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DEMAND FLEXIBILITY FOR LOAD AGGREGATIONS

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Outline

- This presentation deals with understanding the effects of load pattern *representations* on the identification of demand flexibility

- Specific *contents*:
  - Demand flexibility concepts
  - Understanding the users' participation in demand side initiatives
  - Probabilistic characterization of different aggregations of residential loads
  - Aggregation of loads with thermostatic control
  - Data averaging impact on aggregations of loads and local generations
  - Conclusions

DEMAND FLEXIBILITY

CONCEPTS

(averaging time step,
flexibility definitions,
friends and enemies of flexibility)

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*

Data averaging time step

- For energy analysis purposes, the information gathered must have an *integral value* (referring to the time step duration) and *not* a *punctual* (instantaneous) value
- The relevant data is then the *energy* or *average power* at each time step
- The *average power* in a given period is a *conventional* quantity calculated as the *ratio* between the energy consumption in a given time step and the time step *duration*
- Increasing *averaging time steps* make the patterns *smoother*
- However, in this smoothing process, information on relatively *fast variations* are not preserved

Definitions of flexibility

- The current terminology contains a number of words often used in a *qualitative* way:

“smart”
sustainable
resilient
flexible

- Concerning *flexibility*, for the applications to the electrical system it refers to the possibility of deploying the available resources to *respond* in an adequate and reliable way to the load and generation *variations during time* (taking into account the corresponding *uncertainty*), at acceptable *costs*

The Holy Grail?

- In synthesis, *flexibility* has been seen as the "*capacity to adapt*" across time, circumstances (foreseeable or not), intention (positive or negative reactions) and area of application
- Various *definitions* and *metrics* depend on the area of application:

  William Golden, Philip Powell, "Towards a definition of flexibility: in search of the Holy Grail?", Omega, Volume 28, Issue 4, 1 August 2000, pp. 373-384

- Curiously, the term "holy grail" has been used in the recent literature also for other aspects linked with the demand side: *data acquisition* and *smart metering*:

  K. Carrie Armel, Abhay Gupta, Gireesh Shrimali, Adrian Albert, "Is disaggregation the holy grail of energy efficiency? The case of electricity", Energy Policy, Volume 52, January 2013, pp. 213-234

- The current *challenges* are to *define* and *quantify* flexibility in the specific *contexts*

indianajones.wikia.com

Individual or aggregate load?

- The *definitions* of flexibility depend on evaluations carried out at the level of *individual appliances* or for a *load aggregation*
- For *individual* appliances, definitions from the current literature are:
  - consumers' Acceptable Delay Time (ADT): maximum period of time to postpone the operation of an appliance without sacrificing the consumers' comfort

    R. Stamminger, "Synergy Potential of Smart Appliances," EIE, D2.3 of WP 2 from the Smart-A project, Nov. 2008.
  - Appliance Flexibility Index (AFI): is a measure of the adjustable range of time of the appliances

    C. Vivekananthan, Y. Mishra, G. Ledwich, F. Li, Demand Response for Residential Appliances via Customer Reward Scheme, IEEE Transactions on Smart Grid, Vol. 5 (2), 2014, pp. 809–820.
- For both indices, the data depend on the consumers' preferences and are gathered from *questionnaires* and *surveys*

Individual or aggregate load?

- For the *aggregate* load, *various approaches* have been followed, among which:
  - The use of *sensitivity functions* indicating each user's probability of shifting each device's usage by a certain time, given the *reward* in the new period of usage

    C. Joe-Wong, S. Sen, S. Ha, M. Chiang, Optimized Day-Ahead Pricing for Smart Grids with Device-Specific Scheduling Flexibility, IEEE Journal on Selected Areas in Communications, Vol. 30 (6), 2012, pp. 1075–1085.
  - The *unit commitment optimization* approach, to compare flexibility from demand-side resources with the one from fast ramping generation

    D.S. Kirschen, A. Rosso, J. Ma, L.F. Ochoa, Flexibility from the demand side, IEEE Power and Energy Society General Meeting, 2012.
  - An *agent-based* approach based on the Q-learning algorithm, obtaining *flexibility factors* used to simulate demand elasticity

    B. Kladnik, A. Gubina, G. Artac, K. Nagode, I. Kockar, Agent-based modeling of the demand-side flexibility, IEEE Power and Energy Society General Meeting, 2011.

Friends and enemies of flexibility

- The *friends*:
  - Distributed energy resources (generation, storage)
  - Multi-generation with possible *shifting* among different energy vectors
  - Advanced ICT solutions
  - Regulatory provisions (incentives)

- The *enemies*:
  - Uncertainties
  - Thermal inertia and energy payback
  - Customers' lifestyle and comfort
  - Inter-temporal constraints (e.g., storage capacity, ramp rates)
  - Costs
  - Limited revenues for the consumers

UNDERSTANDING

THE USERS' PARTICIPATION

IN DEMAND SIDE INITIATIVES

(Real Time Pricing,
Time Of Use tariffs,
Critical Peak Pricing,
Demand Bidding Programmes)

The European Project SiNGULAR

UNIVERSIDADE DA BEIRA INTERIOR · Smartwatt · EDA · Α.Π.Θ. A.U.Th. · ΔΕΔΔΗΕ · UCLM UNIVERSIDAD DE CASTILLA-LA MANCHA · itc · Gobierno de Canarias · Concepto Sociológico

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SiNGULAR Partners

- List of Partners:
  - *Five* Universities: **AUTH** Aristotelio Panepistimio Thessalonikis (Greece), **POLITO** Politecnico di Torino (Italy), **UBI** Universidade da Beira Interior (Portugal, *project coordinator*), **UCLM** Universidad de Castilla - La Mancha (Spain), **UPB** Universitatea Politehnica din Bucureşti (Romania)
  - *Three* Distribution System Operators (DSOs): **EDA** Electricidade dos Açores (Portugal), **ELECTRICA** (Romania), **HEDNO** Diacheiristis Ellinikou Diktyou Dianomis Elektrikis Energeias (Greece)
  - *Eight* Energy Companies and Agencies: **ALSTOM** (Switzerland), **CS** Concepto Sociologico (Spain), **ENEA** (Italy), **INTELEN** Services Limited (Cyprus), **ITC** Instituto Tecnologico de Canarias (Spain), Comune di **Pantelleria** (Italy), **SMARTWATT** Energy Services (Portugal), **W4E** Wave for Energy (Italy)

SiNGULAR Project Web Site

http://www.singular-fp7.eu/home/

Overview of the SiNGULAR aims

- Investigation of the effects of **large-scale** integration of **RES** and **DSM** on the **planning** and **operation** of **insular** electricity grids

- **Recommendations** as well as **scalable** and **replicable solutions** for all **regulatory, technical** and **economic** challenges of integrating a very large share of RES in insular electricity grids

- Different levels of **research** and **implementation** (operation tools, planning procedures and tools, development of grid codes)

RES: renewable Energy Sources
DSM: Demand Side Management

The demand side in SiNGULAR

- WP8 – *Implementation of DMS*, coordinated by Intelen (Cyprus)
- In progress… until May 2015
- *Demand Response* (DR) programmes:
  - Real Time Pricing (RTP)
  - Time Of Use (ToU)
  - Critical Peak Pricing (CPP)
  - Demand Bidding Program (DBP)

About 100 selected electricity consumers in Crete

- Energy efficiency *tips and behavioural commitments* designed to impact on the user's everyday life concerning:
  - Lighting
  - Heating
  - Cooling
  - Electric Devices

Energy measurements uploaded to the SiNGULAR platform every 15 minutes

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Smart and Sustainable Insular Electricity Grids Under Large-Scale Renewable Integration

Real Time Pricing (RTP)

- Considers that electric energy tariffs change *hourly*
- Each user sets an *acceptable limit* to the hourly consumption cost according to day ahead tariffs
- The user gets a *message* one hour *before* the hourly consumption cost is expected to *exceed* the limit via text, email or social media
- Incentive: *virtual money* (points)

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Time of Use (ToU)

- Electric energy tariffs are set for a specific *time period* on an *advance* basis
- *Price related messages* will be sent to consumers to shift usage to a lower cost period or reduce their overall consumption
- Incentive: *virtual money* (points), lower *monthly bill*

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Critical Peak Pricing (CPP)

- Designed to *reward customers* that reduce or shift their usage during peak hours
- Critical Peaks occur a few times during summer due to *weather* or system conditions with increased demand
- CPP detection occurs through *day ahead events* triggering, based on load forecasting
- Incentive: *virtual money* (points)

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Demand Bidding Programme (DBP)

- The user earns virtual points for *reducing power* during a DBP event
- The user places a *bid* the day before the event
- The user who *manages to reduce usage during the event* will receive *points* based on the *difference* between the *baseline* and the actual energy use for each hour of the event
- Incentive: *virtual money* (points), lower *monthly bill*

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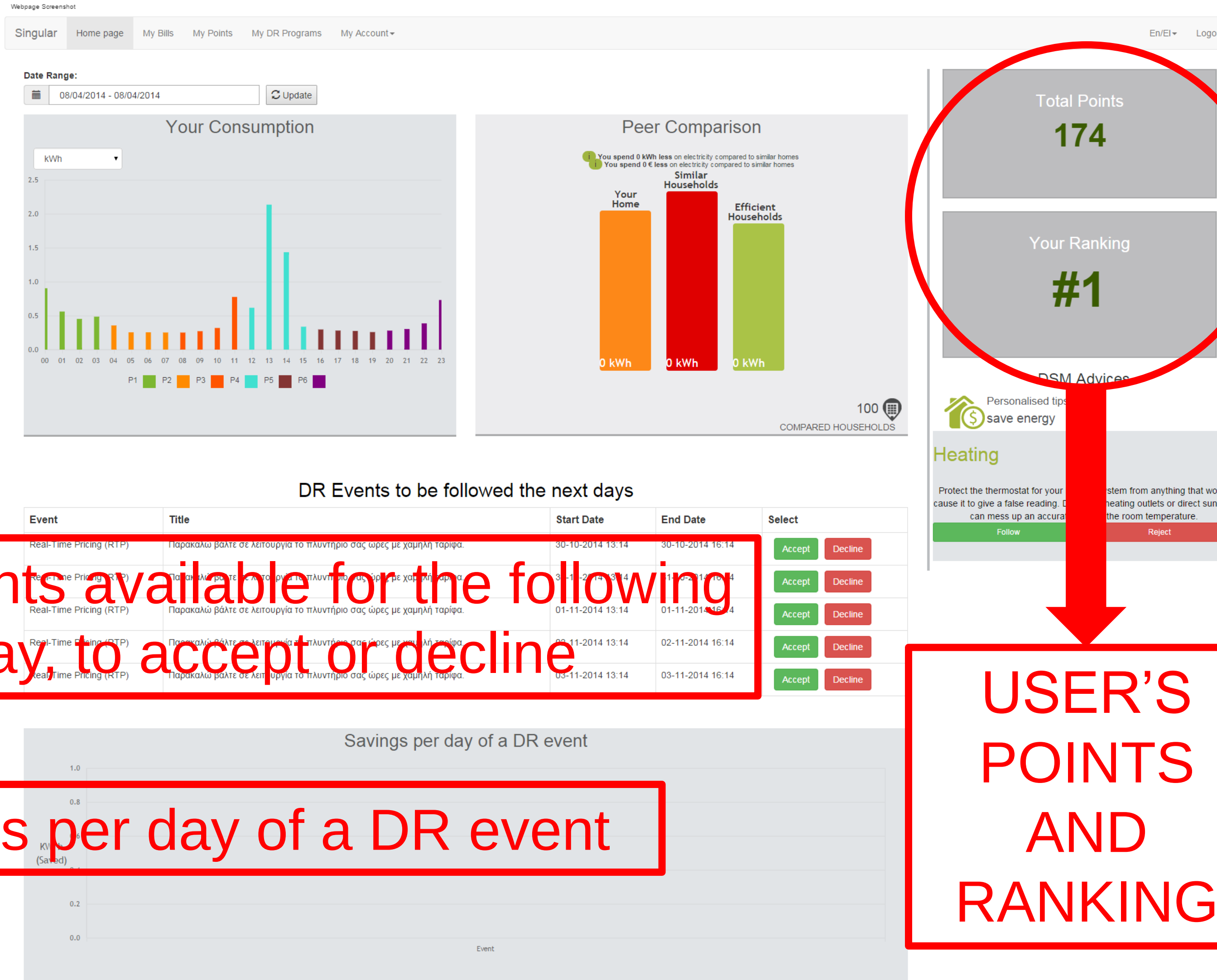
The virtual money (points) system

- The user gains *points* from DR programmes in the following way:
  - Real Time Pricing → 7 points for each kWh saved
  - Time of Use → 3 points for each kWh saved
  - Critical Peak Pricing → 10 points for each kWh saved
  - Demand Bidding Programme → 5 points for each kWh saved
- For each *tip or behavioural commitment* followed → 6 points
- After each *participation* in a DR programme → 10 points

End-User Platform 1



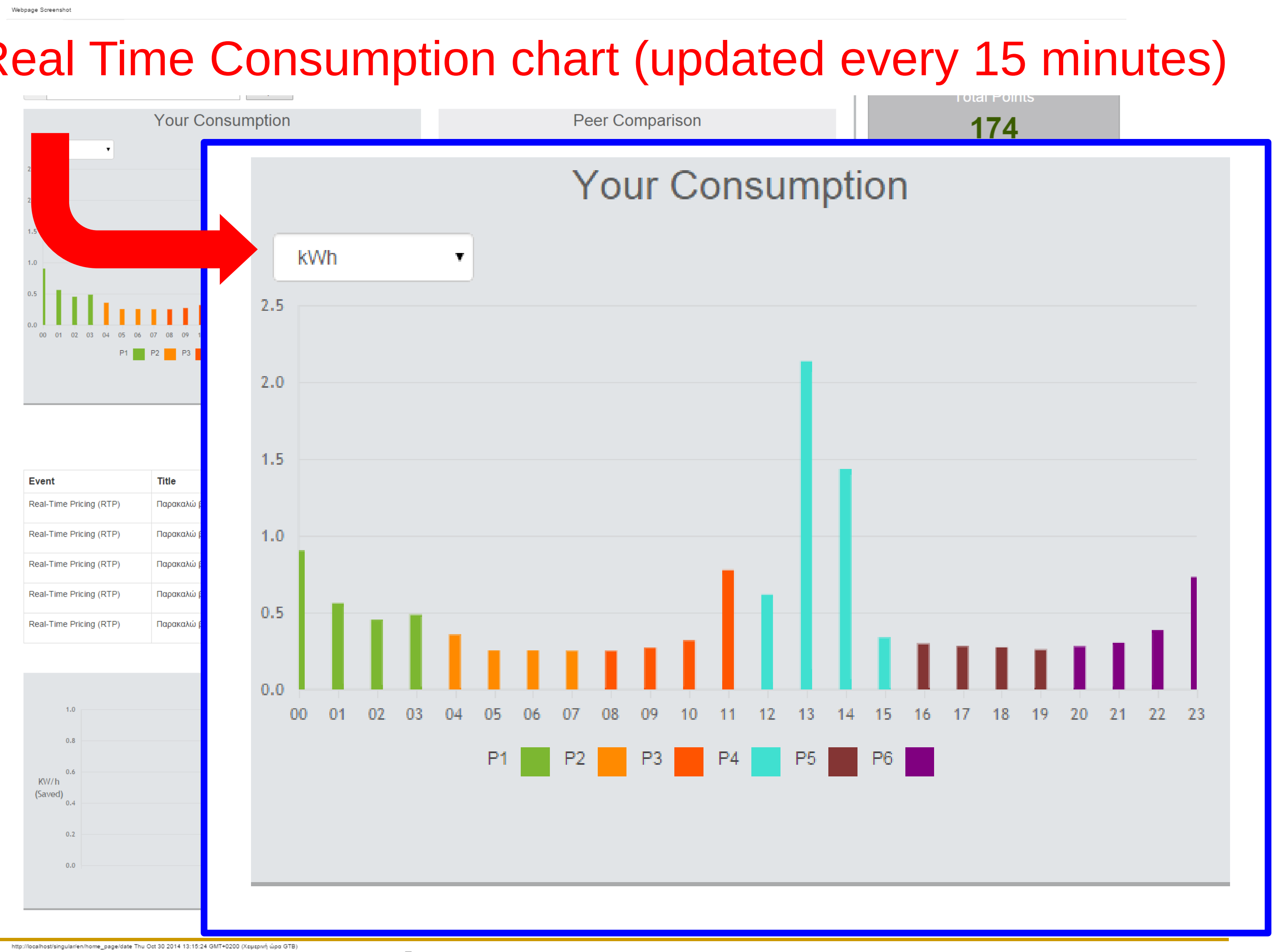
DR events available for the following day, to accept or decline

Savings per day of a DR event

USER'S POINTS AND RANKING

End-User Platform 1

Near-Real Time Consumption chart (updated every 15 minutes)



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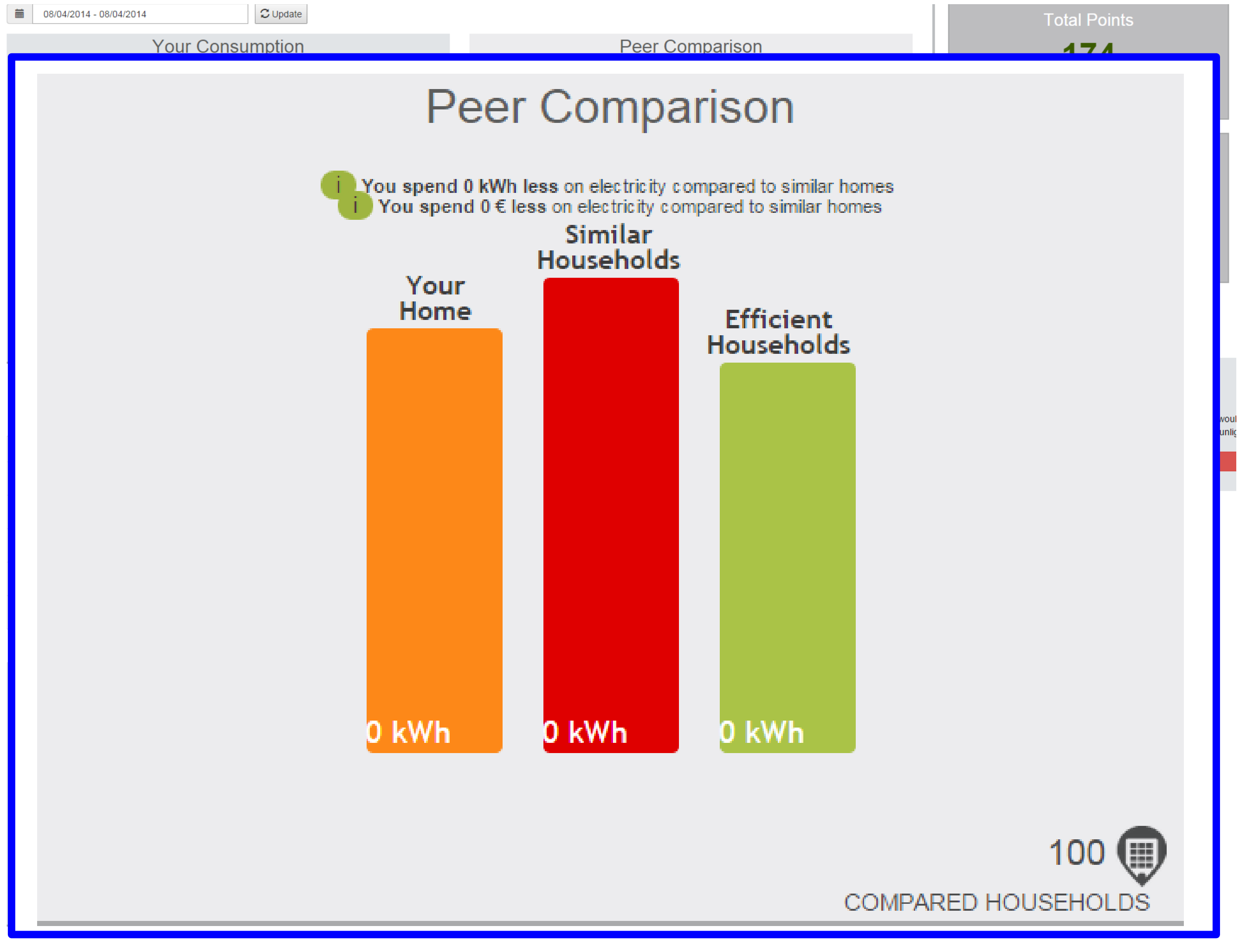
End-User Platform 1

Peer Comparison chart: compare users with similar households



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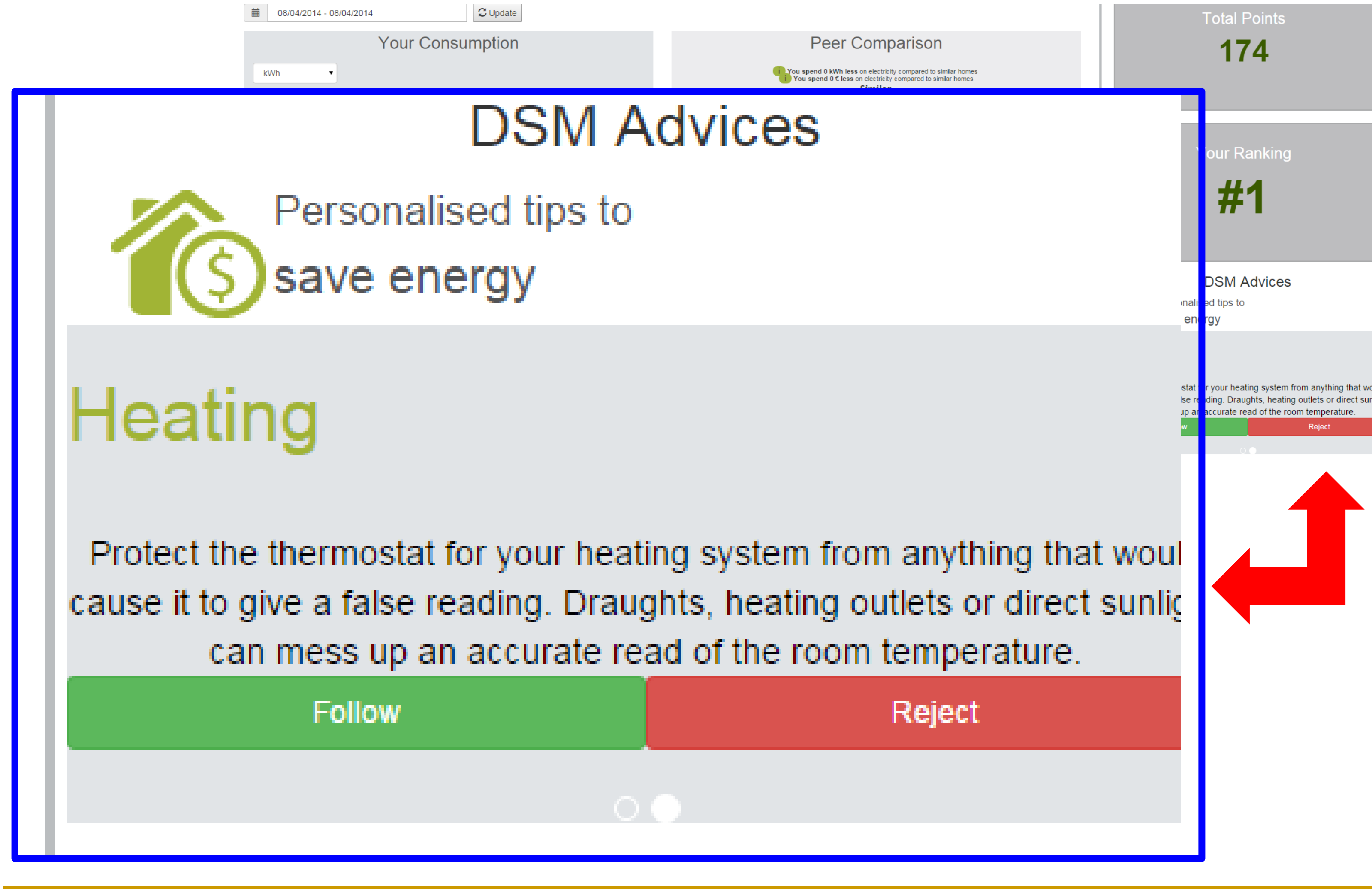
End-User Platform 1

DSM advices (tips and behavioural commitments)



End-User Platform 2

- Electric energy bill *information*, based on tariffs
- *Statistics* on energy usage per tariff

CHARACTERIZATION OF RESIDENTIAL LOAD AGGREGATIONS

(statistical analysis)

Residential load patterns

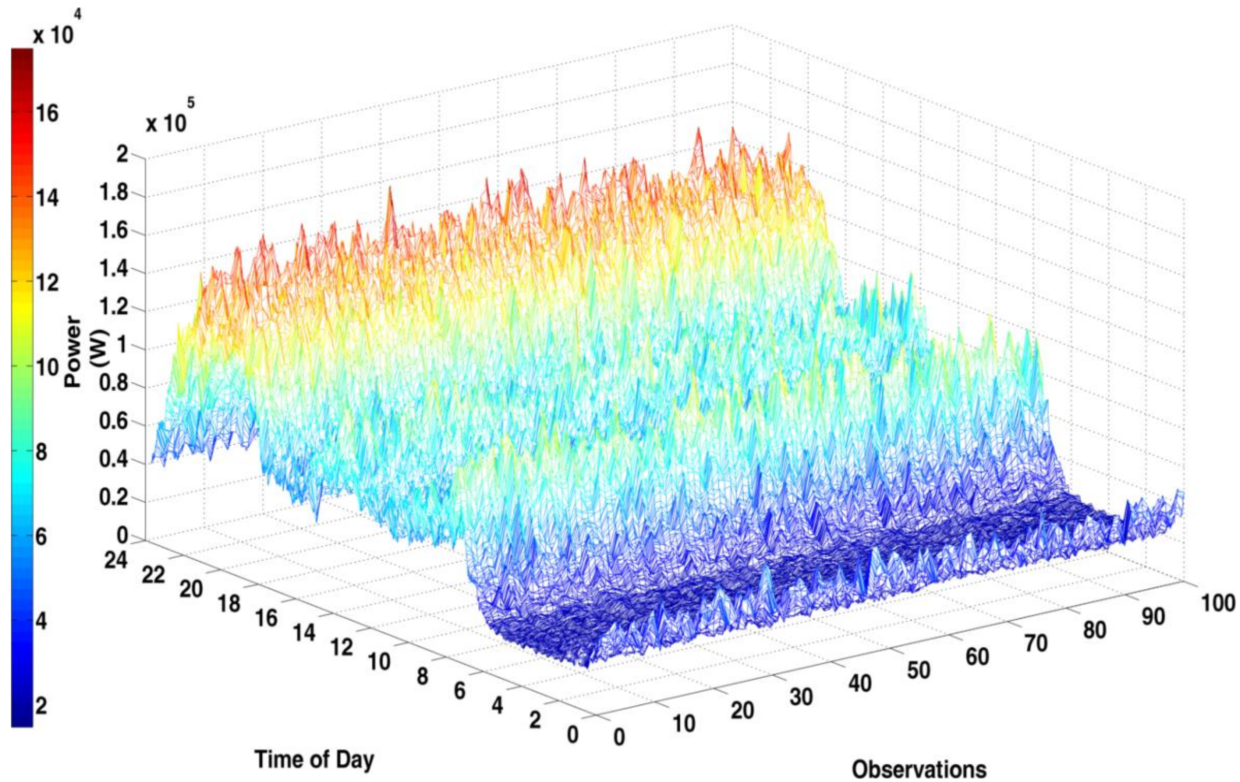
- Drawing *single-customer* residential load patterns is difficult, because of:
  - high dependence on *non-electrical* aspects (family composition, age, lifestyle...)
  - *irregular* usage of the appliances
  - presence of load pattern peaks of *short duration*, mainly dependent on a few high-power appliances
- The main interest is on *aggregating* the load patterns of residential customers, with some *key questions*:
  - how does load pattern *uncertainty* depend 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

Analysis on extra-urban customers

- Study on a *number* of residential customers (families) variable from 10 to 300, 3 kW *reference* (contract) power for every customer

Evolution in time (1-minute data) of the aggregate demand for 150 houses (100 Monte Carlo observations from a *bottom-up* model)

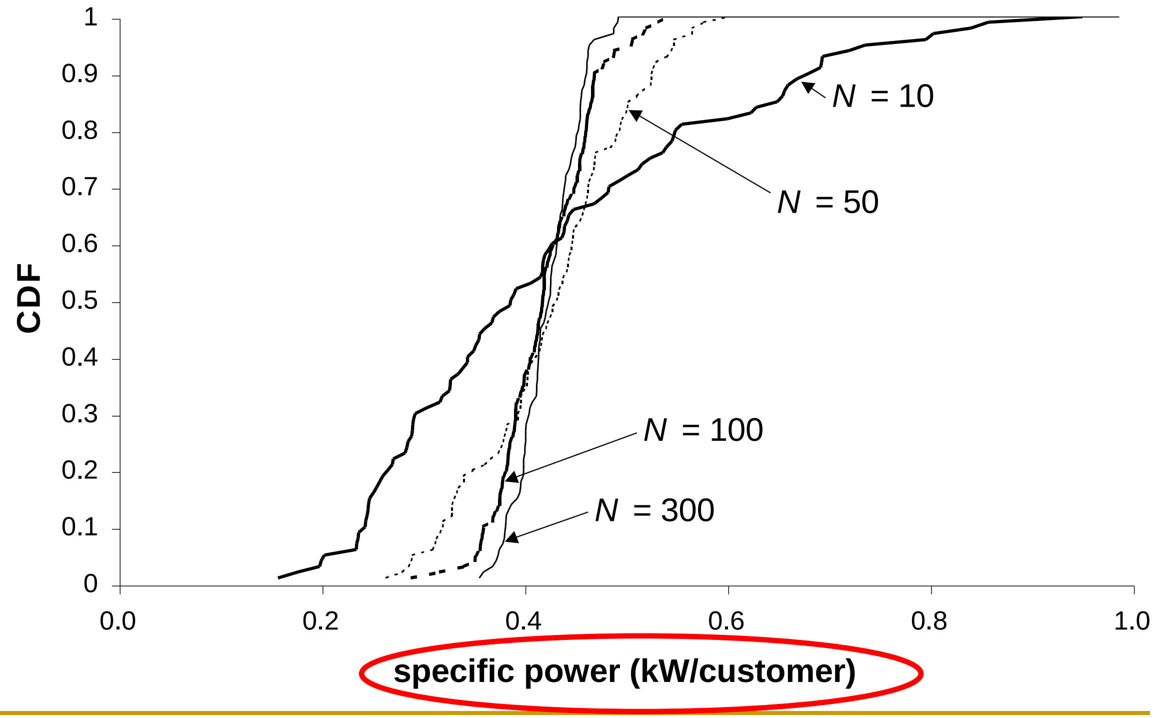


A. Cagni, E. Carpaneto, G. Chicco and R. Napoli, Characterisation of the aggregated load patterns for extra-urban residential customer groups, *Proc. IEEE Melecon 2004* , Dubrovnik, Croatia, May 12-15, 2004, Vol.3, pp. 951-954

Cumulative Distribution Function (CDF) of the specific power

- 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*

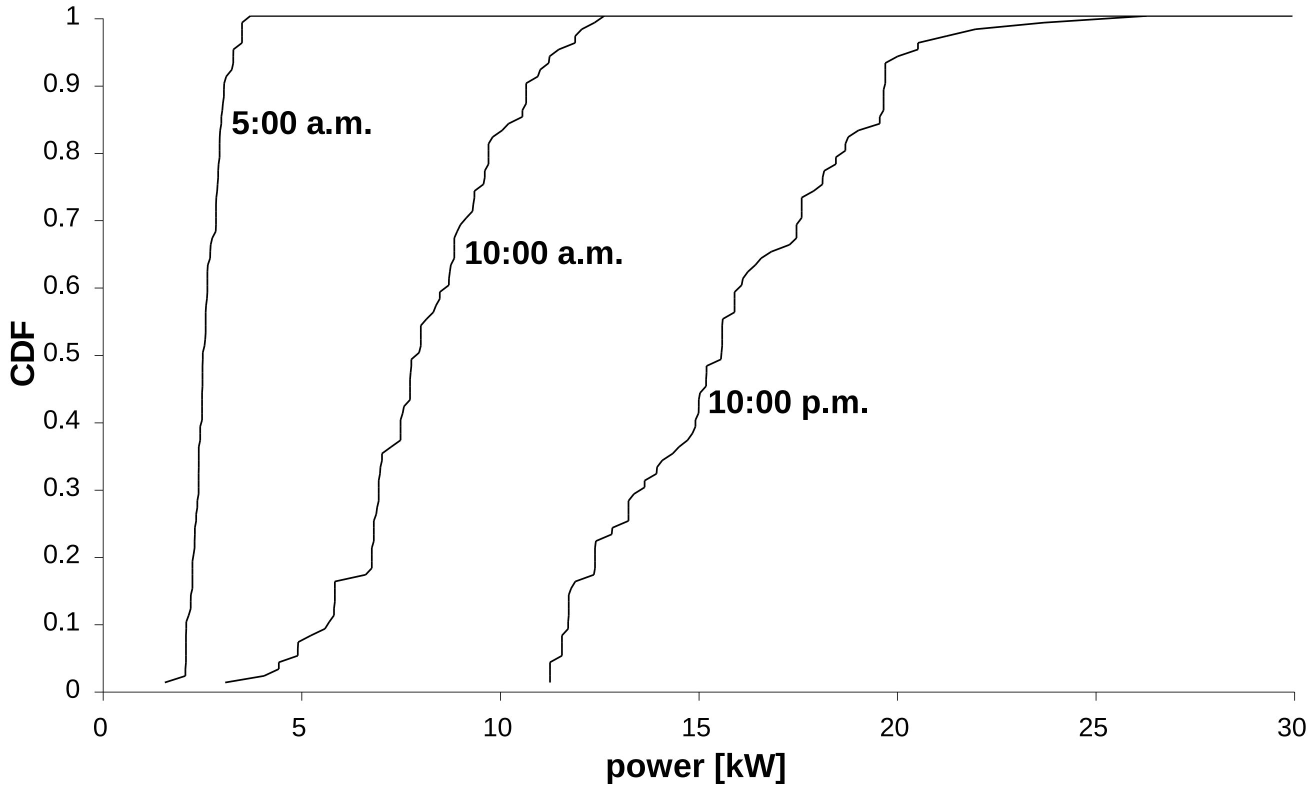
hour 10 a.m.



Cumulative Distribution Functions (CDFs) for a given load aggregation

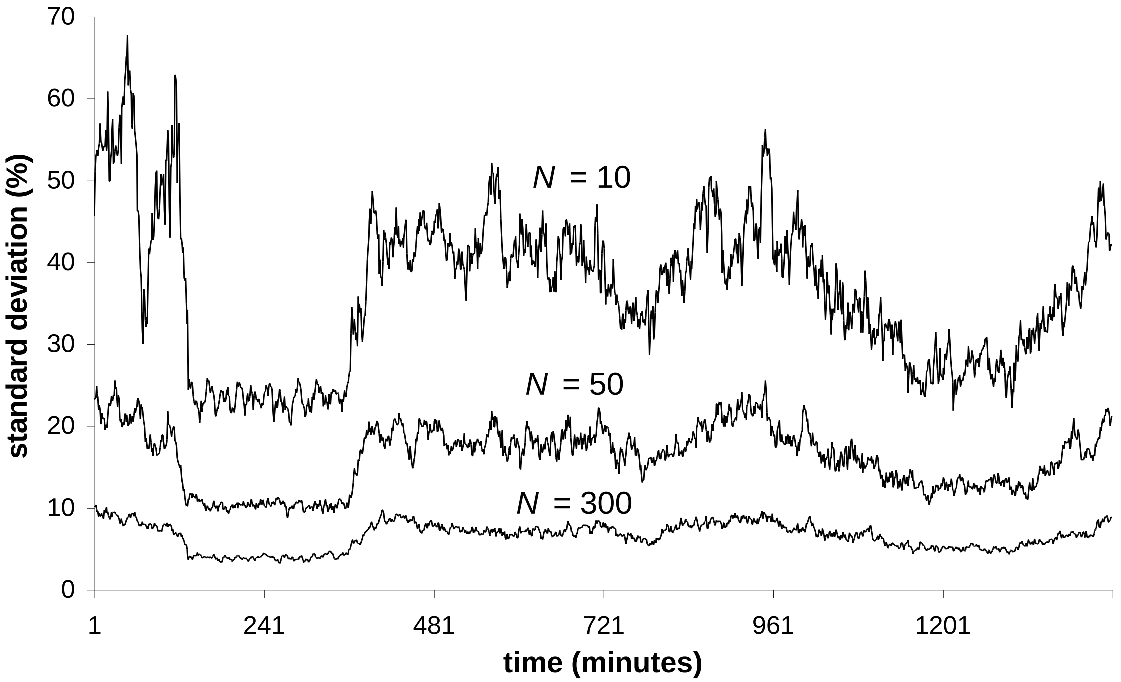
- For a given number of customers, mean value and standard deviation *highly depend on the* hour

***N* = 20**



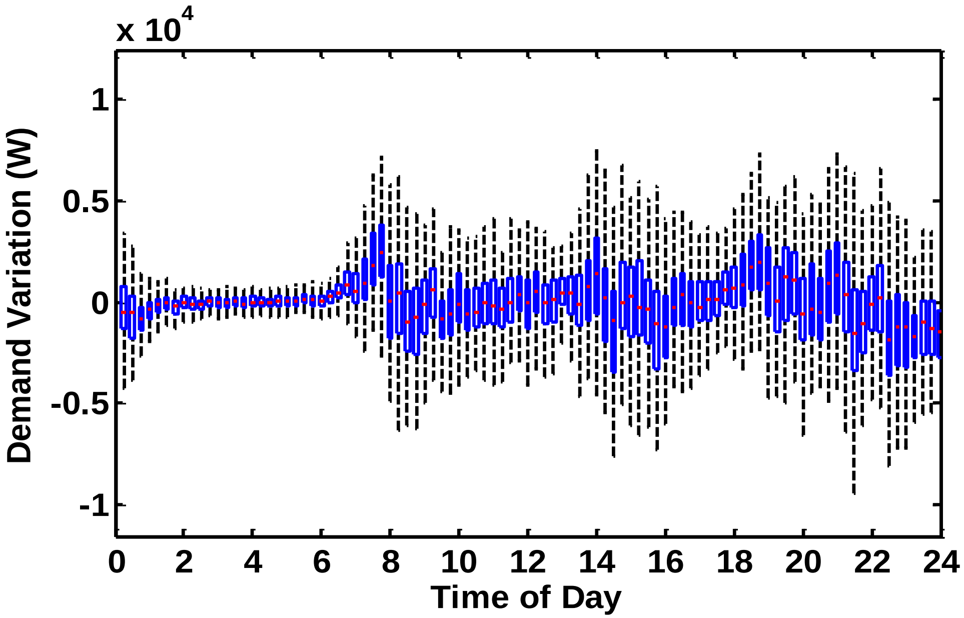
Evolution in time of the standard deviation

- 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)



Analysis of the demand variations

- Statistical analysis of the *demand variations* considering the aggregation level a and the averaging time step s

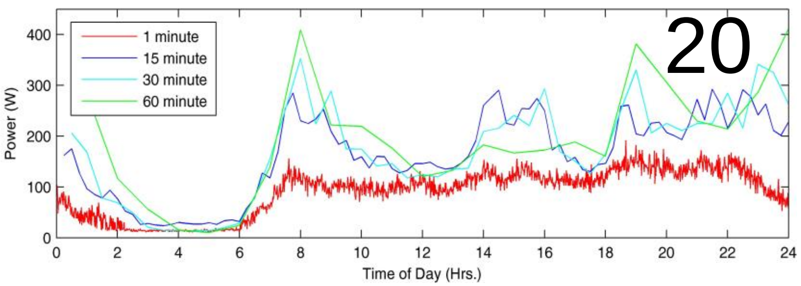


Box plot of the *demand variations* for aggregation of 20 houses with 15-minute averaging time step

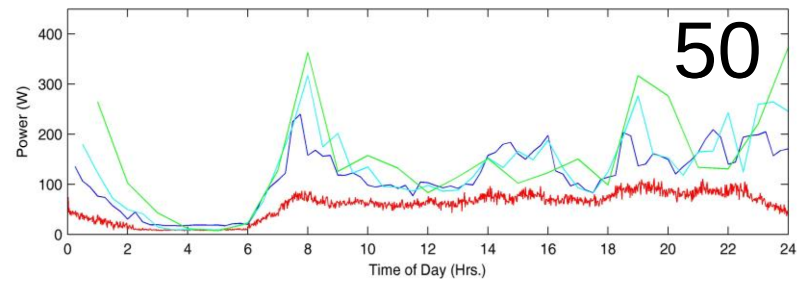
I.A. Sajjad, G. Chicco, R.Napoli, "A Probabilistic Approach to Study the Load Variations in Aggregated Residential Load Patterns", Proc. 18th Power Systems Computation Conference (PSCC), 18-22 August 2014, Wroclaw, Poland, paper 546.

Evolution of the mean load variations

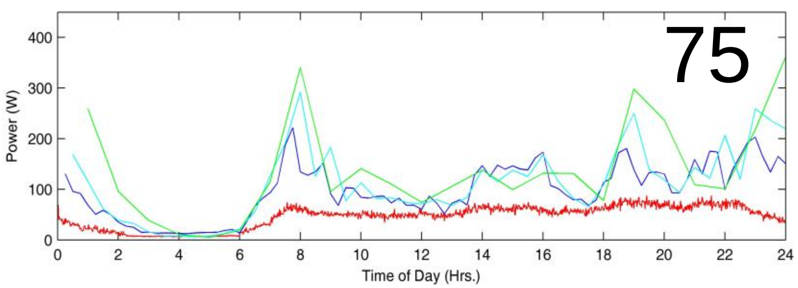
Comparison of daily mean load variations per house
with aggregations of
(a) 20 houses (b) 50 houses (c) 75 houses (d) 150 houses



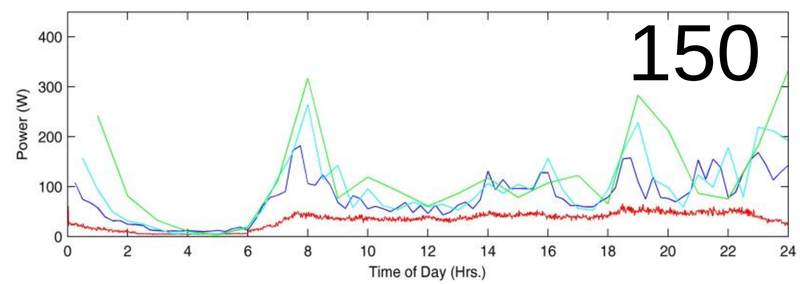
(a)



(b)



(c)



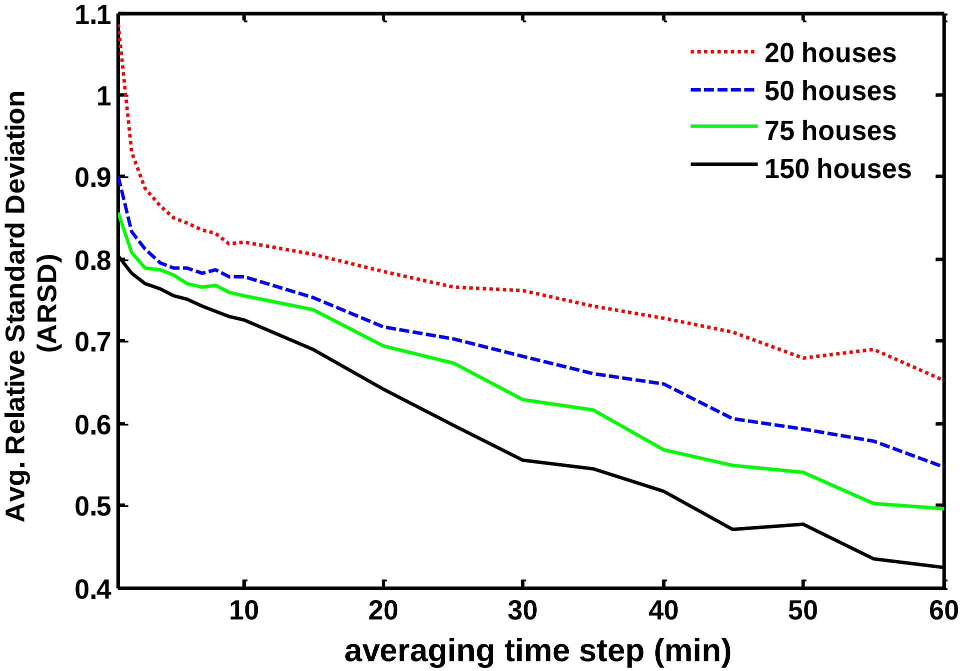
(d)

Analysis of the demand variations

- *Average Relative Standard Deviation* (*ARSD*) calculated using parameter estimation to find out information on the data spread for each combination of aggregation and sampling time
- Higher *ARSD* values give more information about the *variability* of the customer's aggregate behavior

Higher averaging time step means less possibility of following the dynamics of the daily variations

This *reduces* the potential of estimation of demand side flexibility



AGGREGATION OF LOADS

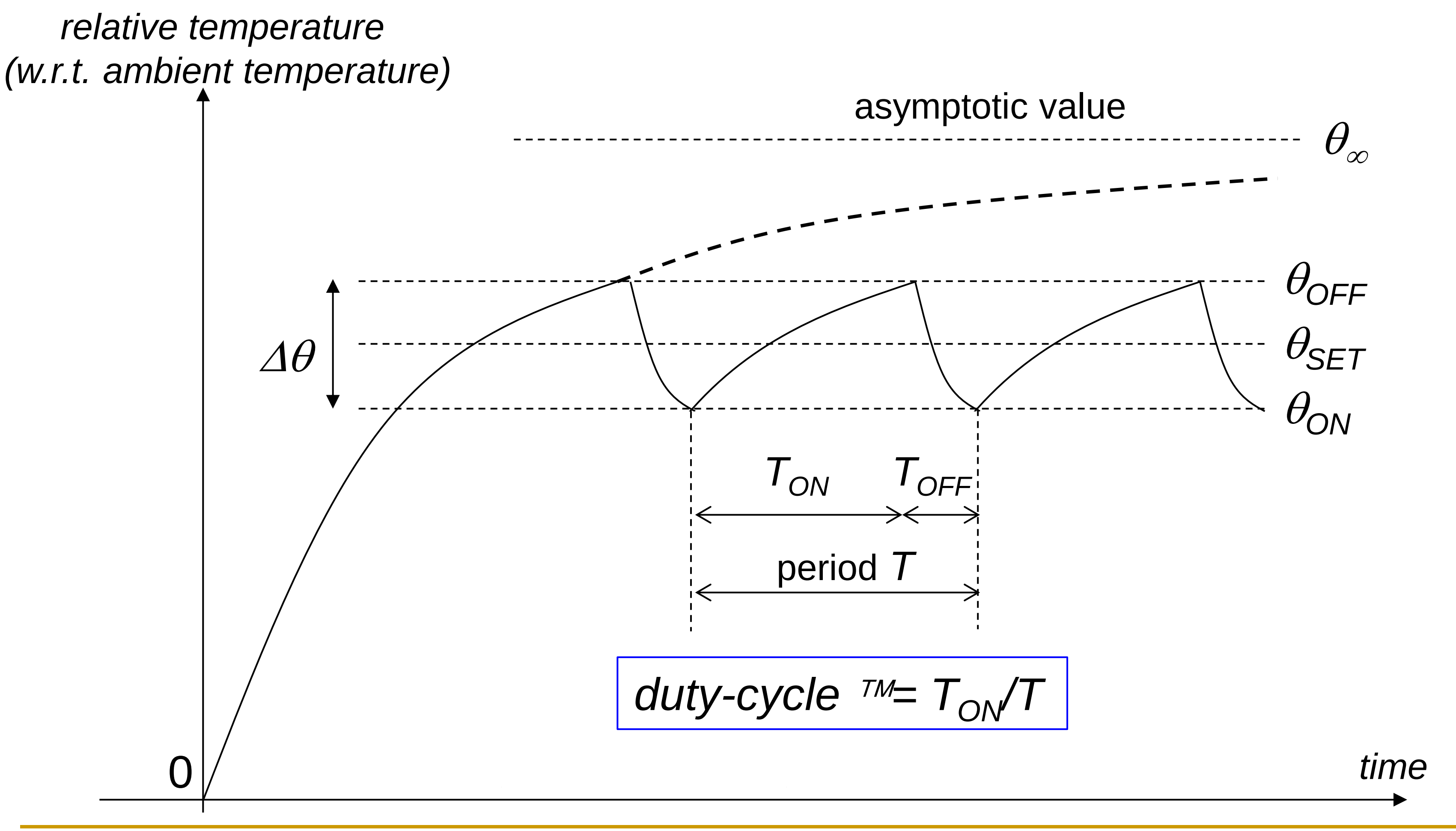
WITH

THERMOSTATIC CONTROL

(load diversity, cold load pickup, energy payback)

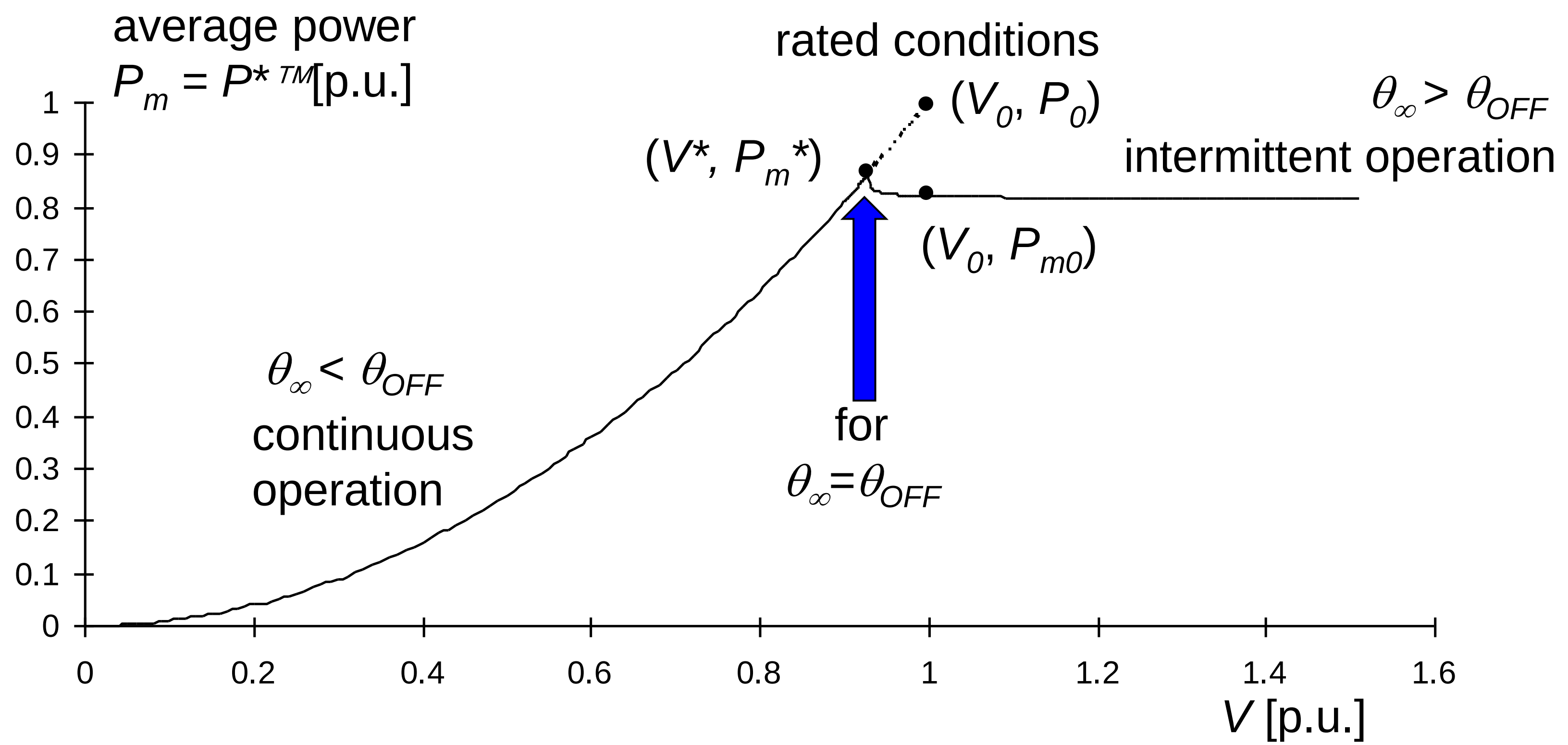
Temperature range for thermostat control

- *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

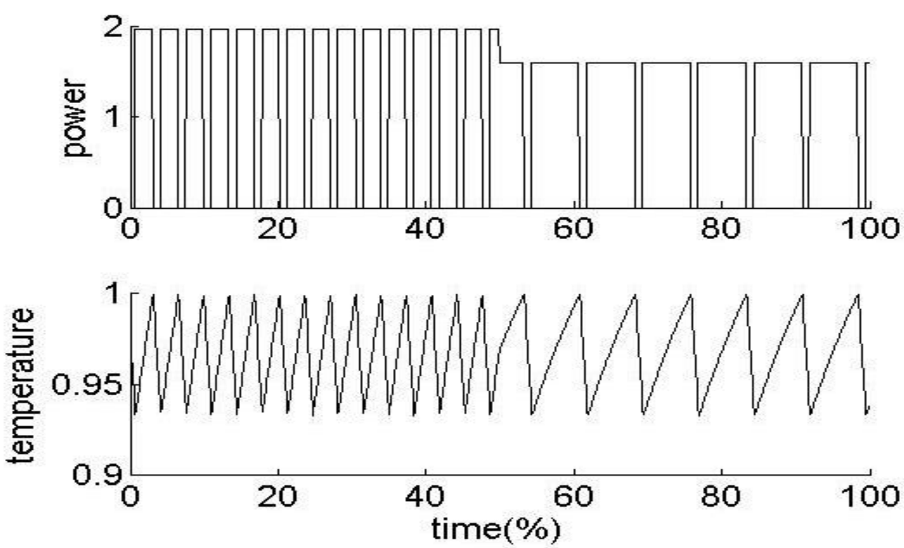


Dynamic model

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

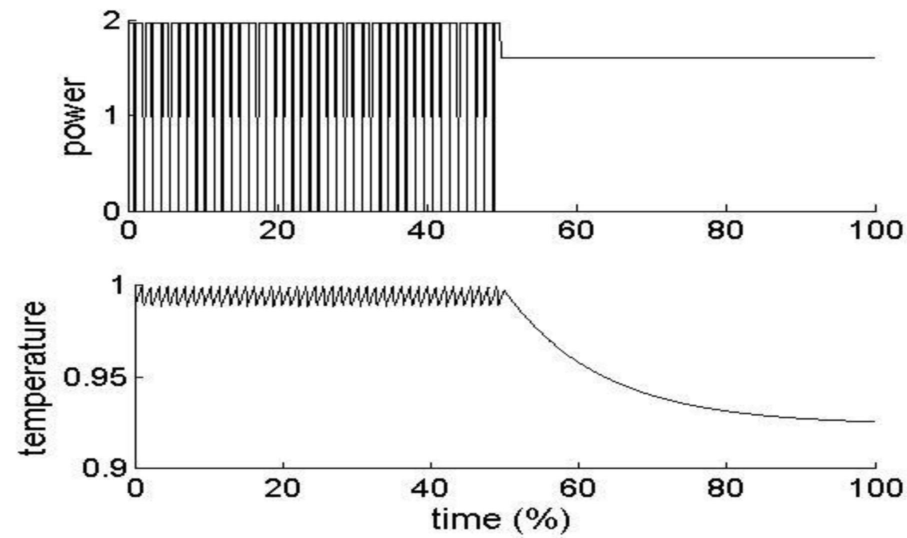
Final point with *cycling operation*

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



Final point with *continuous operation*

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



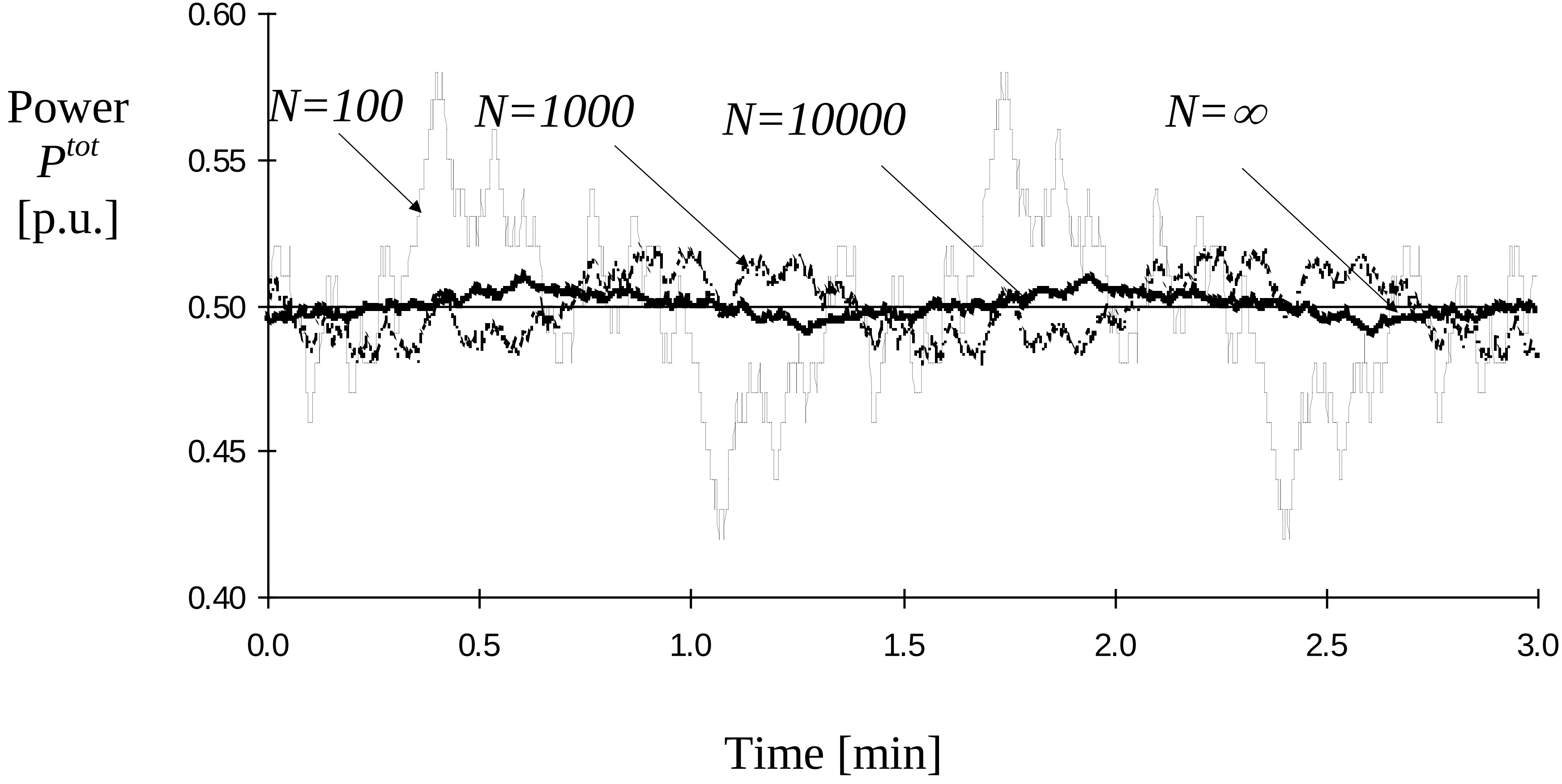
Aggregation of thermostat-controlled loads

- 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.)

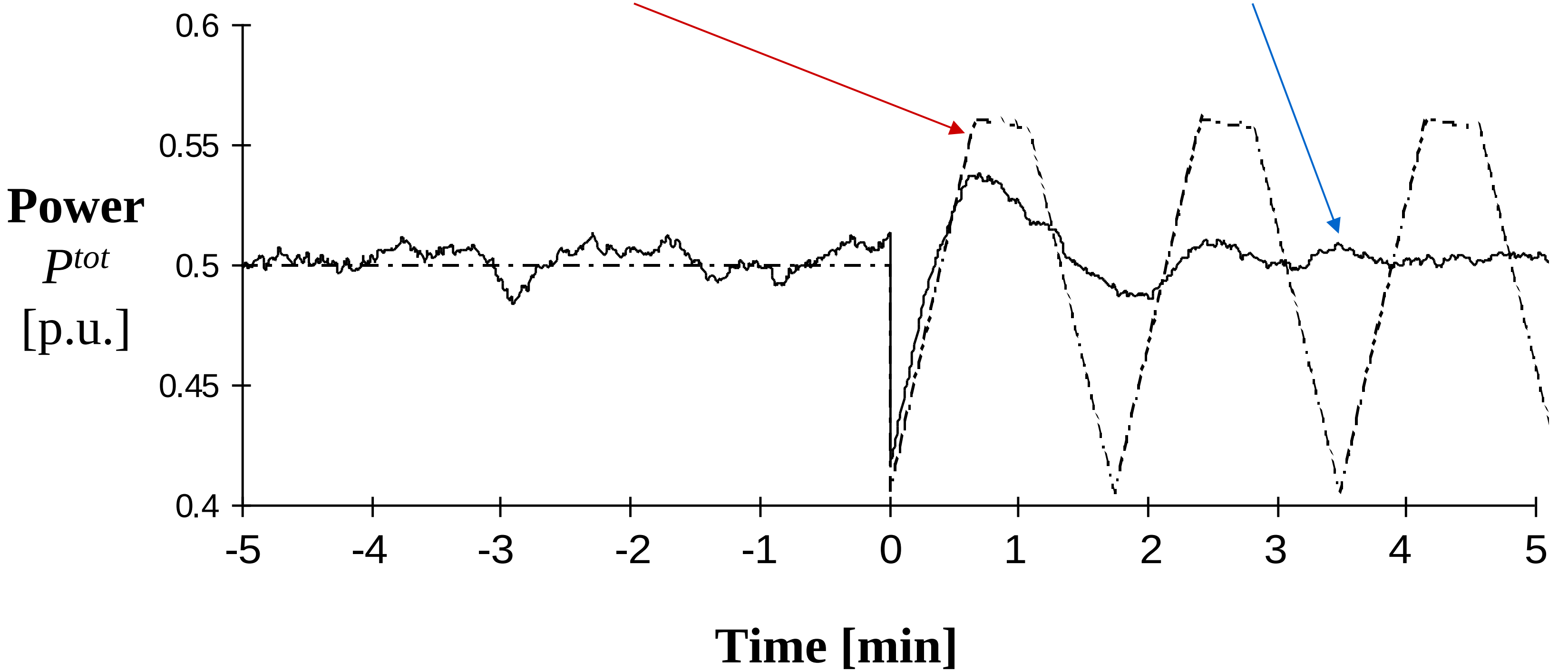


Aggregated load recovery after a step voltage variation

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

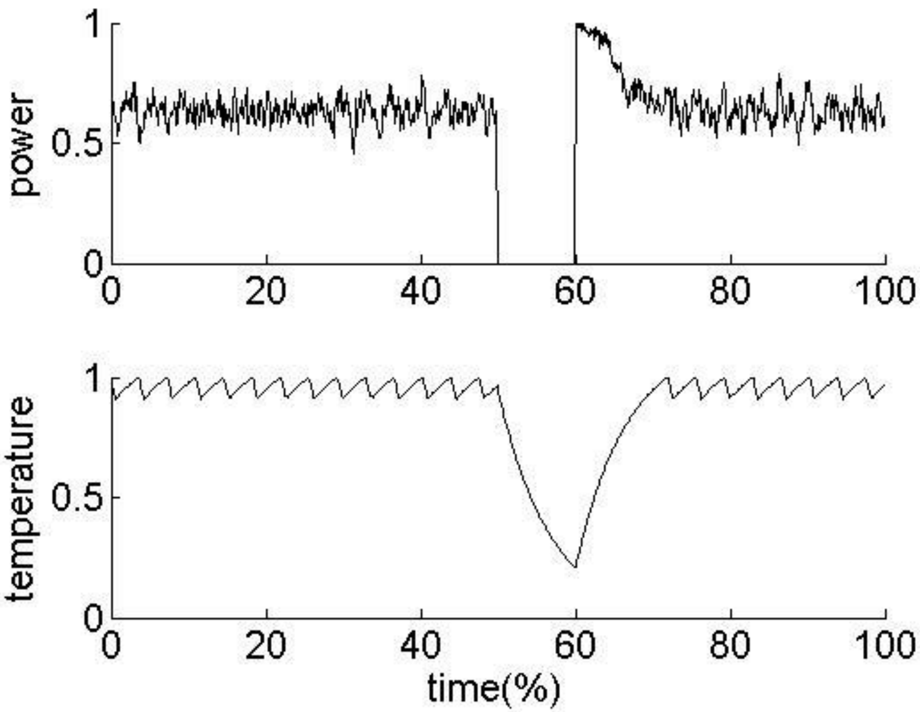
$\Delta\theta = 10^\circ C \pm 25\%, \theta_{\infty 0} = 300^\circ C \pm 10\%, \quad \tau = 10\,\text{min} \pm 50\%$, $P_0 = 1\,p.u. \pm 50\%$

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



Cold Load Pickup (CLP)

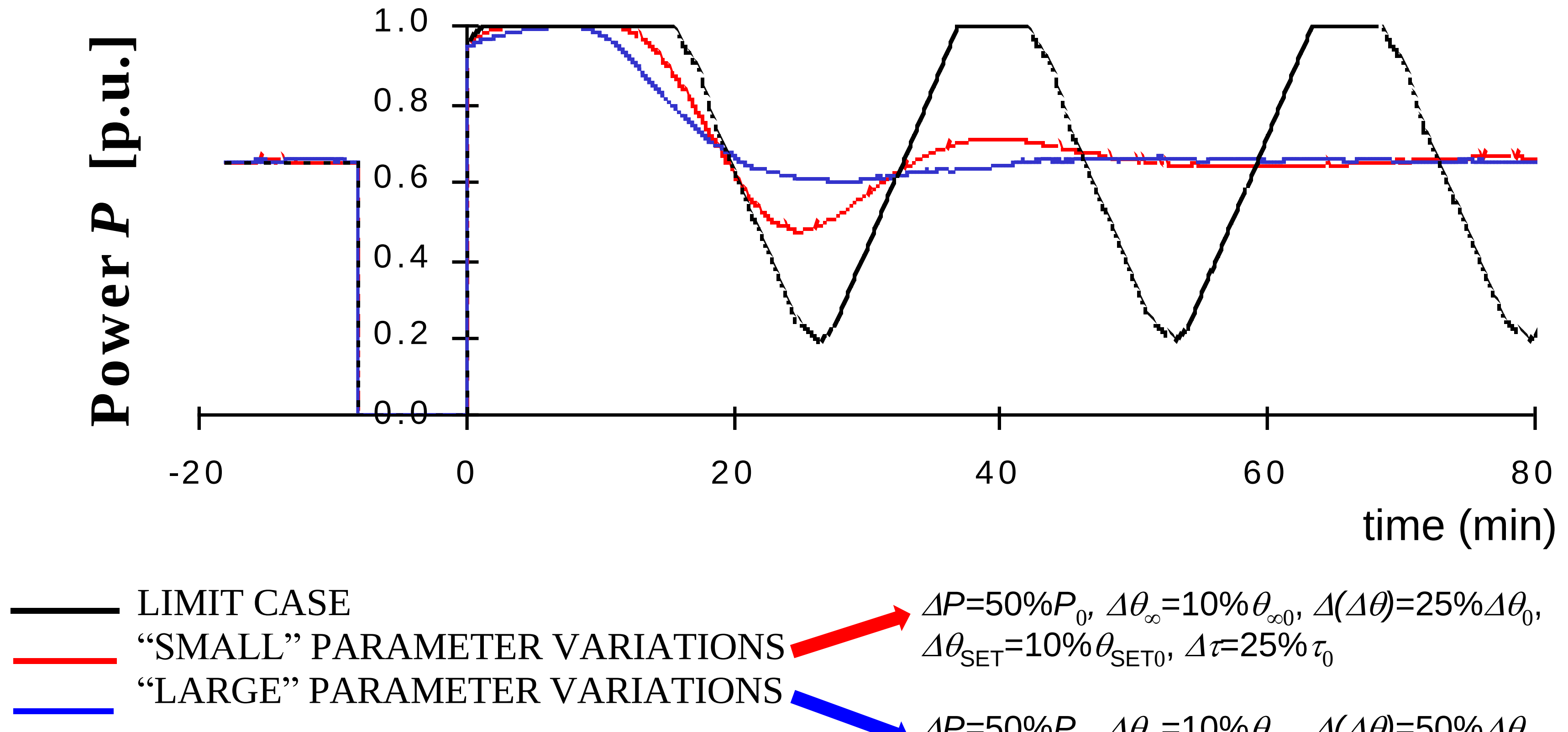
- The results of the analysis of a *supply interruption* for *N = 100* loads is shown in the first graph
- The load is *increasing* due to the *Cold Load Pickup* after the supply restoration
- This may cause *long-term overload* in the distribution system conductors
- The temperature of the aggregated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

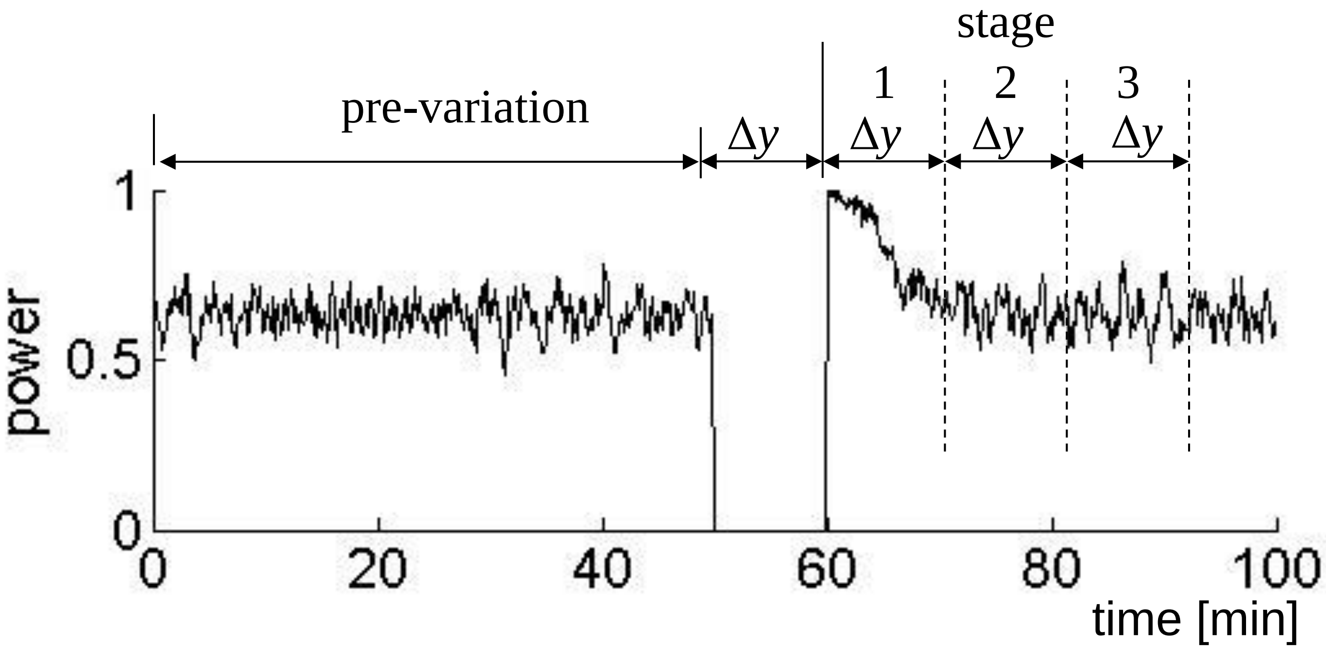


ΔP=50%P_0, $\Delta\theta_\infty$=10%$\theta_{\infty 0}$, $\Delta(\Delta\theta)$=25%$\Delta\theta_0$, $\Delta\theta_{SET}$=10%θ_{SET0}, $\Delta\tau$=25%τ_0

ΔP=50%P_0, $\Delta\theta_\infty$=10%$\theta_{\infty 0}$, $\Delta(\Delta\theta)$=50%$\Delta\theta_0$, $\Delta\theta_{SET}$=20%θ_{SET0}, $\Delta\tau$=50%τ_0

Stages of load recovery

- The *load recovery* can be analyzed by considering *successive stages*, e.g., with the same duration of the interruption
- The power evolution can be partitioned into these stages, computing the *average power* at each stage and referring it to the *pre-interruption* average power



Energy payback factor

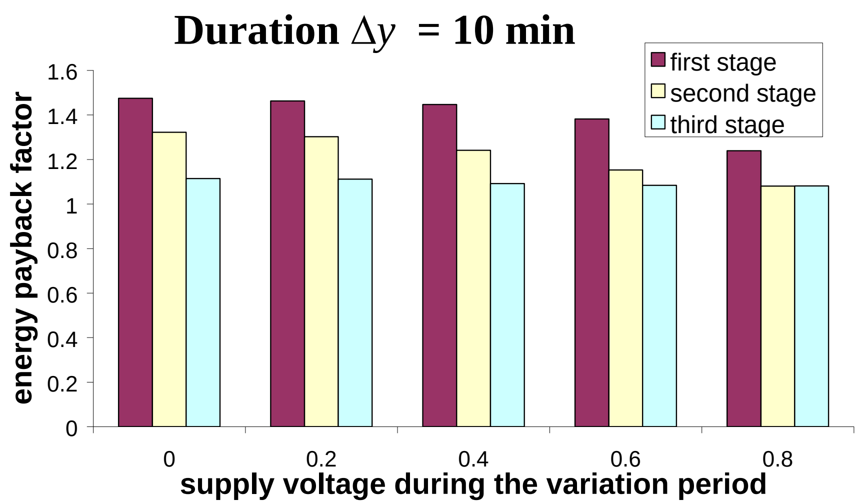
- The energy payback factor $\rho_k(V)$ is defined as the *ratio* between the average power $P_k^{AV}(V)$ at stage *k* of the energy payback period and the pre-interruption average power P_{pre}^{AV}
- For stage *k* = 1, 2, 3:

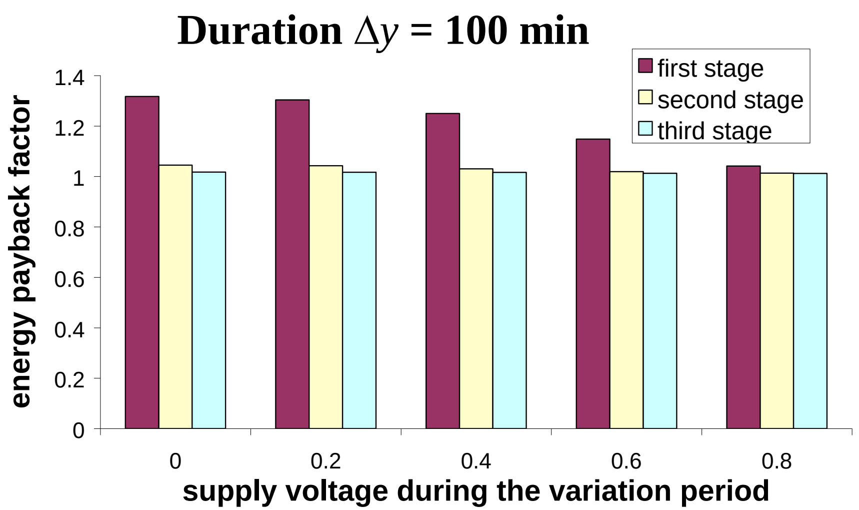
$$\rho_k(V) = \frac{P_k^{AV}(V)}{P_{pre}^{AV}}$$

- The values of the energy payback factor $\rho_k(V)$ are conventionally evaluated at the first *three stages* for different *magnitude* and *duration* of voltage variation

Energy payback factors for different supply voltage variations

- Example for an *aggregation* of *N* = 100 loads





- Energy payback factors values for total voltage interruption: 46%, 32%, 11%
- The energy payback slightly continues after the first three stages

- Energy payback factors values for total voltage interruption: 32%, 4%, 2%
- The energy payback mainly occurs during the first stage

DATA AVERAGING IMPACT

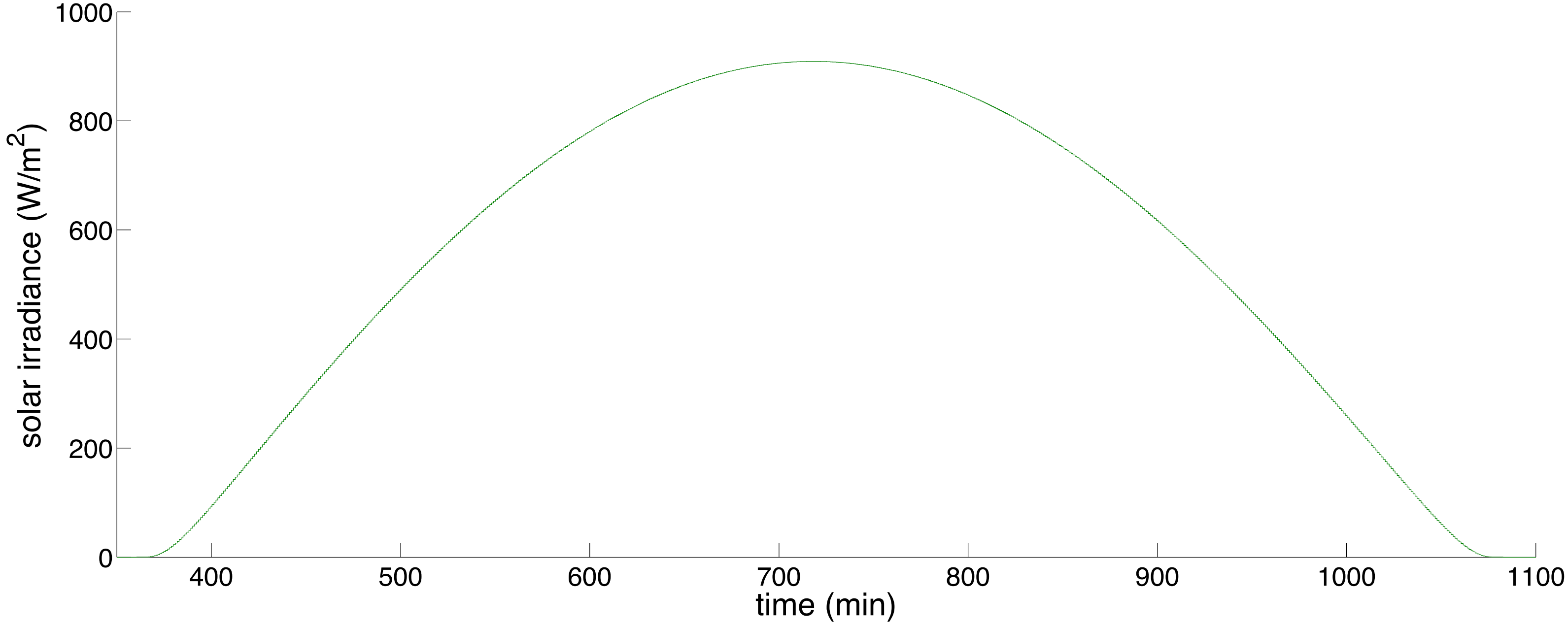
ON AGGREGATIONS OF

LOADS AND LOCAL GENERATION

(net energy output, net metering costs)

Gathering photovoltaic data

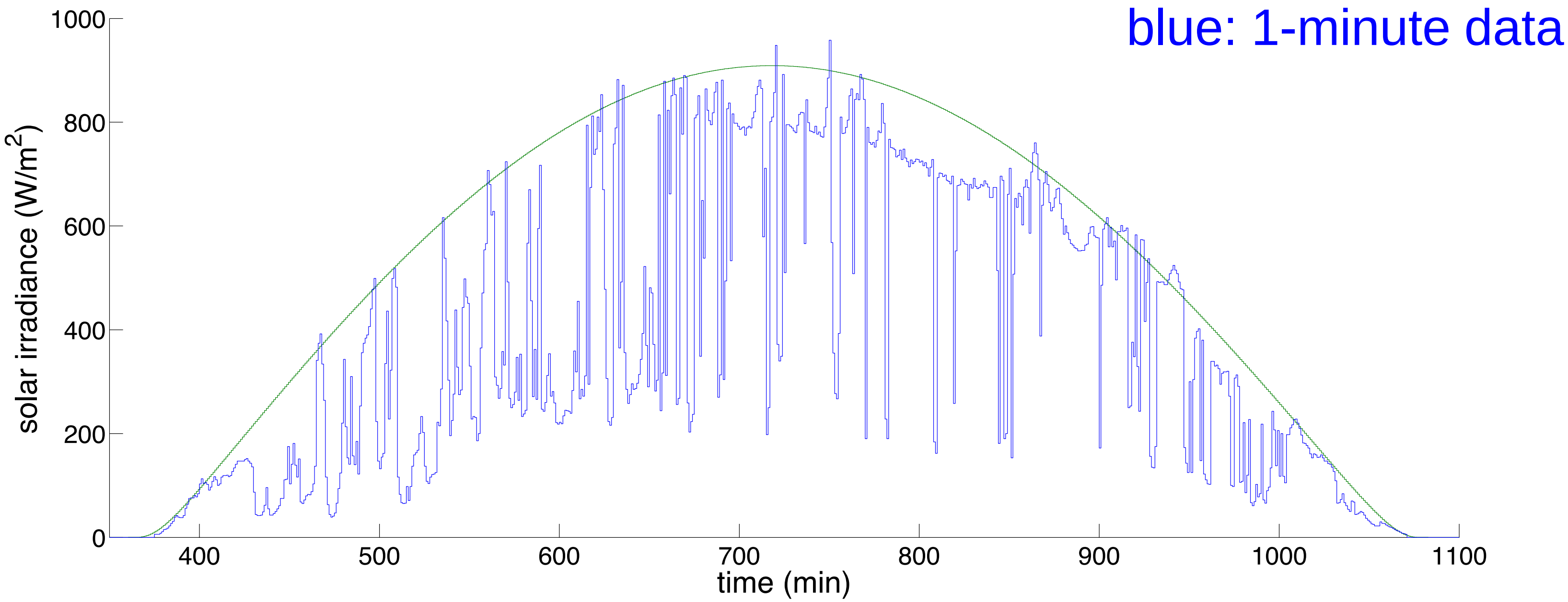
- In a given day, the evolution in time of *solar irradiance* at *clear sky* can be represented by using specific models
- Let us consider the *Moon-Spencer* model



P. Moon and D.E. Spencer, "Illumination from a non uniform sky", *Trans. of the Illumination Engineering Society*, Vol. 37 (12), pp. 707-7261, 1942.

Broken clouds

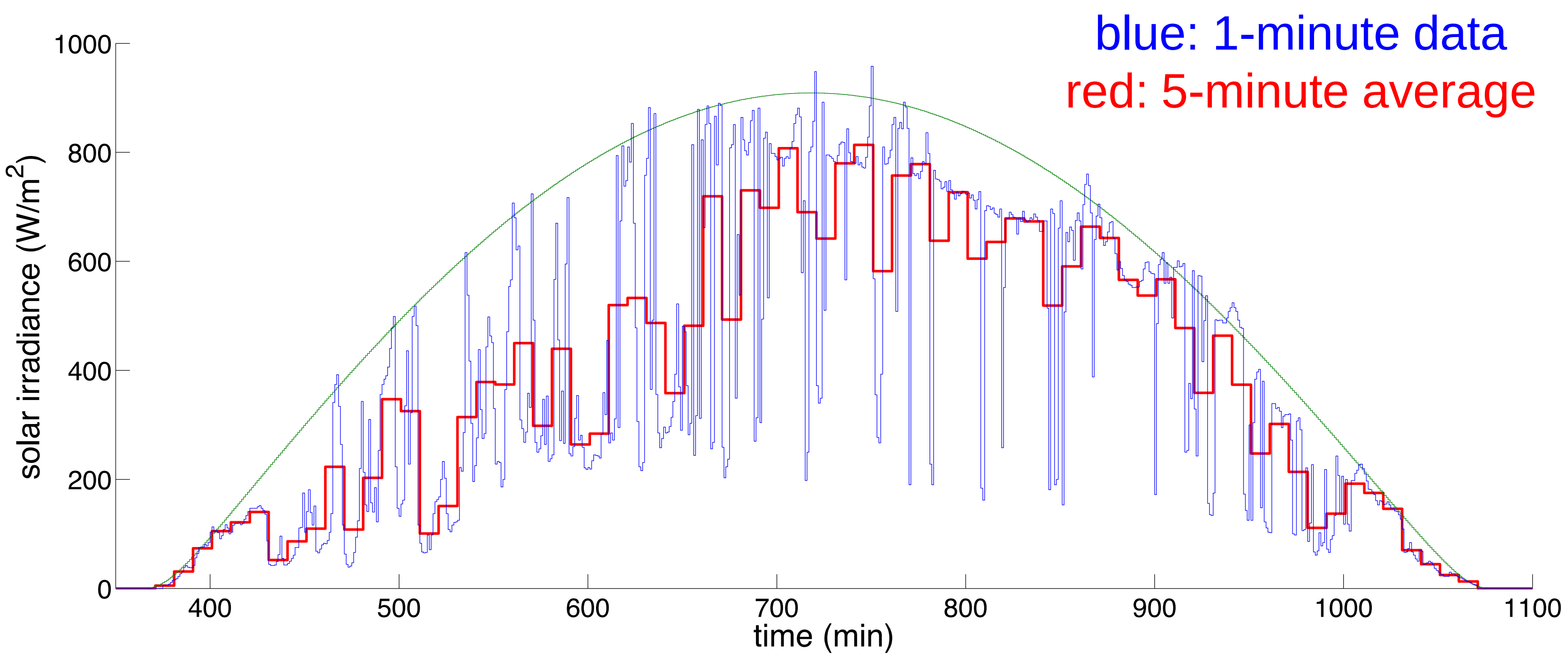
- Fluctuating solar irradiance, with enhanced solar irradiance reaching the ground followed by lower values
- With respect to the solar irradiance at clear sky, dense *broken clouds* can give peaks of solar irradiance of about 150% of followed by drops *to* about 10-20%



F.Spertino, P. Di Leo, V. Cocina, Accurate measurements of solar irradiance for evaluation of photovoltaic power profiles, *Proc. IEEE Grenoble PowerTech*, 2013.

Broken clouds

- The broken clouds do *not* increase the energy content
- Averaging the measurement over a longer time step reveals the *compensation* of the energy content



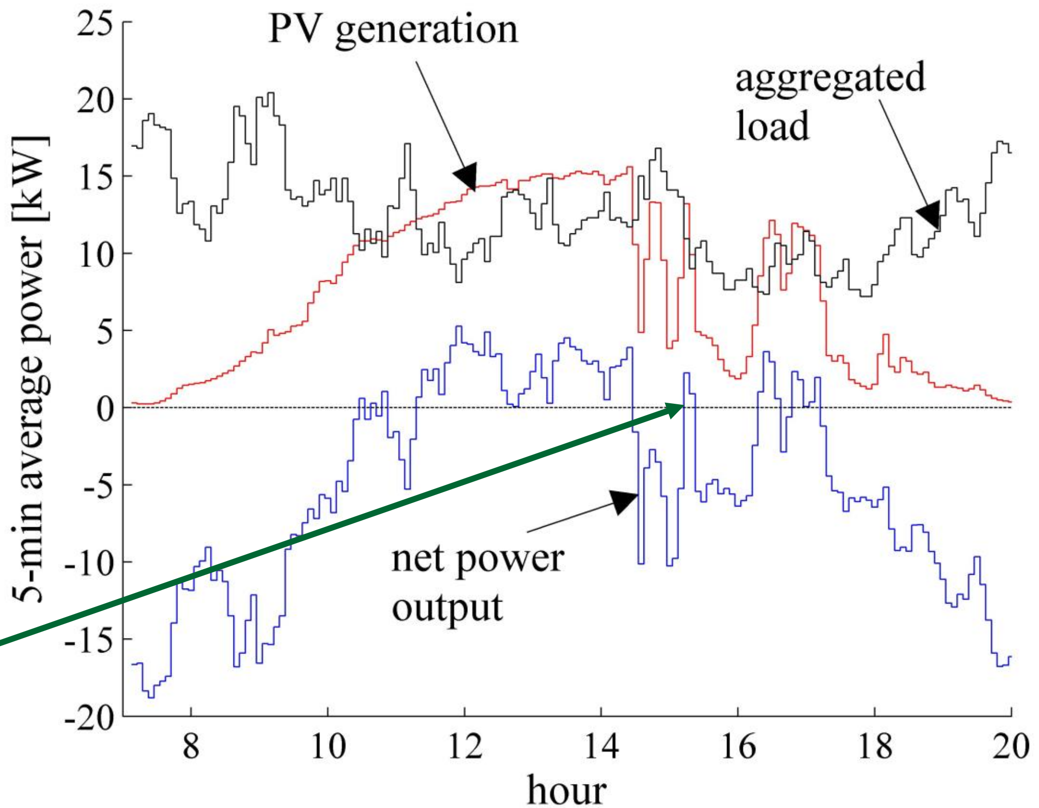
A net output energy example

- An example is shown here on a real system with an aggregated 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

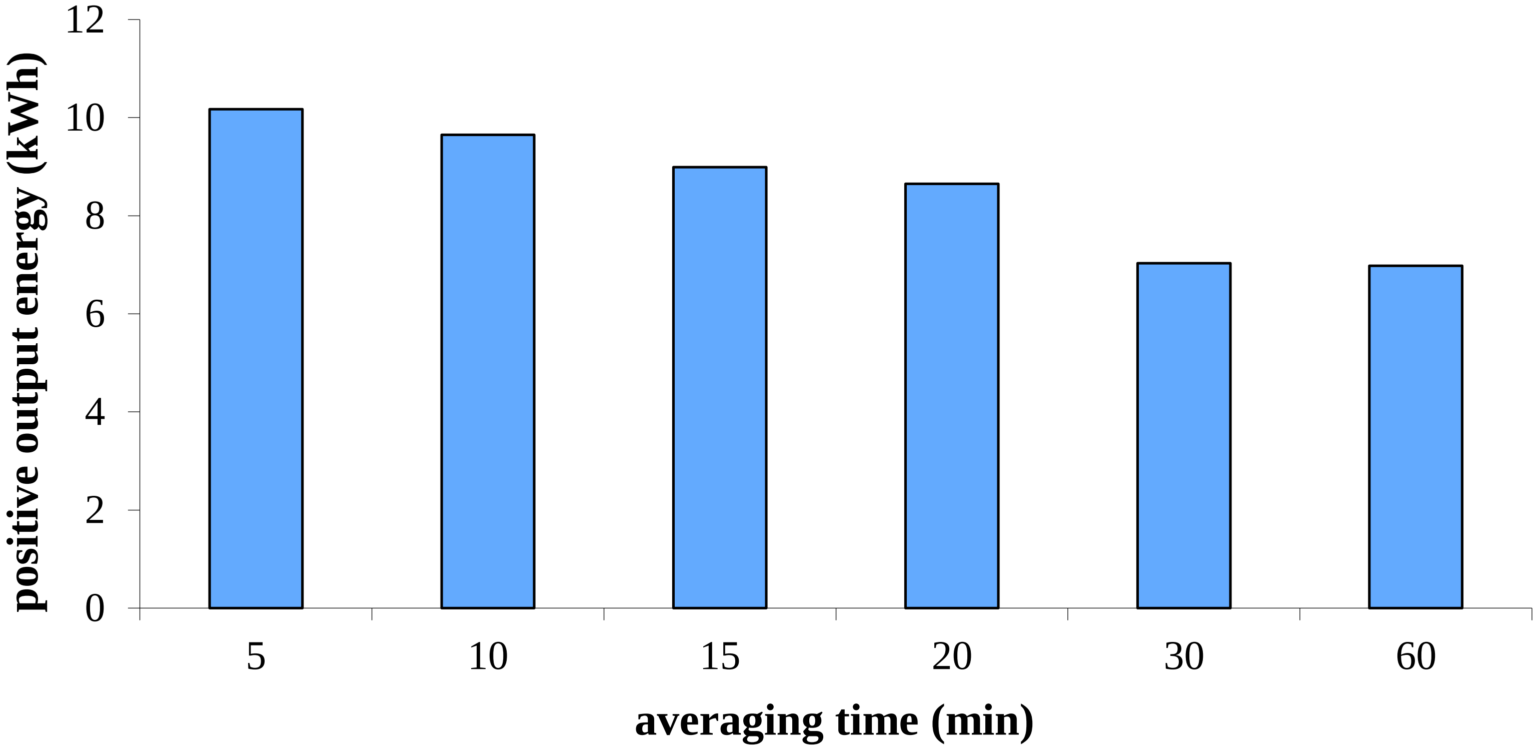
- The system *generates* or *absorbs* power at different times
- The positive *net power output* changes for increasing averaging time steps, due to reduction in the *detail of representation* of the information

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*

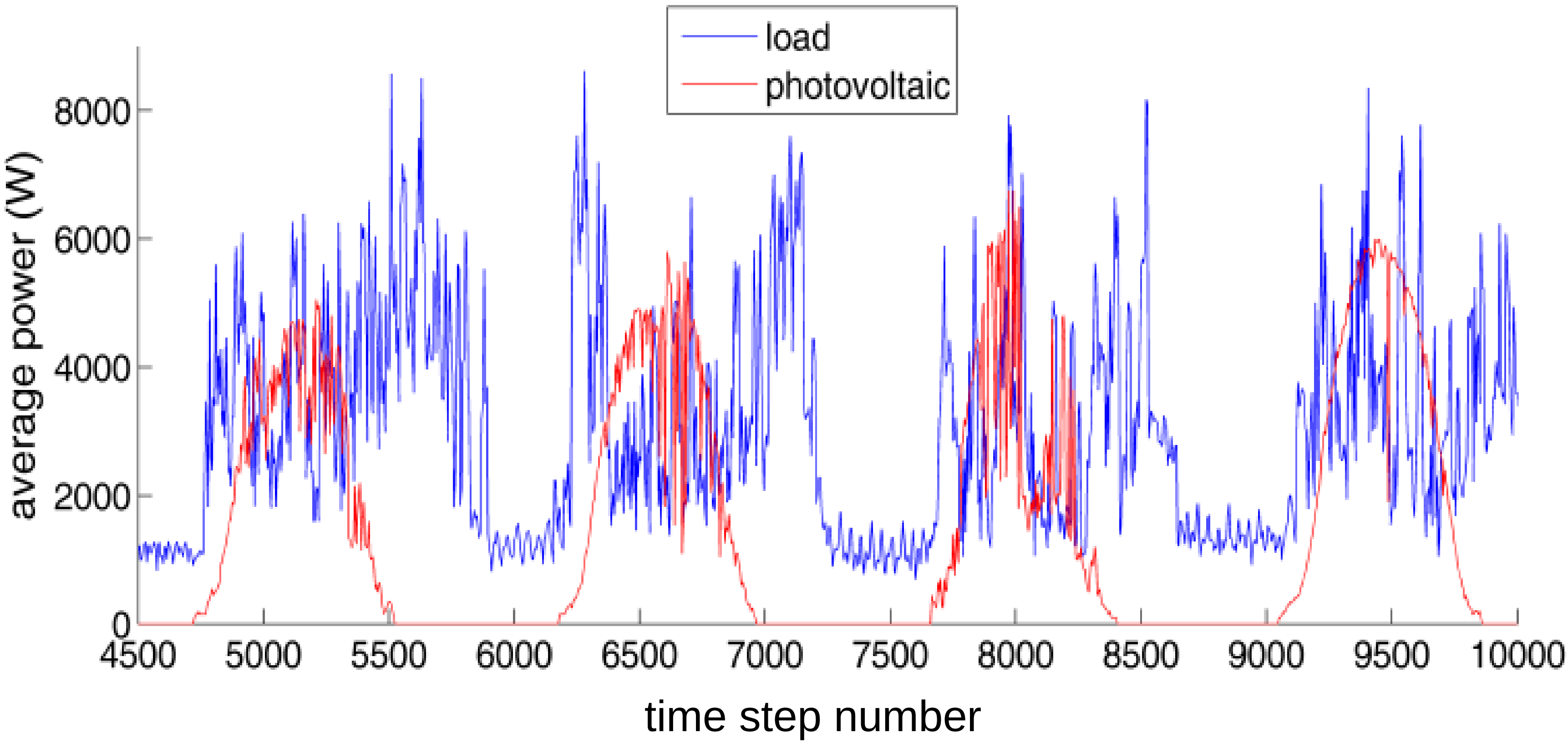
Parametric analysis on averaging time step

- 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

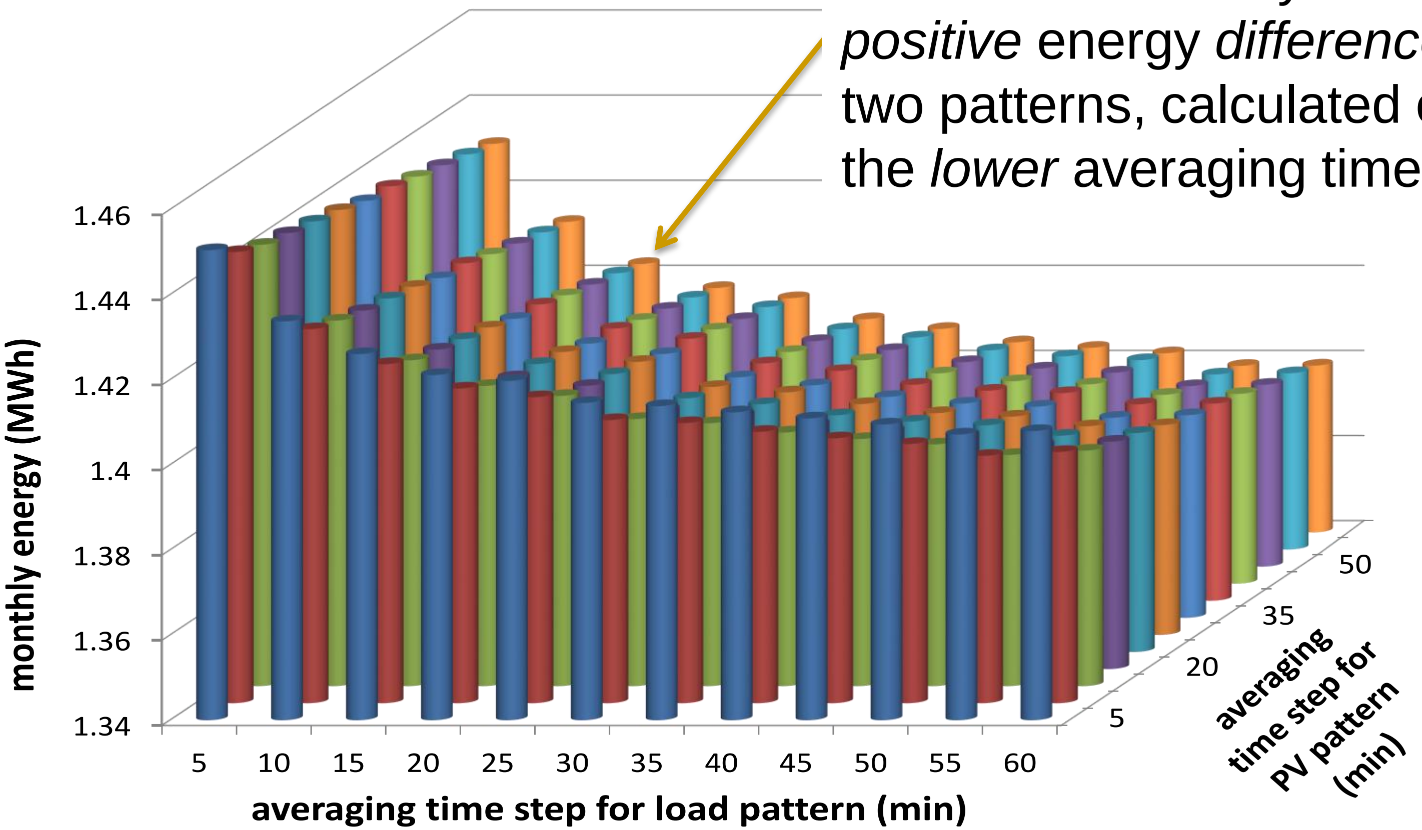
- Example of pattern data for *four* successive days



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



Costs with different averaging time steps

- Positive and negative *net energy* components are associated with their *costs*

  Let us consider:

  T : observation period

  τ_o : base averaging time step

  $\{m, \upsilon\} = 1, \ldots, M$: *multipliers* of τ_o for the load and the generation patterns, respectively

  $\hat{W}_{T,t_0}^{(m,v)}$ and $\breve{W}_{T,t_0}^{(m,v)}$: positive and negative *net monthly energy*

  r_b, r_s: buying and selling energy *rates* (monetary units/MWh)

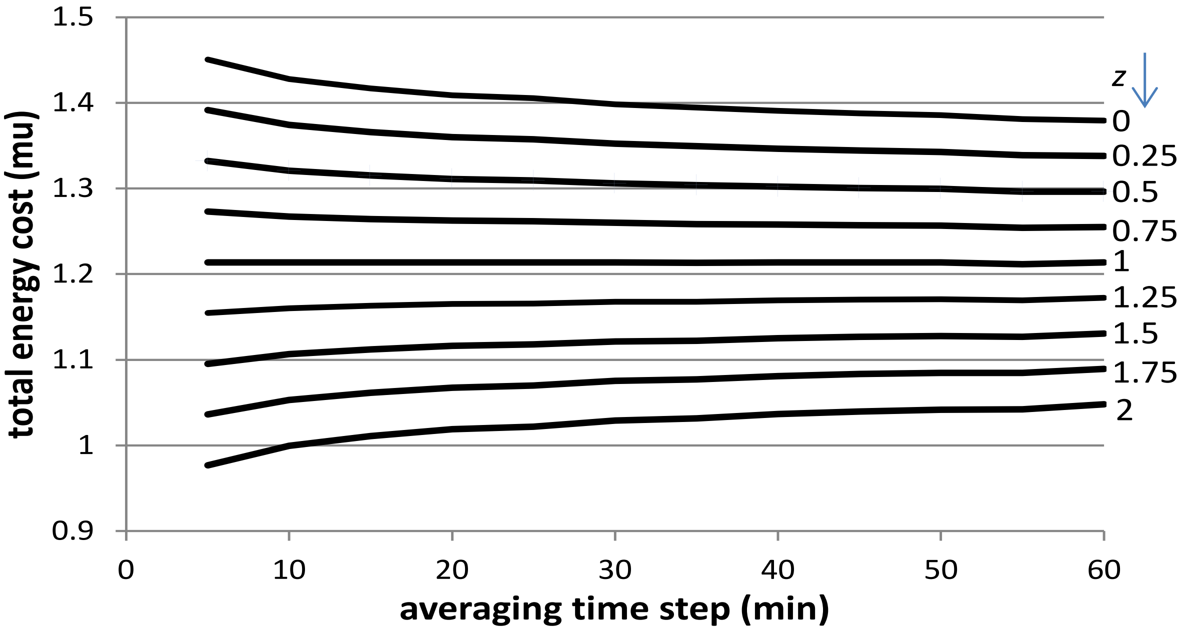
  Energy rate ratio $z = r_s / r_b$

  The *total energy cost* (with positive and negative components) is

$$C_{W_{T,t_0}^{(m,v)}} = r_b \hat{W}_{T,t_0}^{(m,v)} + r_s \breve{W}_{T,t_0}^{(m,v)}$$

Costs with different averaging time steps

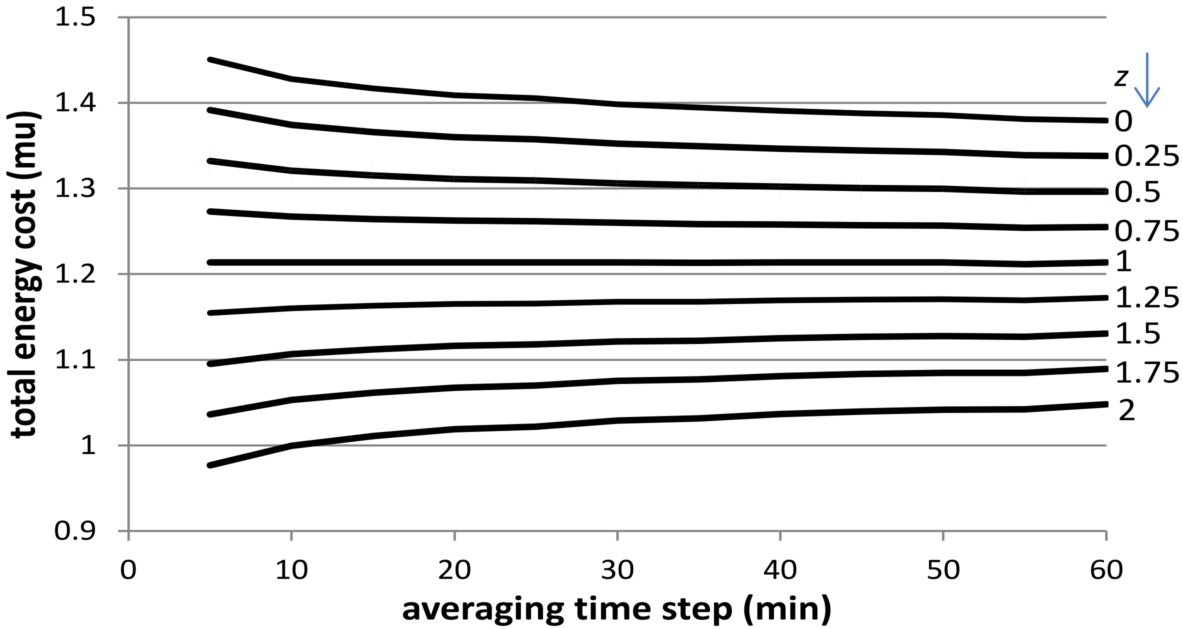
- Example with *the same* (variable) averaging time step for the PV generation pattern and the load pattern
- Parameter z variable from zero (limit case, *no reward* for the energy produced) to 2 (the energy produced is rewarded at *double rate* with respect to the cost of the energy bought)



Costs with different averaging time steps

- $z = 1$ (equal rates): *no difference* in the energy costs (the net energy is always the same and the positive and negative contributions compensate for each other)

- $z > 1$ (higher reward for local generation): convenience to *reduce* the averaging time step, to identify better the energy contributions



LOOKING

AT THE

FUTURE

(forecasting aspects, anticipatory knowledge)

Forecasting aspects

- Load and local generation forecasting are needed to create a *baseline* around which flexibility can be assessed
- The baseline has to be *reliable*, as it is taken as the *reference* to calculate the effects of flexibility and the corresponding economic implications
- The *relations* between the load/generation forecasting *errors* and the outcomes of the flexibility assessment have to be determined in an accurate way
- The forecasting *procedures* themselves have to be adapted to encompass the presence of “flexible” operations as a further source of uncertainty

Anticipatory knowledge

- Recognizing an event of foreseeable duration and pattern in its first instants enables the operator for *anticipating* the pattern evolution at successive time moments
- *Event-driven* analysis and *anticipatory knowledge* can be used to condition the use of *controllable resources* in order to achieve specified objectives (peak load reductions, better fit between local generation and load, and so forth)
- The expected diffusion of *controllable resources* in local systems makes this kind of analysis particularly attractive

Thank you
for your attention

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