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Explicit demand response potential in electric vehicle charging networks: Event-based simulation based on the multivariate copula procedure

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ABSTRACT

This paper proposes a novel combined event-based simulation model for assessing the explicit demand response potential of electric vehicle (EV) charging networks. The model utilizes different multivariate copulas in generation of realistic artificial charging events that effectively retain the complex dependency structures and parameter distributions of real data important for accurate demand response simulation. A deterministic model is used to estimate the maximal explicit demand response potential of individual charging events based on technical requirements of the frequency containment reserve for disturbance situations (FCR-D) market. The proposed model achieved a mean absolute percentage error (MAPE) of 3.27% when considering averaged daily dispatchable FCR-D potentials, and a MAPE of 4.65% in prediction of dispatchable FCR-D potential with one workweek of data. The results and methodology have been verified and validated with real life data and through comparison with a previous non-copula application for EV FCR profile estimation which it outperformed. The combined event-based simulation model can boost active participation of EVs in power network balancing and is suitable for use in various practical and theoretical applications.

1. Introduction

The rapidly accelerating electrification of transport, happening simultaneously with large-scale increase in variable renewable energy sources, can cause major technical challenges for power grid balancing. However, by smart control of electric vehicle (EV) charging, the negative grid impacts of EV charging can be minimized and the charging loads can even be used to support grid stability [1]. Smart control of EV charging is one example of demand side flexibility and demand response (DR) [1,2].

Traditionally demand response is defined as end-users' intentional adjustment of electricity consumption based on external signals [3]. Implicit, or time-based, demand response programs encourage consumers to shift their demand based on time-varying electricity pricing [4]. Explicit, or incentive-based, DR programs are used to aggregate loads that can be controlled when system stability is at risk [4]. Participation in explicit demand response is encouraged through monetary incentives. These incentive-based DR programs aim to supplement generation resources in resolving system and local capacity constraints, and are used to retain system reliability especially during contingency or emergency events [5]. Frequency containment reserves (FCR) are an example of explicit DR aiming to retain the grid frequency at a nominal level. FCR markets are generally reasonable marketplaces for EV charging flexibility due to a focus on capacity availability rather than utilization [6]. In the Nordics, FCR is further divided into two types: FCR-N for normal operation, and FCR-D for disturbance situations [7]. Procured frequency containment reserves can be further divided into upwards and downwards balancing, where upwards balancing means either an increase in electricity production or a decrease in electricity consumption, and vice versa for downwards balancing. When considering non-V2G (non-bidirectional) EV charging, upwards balancing entails a decrease in electricity consumption, that is, a decrease in the EV charging power. In this case, a maximum upwards activation can be achieved by decreasing the EV charging power to zero.

The minimum capacity of a single bid on the Nordic FCR-D market is 1 MW [8]. This implies that multiple EV charging

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Nomenclature

Abbreviations

CPO	Charging point operator
DR	Demand response
EV	Electric vehicle
EVSE	Electric vehicle supply equipment
FCR	Frequency Containment Reserve
FCR-D	Frequency Containment Reserve for Disturbances
FCR-N	Frequency Containment Reserve for Normal Operation
MAPE	Mean absolute percentage error
TSO	Transmission System Operator
V2G	Vehicle-to-Grid, bidirectional power flow

Indices and index sets

i	Index for charging events
t	Time index (hour), 1, …,T

Symbols: Symbol Unit Description

C_{FCR-D}	MW Maintained volume (capacity) of FCR-D
C_{FCR-N}	MW Maintained volume of FCR-N
$C_{prequalification}$	MW Maintained reserve verified by prequalification test
D_{EV}	MWh Maximal FCR-D potential of a single EV charging event
$D_{network}$	MWh Maximal FCR-D potential of an EV charging network
$E_{charging}$	MWh Energy charged during a charging event
E_{max}	MWh Maximum energy charged during a charging event
P_{max}	MW Maximum charging power
P_{min}	MW Minimum power of a reserve unit
$P_{power\ setting}$	MW Current power setting of the reserve unit
$t_{charging}$	h Time needed to charge the required energy
t_{flex}	h Maximum flexibility activation time of the resource
$t_{plug-in}$	h Overall time the EV is plugged-in to the charging point
T_{charge}	hh:mm Time of day of, end of energy transfer/charging
T_{end}	hh:mm Time of day of, end of a charging event (plug-out)
T_{start}	hh:mm Time of day of, start of a charging event (plug-in)

events must be aggregated to fulfill the minimum capacity for participating on the FCR-D marketplace. The reserve market agreement includes a penalty clause for undelivered reserve capacity and the hourly bids for the following day must be submitted before 18:30, making the estimation of dispatchable EV charging load a predictive modelling problem. That is, in order to effectively participate on the FCR-D market, the demand response aggregator will require predictive models that can accurately estimate the dispatchable load profile of the following day. As the marketplace operates on the marginal price principle, accurate dispatchable load modelling is also important when considering the demand response aggregator bidding strategy, which has been studied, for instance, in Refs. [9–11]. Different explicit demand response marketplaces share similar terms and conditions as the Nordic FCR-D denoting that accurate prediction of dispatchable EV charging loads is important worldwide. That is, for EVs to actively participate in power network balancing, accurate simulation models are needed.

Majority of previous research involving EV charging load modelling is based on driver behavior and travel survey datasets [12–21], EV trials [22–24], or theoretical scenarios [25,26]. Estimation of EV charging load profiles is possible based on travel surveys and driving pattern datasets [27], but these vehicle usage-based modelling approaches require multiple assumptions and can be regarded mostly theoretical as the data does not properly cover EV charging [28]. Some studies also utilize mathematical models based on fixed hourly EV charging patterns to construct EV charging load profiles that can be utilized in different modelling problems [29,30]. Due to methodological restrictions and as the utilized data does not cover actual EV charging events, these approaches are unable to fully consider the variability of EV charging which is important in practical-scale demand response modelling.

Event-based simulation models, which utilize EV charging event data and approach the EV charging demand modelling problem from the charging point perspective are still less common than the previous approaches. As these models utilize real charging events, they can better capture the inherent variability of local charging behavior and can thus be used in more accurate local charging demand modelling and prediction. EV load forecasting based on charging event data has been studied, for instance, in Refs. [31–33]. In EV demand response modelling, it is especially important to retain all variability connected to EV charging, as matching estimated dispatchable loads with demand response events is very time-specific and specific to the considered ancillary service marketplace.

There exists some prior research that utilize event-based simulation models in estimation of EV demand response potential. In Ref. [32], the authors developed deterministic models that can be used to calculate maximum FCR loads providable by individual charging events. The deterministic models used in conjunction with a stochastic bidding strategy to maximize profit were evaluated with real public EV charging event data [32]. Authors of [34] used historical data of vehicle availability with actual charging power, battery size and state-of-charge at arrival and departure, to develop a two-stage stochastic optimization problem that maximizes the profit of a risk-averse EV aggregator on the day-ahead FCR market. In Ref. [33], Divshali & Evens developed an application to estimate the optimum day-ahead bidding profiles for EV charging stations in FCR markets. This application used deterministic models and historic data from Finnish public EV chargers to calculate the expected and economically optimal FCR profiles of the charging network non-continuously one day at a time. These previous approaches however do not retain the correlation structures of EV charging events in DR simulation. Disregarding parameter correlations can lead to substantial estimation errors in power consumption profile estimation according to Ref. [35].

This study proposes a novel event-based simulation process for estimating the explicit demand response potential of EV charging networks. The model utilizes multivariate copulas in EV charging event generation in a similar manner as introduced in Ref. [36]. Copula functions are especially suitable for modelling problems involving data with complex non-normal dependencies between variables and where inclusion of variable dependence is crucial. As the variables of EV charging events have significant non-normal dependencies [36], and as ignoring these kinds of correlations can lead to substantial estimation errors in power consumption profile estimation [35], the use of copulas in EV charging modelling problems is justified. Copula functions retain variable correlation structures very well in data sampling [36], which is important in accurate event-based EV DR modelling. Previously copula functions have, for instance, been used to optimize and model charging schedules of EVs participating in implicit DR [37,38], to analyze the impact of EV charging on microgrids [39], to model EV charging in energy management algorithms [40], and to simulate EV charging events [36]. However, there exists no previous studies applying multivariate copulas with real EV charging event data in maximal FCR-D potential simulation. This study aims to bridge this research gap between explicit demand response modelling, event-based EV charging simulation and multivariate copulas.

The proposed combined event-based EV DR simulation model utilizes different copula functions with different EV charging event subgroups to retain the distinctness of the groups and to improve prediction accuracy. Based on Kendall's tau-b coefficients, variable correlation matrices and the Kolmogorov-Smirnov test, the generated artificial sample retains the correlation structures and distributions of real input data including event FCR-D potentials very well. This synthetic EV charging event sample is used in a deterministic model to estimate and predict the aggregated FCR-D potential of the charging network. The combined event-based model can be modified to function on different explicit demand response marketplaces by adjusting the equations used in the DR potential calculation. The proposed methodology is verified and validated with real charging event data and through comparison with a previous non-copula application for EV FCR estimation presented in Ref. [33].

The presented methodology introduces important contributions to the state-of-art research. The novel combination of different multivariate copulas, event-based EV charging simulation and explicit demand response modelling enables highly accurate EV DR simulation. The process can be utilized either with real charging event datasets or with pre-existing charging event dataset dependency coefficients, and it performs well even with fairly short historical datasets, such datasets covering one workweek. Accurate simulation of explicit demand response is important in multiple practical and theoretical use cases ranging from day-to-day bid estimation on DR marketplaces to future smart grid planning. Overall, the proposed methodology can help to boost active participation of EV fleets in power network balancing through accurate predictive EV DR simulation.

2. Methods

The methodology proposed in this study to simulate the demand response potential of EV charging networks can be divided into two main parts. In the first part, the multivariate copula procedure is used to generate artificial EV charging events. The multivariate copula procedure can use either existing dependency information or real charging event datasets in this data generation.

The second part of the methodology focuses on assessment of the demand response potential of the generated charging event pool. The equations for the DR potential assessment vary between DR marketplaces. In this study, the Nordic Frequency Containment Reserve for Disturbances (FCR-D) market and equations provided by Nordic transmission system operators (TSOs) are used to assess the DR potential of charging events.

2.1. Multivariate copula procedure for charging event generation

Accurate EV charging event simulation is challenging with traditional methods assuming independent parameters due to complicated multivariate dependencies between charging event variables [41,42]. One efficient way of retaining these complex dependency structures in modelling and data sampling is the utilization of multivariate copulas [36,43,44]. This paper utilizes and improves the multivariate copula model, developed in Ref. [36], for EV charging event generation based on a real charging event dataset. The multivariate copula procedure can be used in effective analysis, simulation and generation of synthetic EV charging events as it retains the inherent variability and parameter dependencies of real charging events [36].

Copula functions are essentially multivariate cumulative distribution functions with uniform one-dimensional marginal distributions that can be used to capture and describe dependencies between random variables. In simulation applications, copulas are especially useful in synthetic data sample generation, as they enable generation of data points that adhere either to a specified or observed joint distribution. The resulting data sample preserves the variable nature of real instances, and can thus be used to model real-world systems such as EV charging networks accurately [36,44].

This study utilizes and improves the multivariate copula procedure and the copulas introduced in Ref. [36] for artificial charging event generation. The Student-t & Gaussian copulas, from the elliptical copula family, achieved the best goodness-of-fit statistics in the multivariate copula comparison conducted in Ref. [36] with EV charging event data. The five most popular copulas (Gaussian, Student-t, Clayton, Frank and Gumbel) are compared for each data subgroup to find the best performing combination for FCR-D simulation. In this study, the multivariate copula procedure is improved to utilize different copula functions with different EV charging event subgroups to better retain the distinctness of the groups and to improve DR prediction accuracy. Additionally, to improve the reliability of the model in time-sensitive explicit demand response modelling, the copula charging event sampling is modified to be conducted separately for each hour of the day. The inherently distinct subgroups of the EV charging data are presented in section 2.4. Detailed mathematical formulation of the aforementioned copulas are not presented here due to space constraints, but can be found, for instance, in Refs. [44,45].

The improved multivariate copula procedure used for data generation from real-life EV charging datasets is summarized in Fig. 1. When using the procedure with pre-existing dependency coefficients, the process begins from the step “Copula coefficients”. Detailed description of the procedure can be found in Ref. [36]. Differing from Ref. [36], this study conducts the copula sampling separately for each hour of the day, as this improves the reliability of the model in time-sensitive FCR-D modelling.

2.2. Equations for explicit demand response potential calculation

2.2.1. Reserve units in the Nordic FCR-D marketplace

The Nordic power system is a highly integrated transnational system that comprises of Finnish, Swedish, Norwegian and Danish power systems and has connections to multiple additional power systems. The Nordic power systems shares a common electricity market, Nord Pool. Nordic transmission service operators utilize and procure multiple different ancillary services to maintain the power system reliability. For instance, Frequency Containment Reserve for Disturbances (FCR-D) is an active power reserve currently used to limit grid frequency deviation to 49.5 Hz during frequency disturbances.

Fingrid, the Finnish TSO, provides the following equation [46] for ancillary service providers that can be used to solve the maintained *volume* (capacity, MW) of FCR-D, $C_{FCR\text{-}D}$. Here, the $P_{max/min}$ of

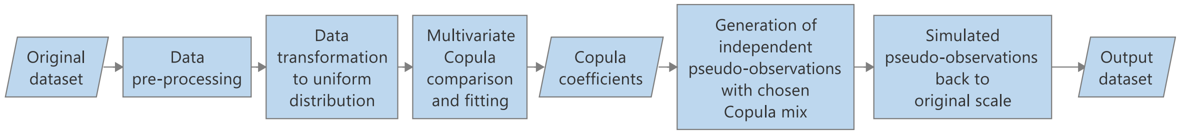

Fig. 1. Multivariate copula procedure for synthetic charging event generation, adapted from Ref. [36].

the original TSO equation is set as the minimum power, P_{min}, of the reserve unit as we are essentially calculating the FCR-D volume of a consumption facility, in our case the FCR-D volume of electric vehicle charging without V2G discharging.

$$C_{FCR-D} = \max\left[\min\left(abs\left(P_{min} - P_{power\ setting}\right) - C_{FCR-N}, C_{prequalification}\right), 0\right] \tag{1}$$

As in this study, we are assessing exclusively the potential of FCR-D, equation (1) can be simplified by setting the volume of the Frequency Containment Reserve for Normal Operation maintained, C_{FCR-N}, to zero. When working with EV charging data, the actual volume of the reserves cannot be verified by prequalification tests, so we further must simplify the equation by removing $C_{prequalification}$. P_{min} can also be considered as zero if the EV charging can be interrupted during a demand response event. These simplifications lead to equation (2), where $P_{power\ setting}$ is the current power setting of the reserve unit excluding any activated reserve power.

$$C_{FCR-D} = P_{power\ setting} \tag{2}$$

That is, the maximum possible FCR-D volume of an interruptible EV charging event is the actual charging power. When assessing a fleet of charging EVs, it can be assumed that the maximum momentary FCR-D potential is the aggregated power of the charging network.

FCR reserves should be capable of full activation for the entire delivery period. Exception to this are reserve units with limited activation capabilities, for instance energy storages which might become completely empty if needed to activate fully for the entire delivery period, these resources must be capable to a full activation of at least 30 min per direction [47]. Non-V2G EV charging on the FCR-D marketplace does not fulfill the terms of a limited activation capability reserve unit, and thus the aggregated EV charging load should be capable of full activation for the entire accepted delivery period.

2.2.2. *Assessing the maximal FCR-D potential of EVs*

Currently, Fingrid procures only FCR-D upwards. Upwards balancing meaning either an increase in electricity production, or in non-V2G EV charging case, a decrease in electricity consumption. A load can be activated as an upwards FCR-D resource after the EV charging has begun.

The maximum activation time of the resource, t_{flex}, can be considered as the maximum time the load can be activated without influencing the energy transfer to the EV. This available flexibility time, t_{flex}, can be calculated by subtracting the time needed to fulfill the energy requirement of the EV, $t_{charging}$, from the overall time the EV is plugged-in to the charger, $t_{plug\text{-}in}$. If the charging power is presumed constant, the charging time can be calculated by dividing the energy charged during the event by the charging power as show in equation (3).

$$t_{flex} = t_{plug-in} - t_{charging} = t_{plug-in} - \frac{E_{charging}}{P} \tag{3}$$

In other words, the EV must begin charging at the latest t_{flex} after the start time of the charging event T_{start} for the EV to charge an equal amount of energy as in the normal charging case. This latest time to begin charging can also be denoted with T_{charge}. That is, the maximum FCR-D upwards potential of an EV charging event occurs when the charging load is decreased to zero right after the start of the charging event, and when the actual charging is conducted as late in the charging timeframe as possible. Fig. 2 illustrates this hypothetical scenario where the P_{max} load occurring at time T_{start} indicates that the charging time before demand response activation is assumed zero to calculate the maximum possible FCR-D upwards potential. It should be noted that, it is unlikely for the FCR-D activation to happen immediately after EV plug-in and the activation rarely happens in full volume. Additionally, in reality, the charging power does not remain constant when charging an EV battery to full capacity.

This means that the maximum volume of FCR-D activation is P_{max} before the time T_{charge}. If t denotes a time during a charging event, the maximum volume of FCR-D activation in this time is defined by equation (4) as,

$$C_{FCR-D,i}(t) = \begin{cases} P_{max,i} & t \le t_{flex} \\ 0 & t > t_{flex} \end{cases} \tag{4}$$

Thereby when considering a single EV charging event, the maximal FCR-D potential, D_{EV}, can be calculated by multiplying the maximum power of the charging event, P_{max}, by the time, t_{flex}, as expressed in the following equation (5).

$$D_{EV} = P_{max} * t_{flex} \tag{5}$$

Thus, the theoretical maximum FCR-D potential can be regarded to be the actual energy charged by the EV subtracted from the maximum energy that could have been charged during the plug-in time of the EV, E_{max}, as show in equation (6).

$$D_{EV} = P_{max} t_{flex} = P_{max}\left(t_{plug-in} - t_{charging}\right) = P_{max} t_{plug-in} - E_{charging} = E_{max} - E_{charging} \tag{6}$$

It should be noted that if the full maximum FCR-D would be activated, and if the EV would be unplugged before the end time of the charging event, the energy demand of the EV would not be fulfilled. However, the majority of under frequency events where FCR-D resources are activated have durations of less than 30 min [48], implying that even if the EV would be unplugged prior to the end time of the event, the energy demand of the EV would be fulfilled almost always.

In the case of an aggregated electric vehicle charging network, the total maximal explicit demand response potential of the network can be calculated with equation (7) by summing up all DR potentials of individual charging events, i.

$$D_{network} = \sum_{0}^{i} D_{EV,i} = \sum_{0}^{i}\left(P_{max,i} * t_{plug-in,i} - E_{charging,i}\right) \tag{7}$$

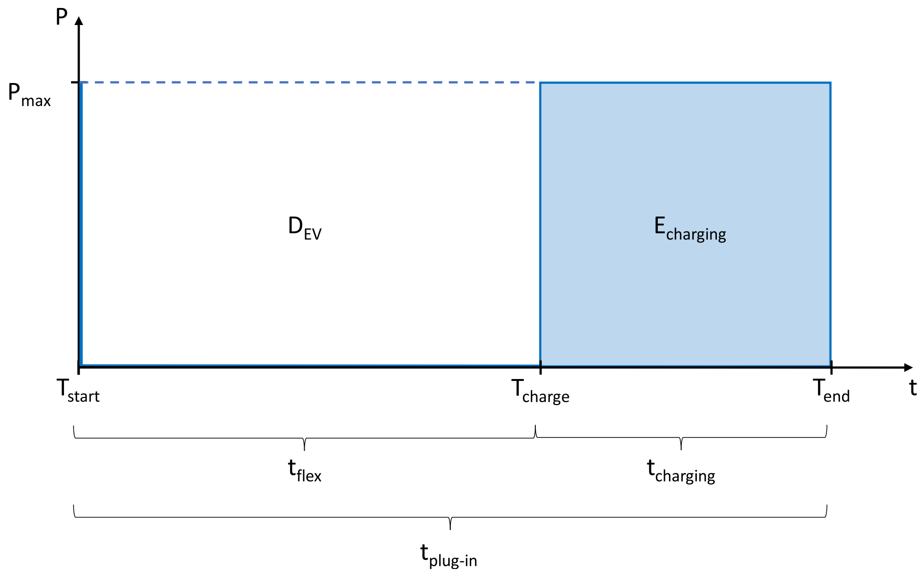

Fig. 2. Maximal FCR-D activation, EV charged as late as possible during a charging event.

2.3. Charging power estimation

Charging point operators, CPOs, do not always record the realized charging powers of EV charging events. The reason for this can range from electric vehicle supply equipment, EVSE, hardware limitations, to the CPO not needing the power time-series for invoicing, as charging rates are generally either energy or time-based. For instance, the EV charging event datasets utilized in Refs. [33,36,49] did not include the realized charging powers of charging events. This problem is apparent also in open EV charging event datasets such as in Ref. [50].

From the perspective of the power grid, the realized charging power is the most important variable of EV charging, as it can be used, for instance, to predict and simulate the impact EV fleets have on the grid. Actual charging power is also needed to calculate the FCR-D potential of EVs with equation (5). To utilize datasets without recorded charging powers, the charging powers of singular charging events must be estimated based on known variables. This can be done by calculating the average charging power based on the charger power rating, duration and the amount of energy drawn during a charging event, as in Refs. [33,49,51,52]. However, this naive method does not consider the power restrictions of EV onboard chargers occurring when charging on AC-charging points and can lead to poor reliability.

Electric vehicle charging can be roughly divided to AC and DC charging based on the EVSE output current type. In DC charging, the EVSE output can be used directly to charge the EV battery, while in AC charging the EV onboard charger is needed to convert the EVSE output AC to DC used to charge the battery. International standard, IEC 61851−1:2017, refers to DC charging as Mode 4 EV charging, and to AC charging from a permanently connected AC charging point as Mode 3 charging. Charging Modes 1 and 2 utilize standard household socket-outlets, do not utilize dedicated EV charging points, and are not intended for permanent use. The main difference between dedicated AC (Mode 3) and DC (Mode 4) EV charging is illustrated in Fig. 3.

In this study, we utilize the same method, for estimation of realized charging powers of charging events conducted on different EV charging Mode EVSE, as in Ref. [36]. That is, for charging events conducted on Mode 4 DC EVSE, the maximum charging power, P_{max}, can be fixed equal to the chargers' maximum power, as the DC output can be used directly to charge the EV battery [53]. In Mode 3 (AC) charging, the EV has to utilize its onboard charger to convert the available AC to DC needed to charge the EV battery. Due to weight, space and cost-constraints, EV onboard chargers typically have lower maximum power ratings than modern Mode 3 charging points, meaning they act as constraints for the actual charging power [54]. Thus, for Mode 3 EVSE, the power ratings of the EV onboard chargers should be taken into account to reach more reliable results in charging power estimation.

As the EV model conducting the charging event is not recorded, it is impossible to identify the maximum charging power of the onboard charger. However, it is possible to estimate the fleet average onboard charger power based on local registration statistics and manufacturer specifications. This estimated fleet average power is utilized in this study as the first guess for the EV charging power, if it is unable to fill the realized charging need, the EV onboard charger has a higher power rating, and the charging power is calculated by dividing the charged energy with event duration. If the calculated power exceeds the maximum power of the EVSE, the charging event is discarded as erroneous.

In this study, the fleet average onboard charger power is estimated to be around 5.5 kW based on Finnish Transport and Communications Agency Traficoms EV registration statistics [55]. This estimated value is well below 22 kW, the most common AC charger power rating of our charging event dataset. The fleet average onboard charging power differs between market areas and should be recalculated when utilizing EV charging event data from other locations. Charging power estimation presented in this subsection becomes redundant if utilizing charging event data with recorded charging powers.

2.4. Description of the charging event dataset

The private EV charging event dataset used in this study was gathered from Finland's largest charging point operator (CPO). The initial data processing and cleaning of the dataset was conducted similarly as, for instance, in Ref. [51]. That is, during data cleaning, the clearly erroneous charging events (events with NULL values, zero energy transfer and impossible charged energies), events conducted on bus and test EVSE, and events lasting either less than 1 min or longer than a week were discarded from the dataset. After

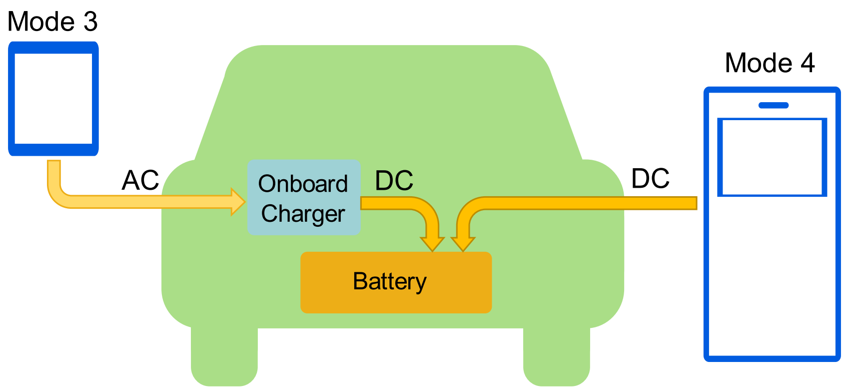

Fig. 3. IEC EV charging Modes 3 and 4.

data processing and cleaning, the dataset covered around 150,000 real charging events conducted on CPO operated private Mode 3 (AC) and Mode 4 (DC) EVSE between January 2018 and June 2019. IEC standardized EV charging Mode 3 is commonly referred to as primary EV charging, and Mode 4 as EV fast charging [53,56]. These private EVSE are located on private properties, for instance at detached houses and parking lots of apartment and office buildings and are thus not intended for extensive public use.

The dataset does not contain any slow home charging events (IEC Modes 1 & 2) made through standard socket-outlets. Due to their lack of dedicated charger units and a CPO, Mode 1 and Mode 2 charging events can be regarded as non-controllable and non-aggregable and thus their absence does not affect the explicit demand response potential of EV charging. In the future, charging events made without a dedicated charger unit could also be utilized in demand response, if a CPO or a DR load aggregator could control the charging event, for instance, through the EV itself. However, charging Modes 1 and 2 are commonly regarded as temporary solutions that will fade out as dedicated EVSE become more common.

The most important variables of the utilized dataset are start time, end time, charged energy, duration, station id, and the maximum charging power of the charger. Of these, start time, energy and duration are used in the multivariate copula procedure to generate synthetic charging events. Event generation is conducted separately for AC and DC chargers, and for weekdays and holidays, to reduce the computational complexity while retaining inherent distinctness of these four subgroups ($AC_{Weekday}$, $AC_{Holiday}$, $DC_{Weekday}$, $DC_{Holiday}$). Actualized charging powers of charging events are not recorded by the CPO due to charger hardware restrictions; these values are estimated based on other known parameters as discussed in section 2.3.

2.5. Validation & model comparison

The proposed combined event-based simulation model was validated by building it up incrementally and validating each component first separately and then together. The methodology for viable activation powers, flexibility times and the resulting FCR-D potentials were first tested separately in simple cases where the optimal operation could be verified. The most suitable multivariate copula (Gaussian, Student-t, Clayton, Frank or Gumbel) for each of the four main subgroups ($AC_{Weekday}$, $AC_{Holiday}$, $DC_{Weekday}$, $DC_{Holiday}$), was chosen based on Akaike and Bayesian information criteria and the fit of the dispatchable FCR-D potential curve. The results of the multiparameter copula procedure were validated by comparing the dependency information of generated artificial data to the original datasets, and by the two-sample Kolmogorov-Smirnov test. Additional verification of the methodology was obtained by comparison of the averaged dispatchable FCR-D potentials gained with the original and artificial datasets.

The proposed model was also validated and compared with an existing non-copula EV FCR profile application presented by Divshali & Evans in Ref. [33]. The application of Divshali & Evans was developed utilizing EV charging event data from the same country, and addressed the same FCR-D marketplace, and thus presented the most viable available comparison point for our methodology. This application is freely available from Ref. [52] and was used to generate comparable FCR-D profiles with the dataset of our study used as the input. Due to differing assumptions made in the models, regarding for instance the AC charging powers, flexibility times and time-resolution, the correct functioning of the deterministic part of our model was further validated through trial runs with the same base assumptions as in Refs. [33,52].

3. Results

The results section is organized as follows. First, we cover the results of the dependency analysis that was conducted between the assessed demand response potential and other charging event parameters on the original real EV charging dataset. These dependencies shed light on which of the parameters affect the demand response potential of EV charging events. The following subsection concentrates on assessment of the reliability of the multivariate copula procedure to the EV FCR-D simulation problem, including dependency analysis of the artificial charging event dataset and validation of the averaged daily flexibility potentials. Next, the proposed framework is used to estimate the future FCR-D demand response potential of an EV charging network. The final subsection focuses on validation and comparison of the model with a pre-existing non-copula FCR-D potential estimation model developed in Ref. [33].

3.1. Dependencies between demand response potential and charging event parameters

The most important variables used to calculate the maximum FCR-D potential of EV charging events with (6) are the charged energy ($E_{charging}$), plug-in duration ($t_{plug\text{-}in}$) and maximum charging power (P_{max}). The starting time of the charging event, T_{start}, would also be crucial for calculating the value of the DR potential on the hourly ancillary markets.

The dependencies between the most important charging event variables and the solved demand response potential were examined via Pearson's, Kendall's and Spearman's correlations. According to all of the examined correlation coefficients, there exists significant correlation between the demand response potential, the charging duration and the charged energy amount. These correlations can be verified from Kendall's correlation matrix (Fig. 4), where three red stars represent a significant correlation with p-value being equal or less than 0.001. The Kendall rank correlation coefficient, also known as Kendall's tau, is a measure of rank correlation that does not assume normal distribution of variables.

Based on Fig. 4, the duration of the charging event and the FCR-D potential have a clear monotonic relationship, that is, the longer a charging event is, the larger the FCR-D potential. The smaller distinct subgroup with a steeper correlation in this potential-duration subplot is caused by events made on high power DC-chargers. There exists a relatively strong positive Kendall's tau-b correlation between the duration and FCR-D potential, a moderate positive correlation between charged energy and duration, and a weak positive correlation between energy and FCR-D potential ranks. These positive rank correlations imply that longer charging events have more exploitable FCR-D potential and that the amount of energy charged during these events is greater. The rank correlations between the start time of the charging event and other variables are quite weak and negative, however, the start time (within each day) is a cyclic quantity with zero set (arbitrarily) at midnight, and these correlations could be regarded as somewhat arbitrary.

Examined Pearson's and Spearman's correlation matrices give corresponding results to Kendall's correlation matrix, the only major difference being that according to Pearson's correlation coefficients, there exists no significant linear correlation between the start time and duration variables. The lack of linear correlation is understandable due to the cyclical nature of time within a day.

Based on these results, the null hypothesis, that there exists no correlation between the considered variables, can be rejected on a 99.9% confidence level. Additionally, as can be seen from Fig. 4, the variables do not clearly follow any standard probability distribution function. The presence of these correlations and the nonstandard probability distributions substantiates the use of the multivariate copula procedure in EV explicit demand response potential simulation.

3.2. Multivariate copula procedure assessment

For assessment and validation purposes, the multivariate copula procedure was used to generate a synthetic charging event sample of the size as the original sample. The demand response potentials for generated events were calculated as described in 2.2. By comparing the resulting dataset with the original dataset, the suitability and fit of the multivariate copula procedure for event generation can be assessed. As discussed in 2.5, multiple copula functions were tried for each of the four subsamples ($AC_{Weekday}$, $AC_{Holiday}$, $DC_{Weekday}$, $DC_{Holiday}$), based on Akaike and Bayesian information criteria, and averaged daily FCR-D potential shapes, the Gaussian copula was found to be the best fit for the AC Holiday subsample, whereas the Student-t copula was found to be most suitable for the other 3 subsamples. These copulas were used to generate equal amounts of artificial charging events as in the original subsample groups. The Kendall's correlation matrix for this artificial multivariate multicopula EV event sample is presented in Fig. 5.

As can be seen when comparing Fig. 5 with Fig. 4, the variable distributions and correlation coefficients are very similar in the artificial and original datasets. That is, the generated artificial sample retains the correlation structures and coefficients of the original dataset very well. For instance, the procedure retains the

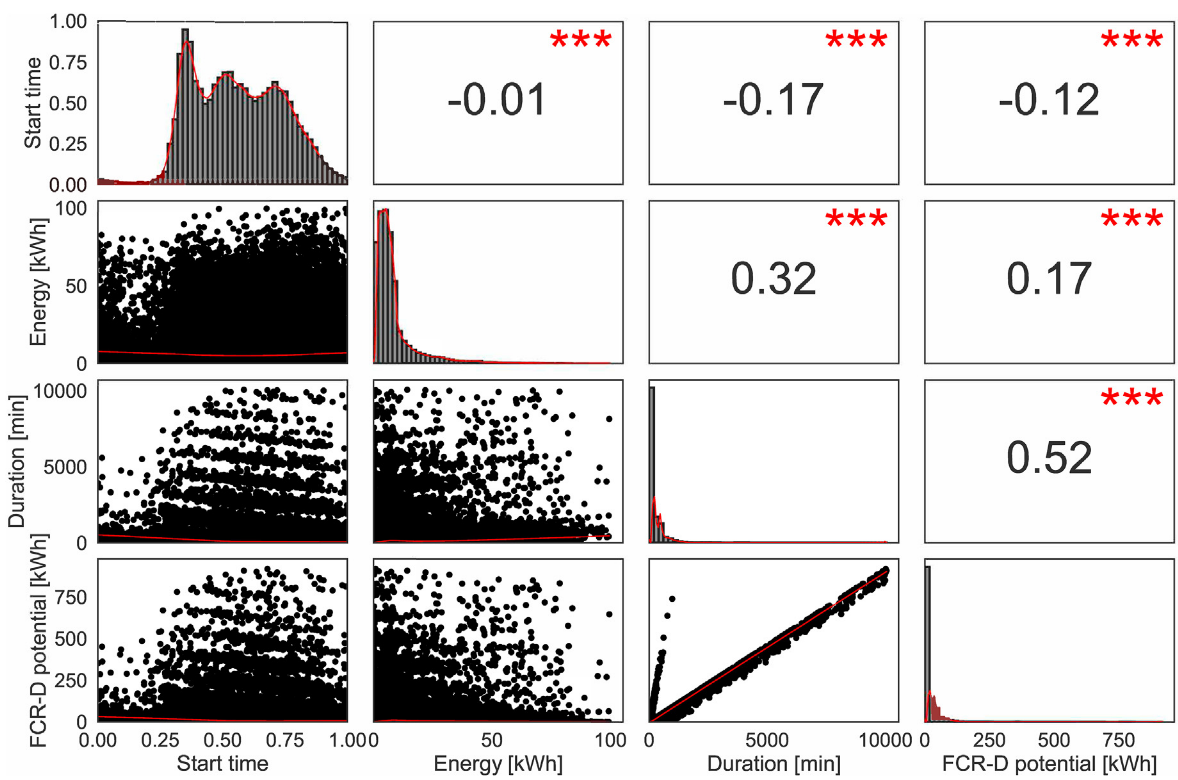

Fig. 4. Kendall's tau-b correlation matrix for the dataset (three stars represent p-value ≤ 0.01).

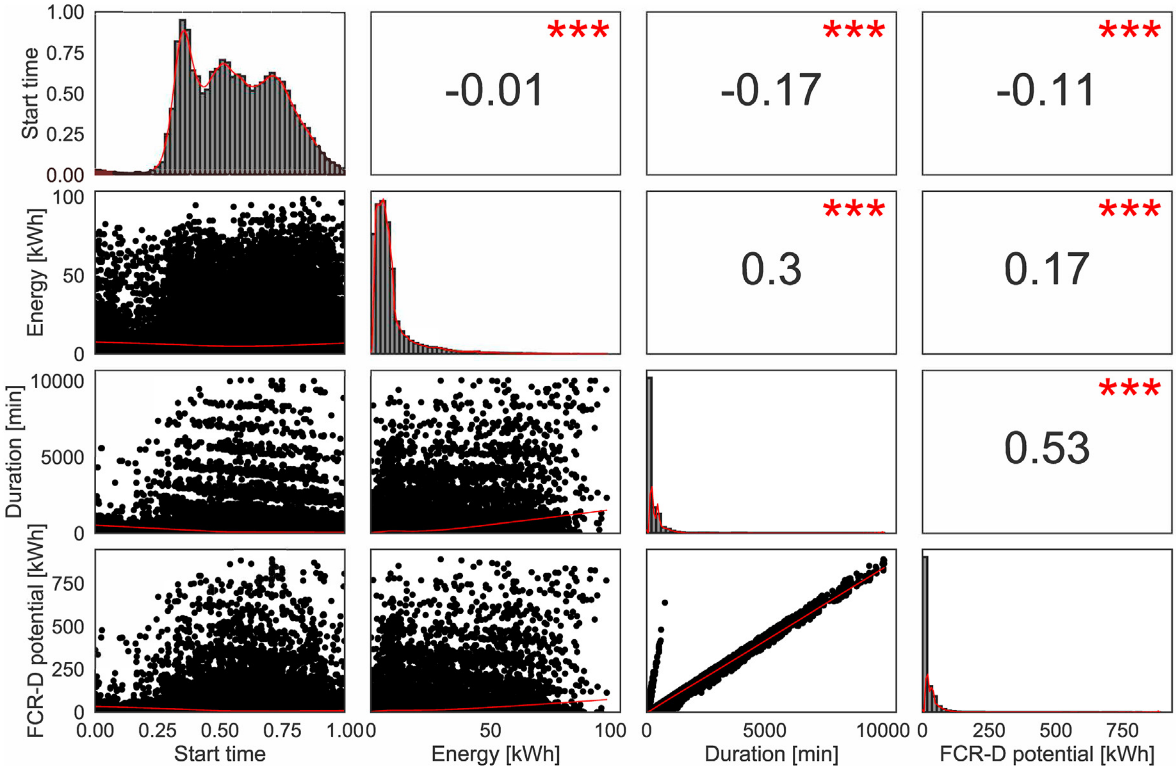

Fig. 5. Kendall's tau-b correlation matrix for the copula sample (three stars represent p-value $\leq$ 0.01).

clear monotonic positive relationship between the FCR-D potential and the duration of charging events, with only small 2% (0.01) deviation between the Kendall's tau-b coefficients of the original dataset and copula sample. There are also no great differences in the other correlation coefficients and scatter plots between original data (Fig. 4) and synthetic data (Fig. 5). Pearson's and Spearman's correlation matrices give similar results to Kendall's correlation matrix implying good performance of the synthetic data generation process.

The two-sample Kolmogorov-Smirnov test was further applied to confirm the similarity of the simulated sample variables with the original dataset (see Table 1). The null hypothesis of the two-sample Kolmogorov-Smirnov test is that these samples are drawn from the same distribution.

The p-values of the variables are all well above the 5% significance level, so the null hypothesis cannot be rejected. High p-values and low values for the KS statistic imply a high probability that the samples are drawn from similar distributions.

The theoretical maximal FCR-D potentials, maximal volumes and flexibility times for the original and artificial event samples were calculated as described in 2.2.2. As described, these values can also be used to graph the dispatchable FCR-D during a certain time. Fig. 6 demonstrates the daily averaged dispatchable FCR-D potential in the assessed private EV charging network on weekdays and holidays. The figure includes the averaged momentary dispatchable FCR-D of both the original data and the artificial event sample gained with the multivariate copula procedure and can be thus used to assess the suitability of the multivariate copula procedure to this use case.

As can be seen from Fig. 6, the procedure can be used to model the momentary dispatchable FCR-D with a high reliability. The mean absolute percentage error (MAPE) of weekdays is 3.03% and of holidays 3.78%, resulting in an average MAPE of 3.27%. The total FCR-D potentials of average weekdays and holidays with the synthetic copula sample were respectively 1.78% and 1.74% less than with the original dataset.

The predictive ability of the proposed simulation procedure can be demonstrated by utilizing one workweeks data to predict the following weeks momentary dispatchable FCR-D potential. In Fig. 7, the charging events of the weekdays of the week 21/2019 were used to predict the dispatchable FCR-D potential of the following week without any public holidays. As can be seen, the momentary dispatchable FCR-D of the artificial copula sample correlates well, MAPE 4.65%, with the curve of the following week plotted with real data. That is, the model can be used to estimate future dispatchable FCR-D, and the model performs quite well with as little data as five days.

The predictive ability was verified with randomly picked workweeks from every month of the year in order to dismiss possible seasonal variation and bias. The dispatchable FCR-D potential curves from the copula model were compared with the curves of the following real weeks. This resulted in prediction MAPEs ranging from 4.65% to 23.8%, with an average of 13.38%. There exists a strong linear dependence between MAPE and the number of events in the input week dataset, that is, the procedure performs distinctly better with more input data. The model performs similarly with holidays and weekends, with similar-sized input datasets. Prediction performance can be improved by utilizing more input data, for instance, data from multiple previous weeks. However, as the number of EVs is currently growing sharply,

Table 1
Kolmogorov-Smirnov test results.

	Start time	Energy	Duration
KS statistic	0.00095	0.00341	0.00226
p-value	0.99999	0.39550	0.87182

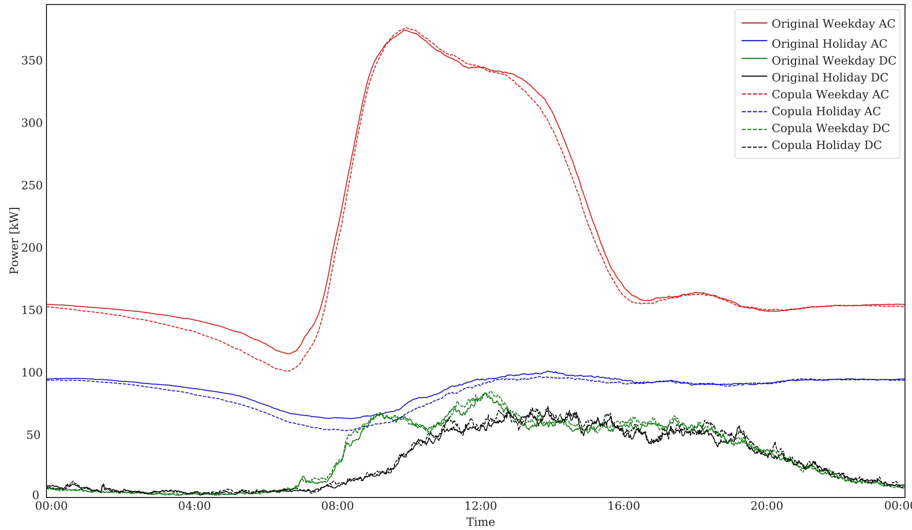

Fig. 6. Averaged dispatchable FCR-D potential, weekdays and holidays.

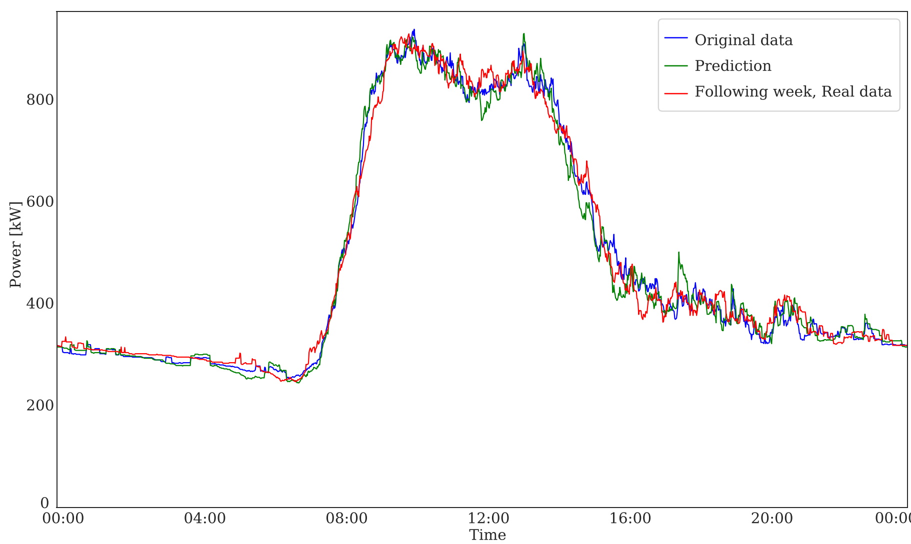

Fig. 7. Prediction of dispatchable FCR-D potential, one workweek of data.

there is more and more EV charging data to be used in the predictive model and the prediction accuracy of the model should continue to improve.

3.3. Estimating future demand response potential

When estimating the future FCR-D potential of EV charging networks with the proposed method, an estimation of the future charging demand is required. When the future charging energy demand is known, we can use the multivariate copula procedure to generate a large enough artificial charging event sample to fulfill the charging demand and use equation (7) to calculate the FCR-D potential of this charging network.

As an example of this use case of the methodology, we estimated the FCR-D potential of Finland in the year 2030. The charging demand of the Finland in 2030 case, is calculated based on the assumption that Finnish government's goal of 250,000 EVs by 2030 is fulfilled, and that the average yearly vehicle travel distances would not change considerably from the present. If this whole fleet would run only on electricity, that is, include only full EV's and plug-in hybrid EV's utilizing no other fuels than electricity, the demand would be around 750 GWh per year in 2030.

Almost 88.1 million charging events simulated with the Student-t copula were needed to fulfill this future EV energy demand. For this event population, the aggregated theoretical maximum demand response potential would be around 1.63 TWh. For an average weekday, this would mean an FCR-D potential of around 5.3 GWh, and for an average holiday 2.6 GWh. The yearly value of this dispatchable FCR-D potential on the yearly marketplace would be around 2.8 million €, assuming the same yearly market price as in 2021 (1.80 €/MW,h). The averaged dispatchable FCR-D potential for weekdays and holidays in 2030 is presented in Fig. 8. It can be seen that the largest dispatchable volume coincides with office hours of weekdays. It should be noted that the charging powers are assumed similar to the original dataset, and the technological advances in EV charging can cause significant alterations to the shape of the future dispatchable FCR-D curve and to the FCR-D potential estimations.

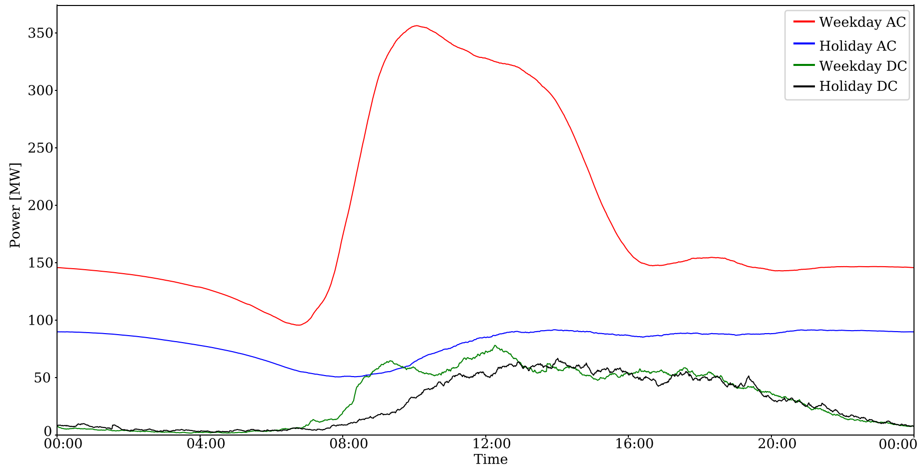

Fig. 8. Averaged daily dispatchable FCR-D potential in the year 2030.

3.4. Model comparison

There exist no previous studies utilizing multivariate copulas in event-based EV FCR-D estimation which complicates valid benchmarking of our model. However, as discussed in chapter 2.5, it is possible to use the application proposed by Divshali & Evens [33,52] to validate the correct functioning of the deterministic part of our model and as a reasonable comparison point for our methodology. Direct comparison between the results of [33] and results presented in this paper is debatable due to differing input data. With the dataset of our study used as the input, the Divshali application produced an expected FCR-D potential of approximately 3.5 MWh for a given day. This value is 27% less than the generic daily averaged dispatchable FCR-D potential of the copula model presented in Figs. 6, and 28% less than when calculated with the original data. The differences are even larger in near-term prediction with the one workweek dataset used in Fig. 7. The results of the application [52], do not differ between weekdays and holidays, so the generic daily averaged FCR-D can be used as a valid reference point.

The differences in simulated FCR-D potentials are partly explainable by differing base assumptions made in this study and in Refs. [33,52]. For instance, the authors of [33] utilize a minimum flexibility time of 30 min, a time-resolution of 15 min, calculate maximum charging powers for AC charging events naively based on charged energy and duration per customer ID, and do not consider the differing charging behavior between weekdays and holidays. Additionally, the application [33,52] does not properly consider charging events continuing over midnight, leading the FCR potentials reset to zero every midnight.

In FCR-D prediction with one workweek of data used as the input, the Divshali application produces a 1.9% larger expected daily FCR-D flexibility potential than our deterministic model with similar flexibility time, AC charging power, and time-resolution assumptions as in Ref. [33]. That is, the deterministic model produces quite similar results as the application of [33,52] with similar base assumptions. However, due to other differing assumptions and calculation methods in the hard-coded application [52], there still exists differences between the FCR-D potential curve shapes, for instance, the potential with [52] unrealistically resets to zero every midnight.

4. Discussion and conclusions

This study introduced a novel event-based EV FCR-D simulation model that utilizes multivariate copulas in synthetic charging event generation. Based on our results, the model performs highly accurately in both charging event generation and FCR-D potential prediction. The proposed methodology reaches a MAPE (mean absolute percentage error) of 3.27% when comparing the averaged daily dispatchable FCR-D potentials of the original dataset and artificial copula data. The MAPE of our model is less than 10% so it can be regarded as highly accurate based on [57], and it is well below the maximum allowable MAPE threshold of 8% utilized in Ref. [38] for EV load profile simulation.

Applicability of the proposed methodology to different predictive modelling tasks was demonstrated with two examples, First, the method performed well when utilizing only data from one week's working days to estimate the momentary dispatchable FCR-D of the following week reaching a MAPE of 4.65% when using the data from the week with most charging events as the input. There existed an almost linear correlation between prediction MAPE and the number of events in the input week dataset, that is, the procedure performed distinctly better with more input data. In the second example, the model was used to estimate the FCR-D potential of the Finnish EV charging network in the year 2030. Based on the results, the aggregated theoretical maximum demand response potential could be as much as 1.63 TWh in 2030, assuming similar driving and charging behavior as today. This estimation is intrinsically prone to advances and changes in i.e., the EV charging technology and ancillary power markets. It should be emphasized that the maximal FCR-D potentials estimated in this study are theoretical maxima, and the realistically exploitable potentials can be significantly lower due to, for instance, actual driver and marketplace behavior.

The proposed simulation model was verified and validated with real data and through comparison with a previous non-copula application for EV FCR simulation. Based on the Kolmogorov-Smirnov test, Kendall's tau-b coefficients and FCR-D potential MAPEs, the model performs highly accurately in both charging event generation and FCR-D potential prediction. Comparison with the non-copula application for EV FCR simulation [33] validated the deterministic part of our model. However, based on this model comparison, it can be noted that the modelling assumptions, especially regarding AC charging power estimation, have a significant impact on estimated FCR potential.

The main source of uncertainty in this study arises from the quality and quantity of the input data. For instance, the absence of realized charging powers in the charging event dataset has a considerable impact on explicit demand response potential assessment. As the CPOs do not log realized EV charging powers, these must be assessed based on other variables and external information to estimate dispatchable demand response potential of EVs, which naturally induces uncertainty to the results. In our study, this uncertainty was curtailed by utilizing the average EV fleet onboard charger power in AC charging power estimation process. The weakness could be remedied completely if the CPOs implemented a way to log the realized charging powers of EV charging events. Additionally, as the dataset used in this study contains only charging events conducted on one CPOs private charging points, and thus lacks public charging and the most common charging method (household socket), there exists considerable uncertainty in the future FCR-D potential estimation scenario. These shortcomings could be overcome with larger and more extensive EV charging event datasets.

It should be noted that the aforementioned shortcomings and uncertainties arise mainly from input data and modelling assumptions. That is, the multivariate copula procedure used to generate artificial charging events based on real input data retains accurately the correlation structures and distributions of the original data crucial for accurate explicit demand response estimation. The proposed combined event-based model can also be modified to function on different explicit demand response marketplaces by adjusting the equations and assumptions used in the demand response potential calculation. These notions support the generalizability of this study, as the proposed methodology can be used in any location with adequate amount of input data available.

In future research, the methodology proposed in this study should be refined to consider the bidding and market aspects of the FCR trade more thoroughly, as has been done for instance in Refs. [32,34]. Subsequently, the model can be adapted to utilize the methodology in estimation of practically exploitable DR. To provide more pragmatic benefits for possible demand response aggregators and EV owners, the refined simulation model should also be able to simulate the FCR-D prices and activation periods. Additionally, it would be useful to utilize more extensive datasets in future studies, especially useful would be the inclusion of charging events conducted at non-CPO controlled household chargers. To further verify the operation, control and exploitable DR potential of aggregated EV charging on DR marketplaces, it would be important to carry out experimental studies in co-operation with TSOs, CPOs, demand response aggregators and EV owners.

Overall, this study has shown that the novel combination of multivariate copulas and event-based deterministic demand response estimation models provides a highly accurate method for explicit EV demand response simulation. Accurate explicit demand response simulation models are essential to facilitate large-scale active participation of EVs in power network balancing. The proposed methodology can be utilized in various practical and theoretical applications ranging from the demonstrated maximal FCR-D potential estimation to future smart grid planning.

Credit author statement

Johannes Einolander: Conceptualization, Methodology, Formal analysis, Writing – original draft; Risto Lahdelma: Supervision, Writing – review & editing

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.

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