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Multivariate copula procedure for electric vehicle charging event simulation

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A B S T R A C T

This paper introduces a novel application area for multivariate copulas in electric vehicle charging event simulation and dependency analysis. We propose a multivariate copula procedure that can be used to generate new synthetic charging events, which retain the complex dependency and correlation structures present in real-world charging events. The paper compares the most popular multivariate copula functions to discover the most reliable one to be used with electric vehicle charging event data. Accurate EV charging event simulation and analysis is crucial in multiple theoretical and practical applications such as charging load and demand response aggregation modelling. Based on multiple goodness-of-fit tests and charging load profiles of simulated charging events, the Student-t copula was found to be the most reliable multivariate copula to be used with EV charging data. Overall, the multivariate copula procedure is effective in analysis and simulation of EV charging events as it retains the inherent variability and complex dependencies of real charging events.

1. Introduction

Electrification of transport was the key trend of the transport sector in 2010s. During the decade, the global number of electric vehicles (EVs) rose from 17,000 in 2010 to 7.2 million in 2019 [1]. This trend is expected to continue, and the IEA estimates that the global EV stock reaches 50 million by 2025, and close to 140 million by 2030 [1]. The electrification of transport reduces oil demand and greenhouse gas emissions but increases electricity demand. According to IEAs Sustainable Development Scenario, the global EV electricity demand could rise to almost 1000 TWh in 2030, an almost elevenfold increase from 2019 levels [1].

The electrification of transport, happening simultaneously with large-scale penetration of variable renewable energy sources, causes major technical challenges for power grid balancing [2,3]. Electricity demand modelling and prediction are crucial in order to ascertain that electricity production equals electricity demand at every given moment [4]. Analysis, modelling and prediction of EV charging behavior is becoming an ever more important part of this demand modelling, especially as uncoordinated EV charging loads tend to coincide with peak demand, which causes stress to the electrical infrastructure on multiple levels [2,5–8]. Additionally, simulation of EV charging behavior is important for charge scheduling, congestion management and estimation of utilizable demand response loads [2,7,9–12].

The importance of EV charging behavior modelling is recognized in multiple previous studies. However, the majority of previous research approach EV charging behavior based on driving pattern and travel survey datasets of internal combustion vehicles [12–19] and EV trials [20–22]. Even though estimation of EV fleet electricity demand is possible based on travel surveys and driving pattern datasets [7], these vehicle usage-based modelling approaches require multiple assumptions and are largely theoretical [23]. These approaches might lead to substantial oversights especially when the focus is on EV charging in a specific location, charging point or charging point network. Event-based simulation approaches, which utilize real-life charging events as a basis for the model, and thus approach the problem from the charging point perspective, are significantly less common. Previous studies that utilize real EV charging event data and cover intervariable dependencies are covered in section 2.2.

Accurate EV charging event simulation is difficult with traditional methods that assume independent parameters as there exists non-normal multivariate dependencies between EV charging

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event variables [24]. The modelling of stochastic dependence is important for obtaining accurate results in problems dealing with this kind of dependent non-normal data [25]. However, so far very little attention has been paid to methods that retain these complex dependency structures in charging event simulation. If these dependency structures are not retained, various problems and inaccuracies can arise especially when the simulation method is used to generate synthetic data to be utilized in follow-up applications, such as in large-scale power system optimization and prediction models.

The novelty of this study is justified by bridging these gaps through novel application of multivariate copulas in event-based EV charging event simulation. In this work, we propose a multivariate copula procedure that retains the inherent variability and complex dependencies of real EV charging events in event simulation. Copulas are an increasingly popular modelling tool for stochastic data with non-normal multivariate dependencies [26]. Traditionally copulas have been used mostly in financial modelling; more recently, copula applications have spread to the field of energy engineering and have been utilized, for instance, in power system modelling and planning [25,27,28], residential heating demand prediction [29], wind and photovoltaic power generation prediction [30] and energy management uncertainty modelling [31]. However, to our knowledge, only a few studies to date have addressed the utilization of copulas with EV charging data [32,33]. There currently exist no scientific studies where dependencies between all variables are retained in EV charging event simulation, or where multivariate copulas from multiple families are used and compared with EV charging event data.

There are three primary aims for this study: 1. To investigate whether multivariate copulas can be used to retain real-life dependency structures in EV charging event simulation 2. To ascertain which multivariate copula family has the best fit with real EV charging event data 3. To determine whether the proposed multivariate copula procedure can be used to model EV charging load profiles accurately. The findings make an important novel contribution to the field of EV charging behavior and load simulation.

2. Background

2.1. EV charging modes

The international standard IEC 16851−1:2017 categorizes different EV charging methods into four Modes based on connection method and characteristics of power supply input and output. In Modes 1 and 2, the charging is conducted from a standard household socket-outlet of an AC supply network. In these Modes, the charging is conducted with a separate cable, and there is no external electric vehicle supply equipment (EVSE). Mode 1 is rated up to 16 A (250 V single-phase, 480 V three-phase), and the charging cable is not fitted with any auxiliary or pilot contacts. Due to some safety concerns, Mode 1 charging is prohibited in a few countries, for instance in the US and UK. The utilized charging cable is the main difference between Modes 1 and 2. In Mode 2, a separate EV charging cable with control pilot and electric shock protection systems is used. Mode 2 current must not exceed 32 A (250 V single-phase, 480 V three-phase). Some countries, such as the US, have limitations on maximum voltage or current of Mode 2, and in Italy Mode 2 charging is prohibited in public areas [34].

In contrary to charging Modes 1 and 2, Modes 3 and 4 require the utilization of dedicated stationary EV supply equipment [34]. Mode 3, sometimes referred to as primary EV charging, utilizes EVSE connected to AC supply network [34,35]. Mode 3 EVSE's have an integrated control pilot function that extends to the EV [34]. Mode 4 EVSE can supply considerably higher charging powers than the other charging modes, and it is commonly referred to as EV fast charging [34]. In Mode 4, the EV charging is conducted with DC from an EVSE connected either to AC or to DC supply network [34]. Like in Mode 3, control pilot and protection functions are integrated into the EVSE [34]. Typical Mode 4 EVSE have a maximum output power of 50 kW, but currently models also exist with rating powers up to 350 kW [35].

Communication between the EVSE and the EV is crucial when considering customer-friendly remote control of charging events. However, this kind of communication is a requisite only in Mode 4 charging [34]. Without real-time information of the charging event parameters, for instance, demand-side management of EV charging has to be based on historical behavior and thus there exists significant uncertainty when assessing the total controllable load. This study concentrates on EV charging Modes 3 & 4, as they are the only charging modes easily controllable by external demand response aggregators due to the presence of dedicated external charging equipment. These are also the only charging modes recommended for long term usage [34].

2.2. Dependencies in EV charging event data

An EV charging event is defined by multiple different interdependent variables. The *plug-in time* and *EVSE maximum power* of a charging event are determined when the EV is connected to an EVSE. The *charged energy*, *realized charging power*, and *event duration* are determined during the charging event. The *charging time* of an EV depends on its initial and final state of charge, and the realized charging power. These parameters however do not give insight on the possible *idling time*, i.e., duration the EV remains connected to the EVSE after the charging is finished [36,37]. Analysis, prediction, and measurement of EV idling time is a crucial part of, for instance, EV demand response modelling and EVSE congestion management.

There exist only a few scientific articles addressing EV idling time estimation. In Ref. [38], the authors compared multiple machine learning algorithms in idling time prediction based on a Dutch public EV charging dataset. The main variables found to impact EV idling time were the plug-in hour and the total energy charged during the event [38]. The average idling time, assessed in Ref. [38], represented around 62.3 % of event duration. In Ref. [39], a study conducted by the same authors as [38], this ratio between idling time and event duration was around 62.1 %.

EV charging event variables have complicated correlation structures. According to analysis done in Ref. [24], EV charging event durations are highly non-normal and are impacted mostly by plug-in time and the EVSE type. The authors found that, especially in events conducted on low power public Mode 3 EVSEs, the event duration is heavily aligned with parking preferences. That is, people tend to leave their EVs parked at these charging stations for extended periods while they might be at work or sleeping [24]. Similar results were gained in Ref. [40], where the authors noted that longest idling times were registered on EVSE located in residential areas. According to Ref. [40], there existed only a weak correlation between EV charging and idling time.

According to Ref. [38], the highest correlations in their dataset were between the total charged energy and the EVSE maximum power, and between the total charged energy and charging event duration. Both of these relations were positive, and the variables were found to be moderately correlated. Other notable correlations were found between EVSE maximum power and event duration, and between plug-in time and the charged energy. The authors managed to predict idling times based on other variables most successfully with the XGBoost algorithm, reaching an R^2 of 60.32 %, RMSE of 1.51 and mean absolute error of 1.11 h [38].

As stated previously, there exists only limited number of scientific publications where copulas are used to model the dependencies in EV charging data. Authors of [32] utilized bivariate copulas to model the pairwise correlation between variables of Chinese EV charging data. They found that there exists a negative correlation between charging event start time and duration, and a positive correlation between duration and charged energy [32]. However, bivariate copulas can only capture dependence structures between two random variables, which makes their application with multivariate EV charging data inherently ineffective. In Ref. [33] a ternary symmetric KDE model was proposed to better take into account the multivariate dependencies in EV charging data. Based on bivariate frequency matrix similarities and histograms, the authors found the model to have a higher fitting level than a joint estimation method based on edge KDE and elliptical copulas [33].

The presence of complicated correlation structures in EV charging event data complicates reliable charging event modelling and simulation. One way to take these joint multivariate correlation structures into account is to utilize multivariate copula functions. Resampling methods could be used to consider underlying distributions and dependencies in EV charging data, but this could lead to imprecision as it can't be assumed that observations are from independent and identically distributed populations. Additionally, utilizing traditional bivariate copulas leads to inaccurate results when dealing with multivariate data such as EV charging events, as they can only be used to describe the dependence between two variables at once. Thus, higher dimensional dependencies present in multivariate data are lost if bivariate copulas are used without any combination method. Separate bivariate copulas can be combined into a higher dimensional copula with, for instance, a pair-copula decomposition method [41].

2.3. Multivariate Copula functions

Copulas are multivariate cumulative distribution functions with uniform one-dimensional marginal distributions that can be used to describe dependencies between random variables. In simulation, copulas can be used to generate synthetic samples from a specified joint distribution. The resulting sample population can be used to model real-world systems, such as EV charging networks, while preserving the variable nature of separate instances. The name “copula” emphasizes the manner copulas “couple” joint distribution functions to their univariate margins. There exist multiple slightly different copula families, of which the elliptical and Archimedean families are most commonly used [42].

Gaussian and Student-t copulas belong to the family of so-called elliptical copulas. Elliptical copulas are widely used especially in statistics and econometrics, due to their easy implementation and multiple useful properties [26]. Elliptical copulas can for instance be easily adapted for use in simulation of multivariate cases. Multivariate Gaussian (or normal) distribution can even be seen as the basis of classical multivariate statistics [43]. Multivariate Gaussian and Student-t copulas are frequently applied especially in financial data modelling [44]. Gaussian copula is usually used as the first tentative model for covariate data, as it can model a wide range of different dependencies. If results gained with the Gaussian copula show large deviations compared to original data, alternative copula models should be tested [43]. For instance, the Student-t copulas are able to capture tail dependence among extreme values and are thus generally superior to the Gaussian copulas in certain applications, such as when modelling multivariate financial return data [45].

Archimedean copula family is the second most popular copula family. Archimedean copulas are popular due to their simple forms, ease of construction and multiple properties [42]. The most commonly used Archimedean copulas are the Clayton, Frank and Gumbel copulas. In basic form, Archimedean copulas with more than two dimensions only allow positive dependencies [26]. There however exist different multivariate extensions for these copulas that allow negative dependencies through different transformations [43].

Theoretical foundation for the application of copulas is heavily based on work of Abe Sklar, and especially on Sklar's theorem [46]. The multivariate Sklar's theorem [42] states that if H is an n-dimensional distribution function with margins F_1, F_2, …, F_n, then there exists an n-copula C so that for all $\mathbf{x}$ in $\overline{\mathbf{R}}^n$,

$$H(x_1, x_2, \ldots, x_n) = C(F_1(x_1), F_2(x_2), \ldots, F_n(x_n)) \tag{1}$$

The n-copula, C, is unique if all $F_1, F_2, \ldots, F_n$ are continuous, otherwise C is uniquely determined on Ran $F_1 \times$ Ran $F_2 \times \cdots \times$ Ran F_n. When $F_1^{-1}, \ldots, F_n^{-1}$ are quasi-inverses of $F_1, F_2, \ldots, F_n$, then for any $\mathbf{u}$ in $\mathbf{I}^n$,

$$C(u_1, u_2, \ldots, u_n) = H\left(F_1^{-1}(u_1), F_2^{-1}(u_2), \ldots, F_n^{-1}(u_n)\right) \tag{2}$$

If X_1, X_2, …,X_n are random variables with distribution functions $F_1, F_2, \ldots, F_n$, and a joint distribution function H, then there exists an n-copula C so that (1) holds [42]. In order to generate synthetic observations x_i from original random variables X_i, we need only to generate uniform observations u_i of the uniform random variables U_i, with a joint distribution function C, and transform these uniform observations back to the original scale. More extensive theory, definitions and mathematical formulation of the random variate generation and multivariate copulas can be found for instance from Refs. [42,43].

The key steps of data generation from a real data sample with the multivariate copula procedure are summarized in Fig. 1. The resulting artificial observations (output dataset) have similar variable dependence structure as the original data.

The utilized multivariate copula influences the joint distribution function used in the sampling, and thus the resulting observations differ between different copulas. For instance, the copula functions describe the tail dependencies of variables in different ways [42]. Scatter plots of typical dependency behavior of the most popular copula functions are presented in Fig. 2. These scatter plots illustrate the differing tail dependency behavior of different copulas that share the same margins and the same Kendall's tau. Due to these differences, multiple copula functions should be considered before choosing the one that has the best fit to the data under analysis. In this study, all five copula functions of Fig. 2 are compared to find the best fitting copula for EV charging event data.

3. Methodology

3.1. Description of the EV charging dataset

The dataset used in this study was gathered from Finland's largest charging point operator (CPO). During initial data processing and cleaning, clearly erroneous, short trial connections lasting less than 1 min and events lasting more than a week were discarded from the dataset. Similar data cleaning decisions were made for instance in Ref. [38]. After data cleaning, the resulting final dataset contains almost 150,000 realistic charging events conducted on CPO operated private EVSEs between January 2018 and June 2019. These private EVSEs contain Mode 3 and Mode 4 chargers installed to private properties not accessible for everyone, e.g., to parking lots of apartment and office buildings.

The dataset can be considered to portray the Finnish private EV charging situation quite well, although it lacks the majority of

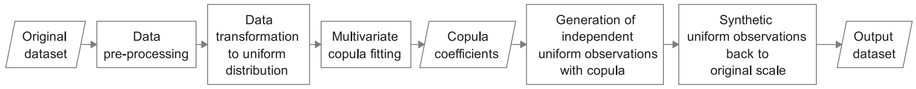

Fig. 1. Key steps of synthetic data generation with multivariate copulas.

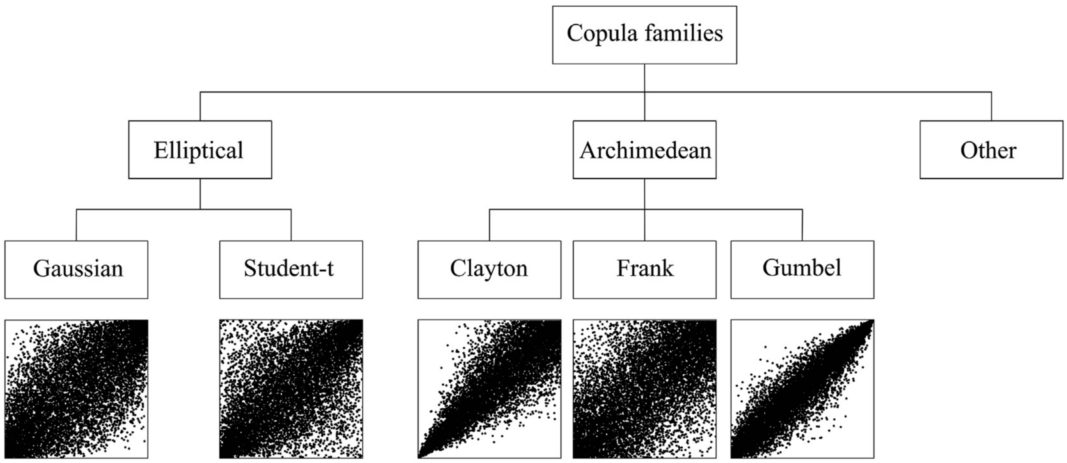

Fig. 2. Most popular copula functions and their dependency behavior (sample size n = 10,000, bivariate distribution) [based on 42,43].

charging events conducted at households. Slow home charging is the most popular EV charging method in most countries, for instance according to US Department of Energy, more than 80 % of EV charging in the US is done at home from household sockets without separate EV chargers [48]. These charging events cannot be remotely controlled and are not monitored by any external party as there is no CPO.

The most important variables of the dataset are: station id, energy, duration, the start and end times of the charging event, and the maximum charging power of the EVSE. Like in Ref. [37], the realized charging powers of charging events are not recorded by the CPO and are thus not a part of the dataset. However, from the grid-perspective the realized charging power is perhaps the most important variable, as it can be used, for instance, to assess the grid impact of EV charging. As the charging powers are not recorded, they have to be assessed based on known variables, as presented in the following subsection. Of these variables, a charging event can be characterized with only charged energy, duration, start time and charging power variables. However, as the charging powers have to be assessed based on other variables, only the three remaining variables are to be used in the copula procedure.

3.2. Estimation of realized EV charging powers

The charging powers have to be estimated based on the maximum charging power of the charging equipment, the charged energy amount, duration of the charging event, and for AC-chargers, based on the average power of onboard chargers. Based on the maximum charging powers of charging stations in the dataset, the charging network contains Mode 3 AC-EVSEs and Mode 4 DC-EVSEs.

The maximum charging power, P_{max}, of an EV charging from a DC charger can be stated equal to the chargers maximum power as the onboard vehicle charger is bypassed in Mode 4 fast charging [34]. However, most plug-in hybrid EV's (PHEV), and some full EV's (FEV), are unable to use fast DC chargers and are limited to slower AC chargers [49]. Mode 3 AC chargers require the use of an onboard charger to convert AC to DC used to charge the EV battery. Due to weight, space and cost-constraints, these onboard chargers typically set a limit for the maximum power EV's can accept from AC-chargers [50]. For instance, the 2019 model of Nissan Leaf Acenta has a 6.6 kW onboard charger, and thus the maximum charging power from a Mode 3 AC-charger is 6.6 kW [51]. The output power of the on-board charger is even lower than the stated power rating, as the average efficiency of onboard chargers is around 90 % [52]. By taking into consideration the restrictions posed by EV onboard chargers, it is possible to get more reliable results than by simply calculating the power based on meter readings as done for instance in Ref. [38].

The weighted average onboard charger power rating of the 20 most popular EV-models in the Finnish EV-fleet is used as the first guess in charging power estimation for events conducted on AC-EVSE. Based on Finnish Transport and Communications Agency Traficoms statistics, the 20 most popular FEV & PHEV-models of Finland cover over 80 % of all EV's in Finland [53]. The weighted average power rating of these onboard chargers is calculated to be 5.5 kW. If this weighted average power is unable to fill the charging need, it means that the EV has a higher rated onboard charger, and the realized charging power is calculated by dividing the charged energy with event duration. If the calculated charging power exceeds the maximum charging power of the EVSE, the charging event is discarded as erroneous. When generalizing the methodology to other areas, the onboard charger average power should be calculated based on local EV fleet. It is also possible that in the future the communication transfer between the EV and the EVSE is extended to record either the true charging power, or the model of the EV, which makes the utilized fleet average redundant and improves overall accuracy.

3.3. Multivariate Copula fitting and comparison

This study assesses the performance of five different multivariate copulas with EV charging event data. The compared copulas are the Gaussian (Normal) and Student-t copulas from the elliptical copula family; and Clayton, Frank and Gumbel copulas from the Archimedean copula family. Mathematical formulations of these copulas can be found for instance from Refs. [42,43]. The copula fitting, synthetic data generation and goodness-of-fit tests were conducted with the R programming language [26,54–56].

As the charging behavior typically differs between DC fast-chargers and slower AC-chargers, it can be assumed that the dependence structures between variables also differ between these charger types. Charging behavior typically also differs between weekdays and weekends or holidays, and this might affect the variable dependence structures. In order to retain the impact of these features, they could be treated as additional variables for the copula. However, copula functions do not perform well with data containing both continuous and discrete or binary variables. Because of this, and in order to minimize the computational complexity of copula modelling, the dataset is divided into four subsets based on the type of EVSE used, and on day type (weekday/holiday) of the charging event. The data subsets used in copula fitting are AC-weekday, AC-holiday, DC-weekday and DC-holiday, where the holiday datasets contain all events conducted during weekends or public holidays.

The goodness-of-fits of the five different copulas for the dataset are assessed by four mathematical methods. First, the fit of the copulas is tested based on Kendall's process with the Cramer-von-Mises test statistic [57–59]. This process returns an approximate p-value with a parametric bootstrap under null hypothesis, which can be used to reject copulas with clearly a poor fit to the data [47]. The approximate p-values gained with different data subsets of this study are combined with the Fisher's combined probability test [60]. The resulting p-values of the copulas are used to assess whether the null hypothesis can be rejected on a 95 % confidence level.

The second method for the copula selection is based on k-fold cross-validation of the hypothesized copula families using maximum pseudo-likelihood estimation [59,61]. The resulting criterion is an approximation of the leave-one-out cross-validated log likelihood [59]. These criteria can be used to compare how well the different copula families fit with the dataset. The preferred copula is the one with the largest cross-validation criterion [47].

The final computational methods for assessing the goodness-of-fit of the copula families are the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) [62,63]. Both AIC and BIC are commonly used to estimate the relative quality of statistical models for given data. Both of these criteria attempt to resolve the overfitting issue which might be caused by model selection based on (log)likelihoods with the introduction of penalty terms. The Akaike information criterion formulated by Hirotugu Akaike in Ref. [62] can be calculated as

$$AIC = -2LL + 2k \tag{3}$$

where LL is the log-likelihood of the model and k is the number of model parameters. There exists only one parameter, θ, in the assessed Archimedean copula families. For trivariate data used in this study, the Gaussian copula has three and the Student-t copula four parameters. When comparing the quality of a model relative to the quality of another model, the preferred model is the one with minimum AIC value.

The Bayesian information criterion introduced in Ref. [63] is quite similar to AIC but has a larger penalty term. BIC can be calculated with (4), where LL and k are the same as in (3), and n is the sample size. In model selection, the model with the smallest BIC value is again the preferred option.

$$BIC = -2LL + \log(n)k \tag{4}$$

The cross-validation criteria, AIC and BIC of different data subsets can be combined by summing up the values gained with different subsets.

The results from the previous goodness-of-fit tests are used to eliminate copulas with a poor fit to the data from further analysis. The best performing copulas are used to sample new charging events that should retain the dependence structures present in the input datasets. The best fitting copula is chosen based on the previous goodness-of-fit methods and on how well the averaged daily power profile of the sampled datasets follows the profile of the original dataset. This averaged power profile encapsulates the distributions and dependencies of charging event datasets quite well and is thus a way to verify the proper function of the copula sampling methodology and usability of sampled charging events in different applications. EVSE load profile prediction is important, for instance, in power grid planning and balancing.

4. Results

4.1. Dependencies in EV charging event data

According to existing literature, as described in section 2.2, there exist complicated dependency structures between variables of EV charging events. The majority of previous dependency research has, however, focused on charging events conducted on public charging points. In this study, the dependencies between the most important charging event variables are examined via the parametric Pearson's product moment correlation coefficient and nonparametric Kendall's and Spearman's correlation coefficients. Kendall's correlation matrix for the original dataset is presented in Fig. 3.

Based on all evaluated correlation coefficients, the most significant correlation exists between the event duration and the charged energy amount. The correlations can be verified from Kendall's correlation matrix (Fig. 3). The red stars in the figure represent two-sided p-values, with tree stars meaning the p-value being equal or less than 0.001. The null hypothesis of the hypothesis test is the absence of association between variables. As the p-values between all variables are equal or less than 0.001, the null hypothesis can be rejected in favor of the alternative hypothesis that there exists an association between variables on a 99.9 % confidence level.

According to the values of the Kendall rank correlation coefficient (Kendall's tau); the observations have similar ranks between variables when considering the charged energy and the duration of the charging event. That is, there exists significant positive Kendall correlation (0.32) between these variables. The Kendall correlation between the start time of the charging event and other variables are lower and negative, but still significant. However, as the start time (within each day) is a cyclic quantity with zero set (arbitrarily) at midnight, therefore, although statistically significant, correlations with the start time might be seen as somewhat arbitrary.

Pearson's and Spearman's correlation coefficients give similar results as Fig. 3, that is, the null hypothesis can be rejected and there exists a correlation between all variables on a 99.9 % confidence level. Pearson's correlation coefficients are however all positive, whereas Kendall's and Spearman's correlation coefficients are negative between start time and other variables.

Due to the presence of dependencies in the data, sampling each variable independently would lead to inaccurate results. Additionally, the variables do not clearly follow any mutual standard probability distribution function. Due to the evidence that the variables are dependent and have nonstandard probability density functions, it is important to model the dependence structure between the variables and preserve these dependencies when sampling new observations based on the original data.

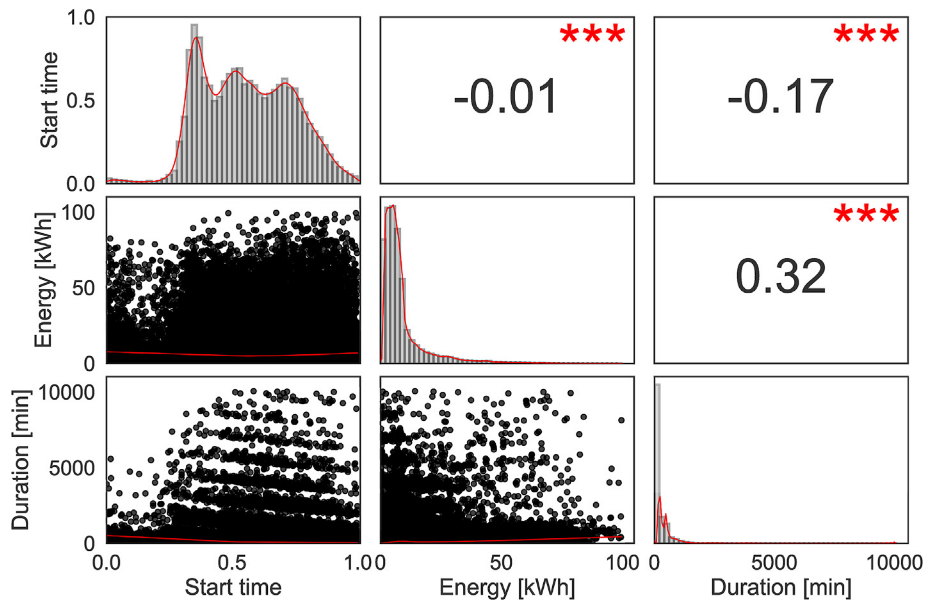

Fig. 3. Kendall's correlation matrix for the dataset (three stars represent p-value $\leq$ 0.001).

4.2. Estimated charging powers and the daily charging load

The average calculated charging power of charging events in the original dataset is 14.3 kW. If considering only the events conducted on AC EVSE, where the onboard chargers act as a constraint, the average charging power was calculated to be 6.2 kW. Most of the AC charging events could be completed with the estimated fleet average onboard charger power of 5.5 kW, only 14.8 % of these events required a higher charging power in order to meet the energy transfer in the event duration.

The realized charging times of charging events were calculated after the estimation of realized charging powers. Based on these results, the total plug-in time of the dataset consists mostly of idling (73.96 %) and only 26.04 % of total time is spent on actual charging. For an average charging event, the idling time is around 51.51 % of total plug-in time. This implies that the majority of plug-in time is spent idling and that some charging events in the dataset have substantially longer idling times than other ones.

The averaged daily charging loads of the analyzed network for the period from January 2018 to June 2019, are presented in Fig. 4. The average daily load portrays the distribution of charging power of the network during an average day; the load is further divided by the number of utilized charging points in the network during the analyzed timespan to get generalizable results. This averaged daily charging load can, for instance, be used to estimate the magnitude and temporal distribution of private EVSE charging power demand if the number of EVSEs in a network is known. As the events conducted on AC and DC EVSE have considerably different charging powers, the load distributions of events carried out on these EVSE types are also plotted separately.

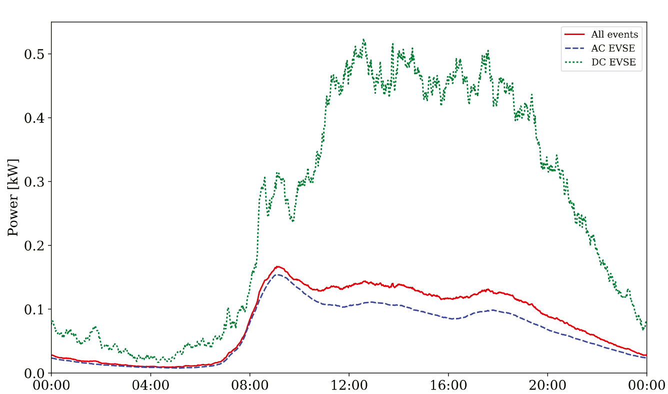

Fig. 4. Averaged daily charging load of the analyzed private EV charging network per EVSE.

As can been seen from Fig. 4, the majority of private EV charging power demand happens between 7:00 and 22:00, with the power demand starting to decrease after 18:00. The average load curves differ from load curves normally used to describe private customer charging due to charging points owned by companies intended for use by their employees and possible visitors, which cause the peak demand of 0.16 kW per EVSE around 9:00. If there were 1,000 similar private charging points, this peak demand would be around 160 kW. Due to higher charging powers of DC EVSE, their load profile is higher and has more variance than with AC EVSE. However, as can be seen from the figure, the analyzed network consists mostly of AC EVSEs and the impact DC EVSE have on the total charging load profile is relatively small.

As the analyzed private EV charging event dataset contains both domestic and office chargers, it is useful to analyze if there are differences between charging loads of weekdays and weekends or holidays. The averaged daily charging load of weekdays is presented in Fig. 5, and of weekends and holidays in Fig. 6.

The charging behavior between weekdays and weekends or holidays differs based on these figures. For instance, the morning peak does not appear during weekends or holidays, and overall, the load distribution is smoother.

In order to retain the variability caused by the used EVSE type (AC or DC) and day of charging (weekday or weekend/holiday), and to minimize the parameters estimated with the copula, the copulas are fitted separately with data from each of these combinations (AC weekday, AC weekend/holiday, DC weekday, DC weekend/holiday). This reduces the parameters from five to three and ensures that differing behavior is captured by the copula procedure.

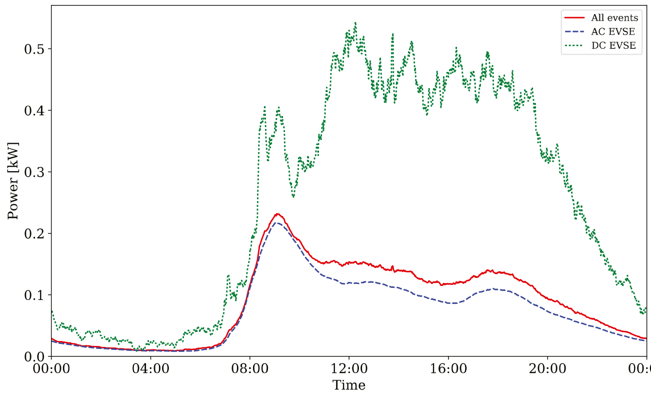

Fig. 5. Averaged daily charging load of weekdays.

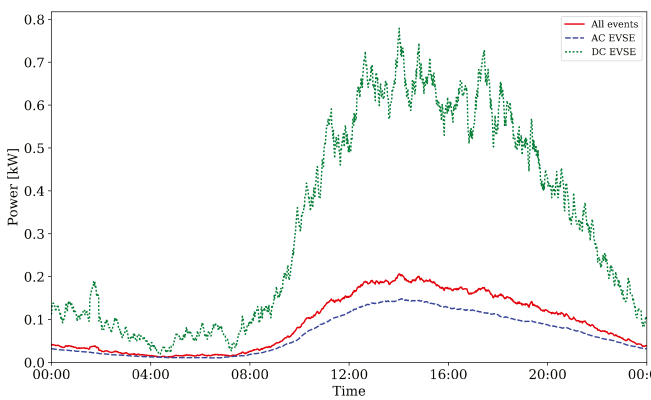

Fig. 6. Averaged daily charging load of weekends and holidays.

4.3. Multivariate Copula comparison

The five different multivariate copulas are compared with the four mathematical goodness-of-fit methods and with the averaged daily charging load curve of sampled charging events as described in section 3.3. The approximate p-values gained with the Kendall's process with the Cramer-von-Mises test statistic imply that none of the compared copula families can be rejected on a 95 % confidence level. The approximate p-values of all copula families were nearly zero, so the null hypothesis could not be rejected even on a 99.9 % confidence level.

The k-fold ($k = 10$) cross-validated log-likelihoods of the compared copula families are presented in Table 1.

Based on cross-validated log-likelihoods, the elliptical copulas clearly outperform Archimedean copulas, and Student-t seems to be the best copula family for this data. To confirm this, the calculated Akaike and Bayesian Information Criteria are presented in Table 2.

The Akaike & Bayesian information criteria calculated based on maximized log-likelihoods of fitted multivariate copulas support the results gained with the Kendall's process and k-fold cross-validation. The elliptical copulas clearly outperform Archimedean

Table 1
Cross-validated log-likelihoods of the evaluated copulas.

	Elliptical copulas		Archimedean copulas		
	Gaussian	Student-t	Clayton	Frank	Gumbel
Log-likelihood	33 246	39 077	5 598	5 673	6 651

Table 2
AIC & BIC of the evaluated copulas.

	Elliptical copulas		Archimedean copulas		
	Gaussian	Student-t	Clayton	Frank	Gumbel
AIC	−67 044	−77 707	−11 612	−11 383	−13 319
BIC	−67 015	−77 668	−11 602	−11 373	−13 309

copula families, and the Student-t copula seems to be the best fit for private EV charging data. The best performing Archimedean copula is the Gumbel copula, but based on previous goodness-of-fit statistics its fit is considerably worse than with elliptical copulas. These three copulas with the best goodness-of-fit results are chosen for further scrutiny. The averaged daily charging load curves gained with charging events sampled with each of these copulas are compared to the baseline gained with the original data. This way it is possible to ascertain that the simulated EV fleet charging event load behaves similarly to the real world. The resulting averaged load curves are plotted in Fig. 7.

The shapes of the load curves in Fig. 7 support the results of the goodness-of-fit statistics. The load curve of the events simulated with the Student-t copula has the best correlation with the averaged load of the original data. Based on the root-mean-square error (RMSE) and mean absolute percentage error (MAPE) of load curves, the load curve constructed with events simulated with the Student-t copula has the smallest deviation from the original load curve. RMSEs and MAPEs of load curves in Fig. 7 are presented in Table 3.

These results are supported also when considering only the events conducted on weekdays (Fig. 8) or on weekends and holidays (Fig. 9). Again, the Student-t copula is the best performer based on RMSE, MAPE and shape of these averaged daily charging load curves.

In addition to outperforming other copula families based on goodness-of-fit statistics and the averaged charging load curves, the correlation coefficients of synthetic charging events sampled with the Student-t copula are closest to coefficients of the original dataset. For instance, the Kendall's correlation coefficients differ only slightly with coefficients of the original dataset. The Kendall's correlation matrix of data sampled with the Student-t copula is presented in Fig. 10, and it is very similar to that of the original dataset presented in Fig. 3.

Charging events simulated with the Student-t copula can be used, e.g., to assess charging load distributions of EV charging networks. For instance, in a private charging network with a total of 10,000 EVSEs, and AC/DC EVSE proportions identical to the input data, the averaged daily charging load of the system would be as presented in Fig. 11. In this hypothesized EV charging network, the

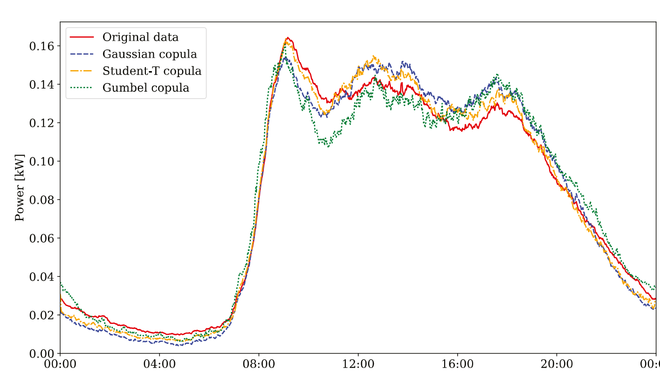

Fig. 7. Averaged daily charging loads per charging point for simulated charging events.

Table 3
RMSE & MAPE of averaged daily charging load curves.

	Gaussian	Student-t	Gumbel
RMSE [kW]	0.0078	0.0050	0.0093
MAPE [%]	17.02	10.88	11.24

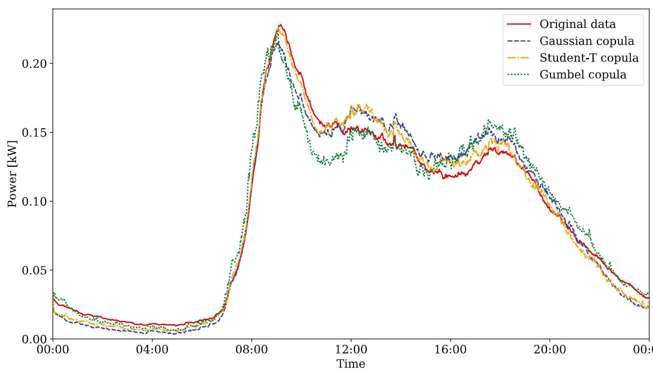

Fig. 8. Averaged daily charging loads per charging point for simulated charging events on weekdays.

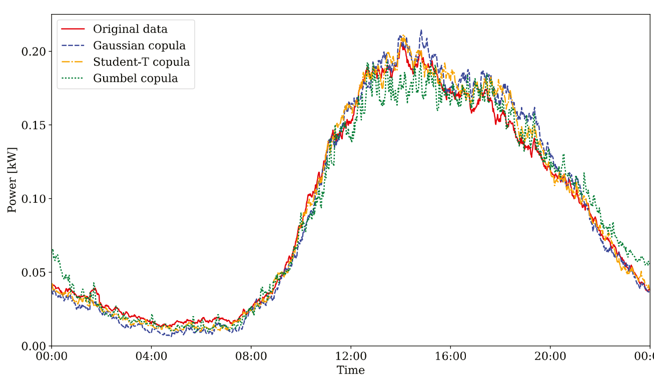

Fig. 9. Averaged daily charging loads per charging point for simulated charging events on weekends and holidays.

peak load of almost 1.6 MW would happen at 9 a.m. As the copula fitting and event sampling were conducted separately for AC and DC EVSE (and for weekdays and holidays), synthetic charging events can be used in applications with any particular proportion of AC/DC EVSE.

5. Discussion and conclusions

The aim of this study was to assess the performance of multivariate copulas in EV charging event simulation and analysis. Five most common copula functions (Gaussian, Student-t, Clayton, Frank, Gumbel) were compared based on multiple goodness-of-fit statistics in order to find the best performing multivariate copula for EV charging events. Based on the multivariate copula comparison, the elliptical copulas (Gaussian & Student-t) outperform Archimedean copulas (Clayton, Frank & Gumbel) in EV charging event simulation. Overall, based on goodness-of-fit statistics and generated averaged daily charging load profiles of the charging network, the Student-t copula is the most reliable multivariate copula to be used with EV charging event data.

The Student-t copula achieved the lowest AIC and BIC of all evaluated copulas, and the generated averaged charging load profile had the smallest deviation from the original averaged daily load curve with RMSE of 0.005 kW and MAPE of 10.88 %. Additionally, the correlation coefficients of charging events generated with the Student-t copula were found to differ only slightly from coefficients of the original real-life EV charging event dataset.

The results of this study endorse the use of multivariate copulas to capture the complex dependency structures that exist between variables of EV charging event data. As the dataset used to train the copula models was gathered from Finnish private EV charging network, and consisted of real charging events, some uncertainties might arise from the inevitable data cleaning. Additionally, as the CPO does not record the realized charging powers of charging events, these had to be estimated based on known variables and on the average onboard charger power ratings of the Finnish EV fleet. This estimation does not affect the reliability of charging event simulation with multivariate copulas but has an influence on averaged charging load power profiles used when comparing simulated charging event populations. When generalizing the methodology to other regions, the onboard charger average power should be calculated based on local EV fleet. It can also be assumed that in the future the communication transfer between the EV and the EVSE is extended to record either the true charging power, or the model of the EV, which makes the utilization of the average fleet onboard charging power redundant, and improves overall accuracy of the presented methodology.

Based on literature, multivariate copulas have not been previously used in EV charging event simulation and synthetic data generation. However, multiple studies have addressed the complicated correlation structures present between variables of public EV charging event data and, for instance, predicted EV idling times based on other variables. The correlations between variables of the dataset used in this study are quite similar as those in Ref. [38], that is the major correlation exists between the total charged energy and the charging event duration. Other correlation structures of the input data are also similar to findings of [24,38,40].

The correlation structures found in Ref. [32] by using bivariate copulas to model the correlation of public EV charging variables also support the findings of our study. According to both studies, there exists a negative correlation between start time and duration of charging events, and a positive correlation between duration and charged energy variables [32]. However, according to our multivariate copula model, there also exists complicated non-linear dependencies between the start time of the charging event and the charged energy variables. The findings of [32] support also the superiority of using the Student-t copula with EV charging data. According to solely AIC-based goodness-of-fit tests conducted in Ref. [32], the bivariate Student-t copula had the best fit in pairwise assessment of intra-day start time and duration, and duration and charged energy. In inter-day EV charging, Ref. [32] found that Student-t had the best fit between start time and duration, but the Clayton copula had a better fit between duration and charged energy variables mainly due to longer charging times. Comparison of our results to results gained in Ref. [33] is impractical as their models' goodness of fit is assessed based on bivariate comparison of frequency matrix similarities and histograms of the simulated and original data. It would be beneficial, in the future, to compare the performance of our procedure to the model of [33] with analogous datasets.

The most important advantage of the proposed procedure is that it can perform very well with data that inherently has complicated multivariate dependencies. The multivariate copula procedure for EV charging event simulation can be used to generate synthetic electric vehicle charging events that retain the multivariate dependency structures of the charging event dataset used as an input for the copula model. This indicates that even though

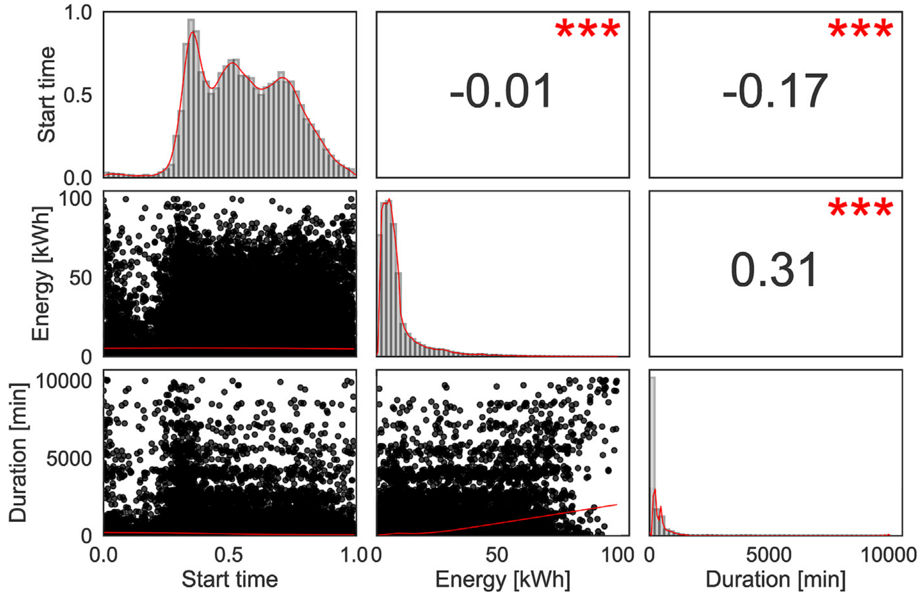

Fig. 10. Kendall's correlation matrix for the synthetic data generated with the Student-t copula (three stars represent p-value $\leq$ 0.001).

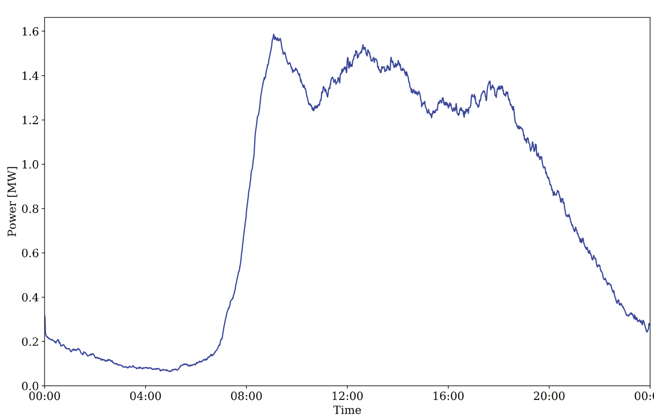

Fig. 11. Averaged daily charging load in a hypothesized 10,000 EVSE network.

this study was conducted with Finnish private EVSE dataset, the procedure and results of this study are de facto generalizable to EV charging networks worldwide. The contributions made here have a wide applicability in both academic and industry settings, and the procedure is useful in multiple applications ranging from charging point congestion planning to prediction of charging load caused by EV charging. The copula procedure for EV charging event simulation can also be utilized in power production, transmission, and storage optimization models, such as [64,65]. As assed in this study, the major charging loads caused by private EV charging coincide strongly with the usual peak demand of electricity thus increasing the peak load of the whole power grid. Large-scale grid optimization becomes increasingly important as variable renewable electricity production is increasing simultaneously with the number of EVs; these developments complicate the balancing of production and consumption in power grids [64,65]. By utilizing EV charging events in demand response schemes, it is possible to use the available flexibility of EV idling as an additional method in grid balancing. The multivariate copula method can also be used to assess the demand response potential of EV charging networks and how large an impact demand response of EV charging networks could have on power grid stability. The procedure also helps to address possible privacy concerns connected to data utilization as the data generated with multivariate copulas is fully synthetic and disconnected from real input data, while retaining all the dependencies and other important characteristics of the original data. As EV charging event data is typically the property of the charging point operator, this additional data privacy of the synthetic data could, for instance, alleviate concerns related to data sharing for research purposes.

In the future, in addition to practical applications of the proposed copula methodology, research should be conducted on additional copula functions and simulation models in order to determine whether there exists a method more suitable than the multivariate Student-t for EV charging event data simulation. Further, more extensive and diverse charging event datasets would be beneficial to verify the results of this study, and to construct generalized copula models that could be used in EV charging event simulation without need for separate input datasets.

Overall, this study has shown that multivariate copulas are an effective method to capture complex multivariate dependency structures that exist in electric vehicle charging event data. The proposed copula procedure can be used to generate novel charging events that reliably retain the dependency structures of real charging events. Generated synthetic charging events can be utilized in multiple practical and theoretical applications ranging from demonstrated EV charging load and demand response aggregation modelling to charging point congestion planning and large-scale smart grid optimization.

Credit author statement

Johannes Einolander: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Visualization. **Risto Lahdelma**: Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition.

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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