Multivariate Dependence Modeling of Electric Vehicle Charging Stochastic Parameters

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***Abstract*— Electric vehicles are considered a sustainable mode of terrestrial transport worldwide because of low- or zero-carbon emissions. Public charging stations, particularly fast and extra fast, play a crucial role in adopting and developing electric vehicles. To enable optimum planning of the fast charging stations, multivariate dependence of electric vehicle charging variables regarding stochastic nature should be taken into account. This paper uses multiple Elliptical and Archimedean copula functions to model the correlation/dependency between the electric vehicle charging characteristic parameters. Typically, by employing the multivariate copulas, synthetic electric vehicle charging data or observations are effectively generated for accurate simulation of multiple theoretical and practical applications, such as planning electric vehicle charging infrastructures while handling inherent variability and complex dependencies of electric vehicle charging characteristic parameters. Simulations are carried out in R.**

Keywords—Copula, Correlation, Dependency, Electric vehicle, Fast charging station, Uncertainty.

NOMENCLATURE

A. Abbreviations and Acronyms

AEV	All Electric Vehicle
BEV	Battery Electric Vehicle
CDF	Cumulative Distribution Function
DSO	Distribution System Operator
ECS	Electric Charging Station
EV	Electric Vehicle
EVCI	Electric Vehicle Charging Infrastructure
EVCS	Electric Vehicle Charging Station
FCEV	Fuel Cell Electric Vehicle
FCS	Fast Charging Station
GHG	Greenhouse Gases
HEV	Hybrid Electric Vehcle
IEA	International Energy Agency
IEC	International Electrotechnical Commission
ICE	Internal Combustion Engine
IEEE	Institute of Electrical and Electronics Engineers
KS Test	Kolmogorove – Smirnov Test
PDF	Probability Distribution Function
PEV	Plugin Electric Vehicle
PHEV	Plugin Hybrid Electric Vehicle
PM	Probabilistic modelling
REEV	Range - Extended Electric Vehicle
RV	Random Variable
SoC	State of Charge
SAE	Society of Automotive Engineers
SST	Solid State Transformer
UFCS	Ultrafast Charging Station
XFC	Extreme Fast Charging

B. Copula Parameters

δ	The second parameter in bivariate Archimedean Copulas
η	Degrees of freedom for Student-t Copula
Φ_ρ	Standard normal CDF
$\Phi^{-1}(u)$, $\Phi^{-1}(v)$	Inverse CDF transformed variables *u* and *v*
Ψ_1, Ψ_2	Symmetry parameters for the Tawn copula
ρ	Pearson's linear correlation coefficient
θ	The parameter for Archimedean copulas
$A(\omega)$	The Pickands dependence function
C	A general copula
$C_{\eta\rho}(u, v)$	Student-t Copula
$C_\rho(u, v)$	Normal (Gaussian) Copula
$C_\theta(u, v)$	Archimedean Copula
$C_{\theta\delta}(u, v)$	Bivariate Archimedean Copula
F(x), G(y)	Two marginal distributions
g(t)	Generator function for an Archimedean Copula
H(x, y)	A joint distribution
t	Data input for an Archimedean's generator function
$T_{\eta\rho}$	T-distribution
$T_\eta^{-1}(u), T_\eta^{-1}(v)$	T-distribution inverse transform of u and v
u, v	Two marginal distributions with uniform margins after being transformed via Probability Integral Transform.

I. INTRODUCTION

Ever-increasing reduction of oil reserves and ecological/environmental crisis are global concerns remarkably caused by fossil fuel consumption, mainly in the transportation sector worldwide [1]. Transportation is one of the most demanding sectors to decarbonize [2] and thus, most nations consider EVs a viable alternative to tackle the aforementioned serious issues [3]. During the last decade, transport electrification was the major trend in the car sector. Based on IEA reports, the sales of electric vehicles (EVs) rose from 17,000 in 2010 to 6.6 million in 2021 [4]. EVs registrations/sales share in the recent five years (2016 - 2021), considering the world's largest EV markets, is illustrated in Fig. 1, highlighting rapid increase in EV sales. Additionally, even though the car industry has been primarily impacted by the COVID19 pandemic and Russia-Ukraine War, 2 million EVs were sold in the first quarter of 2022, demonstrating a 75% rise compared to the previous year [4]. IEA projects that the world EV stock will reach fifty million by 2025 and nearly two hundred million by 2030, representing more than 20% of vehicles sold globally (11-fold from today's levels) [4]. Interestingly, 450 different EV models are available on the market, contributing to the EVs' attractiveness to consumers [4]. It is evident that electrifying the transportation sector has multiple climate/environmental and private/public benefits including greenhouse gas (GHG) emission reduction, reduced noise emissions, decreased O & M costs, human health benefits, and improved efficiency of EVs in comparison to their internal combustion engine vehicles (ICEVs) [4]. Despite reducing emissions, electrified transport increases electricity demand [2]. The EV electricity demand is expected to reach 1100 TWh in 2030, accounting for about 4% of total electricity demand [4]. The power system's capacity should be

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expanded to meet the imposed load by mass EV charging. The uncertainty related to the distribution of disordered charging loads imposed by increasing EV fleets will probably result in a significant difference between the peak and light loads on power grids and waste of finances in electric power distribution equipment [3].

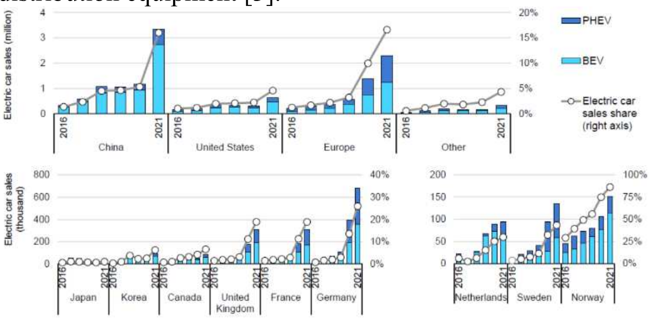

Fig. 1. EV registrations/sales in the world's largest EV markets [4]

Even though residences and workplaces have been considered the main spots to supply EV demand [5], the maximum home charging power is 5 kW and needs an enough off-street charging space. So, residents dweling in apartment blocks and high-density complexes encounter a challenge. Public EV chargers, especially fast or extra fast charging stations, FCSs, and XFCSs, are expected to be the first preferred EV refueling option soon in mature EV markets [2]. It is suggested to expand the public EV chargers by nine-fold, reaching 15 million EV public chargers in 2030, to meet charging events [2, 4]. Nearly 1.8 million public charging spots have been installed worldwide since 2021, including 600000 fast chargers, highlighting the increasing trend in building fast charging infrastructures [1, 4]. With densely populated cities, China owes approximately 85% of fast chargers worldwide, demonstrating leadership in the current EV sector, followed by Europe and the US [1, 4]. In 2021, the number of public fast chargers in the US, Germany, the UK, Norway, France, Spain, and the Netherlands was 22000, 9200, 7700, 6700, 4500, 2600, and 2600, respectively [4]. As FCSs deployment is costly, it is essential to reach optimal planning approaches for proliferating these types of stations to accelerate mass EV adoption [1]. Accurate modeling and prediction of EVs' electricity demand are critical for distribution system operators (DSOs) to balance demand-supply equilibrium at every given moment.

Deterministic modeling approaches are not suitable for estimating the EV load profile because they lack to represent the stochastic/probabilistic nature of the critical random variables. Still, few researchers paied attention on non-deterministic approaches [2]. To find the optimal site and size for FCSs, uncertainties/dependencies related to EV charging behavior should be considered for close-to-real-world simulations in this regard. Otherwise, if the dependency structures in the FCS planning problem are not taken into account, numerous inaccuracies may arise, particularly at the time of producing synthetic data via the simulation techniques to be utilized in subsequent steps for FCS planning models. As the EV penetration level grows in power systems, modeling the stochastic behavior of EVs becomes vital for optimal planning and operation. Several research works have studied the significance of EV charging behavior modeling. However, they mainly dealt with EV charging behavior that are mostly based on ICEVs driving patterns and the corresponding travel survey datasets. In addition, some research works declared that the EV charging parameters are independent [3]. But in the present research work, the authors provide pieces of evidence that such an assumption will result in a biased calculation. To analyze the EV fleets and FCSs power consumption for charging infrastructure planning, the uncertainties of the EV charging events and EV drivers' behaviors should be considered. Accurate EV charging modeling is intricated using conventional methods assuming independent random variables (RVs) parameters expressed as non-normal multivariate dependencies among EV charging random variables. Stochastic dependence modeling is necessary to reach relatively accurate results in FCS planning problem with regard to this type of dependent / correlated non-normal datasets. But, very few research works have been appeared so far regarding these types of complex dependency structures in EV charging behaviors in FCSs.

To model the complex nature of the dependence structure of EV charging characteristics, we turn to the copulas. A copula is defined as a multivariate cumulative distribution function (CDF) bounded to uniform margins over (0, 1) that links marginal distributions to their joint distributions. Due to their versatility, copulas have been used in many applications, such as actuarial science, finance, hydrology, biomedical, and engineering [6]. The rest of his manuscript is elaborated in the following sections: Section II presents a detailed study background. Section III provides transportation datasets and methodology. Section IV demonstrates the simulations and obatined results. Lastly, Section V summarizes conclusions and future works.

II. Background & Methodology

A. Electric Vehicles

Two major classifications for electric vehicles are generally considered according to fuel requirement types, namely, hybrid electric vehicless (HEVs) and all-electric vehicles (AEVs) [2]. Further, plug-in hybrid electric vehicles (PHEVs) and range-extended electric vehicles (REEVs) as two main HEVs are equipped with ICEs and electric motors. However, the electric motors the only driving force for AEVs supplied mainly by various green energy sources [1, 5, 7-10] including fuel cells (i.e., FCEVs) and batteries (i.e., BEVs).

B. EV Charging and Fast Charging Stations

Electric vehicle charging stations (EVCSs) are defined as the public EVs refueling spots. International Electrotechnical Commission (IEC) reports that EVs can be charged under four EV charging modes detailed in Table 1. Nowadays, fast charging station (FCS) is the most favorable charging plan for public charging facilities. In recent years, high-tech FCSs are able to charge EVs up to 80% roughly in 10 - 15 minutes, catching conventional gas refueling stations. FCSs practically charge EVs up to 80% SoC level because the last 20% charging power needs a longer time. In addition, overcharging (SoC > 0.8) and underdischarging (SoC < 0.2), are avoided to extend the EV battery lifetime [1]. The progress of off-board extreme FCs (XFCs) is highly needed for the fast charging of EVs. Recently developed XFCs provide EVs with charging speed similar to gas stations in approximately three minutes with voltage and current ratings above 800V and 400A [11]. Several international EV charging standards are reported in the literature, namely, (i) Society of Automotive Engineers (SAE), (ii) Institute of Electrical and Electronics Engineers (IEEE), and (iii) International Electrotechnical Commission (IEC), among others. IEC and SAE are globally on top of agreed standards [1].

Table 1. Electrical ratings of the available charging spots [1].

Charging Methods	**Slow – AC**			**Fast - DC**			**UltraFast – DC**
Charging Type	**AC Level 1**	**AC Level 2**		**DC Level 1**	**DC Level 2**	**DC Level 3**	
Supply Voltage (V)	1ph 110 – 120 V (US) 230 – 240 V (EU)	1ph 208 – 240 V (US) 400 V (EU)	3ph 400 V	200 – 450 V	200 – 450 V	200 – 600 V	>= 800 V
Max. Current (A)	12 – 20 A (12 – 16 A usable	32 – 80 A (32 A usable)	80 A (64 A usable)	80 A	200A	400 A	> 400A
Max. Power (kW)	1.44 – 2.4 kW (on-board)	7.7 – 25.6 kW (on-board)		Up to 36 kW (off-board)	Up to 90 kW (off-board)	Up to 240 kW (off-board)	400 – 1000 kW
CB Rating (A)	15 A (min.)	40 A (min.)		As required			As required
Installation Cost ($)	Cost < $1000	$2000 < Cost < $10000		$60000 < Cost < $100000			Cost > $100000
Percent of CSs	53%	43%		3%			< 1%
Charging time (hr or min.)	8 – 16 hr	4 – 8 hr		0.5 – 1.2 hr	20 – 35 min	< 10 min	<3 min
Charging Site	Home / Workplace	Private & public outlets		Commercial, analogous to a conventional gas station			Public (primary customer of sub-transmission)

C. Uncertainties and Dependencies in EV Charging

As high penetration/large load demand of EVs into power grids via charging stations, in particular FCSs, is expected soon, it is essential to accurately estimate the imposed load by FCSs. The stochastic nature of the inputs fed into the FCS planning problem requires modeling and data preparation as complex dependencies exist between the inputs [12]. The modeling procedure mainly comprises of two phases: (i) modeling marginal distributions and (ii) obtaining stochastic dependence. As mentioned previously, only few research studies employed copulas in EV charging dataset for dependency modeling [13]. In [14], EVs are all assumed to start charging simultaneously between 5-10 p.m. In [15], EV fleet is highly charged at off-peak time. Here, in an uncontrolled/uncoordinated charging scheme in [15], all EVs depart home in between 8-9 a.m. and come back in the afternoon/evening (i.e., 6-9 p.m.). The load demand is often obtained neglecting EVs' travel patterns. Assuming that EV s'initial SoC and charging start-time are random variables (RVs), the daily distance travelled probability distribution follows a normal distribution [12]. EVs' charging load demand on many stochastic variables such as the number of EVs, charging start time, charging end time, charging duration, daily travelled distance, initial SoC, etc., all are random variables [12]. This study uses some of the aforementioned RVs to model EV charging characteristic parameters.

D. Multivariate and Bivariate Copula Functions

Copulas are defined as multivariate CDFs used to describe dependencies between RVs, and they are leveraged to produce synthetic samples from a given joint distribution [6, 13, 16, 17]. The resulting sample population thereby can be employed for EV charging model. The name "copula" highlights how copulas make connections between joint distribution functions and their correponding univariate margins [16, 17]. Theoretically, copulas are established based on Sklar's theorem [18] and multivariate Sklar's theorem [19]. Accordingly, consider $\boldsymbol{H}$ as an n-dimensional distribution function described by distribution margins of $\boldsymbol{F_1}$, $\boldsymbol{F_2}$, **…**, $\boldsymbol{F_n}$, then for all random variables of $\boldsymbol{x}$ in $\overline{\boldsymbol{R}}^{\boldsymbol{n}}$ and n-copula $\boldsymbol{C}$, Eq. (1) holds [6]:

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

The n-copula, i.e., C, is unique when all $\boldsymbol{F_1}$, $\boldsymbol{F_2}$, **…**, $\boldsymbol{F_n}$ are continuous; otherwise, C is uniquely obtained through **Ran** $\boldsymbol{F_1}$ × **Ran** $\boldsymbol{F_2}$ × **…** × **Ran** $\boldsymbol{F_n}$. If $F_1^{-1}, \ldots, F_n^{-1}$ are quasi-inverses of $\boldsymbol{F_1}$, $\boldsymbol{F_2}$, **…**, $\boldsymbol{F_n}$, thus for any $\boldsymbol{u}$ in $\boldsymbol{I^n}$, we have:

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

To produce synthetic observations of X_i from the original RVs of x_i, just uniform observations of u_i within the uniform RVs of U_i should be generated regarding a joint distribution function C. The aforementioned uniform observations should be transformed back into the initial scale. Due to space limitations, readers are referred to Ref. [19] for extensive detailed study on the RV generation and copulas.

The steps required for synthetic data generation from actual samples using the multivariate copula are depicted in Fig. 2. The final synthetic observations (output dataset) must have a similar RV dependence structure as the original data. Some copulas, such as the normal (i.e., Gaussian) and Student-t, exhibit symmetrical properties along the u = 1–v diagonal lines. That is why they are called elliptical copulas [20]. Archimedean and Elliptical copulas are widely used types of copulas in engineering literature [19]. Differently from the Elliptical copulas, Archimedean copulas leverage generator functions, $g(t)$, to operate. In the initial form, higher dimensioned Archimedean copulas (i.e., n > 2) only allow positive dependencies [6]. However, various multivariate extensions have been reported for these copulas that allow negative dependencies via various transformations. Besides the two above families of copulas, there exist Joe Copula proposed [21] and BBx copulas. Details on widely used Elliptical and Archimedean copula functions are presented in Table 2.

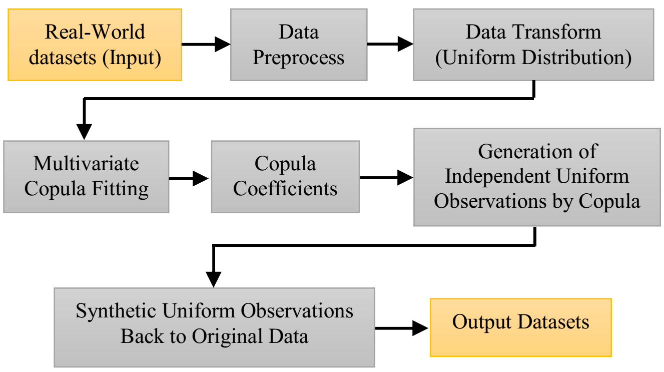

Fig. 2. Required steps for synthetic data generation via copula [22]

Table 2. Details of Popular Elliptical and Archimedean Copulas [6].

Copula Family	Copula	Advantages	Formulation
Elliptical Copulas	**Gaussian (Normal)**	Easy implementation, Linear correlation, Captures some degree of tail dependence between marginals.	$C_\rho(u, v)=\Phi_\rho(\Phi^{-1}(u), \Phi^{-1}(v); \rho)$
	Student-*t*	Easy implementation, Capture extreme value dependence much better in the tails of the copula.	$C_{\eta\rho}(u, v)=T_{\eta\rho}(T_\eta^{-1}(u), T_\eta^{-1}(v); \rho)$
Archimedean Copulas	**Clayton**	Simple form, Ease of construction, Models lower tail dependence very well.	$g(t) = \frac{1}{\theta}(t^{-\theta} - 1)$ $C_\theta(u, v)=(u^{-\theta} + v^{-\theta}-1)^{-1/\theta}$ θ>0
	Gumbel	Simple form, Ease of construction, Models upper tail dependence.	$g(t) = (-lnt)^\theta$ $C_\theta(u, v)=\exp(-((-\ln u)^\theta + (-\ln v)^\theta)^{1/\theta})$ θ ≥0
	Frank	Simple form, Ease of construction, Do not model tail dependence. It is more focused on central dependence or symmetrical dependence.	$g(t) = -\ln(\frac{e^{-\theta t} - 1}{e^{-\theta} - 1})$ $C_\theta(u, v) = \frac{-1}{\theta}\ln(1 + \frac{(e^{\theta u}-1)(e^{\theta v}-1)}{(e^{\theta}-1)})$θ≠0
	Joe	Simple form, Ease of construction, Models dependency with some upper tail dependence.	$g(t) = -ln(1 - (1 - t)^\theta)$ $C_\theta(u, v) = 1 - ((1 - u)^\theta + (1 - v)^\theta - (1 - u)^\theta(1 - v)^\theta)^{1/\theta}$ θ≥0

III. Transportation Datasets

Many substantial EV charging uncertainties influence the FCS planning, such as EV power and energy demand, EV daily traveled distance, EV charging start time, EV charging end time, and the EV charging duration, etc. [2]. The FCS's optimal planning problem should be stochastically solved. In the present work, we used the following three uncertainties for the copulas to get the joint probability:

(1) EV charging start time, T_S,

(2) EV charging end time, T_E,

(3) EV daily distance traveled, D_T.

For this purpose, we used US national household travel survey, NHTS, [23]. This internationally accepted dataset covers transport-related data in the years 1995 and 2009. In the current research, we primarily extracted a specific 2009 NHTS dataset from four large databases, in particular, vehicle and daily trips data, and then utilized it for simulations in the "R" software package. Data preprocessing is essential to filter out irrelevant or erroneous data. Data preprocessing is the second step in synthetic data generation (See Fig. 2). Thus, two datasets, VEHV2PUB and DAYV2PUB, previously obtained from 2009 NHTS synthesized vehicle ID "VEHID" and person ID "PERSONID" in two CSV files. Each household may have different cars driven by other family members. Thus, sorting vehicles versus drivers is a bit time-consuming task. For the current research simulations, we randomly selected only 1,000 households out of nearly 250,000. We could effectively utilize the extracted mixed data for stochastic analyses since it was sufficiently distributed over a broad portion of the 2009 NHTS dataset.

IV. Simulation and Results

The following steps were taken to model dependent RVs via copulas:

(i) Find the most appropriate fitting PDF for each RV,

(ii) Transform sample datasets to uniform space,

(iii) Transform obtained unified data through copulas to select the most promising copula function,

(iv) Obtain RVs correlation,

(v) Use the extracted copula to generate correlated samples.

Histograms of daily distance traveled related to total data and selected data of the 2009 NHTS dataset are depicted in Fig. 3. The average daily distance traveled is 32.24 miles, consistent with the previous reports (i.e., 33 miles) [24]. The Weibull PDFs fitted best to both histograms. Histograms of EV charging start time and end time for selected data of the 2009 NHTS dataset (i.e., 1000 samples) are shown in Fig. 4.

There exist different procedures to determine which distribution fits univariate distribution marginals. Conventionally, Kolmogorov-Smirnov (KS) Test is utilized. However, the p-values of a KS-Test with estimated parameters can be entirely wrong since the p-value does not consider the uncertainty of the estimation. In addition, the test samples would never strictly follow a specific distribution. Hence, even if p-values from the KS-Test may be valid (i.e., > 0.05), one cannot rule out that the data follow a specific distribution. This paper employs the excellent "fitdistrplus" package in the "R" to fit distributions. Here, the Skewness-Kurtosis plot proposed by Cullen and Frey in 1999 is utilized to select the best distribution(s) to fit a sub-sample data of the 2009 NHTS dataset. Due to space limitations, only daily distance traveled illustrations are shown in Fig. 5.

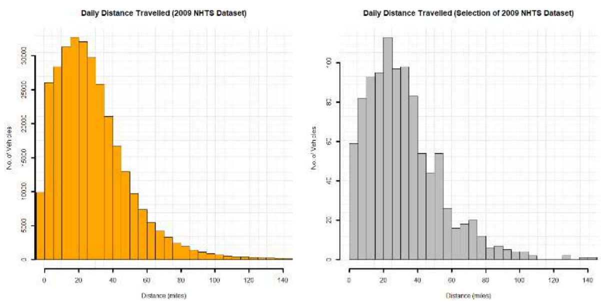

Fig. 3. Histograms of daily traveled distance, D_T, of the 2009 NHTS dataset.

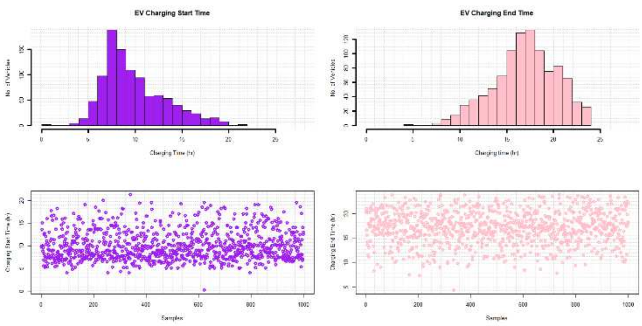

Fig.4. Histograms of EV charging start time (T_S) and EV charging end time (T_E) of the 2009 NHTS dataset.

As seen in Fig. 5, Weibull, Gamma, and Lognormal distributions are appropriate candidates. Fig. 6 depicts the comparison of the fit of the selected three distributions. The

Weibull distribution is the best candidate for daily distance traveled, D_T. Likewise, the most appropriate distributions for EV charging start and end time were Normal and Weibull, respectively. The parameters of fitted PDFs for three RVs are given in Table 3.

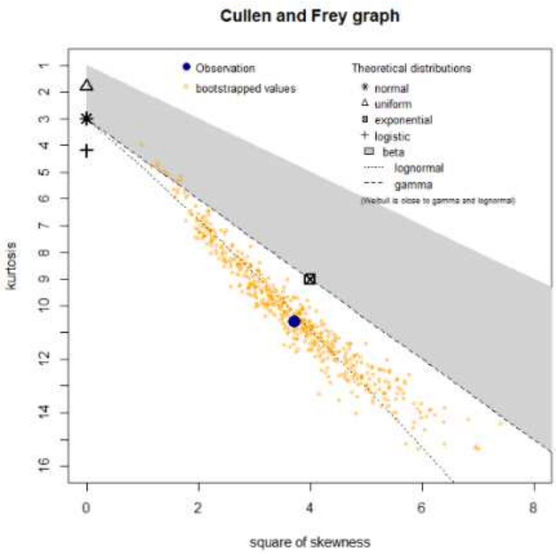

Fig. 5. Cullen and Frey (Skewness vs. Kurtosis) plot employed for determining the best-fitted distributions.

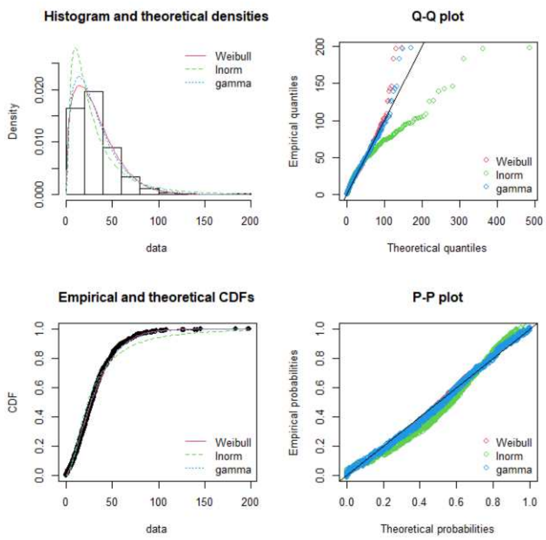

Fig. 6. Four Goodness-of-fit plots for selected.

The correlation of RVs (i.e., D_T, T_S, and T_E) is now obtained. Correlation is a bi-variate study that measures the the association strength between two RVs and the direction (-/+) of the relationship. Table 4 provides a correlation of RVs using different methods of "Kendalls". Pearson and Spearmen, all correlations bounded to (-1, 1). Regarding the relationship's strength, the value of correlation coefficient changes from +1 to -1. A value of ±1 demonstrates a complete association between the two RVs. But, the relationship between the two RVs will be weaker as the correlation coefficient value reaches 0. The coefficient sign (- or +) defines the association direction, that is, "+" and "-" signs refer to a positive and negative relationship, respectively. Fig. 7 visualizes the selected 2009 NHTS data correlation to gain insight into the interpretation. Pearson's and Spearman's correlation matrices provide similar results to Kendall's correlation matrix.

Next, copulas are employed to get the best-fitted ones. Looking at Table 4 and Fig. 7, it is quite clear that a negative correlation exists between D_T and T_S. Thus, if one selects among the Elliptical copula family, Gaussian and Student-t, or Archimedean family, Frank, Gumbel, Clayton, and Joe, only the Gaussian allows for negative dependence. It should be mentioned that Gaussian copula can model negative dependency and Frank copula, which also becomes very close to Gaussian if the degree of the dependency structures is small. Based on the obtained results using the selected copulas for bivariate dependency, the following copulas are best fitted: Frank Copula (D_T and T_S), Gumbel Copula (D_T and T_E), and Tawn-Type-2 Copula (T_S and T_E). Again, due to space limitation, the obtained results are illustrated only for the first best-fitted copula (i.e., Frank Copula). The obtained simulation results for successfully fitted bivariate copula are as follows: Frank (par = -0.54, tau = -0.06). Fig. 8 visualizes PDF, CDF, perspective, and contour plots of multivariate distributions constructed from Frank Copula (member of the Archimedean family) for two RVs (i.e., D_T and T_S). Finally, 1000 simulated samples are obtained regarding 1000 selected samples from the 2009 NHTS dataset, and both are depicted in a single plot in Fig. 9. At the end, the pair correlation of generated observation is found to be similar to the results provided in Table 4, verifying the validity of the obtained results.

Table 3. The obtained distribution parameters of fitted PDFs

Random variable	Fitted distribution	Parameters
Daily distance traveled (D_T)	Weibull	a=1.414797 b=35.432054
EV charging start time (T_S)	Normal (Gaussian)	M=32.24670 Sd=23.60427
EV charging end time (T_E)	Weibull	a=5.94262 b=18.36185

Table 4. Correlation Coefficients of the EV charging characteristic parameters

Correlation methods	RV	D_T	T_S	T_E
Kendall rank correlation coefficient (τ)	D_T	1	-0.06	0.1
	T_S	-0.06	1	0.024
	T_E	0.1	0.024	1
Pearson correlation coefficient (ρ)	D_T	1	-0.026	0.125
	T_S	-0.026	1	0.124
	T_E	0.125	0.124	1
Spearman rank correlation coefficient (ρ)	D_T	1	-0.088	0.145
	T_S	-0.088	1	0.022
	T_E	0.145	0.022	1

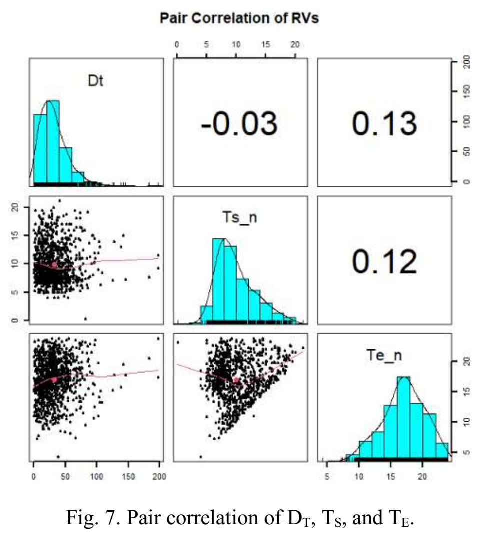

Fig. 7. Pair correlation of D_T, T_S, and T_E.

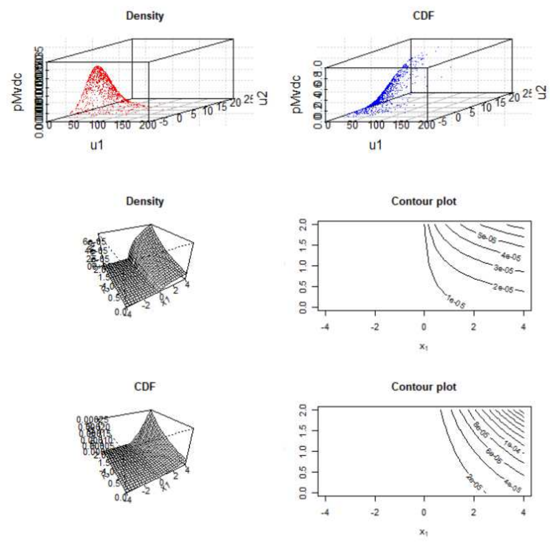

Fig. 8. Multivariate distribution plots of D_T and T_S from Frank Copula

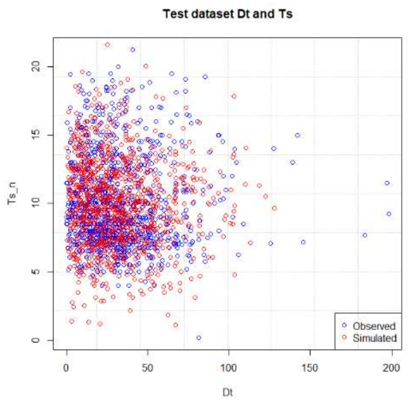

Fig. 8. Correlation of D_T and T_S, initially observed data samples (blue), generated observations (red)

V. Conclusions and Future Works

For the optimal FCS planning, multivariate dependence of EV charging variables regarding stochastic nature should be considered. In this paper, several widely-used Elliptical and Archimedean copula functions are fitted for modeling the correlation between three EV charging characteristic parameters. This paper employed a random selection of samples from the 2009 NHTS dataset. Simulations were carried out in the "*R*" Programming Package. Due to space limitations, only two RVs correlations were comprehensively visualized. For future research, the number of RVs and the size of datasets are increased. In addition, FCS charging will be modeled stochastically using the obtained correlations.

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