FairPlay: A Multi-Sided Fair Dynamic Pricing Policy for Hotels

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Abstract

In recent years, popular touristic destinations face *overtourism*. Local communities suffer from its consequences in several ways. Among others, overpricing and profiteering harms local societies and economies deeply. In this paper we focus on the problem of determining *fair hotel room prices*. Specifically, we put forward a dynamic pricing policy where the price of a room depends not only on the demand of the hotel it belongs to but also on the demand of: *(i)* similar rooms in the area and *(ii)* their hotels. To this purpose, we model our setting as a cooperative game and exploit an appropriate game theoretic solution concept that promotes *fairness* both on the customers' and the providers' side. Our simulation results involving price adjustments across real-world hotels datasets, confirm that ours is a fair dynamic pricing policy, avoiding both over- and under-pricing hotel rooms.

Introduction

In today's digital era, online platforms have emerged as pivotal players in facilitating global commerce and play a key role in the transformation of the hotel industry. Such platforms offer customers a seamless and efficient way to access a vast range of hotel products and services. By providing features such as price comparisons, customer reviews, and instant bookings, these platforms have revolutionised the way in which travellers plan their trips and make their reservations. In turn, this has opened up new opportunities for hotels to expand their reach, increase their revenue streams, and improve their customer experiences through digital marketing and advertising. In general, online platforms, also known as two-sided platforms, host two roles: *(i)* the providers of services and *(ii)* the customers (Patro et al. 2020).

A crucial factor in the success of online platforms is pricing policies, as they directly impact customer satisfaction and loyalty. A pricing policy that is perceived as unfair by customers can lead to negative reviews and a loss of revenue in the long run. Online platforms have adopted various policies depending on their business model, such as dynamic pricing (Bayoumi et al. 2013; Aziz et al. 2011), fixed pricing plans, and negotiation-based pricing (Zhang et al. 2018). In the hotel industry, dynamic pricing policies (DPP) are prevalent among online platforms to optimise hotel revenue while offering competitive prices. However, there is still room for improvement in the current DPPs, as few studies address the relationship between *fairness* and *pricing policy*.

Now, overtourism in popular destinations (Butler 2022; McGarvey and Leonardo 2023) and overpricing of hotels coupled with the proliferation of short-term rentals (e.g., Airbnb), have significant social implications for local communities. Currently, it is very common for hotel owners to abruptly even quadruple their room rates in high-demand periods (Stoller 2017), making accommodation unaffordable for many visitors. As such, many tourists seek accommodation via short-term rentals, resulting in the rise of Airbnb properties while drawing potential long-term rentals off the market. Consequently, the increase in rental costs creates challenges for residents who may find it extremely hard to secure affordable housing options (Rafenberg 2022). It is evident that these problems are affecting communities socially, showing that local authorities need to take action to deal with these tourism-related challenges by adopting several regulatory measures (von Briel and Dolnicar 2021).

At the same time, most approaches used in two-sided platforms may hurt providers' well-being (Graham et al. (2017); Burke (2017)). In general, the providers' prosperity depends on the *exposure* they get in the platform, i.e., the opportunities offered by the platform to their goods to be viewed and potentially selected by the customers (Patro et al. 2020). If the platform favours a small group of providers by constantly exposing them, the remaining providers will not be able to prosper and, therefore, will quit or move to other platforms (Patro et al. 2020). Thus, it is crucial to develop more sophisticated systems that consider the providers' exposure opportunities, i.e., the opportunity to display a provider's product(s) to potential customers in a fair manner.

Against this background, we propose a highly effective approach that ensures two-sided fairness in the context of an online platform for the hotel industry by considering a fair dynamic pricing strategy and providing fair opportunities of exposure to the providers. Specifically, our approach, given a collection of rooms organised in hotels—where the hotels correspond to providers—adjusts each room's price based on the platform's supply and demand. Notably, cooperative game theory (Peleg and Sudhölter (2007); Chalkiadakis et

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al. (2011)) offers an appropriate framework for modelling such settings. That is, in settings with many players (i.e., rooms) that are organised into groups (i.e., rooms belonging to the same hotel), the final payoff share of each player is naturally determined based on the group they belong to, and the other groups formed. Given this, here we model this problem as *a cooperative game* and exploit an appropriate solution concept to promote fairness. We believe that platform's ability to provide fair pricing not only fosters trust and satisfaction among customers but also promotes healthy competition among hotels, leading to improved service quality and customer experiences. Thus, this work aims to contribute to the sustainability and growth of the hotel industry, while enhancing the overall travel experience for all stakeholders involved in a balanced and ethical ecosystem.

Related Work

Multi-sided Fairness. Recently, there is much work on the development of systems aiming for fairness for: *(i)* customers, *(ii)* providers and *(iii)* both of them. However, achieving fairness for all sides is a very challenging task since most of the time customers and providers have conflicting interests and being fair to one means being unfair to the other. The notion of multi-sided fairness itself is defined differently given the particularities of a recommendation task at hand. Bruke et al. (2018) studied two cases of fairness-aware recommenders, i.e., consumer-centred and provider-centred. In their work, they employ the Balanced Neighbourhoods approach in order to deliver personalised recommendations while enhancing the result's fairness. (Sühr et al. 2019) proposed a Ride-Hailing Platform case study, where they introduced mechanisms for achieving two-sided fairness in matching problems. Notably, they assume that over time all drivers should receive benefits proportional to the amount of time they are active in the platform. (Patro et al. 2020) proposed the FairRec algorithm for two-sided fairness in two-sided platforms. Specifically, they treated the fair recommendation problem as a fair allocation problem, providing theoretical guarantees, and evaluating it experimentally on various real-world datasets.

Dynamic Pricing Policy. Dynamic price strategies are used to determine products' or services' prices that change according to factors such as demand, time or customer profile. According to Bandalouski et al. (2018), the products usually subject to dynamic price policies share the following characteristics: *(a)* limited resources, such as rooms, passenger seats, etc.; *(b)* the products or services with a limited period of sale, whose value deteriorates over time; *(c)* the ability to accept pre-orders; *(d)* low per product or service costs and high fixed costs; and *(e)* fluctuating demand for products or services. (Bayoumi et al. 2013) propose a dynamic pricing model for hotel rooms. In particular, in order to compute the final price, the model considers the following factors: *(a)* time from reservation until arrival date, *(b)* hotel's remaining capacity at the time of the reservation, *(c)* the length of stay, *(d)* the number of rooms to be reserved (group size). Aziz et al. (2011) proposed an optimisation model to adjust room prices within a (single) hotel in a daily basis so that it captures the *demand elasticity* and reflects it into the prices.

Game Theory: Fair Solution Concepts. Cooperative game theory (Chalkiadakis et al. (2011)) offers a prosperous field for studying and modelling several economic environments. In particular, it offers several well-funded solution concepts that allow us to characterise an economic setting *wrt* stability and fairness. A well-studied fair solution concept is the *Shapley values* (Shapley 1953), which compute the marginal contribution of each player within a coalition, and adjust their payoff accordingly. Another solution concept, the *Owen value* introduced in (Owen 1977), determines each player's payoff *given* a coalition structure. In particular, the Owen values apply the Shapley value twice: *(i)* among the players in each coalition and *(ii)* among the coalitions in the coalition structure. That is, to compute the Owen values in a game, one shall consider the Shapley values on two auxiliary games: an *internal* game within each coalition and a *quotient* game where each player corresponds to a formed coalition in the coalition structure. Notably, since the Owen value adopts the Shapley value, it retains the latter's appealing properties (Béal et al.(2018), Giménez and Puente (2019)).

A Multi-sided Fair Dynamic Pricing Policy

In this work we propose a dynamic pricing policy that promotes *multi-sided fairness* for the hotel industry. In particular, we put forward a framework that exploits a *fair* game theoretic solution concept in order to determine not only the room prices available in the market but also the 'power' of a hotel's rooms with respect to the others in order to be exposed to customers. Intuitively, the power of a room is proportional to the *demand for rooms in its respective hotel*,[1] and inversely proportional to the demand for rooms of the same type in other hotels. We highlight that, in our view, better quality items (i.e., rooms) should be allowed larger profit margins, as that would increase the overall quality of the platform, and would motivate poor-quality providers to improve their product's quality. To be concrete, we put forward a definition of multi-sided fairness in our domain:

Definition 1 (Multi-sided Fairness) *In a platform containing different entities with conflicting interests, multi-sided fairness aims to balance the trade-offs among these different 'sides'. At the customer side, fairness means guaranteeing that the price of a provided good increases* linearly *to that good's power in the platform. At the provider side, fairness means guaranteeing that* (i) *her profit margin for a provided good is* proportional *to the good's power in the platform;* (ii) *she receives exposure opportunities* proportional *to her power; and* (iii) *every provider has at least one exposure opportunity within a reasonable time period.*

Now, a key choice in our approach is to capture a room's power via the room's Owen values. Then, by using this fair game theoretic solution concept, we recommend prices that are linearly tied to the rooms' Owen values. Thus, the prices are fair on the customer-side, since they increase linearly to the rooms' power. This approach disallows profiteering: owners will not charge rooms with prices considered unreasonably high by the customers—currently, as acknowledged in Forbes (Stoller 2017), it is very common for hotel

[1] The # of a hotel's reserved rooms over its total # of rooms.

owners to abruptly even quadruple their room rates in high-demand periods. At the same time, these prices signify a profit margin for each room that is proportional to the room's power—thus satisfying the first fairness requirement at the provider side. Moreover, we introduce a novel metric that exploits again the Owen value to capture the power of each hotel's rooms given the reservations and the availability in the rooms within a collection of hotels. Subsequently, this metric is used to drive the hotels' exposure opportunities to customers. That is, each hotel has an exposure opportunity proportional to its rooms' power, while we guarantee that all hotels will be exposed to customers. In what follows, we detail how to achieve multi-sided fairness in this domain.

First, we discuss the problem we tackle here, the *Room Dynamic Pricing Problem*. Specifically, there is a *system* which consists of a collection of rooms organised in hotels. A *hotel* is a set of rooms, and each room belongs to exactly one hotel. Moreover, each room can be of exactly one room type: single, double, triple.[2] Our system adopts reservation and cancellation scenarios. That is, a customer at any time can make a reservation of a room or can cancel an already booked room. As such, each reservation or cancellation corresponds to a *timestamp* in our system. At a given timestamp a room can be either *available* or *reserved*. Thus, the Room Dynamic Pricing Problem requires the adjustment of the room prices depending on the *available* or *reserved* rooms in the system at any timestamp.

The Dynamic Hotel-Rooms Game (DHRG)

We model the *Room Dynamic Pricing Problem* as a cooperative game, which we call the *Dynamic Hotel-Rooms Game (DHRG)*. Let $R = \{\delta_1, \cdots, \delta_n\}$ be the set of rooms in the system, and for each room we consider a player in our game. Additionally, let $T = \{T_1^s, T_1^d, T_1^t, \cdots, T_m^s, T_m^d, T_m^t\}$ be the set of all room types per hotel, i.e., $T_i^s \in T$ denotes that hotel h_i has at least one room of room type 'single' (respectively we use d for 'double', and t for 'triple'). We consider an *auxiliary* player for each room type in T; and we denote the set of all the players in the game with $N = \{p_1, \cdots, p_n, p_{n+1}, \cdots, p_k\}$, where n is the number of rooms in R and $k - n - 1$ is the number of room types in T. At a given timestamp t, $A_t \subseteq N$ is the set of *active players*, which contains (1) all currently *available rooms* in the system (i.e., the rooms that are not booked at t), *and* (2) the *available room types per hotel* (i.e., the corresponding types of the available rooms per hotel). The active players that belong to the same hotel h comprise a coalition S_h, while the coalition structure $CS_t = \{S_1, \cdots, S_m\}$ denotes a partition over A_t organising rooms and types in m hotels.

Definition 2 (The Dynamic Hotel-Rooms Game (DHRG)) *Let N be the set of all players, and $A_t \subseteq N$ be a set of* active players *at timestamp t. CS_t is a coalition structure of per-hotel coalitions (assuming m hotels). $v_t : 2^{A_t} \rightarrow \mathbb{R}$ is a characteristic function such that for any $S_h \subseteq A_t$ it denotes the joint contribution of the players in S_h to the demand at timestamp t in rooms* (a) *within their hotel,* (b) *of their room type, and* (c) *the overall demand in the system. The Dynamic Hotel-Rooms Game (DHRG) is a tuple $\langle N, A_t, CS_t, v_t \rangle$.*

Notice that a DHRG is an instance of a repeated game where players change their status from available to reserved, and vice versa. We can efficiently represent the DHRG using a graph-based representation.

Graph Structure. In our model we make the natural assumption that the price of a room depends on a multitude of features, some of which are static while others change across time. In this work we focus on adjusting prices depending on dynamic features and specifically, depending on the availability of rooms in the system. In more detail, we discern dependencies among rooms that share *either (i)* the same hotel *or (ii)* the room type, based on the available rooms at a given timestamp. Such dependencies can be efficiently captured by a graph-based representation scheme with appropriate edges and weights among the nodes, effectively corresponding to an ISG (Deng and Papadimitriou 1994). That is, given a DHRG $G_t = \langle N, A_t, CS_t, v \rangle$, we can build an undirected graph with nodes corresponding to the active players A_t and a set of edges E. There is an edge connecting each player $p \in A_t$ that corresponds to a room r with a player $p' \in A_t$ that corresponds to r's type (with $p, p' \in S_h$ and $S_h \in CS_t$), we call this kind of edge *room-to-type edge*. Moreover, there is an edge connecting every two players $p, p' \in S_h$ (with $S_h \in CS_t$) that corresponds to room types, we call this kind of edge *internal-type-to-type edge*. Finally, there is an edge connecting each player $p \in S_h$ that corresponds to a room type with any other player $p' \in S_k$ that corresponds to the same room type (with $S_h \neq S_k$ and $S_h, S_k \in CS_t$), we call this kind of edge *external-type-to-type edge*.

Note that the graph is built at every timestamp t based solely on the available rooms in the system at t. That is, if a hotel has no room of a particular type available, the corresponding room nodes do not appear in the graph, and thus neither does the node for this room type. Thus, "unavailable" rooms or room types do not appear in the graph. Since the game is defined as an ISG, the value of a coalition S_h is computed as $v(S_h) = \sum_{\{i,j\} \in S_h \cap E} w_{i,j}$, where $w_{i,j}$ is the edge's weight connecting nodes i and j; and the weights of our model are defined as:

1. *room-to-type* edge: $w^{rt} = \frac{1}{a_h^\tau} \cdot \frac{r_h^\tau}{a_h^\tau + r_h^\tau}$, where $w^{rt} \in [0, 1)$, a_h^τ is the number of the available rooms of a specific room type τ within a specific hotel h, while r_h^τ is the number of the reserved rooms of room type τ within hotel h; [3]

2. *internal-type-to-type* edge: $w^{itt} = \frac{r_h^\tau + r_h^{\tau'}}{a_h^\tau + a_h^{\tau'} + r_h^\tau + r_h^{\tau'}}$ where $w^{itt} \in [0, 1)$, $a_h^\tau, a_h^{\tau'}$ are the numbers of available rooms of type τ and τ', respectively, within hotel h, while $r_h^\tau, r_h^{\tau'}$ are the numbers of the reserved rooms of type τ and τ' in h;

3. *external-type-to-type* edge:[4] $w^{ett} = \frac{r_h^\tau + r_{h'}^\tau}{a_h^\tau + a_{h'}^\tau + r_h^\tau + r_{h'}^\tau}$

[2] This is indicative; our system can handle *any* features' set.

[3] Nodes and edges exist only for available rooms, i.e., $a_h^\tau > 0$.

[4] By considering the number of available rooms in hotels other than the current, the characteristic function essentially considers externalities, i.e., it depends on factors other to the particular coalition's membership. Though, this does not turn the game into one

where $w^{ett} \in [0, 1)$, $a_h^\tau, a_{h'}^\tau$ are the numbers of available rooms of a specific room type τ within hotels h and h', respectively, while $r_h^\tau, r_{h'}^\tau$ are the numbers of reserved rooms of room type τ within h and h'.

Intuitively, a room-to-type edge signifies the contribution of one room to the demand of a specific room type within a specific hotel. In particular, the demand of a room type is the portion of the reserved rooms over the total number of rooms of this room type within a specific hotel. As such, each available room of this type contributes equally to this demand, thus $w^{rt} = \frac{1}{a_h^\tau} \cdot \frac{r_h^\tau}{a_h^\tau + r_h^\tau}$.

An internal-type-to-type edge captures the dependencies among rooms of different room types within the same hotel. This type of edge signifies the *joint demand* of the two connected types of rooms (room types τ and τ') within a specific hotel, given by $w^{itt} = \frac{r_h^\tau + r_h^{\tau'}}{a_h^\tau + a_h^{\tau'} + r_h^\tau + r_h^{\tau'}}$. Moreover, we also want to capture dependencies among rooms of *the same room type*. Accordingly, an external-type-to-type edge represents the dependencies among rooms that have a common room type but belong to different hotels. This type of edge denotes the *joint demand* of the two common room types within two different hotels h and h', given by $w^{ett} = \frac{r_h^\tau + r_{h'}^\tau}{a_h^\tau + a_{h'}^\tau + r_h^\tau + r_{h'}^\tau}$.[5]

The *FairPlay* Pricing Policy

This section presents *FairPlay*, our proposed pricing policy. We detail how we apply a fair game theoretic solution concept on a Dynamic Hotel-Rooms Game G_t. Given that the available rooms are naturally organised in the hotels described by the coalition structure CS_t, we consider the Owen value an appropriate solution concept since it can capture both the dependencies between rooms belonging to the same hotel and different hotels. In general computing the Owen value on an arbitrary game can be computationally expensive (Béal et al. 2018). However, using an ISG to represent the DHRG G_t, we can tractably compute it:[6]

Theorem 1 *Given an Induced Subgraph Game (ISG) $G = \langle N, v \rangle$ with weights $w : N \times N \to \mathbb{R}$, the Owen value of a player $i \in N$ is computationally tractable, and is given by:*

$$Ow_i(N, v) = w_{i,i} + \frac{1}{2} \sum_{j \in N \setminus \{i\}} w_{i,j} \tag{1}$$

Since in G_t we have players corresponding to both rooms and room types, from a game-theoretic perspective players representing room types hold some portion of the total power of the game. However, these players are used solely to capture the dependencies among different rooms, and have no physical meaning in the system. Thus, we need to distribute their corresponding Owen values to players connected with them (via room-to-type edges) that represent actual rooms. We assume that rooms of the same type within the same hotel contribute equally to the room type's power. As such, we uniformly distribute the power of a room type to the connected rooms.

The Owen value is, by design, a fair solution concept: it considers both the dependencies among players within the same coalition and dependencies among different coalitions, and extending as it does the Shapley value in games with coalition structures, it readily captures the power of each player in the game (Béal, Khmelnitskaya, and Solal 2018; Owen 1977; Giménez and Puente 2019; Chalkiadakis, Elkind, and Wooldridge 2011). As such, using the rooms' Owen values to adjust their prices, we avoid profiteering in the sense that the customers observe prices reflecting the current 'power' of a room in the system at a given time t. Specifically, we assume that each room has a *Minimum Expected Price (MEP)*[7] determined by room type, location (neighbourhood, city, country), services provided, etc; notably, the MEP corresponds to a lower bound for the room price. Formally, let u_δ be the MEP of room δ, and $Ow_\delta(G_t)$ be the Owen value of δ at t. Given u_δ, the final price, c_δ, recommended at t, increases linearly with room power Ow_δ:

$$c_\delta = u_\delta \cdot (1 + Ow_\delta) \tag{2}$$

Intuitively, $Ow_\delta \cdot u_\delta$ represents the profit margin, $c_\delta - u_\delta$, for room δ given the demand for the rooms in δ's hotel, and the demand for rooms of the same type in the other hotels. Notice this satisfies the first fairness requirement in Def. 1 at the provider side. One can consider the recommended price c_δ as an *upper bound* for room δ's price. As such, we can recommend a range of prices that it is fair for each room δ to claim, while we allow the providers to select the final price between the lower bound (u_δ) and the upper bound (c_δ).

Provider's Exposure Opportunity

Here we introduce the *Exposure-Owen Ratio*, a metric that indicates which hotels should be shown to a potential customer so that fairness regarding the hotels' exposure is achieved. The metric exploits the (already computed) Owen values in order to determine the exposure opportunities that each provider exhibits. An existing metric in the recommender system literature is the *Equity of attention* (Biega et al. 2018), which asks that each item i receives attention att_i (i.e., views, clicks) that is *proportional* to its relevance rel_i to a given query, i.e., $\frac{att_i}{rel_i} = \frac{att_j}{rel_j} \quad \forall i, j$. In a similar way of thinking, we propose a metric that captures the exposure of each hotel proportional to its *power*. We consider this power to be provided by the hotel's Owen value, calculated as the summation over the Owen values of the hotel's available rooms: $Ow_h = \sum_{\delta \in h} Ow_\delta$.

Then, for each hotel h we use a counter, c_h, that indicates how many times this specific hotel has been recommended (or exposed) at any timestamp, so far; and we re-use the Owen values that have already been computed in order to determine the room prices. The *Exposure-Owen ratio*, ϱ_h, for a hotel h is then defined as: $\varrho_h = \frac{c_h}{Ow_h}$. Having computed the ϱ_h ratio for each hotel, we need to pick the top k

with externalities in the formal sense (Chalkiadakis et al. 2011).

[5] If the utility function describing the dependencies among rooms is not "naturally" graph-based, one can always use the *AE-ISG algorithm* (Bistaffa et al. 2022) to obtain an ISG that approximates this function with minimum error guarantees.

[6] The proof is provided in the (Streviniotis et al. 2023).

[7] Intuitively, MEP covers all unavoidable expenses and costs for maintenance, cleaning, commision payments, taxation, etc.

	Athens		Barcelona		Rome	
	#Rms	#Htls	#Rms	#Htls	#Rms	#Htls
Small	160	5	152	6	155	6
Medium	408	17	411	16	437	17
Large	665	27	656	30	652	27

Table 1: Number of rooms and hotels per dataset.

	Athens	Barcelona	Rome
Small	90.48%	93.34%	86.88%
Medium	89.71%	89.17%	87.5%
Large	88.04%	89.89%	89.18%

Table 2: Hotel exposure *vs.* hotels' collective rooms' power.

hotels to recommend (expose) to the customer given a specific timestamp t. In order to achieve the desirable fairness with respect to the exposure of all items in the system, we select the k hotels that exhibit the *lowest* ϱ_h ratio for the requested timestamp among all the available hotels (hence, the exposure opportunities of a hotel are proportional to Ow_h, i.e., its power). Moreover, our exposure metric guarantees each hotel is displayed at least once:[8]

Proposition 1 *Given m hotels, each one will be exposed at least once in the first $\lceil \frac{m}{k} \rceil$ requests, where k is the # of hotels exposed each time.*

Experimental Evaluation

We evaluated our model on real-world datasets. As such, we gathered data from online sources and prepared datasets for three cities that are popular tourist destinations, namely Barcelona, Rome, and Athens. In each dataset one can find the following information per room: hotel name, city, hotel stars, hotel rating, room type, price, and location details. Table 1 details the specifications of the used datasets, which can be found in (Streviniotis et al. 2023).

Experimental Methodology

Here we thoroughly describe our simulation scenarios. We assume a 30-days period where room reservations or cancellations are made within the system. Each reservation or cancellation corresponds to a timestamp that requires the construction of the DHRG (along with the corresponding ISG representation) that reflects the system. We make two natural assumptions: given a day d, one can reserve a room for any day d' where $d' \in [d, 30]$. In case there are no available rooms for some day, no further reservations can be made for this day. Depending on dataset size, a different number of reservations can be made within each day; thus we set at most 50, 100 and 150 reservations per day in the small, medium and large datasets, respectively. Briefly, the simulation process is as follows. Given a simulation day d, we first randomly select the number of reservations to be made for this day and perform these reservations in an iterative fashion. Specifically, for each reservation, we randomly select the reservation day and create a DHRG game based on the available and reserved rooms on that day. We adjust the room prices for the available rooms on the reservation day according to Eq. 2. We select the hotel and the room to book on the reservation day randomly across all available rooms. After each reservation, we randomly select a day in $[d, 30]$, and with probability $p = 0.1$ we cancel one reservation.

Results

This analysis aims *(a)* to confirm whether our proposed pricing policy, *FairPlay*, (orange bars) reassembles the supply and demand of rooms in the platform in each timestamp; and *(b)* to compare (in terms of profitability for consumers and providers) against a *"Static" policy* (green bars) offering a "constant" margin of profit equal to 17% of its MEP.[9] In general, our performed simulations exhibited consistent behaviour across all datasets; however, due to space limitations, we present one representative dataset for analysis.[10] Fig. 1 displays an indicative behaviour of *FairPlay* against *Static* in the large dataset of Athens illustrating demand and room prices. In particular, on 'Day 5' we observe an increase in the room price (of type triple) since the hotel exhibits *(i)* an increase on its reservations of triple rooms (green line), *(ii)* a large increase on its reservations regardless of room type (blue line), and *(iii)* the total reservations of triple rooms across all hotels also increase. Notably, on 'Day 5' 24.13% of the total number of rooms in the hotel is reserved, while it holds 10.34% of the reservations on triple rooms across all hotels; with the price of a triple room being 51.5% higher than its MEP. By contrast, we note that on 'Day 2' FairPlay decreases by $\sim$26% the price of the corresponding room (of type triple) compared to the price on the day before, since *(i)* there is no reserved triple room in the hotel, *(ii)* the total number of reservations in this hotel decreases by $\sim$66%, and *(iii)* the total reservation of triple rooms across all hotels drops as well. Finally, on 'Day 25' FairPlay increases the price of triple rooms compared to the previous day since the number of reserved triple rooms is increased, while the total number of reserved rooms remains the same.

Now, let us assume again that a platform adopts a *static policy* which applies to each room a constant increment of 17% on its MEP at any timestamp. In Fig. 1 we see how the prices of a room are adjusted following *(a)* the FairPlay policy (orange bars) and *(b)* the static policy (green bars)—following the same plan of reservations and cancellations. As we can see, the static policy tends to either *overprice* or *underprice* the rooms. Indicatively, in Fig. 1 on 'Day 5' the static policy allows a profit margin of 17% of the room's MEP, while according to the supply and demand in the system, FairPlay allows a profit margin of 51.5% of the MEP.

[8]The proof is provided in the (Streviniotis et al. 2023).

[9]We consider the value of 17% to be a more than healthy profit margin since such margins normally lie between 5-20%, while at the third quarter of 2022, the profit margin of the hotel and tourism industry worldwide was 14.22% (Lacalle 2021; Department 2022). Moreover, in our experiments, 17% provides a 'balanced' trade-off between overpriced and underpriced rooms. Specifically, we observed empirically that values higher than 20% constantly result in overpricing of the rooms with respect to our method, while values lower than 15% constantly result in underpricing of the rooms.

[10](Streviniotis et al. 2023) contains the extended results analysis.

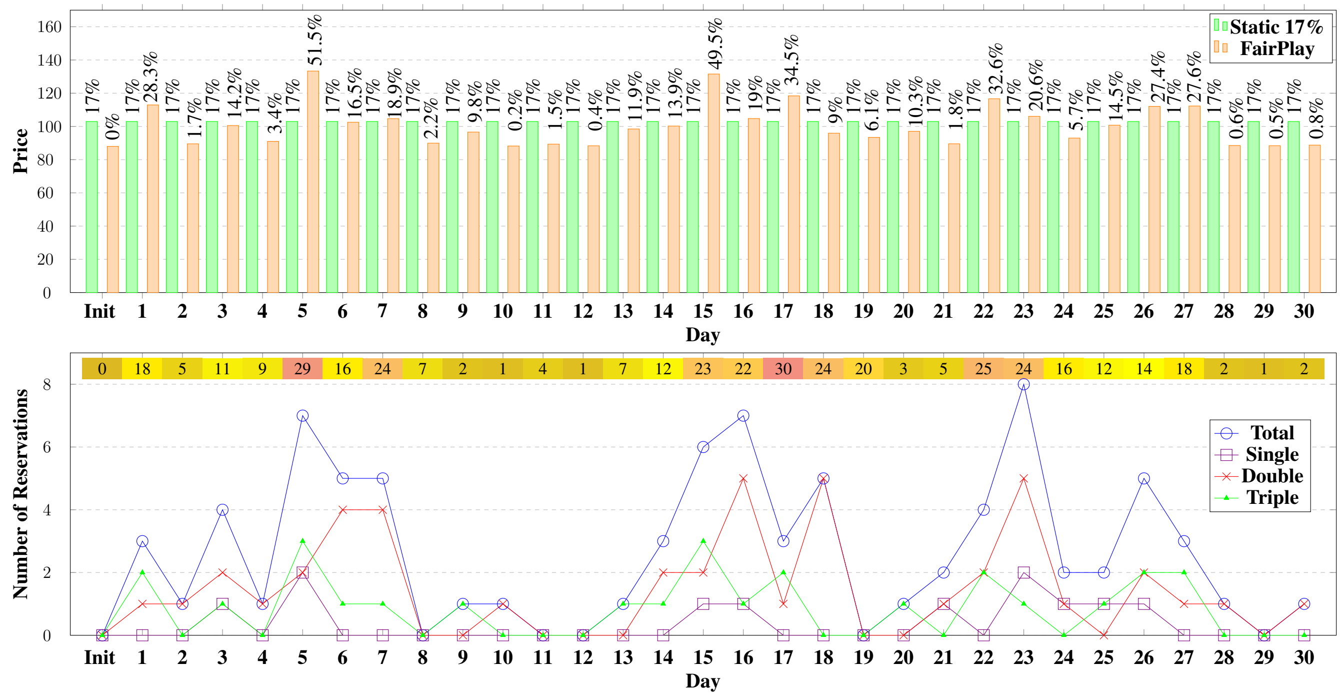
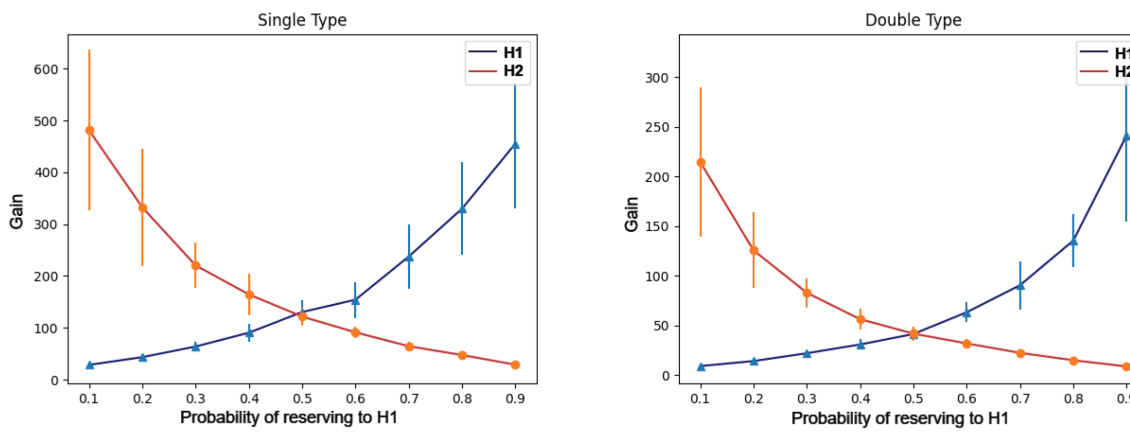


Figure 1: #Reservations and Room Prices with Profit Margin (%) in hotel AT_0004 and total #Reservations of Triple Rooms of all hotels (numbers on the top) per day. Large dataset, Athens, Triple Room.



(a) Single Type - (new) Small Dataset

(b) Double Type - (new) Large Dataset

Figure 2: FairPlay profit margins for (a) single and (b) double type for a 30-day period in (a) small and (b) large dataset.

Notably, we can observe that the static pricing policy has a trend of overpricing hotel's triple rooms, since in 20 days (out of 30) the price is higher than the one that was produced by FairPlay that depends on the supply and demand in the market. Similar behaviour was observed over all experimental settings. Thus, a static pricing policy may harm either the customers when a room is overpriced or the providers when a room is underpriced, compared to our dynamic pricing policy that promotes multi-sided fairness.

Results on the Customer-Side Fairness Now, when the number of reservations of a specific room type (regardless of hotel) increases, while the number of reservations of this type within a single hotel remains stable (or even reduces), then the room prices of this specific type in this hotel drops. Such a behaviour is expected, since it reflects the market scenario where different providers offer similar products, and the customers prefer some providers over the others, thus the "least-preferred" providers shall lower their prices to make their products more appealing to the customers. An interesting finding is that of the extreme case where given a specific room type all hotels but one have "sold out" this room type, then one and only hotel with available rooms of this type has no margin for profits. Intuitively, this behaviour can be considered as fair, since when there is only one provider with a specific room type, while all the other providers are sold-out on this type, then our approach prevents the profiteering of this provider, with the understanding that this provider (i.e., hotel) offers a low-quality product compared to the others. As such, our modelling does not allow this provider to exploit the fact that they are the only one with the product available (handling profiteering in monopoly scenarios).

Results on the Providers-Side Fairness Finally, to evaluate our proposed exposure metric ϱ, we compared two quantities: *(i)* the number of exposures per hotel, and *(ii)* the collective power of the hotels' rooms across all reservation timestamps. We sorted the hotels in each dataset *wrt* each of the two quantities, and measured the pairwise 'missalignments' in order to compute a similarity between two rankings (similar to the Kendall τ coefficient (Kendall 1948)). As Table 2 shows, the percentages of similarity are high. Thus the exposure of hotel h_i compared to hotel h_j is proportional to the joint power of the rooms in hotels h_i and h_j accordingly. Specifically, for each setting (dataset size, city) we achieve a high similarity score (over 85% similarity). Note that even though we score high similarities, we cannot possibly achieve an identical ranking due to two reasons: *(i)* in each reservation timestamp there is no guarantee that the hotel exhibiting the lowest ratio will have available rooms (so it won't be exposed), and *(ii)* our simulation exposes k hotels at a time (corresponding to the 30% of the hotels with available rooms), while we select randomly one of the exposed hotels to make the reservation. The latter affects the dynamics among the rooms, and therefore the Owen values used in the ratio. Regardless, our results do confirm that the ϱ_h is a metric promoting fairness on the providers-side.

High-Quality Providers Fairness

In this analysis we study the ability of our approach to discern the *high-quality* providers, i.e., the providers that offer products that customers (favourably) prefer to consume. Furthermore, we investigate how our game-theoretic DPP adjusts the room prices and consequently the *margin of profits* offered to each provider by the platform.

Thus, let us for the sake of clarity consider a toy example in which our platform contains only two hotels with similar characteristics, i.e., they have the same: *(i)* types of rooms, *(ii)* amount of rooms per type, and *(iii)* MEP. Now, in order to model the quality of each room, we assume that during our simulation customers make a booking at any room of h_1 with some probability p_1, while a reservation at h_2 is made with a probability $p_2 = 1 - p_1$. Thus, we are able to capture the notion of high quality at h_1 by increasing p_1, i.e., h_1 offers a better quality product compared to h_2 (or the rest of the market) and as a result, customers prefer to make a booking at h_1. Similarly, an increment at p_2, will capture a better quality of products (or rooms) at h_2.

Again, we assume a 30-day simulation period to compute the profit margins for a specific room of any type for both hotels. Next, we compute the profit margin of h_1 and h_2 by summing the prices of all the un-reserved rooms. We also generated two new datasets each containing two similar hotels, considering various numbers of rooms per room type. Specifically, each hotel has a total of 50 and 150 rooms in the (new) *small* and *large* dataset, while the number of reservations that can be made within each day is set to 50 and 150.

Fig. 2a depicts the average profit margins per hotel in the small dataset for a single room over 15 simulations. We see that as the probability of reserving a room in h_1 increases, (i.e., when h_1 offers higher quality product than h_2) our pricing policy is able to detect it and offer larger profit margins for h_1. At the same time, it "penalizes" h_2 by decreasing its profits since h_2's quality is significantly lower compared to the rest of the providers. Similar behaviour was observed in the various room types, and the various datasets (see Fig. 2b and (Streviniotis et al. 2023)). Thus, our experimental results show that FairPlay *(i)* detects the difference in terms of the quality of products that each provider offers to the customers; *(ii)* rewards the high-quality providers with larger profit margins; and *(iii)* penalises low-quality providers by allowing tighter profit margins, since such providers could hurt the overall quality of the platform in the long-term.

Conclusions and Future Work

Here we tackled the problem of dynamic pricing policy in the hotel industry. In particular, we proposed a dynamic pricing policy that exploits a well-known game-theoretic *fair* solution concept, namely the Owen values, in order to compute fair prices. We put forward a novel, graph-based representation to model the dependencies among rooms, and we showed that we can tractably compute the Owen values in such a representation. Moreover, we introduced a novel metric that exploits the Owen values to measure the exposure opportunities that each provider (i.e., hotel) receives. Thus, we efficiently employ the Owen value in multiple stages of the process to promote *two-sided fairness*. Finally, we conducted a systematic evaluation of our model using real-world data, confirming that it recommends fair prices *wrt* the supply and demand in the system.

Future work includes extending our model to more general settings by considering dependencies not only based on room types, but on other features as well—e.g., breakfast, hotel stars, ratings, etc. Moreover, an interesting line of research would be to consider the neighbourhood cost of living in order to achieve fair pricing not only for short-term rentals (hotels, Airbnb, etc.), but also for long-term ones (e.g., apartments and houses); and also to apply these ideas to other sectors of the hospitality industry (e.g., to restaurants and bars recommender platforms). Finally, our framework can be employed in domains beyond the hospitality industry—essentially, in any domain in which items can be naturally grouped into teams and there are dependencies among the different groups: e.g., fair pricing on airplane tickets, fair salaries among different companies, and more.

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