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Research paper

A Multi-Criteria Parking Space Proposing System based on Cheetah Optimizer Algorithm

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Abstract

Efficient parking space allocation in urban environments remains a significant challenge due to diverse user preferences, such as cost, proximity, and convenience. This paper proposes a novel intelligent parking assignment framework based on the Cheetah Optimization Algorithm (COA), a bio-inspired metaheuristic inspired by the adaptive hunting behavior of cheetahs. The system integrates user-specific criteria in a multi-stage process, first collecting system and driver data, then applying COA to optimize parking space allocation. Compared to deep reinforcement learning and other metaheuristics like the Genetic Algorithm and Whale Optimization Algorithm, COA demonstrates faster convergence and improved solution quality, as measured by reduced parking time and increased user satisfaction. The results confirm that COA is an effective and robust approach for real-time, personalized smart parking management in dynamic urban settings.

1. Introduction

The Internet of Things (IoT) has become one of the essential components of urban life, especially in smart cities. It has found applications in various domains within smart cities [1, 2].

One such application is establishing smart parking lots [3, 4]. Managing parking efficiently is crucial for addressing traffic congestion in urban centers. Mismanaging parking lots contributes to traffic issues and congestion in city centers. Many cities lack sufficient parking facilities, and accurately estimating the number of available spaces is a challenge [5-8]. Smart parking systems are considered a viable and economically profitable solution to these problems.

Finding a parking space during peak hours can be frustrating, leading drivers to waste time searching, which in turn exacerbates traffic congestion, air pollution, and driver dissatisfaction [3, 5]. Smart parking systems can significantly improve parking lot management, reduce the time spent searching for parking, and enhance driver convenience [7, 8].

This paper proposes a novel intelligent parking assignment framework based on the Cheetah Optimization Algorithm (COA), a bio-inspired metaheuristic inspired by the adaptive hunting behavior of cheetahs. The method integrates user-specific criteria in a multi-stage process. First, it collects system and driver data. Then, COA is applied to optimize parking space allocation. Compared to deep reinforcement learning and other metaheuristics like the Genetic Algorithm and Whale Optimization Algorithm, COA demonstrates faster convergence and improved solution quality. Our findings confirm that COA is an effective and robust approach for real-time, personalized smart parking management in dynamic urban settings.

The rest of the paper is organized as follows. Section 2 reviews existing solutions in smart parking methods. Section 3 describes the proposed method in detail. Section 4 presents the simulation results, and Section 5 offers the conclusions.

2. Related Works

Recent research has proposed various approaches to address intelligent parking space detection and allocation.

Perković *et al.* [9] evaluated the performance of smart parking lot sensors, highlighting the potential of sensors to improve parking lot management, reduce traffic congestion, and enhance driver experience. However, challenges remain in terms of high installation and implementation costs, technical complexities, and concerns regarding privacy and information security.

Mackey *et al.* [10] presented a smart parking system based on Bluetooth low-energy beacons and particle filtering for identifying vacant spaces in central parking lots. This system offers advantages such as high efficiency, reduced installation costs, and compatibility with diverse parking environments. However, it requires a denser deployment of beacons for wider coverage and faces potential signal interference issues.

Alharbi *et al.*[3] proposed a web-based framework for a smart parking system leveraging IoT and web technologies. A key focus of this framework is providing a mechanism for reading car license plates, facilitating real-time information dissemination to drivers and enabling the presentation of parking data statistics. However, reliance on internet connectivity, potential data security vulnerabilities during transmission, and the need for user training pose challenges.

Almeida *et al.* [11] investigated vision-based parking lot management systems using public datasets. These systems offer advantages such as high precision in identifying vacant spaces, real-time information updates, compatibility with various parking environments, and potentially lower installation costs compared to traditional methods. However, they require advanced and complex equipment, raise privacy and security concerns, necessitate suitable infrastructure, and may face performance limitations in adverse conditions.

Canli and Toklu [12] presented an AVL-based settlement algorithm and reservation system for smart parking systems in IoT-based smart cities. This approach aims to enhance parking space allocation accuracy, system efficiency, traffic reduction, and driver comfort, while also providing better services. However, it requires high-speed processing for implementing the settlement algorithm, raises concerns about information security and privacy, necessitates complex infrastructure, and incurs installation and implementation costs.

Alinejad *et al.* [13] proposed an optimal method for managing electric car charging and discharging in smart parking lots, considering drivers' random behaviors. This method aims to optimize charging infrastructure utilization, minimize waiting times, and enhance services for electric vehicle owners while improving energy management and power network efficiency. However, it faces challenges in terms of complex optimization algorithms, the need for updated and precise data, and operational implementation complexities.

Luque-Vega *et al.* [6] introduced an IoT smart parking system called SPIN-V, which utilizes a photography technology-based vehicle presence sensor. SPIN-V offers advantages such as high precision in recognizing vehicle presence, real-time information updates, reduced waiting times, and improved system efficiency. It also contributes to smart city development and enhances driver experience. However, it requires high-speed processing for photography and identification, raises security and privacy concerns, and necessitates installation and implementation costs, along with suitable management and infrastructure for optimal performance.

Zeinalian and Farzaneh [14] presented an on-street parking space proposing method based on the PSO algorithm, considering drivers' personal parameters to propose parking spaces tailored to their demands. This method, while potentially longer in runtime, can handle a greater number of requests.

Zanjireh and Morady [2] introduced a fog computing-based framework where smart cameras at parking entrances and lanes detect vehicles and transmit data to fog nodes. These nodes run a deep learning algorithm that updates reward scores online, enabling effective vehicle detection and vacant parking space identification.

Sotonwa et al. [15] proposed a hybrid optimization method combining Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to achieve faster convergence in solving parking allocation problems. Sahu et al. [16] presented a multi-objective optimization framework for smart parking incorporating digital twin technology, Pareto front optimization, Markov Decision Processes (MDP), and PSO. It constructs a virtual model via digital twin for forward-looking estimation and uses the Pareto front to optimize multiple objectives, such as minimizing search time, energy consumption, and traffic disruption while maximizing parking availability. PSO refines solutions to achieve globally superior distributions. Zhao and Yan [17] developed a multi-agent reinforcement learning (MARL) model for adaptive and dynamic parking allocation. This model leverages reinforcement learning for decision-making based on real-time data and utilizes graph neural networks to capture spatial relationships among parking lots, improving allocation efficiency. Shimi *et al.* [18] introduced a smart multi-storey parking management system named MODM-RPCP, utilizing RFID technology and user preference analysis. This multi-objective decision-making approach aims to reduce average reservation time and server response time.

Finally, Rajyalakshmi and Lakshmanna [19] presented a hybrid dense network optimization (HDDNO) algorithm for predicting parking space availability. This approach combines machine learning and deep learning techniques, employing various optimizers such as Adaptive Moment Estimation (Adam), Root Mean Square Propagation (RMSprop), Adaptive Gradient (AdaGrad),, AdaDelta, and Stochastic Gradient Descent (SGD) to improve prediction accuracy.

These studies highlight the diverse approaches being explored to address smart parking challenges. While significant progress has been made, research gaps remain in areas such as integrating user preferences more effectively, ensuring robust security and privacy, and developing more adaptable and resilient systems that can handle dynamic urban environments.

3. The proposed method

This paper proposes a multi-stage process for identifying parking spaces. Figure 1 illustrates these stages, which are as follows: 1) receiving parking requirements, and 2) utilizing COA to find a suitable parking space.

3.1. Parking System Requirements

The proposed method leverages a parking management system where parking lots announce their available spaces. This system, illustrated in Figure 2, maintains a database of empty parking spaces. The system receives information from each parking lot, including location, number of spaces, and the number of empty and occupied spaces. It then uses this data to allocate the best parking space to each driver based on their individual needs and preferences.

In addition to parking lot information, the system also gathers driver-specific data, such as driver location, urgency of parking need, distance to destination, desired distance to destination, destination address, parking cost limit, parking time requirement. This comprehensive data set enables the system to provide personalized and efficient parking recommendations. The COA is then employed to optimize the parking allocation process based on these factors.

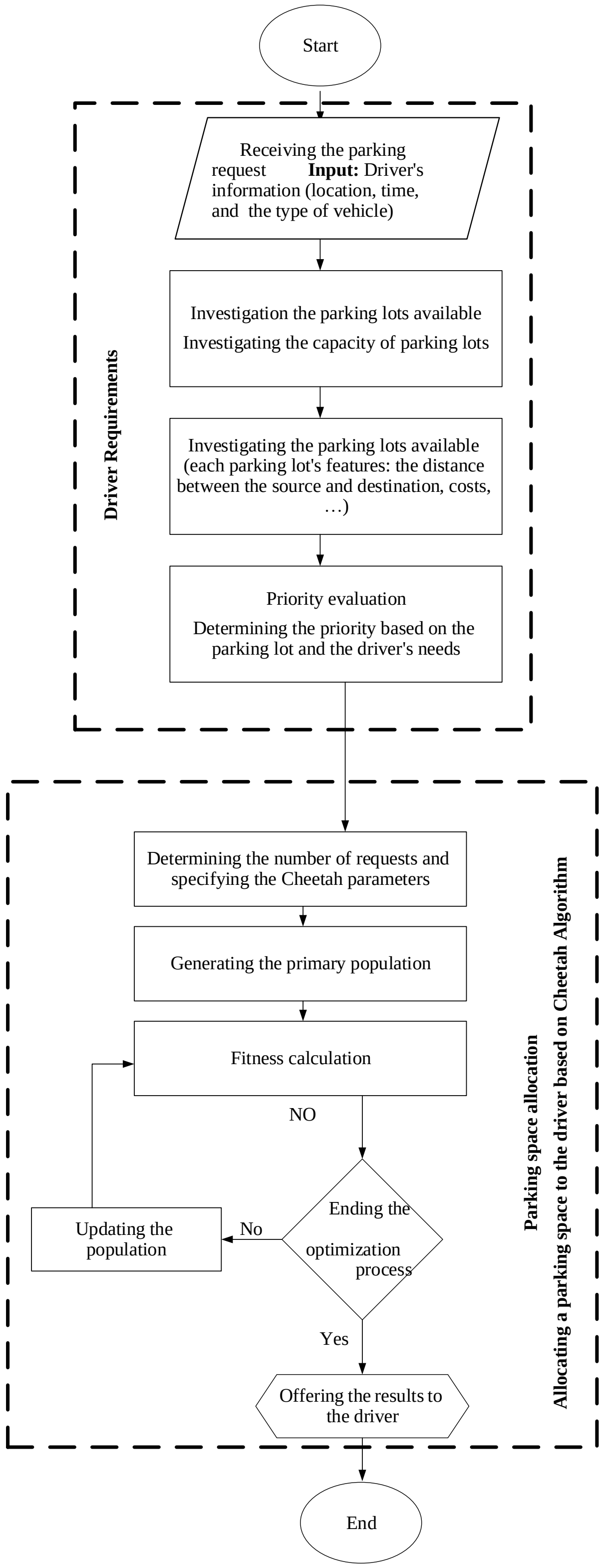

Figure 1. The proposed method flowchart.

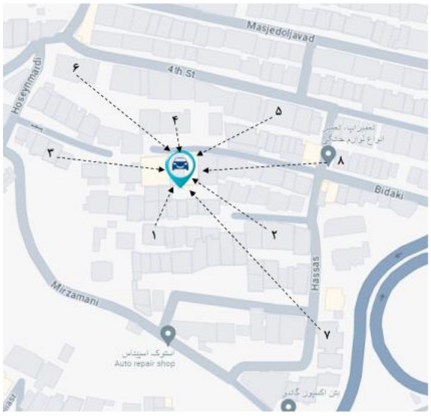

Figure 2. Parking management system.

3.2. Parking Optimization by Cheetah Algorithm

Utilizing COA for allocating parking spaces to drivers is highly justifiable due to its high speed and efficiency. COA specifically considers the optimization of time and resources and is able to allocate the parking spaces available based on the drivers' specific locations and needs in a short time. With the help of machine learning and AI techniques, this algorithm can identify the patterns and predict the future requests which causes the parking space allocation to be effectively done. Moreover, this algorithm creates the possibility of decreasing the urban traffic and congestion because the drivers are quickly and precisely guided towards the nearest and the most proper parking lots. Totally, COA drastically improves the driving experience as well as the efficiency of parking management systems.

In this section, the parking optimization process performed by COA is explained. For finding a suitable parking space based on the driver's request, this algorithm goes through the following process:

- formulation of the problem
- evaluation of the proposed solution
- solution improvement
- ending the optimization process

As mentioned above, for finding the optimal path for parking a vehicle by COA, four processes have been used, as explained below.

3.2.1. Formulation of the Problem

The objective of this section is presenting a mathematical equation to solve the parking problem. For solving this problem, firstly, the system's needs and supply must be determined. In a parking space system, the driver's request and the parking location are among the problem parameters; therefore, for formulating the problem, these two parameters have to be considered. Suppose there are three parking lots and each has 10 parking spaces, so the parking spaces equal 30. In Figure 3, the process of the primary population generation is illustrated.

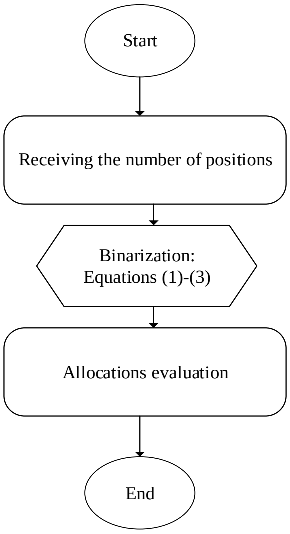

Figure 3. Formulation of allocation problem in Cheetah Algorithm.

In Figure 3, the process of allocating the parking spaces to drivers' requests in COA is indicated, as shown in Table 1.

Table 1. Formulation of parking space allocation problem.

Driver 1		Driver 2		…	Driver ND	
Parking No.	Parking space	Parking No.	Parking space		Parking No.	Parking space
1	3	1	7		2	10

As illustrated, the primary population dimensions for COA equals the number of the drivers' requests which, at the time t, have entered the parking management system, and the parking management system has to allocate a parking space to each request based on the empty spaces. One of the limitations of the problem is the empty spaces; in better words, only one parking space must be allocated to each driver.

COA is a continuous algorithm, but the optimization of finding a parking space is a discrete problem. Normally, this algorithm cannot be used for optimizing the parking space problem; therefore, it must be modified in a way that could solve the problem considered. In the present paper, the Limiting Values Method has been utilized. In other words, for each driver, a random number (between 1 and P+1) is considered so that the following mathematical equation is established:

$$x_i \in [1, P+1] \tag{1}$$

Having the population determined, the lower limit equation is used for changing the continuous data to discrete data as:

$$x_i = \lfloor x_i \rfloor \qquad (2)$$

The continuous data is changed to discrete data by using (2). For instance, number 1.5 changes to 1, and number 29.3 changes to 29; number 1 indicates the first parking space, and number 29 indicates the 29th parking space. Also, to determine the parking number, one can divide the number considered by the number of parking spaces available in each parking lot (n_p). For obtaining the parking number (NP), the following equation is used.

$$NP = \left| \frac{x_i}{n_p} \right| \qquad (3)$$

The solutions obtained are randomly generated in COA. In other words, for each driver, a random number (between 1 and P) is considered. P indicates the number of the locations available for parking a vehicle. The number of the populations considered is shown by N in the proposed method.

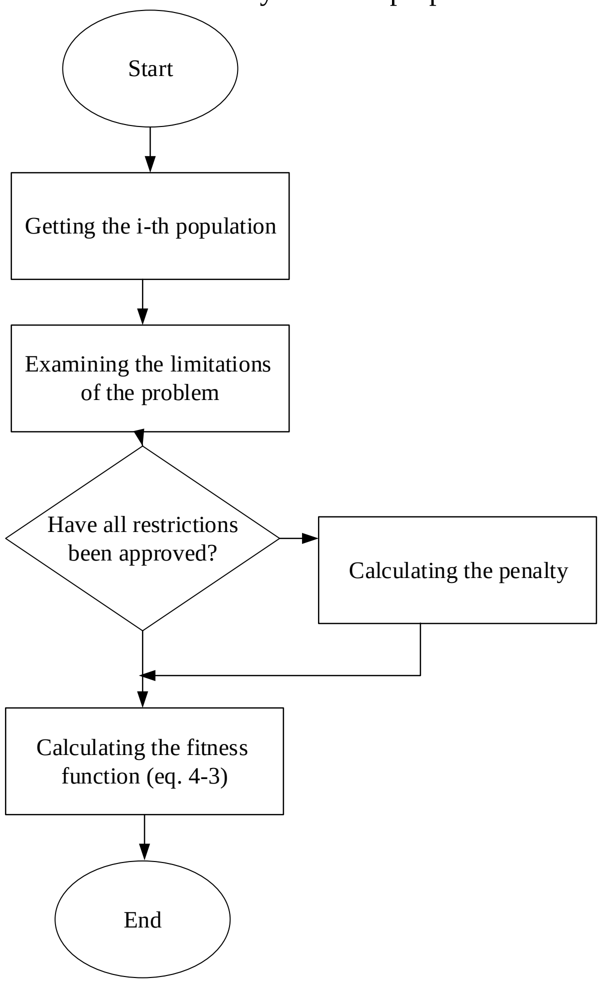

Figure 4. The solution evaluation process for each population.

3.2.2. Evaluation of the proposed solution

One of the important parts of the proposed method is the evaluation of the generated solution. As mentioned in the previous section, the solutions are randomly determined in the primary population. The solutions must take the system limitations into account. The limitations considered in the present study are as follows:

1) Only one parking space should be allocated to each driver.
2) All the drivers' requests should be answered.
3) The parking cost should not be more than the cost determined by the driver.
4) The time that the driver needs to reach his destination from the parking space should not be longer than the time during which the car is parked.
5) Each parking space at moment t should be allocated to only one driver.
6) The number of the vehicles allocated to each parking lot should not be more than the parking capacity.

In Figure 4, the solution evaluation process is illustrated.

Now, based on the limitations considered, the present paper objective is determined, as indicated in (4):

$$\begin{aligned} F = \min(&W_1 * \sum_{i=1}^{n} x_i + \\ &W_2 * \sum_{i=1}^{n} y_i + \\ &W_3 * \sum_{i=1}^{n} z_i) \end{aligned} \qquad (4)$$

In (4), F indicates the target function, x symbolizes the time of requesting a parking space, y shows the time that the driver spends reaching the destination from his current location, z states the distance between the parking space and the driver's destination, and n is the number of the vehicles requesting a parking space. W_1, W_2, and W_3 are the coefficients of the target function significance whose total weight must equal 1; this limitation is stated in (5):

$$\sum_{i=1}^{3} W_i = 1 \qquad (5)$$

3.2.3. Solution improvement

One of the important steps of obtaining the optimal answer is changing the primary solutions. The primary solutions have randomly been determined, therefore, they must be changed in a way that leads to a superior solution. Also, the generated solutions must take the variety of answers into account. If the variety of answers in the solutions considered is not taken into account, the algorithm is situated in local optimum. Local optimum is a situation in the problem in which the algorithm stops being improved; in other words, if the algorithm is trapped in such situation, it cannot reach the global optimum.

COA improves the population considered; such improvement can change the correct answer to an incorrect answer. Each parking space can merely be allocated to one population, therefore, if there are several repetitive locations in population updating process, the new population must be modified.

The following procedure (Figure 5) is utilized for modification. The procedure is illustrated for a better understanding (in this example, the number of requests is supposed to be 6 and the number of parking spaces capable of being allocated is supposed 8):

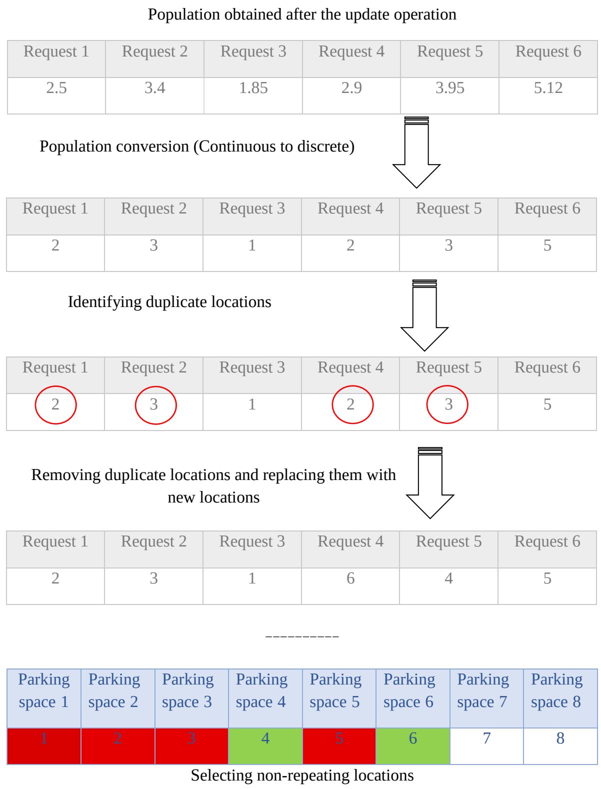

Figure 5. Population modification.

3.2.4. Ending the optimization process (Stopping Condition)

In the present paper, for stopping the optimization process, the iteration method is used. In this method, the algorithm finishes when it reaches a specific iteration number. The number of the iterations considered in this paper is 100.

3.2.5. Advantages of using COA

1. **Rapid Convergence Speed**
   The COA is inspired by the high-speed hunting behavior of cheetahs, enabling it to achieve fast convergence towards optimal or near-optimal solutions. This characteristic is particularly critical for smart parking applications where real-time or near-real-time decision-making is required.
2. **Effectiveness in Complex and High-Dimensional Search Spaces**
   As a metaheuristic optimization technique, COA efficiently explores large and complex search spaces without relying on gradient information or explicit mathematical modeling. This allows for robust identification of optimal parking spots in dynamic urban environments with multiple constraints.
3. **Balanced Exploration and Exploitation**
   COA maintains a well-designed balance between exploration (searching broadly across the solution space) and exploitation (intensifying the search near promising solutions). This balance minimizes the risk of premature convergence to local optima and enhances the quality of the obtained solutions.
4. **Independence from Extensive Historical Data**
   Unlike data-driven machine learning methods that require vast amounts of historical data for training, COA operates effectively with limited prior information. This makes it well-suited for scenarios where data availability is constrained or environments frequently change.
5. **Computational Efficiency and Ease of Implementation**
   The algorithm's relatively simple structure facilitates straightforward implementation and demands lower computational resources compared to deep learning-based approaches. This efficiency is advantageous for integration into embedded systems or real-time smart parking management platforms.
6. **Flexibility for Integration in Intelligent Urban Systems**
   COA can be seamlessly incorporated as an optimization module within larger smart city infrastructures, interoperating with sensor networks and traffic management systems to enhance overall parking utilization and reduce congestion.

3.2.6. Innovation of the proposed method

This study introduces a novel framework for intelligent parking space allocation that explicitly incorporates individual user preferences—such as cost constraints, proximity to destination, and other customizable criteria—into the optimization process. This user-centric approach distinguishes our method from conventional models, which often overlook personalized requirements and treat parking allocation as a purely static or uniform problem.

The adoption of COA is a key innovation, leveraging its rapid convergence and adaptive search phases to efficiently handle the dynamic and multi-objective nature of the parking problem. The COA's balance between exploration and exploitation enables timely decision-making, essential for real-time applications in diverse parking environments, including multi-story facilities and on-street parking.

To our knowledge, this is among the first applications that combine a bio-inspired metaheuristic with fast convergence properties with multi-criteria user-driven optimization in the domain of smart parking. This integration significantly enhances both computational efficiency and the relevance of the suggested parking spaces to individual users' needs.

4. Simulation results

In this section, the results of the proposed method are stated. In Figure 6, the characteristics of the system are indicated for simulating the proposed method.

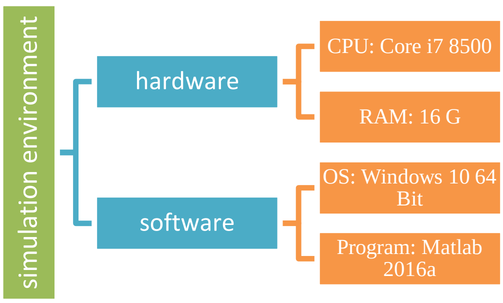

Figure 6. Simulation environment characteristics.

4.1. Evaluation Criteria

To evaluate the proposed method, the following criteria have been used:

- percentage of the requests and allocated parking spaces,
- percentage of answering the drivers in terms of distance,
- percentage of answering the drivers in terms of cost,
- answering the drivers' requests,
- The distance to the parking lot.

In the following, the results of the proposed method are explained. These results have been compared to the following three methods: *WOA, PSO_GA[15], and DRL[17].*

4.2. Evaluation of results

In this section, the results of the proposed method have been compared to other evaluation methods. Before stating the proposed method, firstly, the characteristics of the simulation environment are mentioned:

- The number of the requests is considered to be variable (between 50 and 400 requests).
- The number of parking lots is considered 5, and the capacity of each is considered 20 vehicles.
- The size of the simulation environment is considered to be 100 meters by 100 meters.

The number of the requests is considered to be variable (between 50 and 400 requests). Also, the number of parking lots is considered 20, and the capacity of each is considered 20 vehicles.

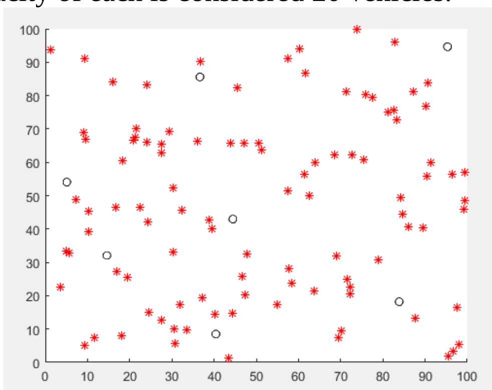

Figure 7. Characteristics of the simulation environment in second scenario.

In Figure 7, the characteristics of the simulation environment are illustrated. In this figure, the stars symbolize the requests related to the parking, and the circles symbolize the parking situation.

To show the efficiency of the proposed algorithm (COA), this method has been compared with methods WOA, PSO_GA[15], and DRL[17].

One of the important objectives of the proposed method is increasing the rate of answering the drivers. In Figure 8, the percentage of answering the drivers by the system regarding parking allocation is illustrated. The more requests, the less answering percentage because, in the proposed method, five parking lots have been used each owning 20 parking spaces; therefore, when the number of requests is less than 140, maximum system efficiency is observed. However, when the number of requests is more than the parking spaces, the systems won't work properly. In the proposed method, due to a proper system of allocating the vehicles to parking spaces, more vehicles are investigated; therefore, the answering percentage has increased. In the proposed method, in each time interval, a number of requests are examined together and the gaps between them are allocated according to the request characteristics. In other methods, each request is examined individually, which may cause the obtained answers not to be in the best overall state.

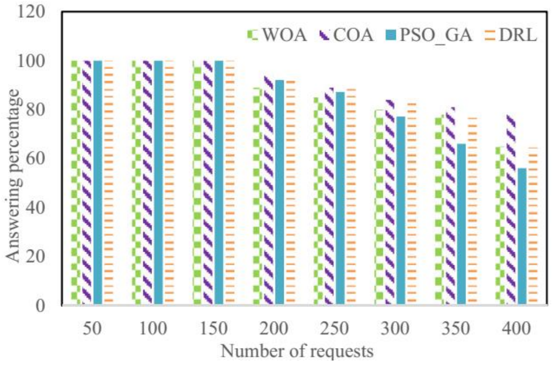

Figure 8. Percentage of answering the drivers by the system regarding parking allocation.

One of the input parameters of the algorithm is the maximum distance expected by the driver from the parking space to the destination; two scenarios may occur:

- The driver distance relative to the determined parking space is less than or equal to the determined distance.
- The driver distance relative to the determined parking space is more than the determined distance.

In this situation, the first scenario is considered the correct, and the second scenario is considered the incorrect recognition.

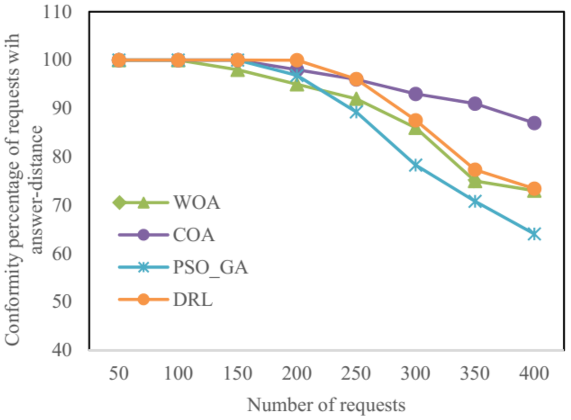

Figure 9. Conformity percentage of the requests with the determined parking spaces in terms of distance.

In Figure 9, conformity percentage of the requests with the determined parking spaces in terms of distance is shown. PSO_GA algorithm is in local optimum; therefore, it cannot do a proper allocation process; as a result, the conformity level of the requests decreases.

Investigating the time spent on receiving a parking space can cause the driver's satisfaction or dissatisfaction. To better understand this issue, suppose that the driver sends his request at 8:33′ and the system determines the parking space at 8:36′; in this case, the time interval between the request and the answer equals 3. Definitely, the shorter the interval, the more satisfied the driver.

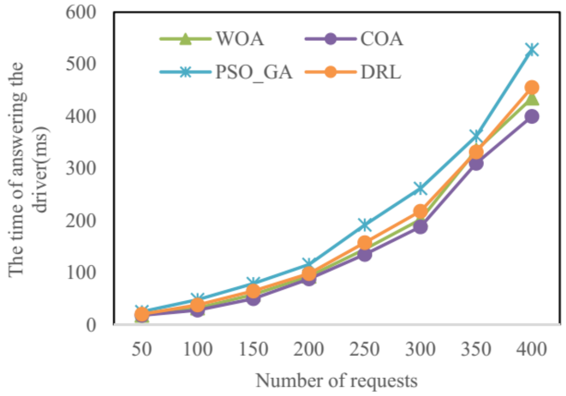

Figure 10. The time of answering the driver.

In Figure 10, the time of answering the driver is determined. As illustrated in this figure, the more requests, the longer the answering time because the number of requests has exceeded the parking spaces; this creates a waiting time, and a waiting time postpones the answering time.

The cost of the determined parking relative to the cost determined by the driver leads to two conditions as follows:

- The driver cost is less than or equal to the determined parking cost.
- The driver cost is more than the determined parking cost.

The first condition is considered the correct, and the second condition is considered the incorrect recognition. In the DRL method, the objective function is to minimize the response time to the driver, so as can be seen in Figure 10, this algorithm has a shorter response time than methods PSO_GA and WOA.

As illustrated in Figure 11, the more requests, the more driver cost for receiving a parking space because, in this situation, a proper parking space is not allocated to the driver leading to a decrease in conformity percentage. The main problem with PSO_GA method is getting stuck in a local optimum, which causes the allocations not to be done optimally and the target parameters not to be optimally met.

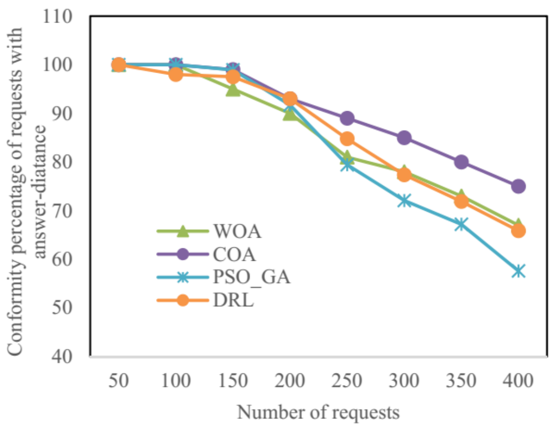

Figure 11. Conformity percentage of the requests with the determined parking spaces in terms of cost.

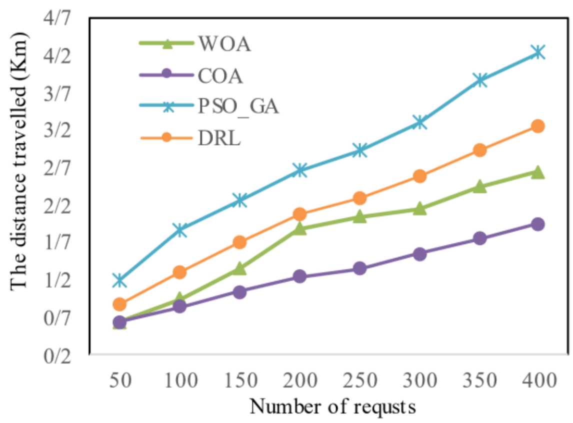

Figure 12. Distance travelled by the driver to the parking space.

In Figure 12, the distance travelled by the driver to the parking space is shown in kilometers. As observed in this figure, as the number of requests increases, the distance lengthens. In other words, when the requests for parking space (the better spaces having been allocated before) increase, the distance the driver travels to reach the parking space lengthens. In PSO_GA, WOA, and DRL, this parameter is not taken into account and the only goal is to allocate an empty parking space to the driver in the shortest possible time. The proposed method is a multi-objective method and one of the most important features is that it provides the possibility of personalized parking space reservation based on the user's required parameters.

4.3. Investigating the impact of algorithm parameters

In this section, the impacts of COA parameters (iteration and number of Cheetahs) on the proposed method's performance was investigated. The number of the requests, parking lots, and size of the simulation environment are respectively 200, 10, and 200 ×200 m². Figure 13 shows the number of cheetahs directly affects the convergence, stability, accuracy, and speed of problem solving in COA.

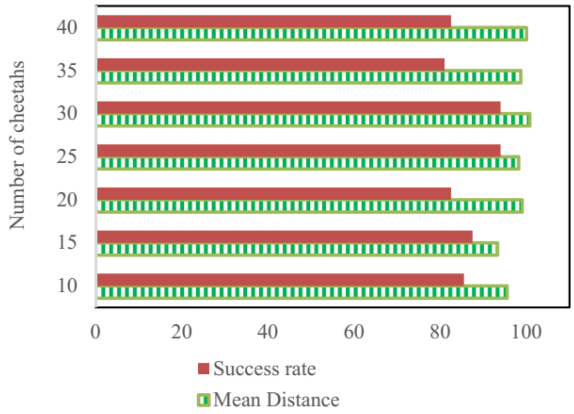

Figure 13. The effect of the number of Cheetahs on the average parking distance to the destination.

Too many cheetahs may increase execution time without significantly improving the quality of the solution. Too few cheetahs may also cause the algorithm to tend towards poor solutions early in the process (getting stuck in a local minimum).
The optimal choice of this parameter requires trial and error or the use of auto-tuning methods.
Figure 14 shows the effect of the number of iterations of the algorithm.

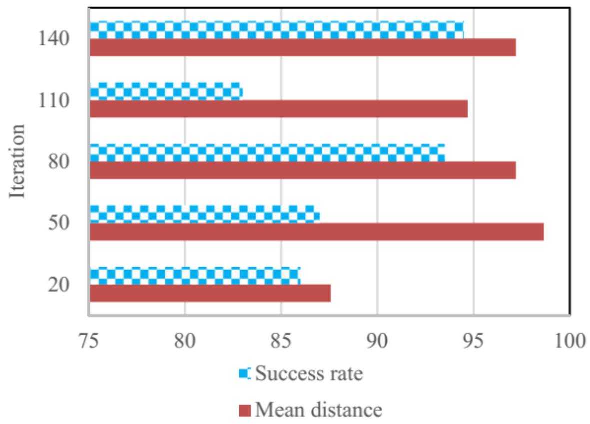

Figure 14. The effect of the number of iteration on the average parking distance to the destination.

As shown in the figure, increasing the number of iterations generally improves solution quality and enhances convergence. However, excessive iterations prolong computational time while yielding diminishing returns in improvement. Like many evolutionary and swarm intelligence algorithms, the COA exhibits rapid progress in early iterations, but its rate of improvement slows over time, eventually converging to a stable value. Beyond a certain point, further increases in iterations provide only negligible gains in solution quality. Thus, selecting an optimal number of iterations is crucial to balancing solution accuracy and computational efficiency.

4.4. Examining the problem size and scalability of the proposed method

This section examines the impact of increasing problem dimensions, including area size and the number of parking lots. The number of the requests, number of cheetahs, iterations of the algorithm are respectively 200, 30, and 100. The size of the simulation environment is considered to be 200 ×200 m². Figure 15 shows the success rate relative to the number of parking spaces. In the field of smart parking, the number of parking spaces plays an important role in the success rate of the system. The success rate usually refers to the percentage of success in finding a parking space and, as a result, the level of satisfaction of users with the system's services. As seen in Figure 15, the greater the number of parking spaces, the greater the probability that users will find a parking space. This leads to an increase in the success rate of the system in guiding cars to free parking spaces.

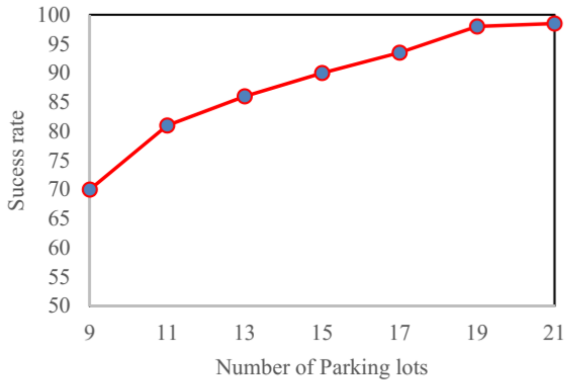

Figure 15. Success rate in parking allocation (number of requests 200 and area size 200 * 200)

Figure 16 shows the effect of the size of the environment on the average distance from the parking lot to the destination. The number of parking lots is assumed to be constant (7).

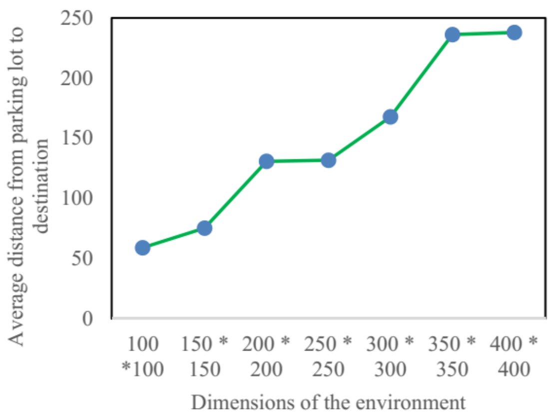

Figure 16. The average parking distance to the destination is 200 requests and the number of parking spaces is 7.

As the area size increases, the distance between different points increases. Naturally, the average distance increases too. As seen in Figure 16, even with a smart parking system, when the number of parking spaces is limited, the driver may be directed to the farthest parking space.

5. Conclusion

This paper presents an adaptive, user-centric smart parking allocation system based on COA. The proposed framework integrates individual user preferences—such as economic cost and spatial proximity—into a real-time, multi-objective optimization process. The methodology follows a multi-stage approach: first, system requirements are defined, including parking lot characteristics and driver needs. Next, COA is applied to identify optimal parking spaces based on these inputs.

Experimental results demonstrate that COA outperforms conventional metaheuristics, including Genetic Algorithms and the Whale Optimization Algorithm, in convergence speed and solution accuracy. Moreover, unlike deep reinforcement learning methods—which often demand large training datasets and significant computational resources—COA offers a lightweight, scalable solution suitable for dynamic urban environments with limited data availability.

COA's ability to adapt to environmental changes while maintaining optimization performance highlights its potential for integration into intelligent transportation systems and smart city infrastructures. Future research could explore hybridizing COA with data-driven learning techniques to enhance adaptability, scalability, and practical applicability in large-scale deployments.

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سیستم پیشنهاددهنده‌ی جای پارک چند معیاره مبتنی بر الگوریتم بهینه‌ساز چیتا

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چکیده:

تخصــیص کارآمد فضای پارکینگ در محیط‌های شهری به دلیل ترجیحات متنوع کاربران، مانند هزینه، نزدیکی و راحتی، همچنان یک چالش مهم است. این مقاله یک چارچوب تخصـیص پارکینگ هوشـمند جدید مبتنی بر الگوریتم بهینه‌سازی یوزپلنگ (COA) ارائه می‌دهد، یک فراابتکاری الهام گرفته از طبیعت که از رفتار شـکار تطبیقی یوزپلنگ‌ها الهام گرفته شـده اسـت. این سیستم معیارهای خاص کاربر را در یک فرآیند چند مرحله‌ای ادغام می‌کند، ابتدا داده‌های سـیسـتم و راننده را جمع‌آوری می‌کند، سـپس COA را برای بهینه‌سازی تخصیص فضای پارکینگ اعمال می‌کند. در مقایسه با یادگیری تقویتی عمیق و سـایر فراابتکاری‌ها مانند الگوریتم ژنتیک و الگوریتم بهینه‌سـازی نهنگ، COA همگرایی سـریع‌تر و کیفیت راه‌حل بهبود یافته را نشـان می‌دهد، که با کاهش زمان پارکینگ و افزایش رضـایت کاربر اندازه‌گیری می‌شـود. نتایج تأیید می‌کند که COA یک رویکرد مؤثر و قوی برای مدیریت پارکینگ هوشمند شخصی‌سازی شده در زمان واقعی در محیط‌های شهری پویا است.

کلمات کلیدی: اینترنت اشیا، سیستم پیشنهاد فضای پارکینگ، الگوریتم تکاملی یوزپلنگ.