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

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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
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 Comfort, …

- **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

- Create a model
- Model
- Solve a problem
- Plan

**Optimization**

**Time**

**Decision variables**
- Given $\mathbf{x} = (x_1, x_2, \ldots, x_n)$
- minimize $f(\mathbf{x})$
- such that
  - $lb_i \leq x_i \leq ub_i$, $i = 1..n$
  - $g_1(\mathbf{x}) \leq b_1$
  - $g_2(\mathbf{x}) \leq b_2$
  - $\ldots$
  - $g_m(\mathbf{x}) \leq b_m$
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**

\[
\min_{x \in X} g_0(x, \xi) \\
\text{t.q. } g_i(x, \xi) \leq 0, \; i = 1, \ldots, m, \\
\xi : \text{random variable}
\]
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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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, …

Mathematical formulation:

\[
\begin{align*}
\min_{x} & \ F(x, y) \\
\text{subject to} & \ G(x, y) \leq 0 \\
\min_{y} & \ f(x, y) \\
\text{subject to} & \ g(x, y) \leq 0
\end{align*}
\]
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]
  - Electrical 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)


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.
More than 100 participants. [http://meta2016.sciencesconf.org](http://meta2016.sciencesconf.org)

25 countries, 3 tutorials, 85 papers

[https://meta2018.sciencesconf.org](https://meta2018.sciencesconf.org)
Hybrid Multi-objective Evolutionary Algorithms for the Residential Demand Side Management with Thermal and Electrical Loads

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7. **Conclusions and Perspectives**

8. **References**
Traditional grid VS Smart grid

- 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

Z. Garroussi, R. Ellaia, EG. Talbi, J. Lucas
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.
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.
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).

![Diagram of energy flow](image)

**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

- \( \eta_e \) and \( \eta_{th} : \) electric and thermal efficiencies,
- \( \beta \) 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: \( s_{ch}^t \) (resp. \( s_{dch}^t \)) is equal to 1 if the battery is charged (resp. discharged) at time slot \( t \) and 0 otherwise.
    - \( P_{ch}^t \) and \( P_{dch}^t \): Charges / discharges rates,
    - \( SOC^t \): The battery state of charge.

- **Battery Parameters**
  - \( SOC^{min} \) and \( SOC^{max} \): maximal and minimal state of charge,
  - \( P_{ch}^{max} \), (resp. \( P_{dch}^{max} \)) is a maximal charging (resp. discharging) rate,
  - \( \eta_{ch} \), \( \eta_{dch} \) are the charging and the discharging efficiencies,
  - \( E_{batt} \) is the battery capacity.

- **Battery constraints**
  - Battery usage constraint: \( \forall \ t \in T \quad s_{ch}^t + s_{dch}^t \leq 1 \quad \forall \ t \in T \setminus \{1\} \)
  - Charges / discharges rates limits:
    \[
    0 \leq P_{ch}^t = P_{MCCHP2B}^t + P_{PV2B}^t + P_{G2B}^t \leq s_{ch}^t \cdot P_{ch}^{max} \quad \text{and} \quad 0 \leq P_{dch}^t = P_{B2EL}^t \leq s_{dch}^t \cdot P_{dch}^{max}
    \]
  - Battery state of charge limits: \( SOC^{min} \leq SOC^t \leq SOC^{max} \)
  - The battery state of charge:
    \[
    SOC^t = \begin{cases} 
    SOC^1 & t = 1 \\
    SOC^{t-1} + \frac{P_{ch}^{t-1} \cdot \eta_{ch}}{E_{batt}} - \frac{P_{dch}^{t-1}}{E_{batt} \cdot \eta_{ch}} & \forall \ t \in T \setminus \{1\}
    \end{cases}
    \]
Thermal energy storage model (TES)

"TES" variables
- $H_{in}^t$: The heat power injected from the TES,
- $H_{dr}^{max}$: The heat power drawn from the TES,
- $s_{in}^t$ and $s_{dr}^t$: The injecting and drawing status at time slot $t$.

"TES" parameters
- $\eta_{in}$ and $\eta_{dr}$: the injecting and drawing heat efficiencies,
- $H_{in}^{max}$ and $H_{dr}^{max}$: the maximal heat injected and drawn respectively,
- $Q_{TES}^{min}$ and $Q_{TES}^{max}$: 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:
  
  \[
  0 \leq H_{in}^t \leq \frac{1}{\eta_{in}} \cdot H_{in}^{max} \cdot s_{in}^t \quad \text{and} \quad 0 \leq H_{dr}^t \leq H_{dr}^{max} \cdot s_{dr}^t \cdot \eta_{dr}
  \]
- 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

- $x_e^t$ : 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,
- $P^t_e$ : The electrical power consumed by $e \in EL$.

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

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

$$\begin{cases} 
\sum_{t \in \lambda_e} x_e^t = 1 & \forall \ e \in EL \\
x_e^t = 0 & \forall \ e \in EL, \ t \in T \setminus \lambda_e 
\end{cases}$$
Thermal loads: HVAC $^1$ and WS $^2$

**Decision variables**
- $H_{HVAC}^t$ and $H_{WS}^t$ are the heat power consumed by the HVAC and the WS,
- $T_{in}^t$: The indoor temperature of HVAC,
- $T_{WS}^t$: The hot water temperature of water storage.

**Parameters**
- $T_{out}^t$ is the outdoor temperature, $C_{air}$ is the specific heat of air,
- $R$ is the thermal resistance of the house wall,
- $T_{cold}^t$ is the cold water temperature,
- $V_{cold}^t$ 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.

**Constraints**
- The indoor temperature $T_{in}^t$ of HVAC: $T_{in}^{t+1} = T_{in}^t \cdot e^{-\frac{t}{RC_{air}}} + (-R \cdot H_{HVAC}^t + T_{out}^t) \cdot (1 - e^{-\frac{t}{RC_{air}}})$
- The hot water temperature $T_{WS}^t$ of water storage: $T_{WS}^{t+1} = \frac{V_{cold}^t \cdot (T_{cold}^t - T_{WS}^t)}{V} + V \cdot T_{WS}^t + \frac{H_{WS}^t}{V \cdot C_{water}}$

- $T_{min}^{HVAC} \leq T_{in}^t \leq T_{max}^{HVAC}$ and $T_{min}^{WS} \leq T_{WS}^t \leq T_{max}^{WS}$

$^1$ Heating, ventilation and air conditioning.  
$^2$ Water storage.
Other constraints

- $H_{AC}^t$ is the heat power of the absorption chiller,
- $P_{EC}^t$ is the electric power of the electric chiller,

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

- The PV and MCCHP power outputs ($P_{PV}^t$, $P_{MCCHP}^t$):
  \[ P_{PV}^t = P_{PV2EL}^t + P_{PV2G}^t + P_{PV2B}^t \]
  \[ P_{MCCHP}^t = P_{MCCHP2EL}^t + P_{MCCHP2G}^t + P_{MCCHP2B}^t \]

- The electrical and heat power balance:
  \[ P_{CR}^t + \sum_{i \in EL} P_i^t = P_{PV2EL}^t + P_{MCCHP2EL}^t + P_{B2EL}^t + P_{G2EL}^t \]

- The cooling demand balance:
  \[ H_{AC}^t \cdot COP^{AC} + P_{EC}^t \cdot COP^{EC} = H_{HVAC}^t \]
Objectives

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

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

Carbon dioxide emissions = $\sum_{t=1}^{T} F_{MCCHP}^t \cdot \mu_g + \sum_{t=1}^{T} (P_{G2B}^t + P_{G2EL}^t) \cdot \mu_t$

- $\mu_g$ is the CO2 emission from the MCCHP ($g/m^3$),
- $\mu_t$ is the CO2 time variable signal from the power grid ($g/kWh$).

Discomfort objective = $\frac{1}{|EL|} \sum_{e=1}^{EL} U_e \cdot 100 + U_{HVAC}^{TL} + U_{WS}^{TL}$

- Discomfort caused by electric loads
- Discomfort caused by HVAC
- Discomfort caused by WS
Objectives II

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

\[ \Delta T_{\text{in}}^{\text{max}} = \max(\Delta T_{\text{in}}^{\text{des}}, T_{\text{HVAC}}^{\text{max}} - T_{\text{ind}}^{\text{des}}) \]

\[ d_t^{\text{in}} = \begin{cases} T_{\text{ind}}^{\text{des}} - T_{\text{in}}^t & \text{if } T_{\text{min}}^{\text{HVAC}} \leq T_{\text{in}}^t < T_{\text{des}}^{\text{HVAC}} - \Delta T_{\text{in}}^{\text{L}} \\ 0 & \text{if } T_{\text{des}}^{\text{HVAC}} - \Delta T_{\text{in}}^{\text{L}} \leq T_{\text{in}}^t < T_{\text{des}}^{\text{HVAC}} + \Delta T_{\text{in}}^{\text{U}} \\ T_{\text{in}}^t - T_{\text{ind}}^{\text{des}} & \text{if } T_{\text{des}}^{\text{HVAC}} + \Delta T_{\text{in}}^{\text{U}} < T_{\text{in}}^t \leq T_{\text{ind}}^{\text{max}} \\ \Delta T_{\text{in}}^{\text{max}} & \text{otherwise} \end{cases} \]

**Electrical loads comfort level parameters**

**HVAC comfort level parameters**
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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

Read input data

External data:
- Electricity price signal,
- Gas Price,
- CO2 emission signal,
- Weather data: outside Temperature.

Home components data:
- User comfort preferences,
- Appliances parameters,
- Critical load profile,
- Hot water demand,
- Battery, MCCHP characteristics,
- Photovoltaic generation profile.

H-MOE parameters:
- Number of generation \( N \)
- Population size
- Crossover probability
- Mutation probability
- Set generation counter \( i=0 \)

Start

Generate partial chromosomes:
- Starting times of electric loads,
- Power and ON/OFF status of thermal loads.

Perform CPLEX decoder and calculate:
- the optimal planning of MCCHP,
- the optimal planning of charging/discharging of the battery.

Evaluation of the three objectives:
- Total energy cost
- Total discomfort
- Dioxide emissions

Fitness assignment

Diversity measure

Replacement selection

Update archive

Number of generation reached?

Yes

Mating selection

Variation operators

Increment the generation counter \( i=i+1 \)

Report pareto optimal front

No

Stop

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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 m³.

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**

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<tr>
<th>Scenarios</th>
<th>Grid</th>
<th>PV panel</th>
<th>Battery</th>
<th>MCCHP</th>
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<td>SS4</td>
<td>✓</td>
<td>x</td>
<td>x</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>SS5</td>
<td>✓</td>
<td>x</td>
<td>x</td>
<td>✓</td>
<td>x</td>
</tr>
</tbody>
</table>

**Table: Electricity prices [Pon, 2016]**

<table>
<thead>
<tr>
<th>Hour</th>
<th>Price (Cents/kWh)</th>
<th>Hour</th>
<th>Price (Cents/kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>14</td>
<td>13</td>
</tr>
<tr>
<td>3</td>
<td>10</td>
<td>15</td>
<td>13</td>
</tr>
<tr>
<td>4</td>
<td>10</td>
<td>16</td>
<td>13</td>
</tr>
<tr>
<td>5</td>
<td>10</td>
<td>17</td>
<td>32</td>
</tr>
<tr>
<td>6</td>
<td>10</td>
<td>18</td>
<td>32</td>
</tr>
<tr>
<td>7</td>
<td>10</td>
<td>19</td>
<td>13</td>
</tr>
<tr>
<td>8</td>
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<td>20</td>
<td>13</td>
</tr>
<tr>
<td>9</td>
<td>13</td>
<td>21</td>
<td>13</td>
</tr>
<tr>
<td>10</td>
<td>13</td>
<td>22</td>
<td>13</td>
</tr>
<tr>
<td>11</td>
<td>13</td>
<td>23</td>
<td>10</td>
</tr>
<tr>
<td>12</td>
<td>13</td>
<td>24</td>
<td>10</td>
</tr>
</tbody>
</table>
Data II

![Critical loads](image1)
![PV power output](image2)
![Hot water demand](image3)

**Critical loads**

**PV power output**

**Hot water demand**

**Outdoor temperature**

**CO2 emissions**
Data III

Electrical loads settings:

<table>
<thead>
<tr>
<th></th>
<th>Minimum starting time</th>
<th>Maximum ending time</th>
<th>Rated power (kW)</th>
<th>Processing time</th>
<th>Preferred starting time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electric Clothes Washer (ECW)</td>
<td>15</td>
<td>23</td>
<td>0.5</td>
<td>2</td>
<td>17</td>
</tr>
<tr>
<td>Electric Dishwasher (EDW)</td>
<td>20</td>
<td>24</td>
<td>0.7</td>
<td>2</td>
<td>17</td>
</tr>
<tr>
<td>Electric Clothes Dryer (ECD)</td>
<td>15</td>
<td>24</td>
<td>1.1</td>
<td>1</td>
<td>20</td>
</tr>
<tr>
<td>Electric Iron (EI)</td>
<td>15</td>
<td>24</td>
<td>1.3</td>
<td>1</td>
<td>17</td>
</tr>
</tbody>
</table>

Table: HVAC, WS, and the battery parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(E_{\text{batt}})</td>
<td>11.50</td>
<td>kWh</td>
</tr>
<tr>
<td>(SOC_{\text{min}}, SOC_{\text{max}})</td>
<td>20,100</td>
<td>%</td>
</tr>
<tr>
<td>(P_{\text{ch}}^{\text{max}}, P_{\text{dch}}^{\text{max}})</td>
<td>2,2</td>
<td>kWh</td>
</tr>
<tr>
<td>(\eta_{\text{ch}}, \eta_{\text{dch}})</td>
<td>90,90</td>
<td>%</td>
</tr>
<tr>
<td>(T_{\text{WS}<em>{\text{min}}, \text{WS}</em>{\text{pref}}, \text{WS}_{\text{max}}})</td>
<td>60,70,80</td>
<td>°C</td>
</tr>
<tr>
<td>(V)</td>
<td>150</td>
<td>Litter</td>
</tr>
<tr>
<td>(T_{\text{cold}})</td>
<td>10</td>
<td>°C</td>
</tr>
<tr>
<td>(C_{\text{water}})</td>
<td>0.01164</td>
<td>kWh/°C</td>
</tr>
<tr>
<td>(C_{\text{air}})</td>
<td>0.525</td>
<td>kWh/°C</td>
</tr>
<tr>
<td>(R)</td>
<td>18</td>
<td>°C/kW</td>
</tr>
<tr>
<td>(T_{\text{HVAC}<em>{\text{min}}, \text{HVAC}</em>{\text{pref}}, \text{HVAC}_{\text{max}}})</td>
<td>15,19,24</td>
<td>°C</td>
</tr>
</tbody>
</table>

The parameter settings of the proposed algorithm are performed with IRACE package [López-Ibáñez 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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8. References
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.

<table>
<thead>
<tr>
<th></th>
<th>H-NSGA-II</th>
<th>H-SPEA-II</th>
<th>H-IBEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>SW1</td>
<td>0.0243403371</td>
<td>0.0584918726</td>
<td>0.0546370992</td>
</tr>
<tr>
<td>SW2</td>
<td>0.0556664411</td>
<td>0.0152721462</td>
<td>0.1527615993</td>
</tr>
<tr>
<td>SW3</td>
<td>0.0776497013</td>
<td>0.202927092</td>
<td>0.1282035293</td>
</tr>
<tr>
<td>SW4</td>
<td>0.0339468387</td>
<td>0.1160753488</td>
<td>0.2105974616</td>
</tr>
<tr>
<td>SW5</td>
<td>0.0145269554</td>
<td>0.0568580755</td>
<td>0.0676583474</td>
</tr>
<tr>
<td>SS1</td>
<td>0.0076601071</td>
<td>0.036452606</td>
<td>0.1061237781</td>
</tr>
<tr>
<td>SS2</td>
<td>0.1494577628</td>
<td>0.137912012</td>
<td>0.2838238053</td>
</tr>
<tr>
<td>SS3</td>
<td>0.0107909415</td>
<td>0.1036178348</td>
<td>0.1189505558</td>
</tr>
<tr>
<td>SS4</td>
<td>0.1367679942</td>
<td>0.1281304919</td>
<td>0.1473547421</td>
</tr>
<tr>
<td>SS5</td>
<td>0.0034731222</td>
<td>0.1318474842</td>
<td>0.1855408505</td>
</tr>
</tbody>
</table>

Table: Hypervolume difference $I_H^-$

<table>
<thead>
<tr>
<th></th>
<th>H-NSGA-II</th>
<th>H-SPEA-II</th>
<th>H-IBEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>SW1</td>
<td>0.0695312903</td>
<td>0.1399811712</td>
<td>0.1541256257</td>
</tr>
<tr>
<td>SW2</td>
<td>0.085396695</td>
<td>0.0420384684</td>
<td>0.228246983</td>
</tr>
<tr>
<td>SW3</td>
<td>0.0707580926</td>
<td>0.2540296487</td>
<td>0.2015655703</td>
</tr>
<tr>
<td>SW4</td>
<td>0.0405099156</td>
<td>0.0938708633</td>
<td>0.1354143033</td>
</tr>
<tr>
<td>SW5</td>
<td>0.0876181793</td>
<td>0.1389579404</td>
<td>0.1777620414</td>
</tr>
<tr>
<td>SS1</td>
<td>0.0976087015</td>
<td>0.1697028734</td>
<td>0.2458384418</td>
</tr>
<tr>
<td>SS2</td>
<td>0.1996094132</td>
<td>0.2015501406</td>
<td>0.335993147</td>
</tr>
<tr>
<td>SS3</td>
<td>0.0473846154</td>
<td>0.1115716753</td>
<td>0.1549966627</td>
</tr>
<tr>
<td>SS4</td>
<td>0.0024881697</td>
<td>0.0902933494</td>
<td>0.1371037166</td>
</tr>
<tr>
<td>SS5</td>
<td>0.0382475399</td>
<td>0.2372136246</td>
<td>0.212046905</td>
</tr>
</tbody>
</table>

Table: Epsilon indicator $I_\epsilon^+$

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 $I_\epsilon^+$ indicator.
Table: Extreme solutions obtained with different hybrid algorithms

<table>
<thead>
<tr>
<th></th>
<th>Total cost (cents/Day)</th>
<th>Discomfort (%/Day)</th>
<th>Dioxide emissions (kg/Day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>H-SPEA-II</td>
<td>236.18 42.0691 1.34333</td>
<td>258.929 23.4842 1.22223</td>
<td>254.031 32.6964 1.11769</td>
</tr>
<tr>
<td>SW1</td>
<td>(247.875 46.0792 1.54679)</td>
<td>(297.892 19.7117 1.38428)</td>
<td>(281.3 21.0199 1.29733)</td>
</tr>
<tr>
<td>H-NSGA-II</td>
<td>249.525 37.5434 1.48546</td>
<td>(300.205 16.1779 1.45802)</td>
<td>(273.066 18.4737 1.25085)</td>
</tr>
<tr>
<td>H-SPEA-II</td>
<td>254.148 37.0506 1.51823</td>
<td>(269.691 19.7542 1.46672)</td>
<td>(263.014 21.2906 1.33974)</td>
</tr>
<tr>
<td>H-SPEA-II</td>
<td>(310.244 33.4301 1.65964)</td>
<td>(339.319 16.8245 1.5369)</td>
<td>(335.684 17.5994 1.49026)</td>
</tr>
<tr>
<td>H-IBEA</td>
<td>(312.225 41.8227 1.7021)</td>
<td>(345.517 18.6417 1.5342)</td>
<td>(329.611 23.7731 1.51532)</td>
</tr>
<tr>
<td>SW4</td>
<td>(328.827 37.3934 1.85679)</td>
<td>(357.192 17.0466 1.71552)</td>
<td>(365.743 20.7889 1.67871)</td>
</tr>
<tr>
<td>H-NSGA-II</td>
<td>(331.563 36.6768 1.91493)</td>
<td>(357.336 17.5842 1.81745)</td>
<td>(362.167 23.2858 1.6931)</td>
</tr>
<tr>
<td>H-SPEA-II</td>
<td>(331.664 32.7062 1.78646)</td>
<td>(357.11 18.4437 1.8551)</td>
<td>(355.224 19.7351 1.71862)</td>
</tr>
<tr>
<td>H-IBEA</td>
<td>(-72.9931 21.5803 0.544708)</td>
<td>(-23.2578 14.6903 0.657818)</td>
<td>(-49.6885 20.1344 0.540056)</td>
</tr>
<tr>
<td>SS1</td>
<td>(H-NSGA-II)</td>
<td>(H-SPEA-II)</td>
<td>(H-IBEA)</td>
</tr>
<tr>
<td></td>
<td>(-72.4745 28.0934 0.725365)</td>
<td>(-48.7607 15.0244 0.612091)</td>
<td>(-52.4888 21.5152 0.550628)</td>
</tr>
<tr>
<td></td>
<td>(-69.604 21.5688 0.648811)</td>
<td>(-37.3865 16.1172 0.680289)</td>
<td>(-53.3416 20.2897 0.591003)</td>
</tr>
<tr>
<td></td>
<td>(-64.1097 28.3678 0.821153)</td>
<td>(-36.4098 15.6568 0.747295)</td>
<td>(-56.2618 19.3548 0.683184)</td>
</tr>
<tr>
<td></td>
<td>(-63.5977 18.2424 0.698382)</td>
<td>(-60.7039 15.5073 0.738167)</td>
<td>(-49.578 20.626 0.688912)</td>
</tr>
<tr>
<td></td>
<td>(-63.9298 20.5616 0.84151)</td>
<td>(-52.863 17.2084 0.865389)</td>
<td>(-55.5362 17.6438 0.758242)</td>
</tr>
<tr>
<td></td>
<td>(254.967 29.0818 1.03564)</td>
<td>(328.273 16.4189 1.09153)</td>
<td>(259.722 34.5909 1.02814)</td>
</tr>
<tr>
<td>SS2</td>
<td>(H-NSGA-II)</td>
<td>(H-SPEA-II)</td>
<td>(H-IBEA)</td>
</tr>
<tr>
<td></td>
<td>(254.986 33.3543 1.02622)</td>
<td>(278.105 18.2089 1.11047)</td>
<td>(289.693 26.6427 1.02362)</td>
</tr>
<tr>
<td></td>
<td>(261.508 31.3641 1.06076)</td>
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<td>(261.816 36.2645 1.06004)</td>
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<tr>
<td></td>
<td>(-278.368 32.5168 1.13227)</td>
<td>(298.91 17.1045 1.1505)</td>
<td>(314.898 22.06 1.11356)</td>
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<td>(299.695 17.1355 1.17855)</td>
<td>(290.793 22.219 1.1459)</td>
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<tr>
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<td>(-286.903 33.1476 1.18542)</td>
<td>(314.17 21.0413 1.23777)</td>
<td>(295.594 44.7761 1.17738)</td>
</tr>
<tr>
<td></td>
<td>(-292.904 32.928 1.22459)</td>
<td>(319.001 18.0125 1.29971)</td>
<td>(295.014 26.6129 1.21484)</td>
</tr>
<tr>
<td></td>
<td>(-303.189 35.1191 1.29182)</td>
<td>(-320.93 17.8953 1.2973)</td>
<td>(-310.61 22.8596 1.24702)</td>
</tr>
<tr>
<td></td>
<td>(-298.337 33.2735 1.24769)</td>
<td>(325.665 19.7429 1.35946)</td>
<td>(308.069 28.4373 1.23646)</td>
</tr>
</tbody>
</table>
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)](image1)

![Figure: Charging & discharging battery in summer (case IV)](image2)

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