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An efficient smart parking pricing system for smart city environment: A machine-learning based approach

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ABSTRACT

Now-a-days, with the ever increasing number of vehicles, getting parking space at right place and on time has become an inevitable necessity for all across the globe. In this context, finding an unoccupied parking slot by the interested vehicle owners with least overhead becomes an NP-Hard problem bounded by various constraints. In-advance availability of information regarding parking occupancy plays a major role in hassle free trip optimization for motorists. It also facilitates services-cum-profit management for the parking owners. It further helps in curbing congestion by reducing cruising time and hence, helps in controlling pollution of the smart cities. Thus, accurate and timely information regarding parking occupancy and availability has become the basic need in the evolution of the smart cities. Motivated by these facts, an occupancy-driven machine learning based on-street parking pricing scheme is proposed in this paper. The proposed scheme uses machine learning based approaches to predict occupancy of parking lots, which in turn is used to deduce occupancy driven prices for arriving vehicles. In order to train, test, and compare different machine learning models, on-street parking data of Seattle city has been used. To the best of our knowledge, this is the first time that parking occupancy prediction system is used to generate occupancy based parking prices for on-street parking system of the Seattle city. Results obtained using the proposed occupancy driven machine learning based on-street parking pricing scheme demonstrate its effectiveness over other existing state-of-the-art schemes.

1. Introduction

In most of the cities around the world, parking is considered to be a big problem because of many reasons, such as increase in population size, number and size of vehicles, limited parking spaces, traffic congestion on roads, locations of parking lots etc. With the rapid increase in the number of vehicles, getting and providing parking slots has become a challenge for the parkers and transport authorities/owners respectively. Usage of private vehicles over public transportation is always individual's choice due to varying comfort levels, less travel time, and ease of travel etc. With increase in private vehicles, cruising time and congestion increases invariably. Most of the vehicles spent significant time on roads in searching parking spaces instead of commuting. This increases congestion on the roads. Situations get even worse during rush hours and near hot spots. This unnecessary congestion leads to overcrowding of vehicles, increase in carbon emissions, and raises various traffic management problems. Similar situation exists in the Seattle city where, vehicles spend more time in searching on-street parking spaces which leads to heightened congestion on the roads.

This problem of cruising congestion happens because of inefficient parking pricing, inappropriate information system, and also due to non-availability of facilities, such as optimal parking occupancy prediction system which can significantly reduce the load on the transport authorities. Pricing plays a major role in situations having high demands and less resources to fulfill them. Thus, solution to the dire parking problem of the Seattle city lies in providing an efficient dynamic pricing scheme for its on-street parking system. Accurate prediction of authorized un-occupied parking spaces along with its prices according to various parameters, is required to handle ever increasing parking demand. Pricing models should take into consideration historical data along with current data for making future prediction which plays significant role in estimating prices. Seattle Transport Department (STD) implements less dynamic Time of the Day (ToD) pricing in such a burning situation of the Seattle city. Demand of parking spaces may change according to the time of the day, i.e., highest in rush hours. Moreover, rush hours may also change

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according to the special arrangements, festivals, holidays etc. Thus, the parking prices should reflect the demand and vary according to the occupancy levels at any time.

Many a systems have been developed over the years, such as Parking Guidance System (PGS), which based on historical and real time data provided the currently available parking space to the user. A ranking algorithm, Parking Rank, used a combination of PGS and a driving cost sensitive algorithm to output the available parking space based on the vicinity to vehicle and cost of pricing [1]. A performance based parking pricing which used a forward looking policy instrument [2] has also been developed. This pricing affected the requirement for parking spaces by varying parking prices via calculated price elasticity of parking space demand measures. Many other techniques, such as machine learning, deep learning and other image processing techniques have also been used to identify availability of parking slots [3]. Many optimization techniques have been used for efficient allocation of parking spaces via optimizing prices for arriving parking requests.

1.1. Motivation

The main motivation of this paper are as follows:

(i) STD unable to manage on-street parking system in the Seattle city which observes high congestion/cruising time problem everyday due to non-availability of parking spaces.
(ii) On-street parking pricing implemented in Seattle city is less dynamic and may not incorporate sudden change in the situations which leads to inappropriate situation of congestion around streets and inefficient management of on-street parking spaces.
(iii) Non-availability of real time or predicted information regarding occupancy levels of parking lots located in different areas of the Seattle city. Prior information about occupancy levels may decrease the cruising/in-search time of travelers.
(iv) Prior knowledge of parking prices (if high or not fit into routine budget of the parkers) may encourage the usage of public transportation over private transportation.

1.2. Contribution

Major contributions of this paper are as follows:

(i) An on-street occupancy prediction scheme is developed for the Seattle city which provides predicted occupancy of different parking lots to the parkers and hence, in getting optimal parking space.
(ii) An occupancy driven machine learning based on-street parking pricing scheme is developed which balances interests of both, i.e., parking authority/owners and parkers.
(iii) In-advance accepted or rejected parking request guides traveler/parker which in turn can decrease cruising time and hence, traffic congestion.

1.3. Organization

Rest of the paper is organized as follows. Section 2 presents work done in the area of parking pricing, its availability and occupancy prediction. Section 3 describes formulation of the parking pricing and prediction problem which have been solved in this paper. Section 4 explains data pre-processing, proposed schemes, i.e., parking occupancy prediction scheme, occupancy driven machine learning based on-street parking pricing scheme, and lastly communication protocol. Section 5 discusses simulation environment, description of data-set, performance measure indexes, and results in two cases, i.e., results obtained on data-set and via simulating real Seattle parking system. Finally, Section 6 concludes this paper (see Table 1).

Table 1
Nomenclature.

Terms	Description
STD	Seattle transport department
LIN	Linear model
DT	Decision tree model
NN	Neural networks model
rF	Random forest model
ToD	Time of the day pricing scheme
Occ	Occupancy based pricing scheme
PR_{id}	Parking request identified as 'id'
$PR_{id}(0)$	Rejected parking request identified as 'id'
$PR_{id}(1)$	Accepted parking request identified as 'id'
Select(S)	Function used to select one element from set S
dt_b	Date for which parking is requested
dt_c	Date on which parking is requested or current date
Unique_Id()	Function which will generate unique id for arrived parking requests
Paid(P)	Function returns 0 if prices 'P' are unpaid and 1 if paid
Prices(PR_{id})	Prices to be paid by requester for parking request identified as 'id'
rows(F)	Function retrieve number of rows in file 'F'
timestamp(h, m, s)	Function convert three values, i.e., hour 'h', minute 'm', and second 's' into full timestamp
SR_{id}	Occupancy status request for parking request identified as 'id'
UR_{id}	Occupancy update request for accepted parking request identified as 'id'
O_c	Actual occupancy of desired parking lot on requested date and time
O_p	Predicted occupancy of desired parking lot on requested date and time
ts_{id}	Total operational slots in desired parking lot of request identified as 'id' on requested date and time.
$flag_{id}^{PS}$	value 1 means parking request identified as 'id' can be accepted and 0 means request should be rejected.
$flag_{id}^{PU}$	value 1 means accepted parking request identified as 'id' is updated in desired parking lot records and 0 means not updated.

2. Literature review

Parking occupancy/availability prediction [4] and its pricing have been regarded as a key factors in curbing congestion and cruising time in search of parking. Over the past decade, a number of parking occupancy prediction models and pricing schemes have been developed to assist parking management in handling various problems, such as congestion, high travel time, and price overheads generated due to mismanagement of parking. The work done in the area of parking prediction and pricing is reported in following two sub-sections. Comparison of proposed scheme with other existing state-of-the-art techniques based on many parameters is done and given in Table 2. Whereas, limitations of existing state-of-the-art techniques are stated in Table 3.

2.1. Parking occupancy/Availability prediction techniques

Many machine learning models, such as Neural networks, Regression tree, Support vector machine, and Random forest; time series models, such as ARMA, and ARIMA; and ensemble

Table 2
Comparison with existing proposals.

Proposals	1	2	3	4	5	6	7	8	9	10	11	12	13
[5]	✓	✗	✓	✓	✗	✓	✓	✓	✓	✗	✗	✗	✗
[6]	✓	✓	✓	✗	✗	✓	✗	✗	✗	✗	✗	✓	✓
[7]	✓	✗	✗	✓	✓	✓	✗	✗	✗	✗	✗	✓	✗
[8]	✓	✓	✓	✗	✓	✓	✗	✓	✗	✗	✗	✗	✓
[9]	✓	✗	✗	✓	✓	✓	✗	✗	✗	✓	✓	✓	✗
[10]	✓	✗	✓	✗	✓	✓	✓	✓	✓	✗	✗	✓	✗
[11]	✓	✓	✓	✓	✓	✓	✓	✗	✓	✗	✗	✓	✗
[12]	✓	✗	✓	✓	✓	✓	✓	✗	✓	✗	✗	✓	✗
[13]	✓	✗	✗	✓	✓	✓	✓	✗	✓	✓	✗	✓	✗
[14]	✓	✗	✗	✓	✓	✓	✓	✗	✗	✓	✓	✗	✗
[15]	✓	✓	✓	✗	✗	✓	✓	✗	✗	✗	✓	✓	✓
[16]	✓	✓	✓	✓	✓	✓	✓	✗	✓	✗	✓	✓	✓
[17]	✓	✓	✗	✗	✓	✗	✗	✗	✓	✗	✗	✓	✗
Proposed scheme	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note-1: Parking pricing, 2: Revenue generated, 3: Parking prices, 4: Time of the day, 5: Geographical location of parking lots, 6: Occupancy, 7: On-Street parking, 8: Parking time limit, 9: Parking categories, 10: Weekday/weekend, 11: Prediction system, 12: Congestion, 13: Accepted/rejected parking requests ✓: considered, and ✗: non-considered.

Table 3
Limitations of existing proposals.

Proposals	Limitations
[5]	Factors, such as trip purposes, influence of parking information, heterogeneity, revenue generated, geographical conditions, weekday /weekend, and accepted/rejected parking requests are not considered. Pricing scheme lacks flexibility in terms of within-day and day to day scales.
[6]	Scheme did not consider cancellation of requests, cross price effect among parking periods, time of the day, geographical factors, parking types, time restrictions on parking, and day of the week.
[7]	Scheme did not model departure time, roadway congestion, and time varying step parking prices on the basis of occupancy. Factors, such as revenue generated, parking prices, parking types, parking time restriction are missing.
[8]	Only deterministic parameters are included which result in inappropriate scheme. Factors, like driver's parking behavior, time of the day, parking strategies, day of the week are missing.
[9]	Traffic demand, real time data are not used. Driving time is not dependent on parking flow is taken as an assumption. Factors, such as parking time limits, parking categories, number of requests accepted or requested, revenue generated, parking prices are missing.
[10]	Efficiency of parking pricing under competition is not explained. Study did not consider factors, such as revenue generated, time of the day and also the influence of accepted and rejected parking requests.
[11]	User heterogeneity and parking time restrictions are not evaluated. No support for dynamic competitive pricing.
[12]	Scheme missed out time-varying step parking pricing in relation to the occupancy. Factors, such as searching time, time restrictions, day of the week, revenue generated and effects of accepted and rejected parking requests are ignored.
[13]	Price elasticity, significance of parking availability on trip making, and impact of performance based parking management over extended time frames are not considered. Study missed out evaluation from the perspective of parking owners and parkers in terms of revenue generated and paid parking prices.
[14]	Lacks implementation and evaluation on real world data. Important factors, such as parking time limits, parking categories, accepted or rejected parking requests, paid parking price, and revenue generated are ignored.
[15]	Long time effect of optimal parking fee, heterogeneous environment, and real time pricing schemes are missing. Several important factors, such as time of the day, geographical location of parking lots, parking time limits, parking categories are not considered.
[16]	Study lacks scalability analysis and parking arrival scenarios according to the real situations.
[17]	High complexity. Lacks in quantification of factors which influence the choice model between curb parking and off-road parking.

techniques have been used so far to predict parking occupancy or availability. Apart from machine learning techniques, queuing theory has also been used in prediction of waiting times before getting occupancy in the parking lot.

Neural networks based prediction system for parking space availability has shown importance of various prime factors, such as time of the day, day of the week, location, and temperature whereas, events, traffic, vacation time, and rainfall play secondary role [18]. Tiedemann et al. developed an parking space occupancy prediction model for the Berlin pilot region which combines raw data timeline into data threads and Neural Gas vector quantization [19]. Also, accuracy of this prediction system improved with the combined use of original temporal relations of raw data and machine learning clustering method. Prediction of parking availability on data-sets of San Francisco, USA and Melbourne, Australia has been done using many different machine learning techniques, such as Regression tree, Neural networks and Support vector regression [20]. In this study, low computational intensive algorithm, i.e., Regression tree got highest prediction accuracy in comparison to the other two algorithms. Bayesian regularized Neural network has also been used to provide reliable and fast prediction of available parking spaces [21]. Other techniques apart from Bayesian regularized Neural networks, includes Support vector regression, ARIMA models, and Recurrent neural networks which have been used in this study. With the use of different spatio-temporal clustering techniques, the trade-off between achievable prediction accuracy and detailed temporal and spatial representation of parking space availability has been demonstrated on the SFpark data [22]. Multivariate autoregressive model has also been used for parking availability prediction for the areas of San Francisco and Los Angeles [23]. This model also took care of spatial and temporal correlations of parking availability. Ensemble method, which combines Regression tree and Support vector regression, i.e., Gradient Boosting Regression Trees (GBRT) has also been used for on-street car parking prediction in smart city environment [24]. Parking space availability prediction has also been done with the use of Wavelet neural networks and its performance was compared with the largest Lyapunov Exponents (LEs) method [25]. Vlahogianni et al. have done two types of prediction, first being the probability of free parking space further extends to be free in subsequent time intervals and second being short term parking occupancy in different regions of city of Santander, Spain [26]. In this study, Weibull parametric models and Neural networks model were used for the prediction. Many machine learning techniques, such as Decision tree, Random forest, Support vector machine and Gradient boosting have also been used for parking availability prediction using SFpark data [27]. Grid search has also been employed in order to find the best model among them. For car parking occupancy rate prediction in Birmingham, UK, a deep learning with Recurrent Neural Networks (RNN) based technique was employed [28]. In this work, GA and ES based meta heuristic approaches have been used along with RNN.

San Francisco parking occupancy has also been predicted using ARIMA model, Linear regression, Support vector regression, and feed-forward Neural networks in which pattern was find out in terms of dual peak, drop before ramp up, and noon peak [29].

Based on the utility, ARIMA time series model has proved its worth over Neural networks model in predicting real time occupancy [30].

A new dimension into occupancy prediction was added when information exchange in the vehicular ad-hoc networks is used for predicting occupancy [31]. Based on the queuing theory and using continuous-time homogeneous Markov model, the prediction has been done with the help of parameters, such as time needed to reach parking lot and age of received parking lot information. This study has been carried out on the model of city of Brunswick, Germany. Hybrid models, combined with Markov Chain Monte Carlo (MCMC) method have also proven their worth in prediction of parking lot occupancy [32]. A continuous-time Markov M/M/C/C queuing model has also used to explain stochastic occupancy change [33]. This model predicted occupancy for any time in future with only one training process whereas, machine learning models needed training for different prediction intervals. Various patents for identification of parking slots and prediction of its availability by taking into account driver's behavior as a key factor, have been evolved over the years [34, 35].

2.2. Parking pricing techniques

Many parking pricing techniques which uses prediction techniques, machine learning methods, dynamic programming and other methods, have been evolved over the years. Various studies have also been carried out which evaluate or study the impact of parking pricing on public and parameters, such as congestion and cruising time.

Parking pricing formulated as Mixed Integer Linear Programming (MILP) problem, has been solved where monetary cost for drivers and parking utilization were minimized and maximized respectively [16]. CPLEX has been used to solve such MILP formulations. Provision of parking information has certain relation with parking pricing [12,36]. In this study, parking flow pattern and prices have been evaluated using linear programming. Moreover, this solution reduced the queue length and hence, congestion. With the formulation of parking choices using Variational Inequality (VI) approach, the parking flow pattern and prices have also been evaluated using linear programming [7]. A balance between parking congestion and level of convenience was achieved by optimal parking pricing. In another dimension, the relation between maximization of revenue for management and reduction in total number of vehicle trips have been studied [37]. In this study, increase or decrease in revenue directly associated with parking prices. Parking pricing problem can also be formulated as minimization of Root Mean Square Error (RMSE) between target and predicted occupancy rates. Lasso and Elastic-net regularized generalized linear models have been used for prediction of occupancy rates [14]. Another variant of parking pricing problem, i.e., Origin–Destination Parking Pricing (ODPP) was solved using meta heuristic algorithm and its comparison with Destination Parking Pricing (DPP) scheme has shown decrease in road travel time, system and social costs [38]. A dynamic macroscopic parking pricing model, where parking prices change according to the number of vehicles searching particular parking space and change in occupancy has also been investigated [15]. Macroscopic Fundamental Diagram (MFD) based dynamic parking pricing approach which solved network level congestion, has also been developed [10]. Dynamic parking pricing has also been tackled using stochastic dynamic programming problem formulations. In such a methodology, linear and exponential demand functions were applied to find a closed-form solution [6]. Impact of pricing on traffic jam and environment, were also considered. Approximate Dynamic Programming (ADP) has also been used to solve the game theoretic dynamic pricing and reservation model [6]. ADP showed reliability in managing the temporal and spatial variations in parking demand. Optimal parking pricing problem has also been formulated as stochastic control problem where, demand was considered as one of the factor to solve it using dynamic programming approach [9].

Hourly parking pricing, unlike to hourly road pricing can reduce or induce demand based on parking dwell time elasticity [11]. Further, this showed that blind implementation of hourly parking pricing is of no use. VI formulations have been used in this study. Further, the impact of San Francisco parking pricing program (SFpark) on cruising time and distance have also been studied [39]. Generalized mixed effect difference-in-difference models have been used on data collected before and after implementation of SFpark program. These models have shown reduction in cruising time and distance after implementation of SFpark program. Various conditions related to parking prices which includes flow of parking economy, shift of power have also been discussed [40]. The impact of charging parking fee per minute over per hour has been shown [41]. This study concluded reduction in duration of the stay and waiting time of new arrivals. SFpark pricing program was intended to improve driver's experience, cruising, and to reduce double parking [13]. The relation between probability of finding parking slot and cruising time along with occupancy rules have been demonstrated. Arrival rate and cruising were simulated using hourly data and results have shown reduction in cruising time using SFpark program. Parking price adjustment scheme which uses MMNL models to balance the demand and functional goals of curb side parking spaces, has also been developed [42].

The study supporting impact of parking pricing over parking performance has also been carried out [43]. Curbing parking pricing based on parking choice behavior was also line of investigation [17]. Further, survey of 400 on-street parking users from different districts of Rome has been carried out to observe impact of parking pricing over its occupancy [44]. Lin et al. further elaborated the role of parking prediction and pricing in various aspects of intelligent transportation system [45]. Also, system such as fog-supported smart city network (FOCAN) architecture [46] has shown the need of fog computing in smart city environment which can have many type of internet enabled devices communicating with each other. In order to deal with parking pricing and cruising time issues, the proposed technique will be useful in such system.

3. Problem formulation

In this section an on-street parking occupancy prediction scheme and occupancy driven machine learning based on-street parking pricing scheme are formulated. In the formulations, uppercase letter denotes the set whereas, same lowercase letter represents its element. Let the letters A, SA, BF, SS, PC, DT, DY, T, M, H, N, and R denote set of areas, sub-areas, block faces, sides of street, parking category, dates, days, timestamps, months of year, hours of the day, natural, and real numbers respectively. Whereas, a_i, sa_i, bf_i, ss_i, pc_i, dt_i, dy_i, t_i, m_i, h_i, n_i, r_i denote ith element of set areas, sub-areas, block faces, sides of street, parking category, dates, days, timestamps, months, hours, natural and real number respectively. In this paper, notations used in order to access these specific elements are A_i, SA_i, BF_i, SS_i, PC_i, DT_i, DY_i, T_i, M_i, H_i, N_i, and R_i respectively. Let $\mathbb{A}$, $\mathbb{SA}$, $\mathbb{BF}$, $\mathbb{SS}$, $\mathbb{PC}$, $\mathbb{DT}$, $\mathbb{DY}$, $\mathbb{T}$, $\mathbb{M}$, $\mathbb{H}$, $\mathbb{N}$, and $\mathbb{R}$ denote subsets of set A, SA, BF, SS, PC, DT, DY, T, M, H, N, and R respectively.

There exists many types of associations in-between above stated sets as observed in data pre-processing phase. These associations are hereby defined as relations on these sets. Each relation is named as f^i where 'i' differentiate one relation from other. All relations used in this paper are defined in following definitions.

Definition 1. Let f^1 be defined as a relation having one-to-many mapping between elements of sets, areas and sub-areas respectively.

$$f^1 : \{a \rightarrow \mathbb{SA} \mid a \in A \wedge \mathbb{SA} \subseteq SA\} \tag{1}$$

Definition 2. Let f^2 be defined as a relation having one-to-many mapping between pair of elements from sets, areas, and sub-areas, and elements of set, block faces respectively.

$$f^2 : \{(a, sa) \rightarrow \mathbb{BF} \mid a \in A \wedge sa \in SA \wedge \mathbb{BF} \subseteq BF\} \tag{2}$$

Definition 3. Let f^3 be defined as a relation having one-to-many mapping between elements of sets, block faces and sides of street respectively.

$$f^3 : \{bf \rightarrow \mathbb{SS} \mid bf \in BF \wedge \mathbb{SS} \subseteq SS\} \tag{3}$$

Definition 4. Let f^4 be defined as a relation having one-to-one mapping between elements of sets, dates and days respectively.

$$f^4 : \{dt \rightarrow dy \mid dt \in DT \wedge dy \in DY\} \tag{4}$$

Definition 5. Let f^5 be defined as a relation having one-to-many mapping between pair of elements from sets, areas and sub-areas, and elements of set, days respectively.

$$f^5 : \{(a, sa) \rightarrow \mathbb{DY} \mid a \in A \wedge sa \in SA \wedge \mathbb{DY} \subseteq DY\} \tag{5}$$

Definition 6. Let f^6 be defined as a relation having one-to-one mapping between elements of sets, time and hour respectively.

$$f^6 : \{t \rightarrow h \mid t \in T \wedge h \in H\} \tag{6}$$

Definition 7. Let f^7 be defined as a relation between elements of sets, areas, sub-areas, months, and hours. This relation provides chargeable parking hours in specific area and sub-area in particular month.

$$f^7 : \{(a, sa, m) \rightarrow \mathbb{H} \mid a \in A \wedge sa \in SA \wedge m \in M \wedge \mathbb{H} \subseteq H\} \tag{7}$$

Definition 8. Let f^8 be defined as a relation between elements of sets, dates and natural numbers. This relation provides the number of days between two dates.

$$f^8 : \{(dt, dt) \rightarrow n \mid dt \in DT \wedge n \in N\} \tag{8}$$

Definition 9. Let f^9 be defined as a relation between elements of sets, block faces, sides of street, and natural numbers. This relation provides the unique identity of parking lot situated at specific side of a particular block face.

$$f^9 : \{(bf, ss) \rightarrow n \mid bf \in BF \wedge ss \in SS \wedge n \in N\} \tag{9}$$

Definition 10. Let f^{10} be defined as a relation between elements of sets, areas, sub-areas, months, hours, and real number. This relation provides the parking price as per the Time of the Day (ToD) pricing scheme being implemented by STD in the Seattle city.

$$f^{10} : \{(a, sa, m, h) \rightarrow r \mid a \in A \wedge sa \in SA \wedge m \in M \wedge h \in H \wedge r \in R\} \tag{10}$$

Definition 11. Let f^{11} be defined as a relation between elements of sets, areas, sub-areas, and natural numbers where natural number represents parking time limit (in hours) of specific area and sub-area.

$$f^{11} : \{(a, sa) \rightarrow n \mid a \in A \wedge sa \in SA \wedge n \in N\} \tag{11}$$

Definition 12. Let f^{12} be defined as a relation having one-to-one mapping between elements of sets, dates and month.

$$f^{12} : \{dt \rightarrow m \mid dt \in DT \wedge m \in M\} \tag{12}$$

Definition 13. Let f^{13} be defined as a relation between elements of sets, block faces, sides of street, dates, hours, and parking category. This relation provides parking category in which particular parking lot is operational in specific hour of the day.

$$f^{13} : \{(bf, ss, dt, h) \rightarrow pc \mid bf \in BF \wedge ss \in SS \wedge dt \in DT \wedge h \in H \wedge pc \in PC\} \tag{13}$$

Definition 14. Let f^{14} be defined as a relation between elements of sets, block faces, sides of street, dates, timestamps, and natural numbers. This relation provides parking occupancy of requested parking lot.

$$f^{14} : \{(bf, ss, dt, t) \rightarrow n \mid bf \in BF \wedge ss \in SS \wedge dt \in DT \wedge t \in T \wedge n \in N\} \tag{14}$$

Definition 15. Let f^{15} be defined as a relation between elements of sets, block faces, sides of street, dates, timestamps, and natural numbers. This relation provides total operational parking slots in particular parking lot at specific time.

$$f^{15} : \{(bf, ss, dt, t) \rightarrow n \mid bf \in BF \wedge ss \in SS \wedge dt \in DT \wedge t \in T \wedge n \in N\} \tag{15}$$

Let each parking lot maintains one record file in order to keep track of dates, timestamps, occupancy status, and total operational slots. Let the file name is represented by '$Status_{pid}$', where natural number 'pid' calculated using f^9 relation denotes parking lot unique id. In order to access particular 'ith' record, notation $Status_{pid}(i)$ is used in this paper. Relations used to operate on such parking record files are stated in following definitions.

Definition 16. Let f^{16} be defined as a relation which provides the date of particular record.

$$f^{16} : \{Status_{pid}(i) \rightarrow dt \mid dt \in DT\} \tag{16}$$

Definition 17. Let f^{17} be defined as a relation which provides the timestamp of particular record.

$$f^{17} : \{Status_{pid}(i) \rightarrow t \mid t \in T\} \tag{17}$$

Definition 18. Let f^{18} be defined as a relation which provides the actual occupancy of parking lot as per particular record.

$$f^{18} : \{Status_{pid}(i) \rightarrow n \mid n \in N\} \tag{18}$$

Definition 19. Let f^{19} be defined as a relation which provides the total operational parking slots provided in a particular record.

$$f^{19} : \{Status_{pid}(i) \rightarrow n \mid n \in N\} \tag{19}$$

In order to use any of the above-mentioned relation, $f^i_{output}(input)$ notation is used in this paper, where input and output to the relation f^i can be a set of elements or any specific element of the set.

The formulations of two proposed schemes are as follows:

(i) On-street parking occupancy prediction scheme: Hourly occupancy prediction of on-street parking system of Seattle city is formulated as follows. Various inputs to the prediction model are area, sub-area, block face, side of the street, day of the week, hour of the requested time, and parking category. Output will be the respective predicted occupancy denoted by O_p.

$$O_p = f_r^{pred}(a_i, sa_j, bf_k, ss_l, dy_m, h_p, pc_q) \tag{20}$$

subject to the following constraints:

$$sa_j \in f^1_{\mathbb{SA}}(a_i) \tag{21}$$
$$bf_k \in f^2_{\mathbb{BF}}(a_i, sa_j) \tag{22}$$
$$ss_l \in f^3_{\mathbb{SS}}(bf_k) \tag{23}$$
$$h_p = f^6_h(t_b) \tag{24}$$
$$h_p \in f^7_{\mathbb{H}}(a_i, sa_j, f^{12}_m(dt_b)) \tag{25}$$
$$dy_m = f^4_{dy}(dt_b) \tag{26}$$
$$dy_m \in f^5_{\mathbb{DY}}(a_i, sa_j) \tag{27}$$
$$pc_q = f^{13}_{pc}(bf_k, ss_l, dt_b, f^6_h(t_b)) \tag{28}$$
$$a_i \in A;\quad sa_j \in SA;\quad bf_k \in BF;\quad ss_l \in SS;\quad dt_b \in DT; \quad t_b \in T;\quad dy_m \in DY;\quad h_p \in H;\quad pc_q \in PC \tag{29}$$

(ii) Occupancy driven machine learning based on-street parking pricing scheme: This proposed pricing scheme considers real or predicted occupancy while computing parking prices for the next arriving vehicle. Occupancy is the heavy weight factor in management of the parking systems. It changes with situations as already explained. Predicted occupancy depends on many factors, such as hour of the day, day of the week, area, sub-area, block face, side of street, and parking category. Thus, prices calculated using proposed scheme will also depends on all of these factors. In order to solve function f_r^{prices}, various parameters are required which have been already defined in Definitions 1–19.

$$Prices_{Occ} = f_r^{prices}(a_i, sa_j, bf_k, ss_l, dt_b, t_b) \tag{30}$$

subject to the following constraints:

$$sa_j \in f^1_{\mathbb{SA}}(a_i) \tag{31}$$
$$bf_k \in f^2_{\mathbb{BF}}(a_i, sa_j) \tag{32}$$
$$ss_l \in f^3_{\mathbb{SS}}(bf_k) \tag{33}$$
$$f^8_n(dt_b, dt_c) \le 6 \tag{34}$$
$$f^4_{dy}(dt_b) \in f^5_{\mathbb{DY}}(a_i, sa_j) \tag{35}$$
$$f^6_h(t_b) \in f^7_{\mathbb{H}}(a_i, sa_j, f^{12}_m(dt_b)) \tag{36}$$
$$f^{14}_n(bf_k, ss_l, dt_b, t_b) < f^{15}_n(bf_k, ss_l, dt_b, t_b) \tag{37}$$
$$f^6_h(t_b) + f^{11}_n(a_i, sa_j) \in f^7_{\mathbb{H}}(a_i, sa_j, f^{12}_m(dt_b)) \tag{38}$$
$$f^{10}_r(a_i, sa_j, f^{12}_m(dt_b), f^6_h(t_b)) \neq \phi \tag{39}$$
$$a_i \in A;\quad sa_j \in SA;\quad bf_k \in BF;\quad ss_l \in SS;\quad dt_b \in DT;\quad t_b \in T \tag{40}$$

4. The methodology

The methodology is divided into three sub-sections. First subsection explains the pre-processing of on-street parking data [47] of the Seattle city. The second sub-section explains the on-street parking occupancy prediction scheme and the last sub-section explains the proposed occupancy driven machine learning based on-street parking pricing scheme for the Seattle city.

4.1. Data pre-processing

On-street parking data released by STD is pre-processed according to following steps.

4.1.1. Data transformation

It has been observed that on-street parking data [47] of the Seattle city is captured at irregular time intervals. Thus, everyday data is transformed into hourly data for all parking lots, where occupancy represents average occupancy in particular hour.

4.1.2. Data encoding

All textual categorical data, such as areas, sub-areas, block faces, sides of the street, and parking category are converted into numeric categorical data.

4.1.3. Imputation

Those areas which do not have any sub-area were assumed to have one sub-area. Such missing values are imputed with one fixed numeric value. Moreover, one entire column named as "Paid Parking Rate" had all missing values. These missing values were imputed using parking price data-set [48].

4.1.4. Normalization

In order to train machine learning models and predict occupancy, on-street parking data is normalized as per Eq. (41). This is done because data features have different range of values.

$$dv_{new}(i) = \frac{dv_{old}(i) - min(dv_{old})}{max(dv_{old}) - min(dv_{old})} \tag{41}$$

Here, 'dv' denotes data values.

4.1.5. Feature selection

In this step, most relevant and informative features are selected from the data-set. The criteria of any feature vector to be selected is less correlation with other feature vectors. The features selected after this step are day, hour of the day, areas, sub-areas, block faces, sides of street, parking category, and occupancy.

4.2. On-street parking occupancy prediction scheme for Seattle city

In order to do anything, approach changes with quantity and quality of the knowledge. At present, Seattle city is experiencing congestion due to high cruising time in getting appropriate parking slot. Absence of system which can provide occupancy status of parking lots in advance is equally responsible for high cruising time and hence, for congestion. People can choose appropriate parking lot if they know its occupancy status in advance. In order to facilitate people which in turn will reduce congestion/cruising time, an on-street parking occupancy prediction scheme is developed. In this work, four machine learning models, i.e., Linear (LIN), Decision Tree (DT), Neural Network (NN), and random Forest (rF) have been trained and tested. The input features for all of these machine learning models are days of the week, hours of the day, areas, sub-areas, block faces, sides of the street, and parking category. After training, model will solve formulation presented in Eq. (20).

The percentages of training and testing data out of total data [47] are 70% and 30% respectively. The R packages used for DT, NN, and rF models are rpart, nnet, and randomForest respectively. The function lm is used to train linear regression. The splitting rule in DT model is based on information and the values of usesurrogate and maxsurrogate are taken as 0. The number of units in the hidden layer of NN model are taken as 10. The output units are taken as linear units. The value of maximum allowable number of weights and maximum number of iterations are taken as 10,000 and 100 respectively. The value of number of trees to grow (ntree) in rF model is taken as 500. Whereas, the value of mtry is taken as 2.

4.3. On-street occupancy driven machine learning based on-street parking pricing scheme for Seattle city

Fixed or less dynamic pricing of any infrastructure/service, such as parking is not at all worthy in today's scenario. Even minute change in situations/factors, such as demand, real road/traffic conditions attract continuous monitoring and remedies. STD implements ToD pricing scheme for on-street parking facility of the Seattle city. According to the Seattle parking data [47], occupancy of on-street parking lots remain more than 50% all the time. Also, it has been found that parking at some areas, such as South Lake Union, First Hill, Cherry Hill, and Westlake Ave N is under utilized. Moreover, in some areas, such as Capitol Hill, Chinatown/ID, Pike-Pine, University District, Uptown, Ballard, Denny Triangle, Fremont, Uptown Triangle, Roosevelt, Green Lake, 12th Avenue, and Columbia city, it is highly utilized. Cherry Hill and Green Lake are those areas where occupancy pattern is different for each day of the week. Thus, in such areas ToD pricing scheme does not seems to be a promising approach. It has been reported by the STD that because of high cruising time, congestion in the Seattle city increases. In order to solve these issues, pricing having in-advance knowledge of occupancy seems to be only promising solution. Thus, an occupancy driven machine learning based on-street parking pricing scheme is proposed for the Seattle city. In the proposed scheme, prices charged by the STD are taken as prices to be charged when occupancy is equal to the half of total operational parking slots. Thus, with increase or decrease in occupancy, prices generated through proposed scheme will increase or decrease respectively. The function f_r^{prices} as formulated in Eq. (30) is solved through this scheme and $Prices_{occ}$ are generated. The method used for this purpose is explained in Algorithms 1, 2, 3, and 4. The proposed pricing scheme is applied on the Seattle parking data-set and is also simulated on Seattle parking system environment.

4.4. Communication protocol for occupancy-driven machine learning based on-street parking pricing scheme

In the proposed pricing scheme, event-driven communication protocol is used to exchange messages between different entities of the transportation system. Here, event is a parking request sent by the parker. Fig. 1 depicts the architecture of the proposed scheme which shows various entities of transportation system communicating with each other in order to determine parking prices. Parkers/travelers/vehicles can send current or advance parking request which will be redirected to the centralized server. Thereafter, request will get processed and subsequently, the server will seek occupancy status from the respective parking lot. Based on real and predicted occupancy, it will generate prices according to the proposed scheme. After payment it will confirm or reject the request and appropriate message will be sent to the parkers/travelers/vehicles. An update will be sent to the parking lot management only upon acceptance of the request.

5. Results and discussions

5.1. Simulation environment and assumptions

The system used for this experiment is having 2.60 GHz Xeon(R) processor, 16 GB RAM. This experiment has been carried out using several simulators. MATLAB R2019 with Parallel computing toolbox, R Studio is used for data pre-processing. R Studio is used for training and testing of all machine learning models. Whereas, MATLAB R2019 with parallel computing toolbox is used to implement and simulate proposed schemes. The Seattle parking system environment is created in MATLAB

Algorithm 1: Parking Request and Booking

Data: $A, SA, BF, SS, DT, DY, T, M, H, f^1, f^2, f^3, f^4, f^5, f^6, f^7, f^8, f^{12}$
Result: $\mathrm{PR}_{id}(0)$ or $\mathrm{PR}_{id}(1)$
$a_i = \mathrm{Select}(A)$
$sa_j = \mathrm{Select}(f^1_{\mathrm{SA}}(a_i))$
$bf_k = \mathrm{Select}(f^2_{\mathrm{BF}}(a_i, sa_j))$
$ss_l = \mathrm{Select}(f^3_{\mathrm{SS}}(bf_k))$
`marker1:`
$dt_b = \mathrm{Select}(DT)$
if $f^8_n(dt_b, dt_c) \geq 7$ **then**
  Print("Advance parking is allowed upto next six days only".)
  Goto `marker1`
else
  if $f^4_{dy}(dt_b) \notin f^5_{\mathrm{DY}}(a_i, sa_j)$ **then**
    Print("Parking in sub-area 'sa_j' of area 'a_i' is free on date 'dt_b'. No booking required")
    exit
  else
    $t_b = \mathrm{Select}(T)$
    if $f^6_h(t_b) \notin f^7_{\mathrm{H}}(a_i, sa_j, f^{12}_m(dt_b))$ **then**
      Print("Parking in sub-area 'sa_j' of area 'a_i' is free at time 't_b'. No booking required")
      exit
    else
      $id = \mathrm{Unique\_Id}()$
      $flag$ = Call Algorithm 2 ($\mathrm{PR}_{id}(a_i, sa_j, bf_k, ss_l, dt_b, t_b)$)
      if $flag == PR_{id}(1)$ **then**
        Print ("Required parking slot booked".)
      else if $flag == PR_{id}(0)$ **then**
        Print ("Required parking slot cannot be booked due to unavailability or low balance".)

Algorithm 2: On-Street Occupancy driven Machine Learning based On-Street Parking Pricing Scheme

Data: $\mathrm{PR}_{id}(a_i, sa_j, bf_k, ss_l, dt_b, t_b), f^4, f^6, f^9, f^{10}, f^{12}, f^{13}, f^{pred}$
Result: $\mathrm{PR}_{id}(0)$ or $\mathrm{PR}_{id}(1)$
$pid = f^9_n(bf_k, ss_l)$
$[O_c, ts_{id}, flag^{PS}_{id}, \mathrm{pos}_s, \mathrm{pos}_l]$ = Call Algorithm 3 ($\mathrm{SR}_{id}(pid, \mathrm{PR}_{id}(a_i, sa_j, bf_k, ss_l, dt_b, t_b))$)
if $flag^{PS}_{id} \neq 1$ **then**
  return $\mathrm{PR}_{id}(0)$
else
  $O_p = f^{pred}_r(a_i, sa_j, bf_k, ss_l, f^4_{dy}(dt_b), f^6_h(t_b), f^{13}_{pc}(bf_k, ss_l, dt_b, f^6_h(t_b)))$
  if $O_c \geq O_p$ **then**
    $temp = O_c$
  else
    $temp = O_p$
  $frac = \frac{(temp+1)-(ts_{id}/2)}{ts_{id}}$
  $\mathrm{Prices}(\mathrm{PR}_{id}) = f^{10}_r(a_i, sa_j, f^{12}_m(dt_b), f^6_h(t_b)) + f^{10}_r(a_i, sa_j, f^{12}_m(dt_b), f^6_h(t_b)) \times frac$
  Get_Prices($\mathrm{Prices}(\mathrm{PR}_{id})$)
  if $(Paid(Prices(PR_{id})) == 1)$ **then**
    `marker3:`
    $flag^{PU}_{id}$ = Call Algorithm 4 ($\mathrm{UR}_{id}(pid, \mathrm{pos}_s, \mathrm{pos}_l)$)
    if $flag^{PU}_{id} == 1$ **then**
      return $\mathrm{PR}_{id}(1)$
    else
      Goto `marker3`
  else if $(Paid(Prices(PR_{id})) == 0)$ **then**
    return $\mathrm{PR}_{id}(0)$

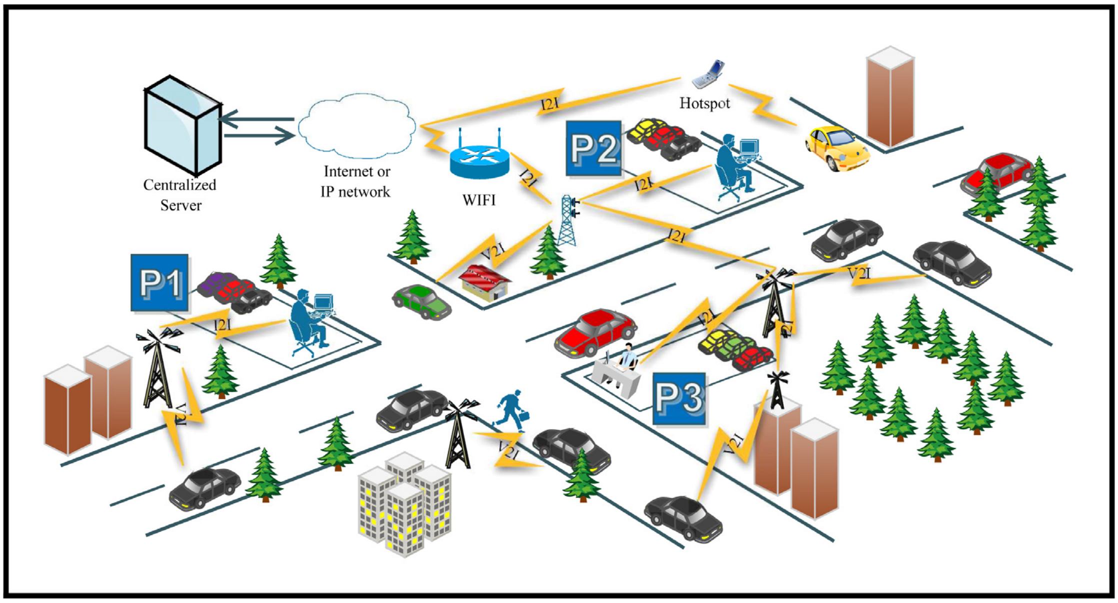

Fig. 1. Occupancy driven machine learning based on-street parking pricing architecture.

Algorithm 3: Get Parking Status

Data: $SR_{id}(pid, PR_{id}(a_i, sa_j, bf_k, ss_l, dt_b, t_b)), f^6, f^7, f^{11}, f^{12}, f^{16}, f^{17}, f^{18}, f^{19}, Status_{pid}$
Result: $O_c, ts_{id}, flag_{id}^{PS}, \text{pos}_s, \text{pos}_l$
for $file\_i = 1$ *to rows*($Status_{pid}$) **do**
  if $((f_{dt}^{16}(Status_{pid}(file\_i)) == dt_b) \wedge (f_t^{17}(Status_{pid}(file\_i)) == t_b)$ **then**
    $\text{pos}_s = \text{file\_i}$
    break
for $file\_i = pos_s$ *to rows*($Status_{pid}$) **do**
  if $f_h^6(t_b) + f_n^{11}(a_i, sa_j) \in f_{\mathbb{H}}^7(a_i, sa_j, f_m^{12}(dt_b))$ **then**
    if $((f_{dt}^{16}(Status_{pid}(file\_i)) == dt_b) \wedge (f_t^{17}(Status_{pid}(file\_i)) == (t_b + f_n^{11}(a_i, sa_j)))$ **then**
      $\text{pos}_l = \text{file\_i}$
      break
  else
    $TP = f_{\mathbb{H}}^7(a_i, sa_j, f_m^{12}(dt_b))$
    if $((f_{dt}^{16}(Status_{pid}(file\_i)) == dt_b) \wedge f_t^{17}(Status_{pid}(file\_i)) == timestamp(tp_{|TP|}, 59, 59)$ **then**
      $\text{pos}_l = \text{file\_i}$
      break
$flag_{id}^{PS} = 1$
for $file\_i = pos_s$ *to* pos_l **do**
  if $f_n^{18}(Status_{pid}(file\_i)) \geq f_n^{19}(Status_{pid}(file\_i))$ **then**
    $flag_{id}^{PS} = 0$
    break
return $(f_n^{18}(Status_{pid}(\text{pos\_s})), f_n^{19}(Status_{pid}(\text{pos\_s})), flag_{id}^{PS}, \text{pos}_s, \text{pos}_l)$

---

based on various associations (such as possible areas, sub-areas, block faces, sides of streets, chargeable/non-chargeable hours, sub-areas in particular area etc.) drawn from the data-set. The parking requests generation method is described in the following sub-section.

Algorithm 4: Update Parking Status

Data: $UR_{id}(pid, \text{pos}_s, \text{pos}_l), f^{18}, Status_{pid}$
Result: $flag_{id}^{PU}$
$flag_{id}^{PU} = 0$
for $file\_i = pos_s$ *to* pos_l **do**
  $f_n^{18}(Status_{pid}(\text{file\_i})) = f_n^{18}(Status_{pid}(\text{file\_i})) + 1$
$flag_{id}^{PU} = 1$
return $(flag_{id}^{PU})$

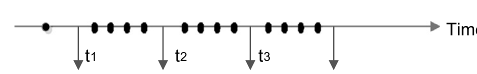

Fig. 2. Illustration of vehicle arrival in particular parking lot of the Seattle city.

5.1.1. Parking request arrival

In simulation of the Seattle parking system, arrival of parking requests is assumed to follow Poisson process. If we plot the arrival of parking requests as a dot on the timeline then it will look like Fig. 2. Let one time interval corresponds to one hour then number of arrived parking requests in particular area will be the same in different interval of time as shown in Fig. 2. The probability of number of parking requests arrived (x) per minute or second can be calculated using probability density function given in Eq. (42).

$$p(x) = \frac{\lambda^x . e^{-\lambda}}{x!} \tag{42}$$

Two values of the requests arrival rate, i.e., λ_1 and λ_2 have been assumed for each area of the Seattle city as shown in Table 5. λ_1 depicts low arrival rate according to total slots available for the parking. Whereas, λ_2 depicts high arrival rate. The units of both, i.e., λ_1 and λ_2 are number of parking requests per hour.

The assumptions used in this experiment are as follows:

(i) If parking request can be fulfilled then it is assumed that parking requester will pay the price and hence, all such requests are accepted.

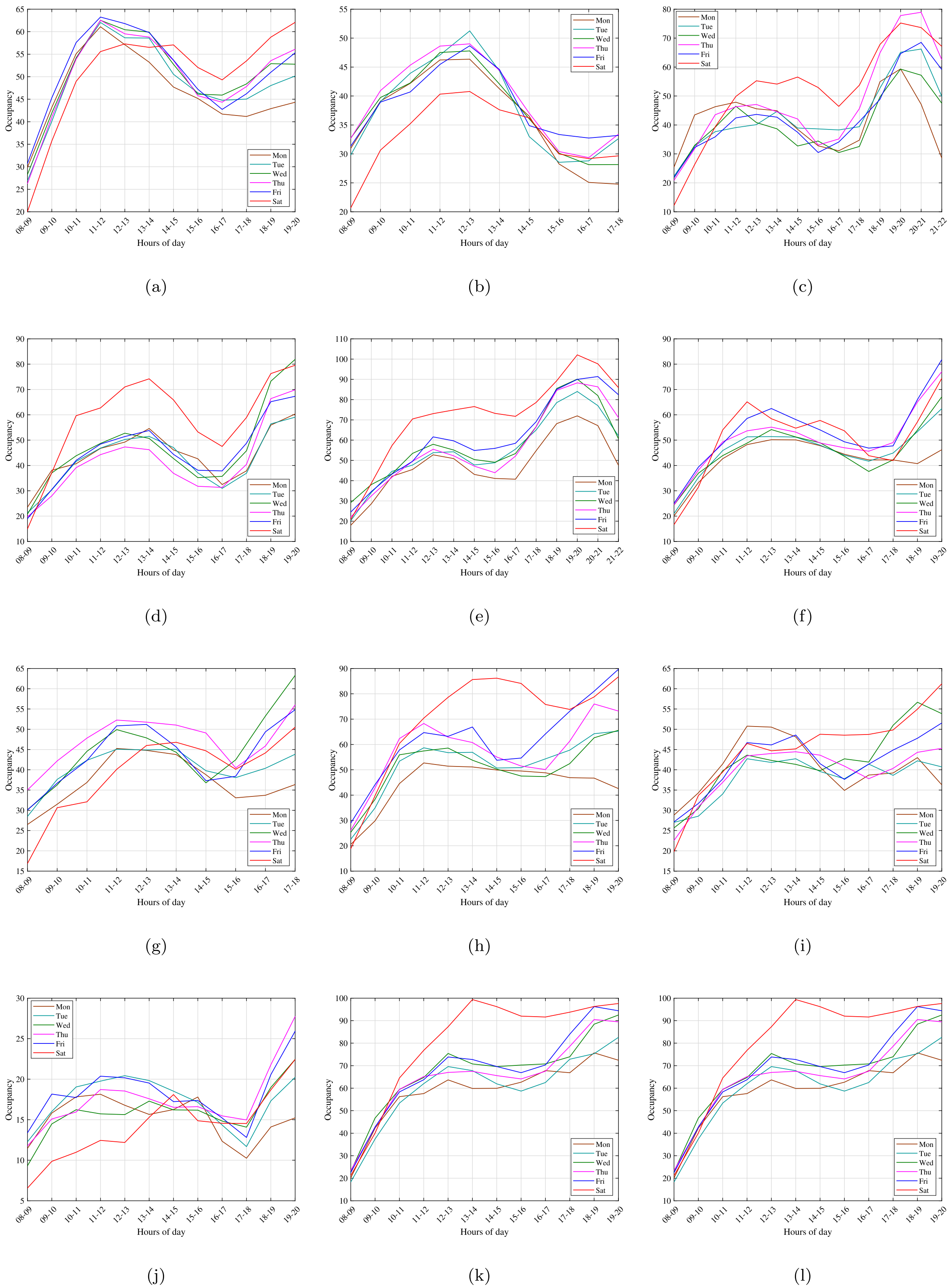

Fig. 3. Occupancy over different days of the week in area (a) Belltown (b) South Lake Union (c) Capitol Hill (d) Chinatown/ID (e) Pike-Pine (f) University District (g) Pioneer Square (h) Uptown (i) Commercial Core (j) First Hill (k) Ballard (l) Denny Triangle.

(ii) If parking request is accepted, then prices will be charged for minimum fixed time limit of requested parking lot.

(iii) Simulation of Seattle parking system is carried out for two weeks. Parking prices and revenue generated shown in the results are average of one week only.

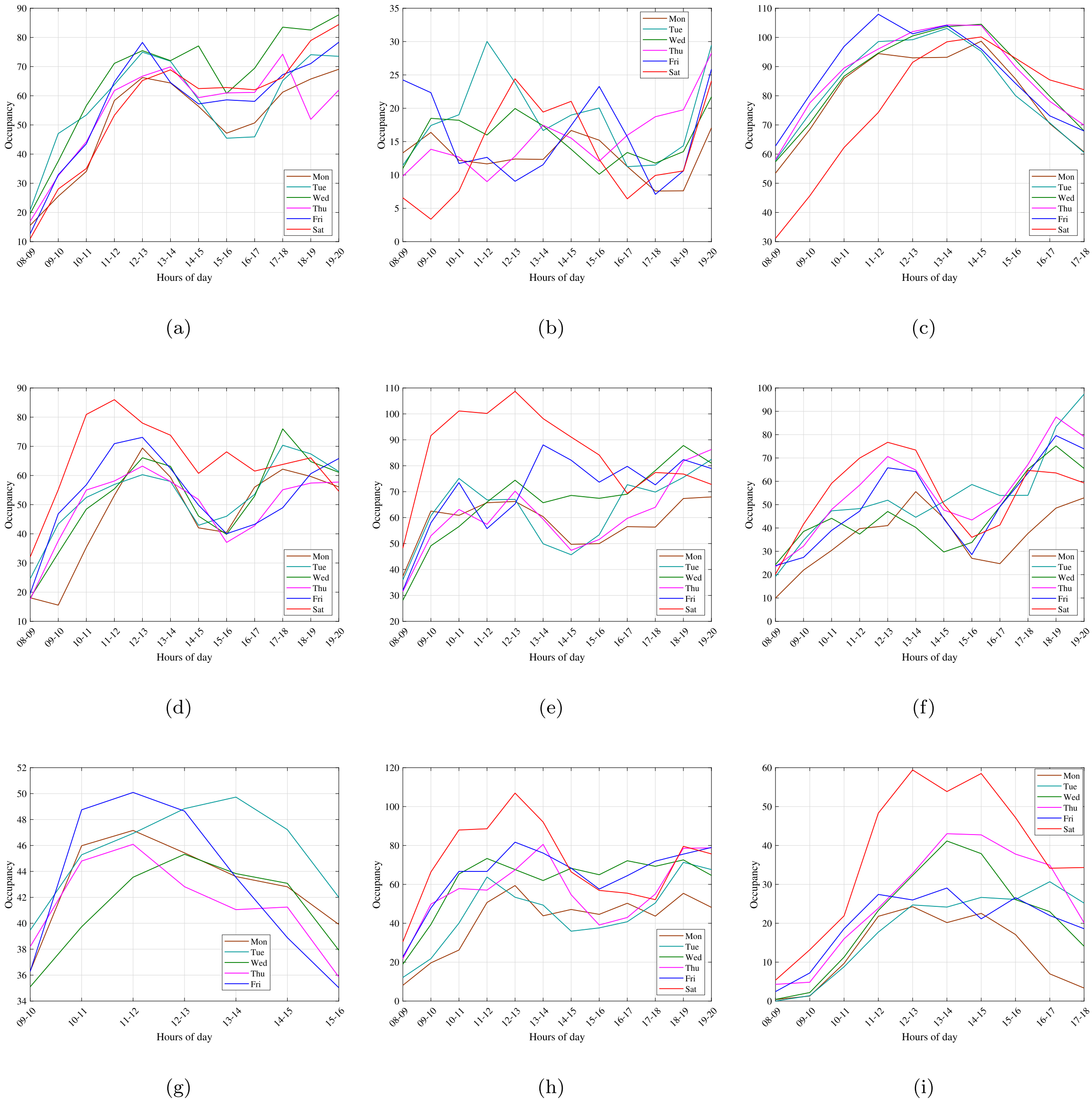

Fig. 4. Occupancy over different days of the week in area (a) Fremont (b) Cherry Hill (c) Uptown Triangle (d) Roosevelt (e) Green Lake (f) 12th Avenue (g) Westlake Ave N (h) Columbia City (i) Ballard Locks.

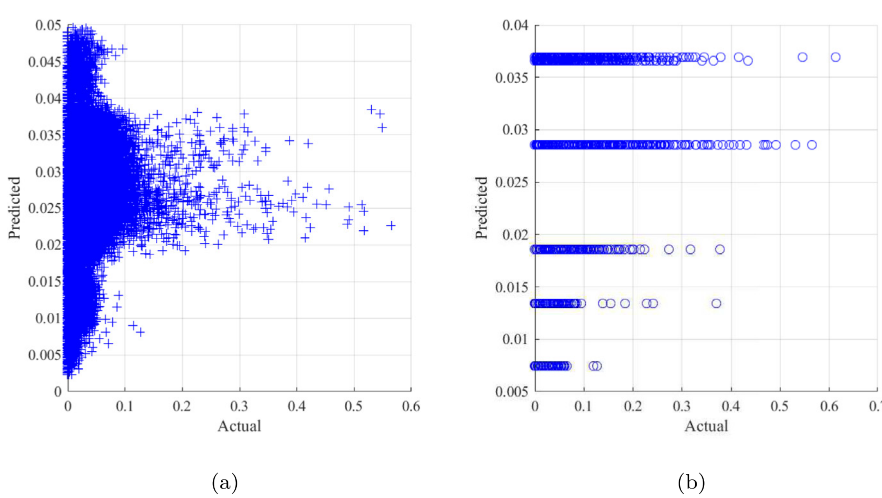

Fig. 5. Scatter plots for occupancy prediction using (a) Linear model (b) Decision Tree model.

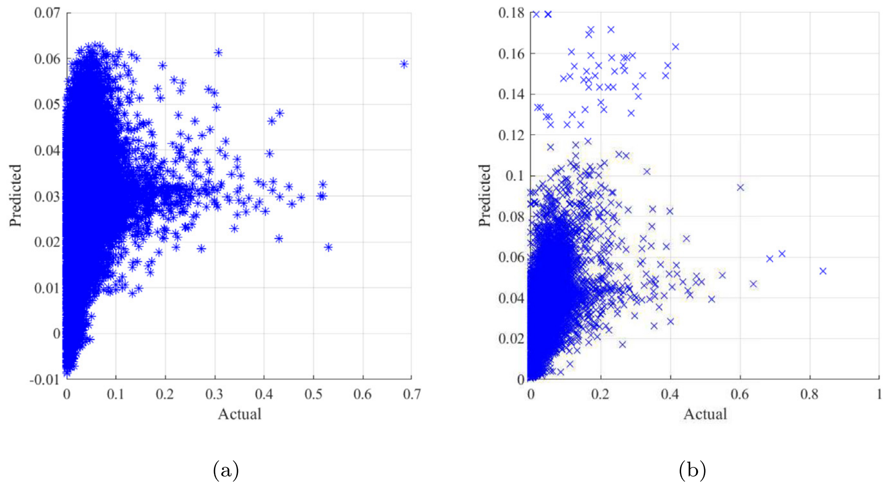

Fig. 6. Scatter plots for occupancy prediction using (a) Neural Network model (b) random Forest model.

Table 4
Performance of machine learning models in predicting on-street parking occupancy of the Seattle city.

Model	r	R^2	MAE	Accuracy	Time (in sec)
LIN	0.25	0.06	0.02	98.17	6
DT	0.37	0.14	0.01	98.36	10.08
NN	0.37	0.14	0.01	98.33	89.56
rF	0.65	0.42	0.01	99.01	9064.75

(iv) Prices and revenue generated results observed by applying proposed scheme on Seattle city data are average of 30 days.
(v) Probability of generated parking request to be a current or advance request is same and equal to 0.5.

5.2. Data description

STD collected data from twenty one paid parking areas. Some of these areas have sub-areas in them. There are eight different types of sub-areas. There are 929 block faces/streets in all areas of the Seattle city. On-street parking facility can be present either on one or all sides of the street. There are eight different types of sides of street exist in Seattle city. There are different types of time limits (i.e., 2 h, 4 h, 10 h and 72 h) on parking. There are three types of parking categories, i.e., restricted parking, paid parking and carpool parking. This data is collected from 1471 unique pay stations located at various street segments of the Seattle city. Parking prices as per the ToD pricing scheme are given in parking price data [48]. The unit of parking prices is \$/h. This parking price data also provides relation between paid parking area, sub area and the time limit of one time parking booking. As per the data, Sunday is the day of free parking in all paid parking areas. Even in some of the areas, evening hours are not chargeable. Parkers/travelers can also pay and book for morning hours one day before in the evening hours. The data is having 25.2 million transactions of 30 days. Moreover, in some of the timestamps paid occupancy is more than the total available parking spaces. As per STD this may be because people closely park their vehicles and optimize the available spaces or due to any other possible reason. Therefore in some of the cases parking occupancy is more than its total capacity.

5.3. Performance measure indexes

The various performance measure indexes used to evaluate proposed schemes are classified into following categories.

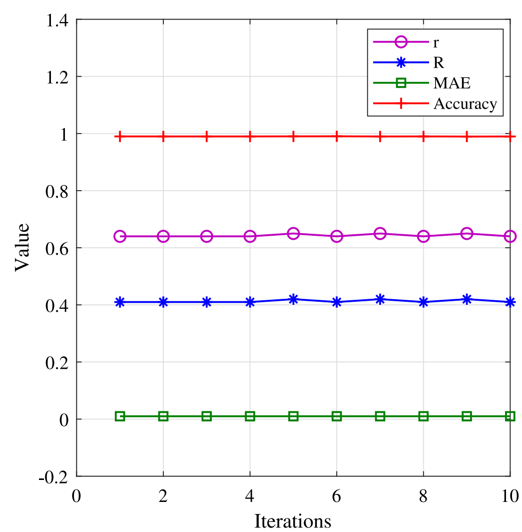

Fig. 7. K = 10 cross validation of random Forest model.

5.3.1. For on-street parking occupancy prediction scheme

In order to evaluate the performance of all machine learning models used to predict occupancy of on-street parking system of the Seattle city, following five performance measure indexes have been used, i.e., Mean Absolute Error (MAE), correlation (r), coefficient of determination (R^2), accuracy, and k-cross validation test. The methods used to evaluate MAE, r, R^2, and accuracy are given in Eqs. (43), (44), (45), and (46) respectively.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|f_i - \hat{f}_i\right| \tag{43}$$

$$r = \frac{\sum_{i=1}^{n}(f_i - \bar{f})(\hat{f}_i - \bar{\hat{f}})}{\sqrt{\sum_{i=1}^{n}(f_i - \bar{f})^2 \times \sum_{i=1}^{n}(\hat{f}_i - \bar{\hat{f}})^2}} \tag{44}$$

$$R^2 = r \times r \tag{45}$$

$$Accuracy = \frac{Correctly\ \ Predicted\ \ Class}{Total\ \ Testing\ \ Class} \times 100 \tag{46}$$

where f_i is the observed parking occupancy, and $\hat{f}_i$ is the predicted parking occupancy.

K = 10 cross validation is used to show robustness of the best prediction model.

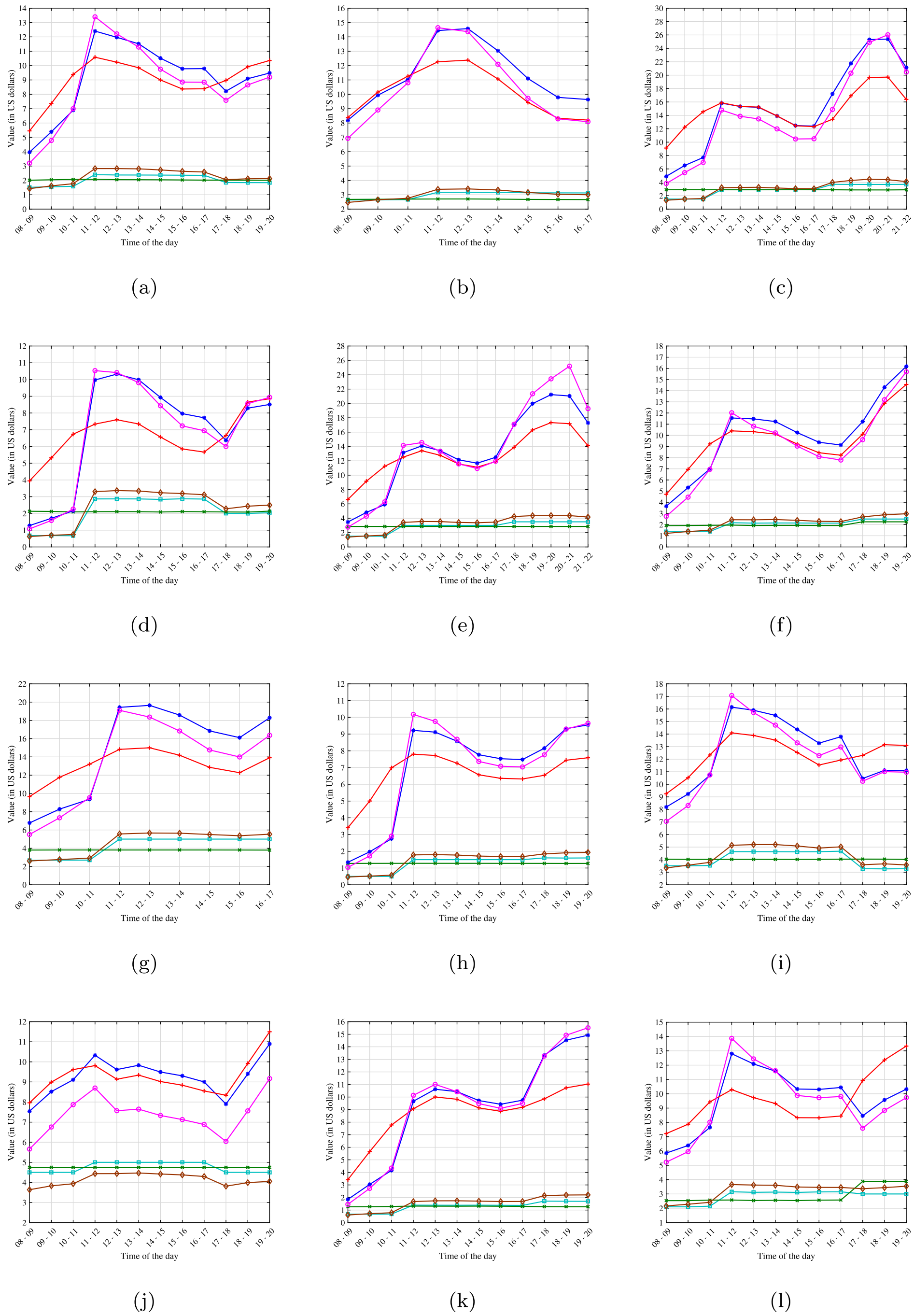

Fig. 8. Prices_{ps} and Revenue^1_{ps} statistics of areas (a) Belltown (b) South Lake Union (c) Capitol Hill (d) Chinatown/ID (e) Pike-Pine (f) University District (g) Pioneer Square (h) Uptown (i) Commercial Core (j) First Hill (k) Ballard (l) Denny Triangle.

5.3.2. For occupancy driven machine learning based on-street parking pricing scheme

In order to evaluate performance of the proposed occupancy driven machine learning based on-street parking pricing scheme for Seattle city, following three performance measure indexes are used.

(i) **Prices_{ps}**: This index shows parking prices to be paid by the next arriving vehicle according to parking pricing scheme 'ps'.
(ii) **Revenue^1_{ps}**: This index shows total revenue generated by the parking authority/owners according to parking pricing scheme 'ps'.
(iii) **Revenue^2_{ps}**: This index shows total revenue that would have been generated if the unoccupied parking slots were filled using parking pricing scheme 'ps' in the same hour of the day in which they were left unoccupied.
(iv) **Number of accepted/rejected parking requests:** This index shows total number of parkers who have been given parking space in case of accepted parkers and who have been denied space in case of rejected parkers.

It is pertinent to mention here that three pricing schemes (ps), i.e., Time of the Day (ToD) pricing scheme, Area based pricing scheme and proposed occupancy driven machine learning based on-street parking pricing scheme have been evaluated and compared in this paper. ToD pricing scheme is currently being

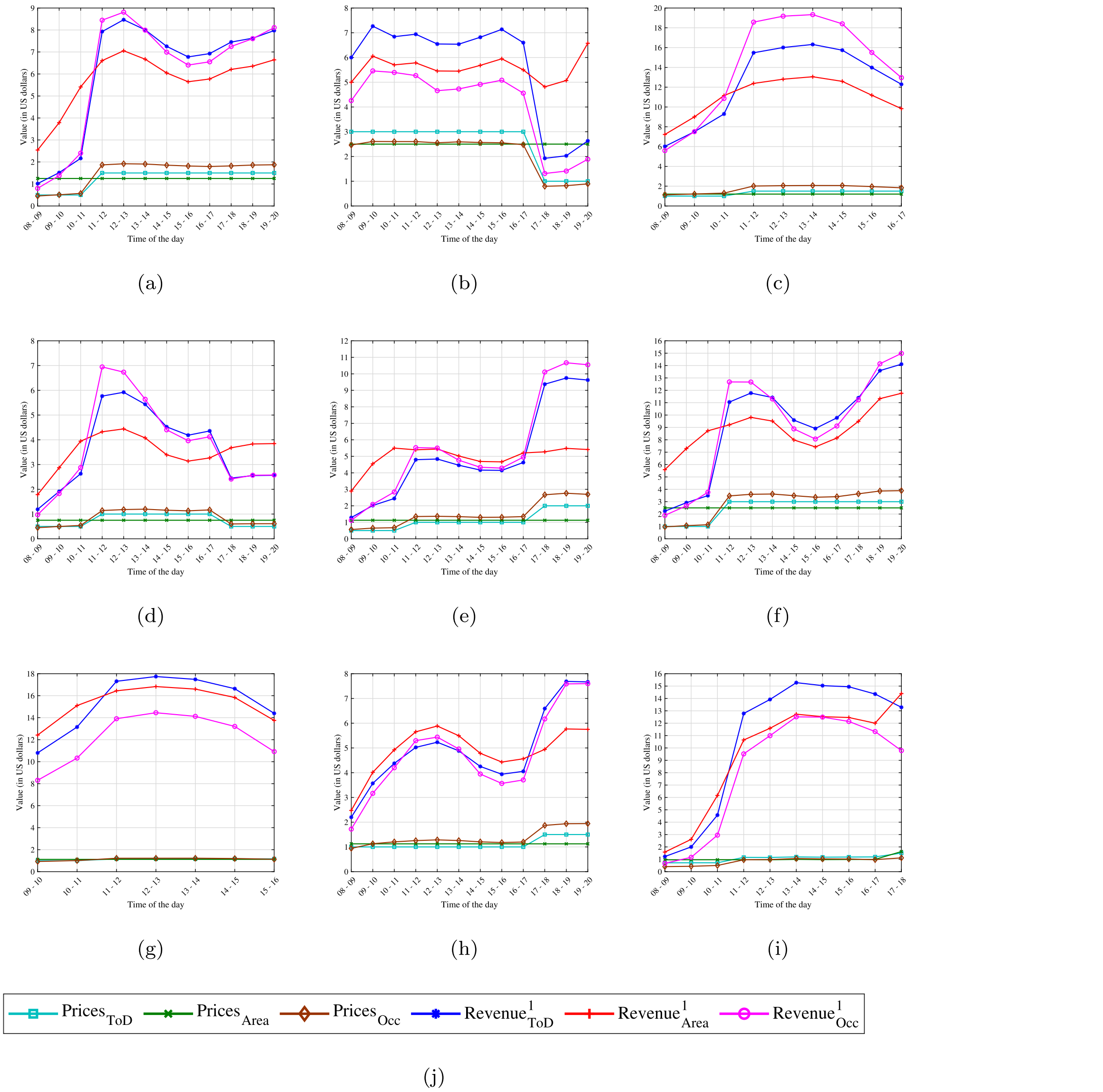

Fig. 9. Prices$_{ps}$ and Revenue$^1_{ps}$ statistics of areas (a) Fremont (b) Cherry Hill (c) Uptown Triangle (d) Roosevelt (e) Green Lake (f) 12th Avenue (g) Westlake Ave N (h) Columbia City (i) Ballard Locks.

implemented by the STD in the Seattle city. Area based pricing scheme is deduced from the ToD pricing scheme. Area based prices are average of the prices to be charged during different time of the day in particular area.

5.4. Discussions

The obtained results are discussed in the following four categories.

5.4.1. Area-wise on-street parking occupancy of Seattle city

It is observed that data is captured at irregular interval of time. Thus, average hourly occupancy of various areas of Seattle city is computed across different hours of the day and plotted in Figs. 3 and 4. These typical occupancy plots show that the occupancy on weekend, i.e., Saturday is comparatively higher than any other day. Occupancy pattern of Cherry Hill and Green Lake do not repeat on different days of the week as depicted in Fig. 4(b) and Fig. 4(e) respectively. Many parking areas of the Seattle city are highly occupied across different times of the day. Morning hours in almost all areas show less occupancy. Whereas, towards the end of chargeable hours of a day, almost all the areas show high occupancy.

5.4.2. On-street parking occupancy prediction scheme

In order to predict occupancy of the Seattle city, four machine learning models, i.e., Linear, Decision Tree, Neural Network and random Forest have been trained and tested. Figs. 5 and 6 illustrates scatter plots of these machine learning models. Table 4 shows values of performance measure indexes of applied machine learning models. The correlation between actual and predicted occupancy for LIN, DT, NN and rF models comes out to be 0.25, 0.37, 0.37, and 0.65 respectively. This shows occupancy predicted by the rF model is highly correlated with the actual occupancy. The coefficient of determination determined by the LIN, DT, NN and rF models are 0.06, 0.14, 0.14, and 0.42 respectively. The higher value of coefficient of determination for rF model claims that linear regression fits to data points better than all other models. The MAE between actual occupancy and predicted occupancy for DT, NN, and rF models is same and equal to 0.01, which is slightly better than the 0.02 of LIN model. In terms of accuracy, all models performed better with having accuracy

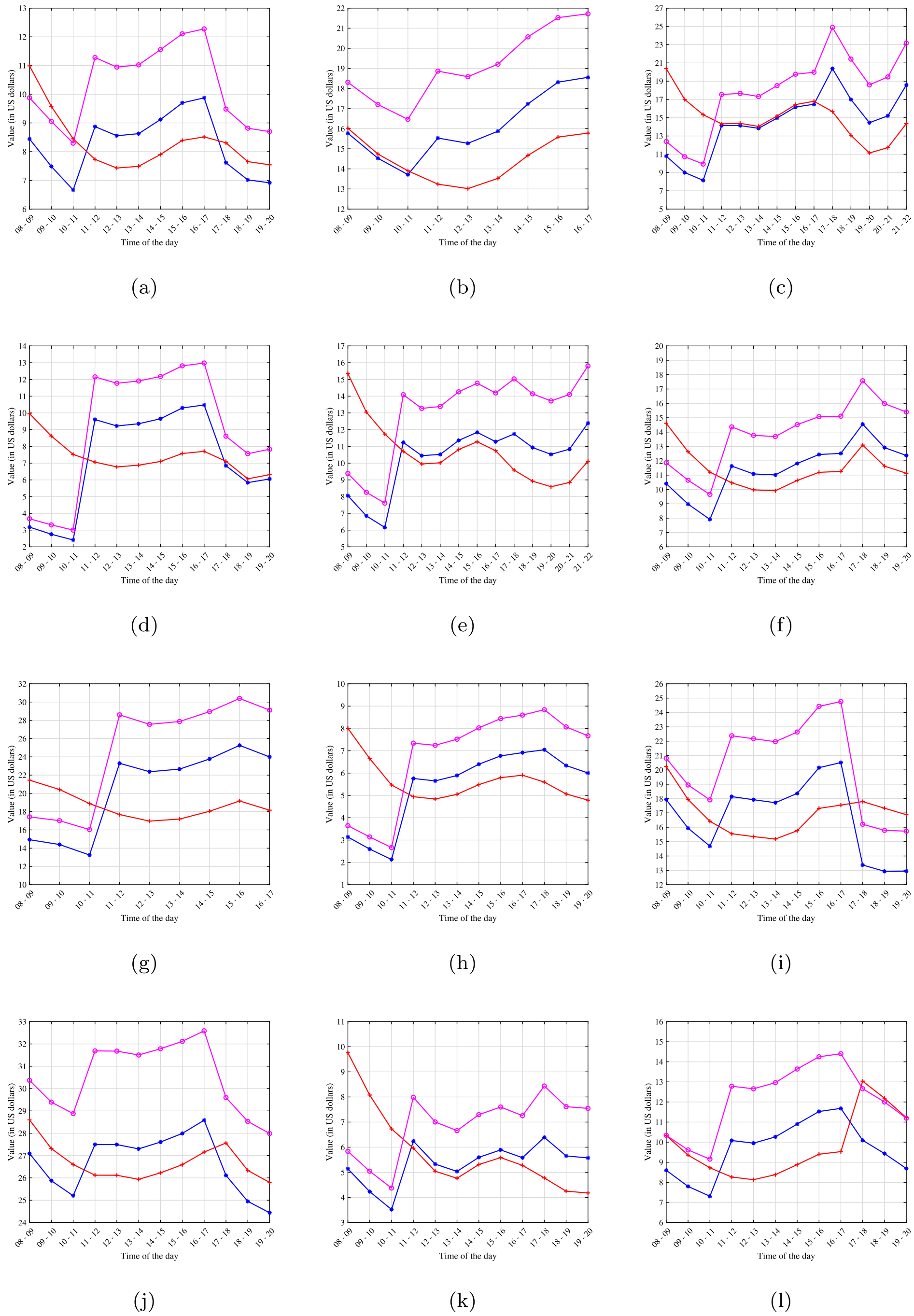

Fig. 10. Revenue$^2_{ps}$ statistics of areas (a) Belltown (b) South Lake Union (c) Capitol Hill (d) Chinatown/ID (e) Pike-Pine (f) University District (g) Pioneer Square (h) Uptown (i) Commercial Core (j) First Hill (k) Ballard (l) Denny Triangle.

greater than 98%, but rF model out performed all other models by achieving highest accuracy of 99.01%. The training time of rF model is higher than all other models because of the complexity involved. Acceptable error rate is take as 5%. k = 10 cross validation test of best model, i.e., rF model is done as depicted in Fig. 7 which proves its robustness.

5.4.3. Occupancy driven machine learning based on-street parking pricing scheme implemented on on-street parking data-set of the seattle city

The area and time of the day wise average worth of proposed scheme for the Seattle city over ToD and Area based pricing scheme in terms of parking prices to be paid by next arriving vehicle and total revenue generated is shown graphically in Figs. 8 and 9. Many highly occupied areas as seen in Figs. 3 and 4 show growth in revenue generated. Whereas, less occupied areas show decrease in parking prices to be charged by next arriving vehicle. Figs. 10 and 11 shows plots of revenue that would have been generated if unoccupied slots were managed efficiently and get allocated. Such situation depicts high occupancy scenario. In such situation, parking authority/owners will gain significantly with the use of proposed scheme in comparison to ToD and Area based pricing scheme. Further, area-wise comparison of proposed pricing scheme with other state-of-the-art techniques in terms of percent gain/loss in parking prices, revenue generated and revenue would have been generated if occupancy were managed efficiently is shown in Table 5. The average parking prices to be

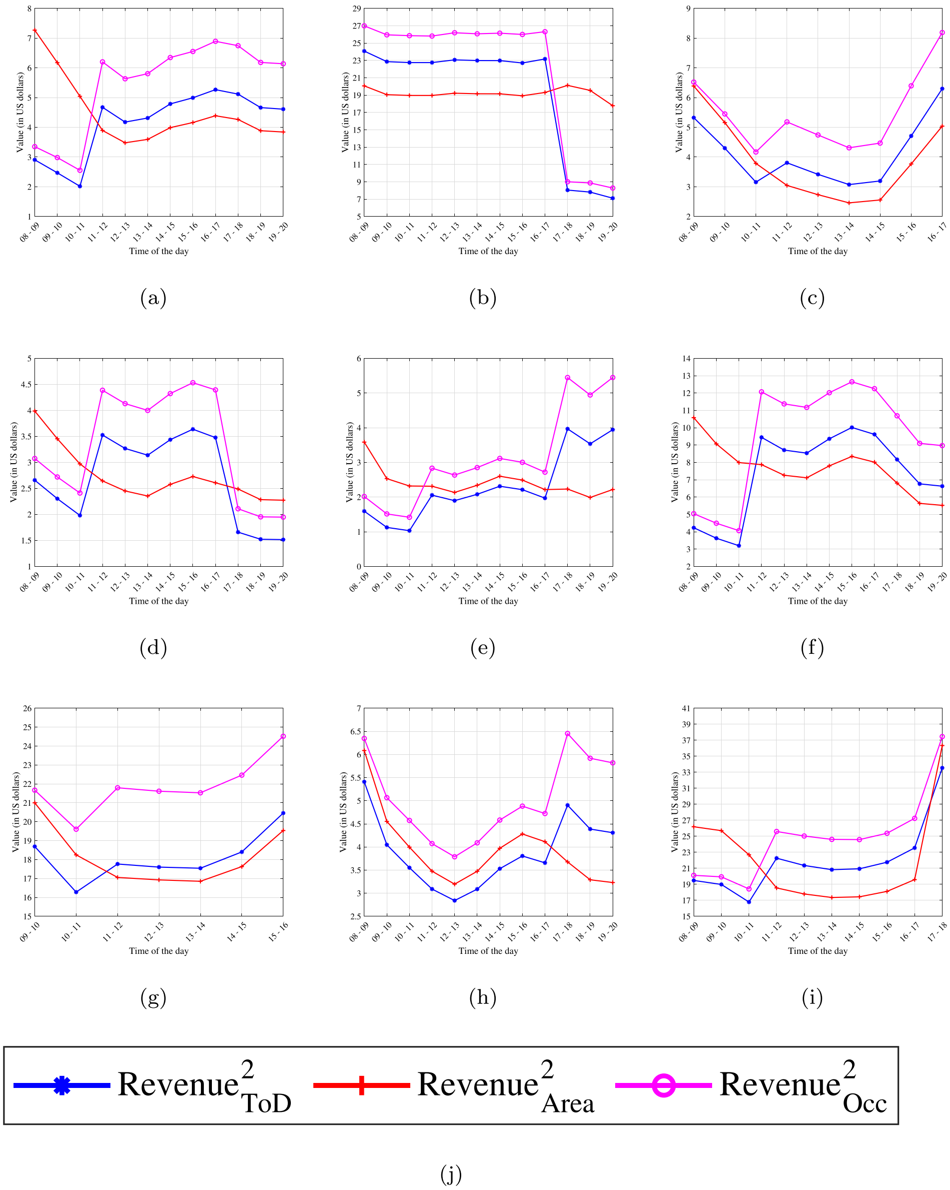

Fig. 11. Revenue$^2_{ps}$ statistics of areas (a) Fremont (b) Cherry Hill (c) Uptown Triangle (d) Roosevelt (e) Green Lake (f) 12th Avenue (g) Westlake Ave N (h) Columbia City (i) Ballard Locks.

paid by next arriving vehicle during different times of the day in whole Seattle city are shown in Fig. 12. The average revenue generated and would have been generated if unoccupied slots were occupied during different times of the day in the Seattle city are depicted in Fig. 13 and Fig. 14 respectively. All results shows positive decrease in prices with respect to decrease in occupancy and increase in revenue generated with respect to increase in occupancy. According to the obtained results, parking prices dropped down by 5.07% and 31.31% in comparison to ToD and Area based pricing respectively in low occupancy situation. Whereas, in the high occupancy situation revenue generated by the parking authority/owner is increased by 5.59% and 24.98% in comparison to ToD and Area based pricing respectively. Also, in the case where occupancy remains full, the revenue would have been generated is increased by 22.20% and 25.93% in comparison to ToD and Area based pricing respectively.

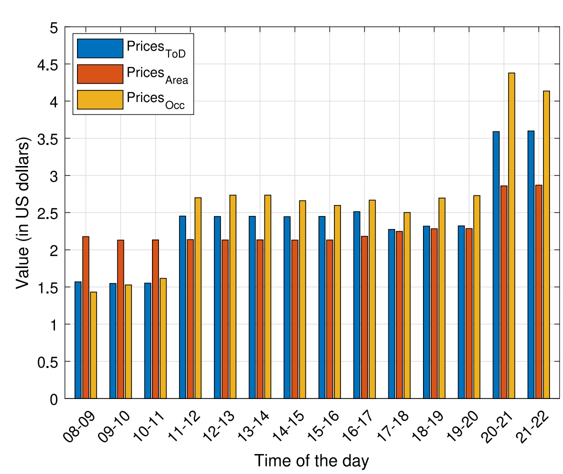

Fig. 12. Average parking prices paid per day by next arriving vehicle according to Seattle on-street parking data-set.

Table 5
Area-wise comparison of proposed scheme with other state-of-the-art techniques with lambda values.

Area Name	λ_1	λ_2	a	b	c	d	e	f
Belltown	227	3022	12.56 (↑)	12.59 (↑)	3.89 (↓)	2.87 (↓)	24.81 (↑)	23.44 (↑)
South Lake Union	216	2874	1.23 (↑)	12.48 (↑)	7.74 (↓)	2.58 (↑)	19.10 (↑)	32.17 (↑)
Capitol Hill	44	582	10.50 (↑)	10.47 (↑)	7.97 (↓)	4.46 (↓)	23.67 (↑)	19.78 (↑)
Chinatown/ID	48	642	14.11 (↑)	14.02 (↑)	1.70 (↓)	1.56 (↑)	25.81 (↑)	21.56 (↑)
Pike-Pine	85	1138	17.02 (↑)	17.02 (↑)	4.51 (↑)	9.50 (↑)	26.24 (↑)	21.58 (↑)
University District	95	1267	9.86 (↑)	11.71 (↑)	8.35 (↓)	3.95 (↓)	21.80 (↑)	21.71 (↑)
Pioneer Square	76	1021	9.22 (↑)	21.36 (↑)	8.63 (↓)	3.51 (↑)	21.23 (↑)	32.75 (↑)
Uptown	72	973	15.59 (↑)	15.34 (↑)	0.36 (↓)	4.42 (↑)	25.63 (↑)	20.14 (↑)
Commercial Core	94	1256	8.02 (↑)	7.77 (↑)	3.61 (↓)	2.56 (↓)	21.50 (↑)	19.89 (↑)
First Hill	124	1658	12.83 (↓)	12.83 (↓)	20.40 (↓)	20.46 (↓)	14.36 (↑)	14.29 (↑)
Ballard	65	869	22.33 (↑)	22.10 (↑)	0.37 (↑)	7.00 (↑)	28.76 (↑)	18.57 (↑)
Denny Triangle	65	869	12.71 (↑)	11.20 (↑)	2.67 (↓)	2.50 (↓)	25.21 (↑)	24.02 (↑)
Fremont	9	125	21.63 (↑)	21.63 (↑)	0.49 (↓)	5.82 (↑)	30.78 (↑)	21.11 (↑)
Cherry Hill	6	91	14.95 (↓)	14.95 (↓)	27.26 (↓)	27.00 (↓)	13.53 (↑)	13.57 (↑)
Uptown Triangle	28	379	30.21 (↑)	44.68 (↑)	13.57 (↑)	28.90 (↑)	32.58 (↑)	41.47 (↑)
Roosevelt	10	134	14.31 (↑)	14.31 (↑)	3.55 (↑)	5.72 (↑)	24.46 (↑)	21.81 (↑)
Green Lake	13	181	33.58 (↑)	33.58 (↑)	8.47 (↑)	12.13 (↑)	36.85 (↑)	30.97 (↑)
12th Avenue	8	118	18.35 (↑)	18.35 (↑)	1.04 (↑)	4.81 (↑)	28.98 (↑)	23.78 (↑)
Westlake Ave N	84	1128	1.24 (↑)	1.24 (↑)	20.72 (↓)	20.32 (↓)	20.87 (↑)	20.39 (↑)
Columbia City	8	112	21.50 (↑)	21.50 (↑)	3.58 (↓)	2.27 (↓)	29.38 (↑)	27.39 (↑)
Ballard Locks	9	128	20.72 (↓)	18.26 (↓)	22.20 (↓)	13.59 (↓)	13.16 (↑)	13.03 (↑)

(a): $Prices_{Occ}$ vs $Prices_{ToD}$, (b): Prices*Occ* vs $Prices_{Area}$, (c): $Revenue^1_{Occ}$ vs $Revenue^1_{ToD}$, (d): $Revenue^1_{Occ}$ vs $Revenue^1_{Area}$, (e): $Revenue^2_{Occ}$ vs $Revenue^2_{ToD}$, (f): $Revenue^2_{Occ}$ vs $Revenue^2_{Area}$, (↑): Increase, (↓): Decrease.

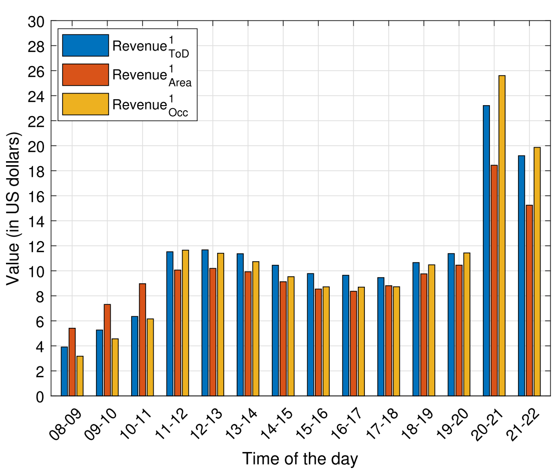

Fig. 13. Average revenue generated per day according to Seattle on-street parking data-set.

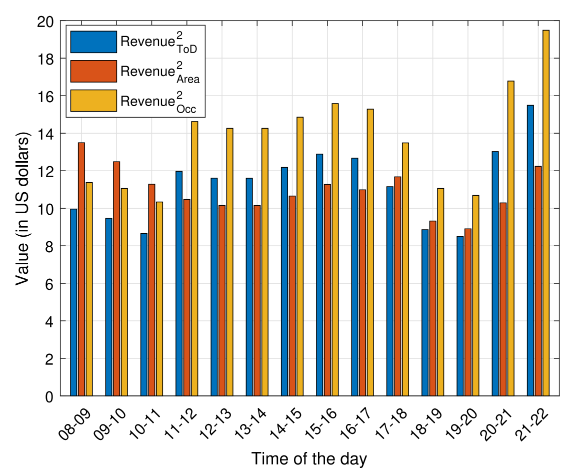

Fig. 14. Average revenue that would have been generated if unoccupied slots were occupied in respective hour of the day as per Seattle on-street parking data-set.

5.4.4. Occupancy driven machine learning based on-street parking pricing scheme simulated on seattle city parking system environment

The parking system of the Seattle city is simulated using proposed pricing scheme and it is found that there is a significant decrease in the average parking prices to be paid by the next arriving vehicle over different times of the day in comparison to ToD and Area based pricing scheme as depicted in Fig. 15. This decrease in the average parking prices is observed on λ_1 values which depicts low occupancy scenario. Whereas, there is a significant increase in average revenue generated over different times of the day using proposed scheme in comparison to ToD and Area based pricing scheme as depicted in Fig. 16. This increase in the average revenue generated using proposed scheme is observed on λ_2 values which depicts high occupancy scenario. The percent decrease in the average parking prices and increase in the average revenue generated per day using proposed technique in comparison to other techniques as per λ_1 and λ_2 values are mentioned in Table 6. In low occupancy scenario average parking prices are dropped down by 13.03% and 10.00% in comparison to ToD and Area based pricing respectively. Whereas, in case of high occupancy scenario, total revenue generated is increased by 3.44% and 4.03% in comparison to ToD and Area based pricing respectively.

Table 7 shows number of current and advance parking requests accepted or rejected under different values of λ which depicts high and low occupancy scenarios. In low occupancy scenario, the number of rejected requests (current or advance) are much lower in comparison to number of accepted requests. Whereas, in case of high occupancy scenario the number of

Table 6
Seattle on-street parking system simulation results.

Scenario (↓)	$Prices_{Occ}$ vs $Prices_{ToD}$	$Prices_{Occ}$ vs $Prices_{Area}$
Low occupancy (λ_1)	Decrease by 13.03%	Decrease by 10.00%
	$Revenue_{Occ}$ vs $Revenue_{ToD}$	$Revenue_{Occ}$ vs $Revenue_{Area}$
High occupancy (λ_2)	Increase by 3.44%	Increase by 4.03%

Table 7
Outcome statistics of different request types for different λ values.

Request outcomes (→)	Accepted		Rejected	
Request types (↓)	λ_1	λ_2	λ_1	λ_2
Current requests	45 112	89 800	953	529 820
Advance requests	45 607	382 911	800	236 265

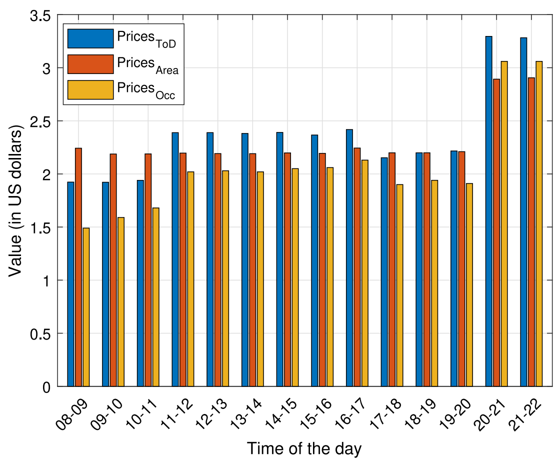

Fig. 15. Average parking prices paid per day by next arriving vehicle according to simulated Seattle on-street parking system.

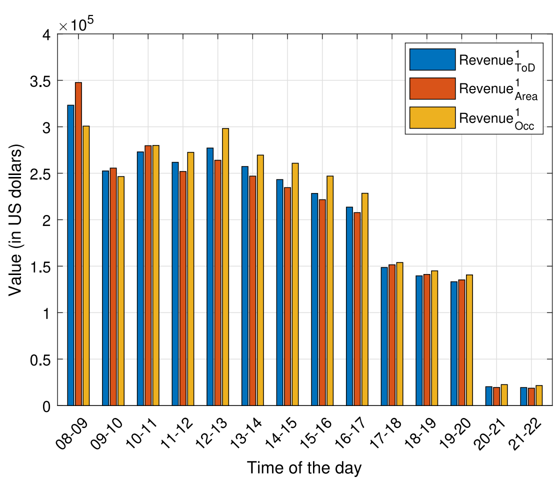

Fig. 16. Average revenue generated per day according to simulated Seattle on-street parking system.

rejected current requests are 85.51% of total current requests and the number of rejected advance requests are 38.16% of total advance requests. This shows that 19.07% of total generated requests in high occupancy scenario already know that they will not be getting desired parking space even if they go there. Such parkers will definitely search for alternate available parking space for themselves. Due to this, there will be decrease in average cruising time per vehicle and hence, congestion will also decrease.

6. Conclusion

We propose an on-street parking occupancy prediction scheme and occupancy driven machine learning based on-street parking pricing scheme for the Seattle city. On-street parking occupancy prediction scheme is implemented and tested using four different types of machine learning models, i.e., LIN, DT, NN and rF. Various performance indexes present random Forest as a best model in predicting occupancy. It achieve highest accuracy, i.e., 99.01% among all used models with acceptable error rate of 5%. K = 10 cross validation test proved its robustness. Unlike ToD and Area based pricing, the proposed occupancy driven machine learning based on-street parking pricing scheme considers real or predicted occupancy while computing prices for the next arriving vehicle. The proposed scheme also facilitates advance booking of parking spaces. The proposed scheme protects interests all stakeholders, i.e., parkers, parking authority/owners, and other commuters on the roads. The proposed scheme favors parking authority/owners in case of high occupancy, otherwise it favor parkers. The performance of proposed scheme is tested over other state-of-the-art techniques, such as ToD and Area based pricing in two cases. In first case, it is tested using Seattle city parking data-set released by STD and in the second case, it tested through simulating Seattle city parking system. Results prove worth of proposed scheme over existing techniques in terms of decrease in parking prices, increase in revenue generated, and decrease in congestion as shown using in-advance knowledge of rejected parking requests. For future work, it would be interesting to investigate level of occupancy in time frames, such as 15 min, 30 min etc. Also, if direct congestion curbing scheme be implemented on this data-set to reduce congestion problem in the Seattle city.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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