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Grid Services Provision from Batteries within Charging Stations by using a Stochastic Planning Method of the EVs Demand

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Abstract: This paper presents a smart methodology to improve the operation of the power system and to deal with technical issues caused by electric vehicles (EVs) charging demand. Direct-current fast-charging stations (DCFCSs) are indispensable for widespread use of EVs since they can fully charge EVs in a short period of time. The integration of battery energy storage (BES) within the DCFCSs is considered a smart option to prevent the power congestion during the peak hours as well as the grid reinforcement costs due to DCFCSs. Therefore, the authors proposed a method to determine an optimal size of BES within DCFCSs considering a stochastic modelling approach to predict EV load demand based on the users’ behaviour and the probabilistic driving patterns. In addition, the BES in this paper is used as multifunctional equipment, which is able to provide ancillary services as peak shaving and frequency regulation. Finally, an economic analysis is carried out to evaluate the technical and economic issues related to BES such as life-cycle costs versus the revenue provided by the transmission system operators (TSOs) for frequency regulation.

Nomenclature

Abbreviations

AC Alternating Current
BES Battery Energy Storage
B/C Benefit-Cost ratio
BMS Battery Management System
CBA Cost-Benefit Analysis
CCS Combined Charging System
DC Direct Current
DSO Distribution System Operator
DCFCS DC Fast-Charging Station
DNTS Danish National Transport Survey
DER Distributed Energy Resources
DWR Downward regulation
UWR Upward regulation
EV Electric Vehicle
EVSEO Electric Vehicle Supply Equipment Operators
FNR Frequency Normal-operation Reserve
IEC International Electrotechnical Commission
ICE Internal Combustion Engine
LV Low Voltage
LTO Lithium Titanate Oxide battery
MV Medium Voltage
NPV Net Present Value
NMC Nickel Manganese Cobalt battery
PDF Probability Density Function
PS Peak Shaving
PBP Payback Period
SoC State of Charge
SD Standard Deviation
TSO Transmission System Operator
TFR Total Frequency Regulation
V2G Vehicle to Grid

Parameters

\( B \) Benefit [€]
\( C \) Costs [€]
\( E \) Energy [kWh]
\( EV_D \) EV demand [kWh]
\( EV_r \) Electric Vehicle range [km]
\( EV_{mp} \) EV market penetration [%]
\( ICE_r \) ICE vehicle range [km]
\( K \) BES cycles
\( P \) Power [kW]
\( T \) Investment life
\( V_{cc} \) EV consumption [kWh/km]
\( d \) Driving distance [km]
\( t \) time
\( l_n \) PFD logarithmic distribution
\( \eta \) Efficiency
\( \mu \) Mean
\( \sigma \) Standard deviation
\( \tau \) EV charging time
\( a \) DCFCS charging power setting
\( \beta \) DCFCS charging duration setting
\( \gamma \) DCFCS power and charging duration setting
\( f \) Frequency [Hz]
\( m \) Angular coefficient of the droop control
\( \rho_{FNR} \) Price paid for FNR services

1. Introduction

THE large-scale electrification of the transport sector has become a major field of research. The direct-current fast-charging stations (DCFCSs) are a good solution to support...
the integration of numerous electric vehicles (EVs) in sustainable cities [1], especially when long-distance travel is considered [2]. In the major European cities, it has been difficult to install DCFCSSs because its progress poses demanding requirements in terms of EVs battery and charging rate restrictions. In addition, there are many issues related to the impact of the DCFCSSs on the low voltage (LV) distribution grid such as congestion during the peak hours, high losses in the feeders [3] and oversizing of electrical equipment [4]. Therefore, DCFCSSs need smart management systems able to predict the required demand and automotive engineers have proposed their standards on the charging modes [5]. Considering the EV market penetration over the next 10 years [6] the integration of public DCFCSSs are essential to support the future EVs demand and to recharge rapidly in urban areas. Therefore, the widespread use of EVs and the installation of the DCFCSSs require further research to evaluate the grid impact and the installation costs for these flexible loads. This topic is sensibly addressed in the literature. The authors of [7] proposed a coordinated charging system to minimise the power and maximize the main grid load force to approach an optimal charging profile for EVs. To mitigate the congestion caused by the EV demand, other studies have proposed a dynamic price for the users to maintain the integrity of the electrical grid [8]. The authors of [9] focused their studies on energy management systems in order to determine an optimal EVs day-ahead scheduling in line with the electricity price.

Furthermore, EV charging infrastructures play important roles within the smart grids, especially with the spread of different kinds of renewable energy and stationary storage sources [10]-[11]. However, to satisfy the EV load demand of the new EV models in urban areas, public DCFCSSs are indispensable to recharge EVs rapidly. In order to reduce the grid impact of the DCFCSSs, in our previous work, battery energy storage (BES) within DCFCSSs are used as peak shaving [12]-[13]. In addition, BES can operate as multifunctional equipment which is able to provide several services such as peak shaving and frequency regulation [14]-[16]. Therefore, the integration of DCFCSSs must meet the EVs demand in order to evaluate the grid infrastructure costs [17]. Additionally, an essential aspect to take into account is the evolution of lithium battery technology and its annual cost reduction [18]. This represents a chance to evaluate possible scenarios of massive EV penetration by developing control methods of BESs within charging stations. In addition, increasing penetration of distributed energy resources (DERs) creates uncertainty between production and consumption. The variable generations due to DERs cause frequency unbalances to the grid. This means that there is a growing need to provide frequency regulation to transmission system operators (TSOs), which is paid from the market for ancillary services. According to state of the art, many researchers are focusing on the transition from the traditional power systems, where the frequency is controlled by a small set of large generating units to the future one where it is controlled by several small DERs [19]-[20] or from BESs [21]. Different projects in Europe have integrated BESs with and without DERs to provide ancillary services such as peak shaving for the distribution system operators (DSOs) and frequency regulation to TSOs [15]-[16].

Assuming the state-of-the-art of the public DCFCSSs, this work proposes a stochastic planning method of the DCFCSSs considering users’ behaviour and the probabilistic driving patterns in order to predict EVs charging demand. According to the stochastic method, a storage charging demand is proposed with the objective of minimising peak EV load and the charging infrastructure costs. The primary objective of the BES is to reduce the DCFCSSs peak-load during the congestion hours (peak shaving) in order to prevent additional grid reinforcement costs due to DCFCSSs. The secondary objective is to optimise the investment costs of BES by increasing the profit of the investment by providing frequency regulation or frequency normal-operation reserve (FNR) during the night when the EV demand can be assumed very low. The performance of the proposed methodology will be verified and analysed via simulations on a realistic case of DCFCSSs in Copenhagen [1].

In conclusion, the main contributions of this paper are:

- To propose a stochastic planning method to analyse the expected charging demand from the DCFCSSs according to different properties and probabilistic driving patterns.
- To propose a method to determine optimal storage charging demand to avoid the DCFCSSs peak load in order to minimise the grid installation costs by integrating BES within DCFCSSs.
- To propose a method to optimise the investment costs of BES by providing primary frequency regulation during the night when the EV demand is low.
- To propose a cost-benefit analysis (CBA) to evaluate the technical and economic issues of the BES as life-cycle costs versus the revenue provided by the TSO for frequency regulation.

The paper is organised as follows. Section 2 discusses the method used to calculate EVs charging demand. Section 3 models the stochastic methods of the EV’s charging load. The optimisation problems are introduced in Sections 4, 5, 6, and the results are presented in Section 8 followed by the conclusions section 9.

### 2. EV charging modes and charging times

According to IEC 61851 “electric vehicle conductive charging system,” four charging modes are classified as Mode 1, 2, 3 and 4 [5]. The charging modes represent the charging power during the whole EV charging process. The EV charging process depends on the EV battery types and its battery management system (BMS). Mode 1, 2 and 3 are designed to charge EVs in alternating current (AC) and the mode 4 in direct current (DC). At the moment the power delivered in AC is between 3kW and 43kW, and it is mainly used at home, offices or public charging stations. The DC method 4 is designed only for public charging stations in order to charge in a short period of time. Charging Mode 4 is implemented for off-board chargers, and according to IEC 61851 part, 23 – 24 and IEC15118 provide the general requirements for the control communication between DC-chargers and an EVs [5]. In addition, the current EVs can provide power to the grid and additional services such as voltage support and frequency regulation by using IEC15118 [22]. The evolution of power electronics with new control interfaces as well as EV batteries will play an important role to develop competitive EVs. Table 1 summarises the main charging modes characteristics...
with their respective powers according to IEC 61851 and IEC 62196 [5]–[23].

<table>
<thead>
<tr>
<th>EV30[kWh]</th>
<th>Mode 1</th>
<th>Mode 2</th>
<th>Mode 3</th>
<th>Mode 4</th>
<th>Mode 4</th>
<th>Mode 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>20% SoC</td>
<td>3.5</td>
<td>11</td>
<td>22</td>
<td>50</td>
<td>150</td>
<td>300</td>
</tr>
<tr>
<td>10% SoC</td>
<td>9.15h</td>
<td>2.8h</td>
<td>1.5h</td>
<td>38min</td>
<td>12.6min</td>
<td>6.3min</td>
</tr>
<tr>
<td>100%</td>
<td>13.7h</td>
<td>4.3h</td>
<td>2.15h</td>
<td>1.28h</td>
<td>25.2min</td>
<td>12.7min</td>
</tr>
<tr>
<td>t1 [km]</td>
<td>368</td>
<td>368</td>
<td>368</td>
<td>368</td>
<td>368</td>
<td>368</td>
</tr>
<tr>
<td>t2 [km]</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
</tr>
</tbody>
</table>

Recently, many companies are starting to develop new DCFCSS with power from 150kW to 300kW and 800V in Combined Charging System (CCS) in order to reduce the charging time [5]. The new DCFCSSs require a strong grid infrastructure with high investment cost. Such large installed capacities require a dedicated connection to the medium voltage (MV) grid, with an appropriate transformer. The transformer has high economic costs and space restrictions, especially if the installation takes place in the cities. In this paper, it is assumed the EVs are charged at the public charging stations in Mode 4 in and around the metropolitan area. Fig. 1, shows the EV charging profile in Mode 4 tested in our laboratory [24]. In particular, Fig. 1 shows the EV charging profile in Mode 4 tested with a charger of 50kW (ABB t53) [25]. The car under consideration is a BMW i3 with 33kWh with 18% state of charge (SoC).

The charging profile in Mode 4 can be mathematically expressed as:

\[
P(t) = \begin{cases} 
P_c, & 0 < t \leq t_1 \\
P_c \cdot e^{-\frac{t}{\tau}}, & t_1 < t \leq t_2 \\
0, & t = t_2 
\end{cases}
\]

where \( P(t) \) is the charging rate at time \( t \), \( P_c \) is the charging power according to charging mode in DC, \( \tau \) is the charging time, \( t_1 \) represents the charging time from 18% to 80% SoC, and \( t_2 \) represents the charging time from 80% to 100% SoC as shown in Fig. 1.

### 3. Stochastic methodology of the EVs charging demand

The EV charging demand is calculated by using the charging characteristics in Mode 4, the arrival charging time and their SoC. The EVs SoC depends on the travel usage and may be considered as a random variable related to the travel distance. According to the Danish National Transport Survey from Technical University of Denmark (DTNS), the average travel distance in Denmark per day is 40.1km with three trips per day and slightly under one hour. The probability distribution of daily travel distance is calculated as shown in Fig. 2 [26].

The distribution of the travel distance is in general expressed as lognormal type, with zero probability of the negative distance and extension to infinity for positive distance [27]. The probability density function (PDF) of the traditional vehicle travel distance is expressed as:

\[
f(d, \mu_d, \sigma_d) = \frac{1}{d \sigma_d \sqrt{2\pi}} e^{-\frac{(d-\mu_d)^2}{2\sigma_d^2}}, \quad d > 0
\]

\( \mu_d \) and \( \sigma_d \) are the mean and the standard deviation of the mentioned normal distribution. The travel distance analysed in Denmark is shown in Fig. 2 which has \( \mu = 3.6913 \) \( \sigma = 0.9361 \). Since the new EVs can reach more than 400km, the probability distribution of daily travel distance of an EV is assumed to be the same as a traditional vehicle. The future EV range will be from 350-650 km with a typical EV lithium-ion battery of 40, 50 and 60kWh and in this case study is considered a mean value of 50kWh and 500km as shown in Table 1. Instead, the EV energy demand \( (EV_D) \) after one-day travel can be calculated as shown in (3) considering a driving distance \( d \) of 40.1 km (2).

\[
EV_D = (d \cdot V_{ec} \cdot \frac{1}{\eta_c})
\]

Instead, \( \eta_c \) represents the efficiency of the DCFCSS, and \( V_{ec} \) is the vehicle energy consumption. The energy consumption is based on this driving pattern, and it changes form the EV performance. The current EVs consumption varies between 0.1 and 0.2 kWh/km [28] and in this paper \( V_{ec} \) considered is
0.15 kWh/km. According to the daily travel distance, the SoC after one day can be calculated as:

$$SoC_0 = SoC_1 - \frac{d}{d_{max}}, \quad 0 < d < d_{max}$$  \hspace{1cm} (4)$$

where $SoC_0$ is the residual battery capacity after one day, the $SoC_1$ is dimensionless with value 1, $d$ is the daily travel distance of the EVs and $d_{max}$ is the maximum range of the EVs. Assuming that $SoC_0$ drops linearly with the travel distance, the PDF can be calculated by substituting (4) into (2) and changing variable form $d$ to $SoC$. After one-day travel distance, the SoC based on PDF is obtained as:

$$f(\text{SoC}_t, \mu_t, \sigma_t) = \frac{1}{(\text{SoC}_1 - \text{SoC}_0)d_{max}\sigma_t\sqrt{2\pi}} e^{-\frac{(t_{\text{SoC}} - \mu_t)^2}{2\sigma_t^2}}$$  \hspace{1cm} (5)$$

Fig. 3 shows the probability density of the battery SoC calculated in (5) after one day travel. The EV daily distance and the probability SoC density are based on the two stochastic variables calculated in (2), (5). The SoC after an amount of days $d_a$ can be calculated as:

$$SoC_{da} = SoC_1 - \frac{d_a}{d_{max}}$$  \hspace{1cm} (6)$$

Where $SoC_0$ is the residual battery capacity after a number of days, the $SoC_1$ is dimensionless with value 1.

3.1. Prediction of the EV charging demand

To predict EVs’ charging-start times different factors need to be analysed carefully, such as the home and work location and the driving distance per day of the EVs’ users. In the metropolitan area, people will need to charge their EVs at the public charging stations because most of them live and work within shared buildings. Instead, outside the metropolitan area, people will prefer to charge at work or home [27]. In this paper, the charging start times of EVs is calculated by analysing internal combustion engine (ICE) vehicles and their refuelling behaviour at the petrol stations. In order to determine the EV start charging time, six-month data from four petrol stations have been collected and analysed [29]. Once the data are collected the mean and the standard deviation from petrol stations can be defined. Fig. 4 shows the refuelling time distribution of four petrol stations in Copenhagen.

The mean and standard deviation (SD) are calculated according to the normal distribution:

$$f(t_{st}, \mu_{st}, \sigma_{st}) = \frac{1}{\sigma_{st}\sqrt{2\pi}} e^{-\frac{(t_{st} - \mu_{st})^2}{2\sigma_{st}^2}}$$  \hspace{1cm} (7)$$

$t_{st}$ is the observation hour during the day at the time $t$. $\mu_{st}$ and $\sigma_{st}$ are the mean and the standard deviation of ICE vehicles sampled at the petrol stations every hour. Fig. 5 shows PDF according to $t_{st}$ at 7 AM, 8 AM 4 PM and 5 PM with their mean and the standard deviation.

3.1. Prediction of the EV charging demand

In this case, study, considering new EVs with a range of 500km or more, the daily travel distance of an EV is the same as a traditional vehicle as well as a number of trips per day. Thank to this evaluation, we can define the correlation between two dependent variables: the arrival time of tradition vehicles at the gas stations with the EVs’ arrival time at the charging stations. In order to convert the refueling time distribution into EVs’ charging start times, two correction factors need to be considered: first, the range in km of ICE vehicles ($ICE_r$) versus the range of EVs in km ($EV_r$), second is the EV maket penetration ($EV_{mp}$) in Denmark. Therefore, $\mu_{st}$ and its $\sigma_{st}$ calculated in (7) need to be converted according to $EV_{mp}$ expressed in [%] in that area and the $EV$, [6].

$$\mu_{st}(t) = (\mu_{st}(t) \pm \sigma(t)) \frac{ICE_r}{EV_r} \frac{EV_{mp}}{100}, \forall t$$  \hspace{1cm} (8)$$

$\mu_{st}(t)$ is the mean number of EVs at the rth hour at the public charging stations, $\mu_{st}(t)$ is the mean number of ICE vehicles at the rth hour at the petrol stations considering $\sigma_{st}(t)$ with a confidence interval of 95%. In Copenhagen $ICE_r$ vehicles have a mean driving range of 710km and the mean of $EV_r$ range in 2020-25 will be 500km [30]. Since the EVs range is lower than $ICE_r$ vehicles range, the charging frequency of
EVs at the DCFCSs will be higher than the frequency of refuelling at the current petrol stations. Therefore, $IC_{ER}/EV_{r}$ defines the correlation between refuelling frequency of $IC_{ER}$ vehicles and the EVs charging frequency. According to (8), Fig. 6 shows the estimated EV arrival time at the fast charging stations around the metropolitan area of Copenhagen with EV market penetration from 5% to 50% [6]. $P_{dc}(t)$ is the total charging load at the time $t$. $P_{dc}$ is the DCFCSs power based on the number of charging spots and their efficiency $\eta_{dc}$.

$$EV_{dc} = (\mu_{ev} \cdot SoC_{min} \cdot d_{max} \cdot V_{ev}) \cdot \frac{1}{\eta_{dc}}$$  \hspace{1cm} (12)

$\mu_{ev}$ is the number of EVs per day calculated as shown in Fig. 6. $V_{ev}$ is the vehicle energy consumption, and it is 0.15kWh/km with a charging efficiency $\eta_c$ in DC of 95% [28]. Table 2 shows different EVs daily demand and the minimum grid power required for supporting the EVs demand (12).

### Table 2. Charging spots based on EVs demand

<table>
<thead>
<tr>
<th>EV Market [%]</th>
<th>EVs per day</th>
<th>EVs per day</th>
<th>Grid power</th>
<th>DCFCS power</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>5%</td>
<td>15</td>
<td>896</td>
<td>72.2</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>10%</td>
<td>20</td>
<td>1792.0</td>
<td>144.3</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>20%</td>
<td>60</td>
<td>3583.9</td>
<td>288.6</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>30%</td>
<td>90</td>
<td>5375.9</td>
<td>433.0</td>
<td>9</td>
<td>3</td>
</tr>
<tr>
<td>40%</td>
<td>120</td>
<td>7167.9</td>
<td>577.7</td>
<td>12</td>
<td>4</td>
</tr>
<tr>
<td>50%</td>
<td>150</td>
<td>8959.9</td>
<td>721.6</td>
<td>15</td>
<td>5</td>
</tr>
</tbody>
</table>

$P_{gr}$ is the minimum required grid power. $\mu_{ev}$ represents the maximum EV demand during the congested peak hour of the day as shown in Fig. 6. The number of charging spots with their power will determine the maximum power required from the grid. Once the EVs daily demand is defined, the network parameters and the charging spots number can be modeled as well as a CBA can be performed according to the EVs demand.

5. Storage charging demand methodology

5.1. Peak shaving via BES

In this section, peak shaving (PS) management is proposed to minimise the EVs load during the congestion by using BES as a stationary application. The introduction of the BES within the DCFCSs minimises the DCFCs operation costs and reduce the charging time during the congestion hours. The cost reduction of the lithium-ion batteries is an important parameter, which must be taken into account. It represents a smart opportunity for integrating the EVs penetration and their charging systems within the power systems. The annual cost reduction of BES is estimated at around 8% [18]. In addition, DCFCSs in combination with the BESs can represent a smart solution to avoid grid reinforcement costs and support the EVs demand during peak hours. In this case study, EVs peak demand will be supported by the BES. Storage charging demand must take into account the system’s overall power balance over a specified time:

$$E_{gr}(t)=E_{gr}(t)-\frac{E_{dis}(t)}{\eta_{gr}} \hspace{1cm} \text{if discharging}$$

$$E_{gr}(t)=E_{gr}(t)+E_{ch}(t) \cdot \eta_{gr} \hspace{1cm} \text{if charging}$$  \hspace{1cm} (14)

$E_{gr} (t)$ is the limited grid energy given or absorbed from the BES, $\eta_{gr}$ and $\eta_{gr}$ are the BES’s converter efficiency at 95% during the discharging and charging process. The $E_{dis} (t)$ is the BES charging energy and $E_{ch} (t)$ is the discharging energy. The objective function is used to minimise the energy...
peak demand by using the minimum BESs $E_b(t)$ within the DCFCSs as described in the following equations:

$$
E_b(t) = \min(E_b(t))
$$

where:

$$
E_b(t) = E_b(t) - \sum_{i=0}^{T-1} (E_{bat}(t) - E_{bat}(t)) + \sum_{i=0}^{T-1} (E_{bat}(t) - E_{bat}(t))
$$

If $E_{bat}(t) > E_b(t)$, discharging BES

If $E_{bat}(t) < E_b(t)$, charging BES

$E_b(t)$ is the BES at the time $t$, $E_{bat}(t)$ is the energy required from the DCFCSs during the discharging and charging process according to available energy $E_b(t)$. During the EVs charging demand, the BES operates in parallel with the DCFCSs and the PS will be provided during the congestion hours due to the high EV demand. The BES charging power is limited by the available grid power $P_g(t)$ at the time $t$. The discharging power is defined by the converter’s power and the difference between the grid and DCFCSs power (14). The BES is calculated based on equations (14) and (15). When the BES is defined, a CBA can be analysed according to the BES size to evaluate the financial feasibility of BES within the DCFCSs by considering the installation costs, grid connection costs and battery life cycle cost.

5.2. Frequency regulation via BES

Frequency regulation is a common ancillary service provided form TSOs in order to minimise the frequency deviation from 50Hz. BESs are a suitable option for frequency regulation due to their fast response. In addition, the frequency regulation in Denmark is one of the most profitable grid services [31]. Considering frequency regulation as a profitable service, a smart methodology is proposed to provide primary frequency regulation with the BES in order to reduce the payback period investment by increasing the revenue. In Denmark, frequency regulation services can be provided in two areas: Western Denmark or (DK1) and Eastern Denmark or (DK2) [32]. The BES under consideration will provide FNR to Energinet, which represents the Danish TSO in DK2. The primary frequency regulation corresponds to a symmetric frequency control activated for both under and over frequencies. The aim is to stabilise the frequency automatically at 50Hz and minimise the frequency deviations by using a droop control as shown in Fig. 7.

The objective of the droop control is to minimise the frequency deviations within the boundary values ($f_{min}$= 49.9 [Hz] and $f_{max}$ = 50.1[Hz]) by injecting or absorbing power from the BES. $P_{bat}$ is power from the BES for the droop control which is implemented in equation (16):

$$
|P_{bat}| = \begin{cases} 
P_{bat} & \text{if } f_{min} > f_{max} \\
-m \cdot (f_{max} - f_{net}) & \text{if } f_{net} < f_{min} < f_{max} \\
-P_{bat} & \text{if } f_{net} < f_{min} 
\end{cases}
$$

$f_{nom}$ is the nominal grid frequency which is equal to 50Hz, $f_{max}$ is the measured grid frequency with 5mHz accuracy in Nordhavn grid. Instead, $m$ is the angular coefficient of the droop control and can be calculated according to the equation (17).

$$
\begin{align*}
\frac{m_{\text{DWR}}}{2} &= \frac{P_{bat}}{P_{bat}} \cdot \frac{\eta_B}{0.2} \quad \text{if } f_{net} > f_{max}, \text{DWR} \\
\frac{m_{\text{UWR}}}{2} &= \frac{P_{bat}}{P_{bat}} \cdot \frac{\eta_B}{0.2} \quad \text{if } f_{net} < f_{min}, \text{UWR}
\end{align*}
$$

$m_{\text{DWR}}$ and $m_{\text{UWR}}$ represent the downward regulation (DWR), and upward regulation (UWR) expressed in [MW/Hz], instead $P_{bat}$ is the bid power in [MW] considering the day ahead ancillary services market [33]. According to the Danish market rules, the minimum bid must be 0.3MW, in addition, the power bid should be submitted to the TSO one or two days ahead. An aggregator, in this case, will be paid from the TSO according to the MWh provided for frequency regulation. Moreover, the service is compensated based on an availability payment and pay-as-bid [31]. In this context, a control strategy is proposed to provide FNR when the BES is not providing other services, i.e., peak shaving. The provision of FNR is proposed in an attempt to decrease the investment costs of the BES according to the characteristics of the BES defined in Section 5.2. Considering the BES characteristics and also the market rules for FNR, the minimum power bid as mentioned must be 300kW. In addition, the power FNR will be provided from the BES during the night when the EVs demand is low as shown in Fig. 8. Moreover, specific time intervals will be used to restore the battery SoC to be able to provide peak shaving during the daytime. FNR is also limited by the available grid power and the converter capacity as well as the BES charging and discharging requirements from the TSO. The proposed method consists of maximising the profit by providing FNR as described in equation (18). The objective function is to maximise the power bid from the $P_{bat}(t)$, which is offered in the day-ahead market from the TSO. Since the profit for this service is calculated based on a capacity payment, it is expected that the profit increases according to the power bid during the year. In this case, $P_{bat}(t)$ represents the required power according to the frequency deviation from 50Hz and the droop control described in the equation (16). The remaining equations represent the operation of the BES regarding the energy $E_b$ and SoC$(t)$ constraints along the entire regulation period called total frequency regulation (TFR). $E_b(t)$ is the energy absorbed or injected from the BES at time $t$ and $\Delta_t$ represents the duration of each interval.
6. Results of the EVs charging demand

In this case study, the future EVs demand in Copenhagen may vary from 15 to 300 EVs per day for each charging station. As shown in Table 2 the minimum power required from the grid depends on the EVs daily demand and EV market penetration. To analyse the EV demand two scenarios have been considered: uncontrolled charging demand and storage charging demand. In all scenarios chargers of 150kW in DC are considered. The 150kW charging profiles are obtained considering the performed tests in our laboratory [24] with 50kW chargers in DC as shown in Fig. 1. In addition, based on the performed tests, the 150kW charging profile will follow the same trend of the 50kW charger as described in equation (1). In order to generate the 150kW-DCFCs load, demand simulations are carried out by using MATLAB/Simulink for the given mean and standard deviation functions (7), (8). The distribution functions of those random variables can be obtained from the equations calculated in Sections 3 and 4.

6.1. Results for uncontrolled charging demand

This scenario considers the EVs daily demand from 15 to 150 EVs in Nordhavn-Copenhagen area as shown in Table 2, and different charging configurations can be utilised to support the EVs demand. As shown in Table 2 the minimum grid power required to support EVs demand varies according to EVs demand. In all scenarios chargers of 150kW are considered. Fig. 7 shows the results from five DCFCs, where all the input parameters are assumed to follow the stochastic demand model calculated in Sections 3 and 4. The DCFCs load profile is one of the most critical parameters obtained from the stochastic model. It shows daily pulsating load profiles of the EVs charging demand on the grid side according to (9), (11). The case study under consideration considers 50 % EV market penetration. Fig. 8 shows five DCFCs of 150kW supplied by two transformers of 500kVA. EVs demand varies during the congested workday, normal day, Saturday and Sunday. According to Table 2, in this scenario, 150EVs and 140EVs are supplied by two transformers during the congested workday and the normal workday. For this grid configuration, high investment costs are required to reinforce the grid with an additional transformer, especially when the EVs demand will increase over the years. Therefore, as shown in Fig.8, in addition to the initial investment, which includes one MV transformer and two or three DCFCs of 150kW over the next 10 years, an additional MV transformer will be required to support the growing number of EVs. The new MV transformer requires a new investment cost which includes new LV and MV dedicated lines, switchboards and the installation costs [28].

\[
\begin{align*}
\max_{t} \sum_{t=1}^{N} P_{c}(t) \\
S_{1} \leq P_{c}(t) \leq P_{b} \\
E_{\text{min}} \leq E_{s}(t) \leq E_{\text{max}} \\
S_{\text{ch}} \leq S_{c}(t) \leq S_{\text{max}} \\
E_{i}(t) = E_{\text{Sol}}(t) = E_{i}(t + \Delta t) + P_{c}(t) + \eta_{s} \\
P_{c}(t) = E_{i}(t + \Delta t) - \eta_{s}, \quad \text{if } P_{c}(t) < 0, \text{DWR} \\
P_{c}(t) = E_{i}(t + \Delta t) + \frac{P_{c}(t) - \eta_{s}}{\eta_{s}}, \quad \text{if } P_{c}(t) > 0, \text{UWR}
\end{align*}
\]

(18)

6.2. Results storage charging demand for PS and FNR

In this section, a simulation-based approach is used to underline the performance of the proposed methodology. For this purpose the following assumptions are considered. Frist, the BES and DCFCs belong to the same private stakeholder called electric vehicle supply equipment operators (EVSEO), which is also responsible for grid upgrade. In this case the private stakeholder can be the DSOs or a private owner of the DCFCs such as the aggregators. Second, the PS is a local grid service provided by EVSEO and it will be performed to manage the EV demand during the congestion hours in order to avoid the grid reinforcement costs. Third, the FNR is a service provided to TSOs, and it is implemented in order to compensate the investment costs of the BES. In order to validate the proposed methodology, a case study is carried out considering EV demand of 140 EVs as shown in Fig. 8. The BES size is subjected according to EV demand in order to provide PS as calculated in the equation (15) and FNR in (18). In addition, the size of the AC/DC converter and the BES size consider the grid constrains, i.e., the transformer capacity as well as the DCFCs power demand calculated in Section 3.
Fig. 9 shows the grid configuration considering 150 EVs charged per day and the BES operation after 1-day simulation.

![Diagram of grid configuration](image1)

![Diagram of EVs demand and BES operation](image2)

According to Fig. 9 the EV charging demand during a normal workday is shown. The peak load is in the morning (between 06:00 and 10:00) and in the afternoon (between 16:00 and 19:00) as demonstrated in Section 3. The BES during peak hours provides PS to support the local grid. Moreover, between 12:00 and 16:00 the BES is used to restore the SoC of the battery and in order to be ready to provide peak shaving during the second peak of the day from16:00 to 19:00. In addition, as shown in Fig. 9 the BES is able to provide FNR during the period from 20:00 to 05:00 of the next day. During this period of time, the BES is charged or discharged according to the measured frequency signal. Instead, periods from 05:00 to 06:00 and from 19:00 to 20:00 are used to restore the battery SoC in order to ensure PS during the daytime. The introduction of the BES helps the DCFCs to avoid the grid reinforcement costs when the EVs peak demand exceeds the grid capacity. As shown in Table 2 shows EVs daily demand from 15 to 90 EVs where the grid reinforcement is not required. Instead, from 100 to 150 EVs grid reinforcement is required to support the demand. Alternatively, as shown in Table 3 the storage charging process can avoid the grid upgrade by using different BESs as grid reinforcement.

### Table 3. Storage charging strategy

<table>
<thead>
<tr>
<th>Number of EVs per day</th>
<th>Grid power [kW]</th>
<th>Power DCFCs [kW]</th>
<th>Overload grid [%]</th>
<th>Overload time [h]</th>
<th>BES [kWh] E₀</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>500</td>
<td>150</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>20</td>
<td>500</td>
<td>150</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>60</td>
<td>500</td>
<td>300</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>90</td>
<td>500</td>
<td>450</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>100</td>
<td>500</td>
<td>600</td>
<td>20</td>
<td>1.04</td>
<td>18.2</td>
</tr>
<tr>
<td>110</td>
<td>500</td>
<td>600</td>
<td>20</td>
<td>1.27</td>
<td>23.5</td>
</tr>
<tr>
<td>120</td>
<td>500</td>
<td>600</td>
<td>20</td>
<td>2.13</td>
<td>28.17</td>
</tr>
<tr>
<td>130</td>
<td>500</td>
<td>600</td>
<td>20</td>
<td>3.18</td>
<td>31.12</td>
</tr>
<tr>
<td>140</td>
<td>500</td>
<td>750</td>
<td>50</td>
<td>5.15</td>
<td>43.7</td>
</tr>
<tr>
<td>150</td>
<td>500</td>
<td>750</td>
<td>50</td>
<td>7.44</td>
<td>586</td>
</tr>
</tbody>
</table>

In addition, the equations (15) and (18) are implemented to maximise the profitability of the BES versus its investment costs by providing PS during the day and FNR during the night. A CBA is carried out in the next section to evaluate the financial performance of the BES as life-cycle costs versus the revenue provided by the TSO for FNR by considering EVs daily demand from 15 to 150EVs.

### 7. Cost-benefit analysis methodology

This section two cases of grid reinforcement are considered. A CBA approach is presented to determine the profitability of the DCFCs investment within power systems considering different EVs charged per day. The first method, Case A uses the BESs as stationary application during the congestion hours to support the increasing EV demand over the years as shown in Table 4 and Section 5. In this case, the BES operates as PS in parallel with the grid and provides FNR during the night when the EVs demand is low. The second method, Case B adopts grid reinforcement by using a new MV transformer to sustain the increasing EV demand over the years as shown in Table 4 and Section 4.

### Table 4. CBA of the Case A and B

<table>
<thead>
<tr>
<th>Number of EVs per day</th>
<th>Number of DCFCs 150kW</th>
<th>Case A grid power [kW]</th>
<th>Case B grid power [kVA]</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>1</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>20</td>
<td>1</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>60</td>
<td>2</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>90</td>
<td>3</td>
<td>500+ BES</td>
<td>1000</td>
</tr>
<tr>
<td>100</td>
<td>4</td>
<td>500+ BES</td>
<td>1000</td>
</tr>
<tr>
<td>110</td>
<td>4</td>
<td>500+ BES</td>
<td>1000</td>
</tr>
<tr>
<td>120</td>
<td>4</td>
<td>500+ BES</td>
<td>1000</td>
</tr>
<tr>
<td>130</td>
<td>4</td>
<td>500+ BES</td>
<td>1000</td>
</tr>
<tr>
<td>140</td>
<td>5</td>
<td>500+ BES</td>
<td>1000</td>
</tr>
<tr>
<td>150</td>
<td>5</td>
<td>500+ BES</td>
<td>1000</td>
</tr>
</tbody>
</table>

In both cases at the beginning, a grid reinforcement in MV grid is required with a transformer of 500kVA as shown in Table 4. Since the EVs demand will increase during the years [6], extra chargers are required to sustain the EVs demand. As shown in Table 4, 500kVA is the minimum grid power required to support the EVs demand from 15 to 90 EVs. Instead, if the EVs demand increases over the years from 100 to 150 EVs per day, new chargers in DC, as well as a new transformer of 500kVA, must be installed. The main objective of the CBA is to evaluate the economic performance of Case A versus Case B. In particular, the...
financial performance of Case A takes into account the BES costs and the lifetime versus a traditional grid upgrade.

The key parameters of the CBA are:
The payback period (PBP) is the amount of time necessary to recover the investment, and it can be calculated as [34]:

\[ PBP = \frac{C_i}{B_t} \]  

(19)

\( C_i \) represents the cost of the investment and \( B_t \) is the annual benefit or revenue per year during the investment period \( T \).

Net present value (NPV) is the present value of cash inflows and the present value of cash outflows [34]:

\[ NPV = \sum_{t=0}^{T} \frac{B_t}{(1+r)^t} - \sum_{t=0}^{T} \frac{C_t}{(1+r)^t} - C_0 \]  

(20)

\( r \) is the discount rate or interest, and \( C_0 \) is the initial investment cost.

Instead, the method used to evaluate the economic performance of one or more investments is called benefit-cost ratio (B/C) and can be expressed as [34]:

\[ \frac{B}{C} = \frac{NPV \text{ (Benefits)}}{NPV \text{ (Costs)}} = \frac{\sum_{t=0}^{T} B_t}{\sum_{t=0}^{T} C_t + C_0} \]  

(21)

The costs and revenues are calculated for the two cases under consideration: the Case A – DCFCSSs with BES and Case B – DCFCSSs considering a new connection in MV grid.

7.1. Case A cost and revenue

In the Case A the annual costs and benefits associated with BES within the charging stations are calculated considering the infrastructure costs and as benefits the consumption of electricity. The total annual costs of the Case A \( (C_{A}) \) are calculated as:

\[ C_{A} = C_i + C_r + C_{OM} \]  

(22)

\( C_i \) is the installation cost, and \( C_{OM} \) is the operation and maintenance cost. Instead, \( C_r \) includes the component costs as the chargers cost \( C_C \), and the batteries cost considering the replacement during the investment life \( t \) (23).

\[ C_r = \sum_{t=0}^{T} B_{ESD} \cdot C_{RES} + C_C \]  

(23)

\( BESD \) is the BES degradation life per year, \( C_{RES} \) represents the BES costs per kWh considering the replacement costs during investment life \( T \). The \( BESD \) can be calculated as shown in (24):

\[ \begin{align*}
E_D(t) &= \int_{t_1}^{t_2} P_{FNR}(t) \cdot dt + \int_{t_1}^{t_2} P_{FNR}(t) \cdot dt \\
K_{PFR} &= \frac{E_D \cdot \Delta T_r}{2 \cdot E_B} \\
BESD &= \frac{K_{PFR}}{K_{RES}}
\end{align*} \]  

(24)

\( E_D(t) \) represents the energy consumed during the PS time, and FNR from \( t_1 \) to \( t_2 \) is the time where the BES works as PS, from \( t_3 \) to \( t_4 \) is the time where the BES works to provide FNR service. Instead, \( K_{PFR} \) considers the number of cycles utilised during the year. \( BESD \) is the BES degradation life per year under a predefined variable work temperature \( \Delta T_r = 0.9814 \) [35]. \( K_{RES} \) are the number of cycles given by the manufacturers.

The total annual benefits or revenue for Case A \( (B_{A}) \) can be calculated as:

\[ B_{A} = (E \cdot C_e) \cdot t + B_{FNR} \]  

(25)

where \( E \) is the daily energy consumed in function of the EV demand calculated in (8), \( C_e \) is the cost of electricity paid by the EV users and \( t \) is the total time in a year. \( B_{FNR} \) are the benefits by providing FNR in DK2 to the TSO. \( B_{FNR} \) can be calculated according to the equation (24):

\[ B_{FNR} = P_{FNR} \cdot P_{bid} \]  

(26)

\( P_{bid} \) is the power bid in MW considering the day ahead ancillary services market paid from the TSO for the available power. \( P_{FNR} \) is the price paid according to the day ahead ancillary services market [33]. Fig. 10 shows the prices in €/MW from 2013 to 2017 for the power bid. The revenue considered in the CBA is calculated considering the year 2017. The prices are given by the Danish TSO Energinet.dk [32]. Considering that FNR will be provided only from 20:00 to 5:00 when the EV demand is low. \( P_{bid} \) according to Fig. 10 can be assumed 40.88 €/MW considering the mean value from 20:00 to 5:00.

In addition, \( f_{mis} \) represents a year signal misused in Nordhaven-Copenhagen grid in 2017 \( P_{FNR} \) is calculated from 20:00 to 5:00 and it is fixed during each hour according to the converter’s power. The AC/DC converter size for the BES is 300kW and 95% efficiency. The battery size is 437kWh according to the case study which considers 140EVs/day as shown in Fig. 9. Table 5 shows the revenue calculated according to FRN prices and the misused frequency in 2017.
7.2. Case B cost and revenue

In the Case B the annual costs and benefits associated to grid upgrade are calculated considering the infrastructure costs such as new lines and a transformer of 500 kVA as well as the installation and DCFCS costs [28]. Instead, the benefits are calculated considering the consumption of electricity from EVs as shown in (26).

The total annual costs for Case B \((C_{t,B})\) are calculated as:

\[
C_{t,B} = C_B + C_t + C_{AM} \tag{27}
\]

where \(C_B\) is the components cost including the chargers, lines and transformer. The total annual revenue for Case B \((B_{t,B})\) can be calculated as shown in (25).

8. Cost-benefit analysis results

In this section, two separate layouts to connect the charging systems within the power systems are considered to analyse the costs and benefits of the BES within DCFCSs. Case A considers a CBA by using BES as a stationary application for PS and FNR to support the increasing EVs demand over the years as shown in Fig. 6. In this case, the BES operates as PS only during the congestion hours and for FNR during the night. Instead, Case B considers a CBA by using a new grid reinforcement to MV grid in order to sustain the increasing EVs demand over the years. In both cases at the beginning, a grid reinforcement to the MV grid is required with a transformer of 500kVA.

8.1. Case A: CBA of DCFCSs considering BES for peak shaving and frequency regulation

The primary objective of the CBA is to establish the infrastructure costs of the Case A and lifetime of BESs. The benefits and the costs of the Case A are calculated as shown in Section 7.1. It was shown that EVs demand from 15 to 90 EVs requires a minimum grid power of 500kVA as the initial investment. Instead, if the EVs demand increases over the years from 100 to 150 EVs, new chargers in DC, as well as a new transformer of 500kVA are required to sustain the new EVs demand in order to avoid new grid reinforcement costs, the BES operates in parallel with the DCFCS as shown in Fig. 9. In Case A, three different lithium –ion technologies are considered, the current technology battery “Lithium Nickel Manganese Cobalt Oxide” (NMC) with 5000 and 10000 cycles [36] and a future scenario “Lithium Titanate Oxide” (LTO) battery with 25000 cycles [37]. The number of EVs charged per day is used to calculate the total annual benefits \(B_{t,A}\) calculated in equation (25) and it is based according to the annual energy consumed from the EVs’ users. Instead, \(C_{t,A}\) is calculated based on the equations (22) and (23). The equations consider the investment costs including the component costs such as DCFCS costs, the replacement costs of the BES at the end of their useful life equation (22), converter costs and the installation costs. When \(C_{t,B}\) and \(B_{t,B}\) are defined, \(PBP\) equation (19), \(NPV\) equation (20), and \(B/C\) ratio equation (21) can be calculated as shown in the proposed Section 7. Fig. 11 shows the flowchart inputs of the proposed CBA methodology.

8.2. Case B: CBA of DCFCSs considering MV grid upgrade

The primary objective of the CBA is to establish the infrastructure costs of Case B in order to justify a standard investment of grid reinforcement in MV. In the Case B when EVs demand increases over the years from 100 to 150 EVs, new chargers in DC, as well as a new transformer of 500kVA are required to sustain the new EVs demand as shown in Fig. 8. The benefits and the costs of the Case B are calculated in Section 7.2. The number of EVs charged per day is used to calculate the total annual benefits \(B_{t,B}\) as shown in equation (25). Instead, \(C_{t,B}\) equation (27) is the investment costs including grid reinforcement costs. The infrastructure costs of the Case B are DCFCS costs, the costs of the new dedicated lines in LV and MV, the cost of the new transformer of 500 kVA as well as the installation costs. When \(C_{t,B}\) and \(B_{t,B}\) are defined, \(PBP\) equation (19), \(NPV\) equation (20), and \(B/C\) ratio equation (21) can be calculated as shown in Section 7. Fig. 12 shows the flowchart inputs of the proposed CBA methodology.

Fig. 11. Case A grid integration of BES within DCFCSs

Fig. 12. Case B DCFCSs with grid upgrade in MV
8.3. Economic assessment of case A and case B: market and technology inputs

In this section, an economic assessment is carried out in order to compare the costs and benefits of the Case A versus Case B. The economical results of the Case A and B are summarised in Fig. 13, which compares the PBP and B/C ratio of the cases under consideration. All the economic parameters used in Case A and Case B are listed in Table 6:

<table>
<thead>
<tr>
<th>Table 6. Costs and benefits inputs of Case A and Case B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case A</td>
</tr>
<tr>
<td>Costs</td>
</tr>
<tr>
<td>BES price €/kWh [18]</td>
</tr>
<tr>
<td>EV demand: 45 kWh</td>
</tr>
<tr>
<td>Electricity price paid by EV users [6]</td>
</tr>
<tr>
<td>Discount rate (r): 8% [38]</td>
</tr>
<tr>
<td>Investment life: 20 years</td>
</tr>
</tbody>
</table>

The grid investment for the upgrade considers 4% discount rate [39]. Instead, the investment in BES can be considered riskier. Therefore, the interest rate used for BES is 8% [38]. Fig. 11 and Fig. 12 compare the financial performance of Case A versus Case B considering three types of batteries with different cycles. As mentioned, Case A considers the integration of BESs to support the grid when the EVs daily demand exceeds 90 EVs. As shown in Fig. 11 in the Case A the red and orange line represent the current technology of lithium-ion NMC battery with 5000 and 10000 cycles [36]. The blue line is the future generation of the lithium-ion LTO battery with 25000 cycles [37]. Instead, in Case B, the black line shows the financial performance by using a new connection in MV grid.

![Fig. 13. Economic comparison of the Case A considering the BES for PS and FNR versus Case B grid upgrade in MV](image)

According to Fig. 13, the economic assessment of case A is subjected to the life-cycle costs of the batteries, and on the contrary, Case B, classic grid reinforcement depends from to the number of EVs charged per day. Case A shows that, with a demand from 90 to 130 EVs charged per day the B/C ratio is higher than Case B. Likewise, with the EVs demand from 140 to 150 the Case A has the B/C ratio higher than Case B as long as the number of BES cycles is higher than 10000. In addition, considering a load demand from 90 to 130 EVs by using small size of BESs as 18 or 30 kWh the CBA for FNR is not economically convenient because the revenues versus the BES life-cycle costs are not extremely high. Therefore, in this case it is recommended to use the BES only for PS. Instead, considering a load demand from 140 to 150 EVs by using big size of BESs as 437 or 586 kWh the CBA for FNR proves to be economically convenient because the total revenues are marginally higher than BES life-cycle costs during the lifetime of the investment. In this case, it is recommended to use the BESs for FNR services and PS as long as the BES cycles are higher than 10.000.

9. Conclusions

In this paper, a stochastic planning method was proposed to determine the DCFCs load profiles and the impact on power distribution systems. The stochastic charging profile was used exclusively to calculate the two key factors of the EVs charging demand: EVs’ charging start times and DCFCs grid impact. According to the stochastic method, a DCFCs load demand was proposed to optimise the required grid capacity of the public DCFCs considering real data from the users’ behaviour. Two layouts were considered within the stochastic planning method: the uncontrolled charging demand and the storage charging demand for PS and FNR.

The EV stochastic charging method with BES was considered by using the BES as a multifunctional device in order to provide auxiliary services as peak shaving and frequency regulation. It was shown that according to the stochastic charging demand and grid constraints the BES can reduce the DCFCs peak EV load during the congestion hours by providing peak shaving in the morning and evening. In addition, an optimal BES was proposed to minimise the grid reinforcement costs of the DCFCs and the BES by using the BES for FNR during the night in order to increase the profit of the entire investment. It was shown that BES operation costs can be minimised by providing peak shaving frequency regulation only under certain conditions.

According to the CBA and the economic assessment the Case A was bound to the life-cycle costs of the batteries, diversely, the Case B classic grid reinforcement was linked to the number of EVs charged during the day. In it was shown that considering a demand from 90 to 130 EVs charged per day the Case A has B/C ratio higher than Case B. Likewise, considering a demand from 140 to 150 EVs the Case A has the B/C ratio higher than Case B as long as the BES cycles are higher than 10000. Besides, considering a load demand from 90 to 130 EVs by using small size of BESs the CBA for FNR is not economically convenient because the revenues versus the BES life-cycle costs are not extremely high. In this case, it is recommended to use the BES only for PS services. Instead, considering a demand from 140 to 150 EVs by using big size of BESs the CBA for FNR proves to be economically convenient because the total revenues are marginally higher than BES life-cycle costs. In this case, it was recommended to use the BESs for FNR services and PS as long as the BES cycles are higher than 10.000.

10. References

[1] Nordhaven project; “Design - dimensioning of the energy infrastructure of future sustainable cities,”


[32] Danish TSO, “Ancillary services to be delivered in Denmark - Tender conditions, energinet.dk., 2018.”


