A Universal Model for Forecasting Customer Service Revenue: A Paid Parking Service Example

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Abstract—**This article presents a method for forecasting revenue from a paid parking customer service, designed for conditions with limited statistical information and constant external conditions. The proposed approach is based on step-by-step modeling: first, the total number of active users is estimated, then the number of customers in a specific time interval is forecast, and then the revenue volume is determined based on established regression relationships. The final forecast is adjusted for seasonal factors, allowing for the reproduction of typical demand fluctuations. Unlike most existing models that use complex machine learning algorithms, this method retains interpretability and can be applied to other customer services at the initial stage of development, when deep data history is not yet available. Common metrics (MAE, MAPE, RMSE, R²) were used to assess forecast accuracy, confirming a high degree of correspondence between the estimates and actual values. The results of the study can be used by parking service operators and city governments in budget planning, revenue forecasting, and the formation of a long-term strategy for transport infrastructure development. A promising direction for further research is to expand the model to account for tariff dynamics, regulatory changes, and the integration of customer behavioral factors.**

Keywords—**Active customer base, interpretable models, paid parking service, revenue forecasting.**

I. Introduction

The issue of parking space allocation and management is a key area of research in intelligent transportation and AI. In recent years, with the dramatic increase in the number of cars and the introduction of paid parking in cities through centralized customer services, the challenge of effective parking management has become acute.

Efficient parking management requires analyzing vast amounts of data and applying algorithms to optimize parking space utilization and, most importantly, forecasting revenue from the Service for both the company's internal budget and the city/regional budget. In the latter case, the challenge is related to the complexity of "defending" and explaining the forecasting methodology to regulatory authorities.

II. Literature Review

Forecasting revenue from customer services is a rapidly developing area of econometrics and applied analytics. Current research covers a wide range of services, including subscription platforms, telecommunications services, and more. Barsotti et al. [1] conducted a systematic review of churn and customer lifetime value (CLV) forecasting methods in the telecommunications sector, demonstrating that cohort approaches and hybrid models (a combination of statistics and machine learning) provide more stable and accurate revenue forecasts. Mena et al. [2] demonstrated that using RFM metrics as time series and processing them with recurrent neural networks allows for accurate prediction of user activity and, indirectly, associated financial flows. Similar approaches are applicable to customer-facing parking services, where transactions are regular and cohort-based. However, all these studies rely on long data series, making them of limited applicability to new services in the early stages of launch, where such data is not yet available in sufficient quantities. In the transportation and parking sectors, the primary focus is forecasting parking demand and occupancy. In a review of occupancy forecasting methods, Channamallu et al. [3] noted that both simple regression models and deep neural network architectures (RNN, LSTM, GCN) are effective for urban services, especially when accounting for spatiotemporal dependencies. Wang et al. [4] proposed a hybrid model combining component decomposition of a time series and LSTM, which allowed them to account for both seasonal and short-term fluctuations in parking occupancy. Zhao et al. [5] used graph recurrent networks to forecast parking occupancy in street segments, demonstrating improved forecast quality by accounting for spatial correlation between zones.

Occupancy models allow for forecasting the number of available spaces and the level of congestion, which is useful for operational management. However, they do not account for the specifics of financial flows: transaction structure, receipt distribution, and payment dynamics are not the focus of analysis.

The relationship between the number of active users and revenue is examined in econometric studies. Guo et al. [6] refined this approach for modern services, emphasizing the importance of accounting for user behavior when changing fares. Zhang et al. [7] showed that integrating parking with additional services (e.g., electric vehicle charging) increases the average ticket and transaction frequency, which directly impacts revenue.

Econometric studies of elasticity demonstrate that the relationship between fares and revenue is nonlinear and depends on a variety of local factors: fare policy,

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competition with alternative services, and the level of development of the transportation network. These relationships can be used for long-term model calibration, but they are poorly suited for short-term revenue forecasting during the launch phase, when fares and regulatory frameworks are fixed and changes are not expected.

Dynamic pricing and demand management are considered as revenue optimization tools. Tilahun et al. demonstrated that adaptive pricing models based on real-time demand forecasting increase revenue collection and reduce parking congestion [8]. Pavlek et al. noted that the greatest impact is achieved by integrating long-term strategic planning and short-term tariff adaptation to current demand [9]. Research in this area shows that adaptive pricing models can simultaneously regulate demand and increase revenue. However, in real-world settings, their application is limited by regulatory policies and social risks. For new parking services, where tariffs are fixed at the start of the project and changes are impossible, dynamic pricing is inapplicable.

Thus, a review of the literature shows that current scientific discussion focuses on:

1. The use of cohort analysis and CLV to forecast customer service cash flows.
2. The use of hybrid statistical and neural network models to forecast parking demand and occupancy.
3. Accounting for seasonality, external factors, and dynamic pricing for accurate revenue modeling.

Despite numerous advances, there remains a lack of integrated methodologies linking user activity and revenue forecasting into a single system. Existing research is limited in its applicability to services in the early stages of development. Their key shortcomings in this context include the following: a focus on mature services with a rich data history; reliance on price elasticity parameters that have not yet been identified in new projects; and an assumption of variable tariffs, whereas in reality they are fixed. These limitations create a niche for the development of new approaches focused specifically on revenue forecasting in the early stages of a service's lifecycle, when tariffs and regulatory conditions are fixed and the amount of available data is limited.

III. Data description

To analyze the data, it was necessary to assemble a data model. In addition to two tables (parking sessions and a list of parking zones), data from other internal sources was also added: a calendar table, including a flag indicating whether a day is a weekday, weekend, or holiday (parking is free on weekends and holidays); and a capacity table by zone (general parking spaces and spaces for vehicles driven by or transporting disabled people) (see Fig.1) [10].

The database information used consists of a list of paid sessions and their characteristics: ID, vehicle category (A, B, BE, C, D, E), session start date and time, session end date and time, payment amount, parking zone ID for the period from January 2022 to December 31, 2024; as well as a list of parking zones: parking zone ID, number of paid and discounted spaces, coordinates, address. The generated "Calendar" table includes the following fields: Date (date), Month (text), Year (integer), Month of the year (text), Month number (integer), Day of the week (text), Day of the week number (integer), Day (integer); the "Working days" table was created using Excel based on a production calendar (the table is linked to the calendar via a 1-to-many relationship), the "Time" table is a generated set of times during the day with a 1-minute increment. Using this data, information is collected on active clients and monthly revenue volumes in the required sections.

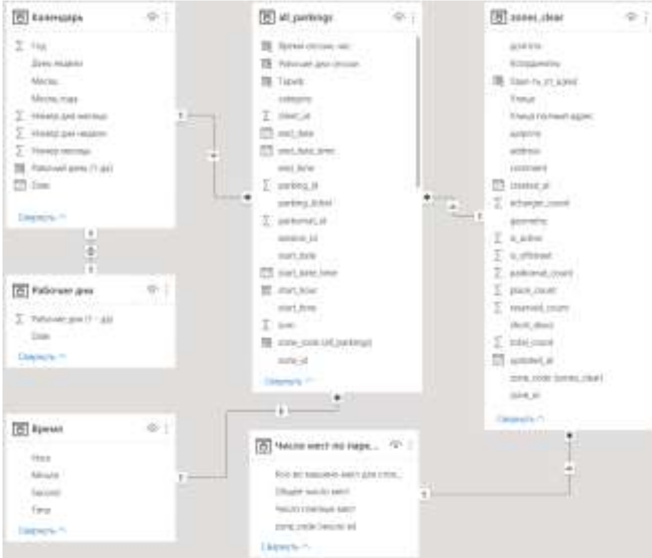

Fig. 1. Data model diagram

IV. Methodology

A key element of the forecast model is a step-by-step forecasting structure, which first calculates the active customer base (ACB) and then, based on this, estimates the total number of transactions and receipts under a stable operating environment.

The active customer base (ACB) is defined as the number of unique users who completed at least one paid parking session during the reporting month. This indicator reflects the scale of user engagement and serves as an aggregate metric for the number of potential customer transactions.

ACB depends on a number of factors, including:

- seasonality (vacation periods, school year, climate fluctuations),
- structural changes in the service (introduction of new zones, rate changes),
- exogenous events (holidays, restrictions, repairs).

However, in the baseline situation ("all other things being equal"), it is assumed that the zone structure, rate policy, and service architecture remain unchanged. This allows us to isolate the component of natural dynamics in customer activity, which can be forecast based on internal statistics. Any customer service grows its customer base: a social network, a bank, a paid parking service, a taxi service. Apparently, there is always a sharp initial increase in the customer base, followed by a gradual decline in growth over each period. A similar phenomenon is observed in the paid parking service.

The monthly AVR forecast is based on the total AVR (the number of unique users who made at least one paid parking request during the reporting month from January 2023 (the service launched in late 2022) to the reporting month). In

other words, the number of unique customers in the system, for example, in November 2024, is equal to the number of unique client_ids in all_parkings table among sessions that began between January 2023 and December 2024 inclusive.
The monthly growth dynamics show a clear trend (see Figure 2) – a gradual, fading increase from 100% in the first month to 2%–1% thereafter. This trend is seasonal (the client base grows more rapidly during the summer months), which is considered in the forecast. The total active client base is calculated based on the monthly growth forecast.

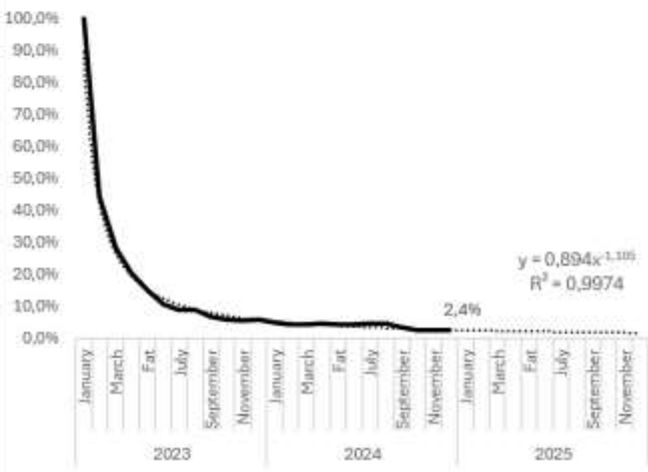

Fig. 2. Actual monthly growth in the total active customer base, %

For the forecast, it is important to calculate the dynamics of the number of active customers for each month, as in the current environment, revenue depends not on the total customer base, but on the number of customers who were active within a month. The number of monthly active customers is strongly correlated with the active customer base (see Fig. 3) – the relationship is linear, $R^2 = 95\%$. Since the customer base forecast has already been created, it is used to calculate the forecast for the number of customers within each month.

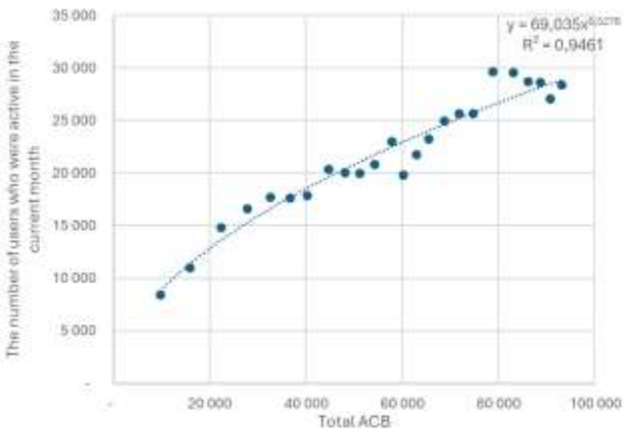

Fig. 3. Dependence of the number of active clients per month on the total volume of the entire client base

Using the equation for revenue dependence on the number of active customers per month (see Figure 4), and considering the seasonality of accruals, a forecast of commercial parking revenue is created (see Figure 5). For comparison, a forecast was made using the same methodology but using data for six months.

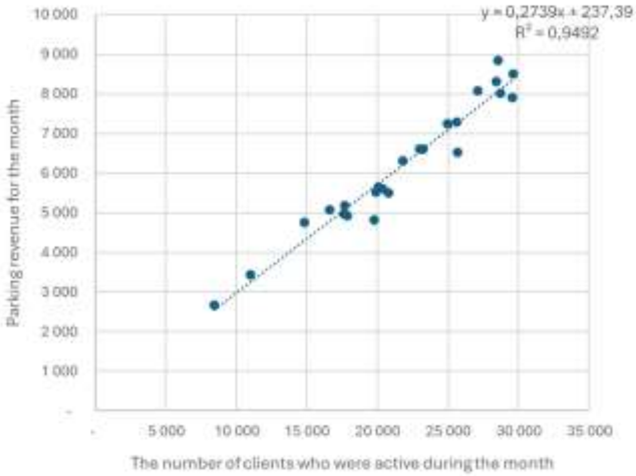

Fig. 4. Dependence of revenue on the number of clients who were active in the month in question

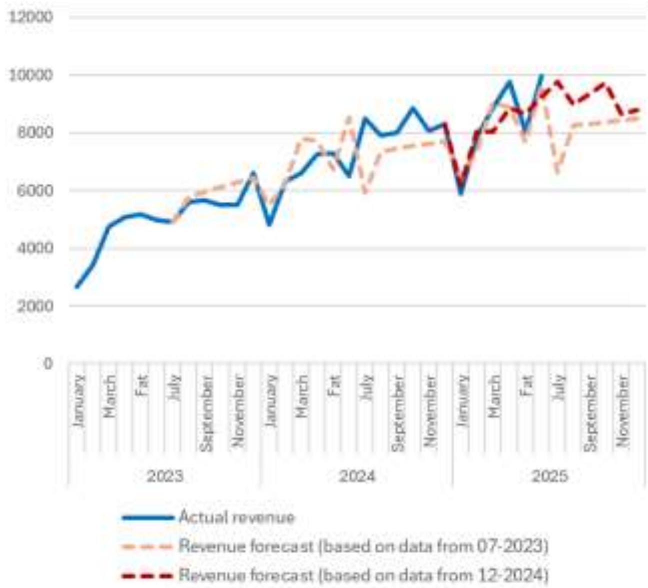

Fig. 5. Dynamics of the actual volume of accruals and their forecast for a model trained on data up to December 2024

V. Treatment of Parking Session Duration

Although parking session duration is a fundamental component of revenue formation, the proposed method does not explicitly model session length. Instead, its effect is implicitly captured through the empirical relationship between the number of monthly active users and the generated revenue.

This modeling choice is motivated by consideration. Empirical analysis shows that, under stable tariff and regulatory conditions, the aggregate effect of session duration is sufficiently reflected in the observed revenue patterns at the monthly level.

An exploratory data analysis was conducted to assess the role of parking session duration in revenue formation. The distribution of session durations was analyzed across the observation period. The results indicate that, despite short-term fluctuations, the empirical distribution of parking session durations remains relatively stable over time (see Figure 6, 7). No pronounced structural breaks or long-term trends in average session duration were detected.

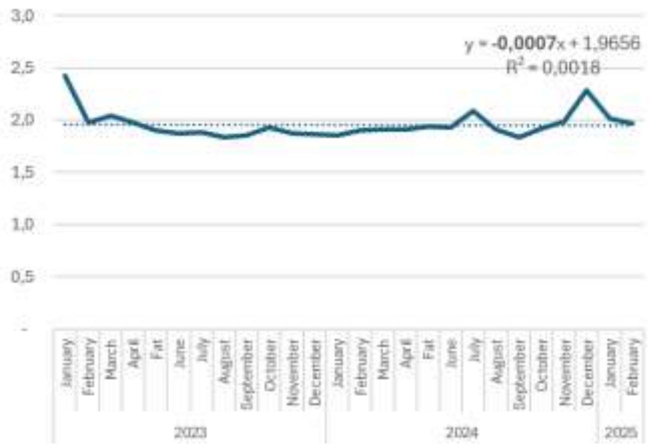

Fig. 6. Dynamics of the average duration of parking sessions

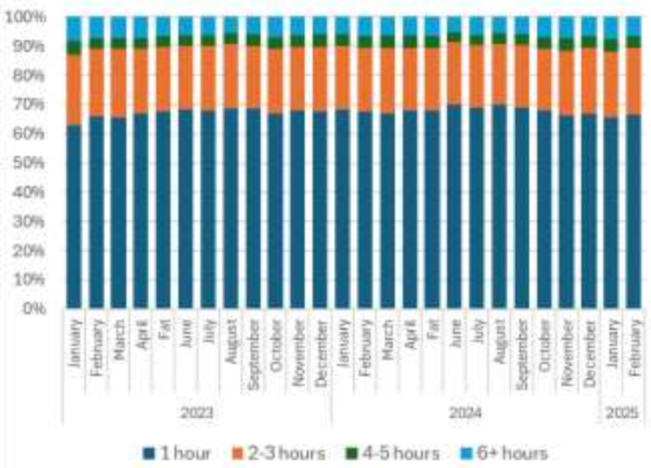

Fig. 7. Stability of parking session duration structure over time

VI. Model Assumptions

The proposed forecasting method is developed under a set of explicit assumptions that define the domain of its applicability and ensure interpretability of the obtained results.

A1 (Stability of regulatory and tariff conditions and other external conditions).

It is assumed that institutional, regulatory, and tariff conditions remain unchanged over the forecasting horizon. In particular, tariff structures, parking regulations, penalty policies, and service availability are assumed to remain unchanged. There are no competitors. The service (mobile application) is working stably. Significant exogenous shocks, such as regulatory reforms or abrupt tariff revisions, are not explicitly modeled.

A2 (Limited historical data availability).

The method is designed for client services operating with short or medium-length historical time series. The forecasting framework prioritizes interpretability and robustness over highly complex data-driven models that typically require extensive historical data.

A3 (Structural stability of revenue generation).

It is assumed that the relationship between the number of monthly active users and the generated revenue is structurally stable during the analyzed period. Seasonal effects are explicitly modeled; however, structural breaks caused by behavioral shifts, competing services, or urban policy changes are not considered.

A4 (Aggregate user behavior homogeneity).

User behavior is assumed to be homogeneous at the aggregate level. Individual-level heterogeneity and micro-behavioral differences are aggregated into macro-level indicators, which is appropriate for revenue forecasting but limits the applicability of the method for individual demand modeling.

A5 (Absence of extreme exogenous shocks).

The forecasting framework does not explicitly model extreme exogenous shocks, such as pandemics, large-scale infrastructure failures, or extreme weather events, which may significantly alter mobility patterns and parking demand.

A6 (Stationarity of parking session duration distribution).

It is assumed that the distribution of parking session durations is stationary over the forecasting horizon. Short-term fluctuations are allowed; however, no systematic long-term shifts in average or dispersion of session duration are considered. Under this assumption, the impact of session duration is implicitly incorporated into the aggregate revenue model.

Under assumptions A1–A6, the proposed method provides a transparent, robust, and interpretable framework for forecasting revenues of client services. The approach is particularly suitable for newly launched urban services and infrastructure systems operating under stable operational and regulatory conditions.

VII. Results

To verify the forecast quality, we used the most common metrics in global time series analysis [11]:

1. MAE (Mean Absolute Error) – the average absolute error, which allows us to estimate the average deviation of forecast values from actual ones [12]:

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^{n=6} |y_j - \hat{y}_i| = 386.80 \tag{1}$$

where:

y_j *is the actual value of monthly revenue;*

$\hat{y}_i$ *is the forecast value of monthly revenue;*

n is the number of "expired" months.

2. RMSE (Root Mean Squared Error) – root mean square error, more sensitive to individual large forecast misses [13]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n=6} (y_j - \hat{y}_i)^2} = 461.16 \tag{2}$$

3. MAPE (Mean Absolute Percentage Error) – average absolute percentage error, reflecting forecast accuracy in relative terms, making it convenient for interservice comparisons [14]:

$$MAPE = \frac{1}{n} \cdot \sum_{i=1}^{n=6} \frac{|y_j - \hat{y}_i|}{y_j} = 4.45\% \tag{3}$$

4. R^2 (determination coefficient) – the proportion of actual data variance explained by the model, traditionally used to assess the adequacy of forecast models [15]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n=6}\left(y_j - \hat{y}_i\right)^2}{\sum_{i=1}^{n=6}\left(y_j - \bar{y}\right)^2} = 0.8862. \quad (4)$$

Table 1. Obtained metric values

Indicator	Value	Interpretation
MAE	386.80	The average forecast-to-actual deviation is ~400 units, which is acceptable for an average receipts level of >8000.
RMSE	461.16	The error is close to the MAE, indicating the absence of significant outliers and systematic errors.
MAPE	4.45%	The average relative error does not exceed 5%, which meets the high standards of applied forecasting for financial services.
R^2	0.8862	The model explains approximately 89% of the variance in the actual data; 11% is accounted for by external and random factors.

A comparison of the forecast with actual data shows that the proposed approach provides high revenue forecast accuracy. Low error values (MAE, RMSE) and a moderate relative error (MAPE) confirm the applicability of the method for cash flow analysis. The determination coefficient R^2 = 0.8862 indicates that the model explains a significant portion of the variance in the actual data, despite the limited sample size.

The data model and insights gained from this study can be used by governments and property owners to forecast customer activity and revenue from parking (and other services) and improve traffic management in smart cities. The approach presented in this article can be applied to other cities. The forecasting methodology can be recommended for practical application in new customer service environments, especially in the early stages of their operation, when the observation history is short and tariff and regulatory conditions are stable.

VIII. Conclusion

This study developed and tested an approach to forecasting revenues from a paid parking customer service based on a consistent assessment of the number of active users and the volume of transactions they generate. The proposed methodology allowed us to account for the specifics of early-stage services, when long-term historical data is lacking and external conditions (tariffs, regulatory restrictions, and organizational policies) remain constant.

Unlike most existing models, which are primarily focused on mature markets and employ complex black-box machine learning methods, the proposed approach ensures interpretability and transparency of results, which is especially important during lengthy approval processes with regulatory authorities. The use of regression relationships between the number of active users and revenue volume, supplemented by consideration of seasonal fluctuations, allows for forecasts with an acceptable level of accuracy with a limited amount of input data. An assessment of forecast quality using classical metrics (*MAE, MAPE, RMSE,* R^2) demonstrated that the proposed model is capable of adequately reproducing the observed revenue dynamics. These metric values indicate high forecast accuracy and the feasibility of the method's practical application in urban parking infrastructure.

These results can be used by city authorities and parking service operators to support budget planning, evaluate the cost-effectiveness of implemented solutions, and develop long-term development strategies. Promising areas for further research include expanding the methodology to include changing tariffs and regulatory parameters, as well as integrating customer behavioral factors (e.g., price sensitivity and availability of alternative transportation services). Additional attention could be paid to modeling uncertainties associated with external factors, such as weather conditions, the emergence of competitors, and the development of related elements of the urban transportation system. The proposed approach demonstrates practical applicability for forecasting revenues from paid parking services and contributes to the development of data-driven and analytically interpretable urban infrastructure management tools.

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