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Power Demand Patterns of Public Electric Vehicle Charging: A 2030 Forecast Based on Real-Life Data

Marco Baronchelli [1], Davide Falabretti [1,*] and Francesco Gulotta [2]

1 Department of Energy, Politecnico di Milano, 20156 Milano, Italy; marco.baronchelli@mail.polimi.it
2 Department of Energy System Development, Ricerca sul Sistema Energetico, 20134 Milano, Italy; francesco.gulotta@rse-web.it
* Correspondence: davide.falabretti@polimi.it

Abstract: As the adoption of electric vehicles accelerates, understanding the impact of public charging on the power grid is crucial. However, today, a notable gap exists in the literature regarding approaches capable of accurately estimating the expected influence of e-mobility power demand on electrical grids, especially at medium and low voltage levels. To fill this gap, in this study, a procedure is proposed to estimate the power demand patterns of public car parks in a 2030 scenario. To this end, data collected from real-life car parks in Italy are used in Monte Carlo simulations, where probabilistic daily power demand curves are created with different maximum charging powers (from 7.4 kW to ultra-fast charging). The results highlight high variability in the power demand depending on the location and type of car park. City center car parks exhibit peak demand during morning hours, linked to commercial activities, while car parks near railway stations and hospitals show demand patterns aligned with transportation and healthcare needs. Business area car parks, in contrast, have a more pronounced demand during work hours on weekdays, with much lower activity during weekends. This study also demonstrates that, in some situations, ultra-fast charging can increase peak power demand from the grid by up to 210%. Given their contribution to the existing literature, the power demand patterns from this research constitute a valuable starting point for future studies aimed at quantitatively assessing the impact of e-mobility on the power system. In addition, they can effectively support decision-makers in optimally designing the e-mobility recharge infrastructure.

Keywords: car park; electric power demand; electric mobility; load profiling; Monte Carlo simulation

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1. Introduction

In recent years, the energy sector has been characterized by a constant evolution driven by the global rise in energy demand. This has led the issues of climate change and global warming to become increasingly relevant. The origins of these phenomena are related to the increasing greenhouse gas (GHG) emissions resulting from human exploitation of fossil fuel resources.

To reduce emissions, the European Union (EU) has introduced a package of legislative proposals called Fit for 55 [1]. The main targets, to be achieved by 2030, include reducing GHG emissions, increasing the share of renewable energy sources in the energy production mix, and improving energy consumption efficiency. In line with the European directives, each member state has drafted a plan to contribute to achieving the above-mentioned objectives to the best of its ability. In all of the national plans, the transport sector plays a pivotal role, given its significant contribution to GHG emissions and the promising potential of electrification [2]. Multiple studies have indeed confirmed that the Life-Cycle Assessment (LCA), in terms of GHG emissions, is generally much lower for battery electric vehicles than for internal combustion engine vehicles [3,4]. Consequently, a wider adoption of electric vehicles (EVs) in the future could help reduce emissions. However, this would certainly increase the energy demand, so the benefits of EV adoption would only be significant if accompanied by a substantial inclusion of renewables in the energy production mix [5]. At the same time, public charging infrastructure must be developed through the installation of an adequate number of charging points (CPs) across the territory. Otherwise, the lack of a functional public charging infrastructure would inevitably slow down the transition to e-mobility [6,7].

To address the potential challenges posed by EV transportation, several studies have been conducted in recent years to assess the expected impact of EV charging's power demand on the electric power infrastructure. These studies consider both planning and operational phases and seek to identify possible remedial actions. In [8], the authors introduced a hybrid technique for estimating the aggregated plug-in EV charging load based on a stochastic model and real-world dynamics. The grid impact analysis was performed using a model of an actual distribution network developed in Pandapower software. In [9], the seasonal variance in charging demand was explored by using a unique Global Positioning System (GPS) trajectory dataset that contained travel, parking, and charging information from 2658 private EVs in Beijing. This dataset was collected over four representative months in 2018. Other studies have aimed to evaluate the public charging demand in large metropolitan areas, based on the projected growth of EVs by 2030 [10]. These studies typically take the 2030 scenario as a reference. Additionally, it should be noted that, although EVs produce zero direct emissions, their charging patterns imply indirect emissions for the necessary electricity production. In this regard, the variability in emission factors, depending on the national energy mix, has been widely investigated in the literature, also considering the different contributions of renewable generation during daytime and overnight hours [11]. Furthermore, some papers have examined other potential impacts of e-mobility on power systems' operation, such as the effects on power quality (charging transients, rapid voltage fluctuations, and harmonics) due to the power consumption of charging station technologies currently under development. These technologies aim at super-fast and ultra-super-fast EV charging [12]. Their impact on power imbalances across three-phase systems is also an examined factor [13].

Properly integrating (private and public) EV charging infrastructure and the electrical grid is crucial. Therefore, the goal of many works in the literature focuses on studying suitable solutions for problems arising from the increasing charging demand of e-mobility on transmission and distribution power systems. To mitigate the adverse effects of EV power requests, the optimal allocation over the territory of EV charging stations is commonly adopted as one of the preferred approaches. In [14,15], this was done while considering EV drivers' activities, home and public charging availability, range anxiety, and the energy consumption of remaining trips [16]. To optimize investments in the power charging infrastructure, the number and capacity of stations to be installed are often optimized based on the demand within a particular area and the required level of service [17].

Another growing area of interest is the exploitation of e-mobility charging flexibility to reduce the impact of power demand on the transmission and distribution grid by also providing regulation services to the power system [18]. In [19], a method was proposed for the real-time management of EV charging processes, aiming to limit the peak load and increase the number of rechargeable EVs. This approach is based on a close interaction between a scheduling algorithm and a power flow evaluation procedure. Meanwhile, in [20], the authors proposed a tool to optimally schedule the charging requests of a fleet of car-sharing EVs in an urban area, to enable their participation in the ancillary service market. Many studies in the literature model the regulation capabilities of EV fleets as mixed-integer linear programming problems, considering factors influencing EVs' profitability, such as uncertainty, drivers' patterns, capacity and State-of-Charge (SoC) constraints, regulation demand, and offer constraints, as well as requirements on power system security [21,22]. Some studies have also investigated the potential for providing ancillary services using V2G (Vehicle-to-Grid) techniques [23–25], while considering the negative effects on battery degradation [26].

Regardless of the methods adopted in the research and their purposes, all studies concerning the integration of EV transportation in electric power systems require detailed and reliable modeling of the EV power consumption profiles from the grid. In [27], a methodology based on a non-parametric kernel distribution function is proposed to generate power profiles for EV parking lots. Different charging strategies are considered, such as instant charging and mono/bi-directional smart charging. However, the model proposed by the authors refers to a single type of car park. Furthermore, the procedure's complexity and lack of open-access results limit its real-world application. In [28,29], an open-access model, named RAMP-Mobility, was designed to simulate EV mobility and charging patterns across several European countries. It simulates minute-resolved mobility patterns for each user by defining operating windows and assuming different user categories (workers, students, inactive users). However, its reliance on national-level data for generating EV charging requests does not allow for an accurate representation of the specific conditions of the individual car parks.

This lack of literature highlights that it is essential to develop models and datasets that are freely accessible to researchers and stakeholders, which can be adopted to predict the charging requirements in different contexts.

In this framework, this study aims to provide realistic power demand profiles of EV charging in public car parks, under a future 2030 scenario. The value of this study lies in the fact that the resulting power profiles could be used in future research to develop e-mobility impact analyses or to assess EVs' potential in providing grid services. It is important to underline that the expected power profiles are neither exhaustive nor representative of all car parks in Italy, as they are closely related to the experimental data collected on the set of sites involved in the study. The dependence of the reconstructed profiles on the characteristics of the relevant car park is actually a strong point of this study. This is because, unlike other data available in the literature, the profiles elaborated here allow for an accurate assessment of the impact of EV charging requests on the electric power infrastructure. Nevertheless, the developed numerical procedure has general validity and can be applied to any parking garage to accurately evaluate the expected charging demand.

The approach proposed in this work consists of the following stages:

- Collection of occupancy data from several real car parks in Italy;
- Definition of an EV fleet model, representative of the spread of electric car models in 2030;
- Probabilistic simulation of the EVs' behavior over a representative day;
- Calculation of power demand patterns of charging vehicles with different maximum output powers of the CPs.

To this end, a probabilistic Monte Carlo algorithm was developed to combine the collected data and simulate the charging processes of the EVs entering the analyzed car parks. The algorithm's results pertain to the power demand generated within each car park during a representative day (weekday, Saturday, or Sunday), with a 1 min time resolution.

In particular, the main contributions of this work can be summarized as follows:

i A bottom–up approach, based on real-life data, is proposed to estimate the EV usage and the corresponding charging profiles in a 2030 energy scenario.
ii The approach allows for estimating the expected charging profiles by considering the unique characteristics of each car park (e.g., usage times, geographical location, proximity of points of interest, etc.) with a very detailed time resolution (i.e., 1 min). This opens the possibility to use these data for future research studies, while also involving sudden phenomena on distribution grids, such as local peak power congestions.
iii An analysis is proposed to identify, for different types of car parks, the expected peak power as a function of the rated power of charging points (i.e., the maximum power that can be delivered to the EV during the charging process). Furthermore, a Monte Carlo simulation is used to realistically capture the stochasticity and variability in the power demand.
iv The power demand patterns from this research are openly available; hence, this work provides a valuable starting point for future studies and can support decision-makers in designing the e-mobility recharge infrastructure and network expansion plans.

2. Public Car Park Data Collection

The first part of the proposed method is dedicated to collecting all of the data needed to perform the required simulations, aimed at defining realistic power demand profiles of public car parks in a 2030 scenario. The simulations start with vehicles entering the car parks at different hours of the day. A fraction of them requires charging. The charging process depends on the rated charging power of the EV, the maximum output power of the CP, the duration of the stay inside the car park, and the percentage of battery left upon entry. The power demand trends of individual EVs over the course of a day are thus determined with a probabilistic approach. By summing the effects produced by all of the EVs entering the parking area during the day, an overall power demand for the car park in the scenario under analysis is obtained. In general, when dealing with e-mobility's expected power demand in future scenarios, most studies in the literature apply top–down approaches to perform estimations, often by deriving power charging patterns according to the forecasted EV spread and usage (for example, in a given region or even in larger areas, e.g., at the national level) [9]. While a top–down approach could effectively evaluate the large-scale impact of electric transportation on energy systems, it is not capable of realistically reproducing power demand profiles of EV charging stations connected to specific points of the electricity network. This information, in turn, is crucial to perform studies at a small scale—for example, on portions of medium-voltage and low-voltage power distribution grids.

To provide a solution to this issue, this work relied on the information on real-time occupancy collected from several real public car parks in Italy. For this purpose, the number of free parking stalls available in 25 real car parks in Northern Italy, made available by the car park manager to customers through its webpage, was gathered. Data were collected from the car parks' webpages with a 1 min time resolution by software developed in MathWorks MATLAB 2024a, Microsoft Excel 365, and Visual Basic. A graphical representation of the different steps comprising the data-scraping tool is reported in Figure 1. First, the HTML code of the websites was downloaded in .txt format and reprocessed in Excel to isolate the data of interest, i.e., the number of car park stalls available at the current time. The collected data were saved with the current timestamp in an Excel file. Several methods were implemented to ensure data quality during the extrapolation process. Firstly, a robust data validation and cleansing procedure was adopted, aimed at detecting and addressing errors and missing data in the collected time series. In particular, during the data extrapolation process from the car parks' websites, the current number of vehicles inside each car park was compared with the total parking spaces available. Occupancy profiles were also individually checked to identify sudden changes or gaps in the collected data, which could indicate anomalies in the data-scraping procedure. Each sample acquired by the procedure was individually timestamped to avoid discrepancies due to time lags or misalignments in the data collected. If any problem occurred, such as unavailable data or an unreachable website, the time of the failure was logged for subsequent verification, and the data-scraping process was temporarily paused. Otherwise, the cycle was repeated every 60 s to sample occupancy data per minute. Car parks with sampled data that were considered unreliable were discarded from the analysis. The described procedure was applied to the websites of different car park companies in Italy. However, only the occupancy patterns collected for the cities of Brescia and Florence (12 and 13 car parks, respectively) showed satisfactory quality and, thus, were considered for the subsequent analyses.

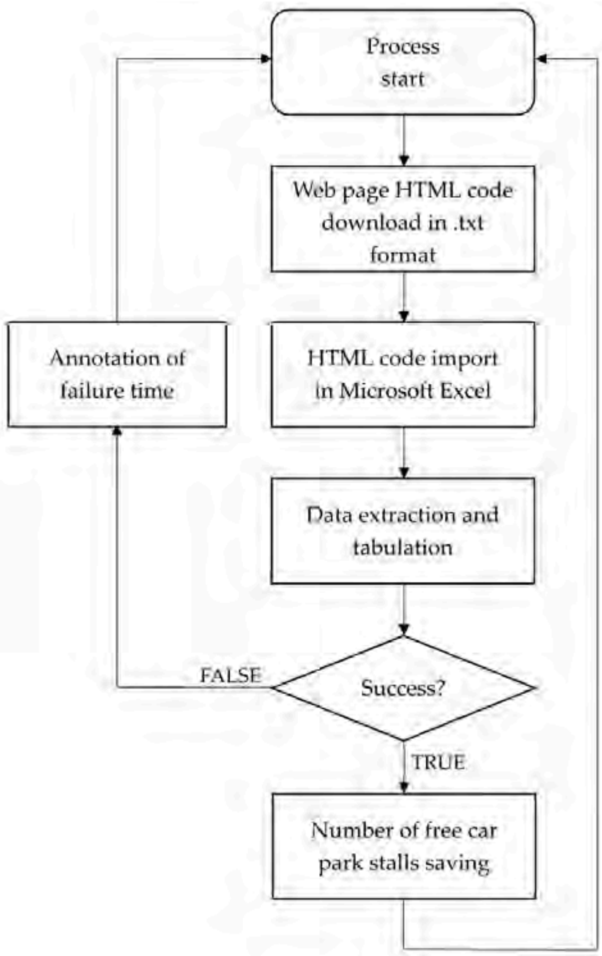

Figure 1. Flowchart of the procedure adopted to extrapolate the car parks' occupancy data.

The data extrapolation was launched on 5 June 2023 and stopped on 4 November 2023, obtaining daily occupancy patterns for weekdays, Saturdays, and Sundays, like the one in Figure 2. In the figure, the mean occupancy value over the entire observation period is shown in blue, the 10th percentile in yellow, and the 90th percentile in red. All of the daily occupancy curves obtained with this procedure are reported in Appendices A.1 and A.2 for Brescia and Florence, respectively. Finally, by means of the collected time series, the number of vehicles entering or leaving the car park during the day was calculated as the variation in occupancy over time.

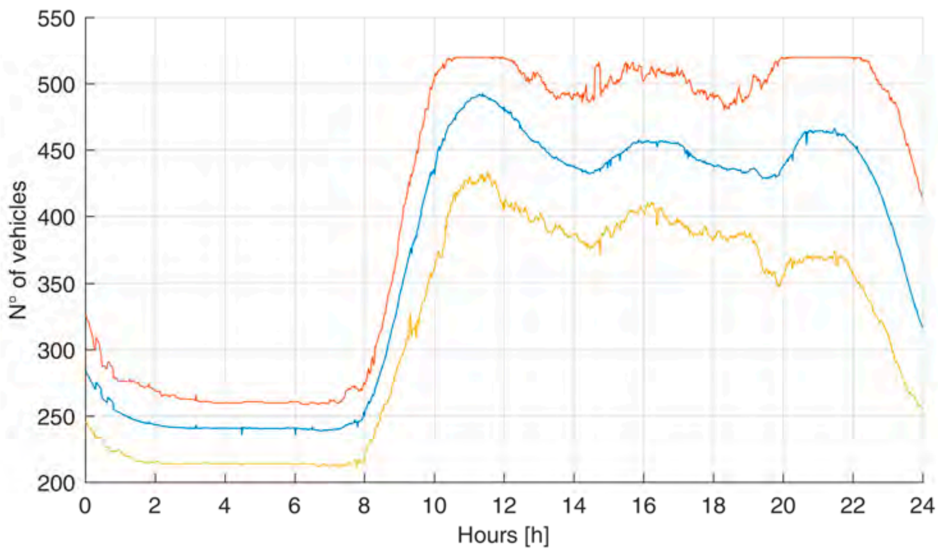

Figure 2. Occupancy pattern for a weekday—"Brescia A" car park. The average value is shown in blue, while 10th and 90th percentiles are represented in yellow and orange, respectively.

By analyzing the 25 car parks considered, it emerged that those in similar urban contexts often show similar occupancy trends. In this respect, the car parks were categorized into four subgroups, depending on their location within the city and their proximity to specific city services or areas (city center, railway station, hospital, and business area) (Table 1). The categorization was based mostly on weekday data curves because, in some cases, the correlation was lost on the weekends due to the lower number of samples. It is important to point out that, in some cases, even when the car parks belong to the same category (i.e., similar city areas), the occupancy trends show notable differences. This is because many other factors can affect the car flow in the car parks, such as the vicinity of tourist points of interest or the closeness of more attractive (e.g., cheaper) parking areas.

Table 1. Car parks' locations.

Location	Brescia	Florence
City Center	A, D, E, J	B, D, J
Railway Station	F, G, H	A, C, H
Hospital	B, C	K, L
Business Area	I, K, L	E, F, I, G, M

Parking areas located near city centers have in common a higher number of parked cars in the morning or at noon. An increase in occupancy rates is also observed during the evening, though the extent varies greatly depending on the specific car park and city involved. Car parks used by commuters and those near railway stations, as expected, usually report higher turnout during working hours. Car parks near hospitals present higher occupancy on weekdays during the mornings, while on Saturdays and Sundays the peak is observed in the afternoon. Finally, parking garages near business areas show higher occupancies during working hours, and in some cases there is a slight decrease during the lunch break.

Table 2 reports the average parking time of vehicles entering each garage. Since the data collected only pertained to the number of cars parked at a given time and did not include information about the duration of the stay, the latter needed to be estimated. This was achieved by adopting a FIFO (First-In-First-Out) approach, assuming that, when the exit of a vehicle is registered from the garage, it is the first vehicle entered that has not yet left the car park. As observed in Table 2, the duration of parking is quite long on average, especially on weekdays, when it often exceeds 4 h. In contrast, it is usually shorter on Saturdays and Sundays, with the average time often being less than 1 h. This is consistent with the reasons for the car trips within cities: on weekdays, they are mainly related to work, while on weekends they are primarily for recreational purposes.

Table 2. Average vehicle stay for each car park.

Brescia Car Parks	Average Stay (min)			Florence Car Parks	Average Stay (min)		
	Midweek	Saturday	Sunday		Midweek	Saturday	Sunday
A	328	323	169	A	257	315	278
B	259	35	48	B	315	268	253
C	235	30	52	C	367	317	197
D	212	204	175	D	347	343	215
E	161	142	29	E	364	362	214
F	94	144	41	F	252	30	177
G	264	296	156	G	123	271	100
H	264	116	79	H	235	245	131
I	221	186	187	I	199	182	141
J	227	234	135	J	273	231	170
K	256	103	41	K	243	268	209
L	280	148	144	L	307	169	159
				M	80	56	44

3. Car Fleet Model

The occupancy trends presented in the previous section were obtained by monitoring the car flow in real car parks in Italy. As of early 2024, the number of battery electric vehicles (BEV) in Italy is fewer than 227,000 out of a total of more than 40 million cars [30,31]. Therefore, the current power absorption of car parks is still very modest and could hardly be used to draw realistic projections for the future. Moreover, reliable projections of the evolution of e-mobility power demand patterns require suitable evaluations of the expected trends in EV technologies.

To address these issues, this work developed a procedure to draft an EV fleet model that realistically represents a 2030 scenario. For this purpose, the following steps were undertaken:

1. For some EV categories, the market share expected in 2030 was evaluated;
2. Then, a realistic charging power demand profile for each EV category expected in 2030 was defined;
3. Finally, an approach was developed, based on the expected daily distance covered by EVs and the relevant technical characteristics, to estimate the State of Charge (SoC) of each EV entering the car park.

The EV fleet model obtained with the above-described approach was next used to calculate realistic power exchanges of future car garages with massive penetration of e-mobility.

3.1. Market Share Expected in 2030 by Electric Vehicle Category

To this purpose, the top 40 best-selling EV models from the past 6 years (2018–2023) in Italy were considered, and each one was associated with its respective percentage penetration within the dataset considered (Table 3) [32]. Then, the EV fleet model developed taking the current EV penetration as a reference was adapted to the future 2030 scenario. For this purpose, the expected share of the most popular battery size classes for EVs in 2030 was defined based on [33] (see Table 4). To apply these shares to the vehicle models in Table 3, the present EV fleet was categorized by battery size class, and each vehicle's market penetration was rescaled according to the expected spread of the relevant battery category in 2030. As shown in Table 4, the battery size class expected to grow the most is the 55–65 kWh range, while those expected to decrease the most are the classes with energy capacities below 45 kWh and above 80 kWh. It is interesting to note that the spread of EVs among the population will likely result in mid-class EV models becoming more common than they are today, as they will likely outperform some electric city cars currently available in the <45 kWh class and will be more affordable for the majority of drivers compared to high-end vehicles in the >80 kWh category.

Table 3. Vehicle characteristics and market share.

EV Model	Market Share 2023 (%)	Market Share 2030 (%)	Net Battery Capacity (kWh)	WLTP Consumption (kWh/100 km)	EV Model	Market Share 2023 (%)	Market Share 2030 (%)	Net Battery Capacity (kWh)	WLTP Consumption (kWh/100 km)
Fiat 500e	12.116	11.040	37.3	13.1	Mercedes EQA	1.115	1.598	66.5	17.0
Smart EQ Fortwo	11.159	10.168	16.7	16.4	Smart EQ Forfour	0.927	0.845	16.7	17.3
Tesla Model 3	9.499	11.702	57.5	14.4	Ford Mustang Mach-E	0.883	0.571	91.0	16.9
Renault Zoe	7.640	7.179	52.0	13.7	Skoda Enyaq	0.854	1.052	77.0	15.1
Renault Twingo	5.905	5.381	21.3	15.6	MG 4	0.849	1.046	61.7	16.3
Tesla Model Y	5.634	6.941	57.5	15.7	Citroen e-C4	0.817	0.768	46.3	14.3
Dacia Spring	5.143	4.686	25.0	12.0	Porsche Taycan	0.797	1.142	71.0	21.5
Peugeot e-208	4.239	3.983	46.3	12.0	BMW i4	0.583	0.377	80.7	14.2
Nissan Leaf	3.546	3.231	39.0	17.0	Cupra Born	0.571	0.369	77.0	16.3
Volkswagen ID 3	3.119	3.842	58.0	17.2	Kia Niro	0.540	0.774	64.8	16.2
Volkswagen e-up!	3.042	2.772	32.3	12.7	Audi e-tron	0.489	0.316	85.0	24.1
Opel Corsa-e	2.889	2.715	46.3	16.8	BMW iX	0.470	0.674	71.0	17.6
Hyundai Kona Electric	2.619	3.755	64.0	14.3	Volkswagen ID 5	0.434	0.281	77.0	14.8
Peugeot e-2008	2.297	2.159	46.3	17.3	Tesla Model S	0.429	0.277	95.0	17.5
Mini Cooper SE	1.903	1.734	28.9	15.5	BMW iX3	0.383	0.549	74.0	18.7
Volkswagen ID 4	1.796	1.161	77.0	17.5	Mercedes EQB	0.366	0.525	66.5	18.9
BMW i3	1.653	1.506	37.9	13.1	Volvo XC40 Recharge	0.355	0.230	79.0	18.7
Audi Q4	1.490	0.963	76.6	16.2	Hyundai Ioniq 5	0.353	0.506	74.0	18.5
Renault Megane	1.305	1.608	60.0	13.3	Tesla Model X	0.338	0.218	95.0	19.1
Opel Mokka-e	1.121	1.054	46.3	17.7	Mazda MX-30	0.332	0.303	30.0	19.0

Table 4. Battery size distribution in current and future scenarios.

Battery Size Class (kWh)	Spread 2023	Spread 2030
<45	45.74%	41.67%
45–55	19.01%	17.86%
55–65	20.41%	26.19%
65–80	6.64%	9.52%
>80	8.22%	4.76%

3.2. Initial State of Charge

Since the power drawn from the grid during charging depends on the initial SoC of the EV's battery, it is essential to know the battery's charge percentage when the charging starts. This mainly depends on the vehicle's energy consumption per kilometer ($Cons$), the distance covered since the last recharge ($Dist$), and the SoC at the end of the previous recharge (SoC_{lr}). Therefore, the assumptions explained in the following section were adopted to define these quantities.

For the energy consumption of each EV, the average electric consumption measured using the WLTP method (Worldwide Harmonized Light-Duty Vehicles Test Procedure), which is the EU standard for the measurement of cars' consumption and emissions, was used. This parameter is typically provided by manufacturers and is expressed in kWh/100 km. The data reported in Table 3 were collected [32].

According to [34], the average daily distance covered by cars in Italy is 43 km. To assign a probability distribution to this parameter, data from a study on the driving habits in the Lombardy region of Italy were utilized [35]. The values of distance obtained from the study were properly rescaled so that their average, weighted by the frequency of daily trips, was equal to 43 km. The probability distribution of the daily distances (*Dist*) obtained by this procedure is shown in Figure 3.

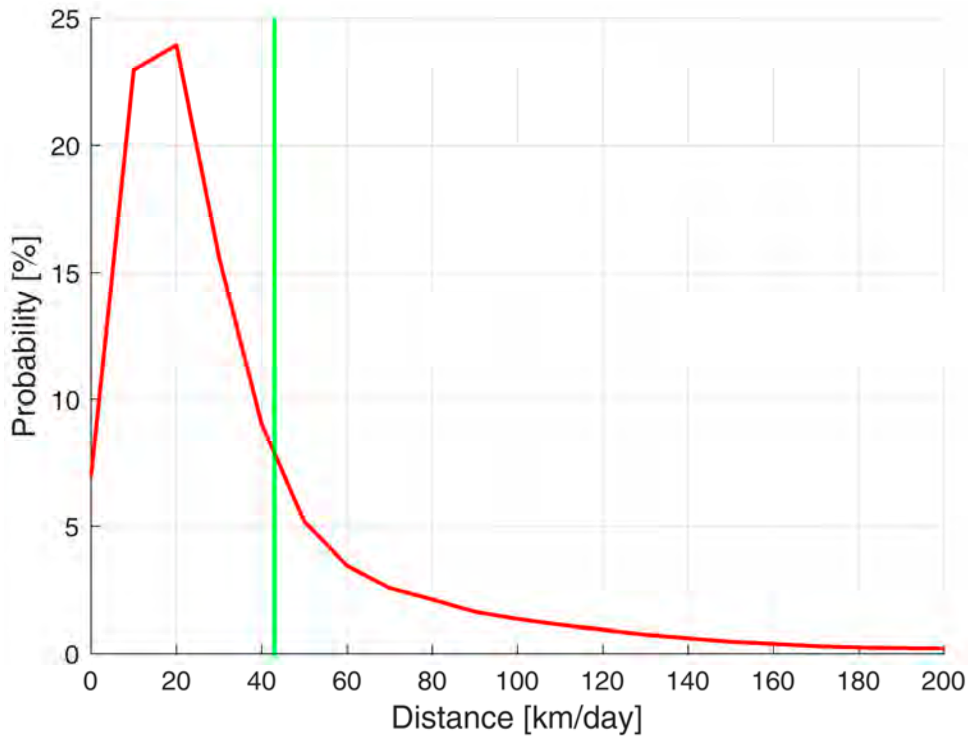

Figure 3. Distribution of the daily distance covered by a driver, in red. In green, the average value.

Concerning the SoC at the end of the last recharge (SoC_{lr}), a random value between 80% and 100% with an even probability distribution was chosen, reflecting the assumption that EVs are near full charge when leaving the previous charging point. This hypothesis is coherent with the common practices described in the literature for EV usage [30]. This has been considered an acceptable simplification, given that a more accurate estimation of the initial SoC would imply a detailed knowledge of many economic and social factors, such as charging tariffs and the availability of home charging, which would be hard to define, especially in a 2030 scenario. For the *i*-th electric vehicle, given the EV's net battery capacity (Cap) and the above-mentioned parameters, the SoC of the vehicle at the start of charging (SoC_{in}) was calculated with the following equation:

$$SoC_{in}(i) = SoC_{lr}(i) - \frac{100 \cdot Cons(i) \cdot Dist(i)}{Cap(i)} \tag{1}$$

3.3. EVs' Charging Power Demand Profiles

Each EV model is characterized by its own charging power profile. Moreover, it is well known in the literature that the SoC of the battery greatly influences the maximum power withdrawal from the grid during charge [36]. This is especially true during the transition from the Constant-Current (CC) charging phase, usually conducted for lithium-ion batteries up to 85% of the charging process, to the Constant-Voltage (CV) phase, which is required to reach the battery's full charge. An example for a real electric car on the market is shown in red in Figure 4.

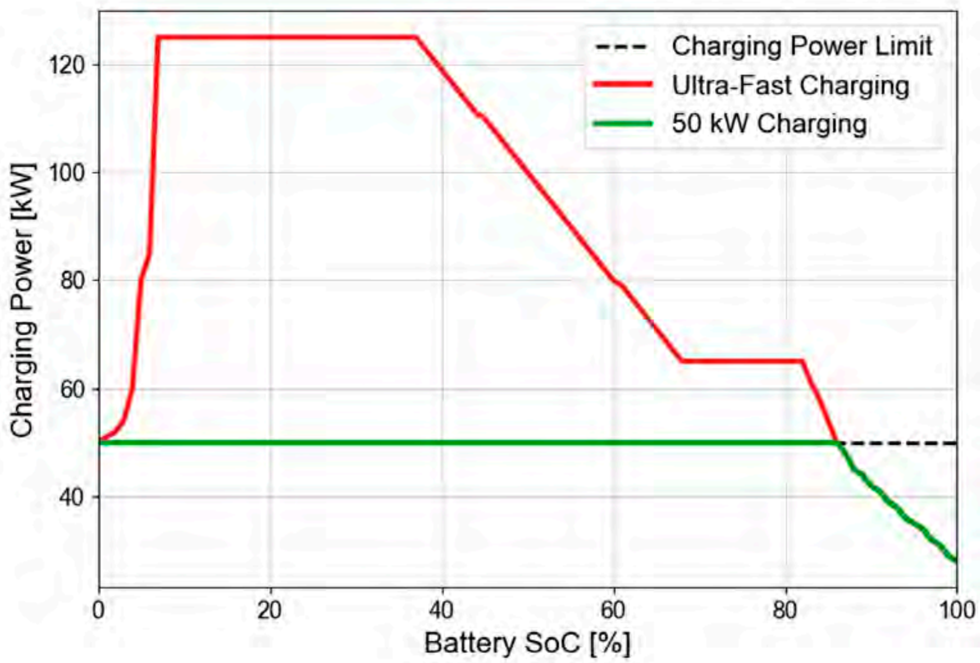

Figure 4. Charging curve of a Cupra Born at 50 kW and ultra-fast charging speed.

The charging curves of the EVs in the representative population considered were obtained from an online database [37], which provides the power withdrawal of each EV model (P_{EV}) as a function of the battery's SoC. Many EVs today require a DC charging station to achieve the fastest charging speed. However, these stations are not always available in public car parks, and sometimes the maximum charging power must be limited to accommodate the power capacity limits of the electricity network infrastructure and the charging station itself. Therefore, a maximum threshold was set for the CP power (P_{CP}). Consequently, the power withdrawn by the vehicle (P_{abs}) was determined as follows:

$$\begin{cases} P_{abs} = P_{EV} & \forall\ P_{EV} \leq P_{CP} \\ P_{abs} = P_{CP} & \forall\ P_{EV} > P_{CP} \end{cases} \tag{2}$$

If P_{EV} is greater than P_{CP}, the power drawn (P_{abs}) is saturated at the maximum power that can be provided by the CP. Otherwise, P_{abs} follows the value of the EV charging curve (P_{EV}). An example of this fact is reported in green in Figure 4, assuming the use of a 50 kW charging station (black dotted line).

4. Evaluation of Car Parks' Power Demand Profiles

After characterizing the EV fleet model, its data were used to calculate the power demand profiles expected in 2030 for the car parks under analysis. To achieve this purpose, the procedure illustrated in Figure 5 was applied to each car park considered for every day of the week (weekdays, Saturday, and Sunday). For a more comprehensive analysis, different maximum charging powers of the charging points available within the car park were considered: specifically, equal to 7.4 kW, 22 kW, 50 kW, and ultra-fast charge (i.e., every vehicle is charged at its maximum withdrawable power). The goal of the numerical procedure was to calculate a cumulative power demand profile for the car park, obtained by summing the power demand requests of each charging EV. For this, a Monte Carlo procedure was utilized to model the various probabilistic factors influencing the EVs' power demand profiles, as explained in Section 3. Monte Carlo algorithms are widely used for simulating the impact of various stochastic parameters on electric power systems. Although other established and reliable approaches exist, the Monte Carlo procedure was chosen in this study as a suitable compromise, because it offers a good balance between result accuracy, ease of implementation, and manageable computational cost.

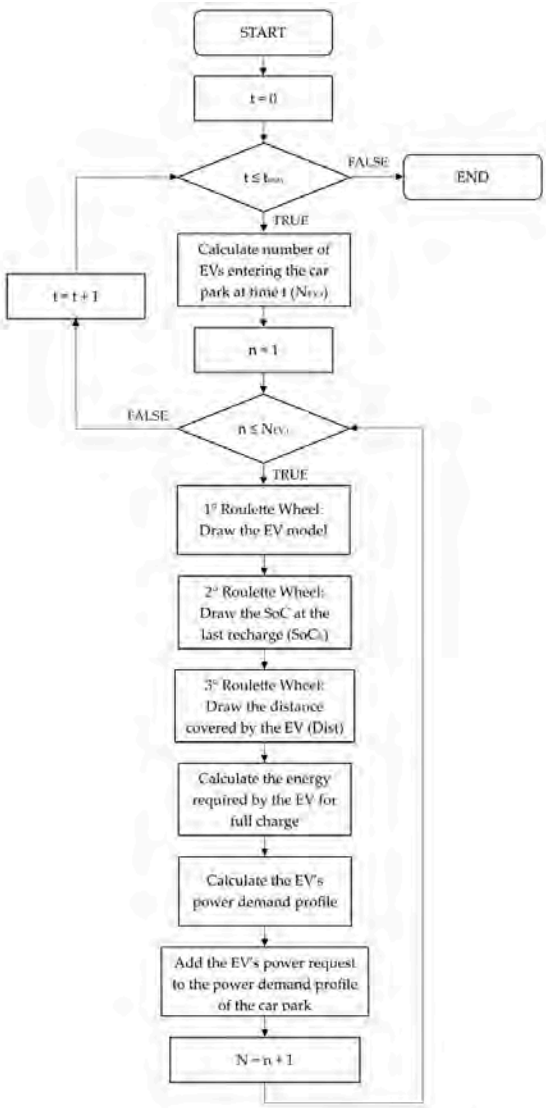

Figure 5. Monte Carlo procedure for power demand profiles' evaluation.

In detail, the procedure outlined in the flowchart of Figure 5 simulates each EV entering the selected car park over time and calculates its power demand based on several probabilistic factors. The simulation begins at time t = 0, representing the start of the simulation period (beginning of the day), and continues until the end of the considered day (simulation time t_{max}). At each timestep t (with 1 min resolution), the number of EVs entering the car park ($N_{EV,t}$) is calculated as the difference between the number of vehicles parked at the previous timestep and the current one. If at least one vehicle is detected entering the car park at that time, the procedure iterates through each identified EV. For each vehicle, a series of draws (i.e., roulette wheels) is performed to determine its characteristics, thereby simulating the diversity of EV models with varying energy needs.

First, the EV model type is randomly selected based on the expected 2030 market share reported in Table 3. Next, a second roulette wheel determines the EV's SoC at the end of its previous recharge (SoC_{lr}, as defined in Section 3.3). This parameter, combined with the distance that the EV traveled before arriving at the car park ($Dist$), as per (1), defines the SoC of the EV's battery (SoC_{in}) upon entry, which, in turn, affects how much energy the EV needs to fully recharge. As already mentioned, an even probability distribution between

80% and 100% is assumed for SoC_{Ir}. Finally, to simulate the diversity in EV users' travel patterns, *Dist* is defined based on the probabilistic distribution in Figure 3.

In the proposed Monte Carlo algorithm, all of the roulette wheel extractions in Figure 3 are performed independently. However, the coherence of the provided values is checked to verify the actual feasibility of the extractions. This is carried out by comparing the distance covered (*Dist*), the EV's initial battery status (SoC_{Ir}), and the overall battery capacity (*Cap*). Incoherent samples are discarded and extracted again.

Once the SoC upon the EV's entry to the car park (SoC_{in}) is calculated, a power demand profile (P_{EV} in Section 3) is assigned to the vehicle based on the energy required to fully recharge the battery. If the required power exceeds the maximum output of the CP (depending on the simulated scenario: 7.4 kW, 22 kW, 50 kW, or infinite for ultra-fast charge), the power absorbed from the grid (P_{abs}) is limited to the CP's maximum power (P_{CP}; see (2)).

Whether the EV remains until fully charged or leaves in advance is determined using the FIFO approach described in Section 2. Specifically, it is assumed that the charging process ends when, starting from the instant of the entry of the considered EV in the garage, a number of vehicles exiting the car park is counted equal to, or greater than, the number of cars entered. If the vehicle leaves before reaching full charge, its contribution to the car park's total power absorption from the network is circumscribed to the actual parking duration.

The EV's power demand resulting from the aforementioned approach is multiplied by three coefficients, which account for the following aspects:

- In 2030, only a small percentage of the vehicles in circulation will be electric. In particular, according to recent estimations, in Italy, an EV penetration of 15% is foreseen by 2030 [38]. Therefore, an equal probability is assumed that any vehicle entering the car park is electric.
- Only a portion of EV owners regularly charge their vehicles at public charging stations. This is a very difficult parameter to estimate, as it depends on several factors, such as users' habits, trip purpose, public recharge cost, etc. Based on [39], this value was set equal to 0.49.
- The data gathered on public car parks pertained to the number of available free parking spots rather than the actual number of vehicles entering/exiting the car park at a given time. Consequently, it is possible that a vehicle's entry may have been missed if it occurred at the same time as another vehicle's exit. According to the investigations performed, this occurrence was quite rare. However, with a conservative approach, to account for any underestimation, the car park's power demand was increased by 10%.

It is important to point out that, rather than estimating a precise value for the aforementioned coefficients, the contribution of the present work to the existing literature especially lies in the numerical procedure developed and the power demand trends obtained. In the authors' opinion, these trends provide a valuable starting point for future research on the impact of e-mobility on the electric power system. In addition, in the case of different hypotheses regarding the aforementioned parameters, it would be sufficient to rescale the power demand according to the new assumptions.

Once all EVs entering at time t have been processed, the simulation advances to the next timestep (t = t + 1) until the end of the day is reached. Concerning the vehicles entering during the last minutes of the day, charging may extend beyond 24 h; in this case, the EV's power demand profile is added to the car park's request of the following day.

By repeating the steps described for each vehicle entering every minute of the day and summing the relevant power demand profiles, the daily power demand curve for the simulated scenario is obtained.

Given the probabilistic nature of the approach, the results vary with each run of the numerical procedure. Therefore, multiple Monte Carlo scenarios were created, each providing a different power demand profile for a given car park. In this way, a probabilistic characterization of the scenario under study was achieved. Specifically, a number of Monte Carlo scenarios equal to 100 was assumed as a suitable trade-off between the accuracy of the results obtained and the computational time.

5. Simulation Results and Discussion

The procedure described in Sections 3 and 4 was applied to data collected from public car parks in the Italian cities of Brescia and Florence (Section 2), obtaining probabilistic demand power profiles of the parking garages for representative days of the year (weekdays, Saturdays, and Sundays) in a 2030 scenario. The influence of the maximum charging power output of the CPs on the power absorption was also taken into account, simulating cases with 7.4 kW, 22 kW, 50 kW, and ultra-fast charging.

All power profiles resulting from the application of the approach are reported in Appendix B. In the charts, the blue color is used for the power trends obtained from each of the 100 Monte Carlo scenarios, while the red color represents the average value calculated.

In this section, the most relevant aspects of the obtained results are discussed. To this end, some representative power demand patterns among all those calculated are analyzed. For a more general discussion, one car park from each of the following categories is considered: car parks (i) in city centers, (ii) near a railway station, (iii) near a hospital, and (iv) in business areas. Regarding car parks located in the city center, Figure 6 shows the curves obtained for the "Brescia A" parking, with a CP maximum output power of 7.4 kW, as an example. It can be observed that this car park, along with the others in the same categories, generally exhibits peak power demand in the early morning, especially on weekdays and Saturdays. This is due to increased urban travel related to working and commercial activities in the city center. On Sunday mornings, the peak is lower and delayed by about one hour. Additionally, an evening peak appears on Sundays, which is most likely related to travel for leisure activities.

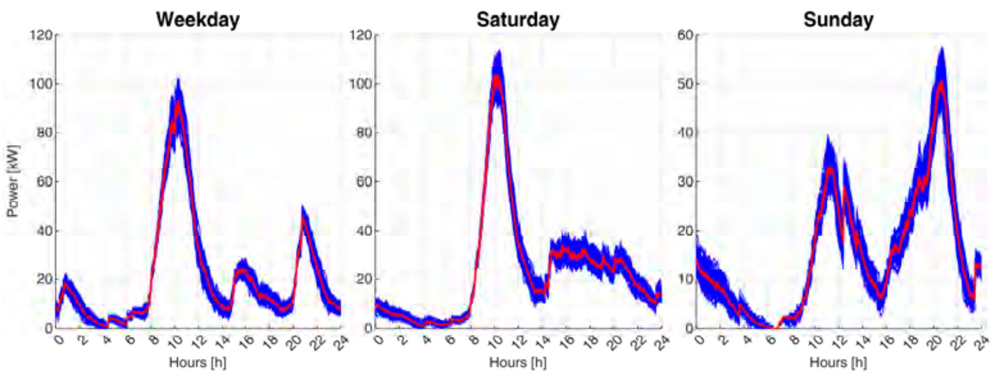

Figure 6. Monte Carlo power demand curves (in blue) of "Brescia A" parking—max. CP output power of 7.4 kW. The average value is shown in red.

For car parks near railway stations, the example of "Florence A" parking is considered, which is shown in Figure 7. On all days of the week, the power demand of these car parks usually has a peak in the morning, when most travelers arrive at the station. The stay usually lasts until the end of the business day. For the car park considered, similar trends are also observed on Saturdays and Sundays. This is most likely due to the tourist appeal of Florence, which keeps railway stations busy even on weekends.

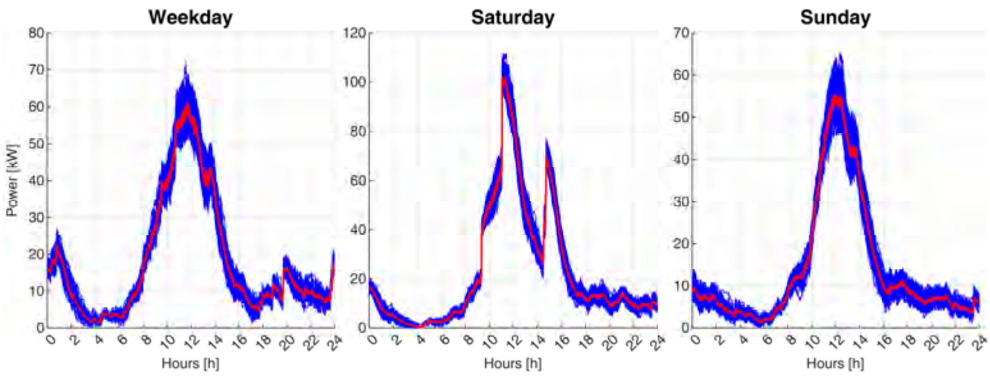

Figure 7. Monte Carlo power demand curves (in blue) of "Florence A" parking—max. CP output power of 7.4 kW. The average value is shown in red.

Regarding car parks near hospitals, their daily profiles can vary widely depending on the specific location and the day of the week. Figure 8 provides an example of the public "Brescia B" parking. A common characteristic of this car park's category is that the power demand profiles tend to concentrate on specific hours of the day, likely corresponding to the hospital's service hours.

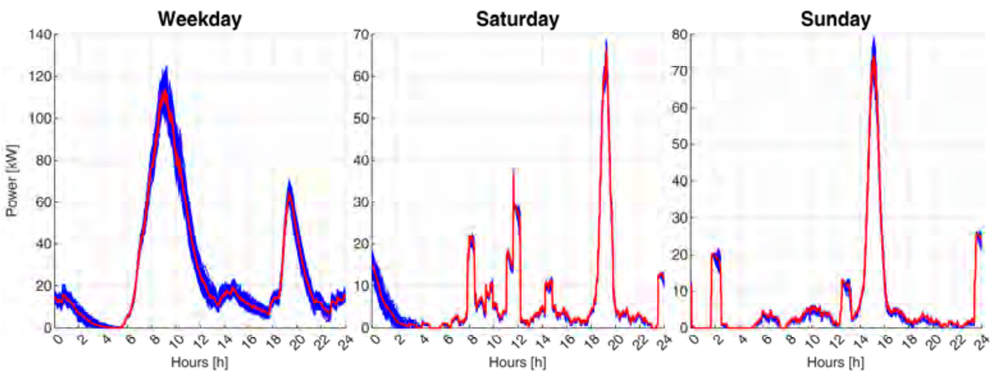

Figure 8. Monte Carlo power demand curves (in blue) of "Brescia B" parking—max. CP output power of 7.4 kW. The average value is shown in red.

Lastly, car parks in business areas show higher power demand on weekdays, especially in the early morning, reflecting work-related travel patterns. In contrast, the power demand is low and evenly spread throughout the day on weekends. Figure 9 provides an example of the curves for the "Brescia I" parking, with a CP output power of 7.4 kW.

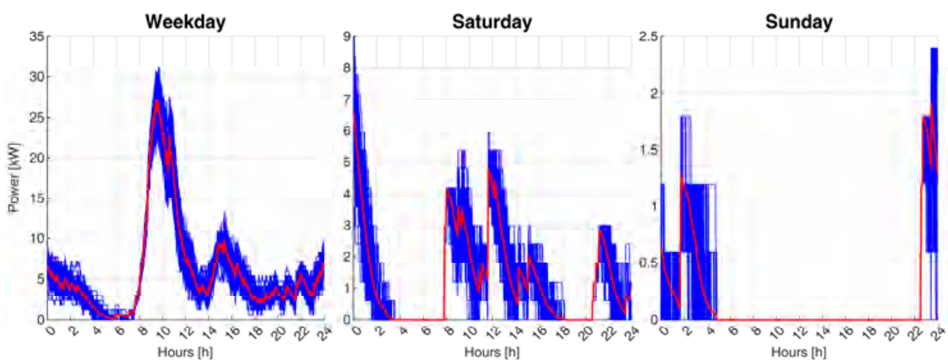

Figure 9. Monte Carlo power demand curves (in blue) of "Brescia I" parking—max. CP output power of 7.4 kW. The average value is shown in red.

For a better understanding of the results obtained by the developed procedure, Table 5 reports the main statistical parameters that characterize the power demand patterns in this study, assuming a maximum output power of 7.4 kW for the CPs. Specifically, the table shows the average and maximum values obtained over the observation period (AVG and MAX, respectively) and the mean standard deviation calculated over the simulated 100 Monte Carlo scenarios (STD).

Table 5. Power demand trends' statistical parameters—max. CP output power of 7.4 kW. All values are in kW.

Car Park		Weekday			Saturday			Sunday		
		AVG	MAX	STD	AVG	MAX	STD	AVG	MAX	STD
Brescia	A	21.39	93.54	1.80	23.79	104.53	1.84	15.18	50.85	1.46
	B	26.62	114.98	1.92	7.01	66.73	0.39	6.76	75.11	0.35
	C	11.18	55.04	1.21	2.09	18.84	0.17	2.23	25.24	0.18
	D	9.86	38.63	1.20	15.83	60.60	1.51	9.39	34.81	1.17
	E	0.91	3.15	0.32	1.67	5.37	0.40	0.33	2.18	0.06
	F	0.21	2.73	0.06	0.83	4.19	0.26	0.13	1.20	0.04
	G	25.69	104.09	1.98	13.49	42.10	1.46	14.87	45.23	1.50
	H	15.34	91.12	1.40	5.80	22.98	0.79	2.91	19.38	0.41
	I	6.05	27.30	0.95	1.29	6.66	0.38	0.19	1.93	0.08
	J	10.80	31.04	1.29	15.06	45.70	1.54	5.87	16.68	0.90
	K	3.96	18.50	0.76	2.24	10.07	0.44	1.23	9.07	0.14
	L	11.07	44.73	1.30	4.84	14.79	0.81	5.56	23.70	0.85
Florence	A	18.18	61.45	1.65	22.61	103.25	1.78	14.18	55.67	1.47
	B	6.55	26.40	0.94	9.54	31.89	1.21	7.01	21.92	1.05
	C	3.40	10.88	0.74	4.53	11.68	0.86	3.98	11.25	0.79
	D	16.46	83.66	1.49	29.23	107.04	2.11	10.48	34.29	1.28
	E	8.29	46.31	1.02	8.91	39.54	1.13	5.36	22.77	0.87
	F	9.25	36.95	1.18	3.56	10.64	0.25	7.89	18.12	1.05
	G	4.26	10.88	0.74	4.78	15.59	0.85	3.12	6.94	0.60
	H	12.21	41.84	1.36	9.87	28.78	1.26	7.03	33.44	0.91
	I	5.06	14.95	0.85	5.84	15.04	0.94	5.55	18.39	0.86
	J	7.22	26.85	1.00	7.98	21.62	1.05	5.70	16.72	0.92
	K	20.72	99.50	1.67	8.25	32.33	1.07	7.70	16.21	1.17
	L	24.61	141.45	1.77	11.53	45.84	1.28	9.56	51.26	1.15
	M	1.70	9.99	0.31	0.98	4.38	0.15	0.68	4.78	0.09

Despite the variations observed across the analyzed scenarios, most car parks present a higher power demand in the morning when people travel from home to public places. Moreover, the results of this study show that the total power demand of a car park is only slightly influenced by the total admissible output of each charging point: while a greater maximum CP power allows for increasing the peak power absorption of the individual EV from the network, a higher recharge power shortens the time required to reach full charge. This, in turn, reduces the probability of simultaneous charging requests from the grid. In general, however, the results of the simulations confirm that fast and ultra-fast charging is expected to cause greater variability in car parks' power demand and, thus, could lead to issues if the electrical grid is not designed properly. These facts are highlighted in the example of Figure 10, where the power demand curves of "Brescia A" parking, obtained with different maximum CP output powers, are reported.

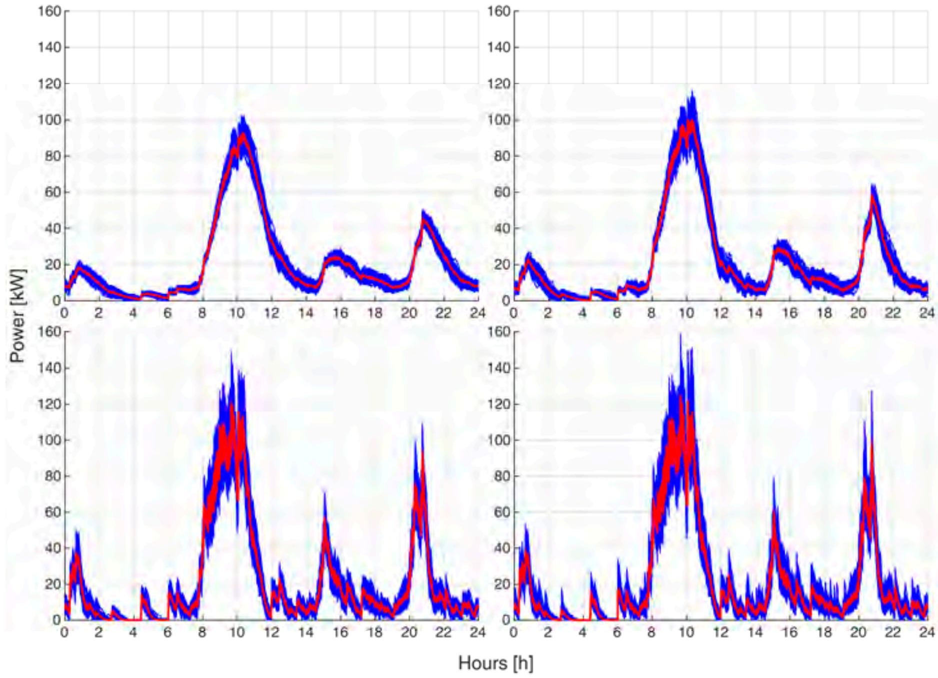

Figure 10. Power demand curves of "Brescia A" parking for different maximum CP output powers (7.4 kW at **upper left**, 22 kW at **upper right**, 50 kW at **lower left**, ultra-fast charge at **lower right**). Monte Carlo samples are in blue; the average values are in red.

Finally, some considerations must be made regarding the influence of the maximum output power of charging stations on car parks' peak demand. In this regard, Figure 11 shows the peak value of the mean power demand calculated in the Monte Carlo scenarios for all analyzed car parks on weekdays (peak of red trends in Appendix B), as a function of the maximum output power of the CPs. Data are reported in terms of the increase in the daily peak power compared to the same quantity recorded with a 7.4 kW maximum charging power. Results relevant to individual car parks are represented in blue, while the average value obtained for all car parks is shown in red.

The results shown in the figure highlight that the peak power demand of car parks equipped with ultra-fast charging points is, on average, 65% higher than that with 7.4 kW CPs. The extent to which maximum charging power affects the power absorption profiles of parking garages largely depends on the characteristics of each car park. In the worst case analyzed, which pertains to the "Brescia E" parking, a 210% increase in peak power was recorded. It is important to note that, according to the collected data (see Appendix A), this car park experiences very low vehicle traffic during the day. Therefore, in such a case, the increase in the maximum charging power of the individual CP has a significant impact on the overall power absorption of the garage. On the other hand, car parks with high daily traffic show a much smaller increase in total peak power (in some cases, even ranging between +30% and 40% of the power obtained with slow charging); in these scenarios, CPs with higher maximum charging power can likely satisfy more users, with a modest impact on overall power demand.

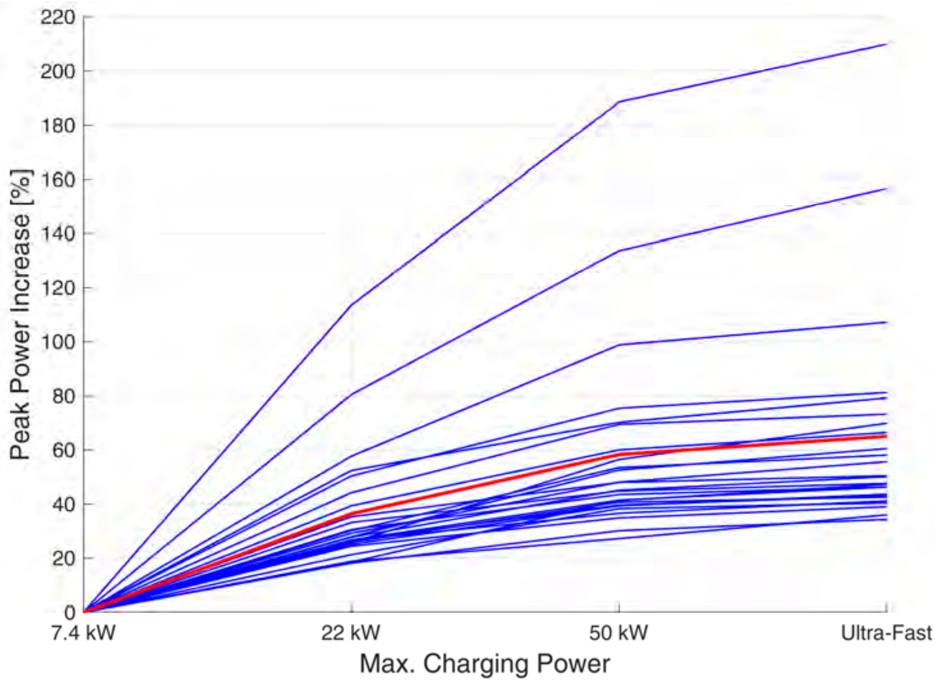

Figure 11. Peak power increase [%] measured on weekdays compared to the scenario with a 7.4 kW maximum power output of the CPs. The average value obtained in the 100 Monte Carlo scenarios is shown in blue, while the average peak power increase is shown in red.

5.1. Comparison with the Approaches in the Existing Literature

To demonstrate the ability of the proposed approach to model the unique characteristics of car parks in real scenarios, in this section, the results obtained in the present study are compared with those from the RAMP-Mobility model, which is an open-access approach available in the literature [28]. As discussed in the literature review, the RAMP-Mobility model is designed to simulate the aggregate mobility and charging patterns at a national level; hence, it cannot capture the different demand patterns that appear with the model proposed in this work. This is clearly shown in Figure 12, which provides a comparison between the probabilistic charging demand obtained by the procedure developed in our study (in blue) and the results obtained adopting the RAMP-Mobility model (in orange) for the "Florence A" car park. Simulations were carried out by adopting the same number of EVs (see Appendix A.2) and charging power (7.4 kW). For our model, the figure shows the average power demand profile, while for the RAMP-Mobility approach, the interquartile range is also shown through the colored area. One can observe that both models exhibit a similar peak power of around 62 kW, differing by less than 3%. However, the RAMP-Mobility model is designed to simulate the overall national mobility usage; therefore, charging requests are more evenly distributed throughout the day. In contrast, the proposed model aligns with daily car park occupancy patterns (see Appendix A.2). This comparison shows that using uncalibrated and not specifically designed models can lead to inaccurate evaluations of car parks' power demand. This flaw can lead to many adverse effects, such as an inaccurate estimation of the peak power required from the main power network, which may subsequently result in poor distribution network planning.

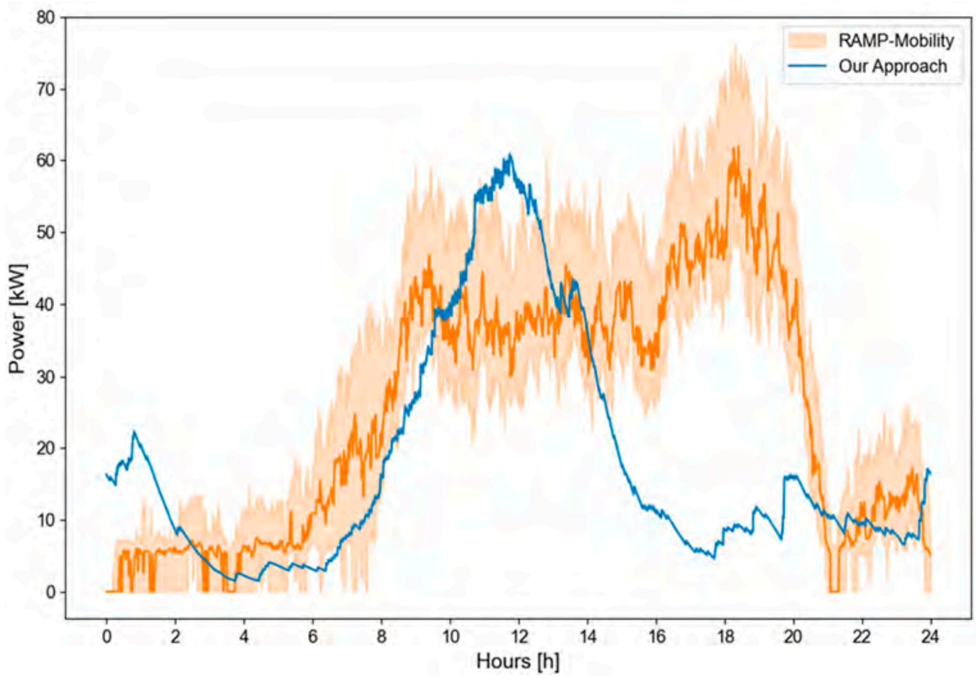

Figure 12. Comparison between the power demand curves of the "Florence A" car park on weekdays, obtained with our approach (average value, in blue) and the RAMP-Mobility model (orange). Max. CP output power of 7.4 kW. For RAMP-Mobility model, the interquartile range is shown through the orange-colored area.

5.2. Main Takeaways for Stakeholders

The results of this study provide important information for distribution system operators, urban planners, and policymakers.

In the presence of a significant EV penetration, the variability in car parks' power demand profiles must be carefully taken into account for properly sizing and developing the electrical distribution network, both in terms of value and time of occurrence of the power peaks. In particular, the numerical simulations performed showed that, for a correct dimensioning, the distribution grid's assets must be capable of withstanding a peak power usually of 3–4 times the average value. The maximum charging power has a great impact on the maximum amount of power required by car parks: with ultra-fast charging, the peaks are, on average, 65% higher than with slow charging points. The time when the maximum value of the daily power trends occurs depends strongly on the urban activities in the proximity of the car park, because they influence the occupancy rates of the parking garages at the different hours of the day. The highest attendance is generally observed during the central hours of the day or in the late afternoon.

In order to support the increasing adoption of e-mobility, it is essential to limit the relevant costs for grid expansion. Therefore, as a possible hint for city planners and policymakers, it would be useful to implement strategies to reduce the peak power of car parks based on a time-shifting of the EV recharge requests. This could be achieved, for example, by adopting variable charging tariffs over the day, or even by offering discounts on the parking cost at particular hours of the day. In addition, a slow charging power should always be preferred every time there is no urgency to accomplish the charging process. Charging tariffs currently in place in many countries are already designed in this direction.

In addition, to reduce the impact of charging requests on the electric power system, urban planners should implement initiatives to support the matching of power demand and generation. For this purpose, incentives for car park managers to foster the installation of dispersed generation power plants (e.g., photovoltaic) could be an option. As an alternative, or in a complementary manner, the creation of energy communities involving charging point operators and distributed generation owners could also be effective. In this regard, particular attention should be given to car parks that exhibit power peaks in the evening, because they could be marginally reduced by photovoltaic production, i.e., the main distributed energy resource available in urban contexts. In this case, peak-shaving strategies performed through energy storage systems could help.

6. Conclusions

Modeling driving patterns across a city is a highly challenging task. As a result, today, there is a notable gap in the literature regarding approaches capable of accurately estimating the impact of e-mobility charging requests on electrical grids, especially in future scenarios. This work aimed to address that gap, by producing realistic demand profiles that can be used in future evaluations of the impact of public charging on the electrical grid.

In addition, this research demonstrates that public charging demand is not a phenomenon that can be encapsulated in a single representative scenario, even if similar power demand trends can be observed among car parks located in comparable urban areas. This also allowed us to highlight that some periods of the day, such as weekday mornings, could be more prone to issues caused by a significant increase in power demand.

While the specific results are tied to the particular situation under examination, thanks to its adaptability, the methodology provided in this study can be extended to different urban contexts and any future scenario. Therefore, the developed methodology provides valuable insights into the impact of EV charging infrastructure on power grids, especially at the distribution level, offering a framework for future analysis. Additionally, these findings can guide urban planners and utility companies in optimizing the placement and capacity of public charging stations, while minimizing the strain on electrical networks.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su17031028/s1, S1: occupancy and power profiles data.

Author Contributions: Conceptualization, M.B., D.F. and F.G.; methodology, M.B., D.F. and F.G.; software, M.B. and D.F.; validation, M.B., D.F. and F.G.; formal analysis, M.B. and D.F.; investigation, M.B., D.F. and F.G.; resources, D.F.; data curation, M.B. and D.F.; writing—original draft preparation, M.B. and D.F.; writing—review and editing, D.F. and F.G.; visualization, D.F.; supervision, D.F.; project administration, D.F.; funding acquisition, D.F. and F.G. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A.1. Daily Occupancy Patterns—Brescia Car Parks

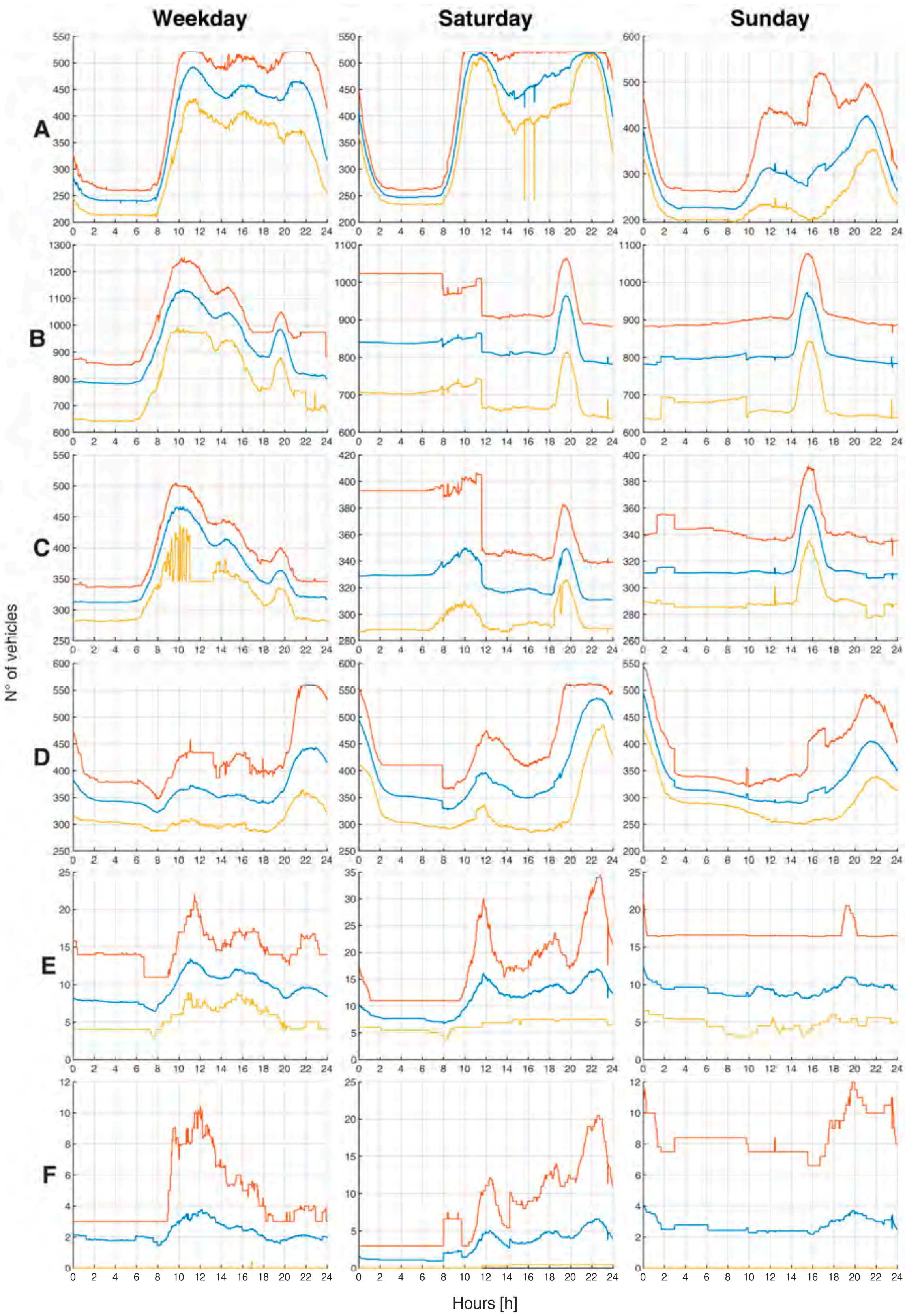

Figure A1. Occupancy patterns for (**A**–**F**) Brescia car parks. The average value is shown in blue, while 10th and 90th percentiles are represented in yellow and orange, respectively.

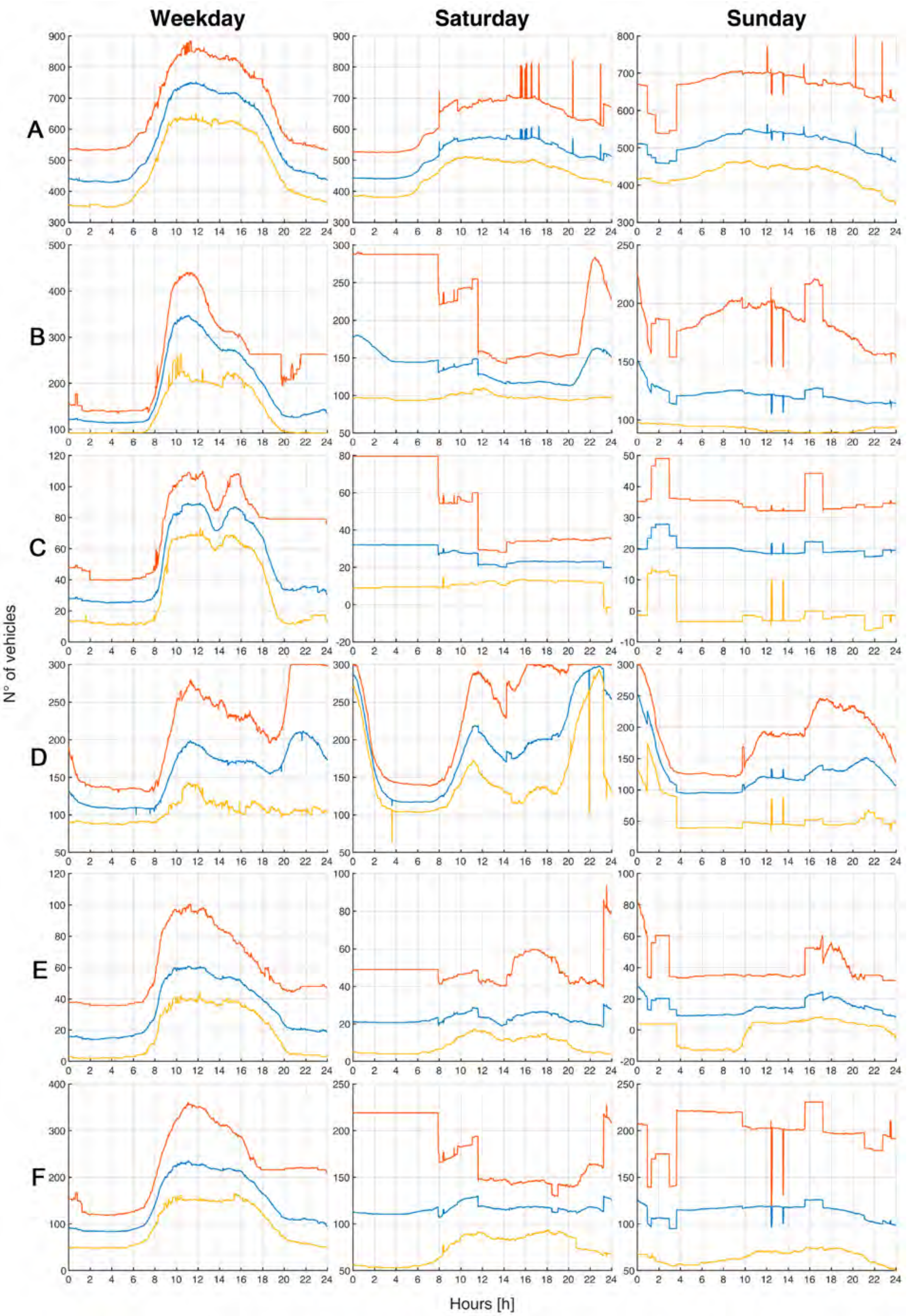

Figure A2. Occupancy patterns for (**A**–**F**) Brescia car parks. The average value is shown in blue, while 10th and 90th percentiles are represented in yellow and orange, respectively.

Appendix A.2. Daily Occupancy Patterns—Florence Car Parks

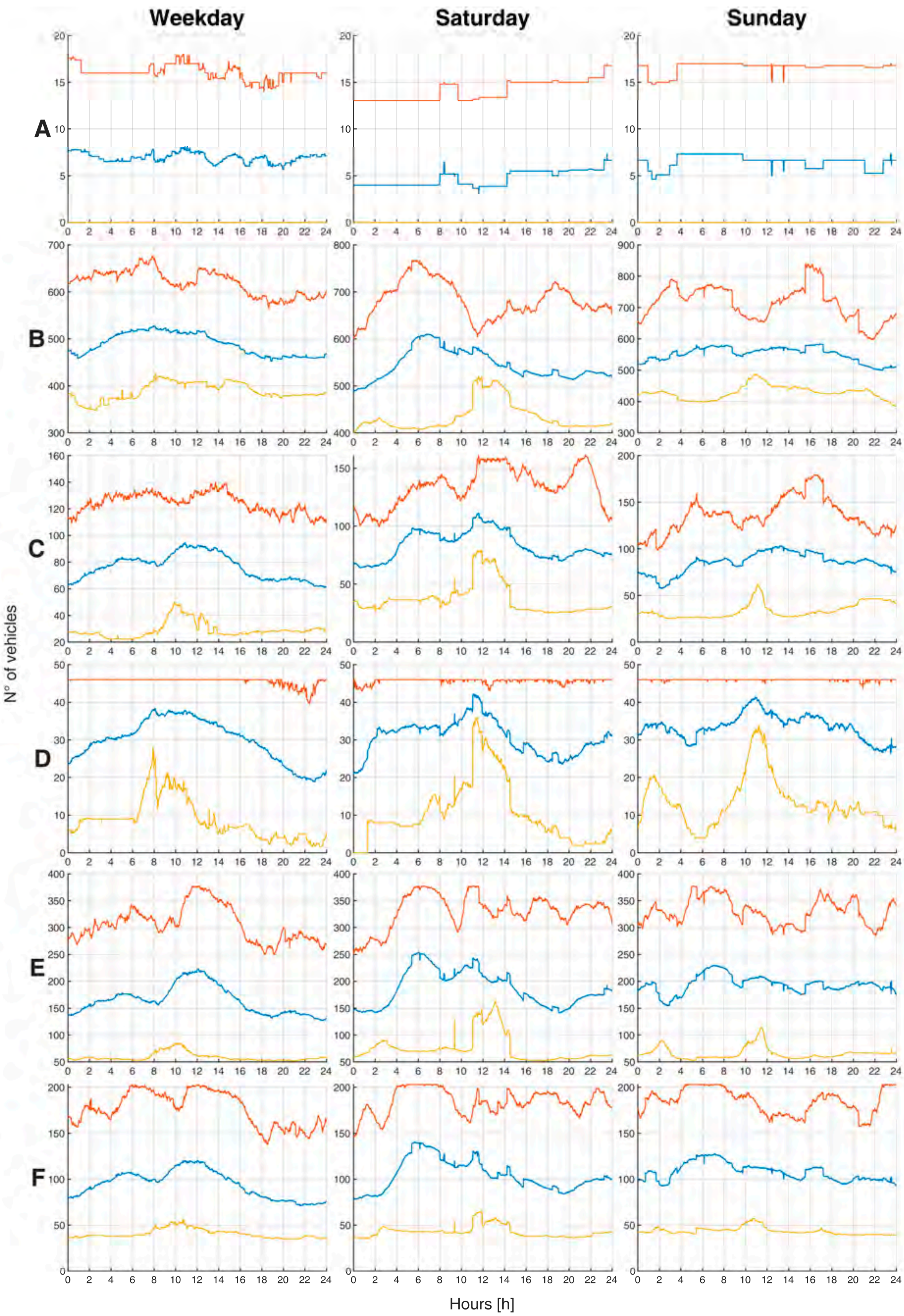

Figure A3. Occupancy patterns for (**A**–**F**) Florence car parks. The average value is shown in blue, while 10th and 90th percentiles are represented in yellow and orange, respectively.

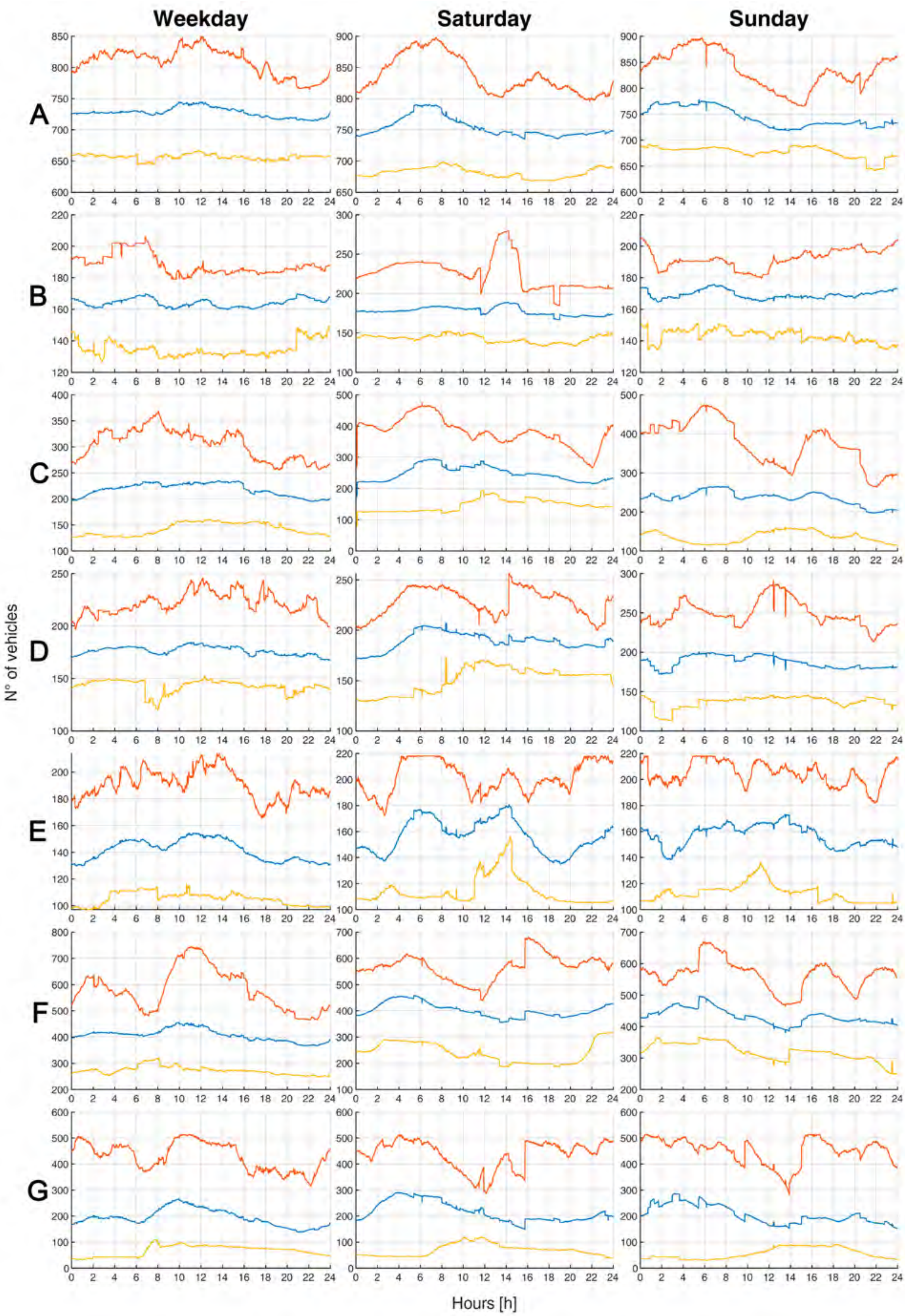

Figure A4. Occupancy patterns for (**A**–**G**) Florence car parks. The average value is shown in blue, while 10th and 90th percentiles are represented in yellow and orange, respectively.

Appendix B

Appendix B.1. Power Demand Patterns—Brescia Car Parks—Max. Charging Power 7.4 kW

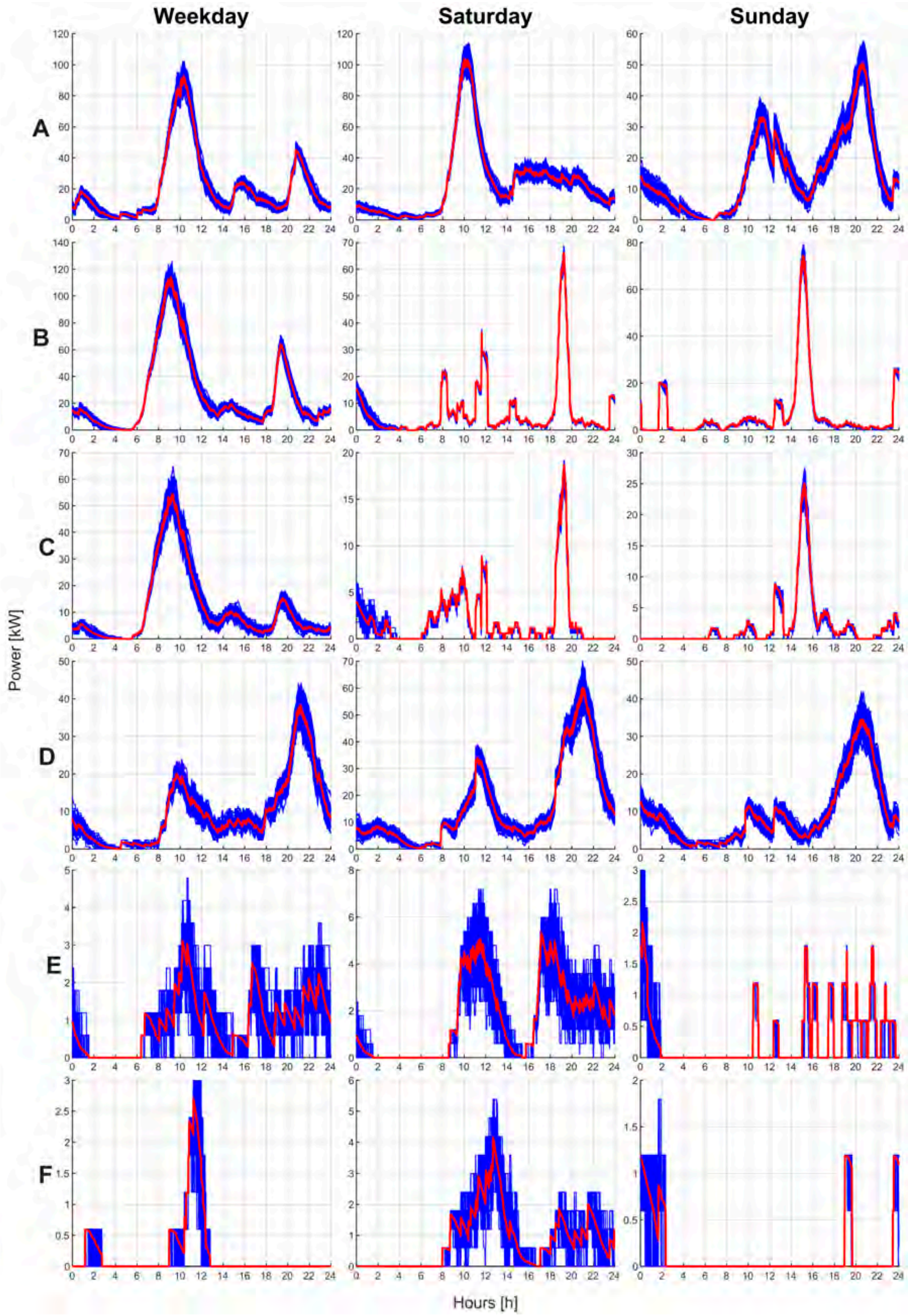

Figure A5. Monte Carlo power demand curves (in blue) for (**A**–**F**) Brescia car parks—max. CP output power of 7.4 kW. The average value is shown in red.

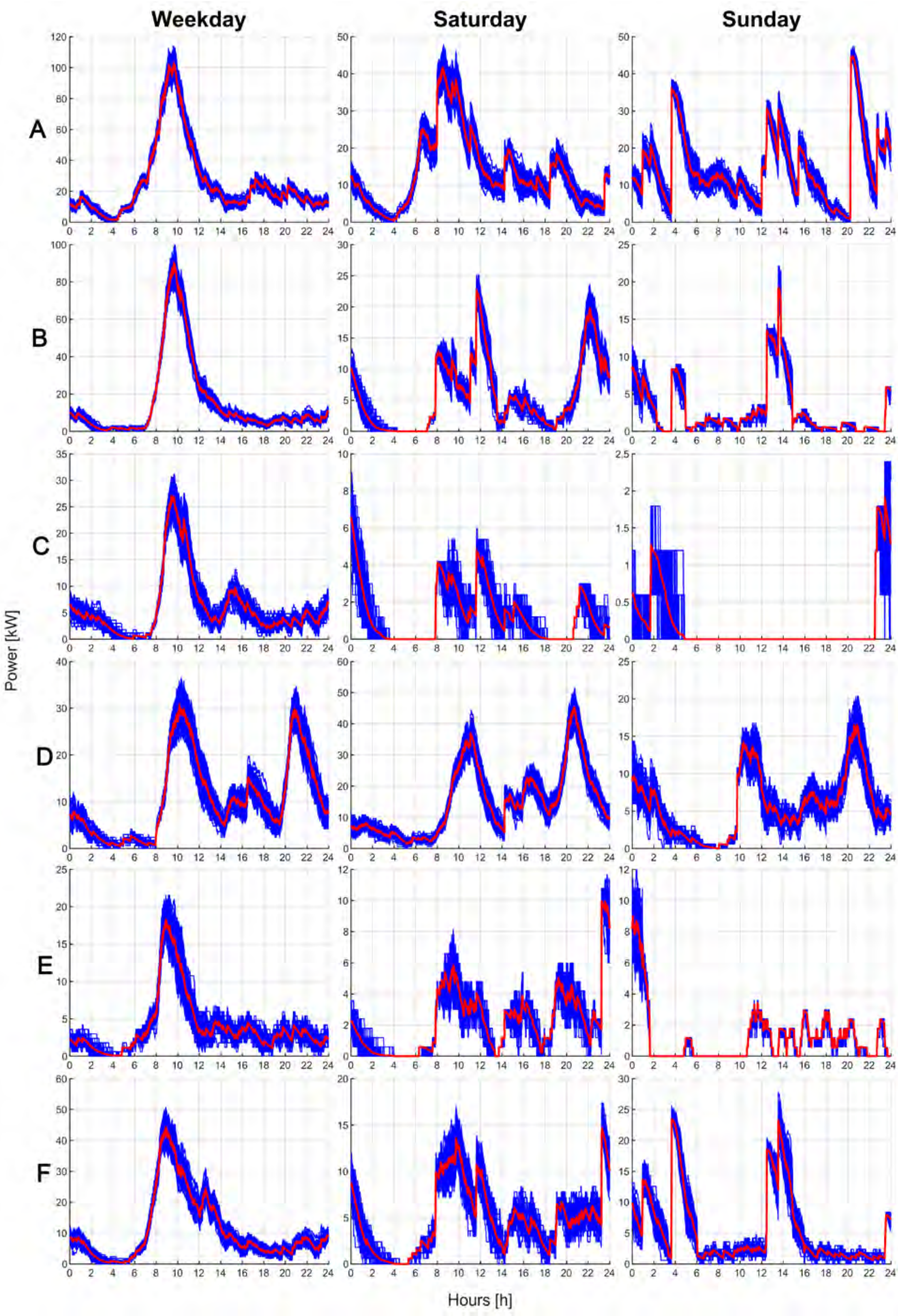

Figure A6. Monte Carlo power demand curves (in blue) for (**A**–**F**) Brescia car parks—max. CP output power of 7.4 kW. The average value is shown in red.

Appendix B.2. Power Demand Patterns—Florence Car Parks—Max. Charging Power 7.4 kW

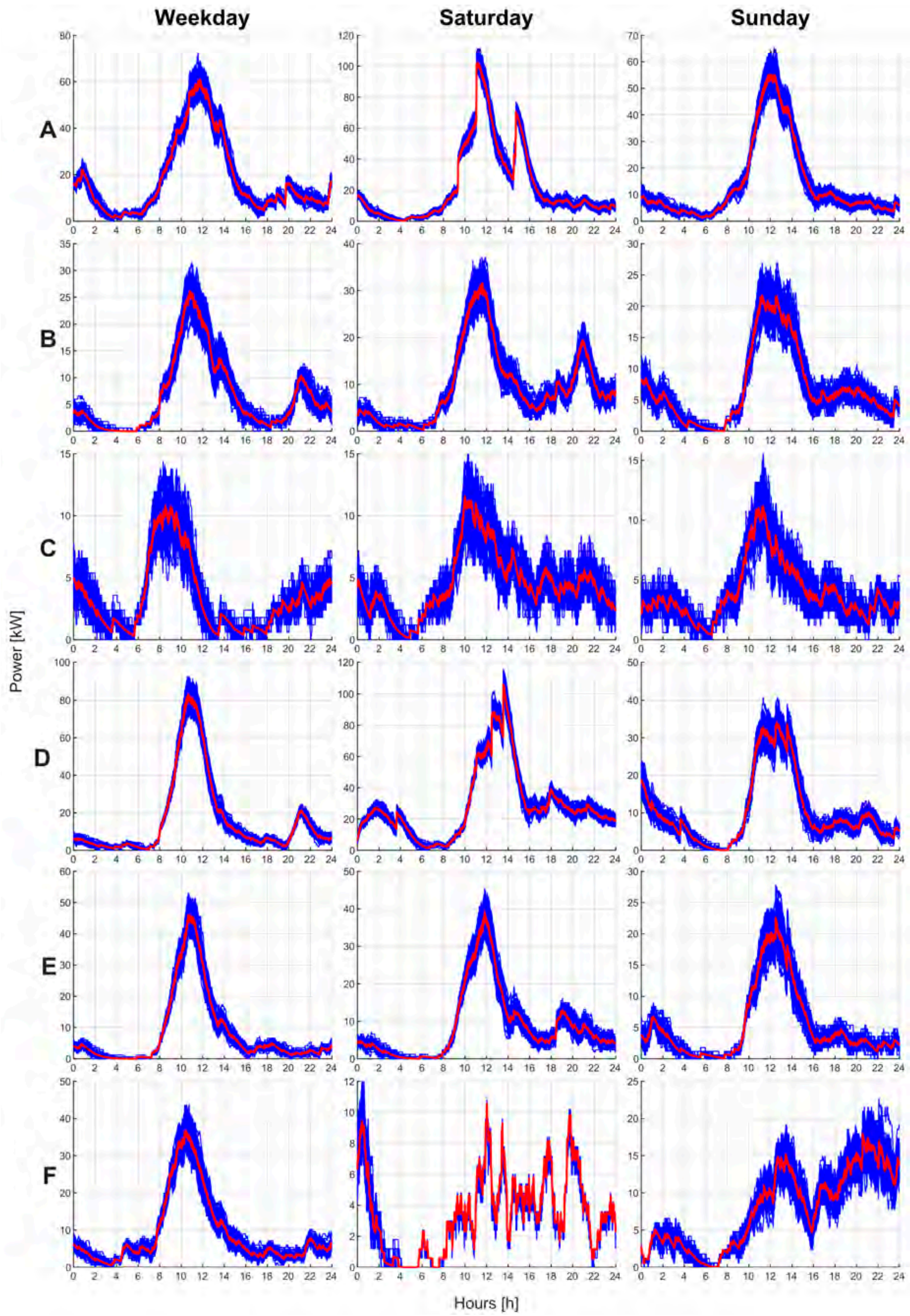

Figure A7. Monte Carlo power demand curves (in blue) for (**A**–**F**) Florence car parks—max. CP output power of 22 kW. The average value is shown in red.

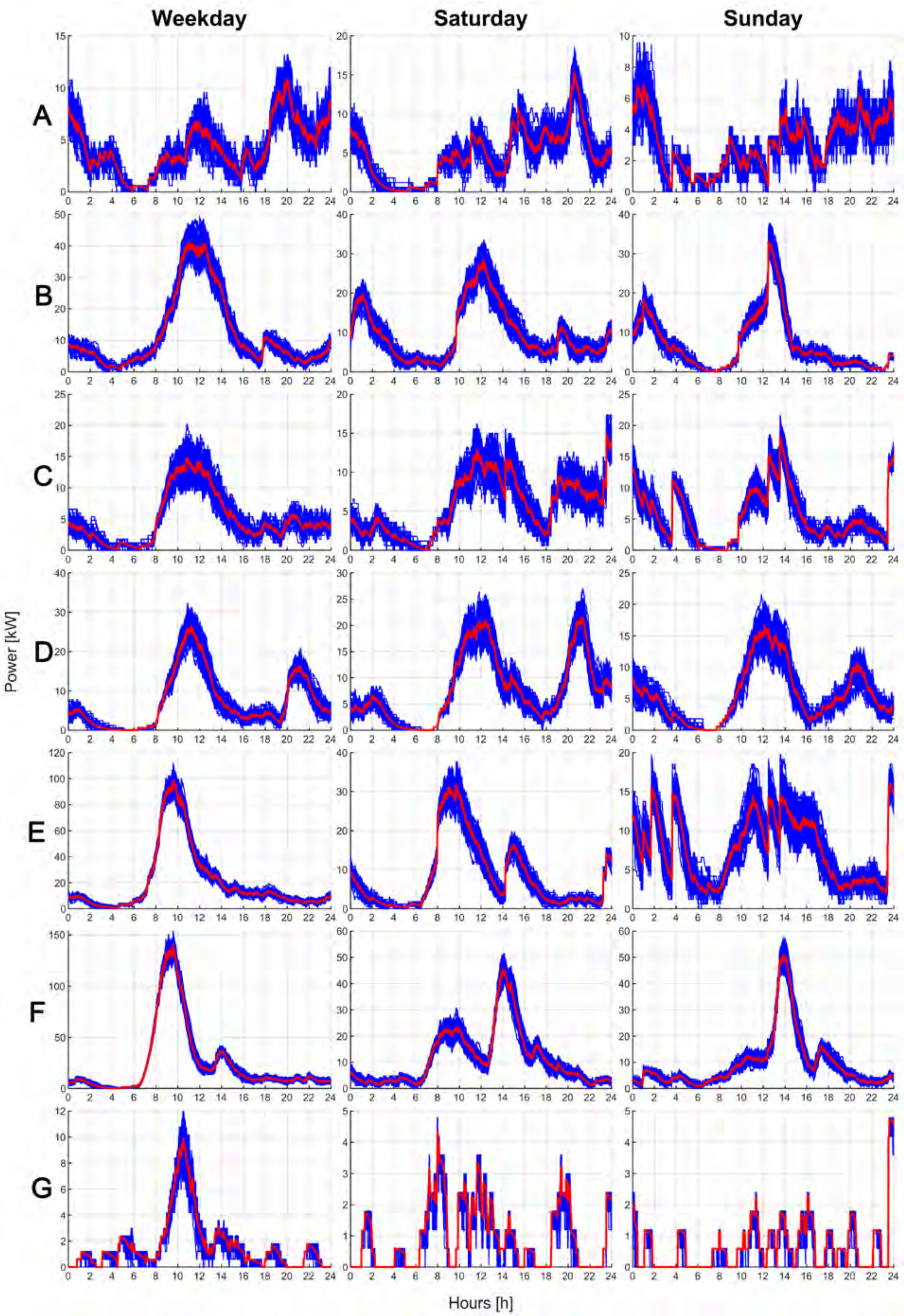

Figure A8. Monte Carlo power demand curves (in blue) for (**A**–**G**) Florence car parks—max. CP output power of 22 kW. The average value is shown in red.

Appendix B.3. Power Demand Patterns—Brescia Car Parks—Max. Charging Power 22 kW

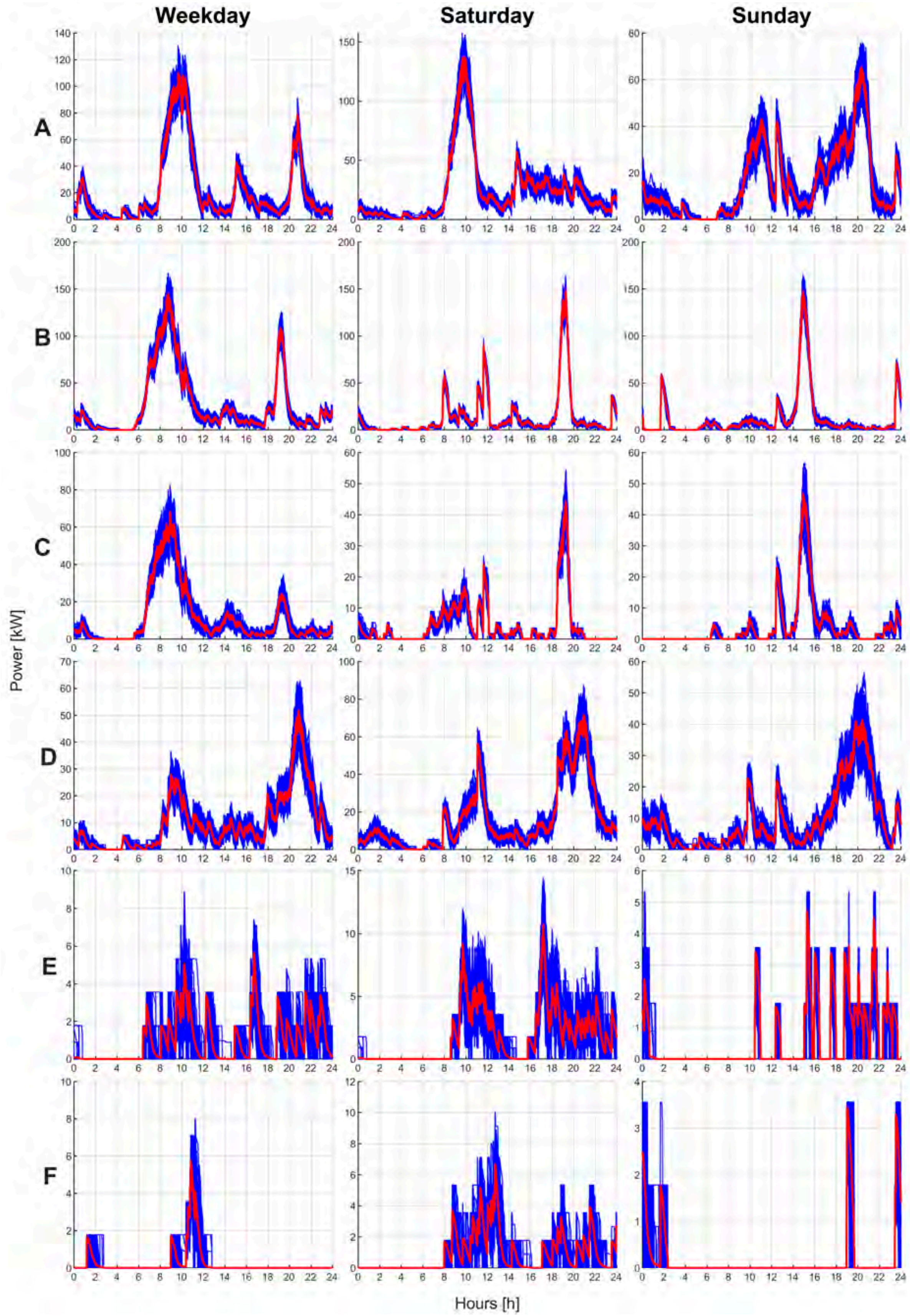

Figure A9. Monte Carlo power demand curves (in blue) for (**A**–**F**) Brescia car parks—max. CP output power of 22 kW. The average value is shown in red.

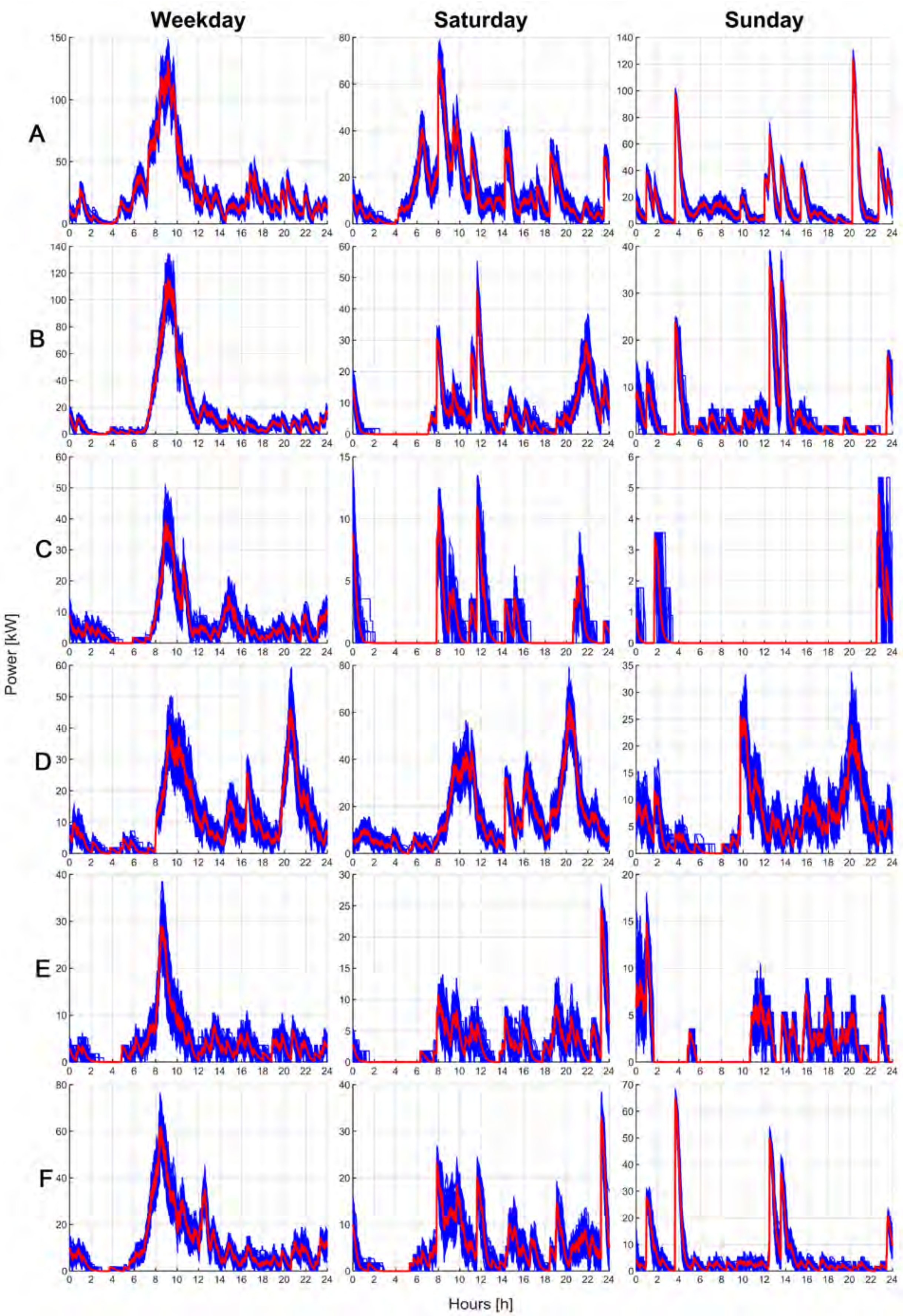

Figure A10. Monte Carlo power demand curves (in blue) for (**A**–**F**) Brescia car parks—max. CP output power of 22 kW. The average value is shown in red.

Appendix B.4. Power Demand Patterns—Florence Car Parks—Max. Charging Power 22 kW

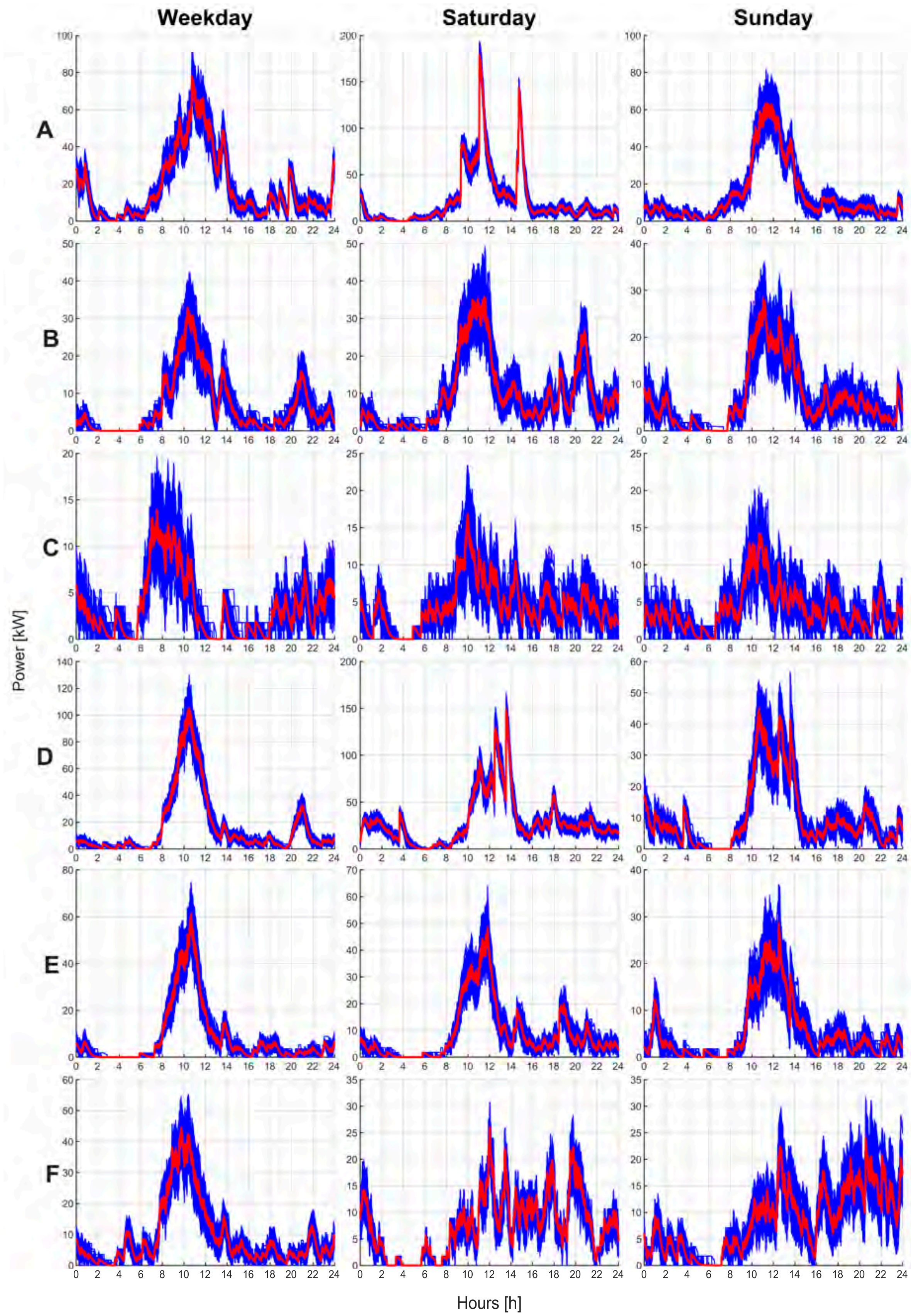

Figure A11. Monte Carlo power demand curves (in blue) for (**A**–**F**) Florence car parks—max. CP output power of 22 kW. The average value is shown in red.

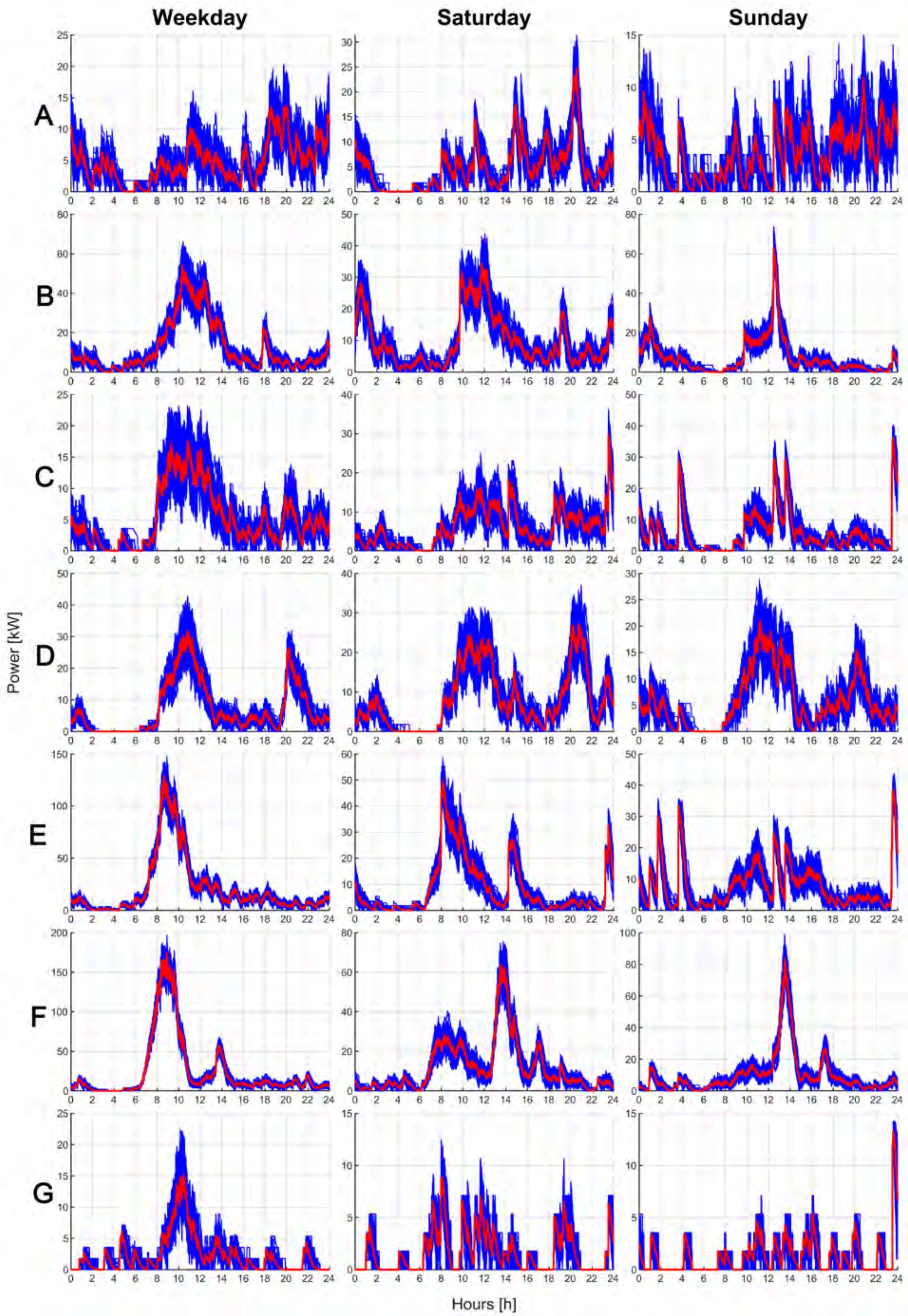

Figure A12. Monte Carlo power demand curves (in blue) for (**A**–**G**) Florence car parks—max. CP output power of 22 kW. The average value is shown in red.

Appendix B.5. Power Demand Patterns—Brescia Car Parks—Max. Charging Power 50 kW

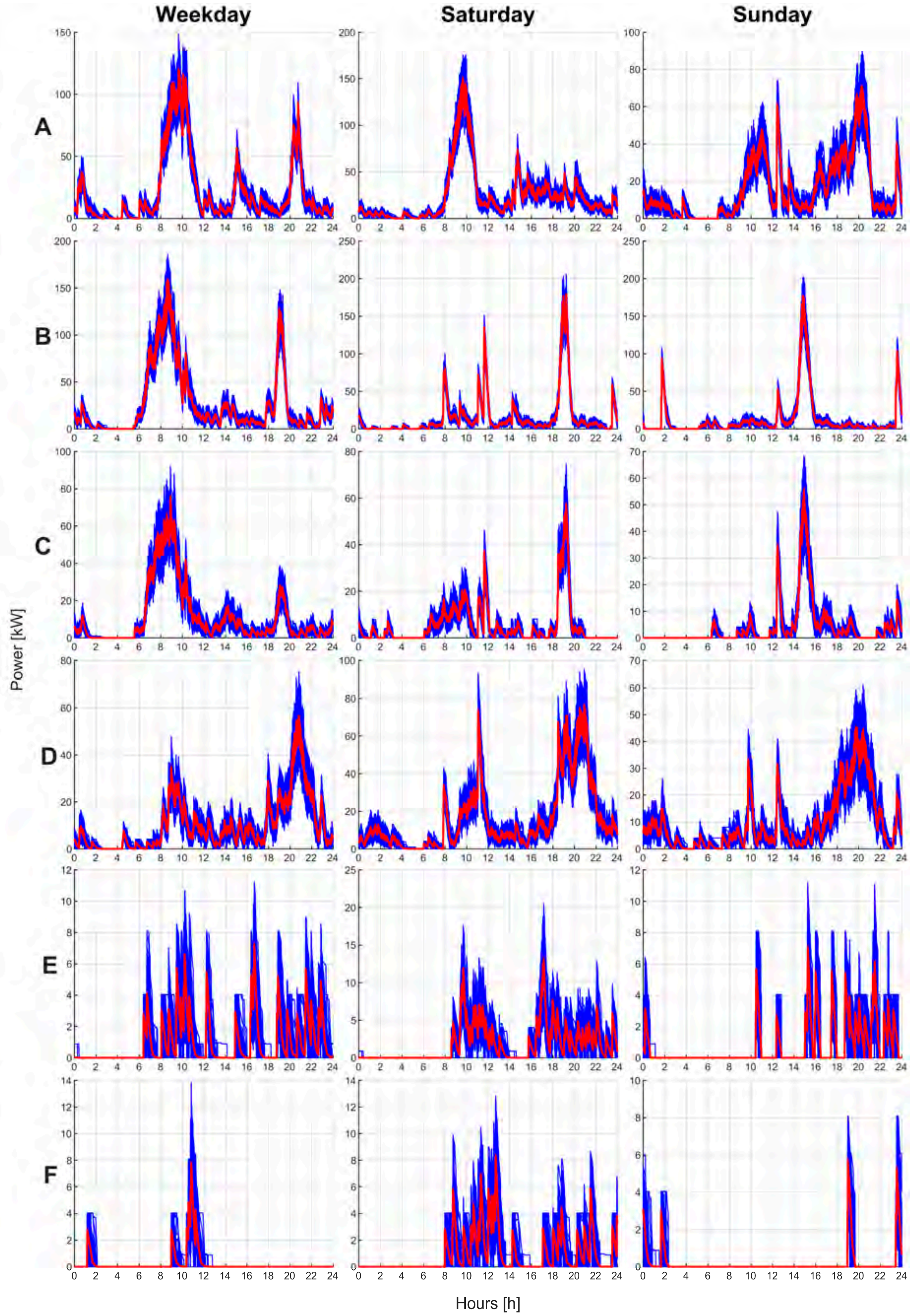

Figure A13. Monte Carlo power demand curves (in blue) for (**A**–**F**) Brescia car parks—max. CP output power of 50 kW. The average value is shown in red.

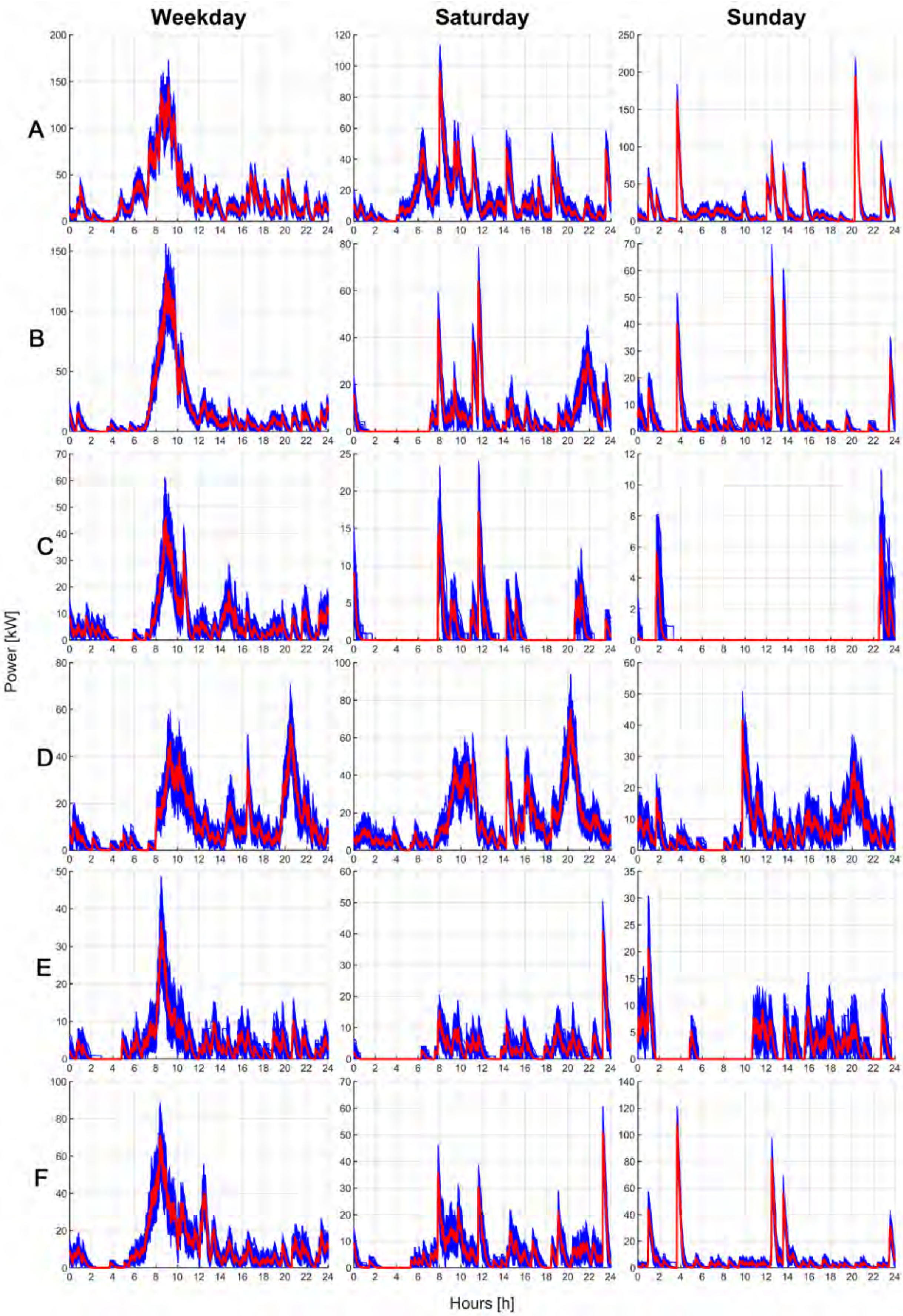

Figure A14. Monte Carlo power demand curves (in blue) for (**A**–**F**) Brescia car parks—max. CP output power of 50 kW. The average value is shown in red.

Appendix B.6. Power Demand Patterns—Florence Car Parks—Max. Charging Power 50 kW

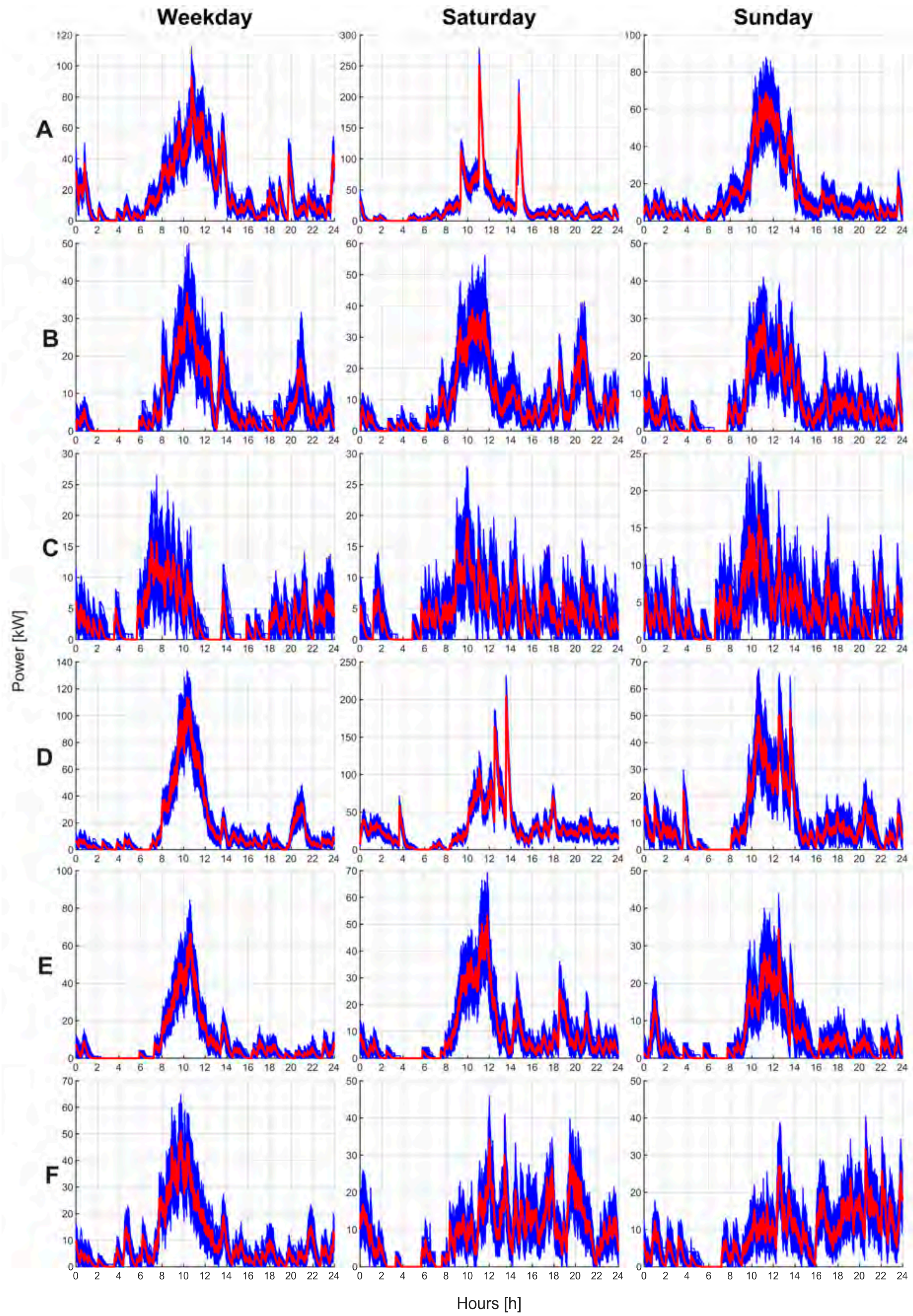

Figure A15. Monte Carlo power demand curves (in blue) for (**A**–**F**) Florence car parks—max. CP output power of 50 kW. The average value is shown in red.

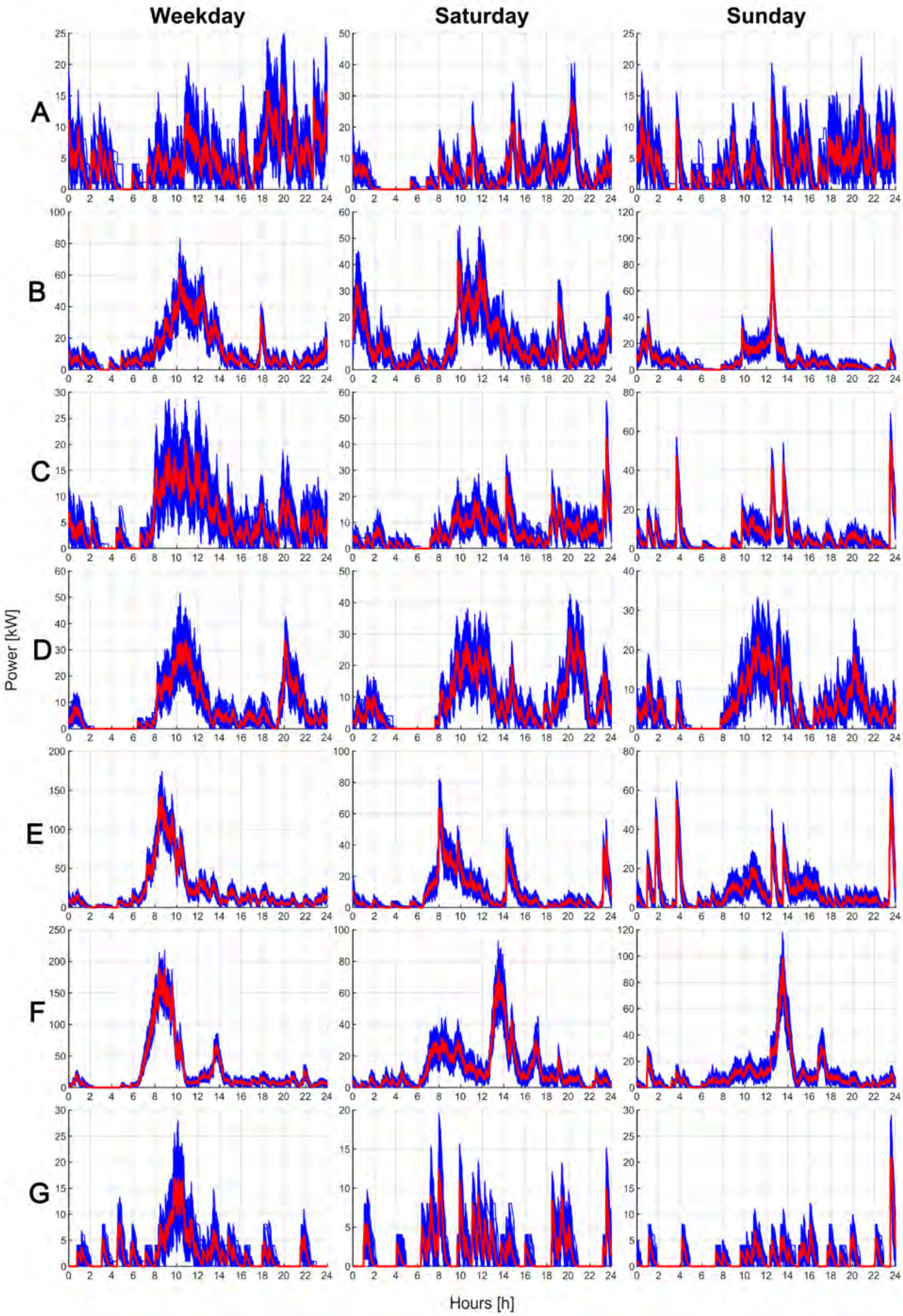

Figure A16. Monte Carlo power demand curves (in blue) for (**A**–**G**) Florence car parks—max. CP output power of 50 kW. The average value is shown in red.

Appendix B.7. Power Demand Patterns—Brescia Car Parks—Ultra-Fast Charge

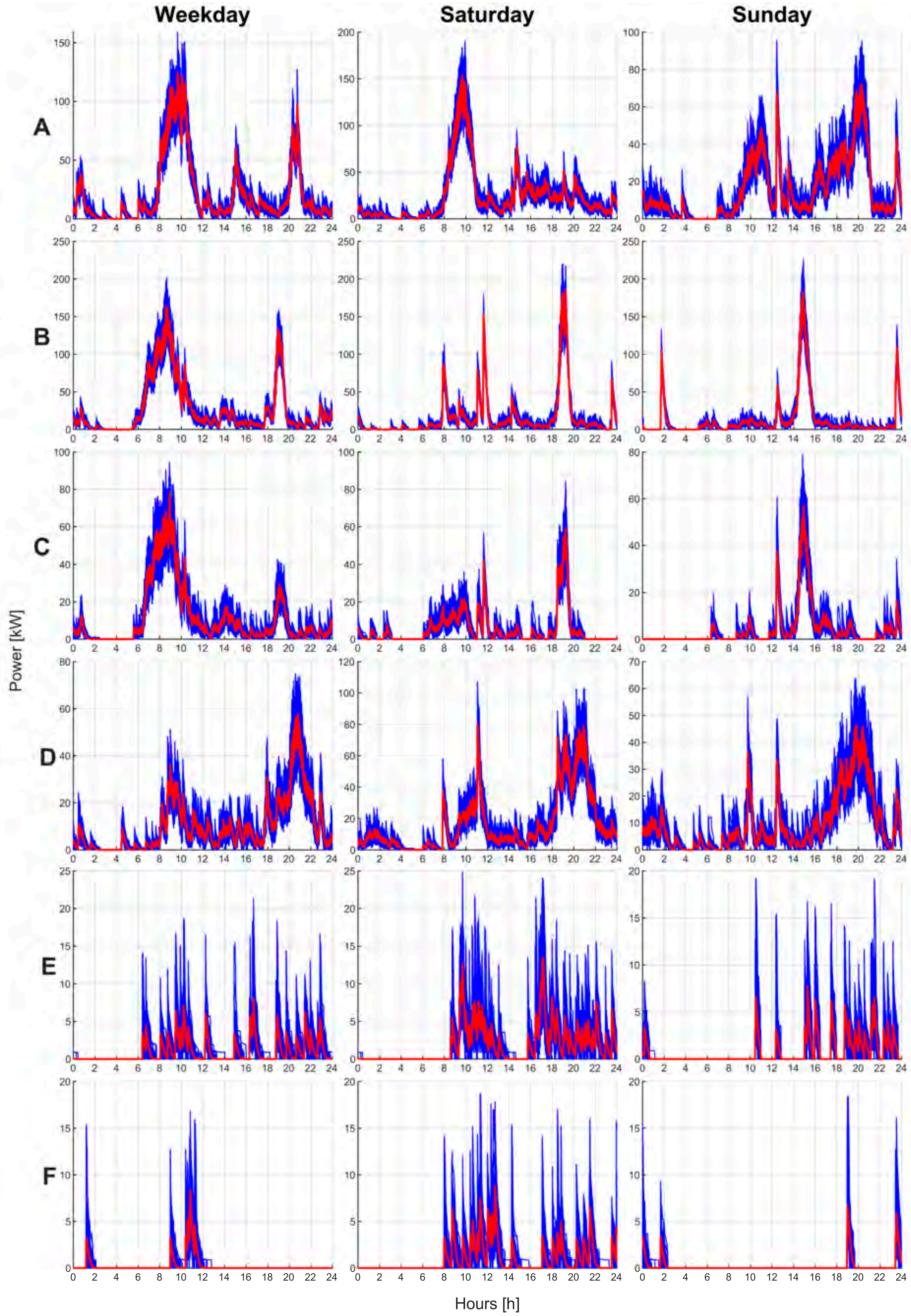

Figure A17. Monte Carlo power demand curves (in blue) for (**A**–**F**) Brescia car parks—Ultra-fast charge. The average value is shown in red.

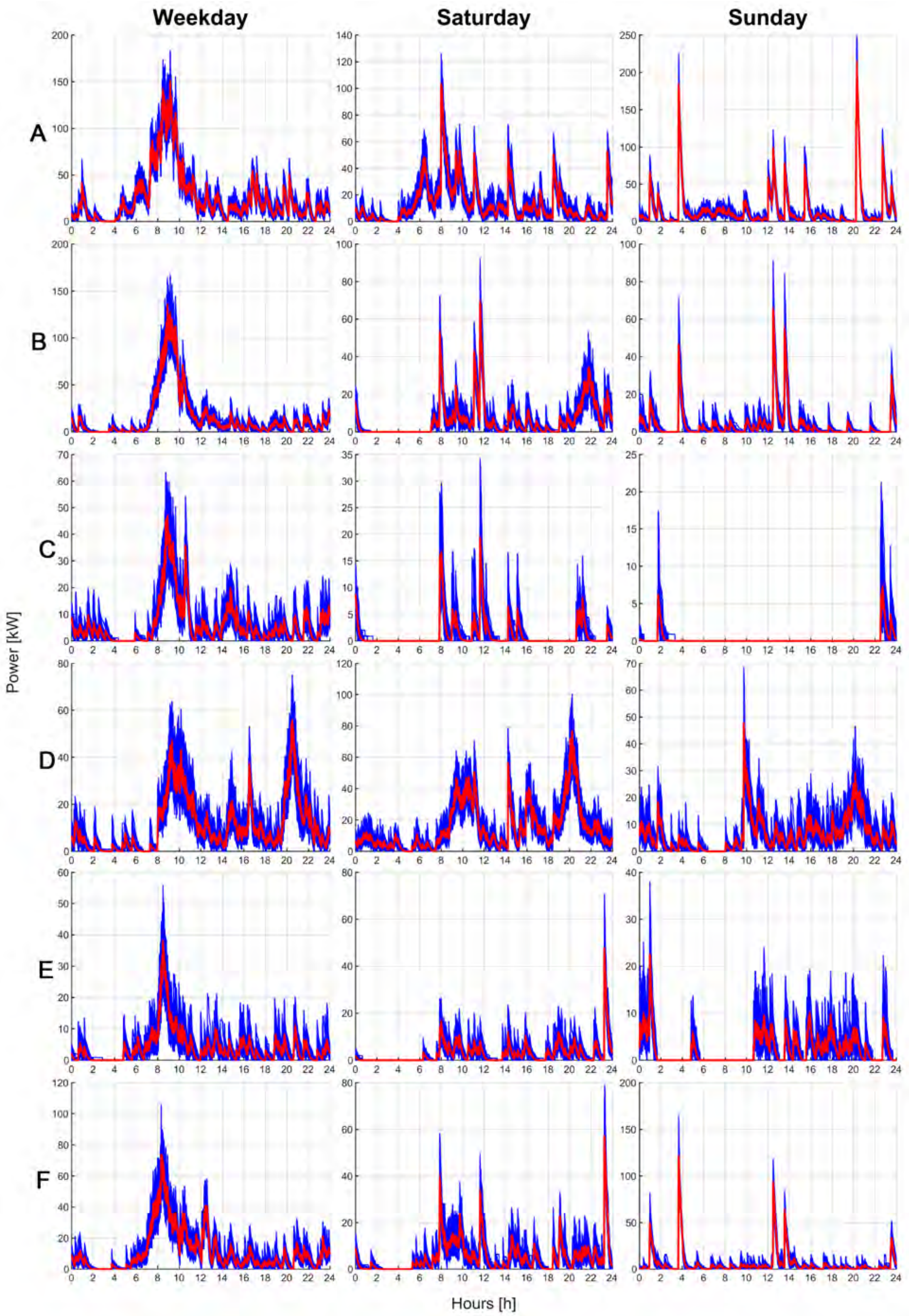

Figure A18. Monte Carlo power demand curves (in blue) for (**A**–**F**) Brescia car parks—Ultra-fast charge. The average value is shown in red.

Appendix B.8. Power Demand Patterns—Florence Car Parks—Ultra-Fast Charge

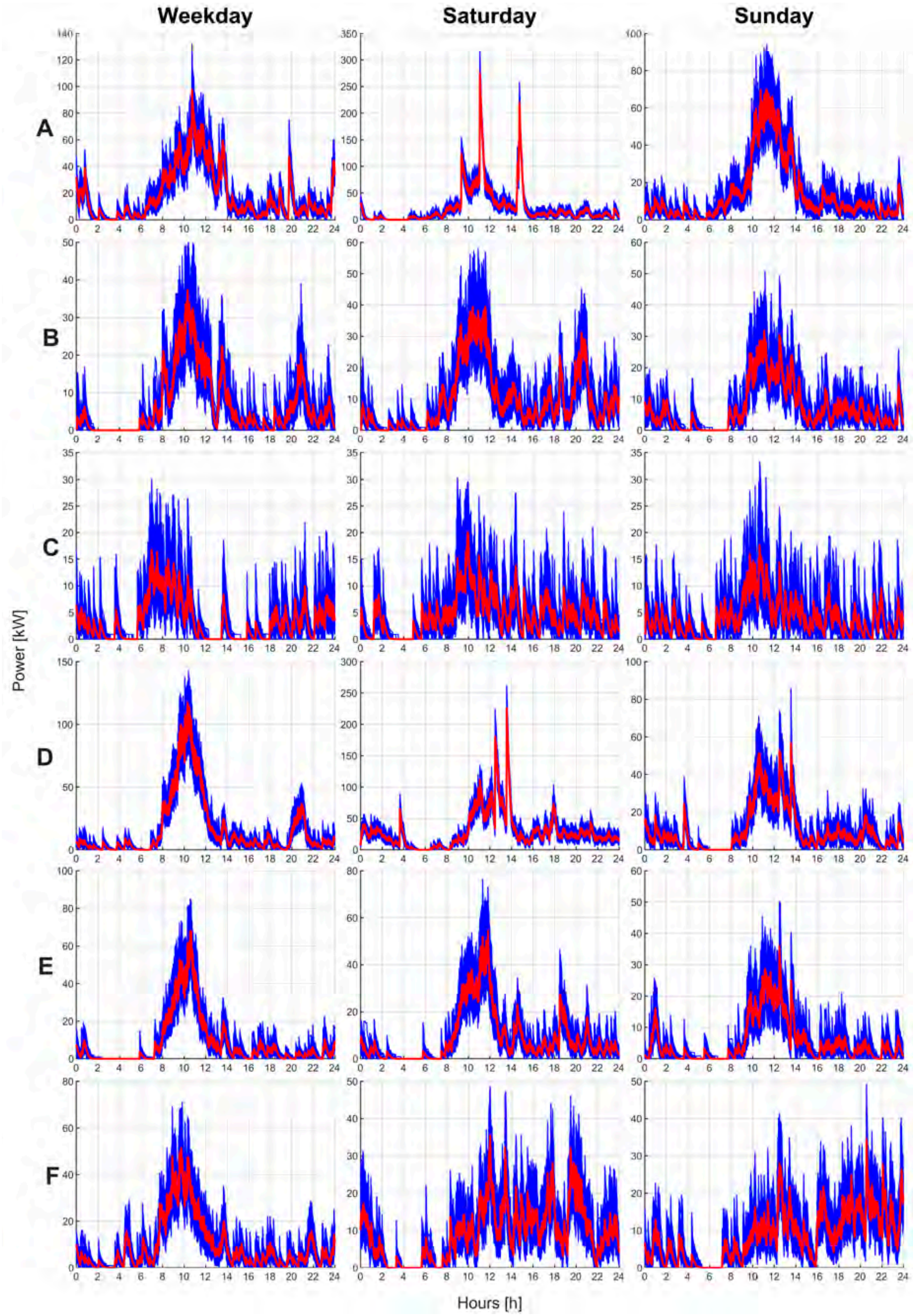

Figure A19. Monte Carlo power demand curves (in blue) for (**A**–**F**) Florence car parks—Ultra-fast charge. The average value is shown in red.

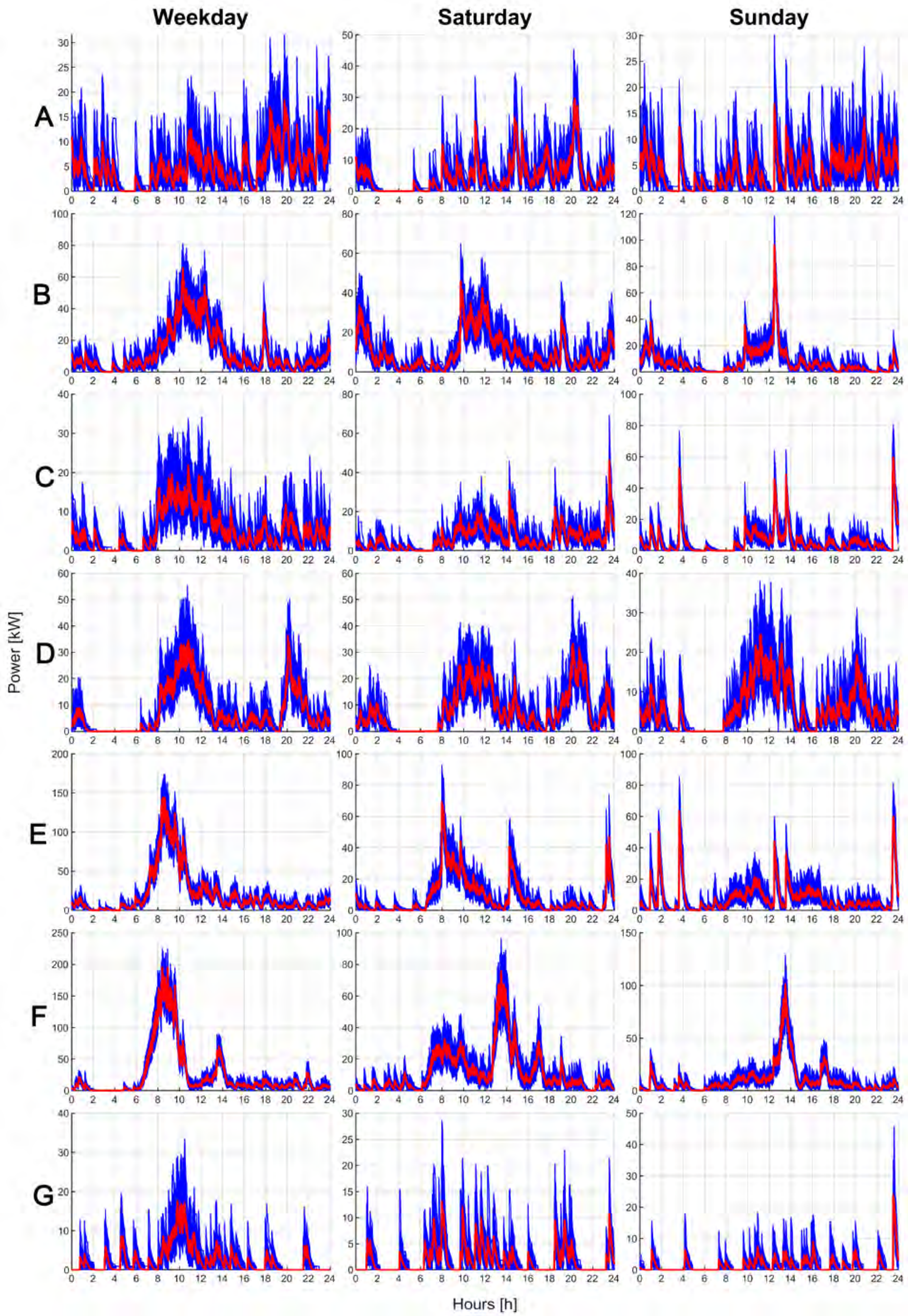

Figure A20. Monte Carlo power demand curves (in blue) for (**A**–**G**) Florence car parks—Ultra-fast charge. The average value is shown in red.

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