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Investigation of car park preference by intelligent system guidance

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ABSTRACT

In recent years, especially in developing countries, the number of vehicles has rapidly increased, leading to an increase in the demand for parking spaces. The most effective method to overcome this is to efficiently manage existing car parks. For this purpose, intelligent transportation system (ITS) applications have been used for facilities. In this study, the effect of guidance according to parking preferences on the utilisation of car parks with the support of an intelligent parking guidance system is examined. The preference and choice of car parks were modelled based on the observed data by developing a simulation program and testing the validity of the model. Subsequently, the effects of various parameters (e.g., parking fees, walking distance, and driving distance) on the selection of car parks, which have been ignored in the existing ITS, were included in the examination of the model. The results indicate that the driving distance and carbon dioxide emission, walking distance, and parking fees are reduced by 17, 14, and 1%, respectively. This study shows that system efficiency can be enhanced by considering additional car park preference parameters in intelligent parking system designs and management.

1. Introduction

The rapidly increasing population and vehicle ownership cause severe traffic congestion and parking problems, especially in city centres. Car parks are among the most important transportation system elements. According to Yardim, passenger cars are only active for 1.5–2.0 h during the day and spend approximately 90% of their economic life in car parks (Yardim, 2005). To satisfy the growing demand, authorities generally attempt to create new car parks; however, the lack of space in urban areas makes the implementation of such planning infeasible. Additionally, parking problems may result in various negative side effects, such as air pollution, noise pollution, fuel consumption, and time loss. The most convenient method for avoiding parking space problems is the use of intelligent parking systems, which improve the efficiency of car park utilisation. Intelligent parking systems are among the guidance technologies that can lead the drivers to the most convenient car park with respect to parking space preference parameters. Several considerations can affect the decision of drivers in their search for parking space. To consider the preferences of drivers relative to the car park and the effects of their behaviours, further studies must be conducted.

Thus, this study aims to maximise the usage efficiency of car parks by directing drivers to the most convenient car park through the intelligent guidance system according to driver preferences. Different parameters affecting the parking space selection preferences of drivers (e.g., parking fee, walking distance, driving distance, traffic congestion caused by the guidance system, and occupancy of car parks) are included in an existing intelligent parking guidance system (IPGS); their effects are evaluated using multi-agent-based simulation tools. For this purpose, the real-time data observed from the İzmir Transportation Centre Information System (İZUM) have been employed for the analysis. The existing IPGS is evaluated and compared with a proposed model that includes additional car park preference parameters. First, a model in which the selection of car parks is simulated with respect to occupancy is developed and verified to represent the existing IPGS. Subsequently, to compare and determine the effects of additional preference parameters on the mean driving duration, walking distance, parking cost, and carbon dioxide emission, the proposed models are further improved. The models developed in this study also aim to create a potential reference point for improving car park utilisation.

This paper is divided into five sections. The second section discusses previous research works related to the preference parameters of car parks, IPGSs, and agent-based models. In the third section, detailed information on the data collection procedure is explained, and the

Abbreviations: DR, Discrepancy ratio; EF, Efficiency factor; IPGS, Intelligent parking guidance system; ITS, Intelligent transportation system; İZUM, İzmir Transportation Centre Information System; PGIS, Parking guidance and information systems; RAF, Real-time availability forecast; RMSE, Root mean square error

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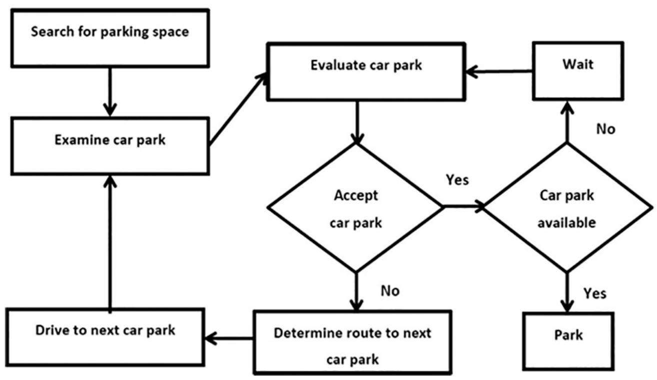

Fig. 1. Parking space selection mechanism (Thompson & Richardson, 1996).

utilised technologies are introduced. Further, in the fourth section, the procedure of the simulation program design and the validity of the program determined by the simulation of observed data are presented. In the same section, the simulation of the proposed model to analyse the effect of different preference parameters on car park choice is explicated. In the next section, a scenario based on random data is created to measure the general effects of different parameters on car park choice. Moreover, the evaluation of the obtained simulation results is discussed, considering carbon emission, walking distance, driving duration, and cost. Finally, the conclusions drawn are presented.

2. Previous study

Car park selection is a dynamic method that is affected by various variables. Thompson and Richardson (1996) reported that the parking choice activity should be regarded as a selection mechanism in which users make a set of subjective decisions based on their own experiences and the circumstances of a given parking space, as illustrated in Fig. 1 (Thompson & Richardson, 1996). A number of considerations can affect the decision of drivers looking for car parks. This includes the driving time to car parks, availability of parking spaces, convenient entry to or exit from the car park, walking time to destination, distance to payment machines, and pricing. Additionally, driver characteristics, such as gender and age, may also influence the choice in parking space (Young, 1986). These characteristics of car park preferences are generally modelled into two approaches. The first approach deals with the car park preference of a driver at the start of car travel (Giuffrè, Siniscalchi, & Tesoriere, 2012; Shin & Jun, 2014; Thompson, Takada, & Kobayakawa, 2001) and the other approach considers the parking space selection in the parking facility (Vo, Van Der Waerden, & Wets, 2016; Zhao, Li, Wang, Li, & Du, 2018). The car park preference of the drivers at the beginning of car travel can be categorised into choices according to route or car park location. If the parking location and route information cannot be provided to the drivers, their preference will be dependent on their previous parking experience (Ji, Wang, Deng, & Saphores, 2008). Generally, three different approaches are used for car parking design and optimisation: a) empirical, b) analytical, and c) multi-agent-based simulation tools (Zhao et al., 2018).

2.1. Studies on parking preferences

Several studies have attempted to evaluate the effects of choice parameters on car park preferences. In an attempt to reduce the traffic congestion in city centres, Thompson et al. developed a procedure that combined both optimisation model and behavioural choice, considering the effect of several parameters, such as driving time, parking time, parking fee, and walking distance (Thompson et al., 2001). Giuffrè et al. have proposed a disutility function that considers the effects of walking time, parking fee, parking space searching time, and travel time (Giuffrè et al., 2012). In their study, Shin and Jun evaluated the effect of parameters, such as driving distance, walking distance, parking cost, traffic congestion, and car park occupancy rate on the car park preferences based on the utility function (Shin & Jun, 2014). Benenson et al. considered the distance to destination and occupancy of parking places as preference parameters for car parks (Benenson, Martens, & Birfir, 2007), whereas Waraich and Axhausen accounted for the walking distance and parking cost (Waraich & Axhausen, 2012). In a different study, Brooke et al. emphasised the influence of various parameters on car park preferences, such as searching time, walking distance, aim of the trip, parking habits, number of parking places visited, acquaintances, travel time, parking duration, heavy equipment, parking bay type, type of carriageway, direction of traffic flow, and road width (Brooke, Ison, & Quddus, 2015). Caicedo proposed a demand assignment model to determine the effects of deploying information to reduce the search time for a parking space, involving driving time and parking distance. In this study, with high computational expenses, the proposed model aims to achieve a 10% efficiency improvement. In view of this, a genetic algorithm is developed to reduce greenhouse gas emissions (Caicedo, 2010). In a further study, Caicedo et al. developed a methodology called real-time availability forecast (RAF) to predict the parking availability by considering iterative requests. In this study, a discrete choice model is proposed, including waiting time, budget, destination, and availability of parking place. The RAF technique was successfully applied to a four-level car park in Barcelona with an error of less than 3% (Caicedo, Blazquez, & Miranda, 2012). Napoli et al. developed an agent-based negotiation software, considering the necessities of both car park users and vendors as well as the availability, distance to the city centre, and parking fee (Di Napoli, Di Nocera, & Rossi, 2014).

2.2. Parking guidance systems

Different technological attempts have been made to find and propose a practical application to solve the car parking problem. The first applications of car park routeing and information systems (PGIS) have been set up with variable message signs along the roads in West Germany in the early 1970s (Axhausen, Polak, & Boltze, 1993). In the 1980s, the information and guidance systems of car parks have also improved rapidly with the development of the concept of telematics, which is defined as the transmission of information through telecommunication network and the operation of information processing through a computer (Nowacki, 2012; Tufan, 2014). The systems supported by technological developments are characterized by their capability to dynamically inform drivers of the parking and traffic conditions (Idris, Leng, Tamil, Noor, & Razak, 2009). In the operation of parking information and guidance systems, many combined analytical methods are employed to serve different purposes and modern technologies, such as wireless sensors, global positioning system, vision-based systems, and vehicular communication. Faheem et al. (Faheem et al., 2013) have emphasised that smart car parking systems provide services, such as car park collection, parking guidance, real-time navigation, parking charge collection, bargaining, and anti-theft protection. The use of parking guidance and information systems (PGISs) is the most common approach intended for leading drivers to an appropriate parking space. A PGIS is generally composed of message boards installed along the road to inform drivers about the occupancy and location of car parks. Drivers are directed to car parks according to the available parking places appearing instantaneously on the message board. However, a driver may not find a free parking space because its availability may change during the driving duration from the message board to the free parking place (Thompson & Bonsall, 1997; Waterson, Hounsell, & Chatterjee, 2001).

The PGIS is composed of four phases. The first phase involves the detection of the number of arrivals and apertures of a car park using a piece of observation equipment. The latter involves the information distribution appliance, which provides information to the drivers regarding the car park availability. Several information distribution methods, such as mobile applications (Hans, Sethi, & Kinra, 2015; Tandon & Gupta, 2019), SMS (Mohandes, Tasadduq, Aliyu, & Deriche, 2015), and web interfaces (Butowsky, Gai, Coakley, Qiu, & Tappert, 2015; Yagi, Watanabe, & Nagayama, 2015), are used to guide drivers. The third phase involves telecommunication networks, such as ZigBee wireless network (Shiyao, Ming, Chen, & Na, 2014), Vehicular ad hoc network (Tandon & Gupta, 2019), wireless sensor networks (Yang, Portilla, & Riesgo, 2012), Wi-Fi (Lin & Hong, 2015), and 3G/4G (Mainetti, Patrono, Stefanizzi, & Vergallo, 2015). The last phase is the control centre, which processes the car park occupancy records and regulates the dissemination of information on the availability of car parks to the drivers (Gabriel, Og, & Fabregat, 2020).

The PGIS informs drivers with accurate real-time information, making the system more advantageous. Accordingly, the system reduces the parking space search duration and improves the utilisation of the available parking space.

2.3. Agent-based models of intelligent parking systems

By modelling the individual behaviours in parking preferences rather than investigating the accumulated traffic flow along the infrastructure, the drivers, designated as 'agents', are simulated and traced using agent-based models (Lejdel, 2020; Longfei, Hong, & Yang, 2009; Mateo, Lee, & Lee, 2009; Yang, Rongguo, & Longfei, 2009). The independence, reactivity, and flexibility features of agents allow the parking guidance systems to be highly dynamic and collaborative in leading to parking places (Gabriel et al., 2020). In general, a utility function is proposed as the decision mechanism of agents in parking place preferences. For instance, Waraich and Axhausen proposed a model with a utility function as a decision mechanism, considering the occupancy of parking places, walking distance, and parking costs in their agent-based models to improve existing traffic models (Waraich & Axhausen, 2012). Li et al. proposed a dynamic parking guidance information system for route negotiation and guidance on parking place availability, price, and route negotiation (Li, Chou, & Lin, 2004). Shin and Jun proposed a model as a guide according to a utility function that involves driving distance, walking distance, parking cost, and traffic congestion. In their studies, the proposed models, both with reservation and non-reservation, are implemented in a multi-agent-based simulation program for Luxembourg. The simulation results were evaluated in terms of average driving duration, walking distance, and parking resource utilisation (Shin & Jun, 2014).

In summary, the efficiency of car park utilisation is related to IPGSs that consider various parking preference parameters and simulation with agent-based models, as investigated in this study.

3. Data collection procedure

Based on the data collected from existing IPGSs, observations are conducted by extracting the IZUM, which is included in the smart transportation system for İzmir province (İZUM, 2017). As part of the IZUM information system, real-time available lot numbers of car parks are served to users throughout the İzmir province. Among the different centres in İzmir Province, the selected site called Alsancak is considered to be the most crowded area where the traffic demand is also higher. This is because, in the commercial, cultural, historical, political, and geographic centres of the city, finding available parking spaces is a problem. In the selected area, only three car parks, which are located close to each other, are included in the IPGS; these are selected for the observation. The information related to the selected car parks is summarised in Table 1, and their locations are shown in Fig. 2. This figure shows that there are two main arterials that drivers may use to reach the selected car parks: Liman Street and Cumhuriyet Boulevard.

The Alsancak multi-storey car park only has one entrance, where the toll collection system can count the number of entering and exiting vehicles. The data collected are instantaneously received by the IPGS and presented to the IPGS user in real-time. Furthermore, the occupancy conditions of the on-street car parks are determined by the sensors installed underground. The data collected by the sensors are presented to the users by the IPGS in real-time.

The observed data were collected from the webpage interface of the IZUM IPGS for six weeks during the morning peak hours on Wednesdays for 60 min. The morning peak hour is the period when the parking demand is at a maximum because the selected area is a city centre with commercial and governmental facilities. In this study, the morning peak hour was selected as the observation period. To cover a wider time period for different working hours, the morning peak hour was extended from 08:00–10:30 a.m. because there are several government offices and commercial areas in the selected city centre. Failures in the IPGS occurred during the observation period; consequently, the start of the 60-min observation period was varied in their selected interval. Based on previous research on traffic flow behaviour, the most congested morning and evening peak hours of the week are on Mondays and Fridays, respectively. Moreover, it has been observed that Tuesday, Wednesday, and Thursday are the typical weekdays with respect to traffic flow patterns (Divgi & Chlebus, 2007; Wen, Sun, & Zhang, 2014). In this study, to provide a steady-state traffic flow, Wednesday was selected as the observation day. The IZUM IPGS shares instant free space information on car parks. For the observed car parks, each change in the number of free parking places was recorded as vehicle arrival or departure. Therefore, during the observation, the total number of arriving and leaving vehicles was recorded for each selected car park. In addition, the start-up occupancy numbers and rates of each car park were recorded at the beginning of the observation; the observed data are summarised in Table 2.

Based on Table 2, the Alsancak multi-storey car park occupancy rate varied in the range 90%–78% at the start of observations. Comparably, those of Kordon 1 (North) on-street car park and Kordon 2 (Sought) on-street car park observed varied in ranges of 96 to 79% and 55 to 86%, respectively. Based on this, the average available (non-occupied) parking capacity at the beginning of the observation was 16%, and the average usage rate during the observation was 11%. For example, in the 5th observation, it can be noticed that the usage rate and available capacity are 11% and 13%, respectively.

4. Design of multi-agent-based simulation program

In this study, a multi-agent-based simulation program, which simulates parking preferences for the three different car parks, is compiled in NetLogo, a multi-agent programmable modelling environment; the interface of the designed simulation program is shown in Fig. 3. In the simulation screen, the parking facilities are defined in three different colours: orange, green, and blue, marked as 1, 2, and 3, respectively (Fig. 3). The (1) orange, (2) green, and (3) blue car parks correspond to Alsancak multi-storey car park, Kordon 1 (north) on-street parking, and Kordon 2 (south) on-street parking, respectively. In the simulation screen, roads are designed in a white layout, and parking facilities are defined in three different colours: orange, green, and blue. In this study, the vehicle speed is considered constant at 40 km/h. In addition, it is assumed that all the vehicles in the simulation ingress from two different arterials (Cumhuriyet Boulevard and Liman Street) and aim to visit a government office, OSYM building (target destination), located in the middle of the zone being analysed (Fig. 2). Another assumption is that the preferences are made according to the number of free spaces in the car parks because the real-time occupancy information on these parking spaces is presented in IZUM.

In the simulation, the departures of vehicles from car parks are actualised according to the 'departure rate'. The departure rate is calculated as the ratio of the number of vehicles that ingress to a car park to that of vehicles leaving the car park during the observation. For

Table 1
Information on observed car parks.

No	Car park	Type	Parking capacity	Cost (For 3 h)
1	Alsancak multi-storey car park	Off-street	550	8.00 TL
2	Kordon 1 (north) on-street parking	On-street	132	8.50 TL
3	Kordon 2 (south) on-street parking	On-street	22	8.50 TL

example, a 50% departure rate means that one vehicle will leave the car park when two vehicles arrive. The 'departure rate' for each car park is used as an input in the program through the data entry section before the simulation starts. The simulation program also assesses the average driving times, walking distances, parking costs, and carbon dioxide emission values to evaluate the simulation results. An output of the graph is also created by the program, which illustrates the occupancy rate during the simulation time. The occupancy rate is calculated by dividing the number of occupied car parks by the total parking capacity.

4.1. Theoretical background for the design of simulation program

To determine the influence of different preference parameters on the choice of car parks, the John-Ho Shin and Hong-Bae Jun approach was examined by comparing it with existing guidance system preferences. In their study, Shin and Jun investigated the influence of car park preference parameters, such as driving distance, walking distance, parking cost, traffic congestion caused by the vehicles directed by the guidance system, and car park occupancy rate (Shin & Jun, 2014). For defined parameters, Shin and Jun proposed a disutility function given by.

$$U_{ij}^2 = (\beta_1 D_{ij}^* + \beta_2 W_{ij}^* + \beta_3 C_j^* + \beta_4 P_j^* + \beta_5 R_{ij}^*)/15 \quad (1)$$

where U_{ij}^2 is a parking disutility function to guide car *i* to car park *j* ($0 \leq U_{ij}^2 \leq 1$); D_{ij} is the driving distance from the current location of car *i* to car park *j*; W_{ij} is the walking distance from car park *j* to the destination of car *i* ($j = 1, \ldots, m$); C_j is the parking fee for car park *j* (TL/3 h); P_j is the number of vehicles guided by the system to car park *j;* R_{ij} is the degree of availability of car park *j* for vehicle *i* ($j = 1, \ldots, m$); β_1 is a weight factor for the driving distance of the vehicle from the current position; β_2 is a weight factor for the walking distance from the guided car park to the destination point; β_3, β_4, and β_5 are the weight factors for the parking fee, traffic, and degree of availability, respectively. All the parameters used in the disutility function are normalised by Eq. (2).

$$X_{ij}^* = (X_{ij} - X_{ij}^{min})/(X_{ij}^{maks} - X_{ij}^{min})\ j = 1, \ldots, m,\ 0 \leq X_{ij}^* \leq 1 \quad (2)$$

In the developed multi-agent-based simulation program, Shin and Jun proposed the disutility function as a preference criterion for car parks. Vehicles are directed to car parks with respect to the disutility

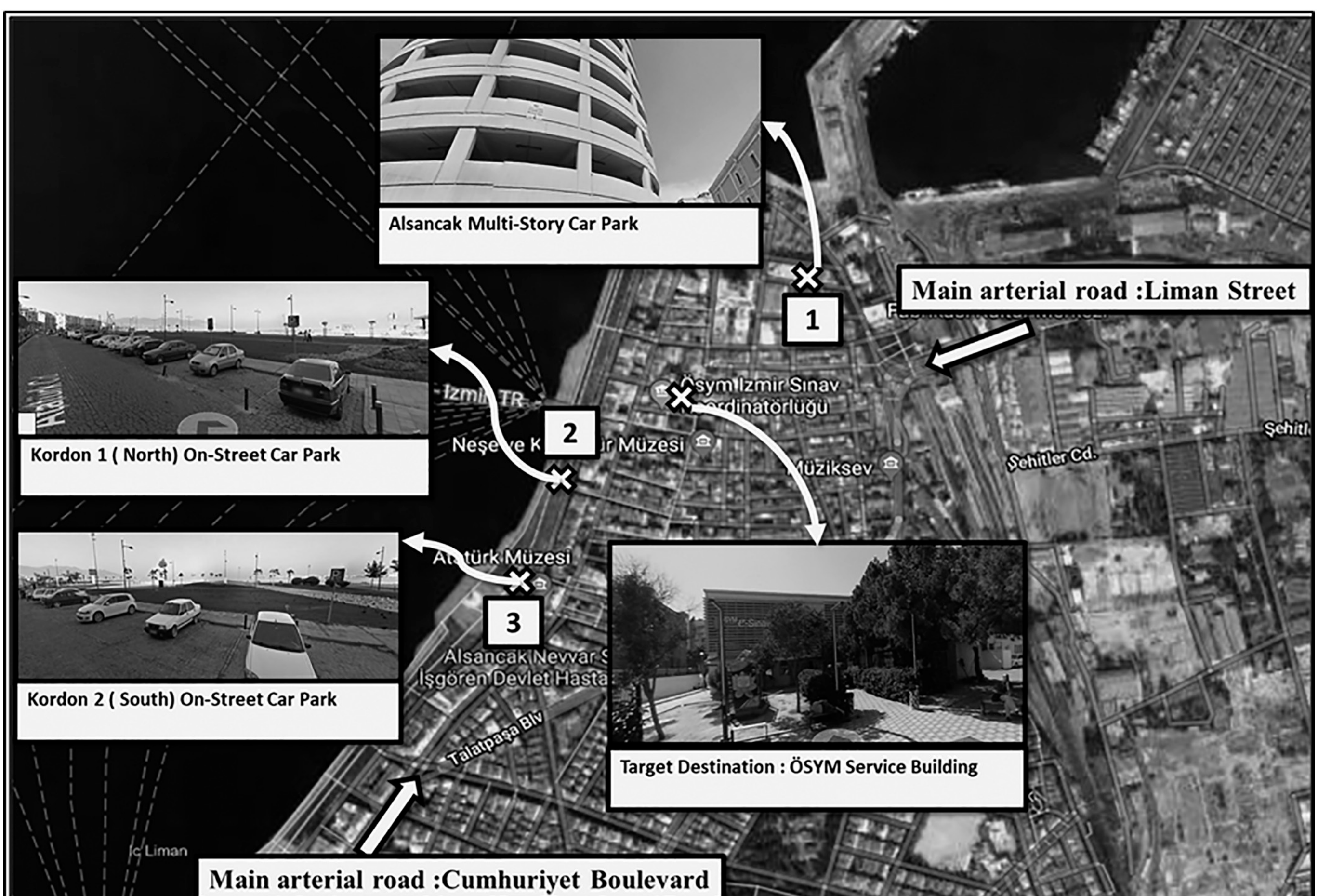

Fig. 2. Main arteries, car parks, and target destination of study region.
Source: Google Earth.

Table 2
Observation data.

Obs. no	Date	Hour	Alsancak multi-store car park				Kordon 1 (North) on-street car park				Kordon 2 (South) on-street car park				Total startup occu. Rate (%)	Total arrivals (veh.)
			Startup occu. (veh.)	Startup occu. Rate (%)	Arrivals (veh.)	Exits (veh.)	Startup occu. (veh.)	Startup occu. Rate (%)	Arrivals (veh.)	Exits (veh.)	Startup occu. (veh.)	Startup occu. Rate (%)	Arrivals (veh.)	Exits (veh.)		
1	19.09.2018	09:20 a.m. 10:20 a.m.	480	87%	46	8	127	96%	5	5	19	86%	3	4	88.92%	54
2	26.09.2018	08:10 a.m. 09:10 a.m.	428	78%	48	6	104	79%	19	11	14	64%	6	3	77.56%	73
3	3.10.2018	08:30 a.m. 09:30 a.m.	452	82%	51	4	119	90%	12	4	15	68%	5	6	83.24%	68
4	10.10.2018	08:28 a.m. 09:28 a.m.	455	83%	60	3	109	83%	23	6	13	59%	4	5	81.96%	87
5	17.10.2018	08:20 a.m. 09:20 a.m.	495	90%	57	3	104	79%	17	5	12	55%	2	0	86.79%	76
6	24.10.2018	08:23 a.m. 09:23 a.m.	497	90%	53	5	106	80%	30	8	12	55%	8	4	87.36%	91
Average start-up occupancy rate				85.06%				84.47%				64.39%			84.30%	

value of each lot; this value is assessed instantaneously by the simulation program. In such an assessment, the mean time between car arrivals *($MTBA_j$)* is calculated for each car park using Eq. (3) to find the degree of availability *(R_{ij})* in Eq. (4) (Shin & Jun, 2014):

$$MTBA_j = \frac{\sum_{k=2}^{q_j} (t_{jk} - t_{j(k-1)})}{q_j - 1} \tag{3}$$

where $MTBA_j$ is the mean time between the car arrivals at car park j within a certain time interval ($j = 1, \ldots, m$); k is the vehicle arrival index at a specific time interval for car park j ($k = 1, \ldots, q_j$); t_{jk} is the kth car arrival time at car park j ($j = 1, \ldots, m$); q_j is the number of cars that arrive in car park j at a certain time period ($j = 1, \ldots, m$).

$$R_{ij} = \frac{\frac{T_{ij}}{MTBA_j}}{f_j} \tag{4}$$

In Eq. (4), R_{ij} is the degree of availability of car park j for the ith vehicle; T_{ij} is the total arrival time of the ith vehicle for car park j; f_i is the number of free parking places in car park j at *a certain time*, *t*.

The driving distance (D_{ij}) and walking distance (W_{ij}) defined in the utility function are procured from Google Maps and inputted to the simulation program. The parking fee parameter, C_{ij}, is obtained from the car park operator of İzmir, İZELMAN Incorporated Company (İzelman, 2018). The number of vehicles the system guides to the car parks (P_j) and the degree of availability of car parks (R_{ij}) are instantaneously computed by a simulation program with respect to the location of vehicles.

The simulation program also calculates the average carbon dioxide emission value per vehicle. In the simulation program, Eq. (5) was used to calculate the carbon dioxide emission (Akçelik, Smit, & Besley, 2014):

$$f_t(CO_2) = f_{CO2} f_t(fuel) \tag{5}$$

where $f_t(CO_2)$ is the instantaneous carbon dioxide release rate (g/s); $f_t(fuel)$ is the fuel consumption ratio (mL/s); f_{CO2} is the carbon dioxide emission corresponding to fuel consumption (g/mL or kg/L). Using Eq. (5), $f_t(CO_2)$ was calculated as 1.36 g/s with respect to a constant vehicle speed of 40 km/h.

4.2. Validity of simulation program

To determine the effect of each preference parameter considered in the study, the β weight factors that emphasise the related parameter in Eq. (1) were considered as values ranging from 0 to 3. First, to simulate the existing IPGS, the weight factor (β5) of the occupancy rate is taken as 3, whereas the other weight factors (β1, β2, β3, and β4) are considered as zero and defined as the M1 model. In this way, the simulation program has been processed with respect only to the occupancy rate of car parks used to define the existing condition. Therefore, M1 is the reference model for testing the validity of the simulation program. In the test, the observed data and M1 simulation results were compared. In the evaluation, the discrepancy ratio (DR), efficiency factor (EF), root mean square error (RMSE), and regression analysis were used. A comparison between the simulation and observation data is implemented using Eq. (6) for analysing the DR. Generally, a DR value between −0.1 and 0.1 indicates that the estimation results of the simulation model are sufficient. The DR values higher than 0.1, less −0.1, and between −0.1 and 0.1 are defined as high, low, and proper estimations, respectively (Özuysal, Çalışkanelli, Tanyel, & Baran, 2009):

$$DR = log_{10}(Q_{park}^{sim} / Q_{park}^{obs}) \tag{6}$$

where ${Q_{park}}^{sim}$ represents the simulated arrival number; ${Q_{park}}^{obs}$ is defined as the observed arrival number. The comparison graph of the observation and simulation data based on the DR analysis is presented in Fig. 4.

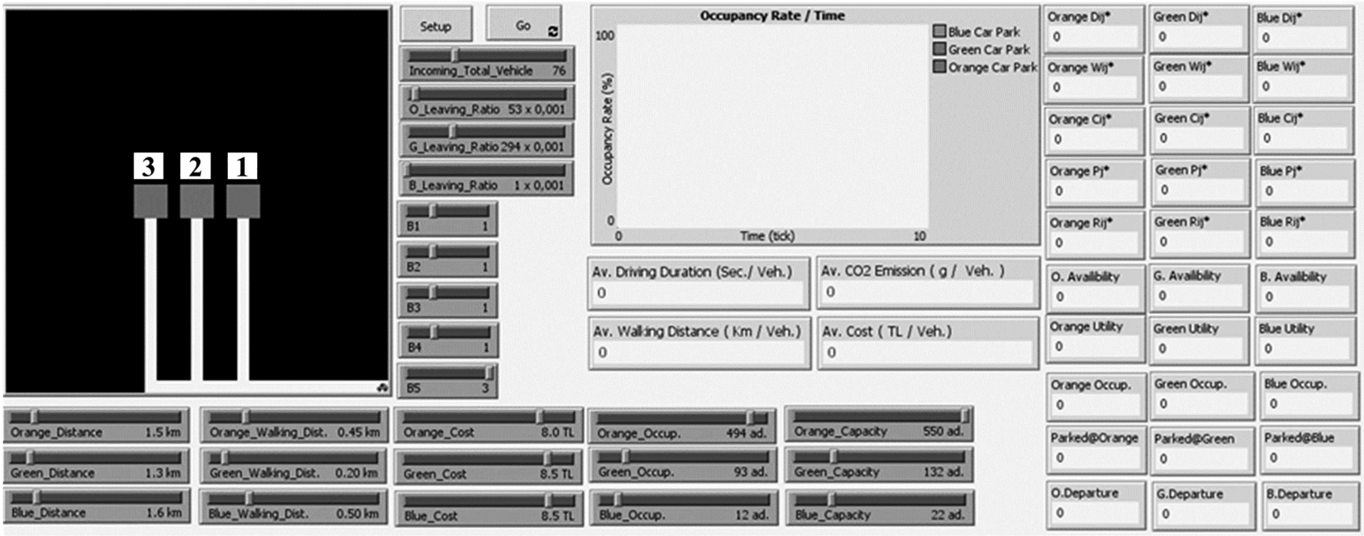

Fig. 3. Utility-based simulation program in Netlogo.

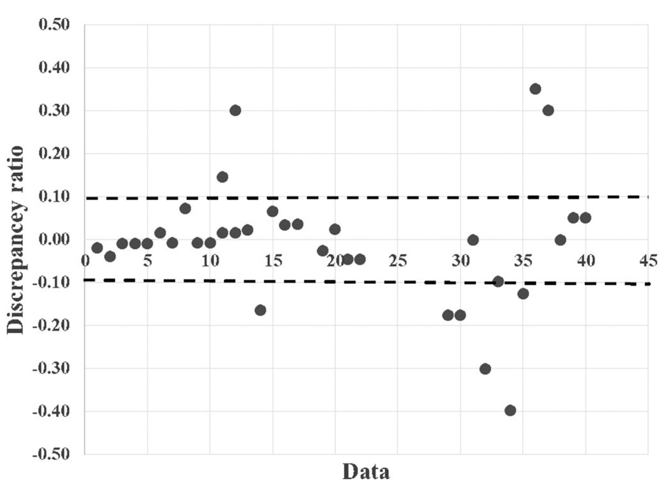

Fig. 4. Discrepancy ratio of observed and simulated arrivals.

As summarised in Table 3, in the DR analysis, the proper, high, and low estimation rates are calculated as 69, 11, and 19%, respectively. Based on a separate DR analysis for each car park, the Alsancak multi-storey car park reached a 100% proper estimation. It was observed that the proper estimation value of the DR analysis was directly proportional to the number of incoming vehicles to the car parks. In the DR analysis for Kordon 1 (north) on-street car park, the proper estimation rate was 67%, and the high and low estimation rates were 17%. In that of Kordon 2 (south) on-street car park, the proper estimation rate was determined to be 42%.

Other statistical methods used for determining the validity of the simulation results include the RMSE and EF. The RMSE and EF are generally used to calculate the errors in model estimation. The EF value calculated by Eq. (7) ranges from minus infinity to one; EF = 1 indicates that the simulation model perfectly matches the observed data, and EF = 0 shows that the model predictions are as accurate as the mean of the observed data. If the EF value is less than 0, then the predictions of the model are not as accurate as the mean value of the observed data (Özuysal et al., 2009). The EF and RMSE analyses are performed using Eqs. (7) and (8), respectively.

$$EF = 1 - \left(\sum_{i}^{N} (Q^{obs}_{park\,(i)} - Q^{sim}_{park\,(i)})^2 / \sum_{i}^{N} (Q^{obs}_{park\,(i)} - \overline{Q}_{park})^2 \right) \tag{7}$$

$$RMSE = \left(\sum_{i}^{N} (Q^{obs}_{park\,(i)} - Q^{sim}_{park\,(i)})^2 / N \right) \tag{8}$$

An EF value of 0.96 indicates that the model and observed data practically match perfectly. In comparing each car park, the EF values are calculated as 0.44, 0.53, and −0.14 for the Alsancak multi-storey car park, Kordon 1 roadside car park, and Kordon 2 roadside car park, respectively. The EF value decreases at the zero border despite the negligible differences between the simulation and observation results because the number of vehicles directed to Kordon 2 (south) off-street car park is low. In contrast, because of the high number of vehicles directed to Alsancak multi-storey car park and Kordon 1 (north) off-street car park, a higher efficiency factor value between the simulation and observation data has been achieved.

Different from those of the other analyses, the RMSE for the Kordon 2 off-street car park error rate was calculated to be lower than those of the other car parks and that of the analysis where all the car parks were evaluated.

Table 3
Observation and simulation comparison results.

		Alsancak multi-storey C.P.	Kordon 1 (North) on-street C.P.	Kordon 2 (South) on-street C.P.	All car parks
Estimation capability of simulation	RMSE	3.64	3.82	1.21	3.95
	Efficiency factor	0.44	0.53	−0.14	0.96
Discrepancy percentages	High estimation *	0%	17%	17%	11%
	Proper estimation **	100%	67%	42%	69%
	Low estimation ***	0%	17%	42%	19%

* Percentages of estimations having a discrepancy over 0.10.
** Percentages of estimations having a discrepancy of −0.10–0.10.
*** Percentages of estimations having a discrepancy under 0.10.

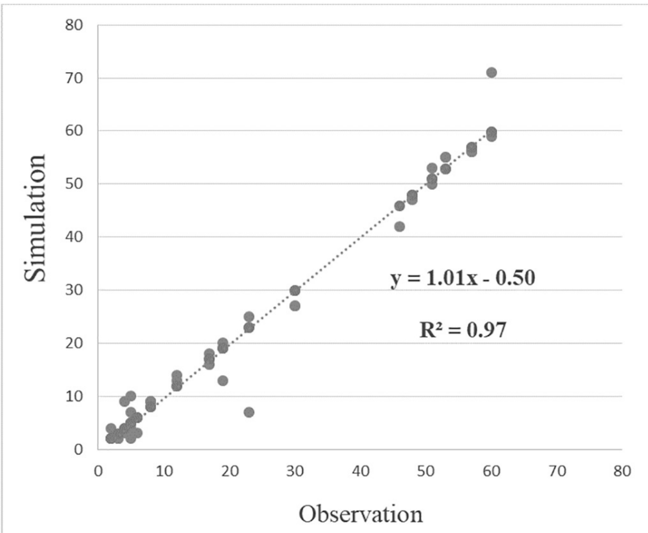

Fig. 5. Observed and simulated arriving vehicles.

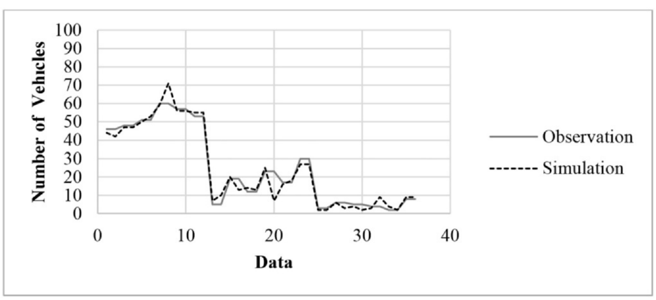

Fig. 6. Observation and simulation data comparison.

Furthermore, the observed number of arriving vehicles and the values obtained from the simulation were compared using the regression analysis; the R^2 value was calculated as 0.97, indicating an acceptable match between the two datasets (Fig. 5). Fig. 6 shows that there is a significant similarity between the observation data and simulation results. The statistical evaluations indicate that the simulation program properly estimates the observation data.

4.3. Simulation of proposed models

In the existing IZUM information system, users are guided with respect to the real-time parking occupancy. Although the IZUM information system is an innovative approach in terms of sustainability for parking management, the inclusion of alternative information features in the system that may affect driver preferences can boost its efficiency. In this study, the parking guidance system was simulated considering five parameters affecting the car park preferences of drivers: driving distance, walking distance, parking cost, number of vehicles directed by the guidance system, and occupancy. The proposed simulation results were assessed in terms of driving time, walking distance, parking cost, and carbon dioxide emission.

4.4. Scenarios for proposed models

To propose new models, including additional car park preference parameters, a set of models with different β weight factors are defined as M2, M3, M4, M5, M6, and M7. In the first proposed model (M2), all β weight factors are defined with a value of 2 to emphasise that all preference parameters seemingly have an equal influence on the car park choice; accordingly, the integrated effects of all parameters are

Table 4
Simulation scenarios by different weight factors (β).

Scenario	Model	β1	β2	β3	β4	β5
1	M1 *(existing IPGS)*	0	0	0	0	3
2	M2	2	2	2	2	2
3	M3	3	1	1	1	1
4	M4	1	3	1	1	1
5	M5	1	1	3	1	1
6	M6	1	1	1	3	1
7	M7	1	1	1	1	3

immediately generated. In the other generated models (M3–M7), to emphasise the effects of all car park preference parameters separately while considering all parameters, the β weight factor of each parameter is assigned a value of 3, from β1 to β5, respectively; the other parameters are given a value of 1. The weight factors of the simulation scenarios are summarised in Table 4.

5. Analysis of simulation results

The defined models listed in Table 4 are simulated to determine the effect of car park preference parameters on the mean of driving time, walking distance, parking cost, and CO_2 emission. In the simulation processes, two types of datasets are evaluated for all models: observed data and randomly generated data. The aim of simulating the observed data is to compare the existing circumstances with the proposed models, whereas the randomised data are used for the general evaluation of various situations. The simulation results are evaluated employing two different approaches.

5.1. Measurement of preference parameter effectiveness with respect to random data

As mentioned, for the purpose of modelling the car park preferences, four different parameters are tested. To evaluate the effects of each parameter on the preferences, random data are generated for use in the simulation with the assumption that there are 100 vehicles heading towards the three car parks, and the capacity of each park is 250 units. Based on the observations, the total parking space in the three car parks can accommodate 704 vehicles. For the purpose of analysis, a scenario where the total capacity and equal heading capacity of each car park are 750 and 250 units, respectively, is created. The major reason for selecting an equal capacity (250 units) is to allow the equal preference for each car park during the analysis and avoid the domination of the occupancy rate preference parameter. In addition, the number of observed arrivals is 54–91 vehicles; in the scenario analysis, 100 vehicles are selected as the approximate maximum number of arrivals. The randomisation ranges of the generated data are summarised in Table 5.

The random simulations results are used to determine the parameter effects on car park choice according to preferability, driving distance, parking cost, and walking distance. The preferability of each parameter is depicted in Fig. 7.

From Fig. 7, it can be observed that preferability depends on each parameter. The driving distance cost and driving distance–walking

Table 5
Randomisation ranges of generated data.

Input parameters	Units	Randomisation range
Driving distance	km	0.5–2.5
Walking distance	km	0.25–0.70
Parking cost	TL	5–15
Vehicles departure ratio of car parks	%	0–9
Occupancy of car parks	unit	20–95

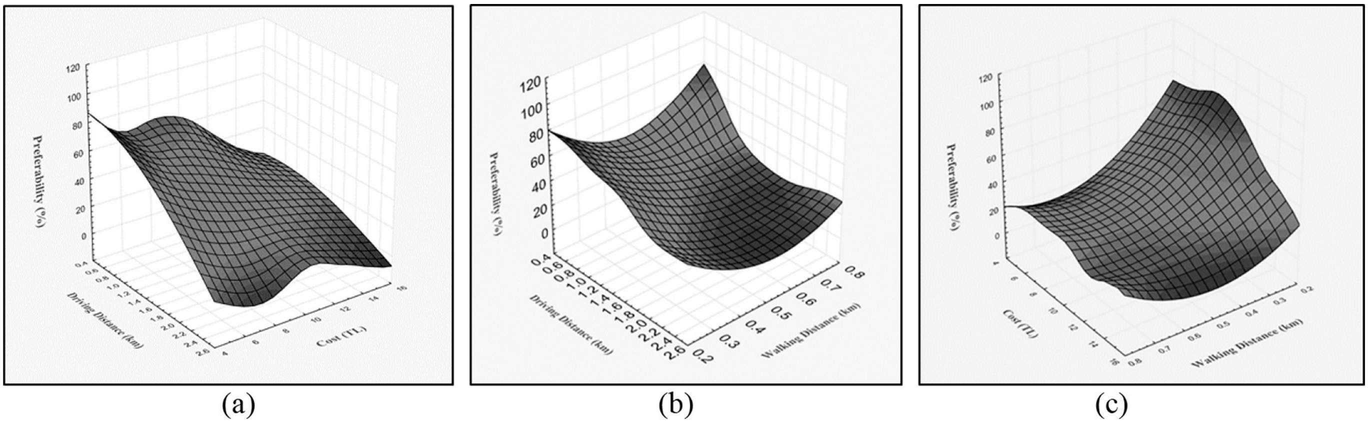

Fig. 7. Effects of preference parameters with respect to random data.

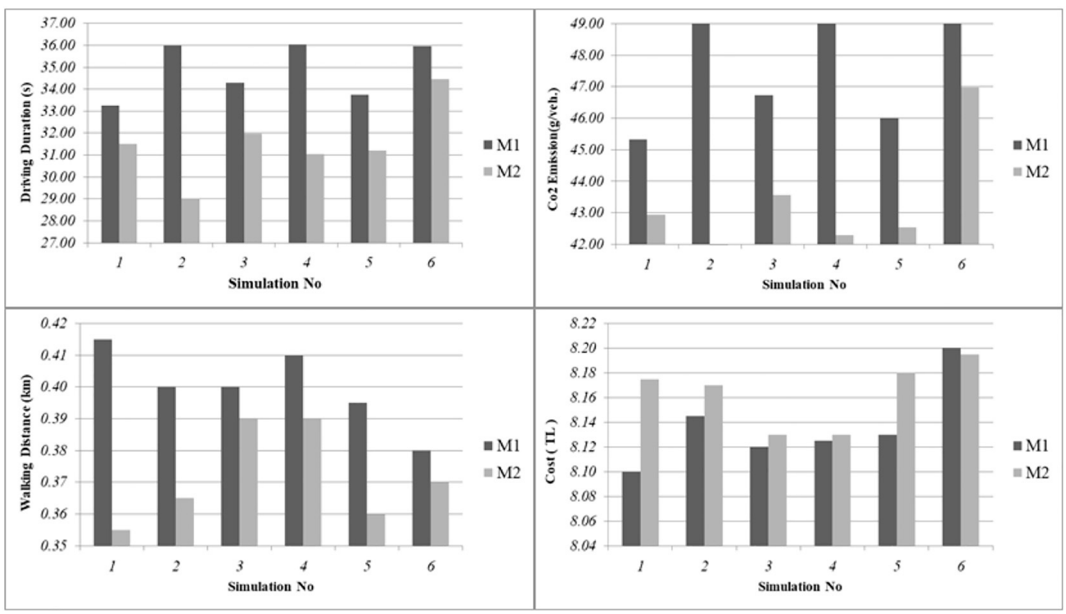

Fig. 8. Comparison between existing IPGS, M1, and M2 model results.

distance are more preferable than the cost–walking distance. As depicted in Fig. 7(a), the preference for car parks and driving distance has an inversely linear relationship, indicating that the preference of drivers decreases as the driving distance of car parks increases. Moreover, it can be observed that the cost and preference for car parks have an inverse proportion; in other words, an increase in cost decreases the preference for car parks. As shown in Fig. 7(b), the driving distance predominates on the preferences of drivers rather than on the walking distance in a selected range of distances. Fig. 7(c) also depicts that the walking distance has a greater influence on the car park preferences than the parking fee. Based on this, the selected parameters clearly impact the car park preferences.

5.2. Comparison between existing IPGS model and proposed models with respect to observed data

Fig. 7 compares the simulation results of models M1 and M2. The comparison indicates that the guidance according to the proposed model (M2) may reduce the driving distance and carbon dioxide emission. In addition, compared with model M1, the guidance concerning the proposed model reduces the walking distance. However, in comparing model M2 with model M1, the mean of parking cost of the former slightly increased, as shown in Fig. 8.

A comparison between model M1 and the proposed models where each car park preference parameter is emphasised is depicted in Fig. 9. In the comparison between models M1 and M3 where the driving distance is emphasised relative to the other preference parameters, the proposed model significantly reduces the driving duration. By contrast, model M4, which emphasises the walking distance with a weight factor of 3, yields a shorter walking distance than model M1. Compared to model M1, model M5 affords an advantage in terms of parking fees. All the preference parameters are included in the proposed models; hence, model M7, which considers the car park occupancy more than the other parameters, also reduces the driving duration for model M1 in which the occupancy of car parks is only considered as a preference parameter.

Considering the economic value of time, walking distance, parking fee, and carbon dioxide emission, the management of the driver preferences through the supplementation of various preference parameters may benefit from intelligent parking guidance systems.

The percent reductions in the values of the assessment parameters of the simulation results are summarised in Table 6. It is evident that the optimum values of the proposed models have explicit benefits of up to 17% in terms of the mean driving duration and carbon dioxide emission. In addition, in terms of walking distance, 14% of the benefit is gained from the optimum results compared with the existing model.

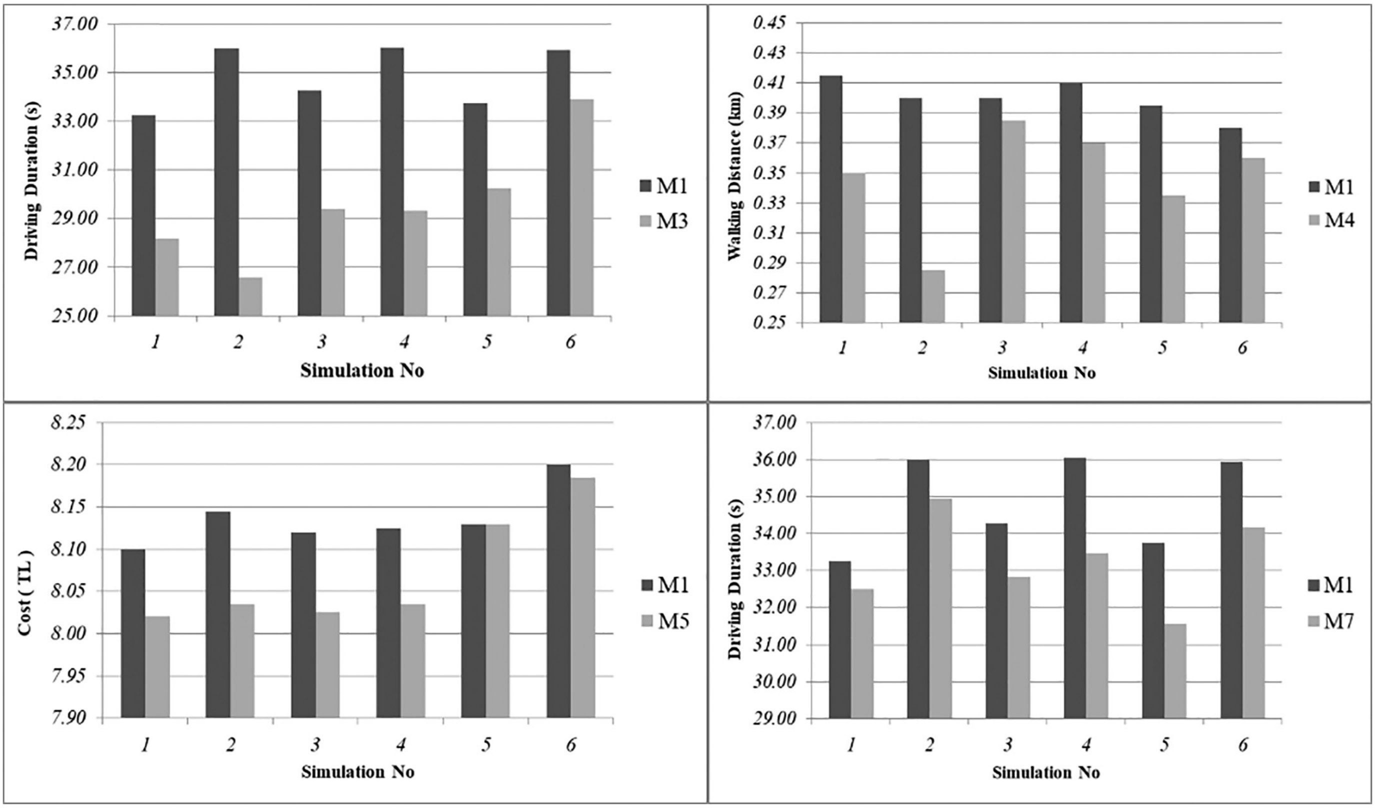

Fig. 9. Comparison of existing IPGS, M1, and results of proposed models.

Table 6
Comparison between existing and optimum model results.

Method	Driving duration (s)	Walking distance (km/veh.)	Parking cost (TL/veh.)	CO_2 (g/veh.)
Existing model (M1)	34.88	0.40	8.14	47.54
Optimum results from proposed models	28.80	0.35	8.07	39.26
Reduction percentage (%)	*17%*	*14%*	*1%*	*17%*

However, the parking cost does not exhibit a distinct reduction because all parking costs are practically equal.

6. Conclusions

In this study, the advantages afforded by car park preference parameters, which may be included in the parking guidance system to improve its effectiveness, are determined based on the observed data obtained from IZUM, an existing intelligent parking guidance system in Izmir. In the existing system, the occupancy information of car parks in the Izmir district serves to guide drivers in finding available parking places. To determine the effects of intelligent parking guidance systems on car park preferences and manage these for the sustainability of existing car parks, additional parameters (e.g., driving distance, walking distance, parking fee, and traffic caused by the guidance of IPGS) have been incorporated in the existing system and thereafter modelled. In the simulations of the existing and proposed models, the effects of car park preference parameters are obtained in terms of the mean driving duration, walking distance, parking cost, and carbon dioxide emission. Based on the simulation results, the following are deduced.

Data were collected by observing the existing IPGS in Izmir/Turkey. Based on these data, a multi-agent-based simulation program was created to simulate existing conditions in the observation zone. The statistical testing of the simulation results validated the formulated simulation program.

To determine the effects of preference parameters on car park choice, additional parameters have been included in the simulation program, and new models have been proposed. To illustrate the effectiveness of the preference parameters, randomly generated data were simulated. The results showed that the car park preference was dependent on each parameter, whereas the driving distance–cost and driving distance–walking distance are more effective than the cost–-walking distance.

In comparing the existing IPGS and proposed models, the single-objective optimisation results yield a 17% benefit in driving duration and carbon dioxide emission, 14% in walking distance, and 1% in parking fee.

In a future study, multi-objective optimisation may be employed to determine the explicit weight factors for the preference parameters, and the effect of different preference parameters may be evaluated.

Author's contributions

Bora Dogaroglu: Drafted and wrote the manuscript, performed observation, generated simulation code, and result analysis.

S. Pelin Caliskanelli: Assisted in analytical analysis, result interpretation and helped in manuscript preparation.

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