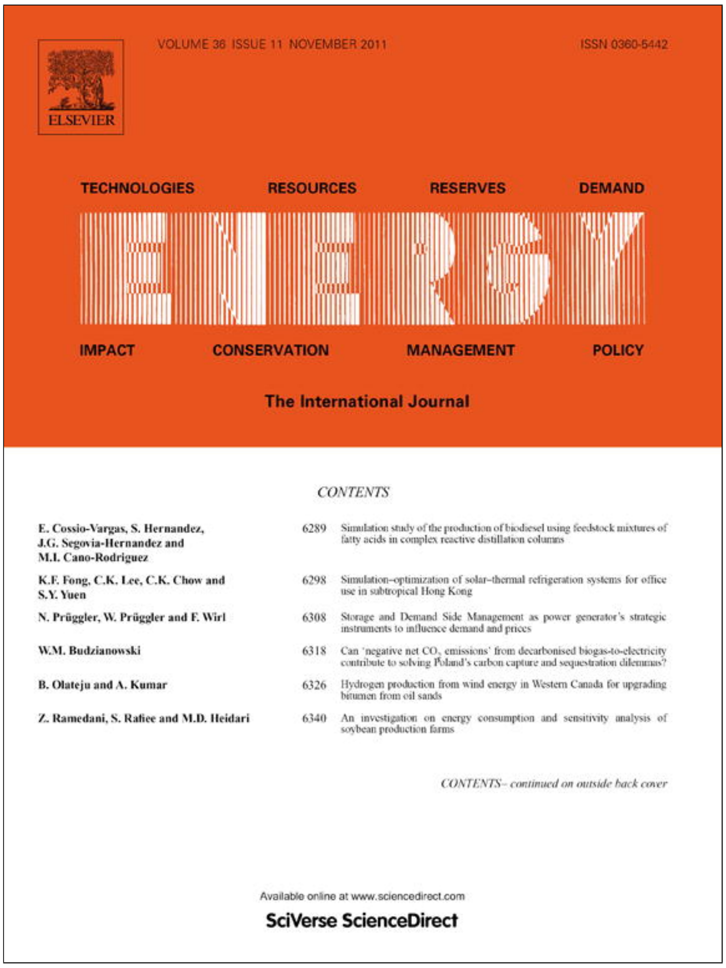
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A statistical approach to electrical storage sizing with application to the recovery of braking energy

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ABSTRACT

In the context of efficient energy use, electrical energy in electric drives plays a fundamental role. High efficiency energy storage systems permit energy recovery, peak shaving and power quality functions. Due to their cost and the importance of system integration, there is a need for a correct design based on technical-economical optimization. In this paper, a method to design a centralized storage system for the recovery of the power regenerated by a number of electric drives is presented. It is assumed that the drives follow deterministic power cycles, but shifted by an uncertain amount. Therefore the recoverable energy and, consequently, the storage size requires the optimization of a random cost function, embedding both the plant total cost and the saving due to the reduced energy consumption during the useful life of the storage. The underlying stochastic model for the power profile of the drives as a whole is built from a general Markov chain framework. A numerical example, based on Monte Carlo simulations, concerns the maximization of the recoverable potential energy of multiple bridge cranes, supplied by a unique grid connection point and a centralized supercapacitor storage system.

1. Introduction

Storage devices have long been common in power systems: let us just mention their use in continuity devices and, more generally, their applications in residential or similar appliances.

Presently, new scenarios are disclosing and new needs are emerging, which let foresee an increasing diffusion of storage systems for the future, also considering the ongoing technological advances in this sector. Supercapacitors are particularly promising either as substitutes of traditional storage devices or as a complement to them or to other types of storage, such as fuel cells, with the aim of reaching the required energy and power performances by means of an optimal system sizing, with respect to both energy profile and duration [1–7].

Supercapacitor technology seems to be very promising in those applications where power supply and absorption are required for small time intervals. Compared to the now common lead storages, supercapacitors feature clear superior power density, efficiency and number of charge-discharge cycles. Under the energy profile, among applications that could undoubtedly benefit from the presence of storage devices, there are the many drives characterized by work cycles where power withdrawal and braking alternate with high frequency: in particular this category includes lifting devices, spinner power suppliers, metropolitan trains [8–11] and electric and hybrid vehicles [8,12–14].

Kinetic or potential energy stored in moving parts can be directly used during braking for supplying power to other drives of the same plant, whereas the excess energy, rather than dissipated or sent into the public distribution network, con be stored in supercapacitors: such energy would be made available for the phases of the work cycle during which the drives as a whole absorb power from the public network.

The expected gains are not only energy recovery, and thus energy savings, but also the reduction of peaks of power demand from the network. The alternative solution of sending all the recoverable energy directly into the public distribution network would be strongly penalized by its modest remuneration, given its availability pattern.

In this article we address the problem of sizing a storage system shared by a number of drives, characterized by given power profiles, under the assumption that they are equipped with converters for the direct recovery of braking energy and that the storage is formed by batteries of supercapacitors.

The identification of the size of storage devices and of rectifiers and converters is a delicate point of a plant design and, when many

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drives are present, it should be addressed with a probabilistic approach [15–22]. The main reason for this is that the drives can combine their work cycles in many different ways, so that the power balance at any given time, that is, the difference between the total absorbed power and the total braking power, can vary widely and often randomly.

Our modeling derives from the acknowledgment that the opportunity of including a storage system in the plant design has to be evaluated in the framework of a life-cycle cost assessment: the money saved from energy recovery should outweigh the cost of a storage system during its useful life. Therefore one has to assume a usage pattern of the drives over time covering the life-cycle. Our approach is to subdivide the life-cycle time into disjoint and adjacent intervals (the *epochs*), such that the only information passed to any epoch from the preceding one is the charge level of the storage system at the end of it. Then, the energy recovered in any epoch depends on this level and on a random mechanism governing the work cycle of the drives. This type of dynamic is Markovian, and, after specifying the random mechanism at work in each epoch, we have a tool for calculating the probability distribution of the total cost of a designed plant, for a given storage size and a rated power of rectifiers and converters. An appropriate comparison of the probability distributions arising from different settings will finally allow to choose the configuration with the smallest life-cycle cost.

In the next section we illustrate a paradigmatic application to bridge cranes. In Section 3 we first develop the general stochastic model for the recovered energy and then we propose an instance of the model so as to characterize the probability distribution of the cost function. In Section 4 we introduce a general form of the cost function to be minimized and, after assigning the specific cost parameters, we proceed to optimization.

2. An application: bridge cranes

Bridge cranes have typical load cycles characterized by a relative low mean power despite of the peak power exchanged during the absorption and braking phases. As shown in [23], due to the inability of the main supply to absorb power from the user, the braking electrical energy can be recovered in a storage system to be used in the next absorption phase, with a consequent reduction of the absorbed energy and peak power from the main grid. In addition, due to the typical high number of working cycles, attention has to be paid in designing the appropriate electrical storage system to optimize the entire system cost.

In [23] design criteria of a storage system based on supercapacitor technology are considered in the case of a single load. The aim of our work is to present a methodology to design a centralized storage system when multiple electric drives are supplied by the same main supply. The plant configuration is reported in Fig. 1.

It consist of a single front-end rectifier with the main grid, an inverter for each induction motor and a centralized storage system connected by a bidirectional DC–DC converter to the DC bus of the inverters to recover the braking energy of all electric drives.

In a bridge crane two typical power profiles can be defined:

1. A traction profile to accelerate and brake the entire system;
2. A lift profile to move up and down the loads.

The case study, without losing generality, considers only the second profile. In Fig. 2 the reference power profile of a single motor drive is shown.

In Fig. 2, P1 represents the power absorbed by the motor drive during uplift, while P2 is the power regenerated in the opposite phase. The regenerated power is lower than the absorbed power, to take into account the global efficiency, which is lower than 1. Each

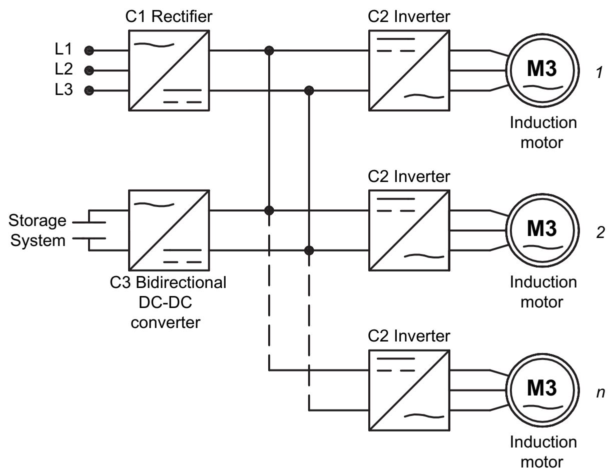

Fig. 1. Electric scheme of multiple bridge cranes supplied by a single main supply and a centralized storage system.

electric drive in Fig. 1 has the same fixed power profile, which is shifted randomly by an amount lower than the time period *T*. The storage system design has to take into account:

1. The cost of each component, with particular attention to the storage system;
2. The contractual electrical energy and power cost;
3. The storage system lifetime.

To maximize saving, it makes no sense to design the storage system to recover all the energy from the electric drives in case all of them are regenerating at the same time, because this event has low probability. The study, consequently, has to consider a statistical approach to determine the probability distribution of the amount of recoverable energy. In this way, the optimal economical solution would take into account the incremental saving relative to the incremental volume of the storage system. From an economical point of view, it is sensible to waste a certain amount of recoverable energy to maximize the entire system saving, because this means a smaller storage system.

The next section shows a methodological approach that is independent of the specific application and the storage system technology.

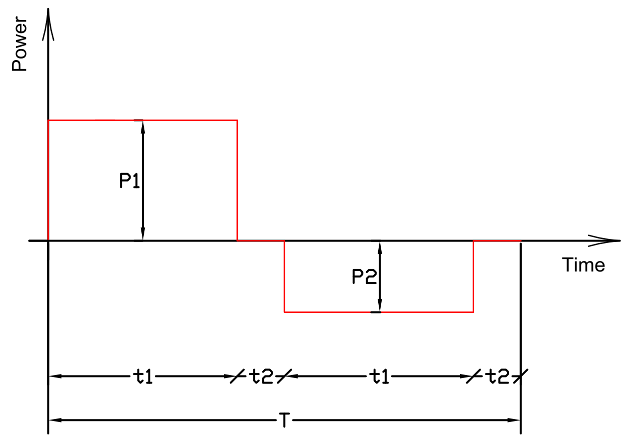

Fig. 2. Reference lift profile of a bridge crane.

3. A stochastic approach to storage system sizing

3.1. A general framework for the analysis of total recoverable energy

The total energy recoverable by a centralized storage system shared by a number of drives is a random function depending on the combination of the power cycles of the different loads. Its evaluation, related to the storage level during cycling, is very important to define the amount of saved money for any given storage size.

The joint stochastic process of the energy recovered and of the storage level can be described in some generality to cover a spectrum of situations broader than the specific application of Section 2.

In fact, let us subdivide the time axis into equal intervals of length L, starting at time zero, so that the interval indexed by t would be $[tL, (t+1)L)$, as $t = 0, 1, 2, \ldots$. We call this interval an *epoch*. Now associate a pair (E_t, S_t) to each interval t, where E_t denotes the total amount of energy recovered and stored in the interval and S_t is the level of the storage at the end of the interval. (Notice that in general E_t may be lower than the total braking energy produced in the interval, whenever the storage capacity is lower than some threshold). Then S_t is obtained from S_{t-1} after subtracting the energy drawn from the storage during interval t and adding E_t, after multiplying by the appropriate discharge and charge efficiency factors.

Suppose L is chosen in such a way that work is done independently in intervals $[0, L)$, $[L, 2L)$, etc. and homogeneously, that is, with a random mechanism which is independent from t. Then, with a finite storage size, the total recovered energy during epoch t, E_t, depends stochastically only on the previous energy level in the storage, S_{t-1}, so that S_t depends only on S_{t-1} and E_t, and we can write

$$\Pr(E_t, S_t | E_{t-1}, S_{t-1}, E_{t-2}, S_{t-2}, \ldots) = \Pr(E_t, S_t | S_{t-1}) \qquad (1)$$

which means that the process (E_t, S_t) is Markovian. If the storage is infinite, then (E_t) is an independent sequence. Marginally, (S_t) is still homogeneous Markovian: letting $S_1^{t-1} = (S_1, \ldots, S_{t-1})$ denote the sequence of the storage levels up to epoch $t-1$, we find that the marginal density of S_t, depending on previous history S_1^{t-1}, is:

$$\Pr\left(S_t \middle| S_1^{t-1}\right) = \int \Pr\left(E_t, S_t \middle| S_1^{t-1}\right) \mathrm{d}E_t = \int \Pr(E_t, S_t | S_{t-1}) \mathrm{d}E_t = \Pr(S_t | S_{t-1})$$

(where the functional form of $\Pr(S_t \mid S_{t-1})$ does not depend on t). Therefore, the probability that the storage is found at a certain level S_t at the end of epoch t, conditionally on the past history of the storage levels, depends only on S_{t-1}. Then, by knowing $\Pr(S_t \mid S_{t-1})$, we can find the marginal stationary distribution $\pi(S_t)$ of the Markov chain (S_t) by solving

$$\pi(S_t) = \int \pi(S_{t-1}) \Pr(S_t | S_{t-1}) \mathrm{d}S_{t-1}$$

with respect to $\pi(S_t)$. The focus on the stationary distribution is appropriate in our case because we are interested in the long-term usage of the storage system.

Knowledge of $\pi(S_t)$ allows to derive the stationary distribution of E_t. In fact, because of the conditional independence relationship (1), the marginal distribution of E_t conditionally on the past is $\Pr(E_t \mid S_{t-1})$, which is found by integrating both terms with respect to S_t, and then

$$\pi(E_t) = \int \Pr(E_t | S_{t-1}) \pi(S_{t-1}) \mathrm{d}S_{t-1}.$$

Now, letting k be the number of epochs corresponding to the useful life of the storage, the total recovered energy is:

$$E_{\text{tot}} = \sum_{t=1}^{k} E_t .$$

Furthermore, let $\mu = \mathbb{E}(E_t) = \int E_t \pi(E_t) \mathrm{d}E_t$, the expected recovered energy in an epoch, and let $\gamma(h) = \mathrm{Cov}(E_t, E_{t+h})$, the covariance between recovered energies in two epochs at distance h, then, by the central limit theorem for Markov chains (see [24], Theorem 17.0.1) it follows that, approximately,

$$E_{tot} \sim N\left(k\mu, k\left\{\gamma(0) + 2\sum_{h=1}^{\infty} \gamma(h)\right\}\right) = N\left(k\mu, k\sigma^2\right)$$

where $N(\cdot,\cdot)$ denotes the Gaussian distribution with mean and variance given by its two arguments, respectively.

Therefore one can completely specify the probability distribution of E_{tot} by calculating the mean and variance parameters μ and σ^2, which depend on the Markov chain transition kernel (1). The mean is known as soon as the stationary distribution $\pi(E_t)$ is available, whereas the variance parameter depends on an infinite sum: if (E_t, S_t) takes value in a finite state space and the transition probability (1) between any two pairs is known, then closed-form expressions exist for σ^2 (see for example [25], Theorem 4.8). Although we present examples where the state space is indeed known to be finite, it will become clear that it is not straightforward to obtain both the elements of the state space and the transition kernel and consequently $\pi(S_t)$, $\pi(E_t)$ and finally the required mean and variance parameters. In view of this, since the main focus of this paper is to investigate whether it is worthwhile to equip the electrical drives with a centralized storage system, we will simulate a large number of epochs and calculate the mean and variance parameters by means of sample statistics, postponing analytical results to future research.

3.2. A more specific model

We present an example which is applicable to all the cases where there are n electrical drives, which work independently of each other, each one following the same cycle repeatedly. The duration of a cycle is denoted by T, which will be referred to as the *basic period*. An epoch $[tL, (t+1)L)$, indexed by t, is formed by an integer number of basic periods $m+1 = L/T$. Time is measured using integers, because we choose the time unit such that the power drawn or generated by a drive can be considered constant during a unit interval, but it is actually continuous.

In particular, without great loss generality and to facilitate exposition, we consider the power level during the absorption and regenerative phases as constant, using a fixed power profile. In principle, some degree of random variation of the power profile could be included in the Markovian transition kernel so that nothing is lost, as far as the methodological approach is concerned, by neglecting this additional randomness.

At the beginning of every epoch t every drive starts its cycle at a time selected randomly among $\{0, \ldots, T-1\}$, constituting a random shift, and repeats itself identically for m basic periods, so that $m+1$ is the smallest integer such that the m cycles are completed within an interval of length $(m+1)T$. The source of randomness in this system is given by the random shifts of the periodic histories of the n drives. We denote by S_t the state of a storage system at the end of epoch t; the storage recovers the braking energy of any drive that cannot be used immediately by another drive. By E_t we indicate the energy recovered using the storage in the same epoch. Then it is easy to see that we are in the framework of the previous section. The description of the system is completed by assigning a curve for the power exchanged by a drive during epoch t: first we define a curve $p(s)$ for the basic period, with $s = 0, \ldots, T-1$, then the curve is extended periodically to the entire epoch letting $p(s) = p(s \bmod T)$ for $s \geq T$ (the mod operator gives the rest of the integer division of s by T). In the following we consider a time unit of 10 s and a basic period duration of 120 s, so that $T = 12$, with the following power curve

$$p(s) = \begin{cases} 10\ \text{kW} & \text{if} \quad s = 0,1,2,3,4 \\ 0\ \text{kW} & \text{if} \quad s = 5 \\ -8\ \text{kW} & \text{if} \quad s = 6,7,8,9,10 \\ 0\ \text{kW} & \text{if} \quad s = 11 \end{cases} \tag{2}$$

Now let U_i be the random shift of drive i, then for any $s \in \{0, 1, \ldots, (m+1)T-1\}$ the power exchanged by this drive is

$$p_i(s) = \begin{cases} 0 & \text{if} \quad s < U_i \\ p(s-U_i) & \text{if} \quad s = U_i, U_i+1, \ldots, U_i+(mT-1) \\ 0 & \text{if} \quad s = U_i+mT, \ldots, (m+1)T-1 \end{cases}$$

A path of $p_i(s)$ for $m = 2$ and $U_i = 5$ is shown in Fig. 3.

The curve of total power for the n drives during epoch t is then given by

$$P(s) = \sum_{i=1}^{n} p_i(s)$$

and it is periodic with period T, repeating itself identically in periods $[iT, (i+1)T)$, as $i = 1, 2, \ldots, m-1$, but not in periods $[0, T)$ and $[mT, (m+1)T)$. Hence, any random quantity extracted from the power curve in subinterval $[T, 2T)$ is identical to that of any other subinterval forming the epoch, except for the first and the last ones. Observe that $P(s)$ gives the power balance at time s, which corresponds to the assumption that all the available power from regenerative braking is immediately drawn by drives requiring power. If $P(s) > 0$ then this power is drawn from the storage or from the network if the storage is empty; if $P(s) < 0$, the excess energy flows into the storage.

There are summaries of the power curve in interval $[T, 2T)$ that may be useful for a quick evaluation of the power exchanged.

The first summary is the probability distribution of $P(s)$, for any $s = T, \ldots, 2T-1$: its higher order percentiles give an indication about the maximal power rating of the rectifier. It can be easily shown that $P(s)$ is linked to a multinomial distribution. Denote by k the number of distinct power levels $(x_1, \ldots, x_k)$ of the basic power curve $p(s)$ and let $r_1, \ldots, r_k$ be the number of occurrences of each level in the curve (thus $\sum_i r_i = T$). Then

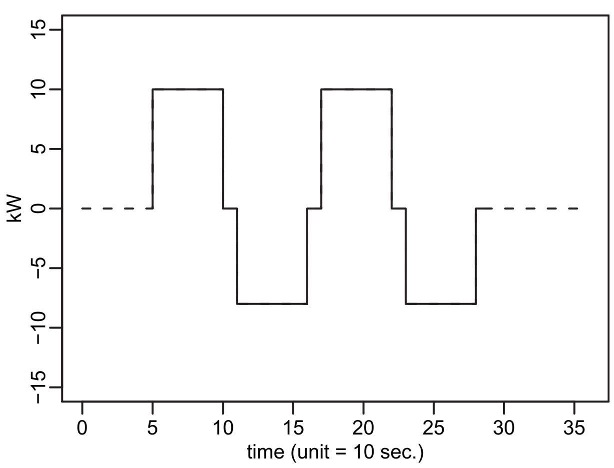

Fig. 3. Power curve with two cycles ($m = 2$), shift 5 and $T = 12$ during interval $[tL, (t+1)L)$, corresponding to $L = 3T = 36$. The two cycles are drawn in solid line.

$$P(s) = \sum_{i=1}^{k} N_i x_i \tag{3}$$

where $(N_1, \ldots, N_k)$ has a multinomial distribution with n trials, k cells and cell probabilities $(r_1/T, \ldots, r_k/T)$. From the moments of the multinomial distribution we find that

$$\begin{aligned} \mathbb{E}(P(s)) &= n \sum_{i=1}^{k} \frac{r_i}{T} x_i \\ \text{Var}(P(s)) &= n \left\{ \sum_{i=1}^{k} x_i^2 \frac{r_i(T-r_i)}{T^2} - 2 \sum_{j>i} x_i x_j \frac{r_i r_j}{T^2} \right\} \end{aligned} \tag{4}$$

and, if n is large, we can find any percentile of the distribution of $P(s)$ from the corresponding percentile of the standard normal distribution with mean and variance as given by (4), thanks to the central limit theorem. If n is small we can find percentile to any desired accuracy via Monte Carlo simulation from the multinomial distribution.

The second useful summary is the probability distribution of the maximal energy level an infinite storage can reach during $[T, 2T)$, when associated to inverters with an infinite power rating. A high probability interval from this distribution is a sensible region for searching the optimal storage size. We cannot give a closed-form characterization of this distribution as simple as the previous one, because the storage levels at any two time units in subinterval $[T, 2T)$ are not independent of each other. However, through Monte Carlo simulation of shifts $(U_1, \ldots, U_n)$ it is easy to obtain a random sample of maximal storage levels and estimate the percentiles by the corresponding sample statistics.

4. Cost function optimization

4.1. The cost function and the search region

With the application introduced in Section 2 and modeled in Section 3.2 we specify a (random) cost function and illustrate a method for finding the searching region of the minimum. Then, by means of stochastic simulation, we compute the probability distribution of the cost function on a set of points in the searching region and compare appropriate summaries in order to choose the best point.

The (random) cost function which we seek to minimize will have the following general form

$$\begin{aligned} C(S, P_{\text{conv.}}; E) = {} & C_{\text{contr.}}(P_R) + C_{\text{rect.}}(P_R) + C_{\text{stor.}}(S, P_{\text{conv.}}) \\ & - V(S, P_{\text{conv.}}; E) \end{aligned} \tag{5}$$

where terms on the right-hand side, taken in their order, indicate: the cost of the power supply contract, as a function of the peak power, represented by the rated power of the front-end rectifier with the main grid (P_R kW); the cost of the front-end rectifier itself; the cost of the storage, as a function of the storage size S[1] (measured in kWh) and of the rated power of the converter between the storage and the drives, $P_{\text{conv.}}$; the value of the energy recovered during the useful life of the storage, as a function of S, $P_{\text{conv.}}$, and the random recovered energy E. Minimization will take place with respect to S and $P_{\text{conv.}}$. All terms in the cost function are nonrandom, except for the last one.

First, with the aim of including the variation of the cost of energy in the analysis, we determine the useful life of the storage

[1] More precisely, S indicates the actual usable energy between the supercapacitor rated voltage and its half. To simplify, we use expressions such as "storage size" and "empty storage" in this article, also when we refer to the usable energy.

system in years, assuming that its duration is 10^6 charge-discharge pairs. If we consider $P(s)$ during a basic period, given the shape of the basic power curve $p(s)$, see (2), the most frequently expected occurrence is a sequence of one charge and one discharge interval (a charge-discharge pair). A Monte Carlo sample of 50 000 sets of random shifts with $n = 10$ drives gives the following frequency distribution of charge-discharge pairs in a basic period: (0, 492); (1, 41065); (2, 8293); (3, 150). The pair (0, 492) corresponds to 492 occurrences of no discharge, that is, the storage has not been used; the pair (1, 41065) confirms that the most likely occurrence is one charge-discharge pair, and so on. The sample mean number of charge-discharge pairs from these data is 1.162. Now let $T = 120$ s, and let the epoch represent a working day of about 8 h, during which $m = 240$ cycles are completed (so $L = 120 \times 241 = 28\,920$ s). Then the expected life of the storage measured in number of basic periods is $10^6/1.162 = 860\,585$; if we take five working days (epochs) per week, then the life of the storage in years is

$$\frac{120 \times 860585}{52 \times 5 \times 8 \times 3600} = 13.79$$

which we round to 14. With $n = 5$ drives the sample mean number of charge-discharge pairs is 1.145, so the duration in years is unchanged.

Another necessary parameter is the nominal voltage of the system, which we set to $V_n = 500$ V. As shown in [1], the total storage system cost is also a function of the system nominal voltage, depending on the cell type used: with the same system rated energy, the system cost decreases by choosing a lower nominal voltage, due to the use of less supercapacitor cells with greater capacitance each.

Then, the non-random components of cost function (5) in Euro are as follows:

$$\begin{aligned} C_{\text{contr.}}(P_R) &= N_{\text{year}}\cdot(VC_1\cdot P_R + FC_1) = 14\cdot(27.20\cdot P_R + 137.1) \\ C_{\text{rect.}}(P_R) &= (VC_2\cdot P_R + FC_2) = 58.88\cdot P_R + 927.52 \\ C_{\text{stor.}}(S, P_{\text{conv.}}) &= C_{\text{supercap}} + C_{\text{conv.}} = (VC_3\cdot V_n + VC_4\cdot S + FC_4) \\ &\quad +(VC_5\cdot P_{\text{conv.}} + FC_5) = (12.44\cdot 500 \\ &\quad +30240\cdot S + 34.09) + (26.04\cdot P_{\text{conv.}} + 1419.6) \end{aligned} \tag{6}$$

where:

- N_{year} is the expected system lifetime in years;
- VC_1 is the variable cost in Euro/kW related to the power supply contract;
- FC_1 is the fixed cost in Euro related to the power supply contract;
- VC_2 is the variable cost in Euro/kW related to the front-end rectifier;
- FC_2 is the fixed cost in Euro related to front-end rectifier;
- VC_3 is the variable cost in Euro/V related to the storage device;
- VC_4 is the variable cost in Euro/kWh related to the storage device;
- FC_4 is the fixed cost in Euro related to the storage device;
- VC_5 is the variable cost in Euro/kW related to the storage power converter;
- FC_5 is the fixed cost in Euro related to the storage power converter.

Now let us turn to the random term of the cost. For every epoch t, energy E_t is recovered, as $t = 1, \ldots, 3640$ ($3640 = 5 \times 52 \times 14$), and

$$V(S, P_{\text{conv.}}; E) = 0.1537 \times \sum_{t=1}^{3640} p_{y(t)} E_t(S, P_{\text{conv.}}) \tag{7}$$

where we have highlighted the dependence of the recovered energy on plant design. Coefficients $p_{y(t)}$ are the ratios between the cost of energy in year $y(t)$ and the current year: $p_{y(t)} = p_1$ as $t = 1, \ldots, 260$ ($260 = 5 \times 52$); $p_{y(t)} = p_2$ as $t = 261, \ldots, 520$, and so on. Coefficients p_1 to p_{14} are obtained from [26], where electricity prices for the industrial sector are reported. Taking 2010 as the baseline year, their values for the current year and the next 13 years are: 1.000, 1.039, 1.078, 1.117, 1.156, 1.195, 1.218, 1.242, 1.265, 1.288, 1.312, 1.319, 1.327, 1.335.

We will minimize this cost with respect to S and $P_{\text{conv.}}$, while setting P_R to $n \times \max_s\{p(s)\}$ kW, occurring when all n drives are requesting maximum power.

The search domain for pairs (S, $P_{\text{conv.}}$) is found by first selecting an interval for S and then by allowing $P_{\text{conv.}}$ to vary in a range consistent with S. We relate the range for S with the maximum energy that can be recovered in a basic period of T time units, when an infinite storage is available. A high probability interval for it is obtainable via Monte Carlo simulation, as explained at the end of Section 3.2. For example, with $n = 10$ drives, a 70% probability interval for the maximal stored energy is approximately (0.067, 0.369) kWh: searching regions for S will be of this type. Now, given S, we argue that the range for $P_{\text{conv.}}$ should be of the following type:

$$LB \le P_{\text{conv.}} \le \min\{360S, |n \min_s\{p(s)\}|\}, \tag{8}$$

where LB is a lower bound to be determined, the reason for the 360 factor is that the time unit is 10 s and S is measured in kWh and $|n \min_s\{p(s)\}|$ is the analytic expression of the maximal braking power the system can reach.

The lower bound LB is just a reference value guaranteeing that the converter is large enough to allow the exchange of typical power values between the load and the storage, such as a suitable percentile of the distribution of $|P(s)|$ (like the median), which is approximately a folded normal distribution (see [27], Section 10.3) with mean and variance parameters given by (4).[2] If the approximation is poor, then straightforward Monte Carlo simulation from the multinomial distribution in Section 3.2 can do the task. With $n = 10$, the median of the folded normal approximation is 18.458, whereas the exact value found from simulation is 18.

The upper bound takes into account both the power flowing from the storage and the power flowing into the storage. For power outflow, focus on $360S$ and on the residual storage capacity at the end of a time unit: if $P(s) \ge 360S$ it is sufficient to have $P_{\text{conv.}}$ not larger than $360S$, because the storage will be empty anyway at the end of time unit s and with fully available storage capacity at the beginning of the next time unit. For power inflow, consider $|n \min_s\{p(s)\}|$: if $360S$ is smaller than this value then the condition $P_{\text{conv.}} = 360S$ insures that the storage gets completely filled in a time unit during large power inflows and no capacity remains unused; if $360S > |n \min_s\{p(s)\}|$, then obviously $P_{\text{conv.}}$ need not be larger than $|n \min_s\{p(s)\}|$. Summing up, the power outflow criterion dictates $P_{\text{conv.}} \le 360S$, whereas the power inflow criterion dictates $P_{\text{conv.}} \le \min\{360S, |n \min_s\{p(s)\}|\}$. Since the second upper bound prevents $P_{\text{conv.}}$ from getting too large (and expensive), we choose this one. With $n = 10$, $LB = 18$ and $|n \min_s\{p(s)\}| = 80$, the searching interval for $P_{\text{conv.}}$ is (18, min {360S, 80}) kW.

For every point in the searching region, a different probability distribution of the cost function is obtained. In order to use all the information in such distributions, a given point should be preferred

[2] The approximation to the median of $|P(s)|$ is $\sqrt{\text{var}(P(s)) \times \text{median}(\chi^2(\text{ncp}))}$; $\chi^2(\text{ncp})$ is a non-central chi-squared distribution with non-centrality parameter $\text{ncp} = \mathbb{E}(P(s))^2/\text{Var}(P(s))$ and its quantiles are computable with common statistical packages.

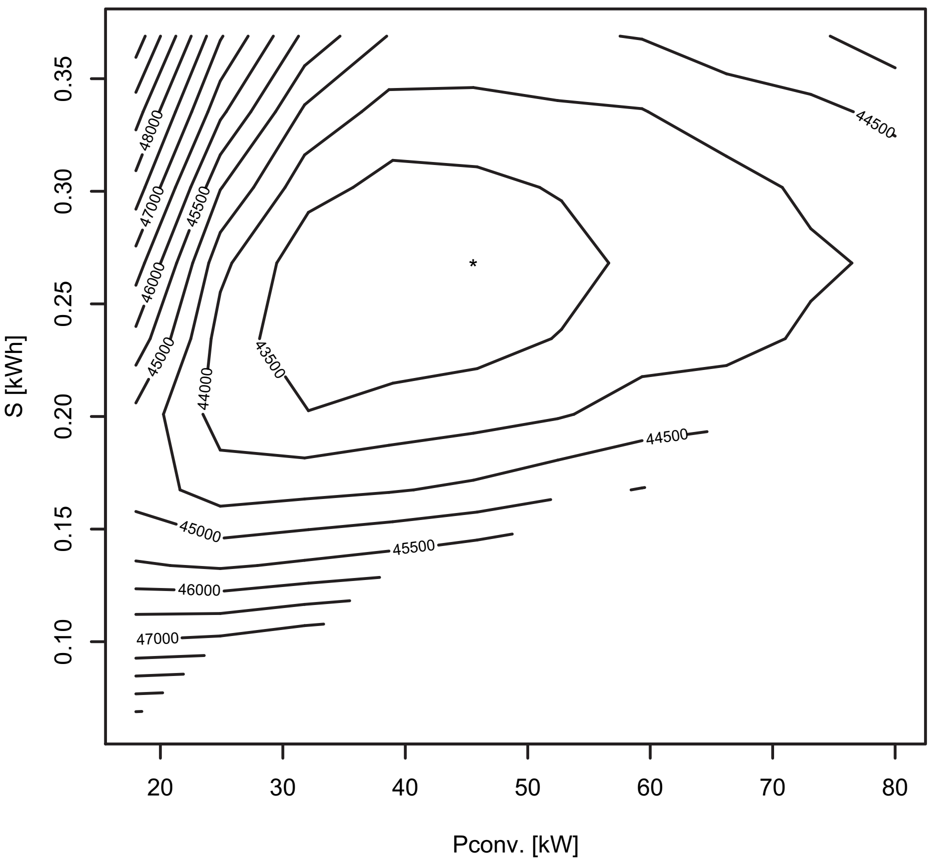

Fig. 4. Monte Carlo estimate of the expected value of the life-cycle cost, (5), with 10 drives and search region given by $S \in (0.067, 0.369)$ kWh and $P_{conv.} \in (18, \min\{360S, 80\})$ kW, with $P_R = 100$ kW. The asterisk marks the point from the searching grid with minimal cost.

over another one if there is a large probability that the cost of this point is smaller than the cost of the other one. We consider the probability to be large if it is greater than 0.5. Notice that we need not calculate this probability explicitly, but we can just compare mean values of cost at different points. Recall in fact that the cost is the sum of all the terms in (6) minus the value in (7). Since the value of recovered energy is the sum of a large number of random terms, the probability distribution of the cost is well approximated by a Gaussian, and it is trivial to show that the difference between two independent Gaussian random variables is negative with a probability larger than 0.5 if and only if the difference between their means is negative. Therefore, we only need to optimize the expected value of the cost function over the searching region. The calculation of the expected values will be done by Monte Carlo simulation.

4.2. Numerical results

We present a first experiment with experimental parameters and search region as at the end of the previous section. We ran a simulation of the system assuming an 80% efficiency factor for both charge and discharge of power into and from the storage (hence the global efficiency is 64%). We describe the simulation by means of positive power balance, occurring when the power requested by the drives is larger than the power returned, and negative power balance, occurring in the opposite case. Recall also that the power balance is constant during an appropriately chosen time unit (10 s, in our case). We assume that when power balance is positive, energy is drawn from the storage if nonempty, as allowed by the rated power of the converter $P_{conv.}$; if the storage empties during the same time unit, then energy is drawn from the mains, up to the limit allowed by the rated power of the rectifier P_R. When power balance is negative, energy flows into the storage up to the limit allowed by $P_{conv.}$ and the storage capacity.

The useful life of the storage system was taken to be about 14 years. We simulated ten 14 years periods as a single sequence of 140 years, amounting to 36 400 epochs. With reference to the notation of Section 3.1, the estimator of μ (the expected recovered energy in an epoch) is the sample mean of the sequence (E_t), denoted by $\overline{E}$. The variance parameter σ^2 depends on the autocorrelations of the sequence at all lags. However, in the present case, autocorrelations beyond lag 1 are never significantly different from zero, when compared with the 95% confidence interval for the null autocorrelation, given by $\pm 1.96/\sqrt{36400} = (-0.010, 0.010)$ (see [28], Sec. 2.4). Thus the estimate of σ^2, denoted by s_E^2, depends only on the sample variance of (E_t) and its lag-one sample autocorrelation.

Using $\overline{E}$ and $s^2{}_E$, the estimated mean and variance of $V(S, P_{conv.}, E)$, at Equation (7), are

$$0.1537 \times \left(\sum_{i=1}^{14} p_i\right) \times 260 \times \overline{E} \quad \text{and} \quad 0.1537 \times \left(\sum_{i=1}^{14} p_i\right) \times 260 \times \frac{s_E}{\sqrt{36400}}$$

respectively. One can see that if all p_i's take unit value, then the estimated mean value of recovered energy in 14 years is simply $0.1537 \times 3640 \times \overline{E}$, that is, the expected recovered energy in an epoch, times the number of epochs, times the cost of a kWh.

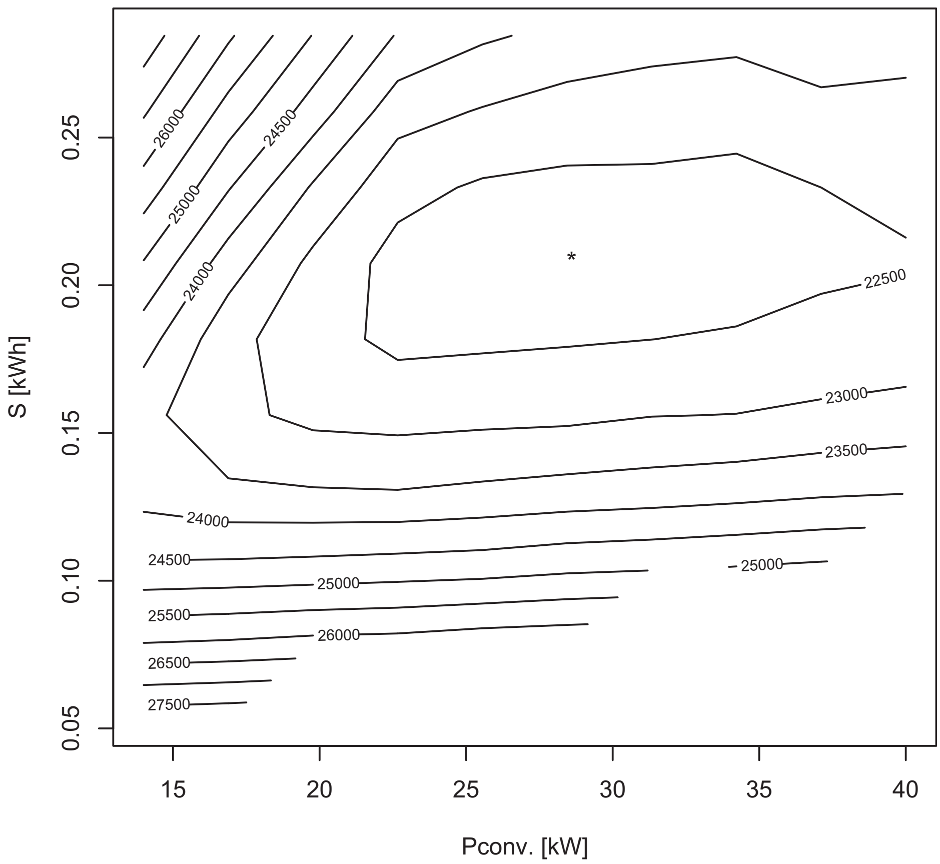

Fig. 5. Monte Carlo estimate of the expected value of the life-cycle cost, (5), with 5 drives and search region given by $S \in (0.053, 0.284)$ kWh and $P_{conv.} \in (14, \min\{360S, 40\})$ kW, with $P_R = 50$ kW. The asterisk marks the point from the searching grid with minimal cost.

The estimated expected value of the cost function (5) over the search region is represented in Fig. 4 as a contour plot. The grid point with minimum cost is $(S, P_{conv.}) = (0.27$ kWh, 46 kW$)$, so the actual minimum is expected to be in a neighborhood of this point, and a search with a more refined grid can be done if needed.

The estimated mean life-cycle cost associated to this solution is 43 084 Euro, with an estimated standard deviation of 60 Euro. The cost without storage system with is 46 815 Euro, corresponding to an 8% saving. A complete analysis should probably include additional maintenance costs on one side and quantify environmental benefits on the other side, however these results show that the adoption of a storage system will not cause any loss.

With $n = 5$ drives, the optimized storage system is in a neighborhood of $(S, P_{conv.}) = (0.21$ kWh, 28 kW$)$, with a cost surface similar to the previous one (see Fig. 5).

The estimated minimum life-cycle cost is about 22 210 Euro, with an estimated standard deviation of 42 Euro. The same plant without storage has a life-cycle cost of 24 831 Euro, with a 10% relative saving.

The optimal storage system for the ten-drive case is smaller than the storage for the five-drive case, in a relative sense. When the drives cycles are all shifted by the same amount, theoretically one could store 0.88 kWh in a basic period with ten drives, using $P_{conv} = 80$: there are five time units where braking power is 8 kW and charge efficiency is 80%, so $0.88 = 0.8 \times (5 \times 8) \times 10/360$. With five drives, the maximal recoverable energy in a basic period is 0.44 kWh, with $P_{conv} = 40$. As a percentage of these maximal values, the optimal values (S, P_{conv}) are about (31%, 58%) with ten drives and (48%, 70%) with five drives. We see that the storage for then drives is relatively smaller, because in this case it is more likely to have drives requesting power when other drives are braking.

5. Conclusions

We showed that it is economically convenient to equip a number of drives, having randomly shifted work cycles, with a storage system for the recovery of braking energy. We indicated a theoretical framework potentially encompassing different concrete situations, based on Markov chain modeling. With the help of an illustrative example concerning bridge cranes, we built and optimized a random cost function spanning the life-cycle of the storage system, giving also a criterion for delimiting the search region. We showed that plants with more drives require relatively smaller storage systems. The optimization was achieved through Monte Carlo simulation of the life-cycle of the storage system.

The bridge-crane example shows that it is possible to achieve not only energy but also economical savings during the whole life of the storage system, even though the possible energy recovery from the traction profile has been disregarded. Furthermore, an ever-increasing importance attributed to the so-called white energy (i.e. saved energy) makes it reasonable to expect economical incentives from the public authorities for applications with recovery of braking energy.

Further research is needed to be able to evaluate the transition kernel and the stationary distribution of the Markov chain, in order to take full advantage of the theoretical framework. Finally, a more complex plant design optimization can also include a surplus of storage to be filled with back-up energy taken from the mains. After selecting a re-fill strategy of the back-up storage, its cost should be balanced against the saving coming from a front-end rectifier with a rated power smaller than the maximal load. The back-up energy would in fact help to smooth the peaks of power required from the mains, allowing for a less expensive power supply contract. This will be the subject of forthcoming research.

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