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AI-Enabled Dispatching Optimisation Mechanism of Shared Bikes

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Abstract. Shared bikes have become a primary supplement to city transportation, offering the advantages of low carbon emissions and convenience. However, low dispatching efficiency restricts their sustainable development and causes a demand-supply imbalance, affecting the user experience. This research discusses a dispatching optimisation strategy for shared bikes based on the application of Artificial Intelligence, which combines demand forecasting, user behaviour analysis, and dispatching optimisation. According to multiple machine learning methods, research demonstrates an enhancement in the accuracy of predicting and dispatching efficiency, including supervised learning, unsupervised learning, deep learning and reinforcement learning. At the application level, we mainly discuss how to predict shared-bike long-term or short-term demand using machine learning models, such as LSTM and XGBoost; analyse user behaviour and station classification based on clustering methods like K-Means; optimise dynamic scheduling strategies for intelligent decision-making through reinforcement learning; and detect abnormal behaviours based on the dedimensional techniques. The discussion part of the research highlights that, although existing research has made significant progress, several challenges remain. Finally, this research argues that integrating predictive analysis and scheduling optimisation will provide an important direction for the construction of an intelligent, low-carbon and sustainable shared bicycle system.

Keywords: shared bike, machine learning, demand forecasting, dispatching optimization, intelligence transportation

1. Introduction

In city transport systems, it is hard to meet people's point-to-point need because of the not enough coverage of public transport. This will make people still need to finish a short trip after getting to the station. In this case, the coming of shared bike has fixed the problem well, it not only making short-distance travel better but also giving a more green and easy way of moving. But, with the fast growth of cities and the ongoing rise of user size, the built-in tidal effects and one-way travel traits of shared bike cause a lot of supply-demand mismatches between stations. Like 'no bikes available' and 'no parking spaces available', which hurt the working efficiency and user experience. Old dispatch plans are often built on past experience and fixed best models, which can not fully take into

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account such many-sided factors changing need. It is also slow to react to changing shifts in user needs.

In this situation, using machine learning methods in artificial intelligence has become a key way to make shared bike work better and give users a better experience.

Machine learning models can use multi-source data, like weather, place, time features, user actions, and so on, during the demand guess stage, greatly making guess correctness better. At the same time, deep learning models such as LSTM and GRU show low mistake rates in short-term guesses, while their mixed methods, like random forests and gradient boosting trees, do better in long-term guessing. Also, based on ongoing contact with the setting, reinforcement learning gives a new way for actively changing the supply of bikes. Real tests, like short-term guesses based on LSTM in Suzhou and long-term guesses using data digging in New York, have shown that AI ways work better than the old ways, getting a change from 'passive answer' to 'active improvement'.

In summary, this study gives a methodical look at the use of machine learning tools in smart shared bike systems. The setup is like this: Chapter 2 talks about the basic ideas of machine learning, covering guided learning, unguided learning, deep learning, and reward-based learning;Chapter 3 looks at how well these AI-led ways work in five main areas: need guessing, user action study, stop grouping, dispatch making better, and oddity finding;Chapter 4 talks about the problems met by recent studies and looks at future paths, trying to give useful ideas for scholars and field workers.

2. Theoretical foundation of machine learning

As an essential branch of Artificial Intelligence, machine learning provides accurate shared bicycle demand forecasting systems according to automatic 'learning' algorithms, thereby laying the technical foundation for dispatch optimisation. Compared to traditional time series models such as Linear Regression and Autoregressive Integrated Moving Average(ARIMA), machine learning shows a better performance in handling nonlinear, multidimensional and large-scale data [1, 2]. Overall, the relevant methods can be mainly included in four categories: supervised learning, unsupervised learning, deep learning, and reinforcement learning.

2.1. Supervised learning

The core concept of supervised learning is training a model to forecast future results based on the labelled historical data. The traditional statistical method, such as Multiple Linear Regression, has the characteristic of being well interpretable, which allows for the analysis of the influence of multiple factors on shared bike demand, including temperature, precipitation, day of the week, and others. Thus, it was commonly used as the baseline model when building a forecasting model. However, when facing case of the threshold effect, linear Regression cannot catch effectively. Because it assumes that the independent variable X has a linear relationship with the dependent variable Y. In contrast, models such as decision trees, random forests, and gradient boosting trees can automatically identify nonlinear features and usually have higher prediction accuracy [3].

2.2. Unsupervised Learning

Different from Supervised Learning, Unsupervised Learning is mainly used to reveal the latent structure of shared bike data. This learning method does not rely on the labelled data to detect. It uses data mining to recognise the latent pattern and structure. In the research of the shared bike

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demand forecasting model with vast amounts of data, applying unsupervised learning, it is possible to discover the underlying features in these data more effectively.

2.2.1. Clustering Methods

Clustering Method is widely used in Unsupervised Learning. Ways like K-Means it can group data based on the use rate of the stations and ite location. By the labels given to each station, workers can easily make a first guess about dispatching plans, so helping in the quick making of scheduling plans. Clustering method can also be used to look at the user's actions, helping companies see usage habits and give more focused custom services.

2.2.2. Dimensionality reduction

Dimensionality reduction aims to find and put together the important features in the multi-dimensional data into one overall measure. In shared bike demand forecasting, by using Principal Component Analysis (PCA) to look at outside factors like temperature, humidity, wind speed, and rainfall into measures such as "weather comfort level" or "event activity index". This type of dimensionality plan will successfully stop extra work, make the model's complexity simpler, and make training better [4].

2.3. Deep learning

Deep Learning, based on the multi-layer neural network, has better performance on handling non-linear relationships. The shared bike demand forecasting contains both features, Time series and spatial characteristics, which traditional forecasting methods cannot account for. Recurrent Neural Networks (RNNs) and their types, such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) were widely used for short-term forecasting, effectively predicting minute-level and hour-level demand based on past data. In a study on the Suzhou public bicycle system, Wang and Kim (2018) reported that LSTM and GRU got prediction errors of only 1 – 2 bikes, showing their advantages. Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs) can capture spatial dependencies, making them good for area and station-level demand prediction [5, 6].

2.4. Reinforcement learning

The central concept of Reinforcement learning is 'trial and error', where an agent interacts with the environment. The agent will fall into a cycle of taking action and receiving feedback, continuously correcting the strategy, until it gets the maximum reward. Different from the other methods in Machine Learning, like Supervised Learning, which tells 'what will happen' based on the forecasting result. The result of Reinforcement learning would be 'how to do'. In the context of bike-sharing, reinforcement learning agents can generate highly feasible dispatching decisions through continuous learning and optimisation. This enables effective bike rebalancing, alleviates shortages or surpluses at stations, and ultimately improves user experience and satisfaction [7, 8].

3. The application of machine learning in bike sharing dispatching

This section will mainly focus on five applications of machine learning: demand forecasting, user behaviour analysis, station category analysis, scheduling strategy optimisation, and anomaly

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detection. It will systematically review the existing research results and summarise the advantages and disadvantages of these methods in practical applications.

3.1. Demand forecasting

An effective dispatching optimisation relies on accurate shared bike demand forecasting. The reliable prediction provides entrepreneurs with the characteristics of each station. The existing studies mainly applied traditional statistical models and machine learning models. As it has better interpretability, the former are often used as benchmarks to compare the enhancement with other forecasting models. However, traditional statistical methods show poor ability to handle non-linear relationships and high-dimensional external factors. In recent years, AI-enabled methods have shown their remarkable advantages. For long-term forecasting, applied methods such as Random Forest and gradient boosting algorithms, such as CatBoost, XGBoost, and LightGBM, provide an effective way to integrate multidimensional factors such as weather, holidays, and geographic attributes to improve both accuracy and efficiency [9]. On the other hand, for short-term forecasting, methods of recurrent neural networks, especially LSTM, achieve outstanding results. For example, in the case of London's bike-sharing system, an LSTM model reached $RMSE = 314.17$ with $R^2 = 0.922$ at the hourly level, clearly demonstrating the capability of deep learning in capturing short-term fluctuations [10]. In general, whether in the long term or the short term, deep learning models with their high-precision predictions ranging from minutes to years effectively support enterprises in their long-term planning and short-term operational optimisation.

3.2. User behaviour analysis

Besides correct demand forecasting, it is also needed to look at the user's behavior for making operations better. This not only helps companies to give more detailed personal services, but also makes the shared bike use rate higher, avoiding waste. In this case, the grouping way from unsupervised learning has a key role, especially the K-Means. Such ways put users into different groups, based on their riding habits, how often they use, common riding time, and so on. For example, users can be split into commute-focused users who use a lot during busy commuting times, leisure users who use often during holidays and weekends, sometimes users who use little and randomly, and so on. Based on different user types, the company can give special deals and rewards. As the related studies have shown, user behavior study has a big part in making operational improvement better and making user happiness higher [11]. But, no matter how user behavior is studied, companies should always be responsible for keeping the privacy and safety of user data.

3.3. Station analysis

During the actual work, most stations show different supply and demand links at different times. So, it is also key to do a system study and grouping of stations for making scheduling better. Like user action study, station grouping also uses clustering ways such as K-Means, putting together their space spread features and past demand data. It helps finding stations into different groups, such as peak travel stations which are marked by high use during travel times, peak free time stations which see high need during weekends and holidays, and rare stations with low use rate and less clear demand forms. Stations can be grouped based on their job roles as either "start stations" or "end stations." This grouping lets operators better decide which stations need vehicle sending and which ones need vehicle filling during scheduling.

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A station can have different roles at different times. So, both the station type and real-time, changing factors should be thought about when making dispatching plans. On this base, station groups can be put together, like those in areas with a lot of business, areas with a lot of fun activities, or near transport centers. By adding this to user type info, it becomes possible to make a first demand time spread table. Then gives a data-based reason for resource sharing. For example, more bikes should be sent to business-heavy zones and crowded living areas on the weekend to handle the travel needs. Also, on holidays, more bikes placed in sightseeing and fun spots can make service better and users happier.

3.4. Dispatching optimisation strategy

The demand forecasting for shared bike not only provides a reference for enterprises to develop long-term operation strategies but also lays a solid foundation for improving bike utilisation rate. In fact, the fundamental reason behind the excess vehicles or insufficient supply at stations is the inherent unidirectionality of user travel behaviour. For instance, when a large number of users set Station A as their destination within a specific period of time, but the users do not plan to return in a short time, or there are no bike departures from that station. In this case, this station will be full or overflow in a short time, and some of the other stations will face a bike shortage as no bikes will be returned to them. Over time, this imbalance can be gradually worse, affecting overall operational efficiency. Thus, these issues of bike dispatch and rebalancing caused by user travel patterns have always been core challenges faced by shared bicycle companies in their actual operations.

To address this problem, there are currently two main types of dispatch strategies. The first one is the enterprise employing staff to drive trucks for large-scale, bulk bike dispatch. The second is based on the user incentive mechanisms to encourage users to participate in rebalancing actively. Bulk dispatching is generally considered the most efficient method, as it is able to alleviate supply-demand imbalances in a short period significantly. However, this will result in high labour and transportation costs. In terms of modelling, traditional research mainly relies on frameworks such as Mixed Integer Linear Programming (MILP) or Vehicle Routing Problems (VRP), which can provide globally optimal solutions in static scenarios [12]. However, during the real operation cases, the traffic flow, user demand, and road conditions are constantly changing at any time. Purely relying on static optimisation models often makes it difficult to respond rapidly.

With the development of Artificial Intelligence, reinforcement learning has been an effective tool to solve these problems. Based on the interaction between agent and environment, the model continuously learning and optimally dispatches strategies through 'trial and error', dynamically adapting to environmental changes. Existing research shows that reinforcement learning can not only respond quickly during peak demand periods but also gradually optimise vehicle rebalancing decisions over long-term operation, achieving improvements in both operational efficiency and user satisfaction [13]. Therefore, reinforcement learning offers a more flexible and intelligent approach to shared bicycle dispatching.

At the same time, the strategy of the user incentive mechanism, although with less efficiency than the former, it is still adopted as it brings lower dispatching cost. The basic concept is first to find stations facing the imbalance problem along the user's intended route. And then, encouraging users to set their origin or destination to the imbalance station by offering price discounts or reward points and other incentives. While this strategy can indeed alleviate supply-demand imbalance locally, the overall dispatch effect remains significantly limited due to the high randomness and unpredictability of user participation [14]. Therefore, in the case of real world operations, this strategy is regarded as a supplementary method to batch scheduling rather than a completely alternative solution.

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3.5. Abnormal behaviour detection

Among the million orders per day, some occasional abnormal behaviours are inevitable. Some of these abnormal behaviours come from the problem of the bike itself, such as bike damage, abnormal positioning signal, random parking, and so on. The others, user-level violations and fraudulent orders, are also the source of error orders. If the enterprise is not able to handle these problems, it will directly lead to the waste of resources, higher operating costs, and even affect user experience and company trust. Therefore, a reasonable abnormal behaviour detection is also an essential part of the operation. Combining with some punishment and management mechanisms is a crucial step for shared bike enterprises to enhance operational efficiency and ensure service quality.

In past work, some people effectively used machine learning ways to get features from the time, space, and user action parts of trip records for finding possible odd actions from a big amount of data. This way has shown that using machine learning to spot odd actions will give a more exact result [15]. Also, deep learning methods have been more and more used in this area. End-to-end neural network models, like autoencoders and spatio-temporal convolutional networks, have shown better modeling power when working with large-scale and high-dimensional data [16]. Also, data mining methods can be used to set up the normal patterns of regular orders, helping the quick finding of differences and starting alerts.

In general, odd finding methods, when used with right penalties and feedback systems, will not only raise the total safety of the platform but also cut needless running costs brought by odd actions. More importantly, these methods help operators deal with broken bicycles right away, so making user happiness better and building stronger trust in the system.

Machine learning has been widely used in shared bike dispatching systems, helping to make a more complete research and operation framework. Supervised learning and deep learning are mainly in charge of exact forecasting and data support, while unsupervised learning looks at finding hidden user behaviour patterns and looking at station groups. Also, reinforcement learning makes improved dispatching plans, and strange behaviour finding keeps the system safe, making sure of safe and steady operation. These four kinds of machine learning ways help each other, working together while doing different jobs, to jointly push the operation of shared bikes to grow in a more efficient, cost-saving, easy and smart way.

4. Discussion

The previous content illustrated the five main applications of Machine Learning in the AI-Enabled dispatching optimisation mechanism of shared bikes. Including demand forecasting, user behaviour analysis, station classification and dispatching optimisation. Taking one with another, these methods demonstrated the performance of Artificial Intelligence in handling supply-demand imbalance, inaccurate prediction results and the huge potential for improving dispatching efficiency.

In the area of demand forecasting, Random Forest and Gradient Boosting work well for long-term forecasting, while LSTM and GRU get better results for short-term predictions, with errors going down to only 1 – 2 bikes. These high-accuracy forecasting methods make a strong base for improving dispatching efficiency.

Using unsupervised learning methods like K-Means Clustering to look at and group user behavior. Users can be grouped as commuting, leisure, or occasional types, and putting this together with demand forecasting helps more focused service plans. But these methods have limits when dealing with high-level mixed data.

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Like looking at user behavior, K-Means Clustering can also be used to find the differences between stations in space and time. By seeing features of stations, the company can set the priority plan in a simple way. But the role of stations can change over time. A station might show a "high demand origin" or a "high demand destination" at different times. This will make it harder to study and make the model more complicated.

Dispatching optimising strategy is the final goal of the previous method. For the scheme of truck dispatching, based on reinforcement learning, the intelligent agent continuously interacts with the environment to optimise the dispatching plan and converge to the final result. At the same time, according to the user incentive mechanism, it can also encourage users to complete a small part of bike migrations, thereby reducing some operational costs. However, the efficiency of this method depends on the user participation rate and the rationality of the mechanism.

4.1. Challenges in practical application:

Although the existing research has shown a remarkable achievement, there are still some challenges that need to be handled:

Due to the large number of external factors that affect the demand for shared bike usage, it is challenging to obtain all the external factors. Even some of the data can not be obtained because of issues like privacy concerns or the inability to quantify all the aspects. Therefore, the current prediction models can not take into account all the factors, and there is still space to improve the accuracy of the forecasting model. After that, when pre-processing the initial data, the biggest challenge is dealing with missing data. Also, the alignment of data granularity is also a matter worthy of attention. Because not every data point will be thoroughly recorded, in this case, discussing how to complete the data reasonably would be a challenge. Finally, the protection of user data privacy can not be ignored.

It is also a challenge to perfectly forecast at present, as the demand for shared bikes usually changes in real time. Although reinforcement learning has shown a strong adaptability, it also requires a high amount of computer power to run the model. Therefore, there is still room for improvement in the real-time adjustment of dispatching strategies.

For the moment, using tracks to dispatch the bikes will bring a massive cost, even it has the most efficiency. The cost would be lower when using a strategy of user incentives. But it is not stable and is unable to meet the dispatching needs of the entire city. Therefore, finding a balance between these two methods is the most important thing for the enterprise.

4.2. Future research direction and improvement

Regarding the future research directions, they can be explored from the following aspects:

The first direction in future prediction models, trying to reduce further the dimensionality of external influencing factors may be a way to alleviate the pressure on the training model and improve efficiency. But it is important to consider the rationality of the composite indicator when dimensioning the data.

By looking at the combination of truck-based dispatching and user rewards, the system can better match users' riding routes with dispatching needs. Even if the user's end goal is not the station without bikes, the system can give small rewards to motivate returning the bike at a middle station with extra vehicles. This method may cut the need for dispatching trucks to go out of the way to pick up bikes at stations with too many bikes, which lowers running costs and greatly improves total dispatching efficiency.

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5. Conclusion

This study goes on to the AI-powered dispatching improvement system of shared bikes, looking at methods paths and working links across need guessing, user and station study, better dispatching plan, and wrong action spotting. The study says that guessing models built on machine learning have shown a strong result on both short-time and long-time guesses. At the short-time guess level, it can even keep the mistake to under 1-2 bikes. For the long-time guess models, it can better balance the steadiness and understandability, which is more fitting for a company to make its plan for the future and better resource sharing. Built on user and station grouping methods, including grouping and size cutting, it is possible to find user kinds, such as "commuting/leisure/occasional", and the "start/end" jobs of sites at different times. This gives a data base for different advertising and importance setting. At the dispatching plan level, reinforcement learning pushes the agent to work with the setting, to make a doable rebalance plan in a changing and unsure setting. As a more money-friendly dispatching extra plan, user rewards system guides the bikes to go back partway along the set travel path. It has cut the stress on the truck dispatching plan. Putting together strange spotting with feature building and end-to-end space-time models can quickly find rule-breaking orders, cut running waste, and make system strength better. In all, AI ways show big pluses in guess rightness, planning speed, and safety steadiness. Artificial intelligence is pushing the running of shared bikes to change from being led by know-how to a smart model that joins data and choosing. By joining high-rightness guessing, fine grouping, smart planning, and problem handling, the platform makes service quality better. The running costs can also be well managed. This joining gives a repeatable and growable technical path for making a low-carbon, easy, and lasting city moving system.

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