Energy Conversion and Management 65 (2013) 272–284

Contents lists available at SciVerse ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

# Application of battery-based storage systems in household-demand smoothening in electricity-distribution grids

Arturs Purvins *, Ioulia T. Papaioannou, Luigi Debarberis

*European Commission,[1] DG JRC, Institute for Energy and Transport, NL-1755 ZG Petten, Netherlands*

ARTICLE INFO

*Article history:*
Received 20 March 2012
Received in revised form 17 July 2012
Accepted 17 July 2012
Available online 17 October 2012

*Keywords:*
Battery
Energy storage
Household-demand smoothening
Peak-demand shaving
Electricity-distribution grid
Photovoltaic

ABSTRACT

This article analyses in technical terms the application of battery-based storage systems for household-demand smoothening in electricity-distribution grids. The analysis includes case studies of Denmark, Portugal, Greece, France and Italy. A high penetration of photovoltaic systems in distribution grids is considered as an additional scenario. A sensitivity analysis is performed in order to examine the smoothening effect of daily demand profiles for different configurations of the battery system.

In general, battery-storage systems with low rated power and low battery capacity can smooth the demand sufficiently with the aid of a simple management process. For example, with 1 kW of peak demand, a 30–45% decrease in the variability of the daily demand profile can be achieved with a battery system of 0.1 kW rated power and up to 0.6 kW h battery capacity. However, further smoothening requires higher battery-system capacity and power. In this case, more elaborate management is also needed to use the battery system efficiently.



## 1. Introduction

The need for energy-storage systems was identified in the European energy infrastructure priorities for 2020 and beyond [1]. Storage technologies can bring additional flexibility to energy systems, an essential prerequisite for high penetration of stochastically variable renewable energy sources (RESs) [2]. Implementing proper storage topologies, such as centralised or semi-centralised facilities, becomes a challenge. Besides, operating these facilities poses an additional challenge. Alongside pumped hydro storage, only a few large-scale compressed-air energy-storage installations are currently undergoing trials. Other alternatives could be storage allocation further down the grid chain at distribution level.

This article analyses this alternative; however, the focus is not on direct damping of power variations from uncontrollable RES but on smoothening household demand[2] with the aid of battery-based[3] storage systems. Demand smoothening is the process by which the daily demand variations are reduced. It is achieved by charging the battery during valley demand and discharging it during the peak demand. The main technical benefits of such demand smoothening in distribution grids are as follows:

- Decreased peak demand and increased valley demand.
- Increased capacity factor of distribution-system corridors.
- Increased security of energy supply, since batteries can act as an additional and independent power supply.

The first two benefits could lead to a simplification in the management of electricity corridors, e.g. smoothened demand could result in fewer voltage variations and, as a consequence, less stress on the system, such as automation in the distribution transformer. Moreover, increasing the capacity factor of electricity corridors would lead to an increase in the overall utilisation of conventional power generators, resulting in higher generation efficiency.

Despite the fact that battery-system applications in demand smoothening in distribution grids are already used commercially in Europe, Japan and USA [3], they have not been the subject of a recent and extensive study. Several studies have addressed the broader issue [4–9]. Castillo-Cagigal et al. [4] and Tan et al. [5] studied the use of batteries in demand smoothening in distribution grids with photovoltaic (PV) installations. In the latter study, the focus was on the battery system itself as an uninterruptible power supply. Papic [6] described installed battery-system applications for peak-demand shaving in factories only in critical situations when peak demand exceeds the peak power of the distribution transformer. Thus the battery system was used to avoid uprating the transformer. Nourai et al. [7] looked at reducing transmission and distribution grid losses due to peak-demand reduction; however here the battery systems also increased the overall demand due to losses in the storage–generation process. Bingying et al.

* Corresponding author. Tel.: +31 224565299; fax: +31 224565616.
*E-mail address:* arturs.purvins@ec.europa.eu (A. Purvins).

[1] The views expressed in the article are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

[2] In this article the term 'demand' refers to the 'electricity demand'.

[3] In this article the term 'battery' refers to the 'secondary electrochemical battery'.

0196-8904/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.enconman.2012.07.018

[8] focused on 'flow battery' systems. Koutsopoulos and Tassiulas [9] stressed that the main driver of such applications at household level could be benefits due to elastic electricity prices in charging/discharging operations and benefits at distribution-grid level due to minimising operation costs.

The literature [5] uses a stochastic method to measure the effect of the battery system capacity in demand smoothening but does not take into account the power of the battery system. Older studies on battery-system applications for demand smoothening are described in a literature review by Divya and Østergaard [3], where they pointed out that most of the studies reviewed lack suggestions on optimal battery capacity and battery system rated power.

The role of electric vehicles in demand smoothening is widely studied in [10–12], pointing out that electric-vehicle batteries could participate in peak-demand reduction. However, demand smoothening is not the aim of the electric-vehicle application. Although the EU technology roadmap [13] expects a large number of electric vehicles to be integrated in the electricity grid by 2020, this is not an aspect covered in this article.

Given this gap in the literature, this article seeks to analyse and measure two technical indicators – battery capacity and battery-system rated power – in direct applications targeting household-demand smoothening with and without PV penetration. The analysis is performed for Denmark, Portugal, Greece, France and Italy. In addition, this article proposes and analyses two battery-system management models: a time-dependent management model for a simple battery system and a demand-tracking management model for a more highly developed battery system.

This article is structured as follows: Section 2 presents demand scenarios, including PV generation. Section 3 describes the battery-based storage system and management models. Section 4 presents and discusses the main results. The last section sets out the conclusions of the analysis.

## 2. Scenarios regarding demand and PV penetration

The subject of this article is smoothening household demand. Thus it should begin by defining household-consumption profiles. These profiles can differ from country to country according to various parameters, mostly ambient and socio-economic conditions. Moreover, household consumption may appear to vary from day to day, depending on the day (weekday, weekend or special holiday) and the season. In order to simplify our study, a detailed daily household profile is considered to be beyond the scope of this article. Representative average daily demand profiles per season are used.

In order to apply realistic household-consumption profiles, the REMODECE database [14] is used. This database provides inventories of daily household-demand profiles at hourly intervals. These profiles cover all the months throughout the inventory year. All the available demand profiles were processed for the countries studied: 189 daily demand profiles in Denmark, 95 in Portugal, 192 in Greece, 106 in Italy and 207 in France. For each country, these profiles were allocated to four seasons: winter, spring, summer and autumn. For each season, an average daily demand profile was calculated, i.e. an average profile of 24 records for each season.

Representative average daily-demand profiles for Denmark and Portugal are depicted in Figs. 1 and 2. Here the season with the highest demand variations (found in spring in Denmark and in winter in Portugal) and with the lowest demand variations (found in summer in Denmark and in autumn in Portugal) are presented. Demand variability is measured as the standard deviation. The

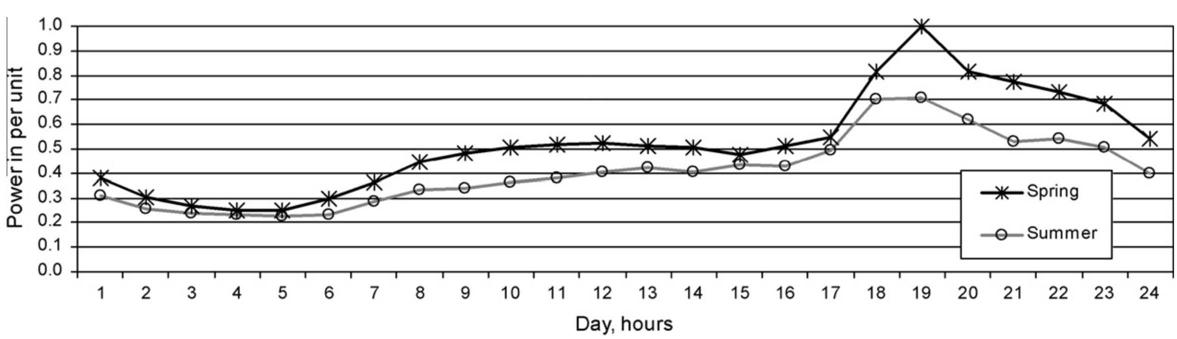


**Fig. 1.** Representative average daily household-demand profiles in spring and summer in Denmark.

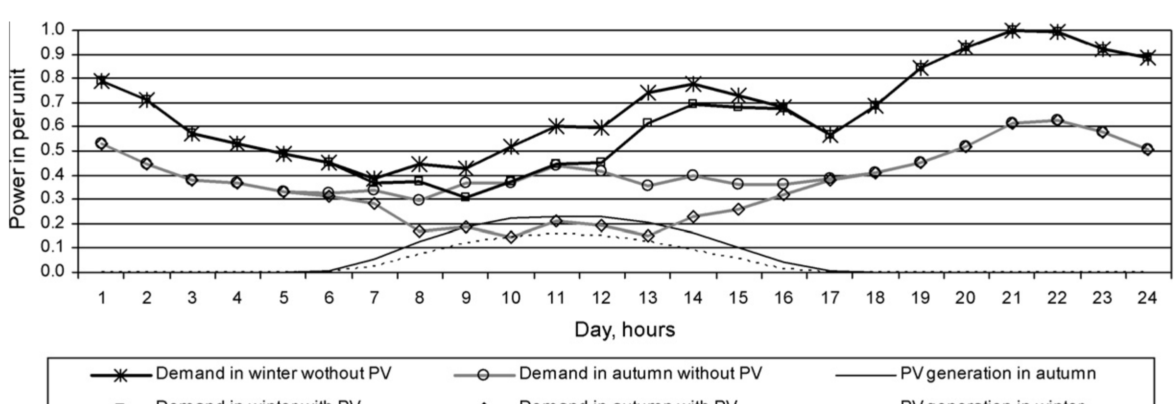


**Fig. 2.** Representative average daily PV generation profiles and household-demand profiles in winter and autumn in Portugal with and without PV.

Table 1
Main demand parameters for the countries studied.

| Country | PV | Highest peak demand – base unit | | Demand variations (Eq. (1)) | | | |
|---|---|---|---|---|---|---|---|
| | | W | Season | Highest | | Lowest | |
| | | | | pu | Season | pu | Season |
| Denmark | No | 895 | Spring | 0.199 | Spring | 0.141 | Summer |
| Portugal | No | 920 | Winter | 0.186 | Winter | 0.093 | Autumn |
| | Yes | 920 | Winter | 0.213 | Spring | 0.151 | Autumn |
| Greece | No | 831 | Autumn | 0.208 | Autumn | 0.114 | Summer |
| | Yes | 831 | Autumn | 0.230 | Autumn | 0.167 | Summer |
| France | No | 2025 | Winter | 0.117 | Winter | 0.073 | Autumn |
| | Yes | 2025 | Winter | 0.125 | Winter | 0.071 | Autumn |
| Italy | No | 759 | Winter | 0.230 | Winter | 0.146 | Summer |
| | Yes | 759 | Winter | 0.229 | Winter | 0.172 | Autumn |

standard deviation indicates how far the daily demand profile's values deviate from the mean value and is calculated as follows:

$$S = \sqrt{\frac{\sum_{i=1}^{N}(x_i - x_{mean})^2}{N-1}} \quad (1)$$

where $N$ is the hours in day, $x_i$ is the value of the hourly demand and $x_{mean}$ is the mean daily demand value.

The representative values of demand profiles in Figs. 1 and 2 are expressed in a per unit (pu) system, i.e. as a fraction of a defined base unit. Each country has its own pu system. The base unit for each country is defined by the value of the highest demand among the average daily demand profiles in all the seasons of the country concerned (Table 1). For example, for Denmark this value is 895 W and is found in the spring profile where the demand is highest (Fig. 1). Consequently, the summer peak demand was calculated to be 0.71 pu. For Portugal, the winter peak demand of 920 W defines the base unit, 1 pu, thus the autumn peak demand is 0.63 pu (Fig. 2).

The highest and the lowest variations of the daily demand profiles among the seasons of all the countries studied are listed in Table 1. France among the other countries studied characterises with the lowest demand variations throughout the year having the maximum demand variations of 0.117 (without PV) in winter. Besides the other countries have their maximum demand variations in a range from 0.186 to 0.230 (without PV), which is much higher.

Furthermore, increased distributed generation (DG) changes the demand seen from the feeder side, since a portion of the household demand can be met locally. When it comes to the distribution-feeder level which supplies household consumers, the most common RES is solar PV. In line with the RES projections in national energy action plans for 2020 [15], annual PV production in Portugal, Greece, France and Italy is expected to be in a range from 108 to 321 kW h per capita. Accordingly, additional scenarios with high PV penetration in Portugal, Greece, France and Italy are examined. However, the planned PV integration in Demark for 2020 (1 kW h per capita) is not sufficient to warrant conducting a study.

For Portugal, PV penetration is assumed to be 25% of the distribution-transformer capacity [16]. Here, in order to express PV generation in the same per unit system as demand, some assumptions need to be made regarding the distribution corridor. Thus a conventional distribution-transformer capacity of 250 kV A is considered. 25% of this capacity would be equal to the PV installed capacity, which is in absolute values 62.5 kWp. Furthermore, for the chosen transformer, an ACSR line of 35 mm$^2$ is assumed. This line has a thermal current limit of 224 A and a 154.56 kV A three-phase capacity. The chosen line then is considered to be at maximum load. The winter demand profile in Portugal is levelled out so that the peak reaches the maximum line capacity, i.e. 154.56 kV A. As the PV installed capacity and the peak winter demand are known, the installed PV capacity can be calculated to be 0.4 pu. The PV penetration limits in the distribution network in Greece, France and Italy are not clearly defined; therefore, in these countries the same PV penetration assumptions as in Portugal were considered.

PV does not operate at peak power continuously so the seasonal average of the daily PV power peak is much lower. For each country and for each season in our study, an average daily PV profile was calculated using 2010 statistical data obtained from the European solar-radiation database [17]. As an example, in Portugal the average daily PV peak is 0.16 pu in winter and 0.23 pu in autumn (Fig. 2). PV penetration increases the demand variability in the most of the cases presented in Table 1. Only in autumn in France and in winter in Italy demand is slightly smoothened due to the PV integration. Besides in Portugal due to the PV penetration the highest demand variations presented before in winter appear now appear in spring (Table 1). Nevertheless, the peak demand is not affected by the PV penetration in the countries studied.

## 3. Battery-based energy storage

The most promising energy-storage system for household-demand smoothening is considered to be battery-based. Other storage technologies at distribution-grid level, such as flywheels, super-capacitors and superconducting magnetic energy storage are designed mainly for peak-power supply/storage [18]. Hydrogen-based energy-storage systems could also be an alternative to batteries but, due to their relatively high cost and low energy-storage efficiency compared to batteries, take-up has not been extensive [18]. Moreover, batteries are conventional technologies widely used in commercial applications. Their modularity [3] makes them easily applicable to installations either at household or at distribution-feeder level.

### 3.1. Technical parameters of the battery system

The battery system for energy-storage purposes in the electricity grid consists of the battery itself and a bidirectional electrical-power converter (Fig. 3). When the battery operates in energy-storage mode, a power converter converts the AC grid power into the appropriate DC form. When the battery operates in generation mode, the DC battery output is converted back to the AC grid power.

The quantity of energy that can be stored is defined by the battery capacity. In this article, the term battery capacity implies the amount of energy that can be drawn from a fully charged battery. Since batteries are typically a modular technology, the required capacity can be reached by connecting battery cells in series and/or in parallel. So, theoretically, it can be assumed that there are no constraints on the capacity of the battery system. A sensitivity

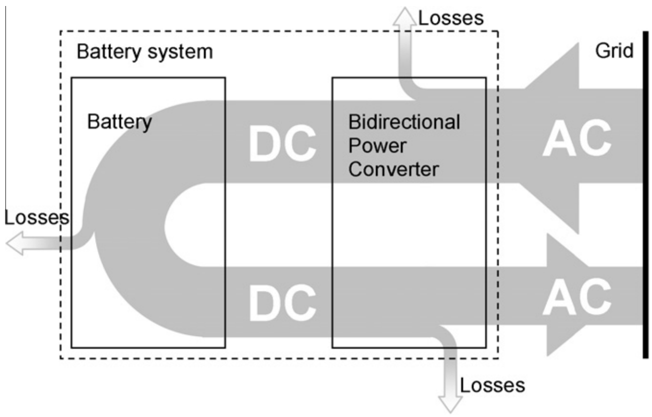


**Fig. 3.** Battery-based energy storage system in electricity grid.

analysis of various battery-system capacities was carried out to study battery application in demand smoothening in distribution grids. The capacities examined increase to the point where further capacity increases do not yield further smoothening effects.

Another technical parameter is the battery system's rated power, which is the maximum rating of the charging/discharging power of the battery system. This indicates how fast energy can be stored (or generated) in the battery system. Even if the battery has enough capacity to store energy at valley demand (or generate at peak demand), the rated power should be high enough to enable the required energy flow (inwards or outwards) in time. Theoretically, there are no constraints on the power rating values resulting from either the electrical power converters, or the battery itself. Thus the sensitivity analysis is carried out on various battery system rated-power values considered to range from zero to the value that does not yield further demand smoothening.

As this is an energy-conversion process, losses in the battery system should be considered. In a battery, losses are due to the conversion of electrical energy into chemical energy in order to be stored and back to electrical energy when it is needed. The efficiency of this process in batteries (electrical–chemical–electrical) varies from 50% to over 95%, depending on the technology [3,19,20]. In this article, battery efficiency ($\eta_{battery}$) is considered to be 85%, which is a rough average between widely used lead-acid and promising lithium ion batteries. For the sake of simplicity, energy losses in the battery are considered to occur only during electrical–chemical conversion.

The electrical-power converter causes additional losses in the conversion process. According to Qian et al. [20] the efficiency of electrical-power conversions is calculated to be 95% in both the DC/AC ($\eta_{DC/AC}$) and AC/DC ($\eta_{AC/DC}$) steps. Accordingly, the total efficiency of the storage–generation cycle of the battery system is equal to

$$\eta = \eta_{AC/DC} * \eta_{battery} * \eta_{DC/AC} = 0.95 * 0.85 * 0.95 = 0.77 \qquad (2)$$

Hence, operating the battery in charging mode requires more energy than in discharging mode due to losses in energy conversion.

### 3.2. Methodology

The distributed energy-storage system is managed in order to decrease peak values and increase valley values in the household-demand profile or at any other point along the distribution grid after the step-down transformer that involves an aggregation of power demands.

This subsection proposes two battery-system management models for demand smoothening. The purpose of these models is to calculate in advance the smoothened profile of the daily demand for a specific battery system. The battery system is then managed in accordance with this smoothened profile, providing the maximum possible smoothening. The first model is time-dependent and designed for a relatively simple battery system operating at constant (rated) power. The second is a demand-tracking model for a more complex battery system that operates at variable power and is therefore more flexible. Both battery-system-management models are set out in MS Excel Visual Basic computer language.

Before the demand smoothening process, a reference value (*Ref*) is calculated, which is used as the input data for both management models. This value is a fully smoothened demand. The flowchart for its calculation is presented in Fig. 4. The input parameters are the daily demand profile at hourly intervals ($Demand = [p_i]_{1\times24}$), the battery-system efficiency ($\eta$) and the calculation step (*Step*). The latter determines the calculation accuracy. The smaller the *Step*, the more precise is the calculated value. Here the battery capacity and the rated power of the battery system are assumed to be unlimited. At the beginning, the average demand ($P_{aver}$) is calculated and the initial reference value (*Ref*) is set equal to it. Then gradually *Ref* is increased by *Step* until the ratio of energy outflow ($E_{gen}$) to inflow ($E_{stor}$) (from/to the battery system) in the whole day is equal to $\eta$. Thus the reference value obtained is slightly higher than the average value of the demand profile, due to the losses in the energy-conversion process.

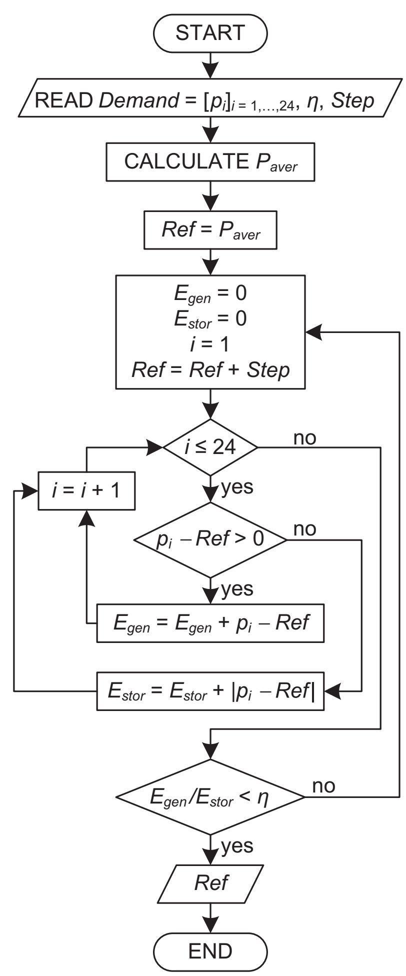


**Fig. 4.** Flowchart for calculating the reference value.

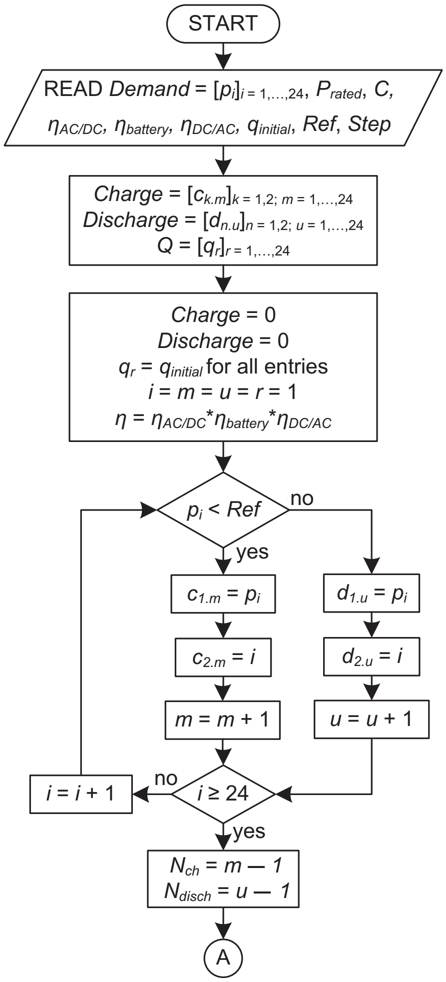


**Fig. 5.** Flowchart of the common part of the time-dependent and demand-tracking battery system management models (part 1 of 2).

After the reference value (*Ref*) is obtained, the smoothened demand profile for both management models is calculated as presented in flowcharts in Figs. 5–7. For reasons of simplicity, the common part of both models is shown in a single flowchart, Fig. 5. For their part, Figs. 6 and 7 show the flowcharts of the unique parts of the time-dependent and demand-tracking models respectively.

Following Fig. 5, the input data for both models are the daily demand profile with hourly intervals ($Demand = [p_i]_{1\times24}$), the rated power of the battery system ($P_{rated}$), the battery capacity ($C$), charging–discharging losses in battery ($\eta_{battery}$), losses in both AC/DC ($\eta_{AC/DC}$) and DC/AC ($\eta_{DC/AC}$) electrical-power conversion processes, the initial state of charge of the battery ($q_{initial}$), a reference value (*Ref*) and a calculation step (*Step*).

At the beginning, both models form three data matrices: $Charge = [c_{k.m}]_{2\times24}$, $Discharge = [d_{n.u}]_{2\times24}$ and $Q = [q_r]_{1\times24}$. Then all entries in the *Charge* and *Discharge* matrices are initially set to zero and all entries in the $Q$ matrix are equated to $q_{initial}$. The entries in the *Charge* and *Discharge* matrices at the end of the smoothening will contain the smoothened demand data. The battery's state of charge for any hour of the day during the smoothening process will be registered in the $Q$ matrix. As an example the *Demand* matrix and the initial entries in $Q$, *Charge* and *Discharge* matrices for the representative average daily household-demand profile in spring in Denmark are presented in Table 2. The *Demand* matrix contains daily household-demand profile previously presented in Fig. 1. In the $Q$ matrix all the entries are set to zero, which is the initial battery's state of charge. Zero (0) in the $Q$ matrix indicates that battery is empty and one (1) indicates that battery is fully charged. The initial state of charge is calculated according to the daily demand profile. Thus the battery at the beginning of the day in Denmark is considered to be empty, due to valley demand in the first hours of the day. At that time, the battery is charged in order to smooth demand. Furthermore, in the flowchart the battery operation mode is determined for each hour according to the reference value. For the example this value is 0.54. If the demand value ($p_i$) is lower than *Ref* (during hours from 1 to 16, Table 2), then it is recorded in the *Charge* matrix along with the respective hour $i$. Similarly the demand and time values are stored in the *Discharge* matrix when the demand is higher than *Ref* (during hours from 17 to 24, Table 2). When demand values have been allocated to all 24 h, the quantity of records is registered for both matrices: $N_{ch}$ for the *Charge* matrix and $N_{disch}$ for the *Discharge* matrix (16 and 8 respectively, Table 2).

It is assumed that the battery's state of charge is the same at the end of the day as it was at the beginning. This assumption is based on the fact that daily demand profiles are approximately similar from one day to another. So, if for an efficient demand smoothening the battery's state of charge should be empty at the beginning of the day, then this should be its state of charge at the beginning of every day. The change of day occurs at 0 am.

Battery-system parameters (battery capacity and battery system rated power) in this article are expressed in the per unit (pu) system. The base units are different for each country (Table 1). For example, using a battery system with a capacity of 0.2 h pu and battery-system rated power of 0.1 pu in Denmark, and knowing that the highest demand among the average seasonal profiles is 895 W in spring, the absolute values of the battery system are 179 W h (895 W * 0.2 h) for battery capacity and 90 W (90 W*0.1) for the battery system's rated power. Similar calculations were conducted for all the other countries studied.

*3.2.1. Time-dependent battery-system-management model*

This subsection presents the unique part of the time-dependent model. As noted above, this unique part presented in Fig. 6 takes as an input the output of the flowchart in Fig. 5. In Fig. 6, the two matrices *Charge* and *Discharge* are initially arranged in descending order. Then the calculation continues with demand smoothening: peak demand is decreased and valley demand is increased with the aid of the battery system. The battery state of charge changes accordingly. Every demand decrease is registered in the *Discharge* matrix as the demand value is decreased by $Step * \eta$ (calculation step multiplied by the battery-system efficiency). The battery state of charge ($q_r$) is decreased by $Step/\eta_{DC/AC}$ for the hours of the day which cover the hour of this demand and beyond. This represents the discharging of the battery during this demand hour. Respectively every demand increase is registered in the *Charge* matrix as the demand value is increased by *Step*. The battery state of charge ($q_r$) is now increased for this hour and beyond by $Step * \eta_{AC/DC} * \eta_{battery}$, representing the charging of the battery. After this smoothening, the battery's state of charge and the smoothened demand values are checked. The smoothening cycle repeats in the same way for the same entries in the *Discharge* and *Charge* matrices given the following conditions:

1. The battery's state of charge ($q_r$) is in the limits for any hour (i.e. $0 \leqslant q_r \leqslant C$).
2. The power reduction through discharging ($p_i - d_{1.u}$) does not exceed the $P_{rated}$ in the hours of smoothening.
3. The power increase through charging ($c_{1.m} - p_i$) does not exceed the $P_{rated}$ in the hours of smoothening.

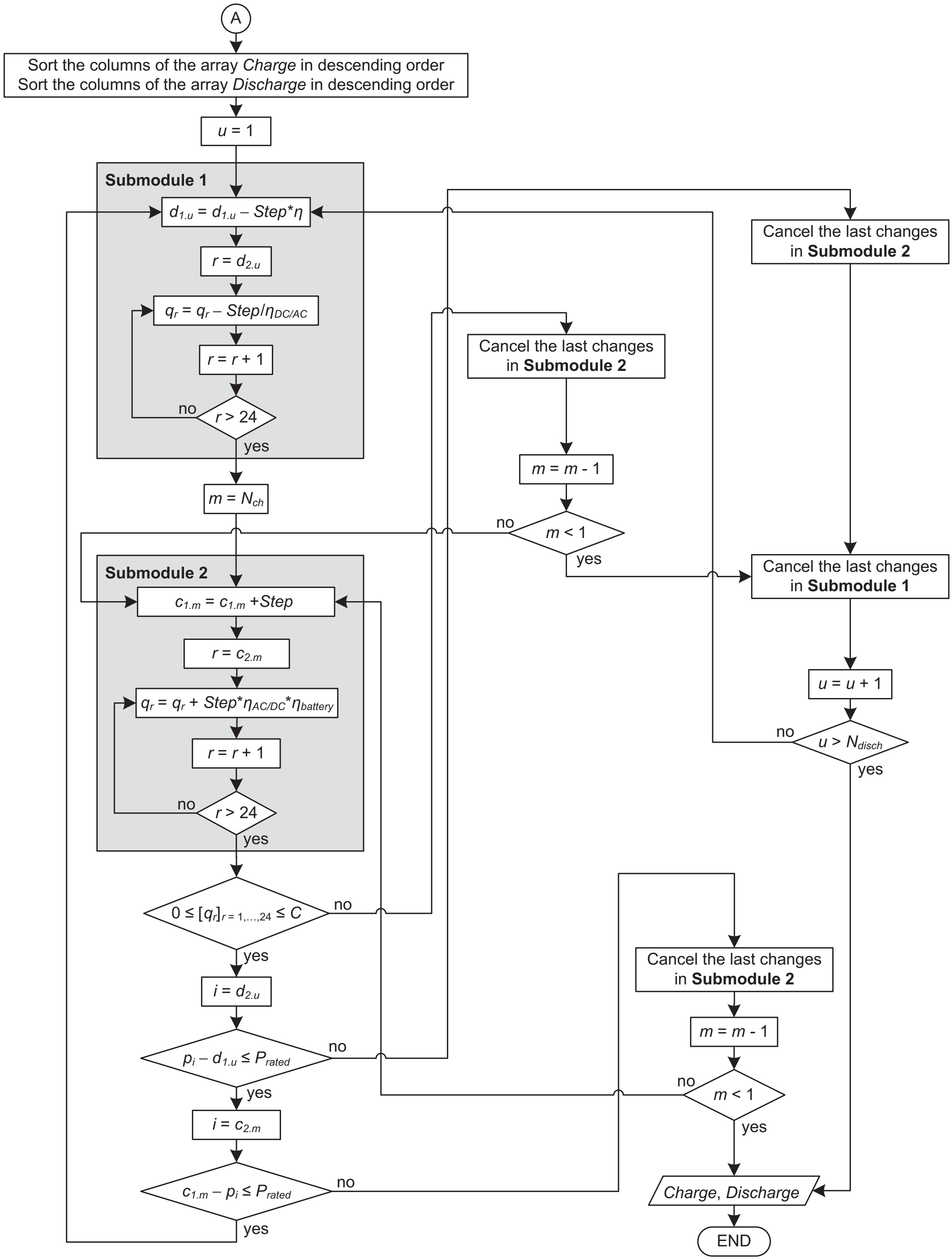


**Fig. 6.** Flowchart of the time-dependent battery system management model (part 2 of 2).

However, if the first condition is not met, then the changes performed in the last smoothening cycle involving the *Charge* matrix and consequently the relevant entries in the *Q* matrix are cancelled. Then all the non-zero entries in the *Charge* matrix ($c_{1.m}$) starting from the smallest are checked successively if the above condition can be met. The smoothening continues for the specific value at which the condition is met. If the first condition cannot be satisfied for any entry in the *Charge* matrix, then changes performed in the last smoothening cycle involving the *Discharge* matrix and consequently the relevant entries in the *Q* matrix are also cancelled. The smoothening then starts over but for the next non-zero entry in the *Discharge* matrix, i.e. the next highest demand ($d_{1.u}$). For any smoothening step, the conditions 2 and 3 are also checked. If not met, then the smoothening

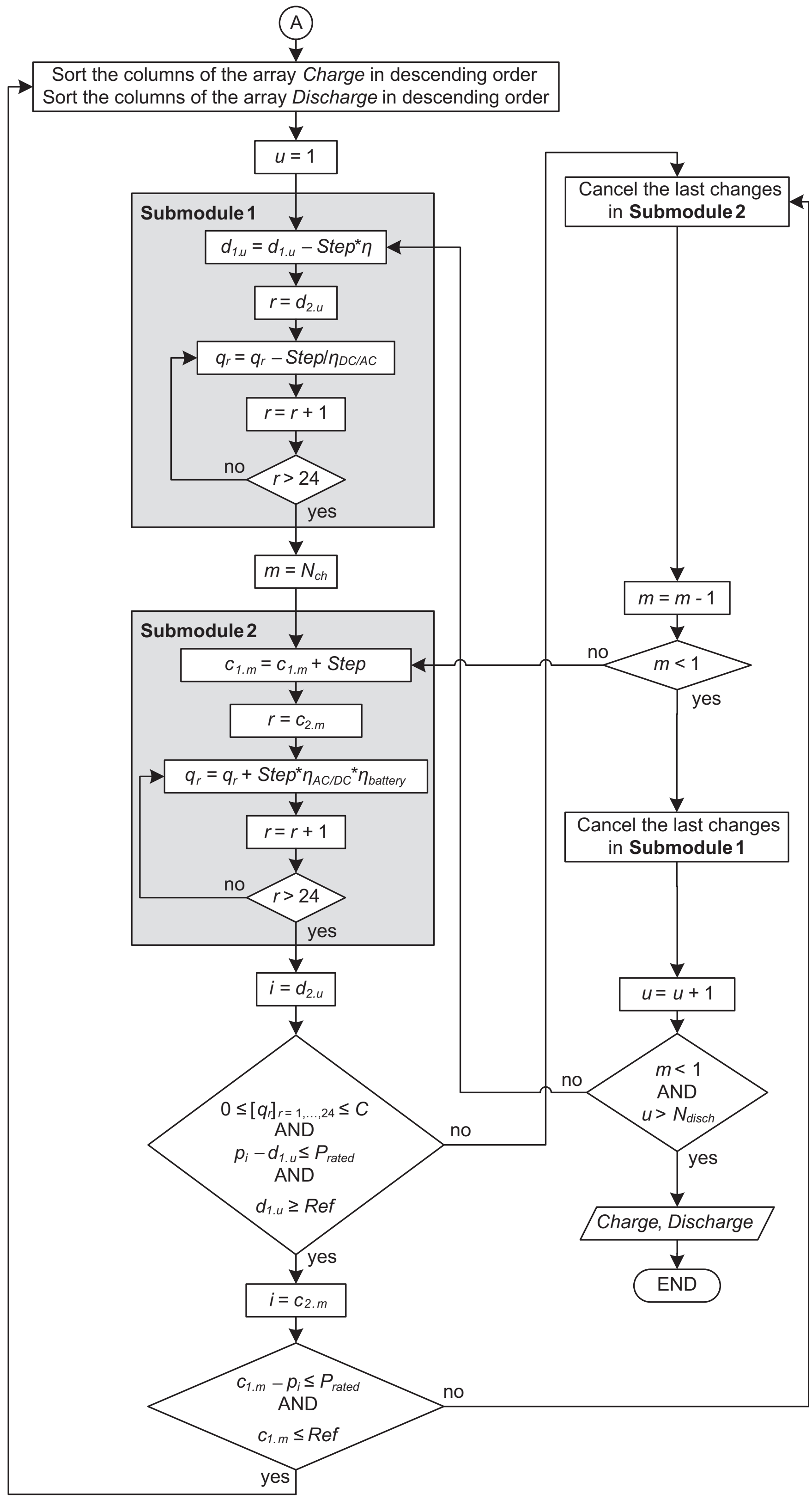


**Fig. 7.** Flowchart of the demand-tracking battery system management model (part 2 of 2).

continues of the next entry of the subject matrix (*Charge* or *Discharge*).

The smoothening is completed when all the possible smoothening combinations of the *Charge* and *Discharge* matrices have been examined and further smoothening is not possible while continuing to fulfil the above three conditions. The final values of the entries in the *Charge*, *Discharge* and *Q* matrices for the representative example (spring in Denmark) are listed in Table 3. The battery

**Table 2**
The *Demand* matrix and the initial entries in *Q, Charge* and *Discharge* matrices for the representative average daily household-demand profile in spring in Denmark.

| Entries ($i$, $r$, $m$, $u$) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Demand*, $p_i$ | 0.38 | 0.31 | 0.27 | 0.25 | 0.25 | 0.30 | 0.36 | 0.45 | 0.48 | 0.50 | 0.52 | 0.53 | 0.51 | 0.51 | 0.48 | 0.51 | 0.55 | 0.81 | 1.00 | 0.82 | 0.77 | 0.73 | 0.69 | 0.54 |
| *Q*, $q_r$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Charge*, $c_{1.m}$ | 0.38 | 0.31 | 0.27 | 0.25 | 0.25 | 0.30 | 0.36 | 0.45 | 0.48 | 0.50 | 0.52 | 0.53 | 0.51 | 0.51 | 0.48 | 0.51 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Charge*, $c_{2.m}$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Discharge*, $d_{1.u}$ | 0.55 | 0.81 | 1.00 | 0.82 | 0.77 | 0.73 | 0.69 | 0.54 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Discharge*, $d_{2.u}$ | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Table 3**
The final entries in the *Q, Charge* and *Discharge* matrices using the time-dependent battery system management for the representative average daily household-demand profile in spring in Denmark.

| Entries ($r$, $m$, $u$) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Q*, $q_r$ | 0.00 | 0.00 | 0.20 | 0.60 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.48 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Charge*, $c_{1.m}$ | 0.53 | 0.52 | 0.51 | 0.51 | 0.51 | 0.50 | 0.48 | 0.48 | 0.45 | 0.38 | 0.36 | 0.31 | 0.30 | 0.36 | 0.45 | 0.45 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Charge*, $c_{2.m}$ | 12 | 11 | 13 | 14 | 16 | 10 | 9 | 15 | 8 | 1 | 7 | 2 | 6 | 3 | 4 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Discharge*, $d_{1.u}$ | 0.80 | 0.64 | 0.81 | 0.77 | 0.73 | 0.69 | 0.55 | 0.54 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Discharge*, $d_{2.u}$ | 19 | 20 | 18 | 21 | 22 | 23 | 17 | 24 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

system parameters applied here are 0.2 pu for rated power and 0.4 h pu for battery capacity. The smoothened demand values are in the *Charge* and *Discharge* matrices ($c_{1.m}$ and $d_{1.u}$ respectively). The hours when the battery system operates in the charging mode ($c_{2.m}$) and in discharging mode ($d_{2.u}$) are defined. The *Q* matrix shows state of charge of the battery during the day indicating that the charge of the battery at the beginning and at the end of the day is the same – zero (battery is empty).

The results of the time-dependent management (*Charge* and *Discharge* matrices of Table 3) are shown in Fig. 8. At the beginning of the day, at the 4th and 5th hour, the battery system operates at rated power (0.2 pu) in charging mode, consuming 0.4 h pu of energy, which is exactly the capacity of the battery. During these hours of valley demand, the demand deviation from the reference is the highest. Due to losses in the energy-conversion processes, the battery does not reach fully charged status and some portion of energy is used in the 3rd hour to charge the battery completely. The 3rd hour has the next highest deviation after the 4th and 5th hours during valley demand. In discharging mode, the battery operates in a similar way. Demand is shaved in the 19th hour and the rest of the battery energy is used to decrease demand in the 20th hour. The battery stays empty until the end of the day, so that at the beginning of the next day the state of charge of the battery is again 0 h pu. Fig. 8 implies that more energy is consumed when the battery system is being charged (from the 3rd to the 5th hour) than discharged (in the 19th and 20th hours). This is due to the battery system's efficiency, which is 0.77.

A battery system with high rated power and high battery capacity may produce the opposite effect, i.e. an increase in demand variability. This can be caused by the battery system being constrained to operate at rated power. These cases are not feasible and are not presented here.

*3.2.2. Demand-tracking battery-system-management model*

This subsection presents the unique part of the demand-tracking model. As in the previous model, this unique part presented in Fig. 7 takes as an input the output of the flowchart in Fig. 5. As with the time-dependent model, in Fig. 7 for the demand-tracking model the *Charge* and *Discharge* matrices are arranged in descending order. The hours with the highest deviations above and below the reference are the first to be smoothened. Thus, the biggest entry in the *Discharge* matrix is reduced and the smallest non-zero entry in the *Charge* matrix is increased by *Step* $^*\eta$ and *Step* respectively. The battery use is registered accordingly. The three conditions as described in the previous subsection and two more conditions are checked. These two additional conditions are:

1. The smoothened demand value through charging ($c_{1.m}$) is equal or smaller to *Ref*.
2. The smoothened demand value through discharging ($d_{1.u}$) is equal or bigger to *Ref*.

If all five conditions are met, the *Discharge* and *Charge* matrices are arranged again in descending order and the cycle is repeated.

However, if these conditions are not met, then the changes performed in the last smoothening cycle involving the *Charge* matrix and consequently the relevant entries in the *Q* matrix are cancelled. Then the next smallest entry in the *Charge* matrix is increased by *Step* and the battery state of charge is changed accordingly. The smoothening continues for the specific entry at

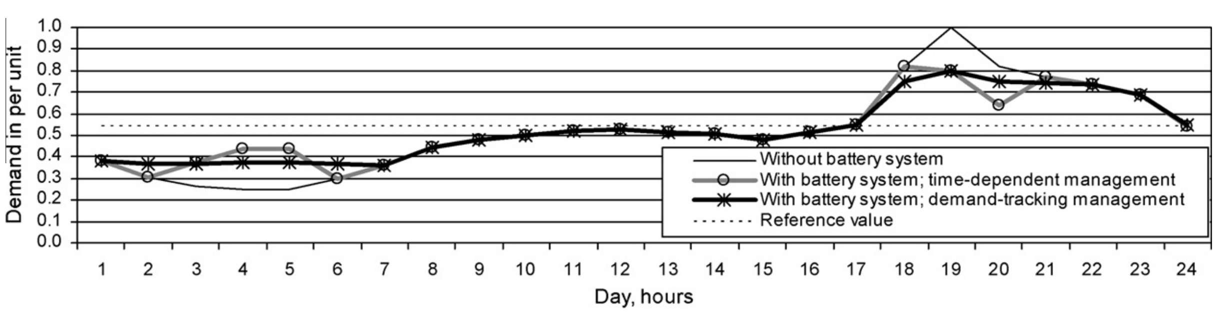


**Fig. 8.** Representative average daily demand profile in spring in Denmark with and without the battery system under the two management models.

**Table 4**
The final entries in the *Q*, *Charge* and *Discharge* matrices using the demand-tracking battery system management for the representative average daily household-demand profile in spring in Denmark.

| Entries ($r$, $m$, $u$) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Q*, $q_r$ | 0.00 | 0.13 | 0.34 | 0.58 | 0.83 | 0.98 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.80 | 0.27 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Charge*, $c_{1.m}$ | 0.53 | 0.52 | 0.51 | 0.51 | 0.51 | 0.50 | 0.48 | 0.48 | 0.45 | 0.38 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0.37 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Charge*, $c_{2.m}$ | 12 | 11 | 13 | 14 | 16 | 10 | 9 | 15 | 8 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Discharge*, $d_{1.u}$ | 0.80 | 0.74 | 0.74 | 0.74 | 0.73 | 0.69 | 0.55 | 0.54 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Discharge*, $d_{2.u}$ | 19 | 18 | 20 | 21 | 22 | 23 | 17 | 24 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

which all five conditions are finally met. If all the entries in the *Charge* matrix have been checked, but the conditions are still not met, then the last changes in the *Discharge* matrix are also cancelled along with the battery state of charge. The next entry now of the *Discharge* matrix is treated in the smoothening cycle. This procedure continues until the conditions are met for a combination of entries in the two matrices. Then the smoothening cycle starts over from arranging the two matrices again.

If no more smoothening is possible for any combination of entries in the *Discharge* and *Charge* matrices under the above conditions, the smoothening is completed. The data of the smoothened demand for the representative example (spring in Denmark) is stored in the *Charge* and *Discharge* matrices as shown in Table 4. As in the previous section the rated power of the battery system and the battery capacity used are 0.2 pu and 0.4 h pu respectively. The battery system's instantaneous power is the difference between the initial demand ($p_i$) and the smoothened demand ($d_{1.u}$ or $c_{1.m}$).

The results of the demand-tracking battery system management (*Charge* and *Discharge* matrices of Table 4) are shown in Fig. 8. As with the time-dependent management system, under the demand-tracking management model, the battery system is fully charged during the first hours of the day at valley demand and fully discharged at the end of the day during high demand (Table 4). Since the demand-tracking management model is used for a battery system with variable power, at the beginning of the day demand is smoothened uniformly between the 2nd and the 6th hour. At peak demand at the end of the day, the demand is smoothened from the 18th to the 21st hour. During the 19th hour, peak-demand shaving is limited due to the rated power of the battery system (0.2 pu).

## 4. Study results and discussion

This section describes and discusses the results of the two battery-system-management models in household-demand smoothening. The representative demand-smoothening results for Portugal and Denmark are presented in detail in order to show the differences in the smoothening characteristics for individual countries and in the battery system effect from one season to another. The overall results for demand smoothening and peak shaving include all the countries studied: Denmark, Portugal, Greece, France and Italy. Various battery-system parameters (system rated power and battery capacity) are used to perform a sensitivity analysis. The demand-smoothening results in this section are expressed as standard deviation values (Eq. (1), Section 2) of average daily demand profiles for the season concerned.

### 4.1. Smoothening results

Fig. 9 presents the smoothening results of average daily demand profiles in spring and summer in Denmark. Spring characterises with the highest demand variations and summer with the lowest. Battery capacity ranges from 0.2 to 1.8 h pu and the battery system's rated power from 0.1 to 0.5 pu. It is noticeable that demand smoothening depends on both battery capacity and the battery system's rated power. For example, during the spring and under the demand-tracking model, for 0.1 pu of battery system rated power, the standard deviation decreases as the battery capacity increases up to 0.6 h pu. Further increases in battery capacity do not produce further smoothening results. This is due to the limited rated power of the battery system (0.1 pu). To obtain further smoothening results, the rated power of the battery system needs to be greater.

Another limitation in demand smoothening is the way in which it is managed. In Denmark in spring, for example, for a battery system with a rated power of 0.2 pu, the standard deviation falls to 0.068 under the demand-tracking model (Fig. 9). On the other hand, under the time-dependent management model, the standard deviation falls to only 0.086. These are the maximum smoothening values that can be achieved at a battery system rated power of 0.2 pu, regardless of the size of battery capacity.

Under the demand-tracking model, as the battery-system parameters increases, so does the smoothening effect (or it remains constant). This trend changes under the time-dependent management model, which does not achieve complete smoothening. A similar smoothening effect was achieved using both management models at low values for the battery system's technical parameters but at higher values the time-dependent management model has less of an effect on smoothening. For example, in Denmark in spring at a relatively low battery-system rated power of 0.1 pu and at low battery capacities of 0.2 h, 0.4 h and 0.6 h pu, both management models achieve a similar smoothening effect. But at a battery-system rated power of 0.4 pu, the management models achieve similar results only when the battery capacity is 0.2 h pu (around 0.17). With higher battery capacity, at the same system rated power (0.4 pu), the demand-tracking management model achieves better smoothening results than the time-dependent management model.

If the time-dependent management model is run with a high battery-system rated power, it can even produce the opposite effect: a decrease in smoothening. For example, a battery system rated power of 0.3 pu produces better demand smoothening than a battery system rated power of 0.4 pu because the system operates at constant (rated) power (Fig. 9).

Fig. 9 shows that in Denmark in summer the standard deviation without a battery system is lower than it is in spring. In summer, less battery capacity and battery-system rated power is required to achieve complete smoothening (standard deviation close to zero). When using the demand-tracking management model in the spring, 1.6 h pu battery capacity and 0.5 pu battery system rated power are required for complete smoothening. To achieve the same result in summer, it requires 1.2 h capacity and 0.3 pu system rated power.

The scenario in Portugal in Fig. 10 represents smoothening results of average daily demand profiles in the seasons with the highest and the lowest demand variations: winter and autumn respectively. The standard deviation of the demand profile in winter without a battery system is similar to that in Denmark in spring

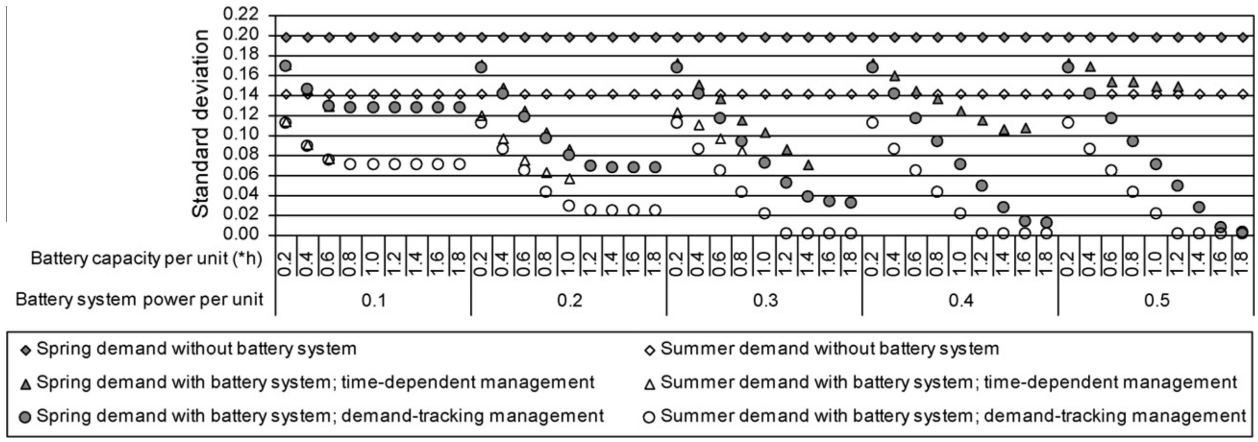


**Fig. 9.** Representative smoothening results of average daily demand profiles in spring and summer in Denmark with different battery-system parameters and management models.

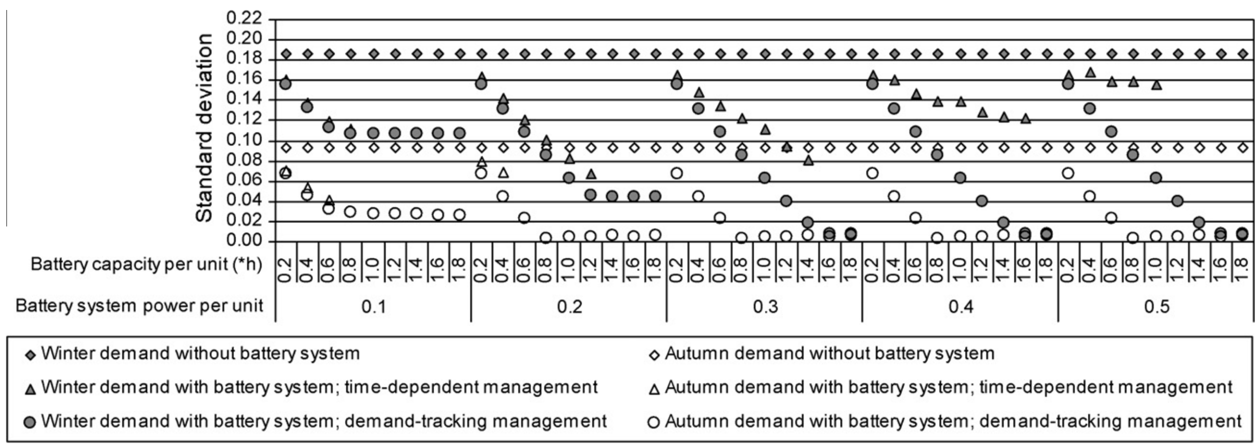


**Fig. 10.** Representative smoothening results of average daily demand profiles in winter and autumn in Portugal with different battery-system parameters and management models – without PV.

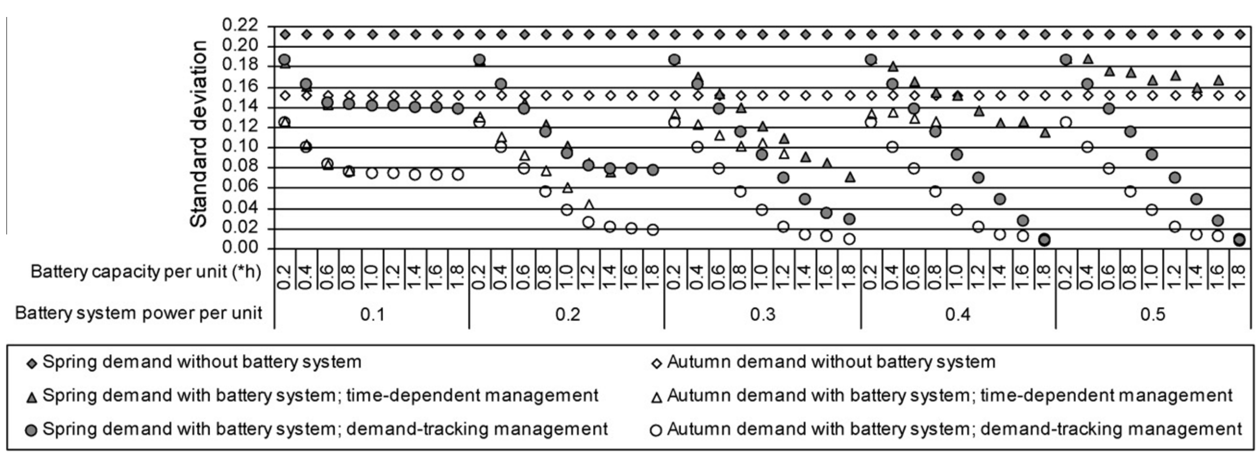


**Fig. 11.** Representative smoothening results of average daily demand profiles in spring and autumn in Portugal with different battery-system parameters and management models – with PV.

(Fig. 9). However, autumn demand in Portugal has a flatter profile than in Denmark during the summer. The case of Portugal was also studied at high PV penetration. Fig. 11 shows that PV integration in Portugal increases the demand variability and changes the season with the highest demand variations from winter to spring. Compared with Denmark, in Portugal without PV penetration the same battery capacity of 1.6 h pu is needed to almost reach zero standard deviation under the demand-tracking management model, but required battery-system rated power is lower, i.e. 0.3 pu. When adding PV to the distribution grid, the requisite system rated power increases to 0.4 pu and battery capacity to 1.8 h pu in order achieve complete smoothening. Figs. 10 and 11 also compare the

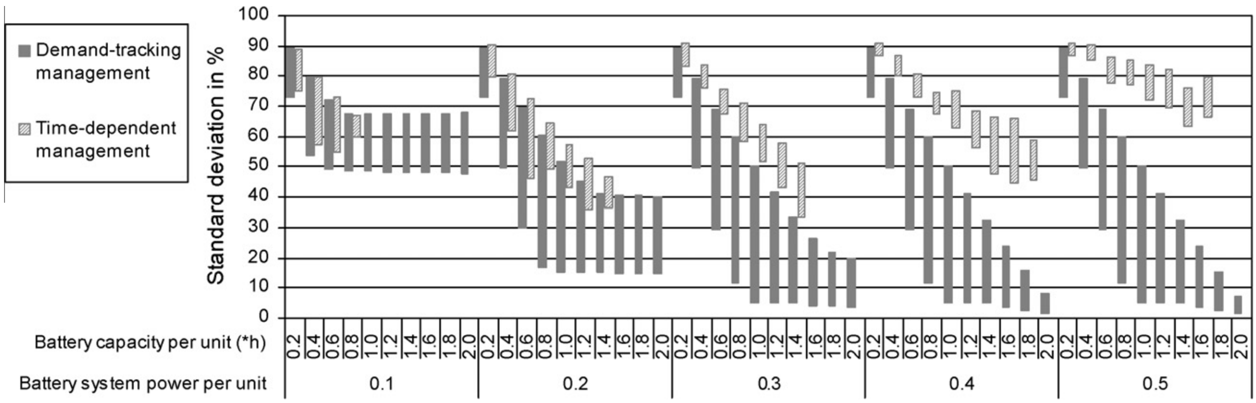


**Fig. 12.** Overall smoothening results of average daily demand profiles during the seasons with the highest demand variations in Denmark, Portugal, Greece, France and Italy (with and without PV) with different battery-system parameters and management models.

**Table 5**
Required battery system parameters for complete and 50% demand smoothening and resulted peak reduction using demand-tracking model.

| Country | PV | Complete smoothening | | | 50% Smoothening | | |
|---|---|---|---|---|---|---|---|
| | | Battery system (pu) | | Peak demand reduction (%) | Battery system (pu) | | Peak demand reduction (%) |
| | | Battery capacity | Rated power | | Battery capacity | Rated power | |
| Denmark | No | 1.6 h | 0.5 | 44 | 0.8 h | 0.2 | 20 |
| Portugal | No | 1.6 h | 0.3 | 28 | 0.8 h | 0.2 | 19 |
| | Yes | 1.8 h | 0.4 | 34 | 1.0 h | 0.2 | 20 |
| Greece | No | 1.8 h | 0.4 | 40 | 0.8 h | 0.2 | 20 |
| | Yes | 2.2 h | 0.5 | 47 | 1.2 h | 0.2 | 20 |
| France | No | 1.0 h | 0.3 | 27 | 0.6 h (0.4 h) | 0.1 (0.2) | 10 (17) |
| | Yes | 1.2 h | 0.3 | 29 | 1.8 h (0.6 h) | 0.1 (0.2) | 10 (20) |
| Italy | No | 2.0 h | 0.4 | 36 | 1.0 h | 0.2 | 20 |
| | Yes | 2.0 h | 0.4 | 39 | 1.0 h | 0.2 | 20 |

two management models compared previously for the case of Denmark. The difference between the two models is similar in both countries.

The overall effect on household-demand smoothening is presented in Fig. 12, including all countries studied in this article. Only the seasons in which the average daily demand profile shows the highest demand variations are presented (Table 1). Both scenarios, with and without PV penetration, are included. Using smoothening results from other seasons would generate the wrong conclusions due to the difference in the ratio between the battery-system parameters and the peak demand. For example, if the battery-system rated power is 10% of Denmark's peak demand in spring, then the battery-system rated power's proportion of the summer peak demand will be more than 10% due to a lower peak in summer. The values on the vertical axis indicate the reduced standard deviation achieved with each battery system, assuming that the standard deviation without any battery system is 100%.

Fig. 12 shows the results for both management models with different battery-system parameters. The variation ranges reflect different smoothening results for different demand profiles. The figure shows that at low battery capacities (0.2 h and 0.4 h pu) and the low battery-system power of 0.1 pu, both management models produce quite similar smoothening results. High range of the smoothening effects is due to different demand profiles. If, for example, the desired reduction of the standard deviation is 30–45%, the required battery-system rated power and battery capacity will probably be close to 0.1 pu and 0.6 h pu respectively. In this case, using a time-dependent management model is sufficient. At higher battery-system parameters, a demand-tracking model shows better results, but the resultant smoothening range may be as much as 50% points. This indicates that for high smoothening results, the demand profile plays an important role.

Individual country results in demand smoothening are listed in Table 5 indicating the necessary (minimum) battery system parameters for complete and 50% demand smoothening. Only demand-tracking model is presented since according to Fig. 12 it is essential for high smoothening. Complete smoothening is considered if the standard deviation falls below 0.01; whereas 50% smoothening means that the standard deviation of demand profile is reduced by half. If the smoothening can be achieved with different battery system configurations, it is also presented in Table 5, but only in the case in which the increase of one parameter (battery capacity or battery system rated power) result in the decrease of the other. For example, in France case without PV, the 50% smoothening can be achieved with battery capacity of 0.6 h pu and battery system rated power of 0.1 pu or with lower battery capacity (0.4 h pu) and higher battery system rated power (0.2 pu).

Table 5 shows that in general the less demanding case is France since it requires lower battery capacity and battery system rated power. This is due to the lower France demand variations (Table 1). In Portugal, Greece and France cases PV penetration increases the required battery system parameters, but in Italy they remain the same. This indicates that each case is country specific which implies the way the demand variations are altered due to the PV penetration.

### 4.2. Peak-shaving results

Another key objective in battery-system applications is peak-demand shaving as it plays an important role in determining the size (rated power) of all power elements in the energy-transfer corridor.

The overall peak-shaving results using a battery system are shown in Fig. 13. It shows only the seasons with the average daily

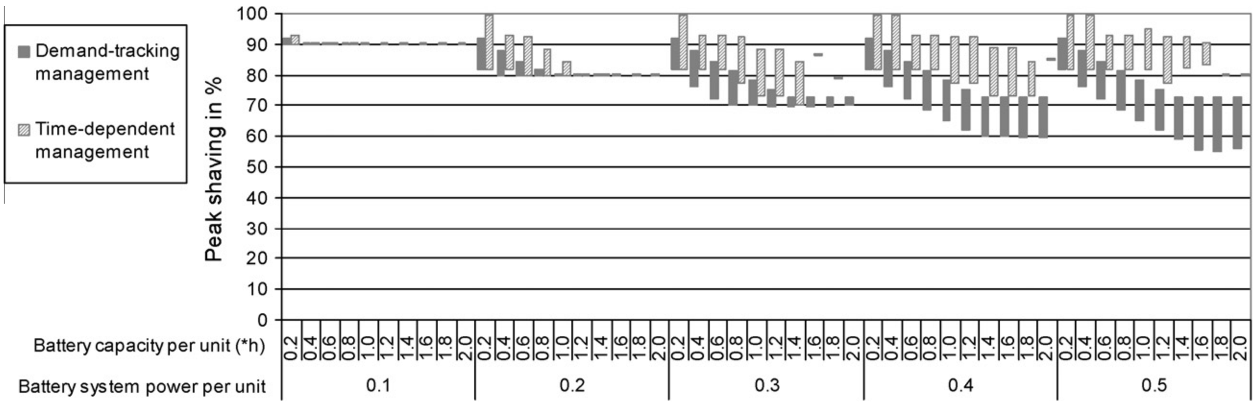


**Fig. 13.** Overall peak-shaving results of average daily demand profiles during the seasons with the highest peak demand in Denmark, Portugal, Greece, France and Italy (with and without PV) using different battery-system parameters and management models.

demand profile which present the highest peak demand (including cases with and without PV generation, Table 1). It is the peak that determines the rated-power values of the electricity-supply corridors. The range in the figure indicates the spectrum of the results from the peak shaving of the demand profiles.

In Fig. 13, the peak demand is considered to be 100%. The best peak shaving is achieved with the demand-tracking management model. For a battery capacity of 1.6 h pu and a battery system rated power of 0.5 pu, the peak decreases by 27–45%. This value is theoretically the maximum peak shaving possible with the current battery-system properties and assumptions (described in Section 3.1). In this case, the demand profile is practically flat, i.e. fully smoothened. For demand profiles with low variations, e.g. in France, the maximum peak demand reduction is close to 30%; whereas in other countries studied with higher demand variations it can reach 40–45%, e.g. in Greece and Denmark case (Table 5).

Maximum peak shaving for other battery-system rated powers (from 0.1 to 0.4 pu) is determined by these power values, provided that there is sufficient battery capacity. For example, following Fig. 13, at a battery-system rated power of 0.2 pu, the maximum peak reduction is 20% and is achieved at a battery capacity of 0.4 h pu under the demand-tracking management model in one or more countries studied. Furthermore, increase in battery capacity to 1.0 h pu leads to the peak demand reduction by 20% in all the studied countries. Also Table 5 approves this fact: in 50% smoothening the peak demand reduction is equal or smaller then the battery-system rated power. Further increases in battery capacity do not lead to any additional peak shaving, since it is limited by the battery-system rated power. However, further increase in battery capacity affects demand smoothening, as stated in the previous section (Fig. 12). Under the time-dependent management model, the peak-shaving results are rather stochastic. It is not sufficient to achieve a high peak reduction.

In general, the range of the peak-shaving effect can vary greatly (up to 15% points) between different demand profiles. This indicates that each demand-peak-shaving case requires a specific study to obtain accurate results. However, for low battery-system parameters, e.g. at system rated power 0.1 pu and battery capacity 0.2 h pu, the results are fairly similar, even for different demand profiles.

### 4.3. Feasibility

Complete smoothening of the demand profile (standard deviation close to zero) in all seasons will sufficiently decrease the annual utilisation of the battery-system rated power and battery capacity. This is due to variations in the demand profile between seasons. Figs. 9–11 show that in both Denmark and Portugal, installing a battery system for complete smoothening throughout the year will reduce the use of the system. It is clear that, in this case, during seasons with lower demand variations, neither the battery capacity nor the system rated power will be completely utilised. This in turn decreases the annual utilisation (capacity factor) of the battery system.

The feasibility of using battery systems for household-demand smoothening from the end user side can be roughly calculated from the life cycle costs (including capital and operating costs) and benefits due to electricity-price elasticity in battery charging and discharging time periods. According to Ekman and Jensen [21], a regulated energy market providing a high range of electricity prices in valley and peak demand hours is essential in order to stimulate investment in these technologies by end users. The proportion of the electricity price comprised by battery charging and discharging times should be lower than the total battery-system efficiency. Thus, each additional charging–discharging cycle could bring additional profit. On the other hand, the quantity of these cycles is limited and varies between the various battery types. According to Sullivan and Gaines [22], a lead-acid battery has a cycle life of around 500 at deep discharge; for lithium-ion batteries, it is much higher – 6000. The daily demand profile is usually characterised by a valley-demand period during the night, in which the battery system operates only in charging mode for demand-smoothening purposes. Over the rest of the day during the peak demand (in the morning and/or evening) the battery operates in discharging mode in order to transfer the stored energy back to the grid. This completes the charging–discharging cycle for the day and it starts again the next day. Considering the one-day cycle period for the battery system, the lead-acid battery would have a life cycle of about 1.5 years, whereas the lithium ion technologies would last for 16 years.

Furthermore, at distribution-grid level, other technical benefits due to demand smoothening (and peak shaving), such as those already mentioned (the increased capacity factor of power-transfer corridors and of conventional power generators, and the heightened security of energy supply) should be considered when carrying out feasibility studies of battery systems.

## 5. Conclusions

This article discusses the overall role that battery-based energy-storage applications can have in household demand smoothening. It proposes two battery-system-management models. The results are provided in relative values and include studies of five countries: Denmark, Portugal, Greece, France and Italy.

On the issue of demand smoothening (reducing the standard deviation), battery storage systems with low rated power and low battery capacity could produce similar effects for different demand profiles. At low battery-system parameters, the two management models also produce similar results. Thus, assuming that the peak power in the daily demand profile is $1 \times$ W, the standard deviation from the initial demand profile could be reduced by 30–45% using a battery system with rated power of $0.1 \times$ W and battery capacity of up to $0.6 \times$ W h. Thus, up to these battery system parameters, a time-dependent management model for a simple battery system operating at constant (rated) power is sufficient. However, to achieve further smoothening, a more elaborate management – such as a demand-tracking management model – is required. This model is designed for a battery system with variable power, an essential requirement for high demand smoothening. Higher battery-system parameters produce different smoothening effects when applied in different demand profiles.

Peak-demand-shaving results in general are more dependent on the demand profile. So, for high peak-demand shaving and also for high demand smoothening, each case should be studied separately to obtain accurate results. Moreover, only the demand-tracking management model is capable of achieving maximum peak shaving (complete demand smoothening).

High PV penetration in the distribution grids studied in the case of Portugal leads to an increase in the required battery-system parameters for complete smoothening, indicating that the daily demand-profile variations increase as a result of PV installation. Similar results are obtained for Greece and France, but not in the Italian case. In the latter, high PV penetration does not significantly influence the smoothening effect of the battery system. However, these results suggest that the issue of variability in demand and generation is even more urgent, given the European energy plans for extensive RES integration.

Similarly, battery systems could provide ancillary services to address the power balance at transmission-grid level. For example, batteries can provide energy storage where high wind-farm generation creates a power surplus. This stored energy can be used later in demand-peak shaving. The need for such services will rise following the trend to increase the penetration of variable RES [23]. In addition, wind-farm generation also varies from one season to another. Seasonal correlation between low demand and high wind-farm generation (or high demand and low wind-farm generation) could create an additional challenge to RES integration [24].

## References


[1] Commission of the European Communities. Energy infrastructure priorities for 2020 and beyond – a blueprint for an integrated European energy network. <http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=SPLIT_COM:2010:0677(01):FIN:EN:PDF> [accessed 07.12].

[2] Purvins A, Wilkening H, Fulli G, Tzimas E, Celli G, Mocci S, et al. A European supergrid for renewable energy: local impacts and far-reaching challenges. J Clean Prod 2011;19:1909–16.

[3] Divya KC, Østergaard J. Battery energy storage technology for power systems – an overview. Electr Power Syst Res 2009;79:511–20.

[4] Castillo-Cagigal M, Gutiérrez A, Monasterio-Huelin F, Caamaño-Martín E, Masa D, Jiménez-Leube J. A semi-distributed electric demand-side management system with PV generation for self-consumption enhancement. Energy Convers Manage 2011;52:2659–66.

[5] Tan CW, Green TC, Hernandez-Aramburo CA. A stochastic method for battery sizing with uninterruptible-power and demand shift capabilities in PV (photovoltaic) systems. Energy 2010;35:5082–92.

[6] Papic I. Simulation model for discharging a lead-acid battery energy storage system for load leveling. IEEE Trans Energy Convers 2006;21:608–15.

[7] Nourai A, Kogan VI, Schafer CM. Load leveling reduces T&D line losses. IEEE Trans Power Deliver 2008;23:2168–73.

[8] Bingying Wu, Buhan Zhang, Biao Mao, Jiajun Zhai. Optimal capacity of flow battery and economic dispatch used in peak load shifting. In: 4th International conference on electric utility deregulation and restructuring and power technologies (DRPT); 2011. P. 1395–400.

[9] Koutsopoulos I, Tassiulas L. Challenges in demand load control for the smart grid. IEEE Network 2011;25:16–21.

[10] White CD, Max Zhang K. Using vehicle-to-grid technology for frequency regulation and peak-load reduction. J Power Sources 2011; 196:3972–80.

[11] Ahn Changsun, Li Chiao-Ting, Peng Huei. Optimal decentralised charging control algorithm of the electrified vehicles connected to smart grid. J Power Sources 2011;196:10369–79.

[12] Valentine K, Temple WG, Max Zhang K. Intelligent electric vehicle charging: rethinking the valley-fill. J Power Sources 2011;196:10717–26.

[13] Commission of the European Communities. A technology roadmap. <http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=SEC:2009:1295:FIN:EN:PDF> [accessed 07.12].

[14] Grinden B, Feilberg N. Analysis of monitoring campaign in Europe, Remodece. <http://remodece.isr.uc.pt/downloads/REMODECE_D10_Nov2008_Final.pdf> [accessed 07.12].

[15] Beurskens LWM, Hekkenberg M, Vethman P. Renewable energy projections as published in the national renewable energy action plans of the European member states. Covering all 27 EU member states; 2011. <http://www.ecn.nl/publications/PdfFetch.aspx?nr=ECN-E-10-069> [accessed 07.12].

[16] Legal PV. <http://www.pvlegal.eu/nc/en/database.html?tx_sbpvlegaldb_pi1%5BbrowseCountry%5D =109&tx_sbpvlegaldb_pi1%5Blifecycle%5D=1830&cHash=f156dcd0e4> [accessed 07.12].

[17] Suri M, Huld T, Dunlop E, Ossenbrink H. Potential of solar electricity generation in the European union member states and candidate countries. Sol Energy 2007;81:1295–305.

[18] Beaudin M, Zareipour H, Schellenberglabe A, Rosehart W. Energy storage for mitigating the variability of renewable electricity sources: an updated review. Energy Sustain Dev 2010;14:302–14.

[19] Perrin M, Saint-Drenan YM, Mattera F, Malbranche P. Lead-acid batteries in stationary applications: competitors and new markets for large penetration of renewable energies. J Power Sources 2005;144:402–10.

[20] Qian Hao, Lai Jih-Sheng, Zhang Jianhui, Wensong Yu. High-efficiency bidirectional AC–DC converter for energy storage systems. IEEE Energy Convers Congress Expos (ECCE) 2010;2010:3224–9.

[21] Ekman CK, Jensen SH. Prospects for large scale electricity storage in Denmark. Energy Convers Manage 2010;51:1140–7.

[22] Sullivan JL, Gaines L. Status of life cycle inventories for batteries. Energy Convers Manage 2012;58:134–48.

[23] Purvins A, Zubaryeva A, Llorente M, Tzimas E, Mercier A. Challenges and options for a large wind power uptake by the European electricity system. Appl Energy 2011;88:1461–9.

[24] Purvins A, Papaioannou IT, Oleinikova I, Tzimas E. Effects of variable renewable power on a country-scale electricity system: high penetration of hydro power plants and wind farms in electricity generation. Energy 2012;43:225–36.