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TIME SERIES ANALYSIS OF SHARED MOBILITY SERVICES USAGE

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Abstract: *The sharing economy refers to an economic system where individuals or entities share resources, assets, or services directly with others, facilitated by an online platform. The asset which is "shared" in the sharing economy and which attracts the attention of various stakeholders is mobility. Shared mobility services, encompassing various modes such as ride-sharing, bike-sharing, scooter-sharing, and carpooling, have emerged as pivotal components of urban transportation systems worldwide. As the shared mobility market is expanding in both developed and developing countries, it is of interest to analyse and predict the usage of shared mobility vehicles. As a case study, we will use ARIMA time series modelling to model the shared scooter usage in Bern, Switzerland. Our study provides insights into the temporal dynamics of shared mobility services, offering valuable implications for urban transportation policy, planning, and management.*

Keywords*: Sharing economy, shared mobility, time series modelling, predictions, ARIMA*

1. INTRODUCTION

With the emergence of the Internet, new business models have developed, including e-commerce, e-learning, social media platforms, sharing economy models, and others. The ones which attract attention are sharing economy models such as shared accommodation, carpooling, carsharing, ride-hailing, and crowdfunding. All these models, even though they are different, have common elements: the customer, the provider, the Internet, the platform, and the regulating environment (Ritter & Schanz, 2019). The form of sharing economy we focus on in this study is shared mobility.

Shared mobility services encompass various modes such as ride-sharing, bike-sharing, scooter-sharing, and carpooling. The value of the shared mobility market is, according to Allied Market Research (2022) 104.95 billion US dollars, with projections indicating up to 1 trillion US dollars in consumer spending by 2030 (McKinsey, 2023). The shared mobility market is closely connected to open innovation as both concepts reinforce collaborative ecosystems. Therefore, it is expected that open innovation will enhance the adaptability and sustainability of shared mobility services in the future, contributing to more efficient urban transportation systems leading to an even greater market growth (Turoń, 2022).

Just some of the benefits of shared mobility are reduced environmental impact, cost savings, traffic decongestion, optimised resource utilisation, social connectivity, and accessibility and flexibility (Li, Liu, & Zhang, 2018). Shared mobility is important for ecology, smart city development, and urban mobility because it promotes environmental sustainability, optimises resource utilisation, complements public transportation, encourages active transportation modes, facilitates data-driven decision-making, and enhances accessibility for all members of society (Ma et al., 2018). At the same time, some drawbacks of the shared mobility concept should be considered. Kireeva et al. (2021) identify the following: complicated rental processes, lack of trust in personal data collection and usage, low sense of privacy, security, lack of trust in the vehicle, and lower comfort compared to passenger cars.

European Union issued a Commission Notice regarding well-functioning and sustainable local passenger transport-on-demand, which advises for regularising ride-sharing practices (EUR lex, 2022). Acknowledgement of the of importance of ride-sharing practices regularisation is at the same time a signal that significant numbers of EU citizens are participating in such a way of transport and that ride-sharing is not just a local phenomenon. As the shared mobility market is rising, the interest of the general public in participating in the shared concept as well, this study has the goal to implement predictive analytics and forecast the usage of shared mobility vehicles. The predictive model chosen is the Time Series analysis and the ARIMA model. The data used in this study is the data for the city of Bern, Switzerland related to the weekly number of shared e-scooters used. Bern was selected as a case study keeping in mind that the city has a diverse shared mobility ecosystem offering shared bikes, e-scooters, and cars, with four companies operating. The mobility data is available from Fluctuo, a company specialised in gathering data on micromobility, public transport companies, and Mobility as a Service (MaaS) providers (Fluctuo, 2024).

The paper is structured in the following manner. In the next section, we provide a literature review on the participation in shared mobility services in Switzerland as well as a review of the studies that aimed to predict shared mobility usage. In the following section, we outline the company Fluctuo and the data on shared mobility they offer and the case study setting. After that, the results of the time series modelling are presented. We finish the paper with the discussion and conclusion.

2. LITERATURE REVIEW

2.1. Participation in shared mobility services in Switzerland

According to the available Eurostat data on participation in shared transport, the level of participation in shared transport in Switzerland is high (Eurostat, 2024). The data showed that in 2021, the percentage of individuals in Switzerland who participated in shared transport (in the last three months) was 0.79%, while in 2023, the last year for which the data is available, it was 1.55%. The same analysis pointed out that between 2021 and 2023, the highest rise in participation in shared transport was among those between 16 and 24 years old (rise from 1.89% to a staggering 4.41%). Interestingly, those living in towns and suburbs and those with medium and no formal education used shared transport more than the EU-27 average. The student population embraced the use of shared transport, as the participation rate was 2.24% in 2023. The presented results indicate that according to official statistics, the usage of shared transport among students is increasing. However, that percentage could be higher.

The Eurostat data indicates that the concept of shared mobility in Switzerland is more accepted by the younger individuals, students and those with medium and lower education. The micro-mobility sector in Switzerland is quite developed, with companies such as Bird, Bolt, Lime, Tier, Voi, Ubeeqo being present. The company which we focus on is Tier. This company currently operates in 33 Swiss cities, including Zurich, St. Gallen, Basel, Bern, and others and is one of the largest mico-mobility platforms in Switzerland.

2.2. Predicting shared mobility using time series

Predicting shared mobility participation is of high interest for numerous stakeholders. So far different approaches to predicting participation or usage of shared mobility services have been taken. In this literature review we focus on studies which employed time series analysis.

The first chosen study by Camilleri and Debattista (2020) focused on optimising shared mobility in Malta, specifically ride-sharing services. Historical data are analysed to predict the total number of ride requests per hour. Various time series forecasting models, including Holt-Winter, ARIMA, and Facebook Prophet, are compared to determine their effectiveness in predicting demand patterns and algorithms. The Holt-Winter model outperformed other models based on Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Exogenous variables like temperature and public holidays were found to have no significant impact on the predictive model.

The second study, authored by Saum and associates (2020), observed the data collected at Thammasat University, Thailand. The type of mobility studied is shared micro-mobility, specifically e-scooters. The data used includes hourly e-scooter demand from January 23 to April 30, 2019. The study employed Box-Cox transformation, Seasonal ARIMA (SARIMA), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to predict the hourly demand and volatility of e-scooters. The model predicts the demand pattern and volatility of e-scooters, which is crucial for operational planning. The results show that the combination of these models provides valuable insights into demand patterns and helps in operational planning for shared e-scooter services.

The study by Boonjubut and Hasegawa (2022), aimed at optimizing the operations of bike-sharing systems, specifically in rebalancing bike availability across stations. It compared three models ARIMA, LSTM (Long Short-Term Memory neural network) and GRU (Gated Recurrent Units neural network) to predict hourly bike demand using data from Jersey City's Citi bike system. The models utilize factors like temperature, hour, humidity, season, weekday, weather, holidays, and wind speed. The study found that the GRU model outperforms ARIMA and LSTM in terms of efficiency, as evidenced by lower prediction errors. The stepwise regression technique was employed to select input variables, enhancing the accuracy of the forecasting models.

The paper authored by Chiotti (2023) investigated the applicability of machine learning models to forecast the number of occupied slots of a particular bike-sharing station in San Francisco (USA) and the number of bikes crossing the Fremont Bridge in Seattle (USA). It focused on analysing micromobility sharing services, particularly bicycle sharing, using machine learning models such as ARIMA, Linear Regression, Lasso, Ridge, Random Forest, and Gradient Boosting. The study aimed to predict bike availability at station-based sharing services and bike flux in specific areas. Results provide practical guidelines for setting up and tuning machine learning models, aiding businesses and local governments in improving service provision. The paper underscores the importance of enriching data with contextual features for accurate predictions and suggests avenues for future research, including incorporating contextual metadata, user data, exploring different mobility vectors, and handling the problem as a classification task.

The presented literature review indicates that time series analysis has been employed with a lot of success in predicting shared mobility and participation. Therefore, we also opted for the application of time series analysis, precisely ARIMA modelling.

3. FLUCTUO DATA AND CASE STUDY SETTING

Fluctuo is a tech company specialising in real-time data analysis for shared micromobility services such as bikes and e-scooters. Their platform tracks over 200 operators worldwide, covering millions of vehicles across cities in Europe (181 cities), North America (13 cities) and Asia-Pacific (8 cities). They provide data on bikes, mopeds, e-scooters, and cars shared on a daily, weekly, and monthly basis (Fluctuo, 2024).

A time series analysis was conducted to examine and forecast the number of trips per week on the e-scooter-sharing platforms in Bern. Specifically, the analysis focused on one out of the two operators: Tier. Data spanning from April 3rd, 2023, to April 1st, 2024, was collected from the Fluctuo platform, consisting of the weekly number of vehicles used. The prediction phase extended from April 8th to May 13th, 2024.

ARIMA (AutoRegressive Integrated Moving Average) models with parameters (p, d, q) and the Box-Jenkins methodology were employed to model the time series. The Akaike Information Criterion (AIC) served as the primary criterion for selecting the best model (Makridakis & Hibon, 1997). Stationarity of the time series was assessed using the Augmented Dickey-Fuller test (ADF), while autocorrelation was examined through the Durbin-Watson test (DW). Additionally, the presence of heteroskedasticity was evaluated using the ARCH test (Albijanić et al., 2023).

4. RESULTS

The first step in the time series modelling is the descriptive statistics analysis of the collected data and the visual inspection of the time series. In Table 1, we present the descriptive statistics of the number of weekly scooter trips offered by Tier in Bern in the observed one-year period. The mean number of trips per week was 1122.40, with a standard deviation of 421.484. A high median indicates that during half of the year Tier is having more than 1189 trips per week. The minimum number of trips was recorded on January 8th, 2024, just 394. However, such a low number of trips could have been expected with the winter season and weather in mind. On the other hand, the maximum number of weekly trips was made on September 4th 2023, as much as 1825. The interquartile range (IQR) is 774, which represents the middle 50% of the data, suggesting a moderate spread between the 25th and 75th percentiles. Looking at the skewness and kurtosis, the data extends more towards the lower values and is slightly less peaked than a normal distribution.

Table 1: Descriptive statistics of the number of weekly scooter trips offered by Tier in Bern

Mean	Std	Median	Min	Max	IQR	Skewness	Kurtosis
1122.40	421.484	1189.00	394	1825	774	-0.127	-1.299

Figure 1 shows that the number of weekly trips in the observed period. Even in the spring and summer months, there have been sharp declines (certain weeks in April, May and even July). As autumn starts, a decline in the number of trips can be noted, which is expected. Interestingly, in late January 2024, there was an unusual peak for the winter months, 863, which is more than the latest recorded value of 853 in April 2024.

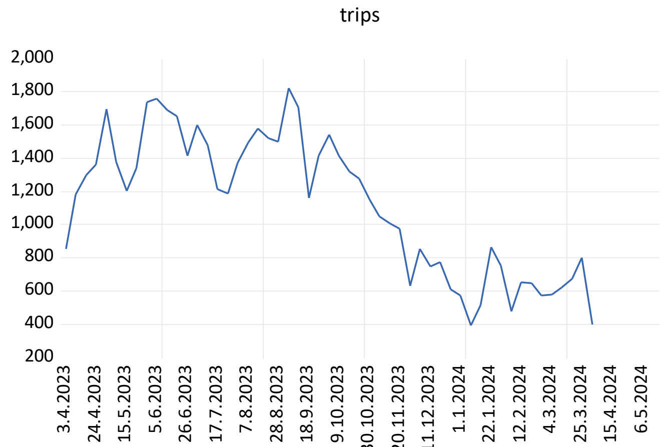

Figure 1: Number of weekly scooter trips offered by Tier in Bern – Time series line graph

The line plots of the recorded time series suggest potential non-stationarity and exhibit observable trends within the data. To assess the stationarity of the gathered data, the Augmented Dickey-Fuller test and Box-Ljung tests were conducted. The results of the ADF test for the time series indicate that the series should be integrated once (Level: ADF=-0.460, $p>0.05$; 1st difference: ADF=-7.419, $p<0.01$). However, after the first difference, the correlogram showed that the time series is over differentiated, as AC in second lag was -0.323, close to 0.5 and statistically significant. Therefore, when modelling the time series, we tried models with both d=0 and d=1. Several models were tested, and the best model was chosen based on the following criteria: lowest AIC, low residuals, as well as good predictive power. For example, model ARMA(2,1) was not chosen as the best model, even though it had the lowest AIC (13.535). We chose ARMA(3,1) as the best model, as it had a low AIC of 13.478 and its predictions and prediction intervals were positive. The ARMA (3,1) model specification is given in Table 2.

All three elements of the time series (the constant, AR and MA) are statistically significant. ARCH test indicated no presence of heteroskedasticity in the model, while the Jarque-Bera test showed that the residuals are normally distributed. The results of the Ljung-Box test indicate the presence of autocorrelation. The graph of residuals, actual values and fitted values is presented in Figure 2. Additional model characteristics include the R^2 which is 0.742, and the F-statistics (47.152, $p<0.01$) which indicates that the model is statistically significant. Considering the model analysis, it can be concluded that the model is of good quality and that it can be used for forecasting.

Table 2: Analysis of the ARMA(3,1) model for the Bern weekly trips for scooters offered by Tier

Test	Item	Statistics
z test of constant	1051.923	6.431**
z test of coefficient AR(3)	0.701359	4.869**
z test of coefficient MA(1)	0.537183	3.498**
Ljung-Box	Residuals - Autocorrelation	Present
ARCH test	Residuals - Heteroskedasticity	0.186
Jarque-Bera	Residuals - Normality	0.310

Note: **p<0.01

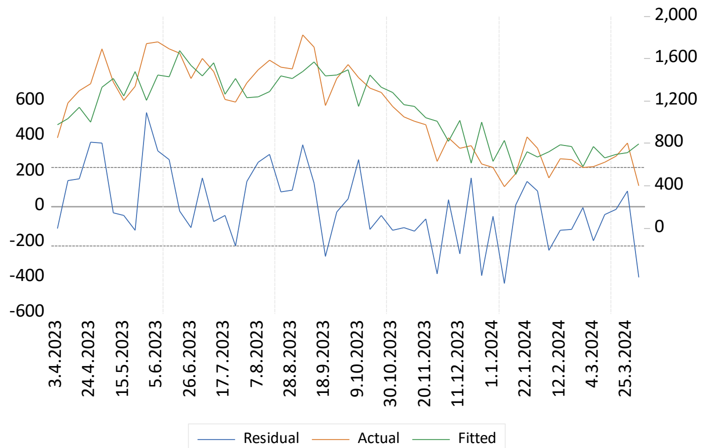

Figure 2: Residuals, actual values and fitted values of the ARMA(3,1) model

Considering that the ARMA(3,1) model has the best fit, assumptions of homoskedasticity are fulfilled, and the model is considered adequate for forecasting time series. The forecast graph is presented in Figure 3.

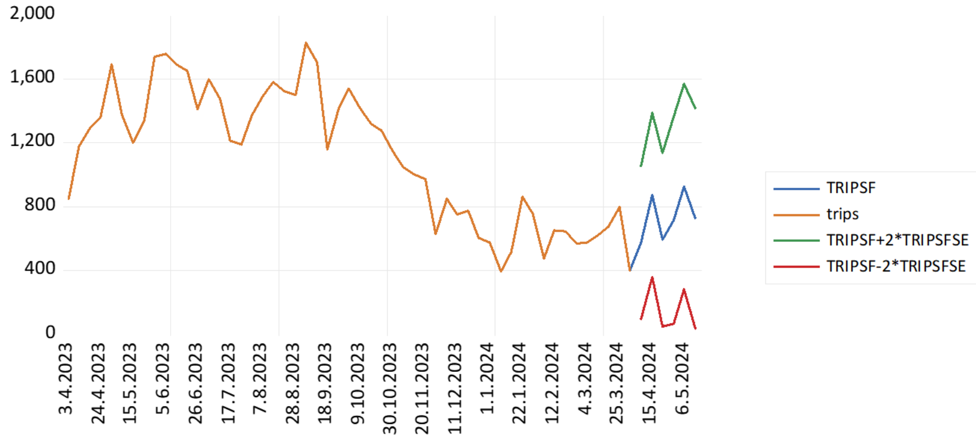

Figure 3: Historical and predicted values of the weekly number of trips for scooters offered by Tier in Bern

With regards to Figure 3, the blue line shows the projected weekly number of trips in April and May 2024, the orange line indicates historical values upon which the forecast was built, the green line presents the upper projection confidence interval, while the red line presents the lower confidence interval. According to the prediction, the number of weekly trips of Tier scooters will be volatile in the upcoming period.

5. DISCUSSION AND CONCLUSION

The presented study aimed to develop a model for e-scooter usage using ARIMA time series modelling in Bern, Switzerland. Several models were tested, and the best model was selected based on the following criteria: lowest Akaike Information Criterion (AIC), minimal residuals, and strong predictive performance. ARMA(3,1) was chosen as the optimal model due to its low AIC and good prediction intervals. Based on the model analysis, it can be concluded that the model exhibits good quality and is suitable for forecasting. According to the predictions, the number of weekly trips of Tier e-scooters is expected to be volatile in the upcoming period.

A potential future direction for the study could involve applying the approach taken by Dobrota et al. (2021), who developed a variety of time series models (e.g., R(p), MA(q), ARMA(p,q), ARCH, GARCH, BMMR, BMMRJD, GBM, GBMJD). Also, Holt-Winter Filtering could be applied as done in the study of Muller and Bogenberger (2015) who modelled booking data of a free-floating carsharing system in Berlin. Another future direction of the study could be the analysis of daily data or analysis of other indicators provided by the Fluctuo platform such as: *Vehicles available, Vehicles used, Trips per vehicle*, and others. Also, a comprehensive analysis of the whole e-scooters fleet in the observed city could be performed.

We hope that this study might serve as a source of insights into the temporal dynamics of shared mobility services, providing valuable information for urban transportation policy, planning, and management. By shedding light on the patterns and trends within shared mobility usage, our findings can be used as initial information for the development of more efficient and sustainable urban transportation strategies. Additionally, this research has the potential to catalyse further research on the topic of modelling and predicting the usage of shared mobility in various domains.

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