Prediction of Bike Sharing Demand and Design

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As a consequence of the persistent trend towards urbanization, cities suffer from negative externalities (traffic congestion, air pollution, noise, etc.) caused by the increase in urban mobility. Since motorized individual transport comprises a sizable proportion of those negative effects, policymakers consider the promotion of active mobility (i.e., walking and cycling) as a way to address the key challenges of growing urban transport. In this regard, bike sharing systems have gained popularity, as they provide a sustainable and affordable alternative to motorized vehicles. Therefore, these systems are increasingly implemented in cities around the world.

Keywords: bike sharing ; demand generation ; mobility on demand ; autonomous bike ; future mobility ; cargo bike

1. Prediction of Bike Sharing Demand

Based on their spatial granularity, the existing methods and approaches of predicting bike sharing demand can be classified into three groups: system-level prediction, cluster-level prediction, and station-level prediction [1].

For system-level prediction, Borgnat et al. [2] analyzed a public bike sharing scheme in Lyon, France, using a combination of statistical signal processing tools to derive temporal usage patterns for a typical week. While including internal (subscribers, number of available bikes) and external (temperature and precipitation) factors, those tools were also used to estimate the number of rentals within the next hour.

Additional research on predicting bike sharing demand at the system level was proposed by Giot and Cherrier [3]. They applied different regression models to predict the hourly bike sharing usage up to 24 h ahead. The used regressors (weather, previous bike usage, and holiday) were obtained from a public dataset containing two years of information on the Washington DC bike sharing system. Within their study, Ridge Regression and AdaBoost Regression were shown to have the best performance.

An approach for system-wide usage prediction over a longer time period was proposed by Cantelmo et al. [4]. Within their study, they introduced a clustering technique for synthesizing mobility data in order to obtain recursive mobility patterns. By validating their approach with existing data from New York City, Cantelmo et al. could show that combining those patterns with weather data enables the accurate prediction of daily bike sharing demand [4].

However, concerning the objective of researchers' study, the presented methods cannot be applied to OSABS demand generation, since the usage can be predicted either for only a few hours ahead [2][3] or with insufficient temporal granularity [4]. An additional impediment to transferability emerges from the constraint that employing data derived from already implemented conventional bike sharing systems only allows for the prediction of demand within these particular systems. This also applies to the multitude of cluster-based (e.g., Refs. [5][6][7][8]) or station-based (e.g., Refs. [1][9][10][11][12][13][14][15][16][17][18]) approaches, as they rely on already existing stations (or subsets of stations).

2. Bike Sharing System Design

To estimate potential bike sharing demand in cities or countries where such systems have not yet been implemented, Todd et al. [19] analyzed data from 322 bike sharing schemes and divided them into five main groups, which were further classified into subgroups with regard to usage, contextual indicators, and the behavioral characteristics of their users. According to their study, this enables a global comparison of scheme performance and provides a basis for new schemes to recognize existing BSS with comparable characteristics that can serve as a reference for predicting potential user demand. However, this approach only allows for a rough estimation of demand on a system level while lacking spatial granularity.

Further, Frade and Ribeiro [20] proposed a methodology to relate bike sharing demand with external characteristics that affect bicycle use. These are trip distance and purpose, slope inclination, and the presence of bike lanes. Within their study, the definition of demand is accomplished in two steps: quantifying demand based on other case studies and defining the effect on demand caused by trip and physical city characteristics. However, researchers are not able to apply this approach to OSABS demand generation since, due to the novelty of OSABS, it was not possible to determine demand based on case studies from existing systems.

Another approach on the dimensioning of bike sharing systems was presented by Garcia-Gutierrez et al. [21]. To enable the prediction of potential bike sharing usage, they derived mobility patterns from a large-scale mobility survey in Mexico. Further, they generated utility models for different modes of transport (foot, bike, public transport, car) based on declared preferences surveys. In combination with mobility patterns, those utility functions enabled the determination of initial bicycle travel matrices. But, since researchers aim to complement all conventional modes of transport (including bicycles) with OSABS, this approach is also not feasible for us.

3. Factors Influencing Bike Sharing Utilization

According to Chen et al. [22], bike sharing usage patterns are mainly impacted by two types of contextual factors. Those include common contextual factors that occur frequently and affect the whole system (e.g., weather and time-related variables). In addition, there are opportunistic contextual factors which happen irregularly and affect only a subset of the system (e.g., social and traffic events). While some studies investigate the effects of opportunistic contextual factors (e.g., calendar events [23] or transit disruption [24]), common contextual factors are more frequently the subject of the recent literature.

To identify temporal usage patterns, Koska et al. [25] analyzed trip data from five German bike sharing schemes. Their findings show that during weekdays bike sharing demand has a slight morning peak and a larger peak in the afternoon. Similar results were obtained by Miranda-Moreno and Nosal [26] during their analysis of a bike sharing system in Montreal, Canada.

On a larger scale, O'Brien et al. [27] analyzed 38 global bike sharing systems and classified them based on temporal characteristics and associated user types. A large proportion of the considered systems also showed two weekday peaks (morning and afternoon) and a broad afternoon peak at weekends, with predicted user types being commuters and weekend leisure users. However, O'Brien et al. also identified further systems that, for example, are primarily used on weekends (leisure users) or have more than two commuter peaks per day (commuters with some utility users) [27]. The temporal characteristics of an even larger number of 322 global bike sharing schemes can also be obtained from Todd et al. [19].

Gebhart and Noland [28] analyzed the effect of different weather variables on bike sharing trips in Washington, DC, USA. Consistent with other studies (e.g., Refs. [23][29][30][31]), their results found that adverse weather like cold temperatures, rain, and increased wind speeds decreases the number of bike sharing trips. In addition, Caulfield et al. [32] claimed that not only the number of trips but also the travel time increase during good weather conditions. In contrast, several studies suggest that temperature has a negative impact on bike sharing demand when it exceeds a certain level [9][33][34].

While looking at temporal and weather effects, An et al. [29] additionally considered natural and built environments influencing bike sharing trips in New York City, USA. However, their findings show that weather impacts bike trips more than topography, infrastructure, or land use mix.

Furthermore, in correlation with previously presented effects of weather variables, several studies could show that the yearly trend in bike sharing usage can be classified into three periods. This includes an off season with low demand during winter months, a main season with high demand during summer months, and a transition phase with growing or falling demand in spring and fall months, respectively [13][25]. This indicates that the long-term influence of weather variables on bike sharing usage behavior can be also expressed through temporal patterns (in terms of yearly profiles or seasons).

In addition to weather conditions and time-related variables, there are many studies analyzing several other factors affecting bike sharing usage on a higher spatial granularity, such as sociodemographic and built environment characteristics (e.g., Refs. [30][35][36][37][38][39]). However, those factors predominantly impact usage behavior on a station level rather than on a system level. In addition, analyzing them requires specific data which are mostly valid for the considered study area only and thus limit the broad and easy transferability of researchers' approach. Hence, related publications are beyond the scope of this research and will not be discussed any further.

For additional research in this regard, researchers recommend the work of Eren and Uz [40], Zhu et al. [41], and Guo et al. [42], who provide a comprehensive literature review of bike sharing influencing factors such as built environment and land use, public transportation, sociodemographic attributes, and safety. Another extensive overview of factors influencing micromobility sharing in general, classified into temporal, spatial, and weather-related factors, system-related factors, and user-related factors, is provided by Elmashhara et al. [43].

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