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The causal relationship between road density and parking occupancy

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Abstract

In order to alleviate traffic congestion-parking challenges, this research investigates the causal relationship between road density and parking occupancy. We use Granger causality tests based on vector error correction modeling. During the daily period of twelve consecutive hours, data were collected on road density and parking occupancy in a parking lot and on-street parking in Tunis city center. The empirical results highlight that the dominant type of Granger causality is unidirectional. Hence, we conclude that there is an endogenous relationship between road density and parking occupancy. The findings of this study indicate a need to rethink policy and can be incorporated into modeling parking.

Keywords: Congestion; Parking; Traffic density; Granger causality test; Time series

1. Introduction

Parking is an essential anchor point for any vehicular travel. Its provision and the policies surrounding it are not only key components of transportation policy and planning; they also have major implications on urban planning and the broader city-building context in which transportation planning takes place. In addition to the role, they play in transportation and the movement of people and goods, for example, parking policies can also have profound effects on land use and urban form, public health, and other socio-economic issues. Indeed, parking availability or lack thereof as a result of the balance of supply and demand affects the modal choice of users, the accessibility and attractiveness of high-density areas as well as the location of various community activities, services, and businesses [1].

In large cities, parking systems are generally characterized by limited local supply and diversified demand based on a spatial breakdown of activities that tends to generate a large number of both short and long-distance trips. These trips are associated with spatially diffuse and temporally variable parking needs. This results in a capacity constraint problem in space and time. The same space, generally rare in dense urban areas, must serve both the movement of people and goods, and the immobilization of vehicles. Parking, thus, significantly affects traffic flow and congestion levels. This can be attributed to two main factors: the immobility of vehicles which creats a physical constraint and the behavior of motorists searching for parking which impedes the movement of traffic (safety and speed), especially during peak periods. As a result, the environmental, economic and social costs, and external effects of traffic are partly generated directly by parking.

Parking and which creates urban traffic systems are indispensable elements of the urban transportation structure [2]. To understand and estimate the interactions between these two systems, three approaches are generally used in the literature: analytical, empirical, and multi-agent simulation tools (SMA). SMA tools are employed to simulate driver behavior and to analyze the search-flow impact of a vacant parking space on road network performance [3-7], whereas

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analytical studies that focus on the interaction relationship among parking and traffic often incorporate economic analyses [8, 9], macroscopic models [3] and traffic allocation models [10]. Meanwhile empirical studies are based on driver surveys [11, 12], video recordings, GPS data [13] and parking occupancy data [14].

It seems that the relationship between parking and urban road congestion has been widely studied by researchers in urban transport. Nevertheless, the causal relationship between parking and urban road congestion has not been addressed so far. In academic literature, most studies tend to focus on the relationship between transportation (infrastructure, air travel, road density, public investment in transportation and communication, etc.), economic growth (GDP, agricultural productivity, employment and income), logistics sector and environmental issues (air quality, energy consumption, CO_2 emissions, etc.).

This paper aims to study, in the Granger sense, the causal direction between road density and parking occupancy via time series data. This is the first paper that investigates this type of relationship. This study can be employed to help decision makers furnish more sustainable parking policies that reduce road congestion and can be also integrated in parking models.

The organization of the paper is as follows: Section 2 introduces the data and summarizes the methodology used to investigate the causality relationship; Section 3 reports the results and discussions; Section 4 assesses the economic costs associated with parking and congestion issues in the study area; and finally, conclusions are provided in Section 5.

2. Material and methods

2.1. Data and methodology

The methodology of this paper pursues the procedures for studying causality between time series data called as Granger causality and other related methods.

2.2. Data description

Figure 1 Study area

The city center of Tunis is the heart of the Tunisian capital. It exerts a pull on a much larger geographic area due to the concentration of jobs (post office, companies, banks, offices, etc.), public facilities and services, particularly in areas such as business, health, culture, food/dining and other leisure activities. However, like other urban centers around the world, this attractiveness consistently generates a high demand for travel that is constrained by a shortage of parking supply. In fact, the heart of the Tunisian capital is currently experiencing a failure concerning the number of vacant parking spaces. This can be explained by the attractiveness of centrality, which greatly exceeds its limited perimeter. Thus, despite the high number of available parking spaces, downtown Tunis suffers from a noticeable certain imbalance between supply and demand for parking. This failure can have negative repercussions on the accessibility and attractiveness of the city centers.

This study aims to gauge the degree of connection between parking occupancy status and traffic congestion using time series data. Data collection was carried out around the Mokhtar Attia Street depicted in Figure 1. The area was targeted as it has three types of parking: on-street parking (spots available on Mokhtar Attia Street), parking lot and underground parking (Central-Park). For technical reasons, we limited ourselves to two types of parking: parking lot and on-street parking.

We used video cameras to measure traffic density and parking occupancy. During March 2018, more than twelve hours of video footage was recorded from 7:00 am until 8:00 pm each day. Thirty samples of video footage, each lasting about three minutes, were taken. This is the daily average for a recording under normal conditions (with no incidents or recurring disturbances). Video is a tool of collecting various data, such as traffic speed and flow. We thus have a sample of 30 pairs (parking occupation, density). As shown in Figure 2, it can be deduced that a relationship between parking occupancy rates and traffic density does indeed exist. It has also been observed that the number of parked cars has grown with the increase in traffic density.

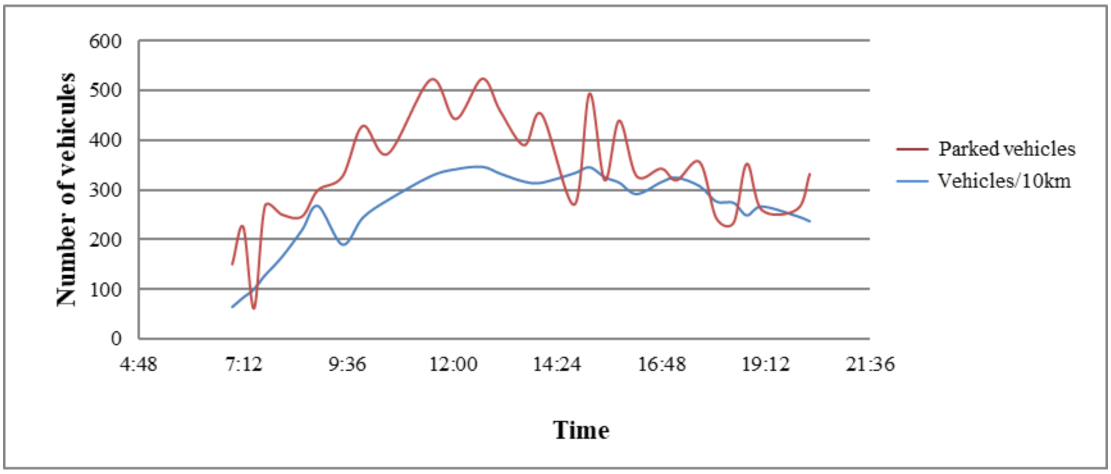

Figure 2 Variations in density and parking occupancy

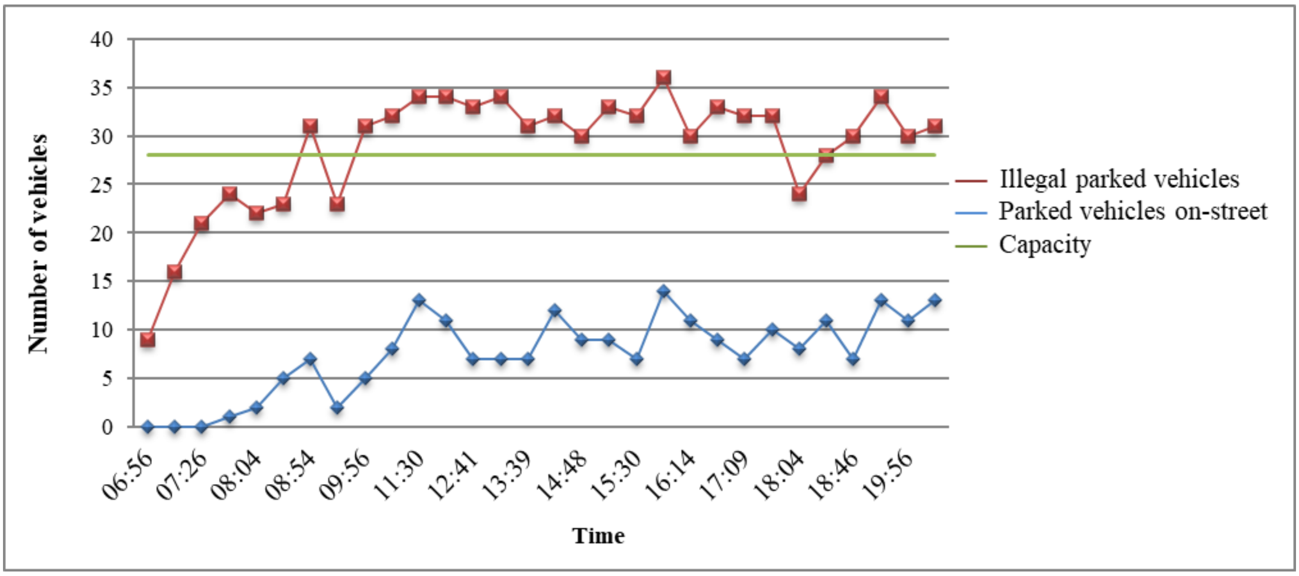

Figure 3 On-street parking occupancy over time

Indeed, when the number of parked cars is increased, the number of vehicles occupying the roadway called traffic density rises, therefore traffic congestion phenomenon occurs. A queue is created at the entrance and exit of the parking lot (Figure 3). In addition, the saturation of on-street parking (Figure 4), causes problems of congestion, by the narrowing of the space open to traffic (for example illegal parking), but also by disrupting road traffic (the maneuvers performed by the driver, when leaving or accessing a parking space).

Conversely, the increase in density is not necessarily accompanied by the amplification of the number of parked cars. For example, if a non-recurring (accident) or recurring (rush hour) traffic congestion is triggered, transit cars will not park. They will wait until traffic becomes fluid so that they can continue their path and reach their final destination.

The number of drivers who park their vehicles in on-street parking spaces changes over time. As illustrated in Figure 3, the occupancy rate for these spaces frequently exceeds its maximum capacity. The number of parked cars rises considerably with the arrival of commuters in the morning and remains relatively consistently throughout the day as motorists with other reasons for travel enter the city center. Figure 3 also shows how the incidence of illegal parking changes proportionally with on-street parking occupancy.

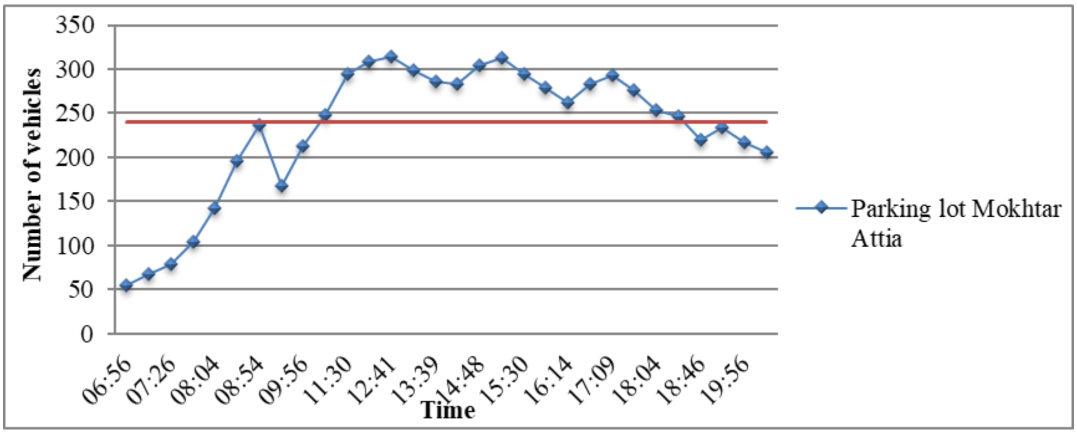

Figure 4 Parking lot occupancy during the day

The number of parked vehicles in parking lot increases over time. They represent drivers heading to downtown Tunis, particularly to the parking lot in Mokhtar Attia. As can be seen, occupancy for this parking lot is quite high during the day. Indeed, our data indicate that it can reach up to 130.83% of its maximum capacity. As an initial step before the causality procedure, descriptive statistics of each of the variables employed in the analysis are described in the following Table.

Table 1 Descriptive statistics

	Parking occupancy (number of parked cars)	**Density road (km)**
Mean	261.16	0.033
Median	278.5	0.033
Maximum	347	0.052
Minimum	64	0.006
Observations	30	30

2.3. Methodology

To measure causality, it is important to consider the stationarity of the time series data. This means that if the two series being studied in our case are not stationary, then we must make them stationary before testing the Granger causality. The first step is to study the properties of the two series in terms of stationarity. Second, one must determine whether the direction of causality exists between the two variables. According to Engle and Granger [15], if the variables are initially nonstationary but become stationary and cointegrated after differencing, then a VECM can be used to discover the multivariable causality in both the short and long term. Moreover, VAR (Vector Autoregressive Model) would be used. Third, we must create the Vector Error Correction Model for all the endogenous variables in the model.

A time series is considered non-stationary if one of its moments (covariance, variance, or mean) is time-independent. A nonstationary series containing a stochastic unit root should be differentiated n times to turn into stationary. Differentiation can assert the mean of a time series by eliminating variations in the level of a time series, and thus suppressing (or minimizing) trend and seasonality. This step is important for two reasons. First, causality tests are too sensitive to the stationarity of the series. Second, the majority of macroeconomic series are not stationary.

To verify the existence of the non-stationarity of a time series, we have adopted unit root tests. Once detected, these tests still make it possible to specify the nature of the non-stationarity, namely process TS (Trend Stationary) or DS (Differency Stationary). Subsequently, we can choose the right method to change a non-stationary series into a stationary series. Several unit root tests exist, such as the Dickey-Fuller tests (1979), and the Augmented Dickey Fuller tests (1981), and the Phillips and Perron tests (1988). We employed the usual unit root test of Augmented Dickey–Fuller (ADF).

According to Granger, a series provokes other series if the knowledge of the history of the first strengthens the prediction of the second. The Granger causality test is a very well answered and easily calculable econometric method specially adapted for time series causality studies [16]. Statistically, it is employed to examine whether a lagged value of one time-series variable provides meaningful data regarding the future value of other time-series variables in the equation [17].

As for multivariate Granger analysis, a Vector Error Correction Model (VECM) or Vector Autoregressive Model (VAR) is generally employed [15, 18]. Therefore, we must determine for each variable the order of the stationarity. Second, it is necessary to determine whether the nonstationary series or their differences have common long-term stochastic trends, known as cointegration. If the two series have the same order of integration, we take to the next step analyzing the presence of cointegration. Significant cointegration indicates there is a long-term relationship between variables [19].

3. Results and discussion

In order to examine the relationship between road density and parking occupancy, we use ADF tests to study the existence of unit roots in the variables. We then analyzed Granger causality and estimated an error correction model (VECM). The results were provided using the Eviews software.

3.1. Unit root tests

Table 2 demonstrates the results of the Augmented Dickey-Fuller tests for all the variables. The null hypothesis of the unit-root tests is: there exists a unit root. However, in the ADF stationarity test, we start by testing and validating the model TS (Trend stationary), then we go further to DS (Differences stationary) with drift, to finally get to DS without drift.

Table 2 Augmented Dickey-Fuller test Results

Null hypothesis: Parking occupancy has a unit root			**Null hypothesis: Road density has a unit root**		
ADF Test	t-statistic	Prob.	ADF Test	t-statistic	Prob.
Model [3]	-1.480360	0.8123	Model [3]	-1.481394	0.8120
Variable : @TREND("1")	-1.478611	0.1523	Variable : @TREND("1")	-1.077014	0.2922
Model [2]	-2.727252	0.0821	Model [2]	-1.711046	0.4150
Variable : C	2.874782	0.0081	Variable : C	1.774440	0.0882
			Model [1]	0.000560	0.6744

First we study stationarity of parking occupation variable. In model [3], the significance of temporal trend (@trend ("1")) variable has to be checked. The Prob (0.1523) is greater than 5%, so the null hypothesis H0 of non-significance is accepted for the coefficient. Hence, the model [3] is rejected.

We proceed to the next model, DS with drift. For validating or rejecting this model [2], the significance of the C constant has to be verified. In our case, the probability of rejecting the Student's test for the C constant (0.0081) is less than 5%, so our coefficient is significantly different from 0. This result means that H1 hypothesis for significance is retained for the constant, which implies that the model [2] is accepted. We proceed then to the stationarity detection: if the t-statistic (-2.7272) is below than the critical value of 5% level, which is equal to (-2.9718) the null hypothesis H0 for non-stationarity is accepted for the variable (or also if prob> 5%).

As a conclusion, the parking occupation variable is non-stationary. That implies that DS process retained is the one with drift, and has at least one unit root. In addition, we do verify stationarity for the road density variable. By applying the ADF test, we found that the trend variable is not significant (Prob> 5%). The model [3] is then rejected and we proceed to the second model.

In our case the probability of rejecting Student's test for C constant (0.0882) is greater than 5%. This result shows that the H1 hypothesis of significance is rejected for the constant, therefore the model [2] is not retained. Hence, we proceed to the next model [1]. As a consequence, the road density variable is non-stationary. It follows a DS process without drift and has at least one unit root.

Finally, the test level for the variables (parking occupancy, road density) showed a non-stationary series, requires testing the first difference. To specify the order of integration of the series, we had to stationary the series by taking the first difference and reapplying the ADF test. By running the stationary test again on the variables in the first difference, we deduce that when first differences are made, the null hypothesis is non-stationary and rejected for all variables. The series are not stationary in levels but stationary at the first difference. In consequence, all variables examined are integrated by one order (I (1)).

3.2. Granger causality analysis

Granger's causality tests (1969) allow us to determine the direction of causality (unidirectional or bidirectional) and to say whether a time series is useful to predict future values of another series. Let's consider two stationary variables, X and Y, observed at T periods. Granger causality (1969) is described as follows: the variable $X_{i,t}$ causes $Y_{i,t}$, if we may need to predict $Y_{i,t}$ in the best way, we had to use all available information, compared to the one without $X_{i,t}$, for each individual $i \in [1, N]$. The F-statistic (or prob.) is employed to test the joint hypothesis of the coefficients regression $\beta_1 = \beta_2 = \beta_3 =. \dots = \beta_i$= 0. Hence, the null hypothesis "X does not Granger-cause" Y is tested. The results of these tests are detailed in the table 3.

Table 3 Granger causality tests Results

Pairwise Granger Causality Tests; Sample: 1 30; Lags: 2		
Null Hypothesis:	**F-Statistic**	**Prob.**
D_PARK does not Granger Cause D_DENSITE	3.338	0.045
D_DENSITE does not Granger Cause D_PARK	1.319	0.288

As outlined in Table 3, our goal was to determine whether traffic congestion generates parking occupancy and vice versa. For the first causality test (whether parking generates congestion), the probability of the Granger test was approximately 0.0446. Since this value is below 5%, we can reject the null hypothesis H0 and then, admit that parking occupancy causes road density.

For the second causality test, we note that the probability (0.2879) is greater than 5% and. Therefore, we accept the null hypothesis H0, which admits that road density does not cause parking occupancy. To conclude, Granger causality testing reveals the existence of a unidirectional causality effect from parking occupancy to traffic density.

3.2.1. Economic urban congestion cost

By calculating the amount of time it takes to travel the Mokhtar Attia Street (see Figure 5), we can estimate the congestion cost induced by the parking problem, as well as its impact on the generalized displacement cost (we limit ourselves to the sample of the previous section)

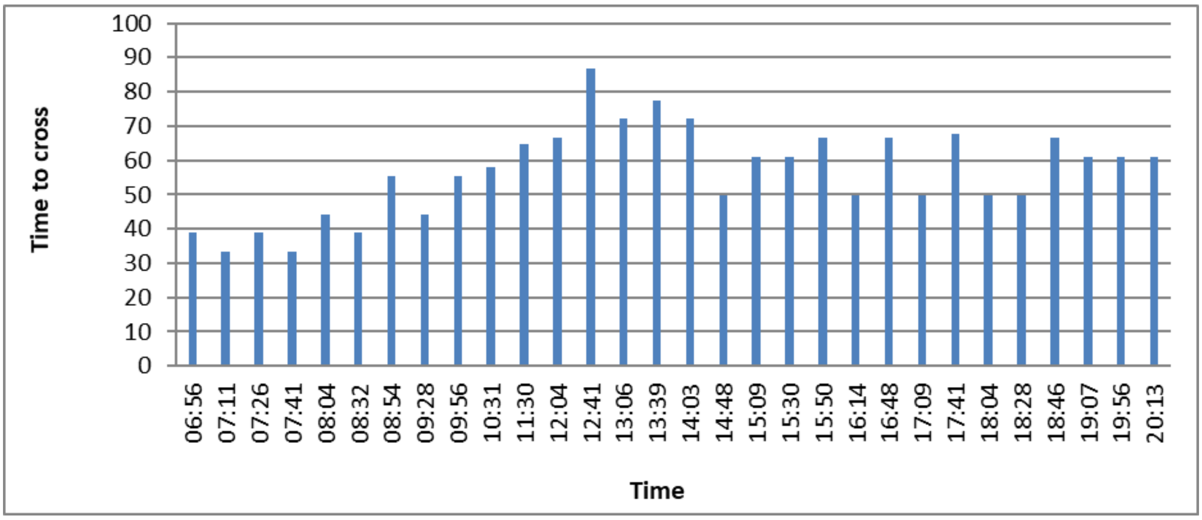

Figure 5 Time to cross Mokhtar Attia Street

The length of the segment on Mokhtar Attia Street that we used to estimate travel times was 277m. A comparison between travel times shows that in the morning the traffic is proportionately more fluid than in the afternoon, where we record the highest travel time. This can be explained by commuters, who leave their workstations for leisure or other reasons. In addition, the parking lot Mokhtar Attia is part of a managed parking system administered by the Municipal Management Agency and is therefore limited to one use per session (one session in the morning between 6:00 am and 1:00 pm; one session in the afternoon between 1:00 pm and 8:00 pm; and one session at night from 8:00 pm to 6:00 am). This can also explain the increase in the time traveled. The time corresponding to 12h41mn, represents the peak of the generalized costs, and that of congestion. In the afternoon, the travel times decrease slightly, but oscillate over time. This could be linked to the fact that departure times from work and activity spaces vary significantly among households.

3.2.2. Road congestion cost

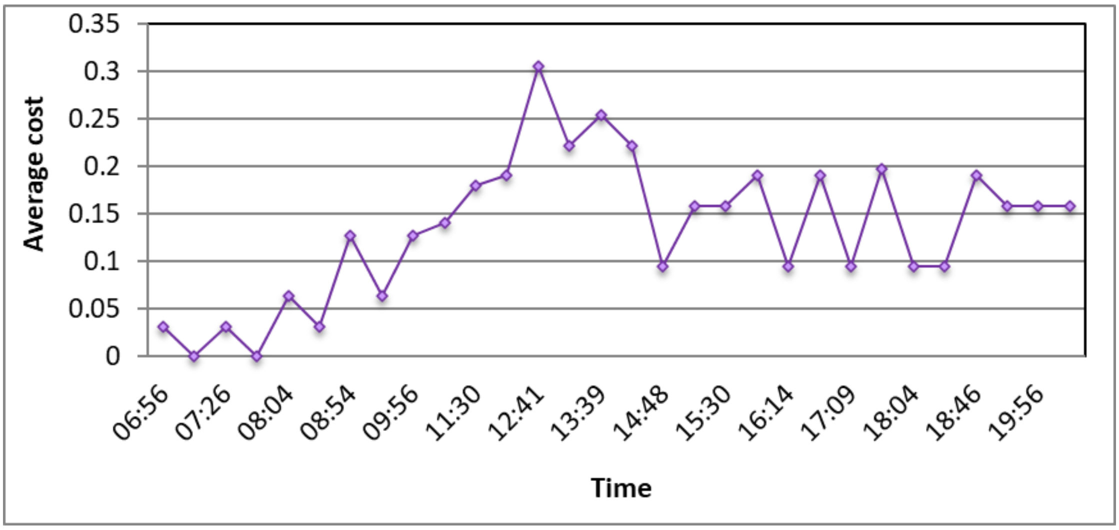

Figure 6 Average cost of traffic congestion

From a macro-economic point of view, it is possible to calculate the total cost of road congestion. The latter can be defined by the time lost (T_p) to travel a road segment multiplied by the driver's time value (w). The cost of road congestion (C_c) is represented by the following formula [19]:

$$(2)\ C_c = T_p \times w = (T_s - T_f) \times w$$

The congestion cost varies over time, reaching the maximum value of (0.305dt) at 12.40pm, and the minimum value of (0dt) at 7.11am (Figure 6). This last value is obtained when traffic is fluid. Congestion has economic repercussions, which affect the delivery time of goods, travel times and accessibility. In addition, congestion has serious social and environmental impacts.

3.2.3. Generalized cost

The generalized cost (C_g) is classically explained by the sum of the displacement private cost (C_p) and the travel time cost (C_t). The components of this equation are defined by:

$$(3)\ C_g = C_t + C_p = (d \times k) + (w \times T_d)$$

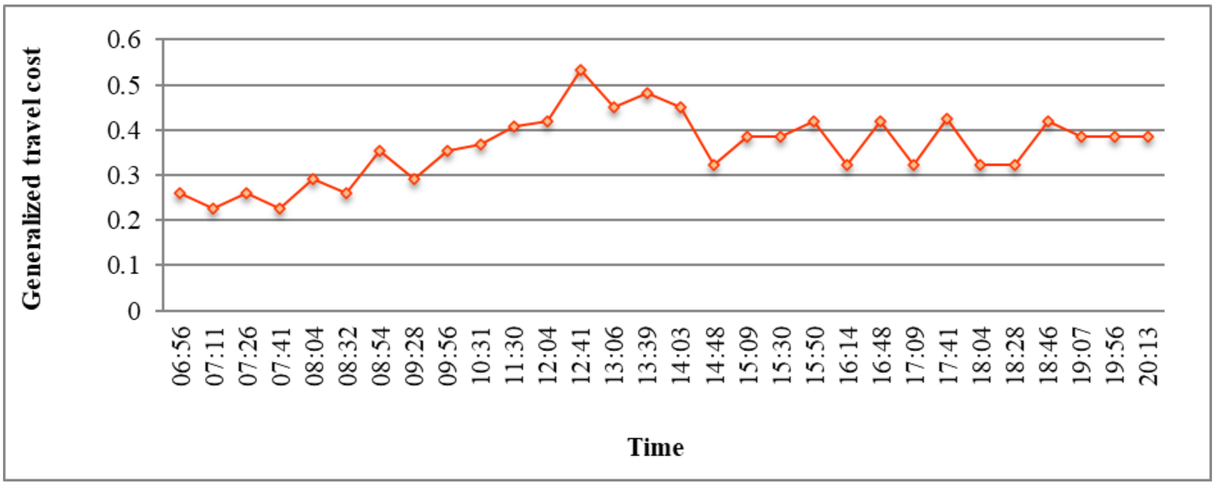

Figure 7 Displacement generalized cost

The cost per kilometer is obtained by multiplying average fuel consumption (7 L/100 km) by the average price of fuel (gasoline + diesel). The generalized cost as shown in Figure 7 varies over time, reaching the maximum value of (0.533 dt) at 12.40 and the minimum value of (0.228 dt) at 7.00 in the morning. The difference between these two last values corresponds to the maximum cost of road congestion, which is equivalent to (0.305dt).

4. Conclusion

Given the role it plays in the socio-economic development of a city, parking remains a major concern for urban centers around the world. It is one of the main components of urban planning. Indeed, a city's parking policies affect the distribution of activities within it. It conditions the fluidity of traffic, influences accessibility to the center, and can affect modal preferences towards vehicles for transport users.

The main purpose of this paper is to demonstrate that parking is a source of road congestion. For this reason, we are interested in the study of the relationship between road density and parking occupancy in the Tunisian transport sector. To this end, we have opted to test the causality relationship. We chose the city center of Tunis as the study area. From the test results, we deduce that there is a unidirectional causal relationship.

However, increased traffic congestion will have negative economic and social repercussions on the downtown area of Tunis, chosen as the study area. In fact, longer travel times will increase vehicle operating costs. Heavier road traffic is often accompanied by a loss of productivity: decrease in GDP, worsening delays for professionals and disruption of goods and/or services delivery. In addition, a more congested road flow hinders the accessibility of the concerned region, and thus reduces its competitiveness. In so doing, the size of business market areas (access to a labor and / or raw material category) and customer delivery (buyers' access to stores) may decrease. These results can be explained in part by insufficient regulatory instruments regarding parking, such as the blue zones applied in the heart of the capital. The blue area is used to increase the car turnover rate by restricting long-term parking, which cannot give optimal solutions for minimizing vehicle kilometers traveled.

Based on the results of Granger causality testing and variance decomposition analyses, some policy considerations can be deduced. Tunisian authorities are aware of the urgency to apply measures that would save the vitality of the city center. They can significantly revise the accessibility of the city center by alternative modes to the car: either by improving the quality of public transport systems or by developing areas that favor a modal shift (park and rides). This latter strategy could reduce the demand for parking considerably. Improving the quality of information disseminated to drivers (for example parking availability, prices, etc.) by installing variable message signs may also help to reduce congestion by ensuring drivers have up-to-date information. The policy makers could focus furthermore on establishing urban transport plan, and reinforcing legislation for the control of illegal parking.

This work is also particularly useful if we consider the study results of the causal relationship between road density and parking lot occupancy, into parking modeling. For this, intelligent systems based on dynamic parking pricing are issues that deserve to be studied. If we have reliable sources for predicting parking occupancy, we could apply dynamic parking pricing to verify the parking demand for each parking facility, as well as the total travel demand in the road network. The dynamic price can be readjusted according to parking occupancy and demands.

Compliance with ethical standards

Acknowledgments

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Disclosure of conflict of interest

The authors have no conflict of interest to be declared.

References

[1] Ben-Hassine S, Mraihi R, Lachiheb A, Kooli E. Modelling parking type choice behavior. International Journal of Transportation Science and Technology. 2021;11(3):653-664. https://doi.org/10.1016/j.ijtst.2021.09.002

[2] Cao J, Menendez M. A Parking-state-based Transition Matrix of Traffic on Urban Networks. Transportation Research Procedia. 2015;7:149-169. https://doi.org/10.1016/j.trpro.2015.06.009.

[3] Ben-Hassine S, Harizi R, Mraïhi R. Intelligent Parking Management System by Multi-Agent Approach: The case of Urban Area of Tunis. 3rd IEEE International conference on advanced Logistic and Transport. 2014:65-71. https://doi.org/10.1109/ICAdLT.2014.6864084

[4] Benenson I., Martens K., Birfir S. Parkagent: An agent-based model of parking in the city. Computers, Environments and Urban systems, 2008, 32, pp. 431- 439. https://doi.org/10.1016/j.compenvurbsys.2008.09.011

[5] Waraich RA, Axhausen KW. Agent-Based Parking Choice Model. Transportation Research Record. 2012;2319(1):39-46. https://doi.org/10.3141/2319-05

[6] Steenberghen T, Dieussaert K, Maerivoet S, Spitaels K. SUSTAPARK: an agentbased model for simulating parking search. Journal of the Urban & Regional Information Systems Association. 2012;24(1):63-77.

[7] Vrancken T, Tenbrock D, Reick S, Bozhinovski D, Weiss G, Spanakis G. Multi-Agent Parking Place Simulation. Advances in Practical Applications of Cyber-Physical Multi-Agent Systems: The PAAMS Collection. 2017;10349:272–283. https://doi.org/10.1007/978-3-319-59930-4_22

[8] Arnott R., Rowse, J. Modeling parking. Journal of Urban Economics. 1999;45(1):97–124. https://doi.org/10.1006/juec.1998.2084

[9] Arnott R, Inci E. An integrated model of downtown parking and traffic congestion. J. Urban Economic. 2006;60:418–442. https://doi.org/10.1016/j.jue.2006.04.004

[10] Gallo M, D'Acierno L, Montella B. A multilayer model to simulate cruising for parking in urban areas. Transport Policy. 2011;18 (5):735–744. https://doi.org/10.1016/j.tranpol.2011.01.009

[11] Shoup DC. The High Cost Of Free Parking. Chicago: American Planning Association. 1997;17(1):3-20. https://doi.org/10.1177/0739456X9701700102

[12] Shoup DC. Cruising for parking. Transport Policy. 2006; 13(6):479–486. https://doi.org/10.1016/j.tranpol.2006.05.005

[13] Weinberger RR, Millard-Ball A, Hampshire RC. Parking search caused congestion: Where's all the fuss? Transportation Research Part C: Emerging Technologies. 2020;120:102781. https://doi.org/10.1016/j.trc.2020.102781.

[14] Millard-Ball A, Weinberger RR, Hampshire RC. Is the curb 80% full or 20% empty? Assessing the impacts of San Francisco's parking pricing experiment. Transportation Research Part A. 2014;63:76–92. https://doi.org/10.1016/j.tra.2014.02.016

[15] Engle RF, Granger CW. Co-integration and error correction: representation, estimation, and testing. Econometrica: J. Econ.Soc. 1987;55(2):251–276. https://doi.org/10.2307/1913236

[16] Seth A, Granger causality. Scholarpedia. 2007;2(7):1667. https://doi.org/10.4249/scholarpedia.1667

[17] Granger CW. Investigating causal relations by econometric models andcross-spectral methods. Econ.: J. Econ. Soc. 1969:424–438. https://doi.org/10.2307/1912791

[18] Enders W. Applied Econometric Time Series. 4th ed. New York: John Wiley & Sons; 2008.

[19] Banerjee, A, Dolado JJ, Galbraith JW, Hendry DF. Co-integration, Error Correction, and the Econometric Analysis of Non-Stationary Data. Oxford: Oxford University Press; 1996. p 320. https://doi.org/10.1093/0198288107.001.0001

[20] Schrank D, Lomax T, Turner S. TTI'S 2010 Urban mobility report, college station. United States: Texas Transportation Institute; 2010. 57 p. https://rosap.ntl.bts.gov/view/dot/61377