

# Multisource elevator energy optimization and control

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**Abstract**—Nowadays, elevators are equipped with storage devices to ensure autonomy in case of grid failure. This paper presents a method that takes advantage of these storage devices to optimize energy consumption and cost. The optimization is achieved by two controllers: a high-level one (using linear programming) and a low-level one (using simple rules). Preliminary results indicate that this method is 35% better than a naive rule-based approach in our context.

## I. INTRODUCTION

New generations of lifts are equipped with energy storage (i.e. batteries and/or supercapacitors) to allow a minimum of autonomy in case of general power failure. This autonomy is crucial for safety (e.g. to evacuate people with reduced mobility) but energy storage may also offer flexibility in power management. It could be used to decrease the energy bill and environmental impact. For instance, the energy produced when the lift brakes may be stored instead of evacuated through resistors; photovoltaic panels can be added; and the energy stored may be used to avoid buying from the grid during peak electricity-use hours.

Reducing energy demand from buildings is a crucial need and a major topic for scientific community and industry. Optimizing the energy consumption of elevators is part of this trend. As we can see in [1], there are many opportunities for improving the energy efficiency of elevators, and most of the research concern the physical parts of an elevator. Literature offers a set white papers dedicated to the (real time) control of multiple sources of energy. On our side, we chose to work on the optimization of a multisource energy system powering an elevator, relying on the cooperation between several levels of control. The work has been conducted by Schneider Electric and the Gipsa-lab, in connection with Sodimas, Grenoble INP and the CEA, and in the scope of the Arrowhead European project.

This paper is organized as follows. Section II provides an overview of work relative to energy optimization for elevators that can be found in the literature. Section III

presents the multi-level optimization system we developed. Section IV presents preliminary results we obtained on the basis of a use case defined by the Sodimas elevator company. Finally, Section VI concludes the paper and introduces future work.

## II. STATE OF THE ART

Energy optimization systems have been widely studied in the literature, especially in the past few years. Several methods have been proposed to optimize a multi-source energy system for elevators: rule-based algorithms, fuzzy logic, neural networks, dynamic programming techniques and model predictive control.

Among them, Paire *et al.* have designed a physical multi-source system to power an elevator. The authors use the associated rule-based control method presented in [2]. In the paper, rules are used to charge or discharge batteries depending on whether the electrical current is below or above a given reference. This control method may be reduced to a simple “if, then, else” structure achieved by physical components. This method allows to control very reactively the system but it cannot take into account external considerations such as the electricity tariff or battery state of health. Therefore, this control method may not be efficient regarding economical objectives.

Bilbao and Barrade [3] have proposed a General Energy and Statistical Description (GESD) of the possible missions of an elevator and a dynamic programming-based energy manager. The GESD describes all possible missions of an elevator in terms of energy requirements and probability of occurrence. Their dynamic programming-based 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 when data are known in advance. But elevator usage is unpredictable by nature (especially on a short time period) and this strategy computed off-line has to be updated in case of an unplanned usage of an elevator.

This work has been partially funded by the Artemis Arrowhead project under grant agreement number 332987 (Artemis/Ecsel Joint Undertaking, supported by the European Commission and French Public Authorities).

Finally, in [1], authors summarize different ways to optimize choices of elevator physical components (motor, drive, etc). An appropriate sizing of these components is a way to optimize energy consumption but it should be coupled with a good control algorithm of multiple sources of energy.

From these observations, we have decided to propose a two-level control system of several energy sources. This system can achieve reactive control of low-level equipment and take into account long-term economical objectives like reducing the energy bill and increasing the batteries lifetime. The contribution of this paper is to propose a system that choose in real-time which sources of energy should supply an elevator depending on future travels and energy tariff.

### III. THE PROPOSED ENERGY OPTIMIZATION SYSTEM

This energy optimization system was described for the first time in [4]. This paper was focused on the whole system and the interactions between the components. The present paper intends to present more specifically the controllers. However, this section is briefly describing the whole system to give to the reader an overview of the context.

The objective of our energy optimization system is to reduce the global bill by minimizing energy costs and optimizing the life of storage devices. We need to decide what to do with the energy in real time: select the best energy sources. Figure 1 shows relations between several components having a role in the optimization process.

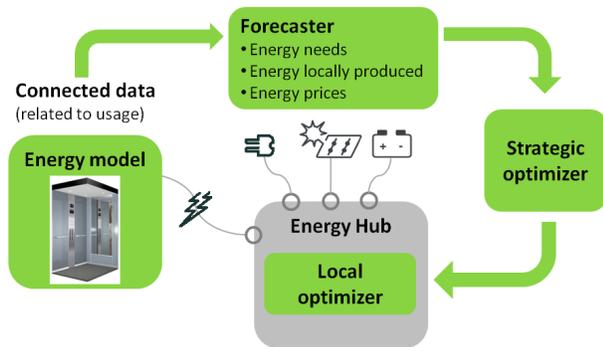


Fig. 1. Software components of our energy optimization system

Firstly, the elevator must be connected to an “energy hub” that allows to use energy from multiple sources. In our application, the elevator can get energy from the grid, a battery, a supercapacitor and a solar panel. A controller is implemented in the energy hub. We call this controller the “local controller”. It must be embedded and highly reactive, and thus it cannot compute the best sourcing strategy on a long time frame.

Therefore, we decided to add a second controller, which we call the “strategic controller”, that computes a guideline on a long timeframe to charge/discharge the battery and to purchase energy from the grid at a reasonable cost according to forecasted energy prices, solar production and energy usage. This strategic controller relies on a forecaster that gives: (i) the predicted amount of energy consumed/produced

by the elevator, (ii) the predicted irradiance, (iii) the predicted energy price. The strategic controller provides set points to the local controller that computes the best trade-off between these set points and the actual energy demand. Indeed, the strategic controller is based on usage forecasts but as elevator travels are by nature unpredictable on a short timeframe, some strategic instructions may be infeasible at some points.

The forecaster is responsible for anticipating the energy needs. Forecasts are built on demand of the strategic controller. Currently the latter asks for the near future prediction (with a one-day timeframe and a 15-minutes timestep for example). The prediction of the energy amount produced or consumed by the elevator is computed from the historical travel data and an energy model. The prediction of the renewable energy production is computed from a weather prediction and a basic solar panel model. The prediction of the energy tariff is only a projection of the energy contract on a specific time. All these predictions are aggregated on a chosen timestep (15 minutes for example).

Although we have not reached final implementation of the whole system, we are able to coordinate all of these components and generate an appropriate strategy for the elevator. In the two following subsections, we describe in details the two controllers.

**Remark** The implementation of two coupled controllers is due to the gap between (i) the time scale relevant for the energy hub real-time control and (ii) the time scale relevant to take into account the energy tariff variations to build a storage strategy.

#### A. The strategic controller

The problem solved by the strategic controller consists of finding the best sources of energy to be used (also considering storage capabilities) during a long timeframe (typically several hours). In practice, the strategic controller computes series of ideal power set points, i.e. a set point for the battery charge/discharge, and a set point for energy to be bought from the grid.

The goal is to minimize costs related to energy purchasing and battery usage within the timeframe. As stated in Section II, such objectives are usually fulfilled by a simple rule-based (physical) controller or by a complex dynamic programming strategy planner. At the opposite, we have chosen as a model a linear optimization problem (model predictive control) in order to solve the problem with multiple objectives quickly.

We use three decision variables :  $u_s[t]$  the amount of energy charged in the battery between time  $t$  and time  $t + \tau$  (with  $\tau$  the timestep between two set points);  $u_d[t]$  the amount of energy discharged from the battery between time  $t$  and time  $t + \tau$ ; and  $u_{pc}[t]$  the amount of energy purchased from the grid between time  $t$  and time  $t + \tau$ .

**Remark** We introduce two different variables for the battery because in our model, there are two different yields that impact the charge and the discharge.

Thus, our theoretical economical objective is the following:

$$\text{Min} \sum_{i=1}^{i \leq H} \left[ c_e[t_i] \times u_{pc}[t_i] + \frac{c_{bat}}{2} \times u_s[t_i] + \frac{c_{bat}}{2} \times u_d[t_i] \right] \quad (1)$$

where  $H$  is the time horizon of the control function,  $c_e[t_i]$  is the electricity price at time  $t_i$  thus  $c_e[t_i] \times u_{pc}[t_i]$  is the electricity bill for the  $i^{th}$  period;  $c_{bat}$  is a coefficient that allows to have a linear approximation of the impact of battery usage on its aging:  $c_{bat} = \frac{c_{inve}}{c_{cye} * c_{ce}}$ .  $c_{inve}$  represents the investment cost of the battery;  $c_{ce}$  is the energy capacity of the battery and  $c_{cye}$  is the maximum number of cycles that the battery can bear.

**Remark** Several ways to introduce the aging cost of using a battery could be used but we want the strategic controller to compute a strategy quickly, so we used a linear cost.

We also consider that the supercapacitor connected to the energy hub is not controllable (in this way, the formulation is applicable to any elevator multi-source system, even if a storage device is not coupled with an actuator). Thus, we need to forecast its behavior in the Linear Program with two variables:  $w_{ps}$  for the amount of energy charged in the supercapacitor and  $w_{pd}$  for the amount of energy discharged. These variables are introduced in the LP as slack variables. In this way, we can simulate the behavior of a supercapacitor that balances remaining energy on the energy hub.

Moreover, a minimum energy amount must be kept into the battery in order to ensure autonomy in case of grid failure. We cannot ensure that with a hard constraint because we need to allow consuming this reserve during a grid failure. Thus, we use a soft constraint (introduced later) with a slack variable  $\rho_{e,min}[t_i]$  that is minimized in the objective function. This lead to use the following objective:

$$\text{Min} \sum_{i=1}^{i \leq H} \left[ 10000 \times c_e[t_i] \times u_{pc}[t_i] + 10000 \times \frac{c_{bat}}{2} \times u_s[t_i] + 10000 \times \frac{c_{bat}}{2} \times u_d[t_i] + 0.0001 \times w_{ps}[t_i] + 1000000 \times \rho_{e,min}[t_i] \right] \quad (2)$$

The following constraints must be taken into account.

- A minimum energy amount must be kept into the battery.

$$x_e[t_i] + \rho_{e,min}[t_i] \geq c_{autonomy} \quad (3)$$

where  $c_{autonomy}$  is the ratio of the battery state of charge that the elevator needs to consume in case of grid failure and  $\rho_{e,min}[t_i]$  is the ratio of the battery state of charge below the  $c_{autonomy}$  limit at the time  $t_i$ . The  $\rho_{e,min}[t_i]$  variables must be null except for the case of grid failure, so they are penalized in the objective function.

- The energetic equation on the DC bus must be satisfied: the sum of consumed energy at time  $t_i$  must be equal

to the sum of energy produced at time  $t_i$ .

$$u_{pc}[t_i] + u_d[t_i] + w_{pd}[t_i] + w_{pr}[t_i] + w[t_i] = w_{ps}[t_i] + u_s[t_i] + w_d[t_i] \quad (4)$$

where  $u_{pc}$  is the amount of energy purchased from the grid;  $u_d$  is the amount of energy discharged from the battery;  $w_{pd}$  is the amount of energy discharged from the supercapacitor (computed by the model as a slack variable);  $w_{pr}$  is the prediction of the amount of energy obtained from the solar panels;  $w$  is the prediction of the amount of energy produced (if positive) or consumed (if negative) by the elevator;  $w_{ps}$  is the amount of energy charged in the supercapacitor (computed by the model as a slack variable);  $u_s$  is the amount of energy charged in the battery; and  $w_d$  is the amount of energy dissipated through the resistor (computed by the model as a slack variable). We can see that we have two variables for charging and discharging the battery that appear in the same equation. However, we do not want to charge and discharge at the same time. But as we penalize these two variables in the objective function, in a optimal solution, at a given time, one of the variables will be null.

- The maximum power delivered by the grid must be respected.

$$u_{pc}[t_i] \leq c_{ppc} \times \tau_i \quad (5)$$

where  $\tau_i$  is the timestep and  $c_{ppc}$  is the maximum power delivered by the grid.

- The state of charge of the battery ( $x_e$ ) and the supercapacitor ( $x_p$ ), normalized between 0 and 1, must be updated at each timestep with the energy charged and discharged.

$$x_e[t_{i+1}] = x_e[t_i] + \frac{c_{rce}}{c_{ce}} \times u_s[t_i] - \frac{1}{c_{rde} \times c_{ce}} \times u_d[t_i] \quad (6)$$

where  $c_{ce}$  is the energy capacity of the battery and  $c_{rce}$  (resp.  $c_{rde}$ ) is the charging (resp. discharging) yield of the battery.

$$x_p[t_{i+1}] = x_p[t_i] + \frac{c_{rcp}}{c_{cp}} \times w_{ps}[t_i] - \frac{1}{c_{rdp} \times c_{cp}} \times w_{pd}[t_i] \quad (7)$$

where  $c_{cp}$  is the energy capacity of the supercapacitor and  $c_{rcp}$  (resp.  $c_{rdp}$ ) is the charging (resp. discharging) yield of the supercapacitor.

- The maximum charging/discharging power of the storage devices needs to be respected.

$$u_s[t_i] \leq \frac{c_{ce} \times \tau_i}{c_{tce}} \quad (8) \quad w_{ps}[t_i] \leq \frac{c_{cp} \times \tau_i}{c_{tcp}} \quad (10)$$

$$u_d[t_i] \leq \frac{c_{ce} \times \tau_i}{c_{tde}} \quad (9) \quad w_{pd}[t_i] \leq \frac{c_{cp} \times \tau_i}{c_{tdp}} \quad (11)$$

where  $c_{tce}$  (resp.  $c_{tcp}$ ) is the characteristic (dis)charging time of the battery (resp. supercapacitor).

Below, we summarize the linear program in vector form. Variables in bold are column vectors.

Let  $A$ ,  $B$ ,  $A'$  and  $B'$  be  $H \times H$  matrices :

$$\mathbf{A} = \text{diag} \left( -\frac{c_{rce}}{c_{ce}}, -\frac{c_{rce}}{c_{ce}}, -\frac{c_{rce}}{c_{ce}}, -\frac{c_{rce}}{c_{ce}} \right)$$

$$\mathbf{B} = \text{diag} \left( \frac{1}{c_{rde} \times c_{ce}}, \frac{1}{c_{rde} \times c_{ce}}, \frac{1}{c_{rde} \times c_{ce}}, \frac{1}{c_{rde} \times c_{ce}} \right)$$

$$\mathbf{A}' = \text{diag} \left( -\frac{c_{rcp}}{c_{cp}}, -\frac{c_{rcp}}{c_{cp}}, -\frac{c_{rcp}}{c_{cp}}, -\frac{c_{rcp}}{c_{cp}} \right)$$

$$\mathbf{B}' = \text{diag} \left( \frac{1}{c_{rdp} \times c_{cp}}, \frac{1}{c_{rdp} \times c_{cp}}, \frac{1}{c_{rdp} \times c_{cp}}, \frac{1}{c_{rdp} \times c_{cp}} \right)$$

Thus the linear program is the following:

$$\text{Minimize} \left[ \begin{array}{l} 10000 \times \mathbf{c}_e \cdot \mathbf{u}_{pc} \\ + 10000 \times \frac{c_{inve}}{2 * c_{cye} * c_{ce}} \times \mathbf{u}_s + 10000 \times \frac{c_{inve}}{2 * c_{cye} * c_{ce}} \times \mathbf{u}_d \\ + 0.0001 \times \mathbf{w}_{ps} + 1000000 \times \rho_{e,\min} \end{array} \right]$$

$$\begin{array}{lcl} \mathbf{u}_{pc} + \mathbf{u}_d + \mathbf{w}_{pd} - \mathbf{w}_{ps} - \mathbf{u}_s - \mathbf{w}_d & = & -\mathbf{w}_{pr} - \mathbf{w} \\ \mathbf{u}_{pc} & \leq & c_{ppc} \times \tau \\ \mathbf{x}_e^+ - x_e[t_1] + \mathbf{A} \times \mathbf{u}_s + \mathbf{B} \times \mathbf{u}_d & = & 0 \\ \mathbf{u}_s & \leq & \frac{c_{ce} \times \tau}{c_{tce}} \\ \mathbf{u}_d & \leq & \frac{c_{ce} \times \tau}{c_{tde}} \\ -\mathbf{x}_e^+ - \rho_{e,\min} & \leq & -c_{autonomy} \\ \mathbf{x}_p^+ - x_p[t_1] + \mathbf{A}' \times \mathbf{w}_{ps} + \mathbf{B}' \times \mathbf{w}_{pd} & = & 0 \\ \mathbf{w}_{ps} & \leq & \frac{c_{cp} \times \tau}{c_{tcp}} \\ \mathbf{w}_{pd} & \leq & \frac{c_{cp} \times \tau}{c_{tdp}} \\ 0 & \leq & \mathbf{u}_{pc} \\ 0 & \leq & \mathbf{w}_d \\ 0 & \leq & \rho_{e,\min} \\ 0 & \leq & \mathbf{u}_s \\ 0 & \leq & \mathbf{u}_d \end{array} \quad \left| \quad \begin{array}{lcl} 0 & \leq & \mathbf{x}_e \leq 1 \\ 0 & \leq & \mathbf{w}_{ps} \\ 0 & \leq & \mathbf{w}_{pd} \\ 0 & \leq & \mathbf{x}_p \leq 1 \end{array} \right.$$

### B. Local controller

The local controller is a piece of software that receives the strategic set points and controls in real-time the energy hub regarding these set points and the current situation.

Firstly, the strategic set points are used to set the amount of energy purchased from the grid and charged or discharged from the battery. Secondly, the supercapacitor is used to compensate the energy lack or profusion regarding the needs, the solar panel production and the previous decisions. Finally, if needed, lacking energy is purchased from the grid, while unusable available energy is dissipated through a resistor.

## IV. RESULTS

For now, we are simulating an elevator and an energy hub on Matlab and the forecaster is just reading predictions from a file. The strategic controller uses GLPK as linear solver. This system allows us to test our controllers on simulated data. Elevator usage data are given by the elevator company Sodimas. Below are some results that were computed based on the following assumptions:

- busy business day: elevator usage is quite high;
- elevator usage data follow a Poisson distribution;
- the current day is cloudy: irradiance is low following data given by meteociel (a weather data base : <http://www.meteociel.fr/>) for a November day in France; solar panels production is low;

- the energy tariff chosen is a peak/off-peak tariff (0.0001044€/Wh / 0.00030€/Wh); the peak period is between 9 a.m. and 6 p.m.;
- one of the storage devices used is a lead-acid battery with an energy capacity of 160 kWh and is controllable;
- the other storage device is a supercapacitor (designed for a power application); it has a 1 kWh energy capacity and is not controllable;
- finally, we consider 2 square meters of solar panels on the building roof.

We first present the results of our controllers, and compare them with a simple rule-based algorithm. All plots were smoothed in order to keep a point every 10 minutes; in this way, the understanding is simplified, but consumption peaks are no longer visible.

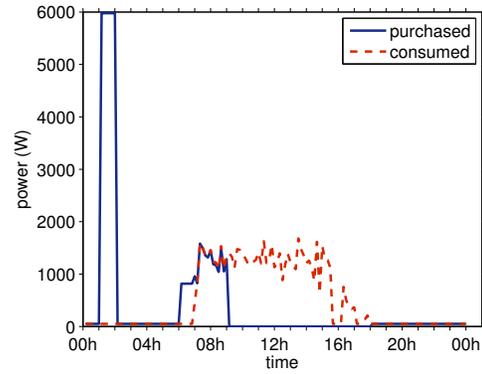


Fig. 2. Purchased vs. consumed energy

First of all, Figure 2 compares the power purchased from the grid and the power consumed by the elevator on a specific day. We can see that a lot of energy is purchased between 1 a.m. and 2 a.m. and between 6 a.m. and 9 a.m. and that energy is consumed all day long. This behaviour is due to the energy peak/off-peak tariff. Before 9 a.m., electricity is cheaper, thus the control system purchases energy from the grid before 9 a.m. and stores it in the battery.

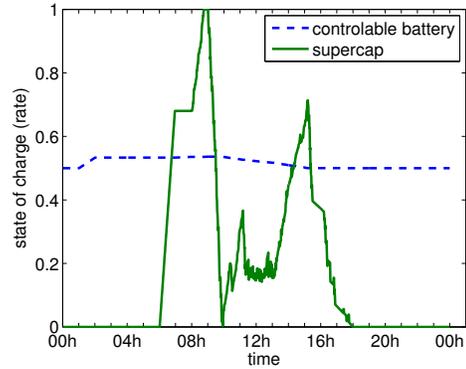


Fig. 3. Storage devices states evolution

Figure 3 shows the evolution of the storage devices state of charge during the day. We can see that the controllable

battery stays more than a half charged all the day long because 50% of its energy capacity is needed to ensure the security autonomy. At the opposite, the supercapacitor is emptied to supply the elevator during the day. It is also used as a buffer but this is poorly visible on this plot because of the smoothing.

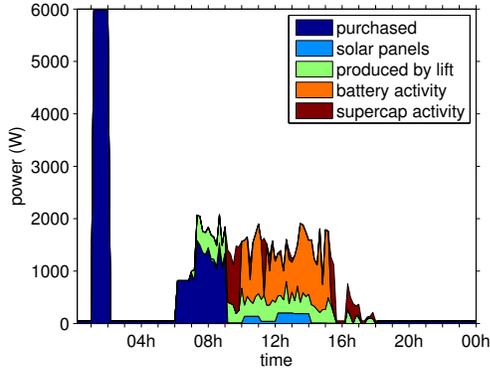


Fig. 4. Different sources of energy used during the day by the strategic controller

Figure 4 details the different sources of energy used during the day. The figure is a layers plot in which each color represents the contribution of a different source to the global quantity of energy needed. We can see that before 9 a.m., almost all energy needed is purchased from the grid, whereas between 9 a.m. and 6 p.m., all energy needed is provided by storage devices and solar panels.

Solar panels directly supply the elevator when it is possible and otherwise supply storage devices. The energy recovered when the elevator brakes, as the energy previously purchased, is entirely used to charge the storage devices.

At the end of such a simulated day, we can split consumed energy into purchased, recovered, and produced by solar panel energy. In fact, during this simulation, almost a quarter of consumed energy was recovered from the lift through storage devices.

Now let us see the results of a simple rule-based controller in the same context. The rule-based controller was implemented to initially use the controllable battery, then let the non-controllable supercapacitor do its job and finally purchase energy from the grid if needed. We can observe in Figure 5 that energy is purchased all day long. This is because the rule-based controller is reactive, unlike the strategic controller, which is predictive.

**Remark** We could improve this controller in order to take into account the variations of energy tariff. But, along this way, we would not know when to stop trying to approximate an optimal control.

The second part of our experiments was dedicated to compare our control system to a simple rule-based one in different contexts described below. Ten tests were launched for each context and means are presented.

Table I presents the results of these tests. The first column indicates which method was used to solve the problem. The

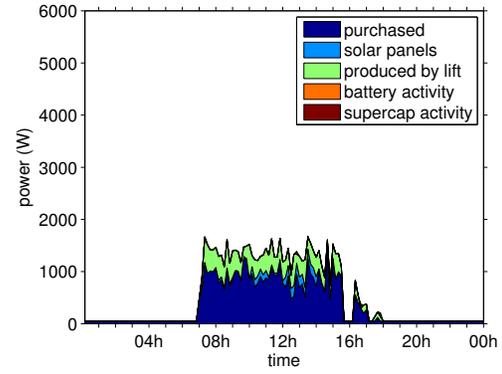


Fig. 5. Different sources of energy used during the day by the rule-based controller

TABLE I  
COMPARISON BETWEEN OUR METHOD AND A RULE BASED ONE

optimization method	uncertainty	electricity bill vs cost of all energy used	battery usage cost vs investment cost
proposed method	0%	34.4%	0.0060%
proposed method	10%	47.3%	0.0049%
proposed method	50%	51.3%	0.0046%
rules	-	70.4%	0%

second column indicates the percentage of uncertainty used to generate forecasts (explained below). The third column shows the electricity bill at the end of the test as a percentage of the electricity bill that would be obtained if no battery was used (worst case). Lastly, the fourth column shows the battery usage cost at the end of the test as a percentage of the battery investment cost.

We decided to introduce different sources of uncertainty in forecasts in order to quantify the robustness of our method:

- uncertainty as to the number of elevator travels,
- uncertainty as to the duration of the travels,
- uncertainty as to the amount of energy consumed/produced during the travels.

For these tests, a single uncertainty parameter was taken for all these uncertainty sources for the sake of the simplicity. However, we could have taken three different parameters to adjust uncertainty sources as we want. When the parameter is  $X\%$ , it means that for each elevator travel, there is an  $X\%$  chance that the travel was not considered in the prediction; there is an  $X\%$  chance that an extra travel that does not actually occur was considered in the prediction; and that all the parameters are unknown with  $X\%$  uncertainty. Then, the error is uniformly drawn between  $-\frac{X\%}{2}$  and  $+\frac{X\%}{2}$  of the real value. Note that the simple rule-based controller does not take into account forecasts so it is not influenced by uncertainty.

The first row is the reference solution: our method was tested without uncertainty. The strategic controller computed the best guideline just one time at the beginning of the simulation for the whole simulation. Because there was no

uncertainties, the solution is the optimal one. The electricity bill was 34.4% of the worst case in which the energy needed is entirely purchased. This means about 65% of the bill is saved. The battery usage cost (relative to battery ageing) was 0.006% of the battery purchase cost. In fact, the electricity bill represents a cost much greater than the battery usage cost.

The second and third rows represent results of our method in a context of uncertainty. These tests were performed with respectively 10% and 50% as uncertainty parameters. The strategic controller was called every 5 minutes with a 12 hours time horizon. Furthermore, forecasts were aggregated on 15 minutes periods in order to reduce the impact of uncertainties on the quality of the strategy. Note that when uncertainty is high (50%), our method results in an electricity bill that is 51.3% of the worst case and a battery usage cost that is 0.0046% of the worst case. This result is (obviously) worse than the result in the first row but reasonably good compared to the worst case.

The last result is for the rule-based controller. It gives an electricity bill that is 70.4% of the worst case.

For the purpose of these tests, we used a peak/off-peak electricity tariff, with a factor three between the peak and the off-peak cost. It allows our optimizer to take a great advantage of the difference between electricity costs. With a typical French tariff, the results of our method would be closer to the results of the naive one. But we could take advantage of a better yield of the battery. These first tests (to be complemented by others) suggest that our method is better than the naive one and relatively robust with respect to uncertainty.

These tests were launched on a Dell precision M4700 laptop computer with a 3.00GHz processor. About 15 minutes were needed to simulate a typical day in real conditions (with uncertainties, the strategic controller is launched every 5 minutes with a 12 hour time horizon). This is encouraging for future tests on a real elevator system. The strategic problem used in this case had 578 decision variables.

## V. OUTLOOKS

As future work, we will support piece-wise linear energy cost in order to penalize consumption peaks. We will improve the forecasting of energy demand (relying on real usage data). We will also try to improve the robustness of the proposed method towards uncertainties.

The local controller is currently a simple rule-based algorithm. In the next versions of this energy optimization system, the local controller could be implemented either as several distributed components on each physical equipment or as a physical rule-based controller on the energy hub only. We could use as a guide the work of Lagorse et al. [5] who put in place a multi-agent control on a multisource system (grid, resistors, solar panel, battery and supercapacitor); they use the grid only when there is no other solution and then minimize the energy bill.

Furthermore, we could investigate using a better battery model. For example, in [6], a multipass dynamic program-

ming technique allows to reduce the energy bill while extending the life of the storage devices; a non-linear chemical battery model is used. We could also optimize the usage of multiple storage devices with an appropriate controller. For example in [7], a model predictive control method is used to optimize energy storage. While in [8], authors explain how to build a policy to change the battery in use among a set of available storage devices in order to approach optimal efficiency (that would be obtained with a huge battery which would meet all the needs); they model the problem as a Markov decision process.

We could also investigate the optimal choice and sizing of energy production systems and storage devices like in [9]. Finally, we could involve users and building managers in the energy saving system like in [10].

## VI. CONCLUSION

In this paper, we have presented a two-layers optimization of multiple sources of energy for an elevator. We modeled the problem of finding the best sourcing strategy with a linear formulation. This allows to compute a strategy quickly and gives better results than a simple "if-then-else" algorithm often used in the literature. First results suggest that the savings could be attractive: during a test day, 24% of the energy needed by the elevator was recovered from braking and 35% of the electricity bill was saved in the better case. However, the reader should note that we have experimented our system with an off-peak electricity tariff three times cheaper than the peak tariff.

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