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Tourist accommodation pricing through peer-to-peer platform: evidence from Seville (Spain)

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ABSTRACT

The expansion of holiday rentals' worldwide makes it relevant to confirm what are the determinants of these accommodations' daily rates. This research aims to compare two models on estimating holiday rentals' daily rate through variables that influence it; using artificial neural networks and hedonic pricing method, with the same cross-sectional dataset and variables with data obtained from Booking.com listings from Seville (Spain), a 'cultural tourism' large European city. Artificial neural networks estimations adapt better than the hedonic pricing method due to non-linear relations involved, although hedonic estimators have a clearer economic interpretation. Variables related to size, location and amenities appear as the most relevant in the models, including also seasonal and special events factors. The models presented, not only help to clarify these variables but also allow estimating a rental price congruent with the characteristics of the dwelling and season, being useful as an objective valuation method for the main agents of the accommodation sector: Owners, clients and peer-to-peer platforms. This study wants to highlight the convenience of using Booking.com listings as the main data source, as two variables presented as relevant for the models (size and location) are not available in other peer-to-peer platforms like Airbnb.

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1. Introduction

In recent years, the expansion of the holiday rentals' global phenomenon, linked to peer-to-peer (P2P) platforms such as Airbnb or Booking.com, has brought a paradigm shift in the tourist accommodation sector, meaning a real disruptive innovation in it (Guttentag, 2015). Thus, this new context has led to new research areas, making it relevant to confirm what are the influential variables of the holiday rentals' daily rate. This type of accommodation can be defined as private properties (or rooms)

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that are offered for tourist use (Wegmann & Jiao, 2017). Although structural models have been used (Toader et al., 2021), according price forecast methodologies such as the hedonic pricing method (HPM) and the artificial neural networks (ANNs) allow the development of models for the daily rate estimation as well as the marginal price's influence that the variables produce on it. These specifications are especially useful for holiday rentals' clients and owners, as they allow testing if the daily rate is similar to what the market would offer under these particular circumstances.

Within the literature analysed, many studies of real estate and tourist accommodation price modelling were founded. Most of the researches employ a HPM approach, however some based on ANNs were also present. Even only one HPM/ANNs comparison is founded on holiday rentals pricing estimation in sun, sea and sand tourism, taking Airbnb as a database (Moreno Izquierdo et al., 2018). Although the majority of studies analysed regarding this type of accommodation in the literature review use Airbnb as the data source, this work tries to cover the gap in holiday rentals in a cultural tourism destination price modelling comparison (MPH/ANNs) by taking Booking.com as a database, which includes several additional variables that Airbnb does not such as the accommodation size or its exact location as no comparison of these models regarding holiday rentals and taking Booking.com listings as the main data source is founded within the literature. Thus, this research aims to compare two models (using HPM and ANNs methods, respectively) on estimating holiday rentals' daily rate, revealing the variables that influence it, taking a non-standard source inside Academia as Booking.com. This is developed with a sample obtained from properties in the city of Seville, a 'cultural-tourism' large European city, in Southern Spain. The subject of the present study focuses on tourist apartments (aka 'AT' from the Spanish 'apartamentos turísticos') regulated by Andalusia Tourism Law (i.e. 'Ley 13/2011') and in tourist dwellings (aka 'VFT' from the Spanish 'viviendas con fines turísticos') regulated by the regional decree named 'Decreto 28/2016'. These models can be useful for agents of the accommodation sector: Owners, clients and peer-to-peer platforms as an accurate daily rate predictor under previously customised conditions of its valuation determinants. Even can be used for fiscal purposes as an objective tax base estimator.

The structure of this work is based on a literature review; then, the scope of research, population, sample, and dataset methodology is described in the next section. Later, the results of the modelling process are detailed. Finally, the discussion and the conclusions are presented.

2. Hedonic pricing and artificial neural networks on real estate and tourist accommodation

The literature review includes the use of HPM models related to real estate, hotel establishments and holiday rentals, followed by the ANN's modelling in these areas. Concerning this last methodology, there are not many works dedicated to the valuation of daily rates in tourist accommodation. There is an HPM/ANN comparison study about holiday rentals (Moreno Izquierdo et al., 2018).

2.1. Hedonic Pricing Method (HPM)

Most authors establish the origin of HPM in Court's (1939) work, being the first to use the term 'hedonic' in their study about the variables that explain the price of cars. Subsequently, Griliches (1971) and Rosen (1974) developed a unified treatment of HPM, thus establishing their theoretical bases, and proposing models of supply and demand of heterogeneous goods, formed by a basket of inseparable attributes. In the same line, Parker and Zilberman (1993) consider that the HPM is based on the fact that the price of a good is formed by an aggregate associated with a set of variables that influence it. Consequently, the final price is obtained from these attributes through the use of regression techniques, but with problems associated with the multicollinearity of these variables.

Regarding real estate valuation, the work of Ridker and Henning (1967) is considered seminal followed by Freeman (1979), Palmquist (1980), Kang and Reichert (1991), Caridad y Ocerin and Brañas Garza (1996) and Broxterman and Kuang (2019). In all of them, the exogenous variables include the size of the property and the amenities available. Other recurrent determinants are related to the distance to the city centre as in Moallemi & Melser, (2020). Recently, Etxezarreta-Etxarri et al. (2020) present a study measuring the 'Airbnb effect' in real estate valuation following HPM. ANNs/HPM models comparative studies have been also carried out; see 'Artificial Neural Network (ANN)' section.

In price estimation for stays in hotel establishments, the first studies are related to sun-and-beach tourism, as in Coenders, Espinet & Saez (2003) and Rigall i Torrent et al. (2011), in which variables related to seasonality are included. In Chen and Rothschild (2010) for Taipei (Taiwan), Andersson (2010) for Singapore, Zhang, Ye and Law (2011) for New York (US) and Kuminoff, Zhang and Rudi (2010) for Virginia (US), the variable selection is especially significant. These works mentioned are responsible for highlighting price determinants referring to the distance from the accommodation to the centre, its size in square meters, availability of television, swimming pool, and pets' allowance, among other amenities.

Later, Soler García et al. (2017) analyse the incidence of special events, such as the April's Fair in Seville (Spain). Some recent works are based on data from Booking.com listings such as Stojchevska, Naumoski and Mitreski (2018) and Nieto García, Resce, Ishizaka, Occhiocupo and Viglia (2019), focused on variables related to amenities of accommodation such as the availability of terrace, balcony, views, bathtub or parking. The study of Mondaca Marino, Guala, Montecinos Astorga and Salazar Concha (2019), by contrast, focuses on variables such as the client's rating summarizing their opinion of the property.

Related to holiday rentals, the study of Pérez Bastidas and Marmolejo Duarte (2014) stands out as one of the first in this area, which presents a comparison of two HPM: One for the valuation of residential rents and the other for dwellings for tourist use, highlighting variables such as washing machine availability, or the district in which the property is located. Subsequently, are the references of Wang and Nicolau (2017), Gibbs, Guttentag, Gretzel, Morton and Goodwill (2018)—the last uses the variable number of photos—and Gunter and Önder (2018) that takes into account the number of occupants. In similar terms, Cai et al. (2019), González Morales et al.

(2019), Lawani et al. (2019), Moreno Izquierdo, Ramón Rodríguez, Such Devesa and Perles Ribes (2019) and Tong and Gunter (2020) use Airbnb as the main data source. Only one holiday rentals' price model that use Booking.com listings as the main data source has been found (Santos et al., 2020).

2.2. Artificial Neural Network (ANN)

Rumelhart, Hinton and Williams (1986) define ANNs as a non-linear model composed of several simple operators with a small amount of memory called process elements (PE) or nodes. These PEs include a vector of inputs and synaptic weights which apply to these vectors employing the propagation rule. Subsequently, an activation function is applied to this result, providing the output value of the PEs, which in turn connects with the input values of the next PEs group. These groups are called layers, which depending on the place they occupy in the network can be input, output and intermediate (or hidden) layers, which can be one or more (see Figure 2 in 'ANN development, network architecture and synaptic weights' section).

In real estate valuation, pioneering works are White (1989) and Borst (1991), which were followed by Tay and Ho (1992) and Worzala et al. (1995), using the size of the property and adding other causal variables. In this line, can be found the works of Caridad y Ocerin and Ceular Villamandos (2001), Caridad y Ocerin, Núñez Tabales and Ceular Villamandos (2008), and Núñez Tabales, Rey Carmona and Caridad y Ocerin (2013). The research field has expanded toward commercial premises' valuation models (Núñez Tabales, Rey Carmona & Caridad y Ocerin 2016). The study by Hu et al. (2019) analyses prices in several cities following various methodologies. In this work, variables related to the location such as distance to the nearest hospital are shown as one of the most noteworthy.

Regarding tourist accommodation models based on ANNs, the literature includes Al Shehhi and Karathanasopoulos (2018) for hotels in the Middle East and Egypt, research that considers the influence of the days of the week on the price. In the same line, Moro, Rita and Oliveira (2018) analysed 23 cities in Portugal using Booking.com and TripAdvisor as main data sources; including variables referring to the proximity to the city centre and seasonality. The study by Moreno Izquierdo et al. (2018) compares HPM and ANNs models using Airbnb as a data source. No work has been found regarding holiday rentals valuation based on ANNs using Booking.com as the main data source. Table 1 presents the studies mentioned that use tourist accommodation estimation models using HPM and/or ANNs.

3. Dataset and specifications methodology

3.1. Scope of research, population and sample

An empirical study is carried out in Seville, the capital of Southern Spain (Figure 1a) and the most populated council in the region of Andalusia (Junta de Andalucía, 2019). The place highlights for its cultural tourism and was chosen as the best city to visit in 2018 by Lonely Planet (2017) within its publication *Best in Travel 2018*, and its ranking as the 6th city for the number of overnight stays in Spain (INE, 2017).

Table 1. Estimation models in tourist accommodation. HPM and ANNs.

Author/s	Year	Methodology	Subject of study
Coenders, Espinet and Saez	2003	HPM	Hotels
Andersson	2010	HPM	Hotels
Chen and Rothschild	2010	HPM	Hotels
Kuminoff, Zhang and Rudi	2010	HPM	Hotels
Rigall i Torrent, Fluvià, Ballester, Saló, Ariza and Espinet	2011	HPM	Hotels
Zhang, Ye and Law	2011	HPM	Hotels
Pérez Bastidas and Marmolejo Duarte	2014	HPM	Residential rents and holiday rentals
Wang and Nicolau	2017	HPM	Holiday rentals
Soler García, Gémar Castillo and Universidad de Mála	2017	HPM	Hotels
Gibbs, Guttentag and Gretzel	2018	HPM	Holiday rentals
Gunter and Önder	2018	HPM	Holiday rentals
Al Shehhi and Karathanasopoulos	2018	ANNs	Hotels
Moreno Izquierdo, Egorova, Peretó Rovira and Más Ferrando	2018	HPM/ANNs Comparative	Holiday rentals
Moro, Rita and Oliveira	2018	ANNs	Hotels
Stojchevska, Naumoski, Mitreski and IEEE	2018	HPM	Hotels
Cai, Zhou and Scott	2019	HPM	Holiday rentals
González Morales, Chica Olmo and Zafra Gómez	2019	HPM	Holiday rentals
Lawani, Reed, Mark and Zheng	2019	HPM	Holiday rentals
Moreno Izquierdo, Ramón Rodríguez, Such Devesa and Perles Ribes	2019	HPM	Holiday rentals
Mondaca Marino, Guala, Montecinos Astorga and Salazar Concha	2019	HPM	Hotels
Nieto García, Resce, Ishizaka, Occhiocupo and Viglia	2019	HPM	Hotels
Tong and Gunter	2020	HPM	Holiday rentals
Santos, Fernández-Gámez, Solano-Sánchez, Rey-Carmona & Caridad-y-López-del-Río	2021	HPM	Holiday rentals

Source: authors.

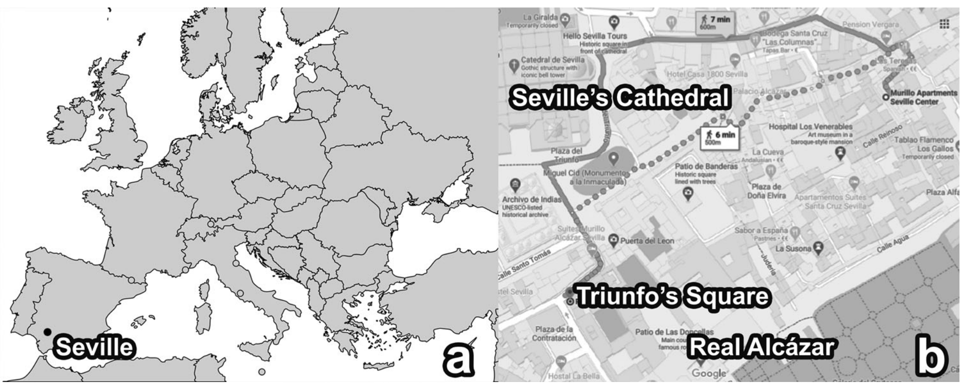

Figure 1. Geographical location of Seville in Europe (A) and point of maximum tourist interest in Seville (B). Source: Mapchart (2020) and Google Maps (2020).

The available accommodation properties in the city of Seville are included in the public regional registry, -'Registro de Turismo de Andalucía' (RTA., 2018)- for AT and VFT. Each AT entry may include more than one apartment, while each VFT registry corresponds to one property. In the data collection process, it is checked that the address in the RTA and Booking match each other. Only cases with complete information are retained. In VFT cases, dwellings with separate rentals per room are excluded to incorporate only prices per apartment in the dataset. Data were collected

Table 2. Population, sample and number of cases analysed.

Typology	Population	Sample	No. of cases
AT	133 registrations	112 registrations, 293 apartments	610
VFT	3,465	665	1,623
Total	3,598	958	2,233

Source: authors based on RTA (2018).

Table 3. Variables considered.

Variable	Typology	Description	Source
PRC	Numeric	Daily rate (in euros)	Booking.com (2018)
ACC	Binary	Accommodation typology (AT/VFT)	RTA (2018)
DIS	Categorical	District where the accommodation is located	IDE Sevilla (2018)
MIN	Numeric	Minutes spent walking from the accommodation to the spot of maximum tourist interest (SMIT)	Google Maps (2018)
OCC	Numeric	Number of occupants	Booking.com (2018)
M2	Numeric	Square meters	
TV	Binary	Television	
WM	Binary	Washing machine	
BAL	Binary	Balcony	
TER	Binary	Terrace	
PAT	Binary	Patio	
VIEW	Binary	View	
SND	Binary	Soundproofing	
PARK	Binary	Parking	
PET	Binary	Pets allowance	
POOL	Binary	Swimming pool	
BATH	Binary	Bathtub	
RAT	Numeric	Rating of users (from 0 to 10)	
PHO	Numeric	Number of photos	
VAP	Numeric	Visual appeal (from 0 to 10)	Authors
HWD	Binary	High season, weekday	Booking.com (2018)
HWE	Binary	High season, weekend	
LWD	Binary	Low season, weekday	
LWE	Binary	Low season, weekend	
SE1	Binary	Special event 1: Holy Week	
SE2	Binary	Special event 2: April's Fair	

Source: elaborated by authors.

from October to December of 2018. Table 2 is a summary of the population and sample sizes, and the number of cases included in the dataset used. This figure is larger than the sample size as there are data taken from the same apartment offered at different prices according to the number of occupants.

3.2. Variables considered

The selection of the cross-sectional variables (Table 3) is based on the literature review as well as the info available in Booking.com listings. The daily rate (PRC) is taken for a two-day stay, which is the average in the city of Seville, according to the Tourism Data Centre of Seville (Centro de Datos Turísticos del Ayuntamiento de Sevilla, 2017). It includes taxes and other expenses such as cleaning. The option for cancellation in a certain period and/or partial refund is preferably selected. Within the same AT registry, whenever different apartments are offered at the same price, the one that offers the highest added value in terms of size and/or amenities is chosen to imitate a rational consumer's behaviour.

The MIN variable reflects the minutes spent walking from the accommodation to the spot of maximum tourist interest (SMIT). In this case, the 'Plaza del Triunfo' is taken as SMIT, as it is located between the Cathedral of Seville and the 'Real Alcázar' (Figure 1b), the two most visited monuments in the city (Centro de Datos Turísticos del Ayuntamiento de Sevilla, 2017). Only the views (VIEW) of panoramas or emblematic monuments of the city are considered, thereby excluding views of courtyards and/or interior gardens. Both parking (PARK) of the accommodation itself and those in the surrounding area are included. Visual appeal (VAP) is taken based on objective criteria, such as the properties' cleanliness, the quality of the photos and/or the presentation of the accommodation. Lastly, the price is recorded on different dates during the year. The high season is considered from April to September and the low season for the rest of the year. There are special events to affect the daily rental, such as the Holy Week (SE1) (i.e. Catholic Easter) and April's Fair (SE2).

3.3. Dataset obtained

Table 4 reflects descriptive statistics of the numeric variables. The variability of the characteristics of these properties is quite large. The most frequent is an apartment with an approximately mean daily rate of €162, for 3 or 4 occupants, around 72 m^2 in size and located at 14 minutes walking from the SMTI. Also, the ratings attributed by the clients vary from medium to maximum satisfaction. Price variations are significant when the special events are taken into account, consequently, a high standard deviation is presented in PRC variable. A prominent standard deviation is also reflected in size (M2).

Descriptive statistics of the categorical variables are shown in Table 5. Most of the properties are located in three districts, near the centre, the touristic areas of the railway station. Also, television and washing machine are present in over 90% of the apartments. The availability of parking places is important in the tourist districts, but, obviously, for the clients who travel by car; this suggests that many apartments are used by Spanish visitors who can use this kind of accommodation as a cheaper alternative to hotels. Also, many tourists come using public transport, and so do not appreciate this kind of facility. Pet allowance is presented in one out of ten accommodations analysed. Pool availability is scarce in the dataset obtained, implying around 4% of the total.

Seasonal factors are taken following a criterion of a proportional division of the year: High and low seasons are split into approximately two equal parts, considering slightly larger the high season sample, due to the overnights increment in this period.

Table 4. Descriptive statistics for numeric variables.

Variable	Mean	Stand. dev.	Min	Max
PRC	161.47	99.091	42	1,164.9
MIN	13.82	8.97	1	94
OCC	3.92	1.878	1	16
M2	72.32	41.057	9	600
RAT	8.847	.6527	6	10
PHO	35.68	11.256	3	56
VAP	8.487	.8343	5	10

Source: elaborated by authors.

Table 5. Categorical variables.

Variable		Counts	% over total
ACC			
	AT	610	27.32%
	VFT	1,623	72.68%
DIS			
	Casco Antiguo	1,893	84.77%
	Triana	216	9.67%
	Nervión	58	2.60%
	Macarena	22	.99%
	Los Remedios	14	.63%
	San Pablo - Santa Justa	11	.49%
	Este	7	.31%
	Sur	6	.27%
	Bellavista	4	.18%
	Cerro Amate	2	.09%
TV		2,219	99.37%
WM		2,016	90.28%
BAL		925	41.42%
TER		779	34.89%
PAT		664	29.74%
VIEW		1,151	51.55%
SND		523	23.42%
PARK		1,038	46.48%
PET		264	11.82%
POOL		98	4.39%
BATH		640	28.66%
HWD		758	33.95%
HWE		308	13.79%
LWD		642	28.75%
LWE		246	11.02%
SE1		169	7.57%
SE2		110	4.93%

Source: elaborated by authors.

Weekday/weekend split is divided around its proportional ponderation that those have in a year. The same criteria are followed for the special events (SE1 and SE2) of one-week duration both.

4. HPM and ANN modelling results

Both types of models (HPM and ANN) have been estimated using IBM's SPSS software. The criteria for selecting the significant variables for estimating the daily rate, as well as the actions taken to optimise the HPM model, are described in 'Variable selection and HPM model optimization' section. The architecture of the ANNs obtained and their synaptic weights are presented in 'ANN development, network architecture and synaptic weights' section. A comparison of both models in terms of goodness of fit is developed in 'Comparison of HPM/ANNs models' section. Finally, an analysis of the variables' influence on the daily rate is described in 'Influence analysis of each variable in the price' section.

4.1. Variable selection and HPM model optimization

The HPM model used is defined in Equation 1. It estimates the price where an ordinary weekday in high season (HWD) is taken as the basis, that is why this variable is not present in the equation, and the other seasonality (HWE, LWD, LWE) and special events (SE1, SE2) variables are present modifying the HWD price taken as reference. The 13 variables non-present in Equation 1 (from the 25 originally considered, see Table 3) are shown as non-relevant in the configuration of the daily rate and consequently discarded. The remaining T tests of the exogenous variables in Equation 1 present very low p-values (lower than 1%), confirming the convenience of maintaining these in the model. Five atypical cases that significantly distorted the model are excluded (using statistical procedures for this purpose as Cook's Distance and DFFITS), corresponding to unusually large apartments. Econometric diagnostics measures have been applied to result in concluding the low importance of multicollinearity. Thus, the variance inflation factor (VIF) of every variable never reaches values higher than 2, being a VIF 10 or more the standard multicollinearity criterion.

The coefficients obtained present the marginal variation in the daily rate that the variable produces. Thus, each additional square meter (M2) increments its price by €0,79, as well as the pool availability (POOL), adds €33,71 to the daily rate. The artificial variables HWD, HWE, LWD, LWE, SE1 and SE2 measure the contribution of different seasonal effects and events. Daily rate decreases by €29,23 in low season (weekdays) comparing to high season weekdays (HWD). In similar terms, prices roses by €154,76 and €127,16 during the special events of Holy Week (SE1) and April's Fair (SE2) respectively.

$$\begin{aligned} \mathrm{PRC} = & -76.73 - 1.161\mathrm{MIN} + 13.679\mathrm{OCC} + 0.792\mathrm{M2} + 12.656\mathrm{SND} \\ & + 33.712\mathrm{POOL} + + 15.129\mathrm{VAP} + 20.025\mathrm{HWE} \\ & - 29.225\mathrm{LWD} - 23.607\mathrm{LWE} + 154.762\mathrm{SE1} + 127.115\mathrm{SE2} + e \end{aligned} \tag{1}$$

4.2. ANN development, network architecture and synaptic weights

The network is developed using the same final dataset and relevant variables as in the HPM model to allow a direct comparison. Several topologies are tested, taking the criterion of selecting the ANNs with the highest predictive value and the lowest error. The final model is a multilayer perceptron MLP (13, 8, 1). The ANN architecture achieved is presented in Table 6.

In the process of network development, a random division of the sample into the training (69.60% of the data) and testing (30.40%) groups is used. The condition of further calculation given without a decrease in error in the test group is taken as the stopping rule for the elaboration of the model. Table 7 also presents the training time obtained and the errors obtained in training and testing groups. In absolute terms, the sum of squares is the arithmetical addition of all the differences in real and estimated values squared (to turn all the data into positive values). In relative terms, the relative error is the difference expressed in percentage of real and estimated values. In this case, both groups present similar developments (24.7% training, 23.6% testing; Table 7).

The synaptic weights of the input layer to the hidden layer (Table 8) and the hidden layer to the output layer (Table 9) are presented. Figure 2 shows the estimated

Table 6. MLP network architecture.

Input layer	Bias	Value = 1
	Factors (binary variables)	SND
		POOL
		HWD
		HWE
		LWD
		LWE
		SE1
		SE2
	Covariates	MIN
		OCC
		M2
		VAP
	Rescaling method for covariates	Standardised
Hidden layer	Number of hidden layers	1
	Number of units in hidden layers	8
	Activation function	Hyperbolic Tangent
Output layer	Dependent variable	PRC
	Number of units	1
	Rescaling method for scale dependents	Standardised
	Activation function	Identity
	Error function	Sum of squares

Source: elaborated by authors.

Table 7. Model summary.

Groups	Performance summary of the obtained network	
	Sum of squares error	191.765
Training	Relative error	.247
1,551 (69.60%)	Stopping rule used	One consecutive step with no decrease in error
	Training time	0:00:00.67
Testing	Sum of squares error	83.054
677 (30.40%)	Relative error	.236
Total	Valid	2,228
	Excluded	5
	Number of cases	2,233

Source: elaborated by authors.

network, with the connexions between the PEs of different layers through their synaptic weights.

4.3. Comparison of HPM/ANNs models

Table 10 presents an overall assessment comparison of both models. First, the coefficient of determination (R^2) is the proportion of the daily price (PRC) explained by the exogenous variables. Second, the mean absolute percentage error (MAPE) is the mean differences between real and estimated prices. Better adjustment values in both goodnesses of fit measures correspond to the ANN model compared to the HPM, as it could be expected as the latter has a larger number of parameters than the former.

Figure 3 shows a comparison of real and estimated prices obtained by both models. Up to €400 in daily rates, both models perform reasonably well, from which the HPM tends to underestimate the values. Regarding the ANNs model, it tends to overestimate mostly up to €600 range, from which it begins to underestimate the prices.

Table 8. Synaptic weights from the input layer to the hidden layer.

		Hidden layer							
Layer	PE and bias	H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	H(1:8)
Input layer	Bias	.365	.155	-.061	-.469	-.225	.188	-.457	.252
	SND = 0	.297	-.515	.153	-.205	-.095	-.466	-.195	.137
	SND = 1	.376	-.284	.488	.25	-.254	.057	.19	.531
	POOL = 0	.225	-.169	-.411	.012	.26	-.164	.11	-.322
	POOL = 1	-.22	-.269	-.034	.002	.482	.396	-.309	.14
	HWD = 0	.026	-.364	-.312	.082	-.406	.486	-.497	-.23
	HWD = 1	-.255	.179	-.193	-.35	-.576	-.097	-.452	-.178
	HWE = 0	.067	-.745	.093	-.241	-.092	.043	.038	.16
	HWE = 1	.184	.302	-.526	-.512	.15	-.282	-.069	-.4
	LWD = 0	-.554	-.453	.302	.309	.147	-.147	-.595	-.363
	LWD = 1	.459	.274	.64	-.428	-.015	-.279	-.154	.471
	LWE = 0	-.456	-.665	-.036	.398	.419	.513	-.518	.31
	LWE = 1	.32	.04	.03	-.351	-.118	.426	.214	.147
	SE1 = 0	.403	-.361	.026	-.643	-.6	-.524	.032	.436
	SE1 = 1	-.477	.117	-.153	.176	-.001	.437	-.021	.166
	SE2 = 0	.613	-.179	.475	-.283	-.162	.356	-.057	.545
	SE2 = 1	-.151	-.153	.073	.187	.301	.093	.378	.416
	MIN	.15	.003	-.165	.065	-.36	-.392	.056	.173
	OCC	-.13	.191	-.065	.111	.424	.368	.45	-.294
	M2	-.254	-.301	-.281	.236	-.147	-.193	.509	.404
	VAP	-.11	.224	.314	.133	.403	.333	-.182	-.306

Source: elaborated by authors.

Table 9. Synaptic weights from the hidden layer to the output layer.

Layer	PE and bias	Synaptic weights to the output layer
Hidden layer	Bias	1.049
	H(1:1)	-.864
	H(1:2)	−1.03
	H(1:3)	-.289
	H(1:4)	1.145
	H(1:5)	.441
	H(1:6)	.222
	H(1:7)	.375
	H(1:8)	.031

Source: elaborated by authors.

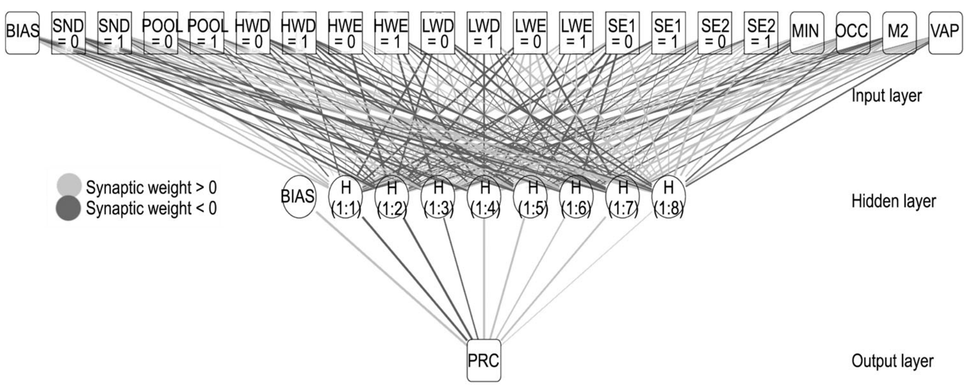

Figure 2. Graphic representation of the ANNs obtained.
Source: elaborated by authors.

4.5. Influence analysis of each variable in the price

The ANNs methodology allows an analysis of the relative importance of exogenous variables (Figure 4). The size of the accommodation (M2) or the number of

Table 10. Overall assessment comparison of HPM and ANNs models.

	HPM	ANNs
Coefficient of determination (R^2)	70.84%	78.16%
Mean absolute percentage error (MAPE)	22.51%	19.73%

Source: elaborated by authors.

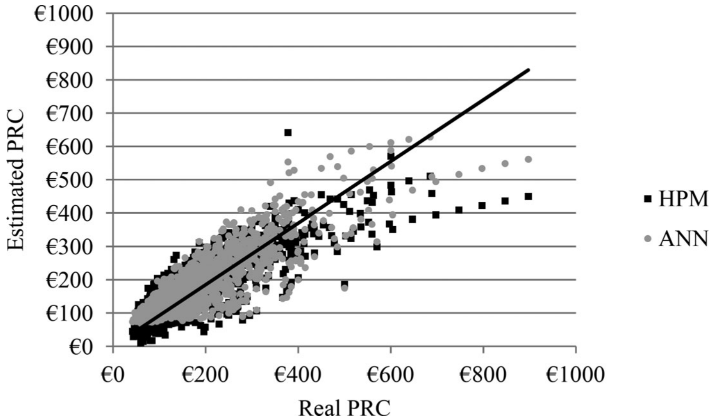

Figure 3. Real/estimated prices comparison of HPM and ANNs models.
Source: elaborated by authors.

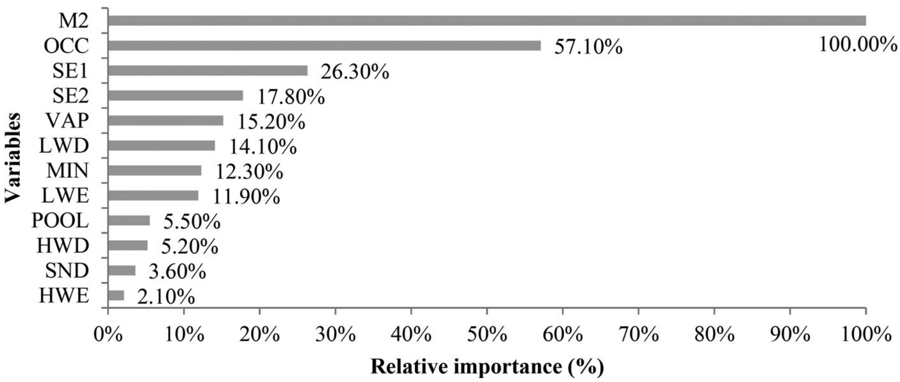

Figure 4. Relative importance of exogenous variables in ANNs model.
Source: elaborated by authors.

occupants (OCC) is of primary importance. The city's special events (SE1 and SE2) also appear, to a lesser extent, as important determinants of daily rates. Subsequently, variables as visual appeal (VAP) or location (MIN) are significant. Accommodation amenities such as pool availability (POOL) or soundproofing (SND) are less influential.

Analysing the direct influence of exogenous variables, Table 11 shows the incidence of the binary variables in the daily rate. Although in the HPM these values are fixed, in the ANNs model they fluctuate constantly, influencing each other, so the factors shown in Table 11 represent the effect of the exogenous variable when the rest of the numeric variables remain in their means and the binaries are equal to their respective modal values. This same criterion is used to show the incidence in the price of all covariates (Figures 5, 6, 7 and 8), taking the price during high season on weekdays (HWD) as the basis.

Table 11. Binary variables' direct influence (in €) of HPM and ANNs models.

Binary variables	HPM	ANNs
SND (soundproofing)	+€12.66	+€12.36
POOL (pool availability)	+€33.71	+€37.56
HWE (high season, weekend)	+€20.03	+€20.42
LWD (low season, weekday)	-€29.23	-€28.07
LWE (low season, weekend)	-€23.61	-€24.14
SE1 (Special event 1: Holy Week)	+€154.76	+€170.61
SE2(Special event 2 April's Fair)	+€127.12	+€114.20

Source: elaborated by authors.

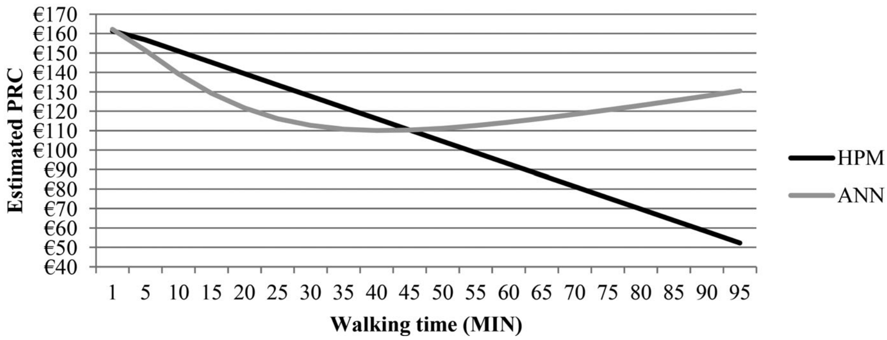

Figure 5. MIN effect in estimated daily rate in HPM and ANNs models.
Source: elaborated by authors.

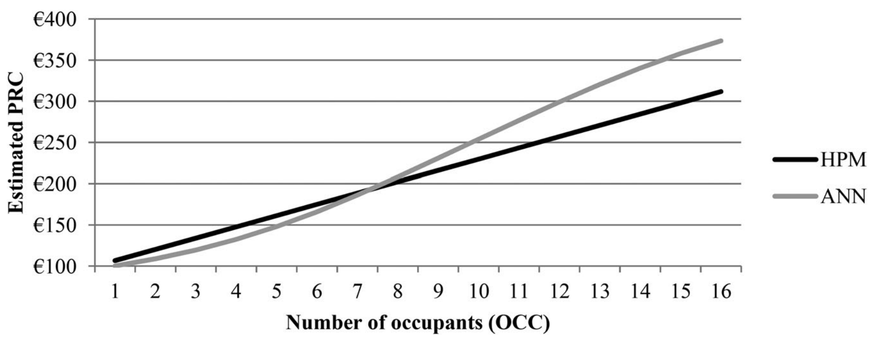

Figure 6. OCC effect in estimated daily rate in HPM and ANNs models.
Source: elaborated by authors.

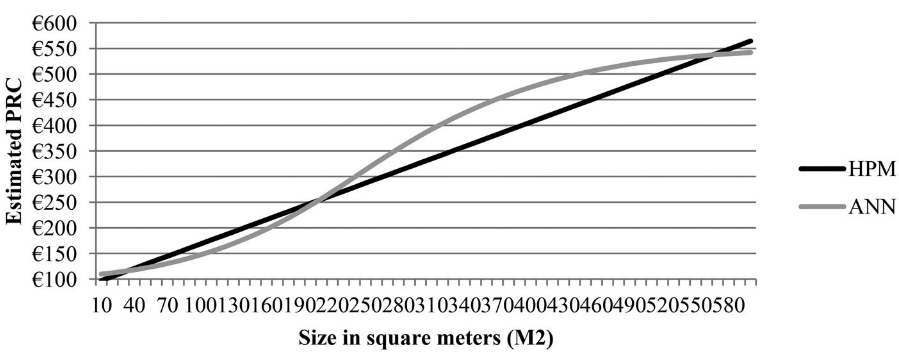

Figure 7. M2 effect in estimated daily rate in HPM and ANNs models.
Source: elaborated by authors.

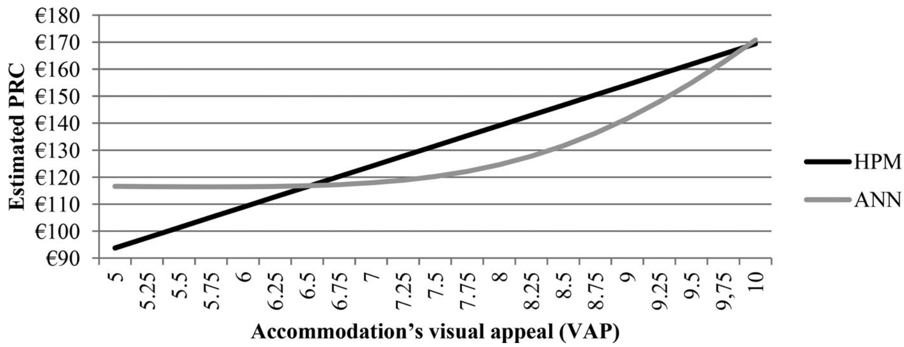

Figure 8. VAP effect in estimated daily rate in HPM and ANNs models.
Source: elaborated by authors.

Table 11 presents similar values for both models, in concordance with a consumer's behaviour, willingness to pay more for pool availability (POOL) or soundproofing (SND). In high season, although the price is higher at the weekend (HWE, around €20 more per day for both models, Table 11) in low season the price is reduced (LWD, LWE). The increase in the demand for accommodation produced in the city's special events (SE1 and SE2) implies prices to skyrocket.

Figure 5 presents the influence of the walking time (MIN) to the spot of maximum tourist interest. Differentiated behaviours are developed by both models. Although the HPM shows its performance in the form of a decreasing straight line, the ANN model presents a decreasing convex curve up to the range of 40 minutes, where it becomes slightly increasing from that point. This phenomenon is produced due to the mutual influence of the variables in the ANN. The significant increase of the accommodations' size (and consequently, in prices) as they are becoming far from the city centre (and old town) is a factor that affects the daily rate more than the walking-time effect.

The influence of the number of occupants (OCC) is shown in Figure 6. Both models present similar behaviours, although the ANNs curve has a convex shape up to a turning point in the 'eight occupants' range. From that position, turns into a concave curve and displays a greater influence on the price than the HPM model. On average, it can be seen how every additional occupant increment price in HPM by €13,68 (see Equation 1) and €18,33 in ANNs' case—obtained dividing €275 (€375 minus €100) into 15 (16 minus 1).

Figure 7 reflects the influence of apartment size (M2). Although both models have similar ascending behaviour, the ANNs curve shows a convex shape from the turning point intersecting with the HPM line for a size of 200 m^2, what means that prices increase less than proportional (diminishing returns' curve shape) from this point. The M2 and OCC variables are those that present a larger effect on the daily rate, which connects to the trend shown in Figure 4 (M2 and OCC in the first and second position, respectively), and, in the M2 case, those analysed in Figure 5 regarding mutual influence among variables, as in the ANN models all variables influence each other. In some special cases, such as properties with a pool availability, the bigger increase in price and size is detected within the ANN model, as the probability of found this item is related to 'luxury-villas' accommodations from 200 m^2, in comparison with a general lineal and 'non-pool-effect' influence in HPM. Also, a greater number of occupants (OCC) in bigger apartments and/or houses may influence in M2 variable from 200 m^2 in the ANN model.

The variation of the accommodation's visual appeal (VAP) is displayed in Figure 8. The convex curve represented by the VAP variable in the ANN model shows a practically null influence (with cutting point to HPM line at 6.5) up to a rating of 7.5 out of 10, from which it presents a pronounced growth to an additional cutting point with the line of the HPM model around the maximum rating (Figure 8), meaning a tendency of the clients to pay more for holiday rentals with ratings above 7.5. Thus, VAP in ANN model has a determinant contribution in daily rate increase from a qualification of 7.5 over 10 hereon, being this consistent with the clear increase of prices for the high-end properties.

5. Discussion

Summarising the information collected in the results, it can be said that, comparing MPH and ANN models, the last reach higher goodness of fit in pricing prediction. This fact is commonly observed in the literature regarding real estate valuation (Núñez Tabales et al., 2013; Núñez Tabales et al., 2016), and same as concluded in holiday rentals' daily rate estimation (Moreno Izquierdo et al., 2018), as ANN models have more complex topology than MPH, as they are non-linear and include more parameters. However, both present similar results regarding variables' influence on price, except the MIN variable (see Figure 5 and comments above).

Entering the analysis of the variables, although a wide set of them are previously considered, only half of them is shown as relevant to estimate daily rates. First, distance to the centre, beach (in coastal destinations), transportation hubs and other 'point of interest' are presented as relevant in the literature (Wang & Nicolau, 2017; Gibbs et al., 2018). The number of occupants' presence is also common (Gibbs et al., 2018; Gunter & Önder, 2018). All of these variables have appeared as determinant in the present research for holiday rentals price estimation.

Accommodation size variable is scarce in holiday rentals' valuation (Pérez Bastidas & Marmolejo Duarte, 2014) as this info is not available in the majority of Airbnb's listings, taken as the main source of data in most of the researches regarding in holiday rentals' price determinants models. The inclusion as relevant of property size is, in turn, more related with real estate valuation, as in Pérez Bastidas and Marmolejo Duarte (2014)—in which a residential and holiday rentals models are compared—or others works exclusively dedicated to real estate (Caridad y Ocerin & Brañas Garza, 1996; Núñez Tabales et al., 2013; Núñez Tabales et al., 2016). The relevance presented in the present research's models developed (see Equation 1 and Figure 4) justifies its inclusion and the convenience of using Booking.com listings (with accommodation size data available) instead of Airbnb.

Regarding amenities, a large number of them were discarded. Only pool availability, in the line of Andersson (2010), Chen and Rothschild (2010), Gibbs et al. (2018), Moro et al. (2018) and soundproof (Stojchevska et al., 2018) are shown as determinants in price. Seasonality effects are abundant in literature, mainly related to sun-and-beach tourism (Coenders et al., 2003; Rigall i Torrent et al., 2011); conversely, special events factors (Soler García et al., 2017) are rarely found. Both types of variables appear relevant in the proposed models of this research, in the context of cultural tourism.

Finally, is worth mentioning some non-relevant variables detected in this work, as the AT/VFT division is not differentiated from the users' point of view. Also, rating appears as no determinant in price, contrary to what happens in Wang and Nicolau (2017), Moreno Izquierdo et al. (2018), and Tong and Gunter (2020); the same can be said about the number of photos on the web, as in Gibbs et al. (2018), Gunter and Önder (2018), Moreno Izquierdo et al. (2018), and Tong and Gunter (2020). All these previous studies use Airbnb listings as the main data source, conversely to the present research that opts for Booking.com. These differences could be partly attributed to the relations between different explanatory variables.

6. Conclusions

Introducing the theoretical implications of the research, and according to the aim proposed of the two models' comparison, it can be concluded that ANN methodology originates significantly higher goodness of fit than HPM. Not only are the exogenous variables explaining the composition of the price to a greater extent, but the error made in its estimates was lower in the case of the ANN model, due to its non-linearity transfer function (in contrast to HPM), and since neural network models are specified with a larger number of parameters. Also, the non-linear influence of some exogenous variables is considered in the multilayer perceptron model used.

Regarding the particular influence of each variable on the daily rate, it is concluded that both models present a rational consumer's behaviour and both display similar development. However, HPM parameters are constant along with all the range of cases, and consequently, have a clearer economic interpretation as constant marginal prices, while marginal prices in ANN are not constant.

Related to the identification of the valuation determinants of the daily rate, it can be said that only twelve variables, from the 25 originally considered, were shown as relevant. Of these, among the most influentials are the size of the accommodation, the number of occupants, the special events in the city, the visual appeal and, to a lesser extent, variables related to seasonality, location and amenities such as swimming pool or soundproofing. This study wants to highlight the convenience of using Booking.com listings as the main data source, as two variables presented as relevant for the models (size and location) are not available in other P2P platforms like Airbnb.

Concerning managerial implications, in a fast-growing sector such as holiday rentals, within a dynamic and highly competitive environment, it is essential for both potential clients and especially the owners of this type of accommodation, to be aware of the determinants that influence the daily rental rate. The models presented, not only help to clarify these factors but also allow estimating a rental price congruent with the characteristics of the dwelling and season, in an easy-customizable variables' conditions by the researcher through the employment of the models obtained, and consequently useful as an objective valuation method for the main agents of the accommodation sector: Owners, clients and P2P platforms as Booking.com owners, for example, can use it to optimise the daily rate according to the characteristics of the property and/or the period of the year. Even, its use can be considered as an instrument of taxable base determination for fiscal purposes by public administrations (councils, mainly). The method follows in the present research, can be easily replicated in every tourist-oriented city in the world with an abundant presence of holiday rentals in it.

As limitations in this study, it can be considered that the public register used (RTA) to define the offer in the case study employed does not inform about the grey market activity, clearly present in this sector, and that it does not inform completely about the availability of accommodation during special events. The RTA also disposes incomplete data information in some cases, as well as Booking.com, where some properties were booked at the moment of the data gathering, and consequently cannot be part of the final dataset (especially on the dates of the special events). But, altogether, the methodology can be extended to other cities with cultural tourist offer without difficulties. In places near the sea or with special views, other location variables need to be added.

Disclosure statement

The authors report there are no competing interests to declare.

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