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Cost-optimal operation of energy storage units: Benefits of a problem-specific approach

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ABSTRACT

The integration of large shares of electricity produced by non-dispatchable Renewable Energy Sources (RES) leads to an increasingly volatile energy generation side, with temporary local overproduction. The application of energy storage units has the potential to use this excess electricity from RES efficiently and to prevent curtailment. The objective of this work is to calculate cost-optimal charging strategies for energy storage units used as buffers. For this purpose, a new mathematical optimization method is presented that is applicable to general storage-related problems. Due to a tremendous gain in efficiency of this method compared with standard solvers and proven optimality, calculations of complex problems as well as a high-resolution sensitivity analysis of multiple system combinations are feasible within a very short time. As an example technology, Power-to-Heat converters used in combination with thermal storage units are investigated in detail and optimal system configurations, including storage units with and without energy losses, are calculated and evaluated. The benefits of a problem-specific approach are demonstrated by the mathematical simplicity of our approach as well as the general applicability of the proposed method.

1. Introduction

Electricity generation from solar and wind resources is volatile and has limited adaptability to changes in electricity demand [1]. For a stable operation of the power system there must be a consistent balance between supply and demand. One option for achieving this balance is the use of energy storage units which can contribute substantially to the expansion of Renewable Energy Sources (RES) and their integration into existing grids [2–4].

Another possible way in which large shares of renewable energy can be integrated and electricity from RES can be used efficiently, especially in times of overproduction, is to replace fossil fuels as the main energy source for heat by converting electricity into heat (Power-to-Heat, PtH) – resulting in a lower overall primary energy consumption and lower CO_2 emissions [5,6]. If combined with thermal storage units, PtH storage systems are a highly flexible option for uncoupling conversion and utilization [5,7]. These heat storage units can be charged at considerably low losses during periods with high shares of excess electricity from RES and provide heat in times of low feed-in [8]. A method for storing heat energy used in Germany was implemented decades ago by night storage heating systems in private households. They operated with low overall efficiencies and subsidized electricity prices at fixed schedules [9]. Today, private households are still suitable for the deployment of PtH storage systems due to the high share of primary energy demand utilized for heating and hot water supply, the overall changes in the energy system and the characteristics of today's heat storage units [10].

If we assume that the electricity price represents the fluctuating availability of energy, these heat storage systems need to be operated in a cost-optimal manner. The optimality of a charging strategy for a PtH storage unit is determined by the overall electricity acquisition costs. The task of identifying optimal strategies is closely related to the field of mathematical optimization and can be described as a minimization problem. Standard solvers can be applied to calculate solutions, albeit with tremendously high overheads in computational time. Hence, the investigation of complex problems may not be possible within a reasonable time frame.

The specific structure of the minimization problem, based on a mathematical model of the storage units, allows the development of a new optimization method which to our knowledge has not yet been implemented. This work introduces an innovative optimization algorithm and presents proof of optimality. The solution of

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storage-related optimization problems can now be calculated in a fraction of the time required by standard algorithms. As a particular example, we focus on PtH storage units installed in private households. For these systems, cost-optimal operating strategies including storage units with thermal energy losses are described and used for an iterative determination of optimal system designs.

Beyond this particular field of application, we illustrate the potential benefits of a problem-specific optimization approach in terms of mathematical simplicity and computational gain as compared with standard solvers.

2. Formulation of the optimization problem

The construction of mathematical energy storage models and the formulation of the corresponding optimization problems, with and without constant as well as non-constant energy losses, are described without units in the following paragraphs. We investigate an electrical charging system with an attached storage unit as a buffer and consider the parameters of electric power consumption and storage capacity. The system needs to be connected to a virtual electricity grid which provides an altering price signal reflecting the availability of electricity. A further precondition is that the energy demand is covered exclusively by the system.

2.1. Formulation without energy losses

Now, we formulate the mathematical model, without energy losses of the storage unit over time or losses during the conversion process. We discretize the considered period of time into n intervals of equal size. The electricity prices are denoted by $c_1, c_2, \ldots, c_n$ and the energy demands are represented by $d_1, d_2, \ldots, d_n$. Furthermore, we define the amount of energy used to charge the storage unit for each time-interval by $x_1, x_2, \ldots, x_n$ and assume that the prices and the demands are known. For technical reasons, the values of x are constrained. Each charge value cannot be negative (no discharge to the electricity grid or re-electrification) and has an upper bound $C > 0$, which implies:

$$0 \le x_i \le C \quad \forall \ i = 1, \ldots, n.$$

To cover at least the energy demand for each time-interval, additional constraints are:

$$\sum_{j=1}^{i} d_j \le \sum_{j=1}^{i} x_j \quad \forall \ i = 1, \ldots, n.$$

The storage level for each time-interval is defined as the difference between the quantity of charges and the quantity of demands up to this time-interval. Due to design-related restrictions, the storage level is bounded above by a maximum storage capacity value $S > 0$. Hence, we have:

$$\sum_{j=1}^{i} (x_j - d_j) \le S \quad \forall \ i = 1, \ldots, n.$$

In order to minimize the total costs to cover at least the energy demand over a period of time of size n, we have to solve the following optimization problem:

$$\begin{aligned} &\min && \sum_{i=1}^{n} c_i \cdot x_i \\ &\text{subject to} && 0 \le x_i \le C, \quad \forall \ i = 1, \ldots, n \\ &\text{and} && \sum_{j=1}^{i} d_j \le \sum_{j=1}^{i} x_j \le S + \sum_{j=1}^{i} d_j \quad \forall \ i = 1, \ldots, n. \end{aligned} \tag{LP}$$

This problem is a special instance of a so-called *linear program* and can be solved using standard algorithms for general linear programs, such as the simplex method or interior point methods [11].

The problem (LP) is also a special case of the problem (P) which is described in Appendix A. Contrary to the methods mentioned above, we utilize the special structure of (P) and hence also of the related problem (LP) to develop a new algorithm. The basic idea of the new algorithm is to charge the storage unit during periods when the acquisition prices are low in order to avoid further purchases at times when the prices are higher. In addition to the price levels, the algorithm also takes into account the demand, the storage level and the maximum charge power for each time-interval. Therefore, the storage units are charged as much as possible at times of negative acquisition costs and as much as required, if the price is non-negative.

The new algorithm to solve the problem (P) is discussed in detail in Appendix A and also the pseudo-code is presented. Below, we present the pseudo-code of the new algorithm exemplary fitted to the problem (LP), if we set $a_i := d_1 + \cdots + d_i$ and $b_i := S + (d_1 + \cdots + d_i)$ for all $i = 1, \ldots, n$. If we further define the permutation σ as described in Appendix A, corresponding to the increasing prices by $c_{\sigma(1)} \le \cdots \le c_{\sigma(n)}$, the pseudo-code of the new algorithm fitted to the problem (LP) is given by:

Inputs:
  a_i, b_i, c_i and the permutation σ
Output:
  A solution x of the problem (LP)
for $k = 1$ to n **do**
  $M_1 \leftarrow \max_{i<\sigma(k)} \{0, a_i\}$
  $M_2 \leftarrow \max_{i \ge \sigma(k)} \{0, a_i\}$
  $m \leftarrow \min_{i \ge \sigma(k)} \{b_i\}$
  if $c_{\sigma(k)} \ge 0$ **then**
    $x_{\sigma(k)} \leftarrow \min\{\max\{0, M_2 - M_1\}, \min\{C, m - M_1\}\}$
  else
    $x_{\sigma(k)} \leftarrow \min\{C, m - M_1\}$
  end if
  for $i = \sigma(k), \ldots, n$ **do**
    $a_i \leftarrow a_i - x_{\sigma(k)}$
    $b_i \leftarrow b_i - x_{\sigma(k)}$
  end for
end for

The optimality of the new algorithm is proven (in Appendix A) and is one key element of this work. Furthermore, the source code of an implementation in Python is included in Appendix C. This method solves problems even for large n in a fraction of time required by standard solvers, because at most $n^2 + 3n$ floating point operations and $3/2n^2 + 5/2n$ comparisons to compute a solution (see: Appendix A) are required.

To demonstrate the efficiency of the new algorithm, we compare the runtimes between the algorithm and the common solver *linprog* in the following. For this comparison, a straightforward implementation of the new algorithm in Python (cf. Appendix C) and the *linprog* implementation as available in MATLAB 2015b were used. The calculations were performed on a desktop computer,[1] based on input data for the problem (P) as

[1] Details: Intel® Core™ i7-930 Processor (2.80 GHz), 12GB RAM, MATLAB 2015b, Python 2.7.