Conception, planification et contrôle de systèmes énergétiques en environnement incertain

Design, planning and control of energy systems in uncertain environments

Chloé Desdouits, Peter Pflaum and Claude Le Pape
Schneider Electric – Global Technology / Internet of Things / Analytics Applications and Programs

Life Is On | Schneider Electric

Agenda

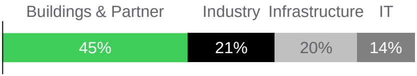
Schneider Electric, the Global Specialist in
Energy Management and Automation

€26.6 billion
FY 2015 revenues

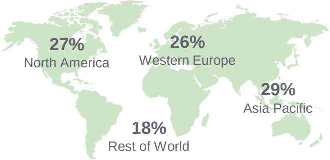
~5%
of FY revenues devoted to R&D

160,000+
people in 100+ countries

Four integrated and synergetic businesses
FY 2015 revenues

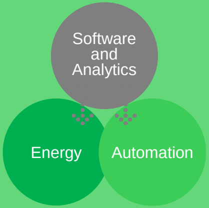


Balanced geographies – FY 2015 revenues



Life Is On | Schneider Electric

At Schneider Electric, we combine **Energy Management, Automation** and **Software** serving 4 markets, i.e. 70% of the world energy consumption



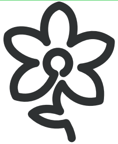
% are calculated on final energy

Source: IEA Explore 2015

Energy Efficiency Optimization Problems

High energy costs

Environmental concerns



Search for solutions to:

- New optimization problems
- Problems with new optimization criteria
    - Amount of energy used
    - Cost of this energy
    - Carbon footprint
- Multi-scale optimization problems
    - To get consistent optimization
    - To reduce losses at all levels

➢ Physics
➢ Complex systems design
➢ Operations management

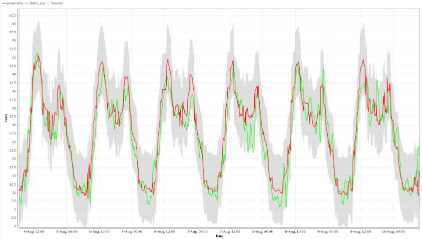
Examples

	Device	Process	System Design
Energy	• Energy profiling • Performance evaluation • Monitoring • Fault detection and diagnostic • Predictive maintenance • Energy efficient control	• Energy consumption disaggregation • Energy-aware planning, scheduling and control, to optimize the use of energy (e.g., drying time, oven pre-heating)	• More efficient electrical installations (reducing power losses) • Energy conservation (e.g., braking energy recovery, building isolation) and storage
Energy Cost / CO_2		• Multi-source energy allocation • Tariff sensitive planning, scheduling and control (including management of demand-response opportunities)	• Multi-source system design and sizing • Energy or goods storage enabling to differ electricity consumption • Contract optimization

Uncertainties

In production or consumption predictions

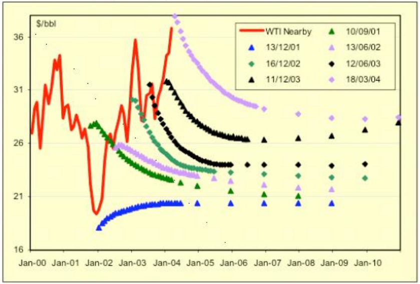
- Due to uncertainty in the activity
- Due to imprecision in the model linking activity prediction and energy production or consumption
- Due to uncertainty in relevant external factors (e.g., weather prediction)



In cost

- In the short term depending on contracts
- In the long term

Figure 1: Oil prices & forward curves 2000-04



Risks

- Unwanted event
  - Safety
  - Electrical network stability (when supply does not meet demand)
  - Resource availability (e.g., not enough water left in the water tower, due to unexpectedly high consumption)
  - …
  - In most cases, such events can be avoided through short-term reactive actions (e.g., decision to start a generator, refill a water tower in urgency, etc.)
  - ➢ Indicators: number of unwanted events per year, number of days per year on which reactive actions have been needed, consequences of non-avoided events, cost of reactive actions, etc.
- Sub-optimality
  - Optimal plan for the nominal case, but huge costs or reduction of benefits in some cases (e.g., photovoltaic farm penalty for not injecting planned power over a given period)
  - ➢ Indicators: average costs or benefits over a long period

Performance Contracting

- A provider (e.g., Schneider Electric) guarantees a level of performance to its customer (e.g., a water distribution company, itself guaranteeing a level of performance to its customer …)
  - Not more than n issues per year
  - At least x% of savings per year versus what would have been the costs with business-as-usual practices
  - ➢ Requires a good definition of the formula establishing the gains (e.g., taking into account external temperature when optimizing building heating or air conditioning)
  - ➢ Requires good management of the risk
    - Suppose I augment the yearly price by P+
    - But the penalty in case my number of failures exceeds n is P-
    - Then I want the probability p of paying the penalty to be smaller than P+ / P-

Event Risk Management: A First Level of Formalization

- Let $g(\theta, w) = 1$ when there is a problem and 0 otherwise
  - For each solution (system design, plan, control strategy, combination) θ and possible scenario (world) w
- Let $J(\theta)$ be my cost function
- No risk version
  - Minimize $J(\theta)$ such that $g(\theta, w) = 0$ for all possible scenarios w → often impossible or very expensive
  - Even though "branching plans" can sometimes be implemented
- Expected cost version
  - Minimize the expected value over all worlds w of $[J(\theta) + g(\theta, w) * \text{penalties}]$ → often too complex
- Mastered risk version
  - Minimize $J(\theta)$ such that the probability that $g(\theta, w) = 1$ is smaller than η
  - With a statistical confidence level $1 - \delta$
  - NB: The link between η, δ, and the number of events n per year depends on statistical dependence or independence conditions

Life Is On | Schneider Electric

Spatiality and Temporality

- Historical data → Statistical model (taking evolutions into account) → Characterization of the possible worlds w
  - More or less data available
  - More or less precise models, e.g., does the characterization distinguish days-of-week, seasons, weather conditions, football matches, etc.
- Temporality of the planning, scheduling and control problem, e.g., planning for one day with relevant information on the day available the day before (e.g., weather prediction)
  - But possibilities to adjust the rate at a much more frequent rate
- Mixing design and planning/control: design is for a long period (the system is designed for several years), planning is typically for a day or a week
- Reasoning over multiple customers and more or less long-term profitability → impact on δ

Agenda

Life Is On | Schneider Electric

Robust EVCS energy management strategy

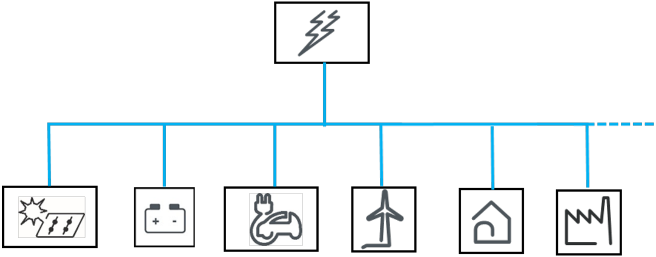
Peter Pflaum, Mazen Alamir & Mohamed-Yacine Lamoudi

Gipsa-Lab, Schneider Electric

4th July 2016

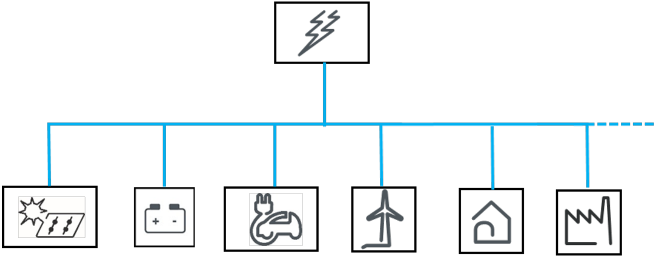
Context

Smart grid scheme:



Context

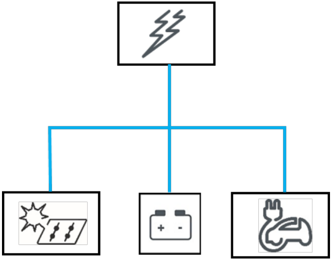
Smart grid scheme:



- Optimal coordination using Model Predictive Control to
  - Reduce energy costs
  - Respect congestion constraints
- Apply **distributed** MPC methods for scalability

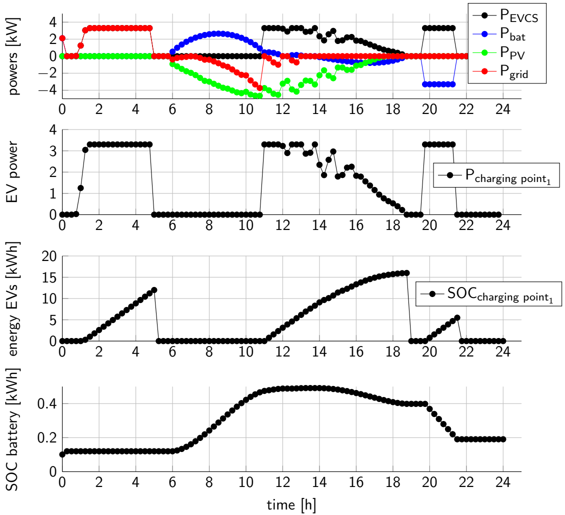
Context

A simple example (EUREF-Campus in Berlin):

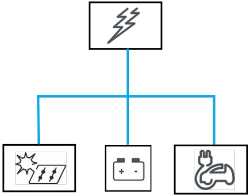


Context

A simple example (EUREF-Campus in Berlin):

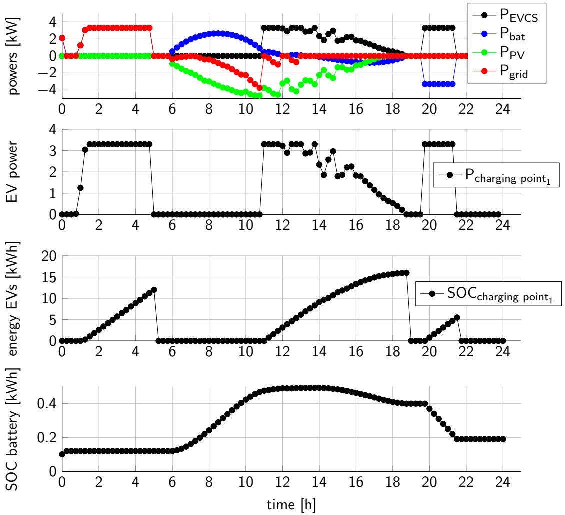


Aim: Maximize auto-consumption

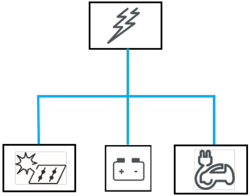


Context

A simple example (EUREF-Campus in Berlin):



Aim: Maximize auto-consumption



- What if the predictions are bad?
- Or simply not available?

EVCS under uncertainties

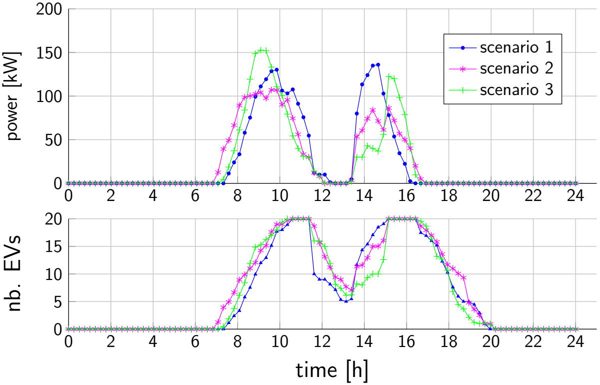
- Context
  - EVCS with M charging points
  - No forecasts of EVs' arrival- and departure times available
  - Known statistic model of the EV behavior obtained from historical data

EVCS under uncertainties

- Context
  - EVCS with M charging points
  - No forecasts of EVs' arrival- and departure times available
  - Known statistic model of the EV behavior obtained from historical data
- Objective
  - provide a day-ahead upper bound profile on the EVCS power consumption
  - guarantee the QoS (Quality of Service)

Motivation for a stochastic optimization approach

- Direct charging strategy ($M = 20$ charging points):



- Best possible QoS, but **no** consumption prediction

Randomized algorithm approach

Given the robust design problem

$$\min_{\theta \in \boldsymbol{\Theta}} J(\theta) \quad \text{s.t.} \quad g(\theta, w) = 0 \quad \text{for all} \quad w \in \mathcal{W}$$

- $\mathcal{W}$ is the uncertainty set
- θ is the design parameter vector
- $g(\theta, w)$ is the feasibility indicator:

$$g(\theta, w) := \begin{cases} 0 & \text{if } \theta \text{ meets feasibility specifications for } w \\ 1 & \text{otherwise} \end{cases}$$

Randomized algorithm approach

Introduce a probabilistic constraint

$$\min_{\theta \in \boldsymbol{\Theta}} J(\theta) \quad \text{s.t. } \mathrm{Pr}_{\mathcal{W}}\{g(\theta, w) = 1\} \leq \eta$$

- $\mathcal{W}$ is the uncertainty set
- θ is the design parameter vector
- $g(\theta, w)$ is the feasibility indicator:

$$g(\theta, w) := \begin{cases} 0 & \text{if } \theta \text{ meets feasibility specifications for } w \\ 1 & \text{otherwise} \end{cases}$$

Randomized algorithm approach

Add a confidence criterion

$$\min_{\theta \in \boldsymbol{\Theta}} J(\theta) \quad \text{s.t.} \;\; \Pr\{\, \Pr_{\mathcal{W}}\{g(\theta, w) = 1\} \leq \eta \,\} \geq (1 - \delta)$$

- $\mathcal{W}$ is the uncertainty set
- θ is the design parameter vector
- $g(\theta, w)$ is the feasibility indicator:

$$g(\theta, w) := \begin{cases} 0 & \text{if } \theta \text{ meets feasibility specifications for } w \\ 1 & \text{otherwise} \end{cases}$$

Randomized algorithm approach

We transformed $\min_{\theta \in \mathbf{\Theta}} J(\theta)$ s.t. $g(\theta, w) = 0$ to

$$\min_{\theta \in \mathbf{\Theta}} J(\theta) \quad \text{s.t.} \quad \Pr\{\ \Pr_{\mathcal{W}}\{g(\theta, w) = 1\} \leq \eta\ \} \geq (1 - \delta)$$

- which can be solved by the *m*-**level randomized strategy**

$$\min_{\theta \in \mathbf{\Theta}} J(\theta) \quad \text{subject to} \quad \sum_{k=1}^{N} g(\theta, \mathrm{w}^k) \leq m$$

Randomized algorithm approach

We transformed $\min_{\theta \in \mathbf{\Theta}} J(\theta) \quad \text{s.t.} \quad g(\theta, w) = 0$ to

$$\min_{\theta \in \mathbf{\Theta}} J(\theta) \quad \text{s.t.} \quad \Pr\{ \Pr_{\mathcal{W}}\{g(\theta, w) = 1\} \leq \eta \} \geq (1 - \delta)$$

- which can be solved by the *m*-**level randomized strategy**

$$\min_{\theta \in \mathbf{\Theta}} J(\theta) \quad \text{subject to} \quad \sum_{k=1}^{N} g(\theta, \mathrm{w}^k) \leq m$$

- with N respecting the following inequality

$$N \geq \frac{1}{\eta}\left(\frac{e}{e-1}\right)\left(ln\frac{n_{\mathbf{\Theta}}}{\delta} + m\right)$$

Randomized algorithm approach

We transformed $\min_{\theta \in \boldsymbol{\Theta}} J(\theta) \quad \text{s.t.} \quad g(\theta, w) = 0$ to

$$\min_{\theta \in \boldsymbol{\Theta}} J(\theta) \quad \text{s.t.} \quad \Pr\{ \Pr_{\mathcal{W}}\{g(\theta, w) = 1\} \leq \eta \} \geq (1 - \delta)$$

- which can be solved by the *m*-**level randomized strategy**

$$\min_{\theta \in \boldsymbol{\Theta}} J(\theta) \quad \text{subject to} \quad \sum_{k=1}^{N} g(\theta, \mathrm{w}^k) \leq m$$

- with N respecting the following inequality

$$N \geq \frac{1}{\eta}\left(\frac{e}{e-1}\right)\left(ln \frac{n_{\boldsymbol{\Theta}}}{\delta} + m\right)$$

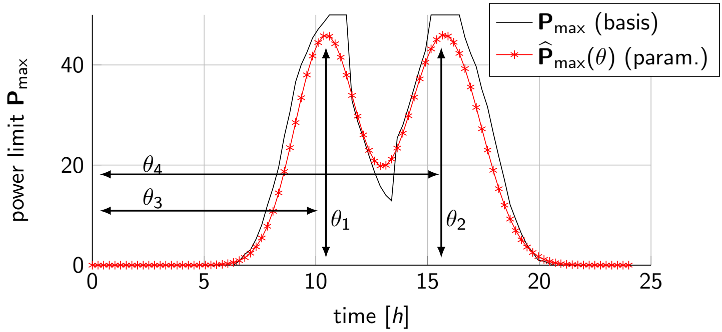
- and the set of design parameter vectors $\boldsymbol{\Theta}$ being of finite dimension $n_{\boldsymbol{\Theta}}$

Application to the EVCS problem

1. For the $n_{\mathbf{\Theta}}$ design parameter vectors $\theta^{(1)}, ..., \theta^{(n_\Theta)}$, generate candidate power profiles $\widehat{\mathbf{P}}_{max}(\theta^{(1)}), ..., \widehat{\mathbf{P}}_{max}(\theta^{(n_\Theta)})$

Design parameter vector θ

- θ allows to modulate the profile $\widehat{\mathbf{P}}_{max}(\theta)$ with sufficient degree of freedom



Application to the EVCS problem

1. For the $n_{\mathbf{\Theta}}$ design parameter vectors $\theta^{(1)}, ..., \theta^{(n_\Theta)}$, generate candidate power profiles $\widehat{\mathbf{P}}_{max}(\theta^{(1)}), ..., \widehat{\mathbf{P}}_{max}(\theta^{(n_\Theta)})$

Application to the EVCS problem

1. For the $n_{\boldsymbol{\Theta}}$ design parameter vectors $\theta^{(1)}, ..., \theta^{(n_\Theta)}$, generate candidate power profiles $\widehat{\mathbf{P}}_{max}(\theta^{(1)}), ..., \widehat{\mathbf{P}}_{max}(\theta^{(n_\Theta)})$
2. Draw N scenarios $w^{(1)}, ..., w^{(N)}$ from a statistical EVCS occupancy model

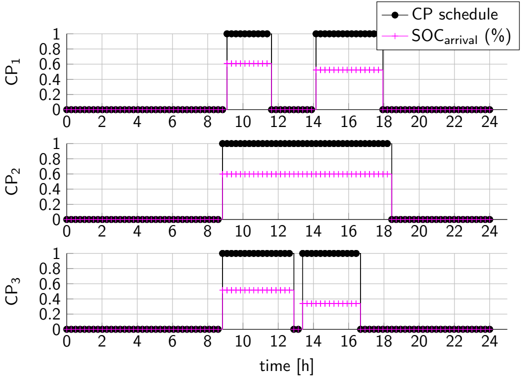
Statistic EVCS occupancy model

- An EVCS occupancy scenario w is defined as

$$w = \{t_{\text{arr},v}, t_{\text{dep},v}, E_{\text{req},v}\}_{v \in \mathcal{V}}$$

- We can draw realizations w from a statistical model which was learned from historical data

Three random charging point schedules



Application to the EVCS problem

1. For the $n_{\mathbf{\Theta}}$ design parameter vectors $\theta^{(1)}, \dots, \theta^{(n_\Theta)}$, generate candidate power profiles $\widehat{\mathbf{P}}_{max}(\theta^{(1)}), \dots, \widehat{\mathbf{P}}_{max}(\theta^{(n_\Theta)})$
2. Draw N scenarios $w^{(1)}, \dots, w^{(N)}$ from a statistical EVCS occupancy model

Application to the EVCS problem

1. For the $n_{\mathbf{\Theta}}$ design parameter vectors $\theta^{(1)}, ..., \theta^{(n_\Theta)}$, generate candidate power profiles $\widehat{\mathbf{P}}_{max}(\theta^{(1)}), ..., \widehat{\mathbf{P}}_{max}(\theta^{(n_\Theta)})$
2. Draw N scenarios $w^{(1)}, ..., w^{(N)}$ from a statistical EVCS occupancy model
3. For the $n_{\mathbf{\Theta}} \times N$ combinations $(\theta^{(i)}, w^{(k)})$
    - Simulate a low-level controller that distributes the available power profile $\widehat{\mathbf{P}}_{max}(\theta^{(i)})$ to the EVs of scenario $w^{(k)}$
    - Check if the QoS is achieved ($g^{(i,k)} = 0$) or not ($g^{(i,k)} = 1$)

Binary feasibility indicator $g(\theta, w)$

- Feasibility indicator in the context of the EVCS

$$g(\theta, w) := \begin{cases} 0 & \text{if the QoS (Quality of Service) is provided} \\ 1 & \text{otherwise} \end{cases}$$

- QoS metric: $\frac{E_{\text{charged}}}{E_{\text{req}}} \geq 0.9$

Binary feasibility indicator $g(\theta, w)$

- Feasibility indicator in the context of the EVCS

$$g(\theta, w) := \begin{cases} 0 & \text{if the QoS (Quality of Service) is provided} \\ 1 & \text{otherwise} \end{cases}$$

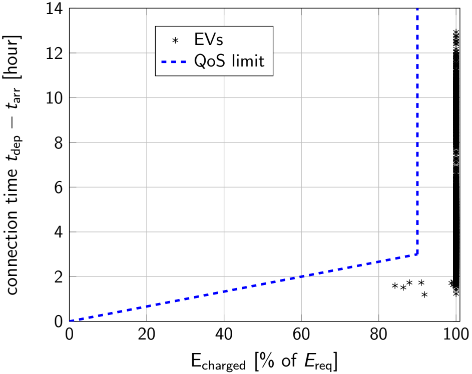
- QoS metric: $\frac{E_{\text{charged}}}{E_{\text{req}}} \geq 0.9 \times \min\left(1, \frac{t_{\text{dep}} - t_{\text{arr}}}{T_{\text{threshold}}}\right)$

Binary feasibility indicator $g(\theta, w)$

- Feasibility indicator in the context of the EVCS

$$g(\theta, w) := \begin{cases} 0 & \text{if the QoS (Quality of Service) is provided} \\ 1 & \text{otherwise} \end{cases}$$

- QoS metric: $\frac{E_{\text{charged}}}{E_{\text{req}}} \geq 0.9 \times \min\left(1, \frac{t_{\text{dep}} - t_{\text{arr}}}{T_{\text{threshold}}}\right)$



Application to the EVCS problem

1. For the $n_{\mathbf{\Theta}}$ design parameter vectors $\theta^{(1)}, ..., \theta^{(n_{\Theta})}$, generate candidate power profiles $\widehat{\mathbf{P}}_{max}(\theta^{(1)}), ..., \widehat{\mathbf{P}}_{max}(\theta^{(n_{\Theta})})$
2. Draw N scenarios $w^{(1)}, ..., w^{(N)}$ from a statistical EVCS occupancy model
3. For the $n_{\mathbf{\Theta}} \times N$ combinations $(\theta^{(i)}, w^{(k)})$
   - Simulate a low-level controller that distributes the available power profile $\widehat{\mathbf{P}}_{max}(\theta^{(i)})$ to the EVs of scenario $w^{(k)}$
   - Check if the QoS is achieved ($g^{(i,k)} = 0$) or not ($g^{(i,k)} = 1$)

Application to the EVCS problem

1. For the $n_{\boldsymbol{\Theta}}$ design parameter vectors $\theta^{(1)}, \ldots, \theta^{(n_\Theta)}$, generate candidate power profiles $\widehat{\mathbf{P}}_{max}(\theta^{(1)}), \ldots, \widehat{\mathbf{P}}_{max}(\theta^{(n_\Theta)})$
2. Draw N scenarios $w^{(1)}, \ldots, w^{(N)}$ from a statistical EVCS occupancy model
3. For the $n_{\boldsymbol{\Theta}} \times N$ combinations $(\theta^{(i)}, w^{(k)})$
   - Simulate a low-level controller that distributes the available power profile $\widehat{\mathbf{P}}_{max}(\theta^{(i)})$ to the EVs of scenario $w^{(k)}$
   - Check if the QoS is achieved ($g^{(i,k)} = 0$) or not ($g^{(i,k)} = 1$)
4. Determine the set $\mathcal{A}$ of feasible $\theta^{(i)}$ that guarantee the QoS

$$\mathcal{A} := \left\{ i \in \{1, \ldots, n_{\boldsymbol{\Theta}}\} \;\middle|\; \sum_{i=1}^{N} g^{(i,k)} \leq m \right\}$$

Validation of the approach

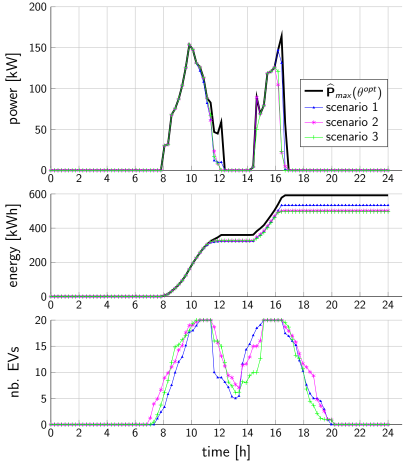
- An EVCS with $M = 20$ charging points located at a company
- $n_\Theta = 256, \quad \eta = 0.05, \quad \delta = 0.05, \quad m = 5,$ resulting in

$$N = \frac{1}{\eta}\left(\frac{e}{e-1}\right)\left(ln\frac{n_\Theta}{\delta} + m\right) = 429 \text{ scenarios}$$

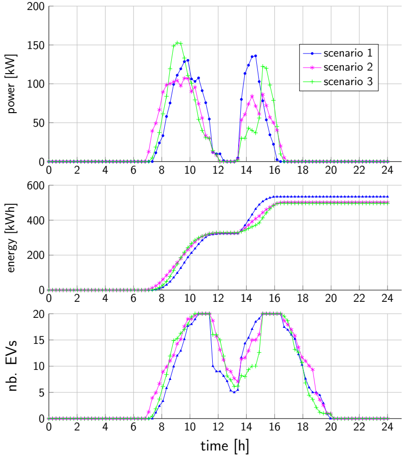
- Computation time $\simeq 10\, min$ ($n_\Theta \times N$ low-level controller simulations)

Comparison: Stochastic approach vs. direct charging

- Stochastic approach



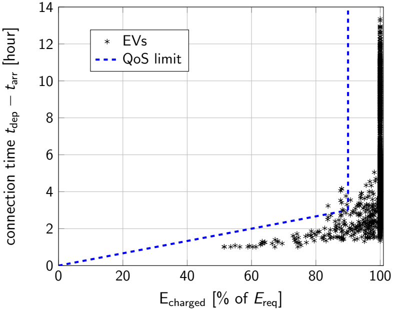
- Direct charging



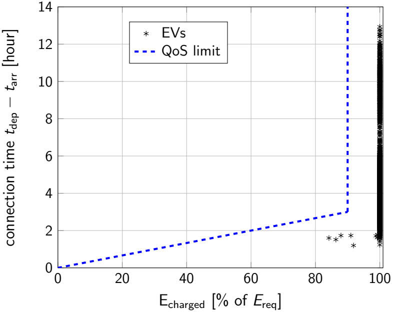
Comparison: Stochastic approach vs. direct charging

What about the guaranteed QoS ?

- Stochastic approach



- Direct charging



Conclusion & Outlook

- Day-ahead computation of an upper bound power profile for an EVCS
- Implementation of a simple real-time controller that respects the upper bound profile
- Probabilistic guarantee of the QoS through randomized algorithms

Conclusion & Outlook

- Day-ahead computation of an upper bound power profile for an EVCS
- Implementation of a simple real-time controller that respects the upper bound profile
- Probabilistic guarantee of the QoS through randomized algorithms

Outlook

- Application to a real EVCS or at least to real data
- Extension by an additional lower bound power profile

Agenda

ARROWHEAD

Chloé Desdouits

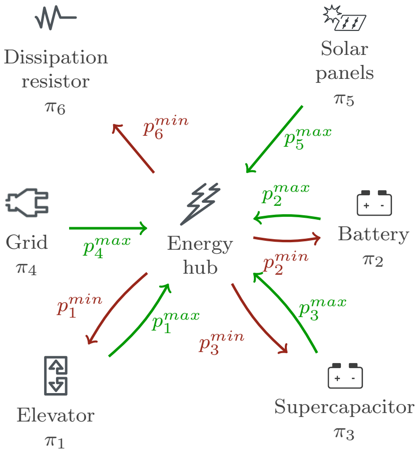
Mazen Alamir, Rodolphe Giroudeau, Claude Le Pape
GIPSA-lab, LIRMM, Schneider Electric

Certification Framework under incertainties of control methods for a multisource elevator

October 2016

Outline

The multisource elevator system

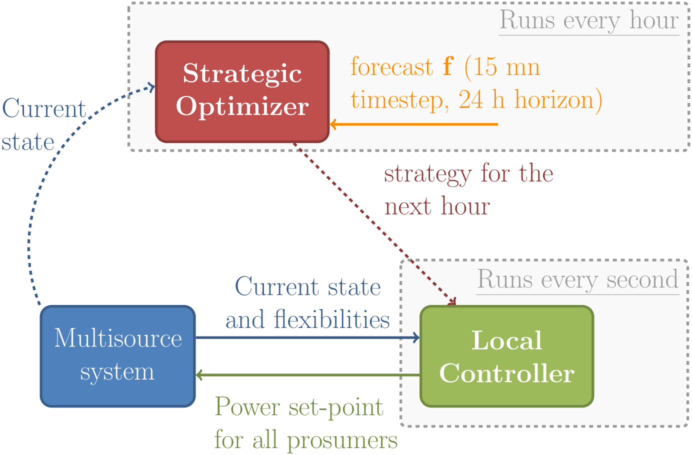


Power versus energy

$\forall \pi_i, e_i = p_i \times \tau$

Outline

Model-based Predictive Control coupled with rule-based control



Model-based Predictive Control

Computes set-points with mathematical programming, depending on predictions, in closed-loop.

INPUT: predictions on 15 minutes periods:

- electricity price,
- solar panel energy production,
- elevator energy consumption.

OUTPUT: set-points on 15 minutes periods:

- Target state of charge for the storage units.
- Target energy amount purchased from the grid.

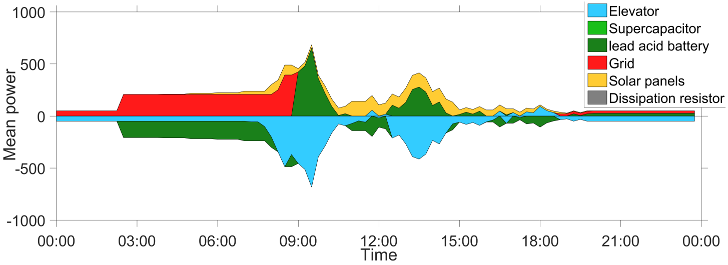
Advantages:

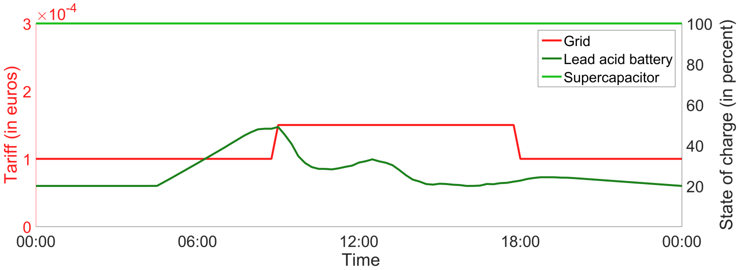
- Takes into account complex constraints/objective

Drawbacks:

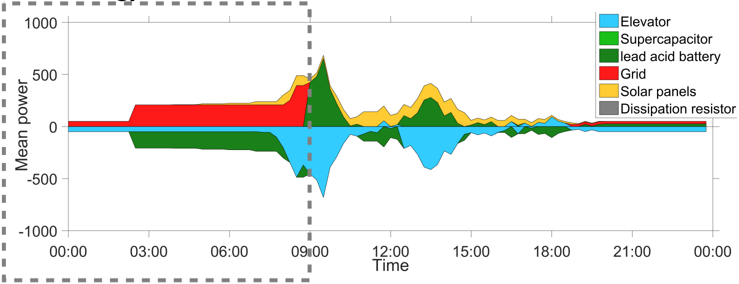
- Sensitive to prediction errors

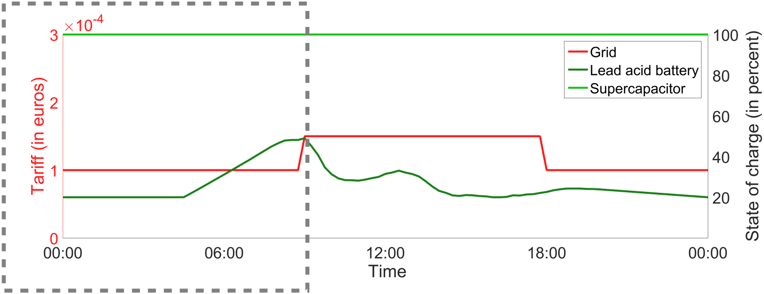
A typical strategy



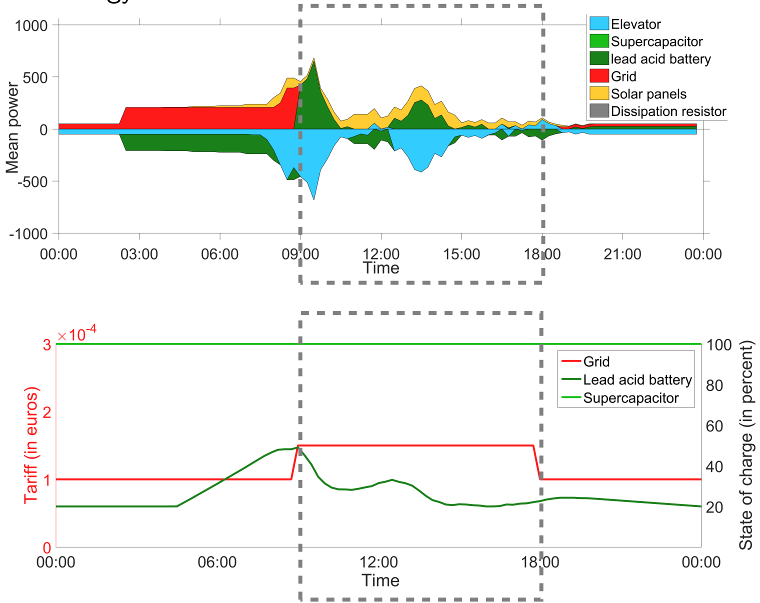


A typical strategy

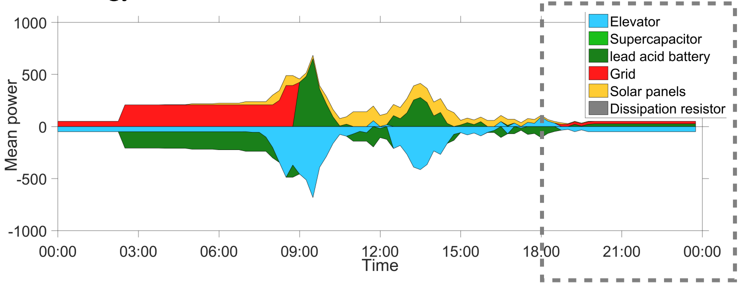


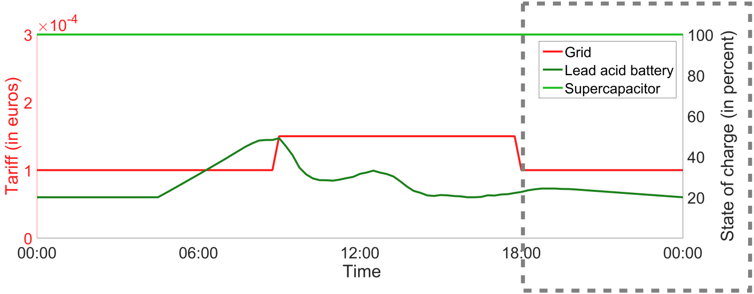


A typical strategy



A typical strategy





Outline

Recall: Randomized algorithm approach

Given the robust design problem

$$\min_{\theta \in \boldsymbol{\Theta}} J(\theta) \quad \text{s.t.} \quad g(\theta, w) = 0 \quad \forall w \in \mathcal{W}$$

Rewrite the deterministic constraints in probabilistic terms

$$\min_{\theta \in \boldsymbol{\Theta}} J(\theta) \quad \text{s.t.} \; \Pr\{\ \Pr_{\mathcal{W}}\{g(\theta, w) = 1\} \leq \eta\ \} \geq (1 - \delta)$$

which can be solved by the *m*-level randomized strategy

$$\min_{\theta \in \boldsymbol{\Theta}} J(\theta) \quad \text{subject to} \quad \sum_{k=1}^{N} g(\theta, \mathrm{w}^k) \leq m$$

- Θ **:** the set of design parameters of cardinality $n_{\boldsymbol{\Theta}}$
- $\mathcal{W}$ **:** the set of uncertainties
- η **:** the probability of constraint violation
- δ **:** the confidence probability
- N **:** the minimum number of i.i.d. samples to generate

$$N \geq \frac{1}{\eta}(\frac{e}{e-1})(ln\frac{n_{\boldsymbol{\Theta}}}{\delta} + m)$$

Design to Avoid Power Peaks

$\mathcal{B}$ **:** a set of possible battery energy capacities (in Wh)

$\mathcal{S}$ **:** a set of possible supercapacitor energy capacities (in Wh)

$\mathcal{F}$ **:** a set of minimal net daily gains to be certified (in €)

Θ **:** the resulting set of design parameters

$$\Theta = \mathcal{B} \times \mathcal{S} \times \mathcal{F}$$

$f(\theta, w, u^*)$ **:** a function that gives the net daily gain g^{net} obtained by the local controller at the end of the day

D **:** the set of design constraints

u^* **:** the applied control strategy

$$\max_{t \in \{0,\ldots,H\}} (|p_4(t)|) \leq p_{max}$$

$$f(\theta, w, u^*) \geq \theta_3$$

$J(\theta)$ **:** the objective function

$$J(\theta) = -\theta_3$$

Which Storage Units to Avoid Power Peaks?

Given:

- the maximum power peak allowed is $p_{max} = 6000$ W
- the set of possible battery energy capacities (in Wh) is $\mathcal{B} = \{3000, 6000\}$
- the set of possible supercapacitor energy capacities (in Wh) is $\mathcal{S} = \{60, 120, 180\}$
- $\eta = 0.05$, $\delta = 0.05$, and $N = \lceil \frac{1}{\eta}(\frac{e}{e-1})(ln\frac{n_C}{\delta})\rceil = 152$
- a French peak / off-peak tariff

Design result

The 3 kWh battery, and the 120Wh supercapacitor are the best choice.

Certification

Avoiding purchasing peaks above 6 kW will cost at most 0.16 € per day in this context.

Design to Achieve Savings

- $\mathcal{T}$ **:** a set of possible electricity tariffs
- $\mathcal{C}$ **:** a set of possible controllers
- $\mathcal{M}$ **:** a set of possible maximum power values from and to the grid
- $\mathcal{F}$ **:** a set of minimal net daily gains that could be certified to the customer (in €)
- Θ **:** the resulting set of design parameters

$$\Theta = \mathcal{T} \times \mathcal{C} \times \mathcal{M} \times \mathcal{F}$$

- D **:** the set of design constraints

$$f(\theta, w, u^*) \geq \theta_4$$

- $J(\theta)$ **:** the objective function

$$J(\theta) = -\theta_4$$

Which Tactic and Tariff to Get Savings?

Given:

- The set of possible electricity tariffs $\mathcal{T} = \{$flat (0.00013), peak/off-peak (0.00015 / 0.00010), spot-like (between 0.0002991 and 0.0009386)$\}$ (€/Wh).
- The set of possible controllers $\mathcal{C} = \{$MinPeaks LC following strategy, Opportunistic LC alone, Secure LC$\}$.
- The set of possible maximum power values from and to the grid $\mathcal{M} = \{[-50000, 0], [-50000, 20000]\}$ (W).
- Two probabilities $\eta = 0.05$, $\delta = 0.05$, and $N = \lceil \frac{1}{\eta}(\frac{e}{e-1})(ln \frac{n_C}{\delta}) \rceil = 187$.

Design result

The considered customer should subscribe to the spot tariff, and install the MinPeak LC coupled with SO.

Certification

The corresponding certified net daily gain is 1.18 € per day. Moreover the mean net daily gain obtained on those samples is 1.52 €.

Outline

Conclusion

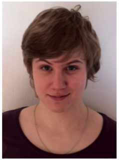
What has been done:

- formalization of the sourcing problem
- implementation of several controllers
- trade-off between minimizing peaks and minimizing electricity bill

Outlooks:

- a real-life experiment
- robustness to uncertainties
- how does tariff influence savings

Questions?


C. Desdouits


M. Alamir


R. Giroudeau


C. Le Pape

Agenda

Life Is On | Schneider Electric

Other examples

- Photovoltaic farm
  - Save money against uncertainty in photo-voltaic production forecast (with a guarantee crafted with respect to the contract between the photo-voltaic farm and the utility)
- Water pumping
  - Save money against uncertainty in water consumption forecast (with a guarantee that only 3 days in a year there is a need to react in urgency)
- Manufacturing
  - Save a combination of multiple costs (tardiness + storage + electricity) against uncertainty either in demand or in product quality tests (some percentage of the products have to be discarded) with a guarantee that less than x% of the customer orders are delivered late
- …

Agenda

Conclusion

- Robust optimization is more and more an important issue in Industry
  - Customers asking for “guarantees”
  - Performance contracting either with respect to such guarantees or engagement on gains
- Different formulation of the needs depending on the use case
  - Absolute guarantee
  - Bound on the probability (e.g., number of days) that a problem occurs, more or less shared between the service provider and customer
  - With a notion of confidence level for the service provider, essential for the profitability of its business
- Practical methodologies emerge
- Difficulties
  - Historical data
  - Statistical model reflecting these data (and enabling to design relevant sets of scenarios for the future if the methodology requires them)
  - Computational time, especially when complex simulation is required

Life Is On | Schneider Electric