A DEMAND-BASED SMART PARKING MANAGEMENT STRATEGY FOR GALLE ROAD CORRIDOR

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Degree of Master of Science in Civil engineering

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Thesis submitted in partial fulfilment of the requirements for the degree Master of Science in Civil Engineering

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DECLARATION

Candidate

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ABSTRACT

This study demonstrates the potential for implementing a demand-based parking management strategy to improve on street parking space utilization in urban areas. It further proposes the development of a mobile application as the most feasible solution to collect real-time occupancy data and implement dynamic pricing. The Galle Road corridor was selected as the study area for this research due to its high vehicle and parking demand, and diverse land use patterns. This research utilizes historical on street parking data analysis to gain insights into vehicle distribution patterns, parking durations, and demand fluctuations. Utilizing vehicle speed data from the Galle Road corridor and on-site parking occupancy surveys, this analysis explores the correlation between vehicle speeds and parking demand and proposes a price-based vehicle management strategy, suggesting that speed variations at specific locations can initially serve as a proxy for parking demand. Although data limitations mean this relationship should be interpreted cautiously, it provides a basis for demand estimation when direct crowdsourced data are unavailable. The proposed strategy identifies high- and low-demand sections, adjusts prices dynamically, and uses guidance to redirect drivers to vacant legal spaces, converting lost parking demand into paid stays and balancing parking distribution. Specifically, real-time price adjustments based on observed demand encourage more balanced parking behaviour and reduced roadside parking congestion in popular areas. Key findings show that dynamic pricing and redistribution can boost overall space utilization and increase total daily revenue. The study further recommends developing a user-friendly mobile application with features that allow drivers to view current parking rates, find available spaces, and report occupancy. Overall, the research offers a novel framework indicating that integrating parking demand with adaptive pricing via mobile application leads to more efficient parking operations and increase the revenue. These insights provide actionable guidance for city planners and parking operators seeking smarter, more responsive parking solutions.

Keywords: *Roadside Parking management, Demand based strategies, Smart parking solutions, Parking pricing*

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1. INTRODUCTION

1.1 Background

Uneven demand for on-street parking is a common urban problem. This imbalance means that popular spaces are over-crowded, and drivers spend extra time cruising for an open space (Parmar et al., 2020). Along these major urban road corridors, where parking demand frequently exceeds supply, roadside parking lots close to high-demand locations are frequently overcrowded. However, available parking spaces can be found in low-demand parking areas, and parking demand can fluctuate significantly over time, on roadside land use. These inefficiencies highlight the need for an efficient Intelligent Parking Management System (IPMS) of roadside parking.

Colombo urban transport system illustrates these challenges sharply in Sri Lanka. The city's road network cannot easily expand to meet soaring demand. Parking availability has become highly limited in certain road sections, leading to inconvenience for the public. Studies illustrate that average traffic speeds in Colombo's busiest corridors have fallen to 10-20 km/h. This congestion imposes massive economic costs on the order of billions of rupees per year because commuters waste time and fuel (Kumarage, 2004). Contributing factors include inadequate public transport, rapid growth in private vehicles, and inadequate traffic management. Recently, Colombo has begun modernizing curb parking. In partnership with Tenaga Car Parks, the city introduced ParkSmart electronic meters on Galle Road and nearby streets. The new digital system and mobile app allow cashless payment by license plate, but fees remain uniform and low. In practice, drivers on Galle Road still face hour-long waits for a space at peak times. While one potential solution to the ongoing parking shortage is the development of additional parking lots, implementing and maintaining such facilities along Galle Road is challenging due to constraints in both funding and available land. These conditions suggest an opportunity by recognizing spatial and temporal demand patterns on corridors like Galle Road and Duplication Road, parking policy can be made adaptive rather than flat. In this research, Galle Road was selected as the primary study corridor due to its significance such as Colombo's major transportation corridor with high traffic volumes, and its municipally regulated parking infrastructure featuring systematically well-organized parking slots providing an optimal observational environment for demand-based parking research.

Parking management systems that utilize crowdsource data are becoming increasingly popular. These systems rely on data gathered from a variety of IoT technologies, including sensors and cameras, to provide real-time information about parking availability in a particular area (Chien et al., 2020). Image-recognition meters, equipped with built-in cameras, can automatically detect space usage and read license plates, enabling seamless billing and enforcement; however, their high unit cost and susceptibility to failures in low-light or obstructed-plate conditions limit widespread deployment and their implementation proves bit challenging for on-street parking contexts.

There are other ways to collect parking demand data without using sensors and cameras such as Mobile applications, through Geolocation, and using parking attendants. Many parking management systems rely on mobile applications that allow users to report parking availability in real-time. Users can simply indicate and report whether a parking space is occupied or available, and this information is then shared with other users in the area. Geolocation data from mobile devices also can be used to track the movement of vehicles and identify areas where parking demand is high. This information can be used to inform decisions about how to allocate existing resources or where to build new parking facilities. An effective numbering system can be used for parking along urban roadways. With this system, each parking space along the roadside will be given a unique number with a letter that will start at one end and go on indefinitely. The range of parking slot numbers in each section is clearly marked with signage that is spaced out at regular intervals. The display of parking space numbers on digital maps is made possible by integrating the numbering system with digital mapping services, making it easier for drivers to find specific spaces.

This research prioritizes mobile application as the best long-term solution for managing parking demand but takes a step-by-step approach to get there. During initial research phases, practical alternative methods are employed, manual parking occupancy surveys are conducted alongside analysis of Google's traffic speed data to estimate demand in contexts lacking real-time monitoring infrastructure. During subsequent development phases, a mobile platform will be deployed to enable driver-reported parking availability, facilitating continuous model optimization. This incremental methodology permits immediate validation of core interventions including dynamic pricing mechanisms and real-time parking guidance systems while progressively advancing toward a participatory framework where crowd-sourced data enhances operational responsiveness. Ultimately, this establishes an adaptive management foundation that calibrates parking policies according to localized demand patterns. Google Distance matrix API can be used to analyse the speeds of the required road sections for distribution (Kumarage et al., 2017). Vehicle speed may serve as a functional indicator of real-time parking demand intensity at the road section level (Ma et al., 2017). Collect speed data, which can be used to identify high demand, low demand, and medium demand sections. This relationship enables the implementation of dynamic pricing strategies to incentivize spatial redistribution of to adjacent low-demand areas, promoting demand-based equilibrium across urban corridors.

Drivers' parking preferences may be influenced by this pricing method, which could lead to better distribution of parking spaces and better use of available resources. Pricing should also vary by demand, day, time, and location. Parking pricing methods can be implemented in accordance with these data. If a driver cannot find a space in their preferred lot and no guidance is provided, they either leave without parking or park illegally (neither generates revenue). With guidance, many of these drivers can be redirected to a legal parking area that has vacancies, converting them into paying customers and create financial incentives that balance parking distribution.

When choosing a suitable parking space, available space, convenience, price, parking restrictions, safety, and security are also important considerations. Parking is generally the first and last interaction that visitors have with a destination and has a major impact on their experience (Litman, 2006). However, pricing have an impact on how drivers choose to park, which could result in a more efficient distribution of parking spaces and the use of the available resources.

In sum, by intelligently reallocating vehicles to low-demand locations, the system aims to reduce searching, reduce congestion on Galle Road, and increase parking revenue. The proposed research will contribute new knowledge on applying demand-based parking management in a Sri Lankan urban context, supported by analysis of local conditions and international best practices.

1.2 Problem statement

Urban on-street parking in rapidly developing cities often exhibits uneven utilization, with some zones experiencing overcrowding while others remain underutilized. This imbalance is mainly due to temporal fluctuations in parking demand and as a result, drivers spend significant time circulating in search of available spaces, contributing to traffic congestion, increased fuel consumption, and reduce urban mobility. A demand-based parking pricing strategy, responsive to actual demand conditions, presents a viable solution to redistribute parking load and enhance the overall efficiency of space utilization.

1.3 Research objectives

- Conduct a comprehensive review of smart parking management strategies, identifying their strengths and limitations in urban roadside settings.
- Analyse spatial-temporal patterns in roadside parking demand along Galle Road using past parking data.
- Propose methods for parking demand and supply analysis and stablish a method for estimating real-time parking demand.
- Develop and evaluate the potential of a dynamic pricing structure based on demand and compare in terms of space utilization and revenue generation.

1.4 Scope of the research

This research develops a scalable, cost-effective framework for managing urban roadside parking without relying on extensive sensors or camera installations. It further proposes redistribution strategies and dynamic pricing that shift parking to low-demand areas, enhancing space utilization, reducing searching time, and improving traffic flow. To achieve these objectives, it is necessary to collect and analyse data on selected routes in urban conditions. Due to time and resource restrictions, the study was limited to one transport corridor, light and medium duty vehicles only. A parking strategy will be proposed based on the data collected on the Galle Road corridor, Sri Lanka.

1.5 Research gap

Existing smart parking initiatives consistently prioritize flexibility and user-centred design, reducing reliance on costly infrastructure. Yet these advances remain fragmented, few integrate predictive demand-based strategies, dynamic pricing, and vehicle redistribution into a unified framework. Our study addresses this critical gap by synthesizing real-time user inputs, spatial demand patterns from parking occupancy surveys, and vehicle speed data into an adaptive management system responsive to urban mobility patterns.

2. LITERATURE REVIEW

2.1 Introduction

As urban areas continue to grow, the need for innovative approaches to on street parking management has become more urgent. This literature review examines the development of smart parking strategies, highlighting the shift from conventional practices to more responsive and participatory approaches that enhance space utilization and enable dynamic pricing.

This chapter summarizes important scholarly perspectives. To build a clear argument, the literature review is organized into subsections:

- Historical evolution of parking management
- Comparison of traditional and smart parking systems
- Innovative approaches in modern parking management
- Crowdsourced and real-time parking data collection
- Traffic speed data and parking occupancy relationship
- Dynamic pricing models for urban parking
- Benefits of dynamic pricing models

2.2 Historical evolution of parking management

Since the early 20th century, when expanding cities had to deal with increasing traffic and decreasing parking supplies, public parking management has experienced a significant transformation. Metered parking changed from mechanical to electronic systems in the middle of the 20th century, allowing for license-plate-based enforcement, pay by phone, and multi-space pay stations. This development demonstrated a trend toward digital convenience and accuracy. By the 2000s, several municipalities, such as San Francisco, began deploying ‘smart meters’ integrated with real-time data systems that used dynamic pricing to maintain curb side availability and reduce cruising.

(Litman, 2006)’s comprehensive framework later formalized these techniques, advocating multi-pronged approaches, such as peak pricing, shared parking, remote lots, and user education to reduce demand rather than merely expanding supply. Traditional parking management has focused on regulating supply and pricing to influence driver behaviour. Early measures included physical restrictions and differentiated rates. (Litman, 2006) argues that well-implemented parking management helps to optimize urban spaces, reduce environmental impacts, and foster more liveable, multimodal communities, ultimately providing more overall benefits than simply increasing parking supply. While the general principles of parking management are well-documented, there is a significant research gap concerning the specific applicability, optimal combination, and public acceptance strategies for these approaches within the unique socio-economic, cultural, and infrastructural context of a rapidly developing South Asian city like Colombo.

(Giuffrè et al., 2012) outline classic tactics such as eliminating parking stalls along some roads during peak periods, adjusting the total number of parking spaces in an area, charging time-based fees, and establishing designated transfer or park-and-ride zones. These approaches aimed to manage parking demand indirectly by changing availability or cost. For example, cities have long differentiated charges by parking duration, and some have restricted on-street parking during rush hours. Many of these measures remain in use today but often lack real-time responsiveness.

Historically, the emphasis was on static rules and infrastructure, which were easy to enforce but could not adapt to fluctuating demand. Even efficiently managed parking resources yield only limited individual benefits. However, when combined the impacts can be synergistic. While these traditional approaches established foundations for more sophisticated methods, they faced notable limitations. For example, fixed minimum parking requirements frequently applied to new developments often resulted in oversupply, inadvertently encouraging driving behaviour, as observed by (Macea et al., 2023). Collectively, these developments highlight a broader transition from rigid, infrastructure-dependent systems toward adaptive, user-focused approaches prioritizing efficiency, scalability, and responsiveness.

2.3 Comparison of traditional and smart parking systems

Urban parking systems have evolved significantly, moving from rigid, infrastructure-intensive methods to more adaptive and technology-enabled approaches. Traditional systems, characterized by fixed-rate meters, static enforcement policies, and mandatory parking minimums, were simple to implement but often inefficient. For instance, (Litman, 2006) highlighted how such methods result in unused spaces and significant land underutilization. These systems lacked the flexibility to respond to real-time changes in demand, leading to imbalances in space availability and congestion around curb side areas.

Smart parking systems leverage real-time technologies such as sensors, mobile applications, and networked communication to dynamically optimize parking resources. The advent of real-time data, connectivity, and computing has allowed parking systems to move beyond fixed rules. As (Giuffrè et al., 2012) emphasize, such 'technically advanced solutions' deploy sensor networks and mobile transactions to construct intelligent systems for public parking prioritizing efficiency through real-time adaptation.

Unlike traditional policies, these systems can adapt to current conditions. For example, rather than simply banning parking on certain streets, a smart system might detect when those streets are full and immediately reroute drivers, or dynamically adjust prices based on real-time congestion levels. The Internet of Things (IoT) serves as a central enabler of these intelligent systems. (Cynthia et al., 2018) detail an IoT-based platform where sensors communicate seamlessly with smartphones and cloud servers to provide real-time navigation and automate digital transactions, demonstrating how technology transforms parking into responsive urban infrastructure. While the IoT-based smart parking system offers significant advancements, its current limitations include challenges with detection accuracy under varying environmental conditions and its present scope being limited to single parking slots, though it is scalable for broader implementation.

Smart parking systems also support features that old systems could not. Reservation-based models, for instance, allow drivers to book a parking space in advance, reducing cruising time and uncertainty. (Chen et al., 2012)While these smart systems significantly enhance monitoring accuracy and user convenience, they typically require dense sensor deployment, mobile application infrastructure, or both elements that may limit scalability in many urban settings. In sum, smart strategies transform parking management from static allocation to a responsive service, enabled by data and connectivity.

2.3.1 Financial comparison

a. Sensor-based strategies

Peer-reviewed studies report substantial per-bay hardware costs and non-trivial installation/maintenance burdens. For example, image-recognition smart parking meters are cited at about USD 2,000–4,000 per unit, while in-ground magnetometers are about USD 100–200 per space, both require communications backhaul and periodic maintenance, and magnetometers generally do not identify vehicles for automated billing, which keeps a need for field enforcement staff (Chien et al., 2020). Similar engineering work highlights that even "low-cost" sensing stacks still involve multiple field devices and upkeep, reinforcing that hardware-centric deployments carry recurring costs beyond purchase price. Comprehensive reviews of smart parking technologies also note the trade-offs among sensor types, networking, and lifecycle costs (Dujić Rodić et al., 2020).

b. Mobile app-based strategy (proposed)

A mobile channel with a built-in payment gateway and QR codes at bays (or on nearby signage) eliminates per-space sensors and smart-meter hardware. Academic work shows QR-based tickets and payments are feasible with smartphones, lowering capital outlay to durable QR signage and routine replacements (Amras et al., 2023). From a payment's perspective, QR acceptance is widely adopted because acquisition and maintenance costs for merchants are low compared with traditional POS, while transaction charges are typically levied on a per-transaction basis by the gateway (an operating expense rather than capital. Empirical studies on QR and mobile payments also document user acceptance and operational benefits (e.g., faster transactions and improved turnover), supporting the suitability of a phone-first model for roadside parking. In this model, parking attendants remain in the loop as they already are on

Galle Road to steward compliance and resolve exceptions, but they no longer depend on costly per-space sensors for occupancy/billing; this aligns with findings that sensor-only approaches often still require field staff for citation or verification (Chien et al., 2020). Academic treatments emphasise that QR generation is effectively free and that deployment relies on low-cost and routine replacements; cost drivers are therefore mainly printing material, mounting, and periodic re-issuance orders of magnitude below camera-meter or fleet-wide in-ground sensor programs. While exact plate prices depend on vendor and durability (weather-resistant substrates), these are small line items relative to sensor hardware and installation.

Table 1: Financial comparison between Traditional and smart strategies

Dimension	**Sensor-based Strategies**	**Mobile application-based Strategies [App+ QR + attendants (proposed)]**
Per-Slot Cost	Magnetometer ≈ USD 100–200 per space; camera/smart-meter ≈ USD 2,000–4,000 per unit.(Chien et al., 2020)	No sensor hardware. QR plate only; generation is free, printing, mounting low-cost.
Installation	Civil works (core drilling, wiring/mounts), device commissioning, network backhaul. (Fahim et al., 2021)	Mount QR plates/signs; provision merchant/payment accounts and app back-end.
Maintenance	Device failures, battery swaps, recalibration; vandalism replacements.(Fahim et al., 2021)	Periodic QR plate replacement App/back-end updates. (Amras et al., 2023)
Enforcement	Still required for verification (esp. with magnetometers). (Chien et al., 2020)	Attendants continue current roles Digital audit trail improves accuracy.(Amras et al., 2023)
Payment processing	Often separate hardware or integration; still subject to merchant processing fees if cards are accepted.	Integrated gateway; low-cost QR acceptance; per-transaction fees apply to volume.
Scalability	New spaces require new devices and install.	New spaces require only QR plate in the applications.
Data for pricing	High-resolution occupancy: camera meters add vehicle ID at high cost. (Chien et al., 2020)	Occupancy/transactions inferred from app logs and attendant validation.

Relative to sensor and camera-based strategies, the mobile application approach concentrates costs in software and payment processing (which scale with usage) and very low unit signage, while avoiding large per-space hardware and installation expenses. Given that attendants already operate on Galle Road, this pathway is financially efficient and operationally credible, with a clear upgrade path to stronger auditability and automated enforcement.

2.4 Innovative approaches in modern parking management

Recent research and pilot projects have introduced innovative frameworks aimed at transforming how cities manage on-street and off-street parking. A landmark example is the smart city project by (Giuffrè et al., 2012), which proposed a IPA architectural model, multi-tiered architecture that integrates parking sensors, edge computing, and cloud orchestration to streamline demand forecasting and dynamic user guidance. Meanwhile, (Macea et al., 2023) develop a reservation-based behavioral model and demonstrate that offering pre-booked spaces can significantly shift parking demand between on- and off-street markets. Furthermore, there is a gap in the literature regarding the study of parking choice behaviour when users have the option to reserve a space, a feature that significantly impacts market dynamics.

(Razzaq et al., 2020) introduce a 'Cloud of Things' system that not only reports occupancy but predicts parking availability and provides an Estimated Time of Arrival for drivers. Their pilot tests demonstrated significant improvements in allocation accuracy when compared to static methods. (Chen et al., 2012) employed crowdsourcing strategies, where drivers report available spaces via application check-outs integrated with map-based guidance to enhance space utilization in urban high-demand on street parking zones. Their study revealed that user-submitted data significantly improves real-time understanding of occupancy, compared to sensor-only systems.

(Margreiter et al., 2017) combined traditional beat surveys with simple mobile data inputs, showing that even minimal technological intervention can offer accurate availability maps without complex infrastructure. Similarly, (Berenger Vianna et al.,

2004) reviewed intelligent transportation systems with a focus on contextual data integration for parking, emphasizing the potential for combining voice-guided assistance, historical usage data, and policy-based pricing to optimize outcomes.

Smartphone applications have become integral to new parking schemes. Beyond guiding to vacant parking spaces, applications now enable reservations and automated payments. (Owayjan et al., 2017) implemented a system for a shopping mall where an application, linked to in-ground sensors, lets customers locate empty spaces, pay parking fees, and even retrieve the location of their parked car. By streamlining entry and exit, these initiatives reduce the friction of parking and improve space utilization.

A pivotal innovation involves real-time variable pricing, extending proven utility-sector models to parking management. Researchers now deploy algorithmic pricing that dynamically responds to demand fluctuations. Illustrating this, (Mackowski et al., 2015) develop a game-theoretic framework for performance-based pricing. Their simulations demonstrate that dynamic adjustment of rates can virtually eliminate circling for parking and greatly reduce congestion. These theoretical models are now transitioning into practice. For instance, (Sarker et al., 2020) integrate a dynamic pricing algorithm within their IoT-enabled platform, optimizing revenue generation while guaranteeing parking availability through real-time adjustments.

In practice, initiatives like San Francisco's SFpark have pioneered adjusting meter rates zone by zone in response to real-time demand (Krishnamurthy & Ngo, 2019). Overall, new parking systems blend IoT sensing, cloud analytics, and algorithmic controls to manage supply and demand proactively.

2.5 Crowdsourced and Real-Time parking data collection

Complementing dedicated sensor infrastructures, several works explore leveraging the crowd for data. (Chen et al., 2012) estimate that roughly 30% of urban traffic in busy areas stems from vehicles cruising for parking, which not only slows traffic but also increases accidents and pollution. Equipping cities with tens of thousands of parking sensors (as San Francisco has done) has immediate benefits, but high deployment cost limits scalability. As an alternative, researchers propose using drivers' mobile devices as mobile sensors. For example, (Chen et al., 2012) design a framework that piggybacks on drivers' navigation applications: when a driver parks, they indicate arrival and departure, and their GPS trajectory is used to infer vacancies. This crowdsourcing approach requires no additional fixed infrastructure and can quickly achieve wide coverage. Similarly, (Margreiter et al., 2017) have studied combining manual parking surveys with anonymized vehicle GPS traces to estimate on-street occupancy more accurately. Although full sensor networks remain sparse, partial data can be enriched by crowdsourced vehicle reports to build near real-time occupancy maps. (Bock et al., 2016) likewise consider how volunteered GPS tracks could feed into dynamic parking maps. These crowdsourced models are robust to free riding by weighting contributions.

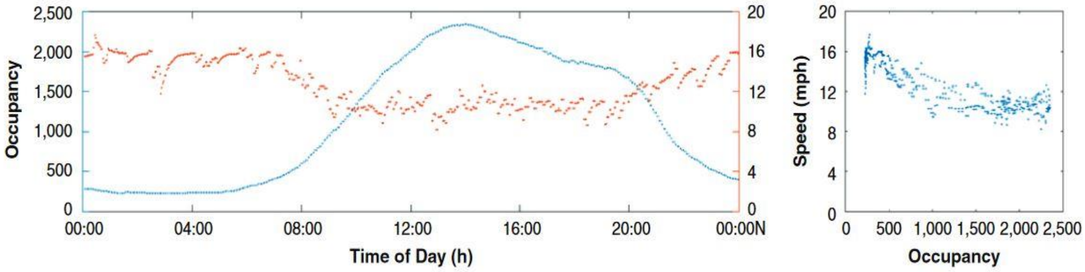
In practice, smartphone parking applications such as SpotHero, ParkMobile collect payment data and may also infer fill rates. Researchers like (Krishnamurthy & Ngo, 2019) list such systems as part of the smart-parking landscape. In sum, real-time data collection now comes both from fixed sensors and from the vehicles themselves, vastly improving the granularity and timeliness of parking information.

2.6 Traffic speed data and parking occupancy relationship

Recent studies examine the quantitative link between parking occupancy and traffic flow speed. Intuitively, heavy on-street parking (illegal or unmanaged parking) constrains road capacity and slows traffic. (Sulistyono et al., 2018) quantify this effect by comparing urban road sections before and after removing on-street parking, they found that freeing curb space increased road capacity by 25% and boosted average vehicle speeds by 11%. This underscores that each parked car on the roadway significantly impedes throughput.

(Ma et al., 2017) take a complementary approach using data analysis. They fuse high-resolution parking occupancy rates with probe-vehicle speed data in San Francisco. Their analysis reveals an inverse relationship; as parking occupancy rises, average speeds fall. In fact, they fit a reverse logistic curve to describe speed vs. occupancy, finding different curve shapes for morning and evening peaks. Using San Francisco as a case study, the researchers sourced parking occupancy data from the

SFPark.org API and traffic speed metrics from the HERE Maps API. Analysis of morning and evening commute periods revealed distinct inverse relationships between occupancy and speed, both quantifiable through reversed logistic functions, demonstrating how peak parking demand non-linearly degrades traffic flow.



(a) (b)

Figure 1: Parking occupancy and average traffic speed of adjacent streets on typical weekday:
(a) speed and occupancy vs time and (b) speed vs occupancy
Source: (Ma et al., 2017)

Figure 1 illustrates the average vehicle speeds in both directions along Mission Street, close to the Fifth and Mission Garage, alongside the parking occupancy levels at the same garage on Wednesday, March 16, 2016 (Ma et al., 2017). Both datasets were synchronized to share a common time stamp for direct comparison. In Figure 1a, the changes in traffic speed and parking occupancy are shown over time. Since the datasets are aligned, Figure 1b presents their relationship more clearly without needing a time axis, each point represents the traffic speed and parking occupancy at a given moment. The plot reveals a noticeable trend: as parking occupancy increases, traffic speed tends to decrease. (Ma et al., 2017) provides the theoretical groundwork for these relationships, validating how parking occupancy patterns shape traffic flow. Crucially, this data-driven understanding of parking-speed dynamics (especially during morning rush hours) empowers cities to design smarter access strategies like timed entry systems or priority zones.

Machine-learning approaches related to traffic are also being applied. (Kumarage et al., 2017) develop a data-driven model for travel time estimation using Google distance matrix API in urban networks using streaming traffic data and machine learning. While their focus is on arterial travel time rather than parking, their work illustrates the principle that dynamic traffic data such as speeds, volumes and bottlenecks can be used in real time to infer conditions. The data collection process for travel time estimation leverages crowd-sourced data and Google Maps' Estimated Time of Arrival (ETA) for reliable and accurate results in Rajagiriya area. The data collected from Google Map APIs underwent validation using the Floating Car data collection method, a common approach for travel time collection. In a parking context, integrating such traffic analytics helps assess the citywide effects of parking interventions. Building upon methodologies established by (Kumarage et al., 2017), this study utilizes Google Distance Matrix API to collect aggregated mobility metrics, specifically vehicle speeds, as a proxy for real-time parking demand. This approach leverages the same data infrastructure validated in prior transportation research while adapting it to Sri Lankan unique urban context.

In the context of Galle Road, this approach relies on combining vehicle speed data gathered via the use of Google Distance Matrix API with on-site occupancy measurements to inform dynamic parking strategies (Dissanayake & Bandara, 2024). Correlation analysis confirmed statistically significant relationships, providing a foundation for dynamic fee structures that optimize revenue while reducing congestion (Dissanayake & Bandara, 2024). This research employs vehicle speed as an initial indicator of parking demand. In practical implementation, this approach would evolve to capture direct demand measurements through mobile applications, enabling empirical validation of the speed-demand relationship while optimizing real-time management.

2.7 Dynamic pricing models for urban parking

Dynamic pricing is a focal area of smart parking management strategy. Unlike fixed-rate schemes, these models adjust prices in real time or by demand forecasts. (Mackowski et al., 2015) propose a theoretical Stackelberg leader-follower game model where a central planner (leader) sets parking rates and drivers (follower) choose where to park. Their simulations indicate performance-based pricing can dramatically improve utilization by raising prices in overcrowded zones and lowering them where capacity exists and the model virtually eliminates circling for parking. While an improvement, these early systems had limitations. Pricing models based on historical data, like SFpark updated infrequently (e.g., every six weeks), limiting their ability to respond to real-time demand fluctuations.

(Sarker et al., 2020) implement a version of this in hardware by devising a dynamic pricing algorithm for their multi-zone smart vehicle parking system architecture. It consists of four layers: sensor nodes, edge gateway, LoRa gateway, and cloud. Their algorithm continuously balances maximizing revenue with providing drivers with available parking spaces, ensuring at least a minimum fee per slot. Similarly, real-world pilots such as SFpark application have used sensor data to vary on-street meter rates by block and time of day. (Krishnamurthy & Ngo, 2019) analyse SFpark application rollout and find that the demand-based pricing program significantly increased transit ridership and reduced traffic flow in designated areas. They report that the economic benefits from reduced congestion and pollution exceed the program costs, indicating strong net gains.

Utility-based parking choice models provide a theoretical foundation for dynamic parking pricing by capturing how drivers evaluate trade-offs among cost, convenience, and availability. Discrete choice frameworks, such as multinomial and nested logit models, quantify how variations in parking fees influence demand distribution across urban zones (Ottosson et al., 2013). In Colombo, the relationship between on-street and off-street parking supply and pricing would need careful study to avoid unintended consequences, such as pushing demand from metered on-street spaces to unregulated or underpriced off-street options.

Empirical studies show that even modest price increases can shift drivers toward less congested locations, balancing demand while maintaining overall satisfaction (Mackowski et al., 2015). Mackowski specifically model a Stackelberg game structure in which parking operators dynamically adjust pricing in response to real-time occupancy, achieving near-optimal utilization and minimizing cruising behaviour. while the paper introduces a promising dynamic pricing model, its practical application and full potential are limited by the need to incorporate more complex real-world interactions, refine behavioural assumptions, and validate parameters with empirical data. Additional case studies such as performance-based pricing in Seattle demonstrate that adaptive pricing linked to occupancy leads to meaningful reductions in cruising and improved access across city blocks (Ottosson et al., 2013). Together, these utility-based and game-theoretic approaches support the concept that dynamically adjusting parking rates based on observed demand can steer driver choices toward underutilized zones, ultimately enhancing space utilization and system-level efficiency. This literature underpins the pricing model proposed in this research.

Dynamic fee strategies for on-street parking have not been fully implemented in Sri Lanka. The Colombo Municipal Council (CMC) currently maintains a fixed fee parking system, charging Rs. 70 per hour for cars and Rs. 40 for three-wheelers since its January 2023 revision. Currently, these standard rates apply across all zones, without adjustments for time-of-day demand or location-based variations. Emerging pilot projects and research show growing interest in demand-responsive pricing. ParkSmart mobile application launched in 2021 through a partnership between Tenaga Car Parks and the CMC faces significant operational limitations. While designed to enable digital payments and real-time slot tracking in corridors like Galle Road and Duplication Road, the application frequently malfunctions due to connectivity issues and backend system failures. Users report transaction errors, inaccurate space availability data, and delayed booking confirmations, undermining its reliability. Critically, it operates on a rigid fixed-fee structure without dynamic pricing capabilities, missing opportunities to optimize occupancy through demand-responsive adjustments. These technical shortcomings, combined with low enforcement compliance, have restricted its effectiveness as a parking management tool.

2.8 Benefits of dynamic parking pricing models

The literature consistently finds that well-designed dynamic pricing and smart parking strategies yield broad benefits. (Krishnamurthy & Ngo, 2019) quantify SFpark application’ s outcomes by optimizing prices, demonstrated measurable success with data showing both increased public transport usage and decreased private vehicle volumes in the implementation zones, generating social welfare gains that outweigh the program’s costs. In other words, when parking becomes more available in high-demand zones, some drivers switch to transit or travel off-peak, cutting congestion and emissions. More generally, (Litman, 2006) notes that efficient parking management including pricing reforms, improves convenience and land use. His case studies show that charging market rates for street parking often keeps spaces available, shortens search times, and raises revenue for public purposes. Over time, these efficiencies compound, fewer drivers circling means smoother traffic for everyone, lower accident risks, and less pollution from idling. Furthermore, smart parking can support sustainability goals by integrating with transit information, it can promote park and ride strategies, as recommended by (Berenger Vianna et al., 2004), who argue that controlling parking spaces is an integral element of traffic and trip demand management.

In summary, modern parking research underscores that combining technology with smart policies leads to win-win outcomes. Despite extensive research on smart management systems and dynamic parking pricing, few studies address low-infrastructure contexts like Colombo, where sensor networks remain limited and real-time occupancy data are scarce. While significant progress has been made, several research gaps remain. From reservation systems and IoT networks to crowdsourced data and dynamic rates, the new initiatives reviewed here all aim to make better use of limited roadside parking space. Similarly, crowdsourced and mobile application driven approaches offer high accuracy, yet their deployment is hindered by initial lack of user adoption and technological infrastructure. Many existing models are designed for specific contexts such as off-street parking and may not apply to the complexities of on-street parking. Current parking system in Colombo urban area, with minimal enforcement and fixed fees on corridors such as Galle and Duplication Road, demonstrates pronounced under and over-utilization, indicating a clear need for a localized solution. By leveraging publicly available speed data from the Google API as an initial proxy for demand by manual occupancy surveys and transitioning to a mobile application for real-time occupancy reporting, this research offers a pragmatic, phased approach that matches to Colombo infrastructure constraints. This method fills the gaps between high-cost sensor networks, establishing a cost-effective pathway toward dynamic pricing and balanced parking utilization tailored to unique urban environment in Colombo.

3. METHODOLOGY

3.1 Case Study Area

This study investigates the development of an effective methodological framework and intelligent interventions for roadside parking control within urban traffic management systems.

Galle Road was selected as the case study area due to its critical role in urban mobility, featuring clearly organized parking bays under municipal council management and its previously established mobile payment infrastructure, specifically the ParkSmart system which offers foundational data and behavioural insights for demand-responsive models. This corridor spanning high-traffic urban areas such as Kollupitiya, Bambalapitiya, and Wellawatta were chosen based on criteria including traffic volume, land-use diversity (e.g.- commercial hubs, residential areas), and historical congestion records. This study focuses on light & medium vehicles because they use most parking spaces on Galle Road. Understanding their patterns helps to design feasible parking strategies that reduce parking congestion and make better utilization of spaces.

Figure 2: Selected urban corridor (Galle Road & Duplication Road)

The study area encompasses the high-demand urban corridor stretching from Kollupitiya to Wellawatta. Historical parking records from the Colombo Municipal Council (CMC) were analysed across this zone to establish occupancy patterns.

6 representative sections (each section is divided into 2–3 subsections based on physical breaks in the curb) along the Galle Road Corridor were selected for synchronized real-time data collection using Google Distance Matrix API and on-site parking occupancy surveys.

Table 1 and figure 3 shows the 6 road sections selected for analysis along Colombo's high-traffic Galle Road corridor and parallel Duplication Road. These road sections were chosen to show different parking demand types across the study area.

Figure 3: Selected 6 road section for the surveys

Table 2: Selected 6 sections along the Galle Road and Duplication Road

Road	Section	From - To
Galle Road	Section 1	Alfred House Ave to Alfred place
	Section 2	Alfred place to 5th lane
	Section 3	5th lane to Deal place
Duplication Road	Section 4	Deal place to 5th lane
	Section 5	5th lane to Alfred place
	Section 6	Alfred place to Alfred House Ave

The selection ensured coverage of varied parking demand scenarios, from short-term parking near markets to long-term parking near office complexes. Observations indicate that some vehicles occasionally deviate from designated parking areas. Motorcycles and three-wheelers often occupy shared spaces with other vehicles when parking capacity is limited, primarily due to spatial constraints.

These sections were strategically selected only for data collection based on their traffic density, mixed land-use characteristics, and recurring parking challenges (e.g.- Kollupitiya to Wellawatta). While the analysis focused on these representative sections, the methodological strategy is designed for scalability across the entire Galle Road Corridor. This ensures that findings, though derived from specific area, support corridor-wide parking management solutions tailored to varying demand patterns and infrastructure conditions.

3.2 Data Collection Methods

To achieve the research objectives, a comprehensive data-driven methodology is required, encompassing the collection and analysis of spatiotemporal parking. Primary and secondary datasets will be systematically gathered to evaluate peak demand intervals, and distribution of parking occupancy across designated sections of the Galle Road Corridor. A methodological framework is to be developed to incorporate the non-sensor and non-camera based (using crowdsourced data) parking management techniques such as mobile applications. demand patterns, infrastructure utilization metrics, and vehicular behaviour dynamics.

A literature review was conducted to examine the development of smart parking strategies, highlighting the shift from conventional practices to more responsive and participatory approaches that enhance space utilization and enable dynamic pricing and the benefits of demand-based pricing. This review critically assessed global best practices in parking regulation, including dynamic pricing models, localized studies on Sri Lanka's transportation infrastructure were analysed to identify challenges, such as mixed-traffic conditions, illegal parking behaviours, and gaps in enforcement mechanisms.

The methodology involved some main steps to collect and analyse data. First, historical parking records were obtained from the Colombo Municipal Council. These records included past information about parking usage, and traffic volumes, and covering a year of 2020 and 2021. This helped identify long-term trends and recurring issues in the study area.

Next, real-time vehicle speed data (as a proxy indicator for parking demand) was gathered in 6 sections of the Galle Road Corridor. This method collects live travel times, section length, and traffic conditions during peak and off-peak times. Route-specific travel times and distances were acquired via Google Distance Matrix API using PyCharm executed Python code (see Appendix I). Vehicle speed values were computationally derived from these fundamental metrics. This vehicle speed data offers significant operational advantages for urban mobility research, including cost-effective deployment, minimal manual intervention, and scalable collection across multiple road sections. This approach enables consistent identification of network-wide travel patterns while freeing resources for higher-value analytical tasks.

At the same time on-site parking beat surveys were conducted along the same selected sections of the Galle Road Corridor to observe parking occupancy. This approach ensured a detailed understanding of temporal parking behaviour and demand dynamics in the study area.

By combining historical records, real-time traffic data, and direct field observations, the study ensured a reliable and comprehensive analysis of parking challenges and solutions for the corridor.

3.2.1 Historical parking data collection

Historical parking data was obtained from the Colombo Municipal Council (CMC) to analyse long-term trends in parking demand and infrastructure utilization within the Galle Road Corridor. The dataset included archived records of parking payment reports spanning the years of 2012, 2020 & 2021 (Bandara & Perera, 2012). These records provided insights into spatial and temporal patterns, such as peak occupancy sections, seasonal fluctuations, and compliance rates with existing parking regulations. Key metrics extracted included land use, daily parking variations, hourly parking variations, duration of vehicle stays, and the distribution of on-street parking usage. This analysis helped identify recurring parking hotspots and assess the effectiveness of past policy interventions. By integrating this historical dataset with real-time observations, the study established a baseline for evaluating evolving parking challenges and regulatory strategies.

3.2.2 Real-time vehicle speed data collection

This research initially uses vehicle speed as a proxy for parking demand but will transition to direct, application-based demand measurements to empirically validate the speed demand relationship and optimize real-time management.

This real-time vehicle speed data was collected using the Google Distance Matrix API to analyse vehicle speed dynamics and congestion patterns along the Galle Road Corridor & duplication Road. Vehicle speed values were calculated from travel times and distances data collected using Google Distance Matrix API utilizing Python automation (see Appendix I) executed within the PyCharm software. This application programming interface (API) provides live travel time update in the particular road section by aggregating anonymized location data from mobile devices and vehicle sensors, enabling the calculation of travel times and speeds across predefined road sections. Data was collected for key road sections within the corridor at 15-minute intervals during 06:00-19:00 over a 13-hour period, ensuring representation of typical weekday variations. The use of Google Distance matrix API offered a cost-effective and scalable alternative to traditional sensor-based monitoring, providing continuous, high-resolution speed data without requiring physical infrastructure installation.

3.2.3 Physical survey data collection

Roadside parking occupancy survey was conducted to collect accurate data on parking utilization patterns along the Galle Road Corridor (Galle Road and Duplication Road). This method involved direct observational fieldwork to document real-time parking behaviours, and occupancy fluctuations in specific area. This survey was conducted on the same 6 road section (Each section is divided into 2–3 subsections based on physical breaks in the curb) selected for speed data collection, spanning a 13-hour period (06:00-19:00) during the same weekday to capture variations in parking demand across peak and off-peak hours. This timeframe was selected to observe morning, midday, and evening traffic patterns, ensuring coverage of commuter activity during high demand. Data collected included the number of parked vehicles and observations were recorded at 30-minute intervals to systematically track occupancy fluctuations.

3.3 Structure of the methodology

As a Summary, the methodology followed a multi-step approach to ensure comprehensive analysis and reliability. First, a literature review was conducted to identify global best strategies and local challenges in urban parking management, informing the study's framework. Next, historical parking and traffic data 2012, 2020 & 2021 were collected from the Colombo Municipal Council (CMC) to establish parking patterns and existing condition. Real-time vehicle speed data (as a proxy indicator) was then gathered using the Google Distance Matrix API, focusing on peak and off-peak hours to assess traffic flow dynamics.

Simultaneously, on-site physical surveys were carried out along predefined sections of the Galle Road Corridor to record parking occupancy ratios during a typical weekday. These surveys were conducted on the same road sections and periods as speed data collection to enable correlation between parking occupancy and vehicle speeds.

A correlation analysis was conducted to examine the relationship between vehicle speeds and parking occupancy rates. Upon verifying the quality of speed and survey data, those results were then used assess the potential revenue generated by the dynamic pricing approach. This sequential, mixed-method design ensured a holistic understanding of parking challenges while balancing empirical rigor and practical applicability.

3.4 Parking demand estimation methodology

3.4.1 Initial Assessment of Parking Demand

The first step in our methodology involves establishing a reliable estimate of roadside parking demand without deploying a dedicated application. Vehicle travel speeds along both Galle Road and Duplication Road were examined to achieve this objective. The analysis utilized speed data collected at 15-minute intervals from the use of Google Distance Matrix API. Road sections with lower average speeds are considered to indicate higher parking demand, as vehicle movements related to searching for parking and roadside activities tend to reduce traffic flow. Concurrently, parking occupancy surveys record the actual number of parked vehicles in each road section, serving as reliable data for validating and calibrating the analysis. Correlation of speed data with observed occupancy counts yields a preliminary demand model representing relative demand across the corridor.

While vehicle speed reductions along Galle Road and Duplication Road serve as an initial proxy for parking demand, it is important to acknowledge that these variations may also reflect area demand rather than local parking activity. Fortunately, API-derived travel times can reveal patterns of network-wide slowdowns by comparing speeds upstream and downstream, it is possible to distinguish general traffic bottlenecks from localized parking effects. However, internal section disturbances such as unsanctioned pedestrian crossings, loading activities, or bus stops are not directly observable via the API. To mitigate this limitation, supplemental API data on nearby land-use and event schedules (e.g., market hours, school dismissals) can be incorporated, offering contextual cues to interpret speed anomalies more accurately. Together, these techniques strengthen the reliability of speed as a demand indicator in the initial assessment phase.

3.5 Data integration into a mobile application

3.5.1 User navigation and parking assistance

When a driver enters a destination, the parking app displays a map of nearby options with color-coded markers. The colours indicate current occupancy, allowing users to see at a glance which spaces are available versus those that are fully occupied. Providing this information in advance is important because, in busy city centres, searching for parking consumes time, adds to congestion, wastes fuel, and frustrates drivers. By presenting real-time availability and pricing, the system enables an informed choice before the driver begins to search on the street.

After the driver selects a location, the mobile app computes an optimal route directly to an open bay. It uses crowd-sourced reports and live traffic conditions to minimize travel time and avoid circling. The routing updates dynamically as congestion and occupancy change an essential feature in urban settings where conditions shift quickly. Without such guidance, drivers often cruise for extended periods. Real-time guidance therefore reduces search time, lowers congestion, and cuts associated emissions.

🟢 Available 🔴 Occupied 🟡 Pending

a. Dynamic re-routing for alternate parking

If the driver's first-choice parking location becomes full or unavailable by the time they arrive, the application first checks nearby partner/adjacent subsections (e.g., two ahead, one behind, and the parallel corridor segment) that are within a short walking distance, currently has low occupancy. If no adjacent/partner space is available, the search expands to farther but still practical alternatives according to the cutoff. To make the alternate location, the system can even highlight a discounted rate at that subsection, as an incentive for the driver to reroute there. The driver's navigation is then seamlessly updated to direct them to this new parking space in real time. It ensures that the driver doesn't waste time hoping for a parking space to free up or resort to illegal parking out of desperation. The guidance continuously updates as conditions change, if another closer parking space opens up or if traffic on the way shifts, the app will adjust the route or suggestions accordingly.

By seamlessly integrating live availability, pricing incentives, and route guidance, the system adapts to changes and keeps driver stress low. Once a parking space is reserved or chosen, the application provides turn-by-turn directions all the way to the precise parking space. Unlike basic navigation tools that might only lead drivers to a street address, this app guides the user to the specific parking facility entrance, right to the exact subsection and slot that has been allocated. The driver no longer has to roam up and down aisles hoping to find the marked space; the app's interface can, for instance, highlight unique parking slot code and navigate there. By eliminating this last-minute search, the system saves time and avoids the circling the lot scenario. Parking slot status is visualized in the interface (using the aforementioned colour codes for occupied/vacant status), so the driver can even see confirmation that their destination slot is open and awaiting them. Overall, the combination of availability and price, optimal routing, and precise last-yard navigation greatly improves the parking experience.

b. Adjacent Subsection Catchment

A key assumption in our approach is that if drivers are not guided to a legitimate low-occupancy parking area when their first choice is unavailable, they might either park illegally or give up on their trip. To prevent such outcomes, the application defines a catchment area of adjacent/partner road subsections around the driver's target destination for searching alternate parking that are within a short walking distance. These are operationalized as $W \leq W_{min}$. This ensures that any suggested backup option is nearby and convenient, rather than randomly sending the driver far off course. In our case study of Galle Road - one-way corridor (from Kollupitiya to Wellawatta), segmented the road network into small subsections, each identified by a unique code. Given the subsection code of the desired parking location, the system automatically computes a set of adjacent subsections to search as follows:

- *Forward sections*: the next 2 subsections ahead of the desired location along the main one-way road (in the direction of traffic flow). These represent going a bit further down Galle Road past the original destination.
- *Backward section*: the one subsection immediately behind the target location on the main road. This represents a section the driver just passed through or would have to backtrack to. (On a one-way street, direct backtracking is not possible, so in practice the driver might have to loop around via a parallel road to reach this section if suggested.)
- *Parallel road sections*: corresponding subsections on a parallel route that runs adjacent to the destination. For example, Duplication, which runs parallel to Galle Road, has its own sequence of subsection codes aligned geographically with those on Galle Road. The system includes the parallel road's subsections that overlap the area of the destination. This accounts for the one-way network by offering an alternate path in the opposite direction if needed.

c. Alternate Parking Suggestions

If the primary and adjacent subsections (two ahead, one behind, and the nearby parallel section) are all fully occupied, the app expands the search beyond the immediate catchment to identify the nearest low-occupancy legal subsections a bit farther away. The guidance clearly informs the driver and applies discount to offset the extra walk and make the option more attractive. Using unique subsection codes, the system ranks these secondary options by occupancy and walking distance, then recommends the best match. This proactive re-routing helps drivers avoid illegal parking or abandoning the trip, while redistributing demand away from saturated blocks and toward underused areas, thereby reducing overflow at popular locations and improving overall network balance., the system intelligently steers drivers to legal parking that they might otherwise overlook. This proactive re-routing not only helps drivers avoid fines and frustration, but also distributes parking demand more evenly across the network, reducing overflow at popular spaces and encouraging use of nearby facilities with available space.

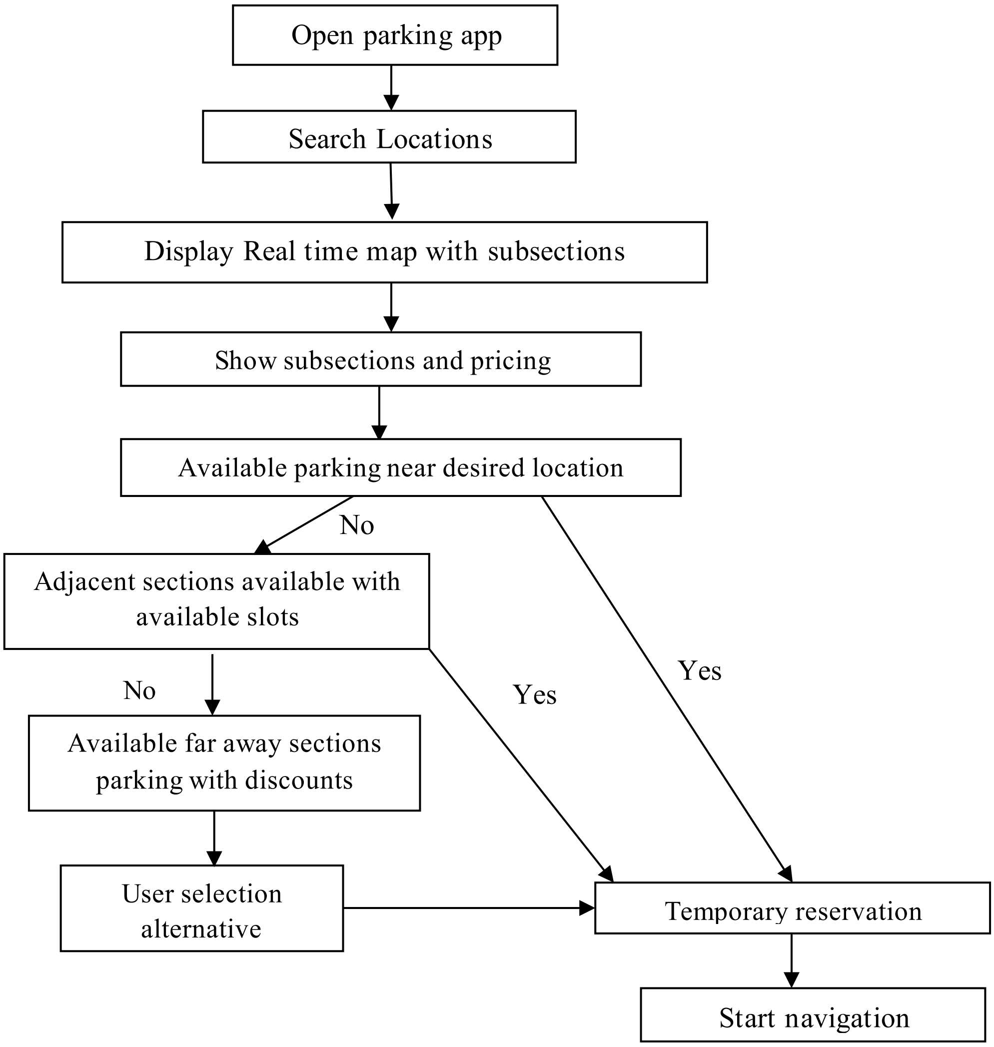


Figure 4: User navigation process via Mobile application

Overall, the mobile interface presents color-coded demand and dynamic fees at a glance, then guides users directly to an available parking space with live, turn-by-turn directions. When a preferred subsection is full, the system applies a structured catchment rule tailored to Colombo's one-way network, first checking two subsections ahead, one behind, and the nearby parallel corridor. If necessary, expanding to the nearest low-occupancy subsections farther away, supported by discounts. This progression reduces cruising and illegal stopping, improves user experience, and redistributes demand from saturated blocks to underused areas, thereby enhancing turnover and revenue potential. By combining simple identifiers (subsection codes), crowdsourced occupancy, and adaptive pricing, the approach remains low-cost and scalable from the Kollupitiya–Wellawatta pilot to other corridors.

3.5.2 Unique code system for roadside parking spaces

To implement our proposed strategy, pricing, and guidance on Galle Road, a unique, hierarchical numbering scheme is adopted. A section is the continuous curb between two consecutive cross-streets (Eg- 5th Lane to Deal Place -Right), assigned a section code (Eg -GR-01). Each section is divided into 2–3 subsections based on physical breaks in the curb (Eg- driveways, bus stops), labelled 01–03. Within each subsection, each individual bay per side is enumerated; sides are coded L (left) and R (right) relative to the one-way traffic flow. Parking slot numbers run from 01 downstream boundary. A full Parking identifier concatenates these elements as Road–Section ID–Sub ID–Slot No-Side. The same convention applies to both sides of the corridor.

GR = Galle Road; SS = section (two digits); SB = subsection (two digits); SL = slot (two digits); S = side (L = left, R = right, defined by the corridor's traffic direction).

- Galle Road, Section 1, Subsection 2, Slot 5, right side → GR-01-02-05-R
- Duplication Road, Section 1, Subsection 2, Slot 5, left side → DR-01-02-05-L

To operationalize the redistribution logic, a set of partner subsections can be pre-defined for each primary parking subsection. This pre-determination can be conducted through a spatial analysis of the road network to ensure that each partner subsection complies with the system's stringent constraints for both additional vehicular travel and post-parking walking distance. Consequently, when occupancy conditions trigger a search for an alternative space, the algorithm can be designed to consider only these pre-qualified partner subsections for vehicle assignment. This approach ensures that any proposed alternative inherently satisfies the established minimum and maximum cut-off limits, maintaining the model's focus on practical and user-centric outcomes.

To illustrate the partner subsection selection methodology, consider a user whose desired parking location is the subsection designated GR-01-03-R. The set of pre-defined partner subsections for this location would be identified through a network proximity analysis. This set would logically include immediately adjacent subsections on the same roadway, such as GR-01-01-R and GR-01-02-R, as they typically incur minimal additional access and walking distance.

Furthermore, to account for roadside orientation, corresponding subsections on the opposite side of the roadway, namely GR-01-02-L and GR-01-03-L, would also be considered, contingent upon the availability of safe and legal crossing points.

Extending the analysis to the wider network, subsections on parallel or duplicate roads, such as those on the designated route DR-01-02 (including both R and L), can be incorporated into the partner set. This inclusion is predicated on their computed network travel and walking distances falling beneath the established maximum thresholds, ensuring they represent a viable and convenient alternative to the user's primary destination

3.5.3 Parking demand estimation via mobile application

In the proposed strategy, the long-term goal is to transition to direct, real-time parking occupancy data collected through a user-driven mobile application. While initial analysis uses speed and survey data only to gain an indicative understanding of demand patterns, the mobile application will enable more accurate and dynamic data collection moving forward.

Upon parking, users will be required to scan a clearly displayed QR code placed at each parking slot or issued by the parking attendant. A critical function of the QR code integration is to provide users with real-time occupancy status for a specific parking subsection. For instance, if a subsection contains ten parking bays and nine active user sessions are recorded via QR scans, the system interface will display one remaining available space. Each parking session's start and end times are recorded by this action, generating unique occupancy records. Depending on operational feasibility, the technology allows either the user or a parking attendant to facilitate the scanning procedure.

Collected data will be automatically uploaded to a database, which aggregates individual check-ins and check-outs to build a real-time occupancy profile of all parking areas. This live dataset will be used to guide users to available spaces, increasing system responsiveness and efficiency. By shifting to a crowdsourced data model, the need for periodic manual surveys is significantly reduced. This approach also increases transparency and encourages user participation through feedback mechanisms and in-app information on availability and rates. Over time, the framework evolves from relying on inferred demand indicators to an accurate, user-verified occupancy map, forming the foundation for adaptive, demand-based parking management.

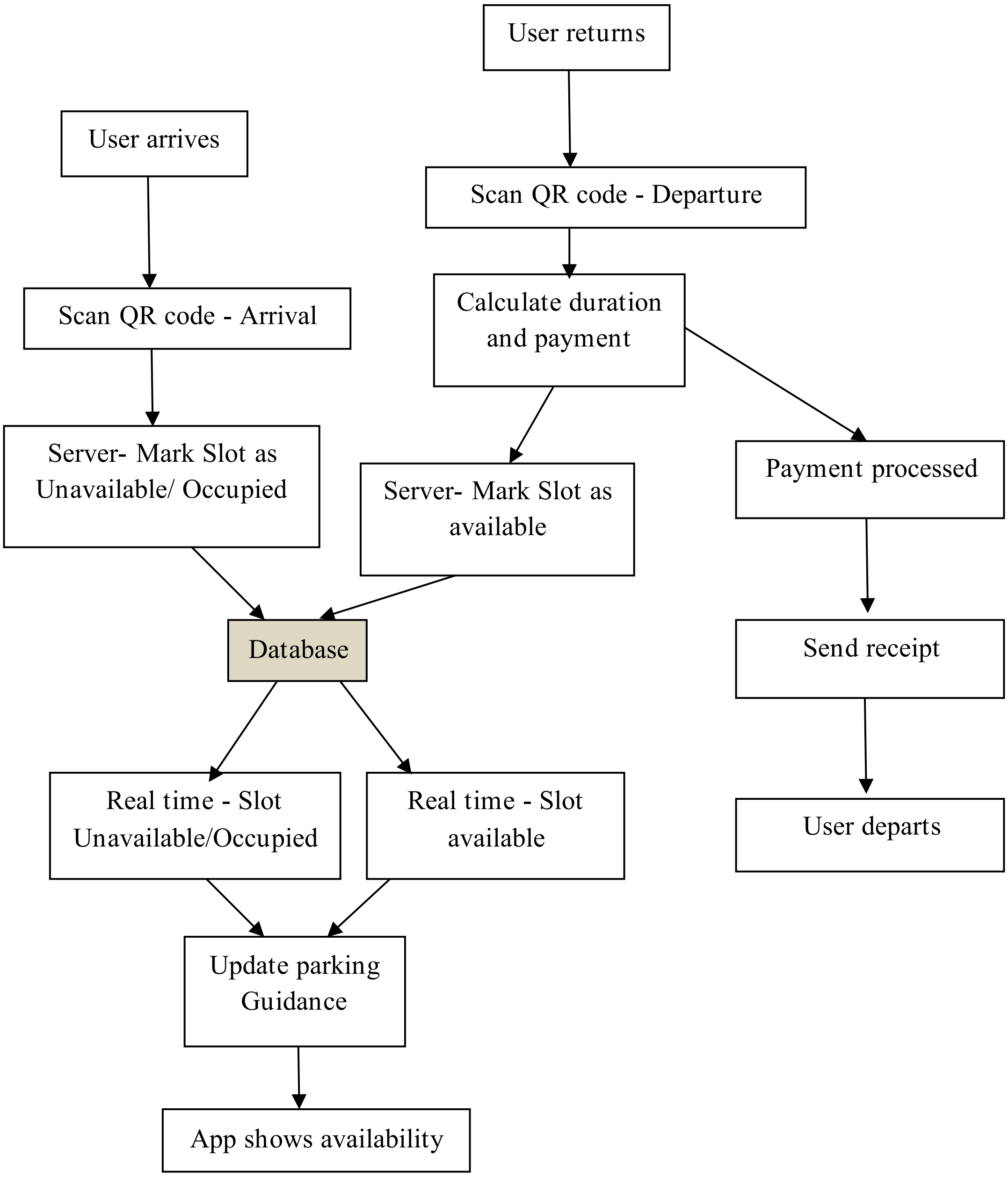


Figure 5: Parking demand estimation via mobile application and user reporting process

3.6 Dynamic parking fee structure

In busy parking areas, many drivers arrive to find their first-choice lot full. Without any guidance to alternate parking, these drivers often either give up and leave or park illegally outcomes that generate no revenue. The key focus is that directing turn away drivers to nearby low-occupancy, legal parking areas fills vacant spaces and converts lost parking attempts into paid stays. This approach is expected to increase total daily parking revenue.

When a driver's preferred (nearest parking slot near the desired place) parking subsection is full, the system employs a structured catchment strategy tailored to Colombo's one-way road network. The algorithm first checks immediate nearby adjacent sections for available spaces, specifically, two subsections ahead, one behind, and the corresponding segment on the parallel corridor. These nearby sections are within a short distance of the desired location, If any have free slots, the driver is simply redirected there without a discount. This ensures minimal inconvenience when alternate adjacent parking section is found. If no adjacent section has available spaces, the system expands the search to the next nearest sections farther away. At this stage, discounted pricing is introduced as an incentive. Discounts are applied only to these additional (farther) sections, not to the immediately adjacent ones. In other words, once a driver must park beyond the normal catchment area (beyond the two-ahead/one-behind range), a discount is offered to compensate for the extra distance and to encourage use of under-utilised parking.

I. *Occupancy-Based Discount Rates*

The discount rate is determined by the real-time occupancy (parking utilisation) of the alternate section. The section's occupancy ratio (O) the proportion of spaces currently occupied, is used as the indicator of demand. The rule is structured with 3 occupancy tiers that apply fixed discount levels, and it applies no discount when occupancy is high.

- High occupancy ($O > 0.5$ or 50%): No discount. If a section is more than half full, it's relatively in demand, so the driver pays the standard fee. Such sections do not need price incentives and prioritizing them could lead to congestion in already popular areas.
- Moderate occupancy ($0.25 \leq O \leq 0.5$): 25% discount. For sections that are 25%–50% occupied, a 25% fee reduction is offered, if the section lies beyond the distance threshold. This moderate discount encourages drivers to use somewhat underutilized sections when they are a bit farther away, without overly sacrificing revenue.
- Low occupancy ($O < 0.25$ or 25%): 50% discount. For sections with very low usage (less than 25% occupied), a 50% fee reduction is provided, for parking there (again, only if beyond the distance threshold). Deep discounts are justified here to attract drivers to these largely vacant areas. Notably, an occupancy this low is a strong sign that the base price is too high or the location is inconvenient, so a significant discount helps correct that imbalance by boosting demand.

II. *Distance Threshold*

The system evaluates two separate distances to determine the suitability of an alternative parking space: the walking distance after parking and the extra driving distance to reach that space. To ensure practicality, strict limits are applied. The walking distance must not exceed an upper limit (e.g., 600 meters), as longer walks are considered unreasonable for users. Additionally, a minimum walking distance (e.g., 300 meters) is set; if the walk is shorter than this, no discount is offered. When calculating these distances, the system accounts for real-world road layouts. This includes factors such as the side of the road the parking is on, and any additional travel required to access sections located in the opposite direction or behind the destination due to one-way streets or traffic rules. This ensures the calculated distances accurately reflect the actual effort required by the driver.

Definitions:

- P_0: base parking price.
- O: occupancy of the candidate subsection.
- W (meters): walking distance from the candidate bay to the driver's destination (computed on the pedestrian network).
- A (meters): extra vehicle distance from the preferred location's legal roadside access to the user's legal access (computed on the directed road network so that side-of-road and upstream loop detours are captured)
- Walking cut-offs: W_{min}=300m and W_{max}=600m
- Access limit: A_{max}=800m
- I_{def} = Deflection indicator
- I_W= Walking distance-eligibility indicator
- I_A= extra vehicle distance-eligibility indicator
- Discount tiers (policy variables): d_{50}=0.50 & d_{25}=0.25

The application never proposes a space that violates either limit: $W>W_{max}$ or $A>A_{max}$

a. Adjacent/ Partner subsections (no-discount) catchment.

When the preferred subsection is full, the application first checks nearby partner/adjacent subsections (e.g., two ahead, one behind, and the parallel corridor segments) that are within a short walking distance. These are operationalized as $W \leq W_{min}$. If any space is available, the driver is redirected there at full price P_0 (no discount).

b. Alternative subsections (discount-eligible) catchment.

If no adjacent/partner space is available, the search expands to farther but still practical alternatives. A user is feasible only if it passes both gates:

- $I_W = 1\ (W_{min} < W \leq W_{max})$, $I_A = 1(A \leq A_{max})$

With $W \leq W_{min}$ remain "adjacent" (no discount), while those with $W>W_{max}$ or $A>A_{max}$ are not proposed.

c. Occupancy step

$R_{occ}(O)$ => High occupancy ($O > 0.5$ or 50%): No discount
Moderate occupancy ($0.25 \leq O \leq 0.5$): 25% discount
Low occupancy ($O < 0.25$ or 25%): 50% discount

d. Deflection flag

$I_{def} = 1$[no vacancy in adjacent/partner subsections]

$I_W = 1\{ W_{min} < W \leq W_{max} \}$

$I_A = 1\{ A \leq A_{max} \}$

e. Final discount and price

$D = I_{def} \times I_W \times I_A \times R_{occ}(O)$

f. Final hourly price

$$\boxed{P = P_o\,(1 - D)}$$

If a space exists within $W \leq 300$ m (adjacent/partner band), the driver is redirected there at full price. Only when adjacent options are exhausted ($I_{def} = 1$) and the candidate satisfies both $300 < W \leq 600$ and $A \leq 800$ does the stepwise discount apply. The discount level depends only on occupancy tier (O) of the desired subsection.

g. Revenue analysis

The revenue calculation proceeds as follows. First, a baseline daily revenue is established by summing the product of occupied spaces and their applicable fees across all subsections and time intervals. Subsequently, capacity-constrained intervals those at or near full occupancy are identified to estimate unmet demand. For these intervals, available capacity in adjacent, underutilized subsections is quantified. The potential redirectable demand is calculated as the minimum of the estimated overflow from saturated subsections and the available capacity in alternative ones.

4. ANALYSIS AND RESULTS

4.1 Analytics on the collected data from the Colombo Municipal Council

4.1.1 Existing Condition

a. *Land Use* - Land use along Galle Road is predominantly commercial with few government organizations located either side of the road. Unity Plaza, Durdan's Hospital, Indian VISA centre, National Savings Bank & State Mortgage and Investment Bank are some of the major traffic attractors.

b. *Traffic Flows* **-** Generally, the Galle Road traffic flow is comparatively uniform during daytime except for short peak in the morning. Average flow is around 3000 vph on Galle Road on a typical working day. The daytime total flow on Galle Road is around 44,000 (12-hour period 07:00-19:00) (Bandara & Perera, 2012). Based on the above information the average daily traffic on the Galle Road is estimated to be around 55,000 - 60,000 vehicles with projections reaching approximately 75,000 vehicles by 2025 (assuming a 4-5% annual growth).

c. *Pedestrian Facilities & Public Transport* - Pedestrian sidewalks are available on both sides of Galle Road. Facilities for disable (both visually impaired and using wheelchair) are also available. Large number of main bus routes operates on Galle Road. Bus stops with bus bays are located in regular interval.

4.1.2 Distribution of Parked Vehicles

According to the 2012 CMC data, the roadside parking facilities have been used by a total of 2682 vehicles (12-hour period 07:00-19:00). Majority of the vehicles seeking parking facilities are cars followed by three wheelers and motorcycles. It is interesting to note that nearly 56% of the parked vehicles are three wheelers and motorcycles that falls into light vehicle category. Very few goods vehicles or service vehicles have used the parking facilities. Distribution of vehicle types seek parking is given in Table 2.

Table 3: Parking distribution

Vehicle Type	**Frequency**	**Percentage**
Car	885	33.0 %
Vans	261	10.7 %
Motorcycle	740	27.6 %
Three Wheelers	770	28.7 %
Goods Vehicle	19	0.7 %
Service Vehicles	7	0.3 %

4.1.3 Parking Durations

Analysis of 2012 parking duration data revealed distinct temporal patterns in vehicle occupancy (Bandara & Perera, 2012). A frequency-over-time distribution (Figure 5) illustrated a daytime average parking duration of 1.3 hours, with individual stays ranging from 15 minutes to over 12 hours and a standard deviation of 2.3 hours. Notably, nearly 80% of vehicles occupied parking spaces for durations under 3.5 hours. Vehicle-specific analysis further highlighted variations: cars, vans, and motorcycles exhibited an average parking time of 1.9 hours, while other vehicle categories (e.g., commercial trucks) averaged 1.3 hours. Three-wheelers, however, demonstrated significantly shorter stays, with an average duration of 0.6 hour.

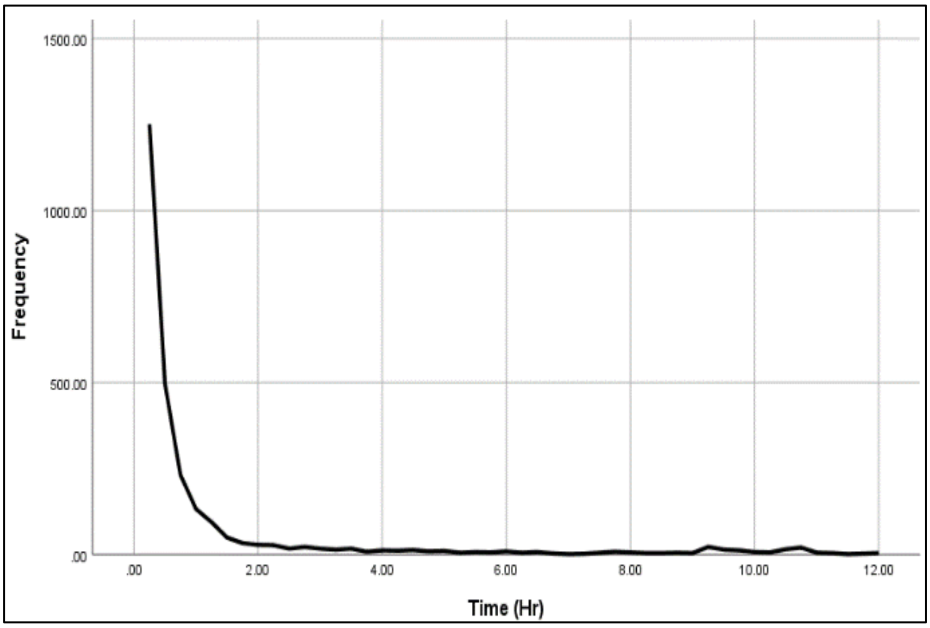


Figure 6: Frequency-over-time distribution

Table 4 Parking durations (Bandara & Perera, 2012)

Duration (hr)	Vehicle Type						Total
	Car	Vans	Motor Cycles	Three Wheelers	Goods vehicles	Service Vehicles	
1	585	193	595	714	18	5	2110
2	89	31	47	35	1	1	204
3	44	9	20	10	0	0	83
4	33	10	5	3	0	0	51
5	26	1	13	2	0	1	43
6	18	1	5	3	0	0	27
7	9	1	6	0	0	0	16
8	10	1	10	0	0	0	21
9	14	2	1	0	0	0	17
10	26	7	21	1	0	0	55
11	27	2	16	1	0	0	46
12	4	3	1	1	0	0	9
Total	885	261	740	770	19	7	2682
Average Stay (hr)	1.9	1.3	1.3	0.6	0.5	1.1	1.3

4.1.4 Majority Payment Locations in Galle Road Corridor

Analysis of parking payment records from the Colombo Municipal Council (CMC) for the years 2020 and 2021 revealed a pronounced most of transactions along the Galle Road corridor, particularly within the road section from Kollupitiya to Wellawatta. Within this section, the Kollupitiya area emerged as the major transaction location, accounting for the highest frequency of parking payments figure 6 & 7. This area, known for its high commercial activity, consistently recorded the highest number of parking payments compared to other parts of the city. The data highlights the significant parking demand in this zone, driven by factors such as proximity to office complexes, retail centres, and public transit nodes. These findings underscore the need for targeted parking management strategies in high-demand areas to address congestion, optimize space utilization, and improve user convenience.

Table 5: Vehicles parking count in 2020 & 2021

Major area	**Parked vehicles count in 2020**	**Parked vehicles count in 2021**
Kollupitiya	16397	15137
Bambalapitiya (Galle Rd)	11340	11725
Wellawatte	680	445
Total	28417	27307

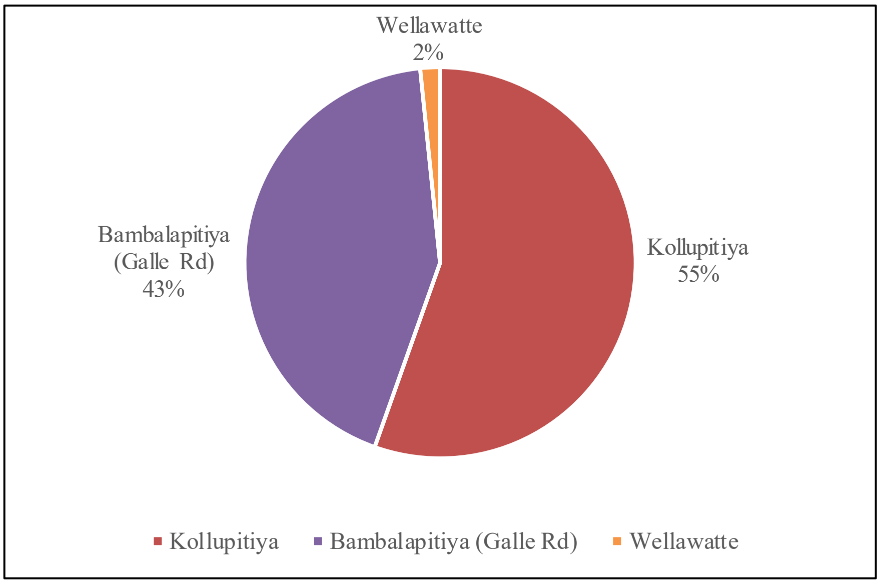


Figure 7: Major parking fee payment locations in 2020

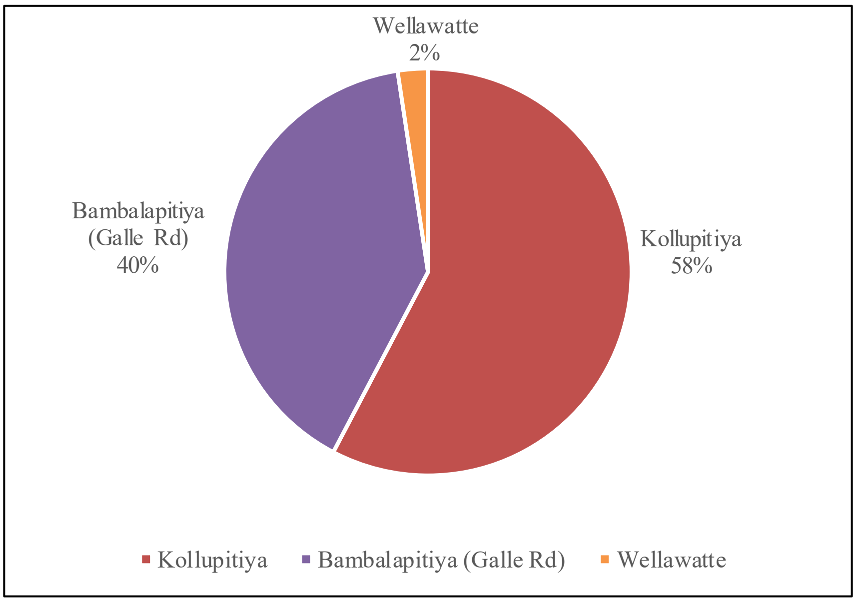


Figure 8: Major parking fee payment locations in 2021

4.1.5 A comparative analysis of day-to-day demand variations

Comparative analysis of vehicle arrival patterns in 2020 and 2021 revealed distinct weekday-weekend variations (Table 5). In 2020, Mondays and Wednesdays recorded higher vehicle arrival rates compared to other weekdays, while Sundays consistently showed the lowest traffic volumes, likely reflecting reduced commercial and commuting activity on weekends (Figure 8).

By 2021, a shift was observed: Mondays emerged as the peak day for vehicle arrivals, followed closely by Tuesdays and Wednesdays. Sundays remained the least busy day in both years, aligning with broader trends of reduced weekend mobility. These findings highlight the influence of weekday work schedules and weekend behaviour on traffic dynamics, providing insights for adaptive parking management and congestion mitigation strategies tailored to temporal demand variations (Figure 9).

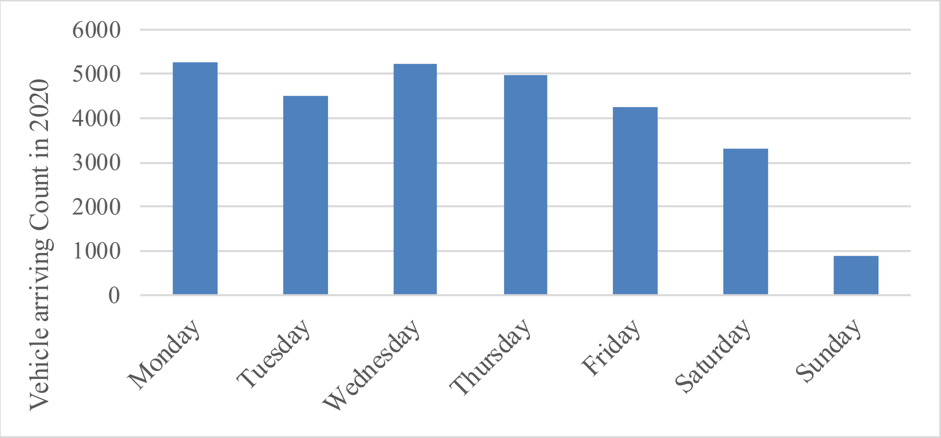


Figure 10: Day variation of parked vehicles in 2020

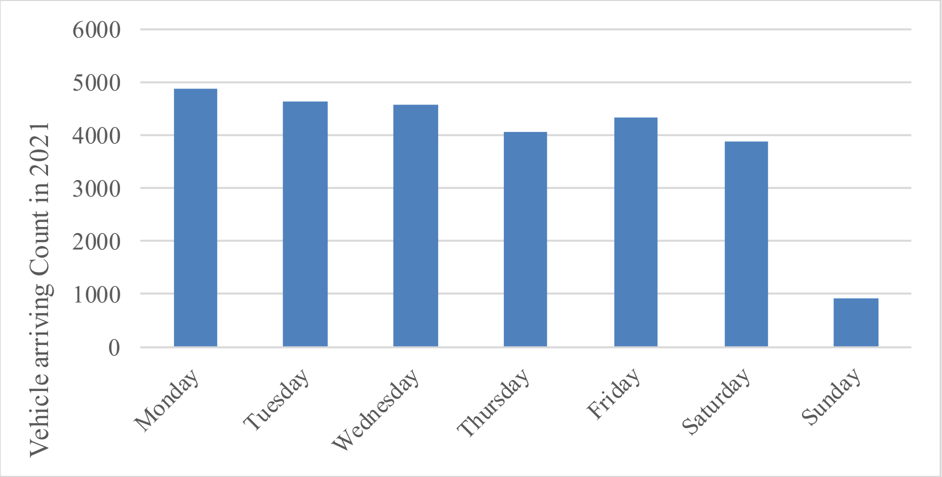


Figure 9: Day variation of parked vehicles in 2021

Table 6: Day to day variation of parked vehicles along the Galle Road

Day	**Area**	**Vehicle arriving Count in 2020**	**Total Count in a day**	**Vehicle arriving Count in 2021**	**Total Count in a day**
Monday	Bambalapitiya	2056	5251	2081	4872
	Kollupitiya	3091		2703	
	Wellawatte	104		88	
Tuesday	Bambalapitiya	1659	4521	1989	4632
	Kollupitiya	2725		2574	
	Wellawatte	137		69	
Wednesday	Bambalapitiya	2028	5211	1985	4574
	Kollupitiya	3074		2524	
	Wellawatte	109		65	
Thursday	Bambalapitiya	2040	4973	1712	4068
	Kollupitiya	2831		2281	
	Wellawatte	102		75	
Friday	Bambalapitiya	1749	4265	1851	4341
	Kollupitiya	2424		2434	
	Wellawatte	92		56	
Saturday	Bambalapitiya	1557	3311	1758	3890
	Kollupitiya	1634		2067	
	Wellawatte	120		65	
Sunday	Bambalapitiya	251	885	349	930
	Kollupitiya	618		554	
	Wellawatte	16		27	
	Total		**28417**		**27307**

4.1.6 A comparative analysis of hourly parking variations

Analysis of 2020 CMC data reveal distinct temporal patterns in vehicle arrivals at major commercial zones along Galle Road. In Kollupitiya peak arrival volumes were observed between 10:00 AM and 01:00 PM, while Bambalapitiya and Wellawatta experienced its highest vehicle count from 11:00 AM to 01:00 PM. These findings collectively indicate a pronounced midday demand surge, with daytime arrivals significantly exceeding those at other periods (Table 6).

Table 7: Hourly parking variations in 2020

Time	Parking vehicles count		
	Kollupitiya	Bambalapitiya	Wellawatta
00:00-01:00	3	0	1
01:00-02:00	2	0	0
02:00-03:00	0	0	0
03:00-04:00	0	0	0
04:00-05:00	1	0	0
05:00-06:00	5	1	0
06:00-07:00	71	7	0
07:00-08:00	214	65	1
08:00-09:00	915	321	8
09:00-10:00	1876	851	58
10:00-11:00	1940	1127	50
11:00-12:00	2038	1415	108
12:00-13:00	2024	1565	117
13:00-14:00	1896	1482	86
14:00-15:00	1571	1314	44
15:00-16:00	1401	1288	47
16:00-17:00	1125	1008	45
17:00-18:00	772	588	59
18:00-19:00	283	231	24
19:00-20:00	121	48	21
20:00-21:00	67	19	5
21:00-22:00	51	9	4
22:00-23:00	10	1	0
23:00-24:00	11	0	2
Total	**16397**	**11340**	**680**

Analysis of 2021 parking payment records shows busiest arrival times occurred in Kollupitiya, between 9:00 AM and 01:00 PM, while Bambalapitiya and Wellawatta saw similar midday peaks from 11:00 AM to 02:00 PM (Table 7). The data from both years consistently show a daily pattern where most vehicles arrive during daytime hours, highlighting how parking demand aligns closely with daytime activity cycles.

Table 8: Hourly parking variations in 2021

Time	Parking vehicles count in 2021		
	Kollupitiya	Bambalapitiya	Wellawatta
00:00-01:00	3	2	0
01:00-02:00	1	0	1
02:00-03:00	1	0	0
03:00-04:00	0	0	0
04:00-05:00	1	1	0
05:00-06:00	5	5	0
06:00-07:00	50	49	1
07:00-08:00	264	220	18
08:00-09:00	827	324	17
09:00-10:00	1614	855	44
10:00-11:00	1709	1231	44
11:00-12:00	1736	1430	57
12:00-13:00	1628	1475	51
13:00-14:00	1363	1430	53
14:00-15:00	1553	1189	34
15:00-16:00	1570	1318	33
16:00-17:00	1262	1004	30
17:00-18:00	899	736	30
18:00-19:00	399	338	19
19:00-20:00	155	71	9
20:00-21:00	63	34	3
21:00-22:00	20	10	1
22:00-23:00	8	3	0
23:00-24:00	6	0	0
Total	**15137**	**11725**	**445**

4.2 Identify the location demand using crowdsourced data and Survey-based analysis

Empirical research consistently reveals an inverse relationship between on-street parking demand and vehicle speeds (Praburam & Koorey, 2015), a pattern attributed to increased cruising behaviour (Ma et al., 2017). While mobile applications offer precise real-time occupancy data (Bhalla et al., 2020), developing and implementing such technology extends beyond this study’s scope. Instead, this research focus on accessible methods to both estimate parking demand and redistribute vehicles from high- to low-occupancy zones, thereby improving turnover and revenue generation.

To establish a demand estimation framework, this study integrates 2 complementary datasets:

- Roadside parking occupancy surveys providing verified occupancy ratios,
- Real-time vehicle speed data using Google Distance Matrix API & Google Directions API, serve as a reliable indicator of parking demand in urban areas.

To test this assumption, a survey was conducted on a typical weekday. Vehicle speeds were monitored along 3 major sections of Galle Road and 3 sections of Duplication Road, connecting Kollupitiya and Bambalapitiya. Simultaneously, on-site surveys were carried out to manually count parked vehicles in these sections, capturing occupancy trends. Selected road sections were chosen for their land-use and recurring congestion, making them representative of broader urban parking challenges. By aligning speed data with physical occupancy ratios, the study sought to identify correlations between traffic slowdowns and parking density. For example, slower speeds during peak hours could indicate higher parking demand, while faster traffic might indicate low demand parking areas

This method approach leverages the established speed-occupancy correlation without requiring user-reported crowdsourced data. By synthesizing ground observations with speed metrics, this framework enables dynamic demand estimation while supporting redistribution strategies.

4.2.1 Travel Speed Distribution (Gathered Using Google APIs)

Travel speeds between Kollupitiya and Bambalapitiya (in Galle Road and Duplication Road) were analysed using Google Distance matrix API and Directions API. Galle Road was divided into 6 sections (3 Sections from Galle Road and 3 sections from Duplication Road) for this study, with speeds measured every 15 minutes during typical weekday hours (06:00 to 18:00).

The results revealed significant variations in vehicle speeds (km/h) across different road sections. Faster-moving sections are highlighted in green, while slower-moving sections marked in red as indicated in the Table 8.

For the correlation analysis, average vehicle speed was calculated over 30-minute intervals, and this 15 min interval-aggregated speed data was used to assess its relationship with parking occupancy. This color-coded visualization helps pinpoint where traffic flows smoothly versus where delays commonly occur.

Table 9: Calculated vehicle speeds (km/hr) at 15 min intervals

Time	Galle Road			Duplication Road		
	Section 1	Section 2	Section 3	Section 4	Section 5	Section 6
6:00 AM	43.37	41.89	39.74	37.33	40.23	40.08
6:15 AM	41.40	40.07	41.33	36.00	38.55	40.08
6:30 AM	38.76	40.07	41.33	33.60	40.23	37.58
6:45 AM	38.76	40.07	41.33	30.55	37.01	37.58
7:00 AM	37.95	38.40	39.74	30.55	37.01	35.36
7:15 AM	37.95	36.86	36.90	28.80	34.27	33.40
7:30 AM	35.72	32.91	34.44	23.44	29.85	32.21
7:45 AM	33.73	29.73	33.33	24.59	27.21	27.33
8:00 AM	29.38	23.04	17.22	23.44	28.04	29.09
8:15 AM	21.95	10.59	4.18	24.00	23.72	23.73
8:30 AM	7.44	5.36	7.28	22.91	25.70	26.92
8:45 AM	7.35	10.84	6.46	26.53	29.85	25.05
9:00 AM	8.67	4.45	4.70	27.55	28.91	27.75
9:15 AM	7.59	4.19	4.20	25.80	28.91	26.92
9:30 AM	8.89	6.31	6.15	23.44	29.85	25.05
9:45 AM	16.12	12.62	12.92	25.20	29.85	30.06
10:00 AM	25.30	21.43	16.14	24.00	28.04	28.63
10:15 AM	28.02	27.11	25.83	28.00	27.21	26.14
10:30 AM	29.38	26.33	28.70	25.20	27.21	26.52
10:45 AM	28.91	27.11	27.19	27.24	30.84	31.10
11:00 AM	30.36	25.60	27.92	27.24	28.04	26.92
11:15 AM	21.95	27.11	30.39	24.00	26.43	27.33
11:30 AM	28.46	27.11	27.92	24.59	28.91	26.14
11:45 AM	28.46	24.91	28.70	21.91	25.01	23.42
12:00 PM	28.46	26.33	28.70	20.38	26.43	25.40
12:15 PM	28.46	24.91	26.49	22.91	27.21	24.71
12:30 PM	28.02	25.60	27.19	26.53	25.01	22.00
12:45 PM	20.70	24.91	21.13	20.76	25.01	18.40
1:00 PM	28.91	26.33	27.19	23.44	27.21	20.50

1:15 PM	28.02	26.33	27.92	25.85	29.85	28.18
1:30 PM	28.91	27.93	28.70	23.44	28.91	27.75
1:45 PM	28.91	26.33	27.92	22.91	28.04	26.92
2:00 PM	28.91	27.93	27.92	24.59	28.04	25.77
2:15 PM	29.38	27.11	27.92	25.85	28.91	25.77
2:30 PM	28.02	25.60	29.52	26.53	29.85	29.09
2:45 PM	30.36	28.80	29.52	25.20	29.85	26.92
3:00 PM	30.87	30.72	31.31	27.24	28.91	23.73
3:15 PM	31.41	30.72	30.39	28.80	29.85	27.33
3:30 PM	31.41	28.80	32.29	27.24	28.91	26.52
3:45 PM	31.96	29.73	31.31	25.20	26.43	22.00
4:00 PM	28.46	30.72	33.33	24.59	25.04	23.14
4:15 PM	27.60	28.80	32.29	21.59	22.21	22.52
4:30 PM	26.79	28.80	31.31	17.89	21.91	20.77
4:45 PM	27.60	27.11	26.49	16.56	18.21	17.27
5:00 PM	24.02	23.33	25.83	15.67	17.13	15.04
5:15 PM	20.29	21.25	19.87	12.60	15.68	7.64
5:30 PM	19.69	20.33	20.20	10.14	6.25	7.74
5:45 PM	23.79	20.95	24.92	14.20	13.61	9.49
6:00 PM	26.79	27.93	30.39	19.35	21.35	11.34
6:15 PM	27.60	29.73	29.52	23.44	25.84	24.37
6:30 PM	28.91	27.93	31.31	26.53	28.91	31.10
6:45 PM	29.86	28.80	30.39	27.24	29.85	32.21
7:00 PM	28.02	27.93	28.70	28.00	29.85	30.06

4.2.2 Survey-based analysis of parked vehicles and parking space availability

To maintain methodological consistency, same 6 sections along Galle Road and Duplication Road were selected for parking occupancy survey. The methodological framework applied to these sections is equally applicable to the broader stretch of Galle Road between Kollupitiya and Wellawatta, which shares comparable traffic and land-use characteristics.

Table 10: Total number of parking spaces in the selected sections

Road	Section	Total no. of Parking slots
Galle Road	1	77
	2	30
	3	33
Duplication Road	4	28
	5	15
	6	44

The data collected on parking space availability, gathered through field surveys, is organized in Table 10 below. This table shows how parking availability changes over time (such as busy hours versus quiet hours) and compares different areas within the study area, providing a clear view of patterns across locations.

Table 11: Occupied parking spaces

Time	Galle Road			Duplication Road		
	Section 1	Section 2	Section 3	Section 4	Section 5	Section 6
6:00 AM	13	6	7	6	3	7
6:30 AM	15	9	13	9	3	9
8:00 AM	24	18	14	14	5	15
7:30 AM	37	22	20	20	8	21
8:00 AM	55	19	31	21	11	30
8:30 AM	72	28	32	21	11	34
9:00 AM	75	29	33	22	12	32
9:30 AM	68	27	31	19	12	31
10:00 AM	67	27	32	18	11	29
10:30 AM	63	26	30	18	9	34
11:00 AM	61	22	29	22	11	31
11:30 AM	58	21	29	19	11	34
12:00 PM	61	20	26	21	12	34
12:30 PM	62	21	24	21	11	30
1:00 PM	62	22	25	22	10	33
1:30 PM	63	23	23	19	11	36
2:00 PM	57	20	24	21	12	31
2:30 PM	60	24	27	19	11	35
3:00 PM	57	20	24	22	9	32
3:30 PM	56	22	21	21	11	35
4:00 PM	56	20	23	25	11	36
4:30 PM	51	22	22	26	13	37
5:00 PM	46	21	22	27	14	41
5:30 PM	44	18	20	24	13	36
6:00 PM	40	21	12	22	11	21
6:30 PM	37	20	14	14	8	20
7:00 PM	30	12	11	15	6	16
Total	1390	560	619	528	270	780

Parking occupancy ratios were calculated by dividing the observed number of occupied parking spaces by the total available parking inventory within each surveyed section. This metric, expressed as a decimal value between 0 and 1, quantifies spatial utilization patterns (as an example, a ratio of 0.75 indicates 75% occupancy). This helps to identify sections and times where parking spaces are either underused or overcrowded.

Table 12: Parking occupancy ration

Time	Galle Road			Duplication Road		
	Section 1	Section 2	Section 3	Section 4	Section 5	Section 6
6:00 AM	0.17	0.20	0.21	0.21	0.20	0.16
6:30 AM	0.19	0.30	0.39	0.32	0.20	0.20
7:00 AM	0.31	0.60	0.42	0.50	0.33	0.34
7:30 AM	0.48	0.73	0.61	0.71	0.53	0.48
8:00 AM	0.71	0.63	0.94	0.75	0.73	0.68
8:30 AM	0.94	0.93	0.97	0.75	0.73	0.77
9:00 AM	0.97	0.97	1.00	0.79	0.80	0.73
9:30 AM	0.88	0.90	0.94	0.68	0.80	0.70
10:00 AM	0.87	0.90	0.97	0.64	0.73	0.66
10:30 AM	0.82	0.87	0.91	0.64	0.60	0.77
11:00 AM	0.79	0.73	0.88	0.79	0.73	0.70
11:30 AM	0.75	0.70	0.88	0.68	0.73	0.77
12:00 PM	0.79	0.67	0.79	0.75	0.80	0.77
12:30 PM	0.81	0.70	0.73	0.75	0.73	0.68
1:00 PM	0.81	0.73	0.76	0.79	0.67	0.75
1:30 PM	0.82	0.77	0.70	0.68	0.73	0.82
2:00 PM	0.74	0.67	0.73	0.75	0.80	0.70
2:30 PM	0.78	0.80	0.82	0.68	0.73	0.80
3:00 PM	0.74	0.67	0.73	0.79	0.60	0.73
3:30 PM	0.73	0.73	0.64	0.75	0.73	0.80
4:00 PM	0.73	0.67	0.70	0.89	0.73	0.82
4:30 PM	0.66	0.73	0.67	0.93	0.87	0.84
5:00 PM	0.60	0.70	0.67	0.96	0.93	0.93
5:30 PM	0.57	0.60	0.61	0.86	0.87	0.82
6:00 PM	0.52	0.70	0.36	0.79	0.73	0.48
6:30 PM	0.48	0.67	0.42	0.50	0.53	0.45
7:00 PM	0.39	0.40	0.33	0.54	0.40	0.36

4.3 Correlation analysis of parking occupancy and vehicle speed dynamics

The relationship between vehicle speeds and parking occupancy was analysed using the Pearson correlation coefficient, calculated via the 'CORREL' function. This measures the strength and direction of linear relation between variables. The resulting coefficient quantifies how closely changes in parking occupancy align with fluctuations in vehicle speeds.

The equation for the correlation coefficient is,

$$\mathrm{Correl}(X, Y) = \frac{\Sigma[(x - \bar{x})(y - \bar{y})]}{\sqrt{[\Sigma(x - \bar{x})^2 * \Sigma(y - \bar{y})^2]}}$$

where $\bar{x}$ and $\bar{y}$ are the sample means AVERAGE (occupancy of the section) and AVERAGE (speed of the section).

The calculated correlation coefficients for the time interval of 06:00 AM to 07:00 PM are presented in Table. This table quantifies the statistical relationship between vehicle speeds and parking occupancy during the specified timeframe, providing a basis for evaluating the assumption that speed data reflects localized parking demand.

Table 13: Correlation coefficients in the selected sections

Section 1	Section 2	Section 3	Section 4	Section 5	Section 6
-0.70455	-0.71156	-0.72048	-0.82005	-0.78734	-0.70913

The negative values shows that higher parking occupancy correlates with lower vehicle speeds and crowded parking zones contribute to traffic congestion. These traffic congestions are most likely caused by factors such as obstructing traffic flow (double-parking), frequent stops as drivers look for available parking spaces, and reduced road capacity from parked vehicles narrowing lanes.

Analysis of these data revealed distinct variations in correlation strength,

- Sections 1, 2, and 3 showed a notable link between these factors, suggesting that higher parking density in these areas directly contributes to slower traffic.
- Sections 4, 5, and 6, located along Duplication Road, also displayed a strong correlation.

The observed negative correlation between parking occupancy and vehicle speeds suggests an inverse relationship, where higher vehicle speeds correspond to reduced parking demand in the analysed sections.

4.4 Parking pricing Structure

The following worked examples illustrate the operation of the two-stage catchment and stepwise discounting rule under realistic corridor conditions. Prices are computed as $P = P_o (1 - D)$, where $D = I_{def} \times I_W \times I_A \times R_{occ}(O)$. The discount tier is determined solely by occupancy via $R_{occ}(O)$, taking values according to the occupancy tiers. Eligibility is governed by the walking and access indicators $I_W = 1$ ($W_{min} < W \leq W_{max}$), $I_A = 1(A \leq A_{max})$, with thresholds. Distances are measured on network-consistent graphs: W on the pedestrian network from the candidate bay to the destination, and A on the directed road network between legal roadside access points, thereby capturing one-way and side-of-road loops. The cases span adjacent/partner redirections with $W \leq W_{min}$ (no discount), discount-eligible alternatives within the stated boundary conditions, and ineligible instances where the limits are exceeded. To reflect the geometry of the study corridor, and prices are reported after applying the discount.

4.4.1 Example calculations for dynamic parking pricing and redistribution

Definitions:

- P_0: base parking price.
- O: occupancy of the candidate subsection.
- W (meters): walking distance from the candidate bay to the driver's destination (computed on the pedestrian network).
- A (meters): extra vehicle distance from the preferred location's legal roadside access to the user's legal access (computed on the directed road network so that side-of-road and upstream loop detours are captured)
- Walking cut-offs: W_{min}=300m and W_{max}=600m
- Access limit: A_{max}=800m
- I_{def} = Deflection indicator
- I_W= Walking distance-eligibility indicator
- I_A= extra vehicle distance-eligibility indicator
- Discount tiers (policy variables): d_{50}=0.50 & d_{25}=0.25

1) Adjacent/partner band (short walk) → full price

- Inputs: $W=180$ m ≤ 300 m; $A=320$ m; $O=0.20$
- Status: adjacent band (no discount by policy).
- Result: $D=0$
- $P=$Rs. 70.

2) Alternative eligible, low occupancy → 50% off

- Inputs: $W = 340$ m; $A = 420$ m; $O = 0.20$.
- $300 < W \leq 600$ and $A \leq 800 \Rightarrow$ eligible.
- Discount: $R_{occ}(O)=0.50 \Rightarrow D = 0.5$
- Result: $P=70(1-0.50) =$ Rs. 35.

3) Alternative eligible, moderate occupancy → 25% off

- Inputs: $W=520$ m; $A=700$ m; $O=0.40$.
- Discount: $R_{occ}(O)=0.25 \Rightarrow D=0.25$.
- Result: $P=70(1-0.25) =$Rs. 52.50.

4) Alternative eligible, high occupancy → 0% off

- Inputs: $W=360$ m; $A=480$ m; $O=0.62$.
- Discount: $R_{occ}(O)=0 \Rightarrow D=0$
- Result: $P=$Rs. 70 (proposable, but no discount).

5) Boundary (walking upper limit) → eligible, 25% off

- Inputs: $W=600$ m; $A=600$ m; $O=0.30$.
- $W=600$ m is eligible (upper bound inclusive); $A \leq 800$.
- Discount: $R_{occ}(O)=0.25 \Rightarrow D=0.25$
- Result: $P=$Rs. 52.50.

6) Not proposed: exceeds walking limit (but still $W \leq A$)

- Inputs: $W=610$ m; $A=700$ m; $O=0.18$.
- $W>600$ m $\Rightarrow$ ineligible.
- Result: not proposed (the app never suggests beyond the maximum walking distance).

7) Not proposed: exceeds access limit (but still W ≤ A)

- Inputs: W=560 m; A=1 km; O=0.18.
- A>800 m ⇒ ineligible (not proposed (the app never suggests beyond A_{max}).

8) Adjacent boundary (walking lower limit) → full price

- Inputs: W=300 m; A=320 m; O=0.24.
- W=300 m is treated as adjacent/partner band (no discount).
- Result: D=0,
- P = Rs. 70

These worked examples shows that the proposed structure behaves consistently across the full range of operational conditions. Prices vary with occupancy tiers while walking and access distances function solely as eligibility constraints, with boundary cases adhering to the stated conventions and infeasible candidates excluded by design. This will the helps that directing turn away drivers to nearby low-occupancy, legal parking areas fills vacant spaces and converts lost parking attempts into paid stays, thereby supporting both utilisation and revenue objectives without compromising policy constraints.

4.4.2 Revenue analysis

The proposed guidance and pricing process is designed to increase total daily revenue by using the collected occupancy data. This section provides a clear, step-by-step explanation of the calculations involved, ensuring the method can be easily understood and implemented. Daily baseline revenue is computed from collected data by multiplying occupied spaces by the applicable fee in each interval and summing across sections and time. Capacity-constrained intervals (at or near 100% occupancy) are then identified to infer lost demand (need to take assumptions for the initial stage). For these same intervals, under-utilised nearby sections are recorded to determine available capacity. Redirectable demand is estimated as the minimum of the assumed overflow from the full section and the empty bays in alternative sections. Additional revenue under guidance can be obtained by applying the relevant fee and expected stay to these redirected vehicles and aggregating over intervals through the mobile app.

a. Baseline computation (current practice)

For each 30-minute interval, multiply the actual number of parked vehicles in each subsection by the half-hour price and sum across all subsections and intervals. This shows baseline daily revenue (fixed price, no guidance, no redirection).

Table 14: Analysis of hourly fixed rate in Galle Road Sections

Time	Section 1		Section 2		Section 3	
	Occupied Spaces	Revenue With fixed rate of 70 (Rs)	Occupied Spaces	Revenue With fixed rate of 70 (Rs)	Occupied Spaces	Revenue With fixed rate of 70 (Rs)
6:00	13	455	6	210	7	245
6:30	15	525	9	315	13	455
7:00	24	840	18	630	14	490
7:30	37	1295	22	770	20	700
8:00	55	1925	19	665	31	1085
8:30	72	2520	28	980	32	1120
9:00	75	2625	29	1015	33	1155
9:30	68	2380	27	945	31	1085
10:00	67	2345	27	945	32	1120
10:30	63	2205	26	910	30	1050
11:00	61	2135	22	770	29	1015
11:30	58	2030	21	735	29	1015
12:00	61	2135	20	700	26	910
12:30	62	2170	21	735	24	840
13:00	62	2170	22	770	25	875
13:30	63	2205	23	805	23	805
14:00	57	1995	20	700	24	840
14:30	60	2100	24	840	27	945
15:00	57	1995	20	700	24	840
15:30	56	1960	22	770	21	735
16:00	56	1960	20	700	23	805
16:30	51	1785	22	770	22	770
17:00	46	1610	21	735	22	770
17:30	44	1540	18	630	20	700
18:00	40	1400	21	735	12	420
18:30	37	1295	20	700	14	490
19:00	30	1050	12	420	11	385
	1390	48650	560	19600	619	21665

Table 14 shows the revenue generated from the first three selected sections along Galle Road, analysing the outcomes of the fixed hourly fee of 70 rupees. This analysis highlights how revenue changes when parking fees are adjusted based on occupancy.

Table 15: Analysis of hourly fixed in Duplication Road Sections

Time	Section 4		Section 5		Section 6	
	Occupied Spaces	Revenue With fixed rate of 70 (Rs)	Occupied Spaces	Revenue With fixed rate of 70 (Rs)	Occupied Spaces	Revenue With fixed rate of 70 (Rs)
6:00	6	210	3	105	7	245
6:30	9	315	3	105	9	315
7:00	14	490	5	175	15	525
7:30	20	700	8	280	21	735
8:00	21	735	11	385	30	1050
8:30	21	735	11	385	34	1190
9:00	22	770	12	420	32	1120
9:30	19	665	12	420	31	1085
10:00	18	630	11	385	29	1015
10:30	18	630	9	315	34	1190
11:00	22	770	11	385	31	1085
11:30	19	665	11	385	34	1190
12:00	21	735	12	420	34	1190
12:30	21	735	11	385	30	1050
13:00	22	770	10	350	33	1155
13:30	19	665	11	385	36	1260
14:00	21	735	12	420	31	1085
14:30	23	805	11	385	35	1225
15:00	22	770	9	315	32	1120
15:30	21	735	11	385	35	1225
16:00	25	875	11	385	36	1260
16:30	26	910	13	455	37	1295
17:00	27	945	14	490	41	1435
17:30	24	840	13	455	36	1260
18:00	22	770	11	385	21	735
18:30	14	490	8	280	20	700
19:00	15	525	6	210	16	560
	532	18620	270	9450	780	27300

Table 15 shows the total revenue for the 3 sections located on Duplication Road. These tables provide a clear overview of how pricing performs in different urban contexts and time periods.

b. Identifying lost demand

Setup - Consider one saturated subsection on Galle Road and one low/moderate-occupancy subsection on Duplication Road during 2 consecutive 30-minute windows (e.g., 09:30–10:30). Because the source is full, a portion of arrivals are turned away in each window. Without guidance, these drivers generate zero revenue (they leave or park illegally). With guidance, they are redirected to the receiver subsection and become paid stays.

c. Redistribution procedure

For each full interval:

- Fill adjacent first (no discount): Count the free bays across the adjacent/partner subsections (two ahead, one behind, and the parallel corridor). Place as many turned-away and illegal parking drivers as possible into these free bays at full price and this protects revenue.
- Fill farther next (with discount): If turned-away or illegal parking drivers remain after adjacent placements, assign them to farther subsections that still have free bays. Apply the occupancy-based discount (25% or 50% for moderate or low occupancy respectively). The final price for these redirected parkers reflects demand level yet remains positive revenue that otherwise would have been lost.

d. Worked Example - 9:30 -10.30 AM (Section 3 ↔ Section 4)

Figure 11 : Selected area for the example (Section 3 & 4)

- Section 3 (capacity 33, occupied 31 → 94%) (free slots = 2)

  Assumption –
    - Sub section 1 (Capacity 10)
    - Sub section 2 (Capacity 13)
    - Sub section 3 (Capacity 10)
- Section 4 (3 Sub sections): capacity 28, occupied 19 → 68% (free slots = 9)

  Assumption –
    - Sub section 1 (Capacity 10)
    - Sub section 2 (Capacity 10)
    - Sub section 3 (Capacity 8)

- Assumption - Illegal or give up drivers: 11 drivers (Section 4 has 9 free slots and 3 has 2)
- Price: Rs. 70/hour → Rs. 35 per 30 min.

The figure shows a direct cross-connection between Section 3 and Section 4 (e.g., via Deal Place) of approximately 350 m. The adjacent threshold is defined as three average subsections (300 m); any section within this distance is treated as adjacent and receives no discount. Section 4 lies within the adjacent catchment of Section 3 for this location and time. Therefore, redirecting Section 3 overflow to Section 4 at 9:30 AM is classified as an adjacent placement and is charged the full price (no discount).

Section 4 has 9 free bays, if assume that this process can absorb all 9 turned-away drivers from Section.

- Because Section 4 is adjacent/partner, these drivers pay full price.
- Added revenue (uplift) in this 30-min interval: 9 drivers × Rs. 35 = Rs. 315
- The total revenue uplift hour ≈ Rs. 630

Section 3 has 2 free bays, if assume that this process can absorb all 2 turned-away drivers from desired Subsection.

- Because Section 3 is adjacent, these drivers pay full price.
- Added revenue (uplift) in this 30-min interval: 2 drivers × Rs. 35 = Rs. 70
- The total revenue uplift hour ≈ Rs. 140

If assume another alternate subsection (W=520 m; A=700 m) has 6 free bays (capacity 10), if assume that this process can absorb all 6 turned-away drivers from desired Subsection

- In the alternate Section, these drivers pay with a discount (Rs. 52.50 per hr)
- Added revenue in this 30-min interval: 6 drivers × Rs. 26.25 = Rs. 157.5
- The total revenue uplift hour ≈ Rs. 315

  - Under practical conditions, redistributing at least 30% (≈5 drivers) turned-away drivers to available sections would yield up to Rs. 350 in additional revenue for that interval in this 9.30-10.30 interval, assuming the base hourly fee is Rs. 70 per vehicle.

5. DISCUSSION

The following discussion examines the key findings from the analysis of Galle Road parking data, highlighting how temporal and spatial demand patterns inform a practical, redistribution strategy and demand-based dynamic pricing.

5.1 Analysis of historical parking data (Colombo Municipal Council data)

The data show clear spatial and temporal patterns in on street parking. When the Galle Road corridor was and examined, certain sections consistently exhibited higher vehicle counts, reflecting concentrated demand in busy areas. The analysis revealed distinct daily patterns in parking demand. Weekdays maintained consistently high occupancy levels during standard business hours, while weekends displayed alternative peak periods reflecting variations in local land use. Parking demand demonstrated significant hourly fluctuations. These surges coincided with high traffic volumes and commercial activity. This analysis of historical CMC data showed that parking demand was not distributed evenly. Instead, it gathered in certain areas, peaked during busy hours, and changed between weekdays and weekends. This pattern confirms that demand varies by time and location, which should be considered in parking management plans.

5.1.1 Parking durations and payment locations

Parking facility usage data revealed that light vehicles particularly private cars (33.0%), followed by three-wheelers (28,7%) and motorcycles (27.6%) accounted for the predominant share of parking demand, prompting this study's specific focus on light vehicle parking patterns.

The distribution of parking durations reinforces these patterns. The analysis showed an average parking duration of 1.3 hours during daytime periods, with individual stays varying substantially from brief 15-minute visits to extended stays exceeding 12 hours. A significant majority (80%) of vehicles remained parked for less than 3.5 hours in high-demand commercial zones.

Analysis of 2020–2021 Colombo Municipal Council (CMC) parking payment records identified Galle Road as the primary transaction corridor, with particularly high activity between Kollupitiya and Wellawatta. Within this section, Kollupitiya recorded the highest concentration (55% in 2020 and 58% in 2021) of parking payments, indicating its status as the zone of peak parking demand (Fig. 6 & 7). In other words, the busiest zones not only held the most vehicles at any moment but also accounted for most fee revenue. Higher parking usage of a few parking zones highlights the uneven spatial distribution of demand. These findings align with the zone-based analysis in the IPMS study, which also identified "demand, rush hours, and day variations" by zone on Galle Road. This area was selected as the suitable location for field surveys due to its demonstrated concentration of parking activity, as evidenced by the CMC payment records.

5.1.2 Day-to-day and hourly variations

Consistent with on-street parking studies elsewhere, Analysis of vehicle arrival patterns revealed distinct weekly variations. In 2020, arrival rates peaked on Mondays and Wednesdays relative to other weekdays, while Sundays consistently recorded the lowest volumes - a pattern consistent with typical weekend reductions in commercial and commuting activity. By 2021, this distribution had shifted, with Mondays showing the highest arrival rates, closely followed by Tuesdays and Wednesdays. Notably, Sundays maintained their position as the day of lowest traffic volume throughout both observation years, reinforcing the persistence of weekend mobility patterns despite the intervening year's changes in weekday arrival distributions

Analysis of 2021 parking payment data revealed distinct temporal patterns across locations. Kollupitiya experienced peak arrival activity during late morning hours (9:00 AM - 1:00 PM), while Bambalapitiya and Wellawatta both showed comparable peak demand cantered around midday (11:00 AM - 2:00 PM). These time-based patterns match results from other areas and the IPMS analysis, which also show clear rush hour peaks and daily parking trends.

5.2 Location demand via vehicle speeds and surveys

5.2.1 Travel speed distribution (initial demand measure)

Developing a mobile application falls outside this study's scope. This research concentrates on practical methods for estimating parking demand and redirecting vehicles from high- to low-occupancy zones to enhance space turnover and revenue potential. To complement static parking data, average vehicle speeds along the corridor served as demand indicators. Reduced mean speeds signalled potential congestion and higher parking utilization in adjacent zones. Empirically, sections with lower speeds that derived from Google distance matrix APIs (Kumarage et al., 2017), correlated strongly with observed parking occupancy peaks. This approach is supported by prior work linking traffic speed and parking occupancy: for example, (Ma et al., 2017) found that during peak commute periods, average vehicle speed and parking occupancy exhibit distinct, correlated patterns. In other words, reduced speeds generally aligned with higher parking demand. Thus, our speed data helped flag the high-demand zones in the initial analysis.

Vehicle speed data was collected at 15-minute intervals (06:00–19:00) for corridor sections using the Google Distance Matrix API. This 13-hour sampling window captured representative weekday speed variations to analyse parking demand dynamics. Speed data analysis demonstrated significantly reduced vehicle speeds along three Galle Road sections between 08:30–10:30. This aligns with our hypothesis that slower speeds indicate higher parking demand, which physical occupancy surveys confirmed. Conversely, Duplication Road sections showed higher speeds during this period, shows lower parking utilization. Correlation analysis revealed a strong negative relationship between speed and parking occupancy in these zones, validating spatial demand patterns.

5.2.2 Parking occupancy (physical survey)

A physical occupancy survey of parked vehicles confirmed the above findings from speed data that collected through Google Distance matrix APIs. Parking occupancy data was collected via the moving vehicle method at 30-minute intervals, recording both occupied spaces and total available spaces. Colombo Municipal

Council (CMC) records supplemented this to analyse parking capacity changes from 2020 to present. The parking ratio (total spaces divided by occupied spaces) was calculated, revealing temporal patterns consistent with vehicle speed data. This correlation empirically validates the use of traffic speed as a proxy indicator for parking demand intensity.

Analysis revealed a persistent spatial imbalance in parking utilization, with peak occupancy approaching full capacity during 9:30 to 10:30 in high-demand sections like Galle Road (all 3 sections), while adjacent zones maintained significant vacant sparking spaces in Duplication Road. This pronounced disparity between high demand and low demand areas indicates supply-demand mismatches across the Galle Road corridor and duplication road.

5.3 Correlation analysis

Correlation analysis empirically validated expected relationships between key variables. In both the Galle Road sections 1, 2, & 3 and the adjacent Duplication Road sections 4, 5 & 6, the analysis revealed a clear inverse relationship between parking occupancy and traffic speed, where higher parking density aligns with slower vehicle speeds, and conversely, faster speeds indicate lower parking demand.

The observed speed-occupancy relationship during rush hours mirrors (Ma et al., 2017) macroscopic framework, which positions vehicle speeds as a key indicator for parking pressure that a finding with direct implications for dynamic pricing and demand-redistribution strategies. Likewise, parking durations and turnover correlated with parking spaces in high-demand areas had shorter average stays (under 3.5 hours) than low demand sections.

Overall, the statistical correlation analysis results confirms that the busiest road sections (highest counts and slowest speeds) are systematically distinct from low-demand areas. These quantitative relationships substantiate dynamic pricing strategies, as occupancy rates directly indicate demand intensity. Adjusting prices in response to real-time occupancy can effectively shape parking usage patterns by incentivizing behavioural shifts toward low demand underutilized parking sections.

5.4 Parking pricing strategy

To improve parking distribution, a dynamic parking pricing strategy was developed. This approach reducing parking price with discounts in underused areas. The goal is to maintain optimal occupancy levels that balance efficient space use with driver accessibility. Empirical evidence from San Francisco's SFpark project demonstrates this method's effectiveness, where variable pricing sustained 60-80% occupancy and significantly enhanced turnover rates (Krishnamurthy & Ngo, 2019).

Without guidance, a driver who cannot find a space in the preferred lot either leaves or parks illegally, generating no revenue. With guidance, these drivers are redirected to vacant legal bays, converting lost demand into paid stays and creating incentives that balance parking distribution. The developed parking pricing equation [$P = Po (1 - D)$] generates dynamic pricing and baseline revenue was calculated from collected occupancy data by multiplying occupied bays by the fee for each interval and summing across sections and time. Intervals at or near full capacity were marked to show lost demand. In the example calculation, Section 3 was almost fully occupied, and the adjacent Section 4 had available bays. The number of turned-away drivers was assumed to equal the number of free spaces; that is, all vacant bays could be filled by redirected drivers.

Extra revenue under guidance was calculated by applying the fee to the redirected vehicles and summing across interval. Baseline revenue represents income earned without guidance; it remains unchanged, because turned-away drivers generate zero revenue. When those drivers are redirected to low-occupancy sections, additional paid parking sessions are created. The total revenue in each interval therefore becomes the baseline revenue + extra revenue from redirected drivers. The extra revenue equals the applicable fee (full rate for adjacent sections, or a discounted rate beyond the catchment) multiplied by the number of redirected drivers and their paid duration. Because this term is strictly positive whenever at least one turned-away driver is accommodated, total revenue is weakly higher and usually strictly higher than the baseline. Hence, under the stated structure (no discount for adjacent placement; discounts only for farther, low-occupancy sections), the guidance and pricing strategy increases revenue while utilising spaces that would otherwise remain empty

Faced with these real-time price differentials, drivers originally targeting Galle Road are likely to reconsider and option for the more affordable parking spaces. As more drivers make this shift, occupancy rates in Duplication Road increase and revenue from that corridor rises, while pressure on Galle Road eases. Over time, such demand-responsive pricing produces a self-adjusting equilibrium, redistributing vehicles from peak to off-peak zones and achieving a more uniform utilization of parking resources. These outcomes demonstrate that demand based dynamic pricing significantly enhances revenue generation while maintaining alignment with real-time demand fluctuations.

5.5 Mobile application integration and vehicle redistribution

To enhance the long-term effectiveness of the proposed parking management strategy, it is essential to consider future integration with a user-friendly mobile application. While the initial phase relies on vehicle speed as a proxy for parking demand, the mobile application will eventually serve as a direct platform for users to report parking occupancy in real time. In the real-world scenario, a mobile application itself will provide real-time demand information, each user's parking session (check-in and check-out) will instantly report occupancy with the use of QR code. For example, our proposed application assigns a unique code (Road–Section ID–Sub ID–Slot No-Side) to every roadside parking slot. This functionality enables users to precisely locate specific parking spaces within facilities, significantly reducing search time and navigation challenges. When a driver parks and checks in, that slot is marked 'Unavailable' in the system, upon payment and exit it becomes 'Available'. Users can use the application to see available spaces and current parking prices in any parking section. If the nearest parking section of driver's desired location is full, the application can suggest adjacent parking areas. If those adjacent sections also unavailable app will suggest far away parking sections with discounts. In other words, the application not only shows dynamic prices based on zone demand, but also actively guides users to less crowded parking. All of this is consistent with the integrated approach envisioned by (Dissanayake & Bandara, 2024), where a mobile platform displays availability and pricing to distribute vehicles more evenly. By With guidance, the drivers are redirected to vacant legal parking spaces, converting lost demand into paid stays and creating incentives that balance parking distribution.

In summary, combining dynamic pricing with navigation support should rebalance the parking network. While low demand parking zones become more attractive due to lower price and application guidance. This dynamic feedback helps redirect drivers to vacant legal spaces, converting lost demand into paid stays and balancing parking distribution. Additionally, the result is reduced parking search and congestion in busy zones, a more even utilization of roadside parking, and increased convenience for drivers who follow application recommendations. Such a demand-responsive system thus facilitates the desired redistribution from to low-demand parking locations. Dynamic parking fee implementation through this mobile application, leverages users' willingness to pay full base fee during high-demand periods, converting parking scarcity into increased revenue. Conversely, discounts during low-occupancy intervals attract drivers and reduce illegal parking. By aligning prices with temporal demand fluctuations and this strategy simultaneously optimizes revenue from idle capacity and reduces traffic congestion caused by parking search behaviour. This integration of parking management strategy reinforces the dynamic and adaptive nature of the proposed system, making it a scalable and sustainable solution for urban parking challenges.

6. CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

This study concludes by showing that a demand-based intelligent parking management system can efficiently locate high demand roadside parking locations and guide demand based dynamic parking pricing strategies. The system is initially based on vehicle speed proxies and is complemented by physical surveys. The proposed pricing structure provides guidance that redirects drivers to vacant legal spaces, converting lost demand into paid stays and balancing parking distribution. In the future, adding a user-centred mobile application will improve demand estimates, let people navigate to available adjacent parking locations in real time, and create a feedback loop that changes with the times. This framework provides a useful road map for urban planners and transportation authorities looking to maximise roadside parking, enhance traffic flow, and promote sustainable city mobility by fusing data-driven insights with adaptable, scalable technological solutions.

6.2 Recommendations

Future implementations should prioritize mobile application development as the platform for real-time demand monitoring and user engagement. A well-designed smartphone app would enable drivers to seamlessly check in/out of parking spaces using QR codes, instantly updating occupancy data and feeding this information to the dynamic parking pricing system. To encourage widespread adoption, the interface should display intuitive maps showing real-time parking space availability and adjacent parking locations and alternative parking spaces with discounts when preferred spaces are occupied. Push notifications and embedded tutorials would further guide users through reservation and payment processes, boosting participation rates and data accuracy.

Successful implementation will require active collaboration between application developers, transportation authorities, and local businesses ensuring smooth integration with city infrastructure, policy alignment, and equitable benefit sharing. Implementing a mobile application will streamline the parking management framework, significantly improving responsiveness, data accuracy, user experience, and scalability. These enhancements will drive measurable gains in operational efficiency while increasing satisfaction for both drivers and municipal planners.

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APPENDIX I - PYTHON CODE FOR TRAVEL TIME ESTIMATION

```python
import requests
import time
import datetime


def get_coordinates(num_points):
    coordinates = []
    for i in range(num_points):
        coord_input = input(f"Enter latitude and longitude for point {chr(65 + i)} (format: lat,lon): ")
        lat, lon = coord_input.split(',')
        coordinates.append((lat.strip(), lon.strip()))
    return coordinates


def get_travel_time(api_key, origin, destination):
    url = ("https://maps.googleapis.com/maps/api/directions/json"
           "?origin={}&destination={}&mode=driving&departure_time=now&key={}".format(origin, destination, api_key))
    response = requests.get(url)
    if response.status_code == 200:
        data = response.json()
        if data['status'] == 'OK':
            total_seconds = 0
            for leg in data['routes'][0]['legs']:
                total_seconds += leg['duration_in_traffic']['value']
            return total_seconds
    return "N/A"


def main():
    num_points = int(input("How many points do you have? "))
    coordinates = get_coordinates(num_points)

    api_key = input("Please paste your Google Directions API key: ")

    time_period = int(input("Enter the time period for data collection in minutes: "))
    num_iterations = int(input("How many times should the data be collected? "))

    for _ in range(num_iterations):
        with open("travel_times.csv", "a") as file:
            for i in range(len(coordinates) - 1):
                origin = ','.join(coordinates[i])
                destination = ','.join(coordinates[i + 1])
                travel_time = get_travel_time(api_key, origin, destination)
                timestamp = datetime.datetime.now().strftime("%Y-%m-%d %H:%M:%S")
                file.write(f"{timestamp},{chr(65 + i)}-{chr(66 + i)},{travel_time}\n")

        print(f"Data recorded at {timestamp}. Next update in {time_period} minutes.")
        time.sleep(time_period * 60)

    print("Data collection completed.")


if __name__ == "__main__":
    main()
```