Certification under Uncertainties of Control Methods for Multisource Elevators

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Abstract. As the interest in regulating energy usage and participating in the demand-response market is growing, new energy management algorithms emerge. Energy consumption of elevators represents about 5% of the overall consumption of a building. Thus, improving energy performance of elevators becomes a relevant challenge. In this paper, a method is described to assist potential customers in choosing the most relevant storage units and control method for their multisource elevator. In order to obtain a certification on electricity cost savings and maximum power peaks, a randomized algorithm is designed. The best storage units design is found for a given use case, and a guarantee (with a fixed probability) is given that the elevator's consumption from the grid will not exceed a given power peak. Moreover, a similar guarantee is given on the minimum savings that could be achieved, choosing a given controller.

Keywords: energy optimization; robustness; randomized algorithm

1 Introduction

Global energy consumption regulation is a major issue nowadays. The will to participate in the emerging demand-respond market encourages industries and building managers to look for energy management algorithms. Coupled with relevant control algorithms, the design of energy efficient systems is investigated.

One of the core questions we often encounter in the optimization of design, planning, and control, is the robustness of the proposed solution to uncertainty in the measured (or predicted) data. This includes robustness of the optimization method to unusual data sets, even when the data are available or more-or-less accurately forecasted at the time at when the optimization method is applied. The robustness question concerns either the optimization criterion itself (i.e., what is the probability that the proposed solution effectively brings improvements over the current practice?) or the satisfaction of some constraints (i.e., what is the probability that the execution of the proposed solution becomes impossible after a given amount of time?). Let us note that, in some cases, an optimization criterion can be replaced by a more or less "soft" constraint which could be violated, but "not too often". For example, a contract may allow peak electrical power over a given day P_{day} to exceed a given limit P_{max}, but not more than a given number of days during the year; otherwise a significant penalty is incurred.

There are an infinite number of daily scenarios of elevator usage; thus we cannot simulate them all. A particular method, that can be used to offer guarantees, relies on the fact that an event (such as exceeding P_{max} on a given day) which is not observed over a representative set of N samples (with a large N) has low probability of occurrence (depending on N). In this paper, we investigate the use of such a method for the design and control of a multisource elevator.

Two use cases are considered. The first use case concerns peak power consumption: what kind of system design allows to satisfy the power peak constraint (with a given probability) and what is the daily extra cost induced? The second use case concerns the choice of relevant controller and electricity tariff in order to enable savings? These two use cases are managed as extensions of our previous work on the multisource elevator control problem [5].

2 The Multisource Elevator Problem

We call "*prosumers*", entities that consume and/or produce energy. An energy hub allows each prosumer to consume power produced by all other prosumers at the same time.

Definition 1. *Let $\mathcal{P} = \{\pi_1, \ldots, \pi_6\}$ be our set of $n_p = 6$ prosumers, all connected to the same energy hub h.*

The set $\mathcal{P}$ of prosumers is composed of: an elevator π_1, that can get energy from a battery π_2, a supercapacitor π_3, the grid π_4 and a solar panel π_5. The supercapacitor is here to absorb power peaks above the maximum power capability of the battery. But the former is more expensive than the latter, while usage age them both. Moreover, energy can be recovered from the elevator when the brakes are applied. Finally, energy can be dissipated in a resistor π_6 if there is too much.

A system composed of an energy hub h and its prosumers can be represented by a star oriented graph rooted in h. There is an arc (π_i, h) if Prosumer π_i can produce energy and the weight of the arc is the maximum power production. In the same way, there is an arc (h, π_i) if Prosumer π_i can consume energy and the weight of the arc is maximum power consumption.

Definition 2. *Let $\mathcal{G} = (\mathcal{P} \cup h, \mathcal{A})$ be the star oriented graph associated to the multisource elevator.*

We suppose that time can be sampled in a regular, uniform way.

Definition 3. *Let $\tau \in \mathbb{R}$ be the sampling period (expressed in hours), and $H \in \mathbb{N}$ be the number of periods considered in predictions and planning. Then time-steps are expressed in the following way: $t_l = t_{l-1} + \tau = l \times \tau, \forall l \in \{1, \dots, H\}$.*

Finally, an electricity cost function $\text{cost}_{\pi_4} : [1, \dots, H] \Rightarrow \mathbb{R}$ gives the price associated to purchasing electricity from (or reselling electricity to) the grid.

Then, we can define the multisource elevator problem:

Instance: a set of prosumers $\mathcal{P}$, a graph $\mathcal{G} = (\mathcal{P} \cup h, \mathcal{A})$, a period $\tau \in \mathbb{R}$, a time horizon $H \in \mathbb{N}$, an energy cost function cost_{π_4}

Solution: S, a $n_p \times H$ matrix of power values

Question: given data $p_{\mathbb{P}}^{max} \in \mathbb{R}$ and $cost_{hub}^{max} \in \mathbb{R}$, can power peaks from and to the grid and the energy bill remain bounded, respectively by $p_{\mathbb{P}}^{max}$ and by $cost_{hub}^{max}$?

3 State of the Art

In order to regulate the energy consumption of an elevator, the energy consumption itself can be decreased, or energy can be recovered and stored into storage units to be reused later. In [7], smart ways to choose elevator physical components (motor, drive, etc) are summarized, as well as appropriate sizing methods.

Coupling elevators with supercapacitors has been studied by many researchers and companies. Some of them investigate how to commute softly between the grid and a supercapacitor, like in [6,9]. In [6], a physical multisource system is designed to power an elevator. Rules are used to charge or discharge batteries depending on whether the electrical current is below or above a given reference. Likewise, [9] presents three rule-based methods to control a battery coupled with an elevator. This method takes into account peak/off-peak tariffs and reduces energy consumption cost by storing energy recovered from the elevator. These methods allow to control very reactively the system, but cannot take into account optimally external considerations such as the electricity tariff or battery state of health. Therefore, these control methods may not be efficient regarding economic objectives.

Works have also been conducted on how to take into account future energy consumption to minimize the energy bill, using storage units. In [2], a General Energy and Statistical Description (GESD) of the possible missions of an elevator is proposed, as well as a dynamic programming-based energy manager. The energy manager is inspired by stock management theory and minimizes the sum of energy (i) absorbed from the grid, (ii) dissipated in the braking resistor and (iii) not provided to the elevator. The optimization is done off-line. This method allows to find an optimal solution regarding economical objectives from probabilities of consumption. But elevator usage is unpredictable by nature and what is to be done when the strategy is unfeasible is not investigated.

This work follows up our previous development on the subject where several energy sources are supposed to be available to be used by the elevator and the problem is to choose between them over time, as stated in Section 2. In

[3], the real-life deployed application was described, including communication process, and web interface. In [4], two coupled controllers were proposed to solve the problem and the interactions between them are studied. The idea was to use a Strategic Optimizer (SO) to solve a linear program and get a sourcing strategy over a day. This sourcing strategy is then sent to a Local Controller (LC) that controls in real-time the energy hub, making a trade-off between the current situation and the strategic instructions. In [5], the sourcing problem and the multisource elevator problem were formalized. Several local controllers were proposed and deterministic experiments were conducted to give a first evaluation of the method potential savings.

The current paper extends the previous work on SO/LC based on a solution introduced in [4] by explicitly handling the effect of the uncertainty on the outcome of the closed-loop operation. A Certification Framework is used to guarantee customer savings on the energy bill and a limit on the power peak consumed from the grid.

4 Design of a Robust Solution

In this section, the goal is to design robust solutions regarding uncertainties. As we want to provide a guarantee that a certain condition will be satisfied at least a great percentage of the days, the uncertainties to be considered concern all elements that vary from a day to another. Let us note that these elements may be more or less known or predictable at time t_0 : the state of charge of the battery is known at t_0; a weather forecast enables to estimate solar production precisely enough for our needs; and a forecast of the elevator's energy needs can also be available but often much less precise. The control method takes such forecasts into account. To certify a property on a given percentage of the days, we have to consider these forecasts as part of the uncertainty set, even though the controller take them as data.

For that purpose, we draw samples of elevator calls according to a statistical model. This model distinguishes multiple types of travels: morning and afternoon arrivals and departures, lunch breaks, inter-floor travels, arrivals and departures of external visitors. Statistical laws are identified based on historical data. For each travel type and relevant pair of floors, these laws provide information on the number of people moving during the day, the distribution of their weights, the distribution of the events, etc. The attendance of the building is tuned depending on the day-of-week and week-of-year. A random generator is used on this basis to generate scenarios. A forecast of elevator energy consumption is built by averaging energy production or consumption on several daily scenarios of the same kind. Thus, there is one forecast per kind of day.

Definition 4. *A drawn scenario of daily elevator consumption, for the kind of day D, is denoted $w^D_{cons} \in W^D_{cons}$. The associated forecast is denoted $\mathbf{f}^D_{cons}$.*

The second kind of uncertainties is solar radiation, uniformly drawn between two bounds: a typical cloudy day and a typical sunny day. The predicted solar production, known at the beginning of each day, is drawn between the daily profile minus ten percent and the daily profile plus ten percent. Note that solar production samples are uniformly drawn, regardless of the kind of day.

Definition 5. *A drawn scenario of daily solar production, is denoted* $w_{prod} \in W_{prod}$*. The associated forecast is denoted* $\mathbf{f}_{prod}$*.*

Thus, let $\mathbf{f}$ be the forecast that feeds SO. It is deterministic and depends only on the kind of day considered.

Definition 6. $\mathbf{f} = [\mathbf{f}^D_{cons}, \mathbf{f}_{prod}]$*, a* $2 \times H$ *matrix, with* H *the number of periods considered for the predictions.*

The last kind of uncertainty is the initial state of charge of storage units at the beginning of a simulated day. These states of charge are uniformly drawn between 0% and 100%.

Definition 7. *Drawn initial state of charge of storage units are denoted* $w_{initSOC} \in [0, 100]^2$*.*

Finally the uncertainty set considered contains the three sources of uncertainties stated before, as well as the forecasts (even if they depend only on the kind of day).

Definition 8. *Let* $W = \bigcup_D (W^D_{cons}) \times W_{prod} \times [0, 100]^2$ *be the uncertainty set considered and* $w^D \in W$ *be a scenario drawn for a given day* D *such that:* $w^D = (w^D_{cons}, w_{prod}, w_{initSOC}, \mathbf{f})$*.*

Now, let us consider two different use cases where a certification has to be given on the control method achievements. In the first one, a customer wants to respect a limit of power consumption enforced by law or by his electricity tariff (that can be much more expensive above a given power limit). In this use case, the aim is to determine the optimal sizing of a battery and a supercapacitor in order to certify that the customer will never exceed the given power limit. In the second use case, a customer already has storage units and wants to use them to participate in the demand-response market. We want to certify that, if he buys our control solution, he will gain X % on his daily electricity bill with a prescribed high probability.

In order to solve these optimization problems, a randomized algorithm is used. The principles of the chosen method are the following. Some key design parameters, relevant for the given problem, are chosen. Then, for all possible values of the design parameters, control algorithms are simulated with several uncertainty scenarios. The design vector, that gives admissible solutions and the best objective value on simulated scenarios, is kept.

Because there is an infinite number of possible uncertainty scenarios, we cannot simulate them all. Thus, in order to get a certification that simulation results are representative, a statistical model of the elevator travels (based on Gaussian laws) has been developed and used in a randomized algorithm.

To obtain this certification, we use results on randomized algorithms shown in [1]. We briefly recall them, and apply them to our context below. Let:

- Θ be the set of possible values of design parameters we want to optimize (i.e.: storage unit possible sizes, different electricity tariffs, etc). The cardinality of Θ is denoted n_C.
- $\theta \in \Theta$ be a vector with n_θ components.
- W be the set of uncertainties (Definition 8), composed of possible elevator consumption curves during a day, solar production curves, and initial state of charge.
- $w^D \in W$ an uncertainty scenario drawn for a given day D, as stated in Definition 8.
- $u^*(\theta, w^D)$ be a vector of target state of charge for the battery and target energy purchase from the grid over the day, given by SO.
- $J(\theta)$ be an objective function to minimize.
- C be a set of constraints on design parameters.
- $g : \Theta \times W \to \{0, 1\}$ be a function that returns zero if all constraints $c \in C$ are satisfied and one otherwise.

Then, we use the following result: if we generate N i.i.d. samples $\{w^{(1)}, \dots, w^{(N)}\}$ from W according to the probability Pr_W and then solve the following sampled optimization problem:

$$\min_{\theta \in \Theta} J(\theta) \text{ subject to } \sum_{l=1}^{N} g(\theta, w^{(l)}) \leq 0 \tag{1}$$

with

$$N \geq \frac{1}{\eta}(\frac{e}{e-1})(ln\frac{n_C}{\delta}) \tag{2}$$

then, the probability for the optimal solution $\hat{\theta}_N$ to the optimization problem, to violate the design constraint is smaller than η, with a confidence probability no smaller than $1-\delta$. In other terms, we can certify, with a probability $1-\delta$, that the control strategy will satisfy the design constraint in at least $100 \times (1-\eta)$ percent of the cases. In order to solve this optimization problem, we use Algorithm 1.

5 Experiments

These experiments were conducted in Matlab [8]. The randomized algorithm is applied to the use cases presented above and the results are discussed.

A solution value is evaluated according to the daily cost c^{daily} Key Performance Indicator (KPI). Let: c^{ebill} be the energy bill of the whole day and c^{aging} be the aging cost associated to the storage units usage that has been done during the day. But depending on the controller, final states of charge can be different. Then we note c^{soc} the cost associated to refill (or to empty) storage units to match their initial state of charge. We consider that corresponding energy is purchased (or sold) at the cheapest tariff.

Definition 9. *The daily cost is defined as* $c^{daily} = c^{ebill} + c^{aging} + c^{soc}$.

Algorithm 1 Randomized algorithm inspired of [1]

$S \leftarrow \emptyset$ ▷ N-set i.i.d. samples to be drawn from W
for each kind of day D **do**
  let n^D be the number of D-days in year
  draw a set S^D of $\lceil \frac{n^D \times N}{365} \rceil$ samples of D-days
  $S \leftarrow S \cup S^D$
end for ▷ at this point $S = \{w^{(1)}, \ldots\}$ is a set of at least N samples, representative of every kind of day
for each $\theta \in \Theta$ **do**
  for each $w^{(l)}$ **do**
    compute the optimal sourcing strategy $u^*(\theta, w^{(l)})$
    simulate a day $w^{(l)}$ using $u^*(\theta, w^{(l)})$
    check if the constraints C are respected: $g(\theta, w^{(l)})$
  end for
  if $\sum_{l=1}^{N} g(\theta, w^{(l)}) = 0$ **then** ▷ θ is feasible
    compute $J(\theta)$ ▷ the objective function value for θ
  end if
end for
keep the feasible θ for which $J(\theta)$ is minimal

5.1 Which Storage Units to Avoid Power Peaks?

In this sub-section, suppose that the objective is to sell our control solution to a customer admitting a very big annual penalty if he purchases electricity from the grid over a given power value p_{max} more than a given number of days during the year. Thus, we want to ensure (with a confidence of $1 - \delta$) that there is probability lesser than η to exceed the power value p_{max}. Among solutions satisfying this condition, the most profitable solution should be chosen.

The theory presented in Section 4 is used to decide which storage units the customer should buy to be certified to achieve his goal. In this experiment, we consider that the customer subscribes to a peak / off-peak tariff and uses our LC that reduces power peaks coupled with our SO. Now let us define:

- a function $f(\theta, w, u^*)$ that gives the daily cost c^{daily} obtained by the local controller at the end of the day, depending on: θ the considered design parameter, w the daily scenario, and u^* the strategy pre-computed by SO.
- a set $\mathcal{B} = \{3000, 6000\}$ of possible battery energy capacities (in Wh).
- a set $\mathcal{S} = \{60, 120, 180\}$ of possible supercapacitor energy capacities (in Wh).
- a set $\mathcal{F}$ of maximal daily costs certified to the customer (in €).
- the resulting set of design parameters $\Theta = \mathcal{B} \times \mathcal{S} \times \mathcal{F}$, and $\theta \in \Theta$ a vector with $n_\theta = 3$ components; the first component is the battery capacity, the second is the supercapacitor capacity, and the third is the corresponding certified daily cost.
- the design constraint c_1, that states the maximum power peak from (or to) the grid should be below p_{max},

$$c_1 : \max_{t \in \{0, \ldots, H\}} (|p_4(t)|) \leq p_{max}$$

- the design constraint c_2, that states the net daily gain should be above the third component of the design parameter:

$$c_2 : \ f(\theta, w, u^*) \leq \theta_3$$

- the resulting set of design constraints $C = \{c_1, c_2\}$
- $J(\theta) = \theta_3$, a maximum daily cost allowed
- the maximum power peak allowed is $p_{max} = 6000$ W
- representativeness and confidence probabilities are $\eta = 0.05$, $\delta = 0.05$, and the corresponding number of drawn samples is $N = \lceil \frac{1}{\eta}(\frac{e}{e-1})(ln \frac{n_C}{\delta}) \rceil = 152$

These parameters given, the optimization problem (1) is solved. Let us note that, in practice, the third component of the design parameters does not have to be introduced. Indeed, θ_3 can be chosen as $\max_{w^{(l)} \in S} f(\theta, w^{(l)}, u^*)$.

In the context studied (chosen elevator, storage units yield, etc), the following report could be done to the customer.

"The smallest supercapacitor (60Wh) does not permit to avoid all consumption peaks above 6 kW. Thus, the best choice is the 3 kWh battery and the 120Wh supercapacitor, because they have the smallest investment cost, avoid peaks, and have the same daily cost as every other case: 0.49 €. For the sake of the comparison, the mean daily cost of a business as usual controller in the same case is 0.33 €. Thus, we can certify (with probabilities given above) that avoiding peaks above 6 kW will cost at most 16 euro cents more per day than with a classical controller."

Note that: 1) the mean daily cost computed on the 152 samples is 0.32 €, far better than the certified value (money is saved actually), 2) these results were obtained without considering reselling energy to the grid, reselling will be considered in the next subsection, 3) as the tariff gap grows, the daily cost induced by the MinPeaks LC decreases.

5.2 Which Tactic and Tariff to Get Savings?

Now, let us consider a case where a customer already has storage units (required for safety reasons) and wants to use them to improve his energy bill. Several control solutions, and electricity tariffs, must be compared to tell this customer which ones are the best for him. The customer wants to show that over period of a given length, gains have been made. For that purpose, let us define:

- a set $\mathcal{T}$ of possible electricity tariffs: $\mathcal{T} = \{$flat (0.00013), peak/off-peak (0.00015 / 0.00010), indexed on spot with the same coefficient for both purchase and sale of energy (between 0.0002991 and 0.0009386)$\}$ (€/Wh). These tariffs are representative of those can be found in France. The flat tariff is cheaper than the others but does not allow a customer to take advantage of his storage units by shifting consumption or inject into the grid. The peak/off-peak tariff is cheaper than the flat one during off-peak hours (18:00 - 9:00) and more expensive otherwise. The indexed on spot tariff is more expensive than the others but varies significantly every hour and remunerates the injection of energy at a high value.

- a set $\mathcal{C}$ of possible controllers (introduced in [5]): $\mathcal{C}$ = {MinPeaks LC that reduces power peaks following strategic instructions from SO, Opportunistic LC that minimizes dissipated energy, Secure LC that does not use storage units at all}. The MinPeaks LC is coupled with the strategic optimizer to take advantage of the storage units to smooth power peaks. The other controllers are on their own to reduce the installation cost of the solution, while achieving savings, or reducing costs.
- a set $\mathcal{M}$ of possible maximum power values from and to the grid: $\mathcal{M} = \{[-50000, 0], [-50000, 20000]\}$ (W). The first possibility deny re-selling electricity to the grid, while the second one allows re-selling.
- a set $\mathcal{F}$ of maximal daily costs that could be certified to the customer (in €)
- the resulting set of design parameters $\Theta = \mathcal{T} \times \mathcal{C} \times \mathcal{M} \times \mathcal{F}$, and $\theta \in \Theta$ a vector with $n_\theta = 4$ components
- the design constraint $c^{'}$, that states the daily cost should stay below the 4th component of the design parameter:

$$c^{'} : \; f(\theta, w, u^*) \leq \theta_4$$

- the resulting set of design constraints $C^{'} = \{c^{'}\}$
- $J(\theta) = \theta_4$, a maximum daily cost allowed
- Two probabilities $\eta = 0.05$, $\delta = 0.05$, and $N = \lceil \frac{1}{\eta}(\frac{e}{e-1})(ln\frac{n_C}{\delta})\rceil = 187$.

In this context, we would give the following report to the customer.

"A business as usual controller that does not use storage units achieves a daily cost of 0.58 € with the flat tariff; while a daily cost of 0.25€ is achieved when re-selling is allowed, with the peak/off-peak tariff.

If re-selling is not allowed, the Opportunistic LC coupled with the peak/off-peak tariff should be chosen. The associated certified cost is 0.27 € per day while the average cost obtained is -0.03 € (which is actually a gain).

If re-selling energy to the grid is allowed, the indexed on spot tariff should be chosen, along with the MinPeak LC coupled with SO. The corresponding certified daily cost is -0.09 € per day. That means that the elevator operational cost and the storage units investment cost are compensated by the gain on electricity bill. Moreover the mean daily cost obtained on those samples is -1.24 €."

6 Conclusion

In this paper, a way to certify, under uncertainties, savings achieved by a control method for a multisource elevator, is proposed. This Certification Framework is based on a randomized algorithm and its associated bound on the number of needed drawn samples, proved in [1].

Using this algorithm, a certified bound on the maximum power peak purchased from the grid by a multisource elevator can be given, as well as a lower bound on the savings achieved. Such a solution could be used by a building manager to participate in the demand-response market. In the same way, a customer can be told the best control solution he should buy for his multisource elevator, and be certified of the minimum economical gain induced.

The experiments show that power peaks can be avoided and a multisource elevator can be made energy cost-free, though this is strongly dependent on the context. The key point of the method presented is the possibility to find the best design in a given context, and the ability to certify the associated savings. This allows a manager to arbitrate if the chosen design worth to be installed or not.

Future work will be focused on the influence of the kind of building and elevator on the potential savings. A real-life experiment would have to be conducted to enforce computation results.

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