A Competitive-Cooperative Approach to Dynamic Pricing for Two-Sided Hospitality Platforms

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Abstract

Fair pricing as an essential scope in the two-sided hospitality web platforms, refers to setting room rates that balance affordability for guests with profitability for the hotel, taking into account factors like market demand, seasonality, and competitive pricing. Unfair pricing practices can lead to customer dissatisfaction and disrupt the competitive balance within the industry. This study extends the FairPlay method, a cooperative game-theoretic approach designed to balance service provider and customer interests, by incorporating local competitor analysis at the room and hotel level. While FairPlay effectively addresses competitive dynamics, it lacks the consideration of regional and agglomeration effects, which are critical for capturing spatial market influences and competitive overlap among hotels in nearby areas. To address this gap, we introduce an enhanced method that utilizes graph node embedding techniques to model regional proximity and inter-dependencies between hotels. By leveraging these embeddings, our approach attempts to adapt to market dynamics that traditional models often miss. Our results demonstrate that embedding-based methodology outputs fairer and more competitive pricing, offering real-time adjustments that better align with local market demands and competitor behaviour. This enhancement significantly improves upon the FairPlay model by integrating regional effects, resulting in more equitable and balanced pricing for the hospitality industry.

CCS Concepts

• **Computing methodologies → Artificial intelligence**.

Keywords

Dynamic Pricing, Node Embedding, Game Theory, Two-sided Platforms

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1 Introduction

In today's fast-paced digital economy, two-sided platforms have transformed various industries by facilitating interactions between providers and consumers. These platforms, which include key sectors such as hospitality, e-commerce, and ride-sharing, have fundamental effect in balancing supply and demand by connecting both sides of the market[25, 28]. In the hospitality sector, online platforms enable hotels to reach a broader audience while offering consumers the convenience of comparing prices, reading reviews, and making quick bookings. This interconnection has made two-sided platforms a pivotal component of the modern economy, driving competition and innovation[18].

Fair pricing is particularly important within these platforms, as it helps maintain a healthy balance between service providers' profitability and consumer satisfaction. In the hospitality sector, fairness in pricing ensures that consumers receive value-based rates while hotels remain financially sustainable [27]. If fairness is not maintained, platforms risk damaging relationships with both consumers, who may feel overcharged, and providers, whose revenues may be compromised. As a result, fair pricing is essential for the long-term sustainability and reputation of these platforms.

To address the challenge of fluctuating demand and supply, dynamic pricing has emerged as a widely adopted solution [12]. This strategy allows hotels to adjust prices in real-time based on demand, optimizing revenue during periods of varying occupancy rates [11]. Dynamic pricing ensures that room rates reflect current market conditions, allowing hotels to capitalize on high demand while offering competitive rates during slower periods. However, while effective in maximizing revenue, many existing dynamic pricing models do not explicitly account for fairness on two-sided platforms. They often focus on optimizing the platform's revenue, which can lead to issues such as overcharging during peak times and disadvantaging smaller hotels with limited visibility. This calls for a more balanced approach that can adapt to market changes while considering the fairness aspect for all stakeholders[7, 22, 30].

One of the challenges encountered in implementing fair dynamic pricing is the agglomeration effect [19, 32, 36]—where hotels in close proximity or with similar characteristics experience correlated demand spikes. This effect can significantly influence pricing fairness, as neglecting it may result in pricing strategies that disproportionately benefit larger or centrally located hotels while disadvantaging smaller, less visible ones. For instance, when demand surges in a particular area, nearby hotels might experience increased bookings, which should be reflected in their pricing strategies. Traditional models that ignore this interconnected demand may fail to capture this subtlety, resulting in uneven competitive dynamics and pricing discrepancies.

The FairPlay model [29], originally designed to integrate fairness into dynamic pricing through a game-theoretic approach. The FairPlay approach, while effective in ensuring fairness in dynamic pricing, has a significant limitation: it does not take the proximity and agglomeration effects among competing hotels into consideration. Specifically, it overlooks how the spatial proximity of hotels can influence demand, as closely located hotels often experience similar fluctuations in booking patterns due to their shared market conditions. This can lead to imbalances, where hotels in high-density areas may be unfairly advantaged or disadvantaged compared to those in less competitive regions. The lack of consideration for these agglomeration effects results in a pricing model that fails to fully capture the complexities of localized competition, ultimately impacting the fairness of the computed room rates. We address the limitations of the FairPlay approach by incorporating proximity and agglomeration effects into our pricing model. Specifically, we employ node embedding techniques, such as Node2Vec[16], to represent the relationships between hotels within a graph structure. This allows us to capture the spatial interdependencies and localized competition dynamics that arise from proximity. By modeling these complex interactions, our approach adjusts pricing based on the interconnected demand patterns of nearby hotels, ensuring that our dynamic pricing strategy is more responsive to local market conditions ensuring a more equitable distribution of rates among hotels, fostering a fairer competitive environment.

Through extensive experimentation on real-world hotel datasets and simulated reservation systems, our node embedding-enhanced model has shown significant improvements over the original FairPlay model in terms of achieving local pricing fairness. By combining deep learning with graph-theoretic principles, this paper introduces a novel, locality-sensitive solution that balances the needs of both customers and service providers, ensuring fair, competitive, and sustainable pricing within the hospitality industry.

2 Related Work

Here's a brief literature review on multi-sided platforms fairness, dynamic pricing policy tailored to the hotel industry and the node embedding algorithms:

Fairness in pricing Fairness in pricing is a vital concept in economics, marketing, and consumer behaviour, reflecting how consumers perceive the prices they pay as fair and reasonable. This perception significantly influences their purchasing decisions, brand loyalty, and overall satisfaction [21]. Price fairness extends beyond cost considerations, encompassing psychological and ethical dimensions such as transparency, equality, and justice [23]. In navigating market competition and consumer expectations, businesses must prioritize fair pricing principles to maintain customer trust and achieve long-term success [20]. Price fairness is inherently complex, involving multiple dimensions that together shape how consumers perceive pricing practices. The emergence of modern consumer markets has introduced new challenges and complexities, creating a need for a deeper understanding of price fairness.

The hotel industry highlights the complexities and significance of pricing fairness. Guests' perceptions of price fairness in hotels are influenced by factors such as pricing transparency, rate consistency, and the overall value offered. For example, when guests understand the reasons behind rate fluctuations and receive high-quality services and amenities that justify the cost, they are more likely to perceive the prices as fair. Research shows that equitable pricing practices can build greater trust among guests and enhance their likelihood of returning, while perceptions of unfair pricing can lead to dissatisfaction and negative word-of-mouth [13]. El Haddad et al. [14] utilized theories from tourism, marketing, and revenue management to investigate how customer perceptions of price fairness affect their behavioral intentions when booking hotel rooms online. Their study highlights the significant role that perceptions of price fairness play in influencing purchase decisions and the likelihood of customers recommending the service to others.

Recent research seeks to define fairness for both service providers and customers while developing strategies to ensure mutual satisfaction. Streviniotis et al. [29] tackle the challenge of establishing fair hotel room pricing by developing a dynamic pricing tool that leverages cooperative game theory to ensure fairness for both guests and providers. They introduce platform exposure metrics and propose a rationale for price increases based on room power. Additionally, studies by Banerjee et al. [6] and Wu et al. [37] highlight the importance of evaluating Recommender Systems from the perspectives of different service providers and customers, with a particular emphasis on fairness.

Alderighi et al. [2] investigate how dynamic pricing affects consumers' perceptions of price fairness, especially in cases with significant rate variations depending on the week of stay and room type. Similarly, Abdelaziz et al. [1] study the effects of exchange rate fluctuations on price fairness and perceived value in the hotel industry.

Dynamic Pricing Policy In the hotel industry, dynamic pricing (DP) has emerged as a key strategy for optimizing revenue by adjusting room rates in response to market demand and other influencing factors. Unlike static pricing, which maintains fixed rates regardless of demand changes, dynamic pricing leverages technological advancements and data analytics. This allows hotels to employ sophisticated algorithms that consider factors such as seasonality, booking trends, and competitor pricing [27]. Traditional models, such as those developed by Bayoumi et al. [7], optimize pricing strategies by considering factors like time to arrival, room availability, and group size. Similarly, Aziz et al. [5] created models that adjust room prices dynamically based on demand elasticity, aiming to maximize occupancy while ensuring profitability. However, recent studies have shifted towards incorporating fairness in dynamic pricing to avoid exploitative practices, such as sudden price spikes during high-demand periods, ensuring that pricing remains balanced and reflective of market conditions for both customers and hotels.

Node Embedding Models Node embedding models are essential for various graph-based machine learning applications, as they transform graph-structured data into low-dimensional vector spaces while retaining important structural and relational properties [10]. These embeddings effectively capture the connections between nodes, making them highly valuable for tasks such as node classification, link prediction, and community detection. By embedding nodes into a continuous vector space, these models enable complex graph relationships to be analyzed using conventional machine learning techniques, enhancing performance and scalability in a wide range of scenarios.

An early and widely adopted model is DeepWalk [26], which utilizes random walks on graphs to learn latent node representations, similar to word embeddings in natural language processing. Node2Vec [16] builds upon DeepWalk by incorporating a biased random walk, enabling the model to balance between local (depth-first) and global (breadth-first) graph exploration. This added flexibility improves the model's capability to capture both micro-level node interactions and the broader structure of the network.

Subsequent approaches, such as LINE [31], prioritize preserving both first-order and second-order proximities in graphs, generating embeddings that capture not only direct connections but also the broader neighbourhood structure. More recent advances include GraphSAGE [17], which introduced an inductive framework that aggregates features from neighbouring nodes. This allows the model to efficiently scale to large graphs and generalize to unseen nodes, addressing the limitations of earlier transductive methods.

3 Methodology

Our contributions are three-fold. Firstly, we introduce a comprehensive, multi-level feature engineering framework that systematically categorizes diverse aspects of the hospitality sector and key parameters affecting dynamic pricing, enabling a generalized approach based on available data. Secondly, we develop a model that effectively segments local competitors within the hotel layer, incorporating nearby market demand to refine our analysis. Lastly, we integrate the FairPlay approach into our model, facilitating the calculation of fair hotel room rates across a variety of market conditions.

3.1 Multi-Level Features and Definitions

To effectively implement dynamic pricing, we start by categorizing key parameters that might affect the hospitality sector's demand at different levels: macroeconomic metrics, city or regional markets, the hotel itself, and individual rooms. Each level provides valuable insights that help shape a well-rounded pricing strategy. This approach allows hotels to adjust room rates based on overall economic trends, local market conditions, and the specific features of their property and rooms.

At the macroeconomic level, indicators like GDP, inflation, and unemployment offer a broad view of the overall economic environment, which directly influences consumer spending and travel patterns. These metrics help identify long-term trends and shifts in demand across the market, providing valuable context for pricing decisions [24].

At the city or regional level, local market dynamics significantly influence pricing strategies. Factors such as regional occupancy rates, average daily rates, tourism events, and seasonality play a crucial role in determining how hotels should adjust their pricing and availability [34]. These indicators help capture localized trends and enable hotels to respond effectively to regional competition.

At the hotel magnitude, factors such as star rating, brand affiliation, location, and available facilities are key attributes that influence a hotel's market competitiveness and allow for pricing differentiation [3, 39]. Customer reviews and service quality also play a significant role in attracting demand, further impacting a hotel's ability to adjust prices effectively [4, 38].

At the most granular level, room attributes like type, view, bed size, and available amenities allow for differentiation in pricing strategies within a single hotel. These features enable hotels to fine-tune pricing based on guest preferences and specific room demand, optimizing revenue for each room category. The Table 1 outlines some major features across the different levels, which collectively serve as key inputs for effective pricing modelling.

In this paper, we concentrate on deploying the room type and locality of hotels. Moreover, in this paper, focusing on the customer side, we define fairness as ensuring that the price of service (room) on the platform increases proportionally to the room's value, taking into account the region it is located in and the competition it faces.

3.2 Node2Vec

The Node2Vec algorithm is a graph-based embedding technique that generates low-dimensional representations of nodes while preserving their structural relationships within a network. It is also capable of capturing both local (close neighbours) and global (community structures) relationships with low computational cost. In the context of hotel pricing, Node2Vec represents hotels as vectors that capture their relationships with other hotels (geographic proximity). This enables a more nuanced analysis of hotel behaviour and pricing trends by considering their position within the broader competitive landscape. In our work, we implement Node2Vec in hotel dynamic pricing procedure to identify similarities between hotels and uncover pricing patterns across the market.

3.2.1 Graph Definition. Let $G = (V, E)$ be a graph where:

- V is the set of nodes (hotels).
- E is the set of edges (proximity between hotels).

Node2Vec uses a biased random walk strategy to explore the graph, combining *Breadth-First Search (BFS)* and *Depth-First Search (DFS)* approaches. For a given node u, a walk of length l is generated as:

$$\text{Walk}_u = \{v_1, v_2, \ldots, v_l\},$$

where $v_1 = u$ and each v_i is a node sampled from the neighborhood of v_{i-1}.

The transition probability from node v_{i-1} to v_i during the random walk is defined as:

$$\pi_{v_{i-1},v_i} = \frac{\alpha_{pq}(t, v_i)}{Z},$$

where:

Level	Feature	Example
Macroeconomic and External Factors	GDP	Measure of overall economic activity and spending.
	Inflation Rate	Affects hotel costs and customer spending power.
	Unemployment Rate	Can impact leisure travel demand.
	Tourism Inflows	Number of tourists visiting the area.
	Exchange Rates	Impacts affordability for international tourists.
	Weather and Natural Disasters	Adverse weather conditions reduce travel demand.
City/Regional	Occupancy Rate	Percentage of rooms filled, reflecting demand.
	Tourism Events	Large events drive local demand spikes.
	Local Economic Activity	Business and industry health impacts business travel.
	Seasonality	Predictable demand changes based on time of year.
Hotel	Star Rating	Quality rating of the hotel (e.g., 5 stars).
	Brand Affiliation	Well-known hotel chains may attract more demand.
	Location	Proximity to key locations (airport, city centre, etc.) and competitors.
	Facilities	Amenities like pools, spas, gyms increase hotel appeal.
	Hotel Age	New or renovated hotels may attract more guests.
	Customer Reviews	Online reviews and ratings influence customer choice.
Room	Room Type	Suite, deluxe, standard rooms have different demand levels.
	Room View	Ocean or city views increase room desirability.
	Bed Size	King, queen, or twin beds cater to different guests.
	Room Size	Larger rooms attract higher prices.
	In-room facilities	Features like Wi-Fi, minibars, and balconies add value to the room.

Table 1: Feature engineering for dynamic pricing in hospitality at various levels

- $\alpha_{pq}(t, v_i)$ is a bias factor that determines the likelihood of walking to node v_i.
- Z is a normalization constant.
- t is the previous node visited before v_{i-1}.

The bias term $\alpha_{pq}(t, v_i)$ is defined based on the distance between nodes t and v_i:

$$\alpha_{pq}(t, v_i) = \begin{cases} \frac{1}{p} & \text{if } d_{t,v_i} = 0 \text{ (going back to the previous node),} \\ 1 & \text{if } d_{t,v_i} = 1 \text{ (staying close to the previous node),} \\ \frac{1}{q} & \text{if } d_{t,v_i} = 2 \text{ (exploring new nodes).} \end{cases}$$

- p is the *return parameter*, controlling the likelihood of revisiting a node.
- q is the *in-out parameter*, determining the tendency to explore outward nodes.
- The distance d_{t,v_i} between t and v_i can take three values: 0 (return), 1 (one-hop neighbor), and 2 (two-hop neighbor)

After generating random walks for each node, Node2Vec aims to maximize the likelihood of observing the neighborhood $N_s(u)$ of node u given its embedding $\phi(u)$:

$$\max_{\phi} \sum_{u \in V} \sum_{v \in N_s(u)} \log \Pr(v \mid \phi(u)),$$

where:

- $\phi : V \to \mathbb{R}^d$ maps each node to a d-dimensional vector.
- $N_s(u)$ is the set of context nodes for u sampled from the random walks.
- $\Pr(v \mid \phi(u))$ is defined using a softmax function:

$$\Pr(v \mid \phi(u)) = \frac{\exp(\phi(v) \cdot \phi(u))}{\sum_{v' \in V} \exp(\phi(v') \cdot \phi(u))}.$$

3.2.2 Final Embedding. After training, each node $u \in V$ has a vector representation $\phi(u) \in \mathbb{R}^d$ that captures the structural properties of the graph.

3.3 Approach

Our research introduces a novel approach that utilizes the spatial proximity of hotels and applies game theory, particularly coalition formation, to optimize dynamic pricing strategies across regions. This methodology aims to strike a balance between competitive pricing, fairness, and enhancing hotel revenue in response to dynamic demand while improving customer satisfaction. The key contributions of this work are as follows:

- Spatial Adjacency-Based Hotel Pricing Optimization:
  Hotels are frequently impacted by regional dynamics, including localized demand shifts, tourist behaviour, and competitor pricing strategies. Our approach builds on this by explicitly modelling the spatial proximity of hotels, treating those in neighbouring regions as interdependent. Hotels in the same or nearby areas often face similar demand patterns, meaning their pricing decisions should be influenced by shared factors. The spatial adjacency model groups hotels based on geographic proximity, taking into account how regional factors like seasonality, local events, and market demand drive pricing strategies.
  Exploiting the spatial structure, we apply graph node embedding models to distinguish hotels based on shared geographic and market characteristics, enabling a localized yet competitive pricing strategy. This partitioning forms the foundation for creating pricing zones, where hotels within the same cluster influence each other's pricing decisions. The adjacency effect ensures that pricing remains competitive while fostering cooperation, encouraging hotels in the same region to adopt more balanced pricing strategies and preventing extreme price disparities that could deter customers.

- Game-Theoretic Coalition Formation for Regional Pricing Using the Owen Value:

To strengthen the pricing strategy, we apply coalition formation grounded in game theory [15] among hotels situated within the same region or spatially adjacent clusters. In this framework, hotels are viewed as rational players in a cooperative game, forming coalitions with shared objectives, such as maximizing regional revenue, boosting occupancy rates, or sustaining competitive market positioning. This cooperative model utilizes the Owen value to fairly distribute profits among coalition members (rooms and hotels), accounting for both the overall coalition structure and the existence of internal subgroups, such as hotels in the same geographic area.

The Owen value [33], as proposed in FairPlay [29], is well-suited for pricing strategies in which hotels collaborate within a broader market coalition while also forming subgroups based on geographic proximity. This dual-layered approach ensures that the pricing mechanism considers both global coalition dynamics and the specific contributions of local groups. The Owen value distributes payoffs in a manner that balances each hotel's contribution to the larger coalition while also recognizing their role within their local subgroup. The Owen value extends the classical Shapley value [35] by incorporating subgroup structures, allowing for a fair distribution of revenue across both local and global coalitions. It ensures that each hotel's contribution to its local group, as well as the overall coalition, is properly recognized and rewarded proportionately. This approach fosters cooperation among hotels within the same region while ensuring that local dynamics are taken into account within the broader market coalition.

- Dynamic Pricing Model The pricing algorithm we propose integrates spatial and cooperative elements into a dynamic pricing model. Rather than treating each hotel as an independent entity, the model leverages the collective intelligence of regional coalitions. Hotels within the same region or coalition dynamically adjust their prices based on shared data, such as room availability, local demand trends, and competitor pricing. The model is designed to adapt over time, responding to fluctuations in demand and supply, while recalibrating coalition strategies to maintain competitiveness. This approach also enhances customer fairness by minimizing extreme pricing volatility that can occur when hotels act independently. By cooperating within regional coalitions, hotels can avoid significant price hikes during high-demand periods, fostering customer loyalty and satisfaction. The balance between maximizing revenue and ensuring fairness results in a more sustainable pricing strategy that benefits both the hotel and the consumer.

To address changes in coalition structures and dynamic room pricing based on hotel locations, we propose extending the existing cooperative game theory framework mentioned in [29] by introducing a partitioning mechanism. This mechanism allows for flexible coalition formation, adapting pricing strategies to different coalition structures influenced by hotel proximity and regional dynamics.

Each hotel coalition can be partitioned based on geographic locations, such as neighbourhoods, districts, or regions. Instead of treating all hotels as a single group, we introduce sub-coalitions, where hotels are grouped by their location. For instance, all hotels within a particular district would form a sub-coalition. This key modification allows for more localized cooperation and pricing strategies, ensuring that hotels within the same area can respond more effectively to shared market conditions while still contributing to the overall coalition strategy.

Building on the graph-based structure of FairPlay, we introduce an enhanced framework that integrates spatial embedding into the dynamic pricing mechanism, resulting in the **Regional Dynamic Hotel-Rooms Game (RDHRG)**. In this framework, let $e = \{e_1, \ldots, e_k\}$ denotes the set of embedding vectors resulting from the Node2Vec algorithm that corresponds to the geographic regions where the hotels are located. Each embedding vector encapsulates the competitive dynamics between hotels, taking into account their spatial proximity and market interactions. Later, we construct an undirected graph, where the nodes represent individual rooms and room types. The graph includes three categories of edges to connect pairs of nodes: room-to-type edges, internal-type-to-type edges, and external-type-to-type edges. These edges serve distinct purposes:

– Room-to-type edges: Indicate how a specific room contributes to the demand for a particular room type within a hotel.
– Internal-type-to-type edges: Capture the relationships between different room types within the same hotel, reflecting dependencies among these room types.
– External-type-to-type edges: Represent interactions between similar room types across different hotels located in similar regions, capturing competitive dynamics.

Furthermore, this graph structure is dynamic, as it is updated at each time step t, allowing it to adapt to the evolving market conditions. The edge weights are defined as follows:

– Room-to-type edge:

$$E_T^{(h)} = \frac{r_T^{(h)}}{a_T^{(h)} * (a_T^{(h)} + r_T^{(h)})}$$

Here, $r_T^{(h)}$ represents the reservations for room type T in hotel h, and $a_T^{(h)}$ represents the available rooms of type T in the same hotel.

– Internal type-to-type edge:

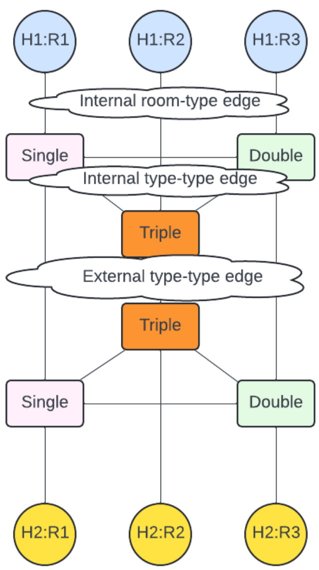
$$E_{T_jT_k}^{(h)} = \frac{r_{T_j}^{(h)} + r_{T_k}^{(h)}}{a_{T_j}^{(h)} + a_{T_k}^{(h)} + r_{T_j}^{(h)} + r_{T_k}^{(h)}}$$

This formula reflects the combined demand and availability between two different room types T_j and T_k within the same hotel h.

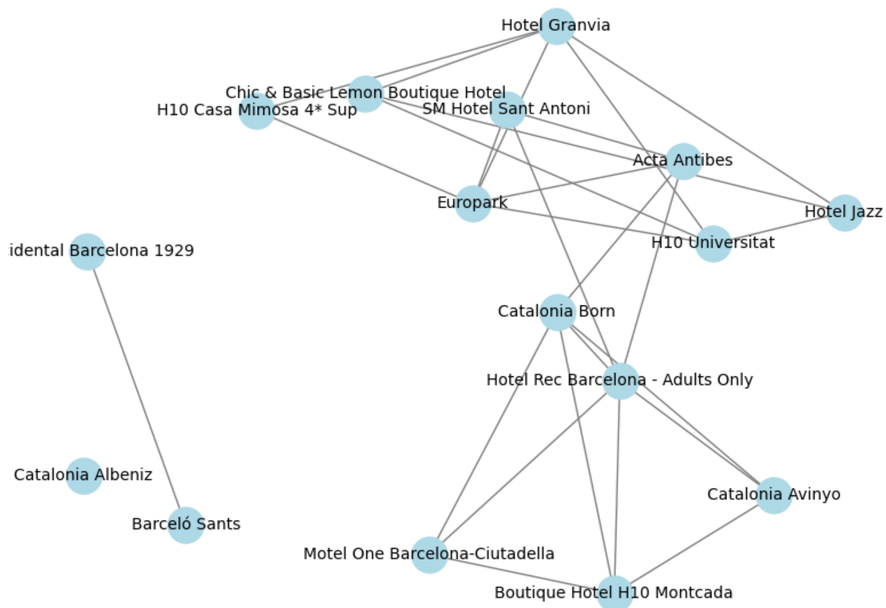
– External-type-to-type edge:

$$E_T^{(h,h')} = \begin{cases} \frac{r_T^{(h)} + r_T^{(h')}}{a_T^{(h)} + a_T^{(h')} + r_T^{(h)} + r_T^{(h')}} & \text{if } siml(h,h') >= \gamma, \\ 0 & \text{otherwise.} \end{cases}$$

$$siml(h,h') = \frac{e_{(h)} \cdot e_{(h')}}{\|e_{(h)}\| \|e_{(h')}\|}$$



(a) Example of graph considering nodes (rooms and types) and edges



(b) connectivity graph of hotels in Barcelona

Figure 1: Graph models in room and hotel levels

This formula models the relationship between room type T in hotel h and the same type T in hotel h'. The interaction is determined by the similarity between hotels h and h' based on their regional embedding. If the cosine similarity $siml(h, h')$ exceeds a threshold γ, the edge is weighted by the combined reservation and availability metrics; otherwise, the edge is set to zero, indicating no significant interaction. Figure 1a exemplifies two different hotels and edge connections among them.

Moreover, to calculate the power of each node in the graph and adjust the prices accordingly, we obtain the Owen value for every node to capture both the dependencies between rooms in the same hotel and other hotels in similar regions. Given a graph $G =< N, E >$, the Owen value of every node i is:

$$Owen_i(N, E) = \frac{1}{2} \sum_{j \in N \setminus \{i\}} w_{i,j}$$

Similar to the FairPlay theorem, this formula calculates the aggregated weights for each node (whether a room or room type) by considering all the edges connected to it, including room-to-type, internal-type-to-type, and external-type-to-type connections. Given that the network includes nodes representing both individual rooms and room types, the room type nodes carry a portion of the system's overall influence. However, these room type nodes are primarily conceptual, designed to capture the relationships between different rooms, without any physical presence in the system. Therefore, it's necessary to redistribute their respective Owen values to the connected rooms through room-to-type edges. We assume that rooms of the same type within a hotel share equal contribution to their room type's influence, so the power of each room type is evenly distributed among its associated rooms.

Finally, by using the Owen values of rooms to adjust their prices, we assume that customers observe prices fair (P_δ) when the current price of a service, increases linearly according to the potential (influence) of a room in the system at a given time t:

$$P_\delta^{(t)} = ALP^{(t)} * (1 + Owen_\delta^{(t)})$$

where ALP is a constant representing the anticipated lowest price of an asset, as determined by the hotel manager.

4 Experimental Evaluation

4.1 Dataset

To assess and analyze the competitive dynamics among hotels in a region and establish a fair room-pricing mechanism, we utilize a comprehensive dataset from Barcelona, which includes information on 16 hotels across the city, with total rooms of 411. The dataset features a variety of attributes: geographic coordinates (latitude and longitude) of each hotel, Google reviews and ratings that reflect customer sentiment, accessibility measures such as proximity to metro stations and beaches, hotel star ratings indicative of service quality, and room-specific details, including room IDs, types, and initial rate.

4.2 Implementation Details

The first analytical step involves constructing a connectivity graph to model the spatial relationships between hotels. In this graph, each hotel is represented as a node, with edges between nodes determined by the Euclidean distance between their geographic coordinates (latitude and longitude). This approach creates a spatial

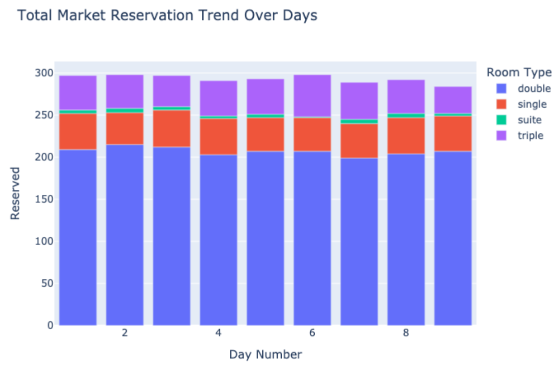


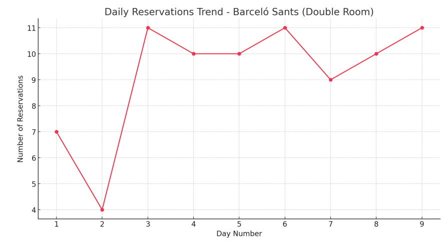
Figure 2: Simulated daily reservation for hotels in city

network where hotels in close proximity are more likely to be connected. An edge is formed between two nodes when the distance between the latitude (x) and longitude (y) of a pair of hotels meets a specified threshold (0.01), which can be dynamically adjusted based on the size of the city. This method captures spatial proximity and potential competitive overlap among hotels. Figure 1b illustrates the structure of the initial connectivity graph.

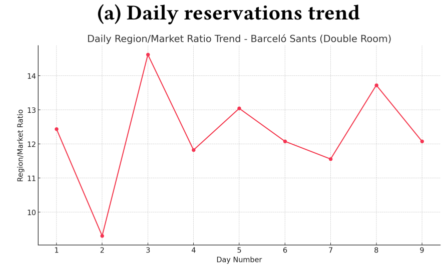
To enhance the analysis, we apply node embedding techniques by fitting the graph into a Node2Vec model in Python3 library with specific parameters (embedding vector dimensions=16, walk-length=50, num-walks=10, p=1, q=1). This model generates vector representations of the nodes, encoding complex structural and spatial relationships within the network. The resulting embedding vectors provide valuable insights, capturing latent features that reflect spatial proximity and potential competitive behaviours among hotels.

Subsequently, we assess the competitive landscape by calculating the cosine similarity between the embedding vectors of each pair of nodes. This similarity measure quantifies how closely two hotels align in terms of common characteristics and competitive positioning within the market. If the similarity score between two hotels exceeds a predefined threshold (γ=0.7), they are classified as regional competitors, forming part of the same competitive coalition. This assumption suggests that these hotels target similar customer segments and compete directly in terms of market positioning, pricing strategies, and service offerings. For example, the result of our model identifies that Hotel Jazz's coalition (region) is defined alongside similar local competitors based on their embedding vectors, which include: [H10 Casa Mimosa 4* Sup, Hotel Granvia, Europark, H10 Universitat, Acta Antibes, Chic-Basic Lemon Boutique Hotel, SM Hotel Sant Antoni], or for Barceló Sant is [Occidental Barcelona 1929].

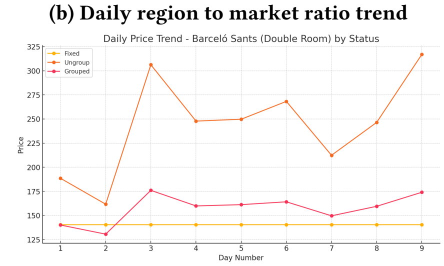
Next, we conduct a simulation of the room reservation and cancellation system to generate daily transaction data. Similar to the approach used in FairPlay [29] for simulating data, on a given day *d*, a user can reserve a room with a booking lead time that falls within the next 9 days, *[d, d+9]*, with a cancellation probability of 1%. The total daily reservations for the entire market are set to 300. Figure 2 demonstrates the total daily reservation for every room type in the city. After identifying the regions for each hotel using the cosine similarity of the embeddings, we apply the RDHRG game method based on the available and reserved rooms for every day.



(a) Daily reservations trend



(b) Daily region to market ratio trend



(c) Daily pricing with several approaches

Figure 3: Daily Trends of Reservations, Region/Market Ratio and multiple pricing status for Barceló Sants - Double Room

4.3 Results

This analysis aims to determine how price changes for double rooms at the "Barceló Sants" hotel are influenced by shifts in the Region/Market demand ratio and the inherent popularity of the rooms. We examine whether price adjustments are primarily driven by broader market conditions or by room-specific demand that persists even when regional demand declines.

- **Influence of Region/Market Ratio on Room Pricing** The Region/Market Ratio serves as a vital metric that illustrates how regional demand compares to overall market (city) trends. A higher ratio indicates stronger regional demand relative to the market, while a lower ratio reflects weaker regional demand. This metric is essential for hotel managers because it directly impacts room pricing strategies. By adjusting prices in response to the Region/Market Ratio, hotels can better align their revenue objectives with demand fluctuations.

In the Figure3b, the Region/Market Ratio displays considerable variation over the days. For instance, there is a noticeable peak on Day 3, signifying exceptionally strong regional demand. This provides an opportunity for hotels to raise room prices to align with the increased demand. Conversely, on days when the ratio drops, such as on Day 2 (below the fixed threshold), regional demand is notably weaker, prompting the need to adjust pricing strategies to avoid losing potential bookings.
Moreover, when the Region/Market Ratio is high, such as on Day 3, both the Grouped (Proposed Method) and Ungrouped (FairPlay) pricing models react by increasing room prices. However, compared to the Grouped method, the Ungrouped pricing strategy tends to exhibit greater price volatility, as it is more responsive to sudden demand surges. While higher prices during periods of elevated regional demand can help maximize revenue, the Ungrouped approach might risk deterring price-sensitive customers due to its sharper price increases.

- **Room Popularity as a Buffer Against Price Decreases** The idea is that when a particular room type is popular, its high demand acts as a safeguard, reducing the need for price reductions, even during periods of decreased overall demand or competitive pressure. Essentially, the popularity of the room functions as a stabilizer, preserving its value and minimizing price cuts.
For instance, the data shows that even when the Region/Market Ratio for double rooms indicates a decline in demand, such as on Day 9, daily reservations (Figure 3a) for that room type in the hotel actually increase. As a result, our dynamic pricing tool helps hoteliers prevent revenue loss from high-demand rooms by strategically adjusting prices based on real-time demand data. This ensures that even during periods of fluctuating market conditions or regional demand shifts, popular rooms continue to generate optimal revenue.
- **Revenue Management and Customer Fairness** Firstly, Grouped Pricing (red line) in Figure 3c demonstrates moderate price increases compared to the fixed rate. This strategy allows for higher revenue generation in response to demand fluctuations, benefiting hotel stakeholders by capitalizing on peak periods while maintaining a balanced approach to pricing. Secondly, the Grouped Pricing method offers a more stable and predictable pricing environment compared to the Ungrouped strategy. The Ungrouped pricing model (orange line) exhibits sharp fluctuations, particularly during periods of high demand such as Days 3 and 9. These sharp increases can create significant disparities in pricing, which may negatively affect customer perception of fairness, especially during peak demand periods. For instance, the substantial price spike on Day 9 under the Ungrouped strategy may deter price-sensitive customers, creating an uneven customer experience.
In contrast, the Grouped Pricing strategy maintains a more consistent and equitable structure. It responds to local market conditions without extreme price changes, aligning more closely with customer expectations. This approach supports fairer pricing for customers, as it prevents sudden and steep price increases during demand surges, which are more common in the Ungrouped pricing model. The more moderate increases seen in the Grouped method on high-demand days such as Day 3 ensure that customers perceive the pricing as reasonable, fostering trust and loyalty.

Overall, the analysis indicates that the pricing of double rooms at Barceló Sants is influenced by fluctuations in the Region/Market Ratio, but is strongly sustained by the room's consistent popularity. Even when regional demand decreases the hotel maintains prices at stable or slightly increased levels, avoiding steep reductions due to the steady demand for double rooms. The dynamic pricing system, particularly under the Grouped Pricing strategy, reflects a careful balance between adapting to market conditions and capitalizing on the room's inherent appeal. This approach optimizes both occupancy and revenue while ensuring pricing remains reasonable and aligned with customer expectations, thereby maintaining price integrity.

5 Conclusion and Future Work

In this study, we introduced a novel strategy for hospitality two-sided platforms, combining the FairPlay pricing model with collaborative game theory and graph embedding techniques to account for spatial density and competitive dynamics among hotels. This approach aims to create a fairer pricing mechanism that reflects both market demand and the competitive landscape.

Looking ahead, we plan to extend our framework by incorporating functionally similar regions, not just spatially adjacent ones, to capture more refined regional pricing influences. We also aim to adapt our method to other sectors, such as ride-sharing and food delivery, where fairness across multi-sided platforms is critical. Additionally, we will explore advanced machine learning techniques, such as deep learning-based graph embeddings, to capture temporal shifts in market conditions and competitive behaviours.

By integrating external data sources like social media sentiment and economic indicators, we hope to refine the models further, ensuring they remain responsive to broader market influences. Ultimately, our goal is to develop a flexible, scalable framework that sets a new standard for fairness in pricing and market positioning across various industries.

As a next step, we aim to enhance our framework by integrating ProcessGPT [8, 9], a generative pre-trained transformer specialized in process understanding and automation. By leveraging ProcessGPT's ability to model complex sequential decision-making and contextual dependencies, we will extend our approach to dynamically adjust pricing strategies based on evolving market conditions. Specifically, we plan to use ProcessGPT to analyze historical pricing patterns, predict competitive responses, and generate adaptive pricing policies that align with fairness constraints. This integration will enable a more context-aware and interpretable pricing mechanism, allowing hospitality platforms to incorporate real-time insights from multi-agent interactions while maintaining transparency and robustness in pricing decisions.

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