Maurizio Tira
Michela Tiboni
Michele Pezzagno
Giulio Maternini *Editors*

New Challenges for Sustainable Urban Mobility: Volume II

Proceedings of the XXVI International Conference on Living and Walking in Cities, 2023

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Editors
Maurizio Tira
Department of Civil, Environmental
Architectural Engineering and Mathematics
Università degli Studi di Brescia
Brescia, Italy

Michela Tiboni
Department of Civil, Environmental
Architectural Engineering and Mathematics
Università degli Studi di Brescia
Brescia, Italy

Michele Pezzagno
Department of Civil, Environmental
Architectural Engineering and Mathematics
Università degli Studi di Brescia
Brescia, Italy

Giulio Maternini
Department of Civil, Environmental
Architectural Engineering and Mathematics
Università degli Studi di Brescia
Brescia, Italy

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Parking Demand Diagnosis by Automated Payment Transaction (APT) Data: An Application in a Small-Sized Tourist City

Martina Carra, Sara Bianchi, Giuseppe Rainieri, and Benedetto Barabino

Abstract The parking demand is a fundamental datum to evaluate and implement integrated policies of sustainable urban mobility in urban areas. Parking demand is hard to quantify and relevant in small- and medium-sized urban systems, especially with a high-tourist interest due to temporary flows and few available resources. The previous studies highlighted how demand assessment is a complex task, usually addressed by prediction models or exploitation of sensors in the field. Nevertheless, studies have yet to focus on the potential of automated payment transaction (APT) technologies in data collection and processing for parking demand analysis. However, they involve several challenges in data handling. This study proposes a method to automatically handle APT raw data to estimate some drivers of parking demand, such as the parking occupancy rates, the parking average time duration, and the rotation index of block-level on-street parking and/or parking area. The method has been experimented in the small-sized and touristic city of Sirmione (Italy) and used 23+ million APT data collected in 2 months of observation. The results are represented by control dashboards that are easy to read and interpret. The experimentation shows that practitioners and public administrations can adopt this method to diagnose parking demand with great accuracy and derive recommendations for future transport and urban planning. In the new paradigm of demand-oriented services, this method is crucial to quantify the ability of administrators to address parking demand.

Keywords Parking occupancy · Monitoring system · Automated payment transaction

M. Carra (✉) · G. Rainieri · B. Barabino
Department Civil, Environmental, Architectural Engineering and Mathematics – DICATAM, University of Brescia, Brescia, Italy
e-mail: martina.carra@unibs.it

S. Bianchi
Department Civil, Environmental, Architectural Engineering and Mathematics – DICATAM, University of Brescia, Brescia, Italy

University School for Advanced Studies IUSS Pavia, Pavia, Italy

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1 Introduction and Literature Review

The management of parking spaces in urban areas has become critical due to the increasing number of vehicles, limited parking availability, and the outbreak of tourist and commuting flows. Along with the imbalance between vehicles number and parking spots available, there are further issues with parking location planning, the lack of parking signage, and unofficial parking. Often, all these issues are effects of ineffective and unsustainable policies that result in (i) heavy problems of traffic congestion and related urban environment pollution, (ii) disuse of integrated strategies with public transport and slow mobility, and (iii) user stress due to time spent looking for an empty parking space [1]. They result in parking-related fights and accidents, waste of money associated with fuel used for drivers, and an annual burden on the national economy. For instance, Cookson and Pishue [2] highlighted how German drivers spend an average of 41 h looking for parking space each year and waste 896 €/year.

In small- and medium-sized touristic cities, previous problems are even more complex for three reasons. First, they are subject to high unsystematic seasonal traffic flows. Second, the compromise among urban livability, tourist attractiveness, and usability is relevant in integrated transport-land use planning. Third, the financial resources available are insufficient to rely on innovative instruments and/or sophisticated forecasting models.

The parking occupancy data have emerged as a powerful tool to address these challenges and develop smarter and greener cities. The occupancy datum is a relevant information of the parking demand in an area. By analyzing historical occupancy patterns, city planners can make informed decisions in implementing planning and management strategies for a sustainable urban environment, i.e., resource allocation, pricing, enhancing traffic flows and urban developments, infrastructure investments, policy formulation, optimizing existing spaces, and determining the need for additional parking structures. Public administrators often need a better perception of the real occupancy rate to guide sustainable policies and face future challenges of integrating transport modes. However, this data-driven approach helps improve parking facilities in line with public transit systems and active mobility, promoting alternative transportation modes and reducing reliance on private vehicles. Strategic parking management based on occupancy data can contribute to reduced vehicle miles traveled and greenhouse gas emissions [3]. Moreover, it can be integrated with urban regeneration projects to enhance traffic flow management and mobility services.

Studies have faced parking occupancy according to two macroapproaches. The former approach considered prediction models to enhance estimation accuracy and guide customers with real-time information. They applied algorithms from queuing theory and Markov model [4] or Laplace transform [5], discrete choice model [6], metaheuristic applying cameras and payment transactions [7], deep learning techniques with neural networks [8–11], sensor-based according to the Internet of Things [12], and Web of Things and machine learning [11]. These studies are almost always associated with the parking type evaluated, i.e., free parking. Furthermore, they mainly evaluated time of day, day of the week, holidays, traffic flows, events, parking sensors, occupancy look-back window, and weather. In addition, most studies have correlated predictions to sensors and real-world data, except for [4]. The latter approach focuses on mechanisms to detect if a vehicle occupies the parking space by sensors that include induction proximity sensor, image [13–17], ultrasonic [18], magnetic [19], radio frequency [20, 21], and infrared [22]. Next, some algorithms were proposed to handle resulting data and return some (real-time) information to users on the parking occupancy status. The focus on sensors mainly concerns wireless systems capable of minimizing the cabling infrastructure. However, sensor-based systems have disadvantages due to inaccuracies caused by some environmental conditions (e.g., light) or network errors, the installation and maintenance costs associated with the sensors themselves, as well as the cabling for data transmission and energy supply. These facts could explain why these studies were applied and focused on enclosed parking systems [13, 18–21]. In both approaches, little attention is paid to automated payment transaction (APT) technologies that are frequently adopted in many public administrations worldwide and could help address the problem of costs and data collection as it happens in other transportation fields [23–25]. However, these technologies involve several challenges, i.e., anomaly correction in the raw data collected, handling data of different natures (e.g., by availability, acquisition device, temporal homogeneity, data configuration, operator heterogeneity), and efficient information processing.

This study aims to propose a method to automatically manage the APT raw data to measure some drivers of parking demand, i.e., the parking occupancy rates, the average time duration of the parking, and the rotation index of each (paid) on-street parking and/or parking area. The method has been experimented with in the case study of the small-sized city of Sirmione (Italy), which has about 1.3 million tourists per year. The methodology used 23+ million data collected in 2 months of observation. The results are depicted by control dashboards and graphs that are easily readable and interpretable. The study is interposed in the goals of compromise between urban livability and tourist attractiveness and usability and related to smart city initiatives.

The paper is structured as follows: Sect. 2 describes the method. Section 3 applies the method to the case study of Sirmione and shows the results. Section 4 concludes the paper by discussing the results and implication of the study.

2 Methodology

The methodology is organized into four phases to (i) address data validation and anomalies in APT data, (ii) integrate a multidata framework validating reference spatial and temporal intervals, (iii) preprocess data, and (iv) determine values of three indexes, provide parking demand diagnosis overall pay and display parking areas in a block level for all hourly time intervals in a period equal to or higher of a month. A description of the processing steps follows.

2.1 Data Validation

The larger the dataset, the greater the accuracy, provided that the system to collect data is well-calibrated. The method considers all APT data collected by different payment systems. Therefore, it is good practice to check the consistency of the data collected since sampling can be biased by situations (e.g., malfunctioning payment devices), leading to flawed data analysis. Phase 1 eliminates anomalous data (e.g., duplicates) corresponding to such events. The data validation assumes an assessment of ticket ID, parking duration values, and/or date values.

Tables 1 and 2 show an instance of raw data, including the most relevant data. However, it should be noted that the invoicing data are unreliable in data validation as they are subject to, e.g., parking passes and membership services, all cases that converge an occupation of the parking lot.

2.2 Adaptive Multidata Framework

Phase 2 sets a common data framework to process hourly parking demand. Data can hardly have a common framework as they could be collected from different payment types and devices (multiplicity of user/driver-machine interaction, e.g., parking meter by credit cards or money, automated device (transponder) onboard vehicle). For instance, each APT can cover several parking lot locations, considering different parking time reference parameters. Therefore, Phase 2 aims to solve all these issues and define a commune dataset by the following steps.

Step 1: Verify the uniqueness of transaction IDs. Some ID duplicates may occur or may still be present progressively for the year or month in which the parking transactions are recorded.

Step 2: Relate each parking meter to a parking lot, parking area, or car park. Therefore, Step 2 proceeds to a spatial reconstruction of the regulated parking supply, highlighting the prevalent parking category (e.g., parking disc, free parking) and vehicles allowed (e.g., vehicular, motorcycles, buses). Consequently, data collected could be related to spatial localization and the maximum parking lots available.

Step 3: Verify the temporal context of the parking data collected. It may concern several elements, but the main ones are listed below: (i) payment operating hours and (ii) parking duration (i.e., delta between the start and end of the hour including or not including the hours not subject to tariffs).

Table 1 Exemplifying raw data of car parks

Parking	Device	Ticket ID	Payment type	Entry parking	Exit Parking	Ticket type	Amount [€]	Invoice	Cancelled
PM	US41	2.82203E+22	Subscribed	13/05/2022 19:03:00	14/05/2022 00:00:00	Pass resident	0	0	0
PM	US42	XXXXXXXXXX4241	Credit card	13/05/2022 20:50:00	14/05/2022 00:03:00	Telepass	10.0	0	0
PM	CA13	3.14104E+22	Ticket Management	13/05/2022 19:01:00	14/05/2022 00:12:00	Short Park Ticket	12.5	1	0
PM	US42	XXXXXXXXXX4196	Credit card	13/05/2022 21:33:00	14/05/2022 00:06:00	Telepass	7.5	0	0

Table 2 Exemplifying raw data of parking meters

Payment type	Results	Parking meters	Zone	Ticket ID	Date	Duration	Amount [€]	Transfer [€]	Cancelled [€]	User duration
Credit card	ok	P4	A	14,981	01/05/2022 01:10:13	04:12:00	10.5	0	0	00:00:41
Cash	ok	P9	B	4740	01/05/2022 01:49:08	01:00:00	2.0	0	0	00:00:15
Credit card	ok	P14	C	5767	01/05/2022 08:33:15	05:34:00	12.5	0	0	00:00:44
Cash	ok	P4	A	14,982	01/05/2022 08:36:58	00:24:00	1.0	0	0	00:00:19

Step 4: Systematize raw data and enrich them defining essential data for control dashboards to be managed in Phases 3 and 4. They are (i) unique IDs of each payment transaction; (ii) parking meter IDs; (iii) date and parking time (i.e., start and end); (iv) time duration of parking (i.e., the delta between the end and start of parking hour); (v) year, month, and day of the payment transaction; (vi) parking time duration admissible; and (vii) the number of parking lots available per parking.

2.3 Preprocessing Data

The parking time duration presents heterogeneous hourly permanence data, distorting the measurement of the index because parking could concern more hours. Therefore, it is necessary to unpack the parking duration and refer to a single time period. The criticality is solvable by applying an algorithm that generates "n" rows of data associated with a transaction equal to a reference time slot of parking lot occupation. Therefore, each row corresponds, e.g., to 1 h of parking lot occupation, enabling us to evaluate the global occupation rate hour by hour, in days and categories of days (holidays, weekdays). For instance, a transaction with a parking duration of 2:50:27 corresponds to "3" time slots, and the algorithm proceeds by adding n. "2" rows, the duplicate of that base (1 + n, i.e., 1 + 2).

2.4 Parking Demand Status

Phase 4 quantifies the average permanence index (μ_k), rotation index (I_k), and occupancy rate (o_k) for a given parking k, parking meter l, and area a on a given day g and time slot f.

Specifically, let:

- i be a transaction index of a parked vehicle,
- $t_{i,k}^{l,a,g,f}$ be the time duration a vehicle is parked
- $\mu_{k,\max}^{l,a,g}$ be the maximum parking time duration
- $n_k^{l,a,g,f}$ be the detected transactions
- $p_{ik}^{l,a,g,f}$ be the parking lots occupied
- $p_{k,\text{tot}}^{l,a,g,f}$ be the parking lots available

The indices are computed as follows:

$$\mu_k^{l,a,g,f} = \frac{\sum_{i=1}^{n} t_i^{k,l,a,g,f}}{n^{k,l,a,g,f}} \quad (1)$$

$$I_k^{l,a,g} = \frac{\mu_{\max}^{k,l,a,g}}{\mu_p^{k,l,a,g}} \tag{2}$$

$$o_k^{l,a,g,f} = \frac{\sum_{i=1}^{n} p_i^{k,l,a,g,f}}{p_{\text{tot}}^{k,l,a,g,f}} \tag{3}$$

Equations (1) and (3) express an average reference value of vehicle types (e.g., car, bus, motorcycle, and camper). Equation (2) describes both the parking efficiency and disservice rates.

3 Results and Discussion

The methodology has been experimented within the small-sized and international touristic city of Sirmione (Italy). Located in Lake Garda, Sirmione develops along a narrow peninsula not easily accessible by high vehicular flows. Most touristic flows come from vehicular transport mode, and several criticalities concern traffic congestion and parking over/underuse. Specifically, the use case was part of a study to rationalize and improve parking supply by upgrading existing decentralized infrastructures (to be implemented relating to urban transformations) and increasing parking capacity to tourist demand. The methodology was implemented on MS Excel running on a standard PC (Intel Core i7, CPU 2.60 GHz, RAM 16.0 GB) and is quasi-automatic and takes a few seconds on the PC.

3.1 Data Validation

ATP data provided by Sirmione municipality from May 2022 to June 2022 were processed. According to Phase 1, the data validation verified duplicates, date, and parking duration. Duplicates were often associated with payment reversals and recognizable by ticket ID. Date values were verified as a sampling of the observation period because errors are often subject to malfunctions of the payment machine and, in the case of Sirmione, have dates to 1994. Finally, parking duration values verified unreliable parking as time duration ≤10 min. Therefore, data validation eliminated 1293 transactions, i.e., 0.81% of sampling.

3.2 Adaptive Multidata Framework

ATP data were heterogeneous and different: (i) cash/card payment transactions referred to parking meters and (ii) cash/card/automated device onboard parking tickets from secure car parks.

Fig. 1 (**a**) Spatial references in Sirmione. (**b**) Zoom on parking supply in main harbor and (**c**) in city zone. (**b**) and (**c**) Categories of parking lots (blue, parking disk; black, free parking; light blue, pay and display parking), parking zones, and parking meters (i.e., P6)

According to Step 1, the transaction ID was checked by counting the numbers of identical transactions using the tool PIVOT in Excel. ID duplicates were identified since ATP data were derived from different devices with monthly and yearly progressions. Therefore, a new transaction ID was performed for all payment transactions.

In Step 2, the spatial reconstruction of the regulated parking supply was performed with Quantum GIS. Thematic maps have defined categories of parking lots (i.e., time-based as parking disc and paid regulation), vehicles associated (i.e., car, motorcycle, loading/unloading goods, disabled, local police, residents, taxi, bus, camper), parking meters, and parking zones associated (see Fig. 1). Therefore, a data field correlated each transaction to parking meters, parking zones, and car parks.

Despite the heterogeneity of data collected, Step 4 systematized raw data homogeneously with essential data for the subsequent preprocessing phase. Explanatory raw data are shown in Table 3.

In Step 3, temporal contexts of data collecting were verified. Payment operating hours were verified by correlation to parking meters and car parks. Moreover, the

Table 3 Exemplifying homogeneous raw data for preprocessing

Transaction ID	Zone	Parking ID	Spatial ID	Data	Month	Day	Day types	Starting time	Finish time	Duration [min]	Time slot**	Occupation hour*	Duration admissible [min]	Max parking lots
6,146,305,142	A	P02	AP02	15/5/2022	5	Sun	H	09:55	10:15	20	9	1	1020	81
4,816,330,552	A	P0M	A0M	23/5/2022	5	Mon	W	11:07	11:19	12	11	1	1020	642
6,050,933,278	C	P10	CP10	01/6/2022	6	Wen	W	11:00	12:58	118	11	2	1020	68
6,687,933,503	B	P04	BP04	01/6/2022	6	Wen	W	13:27	13:42	15	13	1	1020	93
5,166,934,081	D	P11	DP11	02/6/2022	6	Thu	H	13:26	15:47	138	13	3	1020	88

H holidays, *W* weekdays

(*) Referred to 60 min slot; (**) range 1–24 format, value, and arrangement parking data duration varied. For instance, parking duration processing was often amount-based and excluded the free-payment parking hours (i.e., mainly at night). Therefore, a new "duration" field was derived to describe the overall parking duration, i.e., comprehensive of free and payment parking hours.

3.3 Preprocessing Data

According to Phase 3, the algorithm application enabled the processing 635,738 data records subsequently resolved through specific IT functions to operate aggregation. The breakdown by 60 min of the parking slot occupancy is a simplification that is admissible for the calculation operations, although it makes an excess error in estimating the occupancy rate. The detected vehicle by a transaction is presumed to park for the entire reference period, even if the parking duration is less. However, this simplification was necessary as a smaller time interval would have involved computational problems. Nevertheless, the definition of a 60-min time window for occupancy rates is consistent with what is defined by [7, 11]. Moreover, the simplification characterizes transactions from parking meters, while in app and car park transactions,[1] the duration corresponds to the real one.

3.4 Parking Demand Status

Phase 4 computed indexes for each parking meter and car park according to Eqs. (1), (2), and (3), respectively.

First, the average permanence index (μ_k) showed that vehicles stay parked for about 3 h. This value increases near the main harbor (e.g., P8) and up to 4 h near the historic center; conversely, their values decreased toward the peripheral parking meters, e.g., P12 and P13 (Table 4). Similarly, the average rotation index (I_k) by weekdays and holidays highlighted greater values in peripheral parking meters characterized by smaller parking lots (e.g., P12). Conversely, the lowest parking turnover is recorded in parking meters near the historic center and tourist harbor (e.g., P10) with values <5.00. These areas can be identified as the main ones with tourist mobility.

Finally, the occupancy rate (o_k) was computed according to several temporal scales (daily, monthly, and yearly), and some results are shown in Table 5.

Five occupation classes are clustered: green (for a rate lower than 25%), yellow (for a rate between 25% and 50%), orange (rate between 50% and 75%), red (rate

[1] Payment transactions data by car park corresponded to a real parking duration (i.e., 51.02%).

Table 4 Exemplifying results of μ_k and I_k

Parking IDs	Day types	μ_k	Maximum (payment) duration [min]	I_k
P4	Total	02:54:40	1020	5.84
	Weekday	02:56:21	1020	5.78
	Holiday	02:49:25	1020	6.02
P8	Total	03:18:44	1020	5.13
	Weekday	03:21:56	1020	5.05
	Holiday	03:11:31	1020	5.33
P10	Total	03:26:57	1020	4.93
	Weekday	03:28:35	1020	4.89
	Holiday	03:22:44	1020	5.03
P12	Total	02:44:48	1020	6.19
	Weekday	02:48:20	1020	6.06
	Holiday	02:33:30	1020	6.64
P13	Total	02:48:21	1020	6.06
	Weekday	02:44:50	1020	6.19
	Holiday	02:57:52	1020	5.73

Table 5 Exemplifying results of occupancy rate [%]

IDs Park	Month	Day type	7 AM	8 AM	9 AM	10 AM	11 AM	12 AM	1 PM	2 PM	3 PM	4 PM	5 PM	6 PM	7 PM
P4	5	*	0. 34	0.44	2.25	14.52	39.88	69.16	74.78	69.84	51.52	34.60	20.58	13.05	8.41
	5	**	0.96	0.84	6.21	43.49	89.13	107.89	115.77	116.13	115.65	106.69	82.20	52.09	32.62
	6	*	0.68	1.17	7.92	34.90	80.01	112.17	119.35	112.12	87.83	61.34	39.44	25.76	17.69
	6	**	2.28	3.49	23.12	75.27	111.02	122.04	124.46	130.38	127.55	122.45	109.14	88.98	71.64
P 8	5	*	1.61	2.35	5.43	15.25	35.78	49.12	53.37	47.65	35.78	21.41	13.05	6.89	4.84
	5	**	6.81	6.09	11.47	41.22	130.47	152.69	168.82	164.87	134.41	100.72	69.18	44.09	24.01
	6	*	3.52	4.84	9.97	33.43	84.75	122.87	129.33	112.02	84.46	54.11	33.58	20.97	16.57
	6	**	9.27	11.69	31.45	105.65	181.85	203.63	212.90	208.06	178.23	143.15	98.39	62.50	45.97
P10	5	*	0.07	0.33	2.34	9.83	23.26	30.95	32 .22	27 .81	21 .19	13 .64	8.49	4.48	2.34
	5	**	0.00	0.65	6.05	30.23	82.84	99.84	105.23	101.80	88.89	68.79	45.92	23.69	10.78
	6	*	0.33	1.00	6.62	19.85	43.72	61.63	63.50	57.69	46.32	31.02	20.99	12.43	7.02
	6	**	1.10	3.31	12 .87	57.90	99.26	114.52	120.22	119.12	102.57	77.76	53.13	33.64	19.67
P12	5	*	0.23	0.06	0.06	0.58	0.99	1.40	1.46	1.52	1.52	1.23	0.82	0.64	0.58
	5	**	0.16	0.16	0.95	2.22	3.49	5.71	5.40	4.92	4.44	4.13	3.17	1.59	0.48
	6	*	0.40	0.51	0.96	2.27	4.19	4.60	5.25	5.25	4.55	3.99	3.23	2.17	1.11
	6	**	0.42	0.97	2.64	7.92	17.08	22.78	22.78	22.22	20.14	17.08	12.92	6.11	3.19
P13	5	*	0.15	0.26	0.31	0.71	0.82	0.87	0.97	0.71	0.51	0.46	0.41	0.46	0.36
	5	**	1.36	1.25	1.81	2.83	4.20	4.54	5.10	4.54	4.42	3.74	3.06	1.36	0.68
	6	*	0.34	0.44	0.49	1.02	1.31	1.41	1.41	1.75	2.24	2.09	1.60	1.36	0.78
	6	**	2.04	3.06	3.32	5.61	6.76	7.14	7.65	8.04	7.91	7.78	6.51	5.61	4.72

*Weekday; **Holiday

between 75% and 100%), and purple[2] (rate above 100%). However, the possibility of cars parking outside the marked lots is not excluded.

The results clearly showed the critical month, i.e., June, although even May has occupancy rates over 80% (Table 5). However, the increasing trend toward the summer months is evident. Furthermore, the most critical time slot was detected, both on the daily and monthly data, between 10:00 and 17:00. Unsurprisingly, the results highlighted an overuse of the parking in parking meters near the historic center, peninsula (e.g., P4), tourist harbor (e.g., P8 and 10), and on holidays. Simultaneously, processing verified the underuse (almost zero) of peripheral parking meters (P12 and P13).

Three strategies were defined according to the results: (i) implementation of a decentralized park-and-ride facility in Sirmione's south and southeast nodes, linked to cycle-pedestrian routes and bus and shuttle boat services to decongest the peninsula and the historic center; (ii) implementation of the underutilized parking of the eastern node in a park-and-ride facility integrating the same transport services of (i); and (iii) elimination of some parking lots on the peninsula overall dedicated to tourism with overnight stays and extension of the traffic-restricted zone to the whole peninsula.

4 Discussion, Conclusions, and Research Perspectives

Automated payment transaction (APT) technologies can provide a relevant dataset to address parking management issues, overtaking programming complexities of predictive models or expensive and timing limits of sensors. To properly account for these issues, the study adopted a four-phase method able to manage a huge amount of APT raw data. Results addressed data validation and determined parking demand diagnosis by displaying parking areas at a block level for several time slots (e.g., hourly) in several period types (e.g., year, month, day, hour, minutes).

The contributions of the study are as follows:

- Show how to handle flexibly and adaptively huge APT raw data, held by public administrations, for measuring parking demand status.
- Provide a detailed characterization of the parking occupancy rates, the average time duration, and the rotation index for several periods and parking at hand.
- Implement a simplified method reproducible with standard computer science skills.
- Prove the handy effectiveness of the method in the case study of Sirmione.

The paper could be improved in future developments. First, the method had yet to be implemented into a single tool, and elaborated transactions were by offline

[2] Entries in purple refer to an occupancy rate greater than 1, i.e., the parking demand overcomes the supply. It could be counterintuitive. However, this depends on the time slot duration selected for the analysis, i.e., 60 minutes: some vehicles could stay less than 1 h.

approach. However, an online approach could be implemented, facilitating real-time data output and allowing for several services: informative panels to guide drivers to available parking spaces [18]; reducing the time spent searching for parking [2]; managing traffic flows [3]; dynamic pricing strategies [26]; enabling the implementation of variable parking rates based on demand, time of day, or event schedules [27]; and helping in maintaining optimal occupancy levels, leading to reduced search time and minor traffic congestion. Consequently, the potential of the method in smart city initiatives is high in improving the quality of urban life. Moreover, the APT data-driven method cannot integrate unofficial parking data into the framework. Therefore, there may be an unexpressed demand for the occupancy rate. Future developments will be able to investigate the methods of quantifying this demand in the framework according to the relevance of unofficial parking in the different contexts analyzed.

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