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

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Abstract

Today, due to the advancement of technology and the development of cities and road networks in different countries, the issue of transportation has become a very important issue in the world and has received the attention of researchers. This issue has a great impact on the social and economic situation of countries. In this way, countries are facing many crises due to reasons such as the increase in the volume of passengers, the volume of traffic, environmental issues, and air pollution. For this reason, the importance of the intelligence of the transportation industry is strongly felt. On the other hand, with the modernization of today's societies and the increasing use of the Internet, people have been led to use these tools and the potential for intelligent transportation control has been created. For this reason, organizations have emerged in the field of intelligent transportation and provide various services through applications for mobile smartphones or using websites. These organizations have designed systems in two ways to help achieve the goals of smart transportation. These two include the use of Ride-Sharing and Ride-Hailing systems. But these organizations are faced with the production of a large volume of data due to the two-way application of their services, on the one hand, customers and on the other hand, drivers, and in order to have a good share in the competitive market, they must analyse them. For this purpose, organizations may use various methods.

An important and vital issue in Ride-Hailing systems is dynamic travel pricing, which is important for smart transportation services because it can be effective in balancing supply and demand. For this purpose, in this research, the data of Uber company's smart transportation service trips have been used, which includes the trips made with all types of vehicles available in that company in 2018 and in the last two months of the year. After collecting the data, they have been carefully scrutinized and analysed according to the methods and techniques of reinforcement learning and deep reinforcement learning. For this purpose, with the two goals of maximizing income and minimizing waiting time, various methods have been used, among which the best result belongs to Deep SARSA Network algorithm. To validate and rank the methods used in the research, MARCOS multi-criteria decision-making methods have been used to obtain the best and most reliable results.

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

1. Introduction

In recent years, with the advancement of technology and the increasing access to and use of cutting-edge smartphones by individuals, organizations in various industries have emerged and grown. Since transportation has become a vital issue in the world, it has received the attention of researchers. Whereas cities and road networks are improved, the problem has had a tremendous impact on the economic situations of different countries (Olayode et al., 2020). Ride-Hailing intelligent transportation systems serve a great many purposes. One of the most essential of them is dynamic pricing. Ride-Hailing owners believe pricing according to stochastic conditions helps them manage their revenues and handle unforeseen circumstances better. Besides, revenue management can boost drivers' level of satisfaction, and they will be more motivated to accept trips. In this research proposal, firstly, a definition of the research subject is going to discuss. Secondly, we will state its importance and necessity. Recently, researchers have studied the coordination of requests in Ride-Hailing transportation systems and believe this is one of the most vital operational concerns in ride-hailing services. They think that if there is an optimal balance and interaction between delay cost and delay time, this crisis will tackle, although it should be noted that achieving a stable interaction requires special attention to the structure of supply and demand (Qin et al., 2021). Another issue that is investigated in providing services in Ride-Hailing intelligent transportation systems is dynamic travel pricing. In the past, due to unstable environments, there was no suitable pricing policy (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 widely used to make a balance between supply and demand. To handle it, researchers have proposed a dynamic pricing system aimed to minimize the waiting time for passengers. For this reason, in this research, considering the balance between supply and demand pricing of trips will be done dynamically. Correspondingly, our effort will be examining research objectives and innovations. 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:

1. Analysing and investigating factors affecting the price of travel to check the balance between supply and demand
2. Estimating the best price dynamically according to different time, place and other characteristics
3. Developing models with the aim of minimizing waiting time and Maximizing Revenue.

According to the extensive and diverse research that has been conducted by researchers in recent years in the fields studied in this research, in this article, an attempt will be made to respect the innovation and new aspects that research should have by referring to them. Newer ideas and methods that can verify this research will be used. Any research, according to its goals, will need this aspect of being new. For this reason, it can be said that the new aspects and innovation that exist in this research is a new perspective on the problem of dynamic pricing for the purposes of minimizing waiting time and maximizing profit, as well as the balance between supply and demand using reinforcement learning and deep reinforcement learning methods. A set of methods should be examined and compared. Because the research in this field is often done with simple reinforcement learning methods and mathematical modelling, no significant research has been done in this field. These methods cannot be acceptable in the long term and with the advancement of technology and the increase of the obtained data, as well as the greater complexity of the issues, there is a need for a method or methods to compensate for the gaps in these methods and Recognize the prices of each trip dynamically with better accuracy and performance. Another approach that will cause innovation in this research is the use of other effective features in this category of problems. These features include consideration of weather conditions and specific conditions of different days, which have not been considered in previous research. In excess, the general structure of this research is as follows: In the second part related research will be discussed. Then the proposed method will be examined. After that, the results of the proposed methods will be presented, and finally, conclusions and recommendations for future research will be presented.

2. Related work

To achieve profitability in Ride-Hailing systems and intelligent transportation in general, as well as to achieve consistency in the competitive market and reduce operational costs, predictive methods based on machine learning have been used (Akyouz et al., 2020). Also, to optimize the performance of drivers in these systems and to monitor whether to choose or reject passenger requests, which may include additional costs for the service organization of these systems, decision-based machine learning methods such as decision trees are used. In this type of objective, the distance is the most important parameter for drivers to decide whether to approve or reject the request (Do et al., 2019). A vital point is that the performance of the mentioned methods will decrease over time as the amount of data increases, and it will make the success of developing ride-hailing intelligent transportation systems unclear. Because the goal of these systems is to use communication technologies to combine transportation systems based on people, cars, and roads, and this goal must be strictly followed. For this reason, more advanced methods are needed. The problem of pricing and capacity management has been modeled using the nonlinear stochastic integer programming technique and solved using a simulation-based method called Simulated Annealing. Due to the dynamic nature of this issue, decisions about prices and appropriate capacity allocation have been made dynamically (Kamandanipour et al., 2020). The time sequence is very important in intelligent transportation systems. For this purpose, researchers have tried using deep learning models to improve pricing dynamically by considering time sequences. Some have solved the problem by using data mining and machine learning techniques and methods such as Random Forest and XGBoost. In another study, researchers examined the issue of pricing trips in Ride-Hailing systems dynamically from the drivers' point of view. They believe that for a better distribution of drivers in smart transportation networks, various things such as the queuing system, their level of well-being and income, the average travel time, and the possibility of them leaving the system should be taken into consideration. It will lead to accepting a price appropriate to different conditions (Wu et al., 2021). Revenue management is the most important action of a business to stay in the competitive market. So it should be noted that revenue management depends on accurate forecasts. In order to reduce individual costs and minimize the distance a passenger is picked up by the driver of ride-hailing systems, researchers have taken advantage of discount policies and strategies. In such a way that every driver who travels a shorter distance to reach the passenger and pick him up will be included in the travel expenses and also from the passenger's point of view, a discount will be applied to the travel price. In this way, in the long-term horizon, it is possible to help maximize the revenue of the service providers of this type of service (Duan. et al., 2019). The new aspects and innovation that exist in this research is a novel perspective on the problem of dynamic pricing to minimize waiting time and maximize profit, as well as the balance between supply and demand using deep reinforcement learning methods, which should be examined and compared.

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 such 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, questions must be raised and answered appropriately during the research. For this reason, various questions are raised, which include 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?

In general, the emphasis of the research is on estimating the optimal price according to the stochastic conditions and influencing factors over time, as well as with the goals of minimizing the waiting time of passengers and maximizing earnings using modern methods and techniques.

The Dataset used in this research was gathered from the website of the Uber intelligent transportation service company (www.uber.com). This Dataset contains 360,000 trip records done by different types of Uber vehicles from an origin to a destination in the city of Boston. The travel data for the two last months of 2018 (November and December).

We are able to split the Dataset into two parts. The first part belongs to all trip-related attributes. The second part is associated with Weather. Weather plays an important role in accepting or rejecting passenger requests from drivers, and by its nature,

it causes changes in the supply and demand system and is effective in the pricing plan.
To achieve our goals, we utilize CRISP-DM method for the project. The Cross Industry Standard Process for Data Mining (CRISP-DM) is a process model that serves as the base for a data science process. It has six sequential phases:
Business understanding – What does the business need?
Data understanding – What data do we have need? Is it clean?
Data preparation – How do we organize the data for modelling?
Modelling – What modelling techniques should we apply?
Evaluation – Which model best meets the business objectives?
Deployment – How do stakeholders access the results?

In general, in every data project, important things should be paid attention to. Examining these cases will make the project to get favourable results in the end. For this reason, another method called *Isolation Forest* was used to get the final results from outlier data. For the analysis of attributes in our Dataset, we decided to use Correlation for this purpose. The results illustrated the relationships between our characteristics (Figure1).

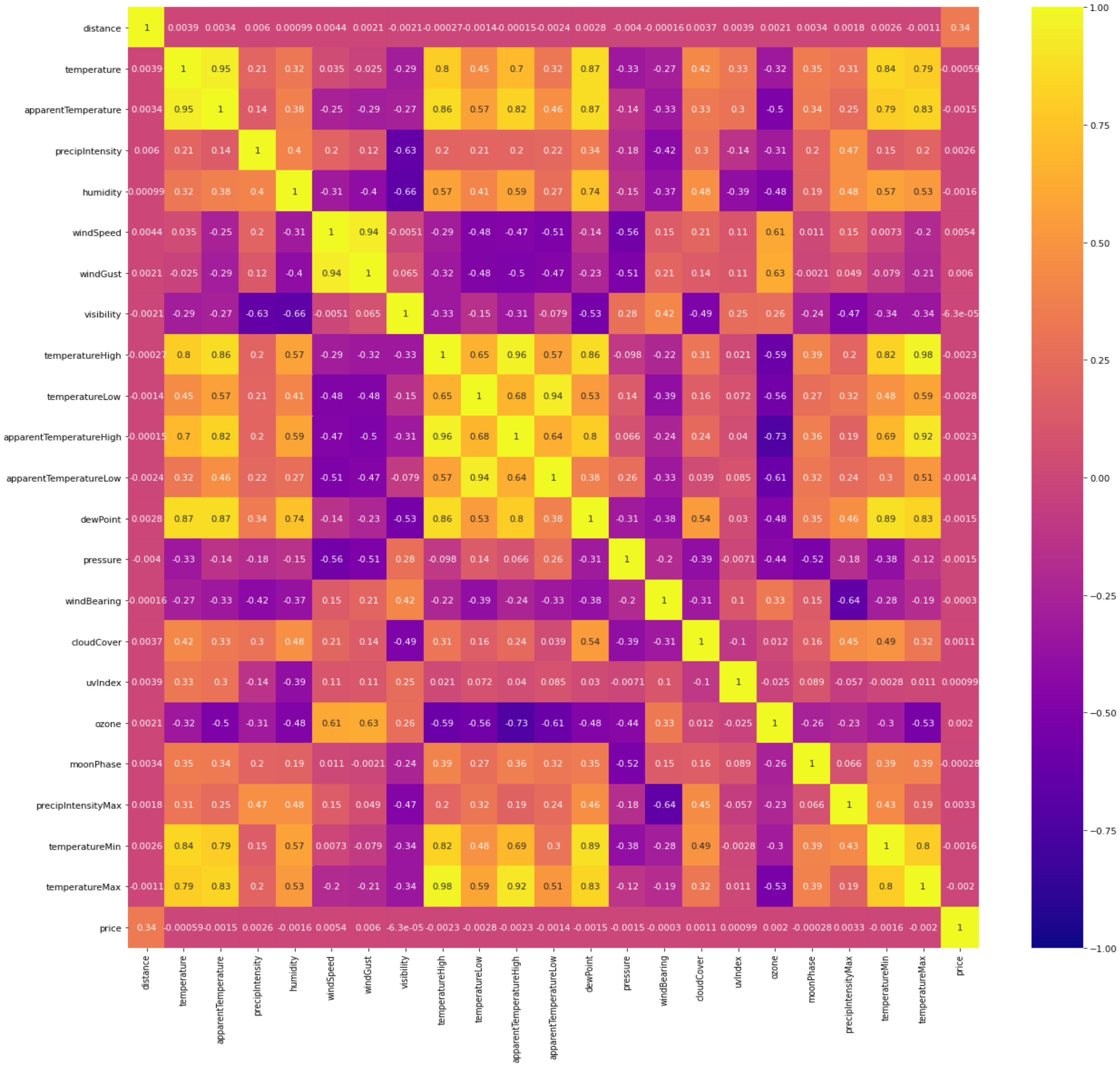

Figure1. Correlation diagram between the variables of the dataset

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 steps are divided into 5 categories.

In the first step, the covariance matrix of the sample should be calculated. Of course, it should be noted that in some cases the use of a correlation matrix is preferred instead of the covariance matrix. In the second step, the calculation of the main components and eigenvalues of the covariance/correlation matrix should be considered. 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.

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.

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.

In the problem of dynamic pricing, RL and DRL methods employed are negligible which is shown in **Table3**. For this reason, we decided to utilize these techniques to reach the goals of our research.

Table3. 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	3
10	Yes	2021	RL	A3C	3
11	Yes	2020	RL	PPO	7
12	No	2018	DRL	TPRO	2
13	Yes	2018	DRL	DDPG	4
14	Yes	2019	DRL	DDPG	8
15	Yes	2018	DRL	DQN	18
16	No	2017	DRL	DQN-LSTM	1
17	Yes	2021	RL	QL	2
18	No	2021	RL	AOC (Adaptive Optimal Control)	1
19	Yes	2012	RL	QL	2
20	Yes	2012	RL	SARSA	2
21	Yes	2019	RL	POMDP	1
22	No	2019	DRL	VPG (Vanilla Policy Gradient)	1
23	Yes	2021	RL	A2C	1
24	Yes	2021	RL	MDP	5
25	Yes	2022	DRL	SAC	1
26	No	2021	RL	MFMDP (Mean-Field MDP)	1
27	No	2021	RL	SARSA	1
28	No	2006	RL	MDP	29

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.
The implementation steps of this algorithm are as follows:
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:

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

Then the objective function will be as follows:

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

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.

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

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.

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

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.

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.

3.7. SAC

Soft Actor Critic (SAC) is an algorithm that optimizes a stochastic policy in an off-policy way, forming a bridge between stochastic policy optimization and DDPG-style approaches. It isn't a direct successor to TD3 (having been published roughly concurrently), but it incorporates the clipped double-Q trick, and due to the inherent stochasticity of the policy in SAC, it also winds up benefiting from something like target policy smoothing. SAC is an off-policy algorithm. An alternate version of SAC, which slightly changes the policy update rule, can be implemented to handle discrete action spaces. The Spinning Up implementation of SAC does not support parallelization.

Unlike other machine learning and deep learning algorithms that have multiple performance evaluation methods, there are limited methods for reinforcement learning and deep reinforcement learning that can be used depending on the problem conditions. These methods can be divided into the following categories (Chan et al., 2020):

1. Risk-based methods
2. Scattering-based methods

In this research, by reviewing the literature and considering the nature of the research problem, risk-based assessment methods are used. The reason for choosing these methods is that dynamic pricing in Ride-Hailing intelligent transportation systems is a changeable thing according to different conditions. In other words, this action takes place under conditions of uncertainty. For this reason, there is a risk of choosing a suitable price to obtain customer satisfaction and maximize revenue.

In this research, two risk-based assessment methods have been used. The first is the conditional value at risk. Conditional value at risk (CVaR) is an expected shortfall. CVaR is derived by taking the weighted average of the "lots" of losses at the tail of the distribution of possible returns beyond the value-at-risk (VaR) cutoff point. Conditional value at risk is used for effective risk management. In general, if the price is stable over time, the value at risk may be sufficient to manage risk. However, the lower the price stability, the greater the chance that VaR does not provide a complete picture of risks, as it is indifferent to anything beyond its threshold.

Conditional value at risk (CVaR) attempts to address the shortcomings of the VaR model. This

method is a statistical technique used to measure the level of price risk in a company in a specific time frame.
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.
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' was chosen.

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).

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

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

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 follows:

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.

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