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Comparison of Genetic Algorithm and Particle Swarm Optimization Techniques in Intelligent Parking System

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ABSTRACT

The search for parking space is a time consuming process which not only affects the economic activities efficiency but also the social interaction and cost. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) were simulated to allocate parking space for vehicles by sending request by request handler to route generator to allocate optimal route from source to destination using Matric Laboratory (MATLAB) Software in an intelligent parking system. This was measured by some parameters such as time taken, cost and user satisfaction. Unlike GA that required some genetic operations which made it unable to handle complexity that increase search space; PSO required small number of parameters and correspondingly lower iteration which made it best alternative. Also, PSO always choose a parking space that can be reached with deadline and within the budget imposed by user, traffic and free slots which made it to achieve high user satisfaction, saves time and cost effective.

Keywords

Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Matric Laboratory (MATLAB) Software.

Introduction

Human mobility is a necessity in today's world. It has a significant impact on both quality of life and the economy of modern societies, to this effect transport system is a key element in developed or developing countries. Out of all the different modes of transport, the one that is used on a massive scale is land transport by road. Transportation systems indicated that 40% of the world population spend at least one hour on the road every day [1]. Such large-scale use of this type of transport has led to congestion problems in densely populated metropolitan areas with all the concomitant negative consequences.

The negative consequences include pollution and its harmful effects on the environment and human health [2]. Too much time on the road means an increase in energy consumption which has a negative impact on both individual and national economies as well as on the environment. Several medical studies have confirmed that road transport congestion results in a deterioration of public health because it increases the risk of heart and respiratory diseases [3]. Moreover, according to the WHO over 7 million people die every year from health problems caused by pollution. One of the causes of this excessive amount of time spent on the road in private road transport is the need to spend time looking for free parking spaces.

Use of these auto mobiles has increasingly posed a demand for infrastructure to manage the parking. All around the world, parking spaces have been constructed and control points put in place. For example, in shopping malls and airports some control points are automated whereby users can do a self-service in the use of the parking space while others are manned by control personnel. On the other hand, parking attendants have been employed in physically controlled parking ways to direct drivers where parking is empty [4].

The systems in place today for managing parking areas have helped a lot in ensuring that motorists easily park and easily leave their destinations. However, the demands of motorists in the fast working environment raise a need for a next generation of parking systems to match the pace at which they work. It is expected that such next generation parking systems will enable remote parking reservation and exhibit some of the features of modern real-time systems such as cell phone payment and car identification using Radio Frequency Identification (RFID) technology. It is predicted that such smart parking systems will play an important role in the transport field in terms of environment impact on climate change and commuter's savings and time management [4].

Meta-heuristic Optimization Techniques

Heuristics are computational methods used to find good and feasible solutions to complex optimization problems, (randomness or local search) [5][6] especially many real-world problems that are combinatorial in nature [7]. Two essential components of meta-heuristics which determine their behaviours are intensification and diversification [8][9] but the balance between these two components is pivotal to the quality of any meta-heuristic solution. Examples of meta-heuristic algorithms that will be considered in this article are Genetic Algorithm (GA) and Particle Swamp Optimization (PSO) Algorithm.

GA, initially a set of solution or a population would be randomly generated. Then at each iteration by using fitness function which is problem domain specific would select the fittest solutions. Most of these functions are stochastic so that only a small proportion of less fit solutions would be selected. This is done to keep the diversity of the population large and to avoid premature convergence and poor solutions. Then would test the selected solutions to find whether the optimal solution is found; if not found, recombination and mutation would be applied to breed the next new solution and this is repeated till the optimal solution is found or fixed number of generation is reached [10,11].

PSO is a nature-inspired algorithm that draws on the conduct of flocking birds, social interactions among humans, and the schooling of fish. Specifically, PSO is a meta-heuristic algorithm that was inspired by the collaborative or swarming behavior of biological populations [12]. PSO is becoming one of the most important swarm intelligent paradigms for solving global optimization problems [13]. This algorithm has unfathomable intelligence background and is appropriate for scientific research and engineering application. Therefore, PSO algorithm has triggered the widespread attention of researchers in the field of evolutionary computation, and has attained a lot of research results over the years [14].

Review of Related Works

Various authors have looked at developing sensor-based technological solutions to improve the use of parking spaces. A wireless sensor network deployed in indoor car parks that showed the occupancy status of each parking space was proposed [15]. Motes (sensor nodes) equipped with acoustic and light sensors are located in each space, and periodically notify whether the space is occupied or available. A vision-based parking management system to manage an outdoor car park using cameras set up around the parking space, sending information, including real-time display, to the ITS centre database was also presented [16].

A scientific solution based on a GPS-based vehicle navigation system was recommended by [17] who modelled the availability of a car park using the poisson process and an intelligent algorithm which helped the driver to choose the parking space with the highest probability of being vacant. A combination of magnetic and ultrasonic sensors to control car parks was suggested. This system was based on a modified version of the min-max algorithm for detection of vehicles using magnetometers and an algorithm for ultrasonic sensors [18].

Srikanth *et. al.,* [19] suggested an intelligent parking management system, consisting of a wireless network that used different types of sensors to detect the presence of a vehicle in every one of the parking spaces; the system informed users and guided them to the location of the available space via network's sensor nodes that communicate by radio frequency.

Magrini [20] proposed a vision sensors network to monitor available spaces in public car parks, using distributed network nodes to perform the required processing and analysis of images while Chen and Cheng [21] proposed a system for locating available spaces in indoor car parks and a guidance system to locate the available space. The architecture of this system is based on a wireless network of ultrasound sensors that detect the presence of a vehicle in each of the parking spaces. The status of each space is transmitted by a sensor node that sends this information via RFID to special routing nodes, which communicate with each other to relay the data packets sent by the sensor nodes to the control centre with a tree topology.

Gu *et. al.,* [22] proposed a system for managing parking spaces on public roads. The system is called Street Parking System (SPS), and uses a three-axis magnetic sensor to detect vehicles and ZigBee technology for wireless communications, achieving a reliability rate close to 99% in vehicle detection. Reve and Choudhri [23] also proposed a similar system, based on a wireless sensor network and LED display system that indicated the available spaces to drivers at the car park access points. Yang *et. al.,* [24] presented a prototype smart parking services system, based on Wireless Sensor Networks (WSNs), for finding free parking spaces. The proposed scheme consists of wireless sensor networks, an embedded web server, a central web server, and a mobile phone application. Each parking space has alight sensor node that detectd the status of the parking space, reporting periodically to the embedded web server via the wireless sensor networks; displaying the status of the parking spaces on the driver's mobile device.

Geng and Cassandra [25] proposed a smart parking system for urban areas. The system's functions include parking detection, reservation guarantee and Vehicle-to-Infrastructure (V2I) or Infrastructure-to-Vehicle (I2V) communication. Considering the requirements of the user, the system assigns and reserves an optimal parking space combining proximity to destination and parking cost, ensuring that the overall parking capacity is efficiently utilized. Tian *et. al.,* [26] proposed an intelligent parking management system based on License Plate Recognition (LPR), which recognized the license plate automatically at the car park access point and provided vehicle information; experimental results showed that this parking management system can achieve 95% accuracy, and can be applied to real-time implementation.

Bagula *et. al.,* [15] classified intelligent vehicle parking space management systems according to the type of sensor detection. He distinguished the systems that monitor the entry or exit of vehicles from the systems that were able to detect whether each parking space is occupied or free. Systems belonging to the first type are easier to deploy and less expensive, appropriate for monitoring the occupancy levels of large outdoor parking areas while systems belonging to the second type provide more useful and more detailed information to users and may be combined with positioning and guidance services to help locate the available spaces. This type of system is used in indoor parking spaces and is more complex and expensive than the entry and exit monitoring systems, as it required that each parking space is equipped with sensors and a more sophisticated communications infrastructure.

Moorthy and Pabitha [27] defined car parking as one of the major problems in a city with high vehicular density. Route allocator was used to find the parking space along with the optimal route to reach the destination. The simulated work using Eclipse IDE was compared with Greedy approach and Random allocation. The results showed that the proposed work achieved better result in terms of time taken, cost and user satisfaction.

Alam *et. al.,* [28] presented a new architecture where the intelligence was distributed and the decisions were decentralized. The proposed architecture was scalable since the incremental addition of new peripheral subsystems was supported by the introduction of gateways which required no reengineering of the communication infrastructure. The LED display system was deployed to tackle the problem of traffic management efficiency in urban areas, where traffic load was substantially increased, by vehicles moving around unnecessarily and to find a free parking space. This can be significantly reduced through the availability and diffusion of local information regarding vacant parking slots to drivers in a given area. Two types of parking systems, magnetic and vision sensor based were introduced, deployed and tested in different scenarios. The effectiveness of the proposed architecture together with the proposed algorithms was assessed in field trials.

Mishra *e.t al.,* [29] presented a low cost IoT based vehicle parking system for a smart city using a cloud computing model: Platform-as-a-Service (PaaS). A HCSR-04 based ultrasonic sensor was used to detect the proximity of a car in a parking lot and detect the status of occupancy of a slot in the parking zone. An IR sensor was deployed at the entry and exit gate to sense the number of car in the parking zone. This prototype and proof of concept were designed using Arduino UNO aided with an ESP-32 NodeMCU for sending the sensor data to a ThingSpeakTM cloud. A Blynk Android app PaaS was used to give user notification for the availability of parking online to users and a resource optimization technique was proposed based on the real time sensor data. This optimization technique aided in a dynamic parking tariff and load balancing strategy for parking spaces in smart cities.

Material and Methods

Experimental Setup of GA and PSO

Parking space allocation depends on dynamicity of parameters like traffic, free slots available, distance and cost; using route allocator to find the parking space along with the optimal route to reach the destination. The simulation of a GA and PSO to allocate parking space for vehicles using MATLAB software is explained and the algorithms for GA and PSO are given below:

Step 1: Generate random population of N, set parameter crossover probability *pc*, mutation probaility *pm*.

Step 2: Evalaute objective function $F_{ij}(t) = f(\vec{x}_{ij}(t)$ based on initial space allocation:

$$\vec{x}_{ij}(t) = Minimize \sum_{i}^{n}\sum_{i}^{m} e^{C_{ij}X_{ij}} \ subject\ to$$

$$\sum_{i=1}^{n} X_{ij} \leq T_j \ \forall j = 1,..,m \ L_i \leq \sum_{j}^{m} X_{ij} \leq U_i \ \forall j = 1,..,n$$

Where i = 1…..m is the set of entity indices, j = 1…….n is the set of space area indices.

$\boldsymbol{C_{ij}}$ is the cost of assigning an entity i to a space area j

$\boldsymbol{T_j}$ is the total space capacity;

$\boldsymbol{L_i}$ and $\boldsymbol{U_i}$ are the lower and upper bound of the number of entities to be allocated.

Step 3: Perform the following operations:

(a) Selesction

(b) Recombination

(c) Mutation

Step 4: Generate new selecred space alolcation cost

Step 5: Go to Step 3 until maximum iteration is reached

Step 6: Output selected space allocation cost based on best fitness value

Step 1: Generate random population of N, set parameter ω_{min}, ω_{max}, C_1 and C_2 of PSO

Step 2: Initialize population of particles havinf positions X_j and velocities V_j

Step 3: Set itersation $k = 1$

Step 4: Calculate fitness of particles $F_{ij}(t) = f\vec{x}_{ij}(t))$and find the index of the best particle *b*.

$$\vec{x}_{ij}(t) = Minimize \sum_{i}^{n}\sum_{j}^{m} e^{C_{ij}X_{ij}} \ subject\ to$$

$$\sum_{i=1}^{n} X_{ij} \leq T_j \ \forall j = 1,..,m \ L_i \leq \sum_{j}^{m} X_{ij} \leq U_i \ \forall j = 1,..,n$$

Where i = 1,..,m is the entity indices, j = 1,...,n is the set of space area indices

C_{ij} is the cost of assigning an entity i to a space area j

T_j is the total space capacity;

L_i and U_i are the lower and upper bound of the number of entities to be allocated.

Step 5: Select $Pbest_{ij}(t) = \vec{x}_{ij}(t)$ and $Gbest_{ij} = x_{bj}(t)$

Step 6: $\omega = \omega_{max} - k * \frac{\omega_{max} - \omega_{min}}{Max_{no} - \omega_{min}}$

where k is the current iteration, ω_{max} is the final weight, ω_{min} is the initial weight, ω is the inertia weight employed to overcome the problem of premature convergence

Step 7: Update velocity and position of particles:

$$\vec{v}_{ij}(t+1) = X\omega\vec{v}_{ij}(t) + c_1 r_1 \left(P_{best} - \vec{x}_{ij}(t)\right) + c_2 r_2$$

$$\left(P_{best} - \vec{x}_{ij}(t)\right) + c_3 r_3 \left(G_{best} - \vec{x}_{ij}(t)\right) x_{ij}(t+1)$$

$$= \vec{x}_{ij}(t) + \vec{v}_{ij}(t+1)$$

Step 8: Evaluate fitness $F_{ij}(t) = f(\vec{x}_{ij}(t+1))$ and find the index of the best particle b_1

Step 9: Update Pbest ofg population:

$$if\, F_{ij}(t+1) < F_{ij}(t)\ then\ Pbest_{ij}(t+1)$$

$$= \vec{x}_{ij}(t+1) else\ Pbest_{ij}(t+1) = Pbest_{ij}(t)$$

Step 10: Update Gbest of population:

$$if\, F_{bj}(t+1) < F_{bj}(t) then\ Gbest_j(t+1) =$$

$$Pbest_{bj}(t+1)\ and\ set\ b = b_1\ else\ Gbest_{bj}(t+1)$$

$$= Gbest_t(t)$$

Step 11: If $k < Max\_no$ then $k = k + 1$ and go to Step 2 else go to Step 11

Step 12: Output optimum solution as $Gbest_{bj}$. $Gbest_{bj} = x_{bj}(t)$

The System Design

The optimal allocaion of route to user's request in the real time environment is a challenging task. The parking space allocation problem can be viewed as selecting a route from source to destination, which is optimal in terms of distance and time thereby minimizing the waiting time of the vehicle and maximizing satisfaction of users. The factors to be taken into account while choosing optimal route is given below:

- Request handler receives the request from any number of homogenous vehicles (car) at time *t*.
- Every vehicle V_k submitted by the user needs to be allocated a parking space P_{sj} which satisfies the parameters like distances, cost and time.
- Optimal allocation of a parking space P_{sj} or the vehicle V_k is viewed as constraint satisfaction problem and it formulated using integer linear programming.

Let the number of users be N_i, the number of parking spaces P_s while the source and destination of the i^{th} user given as S_i and D_j. The objective is to allocate the optimal route from source to destination, which saves time and cost. The route consists of set of paths from source to destination. The route network can be represented as a graph, which represents the set of parking spaces, and represents the edges between them.

Representation of User Request

The vehicle V_k for the user is represented as:

$$V_k \leftarrow \{(V_k)_{id}, Source_{Vk}, Destination_{Vk}, Deadline_{Vk}, Budget_{Vk}\} \ldots\ldots..(1)$$

where $(V_k)_{id}$ represents vehicle id

$SourceV_k$ represents starting place of V_k

$DestinationV_k$ represents end place of V_k

$DeadlineV_k$ represents the maximum time before which the V_k should reach $DestinationV_k$ and

$BudgetV_k$ represents the total cost required to process the user request.

Representation of Parking Space

The parking space P_{Sj} is represented as:

$$P_{Sj} \leftarrow \{(P_{Sj})_{id}, Cost_j, free\_slots\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(2)$$

where $(P_{Sj})_{id}$, represents the parking space id

$Cost_j$ represents the cost per hour for the vehicle V_k and

$free\_slots$ represent the available free slots in parking space P_{Sj}

Representation of Route

A route R_k from source destination is represented as:

$$R_k \leftarrow (S_i - PS_a - PS_c - PS_d - PS_f - D_j) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(3)$$

where S_i and D_j represents the source and destination respectively and each PS_u represents the parking space, i.e. $PS_u \in \{PS\}$. Similarly, there are n numbers of routed available between source and destination.

Problem Formulation

The mathematical formulation of the space allocation problem is given as:

$$Minimize \sum_i^n \sum_i^m C_{ij} X_{ij} \tag{4}$$

$$\sum_i^n X_{ij} \le T_j \forall j = 1, \ldots\ldots\ldots\ldots, m \tag{5}$$

$$L_i \sum_i^m X_{ij} \le U_j \forall j = 1, \ldots\ldots\ldots\ldots, m \tag{6}$$

where $i = 1 \ldots.. m$ is the set of entity indices

$j = 1 \ldots. n$ is the set of space area indices

C_{ij} is the cost of assigning an entity i to a space area j

T_j is the total space capacity

L_i and U_i are the lower and upper bounds of the number of entities to be allocated. Equation (5) indicates that the total number of allocations must not exceed the space area capacity and Equation (6) represents the constraints of the lower and upper bounds.

Results and Discussion

The results obtained by GA and PSO algorithms presented the result from the simulation and the validation of the intelligent car parking system using MATLAB. The model was evaluated based on computation time, cost and user satisfaction with respect to a fixed packing dimension of the parking space at a point in time. The parking scale dimension used in the simulation of the system includes 75 x 50 with respect to car park square cell of 0.5 by 0.5. Also, the system was simulated using numbers of cars ranging from 10, 20, 30, 40 and 50. The GUI of the two algorithms is depicted in Appendices A to E.

Simulation Result with GA

Table 1 offered the result gotten by GA based route allocator at 75 X 50- parking area dimension with square cell of 0.5 by 0.5. Nevertheless, GA based route allocator achieved a cost of 5.12, 4.62, 5.47, 4.84 and 5.08 at number of vehicles of 10, 20, 30, 40 and 50 respectively. The time taken for the vehicle from source to destination attained 145.72s, 131.74s, 126.91s, 127.87s and 128.48s at respective number of vehicles with user satisfaction of 0.70, 0.75, 0.67, 0.68 and 0.64 respectively.

Table 1: Simulation Result using GA

Schedule	No of Vehicles	No of Parking Spaces	Time Taken	Cost	User Satisfaction
1	10	5	145.72	5.12	0.70
2	20	10	131.74	4.62	0.75
3	30	15	126.91	5.47	0.67
4	40	20	127.87	4.84	0.68
5	50	25	128.48	5.08	0.64

Simulation Result with PSO

The result of the simulation gotten by PSO based route allocator at the same dimension is defined in Table 2. The table delineated that the performance of PSO varies with change in the number of vehicles. However, PSO based route allocator realized a cost of 2.51, 3.17, 2.60, 2.71 and 3.21 at number of vehicles of 10, 20, 30, 40 and 50 respectively. In this approach, the time-taken for the vehicle from source to destination accomplished 93.57s, 85.02s, 62.47s, 86.54s and 94.05s at respective number of vehicles, since it chooses the shortest route as the best route and does not consider traffic. User satisfaction achieved 0.80, 0.75, 0.80, 0.75 and 0.76 at different number of vehicles respectively.

Table 2: Simulation Result using PSO

Schedule	No of Vehicles	No of Parking Spaces	Time Taken	Cost	User Satisfaction
1	10	5	93.57	2.51	0.80
2	20	10	85.02	3.17	0.75
3	30	15	62.47	2.60	0.80
4	40	20	86.54	2.71	0.75
5	50	25	94.05	3.21	0.76

Comparison of Table Results between GA and PSO

Table 3, described a combined result of GA and PSO at number of vehicles of 50 with respect to all metrics at 75 by 50 parking lot area. All result obtained in Table 3 presumed that PSO approach had the least time taken compared with the corresponding GA approach. Similarly, cost and user satisfaction of PSO and GA approaches were compared; the study discovered that PSO approach has better performance in cost and user satisfaction than GA approach at number of vehicles of fifty (50). The PSO approach had a cost of 3.21 and user satisfaction of 0.76 at time taken of 94.05s; while GA approach produced a cost of 5.08 and user satisfaction of 0.64 at 128.48s. Hence, PSO outperformed GA.

Table 3: GA and PSO at Number of Vehicles of 50

Techiniques	Cost	Time Taken	User Satisfaction
GA	5.08	128.48	0.64
PSO	3.21	94.05	0.76

Comparison of Graph Results between GA and PSO

Figure 1 demonstrated GA with a higher time taken in choosing the shortest route as the best route for the vehicle from source to destination while PSO time taken was lesser than that of GA.

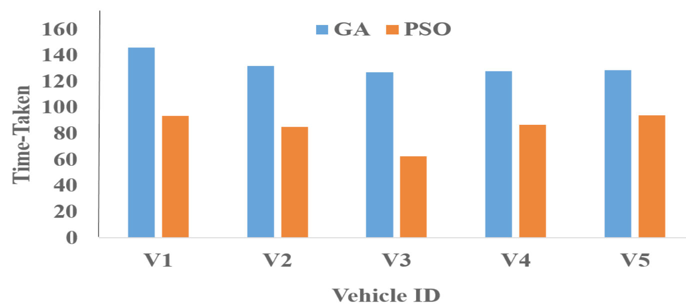

Figure 1: Graph showing Time Taken by GA and PSO

Figure 2 depicted that PSO incurred a less cost in choosing the route based on minimum distance and cost of parking space per second. It also picked the first route as the best route while GA arbitrarily allocated the user request for the route, thus maximizing the time and cost of the request as well as having the highest cost.

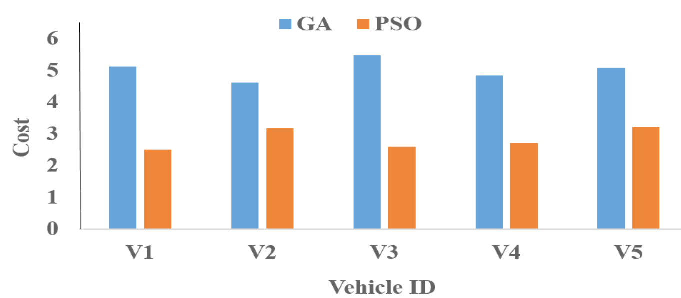

Figure 2: Graph Showing Cost by GA and PSO

GA randomly allocated the route for the request, without considering the time limit and cost. Consequently, vehicles do not reach the destination within the time limit and led to producing less user satisfaction. The shortest route was preferred regardless of free slots and cost, PSO was automatically gave a reduced value as well for user satisfaction compare to GA; this can be seen in Figure 3.

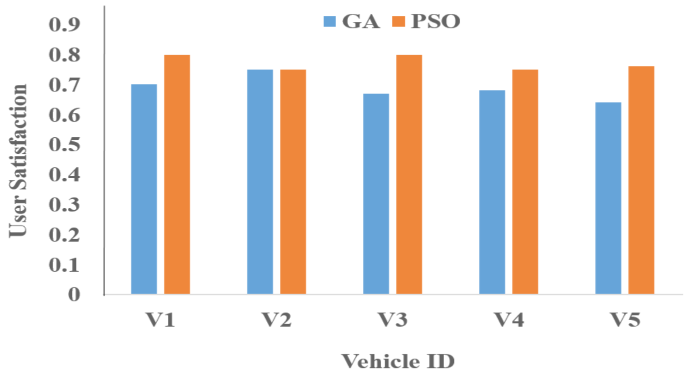

Figure 3: Graph Showing User Satisfaction by G and PSO

In view of the performance achieved, the PSO algorithm based intelligent car parking system is found to be efficient. The intrinsic property of GA in its fast convergence speed assisted PSO which is revealed in terms of the cost value and computation time.

Conclusion

This study simulated a model of car parking space with respect to parking scale dimension using MATLAB. Two optimization algorithms try to allocate the route for the user vehicle in an optimal manner and it was discovered that PSO solved the parking allocation problem by obtaining minimal values in terms of the cost and time taken and high user satisfaction when compared with GA. In opinion to this, GA required some genetic operator like crossover, mutation, selection and so on while a PSO based car parking space allocation algorithm adjusted theparameters which made it easier to implement, GA checked only present fitness function while PSO is a multi-criteria function that checked local and global functions.

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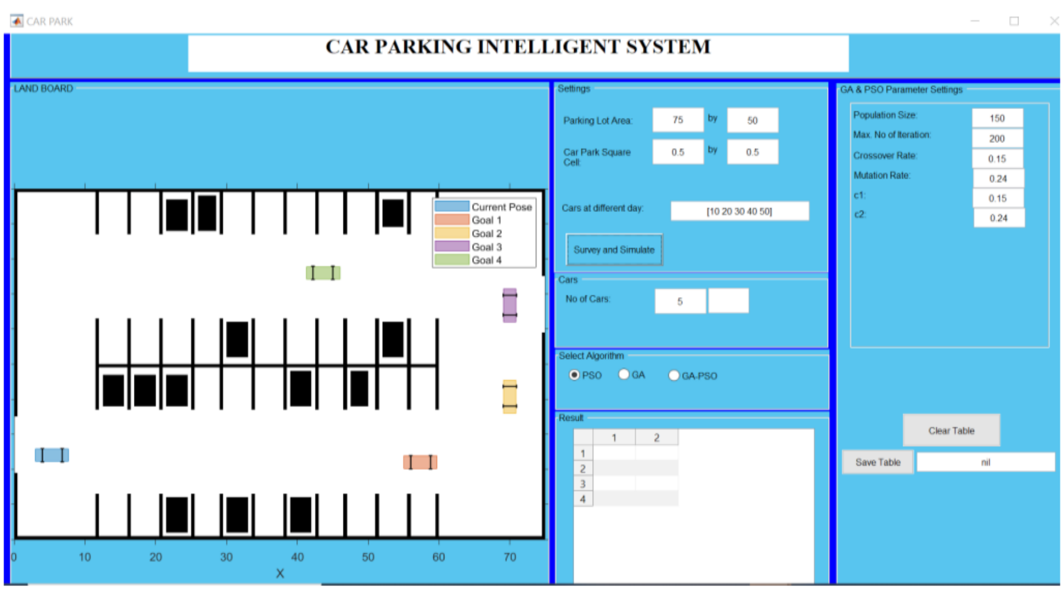
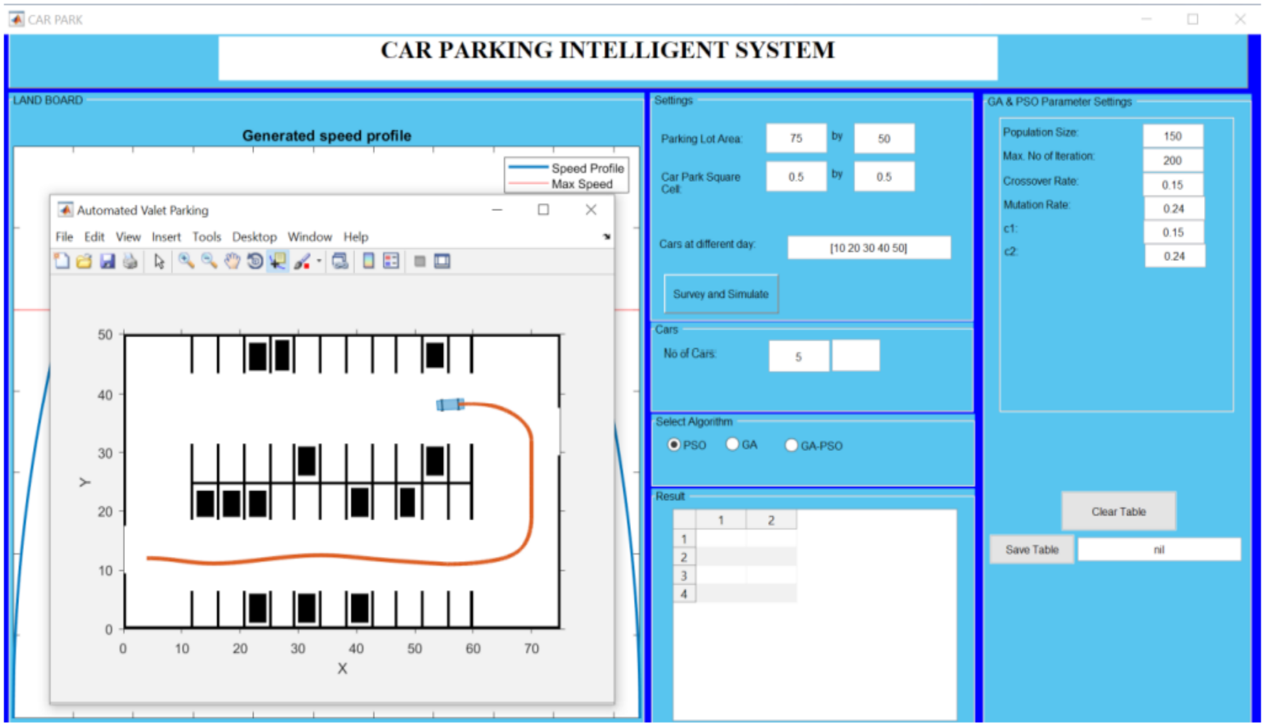
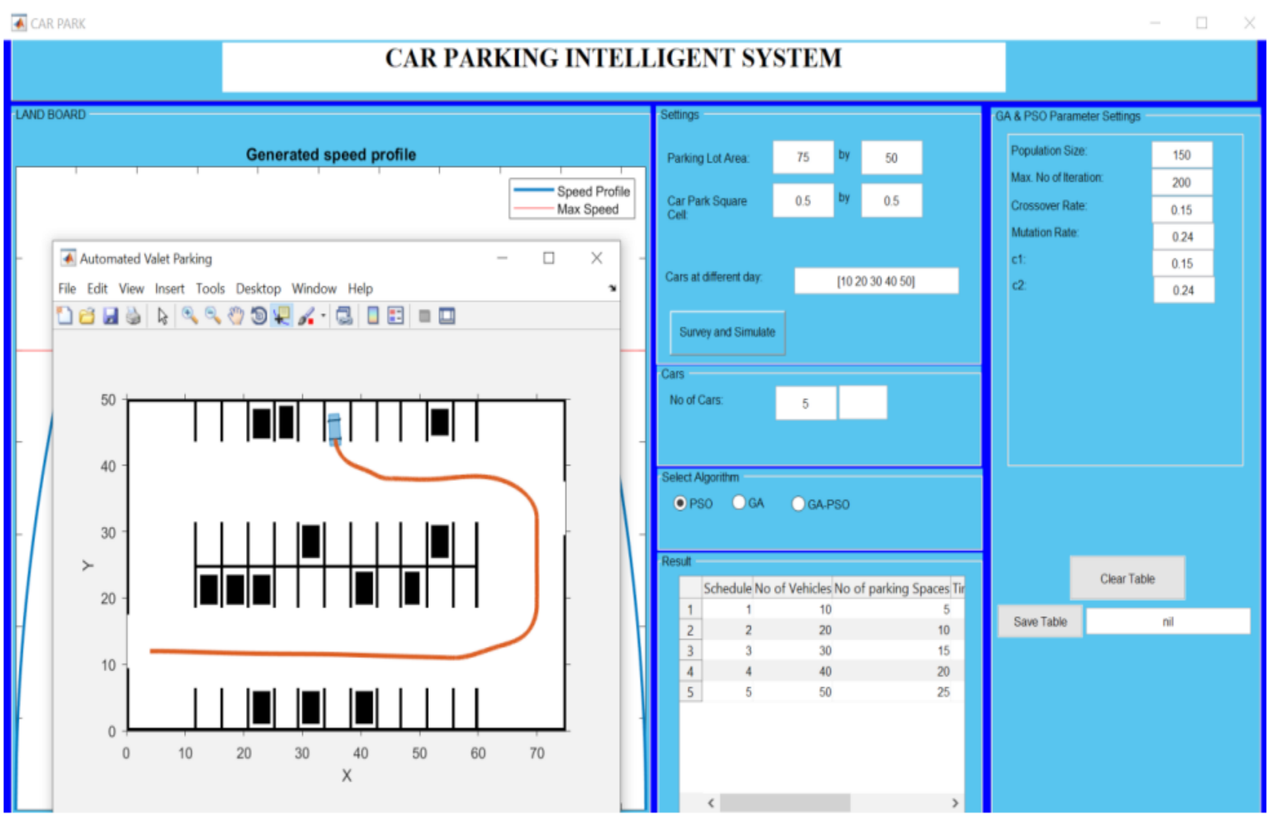
Appendix A: Graphic User Interface Showing Car Parking System at Initial Stage



Appendix B: Graphic User Interface Showing Car Parking System at Processing Stage



Appendix C: Graphic User Interface Showing Car Parking System at Final Stage



Appendix D: Simulation Result using GA 50 Schedule

Schedule	No of Vehicles	No of Parking Spaces	Time Taken	Cost	User Satisfaction
1	10	5	123.60	5.70	0.30
2	20	10	147.95	5.66	0.35
3	30	15	147.00	5.50	0.30
4	40	20	107.85	5.34	0.28
5	50	25	127.83	6.29	0.30
6	60	30	108.33	5.51	0.32
7	70	35	112.49	6.20	0.31
8	80	40	119.23	5.39	0.28
9	90	45	109.42	5.46	0.28
10	100	50	127.56	5.73	0.28
11	110	55	152.25	6.08	0.28
12	120	60	114.38	6.48	0.34
13	130	65	136.87	6.37	0.35
14	140	70	117.85	5.45	0.33
15	150	75	111.99	6.49	0.28
16	160	80	149.00	5.82	0.29
17	170	85	141.93	6.23	0.29
18	180	90	138.96	5.40	0.33
19	190	95	148.31	5.65	0.28
20	200	100	109.07	6.45	0.29
21	210	105	136.24	5.51	0.35
22	220	110	113.62	6.58	0.28
23	230	115	150.26	5.99	0.33
24	240	120	123.15	5.51	0.30
25	250	125	107.92	6.01	0.28
26	260	130	143.74	6.60	0.34
27	270	135	129.78	5.79	0.27
28	280	140	137.49	6.32	0.30
29	290	145	147.11	5.50	0.30
30	300	150	109.68	6.19	0.33
31	310	155	135.18	6.30	0.34
32	320	160	131.89	5.32	0.28
33	330	165	116.19	5.95	0.34
34	340	170	124.66	5.69	0.32
35	350	175	152.60	6.44	0.32
36	360	180	115.99	6.58	0.29
37	370	185	147.11	6.54	0.33
38	380	190	153.30	5.72	0.29
39	390	195	137.82	6.06	0.31
40	400	200	113.53	5.61	0.33
41	410	205	107.67	5.99	0.28
42	420	210	125.18	5.40	0.30
43	430	215	143.17	5.69	0.28
44	440	220	116.52	6.58	0.28
45	450	225	134.14	6.03	0.35
46	460	230	142.18	6.17	0.28
47	470	235	146.45	6.38	0.29
48	480	240	130.12	5.80	0.30
49	490	245	132.13	6.27	0.33
50	500	250	111.20	6.26	0.34
Average	**225**	**127.5**	**129.36**	**5.96**	**0.31**

Appendix E: Simulation Result using PSO 50 Schedule

Schedule	No of Vehicles	No of Parking Spaces	Time Taken	Cost	User Satisfaction
1	10	5	52.10	3.29	0.30
2	20	10	99.51	2.82	0.35
3	30	15	94.58	3.47	0.33
4	40	20	88.68	3.36	0.35
5	50	25	62.13	2.75	0.32
6	60	30	87.10	3.04	0.33
7	70	35	97.43	2.74	0.33
8	80	40	69.47	3.59	0.36
9	90	45	98.42	3.89	0.30
10	100	50	78.50	3.19	0.31
11	110	55	61.24	3.43	0.31
12	120	60	89.82	2.80	0.34
13	130	65	61.80	3.34	0.30
14	140	70	93.34	3.60	0.31
15	150	75	54.74	2.86	0.36
16	160	80	90.99	3.74	0.34
17	170	85	85.28	3.35	0.32
18	180	90	75.63	2.78	0.37
19	190	95	78.89	2.89	0.33
20	200	100	99.13	2.74	0.30
21	210	105	87.49	2.82	0.37
22	220	110	59.16	4.28	0.34
23	230	115	98.61	3.32	0.36
24	240	120	63.79	2.87	0.37
25	250	125	93.91	3.44	0.33
26	260	130	52.16	3.54	0.35
27	270	135	86.61	3.20	0.32
28	280	140	63.29	4.30	0.33
29	290	145	59.48	4.10	0.36
30	300	150	87.88	4.46	0.32
31	310	155	81.01	3.96	0.32
32	320	160	84.29	3.03	0.33
33	330	165	61.37	3.42	0.35
34	340	170	59.24	4.48	0.31
35	350	175	65.38	2.80	0.31
36	360	180	79.98	2.63	0.36
37	370	185	73.90	4.33	0.32
38	380	190	78.94	3.27	0.33
39	390	195	69.14	2.95	0.33
40	400	200	59.44	4.30	0.32
41	410	205	80.62	2.97	0.31
42	420	210	59.03	3.20	0.37
43	430	215	82.19	3.89	0.34
44	440	220	51.15	2.94	0.33
45	450	225	70.87	3.14	0.32
46	460	230	67.49	3.43	0.36
47	470	235	78.42	2.92	0.33
48	480	240	86.99	4.22	0.30
49	490	245	66.94	3.50	0.30
50	500	250	65.92	3.26	0.31
Average	**225**	**127.5**	**75.87**	**3.37**	**0.33**