Dynamic pricing in Ride-Hailing intelligent transportation systems by using Deep Reinforcement Learning

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Abstract

In today's world, the global transportation challenge has gained significant attention from researchers due to technological advancements, urban development, and expanding road networks. This issue has profound social and economic implications for countries, leading to crises arising from increased passenger volume, traffic congestion, environmental concerns, and air pollution. Recognizing the gravity of the situation, the transportation industry is increasingly turning to intelligent solutions. The rise of internet usage in modern societies has facilitated the adoption of intelligent transportation control tools, particularly through the implementation of Ride-Sharing and Ride-Hailing systems.

One crucial aspect in Ride-Hailing systems in recent years is dynamic travel pricing, essential for achieving balance between supply and demand. Unlike the past, where unstable environments hindered suitable pricing policies, modern transportation services are leveraging dynamic pricing systems. Researchers have proposed innovative approaches, employing reinforcement learning and deep reinforcement learning methods, to simultaneously minimize passenger waiting time and maximize revenue. This research utilizes data from Uber Company's intelligent transportation service trips in 2018, covering trips with all available vehicle types. Rigorous analysis and scrutiny of the collected data have been conducted using reinforcement learning techniques. Notably, the Deep State–Action–Reward–State–Action Network (DSARSA) algorithm has demonstrated the most effective results in achieving the dual objectives of maximizing income and minimizing waiting time. To validate and rank the techniques employed, Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) multi-criteria decision-making method (MCDM) has been applied to ensure the selection of the best and most reliable results.

Keywords: *Dynamic pricing, Revenue management, Waiting Time, Reinforcement learning, Deep Reinforcement learning.*

1. Introduction

In recent years, the rise of technology and widespread adoption of advanced smartphones have given rise to the emergence and growth of organizations across various industries. As transportation has become a critical global issue, it has become a focal point for researchers. While cities and road networks continue to advance, this issue has profound implications for the economic situations of diverse countries. (Olayode et al., 2020).
Intelligent transportation systems in Ride-Hailing serve various purposes, with dynamic pricing being one of the most crucial. Owners of Ride-Hailing services recognize the importance of pricing based on stochastic conditions to manage revenues and adapt to unforeseen circumstances. Dynamic travel pricing is particularly significant for modern transportation services as it contributes to balancing supply and demand, addressing challenges that arose from unstable environments in the past lacking a suitable pricing policy. Researchers have proposed dynamic pricing systems to minimize passenger waiting time or maximize revenue, emphasizing the need for effective coordination of requests in Ride-Hailing transportation systems. This coordination is considered a vital operational concern for achieving stable interactions in ride-hailing services. (Qin et al., 2021). Another critical aspect explored in the provision of services within Ride-Hailing intelligent transportation systems is dynamic travel pricing. Historically, the absence of a suitable pricing policy resulted from unstable environments. (Rana and Oliveira, 2014). For this reason, researchers have presented different methods and ideas to solve this problem. For instance, the unbalanced distribution of supply and demand is controlled, and the prices are optimized using different approaches (Lei et al., 2019). Various Reinforcement Learning methods are extensively employed to achieve equilibrium between supply and demand. Researchers have introduced a dynamic pricing system to minimize waiting time for passengers. Our focus will delve into research objectives and innovations in this context. In addition, the other goals such as minimizing the idle time for drivers (O'Keeffe et al., 2021), minimizing waiting time (Haliem et al., 2021), minimizing travel time and distance (Al-Abbasi et al., 2019) and profit maximization (Pandey et al., 2019) employed by many researchers. It should be noted that because of the increasing volume of data and its complexity, neural network and deep learning methods (Feng et al., 2021) or a combination with reinforcement learning (Song et al., 2020) might be beneficial. Based on the main goal, the sub-goals of this research can be expressed in the form of the following:

- Analyzing and investigating factors affecting the price of travel to check the balance between supply and demand
- Estimating the best price dynamically according to a different time, places, and other characteristics
- Developing models to minimize waiting time and Maximizing Revenue.

Based on the extensive and diverse research conducted in recent years, this study aims to embrace innovation and introduce new aspects. New ideas and methods will validate the research, emphasizing the importance of freshness in achieving research goals. The innovative aspects in this study include a novel perspective on dynamic pricing to optimize waiting time and maximize earnings. It also addresses the balance between supply and demand through reinforcement learning and deep reinforcement learning methods. A comprehensive examination and comparison of methods become crucial, considering that existing research often relies on simplistic reinforcement learning and mathematical modeling, lacking long-term acceptability due to increased data and issue complexity. To address these gaps, there is a need for more advanced methods that dynamically recognize trip prices with enhanced accuracy and performance. Another innovative approach involves considering additional features, such as weather conditions and specific daily circumstances, not explored in previous research. The overall structure of the study involves a discussion of related research in the second part, followed by an examination of the proposed method. Subsequently, the results will be evaluated, and conclusions along with recommendations for future research will be presented.

2. Definitions and Related work

- **Intelligent Transportation Systems**

  Not long ago, traditional institutions dominated the provision of taxi services, operating in a fixed manner where customers could request a taxi by phone and specify their destination. While this service persisted over time and still exists to some extent today, it is crucial to note the inherent problems associated with this model. Challenges include issues related to security, optimal route identification, traffic management, fluctuating costs, and a more passive form of customer support (Devi and Neetha, 2017). As time has progressed and technology has advanced, coupled with the comprehensive modernization and widespread use of the Internet today (Rachbini et al., 2020), organizations were established to provide the aforementioned services in an intelligent manner. These services are offered under the title of Ride-Hailing intelligent transportation systems. Theoretically, Ride-Hailing systems are systems that can integrate the flexibility and speed of cars and reduce customer payment costs (Akbari et al., 2020). In these systems, the main goal is to obtain customer satisfaction (Habibah Arshad et al., 2008).

- **Pricing**

  Pricing is the strategic process through which a business decides the optimal selling price for its products and services, often integral to the overall marketing plan. In this decision-making process, businesses typically take into account factors such as the procurement cost, manufacturing expenses, market dynamics, competitive landscape, prevailing market conditions, and the perceived brand and product quality. (Smith, 2011). According to the literature, pricing has different types, which are generally divided into two categories: static and dynamic (Nagle et al., 2016).

- **Revenue Management**

  Revenue management involves the systematic analysis of consumer behavior at a micro level, anticipating demand patterns, optimizing product availability, and leveraging price elasticity to achieve maximum revenue growth and profitability. The primary objective of revenue management is to strategically sell the appropriate product to the right customer, at the right time, with the right pricing, and ensuring the right quality. (Cross, 1997).

- **Machine Learning**

  Machine learning is a field of study that gives the machine the ability to learn and experience without explicit programming (Géron, 2019). In the realm of machine learning, the focus is on understanding how systems can learn and enhance their performance through data analysis. The primary research area in this field revolves around automatic learning, aiming to identify intricate patterns to construct systems capable of making intelligent decisions based on data. (Han et al., 2012). There are different types of machine learning systems. These systems include supervised, unsupervised and semi-supervised learning systems.

- **Reinforcement Learning**

  Reinforcement learning diverges from the aforementioned approaches. Here, the learning system, referred to as an agent, has the capability to observe the environment in a specific state, execute an action, and receive a reward or punishment based on the performed action. The learning system autonomously learns the optimal strategy to attain the maximum reward, with the strategy defining the actions the agent should undertake in particular situations. (Géron, 2019). In this process, the agent's objective is to maximize the cumulative sum of rewards obtained from executing actions in specific situations. The agent aims to optimize not only immediate rewards but also the total rewards accumulated over time. In essence, reinforcement learning involves assessing executed actions rather than training with predetermined correct actions (Sutton and Barto, 2018).

- **Deep Learning**

  Deep learning is a class of machine learning algorithms that use multiple layers to progressively extract higher-level features from the raw input (Deng and Yu, 2014). In deep learning, each layer is designed to transform input data into a more abstract and composite representation. Deep learning serves various purposes, including classification, prediction, and clustering. Moreover, these algorithms can be integrated with reinforcement learning methods to address more complex problems.

- **Deep Reinforcement Learning**

Deep reinforcement learning methods execute parallel and independent computational processes. Each agent operates on a distinct section of the environment with a unique set of parameters. The updates from each agent are transmitted to a global network and amalgamated asynchronously to attain a cohesive global policy (Farazi et al., 2021).

- **Research Background**

  i. **Intelligent Transportation Systems**

  To enhance profitability in Ride-Hailing systems and intelligent transportation overall, as well as to ensure competitiveness in the market and reduce operational costs, predictive machine learning methods have been employed (Akyouz et al., 2020). Additionally, to optimize driver performance and determine whether to accept or decline passenger requests, which may entail additional costs for the service organization, decision-based machine learning methods like decision trees are utilized. In this context, distance emerges as a crucial parameter for drivers to make decisions on approving or rejecting requests (Do et al., 2019). It's noteworthy that the effectiveness of these methods may diminish over time with increasing data volume, posing challenges to the success of developing intelligent ride-hailing transportation systems. Given that the objective of these systems is to integrate transportation systems based on people, cars, and roads using communication technologies, advanced methods are imperative to fulfill this goal.

  ii. **Dynamic Pricing**

  The pricing and capacity management challenge has been addressed by modeling it using the nonlinear stochastic integer programming technique. The solution involves employing a simulation-based method called Simulated Annealing. Recognizing the dynamic nature of the problem, decisions about prices and optimal capacity allocation have been made dynamically (Kamandanipour et al., 2020).
  In the context of intelligent transportation systems, the temporal sequence plays a crucial role. Researchers have explored the use of deep learning models to enhance dynamic pricing by incorporating time sequences. Some have addressed the problem through data mining and machine learning techniques like Random Forest and XGBoost. Additionally, a study focused on dynamically pricing trips in Ride-Hailing systems from the drivers' perspective. They emphasize considering factors such as the queuing system, drivers' well-being, income, average travel time, and the likelihood of them leaving the system for a more effective distribution of drivers in smart transportation networks. Notably, the invoice price is a significant factor impacting both customers and drivers, requiring consideration from both perspectives to ensure quality results in data analysis (Mahshar et al., 2020). It will lead to accepting a price appropriate to different conditions (Wu et al., 2021).

  iii. **Dynamic Pricing and Revenue Management**

  Revenue management is a critical strategy for businesses aiming to thrive in competitive markets. Its effectiveness relies on accurate forecasts. Researchers have addressed individual cost reduction and the minimization of the distance a passenger is picked up by ride-hailing system drivers by implementing discount policies and strategies. Specifically, drivers covering shorter distances to reach passengers receive compensation for travel expenses. From the passenger's perspective, a discount is applied to the travel price. This approach contributes to maximizing the long-term revenue of service providers offering such services (Duan. et al., 2019). In recent years, automated systems have played a significant role in various industries, particularly in manufacturing and transportation. In the intelligent transportation sector, one crucial impact of automated systems is the ability to track routes and movements entirely automatically, eliminating the need for driver intervention. (Hillebrand et al., 2020).

  iv. **Machine Learning in Dynamic Pricing**

  Various approaches are employed to enhance the quality of service in Ride-Hailing services. One such method involves utilizing multi-agent simulation, as proposed by researchers (Bischoff et al., 2018). However, these approaches may face challenges in efficiency as data complexity and technological advancements rapidly increase. To elevate service quality in Ride-Hailing systems, researchers delve into understanding and predicting the nuanced behaviors of passengers and drivers for trips. Different classification and behavior prediction techniques are employed for estimation purposes (Tian et al., 2020). These methodologies contribute to service providers elucidating features like affordability, reliability, and responsibility using available technologies (Brown and LaValle, 2021). The concept of pricing extends to various industries, with rail transport being an example where proper pricing is crucial for profitability. Researchers address pricing and capacity management challenges through advanced decision-making tools, utilizing nonlinear random integer programming and simulation-based methods (Kamandanipour et al., 2020). The dynamic nature of these issues necessitates dynamic decision-making regarding prices and capacity allocation. Additionally, researchers recognize the role of pricing in controlling and managing traffic. They employ dynamic optimization systems, dynamic routers, and regression methods for forecasting based on factors like weather, traffic conditions, and travel attributes (Genser and Kouvelas, 2022; Schwieterman and Smith, 2018). The significance of time sequence in intelligent transportation systems is highlighted, leading researchers to explore deep learning models for dynamic pricing improvements, incorporating algorithms such as long-short-term memory and convolutional neural networks (Liang and Cai, 2022).

v. Reinforcement and Deep Reinforcement Learning in Dynamic Pricing

Advanced spatio-temporal dynamic pricing methods include the application of deep reinforcement learning techniques like approximate policy optimization. These methods utilize forward neural networks to assess the current situation and implement optimal price strategies (Chen et al., 2021). In the realm of intelligent transportation systems, particularly in passenger-driver matching for trips, researchers have conducted extensive studies. For instance, some have employed convolutional neural networks for effective classification of previously unseen samples. Incorporating one-way learning and combining it with passenger clustering, they achieve dynamic matching (Liu et al., 2019).

Facilitating safe, efficient, and sustainable movement of people and goods requires various decision-making tasks. Deep reinforcement learning, amalgamating the capabilities of deep learning and reinforcement learning, presents a versatile framework for sequential decision-making applicable to numerous transportation operations and planning challenges (Farazi et al., 2021). Combining deep learning and reinforcement learning, known as deep reinforcement learning, proves to be beneficial in addressing existing challenges. These methods are integral to achieving artificial intelligence systems at or beyond human levels (Matsuo et al., 2022).

Despite the potential success of deep reinforcement learning in the industrial world, a common challenge shared with many machine learning algorithms is the lack of explainability. This limitation becomes crucial as applications of these methods often require models that can elucidate decisions and actions for full community acceptance. Additionally, the complexity of deep reinforcement learning models poses challenges for developers in debugging, involving factors like environment design, observation encoding, large deep learning models, and the training algorithm for policy (Heuillet et al., 2021).

vi. Other methods in Dynamic Pricing

Under various conditions, prices can be estimated using diverse regression methods and optimized based on factors such as the time of day and day of the week (Zhang et al., 2020). Game theory concepts have been employed in a different study to achieve dynamic pricing goals. Constructing a dynamic game based on rational strategic consumers, a two-period dynamic pricing model for two alternative brands is developed. The Nash equilibrium serves as the dynamic game solution, considering consumer choices and the expected value of products across consumption classes. Two competing firms engage in a pricing game, ultimately reaching a Nash equilibrium (Bi et al., 2014). Another approach involves using a bipolar game theory model for dynamic pricing (Bi et al., 2014).

In a multi-period game theory model, researchers investigate the objectives of "dynamic pricing" and "car allocation" in Ride-Hailing smart transportation systems. Dynamic planning is employed to advance the decision-making process to achieve these goals (Lei et al., 2019). The rise of ride-sharing systems significantly impacts the advancement of self-driving and electric vehicle technologies. Researchers address the pricing challenge posed by a profit-maximizing transportation service provider operating a fleet of autonomous electric vehicles. Initially, a static policy is considered to maximize passenger waiting time and minimize driver profit. The problem is then modeled using various dynamic programming methods and solved with multiple deep reinforcement learning methods to achieve a near-optimal policy. These results contribute to

the stability of using these systems in the service delivery structure (Turan et al., 2020). Similarly, optimization methods are applied to address traffic timing issues of self-driving cars and optimize them, with results utilized for dynamic pricing and understanding passenger behavior for revenue management decisions (Yang et al., 2021).
The research conducted in the field of intelligent transportation systems will be summarized in Table 1.

Table1. Classification of research done in the field of intelligent transportation system

Index	Source	Techniques used	The field of study in intelligent transportation systems
1	Do et al., (2019)	Classification and prediction	Prediction of drivers' behaviour in systems Ride-Hailing
2	Akbari et al., (2020)	Statistical Methods	Analysis of the relationship between different factors for customer satisfaction and retention
3	Zhankaziev et al., (2020)	Statistical Methods	Examining the relationship between security and customer satisfaction
4	Akyouz et al., (2020)	Classification and prediction	Analyzing the relationship between customer satisfaction and performance costs
5	Olayode et al, (2020)	Classification and prediction	Traffic analysis and control in road transport
6	Lan, (2020)	Classification and prediction	Examining customer demand in the systems Ride-Hailing
7	Kaffash et al., (2020)	Classification and prediction	Travel planning and traffic flow forecasting
8	Kuswanto et al., (2019)	Optimization Methods	Analysis of important factors on customer loyalty in the systems Ride-Hailing
9	Gumilar et al., (2019)	Game Theory Methods	Examining the relationship between customer satisfaction and loyalty
10	Mao et al., (2021)	Statistical Methods	Analysis of the impact of different factors on customer satisfaction in systems Ride-Hailing
11	Mahshar et al., (2020)	Statistical Methods	Analysis of the impact of different factors on customer satisfaction in systems Ride-Hailing

The research introduces novel perspectives on dynamic pricing to minimize waiting time and maximize profit, emphasizing the balance between supply and demand using various methods that need thorough examination and comparison. Evaluating the efficiency of ride-hailing intelligent transportation systems involves considering factors like comfort, speed, and travel cost. Methods include formulating related issues in different scenarios and utilizing regression and classification decision trees based on available data (de Sa, 2021).

In addressing the curse of dimensions in real-world problems, the combination of deep learning techniques with machine learning algorithms is suggested to achieve better results. Overcoming this challenge involves utilizing the combination of reinforcement learning and deep learning, known as deep reinforcement learning (Farazi et al., 2021). Researchers propose combining convolutional neural network or recurrent neural network methods with reinforcement learning to address pricing challenges in rail transportation (Shalev-Schwartz et al., 2016).

In a study conducted in 2022 by Xu and colleagues, statistical error evaluation methods such as MAE, MSE, MAPE, and RMSE are employed to assess pricing algorithms and rank them, aiming to identify the most effective method for pricing in their specific problem. Chan et al. (2020) present methods for evaluating the performance of reinforcement learning and deep reinforcement learning algorithms, categorizing them based on problem conditions.

1. Risk-based methods
2. Scattering based methods

In a 2023 study in the energy industry, May and Huang explored the impact of reinforcement learning algorithms on energy consumption under both fixed and dynamic pricing. The findings indicated that dynamic pricing was highly effective, and the utilization of reinforcement learning played a secondary but significant role in minimizing energy consumption.

Additionally, a new multi-criteria decision-making method called the MARCOS method, introduced by Stivic et al. (2019), is employed for ranking research options. This method serves as a valuable approach for evaluating and prioritizing various research alternatives.

According to the extensive and diverse researches that have been conducted by researchers in recent years in the fields studied in this research and according to the review of the literature, the summary of the categories of the studied researches is as follows:

1. Pricing with reinforcement learning and deep reinforcement learning
2. Pricing with reinforcement learning and deep reinforcement learning in intelligent transportation systems
3. Pricing with Reinforcement Learning and Deep Reinforcement Learning in Intelligent Ride-Hailing Transportation Systems

According to the above classification, the research that was done in the field of pricing with the mentioned techniques was mainly in the fields of energy and electricity supply, in supply chains, in the railway industry and in the airline industry. After studying the literature in these fields and familiarizing with other applications, this issue was investigated in intelligent transportation systems. In intelligent transportation systems, mostly articles focused on self-driving cars or traffic control, and very few researches focused on internet taxi systems. For this reason, pricing with reinforcement learning and deep reinforcement learning in Ride-Hailing intelligent transportation systems seemed to be a suitable case as a very important research and a research topic. On the other hand, by reviewing the articles and few researches in this field in Ride-Hailing systems, there are two points of interest:

1. In the research, it was proposed to consider different weather conditions as a proposal for the mentioned problem.
2. In researches, pricing was stated either with the aim of maximizing income or with the aim of minimizing waiting time.

For this reason, as a research and innovation conversation in this research, while considering different weather conditions for dynamic pricing, the goals of maximizing income and minimizing waiting time have been taken into consideration. Also, the complexity of the issues is the need for a method or methods that can compensate for the gaps in these methods and dynamically recognize the prices of each trip with better accuracy and performance. For this reason, reinforcement learning and deep reinforcement learning techniques and methods will be used to achieve the goals of the research. On the other hand, in the research conducted in this field, none of the multi-criteria decision-making methods were used. For this reason, these methods have been used to check the methods and validate the results in this research.

3. Research Method

The primary purpose of the research is to employ Reinforcement Learning Deep Learning techniques for dynamic pricing in an intelligent Ride-Hailing transportation system to maximize revenues. We investigate and find the best price according to the changing conditions in a way that the expected utility can calculate. In other words, our aims are as follows:

- Analysing and investigating factors affecting the price of a trip to check the equilibrium between supply and demand.
- Estimating the most reasonable price dynamically according to a different time, location, and other characteristics using Deep Learning and Reinforcement Learning to prove that other methods are inefficient.

Generally, to achieve research purposes, some questions must be answered appropriately during the research that includes the following:

- What aspects should consider for dynamic pricing in Ride-Hailing systems?
- What RL and DRL-based models perform better for dynamic pricing in ride-hailing systems by simultaneously optimizing waiting time and revenue?
- How can we boost the probability of trip acceptance from drivers, enhance their satisfaction level, and create loyalty?

To accomplish our objectives, we employ the CRISP-DM method for the project. The Cross Industry Standard Process for Data Mining (CRISP-DM) is a process model that forms the foundation for a data science process, comprising six sequential phases (Ulutagay and Nasibov, 2012):

Business understanding: Identifying the business needs and requirements.
Data understanding: Determining the necessary data and assessing its cleanliness.
Data preparation: Organizing the data in a suitable format for modeling.
Modeling: Selecting appropriate modeling techniques for analysis.
Evaluation: Assessing and determining which model best aligns with the business objectives.
Deployment: Establishing how stakeholders can access and utilize the results.

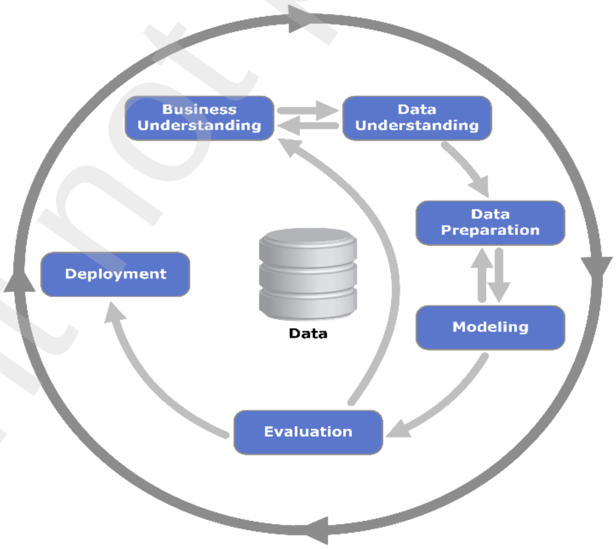

Figure1. CRISP-DM Methodology (Wikipedia.com)

In the First step, it is better to first get a brief understanding of the data and how it is collected and its organizational affiliation (Business and Data Understanding). The data used in this research was obtained from the website of the Uber intelligent transportation service company (www.uber.com). This dataset contains 50 features and 360,000 trips sent by different types of Uber vehicles from an origin to a destination in the city of Boston, USA. Also, this data set belongs to travel data in 2018 and in the last two months of the year (November and December), which has been provided.

In general, the features of the aforementioned data set can be divided into two parts: features related to travel information and features related to weather, which are summarized in the following two sectors:

1. Related to Trip: Number of each trip, Travel time, initial point of travel, travel destination, The type of service (car) chosen by the passenger, and length of trip
2. Related to weather: Air temperature, Apparent temperature, Precipitation intensity, Chance of rain, humidity, wind speed, wind time, intensity of vision, air pressure, The amount of cloud cover, sunrise time, sunset time, Moonrise rate

In the Data preparation step, we are going to utilize various techniques. Mainly, in every data project, important things should be paid attention to such as Data Transformation, Data Cleansing, and Feature Selection. Examining these cases will make the project get favorable results in the end.

One of the most important topics in data preparation and pre-processing is the selection of appropriate features for problem solving. For this purpose, there are different methods. These methods vary according to the type of algorithm that is chosen. Because reinforcement learning methods and techniques have been used in this research, the feature selection method *Principal Feature Analysis (PFA)* was chosen, and finally the selected features are according to the table below. There are different steps to implement this method. These procedures are categorized into five steps. Initially, the initial step involves calculating the covariance matrix of the sample, with a note that, in some instances, a correlation matrix is preferred over the covariance matrix. In the subsequent step, the computation of the principal components and eigenvalues of the covariance/correlation matrix is essential. In the next step, the subspace q must be selected and the matrix A_q can be made from A. This can be chosen by deciding how much data variability to preserve. The conserved variable is the ratio between the sum of the first eigenvalues q and all eigenvalues. In the fourth step, the obtained vectors are clustered using the K-Means algorithm so that the scores obtained by the PCA algorithm can be concluded by clustering. In the last step, for each cluster, the corresponding V_i vector should be found, which is closest to the cluster mean. The corresponding feature, X_i, is selected as the main feature. This step represents the selection of p features. The reason for choosing the closest vector to the average of the two cases. This feature can be considered the central feature of that cluster—a large "spread" in lower dimensional space, and a good representation of the original data (Breitenbach et al., 2022).
Furthermore, For the analysis of attributes in our Dataset (as a part of EDA), we decided to use Correlation for this purpose. The results illustrated that the correlation between main numerical variables is good and they are appropriate for the problem. Additionally, for categorical-based values we employed spearman method and proved the importance of them.

In accordance with the various research conducted by researchers in recent years in the fields related to our research, most of the methods used to solve the problem of dynamic pricing in Ride-Hailing intelligent transportation systems have been statistical techniques or mathematical optimization methods. Furthermore, techniques related to game theory have been used in different research. As a research and innovation chat, in this research, while considering different weather conditions for dynamic pricing, the goals of maximizing income and minimizing waiting time have been taken into consideration. Additionally, the complexity of the issues is the need for a method or some methods that can compensate for the gaps in these methods and dynamically recognize the prices of each trip with better accuracy and performance. For this reason, reinforcement learning and deep reinforcement learning techniques will be used to achieve the goals of the research (Modelling Step in CRISP).
In contemporary years, due to the great importance of dynamic pricing as well as the growing importance of proper service of intelligent transportation systems, more modern and advanced approaches have been utilized to obtain the satisfaction of customers and drivers. Those are called Reinforcement Learning.
In some articles in the literature, those are also combined with Neural Networks and Deep Learning concepts and have created Deep Reinforcement Learning. They have been operated to boost the quality of service.

Table2. Reinforcement Learning and Deep Reinforcement Learning methods used in the literature.

Index	Relevant Topic	Year	Method	Algorithm	Usage Count
1	No	2021	DRL	SQDDPG	1
2	No	2021	DRL	IDDPG	1
3	No	2021	DRL	MADDPG	1
4	Yes	2021	DRL	DDPG	2
5	No	2022	RL	MDP	1
6	Yes	2021	DRL	DQN	6
7	Yes	2021	DRL	DDQN	4
8	No	2021	DRL	HDQN	1
9	Yes	2021	RL	A2C	4
10	Yes	2021	RL	A3C	3
11	Yes	2020	RL	PPO	7
12	No	2018	DRL	TPRO	2
13	Yes	2019	DRL	DDPG	8
14	Yes	2018	DRL	DQN	18
15	Yes	2021	RL	QL	2
16	Yes	2012	RL	SARSA	2
17	Yes	2019	RL	POMDP	1
18	Yes	2022	DRL	SAC	1
19	No	2016	RL	MDP	29

In the problem of dynamic pricing, RL and DRL methods employed are negligible which is shown in **Table2**. For this reason, we decided to utilize these techniques to reach the goals of our research.
Finally, from all of algorithms mentioned in the table of literature, we choose SARSA, and PPO as a RL. In addition, the DRL methods are DSN, and DDPG.

3.1. SARSA

SARSA algorithm is an on-policy reinforcement learning algorithm. In this algorithm, the learning agent first observes the state of the system (S) and selects action (A) based on a specific policy. Next, after selecting the action, the environment determines the next state of the system and the reward. By observing the next state of the system and the received reward, the agent calculates and updates the value of the action-value function. This process will continue until the value of the action value function converges to its optimal value (Sutton and Barto, 2018).
The implementation steps of this algorithm are as follows (Sutton and Barto, 2018):
1. Determining the initial value of α and ε
2. Determining the initial values of Q(S, a)
3. Repeat the following steps for each learning episode:
Select an S status
Choosing action, A in state S with a specific policy (e.g. ε-greedy concept)
Execute action A and view R and change state to S'

$$Q_\pi(s,a) \leftarrow Q_\pi(s,a) + \alpha\,[R - \gamma Q_\pi(s',a) - Q_\pi(s,a)]$$

As shown in the relation above, in the first step, the initial values of alpha and epsilon as well as the values of the matrix Q(S, a) should be determined. Then a state is chosen randomly and with the considered policy the action in this state is adopted and the reward (R) and the next value of the system state are received. At the end, using the observed values, the value of Q(s, a) will be updated.

3.2. PPO

Proximal Policy Optimization will simplify this by using an alternative cut target while maintaining the same performance. First, it is better to determine the probability ratio between the old and new policies as follows:

$$r(\theta) = \frac{\pi_\theta(a \mid s)}{\pi_{\theta_{old}}(a \mid s)}$$

Then the objective function will be as follows:

$$J(\theta) = E[r(\theta)\widehat{A_{\theta_{old}}(s,a)}]$$

When applying PPO to a network architecture with common parameters for both policy (performance) and value (critic) functions, in addition to the truncated reward, the objective function is augmented with an error term in the value estimation and a sufficient exploration number called entropy.

$$J(\theta)\_new = E[J(\theta) - c_1(V_\theta(s) - V_{target}) + c_2 H(s,\pi_\theta(0))]$$

3.3. DSN

As mentioned, SARSA is an on-policy reinforcement learning algorithm. In this algorithm, the learning agent first observes the state of the system (S) and selects the action (A) based on the specific policy and determines the environment of the next state of the system and the reward. Also, the way this process was carried out in mathematical language was also investigated. Now, this algorithm may not be used in some problems due to its inability to solve complex and high-volume problems. For this reason, to solve this problem, the combination of deep learning and this algorithm is used to update the Q value function (Sutton and Barto, 2018).

$$Q_\pi(s,a) \leftarrow Q_\pi(s,a) + \alpha\,[R - \gamma Q_\pi(s',a) - Q_\pi(s,a)]$$

This method has several advantages over SARSA itself, including the fact that it can support a very large amount of data in each iteration of the experiment and avoid overfitting during data training.

3.4. DDPG

DDPG (Lillicrap et al., 2015) or Deep Deterministic Policy Gradient, is a model-free out-of-policy algorithm. As stated, DQN stabilizes Q-function learning by replaying the experience and frozen target network. DQN works in discrete space, and DDPG extends it to continuous space with an actor-critic framework while learning a deterministic policy.

$$\acute{\mu}(s) = \mu_\theta(s) + N$$

3.5. Q-Learning

This Algorithm is a model-free, value-based, off-policy algorithm that will find the best series of actions based on the agent's current state. The core of the algorithm is a Bellman equation as a simple value iteration update, using the weighted average of the current value and the new information (Sutton and Barto, 2018).

3.6. DQN

Deep Q Networks (DQN) are neural networks that utilize deep Q learning in order to provide models such as the simulation of intelligent video game play. Rather than being a specific name for a specific neural network build, Deep Q Networks may be composed of convolutional neural networks and other structures that use specific methods to learn about various processes. In a general sense, deep Q networks train on inputs that represent active players in areas or other experienced samples and learn to match those data with desired outputs (Sutton and Barto, 2018).

3.7. SAC

Soft Actor Critic (SAC) is an algorithm designed to optimize a stochastic policy in an off-policy manner, establishing a connection between stochastic policy optimization and DDPG-style approaches. While not a direct successor to TD3 (as it was published around the same time), SAC incorporates the clipped double-Q trick. The inherent stochasticity of the policy in SAC leads to its benefitting from a mechanism similar to target policy smoothing. SAC operates as an off-policy algorithm, and there exists an alternative version of SAC, which modifies the policy update rule to handle discrete action spaces. It's important to note that the Spinning Up implementation of SAC does not support parallelization.

3.8. CVaR

In contrast to the numerous performance evaluation methods available for machine learning and deep learning algorithms, reinforcement learning and deep reinforcement learning have limited options, depending on the problem conditions. These methods fall into two categories: risk-based methods and scattering-based methods (Chan et al., 2020). This study opts for risk-based assessment methods, considering the dynamic nature of pricing in Ride-Hailing intelligent transportation systems and the associated uncertainty. The research employs two risk-based assessment methods, with the first being conditional value at risk (CVaR). CVaR, also known as expected shortfall, calculates the weighted average of potential losses beyond the value-at-risk (VaR) cutoff point. This method addresses the limitations of the VaR model and is particularly useful for managing risks in situations where prices are unstable over time. The use of CVaR provides a more comprehensive understanding of risks, especially in scenarios where VaR alone may not offer a complete picture beyond its threshold.
Finally, the results of the research problem must respond to the objective function of the two objectives of the following mathematical model:

$$\max E_{predicted}(x) - E_{actual}(x)$$
$$\min E_{predicted}(x) - E_{actual}(x)$$

The limitations of this model are the changes in different weather conditions or travel-related characteristics, which can be achieved by considering them and solving the model.
Of course, it should be noted that the use of a creative method validated in the literature can be a seal of approval on the results obtained from the research. For this reason, in this research, one of the latest Marcus multi-criteria decision-making methods is used to validate the results of the algorithms and rank the options. Benefiting from this method will be done by forming a decision matrix of 7 criteria and 24 alternatives in order to rank the methods for the goals of maximizing income and minimizing waiting time.

4. Results

In conducting any research, special attention should be paid to the way of doing it, especially because this way is unique for each research.

In the preliminary analysis of this data set, it was clear that the highest amount of travel occurred during the times when the weather was cloudy. Also, the least amount of travel has been done during fog. In the comparison made between partly cloudy weather during the day and at night, it is clear that the willingness of drivers to travel and accept it is more at night. Also, the tendency to travel on rainy days is higher than on sunny days. It should be noted that sunny days have fewer trips than even nights without rain.

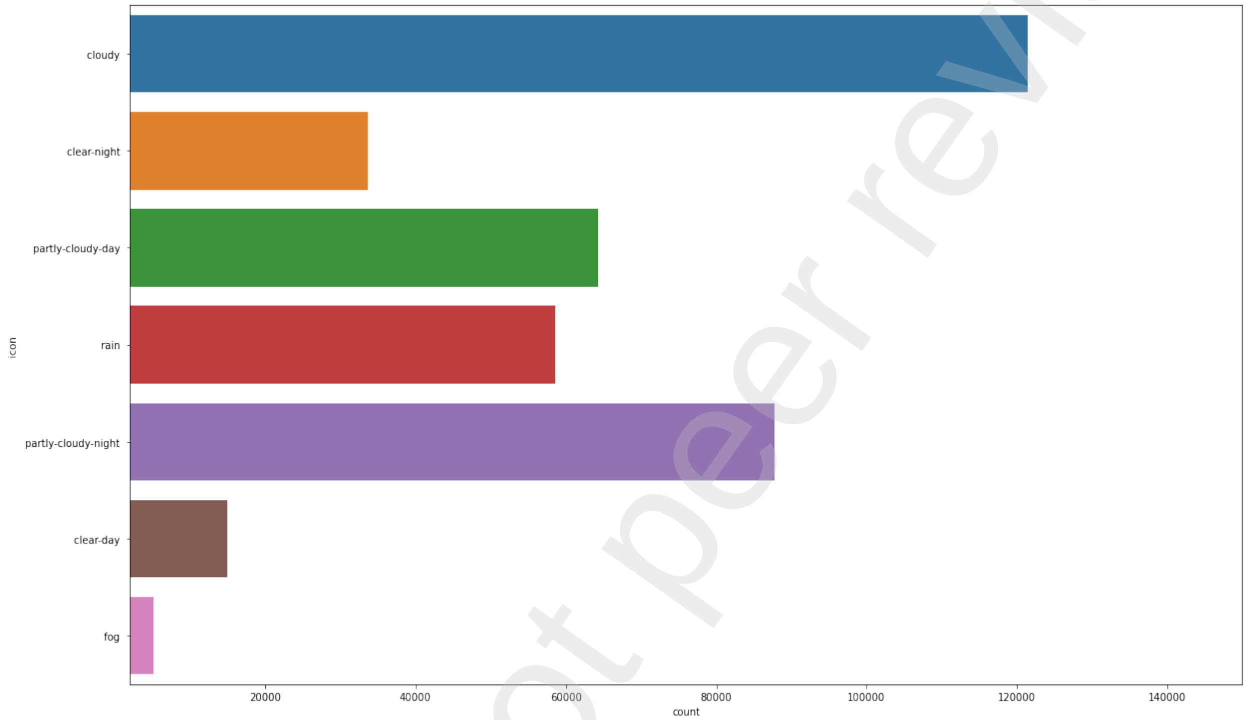

Figure2. Frequency of Uber trips in Boston, USA in different weather conditions

Another point that is important is that most of the trips made in the city of Boston under different conditions were short-term. In other words, and more precisely, it can be said that almost 62% of the trips made have travelled a short distance. After that, approximately 37% of the trips were regular distance trips and finally only approximately 2% of the trips were long distance.

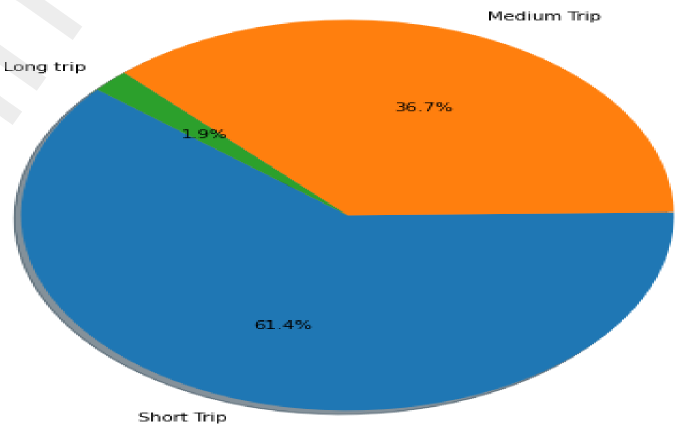

Figure3. Distribution of trips made in the city of Boston under different conditions

As we get closer to the last hours of a day, the waiting time for passengers to arrive from an origin to a steep destination decreases. This shows that as it gets dark, the supply is higher and the time each passenger has to wait for the driver to accept their request decreases. Also, this issue can affect the pricing method. It should be noted that peak hours on different days are also important. For example, the amount of waiting for passengers reaches its peak in the period from 16 to 18 when all administrative centres, universities and schools are closed. The reason is that the demand has increased sharply and drivers are sensitive to the price of trips. Of course, it should be noted that these cases are different from considering different weather conditions.

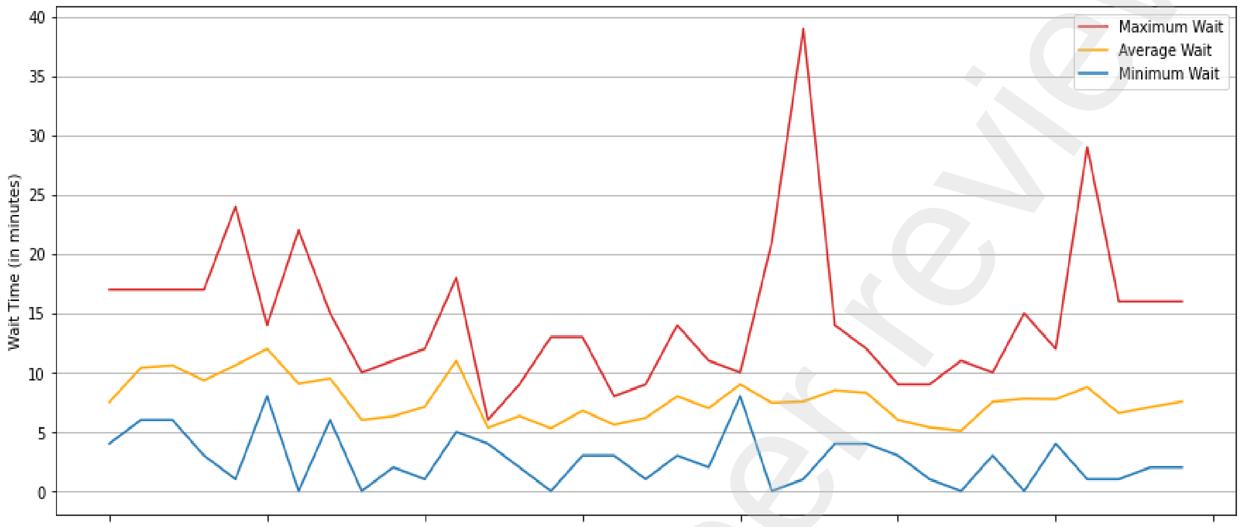

Figure4. Busy and demanding hours in the city of Boston to benefit from the services of the Uber transportation system

As mentioned, the data set of this research includes 50 features and 360,000 trips sent by different types of Uber vehicles from one origin to one destination in the city of Boston, USA. This dataset needs deep preparation to train the algorithm. According to researchers and experts in the field of data science, data preparation and pre-processing need to spend 60-80% of the entire project time (Acuna, 2011). For this reason, special attention has been paid to data pre-processing in this research. According to the nature of the data set used, the need for initial changes in its form is felt. In such a way that the features related to the date were in the form of a time stamp. For this purpose, changes have been made to these features to obtain hours, minutes, and seconds. After that, the spatial coordinates of latitude and longitude are converted into x, y, and z geometric coordinates so that the origin and destination coordinates of the trip can be easily used in the next steps. In the next step, considering that the trips were made at different times and may have been during rush hours due to working days or holidays, changes were made to the data set to determine daily shifts. With the investigation that was done from the city of Boston, it was found that the high traffic hours include the hours in the morning from 6 to 10, noon from 12 to 14, and evening from 15 to 19. In other words, the dataset is divided into three shifts: morning, noon, and evening.
In the next stages of data pre-processing, non-numerical data should be examined. In this dataset, the values of these features are encrypted to become features with binary values. Then the missing data were analysed. In the investigations, it was observed that according to the data collected from the Uber website and the possibility of the data being real, some missing data were recorded, and this type of data was replaced by the nearest neighbour imputation method according to the data of each feature. With the results obtained from the box plot and the way the data is scattered according to the relationship presented in the previous chapter, it was found that there is no data outlier. But because the obtained results are unreliable and may have a negative effect on the final results after the implementation of the algorithms. For this reason, another method called isolated forest was used to get the final results from outlier data. As a result of the implementation of this method, there were 178 outlier data, and according to the type of data set and machine learning methods, it was decided to remove these data from the investigated data set. After determining the assignment of outlier data, the assignment of duplicate data should be determined. As mentioned, duplicate data is data that occupies two rows of the data set exactly. In this case, one of them should be removed to integrate the data set as much as possible. In this data set, it was determined that there are 518 duplicate data, all of which were removed.

One of the most important topics in data preparation is the selection of appropriate features for problem-solving. For this purpose, there are different methods. These methods vary according to the type of algorithm that is chosen. Because reinforcement learning methods and techniques have been used in this research, the feature selection method of 'main feature analysis' (PFA) was chosen, and finally the selected features are according to the table below.

Table3. Selected Features from PFA Method

Index	Feature Names
1	temperature
2	distance
3	windSpeed
4	cloudCover
5	srt_month
6	srt_day
7	precipIntensity
8	srt_minute
9	windGust
10	X
11	Y
12	Z
13	apparentTemperature
14	visibility

In the tables below, the performance of each of the algorithms has been checked by considering each of the characteristics of the data set. According to the method mentioned in the third part for evaluation, the algorithm that can maximize and minimize. By optimizing, we can make sure that the revenue is also maximized and waiting time is minimized by the considered algorithm. To achieve this goal, the MinMax method was first used to scale the predicted and actual data related to the price. It should be noted that according to the central limit theorem in the science of statistics and according to the amount of data under investigation, the distribution of data tends to be almost normal, which can be said that the mathematical expectation is equal to the average value of each of the prices (in dollars).

Table4. Decision matrix based on mathematical hope.

Method	Price						Waiting Time					
	$E_{Safar}(x)$	$E_{Aftabi}(x)$	$E_{Abri}(x)$	$E_{NimeAbri}(x)$	$E_{Meh}(x)$	$E_{Barani}(x)$	$E_{Safar}(x)$	$E_{Aftabi}(x)$	$E_{Abri}(x)$	$E_{NimeAbri}(x)$	$E_{Meh}(x)$	$E_{Barani}(x)$
Q-Learning	27.116	15.531	17.489	8.30	15.073	14.35	9.0039	10.72	8.23	8.30	10.45	14.35
DDPG	25.008	15.431	15.508	8.12	15.143	13.82	8.38	10.47	8.15	8.12	10.77	13.82
SARSA	23.971	16.028	15.160	8.13	15.292	12.91	8.55	10.2086	8.35	8.13	12.02	12.91
DSN	27.680	17.727	15.054	8.34	15.096	12.28	8.52	10.0012	8.13	8.34	10.74	12.28
DQN	25.816	17.472	15.836	8.20	15.499	11.17	8.54	10.35	8.05	8.20	11.40	11.17
DPO	26.341	15.190	14.851	8.35	15.859	12.78	8.26	10.83	8.28	8.35	11.26	12.78
SAC	26.577	17.270	16.773	8.07	15.052	12.10	8.59	10.93	8.26	8.07	12.27	12.10

Table5. Reward-based decision-making matrix.

Method	Price						Waiting Time					
	R_{Safar}	R_{Aftabi}	R_{Abri}	$R_{NimeAbri}$	R_{Meh}	R_{Barani}	R_{Safar}	R_{Aftabi}	R_{Abri}	$R_{NimeAbri}$	R_{Meh}	R_{Barani}
Q-Learning	0.595	0.49	0.511	0.687	0.5001	0.397	0.301	0.262	0.329	0.384	0.452	0.71
DDPG	0.267	0.268	0.289	0.472	0.365	0.408	0.393	0.32	0.429	0.50	0.536	0.437
SARSA	0.307	0.229	0.118	0.122	0.397	0.238	0.331	0.42	0.361	0.381	0.408	0.602
DSN	0.961	0.659	0.582	0.947	0.815	0.849	0.299	0.36	0.326	0.29	0.31	0.4236
DQN	0.872	0.621	0.671	0.773	0.595	0.564	0.233	0.326	0.254	0.45	0.328	0.43
DPO	0.528	0.156	0.563	0.635	0.634	0.493	0.355	0.254	0.387	0.30	0.317	12.78
SAC	0.727	0.662	0.233	0.229	0.312	0.385	0.2406	0.262	0.262	0.612	0.48	0.64

On the other hand, for validation, you can check the rewards received from repeating the experience and implementing each of them. In the basic rules of reinforcement learning and deep reinforcement learning, the algorithm reaches the answer when it can receive the maximum reward. For this purpose, it can be said that the price prediction and also the maximization of income by that algorithm are done optimally and its results can be relied on and used in the real world to receive the maximum reward. Similarly, to minimize the waiting time, this reward must be minimized because our objective function is defined as such. The following table describes the learning rates according to the conditions of each algorithm obtained by the network search method:

Table6. Learning algorithms used in research under different scenarios.

Index	Method	Learning rate under the scenario with weather	Learning rate under the no-weather scenario
1	DSN	0.175	0.257
2	DQN	0.056	0.012
3	DPO	0.11	0.1507
4	Q-Learning	0.118	0.194
5	SAC	0.752	0.683
6	DDPG	0.175	0.190
7	SARSA	0.056	0.0163

At this stage, according to the mentioned learning rates, the reward for each algorithm will be obtained by training the algorithms. The data in this problem are divided in the ratio of 70 to 30 between training and testing data. It should also be mentioned that the optimizer for the implementation of reinforcement learning algorithms of the ADAM method and its cost function is also the mean square error method according to the network search parameter setting method.

In fact, in this research, to accurately evaluate the results, there is a decision matrix with 7 criteria and 24 alternatives that should be examined in the next steps of the algorithm to finally get the best answer.
The entropy weighting method is used in the second step of the MARCOS method, where criteria should be weighted. This method was presented in 1974 by Shannon and Weaver. Entropy expresses the amount of uncertainty in a continuous probability distribution. The main idea of this method is that the greater the dispersion in the values of an index, the more important that index is. Weight is usually assigned to each of the indicators. So that the total weight of the indicators is equal to one. There are various methods to determine the weight of indicators, the entropy method, Linmap method, eigenvector method, and least squares method are the most important methods for determining the weight of indicators. In this research, the entropy method is used because entropy is one of the most practical multi-criteria decision-making methods for calculating the weight of the criteria, which is weighted by the criteria-option matrix.
In the next step, the options should be scaled.
The most common and widely used technique is rescaling, also known as min-max normalization. In this way, in addition to equating the scale of the data, the limits of their change will also be placed in the [0, 1] range. The calculation relationship of this method is given in the data pre-processing section in the third section.
Finally, with the MARCOS the final result will be the ranking of the algorithms. Thesis method, by going through these steps, ranks methods are as follow:

Table7. The final ranking of algorithms according to the MARCOS method.

Method	Rank
DSN	1
DQN	2
DPO	3
Q-Learning	4
SAC	5
DDPG	6
SARSA	7

According to the above table, the DSN algorithm will be known as the best algorithm in optimizing the two goals of maximizing revenue and minimizing waiting time according to different scenarios and the conditions of the research problem. Because it provides more accurate and reliable results.

5. Conclusion and Future Research

According to the results, the proposed method can reduce waiting time robustly and quickly. This would be due to the learning frequency (i.e., an agent learning at every time step) and the small dimensionality of state and action spaces (i.e., distributed learning). However, in comparison to the single bottleneck case, the multiple bottleneck case was slightly inefficient. This might be due to insufficient coordination among the time zones in the current definitions of behavior and reward. In addition, more examination in the scalability of the proposed method is necessary. Future expansion will enable in this research. Firstly, a deep review of the literature with the keywords of dynamic pricing, revenue management, machine learning, reinforcement learning, and deep reinforcement learning in ride-hailing intelligent transportation systems was carried out, as a result of which it was determined what the general purpose of the research is. Follows In the end, after introducing and describing the methods of evaluating and validating the results obtained from the problem-solving techniques, they were implemented in the mentioned software to finally provide the best prices to improve the pricing system dynamically as well as better revenue management. The results of this research are as follows:

1. Discovering and identifying factors affecting dynamic pricing such as factors related to travel and weather conditions.
2. Developing the pricing system.
3. Optimizing revenue management.
4. Optimizing Passenger waiting time

As a suggestion for future research, it can be said that there is a third goal in order to reach a suitable price in the conditions of uncertainty, and that is dynamic matching. Another suggestion that can be made is to combine mathematical optimization methods with machine learning to reach a suitable price under conditions of uncertainty.

Conditions of uncertainty, and that is dynamic matching. Another suggestion that can be made is to combine mathematical optimization methods with machine learning to reach a suitable price under conditions of uncertainty.

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