Blockchain-Enabled Data Analytics-Based Demand Service Optimization for Vehicular Safety

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Abstract: Vehicle safety and demand optimization are being explored using blockchain-enabled data analytics due to the rapid growth of connected vehicle technologies. This system establishes a robust and scalable framework for next-generation intelligent transportation systems (ITS), leveraging cutting-edge data analytics, IoT integration, and decentralized technologies to optimize resource allocation, enhance operational efficiency, and strengthen safety protocols. By harnessing real-time data processing and predictive modeling, the framework enables dynamic traffic flow optimization, reduces congestion, and minimizes environmental impact. Furthermore, the paper explores the integration of blockchain technology within vehicular networks, highlighting its transformative potential in ensuring secure, tamper-proof data exchange among vehicles, infrastructure, and service providers. Key applications include enhanced collision avoidance systems, automated toll collection, and fraud-resistant vehicle-to-everything (V2X) communication. The study also investigates blockchain's role in improving emergency response coordination by enabling instant, verifiable data sharing between first responders, traffic authorities, and connected vehicles. These advancements not only increase road safety and traffic management precision but also lay the foundation for fully autonomous and decentralized transportation ecosystems in smart cities.

1 INTRODUCTION

Smart vehicles have been evolving rapidly in recent years, driving the exploration of innovative technologies to enhance road safety and optimize vehicular operations. A great example of such an innovation is the combination of blockchain technology with data analytics, which has great potential for revolutionizing vehicular safety systems. With blockchain technology, safety-critical information can be exchanged securely, transparently, and decentralized in real-time. With advanced data analytics, this system can optimize demand service by dynamically allocating resources and safety measures according to demand, traffic patterns, and other contextual factors. To ensure vehicular safety, we need to be able to predict potential risks, make on-the-fly decisions, and allocate resources efficiently. Safety systems typically rely on centralized structures that can fail or be compromised. In addition to being tamper-proof, blockchain's inherent decentralized architecture mitigates all of these risks by providing easily traceable and tamper-proof data for safety decisions. The use of data analytics, on the other hand, allows a vast amount of real-time data from vehicles, sensors, and infrastructure to be analyzed to extract meaningful insights.

Vehicle communication has undergone a paradigm shift with intelligent transportation systems (ITS) aimed at improving traffic efficiency, safety, and the overall driving experience [1]. Through the Internet of Vehicles (IoV), vehicles and infrastructure are interconnected at the roadside to facilitate this transformation. A multitude of aspects of vehicular safety and demand-responsive services can be optimized with IoV systems. There are several challenges associated with centralized data management systems, including security vulnerabilities, privacy concerns, and lack of transparency.

Data management and analytics in IoV environments can be improved by using blockchain technology, which provides a decentralized, secure,

and transparent platform [2]. In order to enhance vehicular safety and optimize demand-responsive services, blockchain technology allows vehicles, infrastructure, and service providers to share data securely. An overview of blockchain-enabled data analytics for demand service optimization in vehicular safety is presented in this paper, as well as key findings, challenges, and future research directions. Blockchain can provide access control mechanisms for vehicular networks, as well as secure data sharing [3] [4]. Data analytics techniques will also be applied to blockchain-enabled vehicular data to optimize services such as emergency response, traffic management, and personalized safety alerts. In addition to addressing scalability, interoperability, and regulatory issues related to implementing blockchain in IoV environments, the review will also address scalability challenges. Using blockchain technology, we can trace, track, and see how huge amounts of data are related and simplify the contents without cloud services. Below is a proposed taxi that is a regular taxi as well as a ride-hailing taxi. According to the Figure, this system consists of three main layers. Data collected from taxi drivers and passengers in real-time is the first layer.In addition to enabling imports and exports of goods and services, sustainable transportation and logistics are important to related activities. Transport efficiency increases a good's (or service's) market potential. In addition to achieving other economic, social, and environmental objectives, low-carbon transportation systems can also contribute to the environment [5]. Public health and safety can be improved, access to transportation can be increased, congestion on roads and parking lots can be reduced, consumer costs can be lowered, economic growth can be boosted, and air and noise pollution can be reduced. Using existing techniques, transportation energy consumption can be reduced by 40-50% below 2010 demand, according to estimates [6]. In spite of this, there are a number of obstacles that prevent this potential from being fully realized. Sustainable transportation may be beneficial for reducing global climate change and boosting local economies because of its potential economic, social, and environmental benefits. There are a lot of security problems associated with the Internet of Vehicles (IoV) due to its resource limitations [7].

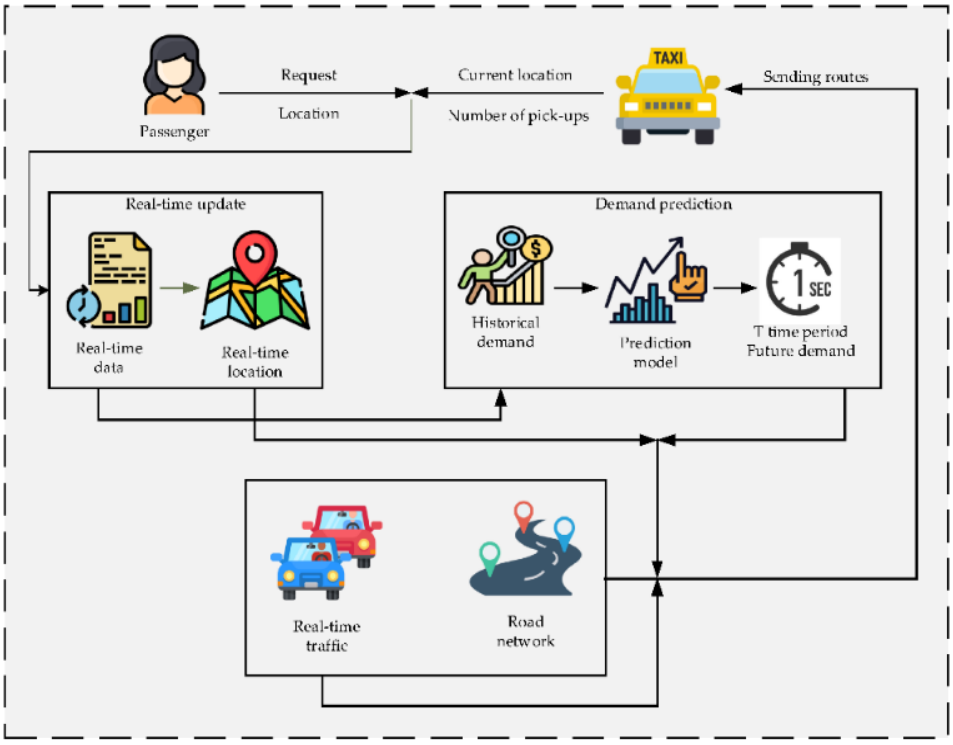

Figure 1: A comparison of regular Taxi and ride-hailing services.

2 LITERATURE REVIEW

The blockchain technology is revolutionizing a variety of industries, including transportation [8]. As a decentralized, immutable, and transparent technology, it is well suited to managing data in IoV environments. Several studies have examined blockchain's application in IoV, focusing on various aspects such as secure data sharing, access control, and trust management [9]. A key benefit of blockchain technology in IoV is its ability to facilitate secure data sharing between vehicles, roadside units, and other entities [10]. Author [3] suggests using smart contracts to protect data from unauthorized access in a consortium-based blockchain-based data-sharing scheme for vehicular edge computing and networks (VECONs).

Furthermore, a reputation-based system ensures that vehicles share data of high quality. A VANET can also use blockchain to establish trust between vehicles and RSUs. To mitigate MAC layer attacks on VANETs, the Author [11] proposed a trust-based approach using blockchain technology. Through their solution, genuine nodes can exchange information securely and privately, ensuring reliable security and privacy. According to Author [12] describes reputation-based voting as a method used to choose miners in an IoV enabled with blockchain technology. Using this scheme, you can prevent voting collusion in IoV and ensure that trusted miners are selected for data sharing.

2.1 Data Analytics for Vehicular Safety

A wide range of data is generated by IoV systems, which can be analyzed to gain valuable insights in order to improve vehicle safety. Analysis of vehicular data provides a means of identifying potential safety hazards, predicting traffic incidents, and alerting drivers in a timely manner. There have been several studies investigating how data analytics techniques can be applied to vehicular safety, focusing on factors such as incident detection, risk assessment, and driver behaviour [13].

The use of deep learning techniques has demonstrated promising results in predicting traffic accidents and providing drivers with timely warnings. An Incident and Evidence Management Framework (SIEMF) was proposed, combining deep learning and blockchain for predictability and secure evidence management [14]. Their system not only enhances road safety and enables forensic analysis but also addresses the challenge of secure evidence management and predictive modelling. Ensemble learning models can predict the trustworthiness of VANET vehicles. In [15], the Author proposes a methodology for predicting the trustworthiness of vehicles using ensemble learning. Using their approach, vehicular networks become more transparent and trustworthy, reducing the risk of fraud or tampering. Through the use of data analytics techniques, IoV systems can improve vehicular safety by generating vast amounts of data [16].

2.2 Demand Service Optimization

In IoV, demand service optimization is achieved through data analytics and communication technologies. This allows real-time resource allocation and management. Drivers and passengers will be provided with personalized services, as well as the optimization of traffic flow and the management of energy consumption. IoV environments can benefit from secure and transparent demand service optimization enabled by blockchain technology [17]. Through blockchain technology, demand response (DR) can be managed securely and transparently in electric energy grids. According to the Author [18], blockchain applications are being explored in the power systems industry, focusing on distributed energy management (DEM), electric vehicles (EVs), and distributed power generation (DPP). The researchers found that blockchain could address some of the challenges related to modern energy grids, including the high penetration of renewable sources and the proliferation of electric vehicles. A study conducted by Author [19] examined blockchain technology in the management of IoV demand response, taking into account incentivization, privacy, and security. A systematic literature review was conducted to explore how blockchain technology can be used as a tool for IoV demand response management, as well as how blockchain can address issues of incentivization, privacy, security, and lack of interoperability.

An artificial intelligence, blockchain technology, and Internet of Things platform was developed to enable multilevel transactions for electric vehicle charging stations [20]. In addition to securing security and fairness while shortening latency, their platform utilizes green energy across microgrids, bidirectional discharging, and demand response bidding. Using blockchain in IoV environments, these studies demonstrate how resource allocation and management can be optimized by providing a secure, transparent, and distributed platform.

2.3 Blockchain-Enabled Data Analytics for Vehicular Safety: Synergies

Data analytics and blockchain technology can enhance vehicular safety and optimize demand-responsive services in IoV environments through the convergence of these technologies. A blockchain-based IoV system can be developed that addresses the challenges of traditional IoV systems by combining security, transparency, and data analytics. Blockchain technology enables IoV environments to share and process data securely and transparently, enhancing security and privacy [21].

The Author [22] presents practical prospects for blockchain-enabled federated learning in the IoV, including full security, privacy, and verifiability. By addressing federated learning's vulnerabilities to poisoning and reverse engineering attacks, they ensure that ITS services are trustworthy. Author [23] presented a 5G-VANET data access solution based on smart contracts and a blockchain oracle that preserves privacy.

3 METHODOLOGY

3.1 Predictability of Taxi Demand

Using $\prod max$ as a measure of maximum predictability, we define it in this section. In this study, we propose the $\prod max$ model to answer the following question:

Problem 1: As a result of a predictive algorithm and sequence of taxi demand D_n^i data at building blocks, we explore the maximum amount of predictability $\prod max$ (maximum potential accuracy) the prediction algorithm can achieve that.

3.1.1 Taxi Demand

There are two channels representing taxi pick-up and drop-off demand in a three-dimensional matrix for each grid of a city, so it can be predicted how many taxis will pick up and drop off at a given time interval. A CNN or LSTM can then be used to determine the spatial/temporal relationship between the two demands [24] - [27]. Analyzing these two demands together, however, reveals inconsistent periodic characteristics. During certain times, taxi demand decreases for pick-up and increases for drop-off, as shown in Figure 1. Combining these two demands into a single layer might obscure their specific characteristics, reducing prediction accuracy. Research has attempted to uncover the hidden modes of change in traffic flows [29].

Taking into account different changes in taxi pickup and drop-off patterns, we built a single demand forecasting model.

3.1.2 Neural Network Architecture Selection

In spatial analysis, CNN has been used widely [27], [28]; however, it is restricted to Euclidean space, which means that taxi zones should be gridded, not irregular. As CNN extracts taxi demand from two distant regions using local characteristics, there may be a high correlation between the demand for taxis in the two regions. As part of our comparison of CNN and LSTM neural networks, we only use LSTM neural networks for taxi demand prediction but conduct experiments using both approaches as well. Thus, we use the stacked denoising autoencoders for traffic data imputing as a method for generalizing the model [29].

3.1.3 Proposed Single Demand Prediction Model

Here is an example of a single demand prediction model for taxi pick-up demand, which is based on LSTMs for modelling the temporal relationship between pick-up demand and different time intervals, as well as a denoising layer for handling random noise in input data. Taxi drop-off demand can also be predicted similarly. This section explains the model for predicting demand for taxis of a single type in detail. A building's taxi demand at time t ($1 \leq i \leq m$ is represented by d_t^i, while its information demand is represented by $1 \leq t \leq n$). As a sequence, $D_n^i = d_1^i, d_2^i, d_3^i, \ldots, d_n^i$ is the historical taxi demand for building block i. Note that D_n^i represents the texi demand from the start of the sequence to the end of the sequence. $D_n^i = 2122$, for example, indicates that there were two pickups at time step 1, one at time step 2, and so forth for block i.

As taxi demand can be highly variable, it can be difficult to predict exactly what d_t^i do. The taxi demand is rounded using a factor q for simplicity. Taxi demands are grouped as one demand for every q taxis. If q =10, then 620-629 in the sequence becomes 620; e.g., if q =10, 620 becomes 620 in the sequence. The prediction errors were kept low by setting $q = 10$ based on the first few tests [18].

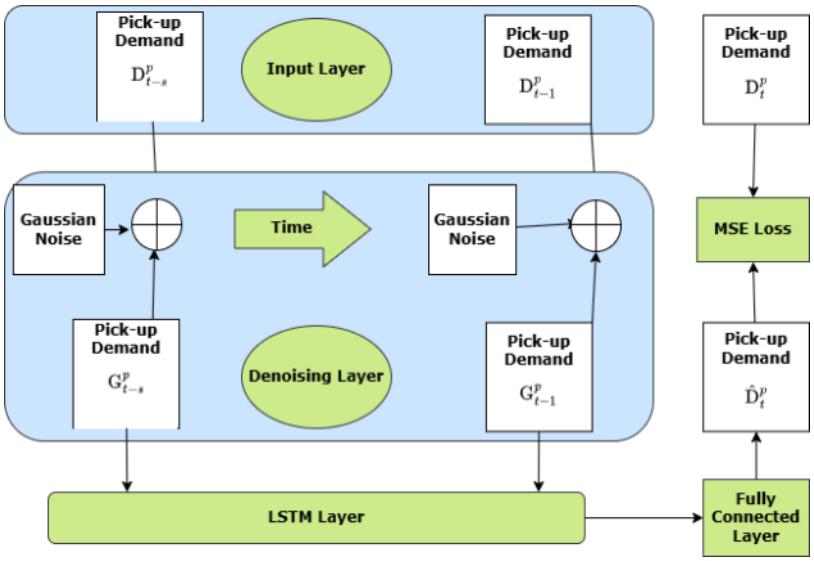

Figure 2: The single demand prediction model structure.

3.2 Component for Matching Taxis to Regions

In each region, vacated taxis are allocated based on future demand estimates and current taxi locations. The first metric is used to ensure that taxi assignments are proportional to demand. Due to this, more taxis will be dispatched to the region where a high demand is expected, and vice versa. To minimize the transition period, it is important to consider the second metric (current taxi locations) to ensure that vacant taxis can reach their designated regions as quickly as possible. Customers searching for rides will have less waiting time during the early part of the period. The demand for taxis in all regions (10, 20, 40, 10) is the same, so in Region A we should have one taxi, in Region B two taxis, in region C four taxis, and in region D one taxi is required.

Figure 3 illustrates an efficient method of matching taxis to regions by using a bipartite weighted graph. Weights representing graph edges are computed using the taxi's shortest distance from the nearest border. As shown in our graph, each of the regions in Manhattan had a different level of demand over that period, so we duplicated the regions with a higher demand multiple times from their normalized levels of demand. In this regard, the taxi-to-region matching component aims to maintain perfect matching while minimizing the sum of weights. The taxis are assigned to one region each. There are usually more taxis than regions in practice. Taxi IDs are identified by index i and index j, and the following duplicates identify region IDs. It follows that j=2 corresponds to the same region as j=3.

Here is an ILP problem that can be used to optimize the matching procedure aforementioned:

$$(P): minimize_{x_{i,f} \in \{0,1\}} \sum_i \sum_j w_{i,j} x_{i,j} \quad , \tag{1}$$

$$Subject\ to: \sum_j x_{i,j} = 1,\ \forall_i, and \sum_i \frac{x_{i,j}}{} = 1,\ \forall_j \ , \tag{2}$$

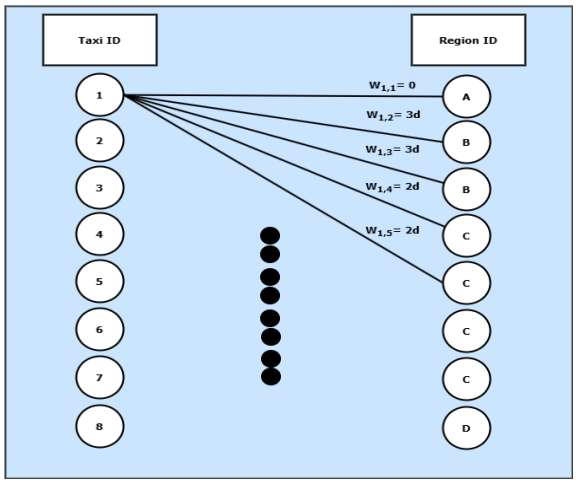

Figure 3: Common matching graph illustration.

Taxi i is either assigned to region j or not, according to $w_{i,f}$, whereas $x_{i,f}$ indicates whether taxi i is associated with region j

The value is 1 in this case. In (P), the taxi is restricted to one region only, ensuring perfect matching.

In addition to the Hungarian algorithm, which is another heuristic minimum-weight perfect matching algorithm, there are several other heuristic minimum-weight matching algorithms as well. By using the polynomial-time $\approx \mathcal{O}(N)$ approach, the problem can be solved much faster than by using a branch-and-bound algorithm based on ILP.

3.3 Taxi Routing Optimizer

Road networks can be constructed using simple search techniques and complex fuzzy logic theories [30]. Traffic networks are analyzed by transforming them into complex intersectional and road graphs. Each road r contains several segments of the same length lr, while the intersections of the roads $r \in \{1, \dots, R\}$ are at most two. It then consists of vertices and edges, the vertices being the connections between segments. Taxi i is currently located at S_i, S_g and has a destination of D_i, D_g with D_i and $S_i$representing the street IDs and S_{g_i} and D_{g_i} representing segments of the streets. In this article, a real-time traffic model is proposed to optimize route planning. Integer linear programs are developed to determine which is the fastest route based on the location and region of vacant taxis at present. A real-time feedback system determines the fastest routes using traffic feedback. Since ILP is solved on a regular basis based on new data received, the best route is determined based on the most recent data. A real-time feedback system determines the fastest routes using traffic feedback [31]. Our approach might update routes every minute.

3.4 Taxi Demand Service with Blockchain Framework

In this section, we describe the blockchain network. Taxi services and passengers benefit from the blockchain framework because it certifies transparency and security. On the basis of IoT devices, security processes track and trace. Using smart devices, ride-sharing entities can track transmissions to provide security. IoT devices and registered vehicles are gathered in the proposed system. Blockchain allows all activities to be tracked by storing data from IoT sensors and vehicles in a database. As a result of blockchain technology, users are prevented from hacking other users' accounts and stealing their points to use for payments. Blockchain technology protects transactions, driver, and passenger profiles, so non-members or users without accessibility IDs cannot access them.

4 RESULTS AND DISCUSSION

According to Figure 4, Hyperledger Fabric is able to process about a million transactions per second. To evaluate the proposed system's performance, three primary user groups were taken into consideration: 500, 1000, and 1500 individuals. A statistical analysis was performed to assess the performance of the taxi demand service based on blockchain technology.

An illustration of the latency of transactions for a blockchain-based taxi demand service is shown in Figure 5. A performance assessment of the designed system was conducted using three defined user groups. A platform's response time measures the system latency. User groups are used to categorize transactions. The Figure shows that latency increases with increasing user numbers.

The comparison between the proposed system and other state-of-the-art methods is presented in Figure 6. This approach achieves the lowest root mean square error. The Figure shows that MLP exhibits the highest RMSE. Spatiotemporal correlations are not taken into consideration by the MLP. However, XGBoost is similar to MAP because it ignores spatial correlation.

Throughout the week, from Monday to Sunday, Figure 7 shows how taxi pickup and drop-off demand varies daily. Record pick-ups are indicated in blue, while drop-offs are indicated in green. According to the Figure, Friday is the busiest day for pickups and drop-offs, with approximately 25,000 pick-ups and 25,500 drops. A maximum of 13,000 pick-ups and drop-offs are recorded on Sunday, the lowest day of the week.

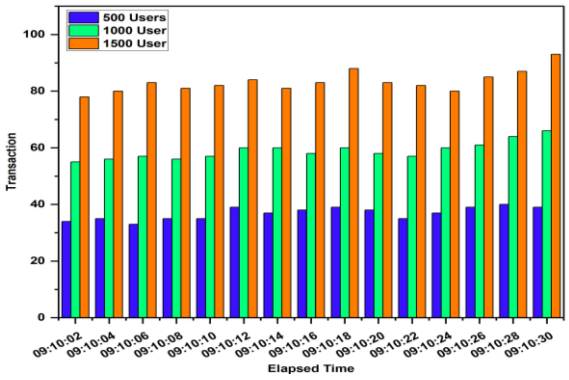

Figure 4: The number of transactions versus elapsed time.

Figures 8 and 9 illustrate the method's excellent performance. As compared to passengers, drivers lose about 14 percent of their utility. Passengers save about 72% of their waiting time, which shows the greatest reduction in waiting time.

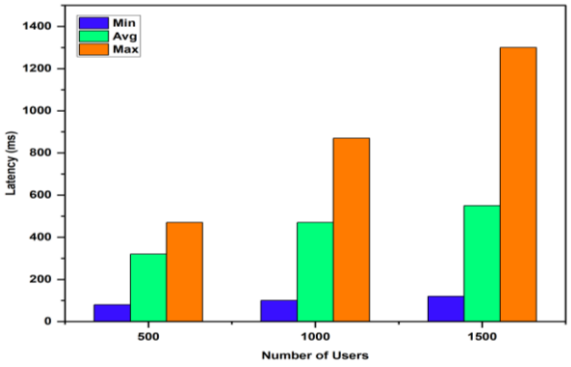

Figure 5: The performance of latency of query transaction versus number of users.

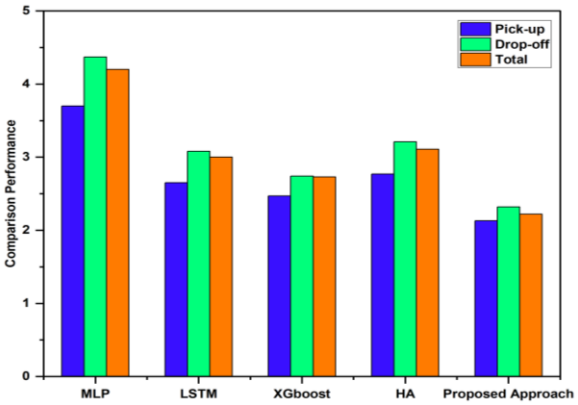

Figure 6: Comparison of various existing model performance.

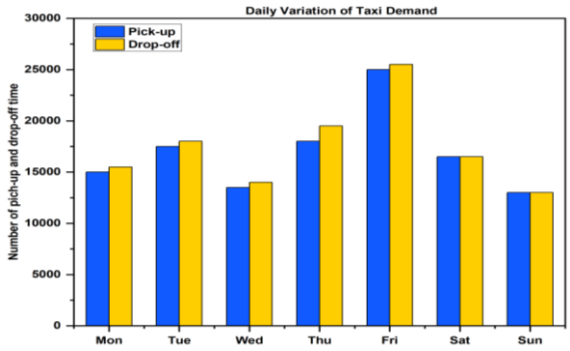

Figure 7: Daily variation of taxi demand.

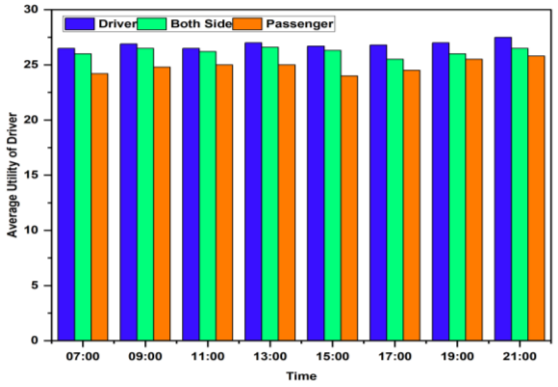

Figure 8: Analyzing the utility of drivers versus time.

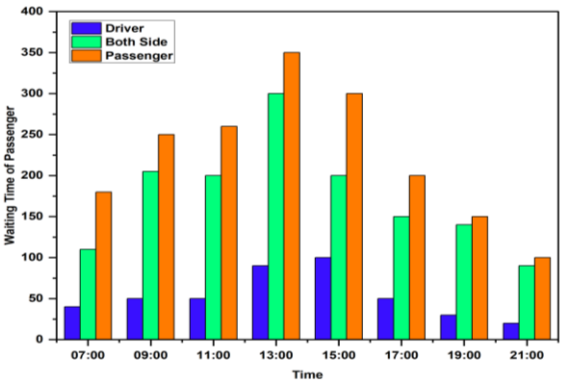

Figure 9: Saving time for the passenger versus time

5 CONCLUSIONS

Blockchain technology combined with advanced data analytics offers a robust framework for tackling critical issues related to vehicular safety management and optimizing taxi demand services. By leveraging this integrated approach, the proposed system effectively ensures the protection of sensitive information, maintains data integrity, and allows for swift real-time decision-making. Consequently, allocation of resources dedicated to vehicle safety - such as emergency response measures, route optimization, and traffic management - can be handled in a more coordinated and efficient manner. Moreover, the transparency offered by blockchain facilitates trustworthy and verifiable transactions among passengers, drivers, and service providers, contributing to enhanced user trust and satisfaction. Despite demonstrating superior accuracy and operational efficiency compared to traditional techniques, the proposed approach still encounters certain practical barriers. These barriers include managing increased data volumes as networks

expand, ensuring compatibility between various technology platforms, and adhering to evolving regulatory frameworks. Therefore, future research directions should emphasize overcoming these hurdles, examining scalability solutions capable of supporting city-wide or regional networks, and exploring innovative methodologies that go beyond existing optimization approaches to further enhance both passenger convenience and overall vehicle safety outcomes.

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