

Network Revenue Management Approach to Multi-Channel Hotel Inventory Control

Sarun Dunsathit*, Kannapha Amaruchkul

Faculty of Applied Statistics, National Institute of Development Administration, Bangkok 10240, Thailand

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ABSTRACT

This study aimed to improve revenue management efficiency for four-star hotels in Chonburi Province by applying demand data analysis together with room capacity allocation. The research methodology began with a comparison of the performance of eight time series forecasting models for four main customer segments: Direct bookings, Online Travel Agencies (OTA), Group bookings, and Travel Agents (TA). The results showed that the Prophet, ARIMA, Naïve, and Mean models provided the highest forecasting accuracy for the Group, OTA, TA, and Direct segments, respectively. The forecasting results were then applied to a network model to plan room allocation. This model was integrated with the concept of price elasticity of demand to improve pricing strategies during periods of high demand. Simulation results indicated that increasing room rates for the Group segment on Fridays and Saturdays generated additional revenue of 37,765.73 THB. These findings confirmed that selecting forecasting tools that match the specific behavior of each customer segment, together with proactive pricing management, was a key approach to significantly improving hotel profitability.

Keywords: Demand forecasting; Demand elasticity; Hotel business; Revenue management; Room allocation

1. Introduction

Revenue Management (RM) impacts increasing the revenue and profitability of service businesses with fluctuating demand and limited resources. This concept has been adopted in the lodging industry since

the 1980s and has continuously gained importance [1]. Historically, RM in the context of hotel business was defined as the process of allocating the right type of capacity to the right customer at the right price with the goal of maximizing revenue or re-

turns. Subsequently, the definition was expanded to include considering the right time and the right distribution channel [2]. RM is highly important to the hotel business due to its unique characteristics: having fixed capacity, room nights considered as perishable inventory, highly segmented markets, and continuously fluctuating customer demand. Given the current increasing competition in the hotel business, the adoption of RM is a crucial tool for achieving maximum efficiency in inventory and revenue management, and it is also a factor determining the survival of the business [3].

Pattaya tourism plays an important role in Thailand's economy, as reflected by the over 11.38 million domestic tourists visiting Chonburi Province during the first eight months of 2025. This represents an increase of 11.79 percent compared to the same period last year. This growth accounts for a powerful portion of the total of over 18 million tourists in Chonburi Province and underscores Pattaya's ability to maintain its appeal as an important destination in Thailand [3]. As a player in this major market, the hotel used in this study is a four-star hotel in Pattaya with 300 rooms. The hotel's customers originate from four main booking channels: Group (Thai customers staying in groups), Travel agent (TA) (international customers booking through sales agents), Online travel agent (OTA) (Thai and international customers booking through online sales agents), and Direct (customers booking directly with the hotel). Customers from each channel have varying lengths of stay and room rates. However, the hotel encounters the problem of low occupancy during weekdays and full occupancy on weekends. Therefore, the objectives of this study are to determine the optimal forecasting method for the demand of each customer segment

and allocate guest rooms to maximize revenue.

2. Literature review

2.1 Hotel revenue management

Hotel revenue management (HRM) is an essential component for service businesses that aim to maximize revenue and profitability during periods of fluctuating customer demand. HRM is often defined as the process of allocating the right capacity to the right customer at the right price to maximize revenue profit. Subsequently, this was expanded to include the right time and the right distribution channel [2]. Prior studies on HRM can be categorized into different activities as follows: Business analysis involves employing many techniques to collect and analyze internal and external data (e.g., demand and supply analysis) to enable the appropriate and successful application of RM [5]. Pricing strategy involves setting minimum prices for market segments and determining the method for adjusting these prices over time to maximize revenue [6]. Demand forecasting involves the quantitative and qualitative estimation of demand, which directly impacts the quality of the RM system through forecasting accuracy. [7]. Inventory and price optimization is a process focused on selling the right inventory at the right price at the right time to the right market segment, considering the customer's willingness to pay [5]. Setting booking controls involves defining and managing rate restrictions to maximize revenue. One crucial control is overbooking, which is a method used to prevent revenue loss due to customer cancellations or no-shows [7]. Distribution channel management is the selection and utilization of online and offline channels to distribute inventory for maximum revenue. Recent research has focused on the impact of the

internet on distribution channels and online pricing [2]. Performance analysis and evaluation involve measuring RM performance using many metrics, such as RevPAR (revenue per available room), and identifying opportunities for improvement [8].

HRM is continuously evolving, shifting its focus from Tactical RM which emphasizes inventory and short-term strategy toward a Strategic RM approach. An important trend is the focus on customer-centric revenue management. Customer-centric RM analyzes customer data to gain insights into the highest-value customers and focuses on maintaining long-term customer relationships [2]. Furthermore, there is the concept of total hotel revenue management, which aims to expand the scope of RM to cover all revenue within the hotel beyond room revenue. Other revenue sources included are food & beverage, spa, and event/meeting spaces. This approach requires considering the interrelationships between different departments to achieve overall optimization [8]. In summary, modern HRM has moved beyond inventory control toward integrating customer insights and advanced technology to strategically optimize revenue and profitability from all sources in the long term.

HRM differs from other service industries because of the network structure of hotel products. In other words, a guest's stay typically lasts several consecutive nights, known as length of stay. This means that the decision to accept a room booking on one night affects the ability to accept bookings on other related nights. The research by Lai and Ng [9] established a framework for this concept. They demonstrated that accepting a room booking on one night creates a displacement effect on the ability to accept bookings on subsequent nights. The solution to this network prob-

lem is highly complicated. As a result, researchers have worked to identify practical approaches that can be applied to real-world operations. Solutions have been proposed using the Rolling horizon method, which addresses the problem by continuously shifting the time period forward to manage new incoming data on an ongoing basis [10]. Additionally, a Decomposition method has been developed. This method makes complex dynamic programming models faster to calculate and can efficiently handle stay-over cases where customers extend their stay [11]. Lai and Ng proposed using a stochastic programming model that accounts for demand uncertainty in both the number of bookings and length of stay [9]. They employed robust optimization techniques to manage these risks and uncertainties. In addition to managing length of stay, capacity management has expanded to include allocating rooms to different distribution channels and service packages. In today's environment, hotels face multiple sales channels, including direct channels and online travel agencies (OTAs), which have different costs. The minimax regret approach, which emphasizes decision-making under worst-case scenarios rather than relying on accurate demand forecasting, has been applied to room allocation. This approach developed an adaptive nested limits strategy that allows high-profit channels to access room quotas allocated to lower-profit channels [12]. Ling et al. studied availability management in the context of cooperation with OTAs, focusing on addressing the problem of high commission fees [13]. The research proposed a method to determine when to close sales on OTAs in order to reserve rooms for direct channel sales. This approach helps reduce costs and increase the hotel's total revenue. From the discussion above,

it is evident that network revenue management has evolved from simply allocating daily room quantities to considering length of stay networks. Furthermore, the scope of capacity management has expanded to address increasingly complex distribution channels and service packages.

2.2 Hotel demand forecast

Forecasting for HRM is considered a critical factor because the accuracy of the forecast directly impacts the hotel's decisions regarding pricing and resource management. Hotel demand forecasting is more complex than general tourism demand forecasting due to the availability of different industry-specific data points that can be used. Historical demand data refers to the actualized stays (occupancy). This data is widely used for short-term forecasting in operations and revenue management due to its ease of collection [14]. Reservation and cancellation data, which reflect the most recent changes in demand, are considered the most accurate indicator for the hotel's future performance. The inclusion of cancellation data is highly crucial because its omission may lead to forecasting errors [15]. Combined or big data is the integration of multiple data types to improve forecasting accuracy. This includes econometric variables and online behavioral data [14].

Demand forecasting methods can be categorized into three main groups: time series models, econometric models, and machine learning models [16]. Time series models utilize historical data to identify trends and chronological patterns and are frequently used as a benchmark in studies. The models in this group commonly used in studies are exponential smoothing, moving average, and ARIMA/SARIMA. Econometric models focus on identifying and measuring the causal relationship be-

tween demand and other explanatory variables (e.g., income, price). Preferred models in this group are the autoregressive distributed lag model, vector autoregression, and mixed-data sampling. The final group are AI or machine learning models, which are highly effective at handling large volumes of data that exhibit nonlinear and highly volatile characteristics. They do not require the relationship between input and output variables to be defined in advance. Well-known models in this group for study include artificial neural networks, long short-term memory, support vector regression, and ensemble/hybrid models. AI-based models often demonstrate superior performance compared to traditional models. However, there remains a consensus that no single model can consistently provide the best results under all conditions. Therefore, selecting the most appropriate method depends on the type of available data, the nature of the problem, and the desired forecasting horizon [15].

2.3 Price elasticity of demand

Price elasticity of demand (PED) is a fundamental principle in microeconomics for analyzing consumer demand. This concept was developed by Alfred Marshall in 1890 [17]. PED is a tool used to measure the responsiveness of consumers to price changes, indicating the degree to which the quantity demanded of a product or service changes when prices fluctuate. In the hotel and tourism business, PED is an important instrument used in determining pricing strategies, investment, and planning [18]. Elasticity values have two characteristics: Elastic demand and inelastic demand. Elastic demand means that consumers are highly sensitive to price and a small increase in price leads to a significant decrease in demand. In this case, a

price reduction will lead to an increase in the quantity demanded. In contrast, inelastic demand means that demand remains relatively constant even with price changes. Customers with inelastic demand are often considered price-insensitive, such as corporate clients [18]. Study results indicate that the PED of the hotel business in Spain differs significantly, depending on variables such as customer market segments and period of stay [19]. In some cases, a positive PED coefficient has been reported. This phenomenon is termed Giffen's paradox or the Veblen effect, which means that demand increases when price increases. This situation may occur because customers anticipate that room rates will rise further in the future, leading them to book earlier to secure the current price [20].

Knowledge of PED has an impact on the business sector. Management can use PED data to customize prices appropriately for each customer segment and increase profitability. Higher pricing can be applied to segments with inelastic demand, such as those purchasing full board/all-inclusive packages, those booking during the high season, and long-stay guests [19]. Adopting PED data helps hotels avoid unnecessary price reductions in response to competitors, as such reductions can negatively affect long-term profitability. Furthermore, integrating PED into an RM system leads to more precise market segmentation. This facilitates the introduction of personalized pricing, allowing operators to dynamically adjust prices based on the behavior of individual customers [18].

3. Methodology

3.1 Data used in this study

This study used room occupancy data from the hotel's property management system (PMS), covering the period from March

1, 2024, to July 31, 2025. The study focused specifically on the superior room category, which comprises a total of 250 rooms. According to the occupancy data, April was identified as a shoulder season, during which the number of international customers began to decline from the beginning of the year and there was an increase in group customers and domestic bookings. During this month, rooms were fully booked on weekends but vacant on weekdays. Therefore, April was selected as the case study period. The occupancy data was segmented by customer group into four booking channels: Group, TA (travel agent), OTA (online travel agent), and Direct. Subsequently, the proportion of length of stay (LOS) and the average daily rate (ADR) were determined for each customer group arriving on each day. The room rates used in the study represent net revenue, with sales costs such as channel commissions already deducted. Regarding operating and service costs, we assumed these to be constant and uniform across all booking channels. This approach allows the model to focus clearly on comparing revenue generation efficiency and demand allocation among customer segments under a standardized cost structure. An example of the proportion of the length of stay is shown in Table 1, and the details of the average room rate are presented in Table 2.

Table 1. Example of LOS proportion.

Arrival day	LOS (days)	Group	TA	OTA	Direct
Monday	1	52.16%	10.56%	57.21%	64.26%
	2	31.24%	42.61%	21.81%	13.44%
	3	10.78%	21.69%	9.82%	18.36%
	4	4.02%	5.95%	6.71%	2.30%
	5	1.54%	3.65%	2.77%	0.33%
	6	0.04%	5.95%	0.67%	0.66%
	7	0.09%	5.57%	0.76%	0.33%
	8	0.13%	4.03%	0.25%	0.33%

Table 2. Average room rate (THB).

Arrival day	Group	TA	OTA	Direct
Sunday	1,100	913	1,438	1,400
Monday	1,000	914	1,425	1,307
Tuesday	937	913	1,310	1,341
Wednesday	911	914	1,340	1,346
Thursday	1,071	908	1,411	1,373
Friday	1,147	896	1,438	1,407
Saturday	1,125	920	1,466	1,470

3.2 Method

This study comprises two main steps, beginning with demand forecasting to determine the number of rooms occupied by each customer segment. The researchers chose to forecast demand separately by booking channel rather than forecasting overall demand and subsequently allocating proportions. This is because guest behavior patterns differ distinctly across channels. For example, the group segment tends to show higher demand for week-day stays compared to other customer categories. Therefore, channel-specific forecasting enables the detection of distinct demand patterns and more accurately reflects the actual conditions of the hotel business. The next step is the application of a network management model to allocate customer demand for maximum revenue generation.

In developing the forecasting model, we used historical occupancy data spanning from March 1, 2024, to March 31, 2025, with all computations performed using R Studio. To ensure reliable performance evaluation, a time-series cross-validation approach was employed. The initial training window was set at 70 days, with the forecast origin rolling forward in 7-day steps to generate a 30-day forecast horizon at each evaluation round. The forecasting accuracy was evaluated using two standard error metrics: root mean square error (RMSE) and mean absolute scaled error (MASE) [16]. RMSE measures the magni-

tude of forecast errors and is widely used, with smaller values indicating better performance. MASE compares the mean absolute error of a forecasting method to that of a naïve benchmark forecast. A MASE value of 1 indicates performance equivalent to the naïve method, while values below 1 indicate superior performance. Because MASE is unit-free, it is particularly suitable for comparing forecast accuracy across customer segments with different scales.

The forecasting models selected for this study comprise two groups: benchmark models and advanced statistical models.

The benchmark models' group was used as a standard for comparison and includes:

- Naive: The future value will equal the last observed value. It is suitable for data with stochastic trends [22].
- Seasonal Naïve (7 days): The future value will equal the value from the last corresponding season [22]. Due to the pronounced weekly seasonality in hotel data, this model serves as a benchmark for capturing weekly patterns.
- Mean: Using the average of all past data. It is used as a reference point for data with low variance and no trend to assess whether simply using the average is sufficient [22].
- Drift: An extension of the naive method that includes a linear trend, calculated from the average change rate between the first and last days [22].

The advanced statistical models' group was used to capture complex parameters such as changing trends or fluctuating seasonality, and it includes:

- ETS (Exponential Smoothing State Space): Applies exponential weighted averaging, which is suitable for data with clear seasonality and can adapt to trends [22]. R package was used to find the optimal ETS parameters.
- ARIMA (Auto Regressive Integrated Moving Average): Forecasts by examining the data's relationship with its past values [22]. R package was used to find the optimal ARIMA parameters.
- Theta: Performs data decomposition by fitting the data's curvature into two components: one to capture the long-term trend and the other to capture short-term dynamics, which are then combined [23].
- Prophet: A generalized additive model (GAM) that represents a time series as the sum of trend, seasonality, and event effects, with automatic trend change points. Its regularized fitting provides robustness to outliers, and missing observations are handled naturally without imputation [24].

3.3 Room allocation

The characteristics of this case study involve multiple customer segments staying for multiple nights at different rates, but all sharing the common resource of room inventory. If the manager manages revenue for each night independently by only selecting the highest-paying customer for that specific night, it may miss out on customers who pay less but stay for multiple nights, resulting in lower total revenue. To address this issue, the study adopts a network revenue management framework in which the

fundamental resource is room–night capacity, defined as the availability of rooms on each night of the planning horizon. Each booking class consumes one unit of room–night capacity on each stayover night, and capacity is allocated jointly across all nights to maximize total revenue.

We define a booking class as a combination of (i) booking channel c , (ii) arrival date a , and (iii) LOS ℓ nights. A combination (c, a, ℓ) represents a booking arriving on date a with a stay of ℓ nights through channel c . The arrival date and LOS jointly determine which room–night resources are consumed. Formally, let $A(j; c, a, \ell) \in \{0, 1\}$ be an indicator that equals 1 if room–night j is occupied by booking class (c, a, ℓ) , and 0 otherwise, for each room–night j in the planning horizon. For example, a booking arriving on Wednesday with a length of three nights occupies Wednesday, Thursday, and Friday. Hence,

$$A(j; c, \text{Wed}, 3) = 1 \text{ for } j \in \{\text{Wed}, \text{Thu}, \text{Fri}\}$$

and

$$A(j; c, \text{Wed}, 3) = 0 \text{ for } j \in \{\text{Mon}, \text{Tue}, \text{Sat}, \text{Sun}\}.$$

The revenue associated with a booking class is the total room revenue generated over the entire stay, calculated as the sum of the nightly room rates from the check-in date through the check-out date implied by the LOS. Let $R(c, a, \ell)$ denote the total revenue earned by accepting a booking class (c, a, ℓ) . For example, using the average room rates in Table 2, a Direct booking with arrival date Wednesday and an LOS of three nights generates total revenue of $R(\text{Direct}, \text{Wed}, 3) = 1346 + 1373 + 1407 = 4126$ THB, corresponding to stays on Wednesday, Thursday, and Friday.

The deterministic network linear program for allocating rooms to each customer segment is shown in model (3.1)–(3.3). The planning horizon is 30 days (one month).

Based on historical records, most LOSs are between 1-8 nights; stays longer than 8 nights account for less than 4.63 percent of all bookings. Sets and indices

- $c \in \{1, 2, \dots, 4\}$: booking channels (1=Group, 2=TA, 3=OTA, 4=Direct)
- $a \in \{1, 2, \dots, 30\}$: arrival date index
- $\ell \in \{1, 2, \dots, 8\}$: length of stay (LOS)

Parameters

- $\kappa(j)$: number of available rooms on night j
- $d(c, a, \ell)$: demand (number of booking requests) for class (c, a, ℓ)
- $A(j; c, a, \ell) \in \{0, 1\}$: 1 if booking class (c, a, ℓ) occupies night j ; 0 otherwise.
- $R(c, a, \ell)$: total revenue generated by accepting one booking class (c, a, ℓ)

Decision variables

$x(c, a, \ell)$: number of rooms (bookings) accepted/allocated for class (c, a, ℓ)

$$\text{Max} \sum_{c=1}^4 \sum_{a=1}^{30} \sum_{\ell=1}^8 R(c, a, \ell) x(c, a, \ell) \quad (3.1)$$

subject to:

$$\sum_{c=1}^4 \sum_{a=1}^{30} \sum_{\ell=1}^8 A(j; c, a, \ell) x(c, a, \ell) \leq \kappa(j) \quad (3.2)$$

$$\begin{aligned} & \forall j \in \{1, 2, \dots, 30\} \\ & 0 \leq x(c, a, \ell) \leq d(c, a, \ell) \\ & \forall c \in \{1, 2, \dots, 4\}, a \in \{1, 2, \dots, 30\}, \\ & \ell \in \{1, 2, \dots, 8\} \end{aligned} \quad (3.3)$$

The objective (3.1) maximizes the total revenue from the accepted bookings.

Constraint (3.2) enforces room-night capacity: total usage of night j across all booking classes cannot exceed the available rooms $\kappa(j)$. Constraint (3.3) bounds the accepted bookings by forecast demand. The optimization problem (3.1)-(3.3) is a linear program (LP) and can be solved efficiently using standard LP solvers such as the simplex or interior-point methods.

Since the output of the forecasting model is the expected number of occupied rooms per night, and the network linear programming model requires input data in the form of booking demand classified by arrival date and length of stay, we conducted a data transformation process. This transformation was done through two calculation steps as follows:

- $A_{c,a}$: Estimated total arrival demand of channel c on day a
- $\hat{O}_{c,a}$: Forecasted occupancy of channel c on day a
- $\bar{L}_{c,a}$: Average length of stay of channel c on day a
- $P_{c,a}(\ell)$: Probability that a customer from channel c on day a would stay for ℓ nights.

The first step transformed the forecasted number of occupied rooms into the total number of bookings that were expected to arrive on each day. This calculation used the average length of stay as an adjustment factor based on the following equation:

$$A_{c,a} = \frac{\hat{O}_{c,a}}{\bar{L}_{c,a}}. \quad (3.4)$$

The next step was to disaggregate the total number of bookings ($A_{c,a}$) into booking demand by the actual length of stay

(LOS). This classification was based on the probability distribution obtained from historical data (Table 1), according to the following equation:

$$d_{c,a,\ell} = A_{c,a} \times P_{c,a}(\ell). \quad (3.5)$$

To validate the accuracy of the proposed method, the researcher recalculated the total revenue using the transformed demand and compared it with the revenue obtained from the occupancy and the average daily rate (ADR). The results indicated that the deviation was only 0.17%, which was considered acceptable and sufficiently accurate for further application in the room allocation model.

4. Results

This study tested the forecasting performance of eight time series models and evaluated the error using root mean squared error (RMSE) and mean absolute scaled error (MASE), with the results categorized by customer segment as presented in Table 3.

For the Group segment, the Prophet model was found to have the highest performance, yielding the lowest error values in both the RMSE (52.31) and MASE (0.68) metrics. Prophet's superior performance over other models is attributed to the fact that the demand behavior of the Group segment exhibits discontinuities and involves large arrivals on certain days. This aligns with the strengths of the Prophet algorithm, which can effectively handle trend discontinuities and complex seasonality.

For the OTA segment, ARIMA was found to be the most suitable model, with an RMSE of 24.95, and was the only model in the advanced model group with an MASE value below 1.0 (MASE = 0.90). The fact that ARIMA exhibited the lowest error indicates that OTA demand does not have

clear long-term trends or seasonality but possesses short-term data dependency.

The naïve model yielded the best results (RMSE 35.68, MASE 1.37) for the TA segment. The fact that the MASE value is greater than 1.0 across all models suggests that the demand behavior of the TA segment exhibits high volatility and lacks clear patterns.

Forecasting for the Direct segment showed very little difference in error values between the benchmark models and the advanced models, reflecting data with high stationarity and low variance. The Mean model yielded the lowest RMSE (10.83), while ETS and Prophet provided the best MASE values (0.82).

The study results indicate that no single forecasting model demonstrated the highest performance across all segments. The researchers proposed a segment-specific model selection strategy, choosing Prophet for the Group segment, ARIMA for the OTA segment, Naïve for the TA segment, and Mean for the Direct segment, to achieve the highest overall accuracy.

The subsequent result is the total revenue derived from the demand converted according to model (3.1) and then allocated rooms using the ODF matrix according to model (3.2). The room allocation results in Table 4 show that the Saturdays of weeks 2, 3, and 4 have high demand, reaching full capacity (250 rooms). During this period, the shadow price is 1,125 Baht, meaning that if one more room were available, the total revenue would immediately increase by 1,125 Baht. The model therefore rejected all TA customers and restricted the Group segment to approximately 22 rooms per night (around 60% of their demand), reserving most rooms for customers willing to pay above the 1,125 Baht threshold.

Since there was spilling customer

Table 3. Forecasting error.

Model	Group		OTA		TA		Direct	
	RMSE	MASE	RMSE	MASE	RMSE	MASE	RMSE	MASE
Naïve	70.63	0.85	27.06	1.02	35.68	1.37	11.41	0.84
SNaïve	73.48	0.92	30.34	1.10	38.55	1.57	12.32	1.00
Mean	55.47	0.76	26.77	0.97	64.76	2.70	10.83	0.85
Drift	73.46	0.88	27.58	1.05	40.65	1.63	12.10	0.94
ETS	54.36	0.71	37.24	1.23	36.01	1.40	11.15	0.82
ARIMA	53.96	0.72	24.95	0.90	37.41	1.43	11.58	0.86
Theta	55.32	0.72	34.85	1.19	38.18	1.46	11.48	0.85
Prophet	52.31	0.68	29.36	1.08	50.94	2.05	11.32	0.82

Table 4. Room allocation and bid price of benchmark policy.

Period	Occupancy	Bid price (THB)	Segment	Demand	Allocated	Acceptance
Sat Wk. 2	250	1,125	Group (1 night)	37.36	21.58	57.76%
			TA (1 night)	23.85	0	0.00%
Sat Wk. 3	250	1,125	Group (1 night)	36.04	21.62	59.99%
			TA (1 night)	23.85	0	0.00%
Sat Wk. 4	250	1,125	Group (1 night)	34.94	22.20	63.54%
			TA (1 night)	23.85	0	0.00%

demand remaining on Saturdays, the researcher proposed strategies to increase room rates to maximize total revenue. The room rates for the TA segment are subject to pre-negotiated annual contracts, making price adjustments difficult. Furthermore, Table 2 shows no clear differentiation between weekday and Saturday pricing for the Group segment. Therefore, the alternative policy was to adjust the room rates for the Group segment on Fridays and Saturdays. The policy involved increasing the price by 5% increments, but the price must not exceed the OTA room rate, as this represented the highest price customers are willing to pay. According to the theory of price elasticity of demand (PED), increasing room rates will result in a decrease in customer demand. However, due to insufficient historical data available to estimate the elasticity for the case study hotel, we considered referencing the PED coefficient from a recent study by Pérez-Ricardo and García-Mestanza [19], which specified the elasticity value at -1.221 for the shoulder sea-

son, to serve as a representative value reflecting guest behavior under similar market conditions. A value of -1.221 means that if the selling price is increased by 1%, customer demand will decrease by 1.221%. Their study covered the corporate customer segment, which aligns with the Group segment, which primarily consisted of corporate clients. The increased room rates and corresponding reduced demand for Fridays and Saturdays are presented in Table 5.

Table 5. Changes in room rates and demand under the price increase policy.

Rate change	Friday		Saturday	
	Room rate	Demand	Room rate	Demand
+5%	1,204.35	-6.11%	1,181.25	-6.11%
+10%	1,261.70	-12.21%	1,237.50	-12.21%
+15%	1,319.05	-18.32%	1,293.75	-18.32%
+20%	1,376.40	-24.42%	1,350.00	-24.42%
+25%	1,433.75	-30.53%	1,406.25	-30.53%
+30%	-	-	1,462.50	-36.63%

After testing the established scenarios by adjusting room rates for Fridays and Saturdays, it was found that a price increase

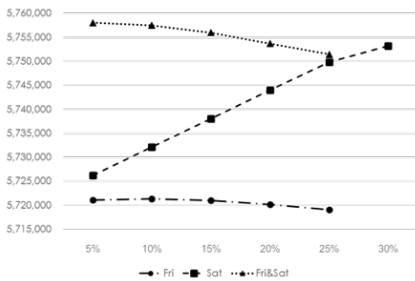


Fig. 1. Total revenue for all scenarios.

of 10% for Fridays and 30% for Saturdays yielded the highest total revenue among the options tested for each day. Therefore, the researchers added experimental plans by adjusting the Saturday room rate up by 30% and incrementally increasing the Friday room rate by 5% at a time. The test results found that adjusting the Friday room rate up by 5% and the Saturday room rate up by 30% resulted in the highest total revenue, as shown in Fig. 1.

An analysis of the results from the new policy, shown in Table 6, reveals that the price increase for the Group segment was highly successful in weeks 2 and 3. Although the Group segment's demand decreased, revenue increased due to the price adjustment, resulting in bid price as high as 1,462.50 Baht. This allowed the hotel to completely reject the TA segment with a 1-night stay to accommodate the Group segment at a high proportion, reaching 96-99% of their demand. However, a slight weakening was observed in week 4 when bid price decreased to 920 Baht. The system was required to allocate 1 room to the TA segment to fulfill capacity.

The summary of the KPI comparison results found that the new policy (adjusting the Group segment price by +5% on Fridays and +30% on Saturdays) was highly successful in increasing profitability. Specifically, it generated an increase in total

revenue of 37,765.73 Baht, resulting from an increase in ADR (Average Daily Rate) of 10.38 Baht and RevPAR (Revenue Per Available Room) of 6.04 Baht. Although the occupancy rate experienced a slight decrease of -0.27%, this is considered a positive trend because the hotel was able to filter out lower-spending customers and replace them with higher-revenue customers, aligning with the objectives of the implemented strategy.

5. Summary

This research focuses on improving revenue management effectiveness for a 4-star hotel in Pattaya. It began by comparing 8 demand forecasting models, which revealed that no single model provided the highest accuracy across all customer segments. Therefore, a strategy of segment-specific model selection was proposed, such as using Prophet for the Group segment and ARIMA for the OTA segment. The forecasting results were then integrated with the room network management model and the theory of price elasticity of demand (PED) to determine a new pricing strategy during periods of high demand.

The study indicates that the policy of increasing the Group segment room rate by 5% on Fridays and 30% on Saturdays is the strategy that generates the highest revenue. Although the occupancy rate decreased slightly due to customer filtering, this resulted in a positive effect on net profit by reducing variable costs and asset depreciation while also improving service efficiency.

The study reveals that the key to HRM is the selection and application of a forecasting model specific to the data behavior of each customer segment, rather than using a single model. This should be coupled with implementing a pricing

Table 6. Room allocation and bid price of new policy.

Period	Occupancy	Bid price (THB)	Segment	Demand	Allocated	Acceptance
Sat Wk. 2	250	1,462.50	Group (1 night)	25.95	24.79	95.53%
			TA (1 night)	23.85	0	0.00%
Sat Wk. 3	250	1,462.50	Group (1 night)	25.04	24.76	98.88%
			TA (1 night)	23.85	0	0.00%
Sat Wk. 4	250	920	TA (1 night)	23.85	1	4.19%

Table 7. Comparison of the results between the benchmark and new policies.

KPI	Benchmark policy	New policy	Change
Total Revenue	5,720,246.57	5,758,012.30	37,765.73
Occupied Room	5,396.36	5,379.32	-17.05
%Occupancy	86.34%	86.07%	-0.27%
Average daily rate (ADR)	1,060.02	1,070.40	10.38
Revenue per available room (RevPar)	915.24	921.28	6.04

strategy that considers PED. Furthermore, hotel managers should shift their focus from solely emphasizing the occupancy rate to generating revenue per available room (RevPAR) and net profit because the study results proved that having a slightly lower number of customers pay a higher price helps increase net profit. This allows the hotel to manage resources and services more efficiently in the long term.

Since the room allocation model in this study uses forecasted demand data as deterministic values, while in reality hotel demand is uncertain and highly volatile, future research should extend to sensitivity analysis. This could include testing the impact under scenarios where demand deviates from forecasted values at different levels, or incorporating confidence bounds of the forecasts. This would enable more effective room allocation decisions and better accommodate the risks associated with market uncertainty. Furthermore, the scope of study should be expanded from room revenue management to the concept of total revenue management, analyzing revenue from other services alongside room revenue. This should include developing

forecasting models that calculate the total spending behavior of customers in each segment, to create pricing strategies that do not focus solely on room rates but ultimately maximize net profit for the overall hotel business.

References

- [1] Binesh F, Belarmino A, Raab C. A meta-analysis of hotel revenue management. *J Revenue Pricing Manag.* 2021;20(5):546-58.
- [2] Denizci Guillet B. An evolutionary analysis of revenue management research in hospitality and tourism. *Int J Contemp Hosp Manag.* 2020;32(2):560-87.
- [3] Erdem M, Jiang L. An overview of hotel revenue management research and emerging key patterns in the third millennium. *J Hosp Tour Technol.* 2016;7(3):300-12.
- [4] Pattaya Mail. Pattaya reports 11 million Thai visitors in first eight months, prepares year-end attractions [Internet]. Available from: <https://www.pattayamail.com/latestnews/news/pattaya-reports-11-million-thai-visitors-in-first-eight-months-prepares-year-end-attractions-520326>. Accessed 2025 Dec 9.

- [5] Denizci Guillet B, Mohammed I. Revenue management research in hospitality and tourism. *Int J Contemp Hosp Manag*. 2015;27(4):526-560.
- [6] Vives A, Jacob M, Payeras M. Revenue management and price optimization techniques in the hotel sector. *Tourism Econ*. 2018;24(6):720-52.
- [7] Bandalouski AM, Kovalyov MY, Pesch E, Tarim SA. An overview of revenue management and dynamic pricing models in hotel business. *RAIRO Oper Res*. 2018;52(1):119-41.
- [8] Wang XL, Heo CY, Schwartz Z, Legohérel P, Specklin F. Revenue management: Progress, challenges, and research prospects. *J Travel Tour Mark*. 2015;32(7):797-811.
- [9] Lai KK, Ng WL. A stochastic approach to hotel revenue optimization. *Comput Oper Res*. 2005;32(5):1059-72.
- [10] Goldman P, Freling R, Pak K, Piersma N. Models and techniques for hotel revenue management using a rolling horizon. *J Revenue Pricing Manag*. 2002;1(3):207-19.
- [11] Aydin N, Birbil SI. Decomposition methods for dynamic room allocation in hotel revenue management. *Eur J Oper Res*. 2018;271(1):179-92.
- [12] Ni G, Feng X, Chen L. Hotel room allocation with multiple sales channels: A perspective of minimax regret. *J Control Decis*. 2019;7(4):359-78.
- [13] Ling L, Dong Y, Guo X, Liang L. Availability management of hotel rooms under cooperation with online travel agencies. *Int J Hosp Manag*. 2015;50:145-52.
- [14] Huang L, Zheng W. Hotel demand forecasting: A comprehensive literature review. *Tourism Rev*. 2022;78(1):218-44.
- [15] Henriques H, Nobre Pereira L. Hotel demand forecasting models and methods using artificial intelligence: A systematic literature review. *Tour Manag Stud*. 2024;20(3):39-51.
- [16] Song H, Zhang H. Tourism demand modelling and forecasting: A Horizon 2050 paper. *Tourism Rev*. 2024;80(1):8-27.
- [17] Seetaram N, Forsyth P, Dwyer L. Measuring price elasticities of demand for outbound tourism using competitiveness indices. *Ann Tour Res*. 2016;56:65-79.
- [18] Chalupa S, Petricek M. Understanding customer's online booking intentions using hotel big data analysis. *J Vacat Mark*. 2022;30(1):110-22.
- [19] Pérez-Ricardo EC, García-Mestanza J. Exploring booking intentions through price elasticity of demand in tourism accommodations using large-scale data analytics. *Eur Res Manag Bus Econ*. 2025;31(1):100271.
- [20] Petricek M, Chalupa S, Chadt K. Identification of consumer behavior based on price elasticity: A case study of the Prague market of accommodation services. *Sustainability*. 2020;12(22):9452.
- [21] Hyndman RJ, Koehler AB. Another look at measures of forecast accuracy. *Int J Forecast*. 2006;22(4):679-88.
- [22] Hyndman RJ, Athanasopoulos G. Forecasting: principles and practice. 3rd ed. Melbourne (AU): OTexts; 2021. Available from: OTexts.com/fpp3. Accessed 2025 Oct 1.
- [23] Assimakopoulos V, Nikolopoulos K. The theta model: A decomposition approach to forecasting. *Int J Forecast*. 2000;16(4):521-30.
- [24] Taylor SJ, Letham B. Forecasting at scale. *Am Stat*. 2018;72(1):37-45.