ABM-GIS simulation for urban freight distribution of perishable food

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Abstract. Freight transport is essential to modern urban civilization. No urban area could exist without a powerful freight transport system. However, the distribution of perishable foods in urban areas is seen as a source of problems, due to traffic congestion, time pressures, and environmental impact. In this paper, an Agent-Based Model integrated with Geographic Information Systems (ABM-GIS) is designed for a time-dependent vehicle routing problem with time windows. This simulation model consists of determining the quickest routes to transport fresh products, estimating Vehicle kilometer traveled VKT and vehicle hour traveled VHT where speeds and travel times depend on the time of the day. Based on a case study, analyses of changes on traffic condition were conducted to get an insight into the impact of these changes on cost, service quality represented by the respect of time windows, and carbon emissions. The results reveal that traffic jams and restrictive time windows lead to additional cost, cause delays, and increase co2 emission. As for a short-term planning, time-dependent scheduling algorithm was proposed and assessed while extending time windows. Results have proved the potential saving in cost, travel time, and carbon emission.

1 Introduction

Freight transport is fundamental to modern urban civilization. No urban area could exist without an efficient freight transport system. Considering the demand for high-quality fresh food, transportation requirements for fresh food delivery have been continually increasing in urban areas [1].

The delivery of these goods is perceived as a source of problems. This is owing to specific characteristics of perishable foods, traffic congestion, the increasing requirement of customers in terms of delivery time, and environmental impact. Traffic growth presents a new challenge for carriers in vehicle routing and scheduling to deliver products. Besides, it brings environmental problems due to the increase in carbon emission. Therefore, establishing the fastest routes, optimal departure from the distribution center to deliver these time-sensitive products is a major problem encountered by carriers.

This study focused on a time-dependent vehicle routing problem with time windows for distributing perishable foods in urban areas. Vehicle routing problem (VRP) had a spatial dimension which is practically neglected in research studies. Therefore, handling geographic data is requisite for efficient routes based on real distances. The most promising solution for so is GIS. In fact, we propose an Agent-Based simulation Model integrated with the Geographic Information System (ABM-GIS) to use real-case while performing distances between customers. In this paper, we aim at producing the fastest routes to deliver perishable foods as fast as possible and estimating VHT and VKT which are valuable for transportation, through the simulation model. We aim also to study the impact of congestion on commercial vehicle tours in an urban area. And as for short-term planning, for daily operations, we propose a time-dependent scheduling approach to optimize departure times from the distribution center.

The remainder of this paper is organized as follows: section 2 provides a background on integrating ABM and GIS, section 3 describes the simulation model, section 4 presents the estimation of VKT and VHT, section 5 highlights the impact of congestion, section 6 presents experimental design and results, section 7 introduces the proposed scheduling methods as well as the enhancement they provide, and we end up with a conclusion.

2 Agent Based Model and GIS integration

Agent-based modeling is a relatively new method compared to system dynamics and discrete event modeling. This modeling paradigm is developed to simulate complex systems through the study of active entities behavior, known as agents. Agent Based System (ABS) has been adopted to solve complex problems, from various domains, such as logistics optimization, traffic, and urban planning. ABS can be used for different purpose: (1) Understanding observed dynamics, processes, and systems, (2) Designing or engineering of processes or systems, (3) Managing a system or process,(4) Formulating theory and explanatory

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- Scenario 1:
  - Customer Demand is received during a traffic peak (rush hour).
  - The speed required to deliver this customer in time lower than or equal to the average speed during the traffic peak interval.
- Scenario 2:
  - Customer Demand is received during a traffic peak (rush hour).
  - The speed required to deliver this customer in time is higher than the average speed during the traffic peak interval.

For an accurate estimation of the VHT, speed changes within the travel time are taken into account. Two cases are considered, in the first case the departure and arrival time of vehicle are in the same time interval [K], thus no speed changes have occurred. In the second case when the arrival time of a vehicle is estimated to be in the interval [K+1] it means the speed has changed during this period.

1: If D_0 and $AT_n \in [K]$

$$2: VHT_0^n = \frac{VKT_0^n}{V_k}$$

3: Else

$$4: VHT_0^n = \overset{K}{VHT_0^n} + \overset{K+1}{VHT_0^n}$$

$$5: VHT_0^n = (T_{k\sup} - D_0) + (AT_n - T_{k\sup}) \times \frac{V_k}{V_{k+1}}$$

5.1.2 Impact of congestion in scenario B

In this scenario customers have the same time windows form 8 to 9 in the morning, because customers are restaurants and this time demand ensures that they can process and serve fresh food to their customers.

5.2. Impact of congestion on costs

To provide insight into the relationship between cost, and changes in the road network, the distribution costs considered in this study include the transportation costs, damage costs, refrigeration, and penalty costs. Since we are interested in measuring the variation, fixed cost will not be included.

5.2.1 Transportation costs

The transport costs include maintenance and repair costs, tires and depreciation costs, and the major component related to the fuel consumption. Fuel consumption, in our study, is weight and time-dependent, because the travel speed and travel time, which depend on departure time, and the loading weight, are taken into consideration in the procedure.

Fuel consumption calculation:

Let KPL_{ij} be the kilometer per liter for a vehicle traveling from the customer i to customer j. The consumption per unit time corresponding LPH_{ij} is calculated as follow:

$$LPH_{ij} = \frac{V_{ij}}{KPL_{ij}} \tag{2}$$

V_{ij} Is the corresponding traveling speed form i to j.

The transportation costs can be expressed as

$$C_{tran} = \sum_{v=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n}(C_{ij}^{v}x_{ij}^{v}d_{ij} + C'^{v}_{ij}x_{ij}^{v}VHT_{ij}^{v}) \tag{3}$$

C_{ij}^{v} Is the sum of variable costs dependent onthe distance traveled (maintenance, tires, depreciation)

x_{ij}^{v} Is a 0–1 variable, x_{ij}^{v} = 1 if the vehicle v passes the road between customer i and customer j, otherwise0.

d_{ij} Distance traveled from node i to j

VHT_{ij}^{v} Vehicle hour traveled from i to j

C'^{v}_{ij} Fuel consumption by unit time of the vehicle v moving from node i to j

5.2.2 The refrigeration costs

Refrigeration is crucial during the transportation of perishable food. Refrigeration costs include the cost caused by energy consumption to keep the adequate temperature during delivery, as well as the cost of additional energy supplied by the refrigeration system during the unloading process.

Refrigeration cost during transportation can be expressed as:

$$C_T = c_e \sum_{v=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} x_{ij}^{v}T_{ij}^{v} \tag{4}$$

$$T_{ij}^{v} = VHT_{ij}^{v} + t'_j \tag{5}$$

Ce: The refrigeration costs during the transportation process of unit time.

T_{ij}^{v} :The traveling time of the refrigerated truck v from the customer i to the customer j.

t'_j :The waiting time of refrigerated vehicle in customer j before unloading.

Refrigeration cost during the unloading process:

$$C_u = c'_e \sum_{v=1}^{m}\sum_{j=0}^{n} y_j^{v}U_j \tag{6}$$

$$C_{ref} = C_T + C_u \tag{7}$$

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$c_e^{'}$: The refrigeration costs during the unloading process of unit time.

U_j: The unloading time which is needed toserve the customer i.

y_j^v is a 0–1 variable, $y_j^v = 1$ if the vehicle k services for customer i, otherwise $y_j^v = 0$.

5.2.3 Penalty cost

Generally, in the distribution of food, customers require to be delivered within a time window. And if the goods do not reach the destination within the time agreed on by the customer, thus the time window is violated and additional penalty cost will be applied. These costs can be expressed as follow:

$$C_p = \sum_{v=1}^{m} \sum_{j=0}^{n} (\alpha \max[Tw_{\inf} - AT_j^v, 0] + \beta \max[AT_j^v - Tw_{\sup}, 0]) \quad (8)$$

AT_j^v : The arrival time of vehicle v to customer j.

$Tw_{\inf}, Tw_{\sup}$:The lower and upper bound of the time window.

α : The cost of waiting for the unit time if refrigerated truck arrives at a customer in advance.

β: The cost of punishing for the unit time if the refrigerated truck is late to the customer.

5.3. Impact of congestion on co2 emission

The traffic growth in urban areas brings further problems of environmental aspects. In recent years there has been increasing interest in estimating the environmental effects of vehicle routing policies.

In our work, we aim to discover the relationship between traffic congestion, restrictive time windows, and co2 emission. For the purpose, we use the "ASIF" equation [12] to quantify carbon emissions in the simulated scenarios.

6 Experimental design and results

In this section, we use a numerical example to quantify the impact of traffic jams on the VHT, costs, and emissions. Section 6.1 describes the problem and parameter setting; experimental results are analyzed in section 6.2.

6.1 experimental design and parameter settings

The delivery service provider places a premium on service quality, hence all scenario use hard time windows, to guarantee that promised delivery times would be met.

To simplify the problem, we make the following assumptions:

(1) The service provider has a homogenous fleet with one type of refrigerated vehicles.

(2) In the scenario A, the customer order does not exceed the capacity vehicle, and the time spent to serve each customer is 15 min.

(3) In the scenario B, the vehicle can serve 3 customers and spend 10 min at each one.

The distribution center DC start operating at 7.In the first scenario corresponding to direct delivery, orders in the simulation model are generated as an event sent to the distribution center randomly during the day. Since we are interested in evaluating the impact of congestion we took a sample of orders received during the morning, characterized by the higher congestion level. We assume that order preparation requires 30 min and the time windows length is 15min.

In the second scenario, the time window is [8h 9h], since the level of congestion from 7 to 8 is upper, simulation run was performed to estimate the travel time for both tours with an average speed corresponding to this time window figure to determine if this time interval is sufficient for delivery, thus:

If $T_{delivery} < 1h$ we start delivery at 8 to avoid congestion

Else $T_{departure} = 8h - VHT^{i}_{w,K-1}$

$VHT^{i}_{w,K-1}$: vehicle hour traveled to deliver the client i from the warehouse during the time interval K-1.

Parameters of refrigerated vehicles are shown in table 1.

Based on the mileage and the estimated VHT, costs and carbon emissions were measured and compared to those in normal conditions.

Table 1. Vehicle parameters

parameter	*value*
Load capacity (kg)	795
Fuel type	gasoline
maximum speed (km/h)	120
fuel consumption when loaded(km/l)	2,65
fuel consumption when empty(km/l)	6,06

6.2 Results and analysis

In this section, we will illustrate experimental results. The VHT has evidently increased during rush hours. This augmentation did not affect customers in scenario A.1, since the demand can be delivered in agreed time. However, in the scenario A.2, the time is violated which leads to additional penalty costs and impacts customer satisfaction. In this case, the time window agreed with these customers should be reviewed to be less restrictive. Another way is to limit the reception of demands to a specific period less congested, but this solution is not practical since we are dealing with restaurant that needs food in a precise time so they can process and serve fresh food to customers (breakfast, lunch…).

The fuel consumption is time-dependent; hence its heavy increases in the scenario A.2.

As we are delivering perishable foods, refrigeration costs are a very important component that should be considered. Regarding the latter, we can say that congestion has a deeply negative impact since even for a slight increase on the VHT, the costs increased by an average of 30%.

Since the co2 emissions are directly related to the fuel consumed, it remains' relatively flat as the trip length and the travel time increase.

In the direct delivery, we have demonstrated that fuel consumption increases with the VHT, however strangely we have noticed in scenario B that with a slight increase in VHT the fuel consumption is less under congestion than under normal traffic conditions in some arcs of the tour and consequently, the carbon emissions are reduced because the travel time saved is not really important. In these arcs it is not really wise to speed up for saving 1 or 2 min in the travel time.

These findings give us an idea about the optimal speed in each segment of the tour. But since we have another crucial component related to the VHT that should be considered while deciding either the speed is advantageous or not. For this reason, we have analyzed the impact on refrigeration cost, and we have found that congestion has a strong impact. It increases costs with an average of 37% on each tour trip.

7 Scheduling and time windows extension

Through the analysis of different scenarios, we have proved that travel time during rush hours is longer than in other periods, which leads to additional cost, impact the service quality and increases the co2 emission. With strict time windows, businesses have difficulties in optimizing these costs.

These findings imply that carriers should reduce travel time. After showing how the departure time of each vehicle from the distribution center affects costs and

Service, this goal can be achieved by changing route start times to avoid congested times and traveling as fast as is allowed by the traffic conditions, and combined with more flexibility in delivery time windows.

For this purpose, we have developed two algorithms to schedule departure in the direct delivery scenario and the LTL delivery while extending the time window. To discover how these changes in policy may lead to cost saving.

7.1. scheduling algorithm

To plan the departure of the vehicle from the distribution center, we have developed two algorithms for each scenario (direct delivery and LTL). These algorithms are used when the demand is received during a rush hour followed by a time interval with less congestion. The concept consists of programming the departure as late as possible to avoid congestion and travel as fast as possible while respecting the time windows.

7.1.1 Scheduling technique for scenario A

The demand is received during the time interval K, let Tw be the length of time windows. For a delivery from the distribution center '0' to a customer 'n', the departure is programmed as follow:

1: If $\overset{k+1}{VHT_0^n} + (T_{k\sup} - T_{DP}) < TW$

2: $D_0^n = T_{k\sup}$

3: **Else**

4: $\overset{k+1}{VHT_0^n} = TW_{\sup} - T_{k\sup}$

5: $D_0^n = T_{k\sup} - \dfrac{D_r}{V_k}$

6: $D_r = VKT_0^n - \overset{k+1}{VHT_0^n} \times V_{k+1}$

7.1.2 Scheduling technique for scenario B

The procedure starts by setting the arrival date to the last customer in the route to the upper bound of the time windows. The departure from the upstream customer is then calculated figure 7.

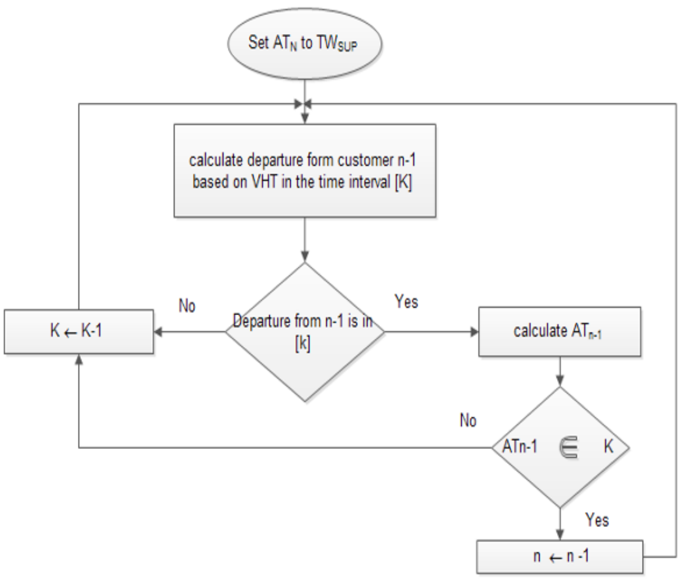

Figure 7. scheduling procedure for scenario B

7.2. Experience and results

To validate the proposed algorithms, they were applied to plan departures for scenario A and B.

In the scenario A, the algorithm is tested to determine the departure from DC to customer 5, which is critical as shown in our previous analyses. The time window is extended by 15 min. In the scenario B, we extend the time windows by 1 hour and we plan departures for 2 vehicles serving the customers in 2 tours.

Experimental results have proved the efficiency of these policy changes in saving costs and reducing emission. Interestingly, for a slight delay of the departure in the scenario A, fuel consumption as well as the co2 emissions have been reduced by 12% and refrigeration cost by 19%.

In the scenario B, policy changes lead to good results, since the travel time was decreased by 20 % even if the improvement in terms of costs is negligible.

8 conclusions

This study aims to solve one of the major problems encountered by carriers, which consist of choosing the optimal routes and program departure to deliver customers intime. Therefore, agent-based simulation combined with GIS is used. Simulation runs were performed to estimate the VKT and VHT. Analyses of network changes (congestion) were conducted to provide insight into the impact of these changes on these 2 values (VHT and VKT) also on cost, service quality, and emissions.

A time-dependent scheduling technique was developed and proved its success in achieving a potential saving, in terms of costs and co2 emission. As a future research, this time-dependent vehicle routing problem will be represented as an optimization model and integrated with ABM-GIS.

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