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Revenue Management System

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Dedications

We dedicate this modest work to:

Firstly, to our parents who consented to our upbringing and well-being. Also, for all their sacrifices, love, tenderness, support, and prayers.

Those who provided us with moral and intellectual support throughout our journey, friends, and colleagues.

Every person who directly or indirectly contributed to the completion of this work.

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General introduction

With the rapid advancement of globalization and technology, Revenue Management has become significantly crucial in businesses. Understanding how to effectively set prices and allocate resources represents a fundamental challenge for companies in all industries. Revenue Management aims to maximize the value of products or services offered by a company by achieving the optimal balance between supply and demand and setting prices accordingly. In this introduction, we will explore the fundamentals of Revenue Management and its importance in achieving profitability and sustained success for companies in the ever-evolving market.

The topic has been divided into three chapters. In the first chapter, we reviewed the key concepts related to Revenue Management. In the second chapter, we examined the significant previous works aimed at improving revenues and addressing revenue loss issues, utilizing various methods including dynamic approaches.

In the third chapter, we described the problem of demand uncertainty and random price distribution. We explained how to address this issue using local algorithms.

Finally, in the last chapter, we highlighted the key findings to achieve revenue optimization. With the rapid advancement of globalization and technology, Revenue Management has become significantly crucial in businesses. Understanding how to effectively set prices and allocate resources represents a fundamental challenge for companies in all industries. Revenue Management aims to maximize the value of products or services offered by a company by achieving the optimal balance between supply and demand and setting prices accordingly. In this introduction, we will explore the fundamentals of Revenue Management and its importance in achieving profitability and sustained success for companies in the ever-evolving market.

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Chapter I

Overview of Revenue Management System

1. Introduction

Businesses face important decisions regarding what to sell, when to sell, to whom to sell, and for how much. Revenue management uses data-driven tactics and strategy to answer these questions in order to increase revenue. The discipline of revenue management combines data mining and operations research with strategy, understanding of customer behavior, and partnering with the sales force. Today, the revenue management practitioner must be analytical and detail oriented, yet capable of thinking strategically and managing the relationship with sales.

2. Historical:

The airlines are credited for developing the foundational science behind revenue management. Almost since the beginning of commercial flight, airlines had attempted to maximize their revenues by focusing on filling as many seats as possible on every flight. This meant predicting how many booked passengers would show up for a flight and how many wouldn't. Overbooking by that predicted amount was the technique that was deployed to meet their objective.

In the early 1970's, airlines began experimenting with "fenced" pricing such as offering a discount to passengers who booked more than 21 days in advance. This meant that airlines now had the opportunity to sell additional seats that may otherwise have gone empty. It also meant that the need for tracking and quantitative analysis grew exponentially since customer response to these fare alternatives varied based on season, day of week, time of day, city pair (origin and destination), reason for travel (business or pleasure) and many other variables. In 1972, Ken Littlewood of British Overseas Airways Company (BOAC) now known as British Airways proposed a rule that discounted fares be accepted if their revenue value exceeded the expected revenue of future full fare bookings. Littlewood's

Rule marked the start of what became yield management and later, revenue management.

In October 1978, President Jimmy Carter signed the airline deregulation act which marked the shift from US airlines being a regulated public utility to being part of a free market system. It was then that the practice of yield management was truly put to the test. It passed. Robert Crandall, former Chairman and CEO of American Airlines, gave yield management its name and has called it “the single most important technical development in transportation management since we entered deregulation.”

A decade later fledgling yield management practices began within the hospitality industry. In fact, it wasn't until 1988 that the first yield management-related article appeared in Cornell Quarterly and some of the larger hospitality brands began to experiment by utilizing yield management principles. Unlike the airlines with scores of specialists skilled at quantitative analysis, yield management responsibilities in the hospitality sector fell into the lap of those in other roles – mainly reservation sales managers.

Today the term yield management is outdated and has been replaced with the term revenue management which reflects a broader perspective. Yield management generally refers to an inventory-centric approach to selling the right product to the right customer at the right time at the right price. The term revenue management refers to a business practice designed to optimize the revenue potential of an asset through all market conditions. It is important to note that yield management principles remain as a fundamental component of revenue management and several conditions must exist for it to apply. Those conditions are as follows:

- A fixed amount of resources are available for sale at any given time
- Resources are perishable (after a given point in time, resources are not sellable)
- Different customers are willing to pay a different price for the same resources
- There is some ability to predict future demand for resources

Important note: Demand does NOT need to exceed supply in order for revenue management principles to apply. In the early days of hospitality revenue management, the discipline was predominantly reactive in nature. The two tactical levers of pricing and inventory controls were used either independently or in conjunction with each other in response to existing demand. The focus was on raising or lowering rates and placing or removing minimum night stay requirements to maximize the room revenue potential for any given property.[1]

3. Definition of Revenue management:

Revenue management refers to applying disciplined data analytics to maximize profitability. It predicts customer behavior at micro-market levels, fine-tunes product pricing, and adjusts availability to maximize revenue. It helps Seas businesses understand their customers better and align their products with the ideal customer profiles (ICPs) by tweaking product pricing, availability, and market placement.[2]

4. Revenue Management Steps

Yield Management is only effective through its 6 steps Each of the 6 steps alone brings a very high added value:

Step 1: Data collection the best decisions are often a mix of intuition and science. In order to understand the impact of these decisions, it is recommendable to store data and to use those to help make better decisions in the future. Automation and decision support tools have evolved as the revenue management discipline has grown and provide business insights that humans are not able to calculate on their own. The ideal solution is when automation provides insights for the revenue management professional and the revenue management professional provides appropriate feedback within the system.

Step 2: Forecasting Predicting future demand based on past results is a good starting point to develop a strategy. Of course, changes in market conditions, competitive supply, capacity constraints, special events, floating holidays, weather conditions, economic climate and other external factors need some additional thought around true demand potential; but the past results provide help to make good predictions and to be prepared against the variations produced by these factors.

Step 3: Pricing People who unknow the scope of the discipline often think that revenue management simply consists in changing prices, or making discounts. The fact is that pricing

is far more complex than this. Basic economic theory would dictate that equilibrium pricing, where the demand curves meets the supply curve, would be optimal. Unfortunately, inventory is perishable so this approach would not utilize all the resource's potential.

Step 4: Inventory Management once future demand has been forecasted and pricing strategies determined, resource allocation or inventory management comes into play. Inventory management simply means opening or restricting inventory for sale based on certain conditions as the available capacity.

Step 5: Distribution Distribution refers to how guests find and book a property. Telephone, Online Travel Agencies, Global Distribution Systems and Internet Booking Engines are all examples of distribution channels. Each one may offer a different value proposition, but each one requires that a revenue management professional think through how to best leverage the potential that each one represents.

Step 6: Communication Communication is crucial because Revenue Management requires that a firm must continually re-evaluate their prices, products, and processes in order to maximize revenue. In a dynamic market, an effective Revenue Management System constantly re-evaluates the variables involved in order to move dynamically with the market. Then communication is causal because the information is constantly varying.[3]

5. Conclusion

Setting revenue goals is an essential part of any business, large or small. This is done by conducting a comprehensive analysis of the financial data of your business, including revenues, expenses, and profit margins, and taking a look at your field and competitors to identify what is realistic in terms of revenue growth, so setting revenue goals is important. An important aspect of any business strategy, by setting clear and achievable goals, companies can plan, prioritize their performance, measure them, motivate their employees, and identify growth opportunities, enabling companies to stay ahead of the competition and achieve their revenue goals.

However, this requires creating a targeted revenue plan carefully studied and planned by taking into account factors such as current revenue streams, growth potential, competition, and pricing strategy, and we follow progress.

Revenue reports are not only useful for future planning, but also useful for analyzing the current situation and knowing the result of your work for any past period you specify.

Chapter II

State of the art

1. Introduction

Chapter 2 provides an overview of previous research conducted on the topic of revenue management problem. This chapter delves into existing literature, exploring various theoretical frameworks, methodologies, and findings related to revenue management. By reviewing prior studies, we aim to gain insights into the evolution of revenue management concepts, the challenges encountered, and the strategies employed in different business contexts. Additionally, this chapter seeks to identify gaps in the existing body of knowledge, paving the way for the current study's contribution to the field of revenue management. Through a comprehensive review of past research, we aim to establish a solid foundation upon which to build our investigation and develop innovative solutions to address contemporary revenue management challenges.

2. Littérature review

2.1. Alexander Erdelyi and Huseyin Topaloglu 2009

The research paper "Using Decomposition Methods to Solve Pricing Problems in Network Revenue Management" November 8, 2009 introduces two approaches for making pricing decisions in network revenue management scenarios. It addresses a setting where the probability of monitoring an itinerary request depends on prices, aiming to dynamically adjust prices to maximize total expected revenue. Both methods rely on dynamic programming analysis, formulating the pricing problem by considering individual flight legs and deriving value function approximations for each leg separately.

These methods are shown to offer upper bounds on the optimal expected total revenue, which are more stringent compared to those obtained by the deterministic linear program commonly used in practice. Computational experiments reveal two key

findings. Firstly, the proposed methods significantly outperform the deterministic linearization program, with an average gap of 7.11% between the expected total revenues obtained by the methods and those of the deterministic linear program. On average, the methods tighten the upper bounds obtained from the deterministic linear program by 3.66%.

Secondly, the two developed methods exhibit different strengths. While one method achieves tighter upper bounds, the other method excels in devising pricing policies that result in higher expected total revenues.[4]

2.2. Josef Meinrad Broder, Ph.D 2011

The thesis titled "Online Algorithms for Revenue Management" by Joseph Meinrad Broder, Ph.D., from Cornell University in 2011, challenges traditional revenue management methods that assume sellers possess a high degree of certainty about their market environment and revenue streams. Instead, it delves into the realm of revenue management in uncertain market conditions. The thesis outlines strategies for sellers to intelligently utilize information about product demand to price and distribute goods effectively.

It presents theoretically grounded approaches for pricing and distribution, considering the emergence of commodities under demand uncertainty. The thesis offers insights into the structure of effective strategies and the inherent challenges associated with such problems.[5]

2.3. Pornpawee Bumpensanti 2019

This research **A Re-solving Heuristic with Uniformly Bounded Loss for Network Revenue Management 2019** addresses the problem of basic network revenue management (quantity-based), where the company decides whether to accept or reject incoming customer orders permanently to maximize expected revenues within limited resources. Due to the curse of dimensionality, exact solutions using dynamic programming become intractable when the number of resources is large. A family of heuristics is

studied, periodically improving the solution approximation of the deterministic linear program (DLP), where customers' random arrivals are replaced by their expectations. They found that repeatedly solving the DLP results in the same revenue loss ranking as solving it once, scaling with the square root of the time horizon and resource capabilities. By periodically solving the DLP and applying thresholds to customer acceptance probabilities, they propose a new solution heuristic, Infrequent Re-solving with Thresholding (IRT), whose revenue loss is bounded by a constant independent of time horizon and resource capacities.

They answer the question positively by proposing the IRT heuristic, showing that its revenue loss remains bounded by a constant regardless of the time horizon and resource capacities. This improves upon a previous result by Jasin and Kumar (2012) for Frequent Re-solving (FR), where the revenue loss depends on the time horizon and resource capacities.

Simulation results indicate that when controls from FR are adjusted by thresholds, the resulting algorithm, FRT, exhibits promising numerical performance and seems to have a bounded revenue loss as well. Although they haven't proved this result yet, Vera and Banerjee (2018) propose a different re-solving heuristic for the NRM problem, achieving $O(1)$ regret. Their analysis technique may aid in establishing the revenue loss bound of FRT.[6]

2.4. Gonzalo Oliveveri Martinez-Pardo 2017

Revenue Management that is a relatively new way to carry out the management in different industries. The success of the application of Revenue Management could be observed in the airline industry that is where Revenue Management is born during the 70s. As a consequence of this success, other industries begin to apply RM during the 90s and the beginning of the 21st century.

The objective of this thesis is to provide an introduction to the Revenue Management because as it is commented, it has been very successful in the industries where it has been implemented. Moreover, it is a very interesting concept because it is in developing process, especially in the industries where the concept is relatively new. I these

industries there are much work to do behind this concept because although in other industries as airlines it is very developed, in each industry, Revenue Management work in a different way, with different models. In fact, different companies of the same industry, work in a different way depending on company's priorities. For these reasons, "Principles of Revenue-Management and their applications" is a good starting point to learn about this concept.[3]

2.5. Evmorfia Argyriou and T.C. Melewar

In a competitive landscape shaped by the digital transformation of the service sector, Yield Management (YM) has emerged as a crucial tool for many companies, particularly within the hotel industry. Over the past two decades, the utilization of this pricing strategy has been fortified by advancements in digital technologies. However, numerous studies have highlighted the tendency of Yield Management Pricing (YMP) to elicit negative consumer sentiments, thereby impacting their behavior. This study aims to delve into the practice of YM within the hotel industry and to illuminate its effect on customer perception. A qualitative inquiry involving industry professionals was conducted to uncover the intricacies of YM implementation in chain hotels in Morocco and to discern its influence on customer attitudes.[7]

2.6. Kalyan T. Talluri 2009

The article "REVENUE MANAGEMENT: MODELS AND METHODS" January 2009 serves as an introduction to revenue management, a sub-field within operations research, with a particular emphasis on simulation techniques. Drawing from excerpts of the book "Revenue Theory and Practice," the researchers delve into the fundamental methodologies developed for practical application in various industries. Over the past 25 years, industries such as aviation and hotels have increasingly embraced simulation as a tool to enhance revenue management strategies.[8]

2.7. Sandra Camus and Jean-Michel Sahut 2015

The article **L'injustice perçue à l'égard du yield management: These antécédents and strategies need to be removed** delves into the unjust constraints surrounding yield management practices. Through a quantitative study involving 505 participants, it focuses on applied scenarios within the hotel industry, highlighting the influence of

various client profile variables (such as PCSP, price sensitivity, hotel loyalty category, usage situation, and frequency of stays) on perceived injustice. For those interested in fairness within the justice system, it advocates for equity on the internet and in procedures related to pricing, client/vendor interactions, and responsibility attribution. These findings suggest that implementing strategies aimed at improving the company's image without compromising return optimization is crucial.[9]

2.8. Alessandro Arlotto, Itai Gurvich 2018

Uniformly Bounded Regret in the Multisecretary Problem In the secretary problem of Cayley [Cayley A (1875) *Mathematical questions with their solutions*. Ed. Times 23:18–19.] and Moser [Moser L (1956) *On a problem of Cayley*. *Scripta Mathematica* 22(3/4):289–292.], n nonnegative, independent, random variables with common distribution are sequentially presented to a decision maker who decides when to stop and collect the most recent realization. The goal is to maximize the expected value of the collected element. In the k -choice variant, the decision maker is allowed to make $k \leq n$ selections to maximize the expected total value of the selected elements. Assuming that the values are drawn from a known distribution with finite support, they prove that the best regret—the expected gap between the optimal online policy and its offline counterpart in which all n values are made visible at time 0—is uniformly bounded in the number of candidates n and the budget k . Our proof is constructive: they develop an adaptive budget-ratio policy that achieves this performance. The policy selects or skips values depending on where the ratio of the residual budget to the remaining time stands relative to multiple thresholds that correspond to middle points of the distribution.

they also prove that being adaptive is crucial: in general, the minimal regret among nonadaptive policies grows like the square root of n . The difference is the value of adaptiveness.

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adaptiveness.[10]

2.9. Zizhuo Wang-Shiming ,Deng -Yinyu Ye 2018

Close the Gaps: A Learning-while-Doing Algorithm for a Class of Single-Product Revenue Management Problems October 24, 2018

The researchers examine a scenario where a retailer sells a single product with limited on-hand inventory during a finite selling season. Customer demand follows a Poisson process, with its rate affected by a single action initiated by the retailer (such as price adjustments, sales commissions, advertising intensity, etc.). The correlation between the action and the demand rate is not initially known. However, the retailer can dynamically learn the optimal action as she maximizes her total expected revenue based on observed demand reactions. Focusing on the pricing problem, they introduce a dynamic "learning-while-doing" algorithm that involves only function value estimation to achieve nearly optimal performance. This algorithm utilizes a series of shrinking price intervals and iteratively tests prices within those intervals using carefully selected parameters. They demonstrate that the convergence rate of their algorithm is one of the fastest among all possible algorithms in terms of asymptotic "regret" (relative loss compared to the optimal solution with full information). Their findings bridge performance gaps between parametric and non-parametric learning methods, as well as between post-price and customer-bidding mechanisms. A key managerial insight from this research is that the values of information on both the parametric form of the demand function and each customer's exact reservation price are less critical than previously believed. Furthermore, their results suggest that firms would benefit more from concurrent dynamic learning and action rather than sequential approaches..[11]

Conclusion

In conclusion, the review of previous research in Chapter 2 highlights the significance and complexity of revenue management, illustrating how advancements in this field require ongoing and in-depth understanding. Previous studies demonstrate a variety of approaches and methodologies that can contribute to addressing revenue management challenges. However, there are still gaps and challenges that require further research and exploration. This underscores the importance of the current study and its potential contribution to enhancing our understanding of revenue management and developing effective solutions. The next chapter will outline the objectives and methodology of the current research, thereby

contributing valuable insights to the field of revenue management and the development of efficient industry practices.

Chapter III

Revenue Management System

1. Introduction

Revenue Management is a strategy aimed at maximizing financial returns from products or services by analyzing data, predicting demand, adjusting prices, and directing pricing policies accurately. It relies on precise interaction between supply, demand, and pricing to ensure the highest possible revenues in line with the company's objectives, whether it's increasing total revenues, profitability, or maximizing booking rates. Revenue Management goals include achieving a balance between supply and demand, optimizing capacity utilization, enhancing customer experience, and increasing the company's competitiveness in the market.

2. Problem description

When demand in each period is random and price-sensitive, but the company has little or no prior knowledge about the demand distribution and how each customer responds to the selling price, the company needs to learn about the demand process when making periodic pricing decisions and inventory replenishments to maximize profit. The question then arises: How can the seller determine its prices to maximize its total revenue in the face of demand uncertainty?

Revenue management system is considered a topic of utmost importance and complexity due to the challenges companies face regarding pricing, demand, and achieving the balance to maximize overall profit and increase revenues. It relies on various strategies and algorithms, most notably dynamic pricing and local algorithms. Therefore, in this chapter, we investigate the revenue management problem under demand uncertainty and how to address this issue through local algorithms.

3. Motivation and goal

The motivation behind revenue management stems from the desire to maximize profits and optimize revenue streams in businesses where pricing and demand fluctuate. Several factors drive the need for effective revenue management:

1. **Demand Variability:** Demand for products or services can vary significantly based on factors such as seasonality, market trends, economic conditions, and competitive influences. Revenue management seeks to capitalize on these fluctuations by adjusting prices and allocation strategies accordingly.
2. **Price Sensitivity:** Customers' sensitivity to pricing changes can greatly impact purchasing behavior. Revenue management aims to understand and leverage price elasticity to set optimal prices that maximize revenue without sacrificing customer satisfaction or market share.
3. **Limited Capacity:** Businesses with finite resources or capacity constraints, such as hotel rooms, airline seats, or event venues, must strategically manage inventory to maximize utilization and revenue. Revenue management helps allocate resources efficiently to meet demand while minimizing wastage.
4. **Competitive Pressure:** In industries with intense competition, companies must employ sophisticated pricing strategies to stay ahead. Revenue management enables businesses to respond dynamically to competitive pricing moves and market trends to maintain a competitive edge.
5. **Profit Maximization:** Ultimately, the primary goal of revenue management is to enhance profitability by optimizing pricing, inventory allocation, and sales strategies. By effectively managing revenue streams, businesses can improve their bottom line and drive sustainable growth.

Overall, revenue management addresses the complex interplay between pricing, demand, and capacity constraints to achieve optimal financial outcomes and enhance business performance.

Maximize revenue by optimizing pricing and inventory allocation decisions for a set of products over a specified time horizon, subject to various constraints and considering demand uncertainty.

Statement:

The statement of a revenue management problem can vary depending on the specific context and objectives. However, here's a general statement that captures the essence of a revenue management problem:

Problem Statement: Revenue Management

Input:

- Demand forecasts for each product and time period.
- Capacity constraints for each product and time period.
- Cost structure (if applicable).
- Pricing constraints and objectives.
- Historical data (optional, for forecasting and optimization).

Decision Variables:

- Pricing decisions for each product and time period.

Constraints:

- Capacity constraints: Ensure that the total inventory allocated does not exceed the available capacity.
- Demand constraints: Ensure that the allocated quantity does not exceed the forecasted demand.
- Pricing constraints: Adhere to pricing policies, such as price floors, price ceilings, and pricing relationships.
- Operational constraints: Consider operational constraints, such as production constraints or distribution constraints.
- Profitability constraints: Ensure that pricing and allocation decisions lead to profitable outcomes.

Objective Function:

Maximize total revenue, which is the sum of revenue generated from each product over the entire time horizon.

Approach:

Develop a mathematical model or optimization algorithm to determine the optimal pricing and inventory allocation decisions that maximize revenue while satisfying all constraints. This may involve techniques such as linear programming, integer programming, dynamic programming, or heuristic approaches.

Output:

Optimal pricing and inventory allocation decisions for each product and time period that maximize revenue while adhering to all constraints.

Implementation:

Implement the solution algorithm in software or integrate it into existing revenue management systems for real-time decision-making.

4. Mathematical formulation

4.1 Problem statement

This statement provides a high-level overview of the revenue management problem, including its objectives, inputs, decision variables, constraints, approach, and expected output. Specific details and complexities may vary depending on the industry, business context, and problem instance.

Mathematical formulation

Revenue management systems are mathematical models used to optimize pricing and allocation decisions to maximize revenue. Here's a simplified mathematical formulation for a revenue management system in the context of a single resource, such as hotel rooms or airline seats, using the basic principles of dynamic pricing.

4.2 Notation

T : The total number of time periods (eg, days, hours).

p_t : The price for the resource in time period t .

d_t : The demand forecast for the resource in time period t .

x_t : The quantity of the resource allocated (sold) in time period t .

R_t : The revenue generated in time period t .

The goal of revenue management is to determine the optimal price p_t and quantity x_t to maximize revenue over all time periods.

4.3 Decision variable

Decision variables are the unknown quantities or factors in a mathematical optimization problem that the decision-maker can control or determine to achieve the desired objective. In the context of the revenue management problem you

presented, the decision variable is x_t , representing the quantity allocated or sold in each time period t .

4.4 Objective

$$\text{Maximize } \sum_{t=1}^T R_t$$

4.5 Constraints

Subject to:

1. Demand constraint :

$$x_t \leq d_t, \forall t$$

This ensures that the allocated quantity does not exceed the forecasted demand.

2. Revenue calculation :

$$R_t = p_t \times x_t, \forall t$$

Revenue in each time period is calculated as the product price and quantity sold.

3. Capacity constraint :

$$\sum_{t=1}^T x_t \leq \text{Capacity}$$

This ensures that the total quantity allocated does not exceed the available capacity.

4. Non- negativity constraint :

$$x_t \geq 0, \forall t$$

The quantity allocated in each time period must be non-negative.

4.6 Formulation

This formulation represents a simplified version of revenue management and can be extended to incorporate additional factors such as price elasticity, inventory replenishment, booking limits, customer segmentation, and dynamic pricing strategies.

$$\text{Maximize } \sum_{t=1}^T p_t \times x_t, \forall t$$

5. Resolution Methods

There are several algorithms and optimization techniques that can be used to solve revenue management problems. The choice of algorithm depends on factors such as problem complexity, size, and computational resources available. Here are some common algorithms and techniques used to solve revenue management problems:

a. Linear Programming (LP):

- LP is a mathematical optimization technique used to maximize or minimize a linear objective function subject to linear constraints.
- Revenue management problems can often be formulated as linear programming problems, especially when demand and pricing are linearly related.
- LP solvers such as the Simplex algorithm or interior-point methods can be used to solve revenue management LP formulations.

b. Integer Programming (IP):

- Integer programming extends linear programming to handle discrete decision variables.
- Revenue management problems with discrete decisions, such as pricing decisions, can be formulated as integer programming problems.
- IP solvers such as branch and bound, branch and cut, or branch and price algorithms can be used to solve revenue management IP formulations.

c. Dynamic Programming (DP):

- DP is a method for solving complex problems by breaking them down into simpler subproblems.
- Revenue management problems with sequential decision-making over time can be solved using dynamic programming.
- DP algorithms, such as the Bellman equation or backward induction, can be used to solve revenue management problems with dynamic pricing and inventory allocation decisions.

d. Heuristic Algorithms:

- Heuristic algorithms are approximate methods that aim to find good solutions to complex optimization problems in a reasonable amount of time.
- Metaheuristic algorithms such as genetic algorithms, simulated annealing, tabu search, or ant colony optimization can be used to solve revenue management problems when exact optimization methods are computationally infeasible.
- Heuristic algorithms can provide near-optimal solutions quickly but may not guarantee optimality.

e. Stochastic Optimization:

Stochastic optimization techniques are used to optimize decisions under uncertainty.

- Revenue management problems with uncertain demand or market conditions can be formulated as stochastic optimization problems.
- Techniques such as stochastic dynamic programming, Monte Carlo simulation, or robust optimization can be used to solve revenue management problems under uncertainty.

f. Machine Learning (ML):

- ML techniques can be used to learn demand patterns, price sensitivities, and other relationships from historical data.
- ML algorithms such as regression models, decision trees, neural networks, or reinforcement learning can be used to inform pricing and allocation decisions in revenue management.

g. Hybrid Approaches:

- Hybrid approaches combine multiple optimization techniques or algorithms to leverage their strengths and overcome their limitations.
- For example, a hybrid approach may use dynamic programming to solve a simplified version of the problem and then use heuristic algorithms to refine the solution.

These are some of the algorithms and techniques commonly used to solve revenue management problems. The choice of algorithm depends on the specific characteristics of the problem and the computational resources available.

5.1 Algorithm and data structure

These are some of the algorithms and techniques commonly used to solve revenue management problems. The choice of algorithm depends on the specific characteristics of the problem and the computational resources available.

Local search algorithm

A local search algorithm is an optimization technique that iteratively explores the neighborhood of a current solution, making incremental changes to improve the objective function. In the context of revenue management, a local search algorithm can be used to find near-optimal pricing and allocation decisions by iteratively adjusting prices and allocations based on the current solution.

Here's a detailed local search algorithm for solving a revenue management problem:

Local Search Algorithm for Revenue Management

a. Initialization:

- Start with an initial feasible solution, which could be obtained through heuristics, randomization, or any other method.

b. Define Neighborhood Structure:

- Define a neighborhood structure that defines how solutions are perturbed to generate neighboring solutions. In revenue management, this could involve adjusting prices, reallocating inventory, or both.

c. Set Current Solution:

- Initialize the current solution to the initial solution obtained in step 1.

d. Repeat Until Stopping Criterion Met:

- Define a stopping criterion, such as a maximum number of iterations, a time limit, or reaching a satisfactory solution.

e. Generate Neighbor Solutions:

- Perturb the current solution to generate a set of neighboring solutions. This could involve adjusting prices, allocating or reallocating inventory, or both, within predefined bounds or constraints.

f. Evaluate Neighbors:

- Evaluate the objective function (total revenue) for each neighboring solution.

g. Select Best Neighbor:

- Select the neighboring solution with the highest objective function value (ie, the solution that maximizes revenue).

h. Update Current Solution:

- Update the current solution to be the best neighboring solution found in step 7.

i. Repeat:

- Repeat steps 5 to 8 until the stopping criterion is met.

j. Output Solution:

- Once the stopping criterion is met, output the current solution as the final solution.

5.2 Complexity

The complexity of a revenue management problem can vary depending on several factors such as the size of the problem instance, the number of products, the number of time periods, the number of demand segments, and the complexity of pricing and inventory constraints.

Revenue management problems are typically optimization problems that fall into the category of combinatorial optimization, and their complexity can range from polynomial-time solvable to NP-hard.

Here are some factors that contribute to the complexity of revenue management problems:

1. Number of Products: As the number of products increases, the problem becomes more complex because of the increased number of pricing and allocation decisions that need to be made.

2. Number of Time Periods: The granularity of time periods affects the complexity of the problem. More time periods mean more decisions to be made, which increases the complexity.

3. Demand Uncertainty: If demand is uncertain and needs to be forecasted, the problem becomes more complex because decisions need to be made under uncertainty.
4. Capacity Constraints: Constraints on the availability of resources (eg, inventory capacity, production capacity) add complexity to the problem as they restrict the feasible solution space.
5. Pricing Constraints: Constraints on pricing (eg, price floors, price ceilings, pricing relationships) can add complexity to the problem by limiting the set of feasible prices.
6. Dynamic Nature: Revenue management problems are often dynamic, with demand and availability changing over time. The dynamic nature of the problem adds complexity because decisions need to be made in real-time or over multiple time periods.
7. Heterogeneous Demand: If demand varies across different customer segments or market segments, the problem becomes more complex as decisions need to be tailored to different segments.
8. Non-linearities: Non-linear relationships between pricing, demand, and revenue can make the problem more complex, requiring non-linear optimization techniques.

In general, revenue management problems are known to be computationally challenging, and solving them optimally often requires sophisticated optimization algorithms and heuristics. The complexity can range from polynomial-time solvable in simple cases to NP-hard in more complex cases.

5.3 Example

1. Hotel rooms

Let's say we're optimizing pricing and allocation decisions for a set of hotel rooms over a 7-day time horizon.

- Neighborhood Structure: In each iteration, we can adjust prices for each room type and reallocate rooms across different room types or time periods within predefined bounds or constraints.
- Stopping Criterion: Stop when a maximum number of iterations is reached or when no further improvement in revenue is observed over several iterations.

2. Airline Seat Allocation:

Scenario: Suppose we're optimizing pricing and seat allocation decisions for a set of airline seats over a 30-day time horizon.

Approach: In each iteration, we can adjust ticket prices for different seat classes (economy, business, first class) and reallocate seats across different classes or flight times within predefined constraints.

Stopping Criterion: Stop when either a maximum number of iterations is reached or when no further improvement in revenue is observed after a certain number of iterations.

3. Restaurant Table Reservation Optimization:

Scenario: Imagine we're optimizing pricing and table reservation decisions for a restaurant over a 14-day time horizon.

Approach: In each iteration, we can adjust reservation prices for different times of the day (lunch, dinner) and reallocate tables across different time slots within predefined constraints.

Stopping Criterion: Stop when either a maximum number of iterations is reached or when no further improvement in revenue is observed after several iterations, indicating that the optimal pricing and allocation strategy has been found.

These examples illustrate similar revenue management scenarios where pricing and allocation decisions are optimized over a specific time horizon, with predefined constraints and stopping criteria to guide the optimization process.

5.4 Discussions

This local search algorithm iteratively explores the space of feasible solutions, making incremental improvements to the objective function until a satisfactory solution is found.

Advantages:

- Local search algorithms can be computationally efficient and scalable.
- They can find good solutions quickly, especially for large or complex problem instances.

- They are flexible and can handle various types of constraints and objective functions.

Disadvantages:

- Local search algorithms may get stuck in local optima and fail to find the global optimum.
- They do not guarantee optimality, as they only explore a subset of the solution space.
- The quality of solutions obtained depends on the choice of neighborhood structure and other algorithm parameters.

6. Conclusion

Overall, local search algorithms are effective for finding near-optimal solutions to revenue management problems, especially in situations where exact optimization methods are computationally infeasible. However, they may require careful tuning and experimentation to achieve good performance.

Chapter IV

Implementation and Results

1. Introduction

In the era of e-commerce and service-based industries, revenue management has become one of the key challenges facing companies. Maximizing revenue requires precise data analysis, accurate demand forecasts, and effective price adjustments.

The implementation phase involves applying the strategies developed for revenue management. Here, local algorithms can be used to adjust prices based on actual demand and available market information. For example, time-based analysis algorithms can be used to identify high-demand periods and adjust prices accordingly, increasing revenue.

In the results phase, the performance of implemented strategies using local algorithms is evaluated. Success can be measured by increased revenue and improved profitability due to enhanced pricing policies and resource utilization.

By using local algorithms in revenue management, companies can achieve optimal results and enhance their competitiveness in the market, effectively achieving their financial goals.

2. Hardware and software environment

Hardware and software environment for data management encompasses a wide range of technologies and tools that collectively enable organizations to store, process, analyze, and manage data effectively and efficiently.

2.1. Hardware

- Brand: TOSHIBA.
- Processor: Intel(R) Core(TM) i5-4300U CPU @ 1.90GHz 2.50 GHz
- Hard Drive: SSD 128.

- RAM: 6 GB
- Operating System: Windows 10.

2.2. Anaconda Navigator

Anaconda Navigator is a graphical user interface (GUI) included with the Anaconda distribution, a popular open-source platform for data science and machine learning. It provides users with a convenient way to manage and navigate through the various tools, packages, and environments available within the Anaconda ecosystem. Essentially, Anaconda Navigator serves as a central hub for accessing and organizing the wide range of data science tools and resources offered by Anaconda, simplifying the process of setting up and managing data science workflows.[12]

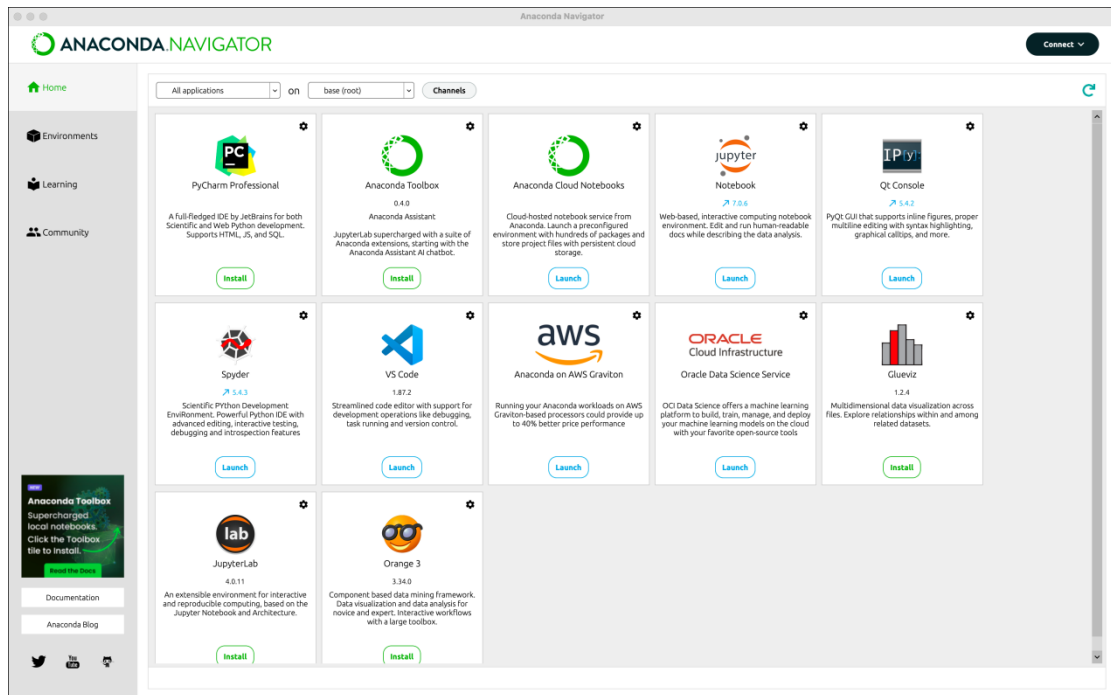


Figure 1: Logo Anaconda[13].

2.3. Jupyter Notebook

A Jupyter Notebook is a web-based interactive computing environment that enables users to create and share documents containing live code, equations, visualizations, and explanatory text. It provides an interface for writing and executing code in various programming languages, such as Python, R, and Julia, and allows for the integration of

rich media and interactive elements like plots, charts, and widgets. Jupyter Notebooks are widely used for data exploration, prototyping, scientific computing, education, and reproducible research.[14]



Figure 2: Logo Jupyter Notebook[15].

2.4. Python

Python is a high-level, versatile programming language widely used in data analysis and prediction. It's known for its readability and ease of learning, making it suitable for beginners and professionals alike. Python also benefits from an active community of developers and users, offering a wide range of libraries and tools for data analysis.

Its role in data management encompasses several aspects:

- **Data Processing:** Python provides powerful libraries like pandas and NumPy for importing and analyzing data from various sources, such as CSV files and databases.
- **Data Visualization:** Libraries like Matplotlib, Seaborn, and Plotly allow for visualizing data in a clear and understandable way, aiding in data exploration and trend identification.
- **Data Analysis:** Advanced libraries like scikit-learn and Statsmodels enable statistical analysis and the application of predictive models to achieve accurate forecasts.

- AI and Machine Learning: Python is used in developing machine learning and artificial intelligence models using libraries like TensorFlow, Keras, and PyTorch, facilitating advanced analytics and precise predictions.

Data Management: Python offers tools for managing and cleaning data, simplifying the data exploration and preparation process.

In summary, Python plays a vital role in data analysis and prediction in data management, providing a variety of tools and libraries that enable analysts and researchers to efficiently explore, analyze, and predict future trends in data.[16]

3. Dataset:

This code simulates a buying or selling process over a certain number of time periods. Let me break down the steps:

- Defining the capacity ratio using `capacity_ratio` with a value of 0.1 and 0.2.
- Defining the number of time periods using `num_periods` with a value of 5 TO 40.
- Repeating the experiment ten times, each time using a different random seed.
- Generating initial prices and demands for each time period.
- Generating random prices for each time period between 10 and 90.
- Generating random demands for each time period between 100 and 900.

Calculating the capacity by summing the demand values for all time periods and multiplying them by the `capacity_ratio`.

For example:

Instance : 0

INPUT DATA

=====

`num_periods`: 20

`capacity`: 10499

`initial_prices`: [19, 51, 82, 84, 70, 90, 13, 61, 11, 77, 85, 26, 45, 77, 37, 51, 36, 23, 85, 31]

`demand`: [132, 563, 876, 681, 459, 734, 467, 492, 894, 110, 494, 599, 329, 511, 851, 189, 830, 241, 535, 512]

4. Implementation steps

installed Anaconda:

We downloaded Anaconda from its official website and followed the instructions to install it on our computer.

opened Anaconda Navigator and created a new environment:

We opened Anaconda Navigator and created a new environment using Python, then we installed the NumPy package in this environment.

understood the source code:

- We opened the source code file and understood how the functions, variables, and algorithm work.

defined the initial data:

- We defined the input data required to run the program, such as the number of periods, initial prices, and demand.

ran the program:

- We ran the source code in the Anaconda environment we created, using Jupyter Notebook.

analyzed the results:

- We analyzed the results obtained after running the program and evaluated the quality of the computed prices and the algorithm's performance.

documented the results:

- We documented the results and wrote a report explaining the experiment and the results obtained.

We iterated and continuously improved:

- We repeated the process as needed and improved the program based on analysis and changes in requirements.

5. Results and discussion

In these tables, we varied algorithm parameters such as ``step_size`` and ``max_iterations``, and observed how they influenced the time needed to reach a solution. Specifically, increasing ``max_iterations`` led to a notable increase in complexity, while augmenting ``step_size`` appeared to decrease it.

Test 1:

- Num_periods = 10,
- Capacity_rate = 1

Instance	max_iterations= 100*num_periods step_size= 0.01	max_iterations= 100*num_periods step_size= 0.02
	Revenue	Revenue
0	334759.63	260251
1	270813.63	205147.23
2	170867	272488.92
3	224007.53	213978.73
4	290327.952	234007.36
5	336893.74	302967.37
6	295778.19	236641.67
7	233479.21	371493.37
8	250855.44	367660.89
9	230159.89	405721
MEAN TIME (ms)	73.4	93.2

Table 1 : Effect of step size and max-iteration=100*num_periods.

Instance	max_iterations= 1000*num_periods step_size= 0.01	max_iterations= 1000*num_periods step_size= 0.02
	Revenue	Revenue
0	313397.40	329291.82
1	251412.70	189436.31
2	252784.02	318469.23
3	175894.95	185690.09
4	283796.82	305031.17
5	206713.89	284051.62
6	285837.82	274035.82
7	236960.42	186445.66
8	148759.68	284714.52
9	228184.02	213537.36
MEAN TIME (ms)	16	14.4

Table 2: Effect of step size and max iteration =1000* num_periods.

Test 2:

- Num_periods = 10,
- Capacity_rate = 2

Instance	max_iterations= 100*num_periods step_size= 0.01	max_iterations= 100*num_periods step_size= 0.02
	Revenue	Revenue
0	281523.13	261857.95
1	188047.76	121810.72
2	336575.64	197440.49
3	338212.13	231894.49
4	160491.36	304123.15
5	266181.81	343220.23
6	242378.32	255324.89
7	356411.97	150590.01
8	198556.99	413243.49
9	266689	311757.99
MEAN TIME (ms)	22.1	3.2

Table 3 : Effect of step size and max iteration=100* num_periods.

Instance	max_iterations= 1000*num_periods step_size= 0.01	max_iterations= 1000*num_periods step_size= 0.02
	Revenue	Revenue
0	293862.36	322526.90
1	250238.43	250320.52
2	261519.15	195973.35
3	297578.22	183351.05
4	372007.06	252289.22
5	208107.16	282797.74
6	320482.57	213944.04
7	232504.67	200052.67
8	297657.08	208995.29
9	188190.83	275021.07
MEAN TIME (ms)	6.3	7

Table 4: Effect of step size and max iteration=1000* num_periods.

Test 3:

- Num_periods = 20 ,
- Capacity_rate = 1

Instance	max_iterations= 100*num_periods step_size= 0.01	max_iterations= 100*num_periods step_size= 0.02
	Revenue	Revenue
0	717841.20	638920.23
1	505859.98	568508.16
2	561447.67	574559.45
3	468904.24	467488.70
4	542002.37	516791.71
5	502615.49	391880.62
6	497528.93	601703.15
7	303653.06	478887.97
8	583165.73	607870.65
9	463388.33	577917.50
MEAN TIME (ms)	15.1	522.1

Table 5: Effect of step size and max_iteration=100* num_periods.

Instance	max_iterations= 1000*num_periods step_size= 0.01	max_iterations= 1000*num_periods step_size= 0.02
	Revenue	Revenue
0	693376.37	538237.03
1	556106.13	396811.95
2	575508.43	488274.13
3	538786.51	532040.92
4	446991.94	547488.85
5	415527.70	485139.32
6	477760.57	526711.22
7	391761.22	574739.64
8	494194.23	424291.75
9	643965.79	775769.17
MEAN TIME (ms)	15.1	16.7

Table 6: Effect of step size and max_iteration=1000* num_periods.

Test 4:

- Num_periods = 20
- Capacity_rate = 2

Instance	max_iterations= 100*num_periods step_size= 0.01	max_iterations= 100*num_periods step_size= 0.02
	Revenue	Revenue
0	653697.97	605445.12
1	453063.60	538278.07
2	468103.99	507912.06
3	425685.43	565740.37
4	415037	601813.75
5	505950.53	443604.55
6	532942.11	580472.74
7	584869.76	442167.06
8	498029.10	578857.02
9	639474.13	615950.09
MEAN TIME (ms)	157.7	13.6

Table 7: Effect of step size and max_iteration=100* num_periods.

Instance	max_iterations= 1000*num_periods step_size= 0.01	max_iterations= 1000*num_periods step_size= 0.02
	Revenue	Revenue
0	414044.04	440660.02
1	465673.25	574188.84
2	523482.20	642127.88
3	527682.16	552934.79
4	493618.60	544258.78
5	712891.87	568268.21
6	469410.62	530024.91
7	469410.62	492013.74
8	485264.27	384677.19
9	454375.90	628871.58
MEAN TIME (ms)	15.4	19.8

Table 8: Effect of step size and max_iteration=1000* num_periods.

Test 5:

- Num_periods = 30 ,
- Capacity_rate = 1

Instance	max_iterations= 100*num_periods step_size= 0.01	max_iterations= 100*num_periods step_size= 0.02
	Revenue	Revenue
0	831635.25	842138.57
1	622263.89	849601.12
2	643093.06	682712.66
3	666883.80	813074.13
4	651012.87	751885.70
5	811976.75	649683.01
6	802268.58	775335.36
7	813763.43	661273.07
8	594383.33	602496.74
9	864887.10	983604.13
MEAN TIME (ms)	32.5	20.5

Table 9: Effect of step size and max_iteration=100* num_periods.

Instance	max_iterations= 1000*num_periods step_size= 0.01	max_iterations= 1000*num_periods step_size= 0.02
	Revenue	Revenue
0	867069.24	947020.53
1	746171.98	705337.91
2	856075.66	890182.07
3	664721.94	782619.13
4	893760.32	933128.72
5	646302.18	640237.84
6	808396.08	849825.32
7	702420.17	700907.23
8	758695.08	558742.15
9	786465.94	671468.95
MEAN TIME (ms)	27.9	37

Table 10: Effect of step size and max_iteration=1000* num_periods.

Test 6:

- Num_periods = 30 ,
- Capacity_rate = 2

Instance	max_iterations= 100*num_periods step_size= 0.01	max_iterations= 100*num_periods step_size= 0.02
	Revenue	Revenue
0	934251.88	963426.99
1	641583.91	735256.35
2	654699.20	717518.76
3	779707.50	879357.77
4	724132.29	640610.43
5	741969.42	574071.64
6	788797.32	863535.39
7	758742.15	792579.87
8	734569.64	896791.05
9	724409.22	778542.38
MEAN TIME (ms)	10.5	10.5

Table 11: Effect of step size and max_iteration=100* num_periods.

Instance	max_iterations= 1000*num_periods step_size= 0.01	max_iterations= 1000*num_periods step_size= 0.02
	Revenue	Revenue
0	621957.508	620471.924
1	631273.0849	597964.741
2	844123.4226	661160.592
3	653196.9846	547359.920
4	939784.6978	671387.185
5	827284.077	750374.244
6	749017.939	666241.124
7	796071.019	705218.531
8	550998.719	756996.3389
9	681327.482	871383.24357
MEAN TIME (ms)	24.6	15.3

Table 12: Effect of step size and max_iteration=1000* num_periods.

Test 7:

- Num_periods = 40 ,
- Capacity_rate = 1

Instance	max_iterations= 100*num_periods step_size= 0.01	max_iterations= 100*num_periods step_size= 0.02
	Revenue	Revenue
0	1102704.04	1114236.18
1	927470.92	1097737.89
2	1031906.92	1223719.51
3	980895.96	935158.15
4	1071635.81	1054983.48
5	874935.88	1056055.54
6	1053566.58	1072824.79
7	912260.64	919652.38
8	1001218.23	948987.26
9	1076970.06	905571.72
MEAN TIME (ms)	49	128.1

Table 13: Effect of step size and max_iteration=100* num_periods.

Instance	max_iterations= 1000*num_periods step_size= 0.01	max_iterations= 1000*num_periods step_size= 0.02
	Revenue	Revenue
0	1133826.23	1026799.11
1	1010011.63	1136261.29
2	1311517.42	865994.26
3	1129120.52	946177.81
4	1029285.37	776073.73
5	923164.15	1064133.75
6	931201.95	814656.96
7	752387.97	918971.12
8	1060778.43	1016438.09
9	1221758.56	920600.49
MEAN TIME (ms)	27.4	15.1

Table 14: Effect of step size and max_iteration=1000* num_periods.

Test 8:

- Num_periods = 40
- Capacity_rate = 2

Instance	max_iterations= 100*num_periods step_size= 0.01	max_iterations= 100*num_periods step_size= 0.02
	Revenue	Revenue
0	1114552.87	1158173.00
1	1064867.11	993251.14
2	769107.15	1123301.40
3	909053.00	892289.50
4	981965.86	1036367.90
5	955248.35	1109473.12
6	962481.52	1127324.62
7	1142023.42	1056063.28
8	990311.03	1023334.26
9	974952.22	930982.32
MEAN TIME (ms)	14	23

Table 15: Effect of step size and max_iteration=1000* num_periods.

Instance	max_iterations= 1000*num_periods step_size= 0.01	max_iterations= 1000*num_periods step_size= 0.02
	Revenue	Revenue
0	1139248.04	1080862.67
1	1102284.66	1008617.23
2	1042302.20	1074981.20
3	1103338.01	940298.87
4	1097261.87	1010788.60
5	1048502.00	1145052.09
6	1007525.35	942174.53
7	1092922.08	898010.92
8	1105890.29	944933.47
9	939579.36	1106078.83
MEAN TIME (ms)	25.8	15.4

Table 16 : Effect of step size and max_iteration=1000* num_periods.

From the provided tables, several observations can be made:

- Impact of Number of Periods and Capacity Rate on Complexity: Increasing the number of periods or the capacity rate leads to larger problem sizes, thus requiring more iterations to achieve the optimal solution. This generally results in increased time complexity.
- Effect of Algorithm Parameters: Changing algorithm parameters such as `step_size` and `max_iterations` affects the time required to obtain the solution.

For instance, increasing `max_iterations` significantly increases complexity, while increasing `step_size` may reduce it.

- **Impact of Capacity Rates:** Changing capacity rates significantly affects complexity, with higher capacity rates generally reducing complexity.
- **Variability in Execution Time:** Significant variability in execution time is also observed across different algorithm versions. This variation may stem from random fluctuations in the experimental environment or in the algorithm's execution itself.

Overall, it can be inferred that the algorithm is sensitive to changes in its parameters and problem size, and time complexity increases with higher number of periods, capacity rates, and larger parameter values.

6. Conclusion

In conclusion, in the dynamic landscape of e-commerce and service-based industries, revenue management emerges as a critical challenge for companies striving for success. It demands meticulous attention to data analysis, precise demand forecasting, and adept pricing strategies.

During the implementation phase, the application of developed strategies is pivotal. Local algorithms stand out as valuable tools, enabling real-time adjustments based on evolving market dynamics. For instance, employing time-based analysis algorithms facilitates the identification of peak demand periods, empowering companies to optimize pricing strategies and augment revenue streams.

As strategies are put into action, the results phase becomes paramount. Here, the efficacy of employing local algorithms becomes evident, as success is quantified through tangible metrics such as revenue growth and enhanced profitability. These outcomes are a testament to the refined pricing policies and resource allocation achieved through algorithmic precision.

Ultimately, the integration of local algorithms into revenue management practices offers companies a pathway to optimal performance and heightened competitiveness in the market. By leveraging these algorithms effectively,

businesses can navigate the complexities of modern commerce and realize their financial objectives with greater efficiency and effectiveness.

General Conclusion

In conclusion, a Revenue Management System stands as a cornerstone in modern business operations, offering a strategic approach to pricing and resource allocation. By harnessing the power of data analytics and dynamic pricing, companies can adapt to market fluctuations, optimize revenue streams, and ultimately enhance their competitiveness and profitability. As industries continue to evolve, the importance of Revenue Management Systems will only grow, serving as a key driver for sustainable growth and success in the ever-changing business environment.

By the end of this study, it can be said that understanding revenue management and its importance is a fundamental step in achieving business objectives. Through analyzing the drivers of work and identifying changes in demand and prices, we were able to identify effective methods to improve company performance.

Using the local search algorithm, we were able to precisely adjust settings to improve algorithm performance, thus achieving a significant improvement in revenue management. Despite the challenges we faced in Chapter Three, the implementation of the local search algorithm demonstrated an effective ability to deal with market changes and improve company performance overall.

It is important to leverage these results and continue continuous improvement in revenue management by developing algorithms and implementing innovative strategies to address future challenges. Revenue management is not just a traditional task, but a dynamic process that requires innovation and continuous adaptation to achieve sustainable success.

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Abstract

Revenue management is the process of pricing and resource allocation aimed at increasing revenue and maximizing profitability. We used local search algorithms in revenue management. The study aims to improve resource utilization and pricing based on real-time demand and supply, enhancing business efficiency and revenue. Algorithms are applied to enhance decision-making processes, particularly in sectors such as hotels, transportation, and services. The research relies on data analysis and the application of local search models to enhance system performance and profitability.

Keywords: Revenue Management, Optimization, Local Search, Métaheuristics.

المخلص

إدارة الإيرادات هي عملية تحديد الأسعار وتوزيع الموارد بطريقة تهدف إلى زيادة الإيرادات وتحقيق أقصى قدر من الربحية. استخدمنا خوارزميات البحث المحلي في إدارة الإيرادات. تهدف الدراسة إلى تحسين استخدام الموارد وتحديد الأسعار بناءً على الطلب والعرض في الوقت الفعلي، مما يزيد من كفاءة الأعمال والإيرادات. يتم تطبيق الخوارزميات لتحسين عمليات اتخاذ القرارات، خاصة في قطاعات الفنادق والنقل والخدمات. يعتمد البحث على تحليل البيانات وتطبيق نماذج البحث المحلي لتحسين أداء النظم وزيادة الربحية.

الكلمات المفتاحية: إدارة الإيرادات، التحسينات، خوارزميات البحث المحلي، الميتاهوريستيك.

Résumé

La gestion des revenus est le processus de tarification et d'allocation des ressources visant à augmenter les revenus et à maximiser la rentabilité. Nous avons utilisé des algorithmes de recherche locale dans la gestion des revenus. L'étude vise à améliorer l'utilisation des ressources et la tarification en fonction de la demande et de l'offre en temps réel, ce qui accroît l'efficacité commerciale et les revenus. Les algorithmes sont appliqués pour améliorer les processus de prise de décision, notamment dans des secteurs tels que l'hôtellerie, le transport et les services. La recherche repose sur l'analyse des données et l'application de modèles de recherche locale pour améliorer la performance du système et la rentabilité.

Mots clés : Gestion des Revenus, Optimisation, Recherche Locale, Métaheuristiques.
