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MULTI-DESTINATION TIME-DEPENDENT VEHICLE ROUTING PROBLEM WITH TIME WINDOWS AND PARKING CONSTRAINTS

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Abstract- Cities are affected by significant traffic jams, mainly caused by a lack of accurate route planning and an unorganized search for parking spaces. Moreover, the latter can lead to high financial and environmental losses. Therefore, we consider these two elements in this work to propose a new efficient dynamic solution for the time-dependent multi-destination vehicle routing problem with parking and time windows constraints. Our solution is based on the improved Grey Wolf optimization algorithm and the least squares support vector machine (IGWO-LSSVM), and the genetic algorithm (GA). The IGWO-LSSVM was developed to optimize the travel time calculation, and the GA algorithm was used to find the best route. The results show that our model leads to efficient solutions. Indeed, the IGWO-LSSVM generates reliable traffic data that is closest to reality. Thus, integrating the parking reservation into the route management process reduces significantly the total travel time.

Keywords: TDVRPTW, Travel Time, Smart Parking, IGWO-LSSVM, Genetic Algorithm.

1. INTRODUCTION

In recent years, traffic congestion has had significant social, economic and environmental impacts. Among its inherent causes are unplanned trips and the random search for available parking spaces. So, an optimizing vehicle routing problem (VRP) that considers the traffic conditions and available parking spaces is needed to ensure a sustainable and resilient transportation system and tackle traffic congestion.

The VRP is currently a crucial research field for several applications (e.g., distribution of goods, waste collection, visiting several destinations) [1-3], it has many variants, among them is the time-dependent vehicle routing problem (TDVRP). In the TDVRP, the driving time to reach a destination varies with the time of day due to several external factors, primarily traffic congestion. Integrating the travel time into path planning is closer to many real-world practical situations such as traffic jams, road works and car accidents.

Several authors studied the TDVRP from different perspectives. In [4], the authors studied the time-dependent shortest path problem with resource constraints. The paper [5] considered that any arc between two destinations has multiple paths. Other research works integrated the time windows constraint in the TDVRP (TDVRPTW); for example, [6] proposed a solution for the TDVRPTW related to the road network based on tabu search, [7] presented a solution for electric TDVRPTW involving waiting times at charging stations.

The complexity of TDVRP and TDVRPTW problems lies in their constraints and mainly in the travel time constraint. Indeed, due to the dynamic nature of traffic, using a constant travel time for all the day results in a poor prediction of the real conditions, and consequently, the generation of incorrect route plans. In general, congestion is a regular phenomenon, and this regularity allows the use of historical data to compute congestion parameters and automatically predict travel time.

However, using these data for solving TDVRP is rarely used by researchers, so in this sense that this article contributes. Furthermore, it is essential to integrate not only traffic conditions but also parking conditions to reduce total travel time. This aspect is important because these two constraints (i.e., the parking constraint and the traffic constraint) influence each other.

Indeed, traffic congestion increases when drivers search for parking in an area where all parking spaces are already occupied. However, the TDVRP with a parking constraint is only addressed by [8], who proposed a TDVRP solution with a real-time free parking constraint. Their solution integrates free curbside parking without including smart parking. Moreover, it does not consider the visiting order of destinations, while this order is important when there are destinations with a fixed service time.

Therefore, this work tries to address these two gaps by proposing a solution to the time-dependent vehicle routing problem with time windows and smart parking reservations (TDVRPTW-SP).

The main contribution of this paper is a framework for solving the TDVRPTW-SP using historical data to predict the travel time of a road arc during the whole day. We add a parking constraint to the TDVRPTW problem to propose a global and optimal solution from the vehicle departure point to the arrival point. In addition, we suggest an improved version of the Least Squares Support Vector Machine (LS-SVM) algorithm to build a reliable and accurate travel time prediction model. The accuracy of our short-term travel time prediction model is improved by incorporating influencing factors, such as vacations days and morning and evening rush hours. In this article, the work is organized as follows. Section 2 presents an overview of recent work on the issues addressed in this paper. Section 3 presents the methodology of our work. Section 4 provides in-depth details of the proposed model. The simulation and results are presented in Section 5, and the conclusion is outlined in Section 6.

2. RELATED WORKS

Travel times within cities often vary greatly during the day and significantly impact the duration of the vehicle routing problem. The time-dependent vehicle routing problem (TDVRP) and its variant with time windows (TDVRPTW) were developed to address this issue. [9] were the first to introduce a TDVRP, and then researchers approached this topic from different perspectives by adding different constraints, objective functions to be optimized and by developing efficient algorithms. Among the most discussed constraints in the literature is the satisfaction of the time windows (TDVRPTW). For example, [10] studied a time-dependent multipath vehicle routing problem with time windows.

The [11] modeled TDVRPTW by proposing an approach to avoid both rush-hour and time-based congestion. [12] addressed the combination of precedence in pickup and delivery, profit-maximizing selection, and minimization of time-dependent routing costs. [13] formulated a time-dependent reliable vehicle routing problem with time windows in a multigraph network in the context of emergency distribution in urban environments. [14] optimized the delivery of perishable products under the TDVRPTW problem. To solve TDVRPTW For electrical vehicle (EV), [15] addressed the optimization of the path between the position of the electric car and the charging stations.

To solve the multi-depot green TDVRPTW, [16] introduced a transportation resource-sharing strategy. Likewise, [17] studied the ecological vehicle routing problem with variable speed during the day and flexible time windows. Similarly, [18] addressed multi-regional co-distribution with reduced distribution costs for green vehicles under multi-depot time-dependent problem with temp windows. There are also works that have addressed the TDVRP problem simultaneously with finding a parking space.

For example, [8] proposed a TDVRP problem with the free parking assignment problem. None of these works simultaneously consider finding smart parking lots for drivers and optimal routing of target destinations while considering traffic conditions and visit order.

To the best of our knowledge, our solution is the first on time-dependent multi-destination route planning with time windows and parking availability constraints. This solution is based on real-time data collected from the road and smart parking.

On the other hand, all research works aimed at solving TDVRP, and its variants have proposed a travel time model that varies during the day and has been used to express the time-dependent (TD) constraint. In [19], the travel speed-dependent function is a progressive function with a constant speed during a period but whose value changes at the initial moment of each period. This approach ensures that a vehicle moves along the arcs according to the FIFO rule. This model has been used in many studies to solve the different variants of TDVRPTW using different heuristic algorithms [10-15]. Few papers use a continuous time-varying velocity function [17], [18], [20-22] to solve TDVRP and its variants. For instance, [18] and [17] used continuous trigonometric functions to characterize the time-varying speed model.

As shown in Table 1, all the above contributions are based on modelling the travel time function using periods with a constant speed or travel time during each period. Due to the dynamic nature of traffic, this method can lead to falsified results far from real conditions and, consequently, generate incorrect route plans. For this reason, this paper aims to propose a new method for solving TDVRPTW-SP with a reliable travel time prediction network. Indeed, we propose a travel time prediction method based on historical data and an intelligent and reliable approach using IGWO-LSSVM.

3. METHODOLOGY

Solving the TDVRPTW-SP is a recent and complex research area aiming to propose efficient optimization methods. Detailed modelling of each parameter of this problem is required to optimize their design in terms of travel time. For this reason, we address in this paper two challenges, (i) Proposing a route management system with automatic smart parking reservation and (ii) Modelling an efficient travel time network using the IGWO-LSSVM algorithm. The approach presented in Figure 1 addresses the challenges mentioned above while satisfying the time windows and smart parking reservation constraints.

The first step in this work is to find a real database and prepare it to obtain reliable data that our algorithms will use. The second step consists of the definition of the problem to be optimized. The third step concerns the development of an IGWO-LSSVM model for the prediction of travel time by integrating different external factors. The fourth step introduces the elaboration of a genetic algorithm by incorporating the previously predicted travel time model for the resolution of the TDVRPTW-SP.

4. THE TDVRPTW-SP PROPOSED MODEL

The TDVRPTW problem has been addressed in various manners. However, the available studies do not incorporate the smart parking availability constraint and do not use a travel time function similar to the real world. In the following section, we present our framework, which successfully addresses both aspects.

Table 1. Comparison of recent works on TDVRPTW

Paper	Contribution of the paper						Objective Function	Optimization tools	TD Solution			Parking availability
	Vehicle	EC	MT	MG	TW	parking assignment			Speed Function	TP	Uncertainty	
[15]	EV, HF	-	-	-	STW	-	Min (The energy consumption + the distance)	VNS algorithm	D	●	-	-
[11]	Homo	CE	-	-	STW	-	Min (The total distribution costs [fixed costs +driver costs + cost of fuel consumption] + carbon emissions)	ACO with a congestion avoidance approach	D	3	-	-
[10]	Homo	-	●	-	STW	-	Min (The total travel distance of all trips)	Tabbu Search	D	5	-	-
[14]	Homo	-	-	-	FTW	-	Max (The total profit expected from accepted orders - loss from rejected orders)	HACO	D	3	-	-
[13]	Homo	-	-	●	HTW	-	Min (delivery times)	RDP, CGA, HCTS	D	4	-	-
[23]	Homo	-	-	-	HTW	-	Min (The number of vehicles and the total travel distance)	AVNS	D	●	●	-
[21]	Homo	-	●	-	STW	-	Min (The number of the vehicles + the total scheduling time [Travel times between the nodes + waiting times + servicing times at the nodes + loading times at the distribution center])	Nearest neighbor heuristic, Tabbu search	C	9	●	-
[12]	Homo	-	-	-	STW	-	Max (The collected profits –The traveling duration)	Tailored labeling	D	5	-	-
[16]	Homo	CE	-	-	STW	-	Min (Total carbon emission + operating cost)	Clarke and Wright Saving, Sweep algorithm, and multi-objective PSO	C	5	-	-
[6]	Homo	-	-	●	STW	-	Min (The total distance)	Tabbu Search	D	5	-	-
[20]	HF, LNV	-	-	-	HTW	-	Min (The total vehicle cost)	Simulated Annealing	C	3	-	-
[17]	HF, GV	CE	-	-	STW	-	Min (The total fuel consumption)	Genetic algorithm	C	4	-	-
[18]	HF, GV	CE	-	-	STW	-	Min (The distribution costs)	Genetic algorithm	C	4	-	-
[22]	HF, LNV	-	-	-	STW	-	Min (The distribution costs)	Simplified swarm optimization	C	5	-	-
This Work	Homo	-	●	-	STW	●	Min (Total travel time)	IGWO-LSSVM and GA	Predicted Travel time			●

*EV: Electrical Vehicle, HF: Heterogeneous Fleet, Homo: Homogeneous Fleet, LNV: limited number of vehicles, MT: Multi-Trip, MG: Multi-Graph, TW: Time Windows, STW: Soft Time Windows, FTW: Floating Time Windows, HTW: Hybrid Time Windows, C: Continuous, D: Discrete, TP: Time Period, EC: Emissions constraints, CE: Carbon emissions, GV: Green Vehicle

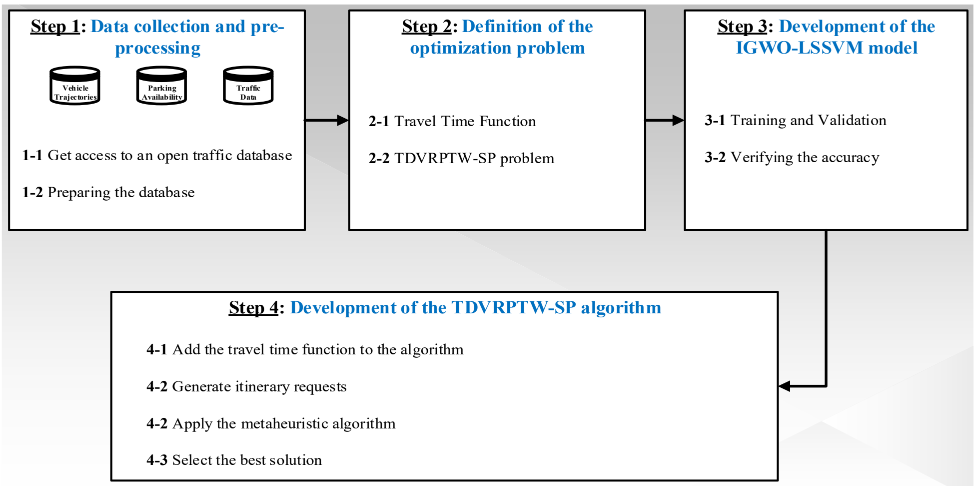

Figure 1. The methodology of the proposed solution

4.1. Solution Overview

This study proposes a multi-destination route planning and management system that addresses the constraints of real-time traffic, time windows, and parking reservations. The proposed solution consists of the Driver assistance module, Route planning module, and Traffic Information provider (See Figure 2). Driver Assistance Module consists of three blocks: Driver request generation, Driver guidance and the vehicle tracker. This module generates multi-destination route requests and sends the driver's current position to the Route planning module. Once the Route planning module has generated the requested itinerary planning, it sends it to the Driver guidance block to guide the driver in his trip.

The Route planning module consists of a computing server for multi-destination route planning and parking reservations. After receiving the driver's request, this module plans the requested itinerary according to the driver's current position and the traffic conditions. The parking reservations are made along the driver's route. As the driver approaches his destination, our algorithm automatically reserves the selected parking space. The TDVRPTW-SP algorithm executed within this module combines an efficient solution for the TDVRPTW problem with an automatic parking reservation that minimizes the travel time, including the time to find available parking.

The IGWO-LSSVM algorithm is executed in the Traffic Information Provider module to provide traffic data to the Route Planning module. The traffic detection infrastructure generates sufficient big data for our algorithm to provide accurate travel time data between every two destinations. Figure 3 illustrates the process of a multi-destination route request in the TDVRPTW-SP. When a driver submits a multi-destination route request (This request contains the target destinations, the time windows for each destination and the driver's current position), this request is forwarded to the route planning module, which plans routes to optimize total travel time.

Indeed, the route planning module solves the TDVRPTW-SP to give the shortest path in terms of travel time. Integrating the travel time requires to know the traffic status in real time. This is achieved by using the Traffic Information Provider Module, which uses the IGWO-LSSVM algorithm to provide accurate information about the traffic situation. If the driver is approaching the next destination and needs to park, the parking assignment block automatically reserves the selected space. Routes are automatically adjusted after visiting each destination in the route based on the driver's position, next destinations and departure time.

4.2. Case Study Definition

The problem analyzed in this work covers n destinations a single vehicle, and lists of nearby parking lots at each destination. It consists in answering a multi-destination route management request. At each destination, the driver needs to find a parking lot. Moreover, he has to respect the time windows of each destination and the maximum capacity of the parking lots during his trip. At the end of the trip, the driver has to return to his initial position (origin) (See Figure 4).

The first node in Figure 4 represents the current vehicle location. Parking lots are represented by rectangular blocks. The other nodes correspond to the destinations of the vehicles. f_{iz} corresponds to the time needed to reach a parking lot z, and f_{iz}' corresponds to the time needed to move from the parking lot z to the destination j.

4.3. The TDVRPTW-SP Problem Definition

Let $G=(A,V)$ be a graph where is a set of arcs and $V=\{v_0,v_1,v_2,...,v_{n+1}\}$ the set of vertices. The start and end nodes are indicated by the vertices v_0 and v_{n+1}.

Each vertex of V has a service time window $[e_i,l_i]$; the start and end nodes, in particular, have open time windows. A collection of n destinations is defined by the vertex set $C=\{v_1,v_2,...,v_n\}$. A travel time f_{ij} has been provided to each arc (v_i,v_j), which is a function generated by our IGWO-LSSVM algorithm depending on the departure time from node i. Furthermore, H represents the discretized planning horizon, where each element t is called a time step.

The set of parking near to each destination is denoted by K. At each time step t, every parking z has a total capacity TC_z as well as a fluctuating residual capacity, marked by C_{zt}. f_{iz} represents the time it takes for a vehicle to get from destination i to parking z. The time it would take the vehicle to travel from his allotted parking z to his destination j, represented by f_{zj}', is also included. The current locations (origins) and destinations are known in advance.

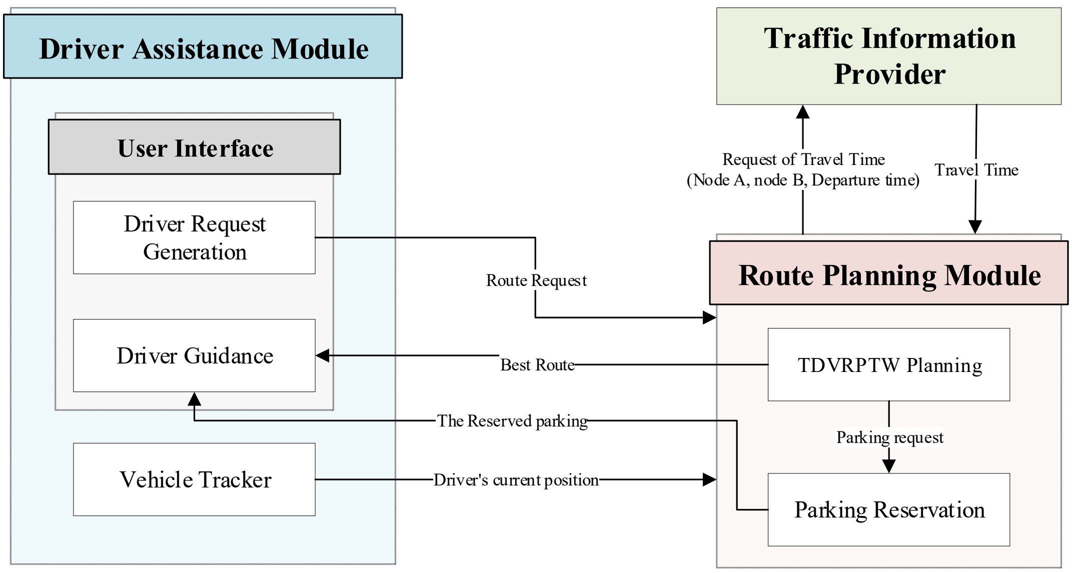

Figure 2. The proposed system overviews

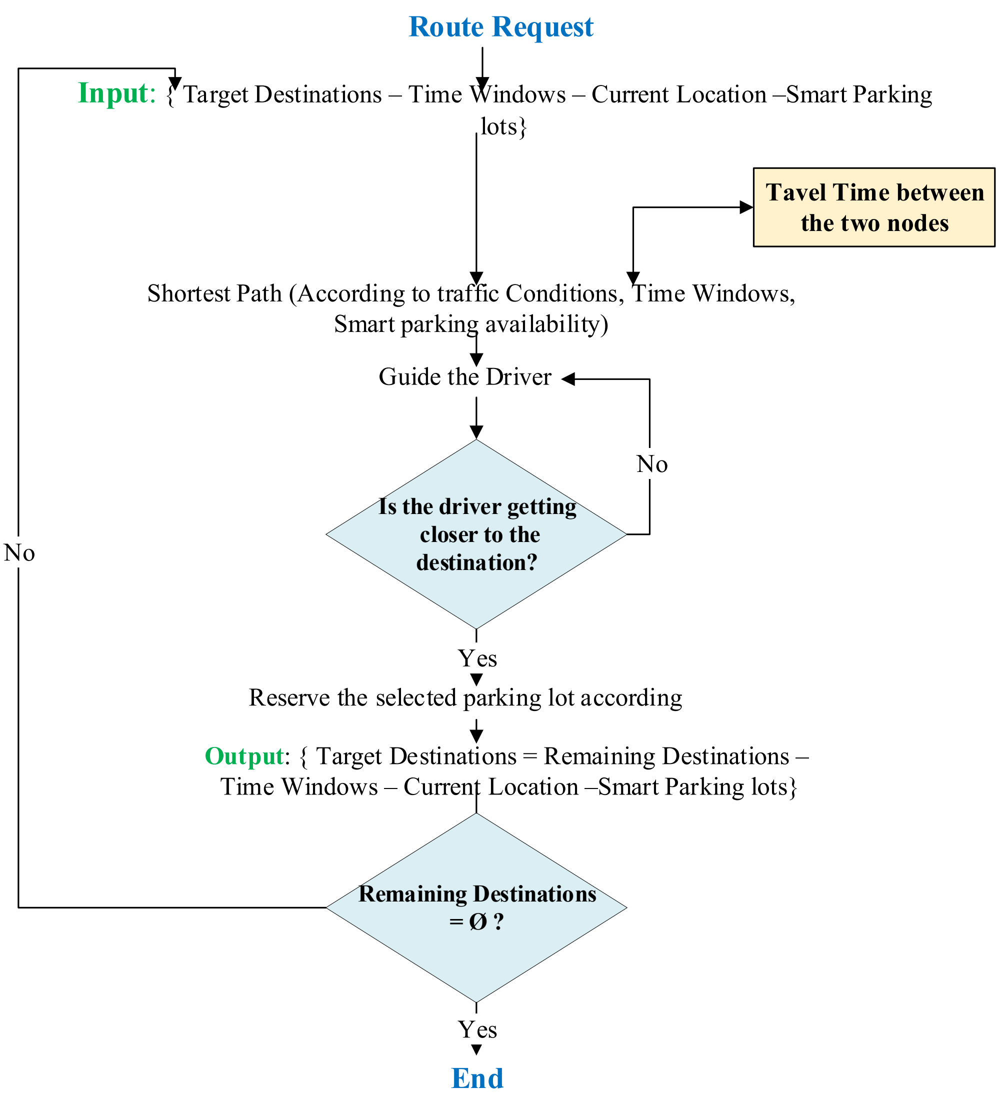

Figure 3. The process of a multi-destination route request

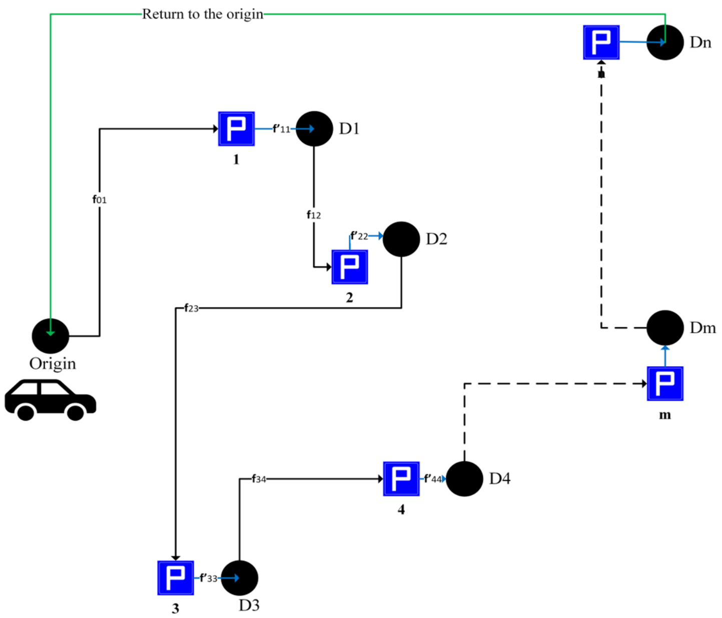

Figure 4. Representation of the TDVRPTW-SP

The mathematical formulation of TDVRPTW-SP uses binary variables: x_{iz} equals one if and only if the parking z is assigned in destination i. x_{ij} equals one if and only if arc ij is traversed by the vehicle. The model can be formulated as follows:

$$\min \sum_{z\in K}\sum_{i\in V}\sum_{j\in V}\left[f_{iz}(t)+DP_z+f_{zj}'(t+f_{iz}(t)+DP_{iz})\right]x_{ij}x_{iz}' \quad (1)$$

$$\sum x_{ij}=1\ ,\ \forall i\in \mathrm{C} \quad (2)$$

$$\sum_{i\in V} x_{im}-\sum_{j\in V} x_{mj}=0 \quad (3)$$

$$x_{i0}=0\ ,\ \forall i\in V \quad (4)$$

$$x_{n+1i}=0\ ,\ \forall i\in V \quad (5)$$

$$e_i\sum_{j\in V} x_{ij}\le y_i\ ,\ \forall i\in C \quad (6)$$

$$l_i\sum_{j\in V} x_{ij}\ge y_i\ ,\ \forall i\in C \quad (7)$$

$$x_{ij}x_{iz}'\left[(y_i+DP_z)+f_{zj}'(y_i+DP_z)\right]\le y_j \quad (8)$$

$$\sum_{z\in k} x_{iz}'=1\ ,\ \forall i\in C \quad (9)$$

$$C_{zt}x_{iz}'\le TC_z\ ,\ \forall z\in K\ ;\ \forall i\in C \quad (10)$$

$$x_{ij}=\begin{cases}1\text{ if the arc } ij \text{ is traversed}\\ 0 \text{ otherwise}\end{cases}\quad \forall(i,j)\in A \quad (11)$$

$$x_{iz}'=\begin{cases}1\text{ if the parking } z \text{ is traversed}\\ 0 \text{ otherwise}\end{cases}\quad \forall i\in C\ ;\ \forall z\in K \quad (12)$$

$$y_i\in \mathrm{R}\ ,\ \forall i\in V \quad (13)$$

The objective function (1) is to minimize the total travel time of the vehicle from its current position to its target destinations, including the travel time f_{iz} to reach its assigned parking z in each destination i, the time spent in i (equivalent to the time the vehicle is parked DP_z), and the time f_{zj}' needed to reach the next destination from parking z.

The constraints are defined as follows: all destinations must be visited precisely once (2); if the vehicle arrives at a destination, it must also depart from that destination (3); the routes must begin and end at the origin (4) and (5); the service time must meet the start (6) and end (7) times of the time windows; and the start time of the service must take into account travel time between destinations (8); only one parking lot will be assigned to the vehicle at each destination i from the set of potential parking lots K (9); the current capacity C_{zt} of parking lot z at arrival time t will not exceed the maximum capacity of the lot (10). The type and domain of the decision variables are shown in (11), (12) and (13).

4.4.1. Travel Time Optimization

Travel times often vary greatly during the day and have a significant impact on itinerary duration. Several authors have proposed discrete and continuous function models to compute the travel time from one node to another at a given time. However, these models are based on dividing the day into periods, which implies a constant travel time for each period. In this paper, we try to get closer to the traffic reality by proposing a performant solution using the IGWO-LSSVM model to generate a reliable travel time function.

The use of IGWO-LSSVM in travel time function modeling methodologies is a crucial component in achieving the desired results, as it provides a better level of accuracy than other methods. The LSSVM model is proposed by [24]. Instead of the convex quadratic programming problem that the normal SVM solves, LSSVM solves a set of linear equations. We used for this study the Radial Basis Function (RBF) kernel, given its suitability for nonlinear cases. The values of both the regularization parameter γ and the kernel parameter σ have a significant impact on the LSSVM model's generalization performance. To do this, we used IGWO to optimize the LSSVM model's two parameters (i.e., γ and σ). The goal of this algorithm is to discover the best combination of the two parameters γ and σ that will reduce the mean absolute percentage error (MAPE) (See Equations 14 and 15).

$$MAPE=\sum_{i=1}^{n}\left|\frac{y_i-y_i'}{y_i}\right| \quad (14)$$

$$\begin{cases}\min f(\gamma,\sigma)=\dfrac{1}{n}\displaystyle\sum_{i=1}^{n}\left|\frac{y_i-y_i'}{y_i}\right|\\ \gamma\in[\gamma_{\min},\gamma_{\max}]\ ,\ \sigma\in[\sigma_{\min},\sigma_{\max}]\end{cases} \quad (15)$$

We used the performance indicators listed below to evaluate the proposed model's performance and accuracy:

The mean absolute error (MAE)

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|y_i-y_i'\right| \quad (16)$$

The mean absolute scaled error (RMSE)

$$MSE=\frac{\frac{1}{J}\sum_j|e_i|}{MAS\,(\text{On the training Set})} \quad (17)$$

Coefficient of Determination (R^2)

$$R^2=1-\frac{\sum_{i=1}^{n}[y_i-y_i']^2}{\sum_{i=1}^{n}[y_i-\overline{y_i'}]^2} \quad (18)$$

where, y_i the input data, y_i' the predicted Data, n the number of observations, $\overline{y_i}'$ the mean of y_i' for all i and e_j is the forecast error for a given period (with, the number of forecasts).

4.4.2. The TDVRPTW-SP Algorithm

The TDVRPTW-SP algorithm aims to identify the best route in terms of minimum travel time and reserve a parking space automatically as the driver gets closer to his destination (see Algorithm 1). Its goal is to determine the quickest route possible, starting from the driver's current location and visiting all destinations at the same time, in order to reduce total journey time. For each pair of nodes in the graph (i.e., the union of the current origin and the set of remaining destinations not yet visited), we calculate the trip time to the parking spot using the function provided by our IGWO-LSSVM model (Line 5). The genetic algorithm (Line 6) is then used to choose the initial destination of the generated optimum route (Line 7).

After the driver approaches this destination, the selected smart parking reservation is automatically made (Line 9-12). If a parking space is allocated, the mobile of the driver directs him to it (Line 11). Lines 14-16 update the driver's current origin and departure time to the next destination, as well as the set of visited places. The whole algorithm is repeated until the list of remaining destinations to visit is depleted (Line 4).

Algorithm 1. TDVRPTW-SP Pseudo-code

Input: Target Destinations $D_m = \{D_1, \ldots, D_i, \ldots, D_n\}$,
Parking lots $K = \{k_1, \ldots, k_z, \ldots, k_m\}$, Time Windows (TW),
Current location (Cu), The time to get to the parking lot (M)
Travel Time Function Tr (D_i, D_{i+1})
Output: Best route, The reserved parking spot
1 $D_m \leftarrow D_m$ // List of remaining destinations to be visited.
2 $t_0 \leftarrow$ Starting time
3 $Cu \leftarrow D_0$
4 While (Remaining-Destinations! = Ø)
5 Compute Travel time function between Cu and all remaining destinations
6 Best route ← Find to best route using genetic algorithm (D_m, TW)
7 while ($t < Tr\ (Cu, D_i)$) // (D_i the destination chosen by the TDVRPTW)
8 Guide the Driver
9 if $t \leftarrow t_0 + Tr\ (Cu, D_i) - M$ do
10 {Reserve the selected parking lot
11 Send a message to the driver indicating the reserved parking lot}
12 end if
13 end
14 $t_0 \leftarrow t_0 + Tr\ (Cu, DP_z) + Tr\ (DP_z, D_i) + DP_z$ (DP_z Parking time spent at destination D_i)
15 $D_m \leftarrow D_m / \{D_i\}$
16 Cu $\leftarrow D_i$
17 End

To find the best route, we deploy a genetic algorithm combined with the model of travel time discussed in the previous section (See Algorithm 2). Heuristics based on genetic algorithms have been widely used in the TDVRPTW due to their effectiveness and efficiency [17], [18].

J. Holland developed the genetic algorithm in 1975 at the University of Michigan [25]. From an initial stochastically generated population, the GA evolves this population through several phases:

- Initialization phase: The fitness function is used to assess the feasibility and suitability of the individuals in the initial population. In our case, the fitness function is the total travel time, including the time to reach the target destination and the time spent in the parking lot.
- Selection: This allows the selection of potential parents according to their fitness (calculated by the evaluation function that tests the feasibility and performance of the solution in terms of travel time, time windows, and parking constraints).
- Application of genetic operators (mutation, crossover, reverse) to create offspring on the selected parent chromosomes.
- Calculating the individual quality (fitness), then replacing the offspring with their appropriate chromosomes to create a new population.
- This process will be repeated by the genetic algorithm until the predetermined number of generations has been produced.

Algorithm 2. Best Route Pseudo-code (GA)

Input: The destinations nodes
Time window for each node
The parking lots
Travel time function
Output: Shortest path and selected parking
Time spent
Genetic parameters: Population size
MAXGEN (Program stops when it reaches the MAXGEN)
Probability of Generation GAP
Probability of Crossover
Probability of Mutation

Initialization phase: Chrom=Initialization the population
gen=1
while (gen <= *MAXGEN*)
Calculate the degree of adaptation (According the Fitness function)
Calculate the time spent
Set the optimal individual
Select of potential parents
Crossover operation
Mutation operation
Reverse
Parental reinsertion into offspring
gen=*gen*+1
end
Find the path with the minimum total travel time
End

5. RESULTS AND DISCUSSION

In this section, we describe the real data set collected from road traffic and smart parking, parameters of the proposed algorithms (IGWO-LSSVM and GA model), performance measures, results, and discussions.

5.1. Dataset Collection

In this study, we used a collection of vehicle traffic datasets provided by the city of Aarhus in Denmark. These data incorporate 449 observations in total and provide the measured travel time between two nodes for a specified time over six months [26].

In addition, we used a smart parking data stream provided by the city of Aarhus. There are eight smart parking lots (located in the same geographical area where the traffic data was collected) giving information over the same six-month period. (55,264 data points in total).

The collected data cannot be used directly for the IGWO-LSSVM model training to generate the travel time function or the TDVRPTW-SP to plan routes and reserve parking spaces. They must first be pre-processed, as certain anomalies in the collected data will seriously affect the quality of the results. For the pre-processing of our data, we proceed as follows: First, all samples are cleaned to provide a simple, complete, and clear set. Indeed, we checked if there are empty or missing values and noise in the dataset (duplicate data or data segments, which have no value for a particular search). In addition, if there are missing data in the dataset, we supplemented the data with the most appropriate observations. Then, we transformed the data into an appropriate format so that the computer could learn from the data.

5.2. Parameter Settings

To evaluate the proposed TDVRPTW-SP while providing the travel time function, we used two algorithms, GA and LSSVM combined with IGWO. To obtain the best results for GA, the operating parameters such as maximum number of iterations and population size are set to 100 and 60, which is recommended by the work of Piotrowski et al. [27] and actually they provide the best solution. The other parameters associated with each algorithm are shown in Table 2. In addition, all algorithms are coded with MATLAB R2021a, and all experiments were performed on an Intel Core i5, 2.5 GHz processor with 8 GB of RAM.

Table 2. Parameters of GA and IGWO-LSSVM

Algorithm	Parameters
IGWO-LSSVM	*PS*=30, maximum iteration = 100, $\gamma \in$ [1, 10000], $\sigma \in$ [0.1, 100]
GA	*PS*=60, maximum iteration = 100, crossover probability: *pc*=0.9, mutation probability: *pm*=0.05, generational probability *GGAP*=0.9

5.3. IGWO-LSSVM Simulation for Travel Time Optimization

An evaluation of the accuracy and quality of the presented IGWO-LSSVM algorithm should be conducted before proceeding with the TDVRPTW-SP optimization, using the performance indices MAE, MASE and R^2. To interpret these parameters, we use the following rule: The smaller the values of these parameters, the higher the accuracy of the prediction model. In contrast, a high value of R^2 indicates a high level of correlation. As a result, the closer R^2 is to 1, the more reliable our model's result is. There is no rule in terms of a reference value for assessing the IGWO-LSSVM model through these indicators since it depends definitely on the number of observations trained as confirmed by several authors.

The choice of LS-SVM combined with IGWO is justified by a comparative study with the most widely used algorithms for road traffic prediction. Several authors have applied artificial neural networks (ANN) to predict road traffic using for example the Hopfield network, the feedforward network and backpropagation. Backpropagation neural network (BPNN) is the most commonly used ANN in the transportation field [28]. On the other hand, some authors have used hybrid neural networks to predict road traffic. The work [29] demonstrated that an artificial neural network trained by a particle swarm optimization model (ANN-PSO) and an artificial neural network heuristic model (ANN) are sufficiently robust in predicting traffic flow.

Deep learning algorithms (DML) are the most used to predict traffic road, because they can analyze a large data set. Furthermore, without any prior information, DML algorithms may extract characteristics from incoming data compared to Shallow machine learning (SML) Including ANN. Among all DML models, time series prediction is better served by the Recurrent Neural Network (RNN). RNN has been coupled with other algorithms in a few publications, for example, the combination of convolutional neural network (CNN) with (RNN) [30].

Furthermore, through several research works, the LS-SVM model has proven its good potential and its adequacy for short-term traffic flow forecasting. In this sense, we propose an improved LSSVM model (IGWO-LSSVM) to optimize the kernel function parameters efficiently and effectively. The choice of IGWO is justified by a comparative study with several algorithms (Ant Lion Optimizer (ALO), Accelerated Particle Swarm Optimization (APSO), Grey Wolf Optimization (GWO) and Coupled Simulated Annealing (CSA)) that are combined with LSSVM.

Table 3 shows the evaluation results of the different methods. We can notice that the proposed method obtains the lowest prediction errors in a negligible time of 4 seconds. Indeed, the IGWO-LSSVM gives the best predictions with lower values for the overall indices, including MASE, MAE, MAPE, and a higher value for R^2, which indicates a clear correlation between targets (Input) and results (Output), which is equal to 1. Overall, the proposed approach works well for forecasting short term traffic flows.

Table 3. Prediction errors

		MAE	MAPE	MASE	R^2	Elapsed Time
RNN		1.4110	0.0078	2.0127	0.9975	1 min 41s
RNN-CNN		11.5656	0.0598	14.1519	0.8845	14 s
ANN		0.6116	0.0354	2.3518	0.99847	20 s
ANN-PSO		17.6877	0.1157	22.7695	0.8218	1 min 22s
LSSVM	GWO	0.02291	0.01161	0.000976	0.9999996	11 s
	APSO	0.02331	0.01181	0.00099	0.9999996	12s
	ALO	0.05661	0.02892	0.00241	0.9999962	12 s
	CSA	0.02052	0.01037	0.00087	0.9999997	23s
IGWO-LSSVM		0.00945	0.00497	0.000403	1	4s

As shown in Figure 5, the prediction results by the proposed approach closely follow the real data, which indicates that the proposed method is able to predict the short-term travel time data with minor errors.

Basically, based on the obtained results, the proposed IGWO-LSSVM can provide accurate results and has a remarkable ability to generate the travel time between two nodes in real-time in the studied case. In this sense, the limitations of the traditional travel time function are avoided by modelling the travel time function to improve the optimization result of TDVRP and its variants and obtain high-quality solutions.

Using the same dataset, the IGWO-LSSVM model and the improved LSSVM models are compared to demonstrate the superiority of the suggested approach. Figure 6 presents the prediction results for each approach. We can highlight that the IGWO-LSSVM model gives the best result compared to the other models, which justifies our choice.

5.4. TDTSPTW-SP Simulation

5.4.1. Generation of Itinerary Requests

The itinerary requests used to drive the simulation are randomly derived with multiple destinations, ranging from 3 destinations to 11 destinations. This process allows us to: (i) select only the destinations in the city of Aarhus, which are the most congested, since we are more interested in evaluating TDVRPTW-SP in congested areas with sufficient vehicle traffic and parking conflicts; and (ii) have queries with numerous destinations. The parking duration (time of parking, time it takes to walk from the parking spot to the destination and back) is randomly chosen in the range [10 min, 20 min], to ensure a reasonable duration.

5.4.2. Results and Discussion of TDVRPTW-SP

Our approach is designed to provide an optimized itinerary with traffic and parking constraints. As shown in Figure 7 (example response to an itinerary request with 11 destinations), our algorithm with the new travel time calculation method is able to generate a solution for our study case. Furthermore, to demonstrate the effectiveness of our algorithm with multi-destination problems, Table 4 compares the performance of the TDVRPTW-SP solution with increasing the number of destinations. As we can see, the elapsed time during the simulation increases with the number of destinations, but it remains an optimal time even with 11 destinations, which shows that our approach performs well.

Moreover, to prove the effectiveness of adding a smart parking constraint to the TDVRPTW, a comparative study is performed between TDVRPTW and TDVRPTW-SP (see Figure 8 & 9). In the case of TDVRPTW, drivers have to travel more to find a parking space, which further increases congestion. TDVRPTW-SP directs drivers to pre-reserved parking places. As a result, cars have to travel fewer distances in order to get a parking spot. This not only cuts down on their journey time, but it also lessens traffic congestion on the roads.

In fact, as shown in Figure 8, with a five-destination route, TDVRPTW-SP can reduce driving time by up to 25 minutes. Reduced driving time is critical since it reduces traffic congestion and, by extension, gasoline costs and pollution.

In addition, the effort and time required to find a parking space are optimized, especially since the number of parking spaces is limited. In general, the performance advantage of our model is greater as the number of destinations increases, as shown in Figure 9 when the number of destinations is 11, our model reduces travel time by 65 minutes. The findings show that TDVRPTW-SP can have a considerable impact on city driving and parking.

Table 4. Simulation of TDVRPTW

	Tavel Time	Elapsed time
3	1881188	0.309206
4	196.2	0.270037
5	198.6	0.296707
6	224.7	0.267811
7	244.1	0.303308
8	255.7	0.344924
9	263.8	0.4058
10	269.1	0.391847
11	288.9	1.472594

6. CONCLUSIONS

The topic of multi-destination vehicle routing with smart parking, traffic, and time windows restrictions was solved in this research (Using a travel time network generated by IGWO-LSSVM). This problem has real-world implications, such as when users visit multiple administrations in one trip and have a specific service time. To solve it, we modelled an efficient travel time network to meet the TD (Time-dependent) constraint and an algorithm to find the sequence of destinations that reduces the total travel time of the trip, including the parking time. This is the first work on the TDVRPTW that we are aware of a smart route management system taking into account traffic conditions, real-time parking, and time windows and a forecasting method of travel time calculation.

Using a large database of real vehicle tracking, we tested the TDVRPTW-SP algorithm in a realistic experimental study. The outcomes of the experiments showed that there is a very significant improvement potential. However, our solution is limited to managing a single-vehicle itinerary, so it is unsuitable for more complex applications. We aim to address this issue in our future contributions to propose a general solution. We also plan to improve our model by integrating more real-life parameters (multi-graph problem, travel time uncertainty). Indeed, for the problem studied in this paper, we consider only one path between two sequential nodes. However, in reality, there is more than one path between two nodes, i.e., a node can be reached by several links. Therefore, we will need to take this concept into account to make an optimal decision. In addition, we will consider a stochastic TDVRPTW to generate vehicle routes taking into account travel time uncertainty to strengthen our model and be sure not to miss time windows.

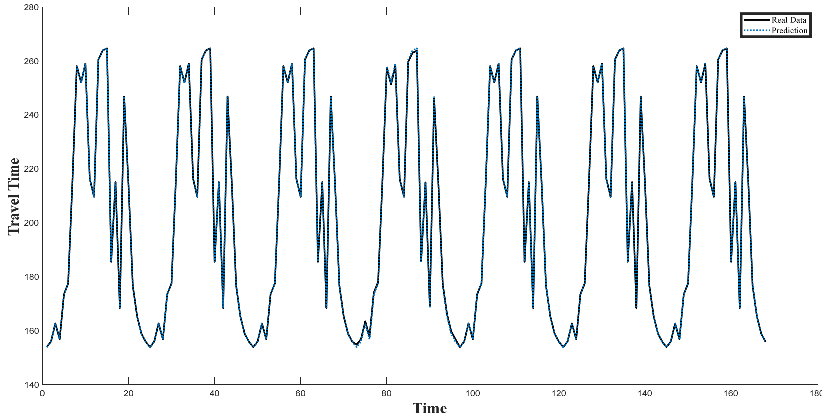

Figure 5. IGWO-LSSVM Travel Time prediction

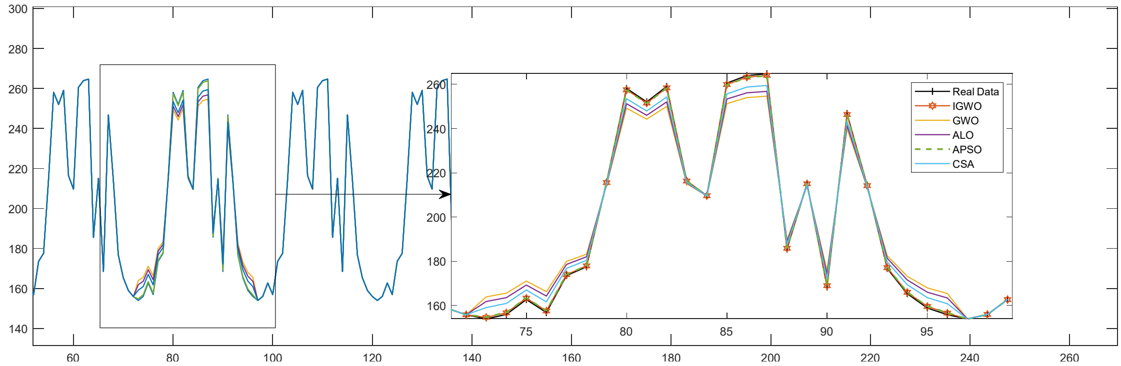

Figure 6. Comparison of improved LSSVM algorithms for travel time prediction

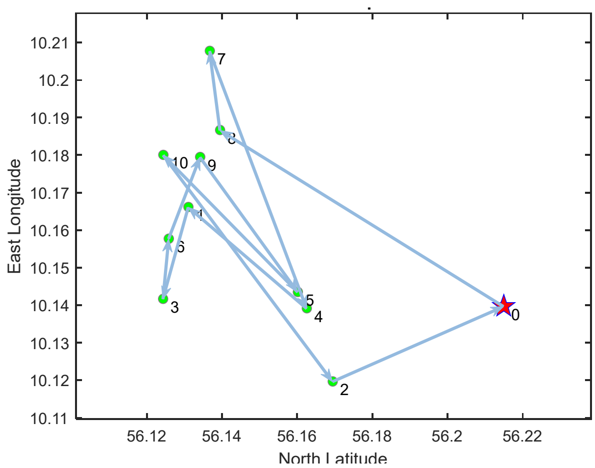

Figure 7. Best Route of TDVRPTW-SP with 11 destinations

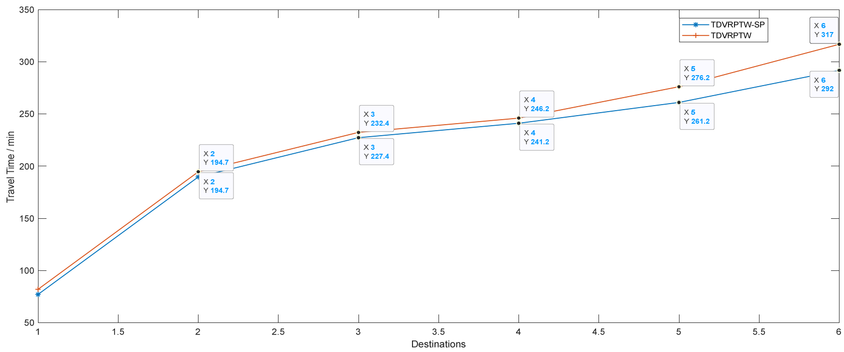

Figure 8. Comparison of TDVRPTW and TDVRPTW-SP (5 Destinations)

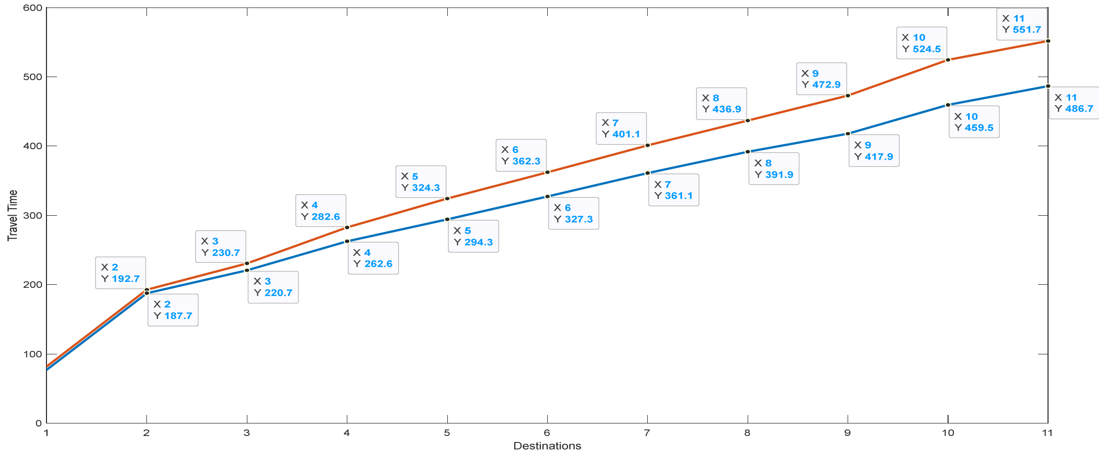

Figure 9. Comparison of TDVRPTW and TDVRPTW-SP (11 Destinations)

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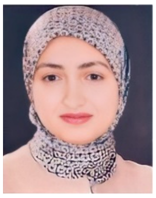
BIOGRAPHIES



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