10-5-2022

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Hindawi
Scientific Programming
Volume 2022, Article ID 2333821, 14 pages
https://doi.org/10.1155/2022/2333821

Research Article

Multicriteria Decision Making for Carbon Dioxide (CO_2) Emission Reduction

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Received 2 March 2022; Revised 10 September 2022; Accepted 17 September 2022; Published 5 October 2022

Academic Editor: Debo Cheng

The fast industrial revolution all over the world has increased emission of carbon dioxide (CO_2), which has badly affected the atmosphere. Main sources of CO_2 emission include vehicles and factories, which use oil, gas, and coal. Similarly, due to the increased mobility of automobiles, CO_2 emission increases day-by-day. Roughly, 40% of the world's total CO_2 emission is due to the use of personal cars on busy and congested roads, which burn more fuel. In addition to this, the unavailability of parking in all parts of the cities and the use of conventional methods for searching parking areas have added more to this problem. To solve the problem of reducing CO_2 emission, a novel cloud-based smart parking methodology is proposed. This methodology enables drivers to automatically search for nearest parking(s) and recommend the most preferred ones that have empty lots. For determining preferences, the methodology uses the analytical hierarchy process (AHP) of multicriteria decision-making methods. For aggregating the decisions, the weighted sum model (WSM) is adopted. The methods of sorting, multilevel multifeatures filtering, exploratory data analysis (EDA), and weighted sum model (WSM) are used for ranking parking areas and recommending top-*k* parking to the drivers for parking their cars. To implement the methodology, a scenario comprising cars, smart parkings are considered. To use EDA, a freely available dataset "2020testcar-2020-03-03" is used for the estimation of CO_2 emitted by cars. For evaluation purpose, the results obtained are compared with the results of traditional approach. The comparison results show that the proposed methodology outperforms the traditional approach.

1. Introduction

Carbon dioxide (CO_2) is a greenhouse gas that causes trapping of heat in the environment, which leads to the problems of melting ice caps and rising ocean levels, causing flooding [1, 2]. The CO_2 emission is caused by human activities, such as vehicles on the roads, burning of coal and gases in factories, massive use of fossil fuels, deforestation, waste disposal, and mining [1, 3]. In transportation, a typical passenger car produces approximately 4.6 metric tons of CO_2/year. This amount is with the assumption that the fuel economy of the average gasoline vehicle is approximately 22.0 m/g (miles per gallon) and has total mileage of around 11,500 m/y (miles/year). Every gallon of gasoline consumed generates about 8,887 grams of CO_2 [4]. In different parts of the world, countries are importing vehicles, especially personal cars on regular basis without looking into the requirement of parking and atmospheric pollution caused by the emission of CO_2. This makes cities more polluted with CO_2 emission, because personal cars are counted toward the key sources of CO_2 release in the transport, as shown in Figure 1.

Figure 1 shows that maximum CO_2 emitted to the environment is due to the transportation of passenger cars (41% of the total transportation) followed by the shipping transportation and busses, which are 11% and 7%, respectively.

For the reduction of CO_2 emission in the environment and subsequently the global warming, different measures can be taken. To name a few such preventive measures,

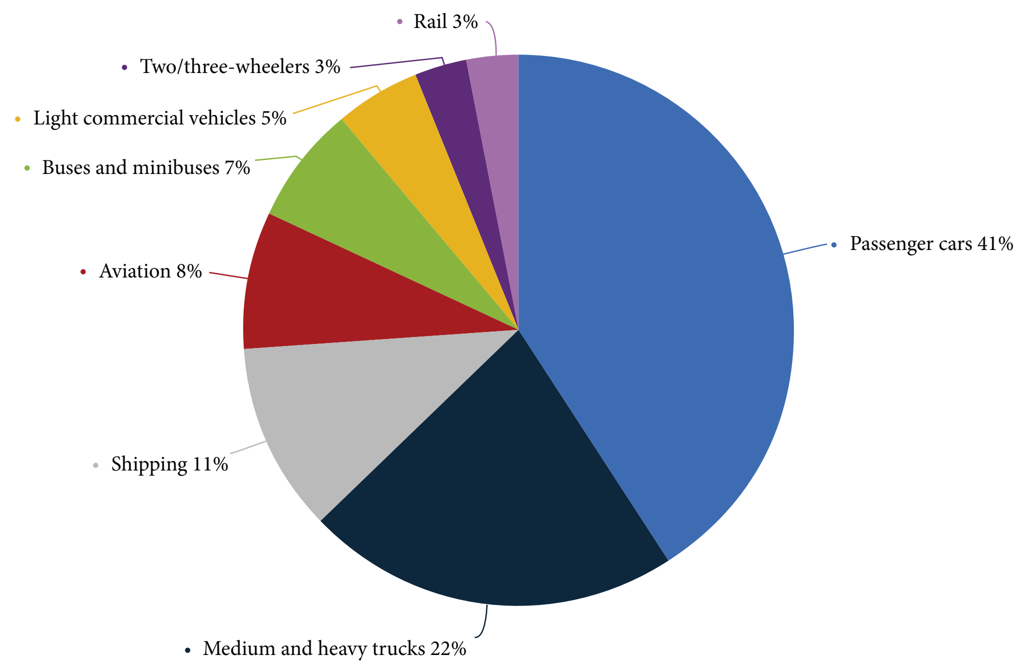

Figure 1: Statistics of the CO_2 emission by transport sector, a survey conducted in 2020 [5].

renewable energies, efficient use of energy and water, sustainable conveyance, sustainable setup, sustainable cultivation, and forestry are accountable for the consumption and recycling [6]. Each of the sources can be handled carefully to minimize the rate of emission of CO_2 into the environment. As a principal of research, it is hard to tackle all the measures simultaneously for the treatment of reduction of the CO_2. However, the sustainable transportation can make a major contribution in this reduction process. Hence, it is considered as a focused area in this research paper. As we know, the availability of a large number of parkings in a city can positively contribute to the issue; however, finding an appropriate parking is a key issue for which the concept of smart parking system is proposed here. Smart parks help in the design of a management system for smart parking over the cloud that facilitates drivers in automatically find a nearest parking area with empty parking lots. This leads to lowest emission of CO_2 by the vehicle and eventually contributes to the global efforts of reducing CO_2 level in the environment. Therefore, this research article is about the design and consequently of developing a smart parking solution with the use of Internet of Things (IoT) and multicriteria decision making. The planned smart parking solution is a key need for smart cities [7], where the infrastructure, including parking lots, is supposed to be sufficiently smart so that to manage the vehicles. To understand the proposed concept, recent advancement in the IoT-based technology, cloud servers management, and multicriteria decision making have immensely played their roles [8]. The applications of smart city are being applied in different countries to advance the quality of life and improve fuel consumption and time to eventually decrease pollution and CO_2 emission into the environment [9]. A sustainable infrastructure, composed of smart cities and smart parking, not only aids in reducing CO_2 but also contributes toward the increased revenue, reduction in traffic congestion, detection of traffic violations, and many more. In busy urban areas, searching for a parking is one of the most significant and challenging issues faced by car drivers [10]. Roughly, in a city, on average, a car moves about 10% of its total travel time, while during the rest of the time, it may be immobile temporarily or parked always [11]. Therefore, a smart parking system can best manage the drivers time and solve their problems of parking vehicles in the city with low level of ingesting of fuel and emission of CO_2.

In the proposed cloud-based smart parking solution, the authors have proposed an integrated methodology based on the research design, which exploits an android mobile application, transportation vehicles, and a list of available parking areas to recommend an appropriate parking to the driver for parking his/her car. The methods adopted to perform the task of appropriate parking recommendation are enlisted as follows: arranging values as sorted list, multilevel filtering for excluding unnecessary parking areas, exploratory data analysis (EDA) for modeling vehicles' features to their CO_2 emission values, the analytical hierarchy process (AHP) for weighting the parking features, and weighted sum model (WSM) for aggregating the final scores to rank all the parkings.

The study has the following key contributions:

(i) Design of an intelligent cloud-based car parking recommendation framework for the recommendation of appropriate parking(s) to drivers in busy urban areas

(ii) Identification of unique parking features, weighting, and ranking the features for wise decision making

(iii) Integration of multilevel multifeatures filtering techniques with exploratory data analysis (EDA) and weighted sum model (WSM)

(iv) Integration of users' sentiment analysis for the selection of highly reputed and secure car parking(s)

The remaining paper is structured as follows: Section 2 is about the existing study review; in Section 3, description of the planned methodology is presented; Section 4 covers experimental results; Section 5 validates the results and evaluates the system by comparing the results with conventional approach; and finally, the work done is conclude in Section 6.

2. Literature Review

The environment around us has a number of components, in which carbon dioxide (CO_2) is the fourth most abundant component. Its concentration is approximately over 400 ppm (parts per million) in the atmosphere. Before the industrial revolution in the world, there was around 270 ppm in the atmosphere, and hence, an increase of almost 40% is observed in the air [12].

Research community has worked on CO_2 from different perspectives, that is, its reduction in the environment using advanced technology and natural ways, its storage, conversion, and utilization etc.

Scope of the study is to use smart parking and multicriteria decision-making methods for solving the issue of reducing the emission of CO_2, and thus, the subsequent subsections are structured accordingly.

2.1. CO_2 Emission Reduction Using Smart Parking. Several systems have been developed by researchers using diverse set of techniques and methodologies to assist drivers in finding nearest parking lots. In the indoor parking systems [13, 14], the Dijkstra algorithm is used for finding the closest distanced parking lots in a parking. Similarly, in the outdoor smart parking system [8], the genetic algorithm has been applied to find the nearest parking for the users. In [15], Orang Kurang Upaya (OKU) stickers are used by disabled drivers, which implements *k*-nearest neighbors (KNN) algorithm, Otsu binarization, and threshold values. These systems are tested in real-world environment. Similarly, in [16], the authors have used KNN algorithm for finding nearest location of parking area. In [17], Internet of Things (IoT)-based solution is provided for overriding the hazards of parking and explaining how it can help in minimizing the emission of greenhouse gases. In this study, IoT technologies, such as Raspberry Pi, distance sensor, and Pi camera, are used to enable smart parkings for intelligently handling cars in the parking lots. These hardwares work together for collecting data and transmitting updates to cloud storage. In [18], exploratory analysis, the method of three-stage least square is used for modeling the emission of carbon monoxide, carbon dioxide, and hydrocarbon from inspection/maintenance testing data for identifying pollution violators. In China, Logarithmic Mean Divisia Index (LMDI) is used for determining factors affecting CO_2 emissions in transportation sector [19, 20]. In a similar study, a routing algorithm called Vehicular Ad-hoc Network (VANET) is used which exploits Updating Block Route Algorithm (UBRA) [21]. Authors of this work claim that their proposed UBRA saves up to 23.6% fuel consumption and 9% CO_2 emission when compared with existing approach. Similarly, Gauss Optimized Cuckoo Search Algorithm, Wavelet Neural Network, and Ridge Regression [22] are applied and simulated in China's Power Generation; Geographic Information System (GIS) is used in geothermal electricity production [23]; and three-layer perceptron neural network (3-layer PNN) is used in transportation for predicting CO_2 emission [24, 25].

2.2. CO_2 Emission Reduction—The Use of Multicriteria Decision Making. Similarly, multicriteria decision making has also been adopted to reduce the emission of CO_2 in the atmosphere. In [26], multicriteria decision making using fuzzy set theory is proposed and assessed for evaluating diverse options for reduction of the emission of CO_2 produced by the vehicle on roads in India. Regarding the reduction of CO_2 and storing it in the geological reservoirs, [27] have proposed carbon capture and storage (CCS) method. CCS catches the emitted CO_2 of fossil-fueled power plants and uses geological reservoirs to store it safely. The authors of this study use multicriteria decision analysis (MCDA) for building a risk assessment model. This model helps the management in deciding an appropriate location for the CO_2 storage and furthermore helps in choosing a mitigating action for reducing the risks of CO_2 emission.

As CO_2 emission is increasing so, carbon capture and storage (CCS) technologies are the better solutions to storage CO_2. Locating a best location for CO_2 storage is one of the critical problems, which is solved by the use of TOPSIS, a multicriteria decision making (MCDM) tool in the study conducted in Turkey [28].

To investigate the fundamental effect of wind and solar energy generation, economic growth, burning of fossil fuel, and then alleviate the environmental degradation in the world's top three energy consumers and CO_2 emitters nations China, India, and the USA, Gaussian techniques for order of preference by similarity to ideal solution (G-TOPSIS) has been used in the research [29]. Likewise, for comparison of the products that use carbon dioxide, researchers [30] have used MCDA methods.

Methods, TOPSIS, and Shannon entropy weight elicitation have been exploited by researchers to select appropriate product [31]. Apart from the technology-based solutions, CO_2 emission can be reduced by applying natural solutions, such to decreasing number of flights, use of efficient driving techniques, plantation move, transformation to clean energy, eating less red meat, reducing or even making efficient use of the energy consumption at homes, and many other such solutions [32].

However, the natural solutions are out of the scope of this study, and hence, we proceed with the smart parking solution using multicriteria decision making. The current work is an extension of the already conducted preliminary study in which weighted sum model (WSM) and linear discriminant analysis are adopted [33]. In that study, the concept was realized but not fully covered using extensive sets of experiments. In this study, we have substantially improved the initial study methodologically and experimentally.

In summary, the existing work is critically analyzed and a number of shortcomings have been identified, which are enlisted as: the existing studies are either used for finding nearest parking area or empty lots in the parking areas, or they have been used in the prediction of CO_2 emission level in the domains other than transportation. They lack the use of parking and vehicle features to rank and select the best parking lot(s) to park the vehicle(s). Similarly, in the literature, the users' online reviews/sentiments, regarding the parking they used, have not been considered to select preferred parking areas.

To overcome the shortlisted limitations and address them, a cloud-based smart parking methodology is proposed, which uses multilevel multifeatures filtering, EDA, and WSM to select an appropriate parking and parking lot within a busy city. This methodology benefits the drivers with automatic recommendation of a nearest and suitable parking area with empty parking lots in busy urban areas for parking the vehicles.

3. Methodology

This study has proposed a smart parking system with a novel smart parking-based CO_2 emission reduction strategy. This strategy uses a cloud-based methodology to automatically search for a nearest parking and then recommend the most preferred parking lots within the nearest park for parking the vehicles. To accomplish this task and assist the drivers, a recommender system is required. To develop this system, a framework needs to be designed whose architecture is depicted in Figure 2. Different components of the proposed architecture are explained in the subsequent subsections.

Algorithm 1 takes GPS current position of the car along with a preset value of r for the distance as the two parameters to call procedure mulLevelFirtering. As a result, it returns a list of top-k empty parking as output, which passed to procedure mulCritAnalysis as a parameter. This procedure returns a weighted list, WSM, of the top-n available parkings as output, which is passed as input to Ranking procedure for ranking the parking based on their weights. The ranked list is displayed on the drivers' mobile for final selection of a nearest parking having lower level of CO_2 emission for parking the vehicle. Once the car is parked, the smart parking system datacenter (SPSD) is updated to serve as real-time datacenter for other requests.

The details of different procedures, components, and subsystems are provided in the subsequent sections.

3.1. Mobile App. The interfacing component of the proposed system is an android-based mobile application, which is used to enable interaction of the drivers with the parking management system and get car park(s) as recommendations. The application sends geo position, gP, of the vehicle along with the radius $r = 0.5$mile as parameters to the parking management system, $cMgt$Park, function, as shown in the following equation:

$$\mathrm{lPrefP} = cMgt\mathrm{Park}\,(gP, r). \tag{1}$$

In (1), default value for r is set to 0.5mile, which means that list of preferred parkings, lPrefP, available at a radius of 0.5 mile be fetched from the parking management cloud.

3.2. Parking Management (Cloud). Parking management (cloud), $cMgt$Park, is the core module of the planned smart parking solution. Key processing of the proposed system takes place in the parking management cloud. Drivers on the cars request for preferred parking having empty lots. The request is forwarded to parking management cloud, which after applying all the processing returns the preferred parking. In Figure 2, the parking management cloud is depicted within the cloud symbol and comprised of the components and processes: smart parking system cloud datacenter (SPSD), multilevel filtering, CO_2 prediction model creation, CO_2 prediction model, visitors' sentiment analysis, parking features and user sentiment (PFRD), multicriteria decision making, and ranking methods are used to return the preferred list of parkings. Details of each of these processes are explained in the subsequent subsections.

3.2.1. Smart Parking System Cloud Datacenter (SPSD). Smart parking system cloud datacenter (SPSD) is a cloud-based database, which stores real-time data of the available and registered parkings within the city along with other relevant parking features, such as space for vehicles in terms of parking lots, opening and closing hours, security, and organizations. This is the central storage of the real-time data updated in real time whenever a vehicle enters the parking or leaves it. It is triggered by the multilevel filtering Procedure 1 whenever the driver searches for nearby parking.

3.2.2. Multilevel Filtering. In this module, three levels filtration takes place. The criteria for filtration are distance of the vehicle from the parking area, serving timings of the parking areas, and availability of empty lots. Output of this process is the list of parking areas with empty lots at a distance of r, the distance measured from recent position of the car. Algorithmic representation of the multilevel filtering approach is shown in Procedure 1.

Procedure 1 returns sorted list of top-k parkings, with empty lots to Algorithm 1. The sorting process is performed using merge sort algorithm [34].

3.2.3. Sentiment Analysis—Parking Features and Users' Reviews Identification. Each parking area is associated with a number of characteristics, which determine the suitability of a parking to be selected by drivers. This feature set is subjective and varies for different users in terms of number and nature of features. However, a reasonable list can be sorted out, which is done in this study. By consulting technical experts and users in the subject field and critically analyzing

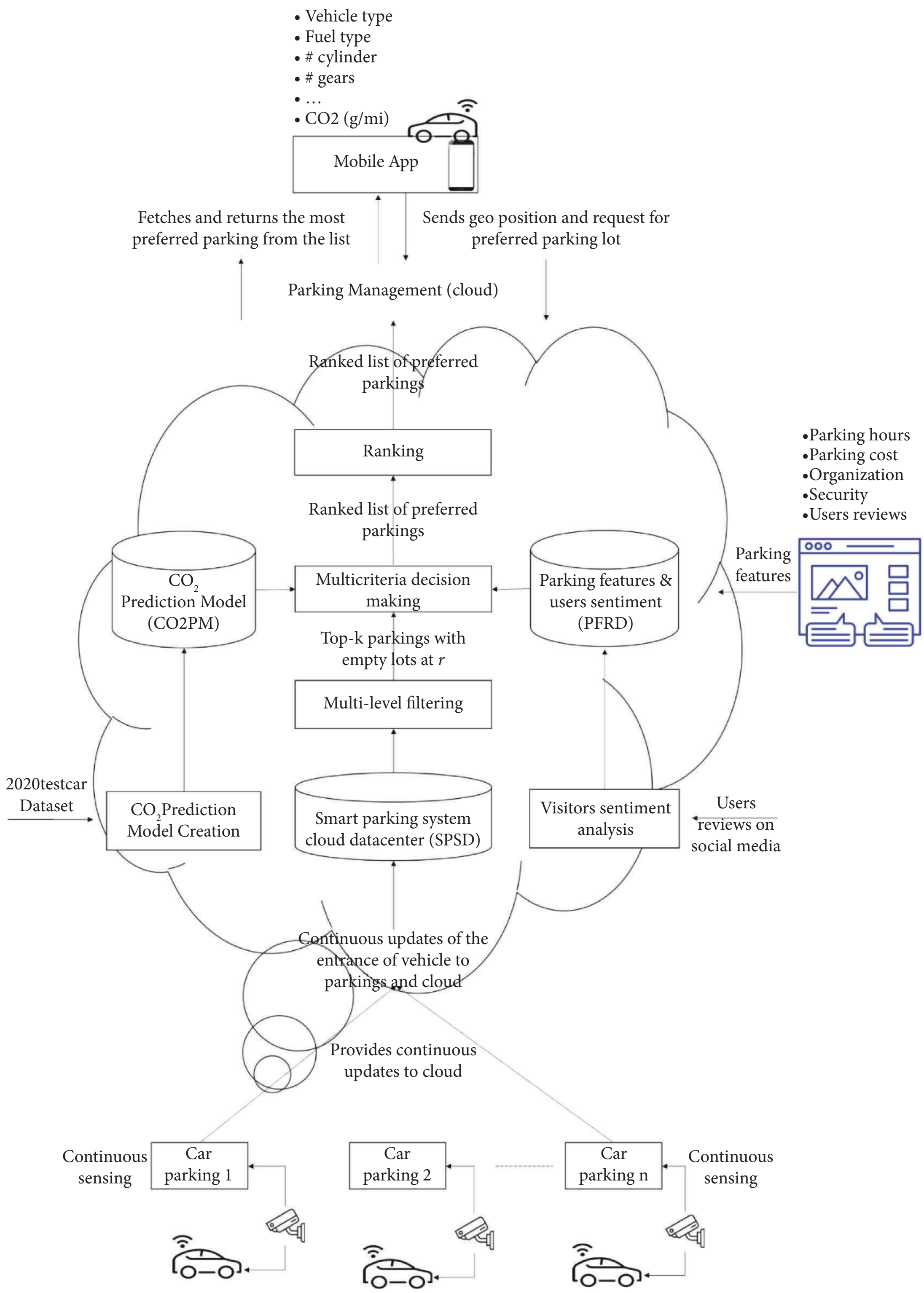

Figure 2: Working of a cloud-based smart parking management system.

published articles, a unique set of parking features, shown in Table 1, are identified [35].

The set of these features forms a features space represented by a dataset named parking features and users' reviews dataset (PFRD), mathematically denoted by the following equation:

$$\text{PFRD} = \{\text{Security}, \text{Sentiment}, \text{Organization}, \text{Cost}\}. \quad (2)$$

The users' sentiment feature is supposed to be collected from users' reviews on social media and parking sites/forums using the state-of-the-art sentiment analysis techniques [36]. Motivation for using these features is to help in

```
Begin
    Inputs:
P – {p_1, p_2, ..., p_n}; //the list of n parkings
        r–distance of radius r around the vehicle. Its default value is 0.5 mile
        gP–current GPS location of the car
    Output:lPrefP; //list of preferred parkings
    empty lots
topKempP = mulLevelFirtering (gP, r); //call Procedure 1; see Section 2
WSM = mulCritAnalysis(topKempP); //call Procedure 2; see Section 5
lPrefP = Ranking(WSM); //call Procedure 3; Section 5
display lPrefP to the driver;
select the preferred parking from the list lPrefP;
Park the vehicle;
Update SPSD; //smart parking system datacenter
End
```

ALGORITHM 1: List of preferred car parking selection for CO_2 emission reduction.

```
Procedure mulLevelFirtering (gP, r)
Begin
    Inputs:P – {p_1, p_2, ···, p_n}; //the list of n parkings in SPSD.
      SPSD-Smart parking system's cloud datacenter
      r–distance of radius r around the vehicle. Its default value is 0.5 mile
    Output:topKempP; //list of top-k parkings with empty lots
            foreach park p in SPSD
    if p is within r then
            if p has Parking hours = Open then
                        if p empLots = Yes then //empLots is a flagged set for parkings in SPSD that has empty lots.
update empPwith info of p; //empP is the list of parkings with empty lots.
                end if
            end if
        end if
  end for
sort empP in ascending order of the distance r; //merge sort algorithm is used
topKempP <— assign (empP, K); //K is an integer representing number of parking in which the driver is interested to consider
for parking his/her vehicle
return topKempP;
End
```

PROCEDURE 1: Multilevel filtering for retrieval of parkings with empty lots within distance r.

TABLE 1: Parking features and users' sentiment.

S. no.	Features	Description
1	Security	Availability of watchman, surveillance system, and road safety
2	Organization	Structure, spacing in lots, ease in entrance, parking, and at exist
3	Sentiment	Positive/negative/neutral
4	Cost	Cost @/hour

retrieving those parks, which not only reduce the emission of CO_2 but also help in recommending those parking areas, which are secure, properly spaced, have good reputation and serve the visitor with minimum cost/hour. These features are prioritized with different weights, estimated using AHP method [37, 38].

3.2.4. Creation of the CO_2 Prediction Model. The emission of CO_2 by a vehicle depends on a number of vehicle's features [39, 40]. To approximate the release of CO_2 by a vehicle in hands, CO_2 prediction model needs to be developed. In this research, to create the required model, a freely available dataset named "2020testcar-2020-03-03" [41], comprising relevant data of the vehicles, is used for the creation and testing of the fuel economy of the vehicle. This dataset is comprised of 67 features and 4,304 records of the tests of vehicles from 27 different manufacturers. For modeling the CO_2 emission, we have extracted 7 features, including Model Year, Vehicle Type, Rated Horsepower, # of Cylinders, # of Gears, and Test Fuel Description, as the condition attributes, and CO_2 (g/mi) as the prediction/estimation attribute. A test dataset is presented in Table 2.

The prediction model is developed by adopting exploratory data analysis (EDA) from the machine learning

Table 2: "2020testcar-2020-03-03" dataset for CO_2 prediction model creation.

Model year	Test Veh Make	Vehicle Type	H-Power	# of Cylinders and Rotors	# of Gears	Test Fuel Type Desc	CO_2 (g/mi)
2020	Aston Martin	Car	600	12	8	Tier 2 Cert Gasoline	466.87
2020	BMX	Both	617	8	8	Tier 2 Cert Gasoline	617.33
...	...	...	...	...	...	...	...
2020	Mini	Car	134	3	7	Tier 2 Cert Gasoline	251.37

field [42]. EDA tries to build hypotheses for the data in hand using insights gain from it. One of the algorithms of EDA used for regression analysis is linear regression, which is adopted in this study. The regression model learns the relationship between the vehicle predictive features and CO_2 emission and stores it in CO_2 prediction model (CO_2PM). This model is further used in the process of multicriteria decision making. During search for preferred parking, the CO_2PM is executed to predict the amount of CO_2 emission for the vehicle under drive. The estimated value is appended in real time, as a new feature with PFRD, as shown in the following equation:

$$f\text{Set} = \{\text{CO2 emitte d, Security, Sentiment, Organization, Cost}\}. \quad (3)$$

Generalized form of (3) is shown as follows:

$$f\text{Set} = \{f_1, f_2, \cdots, f_n\}. \quad (4)$$

These features are collectively used for ranking the parking areas; however, weights need to be computed for each of the features. The next phase explains the process of estimating the weights.

3.2.5. Multicriteria Decision Making. The problem of appropriate parking selection is a multicriteria decision making (MCDM) problem, which needs consideration of different aspects of a car parking rather than only relying on the amount of CO_2 emitted by the vehicle. These features include parking hours, parking cost, parking organization, security measures taken by the parking owners, and users' reviews on the social media, which are depicted in Figure 1 and mathematically represented in (3) and (4). Each of the features contributes differently in the final selection of an appropriate parking. Some of the features contribute more than the other, and hence, their weights matter a lot. Therefore, in the subsequent sections, we compute priority levels of the participating features and then summing up to get the aggregate score for the ranking phase of the proposed strategy.

(a) Criteria Weighting. The idea of using weights for parking features, users' sentiment, and CO_2 emission level is that these features do not have the same importance and shall be treated differently. Definitely, vehicle CO_2 emission feature is of higher importance than security, which in turn is of higher importance than the other features, such as security, organization, and parking hours. To estimate realistic weights/importance score for these features, we have adopted Saaty's method [38], which exploits knowledge of the domain experts to materialize the weights. This method is based on the evaluation of relative significances. Pair-wise comparisons of the features are performed, which express how many times the i^{th} criteria (e.g., CO_2) in the pair is more significant than the j^{th} criteria (e.g., security). The process of pair-wise comparison is shown in Table 3, and the final weights, obtained, are presented in Table 4.

The weights computed for each feature in the feature vector are pictorially represented in the following equation:

$$fWt = \{w_1, w_2, \cdots, w_n\}. \quad (5)$$

In the features considered, CO_2 emission and cost are cost features/criteria, while the rest of three features are benefit features/criteria. For cost criteria, smaller values are favorable, while in benefit features, higher values are considered favorable.

(b) Creating Weighted Sum Model-Multicriteria Decision Making. This module integrates outputs of CO_2PM and PFRD with top-k parking areas at a distance of radius r, having empty lots, by applying weighted sum multicriteria decision-making model (WSM) [43], as shown in the following equation:

$$\text{WSM}_i^{\text{WSM}_{\text{score}}} w = \sum_j^n w_j * f_j^i, \quad (6)$$

where $i = 1, 2, \cdots, m$ and $j = 1, 2, \ldots, n$

In the WSM, w_j comes from (5) and f_{ij} from equation (4), where the literal "i" denotes the i^{th} car park.

Working of the multicriteria decision-making method used, that is, WSM, is algorithmically presented in Procedure 2.

Output of Procedure 2 is a two-dimensional array, WSM, of n parkings within the radius r along with the weighted score. The first index in the array is the parking number, and the second is the aggregate scores associated with the parking. This array is used in the subsequent steps, that is, ranking process of the multicriteria decision making, and the result is returned to the calling Algorithm 1.

3.2.6. Ranking Parking within Radius r. Before applying ranking, the list of parking areas represented by the weighted array, $\text{WSM}_i^{\text{WSM}_{\text{score}}}$, is sorted in descending order of their scores. For the purpose, we adopted sort function from MS Excel, which is shown in the following equation:

$$\mathbf{WSM_{Sorted}} = \mathbf{SORT}(\mathbf{WSM}, \mathbf{-1}). \quad (7)$$

In (7), **WSM** represents the column holding aggregate scores of the parkings, by which we want to sort the array.

Table 3: Features relative weighting using the analytical hierarchy process (AHP).

	CO_2 emission	Security	Sentiment	Organization	Cost
CO_2 emission	1.00	2.00	5.00	7.00	9.00
Security	0.50	1.00	3.00	5.00	8.00
Sentiment	0.20	0.33	1.00	3.00	6.00
Organization	0.14	0.20	0.33	1.00	5.00
Cost	0.11	0.13	0.17	0.20	1.00

The second argument (−1) is used to set the sorting order from largest to smallest, that is, descending order.

After sorting process, the sorted list $\mathbf{WSM_{Sorted}}$ is ranked to prioritize the parkings on the basis of their scores to help the driver choose the appropriate parking for his/her car. For this purpose, rank function of MS Excel 2016 is used, which is shown in the following equation:

$$\mathbf{WSM_{ranked}} = \mathbf{RANK}(\mathbf{number}, \mathbf{ref}, [\mathbf{order}]). \quad (8)$$

In (8), number is the first argument that takes parking score of the first parking in the sorted list $\mathrm{WSM_{Sorted}}$. Rest of the scores are matched with the first score to decide their ranks. The second argument ref is the range of score, which are compared for ranking. The last argument or de r is an optional one and has value 0 for descending order and 1 for ascending order. In our case, we used "0" to get the ranking in descending order.

Working of the sorting and ranking process is shown in Procedure 3.

Procedure 3 returns the list of top-n preferred parking to the calling program, Algorithm 1, which is presented to the driver on his/her mobile screen using the Android application. The procedure makes use of (7) and (8) to accomplish this task.

3.2.7. Continuous Updates on SPSD. In this phase, physical hardware, such as ultrasonic sensor, raspberry pi, and camera, is supposed to be used. These devices are used to help the driver properly park their vehicle at the available lot in the finally selected car park and consequently update the SPSD database. Along with these hardware resources, number plate recognition can also be used by using any of the available image recognition methods, such as [44] to automatically provide the SPSD with latest updates.

4. Experimental Results

To understand the proposed research idea and simulate its implemented model, we have considered a scenario, which is presented as follows.

4.1. Experimental Scenario. In the scenario, a city with 100 parking areas and 10 vehicles/cars is considered. The 10-sample cases, with vehicle characteristics, are shown in Table 5.

4.2. Objective of the Scenario Implementation. Objective of the subject scenario is to determine whether the proposed methodology recommends the drivers with parking lots that result in low level of CO_2 emission as compared to searching for parking lots using conventional approach.

Table 4: Feature relative weights.

Feature	Weights
CO_2 emission	0.57269
Security	0.19348
Sentiment	0.13898
Organization	0.06873
Cost	0.02611

4.3. Datasets Used. Two datasets, "2020testcar-2020-03-03"[41] (see the details in Table 2) and SPSD, are used to realize the scenario. SPSD is a synthetically created dataset for 100 parking areas with parking features, shown in Table 6.

In the SPSD, the parking hour and empty lots information are updated by the continuous monitoring/sensing module of the proposed smart parking system. The information on security, users' sentiment, organization, and cost are collected from owners and customers using survey approach.

4.4. Experimental Environment and Setup. In this research, we have used Weka 3.8 Machine Learning library as a simulation tool on a standalone Intel(R) Core(TM) i5-8250U CPU @ 1.60 GHz 1.80 GHz system having 8 GB internal memory. The CO_2 prediction model is developed by adopting exploratory data analysis (EDA) [31] of the Weka library. For the estimation of realistic weights/importance score of the features, we have adopted Saaty's method [27], implemented in Sanna Excel plugin that uses AHP method [37, 38]. Similarly, for the sorting and ranking processes, MS Excel 2016 is used. All the tools, that is, EDA, AHP, and MS Excel's Rank and Sort functions, have been used with their default parameters. However, the radius parameter used by the drivers in their first call from the android application is kept 0.5 mi.

4.5. Experiments and Results Analysis. Different experiments are performed using the proposed methodology/procedures. These are shown below.

4.5.1. Experiment-1. In the first experiment, multilevel filtering procedure is executed. Each vehicle, in the scenario, sends its current GPS location with parameter $r = 0.5$ mi to the smart parking cloud, which uses SPSD to retrieve the list of all available car parks at a distance of 0.5 mi away from the current position of the car, currently opened, and having empty lots. A sample of the results is shown in Table 7.

In Table 7, the results show that when multilevel filtering procedure is executed, 80/100 parkings are filtered out and a list of 20 parks are shortlisted for onward consideration and processing for final selection. These 20 parks are at different distances from the current position of the car, in search of parking.

Procedure mulCritAnalysis (topKempP)
Begin
Inputs: topKempP; //the list of top-k parkings at a distance r from geo position of the vehicle and having empty lot.
fSet = $\{\mathbf{f_1}, \mathbf{f_2}, \cdots, \mathbf{f_n}\}$; //the list of **n** features as per **equation(4)**.
fWt = $\{\mathbf{w_1}, \mathbf{w_2}, \cdots, \mathbf{w_n}\}$; //the list of weights for **n** features as per **equation(5)**.
Output:WSM; //a two-dimensional array holding the list of **n** parkings within radius **r** with their aggregate scores.
(1) **for each** park **p** ∈ **topKempP**
(2) $\mathrm{WSM}_i^{\mathrm{WSM}_{\mathrm{score}}} = \sum_j^n w_j * f_j^i$; //see (6), where w_j is weight value in the weight vector fWt, assigned to feature f_j in the feature set fSet for the i$^{\text{th}}$ car park, where $i = 1, 2, \cdots m$ and $j = 1, 2, \ldots, n$.
(3) **end for**
(4) **Return** WSM
End

Procedure 2: Multicriteria decision making using weighted sum model.

Procedure Ranking (WSM)
Begin
Inputs:
WSM; //two-dimensional array containing list of parkings at radius r associated with their aggregate score.
Output:lPrefP; //the list of preferred, top k, parkings.
(1) $\mathbf{WSM_{Sorted}} = \mathbf{SORT(WSM, -1)}$; //see (7)
(2) $\mathbf{WSM_{ranked}} = \mathbf{RANK(number, ref, [order])}$; //see (8)
(3) $\mathbf{lPrefP} < -\mathbf{WSM_{ranked}}$;
(4) Return **lPrefP**
End

Procedure 3: Ranking top-K parkings having empty parking lots.

Table 5: Sample of ten (10) cars as test cases.

V#	Test Veh Make	Vehicle Type	*H*-power	# of Cylinders	# of Gears	Test Fuel Type Desc
1	Aston Martin	Car	503	8	8	Tier 2 Cert Gasoline
2	BMW	Both	228	4	8	Tier 2 Cert Gasoline
3	Alfa Romeo	Both	280	4	8	Tier 2 Cert Gasoline
4	Chrysler	Car	359	8	5	Tier 2 Cert Gasoline
5	MINI	Car	134	3	6	Tier 2 Cert Gasoline
6	Fiat	Car	237	4	6	Tier 2 Cert Gasoline
7	Dodge	Car	707	8	8	Tier 2 Cert Gasoline
8	Dodge	Truck	360	8	8	Tier 2 Cert Gasoline
9	Dodge	Car	173		4	Tier 2 Cert Gasoline
10	Fiat	Both	160	4	6	Tier 2 Cert Gasoline

Table 6: Smart parking system dataset.

P#	Parking hours	Empty lots	Security	Sentiment	Organization	Cost
1	Open	*y*	0.7	0.2	0.3	0.2
2	Open	*n*	0.3	0.7	0.5	0.1
. . .	. . .	. . .	. . .	. . .	. . .	. . .
100	Open	*y*	0.3	0.8	0.5	0.3

Table 7: Results of the multilevel filtering approach.

P#	Distance in mi (r)	Parking hours	Empty lots	Security	Sentiment	Organization	Cost
5	0.35	Open	*Y*	0.1	0.9	0.1	0.2
8	0.20	Open	*Y*	0.2	1.0	0.4	0.8
11	0.37	Open	*Y*	0.4	0.9	0.5	1.0
. . .	. . .	. . .	. . .	. . .	. . .	. . .	. . .
90	0.4	Open	*Y*	0.8	0.6	0.7	0.4

Table 8: Results of CO_2 prediction model creation.

V#	CO_2 (g/mi)
1	259.04
2	296.47
3	218.49
4	490.51
5	207.11
6	274.82
7	313.03
8	514.00
9	248.00
10	258.69

Table 9: The list of candidates' parkings with their features.

P#	Distance in mi (*r*)	CO_2 (Est) emission	Security	Sentiment	Organization	Cost
5	0.3501	90.70	0.11	0.91	0.11	0.22
8	0.2018	52.28	0.23	1.00	0.42	0.83
11	0.3690	95.58	0.43	0.94	0.49	0.99
18	0.2663	68.98	0.60	0.37	0.21	0.06
20	0.3014	78.08	0.91	0.11	0.39	0.39
27	0.0049	1.26	0.06	0.36	0.88	0.82
29	0.2897	75.04	0.19	0.04	0.42	0.53
34	0.1309	33.91	0.53	0.85	0.56	0.03
36	0.3400	88.08	0.48	0.65	0.48	0.98
45	0.3766	97.54	0.10	0.63	0.74	0.39
50	0.0266	6.90	0.74	0.62	0.57	0.54
54	0.1240	32.13	0.62	0.39	0.20	0.50
55	0.1460	37.82	0.35	0.97	0.86	0.59
56	0.4348	112.63	1.00	0.02	0.01	0.14
66	0.0519	13.45	0.70	0.92	0.35	0.88
71	0.4152	107.55	0.56	0.70	0.07	0.96
77	0.2213	57.34	0.47	0.53	0.52	0.75
79	0.0446	11.55	0.18	0.84	0.38	0.60
89	0.4535	117.47	0.80	0.64	0.12	0.52
90	0.3504	90.77	0.82	0.60	0.70	0.38

4.5.2. Experiment-2. In this experiment, CO_2PM is executed to predict the amount of CO_2 emission for the vehicle in search of parking lots in the scenario city. Table 8 shows the predicted amount of CO_2 that the vehicles of Table 5 will emit.

The linear regression algorithm of the explorative data analysis (EDA) technique develops the regression model, which helps in the prediction of the amount of CO_2 emitted for the ten cars selected in the scenario. The amount of CO_2 emitted is measured in gram per mile (g/mi). In this modeling and results, generation 7 features of the vehicle, that is, Model Year, Vehicle Type, Rated Horsepower, # of Cylinders, # of Gears, and Test Fuel Description, are used as the condition attributes. Column 2, that is, CO_2 (g/mi), of Table 8 is the prediction attribute whose value is the estimated value of CO_2 emitted by the particular vehicle.

4.5.3. Experiment-3. Before executing the ranking methodology, outputs of CO_2PM and multilevel filtering procedure are integrated in such a way that for each predicted value of the CO_2, the CO_2 (g/mi) is multiplied with the distance of the vehicle from the parking areas, available within the radius $r = 0.5$ mi. In our scenario case, a list of 20 parking areas is considered for ranking using weighted sum model (WSM). For example, for vehicle #1's predicted CO_2 (259.04 g/mi), the list of alternative parking areas is shown in Table 9.

In this integrated candidate list of parking areas, column 2 is based on the current GPS values of the vehicle #1, column 3 is the result of product of column 1 and estimated CO_2 value for the same vehicle, and the rest of the columns are features of the parking areas.

For applying algorithm 1, the values of Table 9 are normalized by dividing each value of the benefit criteria (CO_2 emission and cost) by max value in the column and of the cost criteria (security, sentiment, and organization) by dividing the max value of the column by the respective value at that particular position. After normalization, the WSM scores are computed. The data/WSM score are ready for ranking, which is depicted in Table 10.

Results of Table 10 show ranking of all the available 20 parking areas, in the range of $r = 0.5$ mi, for the scenario's ten vehicles. The last column "*R#*" shows rankings for the parking areas, at column 1st (i.e., "*P#*"). The mobile app recommends top-*k* ($k = 3$) parks to the drivers.

Table 10: Ranking results of the weighted sum model for recommending parking areas that will result in low level of CO_2 emission

V#10	*V*#9	*V*#8	*V*#7	*V*#6	*V*#5	*V*#4	*V*#3	*V*#2	*V*#1		
P#	WSM score	WSM score	WSM score	WSM score	WSM score	WSM score	WSM score	WSM score	WSM score	WSM score	R#
29	0.08634899	0.08634899	0.08634898	0.08634896	0.08634895	0.08634902	0.08634899	0.08634899	0.08634898	0.08634898	**20**
5	0.16821174	0.16821174	0.16821172	0.16821171	0.16821170	0.16821175	0.16821173	0.16821173	0.16821173	0.16821172	**19**
45	0.17461794	0.17461794	0.17461793	0.17461792	0.17461790	0.17461796	0.17461794	0.17461793	0.17461793	0.17461793	**18**
18	0.20704032	0.20704032	0.20704030	0.20704029	0.20704027	0.20704034	0.20704032	0.20704031	0.20704031	0.20704030	**17**
56	0.20911186	0.20911186	0.20911185	0.20911184	0.20911183	0.20911187	0.20911186	0.20911185	0.20911185	0.20911185	**16**
54	0.21355775	0.21355775	0.21355771	0.21355768	0.21355764	0.21355780	0.21355775	0.21355773	0.21355773	0.21355772	**15**
71	0.21903822	0.21903822	0.21903821	0.21903820	0.21903819	0.21903823	0.21903822	0.21903821	0.21903821	0.21903821	**14**
77	0.21950497	0.21950497	0.21950495	0.21950493	0.21950491	0.21950500	0.21950497	0.21950496	0.21950496	0.21950496	**13**
36	0.22962821	0.22962821	0.22962820	0.22962819	0.22962817	0.22962823	0.22962821	0.22962821	0.22962821	0.22962820	**12**
8	0.23096773	0.23096773	0.23096771	0.23096769	0.23096766	0.23096776	0.23096773	0.23096772	0.23096772	0.23096771	**11**
20	0.23331192	0.23331192	0.23331191	0.23331189	0.23331188	0.23331194	0.23331192	0.23331191	0.23331191	0.23331191	**10**
79	0.24511243	0.24511242	0.24511232	0.24511223	0.24511212	0.24511256	0.24511241	0.24511237	0.24511236	0.24511233	**9**
89	0.26058399	0.26058399	0.26058398	0.26058397	0.26058396	0.26058400	0.26058399	0.26058398	0.26058398	0.26058398	**8**
11	0.26178335	0.26178335	0.26178333	0.26178332	0.26178331	0.26178336	0.26178335	0.26178334	0.26178334	0.26178334	**7**
55	0.29129012	0.29129012	0.29129009	0.29129006	0.29129003	0.29129016	0.29129012	0.29129010	0.29129010	0.29129009	**6**
90	0.30773453	0.30773453	0.30462896	0.30773450	0.30773449	0.30773455	0.30773453	0.30773452	0.30773452	0.30634760	**5**
34	0.31368953	0.31368953	0.31368949	0.31368946	0.31368942	0.31368957	0.31368952	0.31368951	0.31368950	0.31368949	**4**
66	**0.34704794**	**0.34704794**	**0.34704785**	**0.34704777**	**0.34704768**	**0.34704806**	**0.34704793**	**0.34704789**	**0.34704788**	**0.34704786**	**3**
50	**0.38097423**	**0.38097423**	**0.38097405**	**0.38097390**	**0.38097372**	**0.38097446**	**0.38097421**	**0.38097414**	**0.38097412**	**0.38097408**	**2**
27	**0.70367951**	**0.70367949**	**0.70367853**	**0.70367767**	**0.70367668**	**0.70368075**	**0.70367940**	**0.70367899**	**0.70367887**	**0.70367865**	**1**

Table 11: Distance-based ranking of the parkings.

P#	Distance of the parkings from current positions of the vehicles	*R#*
89	0.453500121	20
56	0.434811515	19
71	0.415196551	18
45	0.376551741	17
11	0.368964167	16
90	0.350393861	15
5	0.350130712	14
36	0.340031028	13
20	0.301407403	12
29	0.289669795	11
18	0.266296081	10
77	0.221338441	9
8	0.201819481	8
55	0.145994488	7
34	0.130900167	6
54	0.124018414	5
66	0.05190939	4
79	**0.044592038**	**3**
50	**0.026649037**	**2**
27	**0.004859672**	**1**

Table 12: Comparison of the proposed smart parking solution with the conventional solution.

Vehicle #	Distance from the vehicle (mi)	Rate of the CO_2 emission (g/mi) for the vehicle	Selected parking using conventional approach	Selected parking using the proposed smart parking system	Estimated CO_2 emission using conventional approach	Estimated CO_2 emission using the proposed smart parking system
1	0.004859672	259.04	27	27	1.258849322	1.258849435
2	0.201819481	296.47	8	27	59.83342144	1.258849435
3	0.350130712	218.49	5	27	76.50005929	1.258849435
4	0.266296081	490.51	18	27	130.6208905	1.258849435
5	0.004859672	207.11	27	27	1.006486578	1.258849435
6	0.221338441	274.82	77	27	60.82823035	1.258849435
7	0.201819481	313.03	8	27	63.17555204	1.258849435
8	0.004859672	514	27	27	2.497871185	1.258849435
9	0.434811515	248	56	27	107.8332557	1.258849435
10	0.453500121	258.69	89	27	117.3159462	1.258849435
				TOTAL	**620.8705627**	**12.58849435**

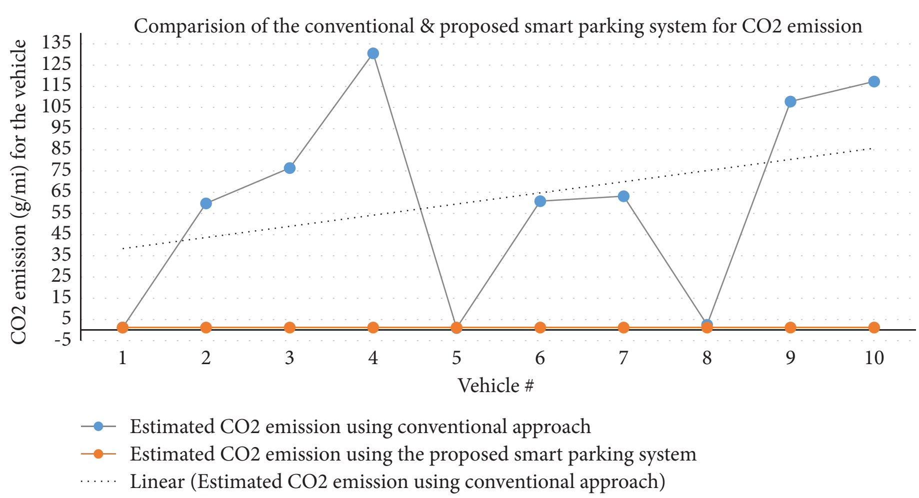

Figure 3: Comparison of the proposed smart parking system with the conventional approach.

5. Validation and Evaluation

To validate whether the parks recommended by the proposed methodology are the preferred ones and will really lead to minimum level of CO_2 emission, two experiments are performed.

5.1. Validation Using the Distance-Based Method. In the first experiment, the available 20 parking areas in the specified range of the vehicles are ranked based on distance from the current positions. The ranking produced is shown in Table 11, which shows that top 1 and top 2 parking areas (P27 and P50) are the same as those recommended by our methodology, which defiantly result in lowest level of CO_2 emission. The parking P66 recommended by our methodology is at rank 4 in the distance-based ranking due to lowest values of the other parking features. This validates the proposed methodology with an accuracy of 100% for top-1 and top-2 parking areas.

5.2. Evaluation Using the Conventional Method. In the literature, as no baseline system is available to compare with the proposed methodology, therefore we considered a scenario in which the parking areas are randomly selected by drivers of the ten vehicles. A random query is executed 10 times for the 10 vehicles over the 20 available parking areas to determine the level of CO_2 emission. Comparison of the results is presented in Table 12.

The comparison graph is shown in Figure 3.

These comparison results show that in conventional approach, 3/10 vehicles could manage to find the preferred parking lots as compared to the proposed smart parking system approach where 10/10 vehicles succeeded in finding the preferred parking lots. Overall, the ratio of CO_2 emission using conventional and the proposed methods is 620.9 (g):12.5 (g) for the 10 vehicles over the 20 available parkings.

6. Conclusion

In this study, a novel smart parking solution is proposed, which uses exploratory data analysis, multilevel filtering, and weighted sum models for exploiting parking and vehicle features to rank the available parking areas. The proposed methodology ranks all the available parking areas using multiple criteria and gives option(s) of the preferable parking areas. The features are weighted, and highest weight is assigned to CO_2 emission rate of the vehicle; therefore, the methodology guarantees the choice of a parking, which results in the minimum level of the emission of CO_2. The comparison results show that the proposed methodology helps in reducing the CO_2 emission.

Data Availability

The data used to support the findings of this study can be made available on request to the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research study was supported by Zayed Research Incentive Funds (R18055), Zayed University, United Arab Emirates.

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