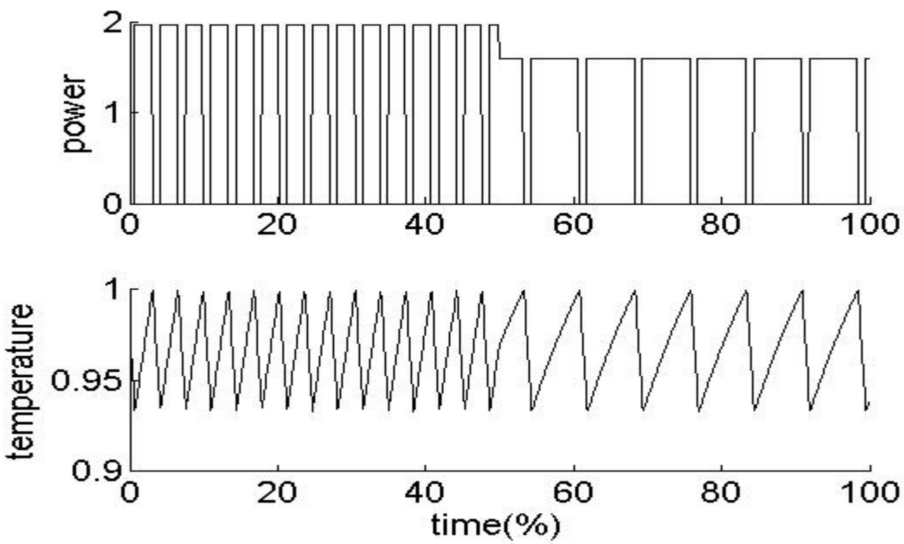


Dynamic model

- A *single* thermostat-controlled load responds to a *voltage variation* by establishing a new operating cycle of different duration

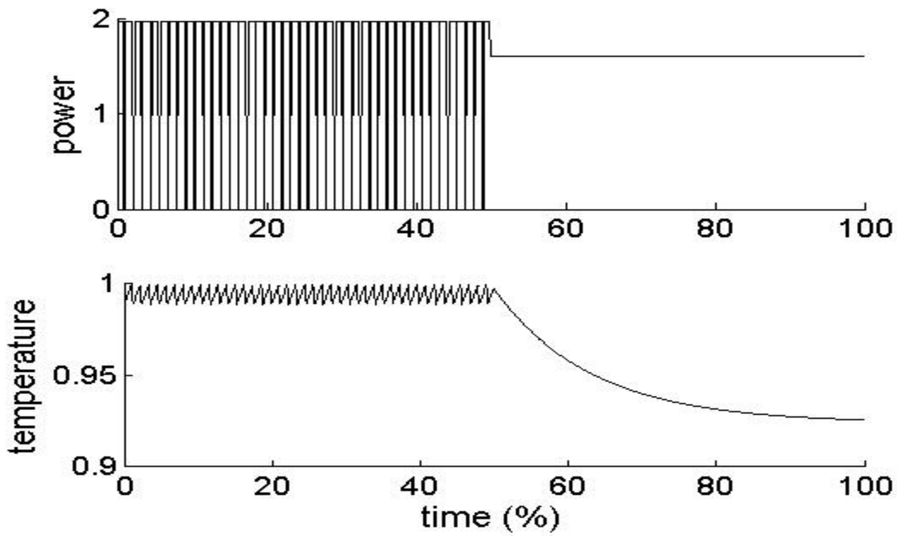
Final point with *cycling operation*

for $\theta_\infty > \theta_{OFF}$



Final point with *continuous operation*

for $\theta_\infty <= \theta_{OFF}$



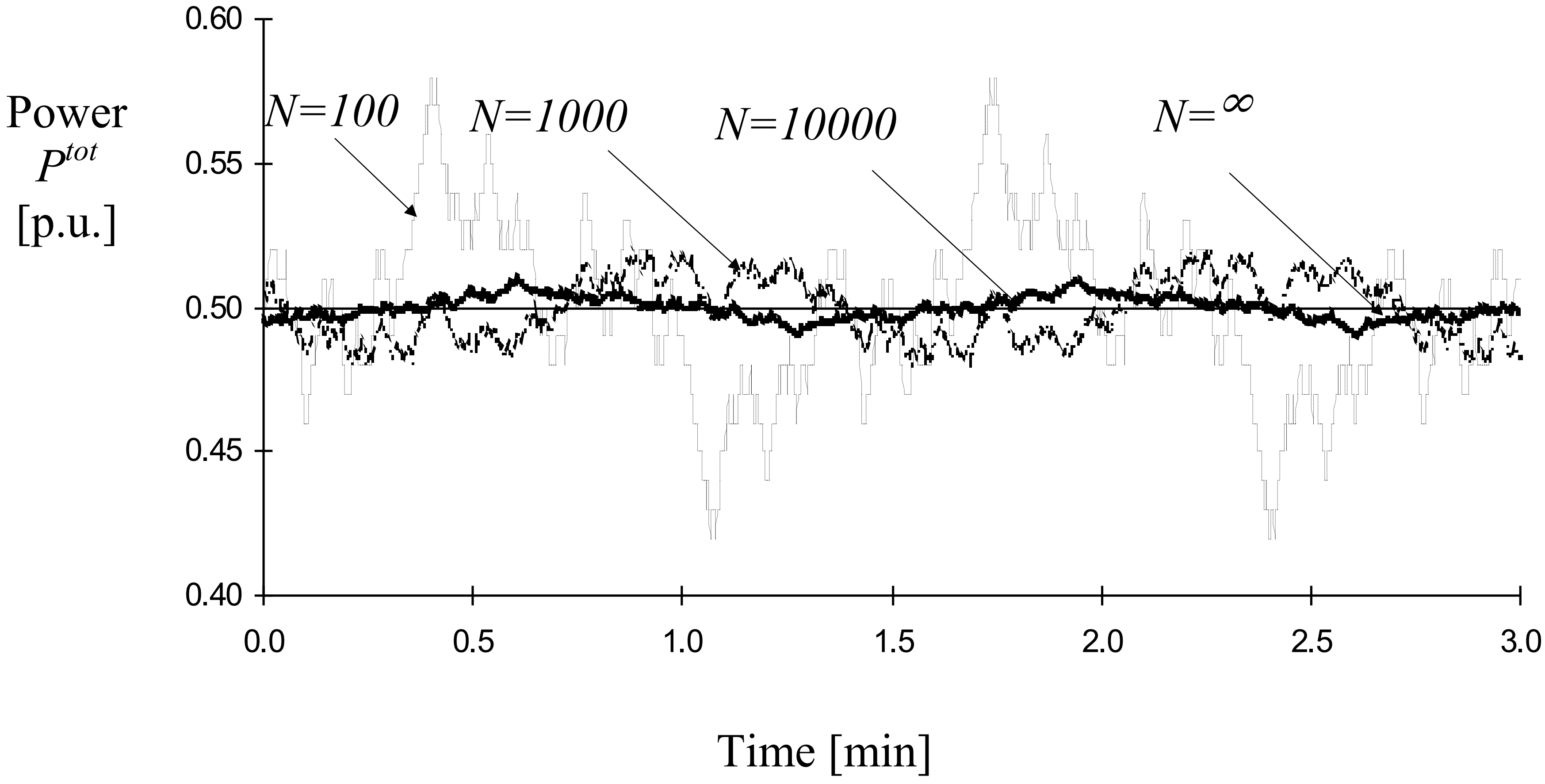
Aggregation of thermostat-controlled loads

- The model of the *single load* is not sufficient to represent the behavior of an aggregation of thermostat-controlled loads
- *Load diversity* (shifting in time of the cycling operation due to lack of *synchronism* among the loads) and *structural differences* between the loads have to be considered by using probabilistic analysis techniques
- *Cold Load Pickup*: after a *long interruption*, when power is restored, many of the automatically controlled appliances will demand power simultaneously, resulting in a temporary *loss of diversity* and possible *overload* of the connecting lines
- *Energy Payback*: in the *load recovery* after a voltage interruption, an *extra amount* of energy is required to bring all the loads to a temperature inside the range for thermostat control

Aggregation of thermostat-controlled loads

- Load *diversity* is addressed by considering a *time reference instant* and choosing at random the position of the duty-cycle of each load
- A *limit case* is considered with *N identical* loads with uniformly distributed cycles over the period *T*
- *Other cases* are defined with variations of the *parameters* chosen inside given *ranges*, for:
  - temperature setpoint and deadband
  - rated power
  - thermal time constant
  - difference between the asymptotic temperature and the ambient temperature

N structurally equal loads with the same total mean power (0.5 p.u.)

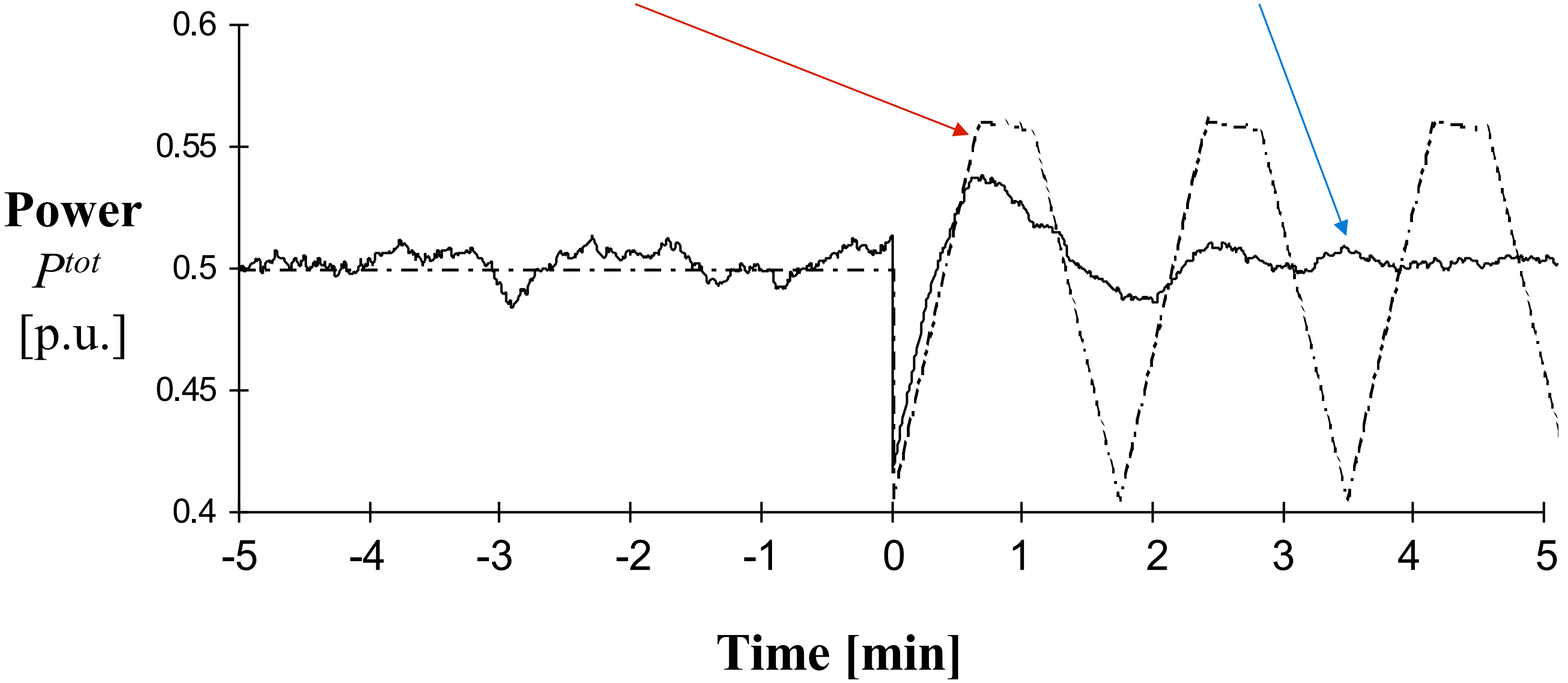


Aggregated load recovery after a step voltage variation

V_0 = 1 p.u., voltage variation ΔV = -10%, $\theta_{SETO} = 150^\circ C \pm 20\%$

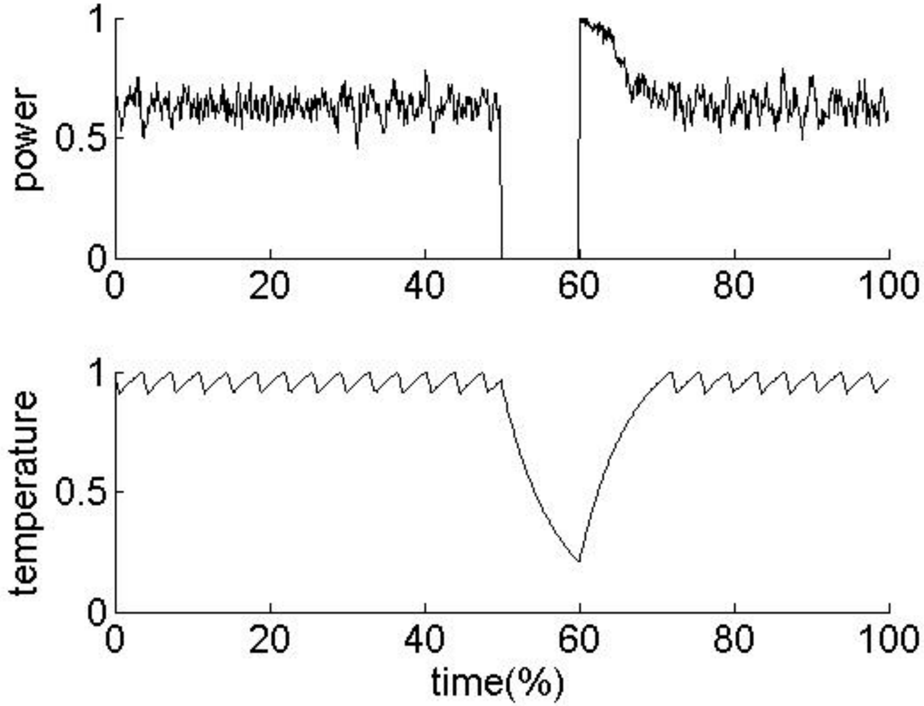
$\Delta\theta = 10^\circ C \pm 25\%, \theta_{\infty 0} = 300^\circ C \pm 10\%,\ \tau = 10\,\text{min} \pm 50\%\ , P_0 = 1\,p.u. \pm 50\%$

limit case and simulation with **10,000 different loads**



Cold Load Pickup (CLP)

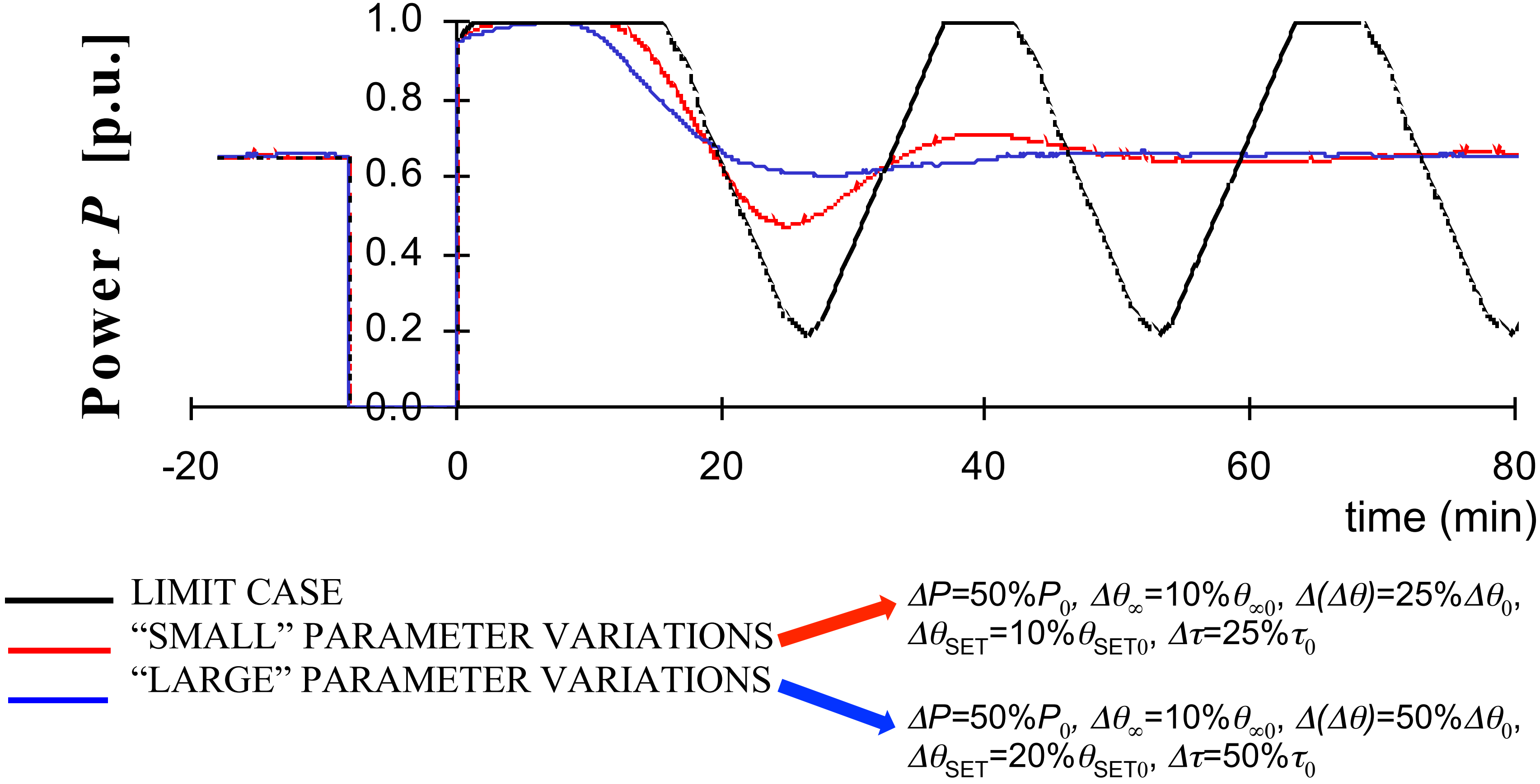
- The results of the analysis of a *supply interruption* for *N = 100* loads is shown in the first graph
- The load is *increasing* due to the *Cold Load Pickup* after the supply restoration
- This may cause *long-term overload* in the distribution system conductors
- The temperature of the aggregated load drops *below* the *thermostat ON limit* during the supply interruption



Example of thermostat-controlled load dynamics with Cold Load Pickup (aggregate load and temperature for a single load)

Example with aggregation of different loads

- Cold load pickup of 10,000 loads with *random parameters* after an interruption of duration Δt = 8 min



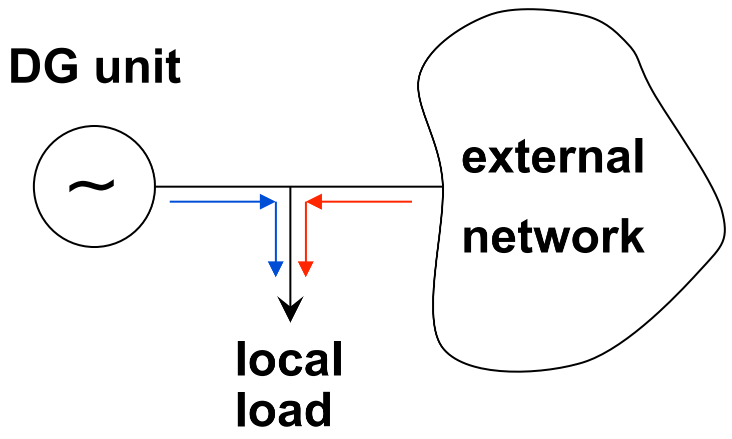
AGGREGATION OF

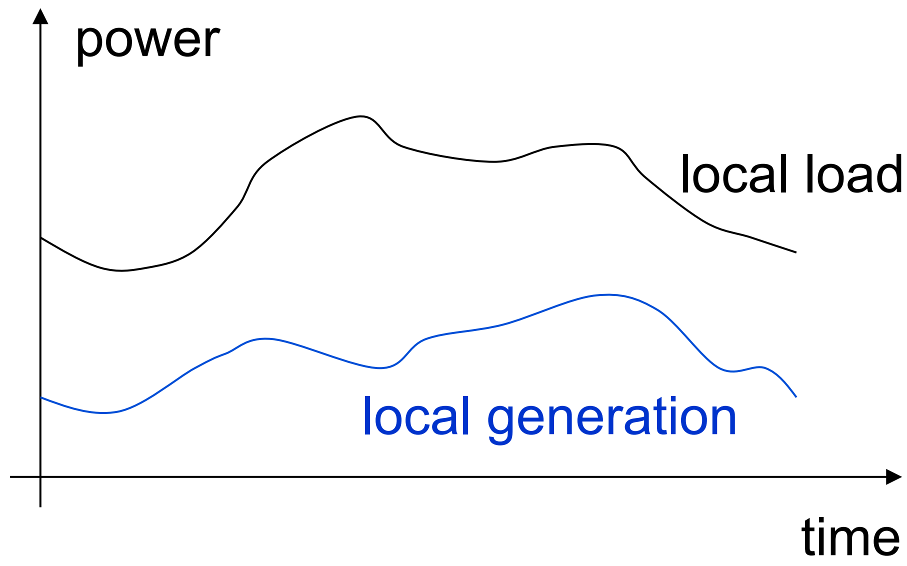
LOADS AND LOCAL GENERATION

(peak shaving and net metering modes, net energy output, data averaging impact)

Modes of operation with local generation

- ***Peak shaving***
  - the DG unit is *always connected* to the external network
  - the local generation *never exceeds* the local load
  - the power flow from the external network to the local load is always *unidirectional*

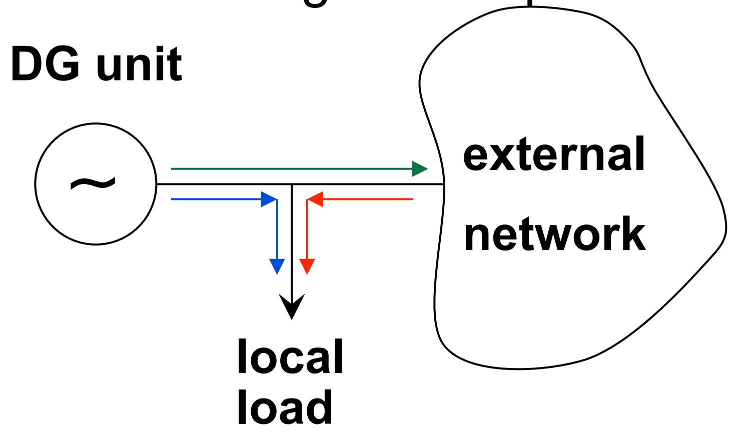


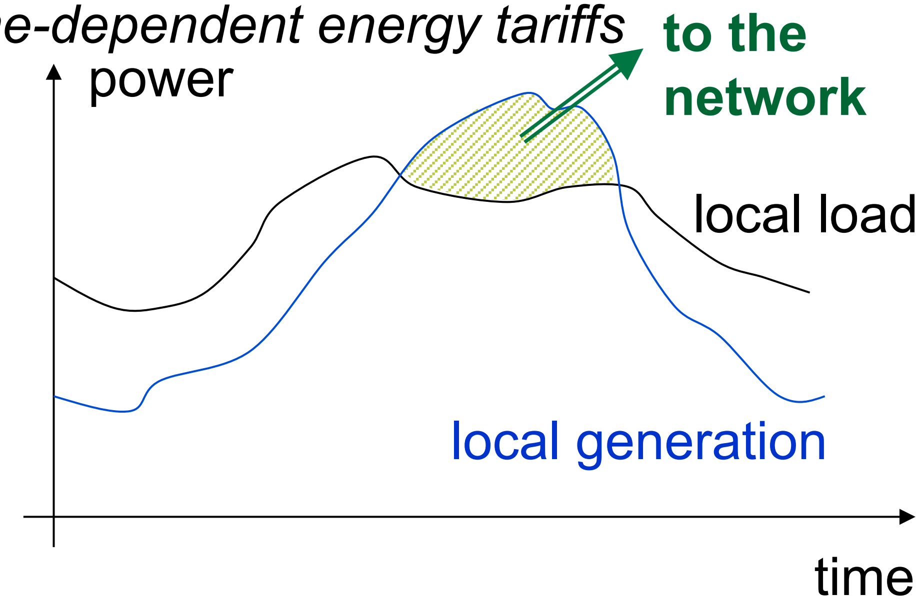


unidirectional power flow

Modes of operation with local generation

- ***Net metering***
  - the DG unit is *always connected* to the external network
  - the local generation *may exceed* the local load
  - the power flow may be in *both directions* (from and to the local system)
  - *separate metering* of the energy flows in the two directions is required for enabling the adoption of *time-dependent energy tariffs*

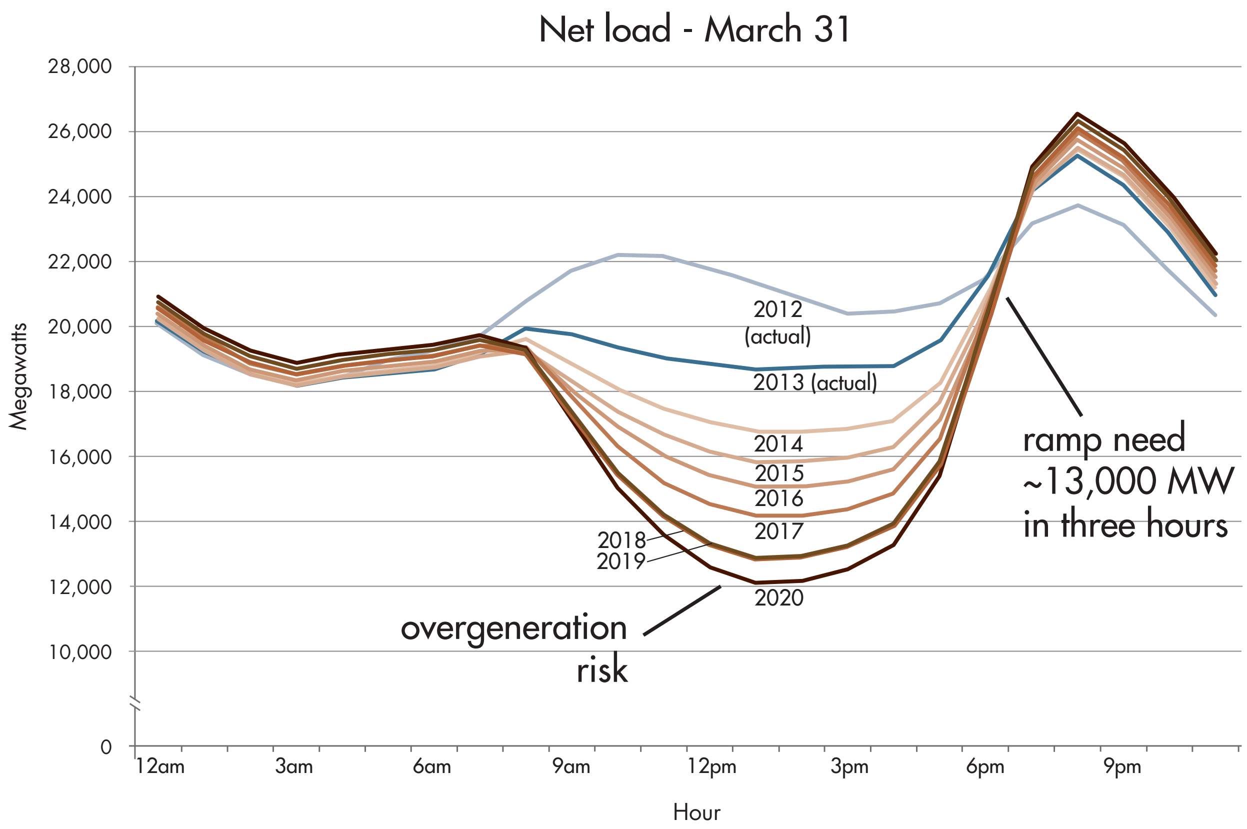




bi-directional power flow

The “duck chart”

- Progressive *growth of local generation* impacts the evolution in time of the net load, changing the traditional view of the demand side
- The “*duck chart*” refers to data from California

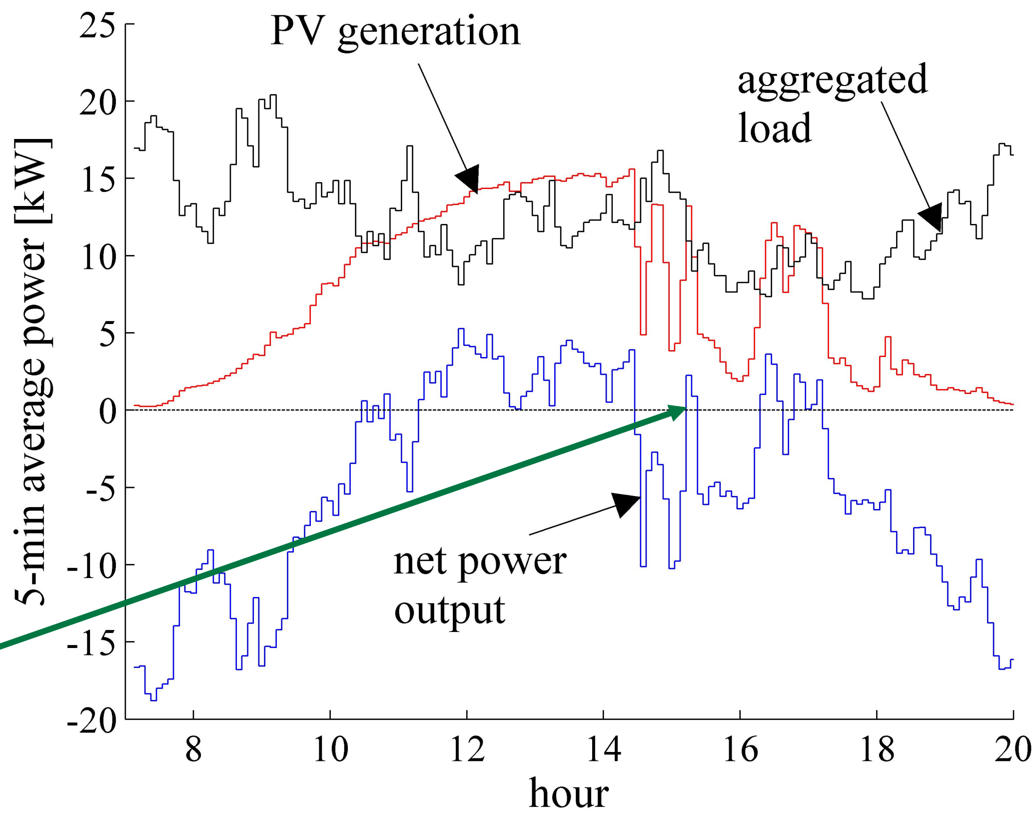


A net output energy example

- An example is shown here on a real system with an aggregate load composed of *residential* consumers and general *building services* (sum of rated powers about 150 kW), and a 25 kW_p photovoltaic (PV) plant
- *Average power* data have been gathered each 5 min in a mid-May day, from hour 7 am to hour 8 pm
- In the time period of analysis, the load consumes 161.3 kWh, and the PV system produces 94.7 kWh
- Globally, the *equivalent* production and consumption system *consumes* 66.6 kWh (*net* energy)

Equivalent system and net output

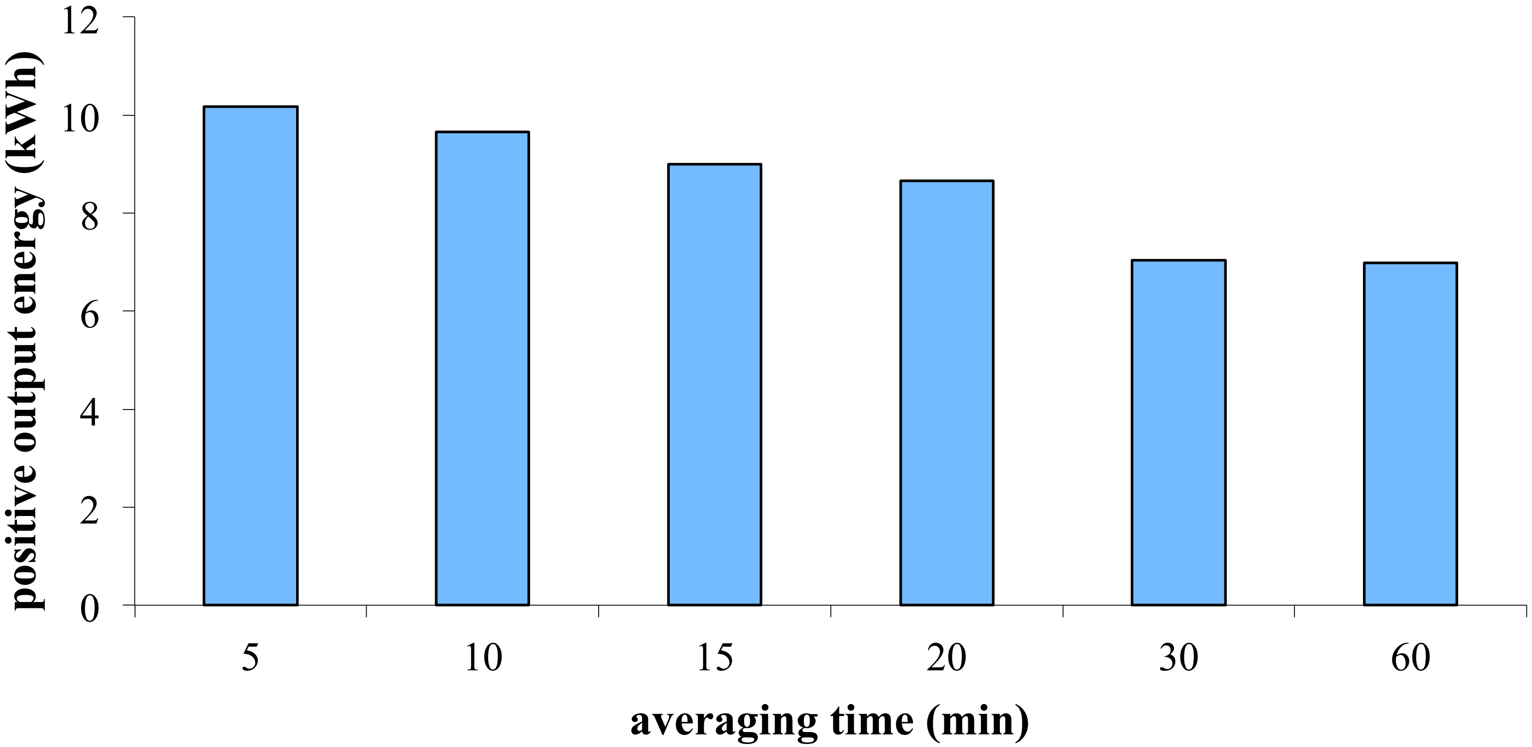
- The system *generates* or *absorbs* power at different times
- The positive *net power output* changes for increasing averaging time steps, due to reduction in the *detail of representation* of the information



The *positive* net power output segments around 3:30 pm *disappear* when the averaging time increases

Effects of different averaging time steps

- The set of data gathered has been used to create *reduced* data sets at *different averaging times* (multiples of 5 min) storing the data on *daily* energy produced and consumed



Hints on the averaging time step

- The *effectiveness* of net power analysis is conditioned by the data set with the *lowest averaging time step*
- When the *difference* between positive and negative net power values is of interest (e.g., due to different economic treatment), *similar* (and possibly *high*) averaging time steps should be used for gathering production and consumption data
- Improving the averaging time step *only* for one of the two types of data could look *ineffective*

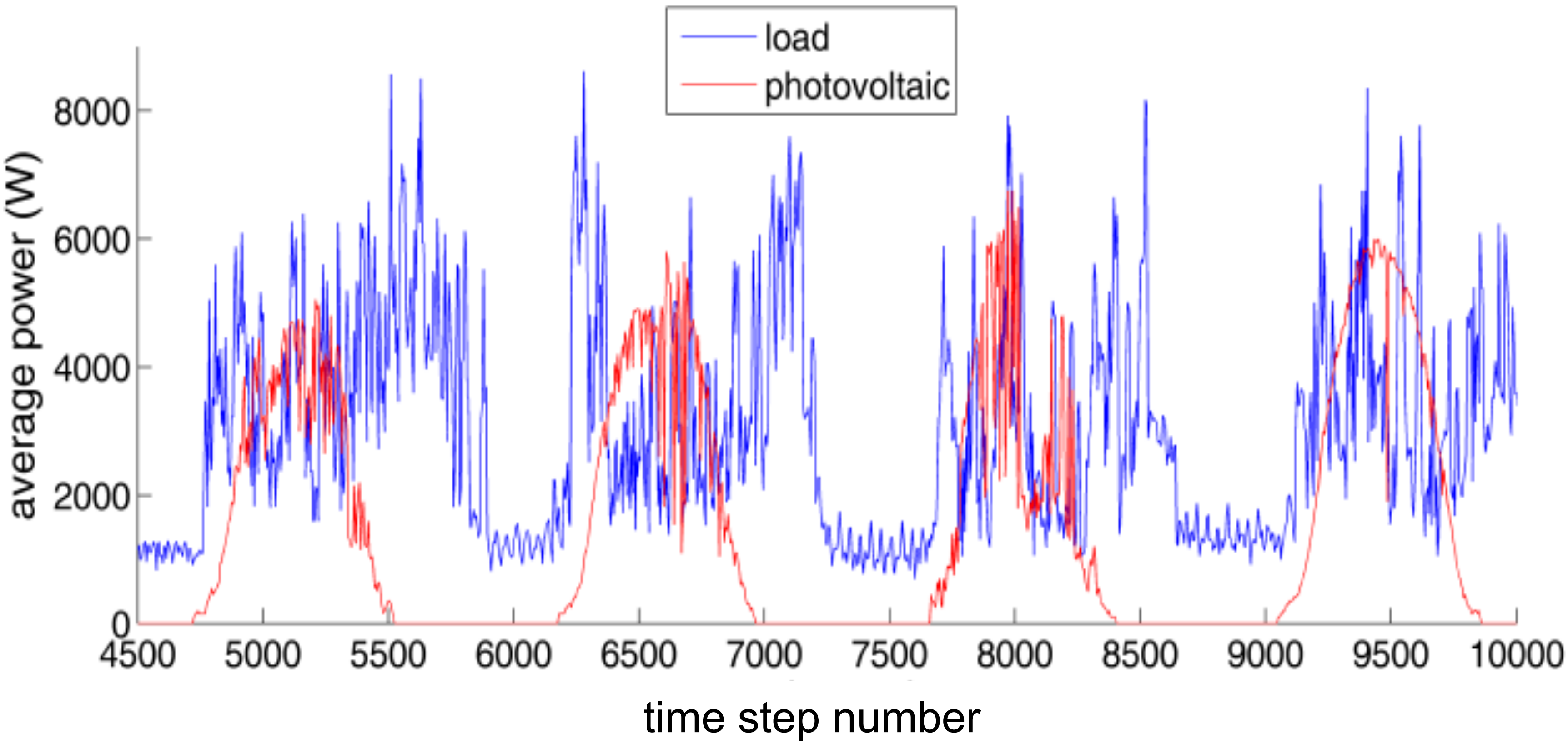
Parametric analysis on averaging time step

- Analysis for a grid-connected *local* system containing PV generation and load
- *Generation* PV plant with rated power 7.5 kWp and data gathered at *irregular time intervals* and processed to get a 5-min averaging time step pattern
- *Load* composed of 10 residential flats, with reference power 30 kW (sum of the contract power values), gathered with *regular* time step 1-min and processed to get a 5-min averaging time step pattern

G. Chicco, V. Cocina, A. Mazza and F. Spertino, “Data Pre-Processing and Representation for Energy Calculations in Net Metering Conditions”, *Proc. IEEE Energycon 2014*, Dubrovnik, Croatia, 13-16 May 2014, paper 262.

Load and PV patterns averaged at 5 min

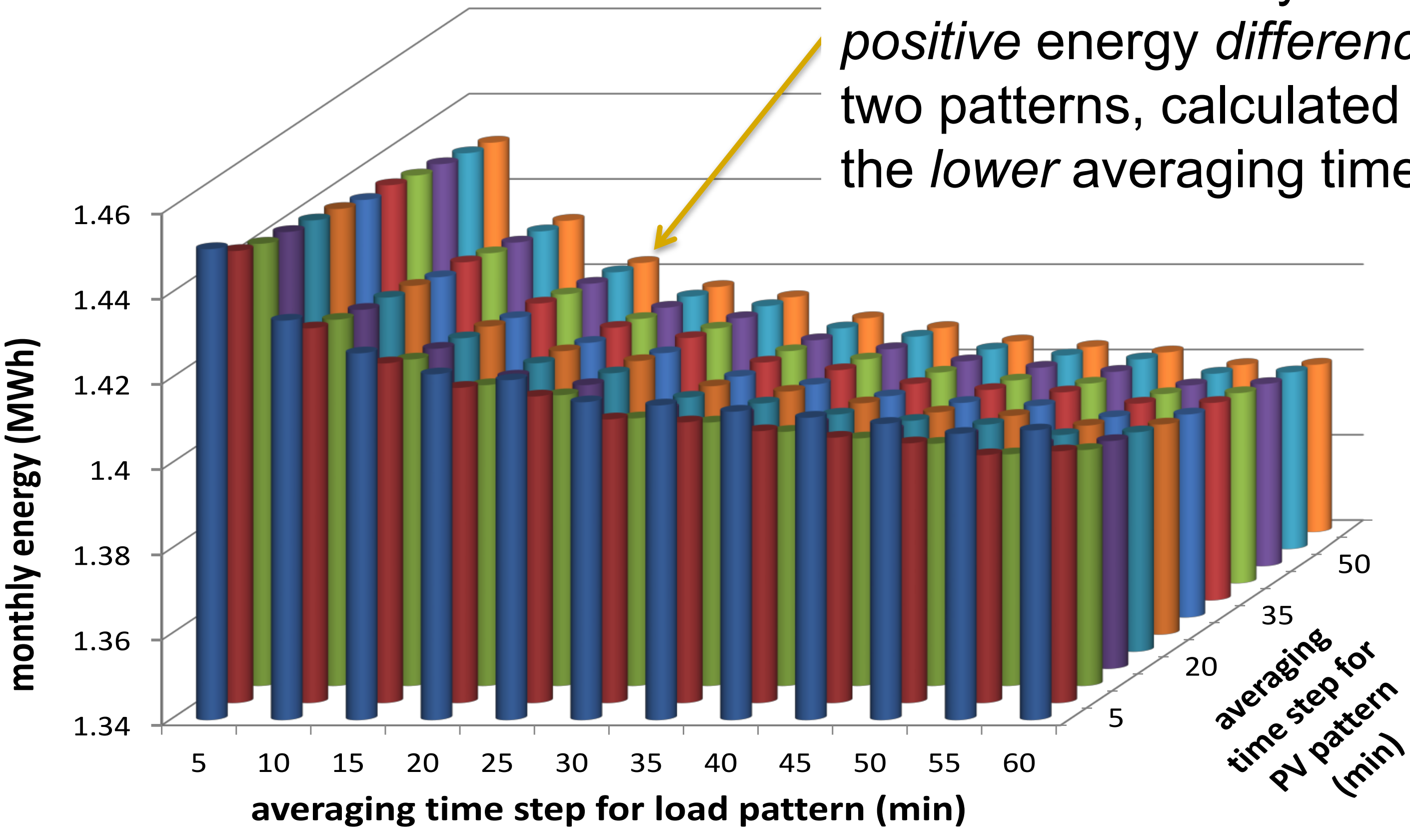
- Example of pattern data for *four* successive days



Parametric analysis

- The averaging time step differences have a visible effect on the *net positive monthly* energy

The individual entry is the sum of the *positive* energy *differences* between the two patterns, calculated on the basis of the *lower* averaging time step




Thank you for
your attention

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