A Multiobjective approach for demand side management in smart grids

Zineb Garroussi[1,2] Rachid Ellaia[1,2] El-Ghazali Talbi[2,3]

[1]Laboratory of Study and Research in Applied Mathematics, Mohammadia School of Engineering.
BP. 765, Ibn Sina Avenue, Mohammed V University, Rabat, Morocco
[2]Inria Lille - Nord Europe, DOLPHIN Project-team, 59650 Villeneuve dAscq, France.
[3]Université Lille 1, LIFL, UMR CNRS 8022, 59655 Villeneuve dAscq cedex, France
zinebgarroussi@emi.ac.ma

In collaboration with Jean-Yves Lucas (EDF)

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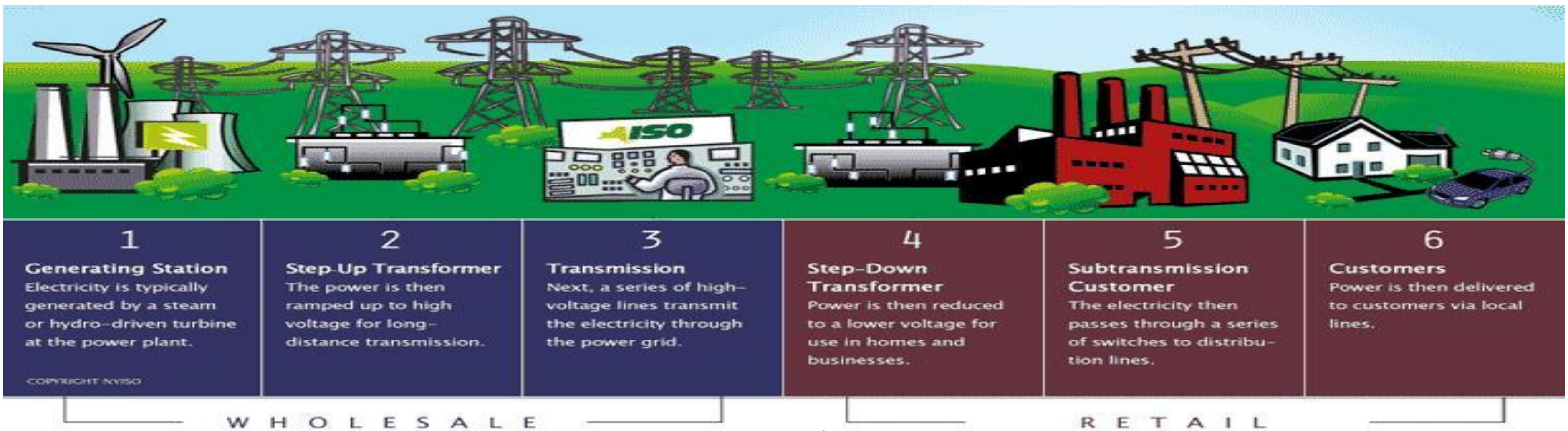
Wholesale Electricity Market vs Retail Electricity Market

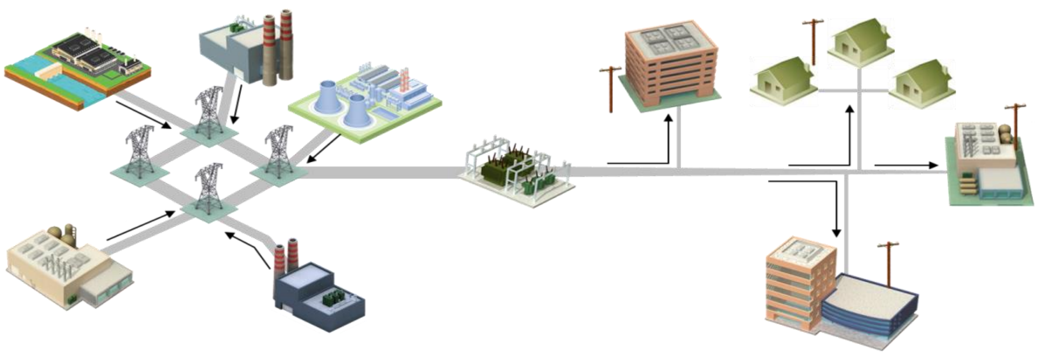
- In the wholesale electricity market, the cost of the electricity supply changes substantially depending on the season and time of day.
- In the retail electricity market, consumers usually paid their electricity consumption based on static prices.
- The electricity demand remains relatively unresponsive to the wholesale prices.
- Need massive investment of extra production capacities and distribution networks.



Source: www.nyiso.com

Emerging smart grid technologies encourage demand side management of electricity consumption

Traditional grid vs Smart grid

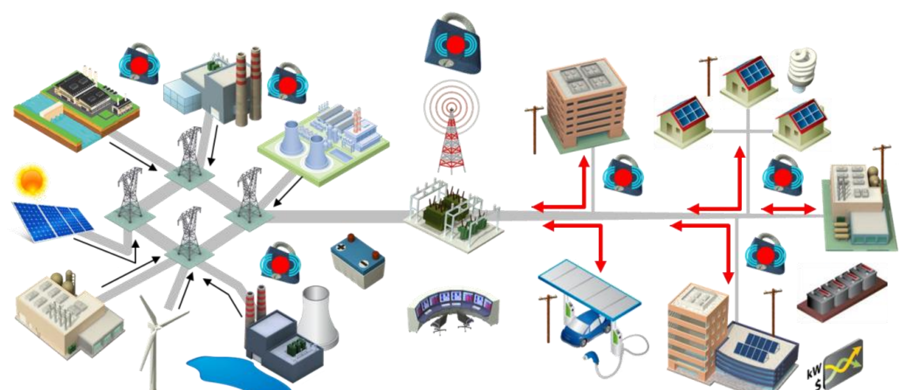


- One-way power flow,
- Centralized distribution,
- Simple interaction.

Source: www.epri.com

Smart grid: efficient supply of electricity, durable, economic, viable and secure.

- Distributed heterogeneous generation,
- Two-way information flow,
- Two-way power flow,
- Smart meters,
- Real-time interaction.

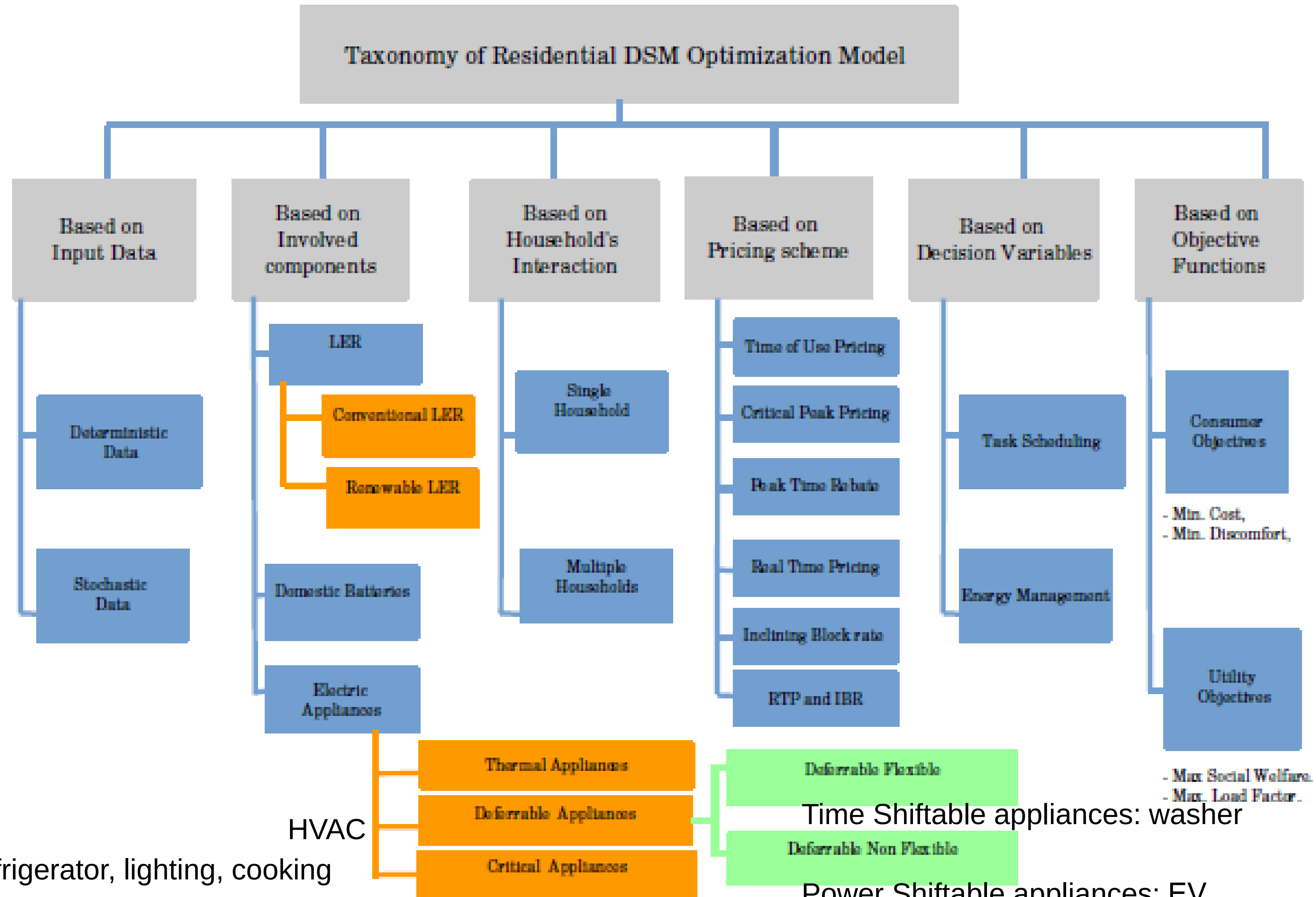


Source: www.epri.com

Demand side management

- Demand side management (DSM) is a key for future energy management.
- Demand side management refers to the policies that are intended to either curtail or shift energy consumption with the aim to achieve financial, societal and environmental **benefits**.
- Benefits of DSM :
  - Cost reduction,
  - Load factor improvement,
  - Managing energy demand-supply balance with the local energy generation and storage system,
  - Carbon emission reduction,
  - Energy efficiency.

Demand side management



HVAC

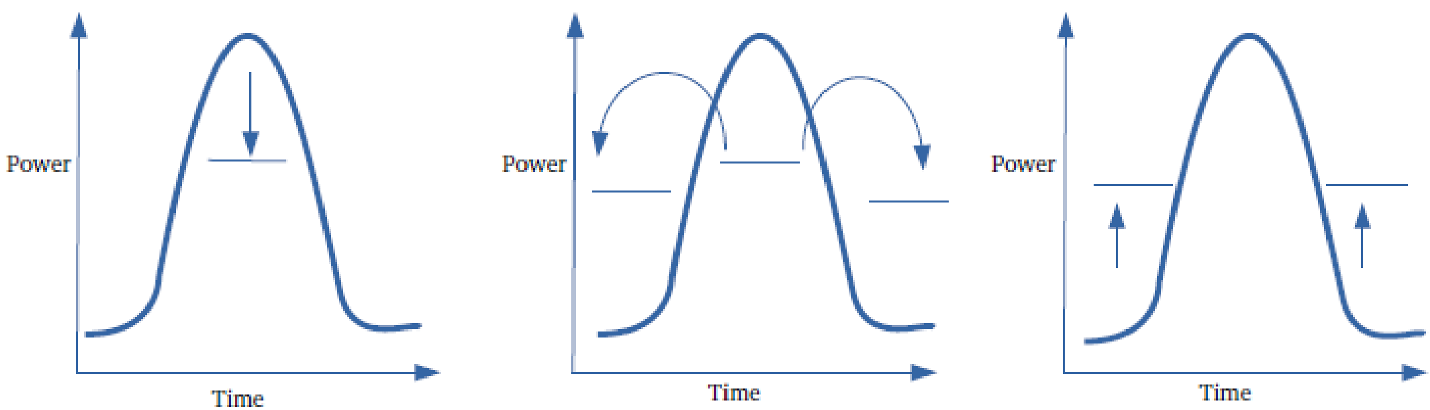
refrigerator, lighting, cooking

Time Shiftable appliances: washer

Power Shiftable appliances; EV, …

Home Energy management system

- Residential sector : 14% of the total energy consumption - 2040
- An automated home energy management system allow:
  - Automate the consumers' electricity use in response to the grid, weather conditions, and the desired comfort level.
  - Schedule the electricity used during on-peak periods through some demand response techniques, including peak shaving, flexible loads shifting, and valley filling.



Peak Clipping *Load Shifting* *Valley Filling*

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Related work I

- [Ha et al., 2006]
  - Tackles the anticipation layer of a home automation system.
  - The problem is formulated as a constraint satisfaction problem.
  - Two objectives are considered: the energy cost and the user comfort.
  - The thermal comfort criterion was defined by the threshold and treated as a constraint.
  - NP-Hard complexity of the problem → Tabu Search (TS) is applied,
  - Hierarchical optimization: minimizing a penalty function of constraint violation in a first phase and the energy cost in the second phase once a feasible solution was found.

  - Relatively high computation time to schedule only two electricity consumption tasks and two heating systems.
  - The TS algorithm settings are problem dependent, and different strategies are proposed to deal with all situations.
  - One home

Related work II

- [Allerding et al., 2012]
  - A non linear formulation of a simple electrical load management in smart
  - homes where appliances have a non linear time varying power consumption.
  - Customized evolutionary algorithm combined with a local search technique.
  - No Thermal comfort consideration.
- [Soares et al., 2014]
  - Multiobjective genetic approach.
  - Two objectives : electricity bill and the end-user's dissatisfaction.
  - One home.
- [Zhu et al., 2015]
  - A cooperative particle swarm optimization (PSO)
  - Set of smart homes.
  - Time shiftable devices and thermal devices.
  - Coordination between homes leads to reduce the electricity cost and avoid peak rebounds.
  - Scalarization of objectives.

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Proposed Model

- Schedule the controllable appliances in **multi-home** context over one day horizon.

- The algorithm schedules the household appliances, ensures a comfort level, as well as flattens the total aggregated load curve of all houses.

- **Two kinds of household appliances**
  - **Time shiftable appliances** (TSA)
  - **Thermal appliances** (TA)

- Decision variables
  - Task scheduling: when to activate the electric components
  - Energy management. amount of energy that can be allocated to each electrical component or (consumer) at each time slot.

Proposed Model

- Three objectives
  - Min total electricity cost
  - Min Discomfort
  - Avoiding peak rebounds
    - Standard deviation of electricity consumption

- The discomfort is divided in two parts :
  - Timing discomfort : modeled by lowering the delay time in the use of time shiftable appliances due to the load shifting.

  - Thermal discomfort: attribute a penalty to deviations from the desired thermal state.

Notations

t is the time slot indice,

h is the house indice,

T is the number of time slots representing the scheduling horizon,

H is the number of houses,

c_t is the electricity price of the grid at time slot t

a is the appliance indice,

$\mathcal{A}$ set of time shiftable appliances,

$\mathcal{C}$ set of thermal appliances,

$P^{a}_{h,t}$ is the power consumed by the appliance a at time slot t in the $h-th$ house,

$U^{h,a}_{TSA}$ is the delay time of the $a-th$ TSA of the $h-th$ house,

$U^{h,c}_{TA}$ is the discomfort level of $c-th$ TA of the $h-th$ house.

Objectives functions

- The multi-objective optimization problem is formulated as follows:

$$F_{cost} = \min \sum_{h=1}^{H} \sum_{t=1}^{T} \sum_{a \in \mathcal{A} \cup \mathcal{C}} P_{h,t}^{a} \times c_t$$

$$F_{discomfort} = \min \frac{1}{H} \sum_{h=1}^{H} \sum_{a \in \mathcal{A}} \frac{U_{TSA}^{h,a}}{a} + \frac{1}{H} \sum_{h=1}^{H} \sum_{c \in \mathcal{C}} \frac{U_{TA}^{h,c}}{c}$$

$$F_{std} = \min \sqrt{\frac{\sum_{t=1}^{T} (\sum_{a \in \mathcal{A} \cup \mathcal{C}} P_{h,t}^{a} - Ideal)^2}{T}}$$

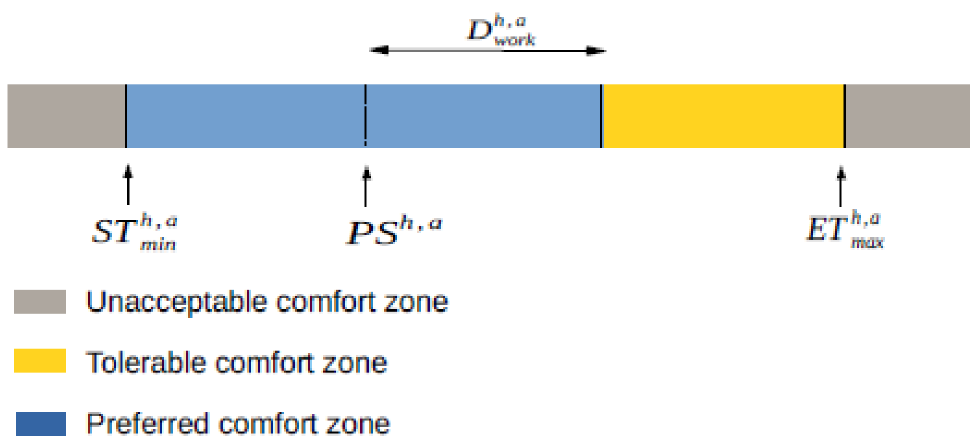
- Where Ideal is the average load for all household appliances:

$$Ideal = \frac{\sum_{h=1}^{H} \sum_{t=1}^{T} \sum_{a \in \mathcal{A} \cup \mathcal{C}} P_{h,t}^{a}}{T}$$

Time shiftable appliances (TSA)

$$U_{TSA}^{h,a} = \begin{cases} 0 & \text{if } ST_{min}^{h,a} \leq ST_{current}^{h,a} \leq PS^{h,a} + D_{work}^{h,a} \\ \frac{ST_{current}^{h,a} - PS^{h,a}}{ET_{max}^{h,a} - D_{work}^{h,a} - PS^{h,a}} \times 100, & \text{if } PS^{h,a} + D_{work}^{h,a} < ST_{h,current}^{a} \leq ET_{max}^{h,a} - D_{work}^{h,a} \end{cases}$$

- $ST_{current}^{h,a}$ is the current starting time,
- $ST_{min}^{h,a}$ is the minimum starting time,
- $PS^{h,a}$ is the preferred starting time,
- $ET_{max}^{h,a}$ is the maximum ending time,
- $D_{work}^{h,a}$ is the processing time duration of the $a - th$ TSA of the $h - th$ house.



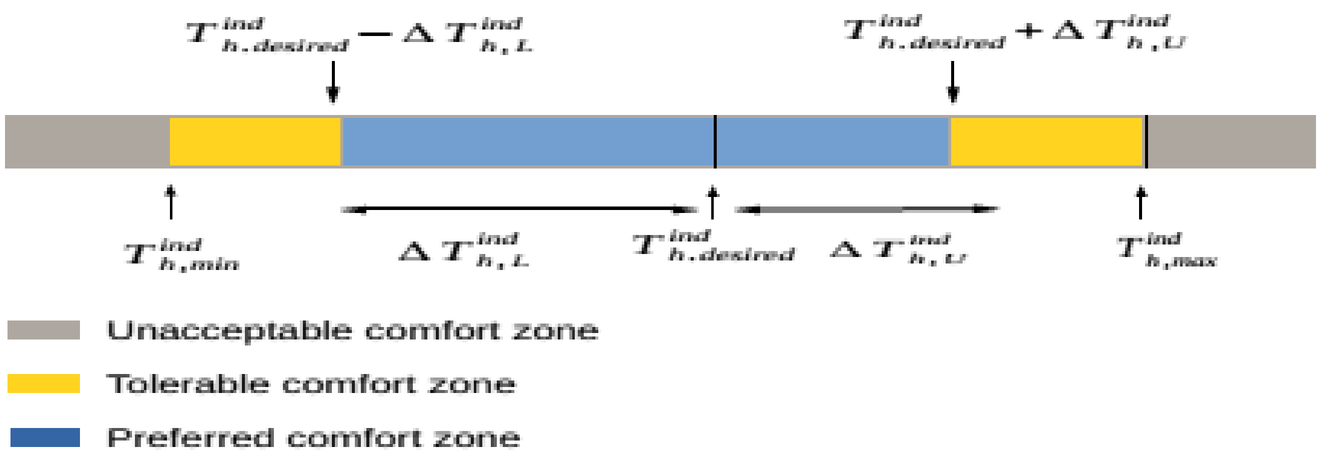
Thermal appliances

- Indoor temperature model: at every time slot t of the household h [Althaher et al., 2015]:

$$T^{in}_{h,t+1} = \epsilon T^{in}_{h,t} + (1-\epsilon)(T^{out}_{h,t} \pm \frac{COP \cdot p^{hvac}_{h,t}}{A})$$

  - ϵ is the inertia factor,
  - A is the thermal conductivity (kW/C),
  - COP is the coefficient of performance,
  - $T^{out}_{h,t}$ is the outdoor temperature at time slot t of the household h.

Illustration of thermal appliances appliances comfort level parameters :



Discomfort level of HVAC

- The discomfort level of the HVAC

$$U_{TA}^{h,HVAC} = \frac{100}{T}\sum_{t}^{T}\frac{d_{h,t}^{in}}{\Delta T_{h,max}^{in}}$$

$$\Delta T_{h,max}^{in} = max(T_{h,t}^{des} - T_{h,min}^{in}, T_{h,max}^{in} - T_{h,t}^{des})$$

$$d_{h,t}^{in} = \begin{cases} T_{h,t}^{des} - T_{h,t}^{in} & \text{if } T_{h,min}^{in} \leq T_{h,t}^{in} < T_{h,t}^{des} - \Delta T_{L}^{in} \\ 0 & \text{if } T_{h,t}^{des} - \Delta T_{h,L}^{in} \leq T_{h,t}^{in} < T_{h,t}^{des} + \Delta T_{h,U}^{in} \\ T_{h,t}^{in} - T_{h,t}^{in} & \text{if } T_{h,t}^{des} + \Delta T_{U,h}^{in} < T_{h,t}^{in} \leq T_{h,max}^{in} \\ \Delta T_{h,max}^{in}, & \text{otherwise} \end{cases}$$

- $T_{h,min}^{in}$ is the minimal temperature,
- $T_{h,max}^{in}$ is the maximal temperature,
- $T_{h,t}^{des}$ is the desired temperature,
- $\Delta T_{h,L}^{in}$ is the lower dead band limits,
- $\Delta T_{U,h}^{in}$ is the upper dead band limits.

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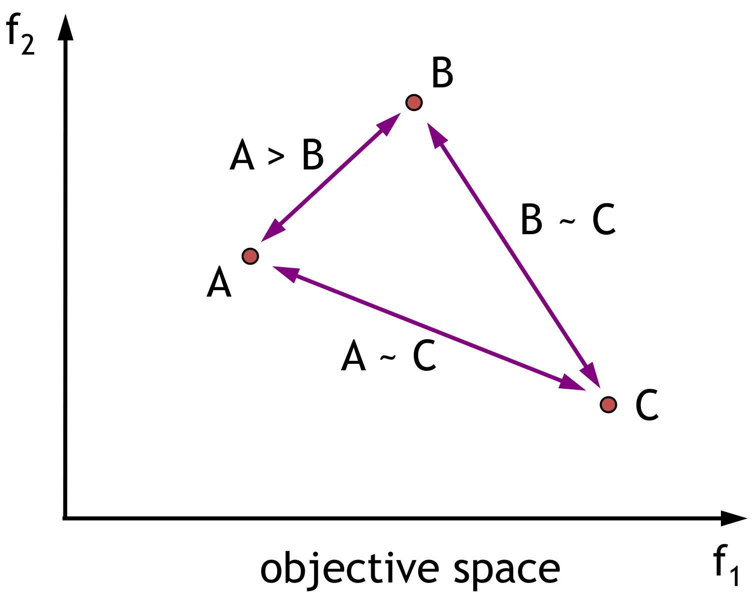
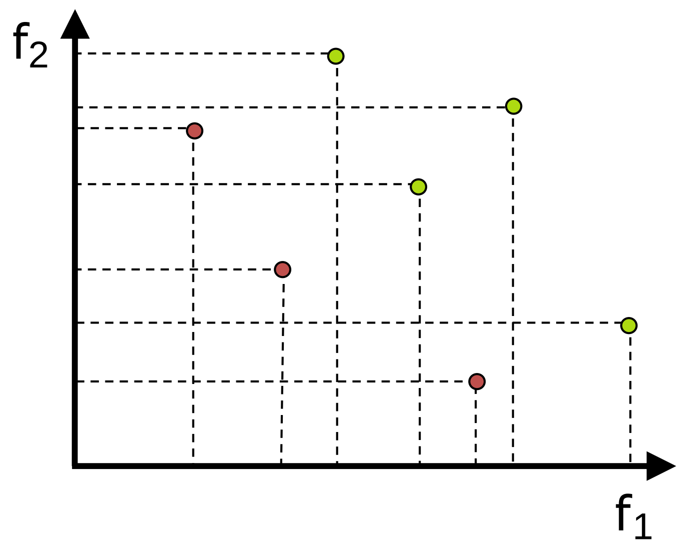
Pareto dominance [Pareto 1896]

- An objective vector $z \in Z$ dominates an objective vector $z' \in Z$ iff
  - $\forall i \in \{1,\ldots,n\}, z_i \leq z_i'$
  - $\exists j \in \{1,\ldots,n\}, z_j < z_j'$

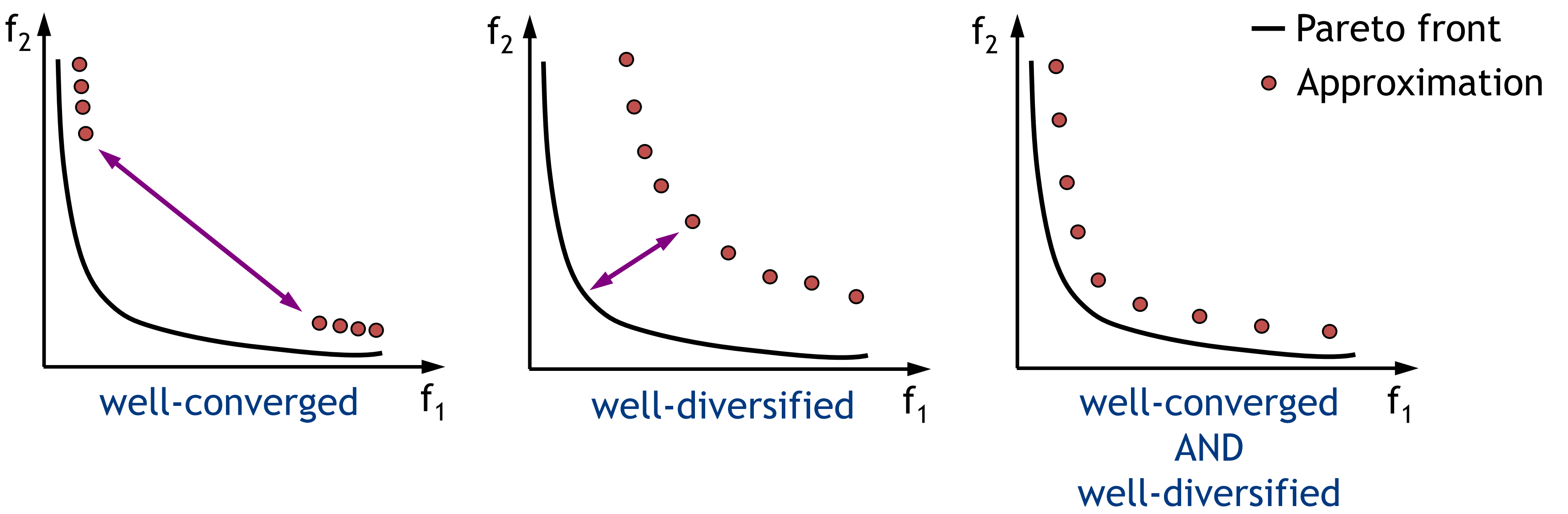


Non-dominated solution
(eligible, efficient, non inferior, Pareto optimal)



What is a Good Approximation?

- Approximating an efficient set is itself a bi-objective problem
- Min the distance to the Pareto front
  - ➔ well-converged efficient set approximation
- Max the diversity in the objective space (and/or decision space)
  - ➔ well-diversified efficient set approximation

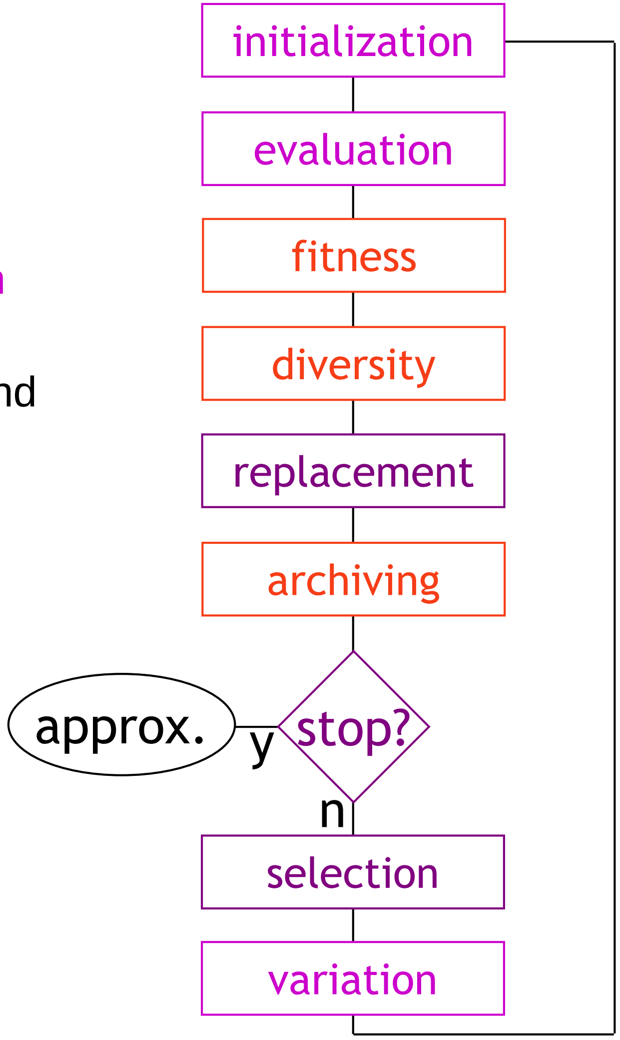


Design issues of multi-objective metaheuristics

- **Fitness assignment**
  - Guide the search towards Pareto optimal solutions for a better convergence.
- **Diversity preserving**
  - Generate a diverse set of Pareto solutions in the objective space and/or the decision space.
- **Elitism**
  - Preservation and use of elite solutions.
  - Allows a robust, fast and a monotically improving performance of a metaheuristic

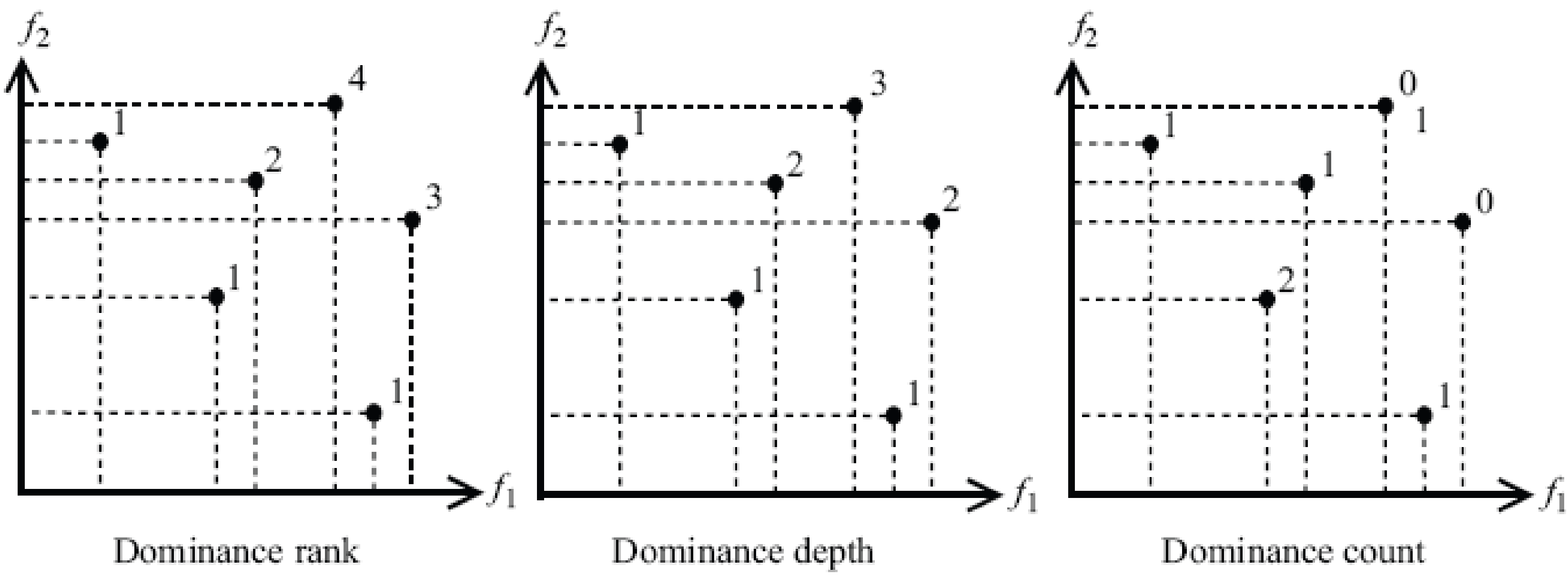
A Model for Evolutionary Algorithms

- Problem-dependent components
  - Representation $X = [ST^{current}, P^{HVAC}]$
  - Initialization (Random in feasible interval), Evaluation (3 objectives),
  - Variation (1-point crossover, mutation starting time and power)
- Multi-objective specific components
  - Fitness assignment
  - Diversity preservation
  - Archiving
- Metaheuristic specific components
  - Selection
  - Replacement
  - Stopping condition



Fitness assignment: Pareto ranking

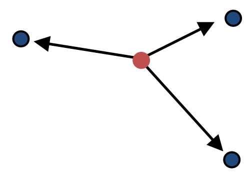
- Pareto-based fitness assignment strategies
  - Dominance rank (*e.g.* used in MOGA)
    - Number of solutions which dominates the solution
  - Dominance depth (*e.g.* used in NSGA and NSGA-II)
  - Dominance count (*e.g.* combined with dominance rank in SPEA and SPEA2)
    - Number of solutions dominated by the solution



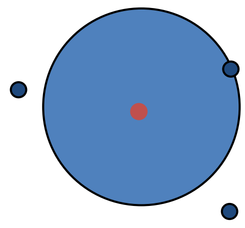
Diversity: Statistical density estimation

- Kernel methods (sharing)
  - Neighborhood of a solution in term of a function taking a distance as argument
- Nearest neighbour techniques
  - Distance of a solution to its k^{th} nearest neighbour (ex. Crowding)
- Histograms
  - Space divided onto neighbourhoods by an hypergrid (ex. Sharing)

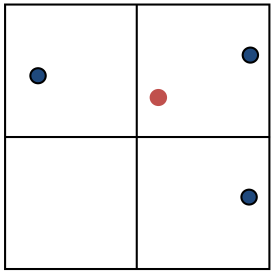
➔ decision / objective space



kernel



nearest neighbor



histogram

EMO Algorithms as Instances of the Model

Components	NSGA-II [Deb et al. 02]	SPEA2 [Zitzler et al. 01]	IBEA [Zitzler and Künzli 04]	SEEA [Liefooghe et al. 10]
fitness assignment	**dominance-depth**	**dom-count + dom-rank**	**quality indicator**	none
diversity preservation	crowding distance	k^{th} nearest neighbor	none	none
archiving	none	**fixed-size archive**	none	**unbounded**
selection	binary tournament	elitist selection	binary tournament	elitist selection
replacement	elitist replacement	generational replacement	elitist replacement	generational replacement
stopping condition	number of generations	number of generations	number of generations	user-defined

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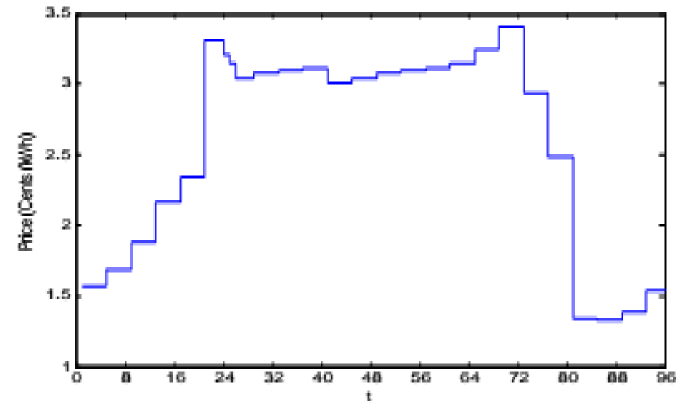
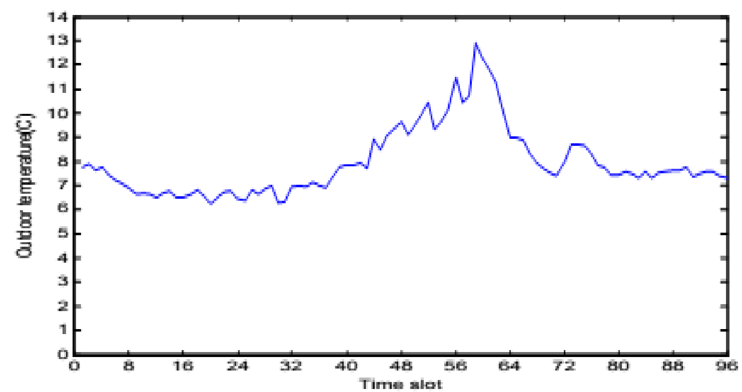
Data I

- The number of households is H = 5
- The 24 hour day-time is divided into T = 96 equal time slots, each time slot t ∈ {1, ..., T } is 15 mn.
- Time-varying prices



Electricity price

- Outdoor temperature curve.



Outdoor temperature

Data II

- Parameter settings of TSA (Time Shiftable Appliances)

Time shiftalbe appliance a \ Time slot parameter	$ST_{min}^{h,a}$	$ET_{max}^{h,a}$	$D_{work}^{h,a}$	$PS^{h,a}$	Power load profiles
Electric clothes washer (ECW)	20	96	3	24	$[0.52, 0.65, 0.52]$
Electric clothes dryer (ECD)	20	96	4	24	$[2.95, 2.91, 2.90, 0.19]$
Electric dishwasher(EDW)	20	96	7	24	$[1.2, 1.2, 0.2, 1.1, 0.68, 0.8, 0.6]$

- The HVAC settings data are taken from [Althaher et al., 2015]

$(P_{h,max}^{HVAC} = 3.5kW, COP = 2.5, \epsilon = 0.98, A = 0.45kW/^{\circ}C)$, $T_{h,min}^{in}$, T_{h}^{des}, $T_{h.max}^{in}$, $\Delta T_{h.L}^{in}$ and $\Delta T_{U.h}^{in}$ are $15^{\circ}C, 20^{\circ}C, 24^{\circ}C$, 2, and 3 respectively.

- RACE tool for tuning EA parameters: Population size is 100, Number of iterations is 100, Crossover probability is 0.25, Mutation probability is 0.35.

- All the simulations are carried out with
  - ParadisEO 2.0.1 metaheuristic framework [Talbi, 2009] http://paradiseo.gforge.inria.fr
  - Executed on Intel Core i3 380M 2.53 GHz personal computer with 4.0 gigabyte of RAM

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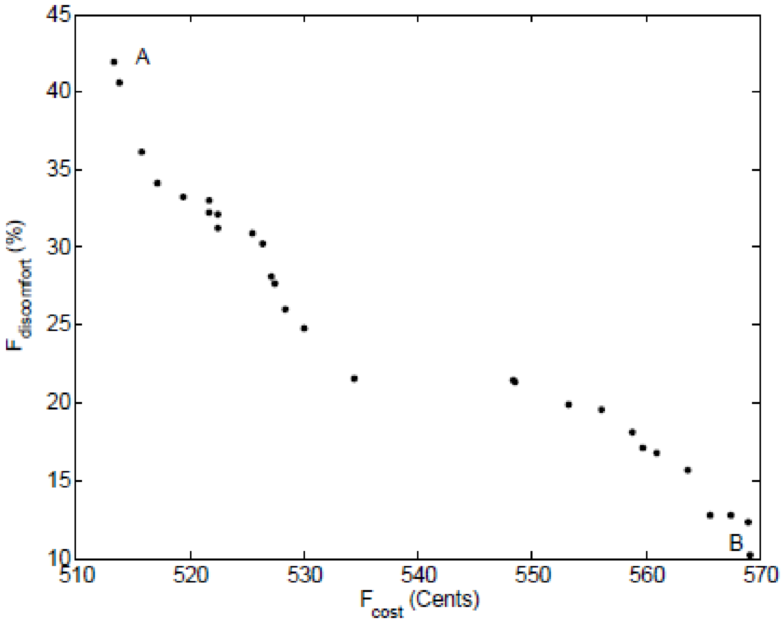
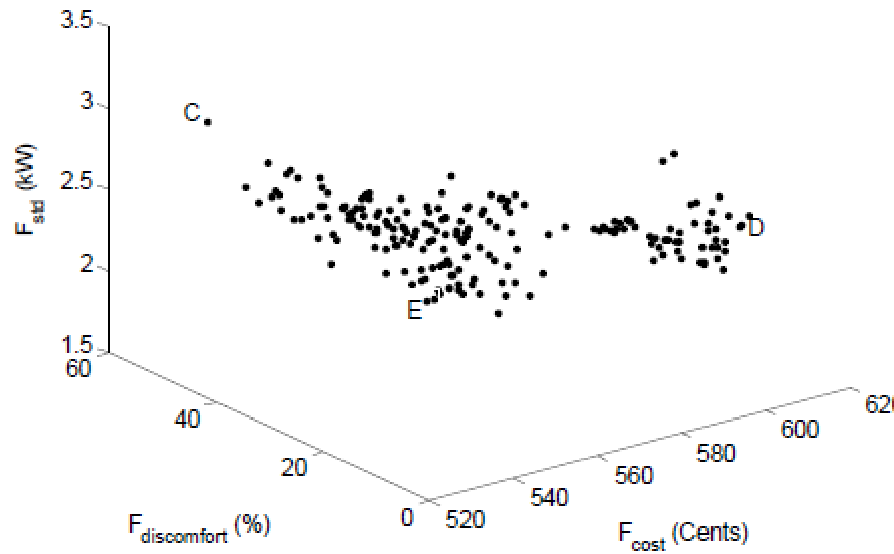
Simulation results

The pareto optimal front in the two (F_{cost} and $F_{discomfort}$) and (F_{cost}, $F_{discomfort}$ and F_{std}) objective spaces.



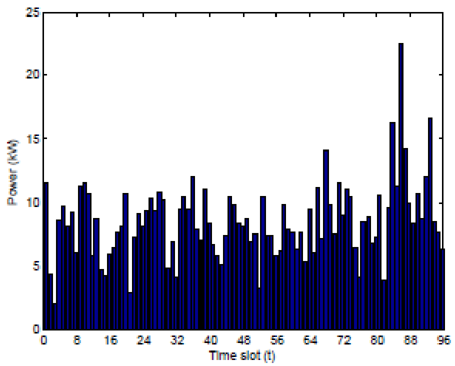


Solutions	Cost (Cents)	Discomfort (%)	STD (kW)	Mean Power (kW)	Maximum peak (kW)	Runtime (s)
Case I (Two objectives)						
Solution A	**513.412**	41.9427	3.00948	8.5504	22.4679	6.33
Solution B	569.159	10.1546	3.07063	9.1471	21.4435	
Case II (Three objectives)						
Solution C	528.72	48.15560	3.036960	8.9053	18.5217	9.12
Solution D	603.545	7.321010	2.506480	9.7048	16.3013	
Solution E	561.982	31.7631	**1.95812**	9.0863	**15.0263**	

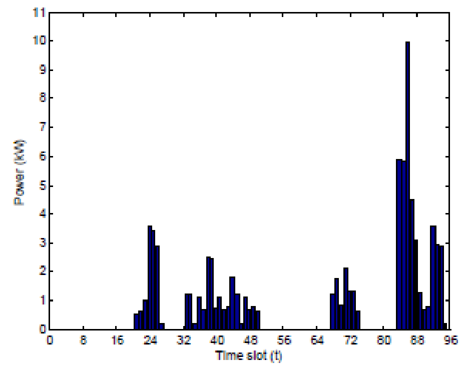
Results

- The power transmitted from the grid to the TSA
- The total power demand,
- The mean indoor temperature of all houses.

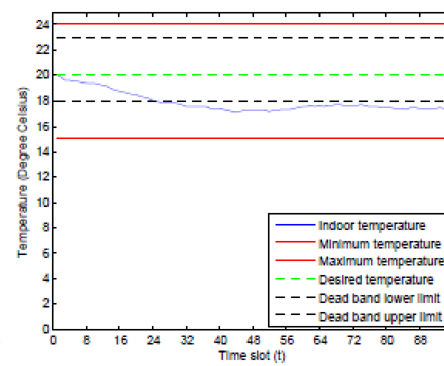
Solution A



(a) Total power

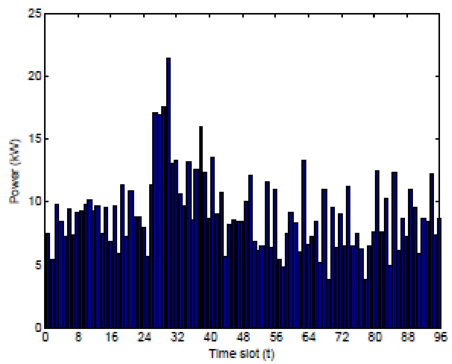


(b) TSA power

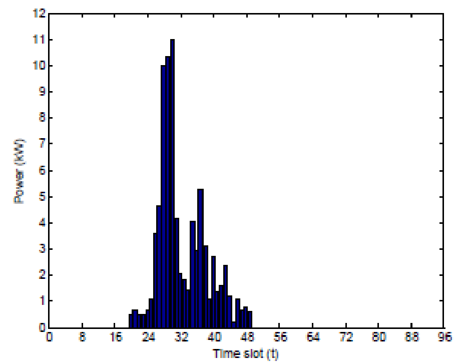


(c) Indoor temperature

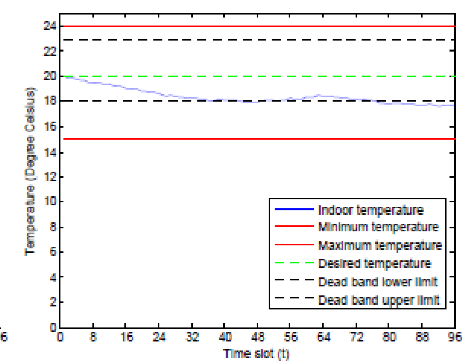
Solution B



(a) Total power



(b) TSA power

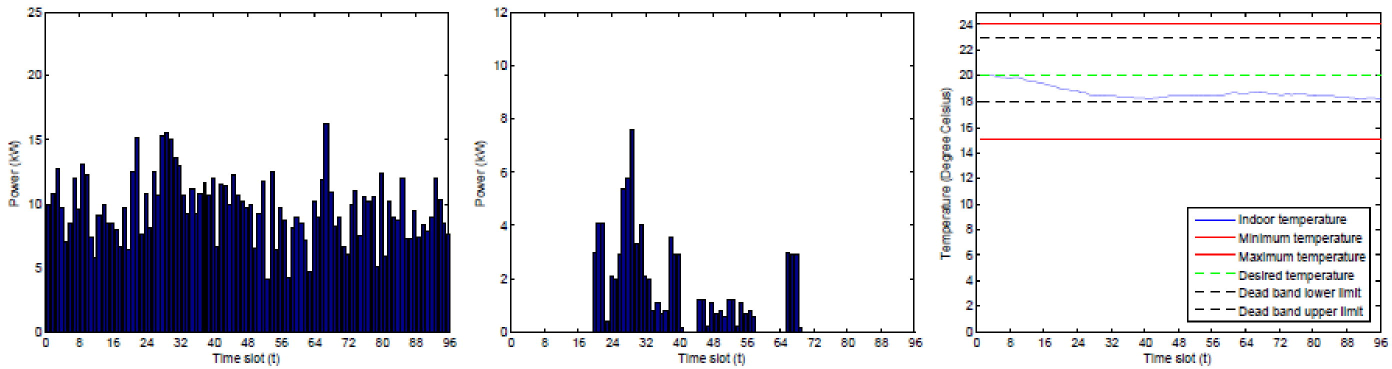


(c) Indoor temperature

- The solution (A) is the most favorable economically.
- The maximum power peak was at its highest level
- Mean indoor temperature is below the dead band lower limit for most of the time slots.

Experimental results

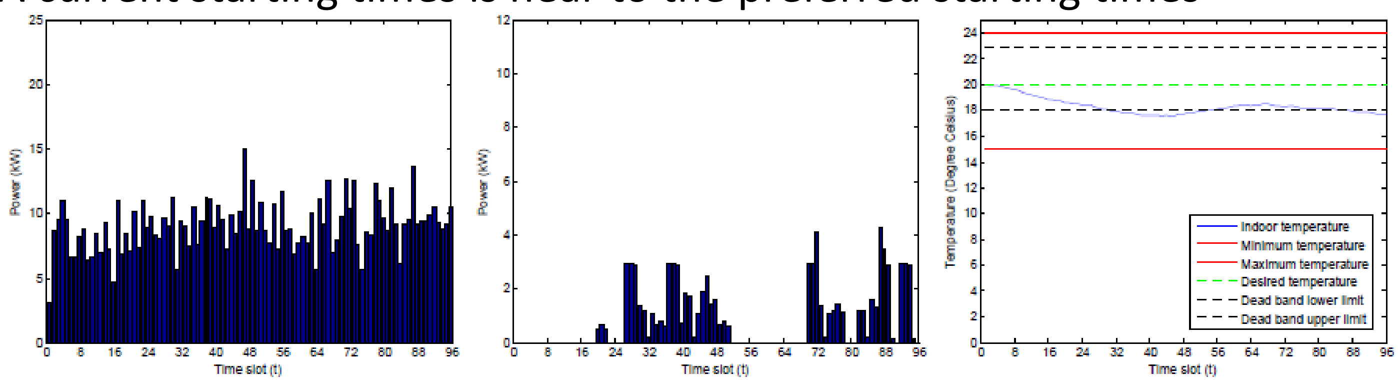
Solution D



(a) Total power (b) TSA power (c) Indoor temperature

- Solutions (B) and (D) are the most favorable for timing and thermal comfort.
- The mean indoor temperature is between the dead band lower limit and the desired temperature for most of the time slots to guarantee the preferred thermal comfort
- Scheduling of TSA current starting times is near to the preferred starting times

Solution E



(a) Total power (b) TSA power (c) Indoor temperature

- Solution (E) is the most favorable from the point of view of the grid with the lowest maximum peak and minimal standard deviation

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Conclusions

- A multi-objective optimization model to schedule the controllable appliances in multi-home context.
  - Electricity cost
  - Discomfort
  - Peak rebounds

- Time shiftable appliances (TSA) and thermal appliances (TA)

- Multi-objective evolutionary algorithms to generate the Pareto front

Perspectives

- Application to large scale problems (thousands of homes)
- Extending mathematical models
  - Local energy production (ex. Photovoltaic)
  - Storing devices (battery)
- Hybrid optimization algorithm – Matheuristic
  - Evolutionary algorithm (discrete) + mathematical programming (continuous)
- Multi-criteria decision making: A-posteriori decision making
- Uncertainty management: price, production, …