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PROBLEM DESCRIPTION

Santander Cycles has engaged external consultants to address challenges and identify opportunities to enhance the performance of its bike-sharing scheme. The rise of competitors like Lime has led to a decline in overall usage, putting pressure on Santander to remain competitive while maintaining profitability. One of the key operational challenges is the significant cost of redistributing bikes across London stations to ensure consistent availability, particularly during peak demand. This inefficiency not only increases operational expenses but also impacts user satisfaction when bikes are unavailable at high-demand locations.

At the same time, Santander has observed inelastic demand during commuter hours, providing an opportunity to optimise pricing strategies to boost profit margins. Developing a model that leverages dynamic pricing could allow Santander to capitalise on commuter willingness to pay while encouraging usage during off-peak hours through targeted discounts. This dual approach could help redistribute demand more efficiently, reducing operational costs and ensuring long-term sustainability.

With the overall demand for bike-sharing at its lowest in a decade, Santander Cycles must adapt quickly to address these challenges. By implementing a data-driven pricing and operational strategy, the scheme can not only recover lost revenue but also position itself as a more competitive and user-centric service. The focus is to balance short-term revenue gains with long-term business sustainability, ensuring that Santander Cycles remains a viable and attractive transport solution in London’s evolving mobility landscape.

DATA & ASSUMPTIONS

Santander Cycles operates 800 docking stations across London; however, our analysis is based on data from 797 docking stations (TfL, 2024). The pricing structure includes a flat fee of £1.65 for up to 30 minutes, with an additional £1.65 charged for every 30-minute increment thereafter (BBC, 2024). According to data from the TfL, the average ride duration is 17 minutes, with a standard deviation of 5 minutes. For simplicity in modelling, we assume all rides incur a flat fee of £1.65.

Based on typical commuting patterns and external demand studies, we segmented daily demand into peak and non-peak hours using a ratio of 65:35. This proportion was based on evidence from Chibwe et al. (2021), who found that a high proportion of bike-sharing trips in London was due to commuting. Stations were classified as high-demand if bike availability was below 25% at the time of observation. This threshold allowed us to dynamically allocate resources and tailor pricing strategies for these stations.

Consumer willingness-to-pay (WTP) was modelled using normal distributions for peak and non-peak times, with the mean and standard deviation estimates derived from external sources. The prices were designed to remain below £3.40, ensuring competitiveness with alternative public transport options, such as the Tube. As the Santander Cycle scheme is sponsored by TfL, peak times are aligned with TfL's definitions, occurring from 6:30-9:30 AM and 4:00-7:00 PM on weekdays (Monday to Friday).

In this model, we assume that demand exhibits linear elasticity with respect to price, implying that a change in price has a proportional and predictable effect on demand. These assumptions are essential in underpinning the dynamic pricing and demand redistribution models, enabling revenue optimisation and enhanced user satisfaction.

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METHODOLOGY

Our methodology combines simulation-based demand modelling with optimisation techniques to achieve distinct aims in each section. The first section addresses revenue maximisation, while the second focuses on improving utilisation by redistributing demand across the network. Using explicit constraints and real-world assumptions to ensure that the findings are practical and actionable.

First, we simulated demand based on quarterly demand for specific stations; we converted the quarterly demand to daily to gain more observations over all the data. We then segment the demand data into high and low based on the high and low demand data sets with the livecyclehires.csv file. From this, we further segment our data to determine peak and non-peak times for peak and non-peak prices. The code uses simulations extensively to model demand, WTP, and usage patterns. For instance, Poisson distributions simulate station-level demand, and normal distributions simulate users' WTP during peak and non-peak times. Now that we are ready to implement dynamic programming to reach our given objectives let us look at the specific sections in detail.

Section 1A: Optimising Single Price for Revenue

Part 1A focuses on determining an optimal single price for bike hires that maximises total revenue. A key aim here is to set a uniform price applicable to both peak and non-peak hours across all stations. We define an objective function using 'eval_f_single', which calculates total revenue for a given price. It sums the demand across all stations, considering the users' willingness to pay (WTP) for peak and non-peak periods. We compute the revenue as the product of total demand and the price. Using the 'nloptr' package, we optimise by applying the COBYLA algorithm to find the price that maximises revenue; we impose constraints to ensure that the price remains within realistic bounds (£1–£3.5). We extract and display the optimised price and corresponding maximum revenue, providing insights into the revenue potential with a single-pricing model.

Section 1B: Dual Pricing for Peak and Non-Peak Times

In this section, we extend the single-pricing model by introducing distinct prices for peak and non-peak times, aiming to optimise revenue further. We introduce a new objective function, 'eval_f', which calculates revenue by separately accounting for peak and non-peak demands. We then compare each station's WTP against the proposed peak and non-peak prices and compute the total revenue accordingly. We include inequality constraints, 'eval_g_ineq', ensuring that the non-peak price is always less than or equal to the peak price, reflecting real-world pricing logic. The optimisation framework is similar to the single-price case but now searches for two variables: the peak price and the non-peak price. The optimised dual-pricing strategy increases revenue compared to the single-price model, along with the percentage improvement.

Section 2: Improving Bike Utilisation through Tax and Discount Rates

The second part shifts focus from revenue optimisation to improving bike utilisation. We achieve this by introducing tax and discount rates for high- and low-demand stations, respectively, to redistribute bike usage better. We classify stations as high- or low-demand based on their availability and demand levels. High-demand stations experience peak usage and may benefit from higher pricing through a tax, whereas low-demand stations require discounts to incentivise usage.

The objective function 'eval_capacity' simulates the impact of tax and discount rates on bike utilisation. We ensure that high-demand stations are taxed, raising prices, while low-demand stations are discounted. The function calculates the number of bikes utilised by checking users' WTP against the adjusted prices. We optimise both the tax and the discount rates using the COBYLA algorithm, balancing the pricing adjustments to maximise bike utilisation while considering overall system capacity. From this, we can identify the optimal rates (35.97% tax for high-demand stations and 7.34% discount for low-demand stations), leading to a measurable improvement in bike utilisation (723 additional bikes utilised, an 8.17% increase). We then create visualisations employing ggplot2 to enhance our understanding and interpretation by illustrating how pricing adjustments affect revenue and bike utilisation.

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RESULTS

Our analysis focused on optimising revenue and capacity utilisation for the Santander Cycle Scheme using single and tiered pricing strategies and dynamic adjustments based on station demand.

Single Price Strategy

Using a single price across both peak and non-peak times, we optimised for maximum revenue while simplifying operational complexity. By analysing each station's willingness-to-pay (WTP) data, we determined that the optimal price was £2.47, resulting in a maximum revenue of £190,993.01. This strategy balances demand while maintaining consistent pricing, reducing complexity in implementation but potentially leaving revenue opportunities untapped during peak periods.

Tiered Pricing Strategy

We implemented a dual pricing strategy to address differences in consumer behaviour during peak and non-peak times. This involved setting higher prices for peak periods and lower prices for non-peak periods, aligning with the observed inelastic demand during commuter hours.

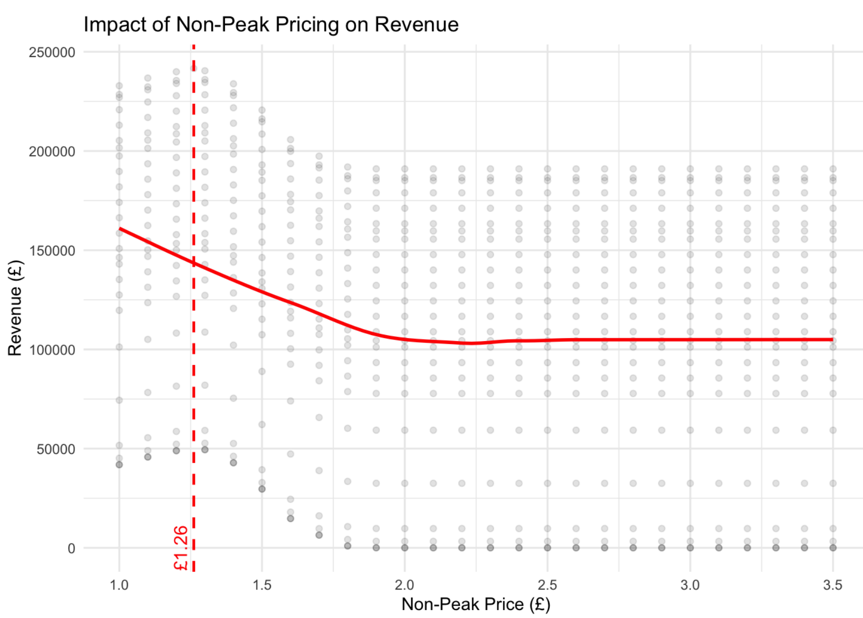

Figure 1 Impact of Increase Non Peak Price

The optimal prices were determined to be £2.49 for peak times and £1.26 for non-peak times, yielding a maximum revenue of £241,629—a 26.51% increase compared to the single-price strategy. This result demonstrates the effectiveness of dynamic pricing in capitalising on peak-period demand while attracting price-sensitive users during non-peak hours.

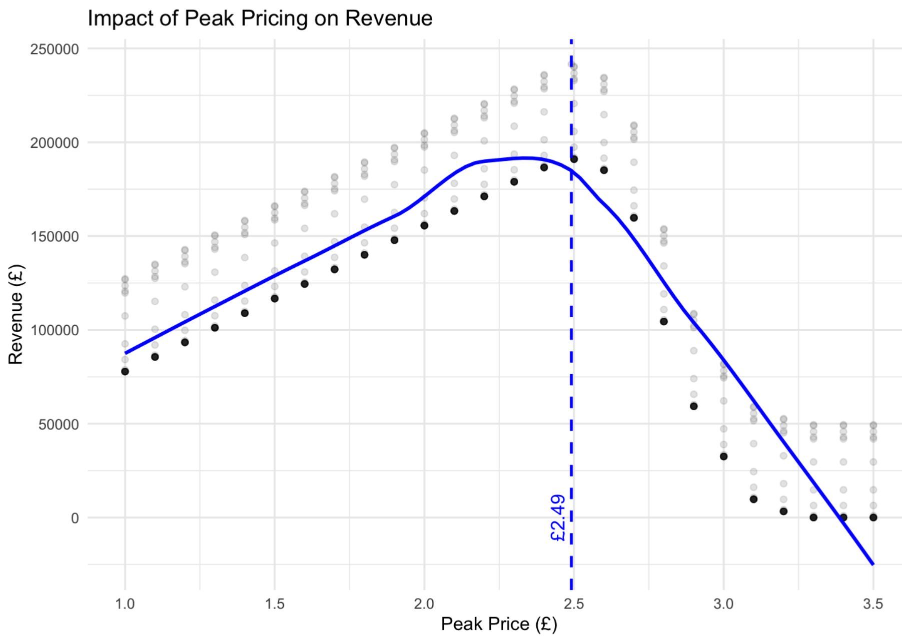

Figure 2 Impact of Increase Peak Price

Figures 1 and 2 highlight the differences in price elasticities between non-peak and peak users, emphasizing the importance of implementing pricing strategies specifically tailored to these time periods.

Dynamic Redistribution Incentives

To address the operational inefficiencies caused by uneven bike distribution across high-demand and low-demand stations, we evaluated the impact of introducing discounts for low-demand stations and a tax for high-demand stations, aiming to incentivise usage patterns that align with redistribution goals and maximise capacity utilisation.

- **High-demand Stations:** A 35.97% tax rate was applied, increasing the effective price to £3.36. This adjustment would help moderate excessive demand at high-demand stations, alleviating strain on availability and reducing redistribution costs.
- **Low-demand Stations:** A 7.34% discount rate was introduced, lowering the price to £2.29. This strategy would encourage more significant usage at low-demand stations, improving utilisation rates and balancing supply across the network.

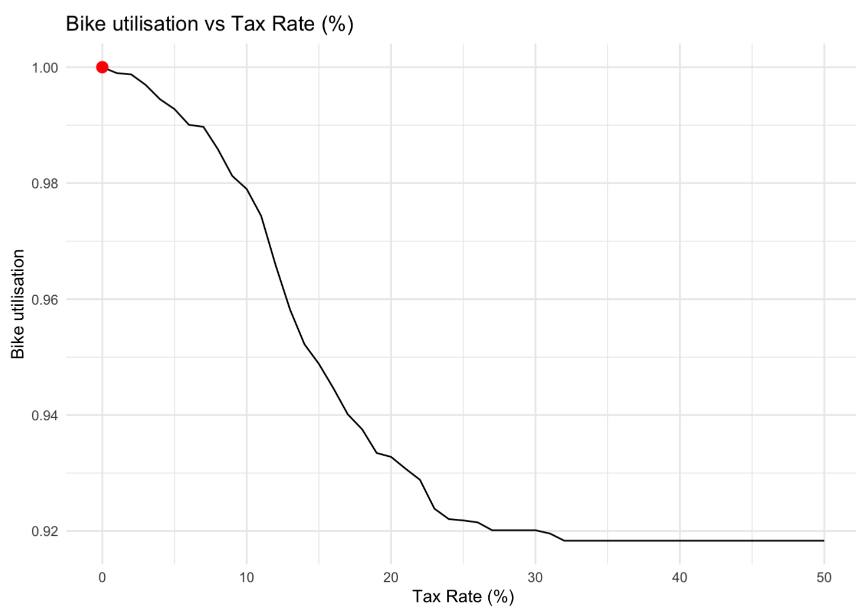

Figure 3: Bike Utilisation vs Tax Rate

Key Insights:
Utilisation starts high at lower tax rates but steadily declines as the tax rate increases. The optimal tax rate of 35.97% corresponds to a local maximum in utilisation before it begins to decline sharply. Setting the tax rate too high results in reduced affordability, lowering overall utilisation.

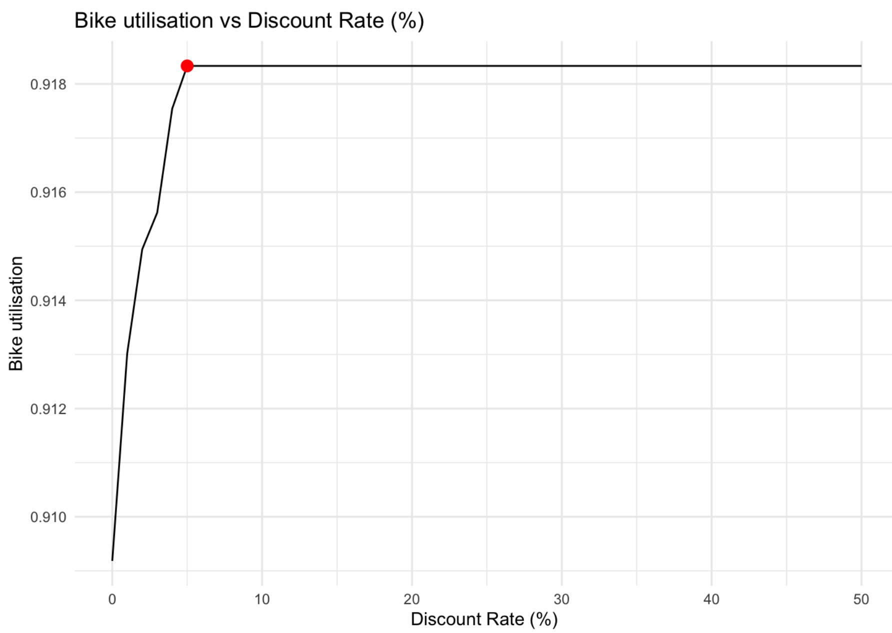

Figure 4: Bike Utilisation vs Discount Rate

Key insights:
As shown in the plot, bike utilisation increases rapidly as the discount rate rises from 0% to approximately 7.34%. Beyond this point, utilisation levels off, indicating diminishing returns. The optimal discount rate of 7.34% balances utilisation gains with minimal revenue loss.These insights validate the optimisation results and highlight the trade-offs involved. While moderate adjustments to tax and discount rates improve utilisation, pushing rates beyond optimal values has limited or even negative effects.

As a result, the strategy would improve bike utilisation by 723 bikes, equating to an 8.17% increase in overall usage. This demonstrates the potential of demand-based pricing to enhance operational efficiency, reduce reliance on costly manual redistribution, and better align resource allocation with user behaviour. These findings emphasise the importance of flexible pricing models in addressing both revenue and operational challenges.

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RECOMMENDATIONS

Based on our analysis, the following strategies are recommended to enhance the Santander Cycle Scheme's performance, improve revenue, and address operational inefficiencies. These proposals are grounded in empirical evidence derived from our pricing optimisation models and redistribution strategies.

1. Implement Tiered Pricing for Peak and Non-Peak Hours
Our analysis shows that introducing tiered pricing for peak and non-peak times can significantly boost revenue. The optimal prices identified are £2.49 for peak hours and £1.26 for non-peak hours. This strategy leverages the inelastic demand during peak hours while attracting more price-sensitive customers during non-peak times.

This approach increases revenue by 26.51%, raising total revenue to £241,629.21 compared to a single price strategy. However, while some commuters may resist price changes during peak hours, the affordability of non-peak pricing could broaden the customer base and improve overall satisfaction (Wallimann et al., 2023). To implement this, adjust existing pricing structures and communicate the benefits of tiered pricing to customers, emphasising affordability in off-peak times.

2. Adopt Dynamic Redistribution Incentives
Our results suggest that dynamic pricing based on station-specific demand can address the challenge of uneven bike availability. A 35.97% tax at high-demand stations (price £3.36) and a 7.34% discount at low-demand stations (price £2.29) encourage balanced usage across the network.

The expected benefit is that this strategy will improve bike utilisation by 723 bikes, equating to an 8.17% increase, while reducing redistribution costs associated with manually balancing bike availability (Haider et al., 2018). Although there is a trade-off, higher prices at high-demand stations may deter some users, but this is offset by better availability and increased usage at low-demand locations. To implement this, we suggest gradually introducing the tax and discount system, supported by targeted marketing, to explain the rationale and benefits of balanced station usage.

3. Monitor and Refine Pricing Strategies

Continuous monitoring of customer behaviour and demand patterns is essential for maintaining the scheme's efficiency. Leverage real-time data analytics to adjust prices dynamically and ensure optimal bike availability across stations. Real-time adjustments are beneficial as they can sustain high utilisation rates and respond effectively to changes in demand. To carry this out, invest in technology for real-time demand tracking and train staff to manage dynamic pricing tools (Bhagyashree, 2024).

These strategies aim to balance revenue optimisation and operational efficiency. By implementing tiered pricing, dynamic redistribution incentives, and real-time monitoring, the Santander Cycle Scheme can achieve sustainable growth, enhance user satisfaction, and address competitive pressures effectively. Strategic communication with customers will be crucial to ensure a smooth transition and maximise the benefits of these changes.

REFERENCES

Transport for London | Every Journey Matters, T. *What you pay, Transport for London*. Available at: https://tfl.gov.uk/modes/cycling/santander-cycles/what-you-pay?intcmp=2315 (Accessed: 12 December 2024)

Chibwe, J., Heydari, S., Imani, A.F. and Scurtu, A., 2021. An exploratory analysis of the trend in the demand for the London bike-sharing system: From London Olympics to Covid-19 pandemic. *Sustainable Cities and Society*, *69*, p.102871.

Wallimann, H., Blättler, K., & Von Arx, W. (2023). Do price reductions attract customers in urban public transport? A synthetic control approach. Transportation Research Part a Policy and Practice, 173, 103700. https://doi.org/10.1016/j.tra.2023.103700

Haider, Z., Nikolaev, A., Kang, J. E., & Kwon, C. (2018). Inventory rebalancing through pricing in public bike sharing systems. European Journal of Operational Research, 270(1), 103–117. https://doi.org/10.1016/j.ejor.2018.02.053

Bhagyashree. (2024, October 25). How Real-Time Price Tracking Software can Boost your dynamic Pricing Strategy. PromptCloud. https://www.promptcloud.com/blog/price-tracking-software-for-dynamic-pricing-strategy/