

Vehicle Routing Under Dynamic Network Conditions: A Bayesian Approach

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Abstract

Routing problems have been extensively studied in operations research because of their wide application in transportation and logistics. In this study, we consider routing problem in a road network of which the traveling conditions change over time and sometimes are uncertain. Such problems can arise in humanitarian logistics, resident evacuation, and emergency resource delivery after natural disasters and severe weather events. We provide a methodology to support route planning with limited information of the network conditions and route updating as new information becomes available. The dynamic network condition is modeled by a time-varying speed reduction factor. We update the estimation of this factor by integrating prior estimation with the latest travel data from the vehicles in a Bayesian inference framework. Ant colony optimization method is used to find the optimal route in both planning and updating phases. A real-world case study shows the effectiveness and necessity of considering dynamic uncertain network conditions in routing.

Keywords Dynamic decision making, Bayesian inference, Vehicle routing, Ant colony optimization

1 Introduction

Routing problems are classical combinatorial optimization problems, where route for vehicles must be determined to visit customers in several geographically dispersed locations. Vehicle routings are influenced by numerous external factors affecting the networks which along with their forecasts are usually dynamic and unexpected even with the technological advancement and accessible internet service. Some of the recent studies have considered routing in specific real-life dynamics and network situations such as probabilistic weather conditions [1], and traffic congestion [2], [3]. Sudden extreme change in weather forecast and road conditions are very common, especially in post-disaster scenarios [4]. The chaos and communication failures during disasters may lead to disruptions and delays regarding the transmission of the disaster's information. The actual weather and infrastructure conditions may divert drastically from the anticipated. We define the dynamicity of network as the combined effect of traffic, weather, natural disaster, condition of the road and other infrastructure, and other factors on the speed of the vehicles. In particular, we consider such cases where the information of the network condition is not completely available or reliable. Some real-life scenarios where these problems are likely to occur are include emergency resource delivery or evacuation after occurrence of natural disaster, and pickup and delivery service of logistics service provider despite the anticipation of a weather event. In these scenarios, routing decisions should be made in anticipation of certain changes in external factors and updated using the newly available information of the network condition.

In this paper, we focus on vehicle routing under dynamic and uncertain network conditions. By employing a Bayesian approach incorporating real-time and vehicle-collected road information, we propose an online decision-making methodology to improve vehicle routing in network conditions mentioned heretofore. We propose the problem in Section 2 and our methodology for both planning and updating the routes in Section 3. We then demonstrate the methodology using a real-world case study in Section 4, and finally conclude the paper in Section 5.

2 Problem description

Consider a graph $G = (V, A)$ where $V = \{1, 2, 3, \dots, z\}$ is the set of nodes and $A = \{(i, j); i, j \in V\}$ is the set of arcs. Suppose that the depot at node 1 is the start and destination of any route. The nodes are categorized into primary nodes $P = \{p_1, p_2, \dots, p_s\}$ that require service (visited by a vehicle), and secondary nodes that do not need service. The distance and maximum allowable vehicle speed of an arc $(i, j) \in A$ are denoted by L_{ij} and v_{ij}^{max} respectively. We use $0 \leq k_{ij}(t) \leq 1$ to denote the speed reduction factor associated with arc (i, j) due to external factors if the vehicle leaves node i at time t . $k_{ij}(t) = 0$ if the arc (i, j) is completely inaccessible at time t , and $k_{ij}(t) = 1$ if the vehicle can attain its maximum speed v_{ij}^{max} . Let $v_{ij}(t) = v_{ij}^{max} k_{ij}(t)$ be the average travel speed on (i, j) when the vehicle leaves node i at time t . Then the travel time at that condition is denoted by $T_{ij}(t) = L_{ij}/v_{ij}(t)$. Prior to route planning, $k_{ij}(t)$ is estimated for all (i, j) and $t \geq 0$ based on limited and uncertain information and hence may be inaccurate. To make the estimation more accurate, we suppose that a vehicle can collect data of the road conditions in real time while executing a route. Consequently, the routing decisions can be updated with new information. To simplify the problem, we assume that the unexecuted portion of a route can be updated based on the collected information only after the vehicle visits any primary node.

3 Methodology

The methodology can be divided into a) modeling the dynamic network, b) finding the best route, c) and updating the network condition and the routes. While executing the planned route, the network model is updated using the newly acquired network information, and the planned route is updated accordingly.

3.1 Modeling the dynamic network

Let $k_{ij}(t) = \hat{k}_{ij}(t) + \epsilon_{ij}$ where $\hat{k}_{ij}(t)$ is the estimated condition forecasted based on past records, current weather forecast, road conditions, etc. Let $\epsilon_{ij} \sim \mathcal{N}(\mu_{ij}, \sigma_{ij}^2)$ be the forecast error. Hence the travel speed, $v_{ij}(t) = v_{ij}^{max} (\hat{k}_{ij}(t) + \epsilon_{ij})$. We divide the set of arcs into h disjoint zones based on the level of external impact on the road condition and level of uncertainty in estimating $k_{ij}(t)$. For any zone h and all arcs (i, j) that belongs to zone h , we assume that $\epsilon_{ij} \stackrel{iid}{\sim} \mathcal{N}(\mu_h, \sigma_h^2)$ for all $(i, j) \in A_h$. Therefore, $v_{ij}(t) = v_{ij}^{max} (\hat{k}_{ij}(t) + \mu_h)$ if $(i, j) \in A_h$.

3.2 Finding the best route for one vehicle

Although the major challenge of this research is to incorporate dynamicity and uncertainty to routing decision, a good methodological technique is required to make the decisions. Metaheuristic methods are used to solve TSP includes trajectory methods (e.g., simulated annealing, Tabu search, GRASP and meta-RAPS) and population methods (e.g., genetic algorithm and ant colony optimization) [1]. In this research, we use the ant colony optimization (ACO) as the route optimization method. ACO is a metaheuristic method that is used for finding good routes based on the behavior of ants searching for food. To use ACO in our study, we set I to be the maximum number of iterations and set the size of the ant population to be S . For a move between any two primary nodes, we associate a pheromone level τ initialized to be the same for every move.

In each iteration, each ant follows the same procedure as follows. An ant starts from the depot (node 1) and calculates the inverse of the travel time, the attractiveness η , from its current location to each unvisited primary node. The ant then generates a random number $0 \leq r \leq 1$ and compares with $0 \leq q_0 \leq 1$ set a priori. If $r \leq q_0$, then the ant takes the next move as the one that has the highest value of $\frac{\tau \eta^\beta}{\sum \tau \eta^\beta}$, where the preset parameter β balances the weight between pheromone and attractiveness of a move. If $\tau \eta^\beta = 0$ for each move, the ant will choose the first primary node from the list of unvisited primary nodes. If $r > q_0$, the ant decides its next move randomly. After reaching the next primary node, the ant repeats the process above.

After all the ants finish visiting all primary nodes and return to the depot, the total travel time of each ant's route, L_s , is calculated. The route with shortest travel time is compared with the best route on record to decide if the best route needs to be replaced. Before entering the next iteration, the pheromone of the move between any two primary nodes is updated as $\tau_{new} = (1 - \rho)\tau_{old} + \sum_s \frac{Q}{L_s}$, where $0 \leq \rho \leq 1$ is the preset evaporation rate, Q is a preset parameter balancing the weight between existing and new pheromone, and the sum is taken over all such s that takes the move. Therefore, a move is likely to have higher pheromone if the travel time of the route is shorter, and/or has been chosen by multiple ants.

Among all the parameters, the ant population j and number of iterations I are the less sensitive parameters compared to the others since a fairly large size of j and I provide a solution good enough with a certain combination of values of the other parameters. Li and Zhu [5] conducted a comparative parametric analysis of ρ, Q and β of ACO. Their study shows that the pheromone evaporation coefficient, ρ , with a value too small reduces the global search ability, but with a value too large slows down the convergence speed. Pheromone intensity Q can have any positive value. A large value of Q leads the algorithm to fall into a local optimum, but a small value slows down the optimization speed. β represents the relative importance factor between pheromone τ and attractiveness η . By setting $\beta = 1$, equal emphasis is placed on both τ and η . The randomness in the algorithm is captured by q_0 .

Note that the attractiveness η_{ij} depends on the travel time $T_{ij}(t)$ which subsequently on the speed reduction factor $k_{ij}(t)$ which changes over time. So, $T_{ij}(t)$ must be calculated every time an ant considers the next move. Since not all the primary nodes are directly connected, the pheromones are considered not along actual arcs, rather the move of going from the current location to another primary node. To find the shortest path between two primary nodes, we use Dijkstra's shortest path algorithm before each move with the only adjustment being that the travel time of each arc is dynamic, depending on the starting time t and the value of $k_{ij}(t)$.

To find the best route for multiple vehicles instead of single one, we can replace one ant with a group of ants and rephrase the objective to minimize the total travel time of all the routes.

3.3 Updating the routes

Now, considering the network condition changed significantly after making the routing decisions, we need an online updating procedure of the routes using real-life information at that moment. For updating decisions based on new information, the past literature has used both Bayesian inference [6] and Nash equilibrium [3] in various scientific fields. But due to lack of studies linking probability distribution with vehicle routes, Bayesian inference in routing decisions has not been ventured as much as in other fields.

Once the vehicle has traveled from one primary node to the next one, the actual speed in each of the arc of the path between the nodes is observed and contains new information about the real network conditions. Using the real speed in each arc observed by the vehicle while moving between two primary nodes, we employ Bayesian inference to update the distributions of ϵ_{ij} . More specifically, we update μ_h and σ_h^2 if the vehicle travels any arc in zone h . Bayesian inference is a statistical method specifying how one's beliefs may be updated upon observing data. It updates the prior distribution of a random variable by using the information contained in newly collected samples or observed data. For a set of independent and normally distributed data points X of size n , where each individual point x follows $\mathcal{N}(\mu, \sigma^2)$. Let the conjugate prior distribution follow $\mu \sim \mathcal{N}(\mu_0, \sigma_0^2)$. If a vehicle travels $n \geq 1$ arcs in zone h to move from p_i to p_j , we can use the actual speed to calculate the actual error of the speed reduction factor. Repeating this for all n arcs, we have a sample of the actual errors in zone h . If the sample mean and sample variance are μ and σ^2 respectively, we update μ_h and σ_h^2 using Bayesian inference where the posterior distribution has the following parameters [7].

$$\frac{1}{\sigma_h'^2} = \frac{1}{\sigma_h'^2} + \frac{n}{\sigma^2} \quad (1)$$

$$\mu_h'' = \frac{(1/\sigma_h'^2)\mu_h' + (n/\sigma^2)\mu}{(1/\sigma_h'^2) + (n/\sigma^2)} \quad (2)$$

Here $(\mu_h', \sigma_h'^2)$ denote the prior estimation of (μ_h, σ_h^2) while $(\mu_h'', \sigma_h''^2)$ denote the updated posterior estimation. This procedure is repeated until the vehicle visits every primary node. After that we call the route optimization routine to update the remaining of the route from p_j to node 1.

4 Case study and results

In this section, we demonstrate the methodology in a simplified version of a complicated real-life case study. The chosen dynamic event is Hurricane Florence, the powerful hurricane that created havoc in the Carolinas in September 2018. Extensive power outages occurred across the states due to the uprooting of trees and power lines. Most roads

and highways in the coastal area experienced flooding due to heavy rainfall and Florence was declared as the wettest North Carolina hurricane on record. [8].

4.1 Network

For the case study, we create a network with 64 nodes situated at the public health service center in certain counties of North Carolina since they are usually considered for distributing the relief supplies to the local people. We assume that the depot is at node 1 in Wake County. Forty primary nodes have been considered in all the coastal and some other random counties. 23 more nodes have been considered as the secondary nodes. Though numerous combinations of roads and streets interconnect the nodes, we simplified the network by considering that only one arc connects two neighboring nodes. Hence, the network is comprised of only 160 arcs. Federal Emergency Management Agency (FEMA) has visualized the frequency of hurricanes in counties of North Carolina since 1953 [9]. Four distinct zones can be observed in Figure 1. We have excluded the least affected zone from our network and divided the network into the other three zones. Every arc between two nodes belongs to one distinct zone.

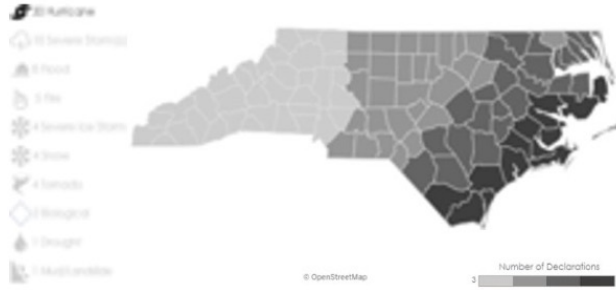


Figure 1: Disaster declaration for hurricanes in counties of North Carolina

The maximum speed is set to be $v_{ij}^{max} = 70$ mph for all (i, j) which is the speed limit in freeways of North Carolina. With forecast of weather, road and traffic congestion condition, the average speed at each zone is predicted for the next two days, with $t = 0$ being the departure time of the vehicle. The forecasted values of speed reduction factor $\hat{k}_{ij}(t)$ are given in Table 1.

Table 1: Values of $\hat{k}_{ij}(t)$ for different zones over time

Condition of total travel time	Value of $\hat{k}_{ij}(t)$		
	Zone 1	Zone 2	Zone 3
$0 \leq t \leq 12$	1.0	1.0	1.0
$12 \leq t \leq 24$	0.6	1.0	1.0
$24 \leq t \leq 36$	0.4	0.6	1.0
$t \geq 36$	0.2	0.4	0.6

The real travel speed reduction factors $k_{ij}(t)$ have been taken using the real-life data of rainfall and visibility on September 16 and 17 in the year 2018 around the time Hurricane Florence hit the state. To convert the weather information into speed reduction factor, we primarily used hourly rainfall data collected from historical Automated Surface Observing Systems (ASOS) station data provided by the Iowa Environmental Mesonet (IEM) at Iowa State University and followed Wright for converting it to $k_{ij}(t)$ [1]. Since some of the stations do not have recorded amount of rainfall, visibility has been selected as the secondary category to find the value of $k_{ij}(t)$, and the conversion ratio follows the study of Agarwal et al. [10]. Conversion chart for these two weather events is presented in Table 2.

4.2 Routing decisions

For executing the ant colony optimization algorithm, we used $\beta = 1, Q = 1, \rho = 0.9, j = 100$, and $I = 20,000$. We set the cutoff probability level of randomness $q_0 = 0.5$ to incorporate less randomness.

Table 2: Conversion chart to find the value of $k_{ij}(t)$

Weather phenomenon	Condition	k
Rain	light	0.9
	moderate	0.6
	heavy	0.4
Visibility (miles)	1-0.5	0.94
	0.5-0.25	0.93
	0.25	0.89

In Setting I, we consider that the routing decisions are made under static and deterministic road network conditions. The average vehicle speed is considered to be k_{ij}^{max} for all (i, j) . In Setting II, we consider that the routing decisions are made after analyzing the predictions of dynamic weather and road and traffic conditions, and route is not updated once made. While executing route according to decision from setting II, the actual travel speed of the vehicle in the arcs it passes is collected as samples after visiting each of the primary nodes. Then the mean μ_h and variance σ_h^2 of the estimated error of the speed reduction factor for each zone is updated using Bayesian inference in setting III. With the updated network condition, we use ACO again to update the remaining of the route. The same procedure is repeated until the vehicle finishes visiting all primary nodes and comes back to the depot at node 1. The total route duration in all three settings are presented in table 3 while the routes are highlighted in Figure 2.

Table 3: Comparison among routes in different settings with one vehicle

	Setting I	Setting II	Setting III
Route I	29.21 hours	39.85 hours	31.61 hours
Route II		36.91 hours	36.71 hours
Route III			25.38 hours

To compare the routes, we compute the travel times of Route I in Settings II and III, and Route II in Setting III. Comparing Route I and Route II in Setting II, we see that 2.94 hours can be saved by considering the dynamic network conditions. Comparing Routes II and III in Setting III, 11.33 hours can be saved by updating the dynamic network conditions while executing Route II. The result shows that the actual duration of the travelled route always improves routes compared to the planned ones. With a large and complex network compared, this case study makes a strong point about the importance of updating network forecast and routes to make more effective routing decisions.

5 Conclusion

In the research, we have characterized the network to be changing over time due to the combined effect of external factors. We have developed the methodology for solving the routing problem with single vehicle using ant colony optimization. The uncertainty of the network has been handled by updating the routes using Bayesian inference. The effectiveness of the proposed methodology has been validated by applying it to one real-life case study. The major contribution of the study is the concept and methodology of adapting to the change of network and updating the planned route while in execution. The research can be extended by refining the vehicle and demand constraints, the quality of data conversion, and the methodology itself. The real-life scenario has been simplified in this study by ignoring carrying capacity, time window and other vehicle constraints as well as variation and uncertainty of customer demand. This study can be extended and enriched further by avoiding these simplifications. Also, the meteorological aspect of this research has not been ventured extensively. Emphasizing mostly on the effect rather than the cause behind it, the case studies observe only the rainfall and visibility in a time window to make assumptions of vehicle speed. The cumulative effect of other factors from previous hours have not been considered and this also has the eligibility to be improved in the future analysis. Finally, the ant colony optimization algorithm can be investigated further with different combinations of parameter values to check how the results converges.

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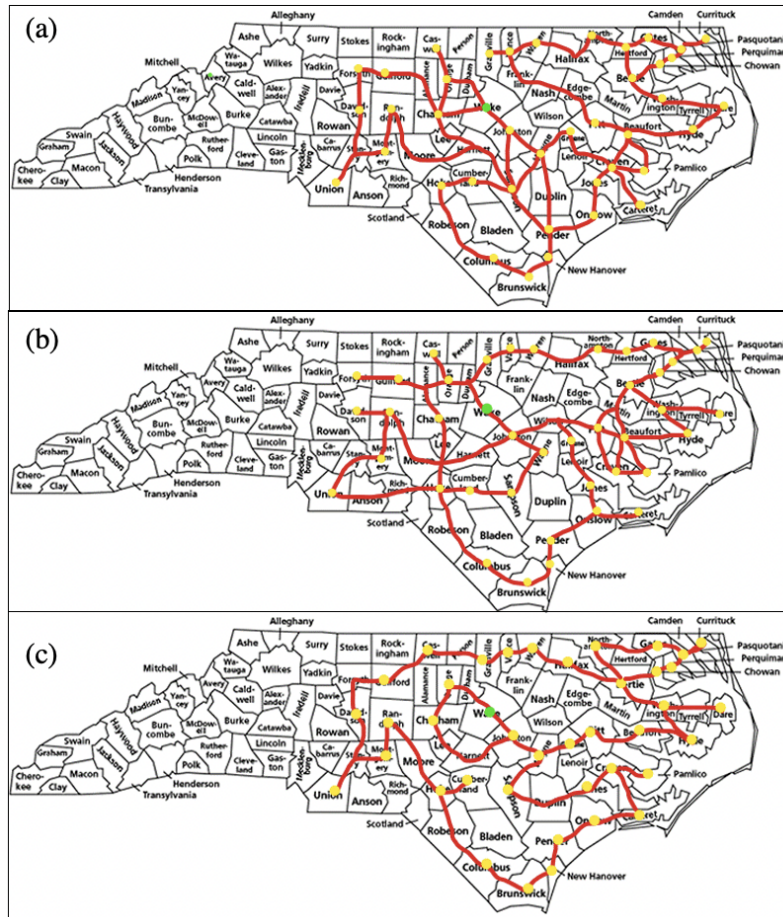


Figure 2: Route in (a) setting I, (b) setting II, and (c) setting III

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