VTT Technical Research Centre of Finland

Optimum day-ahead bidding profiles of electrical vehicle charging stations in FCR markets

Hasanpor Divshali, Poria; Evens, Corentin

Published in:
Electric Power Systems Research

DOI:
10.1016/j.epsr.2020.106667

Published: 01/01/2021

Electric Power Systems Research 190 (2021) 106667

Contents lists available at ScienceDirect

Electric Power Systems Research

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

Optimum day-ahead bidding profiles of electrical vehicle charging stations in FCR markets

Poria Hasanpor Divshali*, Corentin Evens

Smart Grids, VTT Technical Research Centre of Finland, Espoo, Finland

ARTICLE INFO

Keywords:
Ancillary service
Electrical vehicle charging stations
Frequency containment reserves markets

ABSTRACT

This research developed an application for electrical vehicles charging stations (EVCS) to estimate the optimum day-ahead bidding profiles in frequency containment reserves (FCR) markets and this paper presents the stochastic methodology behind this application. To achieve this, first, deterministic models are developed to calculate the maximum FCR that could be provided by each charging event (cycle) of an electric vehicle (EV). These models are established based on the technical requirements of FCR in the Nordic flexibility market, namely the frequency containment reserve for normal operation (FCR-N) and frequency containment reserve for disturbances (FCR-D). In the next step, these deterministic models will be combined with historical data of charging records in EVCS to calculate the probability density functions of the FCR profiles. Finally, the proposed application estimates the optimum FCR profiles, which maximise the expected profit of EVCS from participating in the day-ahead flexibility market, by performing a stochastic optimisation. The performance of the proposed application is evaluated by using empirical charging data of public EVCS in Helsinki area.

1. Introduction

Electrical vehicles (EVs) are actively growing as a more environment-friendly and economic alternative to conventional vehicles. In addition to the higher efficiency of electric motors compared to internal combustion engines, EVs can be charged with electrical energy produced by renewable energy sources to further reduce the greenhouse gas emissions.

This massive deployment of EVs will have a significant impact on future power grids. On one hand, this large amount of energy required for EVs coupled with the uncertainty in charging times and durations may result in serious technical and economic challenges. On the other hand, the EV chargers can immediately change their consumption (or production, in case of vehicle to grid), which could provide a unique opportunity for flexibility support. A comprehensive survey of the main challenges and opportunities of the presence of EVs in the future power grids is detailed in [1].

Methods to mitigate the effect of EV charging in power systems are suggested by several researchers [2–5]: A community energy management system using real-time pricing to minimise the cost of each EV is suggested in [2,3]; a smart charging methodology for optimising the combined charging profile of a large number of EVs is proposed in [4]; and two-stage energy management for EV charging in an area with semi-predictable EV behaviour is proposed in [5].

However, none of the above-mentioned research considers properly the effect of the driving pattern model and EV charging time and duration uncertainty on power systems. In this regards, an energy management system using driving pattern prediction is proposed in [6]. Accordingly, several researchers focus on modelling and forecasting EVs using the driving behaviour [7–14] to mitigate the adverse influences of EVs on power systems. A Monte Carlo-based method combined with the national household travel survey is used in [7,8], while a modified Monte Carlo is proposed in [9] by removing less likely scenarios. A method based on a traffic flow model is presented in [10] to estimate the EV charging station loads. ARIMA based methods using historical data of driving pattern for forecasting electrical demand of parking lots are presented in [11,12]. Similar strategies are proposed in [13] using fractional ARIMA and in [14] using hybrid kernel density estimator, in order to improve the forecasting of EVs uncertainty.

However, this research [6–14] uses the driving behaviour of conventional vehicles to estimate the EV driving model, which may lead to some errors due to differences between EVs and conventional cars. On the other hand, some researchers use real data of existing EV charging to model their behaviour [15–18]. Authors in [15] define a risk level of EVs charging demand based on historical data in the UK to give an indication of the potential impact of EVs on distribution grids. Electric

* Corresponding author.
E-mail address: Poria.Divshali@VTT.fi (P. Hasanpor Divshali).

https://doi.org/10.1016/j.epsr.2020.106667
Received 24 September 2019; Received in revised form 12 March 2020; Accepted 1 August 2020
Available online 06 August 2020

load profile from empirical data in Germany is analysed in [16]. ARIMA based aggregated forecasting of large amounts of EV load profiles is proposed in [17], and the autoregressive time series method is compared to reserve transmission neural networks in [18] for the forecasting of realistic EV load profiles.

Research [15–18] analyses the empirical charging data of EVs to predict the uncertainty in EV profiles while none of them developed a strategy to enable EV flexibility to provide services beyond their local grids. In order to utilize the EV flexibility potential across all the power systems, a market-based strategy is necessary. This research, as a part of the EU-SysFlex project [19], develops an application for electrical vehicles charging stations (EVCS) to estimate the optimum day-ahead bidding profiles in frequency containment reserves (FCR) markets.

The methodology behind this application develops first the deterministic models to calculate the maximum available FCR that an EV can provide in one specific charging event (cycle). These models are established based on the technical requirements of the Nordic FCR market, named FCR-N for normal operation and FCR-D for disturbances. Because the behaviour of EV charging is stochastic by nature, in the next step, the proposed methodology calculates probability density functions (PDF) of the FCR profiles using deterministic models and historical data of charging events for EVCS. Finally, the optimum FCR profiles, which maximise the expected profit of EVCS from participating in the day-ahead flexibility markets, is estimated by performing a stochastic optimisation. The proposed application is tested using the empirical charging data of public EVCS in Helsinki area from 2015 to 2018. The main contributions of this paper are:

(1) Develop deterministic models for EV flexibility based on technical requirements of the Nordic FCR (FCR-N and FCR-D),
(2) Propose a stochastic bidding methodology for EVCS in the FCR markets to maximise the expected profit, without compromising EV owner privacy,
(3) Evaluate the proposed method using empirical EV charging records to analyze the potential of EVCS in FCR market.
(4) Develop an application for EVCS to estimate the optimum day-ahead bidding in FCR markets, freely available in [20].

The remainder of this paper is organized as follows: Section 2 describes FCR in the Nordic flexibility market; Section 3 forms deterministic FCR models for a single charging event of an EV; and Section 4 develops a stochastic methodology behind the proposed application to estimate the optimum FCR profiles in the day-ahead market. Section 5 analyses the results of the proposed application using the data gathered from the EVCS of the Helsinki area. Finally, Section 6 concludes the papers.

2. Frequency containment reserves market

This paper focuses on developing a stochastic bidding methodology of EVCS to participate in the flexibility markets. Flexibility markets are set up for different products (services), such as various frequency controls, voltage control, and congestion management. These products are defined in details in the technical requirements for each market. A summary of flexibility markets in different European countries is described in the deliverables of the RealValue [21] and SmartNet [22] projects.

Using available EV charging data for the Helsinki area, this paper focuses on the Nordic (Finnish) flexibility markets. Investigating all of these products lies beyond this paper's scope. Here, the frequency containment reserves (FCR) is selected based on better remuneration. In the Nordic flexibility markets, FCR is split into two parts: FCR-N and FCR-D.

The Finish TSO, Fingrid, determined the technical requirements of both FCR-N and FCR-D in [23]. The following subsections review the relevant parts of these requirements necessary to model the ability of EV to provide FCR.

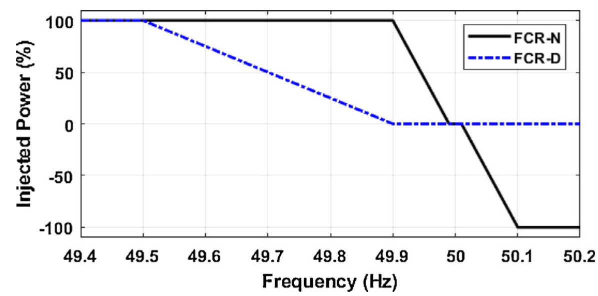

Fig. 1. The FCR-N and FCR-D control curve

2.1. FCR-N

The aim of FCR-N is to assist the power system by reacting to frequency deviations within the range from 49.9 to 50.1 Hz. For this purpose, the FCR-N providers measure continuously the frequency and change their output power according to the frequency as shown in the control curve in Fig. 1, where 100% in injected power represents the total amount of contracted FCR-N service provision.

As shown in Fig. 1, FCR-N is a symmetrical reserve product. This means that it must be possible to activate the reserve capacity both as upward balancing and downward balancing. Upward balancing (up-regulation) means an increase in electricity production or a decrease in consumption, and downward balancing (down-regulation) means a decrease in production or an increase in consumption.

In addition, the technical requirement of FCR-N states that the providers "*shall be capable of activating the reserve in full for the entire delivery period*". However, the unit with limited activation capacity, e.g. battery storage system or EV, "*shall be dimensioned so that the unit is capable of continuous full activation for at least 30 minutes*".

The FCR-N providers are compensated for providing capacity and energy. The provided energy is remunerated according to the balancing market prices, which are determined in real-time. Investigating the historical data shows that the energy remuneration may create some profit for flexibility providers, but also that it is heavily outweighed by the capacity remuneration. The detailed analysis of the energy market including imbalance settlement for FCR provision is performed in [24], which shows that it has a negligible effect. In addition, the amount of energy, the price, and the profit are not clear when flexibility providers make the bid in the day-ahead market.

The capacity fee is paid based on the provided capacity even when it doesn't get activated. The capacity fee is determined on a yearly or hourly basis, based on the chosen market agreement. For a yearly agreement in 2019, the capacity fee for FCR-N is 13.5 €/MW,h [25]. In the hourly market, the capacity fee is determined by competition for each hour in a day-ahead market. It is important to mention that, in Finland, FCR providers must pay a penalty equal to the capacity fee if they fail to provide the energy promised on the day-ahead market.

2.2. FCR-D

The aim of FCR-D is to regulate the power system frequency after a larger disturbance. The FCR-D, in the Finnish market, is procured only for under-frequency disturbances. Fig. 1 shows the control curve for FCR-D, which start injecting power when the frequency is under 49.9 Hz.

In a similar way to FCR-N, units with limited activation capacity shall offer FCR-D so that they have enough energy capacity for 30 minutes. Also, FCR-D products are remunerated based on energy and capacity. On the yearly market, the capacity fee in 2019 is 2.4 €/MW,h [25].

Although FCR-D has lower reimbursement level than FCR-N, it has

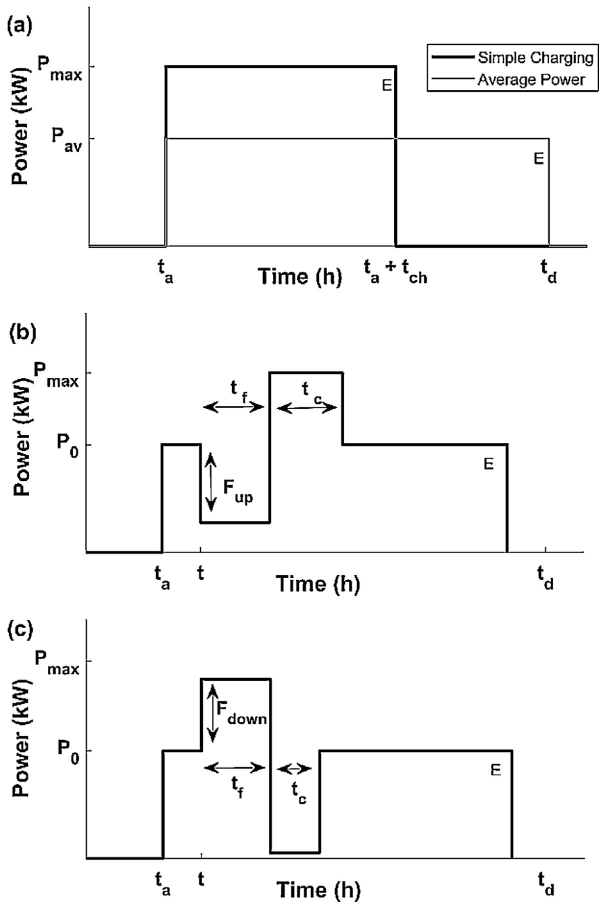

Fig. 2. The charging profiles (a) The simple charging profile and average power charging of an EV, (b) providing F_{up} kW up-regulation reserve,)c) providing F_{down} kW down-regulation reserve for t_f hours.

the potential to generate more profit for the provider for two reasons, especially in the case of EVCS. The first reason is that FCR-D is only up-regulation reserve, while the FCR-N is symmetrical. Providing up-regulation reserve for demand means a decrease in power consumption, which is more practical for EVCS than increasing their consumption. The second reason is that FCR-D reserves are activated less often than the FCR-N ones, interfering less in the normal operation of EVCS. The threshold for FCR-D activation is a frequency below 49.9 Hz, while FCR-N must be activated whenever the frequency is out of the dead band of 49.99 to 50.01 Hz.

3. Deterministic FCR model for a charging event

Without any incentive to do otherwise, an EV plugged to an electricity source charges with its maximum possible power until the battery is fully charged. Fig. 2a shows this simple charging profile for an EV arriving at t_a and departing at t_d, with a need for E kWh electrical energy. This diagram neglects the fix voltage charging phase, which happen for high SOC level at the end of the charging cycle. In these circumstances, the required time (t_{ch}) for charging E kWh energy to the EV can be calculated by:

$$t_{ch} = \frac{E}{P_{\max}\eta}, \tag{1}$$

where P_{max} is the maximum power of EV chargers and η is the efficiency of the charger.

Since the plugged-in time ($t_p = t_d - t_a$) could be longer than the required charging time (t_{ch}), the EV may have some flexibility to alter its charging power. For instance, the EV could follow a flat profile with the average power (P_{av}) as shown in Fig. 2a.

$$P_{av} = \frac{E}{\eta\,(t_d - t_a)}. \tag{2}$$

In this case, the EV may adapt itself to the power system dynamics without making any change in the state of charge at the end of the plugged-in period. The following subsections model this flexibility in up-regulation and down-regulation and then transfer these models to FCR-N and FCR-D definitions, according to the market regulations and EV constraints.

3.1. Up-regulation reserve

Fig. 2b shows an EV charging profile, which provides $F_{up}(t)$ kW up-regulation reserve at time t for t_f hours, while still charging the EV battery to the desired level of energy. For this purpose, the profile compensates the decrease caused by up-regulation, by increasing the charging power after $t+t_f$, for t_c hours.

Providing up-regulation reserve is limited by power and energy constraints of the EV. The power constraint limits the maximum $F_{up.i}\,(t)$ to $P_{0,i,}$ as can be seen in Fig. 2b; where $P_{0,i}$ is the consumption power of the EV in the moment of providing up-regulation reserve. The energy requirement of EV makes another constraint in the up-regulation reserve. Since the FCR providers must be dimensioned so that having the ability to continue full activation for half an hour ($t_f \geq 0.5$), and providing flexibility should not change the amount of the charging energy in the EV, the following constraint must be satisfied:

$$P_{\max,i}\,\eta_i\,(t_{d,i} - t - 0.5) \;\geq\; E_i - E_i(t) \\ -0.5\,\eta_i\,(P_{0,i} - F_{up,i}(t)), \tag{3}$$

where the subscript i refers to the ith charging event; $E_i(t)$ is the charged energy to the EV from $t_{a,i}$ until time t in the ith charging event; and E_i is the energy requirement of EV in this charging events. The left term in (3) states the maximum possible charging energy into the EV after providing up-regulation reserve, while the right term formulates the required energy to the EV after providing the up-regulation reserve.

Assuming a flat charging profile for the EV before time t, $E_i\,(t)$ can be replaced by $P_{0,i} * \eta_i * (t - t_{a,i})$. In these circumstances, the up-regulation reserve provided by the ith charging event in time t, can be calculated as:

$$F_{up,i}(t,\, P_{0,i}) \\ = \min\left(P_{0,i},\ \frac{P_{\max,i}\,\eta_i\,(t_{d,i} - t - 0.5) + P_{0,i}\,\eta_i(t + 0.5 - t_{a,i}) - E_i}{0.5\,\eta_i}\right). \tag{4}$$

A downside of up-regulation provided by EVCS is that, in order to offer the capacity, the charging of the EV battery has to be performed at a power level lower than the maximum. This means if the user to unplug their vehicle earlier than the expected departure time, there is a risk of the car not being fully charged. However, since most of the time the under frequency events has duration less than 30 minutes, as shown in [24], the risk of the car not get enough charge is low.

3.2. Down-regulation reserve

Fig. 2c shows an EV charging profile providing down-regulation reserve at time t ($F_{down}(t)$ kW) for t_f hours while needing t_c hours to compensate the extra charging in the profile to keep the EV charging in the desired level.

As shown in Fig. 2c, the down-regulation power is limited by P_{max} - P_0. Also, the energy requirement of EV (E_i), makes another constraint in down-regulation reserve. Since the charging should be stopped, if the EV charged to the desired amount of energy, and the FCR should be available for half an hour; the following constraint must be satisfied:

$$E_i(t) + 0.5\,\eta_i\,(F_{down,i}(t) + P_{0,i}) \leq E_i. \tag{5}$$

The right term in (5) represents the charging energy into the EV after providing down-regulation reserve and the left term formulates the required energy of the EV. Assuming the flat charging profile for the EV before time t, the down-regulation reserve in time t can be calculated as:

$$F_{down,i}(t, P_{0,i}) = \min\left(P_{\max,i} - P_{0,i}, \frac{E_i - P_{0,i}\eta_i(t + 0.5 - t_{a,i})}{0.5\eta_i}\right). \tag{6}$$

In practice, the recovery period t_c could be shifted to the end of the charging period to make it more likely for the EV user to have their car fully charged even when they unplug it earlier than the expected departure time.

3.3. FCR-N model

The FCR-N capacity is remunerated according to times that the capacity is available. Therefore, the optimum initial charging power of ith charging event to provide FCR-N ($P^*_{0,i,N}$) must be selected to maximize the capacity over the plugged-in time, as follows:

$$\begin{aligned} &\underset{P_{0,i}}{\text{Max}} \left(\int_{t=t_a}^{t_{d,i}} \min(F_{up,i}(t, P_{0,i}),\ F_{down,i}(t, P_{0,i}))\, dt \right), \\ &\text{s.t.} \\ &\quad P_{av,i} \le P_{0,i} \le P_{\max,i} \end{aligned} \tag{7}$$

where $F_{up,i}$ (t, P_0) and $F_{down,i}$ (t, P_0) are respectively calculated from (4) and (6); and the power constraint comes from the fact that the charging events should provide E_i kWh energy regardless of the reserve production. The problem (7) is a simple single variable optimization with an upper and lower bound for the variable. This optimization can be solved with different methods. This paper used the *fminbnd* function of MATLAB. Then, the optimum FCR-N capacity provided by the ith charging event at time t ($F_{FCR-N,i}$ (t)), can be calculated as follows, while $P^*_{0,i,N}$ is obtained from (7).

$$F_{FCR-N,i}(t) = \min(F_{up,i}(t, P^*_{0,i,N}),\ F_{down,i}(t, P^*_{0,i,N}))\, dt\ , \tag{8}$$

3.4. FCR-D model

Since the FCR-D reserve is only in the up-regulation direction, the optimum initial charging power to provide FCR-D from ith charging event ($P^*_{0,i,D}$) should be selected to maximise the up-regulation capacity over the EV plugged-in time, as follows:

$$\begin{aligned} &\underset{P_{0,i}}{\text{Max}} \left(\int_{t=t_{a,i}}^{t_{d,i}} F_{up,i}(t, P_{0,i})\, dt \right), \\ &\text{s.t.} \\ &\quad P_{av,i} \le P_{0,i} \le P_{\max,i} \end{aligned} \tag{9}$$

where $F_{up,i}$ (t, P_0) is calculated from (4). According to Fig. 2b and (3), the time t will be close to the departure time, the provided up-regulation amount is decreased. Therefore, in order to maximise the FCR-D, the EV must be charged as much as possible in the beginning part of the plugged-in time ($P^*_{0,i,D} = P_{max,i}$). In these circumstances, the FCR-D can be calculated as:

$$F_{FCR-D,i}(t) = \begin{cases} \min\left(P_{\max,i}, \frac{P_{\max,i}\eta_i\,(t_{d,i} - t_{a,i})}{0.5\eta_i}\right) & t \le t_{a,i} + t_{ch,i} \\ 0 & t > t_{a,i} + t_{ch,i} \end{cases}. \tag{10}$$

4. EV charging stations

A deterministic FCR model for a single charging event of an EV is developed in Section 3. However, the EV behaviour, such as arriving time, departure time, desired energy level, is not deterministic. To model the uncertainty of the EV behaviour and the effect on the FCR model, this paper focuses on EV charging stations (EVCS) and develops a stochastic planning method for EVCS to participate in the FCR market. In this regards, first, the probability density function (PDF) of FCR potential of EVCS is calculated using historical data to predict the available FCR in the day-ahead market. Then, the expected profit of providing FCR is maximised using a stochastic optimization.

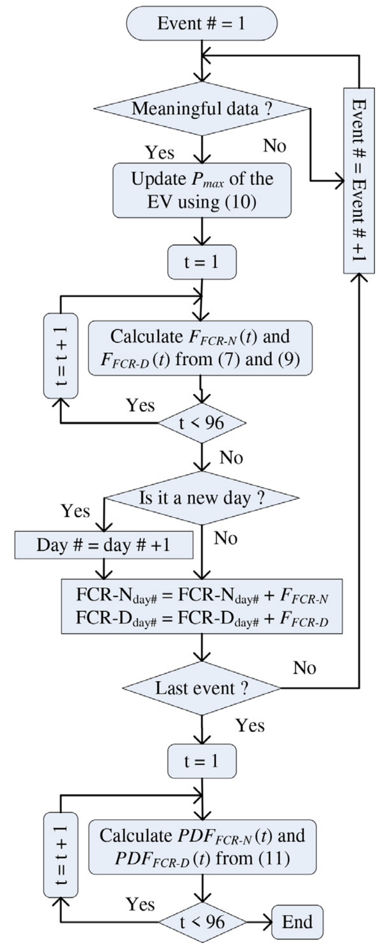

Fig. 3. Proposed method to calculate the aggregated PDF in EVCS

4.1. Stochastic behaviour

This subsection proposes a method to obtain PDF of the FCR provided by EVCS, using historical data of charging events. For this purpose, the proposed method calculates the FCR model for all historical charging events, as described in the flowchart of Fig. 3. In this flowchart, a cleaning process, as will explained in Section 5, is performed to remove all meaningless records; *Event#* and *day#* are used to point respectively the event counter and day counter.

Although the FCR models developed in (7) and (9) need the maximum charging power for the EV ($P_{max,EV,i}$), the EVCS normally do not have access to EV information, such as EV type, the maximum charging power, and the battery size. EVCS can record all charging events data including:

- The customer ID encrypted for data protection,
- The station ID, and the maximum station power,
- The type of charging, whether AC or DC,
- The arrival and departure time (t_a and t_d),
- The total charged energy (E in kWh),

without compromising EV owner privacy. Therefore, the proposed method estimates and updates the maximum charging power ($P_{max,EV,j}$) for jth customer ID (or jth EV), as follows:

$$P_{\max,EV_j} = \begin{cases} \max(P_{\max,EV_j}, P_{av,i}) & \text{ACcharging} \\ P_{\max,EV_j} & \text{DCcharging} \end{cases}, \tag{11}$$

where $P_{av,i}$ is the average charging power of ith charging event, which can be calculated using the available data using (2). It is important to notice that when an EV is charging at a DC charging station, the on-board charger of the EV is bypassed. In this circumstance, 1) the event data should not be used for updating the maximum charging power of the EV, and 2) the amount of $P_{max,EV,j}$ for the event should be replaced by the rate of DC charger.

After finding the maximum power for each EV, the FCR profile resulting from a single charging event can be obtained by solving (8) and (10), respectively for FCR-N and FCR-D at each time interval. Here, each day is divided into 96 time-interval to calculate the FCR profiles with a 15-minute resolution. Then, the EVCS daily FCR profiles will be formed by aggregating the results of all the charging events occurring in one day.

These daily FCR profiles will be used to calculate the probability of having f kW of FCR-N or FCR-D flexibility at time t, shown by $PDF(f,t)$ in general form. These PDF can be calculated by partitioning the FCR power to several bins in each time interval and counting the members of each bin over to the total numbers, as follows:

$$PDF(f, t) = \frac{N_f(t)}{\sum N_f(t)} \tag{12}$$

where N_f is the number of days that FCR power calculated from (8) and (10) in time t is equal to f (placed in the bins with the centre of f). The function of *histcounts* in MATLAB can perform this partitioning process.

4.2. Optimum FCR profile

Having the PDF, the expected available FCR profile for the following day can be calculated as follows:

$$F_{ex}(t) = \int PDF(f, t) f(t) df, \tag{13}$$

where $F_{ex}(t)$ is the expected available FCR in time-interval t, and can be either FCR-N or FCR-D. However, since the flexibility market has a penalty for providing less FCR than promised, as mentioned in Section 2, it is not optimum to participate in the market by the expected available FCR. The optimum profile, which maximises the expected profit, should account for the uncertainties for the FCR availability.

The profit of the flexibility provider (PR) can be calculated as follows:

$$PR(F, t) = \begin{cases} F\pi & f \geq F \\ f\pi - (F - f)\pi^- & f < F \end{cases}, \tag{14}$$

where F is the amount that flexibility provider promised for the time t; f is the actual amount of FCR that is provided in real-time and can be estimated using the PDF in (11); π is the remuneration amount in €/MW,h; and π^- is the penalty of not providing the promised FCR. Therefore, the expected profit (PR_{ex}) of the flexibility provider from participating in the reserve market will be:

$$PR_{ex}(F, t) = PDF(f \geq F, t) F \pi + \int_0^F (f\pi - (F - f)\pi^-) PDF(f, t)\, df, \tag{15}$$

$$PDF(f \geq F, t) = 1 - \overbrace{\int_0^F PDF(f, t) df}^{CDF(f,t)}, \tag{16}$$

where CDF is the cumulative density function. In order to maximise the expected income, F must be selected so that $\partial PR_{ex}/\partial F = 0$. Therefore, the optimum FCR value (F_{op}) can be calculated from (14) and (15) using Leibniz's rule as follows:

$$\frac{\partial PR_{ex}(F_{op}, t)}{\partial F_{op}} = \pi - \pi\, \mathrm{CDF}(F_{op}, t) - \pi^- \mathrm{CDF}(F_{op}, t) = 0, \tag{17}$$

$$\mathrm{CDF}(F_{op}, t) = \frac{\pi}{\pi + \pi^-}. \tag{18}$$

In other words, the flexibility provider should participate in the reserve flexibility market with a power of F_{op}, which satisfies (18). In the current Finnish reserve market regulations, $\pi = \pi^-$; therefore, the maximum expected income is achieved by bidding the median of the FCR distribution. At this stage, the flexibility providers could decide which market, e.g. FCR-N, FCR-D, or a combination of them, presents the highest expected profit by calculating (18) for all the available markets, using (8) and (10).

The proposed methodology estimates the optimum day-ahead profile for FCR market while assuming no change happens in the total energy charged into the EV. In addition, the technical requirements of FCR in the Nordic area consider the duration of frequency events 30 minutes while it lasts much shorter in many cases as discussed in [24]. However, if an EV depart much earlier than schedule time during an under-frequency event, it gets less charge than the desired value. This issue can create a false record in historical data, which may lead to a slight error in future estimation. Therefore, the online control methodology needs to add the effect of flexibility providing in the historical data. Developing the online control methodology of EVCS, which decides which EV need to change the charging power in case of any frequency events is the subject of future work.

It is worth to mention that the developed methodology will not use the V2G ability of EV and just alter the charging profile of EV. Therefore, it will be negligible effects in the degradation model of EV's battery. Authors studied the degradation behaviour of battery storage systems in the FCR market in [24], which shows it has not considerable cost even in case of charging and discharging in the storage system.

5. EVCS in helsinki

This section evaluates the results of the proposed application and the developed strategy using EVCS charging records in the Helsinki area and investigates the empirical potential of EVCS in providing FCR-N and FCR-D. Fig. 4 shows the user interface of the proposed application, which freely available in [20].

The EV charging data includes the charging records of 60 public EVCS in the Helsinki area from Oct 2014 until Oct 2018, which contains about 41,000 charging events of about 2,500 customer IDs, after the cleaning process.

Before using historical data, a clean-up process is performed to remove meaningless records. At this stage, the proposed method removes an EV charging event if it presents at least one of the following issues:

- Missing items,
- Duration plugged-in less than five minutes,
- Energy charged less than 0.1 kWh or more than 100 kWh,
- Charging power more than the charging station rate.

The stochastic behaviour of these EV charging events, such as arrival time, plugged-in time, and charging energy, are analysed in [26]. It is worth to mention that the EV charging data does not included the efficiency of the EV. Here, the efficiency of the EV charging process considered 90%.

5.1. FCR in EVCS

Here, the methodology proposed in Section 2 and 3 is used to calculate the FCR-N and FCR-D potential for EVCS in the Helsinki area.

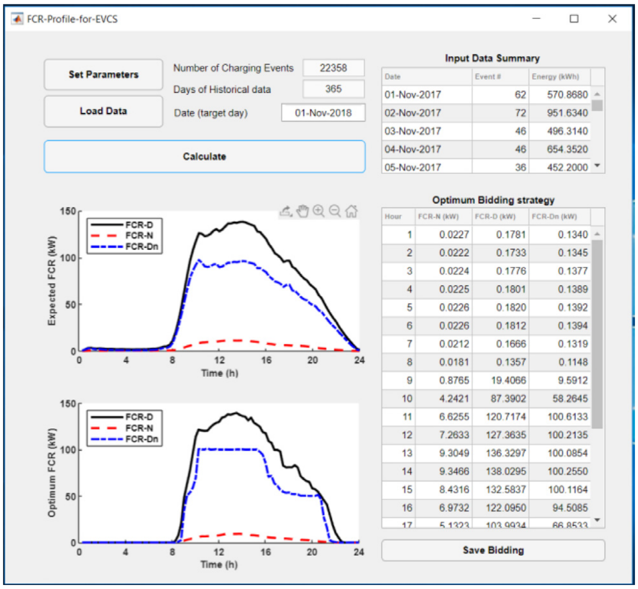

Fig. 4. . The user interface of the proposed application for EVCS to estimate the optimum day-ahead bidding profiles in FCR, freely available in [20].

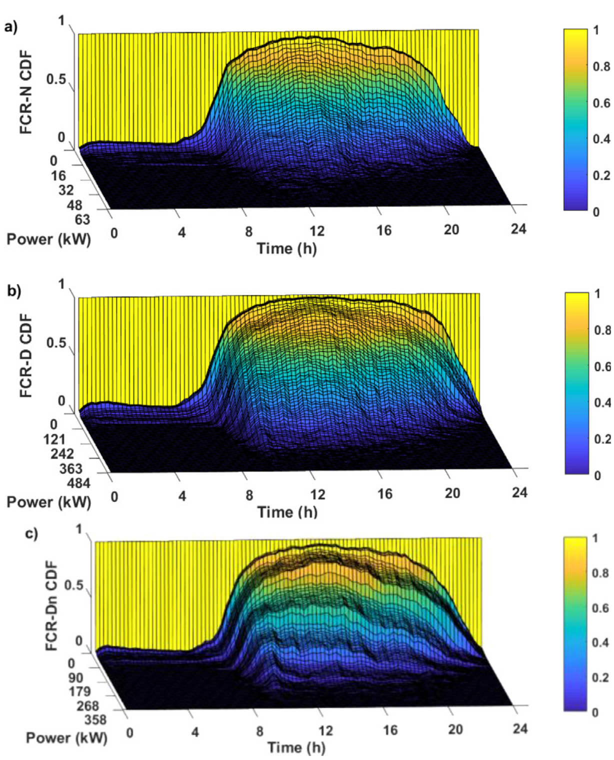

Fig. 5. The cumulative density function (CDF) of a) FCR-N, b) FCR-D, and FCR-Dn for different time of a day provided by EVs.

Fig. 5 shows the CDF for FCR capacity, which can be provided by EV connected to public EVCS in the Helsinki area, based on last year records. Fig. 5a shows the CDF for FCR-N, while Fig. 5b illustrates the CDF of FCR-D.

Analysing the EV behaviour shows that the EVCS can provide much larger down- than up-regulation. The reason is that the plugged-in time of EV is not much longer than the required charging time at full power. Therefore, in most cases, $P_{max} - P_{av} < P_{av}$, and the amount of up-regulation is much smaller than down-regulation.

In this case, EVCS can still provide some extra up-regulation after providing FCR-N. This could be used to provide FCR-D services with

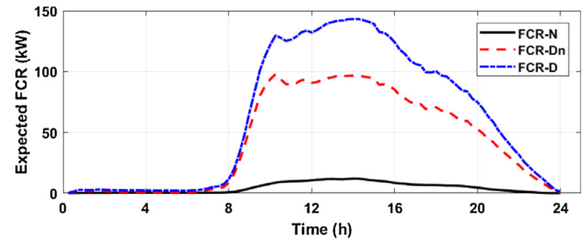

Fig. 6. The expected FCR profiles of EVCS in the Helsinki area.

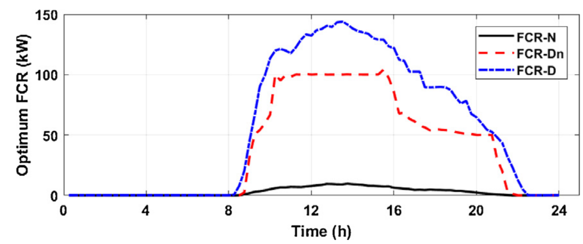

Fig. 7. The optimum FCR profiles of EVCS in the Helsinki area.

what remains after the FCR-N provision. That extra potential is named FCR-Dn in this paper. Fig. 5c shows the CDF for FCR-Dn.

Using these CDFs, the expected FCR and the optimum profile can be estimated using (13) and (18), respectively. Fig 6 shows the expected FCR profiles, while Fig. 7 shows the optimum profiles. Comparing Figs. 6 and 7 shows that the optimum profiles, which make the maximum expected profit are quite similar to the expected profiles. This similarity is due to the fact that the current market regulations in Finland have the penalty equal to the remuneration price ($\pi = \pi^-$).

As shown in Fig. 7, the most expected value for the FCR of EVCS will be almost zero during the night. This is because of the fact that people use public charging stations mostly during day times. The data used in this study excludes private charging stations, where the EV owners charge their car at home, during nights.

The maximum expected FCR-N of these EVCS is about 12 kW happening at 2:00 p.m., while the maximum expected FCR-D is about 143 kW happening at the same time. Looking at an expected profile of FCR-Dn shows that EVs can still provide a considerable amount of FCR-D after providing FCR-N.

The maximum FCR capacity calculated here for public EVCS in the Helsinki area is not significant in comparison to the total needs for Finland (140 MW FCR-N and 260 MW FCR-D [27]). This is due to the fact that the numbers of vehicles and stations in the Helsinki area are still very low.

Based on the historical data until Sep. 2018, the available capacity has been calculated for the month of Oct. 2018. Table 1 presents the average daily profit which would have been obtained by providing FCR services, including the incomes for capacity and the penalty at times when the delivery would not have been possible. The profit is calculated in three categories: FCR-N, FCR-D, or as a combination of FCR-N and FCR-Dn. Although FCR-N has a larger remuneration per capacity, the profit of providing FCR-N is less than FCR-D because EV cannot

Table 1
The average daily profit (euro) of the last month of providing FCR

		FCR-N	FCR-D	D + N *
Proposed Method	Absolute	3.846	9.452	10.99
Ideal Estimate	Per events	0.057	0.148	0.170
	Per kWh	0.006	0.017	0.019
	Absolute	5.608	16.48	17.09
	Per events	0.080	0.238	0.247
	Per kWh	0.009	0.027	0.028

* The Combination of FCR-N and FCR-Dn.

provide large down-regulation compared to up-regulation reserves. Table 1 shows that providing a combination of FCR-N and FCR-Dn is the most profitable choice.

However, providing just FCR-D may be a wiser choice for public EVCS. As explained in Section 3.4, in order to achieve the maximum FCR-D, the EV should start to charge the battery immediately with the maximum power, which is the most desirable way for a public charging station. In addition, because the departure time is not deterministic, charging the EV by P_{av} in order to have some FCR-N capacity will lead to a lower than expected state of charge in case of an early departure.

Furthermore, in FCR-D the reserve is provided whenever the frequency is less than 49.9 Hz, while the FCR-N must provide reserve whenever the frequency is out of the dead band of (49.99, 50.01) Hz. Analysis of the frequency records for the Nordic power system (available in the open data of Fingrid [28]), shows that FCR-D providers must active their flexibility less than 1 % of the time while FCR-N providers need to activate their resources about 80% of the time.

Table 1 compares the profit resulting from the proposed methods with an ideal estimation where the profile forecasting was assumed perfect and the measured data was substituted to the estimations. This comparison shows that the methodology presented here allows extracting about 62% of the ideal available profits. While a perfect forecast and estimation will remain impossible, the uncertainty would be reduced if the data included more EV charging events.

In addition, Table 1 shows the average profit for each charging event and per kWh of energy used for EV charging. This table states that the income for combined FCR-N and FCR-Dn per kWh of energy is about 2 euro cents (1.9 – 2.8), which is about half of the average energy cost in Finland (about 4.6 euro cents in Oct 2018 [29]).

Comparing EV charging data of 2014 with 2018, shows a considerable growth in the energy consumption and the potential of FCR provision by EVCS, as discussed in [30]. However, the current impact of the EVCS installed in the Helsinki area is still very little compared to the national needs for frequency control, as shown in Figs. 6 and 7. The Authors in [30] show that the EV growth continues at the same rate as in the last three years, they will provide five times more flexibility while using ten times more energy in 10 years.

However, It is expected that the EV growth will be faster in the future, due to several reasons, such as more government incentives, reduction in the battery price, increase in the fuel costs and emission taxes. In addition, by increasing the charger rate in the future, EV potential to provide FCR will be increased.

6. Conclusion

This research developed an application for EV charging stations to estimate the optimum day-ahead bidding profiles in FCR markets and this paper presents the stochastic methodology behind this application. In this regard, mathematical models for the available FCR of an EV charging event are developed based on the technical requirements for the provision of reserves for the two FCR markets in Finland. Then, a stochastic methodology is implemented, using aggregated probability density function of EVs flexibility, in order to estimate the day-ahead potential and maximise the expected profit.

Using the developed models and the proposed methodology, this paper analyses the behaviour of public charging stations in the Helsinki area from 2015 till 2018. The results show that although FCR-N has 5 times higher remuneration for available capacity than FCR-D, it will lead to much lower profit due to the difficulties for charging stations to provide down-regulation reserve. The most profitable choice of the electricity reserve market for charging stations is a combination of FCR-N and FCR-D products. The comparison of the proposed planning strategy with the ideal estimation shows that the proposed method gives a little more than 60 % of the maximum possible revenues from FCR services provision and that it would cover about 50% of their charging energy costs. It is important to notice that reaching the maximum possible revenues from FCR is impossible due to stochastic behaviour of EV while the uncertainty would be reduced if the data included more EV charging events.

The study also concludes that, although a combination of FCR-N and FCR-D products is the most profitable choice, providing only FCR-D could be more practical. It would decrease the profits by a narrow percentage but lead to lower effects on EV owners' preference. The optimum charging strategy in order to provide FCR-D is to start charging at the maximum power immediately when the vehicle is plugged in, which is the preferred charging profile for the users of public EVCS (this would be different for over-night charging at private charging stations).

It is worth to mention that this paper focuses on determining what products should be sold in which quantities by EVCS. The implementation and online control of the EVCS in order to activate the planned FCR requires more research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The research leading to this work was being carried out as a part of the EU-SysFlex project (Pan-European system with an efficient coordinated use of flexibilities for the integration of a large share of RES), which received funding from the EU's Horizon 2020 programme under grant agreement No 773505.

The authors would like to thank Suvi Takala and Antti Hyttinen, from Helen Ltd, who helped with providing EVCS data.

References

[1] P. Hasanpor Divshali, B.J. Choi, Electrical market management considering power system constraints in smart distribution grids, Energies 9 (6) (2016) 1–30.
[2] P. Hasanpor Divshali, B.J. Choi, H. Liang, L. Söder, Transactive demand side management programs in smart grids with high penetration of EVs, Energies 10 (10) (2017) 1–18.
[3] P. Hasanpor Divshali, B.J. Choi, H. Liang, Multi-agent transactive energy management system considering high levels of renewable energy source and electric vehicles, IET Gener. Transm. Distrib. 11 (15) (2017) 3713–3721.
[4] M.S. Islam, N. Mithulananthan, D.Q. Hung, A day-ahead forecasting model for probabilistic EV charging loads at business premises, IEEE Trans. Sustain. Energy 9 (2) (2018) 741–753.
[5] D. Wu, H. Zeng, C. Lu, B. Boulet, Two-stage energy management for office buildings with workplace EV charging and renewable energy, IEEE Trans. Transp. Electrif. 3 (1) (2017) 225–237.
[6] D. Van Der Meer, G.R.C. Mouli, G.M.E. Mouli, L.R. Elizondo, P. Bauer, Energy Management system with PV power forecast to optimally charge EVs at the workplace, IEEE Trans. Ind. Inform. 14 (1) (2018) 311–320.
[7] Y. Zhou, Z. Li, X. Wu, The multiobjective based large-scale electric vehicle charging behaviours analysis, Complexity (2018) 1–16 Oct. 2018.
[8] C.B. Harris, M.E. Webber, An empirically-validated methodology to simulate electricity demand for electric vehicle charging, Appl. Energy 126 (1) (2014) 172–181.
[9] P. Pflaum, M. Alamir, M.Y. Lamoudi, Probabilistic energy management strategy for EV charging stations using randomized algorithms, IEEE Trans. Control Syst. Technol. 26 (3) (2018) 1099–1106.
[10] S. Su, H. Zhao, H. Zhang, X. Lin, F. Yang, Z. Li, Forecast of electric vehicle charging demand based on traffic flow model and optimal path planning, 2017 19th International Conference on Intelligent System Application to Power Systems, ISAP, 2017.
[11] M.H. Amini, O. Karabasoglu, M.D. Ilić, K.G. Boroojeni, S.S. Iyengar, ARIMA-based demand forecasting method considering probabilistic model of electric vehicles' parking lots, IEEE Power and Energy Society General Meeting, 2015.
[12] M.H. Amini, A. Kargarian, O. Karabasoglu, ARIMA-based decoupled time series forecasting of electric vehicle charging demand for stochastic power system operation, Electr. Power Syst. Res. (2016).
[13] N. Korolko, Z. Sahinoglu, D. Nikovski, Modeling and forecasting self-similar power load due to EV fast chargers, IEEE Trans. Smart Grid 7 (3) (2016) 1620–1629.
[14] Y.W. Chung, B. Khaki, C. Chu, R. Gadh, Electric vehicle user behavior prediction using hybrid kernel density estimator, 2018 International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2018 - Proceedings, 2018.
[15] E. Xydas, C. Marmaras, L.M. Cipcigan, N. Jenkins, S. Carroll, M. Barker, A data-

driven approach for characterising the charging demand of electric vehicles: a UK case study, Appl. Energy 162 (1) (2016) 763–771.
[16] J. Schäuble, T. Kaschub, A. Ensslen, P. Jochem, W. Fichtner, Generating electric vehicle load profiles from empirical data of three EV fleets in Southwest Germany, J. Clean. Prod. 150 (1) (2017) 253–266.
[17] H.M. Louie, Time-series modeling of aggregated electric vehicle charging station load, Electr. Power Compon. Syst. 45 (14) (2017) 1498–1511.
[18] S. Wang, G. Xue, C. Ping, D. Wang, F. You, T. Jiang, The application of forecasting algorithms on electric vehicle power load, 2018 IEEE International Conference on Mechatronics and Automation (ICMA), 2018, pp. 1371–1375.
[19] "EU-SysFlex." [Online]. Available:eu-sysflex.com/. [Accessed: 03-Aug-2018].
[20] "Tool for electrical vehicle charging stations (EVCS) to estimate day-ahead bidding in FCR markets, available." [Online]. Available: github.com/poriahd/EU-Sysflex—–FCR-tool-for-EVCS. [Accessed: 26-Feb-2020].
[21] E. Sarah Darby, Juha Forsström, Sarah Higginson, REALVALUE D6.3: market design & business models report, (2017).
[22] E. Julia Merino, I. Gómez, E. Turienzo, "SmartNet Project D1.1: ancillary service provision by RES and DSM connected at distribution level in the future power system," 2016.
[23] FINGRID, "The technical requirements and the prequalification process of frequency containment reserves (FCR)," 2019.
[24] P. Hasanpor Divshali, C. Evens, Optimum operation of battery storage system in frequency containment reserves markets, IEEE Trans. Smart Grid (2020) vol. accepted.
[25] FINGRID, "Yearly market agreement for frequency containment reserves," 2019.
[26] P. Hasanpor Divshali, C. Evens, Behaviour analysis of electrical vehicle flexibility based on large-scale charging data, IEEE PES Powertech (2019) 2019.
[27] FINGRID, "Application instruction for the maintenance of frequency controlled reserves," 2018.
[28] FINGRID, "Frequency - historical data - datasets - fingridin avoin data." [Online]. Available:data.fingrid.fi/en/dataset/frequency-historical-data. [Accessed: 29-May-2019].
[29] "NORDPOOL Data." [Online]. Available:www.nordpoolgroup.com/Market-data1/#/nordic/table. [Accessed: 03-Aug-2018].
[30] P. Hasanpor Divshali, C. Evens, Stochastic bidding strategy for electrical vehicle charging stations to participate in frequency containment reserves markets, IET Gener. Transm. Distrib. (2020).