LIRIMA Team MOHA

Mixed Multi-objective Optimization using Hybrid Algorithms Application to smart grids

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Université de Lille 1 SCIENCES ET TECHNOLOGIES

Inria INVENTORS FOR THE DIGITAL WORLD

ECOLE MOHAMMADIA D'INGENIEURS

Outline

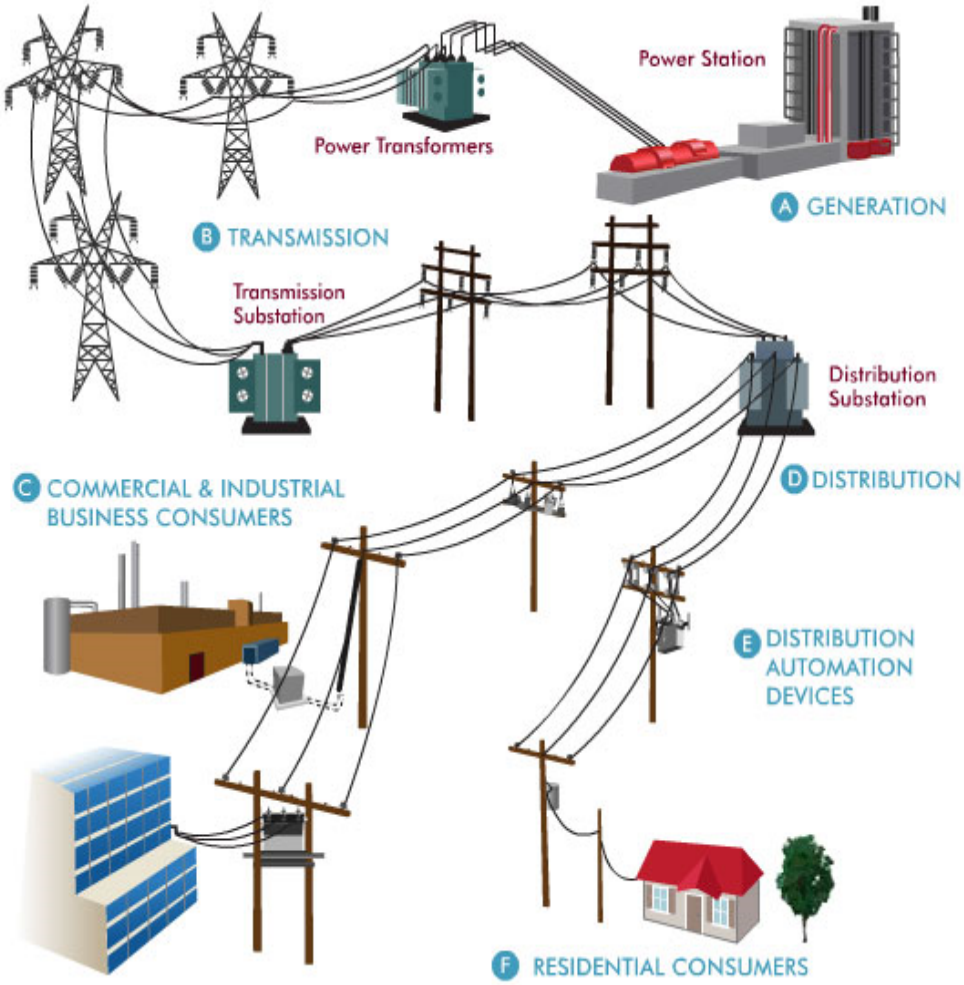
- Composition
  - INRIA & EMI
- Application issues
  - Smart grids
- Scientific issues
  - Multi-objective optimization under uncertainty
  - Large scale mixed optimization
- Perspectives
- Outputs
  - Publications
  - Projects with industry
  - Organization of conferences – workshops
- Technical presentation

Composition

- **Principal investigator (Inria):**
  - Prof. El-ghazali TALBI, DOLPHIN → BONUS, INRIA Lille Nord Europe, France
- **Principal investigator (Main team):**
  - Prof. Rachid ELLAIA, LERMA, Mohammadia School of Engineers, Mohamed V University, Rabat, Morocco
- INRIA Lille Nord Europe, France
  - Prof. E-G. Talbi
  - O. Bahri (PhD student) – *Defended Phd in May 2017*
    - ***A fuzzy framework for multi-objective optimization***
  - Prof. N. Melab
- EMI Rabat, Morocco
  - Prof. R. Ellaia
  - Asmae Gannouni (PhD student) – *Phd defense in Dec 2017*
    - ***Multi-objective optimization under uncertainty***
  - Zineb Garroussi (PhD student) – *Phd defense in Dec 2017*
    - ***Multi-objective demand side management in smart grids***
  - Prof. M. Maaroufi
  - Jihane Serrar (PhD student) – *start her Phd Sept 2017*

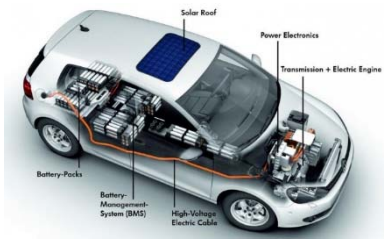
Traditional grid

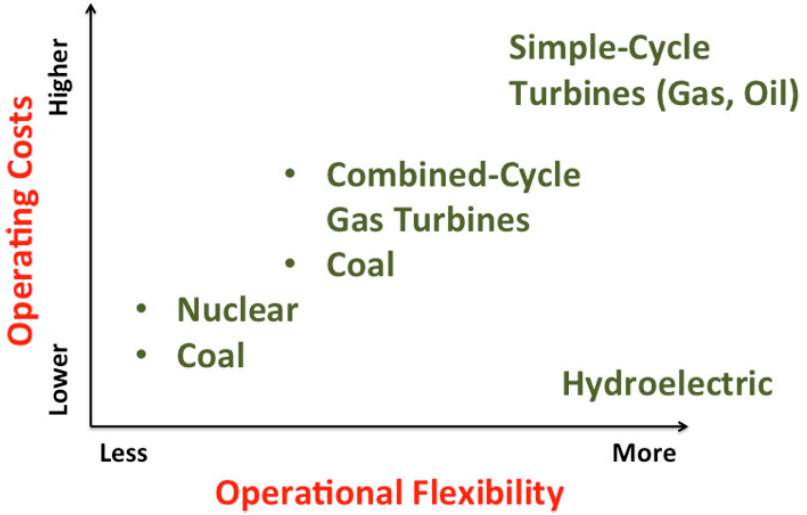
- Designed 130 years ago
  - First coal plant: Thomas Edison,1882
- **Generation**
  - Electrical power is centrally generated at large power plants
- **Transmission**
  - Grid: transmission network
- **Distribution**
  - Consumption is distributed over a large geographical area
- Energy demand will triple by 2050
- Deregulation/liberalization market
- Power loss : 6% in US, worse for other countries
  - USA: estimated $25 billion per year
- Environment impact
  - Greenhouse Gas (GHG) emissions: contribution of 34%

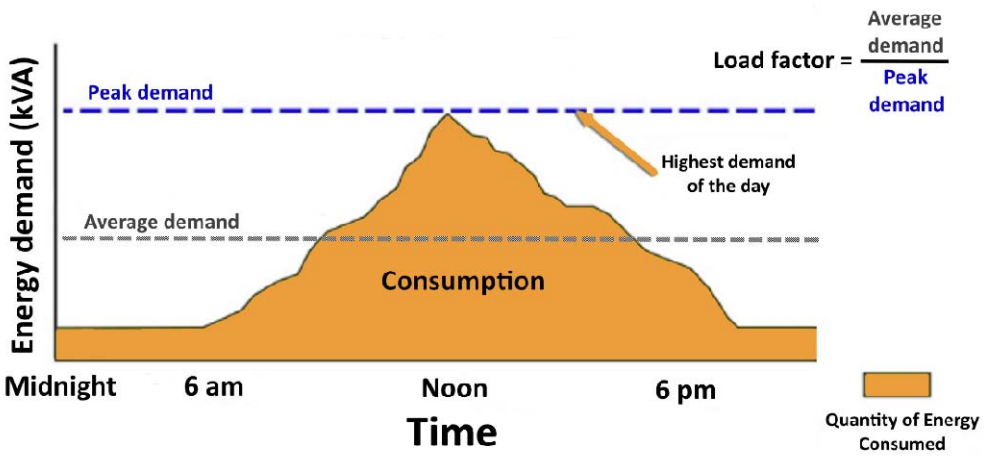


Challenges and constraints

- Electricity difficult to store
  - Advances in battery design
  - Electrical vehicles (EVs)
- **Flexibility**: Energy production is very hard to change quickly
  - Most of the flexibility is provided by fossil fuel power stations
- Energy demand fluctuates widely during the day/seasons/weather
- Electricity generation must match consumer demand every minute (power flow equations)
- Peak load versus off-peak load
  - Low utilization of the grid during off-peak times
- Volatility in prices

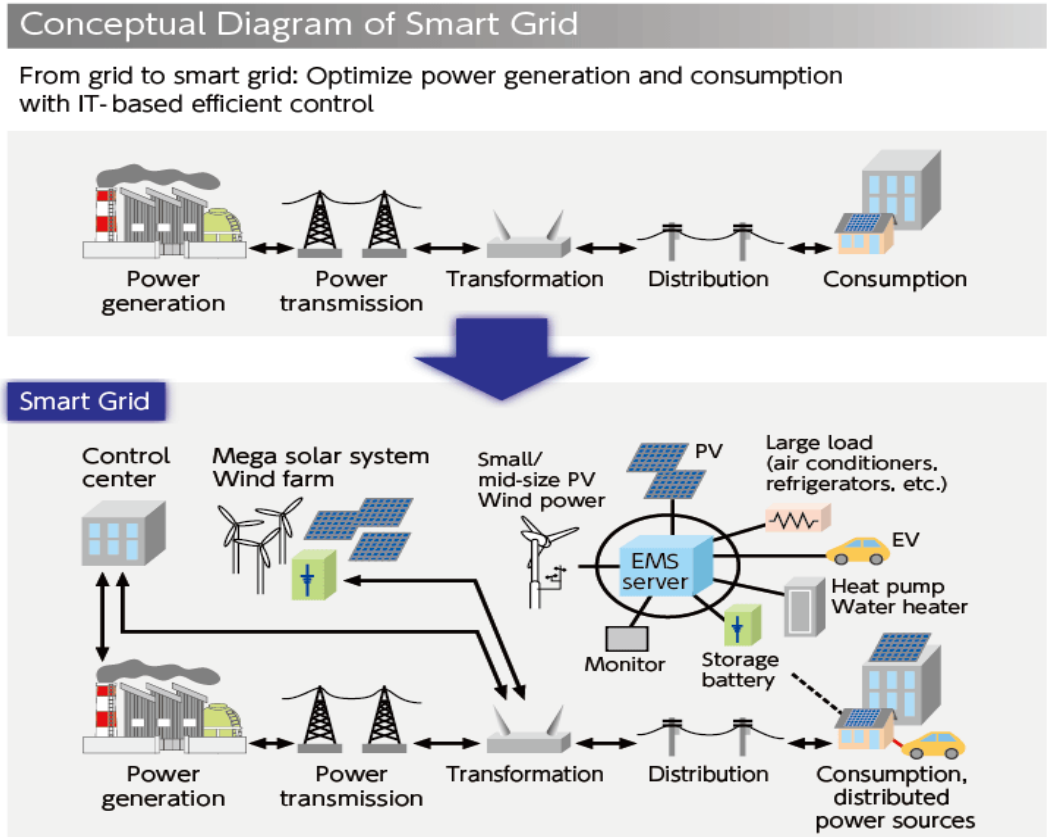






From Traditional Grid to Smart grids

- Distributed heterogenous efficient reliable generation
  - Plants are distributed almost the same way the consumers are
  - Minimal transmission of power to distant consumers
- Two-way information flow
  - Real-time demand, …
- Two-way power flow
- Smart meters: usage data
- Flexible controllable load & generation
- Renewable energy
- Energy storage
  - Plug in electric vehicles
- Smart appliances
  - Customers can respond to price signals sent from the utility



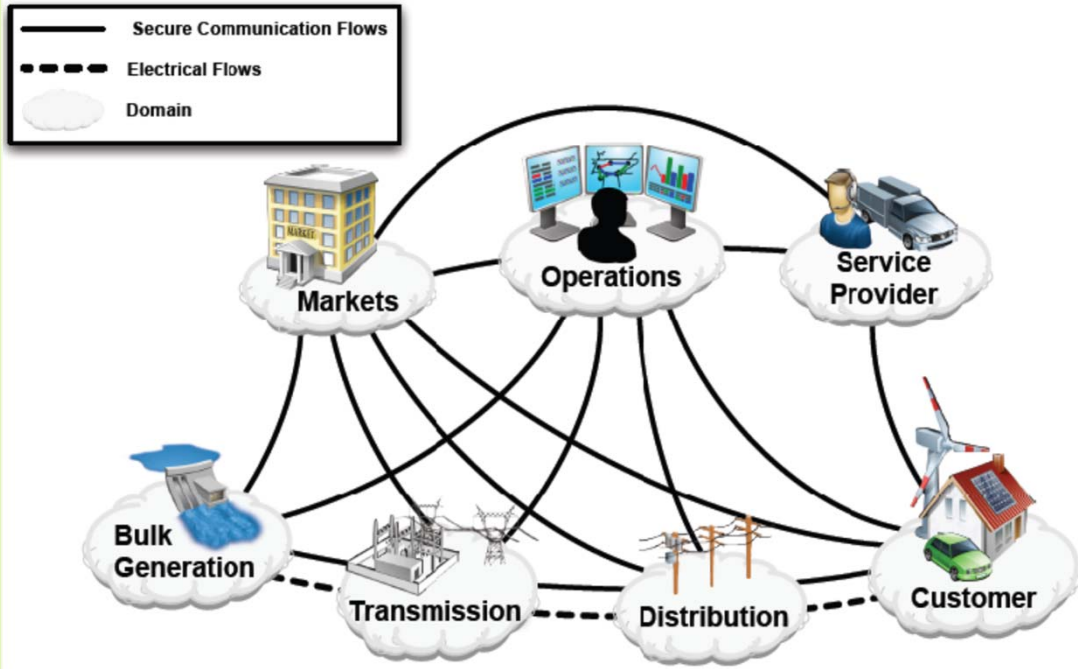
"A Smart Grid is an electricity network that can intelligently integrate the actions of all users connected to it – generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies."

– Schneider Electric (2010)

Optimization challenges in Smart Grids

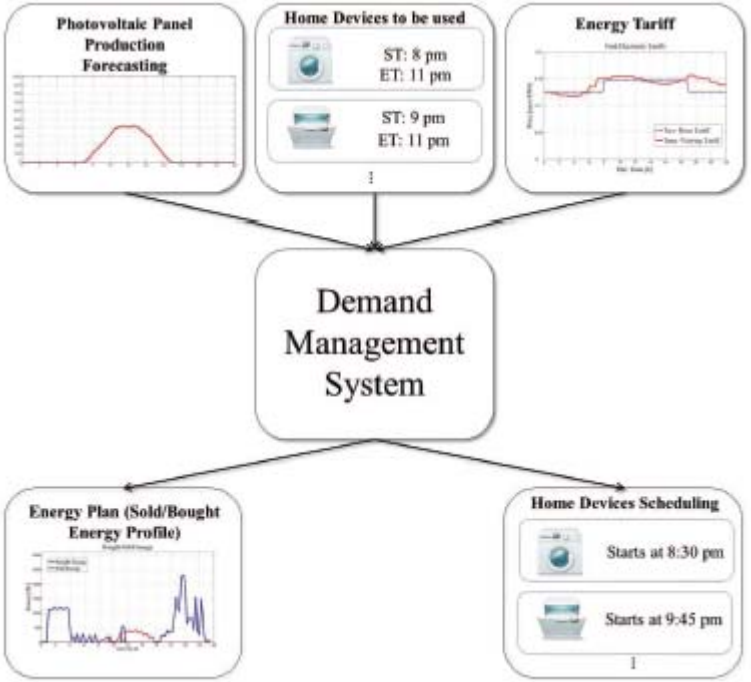
- Generation optimization
  - Unit commitment
  - Economic dispatch
- Transmission optimization
- Distribution optimization
- Pricing and markets
  - Dynamic pricing
- **Customer management**
  - **Demand response management**

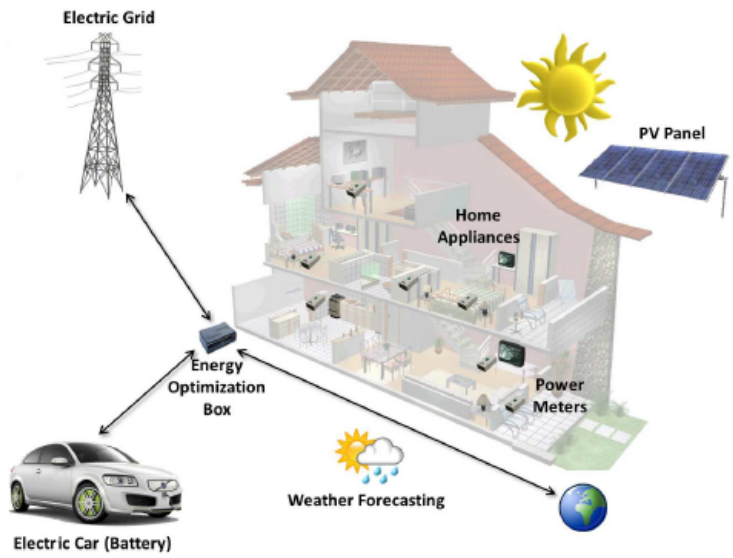
NIST Model



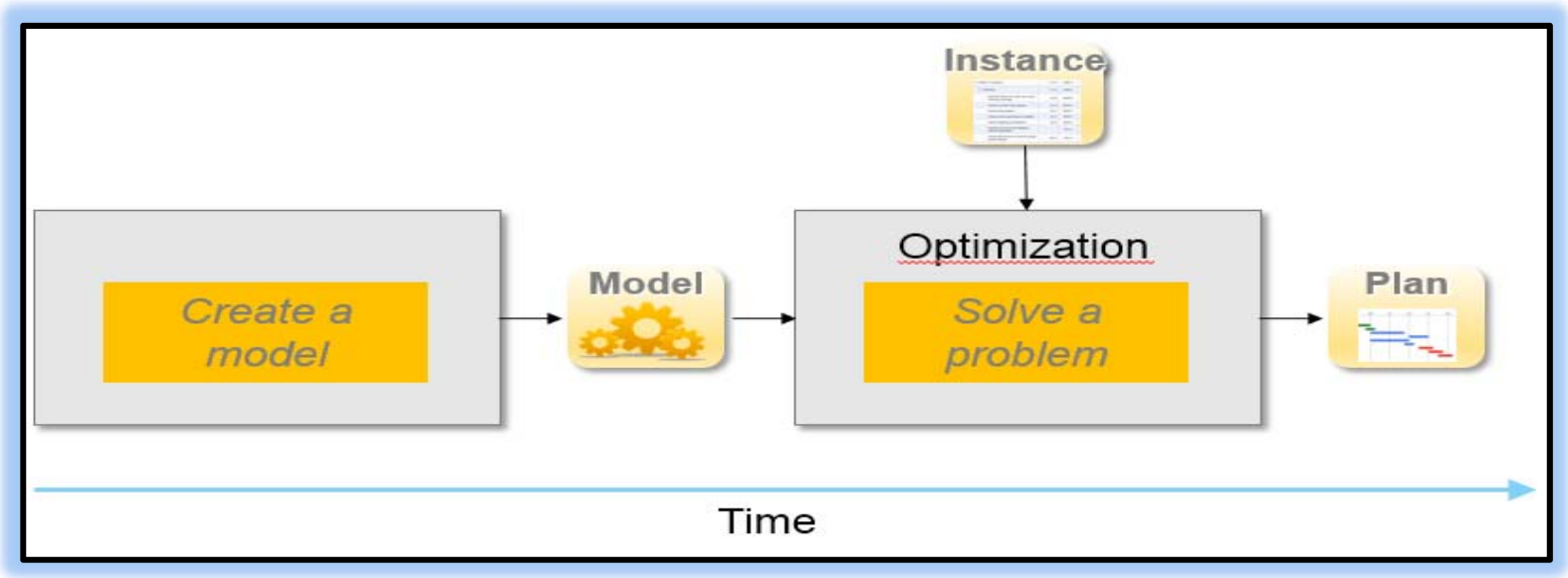
House energy demand response

- Given
  - Local production (wind, solar, …)
  - Local load
  - Energy tariff
- Find
  - Home devices scheduling
  - Energy plan
    - Buy/sold/store
- Objectives
  - Min Bill, Max Profit
  - Min Peak demand, Max Confort, …
- Constraints
  - Production
  - Batterie constraints
  - Home devices scheduling
    - Time windows
- Literature solutions
  - ILP (Integer Linear Programming) [A. Barbato 2012]
  - Mixed Linear Integer Programming [D. Zhang 2011]
  - Multi-objective hybrid evolutionary algorithms [Z. Garroussi, E-G. Talbi & R. Ellaia, 2016]





Optimization issues



Decision variables → Given $\vec{x} = \langle x_1, x_2, \ldots, x_n \rangle$

Objective → minimize $f(\vec{x})$

such that

Bounds → $lb_i \leq x_i \leq ub_i, \quad i = 1..n$

and

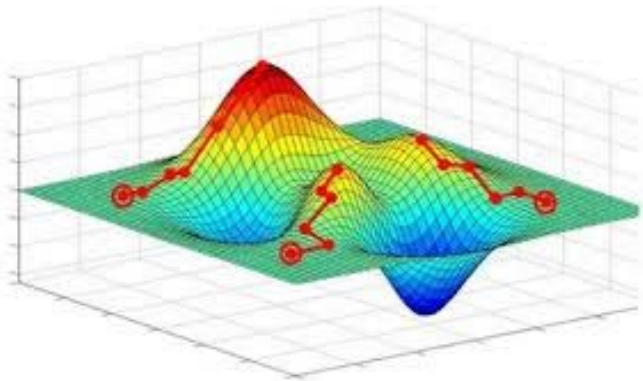
Constraints →

$g_1(\vec{x}) \leq b_1$

$g_2(\vec{x}) \leq b_2$

$\ldots$

$g_m(\vec{x}) \leq b_m$



Optimization Challenges

- **Large scale problems**
  - Huge number of generators, clients, big data
    - USA: 12M distributed generators, 3M miles lines, …
- **Multi-objective problems**
  - reliability, availability, efficiency, sustainability, cost.
- **Mixed optimization**
  - Continuous and discrete variables
- Multi-periodic planning and optimization
  - Distribution networks evolution (different scenarios)
- Optimization under uncertainty
  - Stochastic data
    - *Ex: wind and solar production (weather), demand, prices, …*

e.g: stochastic program

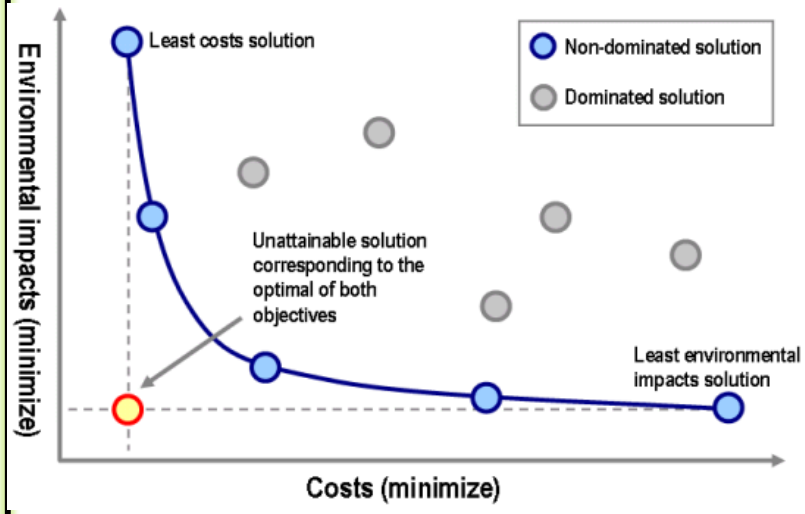
$$\text{"}\min_{x \in X}\text{"}\, g_0(x, \xi)$$

$$\text{t.q. } g_i(x, \xi) \leq 0, \; i = 1, \ldots, m,$$

ξ : random variable

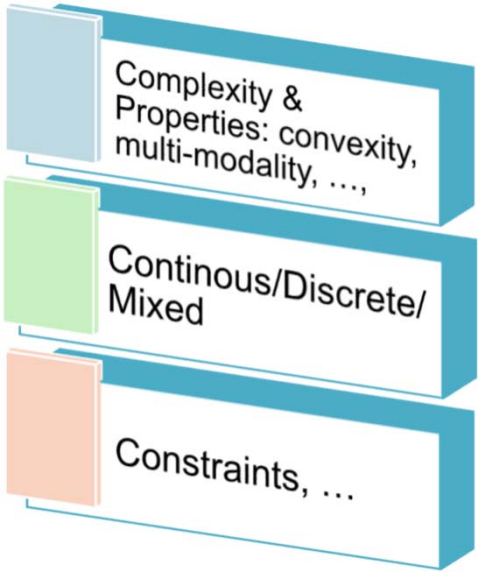
Multi-Objective optimization

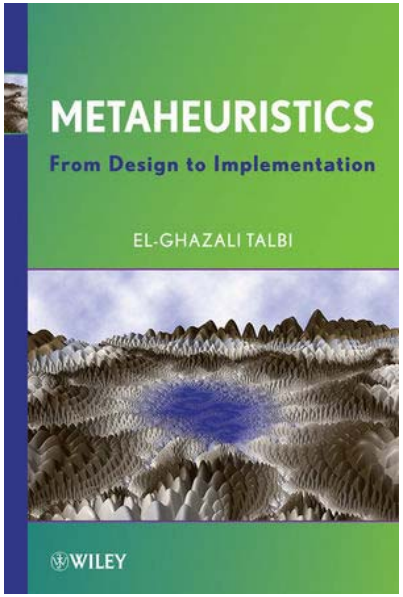
- Economics
  - Keeping downward prices on electricity prices, reducing the amount paid by consumers
- Efficiency
  - Reducing the cost to produce, deliver, and consume electricity
- Reliability
  - Reducing the cost of interruptions and power quality disturbances
  - Reducing the probability and consequences of widespread blackouts
- Security
  - Reducing dependence on imported energy as well as the probability and consequences of manmade attacks and natural disasters.
- Environmental friendliness
  - Reducing emissions by enabling a larger penetration of renewables and improving efficiency of generation, delivery, consumption.



Optimization methods

- **Hybrid (Exact and Approximation Algorithms)**
  - Mathematical programming
    - Linear programming,
    - Mixed integer programming
    - Relaxation (Lagrangian, SDP,…)
  - Artificial intelligence - Metaheuristics
    - **Single-solution based algorithms**: local search, tabu search, …
    - **Population based algorithms**: evolutionary algorithms, particle swarm, …





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ET1 El-ghazali Talbi; 15/03/2017

Optimization Perspectives

- Bi-level optimization & Game theory
  - Dynamic pricing

- Optimization & Simulation
  - Meta-modeling, Surrogates
  - High performance computing, Parallel algorithms
    - GPU, Multi-cores, Cluster, Heterogeneous computing

- Optimization & Machine learning
  - Forecasting (demand, renewable generation)
    - Short-term, medium-term, long-term
    - Neural networks, deep learning, …

Upper-level / Leader

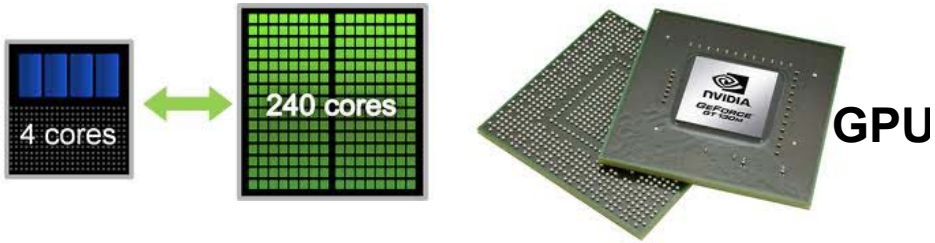
Lower-level / Follower

$$\min_x F(x, y)$$

subject to $G(x, y) \leq 0$

$$\min_y f(x, y)$$

subject to $g(x, y) \leq 0$



GPU

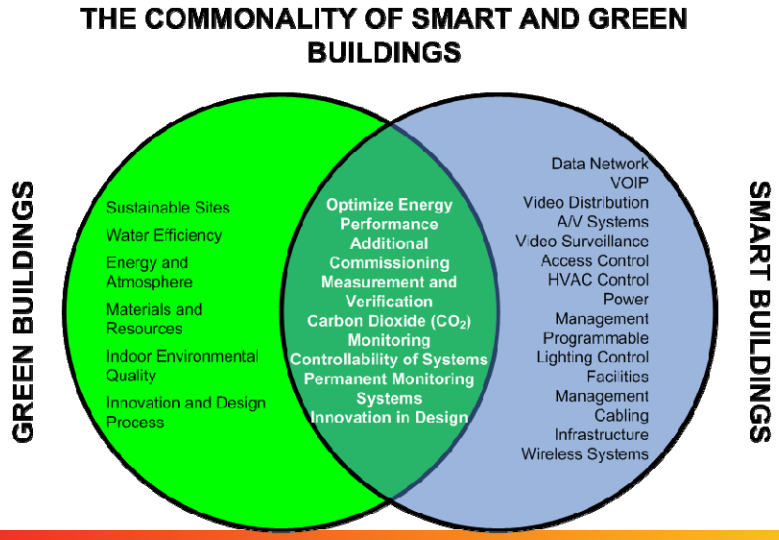
Smart Grid Application perspectives

- Smart grids and Logistic/Transportation systems
  - Electrical vehicles (charging systems)
    - Electric vehicle routing problem

      [J. Serrar, E-G. Talbi, R. Ellaia, 2017]
  - Electrial buses

- Smart grids and Cloud computing systems
  - Green data centers
    - Energy-aware Job Scheduling
    - Cooling

- Smart grids and Smart city
  - Urban configuration
    - Smart green building
- Electrical vehicles as storing devices
  - More flexibility



Publications – Smart grids (modeling and solving)

- Garroussi, Z., & Ellaia, R., and Talbi, E.G., **A Multiobjective approach for demand side management in Smart Grids**. In 2016 The 6th Int. Conf. on Metaheuristics and Nature Inspired Computing (META'16), Oct 2016
- Garroussi, Z., & Ellaia, R., and Talbi, E.G., **Appliance Scheduling in a Smart Home Using a Multiobjective Evolutionary Algorithm**. 4rd International Renewable and Sustainable Energy Conference (IRSEC) IEEE, Nov 2016.
- E-G. Talbi, Z. Garroussi, R. Ellaia, **"Multi-home demand side management in smart grids"**, *PGMO Days Optimization and Operations Research, EDF R&D Saclay, France, Nov 2016.*
- Invited Keynote speaker of E-G. Talbi, "**Optimization of smart grids: opportunities and directions"**, ICOA'2017, International Workshop on Optimization and Applications, Meknes, Morocco, March 2017.
- Z. Garroussi, R. Ellaia, E-G. Talbi, J-Y. Lucas, **«**». *ICCAIRO'2017* I**Hybrid Evolutionary Algorithm for Residential Demand Side Management with a Photovoltaic Panel and a Battery**nt. Conf. on Control, Artificial Intelligence, Robotics & Optimization*, Praga, Czech Republic, May 2017.*
- Z. Garroussi, R. Ellaia, E-G. Talbi, J-Y. Lucas, **«Hybrid multi-objective evolutionary algorithms for the residential demand side management with thermal and electrical loads»**. *MIC'2017 Metaheuristics International Conference, Barcelona, Spain, July 2017.*

Publications - Multi-objective opt. uncertainty

- A. Gannouni, R. Ellaia and E-G. Talbi, **«Solving Stochastic Multi-objective Vehicle Routing Problem using Probabilistic Metaheuristic"**, International Workshop on Transportation and Supply Chain Engineering IWTSCE16. Nov 2016, Rabat, Morocco.

- A. Gannouni, R. Ellaia and E-G.Talbi. **"A stochastic version of dominance-based multi-objective local search"** . 5th International congress of the SM2A, March 2017, Meknes, Morocco.

- A. Gannouni , R. Ellaia and E-G. Talbi, **"Solving stochastic green transportation problem using metaheuristic: Modeling and simulation»** , 7th International Conference on Approximation Methods and Numerical Modelling in Environment and Natural Resources: Mamern'17, May 2017, Oujda, Morocco.

- J. Serrar, E-G. Talbi, R. Ellaia, **Electrical multi-objective vehicle routing problem**, Project Report, July 2017

Industrial impact and projects

- EDF contract (2015-2016)
  - **Electrical load management in smart homes**

- EDF contract (2017-2018)
  - **From single to multiple domestic consumers in smart grid management**
  - Investigate the possibility of jointly optimizing many houses energy smart management systems located in the same sub network
  - Propose to build as a result of the project a database of householders demand signals, including various types of flexibility.

Events – International conferences

- More than 100 participants. http://meta2016.sciencesconf.org
- 25 countries, 3 tutorials, 85 papers

https://meta2018.sciencesconf.org

Hybrid Multi-objective Evolutionary Algorithms for the Residential Demand Side Management with Thermal and Electrical Loads

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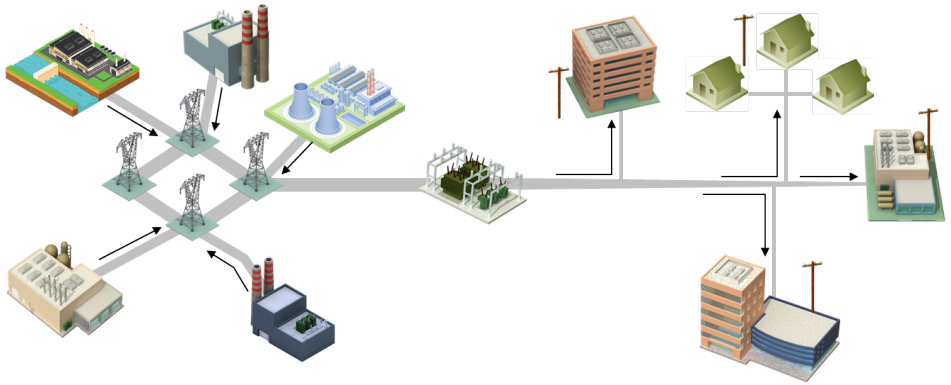
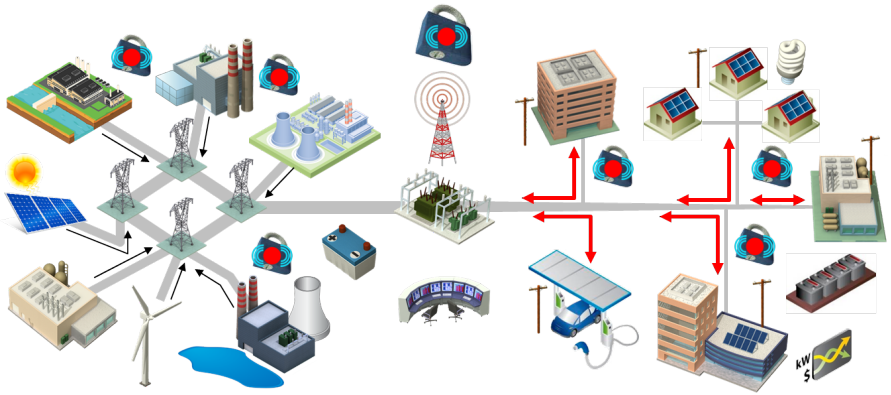
Traditional grid VS Smart grid



Source: www.epri.com

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

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

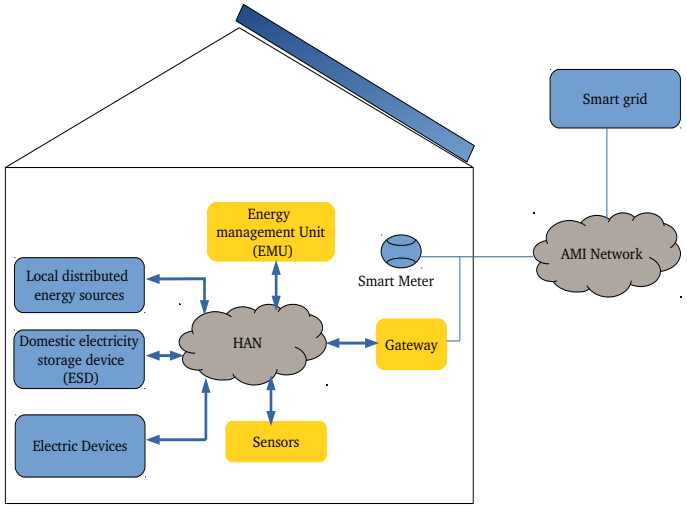


Source: www.epri.com

Demand Side Management (DSM)

- 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.

Home Energy management system



Through an **automated home energy management system** it will be effectively to:

- 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

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Proposed residential DSM

- The micro-combined heating, cooling and power system (MCCHP),
- The thermal energy storage (TES),
- The battery (B),
- The photovoltaic panel (PV),
- and the different electrical and thermal loads (EL & TL).

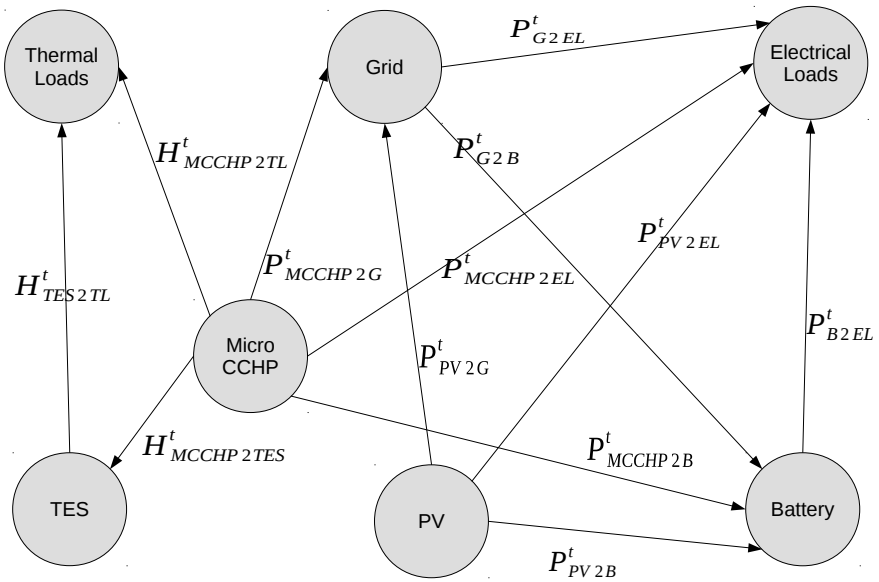


Figure: The electrical and thermal power flow between the different components of our proposed residential DSM framework.

The micro-combined heat, cooling, and power model (MCCHP)

MCCHP Decision variables =

$\forall t \in T$,
- P^t_{MCCHP} : $MCCHP$ electrical power output, - H^t_{MCCHP} : $MCCHP$ thermal power output,
- F^t_{MCCHP} : The natural gas consumption of the MCCHP,
- s^t_{MCCHP} : $MCCHP$ on/off status.

MCCHP Parameters =

- η_e and η_{th} : electric and thermal efficiencies,
- β is the converting factor of 1 kWh to m^3 natural gas,
- rr_e is the ramp rate of the MCCHP (kW/h),
- P^{min}_{MCCHP} (H^{min}_{MCCHP}) and P^{max}_{MCCHP} (H^{max}_{MCCHP}) : The minimum and the maximum electrical (thermal) output.

MCCHP constraints =

- The relation between $P^t{}_{MCCHP}$ and $H^t{}_{MCCHP}$

$$P^t_{MCCHP} = \frac{\eta_{th}}{\eta_e} \cdot H^t_{MCCHP}$$

- The natural gas consumption of the MCCHP F^t_{MCCHP} in m^3 is given as: $F^t_{MCCHP} = \frac{P^t_{MCCHP}}{\eta_e} \cdot \beta$

- Other operational constraints of the MCCHP are modeled as follows:

$$s^t_{MCCHP} \cdot P^{min}_{MCCHP} \leq P^t_{MCCHP} \leq s^t_{MCCHP} \cdot P^{max}_{MCCHP}$$

$$s^t_{MCCHP} \cdot H^{min}_{MCCHP} \leq H^t_{MCCHP} \leq s^t_{MCCHP} \cdot H^{max}_{MCCHP}$$

$$|P^t_{MCCHP} - P^{t-1}_{MCCHP}| \leq rr_e$$

$$|H^t_{MCCHP} - H^{t-1}_{MCCHP}| \leq \frac{\eta_{th}}{\eta_e} \cdot rr_e$$

Battery model

Battery Decision variables =

$\forall t \in T$,
- Two binary variables are defined: $s^t{}_{ch}$ (resp. $s^t{}_{dch}$) is equal to 1 if the battery is charged (resp. discharged) at time slot t and 0 otherwise.
- P^t_{ch} and P^t_{dch} : Charges / discharges rates,
- SOC^t : The battery state of charge.

Battery Parameters =

- SOC^{min} and SOC^{max} : maximal and minimal state of charge,
- P^{max}_{ch}, (resp. P^{max}_{dch}) is a maximal charging (resp. discharging) rate,
- η_{ch}, η_{dch} are the charging and the discharging efficiencies,
- E_{batt} is the battery capacity.

Battery constraints =

- Battery usage constraint: $\forall \ t \in T \ s^t_{ch} + s^t_{dch} \leq 1 \quad \forall \ t \in T \setminus \{1\}$
- Charges / discharges rates limits :

$$0 \leq P^t_{ch} = P^t_{MCCHP2B} + P^t_{PV2B} + P^t_{G2B} \leq s^t_{ch} \cdot P^{max}_{ch} \quad \text{and} \quad 0 \leq P^t_{dch} = P^t_{B2EL} \leq s^t_{dch} \cdot P^{max}_{dch}$$

- Battery state of charge limits: $SOC^{min} \leq SOC^t \leq SOC^{max}$
- The battery state of charge :

$$SOC^t = \begin{cases} SOC^1 & t = 1 \\ SOC^{t-1} + \dfrac{P^{t-1}_{ch}\eta_{ch}}{E_{batt}} - \dfrac{P^{t-1}_{dch}}{E_{batt}\eta_{ch}} & \forall \ t \in T \setminus \{1\} \end{cases}$$

Thermal energy storage model (TES)

"TES" Decision variables =

- H_{in}^{t} The heat power injected from the TES, - H_{dr}^{max} The heat power drawn from the TES,

- $s^{t}{}_{in}$ and $s^{t}{}_{dr}$: The injecting and drawing status at time slot t.

"TES" Parameters =

- η_{in} and η_{dr} are the injecting and drawing heat efficiencies,

- H_{in}^{max}, H_{dr}^{max} are the maximal heat injected and drawn respectively,

- Q_{TES}^{min}, and Q_{TES}^{max} are the minimum and the maximum energy content limits of the TES.

"TES" constraints =

The heat power injected H_{in}^{t} and drawn H_{dr}^{max} from the TES are bounded as:

$0 \leq H_{in}^{t} \leq \frac{1}{\eta_{in}} \cdot H_{in}^{max} \cdot s_{in}^{t}$ and $0 \leq H_{dr}^{t} \leq H_{dr}^{max} \cdot s_{dr}^{t} \cdot \eta_{dr}$

- The power flow of the TES in any given time slot t : $s_{in}^{t} + s_{dr}^{t} \leq 1$

-The TES energy content Q_{TES}^{t} : $Q_{TES}^{t+1} = Q_{TES}^{t} + (H_{in}^{t} \cdot \eta_{in} - \frac{H_{dr}^{t}}{\eta_{dr}})$

- The TES energy content Q_{TES}^{t} is limited : $Q_{TES}^{min} \leq Q_{TES}^{t} \leq Q_{TES}^{max}$

Electrical loads

Electrical loads Decision variables =

- ${x_e}^t$: the working status of an electric load for each $e \in EL$ and for each time slot t, - ${x_e}^t$=1 if the electric appliance e starts at time t and 0 otherwise,
- P_e^t The electrical power consumed by $e \in EL$.

Electrical loads Parameters =

- EL is the set of electrical loads,
- q_e^t is the required amount of electricity of e at time slot t, D_e is the processing time of e,
- The load profile $q_e = \{q_e^1, q_e^2, \cdots, q_e^{D_e}\}$ for each electric load $e \in EL$,
- MST_e, ET_e are respectively the minimum starting time and a maximum ending time of e.

Electrical loads constraints =

- The time window λ_e of each e is defined as follows: $\lambda_e = [MST_e, \ldots, ET_e - D_e + 1]$
- The electrical power consumed P_e^t by e : $P_e^t = \sum_{d \in D_e, d \leq t} x_e^{t-d+1} \cdot q_e^d \quad \forall \ e \in EL, t \in T$
- This constraint guarantee that each $e \in EL$ starts once within the time window λ_e :

$$\begin{cases} \sum_{t \in \lambda_e} x_e^t = 1 & \forall \ e \in EL \\ x_e^t = 0 & \forall \ e \in EL, \ t \in T \setminus \lambda_e \end{cases}$$

Thermal loads : HVAC [1] and WS [2]

Thermal loads Decision variables =

- H^t_{HVAC} and H^t_{WS} are the heat power consumed by the HVAC and the WS,
- T^t_{in}: The indoor temperature of HVAC,
- T^t_{WS}: The hot water temperature of water storage.

Thermal loads Parameters =

- T^t_{out} is the outdoor temperature, C_{air} is the specific heat of air,
- R is the thermal resistance of the house wall,
- T_{cold} is the cold water temperature,
- V^t_{cold} is the volume of the cold water,
- V is the volume of the electric water storage, C_{water} is the specific heat of water,
- T^{min}_{HVAC}, T^{min}_{WS}, T^{max}_{HVAC} and T^{max}_{WS} are the minimal and maximal acceptable temperature respectively, of HVAC and hot water in the WS.

Thermal loads constraints =

- The indoor temperature T^t_{in} of HVAC: $T^{t+1}_{in} = T^t_{in} \cdot e^{\frac{-t}{RC_{air}}} + (-R \cdot H^t_{HVAC} + T^t_{out}) \cdot (1 - e^{\frac{-t}{RC_{air}}})$
- The hot water temperature T^t_{WS} of water storage: $T^{t+1}_{WS} = \frac{V^t_{cold} \cdot (T_{cold} - T^t_{WS}) + V \cdot T^t_{WS}}{V} + \frac{H^t_{WS}}{V \cdot C_{water}}$
- $T^{min}_{HVAC} \leq T^t_{in} \leq T^{max}_{HVAC}$ and $T^{min}_{WS} \leq T^t_{WS} \leq T^{max}_{WS}$

[1] Heating, ventilation and air conditioning.
[2] Water storage.

Other constraints

Other Decision variables =

- H^t_{AC} is the heat power of the absorption chiller,
- P^t_{EC} is the electric power of the electric chiller,

Parameters =

-COP^{AC} is the coefficient of performance of the absorption chiller,

-COP^{EC} is the coefficient of performance of the electric chiller,

Other constraints =

- The PV and MCCHP power outputs (P^t_{PV}, P^t_{MCCHP}): $P^t_{PV} = P^t_{PV2EL} + P^t_{PV2G} + P^t_{PV2B}$

$$P^t_{MCCHP} = P^t_{MCCHP2EL} + P^t_{MCCHP2G} + P^t_{MCCHP2B}$$

- The electrical and heat power balance:

$$P^t_{CR} + \sum_{l \in EL} P^t_l = P^t_{PV2EL} + P^t_{MCCHP2EL} + P^t_{B2EL} + P^t_{G2EL}$$

$$H^t_{MCCHP2TL} + (H^t_{MCCHP2TES} \cdot \eta_{in} - \frac{H^t_{TES2TL}}{\eta_{dr}}) = H^t_{WS} + H^t_{AC}$$

- The cooling demand balance : $H^t_{AC} \cdot COP^{AC} + P^t_{EC} \cdot COP^{EC} = H^t_{HVAC}$

Objectives I

$$\text{Total cost} = \underbrace{\sum_{t=1}^{T}(P_{G2EL}^{t} + P_{G2B}^{t}) \cdot \pi_{t}^{buy}}_{\text{Electricity cost}} + \underbrace{\sum_{t=1}^{T}(F_{MCCHP}^{t} \cdot \pi_{gas})}_{\text{Natural gas consumption cost}} - \underbrace{\sum_{t=1}^{T}(P_{PV2G}^{t} + P_{MCCHP2G}^{t}) \cdot \pi_{t}^{sell}}_{\text{Revenue}}$$

- π_{buy}^{t} : The purchased electricity from the grid at each time slot t,
- π_{gas}: The purchased natural gas price,
- π_{sell}: The selling electricity from the PV to the grid (constant).

$$\text{Carbon dioxide emissions} = \underbrace{\sum_{t=1}^{T} F_{MCCHP}^{t} \cdot \mu_{g}}_{\text{emissions from MCCHP}} + \underbrace{\sum_{t=1}^{T}(P_{G2B}^{t} + P_{G2EL}^{t}) \cdot \mu_{t}}_{\text{emissions from the Grid}}$$

- μ_g is the CO2 emission from the MCCHP (g/m^3),
- μ_t is the CO2 time variable signal from the power grid (g/kWh).

$$\text{Discomfort objective} = \underbrace{\frac{1}{|EL|}\sum_{e=1}^{EL} U_{e} \cdot 100}_{\text{Discomfort caused by electric loads}} + \underbrace{U_{TL}^{HVAC}}_{\text{Discomfort caused by HVAC}} + \underbrace{U_{TL}^{WS}}_{\text{Discomfort caused by WS}}$$

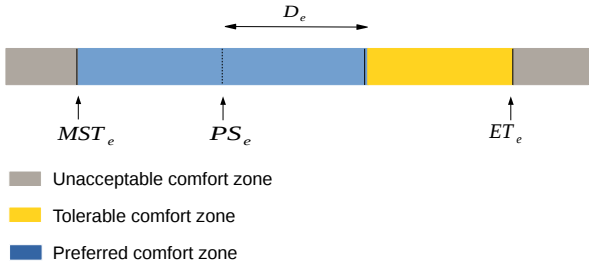
Objectives II

$$U_e = \begin{cases} \frac{PST_e - ST_e}{PST_e - MST_e} & if \quad MST_e \leq ST_e \leq PST_e \\ \frac{ST_e - PST_e}{ET_e - D_e + 1 - PST_e} & if \quad PST_e < ST_e \leq ET_e - D_e + 1 \end{cases}$$

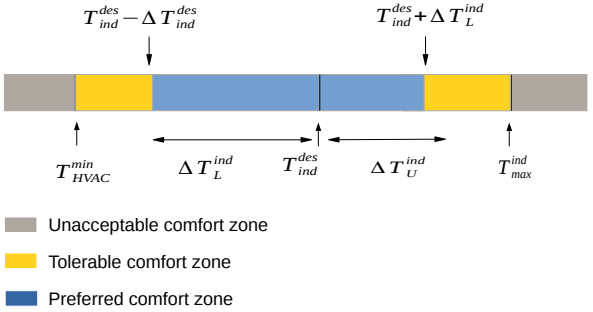
$$U_{TL}^{HVAC} = \frac{100}{T} \sum_t^T \frac{d_{in}^t}{\Delta T_{max}^{ind}}$$

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

$$d_{in}^t = \begin{cases} T_{ind}^{des} - T_{in}^t & \text{if } T_{HVAC}^{min} \leq T_{ind}^t < T_{ind}^{des} - \Delta T_L^{in} \\ 0 & \text{if } T_{ind}^{des} - \Delta T_L^{ind} \leq T_{ind}^t < T_{ind}^{des} + \Delta T_U^{in} \\ T_{ind}^t - T_{des}^{ind} & \text{if } T_{ind}^{des} + \Delta T_U^{ind} < T_{ind}^t \leq T_{max}^{ind} \\ \Delta T_{max}^{ind}, & \text{otherwise} \end{cases}$$



Electrical loads comfort level parameters



HVAC comfort level parameters

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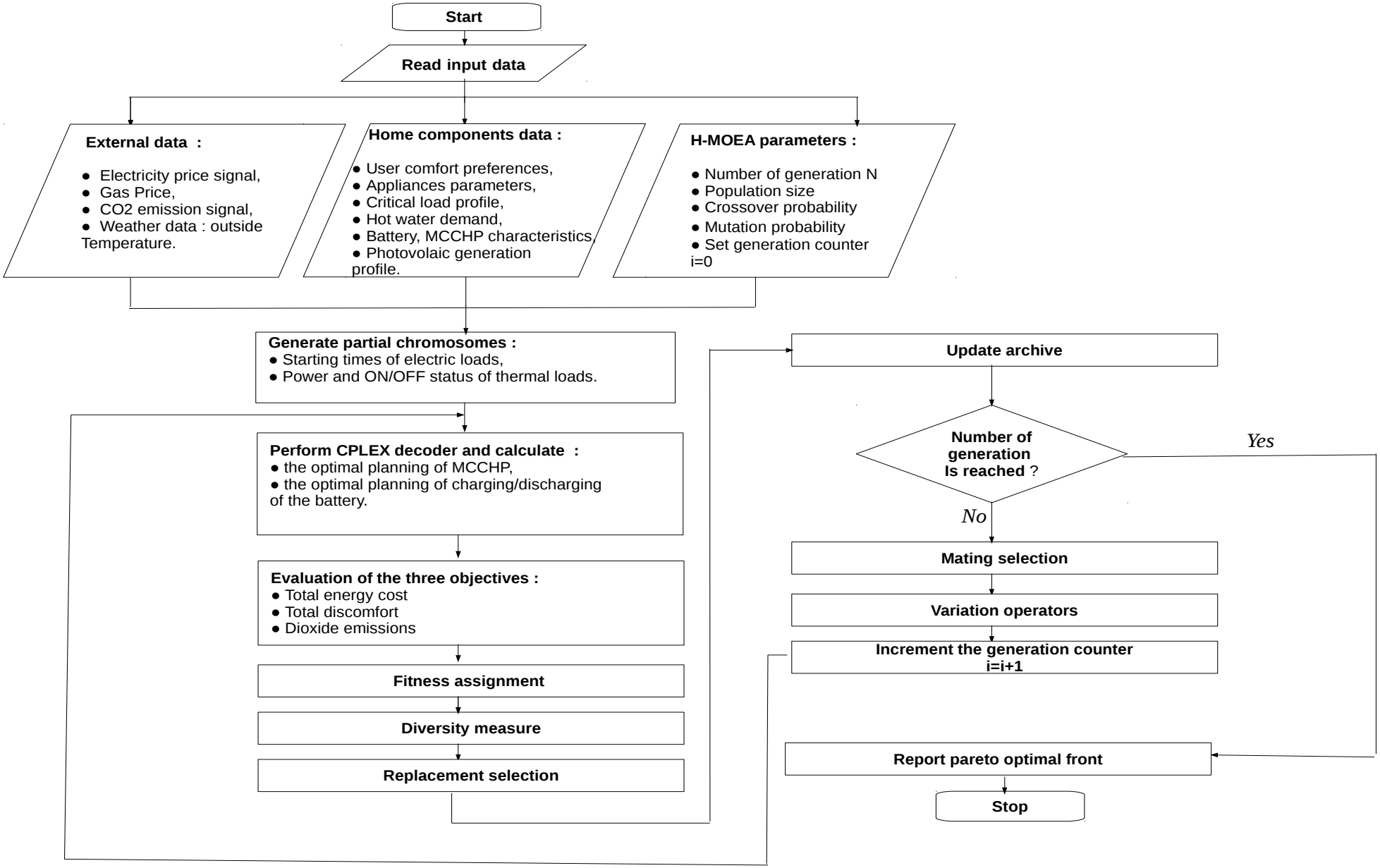
Hybrid Multiobjective Evolutionnary Algorithm (H-MOEA)

- A hybrid algorithm based on combining a multiobjective evolutionary algorithm and an exact solver (CPLEX).
- Solutions in are incompletely represented, and optimally the exact solver determines the missing parts of the encoding.

- Deal with constraints and guarantee the feasibility of solutions for our multiobjective scheduling problem.

Proposed H-MOEA



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Data I

- A time horizon of 24 hours is considered and subdivided in 24 time slots of one hour each.
- Natural gas price is 56 cents per m^3.
- The feed-in tariff is 12.6 cents per kWh for photovoltaic [Ministry of Ecologie et al.,], 6.1 cents per kWh cents for the MCCHP [Ministry of Ecology and Energy,].

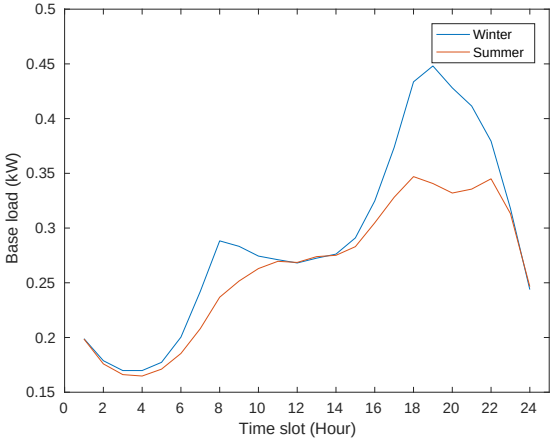
Table: Scenarios developed for analysis

	Scenarios	Grid	PV panel	Battery	MCCHP	TES
Winter	SW1	✓	✓	✓	✓	✓
	SW2	✓	✓	×	✓	✓
	SW3	✓	×	✓	✓	✓
	SW4	✓	×	×	✓	✓
	SW5	✓	×	×	✓	×
Summer	SS1	✓	✓	✓	✓	✓
	SS2	✓	✓	×	✓	✓
	SS3	✓	×	✓	✓	✓
	SS4	✓	×	×	✓	✓
	SS5	✓	×	×	✓	×

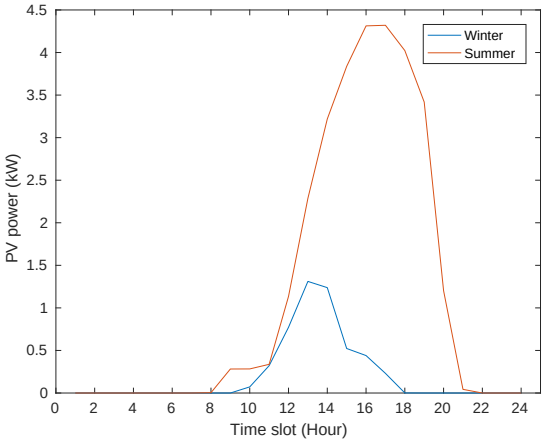
Table: Electricity prices [Pon, 2016]

Hour	Price (Cents/kWh)	Hour	Price (Cents/kWh)
1	10	13	13
2	10	14	13
3	10	15	13
4	10	16	13
5	10	17	32
6	10	18	32
7	10	19	13
8	13	20	13
9	13	21	13
10	13	22	13
11	13	23	10
12	13	24	10

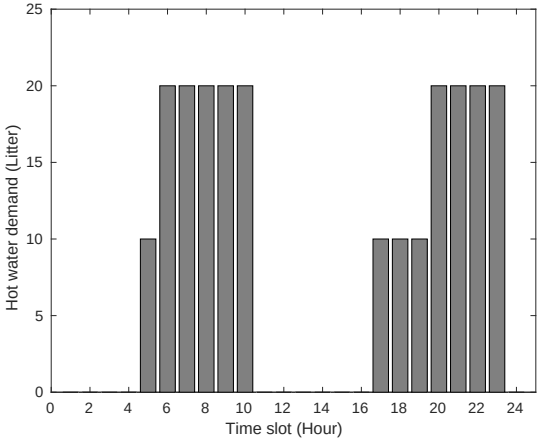
Data II



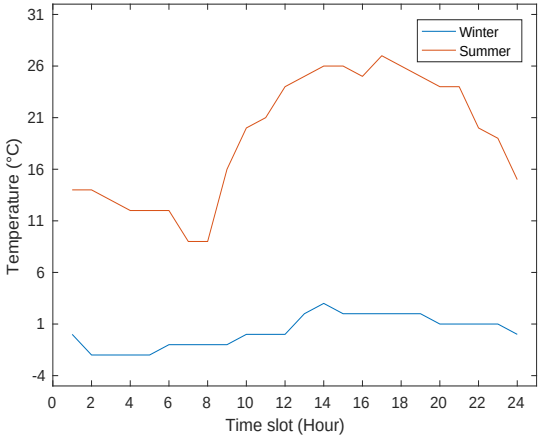
Critical loads



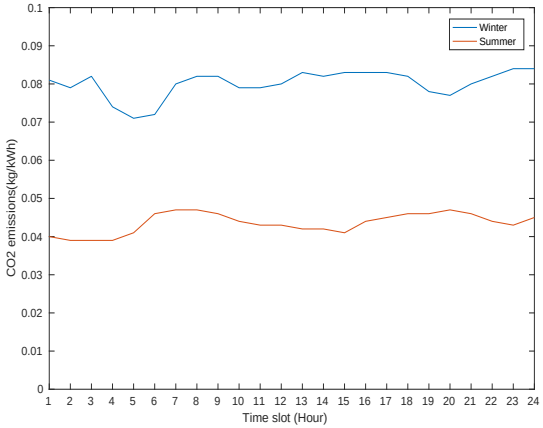
PV power output



Hot water demand



Outdoor temperature



CO2 emissions

Data III

- Electrical loads settings:

	Minimum starting time	Maximum ending time	Rated power (kW)	Processing time	Preferred starting time
Electric Clothes Washer (ECW)	15	23	0.5	2	17
Electric Dishwasher (EDW)	20	24	0.7	2	17
Electric Clothes Dryer (ECD)	15	24	1.1	1	20
Electric Iron (EI)	15	24	1.3	1	17

Table: HVAC, WS, and the battery parameters

Parameter	Value	Unit
E_{batt}	11.50	kWh
SOC^{min}, SOC^{max}	20,100	%
P_{ch}^{max},P_{dch}^{max}	2,2	kWh
η_{ch},η_{dch}	90,90	%
T_{min}^{WS}, T_{pref}^{WS}, T_{max}^{WS}	60,70,80	$^{\circ}C$
V	150	$Litter$
T_{cold}	10	$^{\circ}C$
C_{water}	0.01164	$kWh/^{\circ}C$
C_{air}	0.525	$kWh/^{\circ}C$
R	18	$^{\circ}C/kW$
T_{min}^{HVAC}, T_{pref}^{HVAC}, T_{max}^{HVAC}	15,19,24	$^{\circ}C$

- The parameter settings of the proposed algorithm are performed with IRACE package [López-Ibánez et al., 2011].
- The parameters fixed by this package are: Population size is 100, the number of iterations is 200, the probability of the uniform crossover is 0.5, the probability of mutation is 0.6.

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Results I

- Tables show respectively the average values of the hypervolume difference [Zitzler and Thiele, 1999] and epsilon indicators [Zitzler et al., 2003] over ten independent runs of the three hybrid algorithms performed for each scenario.

	H-NSGA-II	H-SPEA-II	H-IBEA
SW1	**0.0243403371**	0.0584918726	0.0546370992
SW2	0.0556664411	**0.0152721462**	0.1527615993
SW3	**0.0776497013**	0.2029272092	0.1282035293
SW4	**0.0339468387**	0.1160753488	0.2105974616
SW5	**0.0145269554**	0.0568580755	0.0676583474
SS1	**0.0076601071**	0.036452606	0.1061237781
SS2	0.1494577628	**0.137912012**	0.2838238053
SS3	**0.0107909415**	0.1036178348	0.1118950558
SS4	0.1367679942	**0.1281304919**	0.1473547421
SS5	**0.0034731222**	0.1318474842	0.1855408505

Table: *Hypervolume difference* I_H^-

	H-NSGA-II	H-SPEA-II	H-IBEA
SW1	**0.0695312903**	0.1399811712	0.1541256257
SW2	0.085396695	**0.0420384684**	0.228246983
SW3	**0.0707580926**	0.2540296487	0.2015655703
SW4	**0.0405099156**	0.0938708633	0.1354143033
SW5	**0.0876181793**	0.1389579404	0.1777620414
SS1	**0.0976087015**	0.1697028734	0.2458384418
SS2	**0.1996094132**	0.2015501406	0.335993147
SS3	**0.0473846154**	0.1115716753	0.1549966627
SS4	**0.0024881697**	0.0902933494	0.1371037166
SS5	**0.0382475399**	0.2372136246	0.2120466905

Table: Epsilon indicator I_ϵ^+

- These two tables clearly confirm the superiority of the hybrid NSGA-II since it outperforms in seven out of ten cases for I_H^- and nine out ten for I_ϵ^+ indicator.

Results II

		Total cost (cents/Day)	Discomfort (%/Day)	Dioxide emissions (kg/Day)
SW1	H-NSGA-II	(**230.146** 31.7277 1.30133)	(253.051 **14.1764** 1.29883)	(250.872 21.1537 **1.11459**)
	H-SPEA-II	(**236.18** 42.0691 1.34333))	(258.929 **23.4842** 1.22223)	(254.031 32.6964 **1.11769**)
	H-IBEA	(**232.644** 39.5736 1.24945)	(268.483 **17.1586** 1.21356)	(241.563 21.1977 **1.16289**)
SW2	H-NSGA-II	(**247.875** 46.0792 1.54679)	(297.892 **19.7117** 1.38482)	(281.3 21.0199 **1.29733**)
	H-SPEA-II	(**249.525** 37.5434 1.48546)	(300.205 **16.1779** 1.45802)	(273.066 18.4737 **1.25085**)
	H-IBEA	(**254.148** 37.0506 1.51823)	(269.691 **19.7542** 1.46672)	(263.014 21.2906 **1.33974**)
SW3	H-NSGA-II	(**280.584** 46.3396 2.29878)	(315.765 **15.9377** 1.4796)	(302.618 21.1875 **1.35252**)
	H-SPEA-II	(**281.252** 38.7108 1.63555)	(311.186 **18.7305** 1.53399)	(301.264 25.9001 **1.3697**)
	H-IBEA	(**285.501** 32.7526 1.61504)	(327.722 **16.0817** 1.54173)	(310.338 24.3653 **1.35824**)
SW4	H-NSGA-II	(**310.015** 39.0927 1.67187)	(380.583 **18.3769** 1.54573)	(342.415 19.1793 **1.46888**)
	H-SPEA-II	(**310.244** 33.4301 1.65964)	(339.319 **16.8245** 1.5369)	(335.684 17.5994 **1.49026**)
	H-IBEA	(**312.225** 41.8227 1.7021)	(345.517 **18.6417** 1.53542)	(329.611 23.7731 **1.51532**)
SW5	H-NSGA-II	(**328.827** 37.3934 1.85679)	(357.192 **17.0466** 1.71552)	(365.743 20.7889 **1.67871**)
	H-SPEA-II	(**331.563** 36.6768 1.91439)	(357.336 **17.5842** 1.81745)	(362.167 23.2858 **1.6931**)
	H-IBEA	(**331.664** 32.3702 1.78646)	(357.11 **18.4437** 1.8551)	(355.224 19.7351 **1.71862**)
SS1	H-NSGA-II	(-**72.9931** 21.5803 0.544708)	(-23.2578 **14.6903** 0.657818)	(-49.6885 20.1344 **0.540056**)
	H-SPEA-II	(-**72.4745** 28.0934 0.725365)	(-48.7607 **15.0244** 0.612091)	(-52.4888 21.5152 **0.550628**)
	H-IBEA	(-**69.604** 21.5688 0.648811)	(-37.3865 **16.1172** 0.680289)	(-53.3416 20.2897 **0.591003**)
SS2	NSGA-II	(-**64.1097** 28.3678 0.821153)	(-36.4098 **15.6568** 0.742795)	(-56.2618 19.3548 **0.683184**)
	H-SPEA-II	(-**63.5977** 18.2424 0.698382)	(-60.7039 **15.5073** 0.738167)	(-49.578 20.626 **0.688192**)
	H-IBEA	(-**63.9298** 20.5616 0.84151)	(-52.863 **17.2084** 0.865389)	(-55.5362 17.6438 **0.758242**)
SS3	H-NSGA-II	(**254.967** 29.0818 1.03564)	(328.273 **16.4189** 1.09153)	(259.722 34.5909 **1.02814**)
	H-SPEA-II	(**254.986** 33.3543 1.02622)	(278.105 **18.2089** 1.11047)	(289.693 26.6427 **1.02362**)
	H-IBEA	(**261.508** 31.3641 1.06076)	(277.51 **19.6841** 1.10304)	(261.816 36.2645 **1.06004**)
SS4	H-NSGA-II	(**278.368** 32.5168 1.13227)	(298.91 **17.1045** 1.1505)	(314.898 22.06 **1.11356**)
	H-SPEA-II	(**280.717** 32.4302 1.15513)	(299.695 **17.1355** 1.17855)	(290.793 22.219 **1.1459**)
	H-IBEA	(**286.903** 33.1476 1.18542)	(314.17 **21.0413** 1.23777)	(295.594 44.7761 **1.17738**)
SS5	H-NSGA-II	(**292.904** 32.928 1.22459)	(319.001 **18.0125** 1.29971)	(295.014 26.6129 **1.21484**)
	H-SPEA-II	(**303.189** 35.1191 1.29182)	(320.93 **17.8953** 1.2973)	(310.61 22.8598 **1.24702**)
	H-IBEA	(**298.337** 33.2735 1.24769)	(325.665 **19.7429** 1.35946)	(308.069 28.4373 **1.23646**)

Table: Extreme solutions obtained with different hybrid algorithms

Figures of the best F_{std} solution for case IV for summer data. II

- The battery SOC, the power charged and discharged from the battery are shown in the following figures.

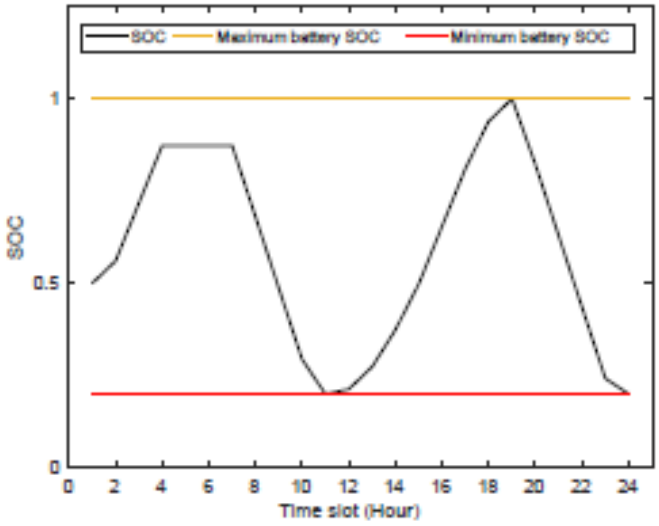

Figure: Battery SOC in Summer (case IV)

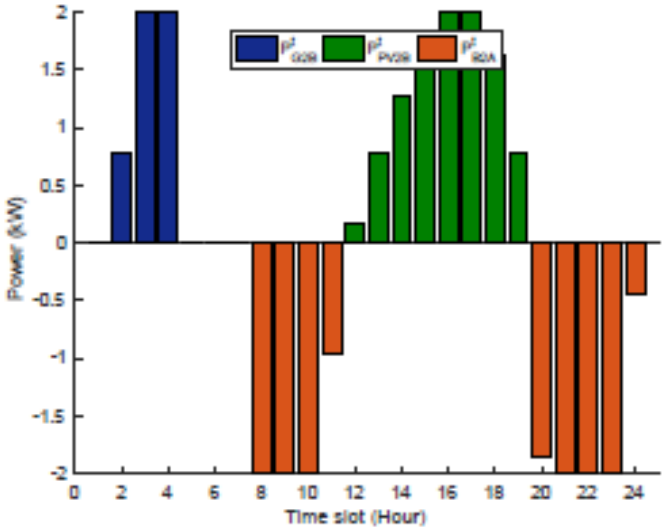

Figure: Charging & discharging battery in summer (case IV)

- As we can see, the battery SOC is between the SOC^{min} and the SOC^{max}.

Figures of the best F_{std} solution for case IV for summer data. I

- The indoor and the hot water temperatures have been set within the lower dead band limits (i.e., 17, 65) and the upper dead band limits (21, 75) for most of the time slots.

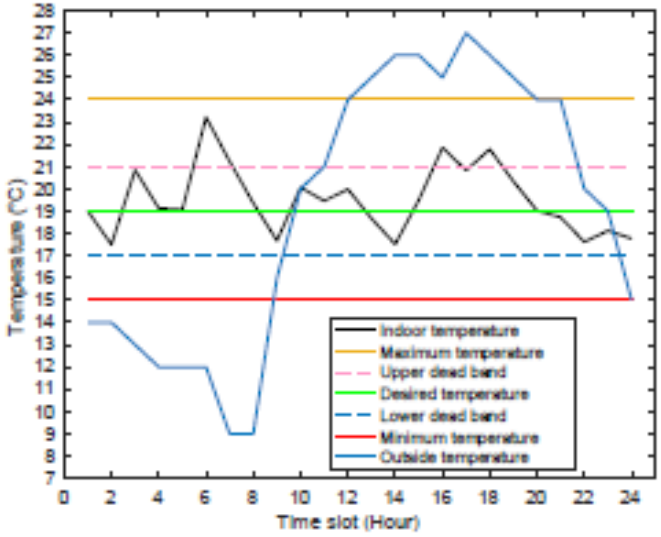

Figure: Indoor temperature in summer (case IV)

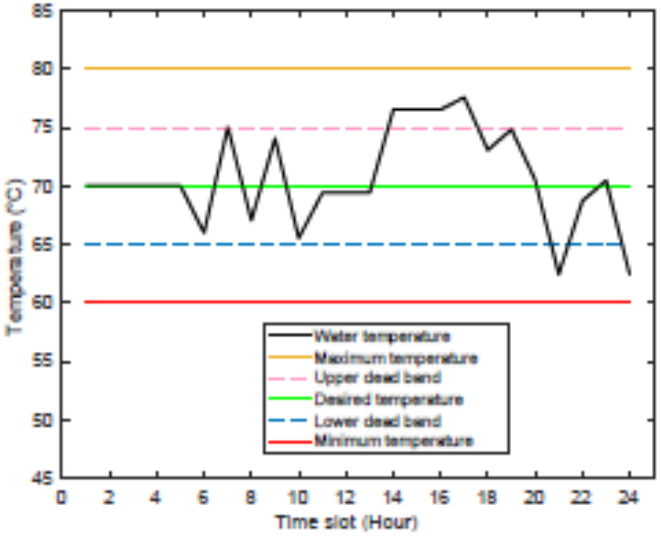

Figure: Water temperature in summer (case IV)

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Conclusions and Perspectives

- Residential DSM model = constrained mixed integer linear problem
  Objectives = minimization of the total energy cost, the user discomfort and the dioxide emissions over a 24-hour horizon.

- A hybrid approach by combining the multiobjective evolutionary algorithms (NSGA-II, SPEA-II, and IBEA) and an exact solver (CPLEX).

- Simulation results showed the effectiveness of our proposed approach to handle the constraints associated with our optimization problem in order to ensure the feasibility of the solutions.
- Take into account the uncertainty related to input data. (PV production, electricity prices, the outdoor temperature, the hot water demand ....).
- Multi-home scenarios, big data.