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Adaptive Vehicle Routing under Dynamic Uncertain Network Conditions

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ABSTRACT

ADAPTIVE VEHICLE ROUTING UNDER DYNAMIC
UNCERTAIN NETWORK CONDITIONS

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Routing problems, such as Traveling Salesman Problem, Vehicle Routing Problem, and their variants, have been extensively studied in operations research because of their wide application in transportation and logistics. In this thesis, we consider routing problems 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 severe weather events and natural disasters. We provide a methodology to support routing decisions including route planning with limited information of the network conditions and route updating as new information becomes available. The dynamic network condition is modeled by defining a time-varying speed reduction factor. We update the estimation of this speed reduction factor by integrating prior estimation with the latest travel data from the vehicles in a Bayesian inference framework. The ant colony optimization method is used to find the optimal routes in the planning phase and updating phases. Two case studies show the effectiveness of the proposed methodology for both the single-route and multiple-route problems and the necessity to consider dynamic uncertain network conditions.

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ADAPTIVE VEHICLE ROUTING UNDER DYNAMIC UNCERTAIN NETWORK CONDITIONS

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CHAPTER 1

INTRODUCTION

Routing problems such as Vehicle Routing Problem (VRP) and Traveling Salesman Problem (TSP) are classical combinatorial optimization problems, where a route for a single vehicle in TSP and a set of routes for multiple vehicles in VRP must be determined to visit customers in several geographically dispersed locations. Algorithms have been extensively developed to solve both VRP and TSP under static and deterministic network conditions. Nevertheless, no decision is optimal forever in this dynamic world, and continuous research and analysis are required to check and update these decisions. Accordingly, recent studies have considered routing problems in real-life dynamics and network situations. For example, Wright (2019) solves TSP under probabilistic weather conditions, whereas Lammel et al. (2010), Kanoh and Ochiai (2012), and many others work on routing problems with traffic congestion. Moreover, the external factors affecting the networks and their forecasts may not be static. Thanks to technological advancement and easily accessible internet service, a sudden extreme change in weather forecast may be unexpected in today's day-to-day life. Chen and Chou (2009) have assumed that information about disaster impact is also available immediately. But as Galindo and Batta (2013) point out, unexpected changes in weather and road conditions are very common, especially in post-disaster scenarios, and the chaos and communication failures during disasters may lead to disruptions and delays regarding the transmission of the disaster's information. In these cases, the road condition may be predicted based on how severe the disaster is that has hit that place, how long it is going to last, and a few other aspects. But the actual weather and infrastructure conditions may be uncertain and much apart from the anticipated. Some real-life scenarios where these problems are very likely to occur are as follows:

a) After a natural disaster such as earthquake or cyclone takes place, routes need to be determined to deliver food, medicine, and other emergency resources to the people living in the affected area. But the weather and traffic forecasts to use for that purpose may have been obtained hours ago.

b) When meteorologists warn about a natural disaster, people in the anticipated affected area may need to be evacuated from there. But the anticipated event may not evolve according to the forecast, and the road network condition may become quite different than anticipated.

c) A logistics service provider may have to continue pickup and delivery service despite the anticipation of a weather event. Even though the service provider plans the route considering the weather forecast, the route may change due to the actual unfolding of the weather event during execution.

The common idea in all the scenarios mentioned above is that routing decisions should be made in anticipation of certain changes in external factors and updated using the newly available information of the network condition. Our study investigated routing problems in such a dynamic network. Routes were generated and updated while the uncertain and dynamic change of network conditions depended on the weather, infrastructure, and other external factors.

1.1 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 is at node 1 and node 1 is the start and destination of any route. The nodes are categorized into two groups. The ones that require service (visited by a vehicle) are called primary nodes and are denoted by $P = \{p_1, p_2, \dots, p_s\}$. The nodes that do not need service are called secondary nodes. The distance of an arc $(i, j) \in A$ is denoted by L_{ij}. The maximum speed for a vehicle in arc (i, j) is v_{ij}^{max}. Suppose that the actual travel speed may be less than v_{ij}^{max} and may change over time due to various factors such as severe weather events, traffic, natural disasters, etc. We use $k_{ij}(t)$ to denote the speed reduction factor associated with arc (i, j) if the vehicle leaves node i at time t. Set $0 \leq k_{ij}(t) \leq 1$. If the arc (i, j) is completely inaccessible at time t, then $k_{ij}(t) = 0$. If the vehicle can attain its maximum speed v_{ij}^{max}, then $k_{ij}(t) = 1$. 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 of arc (i, j) given the vehicle leaving node i at time t 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 $t \geq 0$. However, such estimation is based on limited and uncertain information and hence may be inaccurate. To make the estimation more accurate, we suppose that once on the road executing a route, a vehicle can collect data of the road conditions in real time. Consequently, the routes can be updated at any time with new information. To simplify the problem, we assume that the unexecuted portion of a route can be updated only after the vehicle visits any primary node, based on information the vehicle has collected.

Figure 1 shows an example of $k_{ij}(t)$ over 24 hours. For $0 \leq t \leq 6, k_{ij}(t) = 0.8$, which means that the average vehicle speed will 80% of the maximum speed. After that, $k_{ij}(t) = 0.5$ for $6 \leq t \leq 12$, $k_{ij}(t) = 0.4$ for $12 \leq t \leq 20$, and $k_{ij}(t) = 0.3$ for $20 \leq t \leq 24$.

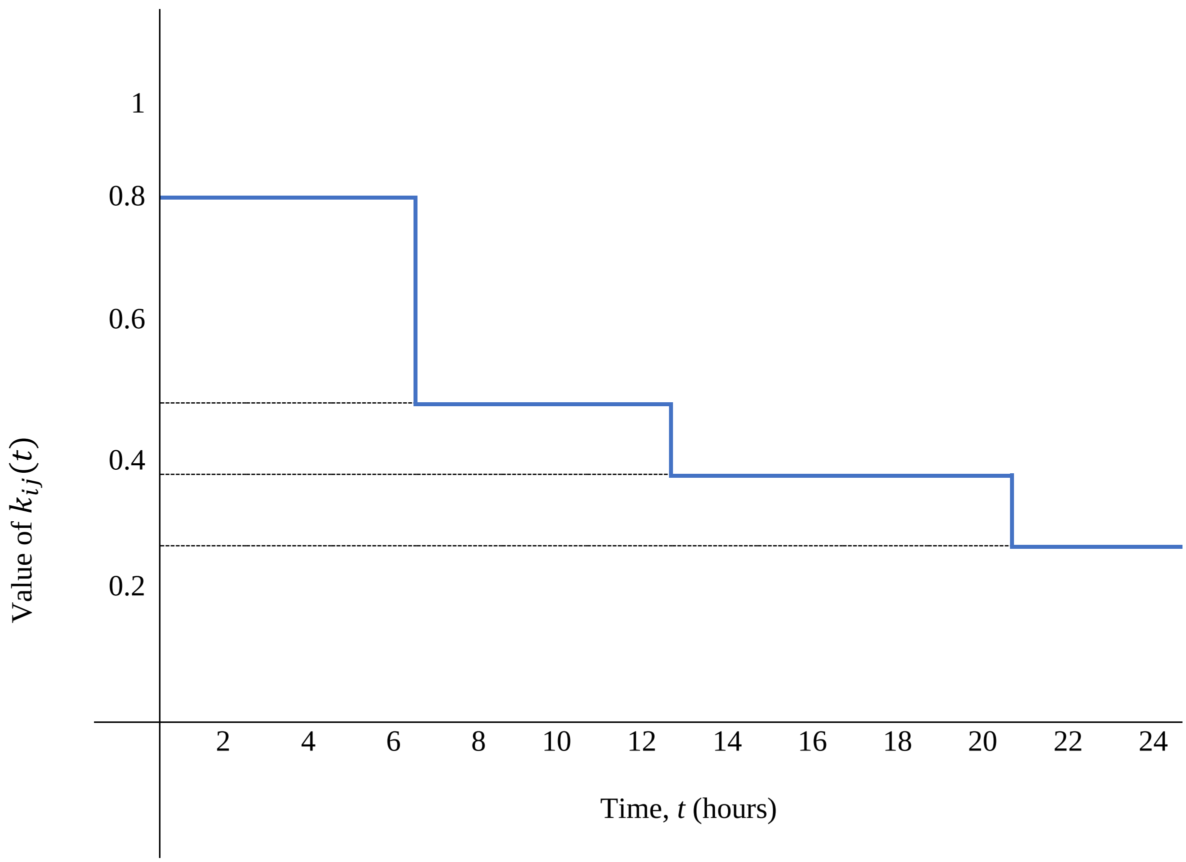

Figure 1. An example of $k_{ij}(t)$.

The research problem of this thesis is to minimize the total travel time of the routes when they are planned and updated, given the latest available network conditions. We investigated routing scenarios with single and multiple vehicles, which can be viewed as variants of Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP) respectively.

1.2 Objectives and Scope

The objective of this research is to improve decision making for vehicle routing under dynamic and uncertain network conditions by creating methodology that incorporates real-time, vehicle-collected road information.

The scope of this research is limited to the routing decisions given estimated and updated road information. The method of converting weather events and natural disasters to the estimation of the network condition before route planning and the data collection procedure of real travel speed are out of scope. But the method of using the data to update the estimation of the network condition is in scope. All problem parameters other than the traveling speed reduction factor $k_{ij}(t)$ are assumed to be deterministic. The capacity of any vehicle is considered to be adequate. Positive and uncertain service times, service time window, and vehicle capacity constraints are out of scope.

1.3 Benefits and Deliverables

This study will improve the routing decisions in a dynamic network with uncertain and unreliable traveling conditions. Such an environment is often perceived as the after-effect of severe weather events and natural disasters. This research will provide real-time or nearly real-time decision support for logistics needs including the delivery of humanitarian aid, equipment, and healthcare services and evacuation of residents. The thesis will also create a methodological framework for integrating real-time data from multiple sources to capture the traveling conditions for better routing. Lastly, this project will advance the knowledge body of operations research, logistics, and statistical decision analysis.

The anticipated deliverables from this study are listed below:

1. A methodological framework for solving the stated problem
2. A computer program for implementing the methodology tested on case studies
3. A comprehensive report documenting the research and the results

CHAPTER 2

LITERATURE REVIEW

Routing problems of various types under dynamic network conditions have been investigated in literature for decades. The following are the most important features that define this research:

- Type of routing problems
  - Closed-loop route
  - Other types of routes
- The effect of external factors
- Updating decisions with real information.

Table 1 lists a collection of the most related and latest studies and indicates their relevance to the declared features. The rest of the section helps in better understanding of the concepts that will be used to solve the described problem.

Table 1
Literature review table

Sources \ Categories	Type of routing problems		Effect of external factors	Updating decision with new information
	Closed-loop route	Other types of route		
Boeckmann (2019)				√
Chen and Chou (2009)	√		√	
Cheong and White (2012)	√		√	√
Chiu et al. (2007)		√		
Cordeau et al. (2014)	√		√	
Hu et al. (2019)		√	√	
Kanoh and Ochiai (2012)	√		√	
Katz and Ehrendorfer (2006)			√	√
Kourniotis et al. (2000)				√
Lammel et al. (2010)		√	√	√
Mishra et al. (2014)				√
Paul and Batta (2011)			√	
Rizzoli et al. (2007)	√		√	
Shiri and Salman (2019)			√	
Victoria et al. (2015)	√			
Wright (2019)	√		√	
Yi and Kumar (2007)	√			
The present study	√		√	√

2.1 Type of Routing Problems

Much of the reviewed literature considers routing in disastrous situations such as evacuation strategy planning and distribution of humanitarian logistics. In these situations, the optimized route is not necessarily a closed-loop route. We review the types of routes and their solution methods.

2.1.1 Closed-Loop Route

Chen and Chou (2009) consider an evacuation plan of two parts: selecting waiting stops and service locations and dispatching the rescue vehicles. The consequent vehicle routing problem is solved by the Clarke and Wright method. Victoria et al. (2015) consider a VRP for humanitarian logistics with capacitated vehicles and time-dependent demands. The VRP is formulated as a mixed-integer programming problem and solved by a two-phase metaheuristic method. Rizzoli et al. (2007) used ant colony optimization (ACO) to solve variants of VRP, such as the VRP with time windows, the time-dependent VRP, the VRP with pickup and delivery, and the dynamic VRP. Yi and Kumar (2007) also used ant colony optimization to solve a Traveling Salesman Problem for humanitarian logistics without considering any dynamicity of network or demand. Cordeau et al. (2014) and Kanoh and Ochiai (2012) consider time-dependent TSP in traffic congestion. Cordeau et al. (2014) formulated the TSP as ILP and used branch and cut algorithm to solve, while Kanoh and Ochiai (2012) used the ant colony optimization algorithm to find the solution for their TSP. Wright (2019) used simulated annealing to find the solution to his TSP under different weather conditions. Cheong and White (2012) studied pickup and delivery services in urban areas with traffic congestions. They used a Markov decision process to model the dynamic TSP and apply the best-first heuristic search algorithm to determine the optimal policy.

The problems description and formulations of this literature point out that dynamicity of network can be captured from different perspectives. Dynamicity has been defined as the change of demand (Yi & Kumar, 2007; Victoria et al., 2015) and vehicle speed (Cheong & White, 2012; Cordeau et al., 2014) over time. Metaheuristics are the most popular techniques for solving both TSP and VRP.

2.1.2 Other Types of Route

Both Chiu et al. (2007) and Lammel et al. (2010) discuss emergency evacuation problems. Chiu et al. (2007) assume their area to be divided into hot zone and safe zone. A certain number of evacuees from different points of the hot zone plan to reach the safe zone at short notice. Chiu et al. (2007) used a dynamic flow optimization model to minimize the total system travel time. Lammel et al. (2010) also considered an emergency evacuation situation where every person attempts to find the shortest route separately. Hu et al. (2019) investigated a multistage disaster relief distribution problem and used a progressive hedging algorithm (PHA) to plan the routes.

2.2 Effect of External Factors

External factors are one of the main causes of the dynamicity of the road network. Traffic congestion and weather conditions are often considered in the literature.

Hu et al. (2019) characterized the uncertain and dynamic road capacity in a post-disaster situation. Chen and Chou (2009) studied the best evacuation plan to avoid potential traffic chaos after disasters. Chiu et al. (2007) determined the optimal traffic volume for each route after defining the post-disaster network into zones. Lammel et al. (2010) introduced a scenario with a dynamic traffic-based evacuation that executes the routes of all agents simultaneously.

Rizzoli et al. (2007) define dynamic VRP as the variants of VRP where travel times are uncertain, depend on traffic conditions, and customers' order information is partially available. Cordeau et al. (2014), Kanoh and Ochiai (2012) and Cheong and White (2012) considered general traffic congestion in normal urban areas without any disastrous conditions. Cordeau et al. (2014) used the traffic information system to predict average vehicle speed in specific times and spaces. Kanoh and Ochiai (2012) represented traffic congestion with the change in travel time. Wright (2019) summarized how previous literature, such as TRB (2000), Agarwal et al. (2005) and Hranac et al. (2006), work on the effect of different weather events including rain, snow, wind, and others on the traveling speed and investigated how these effects impact the TSP. Paul and Batta (2011) show how the severity of a disaster and road damage impact transportation models while Shiri and Salman (2019) discuss how roads damaged or blocked due to disasters affect the routing decisions.

Most of the past literature focusses on the effect of one external factor like weather, traffic or disaster, ignoring the other factors. While canvasing disaster as the primary factor affecting the routes, Hu et al. (2019) suggest preparing for possible secondary disaster after occurrence of a major one. They examine historical data to analyze the frequency of secondary disasters on each arc but ignore adapting the routes with the change of network conditions. So does Chen and Chou (2009), Paul and Batta (2011) and Shiri and Salman (2019) in their respective studies. Contrary to them, Chiu et al. (2007) incorporate prevailing traffic condition in different zones, but they rely on GPS and cellular and internet data and do not consider the plausible failure of the methodology due to internet connection failure that our study is prepared for.

2.3 Updating Decision with Real Information

In the past literature, Bayesian inference and Nash equilibrium have been used most frequently to update decisions. Lammel et al. (2010) sought system-optimal routes using a Nash equilibrium-based approach instead of individual optimal routes. Cheong and White (2012) show that updating their route by using traffic probability distributions after reaching every point can save the expected cost. Katz and Ehrendorfer (2006) used the Bayesian approach to find out the posterior distribution of a weather event by taking samples of real-life occurrences. They show that this approach can reduce the expected expense incurred by the decision-makers. Bayesian inference has been used in various fields of study to improve analysis and decision making. Kourniotis et al. (2000) observed a set of chemical accidents and refined the theoretical distribution of severity with Bayesian analysis. They considered the parameters of the accidents as random variables and a random sample of data extracted from the population of historical accidents as new information. Mishra et al. (2014) also used Bayesian inference to deal with a certain level of uncertainty in evaluating dynamic elastic modulus of granite stone from sonic and ultrasonic tests. They combined initial information with new information to provide more realistic results on dynamic elastic modulus. Boeckmann (2019), on the other hand, considered the variability of foundation resistance across a site as an uncertain parameter with its own prior probability distribution and used Bayesian inference to update probability distribution of the variability with load test results as samples.

Bayesian inference has been the primary choice to update probability distribution of random variables in many scientific fields. Since routes have not been linked with probability distribution in past literature, Bayesian inference has not ventured in routing decisions as much as in other fields. By expressing the external factors as probability distribution, it is possible to update them using Bayesian inference.

2.4 Justification

The literature has demonstrated the importance of considering external factors in routing decisions. While the reviewed literature mainly focuses on traffic and weather conditions, this study intends to 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. Moreover, it was indicated by numerous articles that the real-time information helps decision makers in re-thinking and re-optimizing. The routing decisions will benefit from using real-time information and not rely on internet-driven traffic data only.

CHAPTER 3

METHODOLOGY

The methodology can be divided into the following three parts: a) modeling the dynamic network, b) finding the best route, c) and updating the network condition and the routes if necessary. The first two parts are required in the planning stage, whereas the third one is applicable in execution. After modeling the network based on current available information, the best routes are found and planned. While executing the planned route, the network model is updated using the newly acquired network information, and the planned routes are updated accordingly.

3.1 Modeling the Dynamic Network

Suppose the estimation of $k_{ij}(t), t \geq 0$, is available as a forecast by the time when the route is planned. This forecast can be based on past records, current weather forecast and road conditions, assessment of the impact of the natural disaster, etc. This estimation is denoted by $\hat{k}_{ij}(t)$ and the forecast error is denoted by ϵ_{ij}. Therefore, we have $k_{ij}(t) = \hat{k}_{ij}(t) + \epsilon_{ij}$. To capture the uncertainty of the network condition, we assume that ϵ_{ij} is normally distributed to random variable with mean μ_{ij} and variance σ_{ij}^2. Hence the travel speed becomes $v_{ij}(t) = v_{ij}^{max}\left(\hat{k}_{ij}(t) + \epsilon_{ij}\right)$.

Suppose the network can be divided into multiple zones by the level of external impact on the road condition and, consequently, level of uncertainty in estimating $k_{ij}(t)$. Formally, we divide the set of arcs A into disjoint subsets $A_1, A_2, \ldots, A_H$, called zones. For any zone h and all arcs (i, j) that belongs to zone h, we assume that ϵ_{ij}s are independent and identically distributed. That is, $\mu_{ij} = \mu_h$ and $\sigma_{ij}^2 = \sigma_h^2$ for all $(i, j) \in A_h$. Therefore, $v_{ij}(t) = v_{ij}^{max}(\hat{k}_{ij}(t) + \mu_h)$ if the arc (i, j) is in zone h. We assume that the zones do not shift over time. This approach is similar to Victoria et al. (2015), who divided their study area into critical and noncritical zones depending on the severity of the disaster effect. Cheong and White (2012) also considered the roads of their network as either congested or not congested.

3.2 Finding the Best Route for One Vehicle

Given the network conditions in the route planning phase, we need to find the best route for the vehicle to leave from node 1, visit all primary nodes, and return to node 1. Whenever the vehicle finishes servicing a primary node, and if the network conditions change or are updated, we need to update the remaining of the route that includes unvisited primary nodes and node 1. 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. In general, the routing problems (TSP and VRP) are NP-hard. The fact that the travel speed may change over time in this study makes the problem dynamic, adds extra complexity and requires metaheuristics to be solved. As mentioned by Wright (2019), metaheuristics method 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). All of these metaheuristics have been ventured by many researchers to solve TSP. Lazarova and Borovska (2008) compared the efficiency of ant colony optimization, genetic algorithm and simulated annealing metaheuristics for solving TSP. In the results from their study, ant colony optimization (ACO) had the best performance in view of the speed and solution quality. Therefore, in this research, we use the ACO algorithm as the route optimization method. The accuracy of ACO is demonstrated in Appendix A, where the results from ACO are compared with the optimal ones for different-sized network problems, and very small percent of mean and standard deviation has been observed for the result gap.

The ant colony optimization (ACO) is a metaheuristic method that can be used for finding good routes based on the ant behavior of searching for food. Each ant initially wanders randomly. After finding a source of food, the ant walks back to the colony leaving pheromones in its path. When other ants come across the pheromones, they are likely to find the best path with a certain probability while others still randomly scout for closer food sources. Over time, as more ants find the shortest path, the pheromone marks get stronger until there are a couple of streams of ants traveling to various food sources near the colony.

To use ACO for the routing problem 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 from any primary node to any other primary node, we associate a pheromone level τ, which is 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 considers the unvisited primary nodes. The ant calculates the travel time from its current location to each unvisited primary node. The inverse of the travel time is defined as the attractiveness η of the move from the current location to an unvisited primary node. To decide the next primary node in the route, the ant generates a random number r between 0 and 1 and compares with q_0, which is a number between 0 and 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 value of $\frac{\tau\eta^\beta}{\sum \tau\eta^\beta}$ will be undefined. It implies that all moves are indifferent, and 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 is calculated and denoted as L_s. 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 from any primary node to any other primary node is updated as $\tau_{new} = (1 - \rho)\tau_{old} + \sum \frac{Q}{L_s}$, where ρ between 0 and 1 is the preset evaporation rate, Q is a preset parameter balancing the weight between existing pheromone and new pheromone, and the sum is taken over all such s that takes the move. Therefore, the shorter travel time a route has, the higher will be the pheromone level for its moves. A move chosen by multiple ants is also likely to have higher pheromone.

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 (2016) 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 τ and η. The randomness in the algorithm is captured by q_0.

Note that the attractiveness η_{ij} depends on the travel time $T_{ij}(t)$. Since the travel time $T_{ij}(t)$ depends on the vehicle speed reduction factor $k_{ij}(t)$, which changes over time, $T_{ij}(t)$ 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. Therefore, we need to find the shortest path from a primary node p_i to any other primary node p_j at time t. For that purpose, we use Dijkstra's shortest path algorithm with the only adjustment being that the travel time of each arc is dynamic, depending on the starting time t and the value of $k_{ij}(t)$.

3.3 Finding the Best Routes for Multiple Vehicles

While working with multiple vehicles, the objective is to minimize total travel time of all routes. The primary challenge of extending the ACO methodology from single to multiple vehicles is to decide which vehicle would select its next destination at what sequence and how to manage the ant colonies.

We balance the travel duration of the vehicles so that the vehicle drivers can have fair share of responsibilities. The vehicle which has travelled the least so far is selected to add a new node to its route. But if vehicles have the same travelled duration, the tie is broken by selecting the vehicles sequentially. Assume there are total N vehicles available, and they are marked as $1, 2, 3, \ldots, N$. At the beginning of the process, while all the vehicles are at node 1 with zero travelled duration, vehicle 1 is the first chosen vehicle to select its destination. After that we have one vehicle (vehicle 1) with positive planned travelled duration and $N - 1$ vehicles with zero planned travelled duration. Vehicles $2, 3, 4, \ldots, N$ are chosen one by one to select the first destination of their planned routes. After all vehicles have added one destination to their planned routes, the vehicle that has the least travel duration so far is chosen to add the second destination. If the travel duration is tied again between multiple vehicles, they are again chosen sequentially. The same procedure is continued until all the primary nodes are covered and all the vehicles come back to node 1.

The methodology of creating routes for multiple vehicles is an extension to the methodology for finding one route. One ant of the algorithm for TSP is replaced by a group of N ants. Hence, instead of having total S number of ants, we have S groups of ants with N in each group. In one iteration, each ant generates one single route. The combined travel duration of the N

ants is recorded. Denote the total travel time of the groups as $N_1, N_2, N_3, \ldots, N_S$. If N_n is the lowest of them, that value is recorded as the smallest travel duration found in that iteration and the routes created by the nth ant groups are recorded as the best routes found in that iteration.

The destination to add to a route is chosen in the same process as mentioned for TSP. Pheromone level of the move between primary nodes τ is updated after each iteration and attractiveness for move between two primary nodes η is calculated before each move. Both these parameters play the same vital roles as in TSP. Since the pheromone level does not depend on current position of any ant, τ stays the same for all ant groups. But attractiveness depends on where an ant is and how much time it has travelled so far. Hence, η changes for ants of different groups.

3.4 Updating the Network Conditions

Once the vehicle has traveled from one primary node p_i to the next primary node p_j, the actual speed in each of the arc of the path from p_i to p_j is observed and contains new information about the real network conditions. With this information, we use Bayesian inference to update the distributions of ϵ_{ij} more specifically, 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 $x \sim N(\mu, \sigma^2)$ with variance σ^2, the conjugate prior distribution is also normally distributed. If the prior distribution follows $\mu \sim N(\mu_0, \sigma_0^2)$, the posterior distribution according to Winkler (1972) is as following:

$$\frac{1}{\sigma_1^2} = \frac{1}{\sigma_0^2} + \frac{n}{\sigma^2}$$

$$\mu_1 = \frac{(1/\sigma_0^2)\mu_0 + (n/\sigma^2)\mu}{(1/\sigma_0^2) + (n/\sigma^2)}$$

We use the formulas in our case study to update error distribution of speed reduction forecast in each zone. Suppose that from p_i to p_j the vehicle has traveled $n \geq 1$ arcs in zone h. For any such arc, we know the actual speed when the vehicle travels it. We can use that information 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. Suppose the sample mean and sample variance are μ and σ^2, respectively. Using Bayesian inference, we update μ_h and σ_h^2 with the following equations:

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

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

In these two equations, $({\mu_h}', {\sigma_h'}^2)$ denote the prior estimation of (μ_h, σ_h^2) while $({\mu_h}'', {\sigma_h''}^2)$ denote the updated posterior estimation. After μ_h and σ_h^2 are updated for all zones that the vehicle travels from p_i to p_j, we call the route optimization routine to update the remaining of the route from p_j to node 1. This procedure is repeated until the vehicle returns to node 1.

3.5 Algorithms

The overall procedure of the methodology is summarized in the following two algorithms: one for the technique of updating route, another for the process of the ant colony optimization.

3.5.1 Algorithm of Updating Route

Input: nodes, arcs with respective lengths, arc-zone classification, v_{ij}^{max}, $\hat{k}_{ij}(t)$.

Set parameters for ACO ($\eta, \tau, q_0, \beta, Q, \rho, S, I$).

1. Use ACO to find the initial planned route.
2. Go to the next primary node of the route and check value of $k_{ij}(t)$ at every passed arc as sample.
3. Find out the error of $k_{ij}(t)$ at every arc and calculate sample error mean and variance.
4. Update the set of values of $k_{ij}(t)$ for every i, j, t.
5. Use ACO again to update the route.
6. Repeat steps 2 to 5 until all primary nodes are visited.
7. Add the depot as the last node of the route.

3.5.2 Algorithm for ACO

For iteration = 1 to I and each ant s:

1. Locate the current node. Enlist all unvisited primary nodes.
2. With the latest available $k_{ij}(t)$, find the traveling time and the shortest path from the current location to all unvisited primary nodes. Update η for each move.
3. Generate a random number r. Decide the next move by comparing r with q_0.
4. Go to the chosen primary node and update the unvisited primary nodes.
5. Repeat steps 2 to 4 until all nodes have been visited. Then add node 1 as the final destination and calculate total travelled time.
6. Compare the travel time of the best route found and the best route on record. If total travel time is improved, replace the best route on record as the best route found in this iteration.
7. Update τ using the formula $\tau_{new} = (1-\rho)\tau_{old} + \sum \frac{Q}{L_s}$ for every move. Enter the next iteration.

CHAPTER 4

CASE STUDY – A HYPOTHETICAL NETWORK

A hypothetical case is used to show that the methodology is effective in finding a better route by considering the dynamic and uncertain network conditions rather than treating the network as static. We set up the network with time-varying traveling conditions that are not completely known to the route planner *a priori*. We compare the best routes found by ACO in three settings: one with static network conditions, one considering the dynamic network but no updates after the vehicle is on the road, and one considering updating real road conditions in a dynamic network.

4.1 Network

For the case study, we create a hypothetical network with 35 nodes and 87 arcs. The depot is located at node 1. There are nine primary nodes that must be visited and served, and they are numbered as 2, 3, 4, 5, 6, 7, 8, 9, 10. The other 25 nodes are secondary nodes. The arcs that connect the nodes in this network represent a collection of roads and streets. The arc lengths are listed in Appendix B. We divide the network into four zones. Table 2 shows the arc-zone classification.

Table 2
Arcs in different zones

Zone 1	Zone 2		Zone 3			Zone 4
(1,11)	(1,33)	(16,22)	(3,23)	(6,29)	(25,26)	(7,9)
(1,12)	(2,18)	(16,35)	(3,24)	(7,20)	(26,29)	(8,27)
(1,13)	(3,16)	(17,18)	(3,27)	(7,21)	(27,28)	(8,28)
(2,12)	(3,22)	(18,19)	(3,35)	(7,25)	(27,35)	(8,30)
(2,13)	(4,16)	(19,20)	(4,18)	(7,26)	(28,29)	(8,32)
(2,14)	(5,13)		(4,19)	(7,29)	(33,34)	(9,10)
(2,15)	(5,15)		(4,22)	(8,35)		(9,21)
(11,12)	(5,20)		(4,24)	(10,34)		(9,31)
(11,14)	(5,33)		(4,25)	(19,25)		(9,34)
(12,13)	(11,16)		(4,26)	(20,21)		(10,30)
(12,14)	(14,16)		(5,21)	(20,25)		(10,31)
(13,15)	(14,17)		(6,23)	(21,34)		(10,32)
	(14,18)		(6,24)	(22,24)		(28,30)
	(15,18)		(6,26)	(23,24)		(29,31)
	(15,19)		(6,27)	(23,27)		(30,31)
	(16,17)		(6,28)	(24,26)		(30,32)

Figure 2 illustrates the network. The primary nodes have been painted red, and the secondary nodes are painted blue. Arcs of zones 1, 2, 3, and 4 have been painted blue, orange, red, and black respectively. The maximum speed is set to be $v_{ij}^{max} = 80$mph for all (i, j). With forecasting of weather, road condition and traffic congestion condition, the average speed at each zone is predicted for the next two days, with $t = 0$ being the time the vehicle leaves the depot.

$\hat{k}_{ij}(t)$ was forecasted for each zone for different time duration such as from the beginning of the travel and 12 hours, 12 and 24 hours, 24 and 36 hours, and more than 36 hours. The forecasted values of speed reduction factor, $\hat{k}_{ij}(t)$, are given in Table 3.

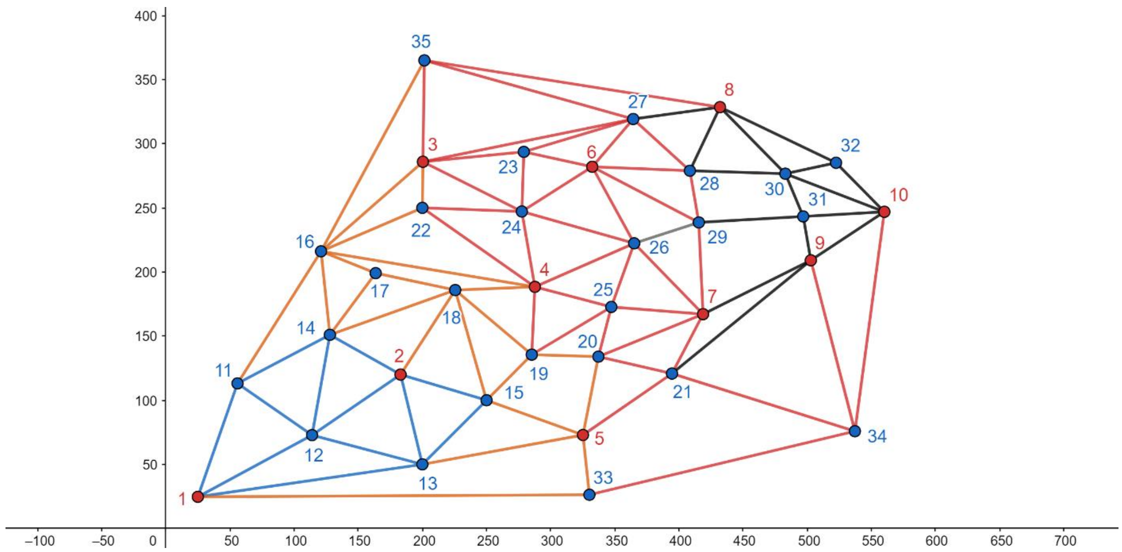

Figure 2. The network in the case study.

Table 3
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	zone 4
$0 \leq t \leq 12$	1.0	1.0	0.8	0.6
$12 \leq t \leq 24$	1.0	0.9	0.8	0.5
$24 \leq t \leq 36$	0.9	0.8	0.6	0.4
$t \geq 36$	0.9	0.8	0.5	0.2

In this hypothetical case, we generate the real travel speed reduction factors $k_{ij}(t)$ as in Table 4. The values of $k_{ij}(t)$ will be used to evaluate the actual total time of a route and to provide vehicle-collected data during route execution.

Table 4
Values of $k_{ij}(t)$ for different zones over time

	Value of $k_{ij}(t)$			
	zone 1	zone 2	zone 3	zone 4
$0 \leq t \leq 6$	1.0	0.8	0.7	0.6
$6 \leq t \leq 8$	1.0	0.8	0.63	0.45
$8 \leq t \leq 9$	1.0	0.8	0.59	0.45
$9 \leq t \leq 11$	1.0	0.8	0.55	0.245
$11 \leq t \leq 24$	1.0	0.6	0.55	0.163
$24 \leq t \leq 27$	0.9	0.6	0.43	0.063
$27 \leq t \leq 31$	0.9	0.6	0.39	0.063
$31 \leq t \leq 36$	0.9	0.6	0.35	0.063

To set the parameters for the ant colony optimization algorithm, we conducted a small study with the network by changing the values of q_0 and ρ over 100 iterations, $\beta = 1$, $Q = 1$ and $j = 100$. The result is summarized in Table 5.

Table 5
Comparative parametric analysis of ACO for the case study

q_0	ρ	Objective value
0.100	1.000	24.709
0.100	0.900	23.725
0.100	0.800	21.991
0.200	0.800	24.546
0.250	0.800	21.475
0.277	0.800	21.308
0.300	0.800	23.099

The least value was obtained with $q_0 = 0.277$ and $\rho = 0.8$. Analyzing the results from Table 5, we used $q_0 = 0.277$, $\beta = 1$, $Q = 1$, $\rho = 0.8$, $j = 100$, and $I = 10000$ for executing the ant colony optimization algorithm.

4.2 Setting I: Static Network

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 v_{ij}^{max} for all (i, j). Table 6 shows the best route (Route I) for one vehicle, along with the shortest path for each move, provided by ACO algorithm. Table 7 shows the best-found routes (Route IA and IB) in the same case but with two vehicles.

Table 6
Route I under static network condition

Move	Path
$1 \rightarrow 2$	$1 \rightarrow 12 \rightarrow 2$
$2 \rightarrow 4$	$2 \rightarrow 18 \rightarrow 4$
$4 \rightarrow 3$	$4 \rightarrow 22 \rightarrow 3$
$3 \rightarrow 6$	$3 \rightarrow 23 \rightarrow 6$
$6 \rightarrow 8$	$6 \rightarrow 27 \rightarrow 8$
$8 \rightarrow 10$	$8 \rightarrow 32 \rightarrow 10$
$10 \rightarrow 9$	$10 \rightarrow 9$
$9 \rightarrow 7$	$9 \rightarrow 7$
$7 \rightarrow 5$	$7 \rightarrow 21 \rightarrow 5$
$5 \rightarrow 1$	$5 \rightarrow 13 \rightarrow 1$

Table 7
Route IA and IB under static network condition

Route IA			Route IB	
Move	Path		Move	Path
1 → 3	1 → 11 → 16 → 3		1 → 5	1 → 13 → 5
3 → 6	3 → 23 → 6		5 → 7	5 → 21 → 7
6 → 4	6 → 24 → 4		7 → 9	7 → 9
4 → 2	4 → 18 → 2		9 → 10	9 → 10
2 → 1	2 → 12 → 1		10 → 8	10 → 32 → 8
			8 → 1	8 → 27 → 3 → 16 → 11 → 1

Route I is highlighted in Figure 3, whereas Route IA and IB are illustrated in Figure 4. The planned travel time of Route I with one vehicle and the total planned travel time of IA and IB with two vehicles are 18.33 and 27.6 hours respectively, whereas in the actual network conditions, the travel time will be 59.03 and 52.74 hours.

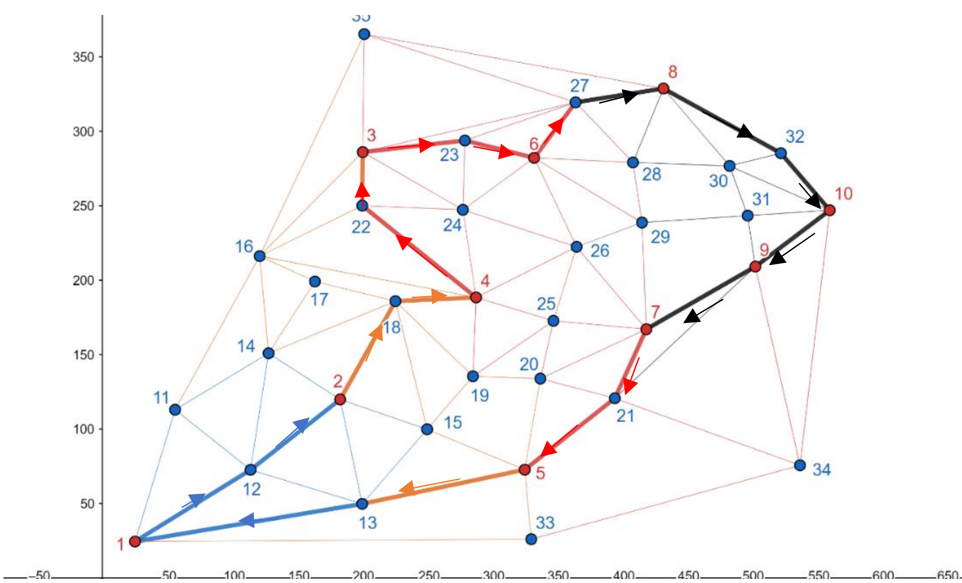

Figure 3. Route I.

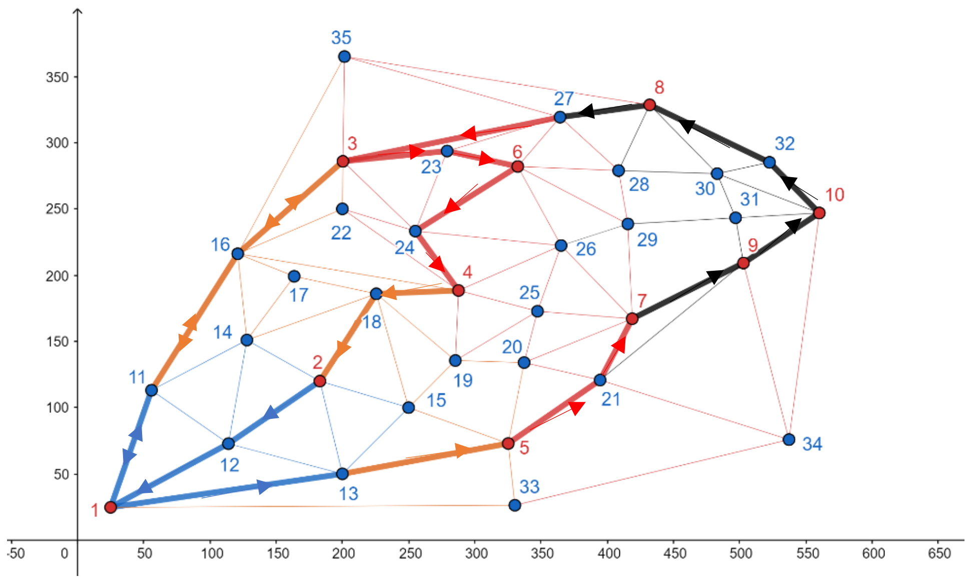

Figure 4. Route IA and IB.

4.3 Setting II: Dynamic Network Without Route Updating

In Setting II, we consider that the routing decisions are made after analyzing the predictions of weather, road and traffic conditions and the predicted values of $\hat{k}_{ij}(t)$ listed in Table 3. Table 8 shows the best route (Route II) for one vehicle, along with the shortest path for each move, provided by ACO algorithm in this situation.

Table 9 shows the best-found routes (Route IIA and IIB) in the same situation with two vehicles. The planned travel time of Route II with one vehicle and the total planned travel time of IIA and IIB with two vehicles are 24.10 and 33.1 hours respectively, whereas in the actual network conditions, the travel time will be 47.95 and 52.27 hours. Route II is highlighted in Figure 5 and Route IIA and IIB are illustrated in Figure 6.

Table 8
Route II under dynamic network conditions without route updating

Move	Path
$1 \rightarrow 5$	$1 \rightarrow 13 \rightarrow 5$
$5 \rightarrow 7$	$5 \rightarrow 21 \rightarrow 7$
$7 \rightarrow 9$	$7 \rightarrow 9$
$9 \rightarrow 10$	$9 \rightarrow 10$
$10 \rightarrow 8$	$10 \rightarrow 32 \rightarrow 8$
$8 \rightarrow 6$	$8 \rightarrow 27 \rightarrow 6$
$6 \rightarrow 3$	$6 \rightarrow 23 \rightarrow 3$
$3 \rightarrow 4$	$3 \rightarrow 22 \rightarrow 4$
$4 \rightarrow 2$	$4 \rightarrow 18 \rightarrow 2$
$2 \rightarrow 1$	$2 \rightarrow 12 \rightarrow 1$

Table 9
Route IIA and IIB under dynamic network conditions without route updating

Route IIA			Route IIB	
Move	Path		Move	Path
$1 \rightarrow 3$	$1 \rightarrow 11 \rightarrow 16 \rightarrow 3$		$1 \rightarrow 5$	$1 \rightarrow 13 \rightarrow 5$
$3 \rightarrow 6$	$3 \rightarrow 23 \rightarrow 6$		$5 \rightarrow 7$	$5 \rightarrow 21 \rightarrow 7$
$6 \rightarrow 4$	$6 \rightarrow 24 \rightarrow 4$		$7 \rightarrow 9$	$7 \rightarrow 9$
$4 \rightarrow 2$	$4 \rightarrow 18 \rightarrow 2$		$9 \rightarrow 10$	$9 \rightarrow 10$
$2 \rightarrow 1$	$2 \rightarrow 12 \rightarrow 1$		$10 \rightarrow 8$	$10 \rightarrow 32 \rightarrow 8$
			$8 \rightarrow 1$	$8 \rightarrow 28 \rightarrow 29 \rightarrow 26 \rightarrow 4 \rightarrow 18 \rightarrow 2 \rightarrow 12 \rightarrow 1$

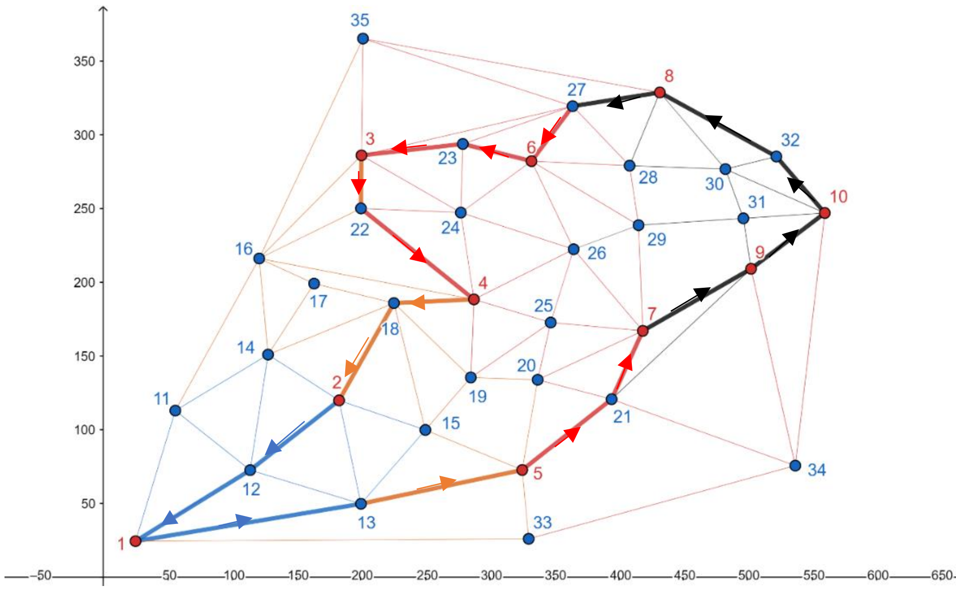

Figure 5. Route II.

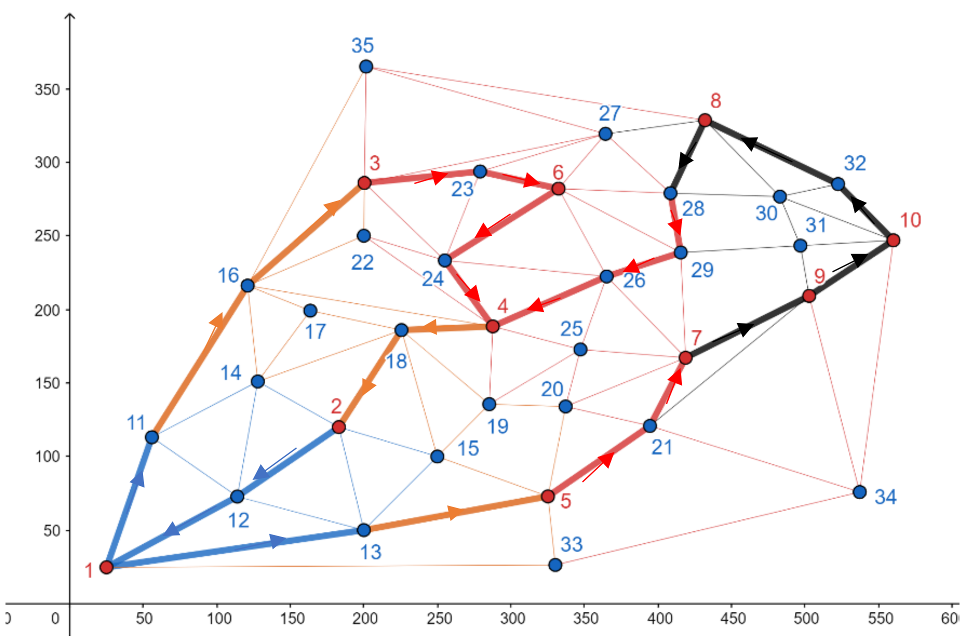

Figure 6. Route IIA and IIB.

4.4 Setting III: Dynamic Network with Route Updating

While executing Route II and after visiting each of the primary nodes, the actual travel speed of the vehicle in the arcs it passes is collected as samples. Then the mean μ_h and standard deviation σ_h of the estimated error of the speed reduction factor for each zone is updated using Bayesian inference. The updates of μ_h, σ_h and the route after reaching the first primary node in Route II is shown in Table 10. The rest of the steps are included in Appendix B. Since the vehicle does not pass zones 3 and 4 for this move, the distribution remains unchanged for those zones.

Table 10
Update of error ϵ_h and route

Move	Path	Zone 1		Zone 2		Zone 3		Zone 4		Updated route
$1 \rightarrow 5$	$1 \rightarrow 13 \rightarrow 5$	n	1	n	1	n	-	n	-	$1 \rightarrow 13 \rightarrow 5 \rightarrow 21 \rightarrow 7 \rightarrow 9 \rightarrow 10 \rightarrow 32 \rightarrow 8 \rightarrow 27 \rightarrow 6 \rightarrow 23 \rightarrow 3 \rightarrow 22 \rightarrow 4 \rightarrow 18 \rightarrow 2 \rightarrow 12 \rightarrow 1$
		μ	0	μ	-0.2	μ	-	μ	-	
		σ^2	0	σ^2	0.02	σ^2	-	σ^2	-	
		μ'	0	μ'	0	μ'	-	μ'	-	
		σ'^2	0	σ'^2	0	σ'^2	-	σ'^2	-	
		μ''	0	μ''	-0.2	μ''	-	μ''	-	
		σ''^2	0	σ''^2	0.02	σ''^2	-	σ''^2	-	

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. Then the vehicle comes back to the depot at node 1. The new best routes, Route III (for one vehicle) and Route IIIA and IIIB (for two vehicles), are presented in Tables 11 and 12 respectively.

Table 11
Route III under dynamic network conditions with route updating

Move	Path
$1 \rightarrow 5$	$1 \rightarrow 13 \rightarrow 5$
$5 \rightarrow 7$	$5 \rightarrow 21 \rightarrow 7$
$7 \rightarrow 9$	$7 \rightarrow 9$
$9 \rightarrow 10$	$9 \rightarrow 10$
$10 \rightarrow 8$	$10 \rightarrow 32 \rightarrow 8$
$8 \rightarrow 3$	$8 \rightarrow 35 \rightarrow 3$
$3 \rightarrow 6$	$3 \rightarrow 23 \rightarrow 6$
$6 \rightarrow 4$	$6 \rightarrow 24 \rightarrow 4$
$4 \rightarrow 2$	$4 \rightarrow 19 \rightarrow 15 \rightarrow 2$
$2 \rightarrow 1$	$2 \rightarrow 12 \rightarrow 1$

Table 12
Route IIIA and IIIB under dynamic network conditions with route updating

Route IIIA			Route IIIB	
Move	Path		Move	Path
$1 \rightarrow 3$	$1 \rightarrow 11 \rightarrow 16 \rightarrow 3$		$1 \rightarrow 5$	$1 \rightarrow 13 \rightarrow 5$
$3 \rightarrow 6$	$3 \rightarrow 23 \rightarrow 6$		$5 \rightarrow 7$	$5 \rightarrow 21 \rightarrow 7$
$6 \rightarrow 4$	$6 \rightarrow 24 \rightarrow 4$		$7 \rightarrow 9$	$7 \rightarrow 9$
$4 \rightarrow 2$	$4 \rightarrow 18 \rightarrow 2$		$9 \rightarrow 10$	$9 \rightarrow 10$
$2 \rightarrow 1$	$2 \rightarrow 12 \rightarrow 1$		$10 \rightarrow 8$	$10 \rightarrow 32 \rightarrow 8$
			$8 \rightarrow 1$	$8 \rightarrow 28 \rightarrow 29 \rightarrow 26 \rightarrow 25 \rightarrow 19 \rightarrow 15 \rightarrow 13 \rightarrow 1$

The total duration of Route III is 44.23 hours, and the route is highlighted in Figure 7. The total duration of Route IIIA and IIIB combinedly is 51.86 hours. The routes are illustrated in Figures 7 and 8.

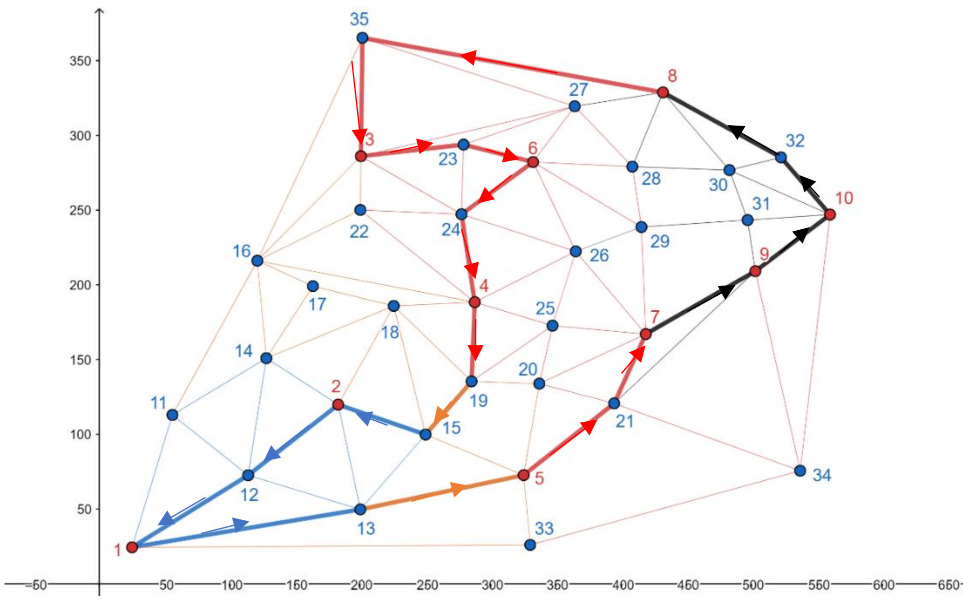

Figure 7. Route III.

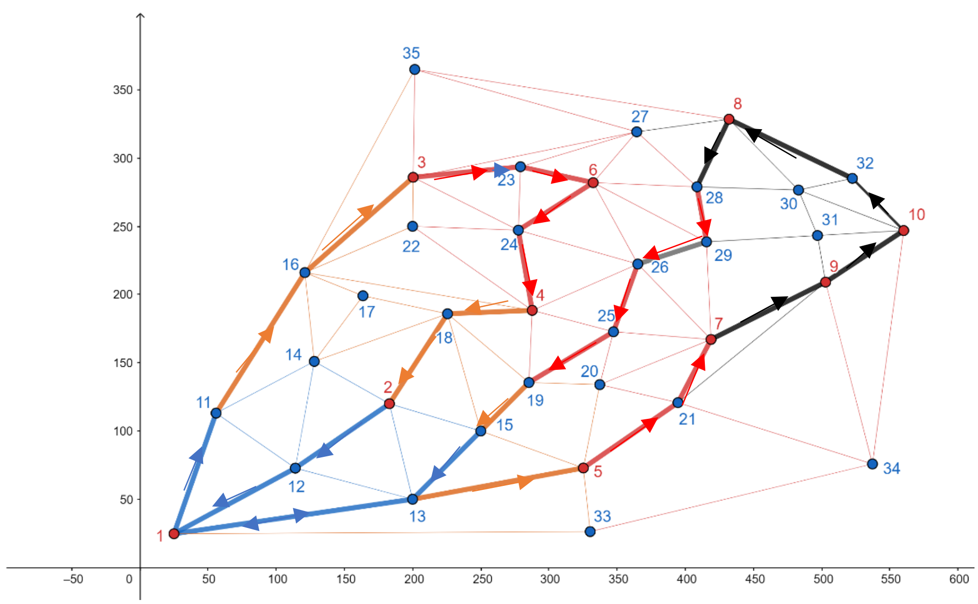

Figure 8. Route IIIA and IIIB.

4.5 Result Analysis

To compare the three settings of the single vehicle case (Table 13), we compute the travel times of Route I in Settings II and III. We also compute the travel time of Route II in Setting III. By comparing Route I and Route II in Setting III, we see that we can save 11.08 hours by considering the dynamic network conditions. By comparing Route II and Route III in Setting III, we see an additional 3.72 hours are saved in travel time if we update the dynamic network conditions while executing Route II. Similarly, with two vehicles (Table 14), we can save 0.47 hours by considering the dynamic network conditions and 0.61 hour if we update the dynamic network conditions while executing Route IIA and IIB.

Table 13
Comparison among routes in different settings with one vehicle

	Setting I	Setting II	Setting III
Route I	18.33 hours	24.24 hours	59.03 hours
Route II		24.10 hours	47.95 hours
Route III			44.23 hours

Table 14
Comparison among routes in different settings with two vehicles

	Setting I	Setting II	Setting III
Route IA and IB	11.31 + 16.30 = 27.61	12.23 + 20.97 = 33.20	15.13 + 37.61 = 52.74
Route IIA and IIB		12.23 + 20.85 = 33.08	15.13 + 37.14 = 52.27
Route IIIA and IIIB			15.13 + 36.73 = 51.86

4.6 Discussion

Travel duration of executed route significantly improved from the planned one in TSP and slightly in VRP by following our developed methodology. The key factor lies in updating the forecast error distribution, estimation of speed reduction factors and eventually the routes. Adding only the dynamicity of network in the problem did not always improve the route in Setting II. It implies that without data collection and the updates, the forecast of network condition alone cannot improve the routing decisions.

The result in Setting II does not always improve the duration. Route II in this case study is Route I traveled in the reverse direction. In fact, in Setting I, reversing Route I will result in the same travel time because the network is considered static. However, in Setting II, we consider the dynamic change of speed reduction, and hence reversing the direction of a route may lead to different travel times. Consequently, Route I is worse than Route II in Setting II. The same route in Settings II and III can have different duration depending on the direction of the route since the travel duration of the same arc depends on when it is travelled in both the settings.

In the scenario with two vehicles, Route A has stayed the same for Settings I, II and III. Only Route B has changed in different settings and the total saved time is also very small. In practice, the time savings by updating the road conditions and the route in Setting III will partly depend on the accuracy of the initial estimation of the network conditions. If it is estimated well, the best route in Setting III may not diverge too much from that in Setting II. But if the initial estimation is highly inaccurate, drastic changes can occur when the route is updated in Setting III.

As a metaheuristic method, ACO can provide an excellent solution but does not guarantee an optimal solution. For different problem instances, the parameters of the algorithm including q_0, β, Q, j, I need to be tuned for better solution quality.

CHAPTER 5

CASE STUDY – HURRICANE FLORENCE

We conducted another case study by simplifying a complicated real-life network. The chosen dynamic event is Hurricane Florence, the powerful and long-lived Atlantic hurricane that created havoc in the Carolinas in September 2018. According to "Hurricane Florence" (2020) and Gleason (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.

5.1 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 public health service centers are safe options for distributing the relief supplies to the local people. We have numbered the nodes for the ease of our analysis. We assume that the depot is at node 1 in Wake County. Forty primary nodes are numbered from 2 to 41 and the other 23 nodes are the secondary nodes. Nodes in all the coastal counties and some other random nodes from the network have been considered as the primary nodes. The associated number for each considered county is presented in Table 15 and visualized in Figure 9.

Table 15
Counties under consideration and their corresponding numbers

1	Wake	17	Randolph	33	Sampson	49	Rockingham
2	New Hanover	18	Chowan	34	Chatham	50	Scotland
3	Dare	19	Cumberland	35	Washington	51	Alamance
4	Beaufort	20	Gates	36	Granville	52	Anson
5	Craven	21	Caswell	37	Perquimans	53	Duplin
6	Columbus	22	Currituck	38	Bertie	54	Durham
7	Carteret	23	Guilford	39	Forsyth	55	Martin
8	Hyde	24	Vance	40	Hertford	56	Person
9	Onslow	25	Pasquotank	41	Greene	57	Harnett
10	Brunswick	26	Warren	42	Edgecombe	58	Moore
11	Jones	27	Northampton	43	Halifax	59	Franklin
12	Pamlico	28	Montgomery	44	Lee	60	Robeson
13	Pender	29	Orange	45	Camden	61	Stokes
14	Johnston	30	Union	46	Bladen	62	Stanly
15	Pitt	31	Wayne	47	Richmond	63	Nash
16	Hoke	32	Davidson	48	Lenoir	64	Wilson

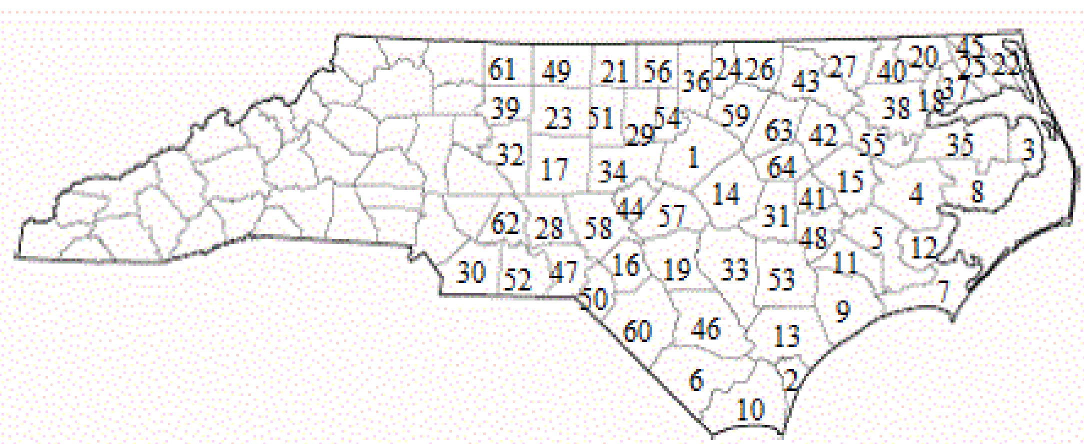

Figure 9. Numbered nodes.

In real life, numerous combinations of roads and streets interconnect the nodes with each other. However, we simplified the network by considering that only one arc connects two neighboring nodes. Hence, the network is comprised of only 160 arcs. The arc lengths are listed in Appendix C.

According to "Data Visualization: Disaster Declarations for States and Counties" (2020), the Federal Emergency Management Agency (FEMA) has visualized the frequency of hurricanes in counties of North Carolina since 1953 (Figure 10). Four distinct zones can be observed in Figure 10. 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. The arc-zone classification is summarized in Table 16.

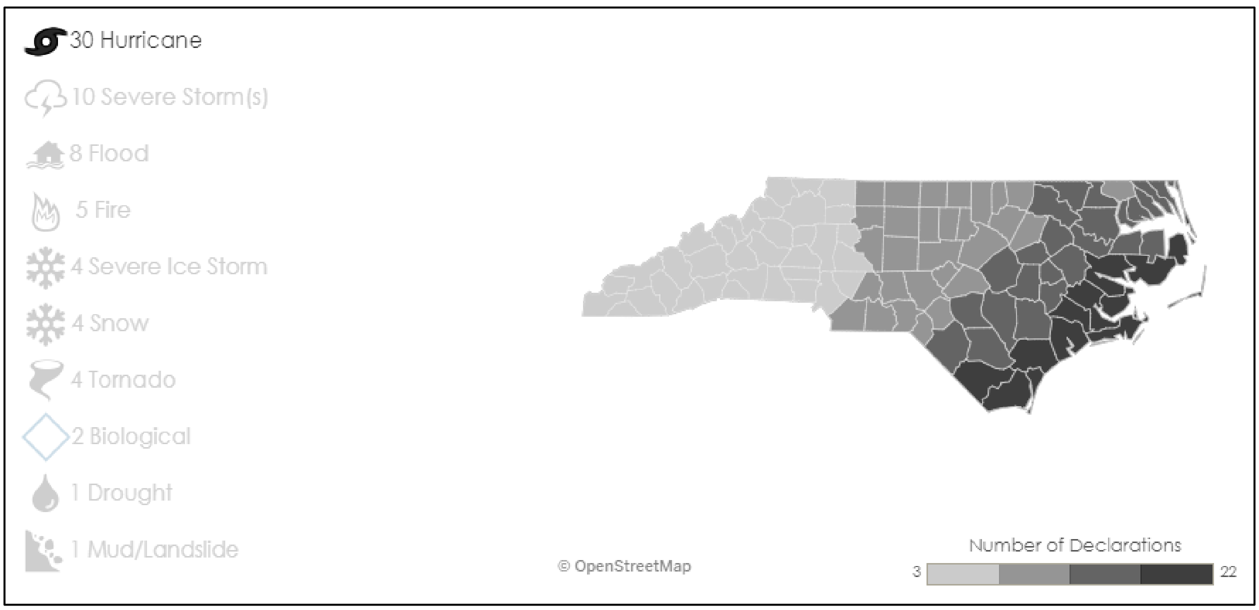

Figure 10. Disaster declaration for hurricanes in counties of North Carolina.

Table 16
Arcs in different zones

Zone 1		Zone 2				Zone 3			
(2,10)		(1, 14)	(18, 38)	(33, 53)		(1, 34)	(21, 23)	(29, 56)	(49, 61)
(2,13)		(5, 15)	(19, 46)	(35, 38)		(1, 36)	(21, 29)	(30, 52)	(50, 58)
(3, 8)		(5, 48)	(19, 57)	(38, 40)		(1, 44)	(21, 49)	(30, 62)	(52, 62)
(3, 35)		(6, 60)	(19, 60)	(38, 43)		(1, 54)	(21, 51)	(32, 39)	(54, 56)
(4, 5)		(8, 35)	(20, 25)	(38, 55)		(1, 57)	(21, 56)	(32, 62)	(57, 58)
(4, 8)		(9, 53)	(20, 37)	(41, 48)		(1, 59)	(23, 32)	(33, 57)	(59, 63)
(4, 12)		(11, 53)	(20, 40)	(41, 64)		(14, 57)	(23, 39)	(34, 44)	
(4, 15)		(13, 33)	(22, 45)	(42, 43)		(14, 59)	(23, 49)	(34, 51)	
(4, 35)		(13, 46)	(25, 37)	(42, 55)		(14, 63)	(23, 51)	(34, 54)	
(4, 55)		(14, 31)	(25, 45)	(42, 63)		(16, 19)	(23, 61)	(34, 58)	
(5, 7)		(14, 33)	(26, 43)	(42, 64)		(16, 44)	(24, 26)	(36, 54)	
(5, 11)		(14, 64)	(27, 38)	(43, 55)		(16, 47)	(24, 36)	(36, 56)	
(5, 12)		(15, 41)	(27, 40)	(46, 60)		(16, 50)	(24, 59)	(36, 59)	
(6, 10)		(15, 42)	(27, 43)	(48, 53)		(16, 57)	(26, 59)	(39, 49)	
(6, 13)		(15, 48)	(31, 33)	(50, 60)		(16, 58)	(26, 63)	(39, 61)	
(6, 46)		(15, 55)	(31, 41)	(63, 64)		(17, 23)	(28, 32)	(43, 59)	
(7, 9)		(15, 64)	(31, 48)			(17, 28)	(28, 47)	(43, 63)	
(7, 11)		(16, 60)	(31, 53)			(17, 32)	(28, 52)	(44, 57)	
(9, 11)		(18, 20)	(31, 64)			(17, 34)	(28, 58)	(44, 58)	

The speed limit in North Carolina is 70 mph on freeways, 60 mph on divided roads and so on. To simplify the calculation, the maximum speed is set to be $v_{ij}^{max} = 70mph$ for all (i, j). With forecasting of weather, road condition and traffic congestion condition, the average speed at each zone is predicted for the next two days, with $t = 0$ being the time the vehicle leaves the depot. The forecasted values of speed reduction factor $\hat{k}_{ij}(t)$ are given in Table 17.

Table 17
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 (2019) for converting it to $k_{ij}(t)$. 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. (2005). Conversion chart for these two weather events is presented in Table 18.

The values of $k_{ij}(t)$ will be used to evaluate the actual total time of a route and to provide vehicle-collected data during route execution. For executing the ant colony optimization algorithm, we used $q_0 = 0.5, \beta = 1, Q = 1, \rho = 0.8, j = 100\ and\ I = 20000$. We increased the cutoff probability level of randomness q_0 from 0.277 to 0.5 to incorporate less randomness in this complex network case study.

Table 18
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

5.2 Setting I: Static Network

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 v_{ij}^{max} for all (i, j). Table 19 shows the best-found route (Route I) with one vehicle, along with the shortest path for each move, provided by ACO algorithm in this situation. Table 20 shows the best-found routes (Route IA and IB) in the same situation with two vehicles. Route I is highlighted in Figure 11, whereas Route IA (red) and IB (green) are illustrated in Figure 12. The planned travel time of Route I with one vehicle and the total planned travel time of IA and IB with two vehicles are 29.21 and 33.18 hours respectively, whereas in the actual network conditions, the travel time will be 31.61 and 38.61 hours respectively.

Table 19
Routes of one vehicle under static network condition

Move	Path	Move	Path
1 – 34	1 – 34	5 – 4	5 – 4
34 - 29	34 – 29	4 - 15	4 – 15
29 - 21	29 – 21	15 - 24	15 - 42 - 63 - 59 - 24
21 - 14	21 - 29 - 54 - 1 – 14	24 - 36	24 – 36
14 - 33	14 – 33	36 - 26	36 - 24 – 26
33 - 17	33 - 57 - 58 – 17	26 - 27	26 - 43 – 27
17 - 28	17 – 28	27 - 40	27 – 40
28 - 30	28 - 62 – 30	40 - 38	40 - 38
30 - 32	30 - 62 – 32	38 - 18	38 - 18
32 - 39	32 – 39	18 - 37	18 - 37
39 - 23	39 – 23	37 - 25	37 - 25
23 - 13	23 - 51 - 34 - 44 - 57 - 33 – 13	25 - 22	22 - 45 - 25
13 - 31	13 - 53 – 31	22 - 20	22 - 45 - 25 - 20
31 - 19	31 - 33 – 19	20 - 35	20 - 40 - 38 - 35
19 - 16	19 – 16	35 - 3	35 - 3
16 - 6	16 - 60 – 6	3 - 8	3 - 8
6 - 10	6 – 10	8 - 12	8 - 4 - 12
10 - 2	10 – 2	12 - 7	7 - 5 - 12
2 - 9	2 - 13 – 9	7 - 41	7 - 5 - 48 - 41
9 - 11	9 – 11	41 - 1	41 - 31 - 14 - 1
11 - 5	11 – 5		

Table 20
Routes of two vehicles under static network condition

Route IA		Route IB	
Move	Path	Move	Path
1 - 31	1 - 14 - 31	1 - 14	1 - 14
31 - 33	31 - 33	14 - 27	14 - 63 - 43 - 27
33 - 34	33 - 57 - 44 - 34	27 - 26	27 - 43 - 26
34 - 29	34 - 29	26 - 41	26 - 63 - 64 - 41
29 - 17	29 - 51 - 17	41 - 15	41 - 15
17 - 28	17 - 28	15 - 6	15 - 41 - 31 - 33 - 46 - 6
28 - 30	28 - 62 - 30	6 - 10	6 - 10
30 - 16	30 - 52 - 47 - 16	10 - 2	10 - 2
16 - 19	16 - 19	2 - 11	2 - 13 - 9 - 11
19 - 13	19 - 33 - 13	11 - 12	11 - 5 - 12
13 - 9	13 - 9	12 - 36	12 - 4 - 15 - 42 - 63 - 59 - 36
9 - 7	9 - 7	36 - 24	36 - 24
7 - 5	7 - 5	24 - 21	24 - 36 - 56 - 21
5 - 4	5 - 4	21 - 23	21 - 23
4 - 38	4 - 55 - 38	23 - 39	23 - 39
38 - 18	38 - 18	39 - 32	39 - 32
18 - 37	18 - 37	32 - 1	32 - 17 - 34 - 1
37 - 25	37 - 25		
25 - 22	25 - 45 - 22		
22 - 20	22 - 45 - 25 - 20		
20 - 40	20 - 40		
40 - 8	40 - 38 - 55 - 4 - 8		
8 - 3	8 - 3		
3 - 35	3 - 35		
35 - 1	35 - 55 - 42 - 63 - 59 - 1		

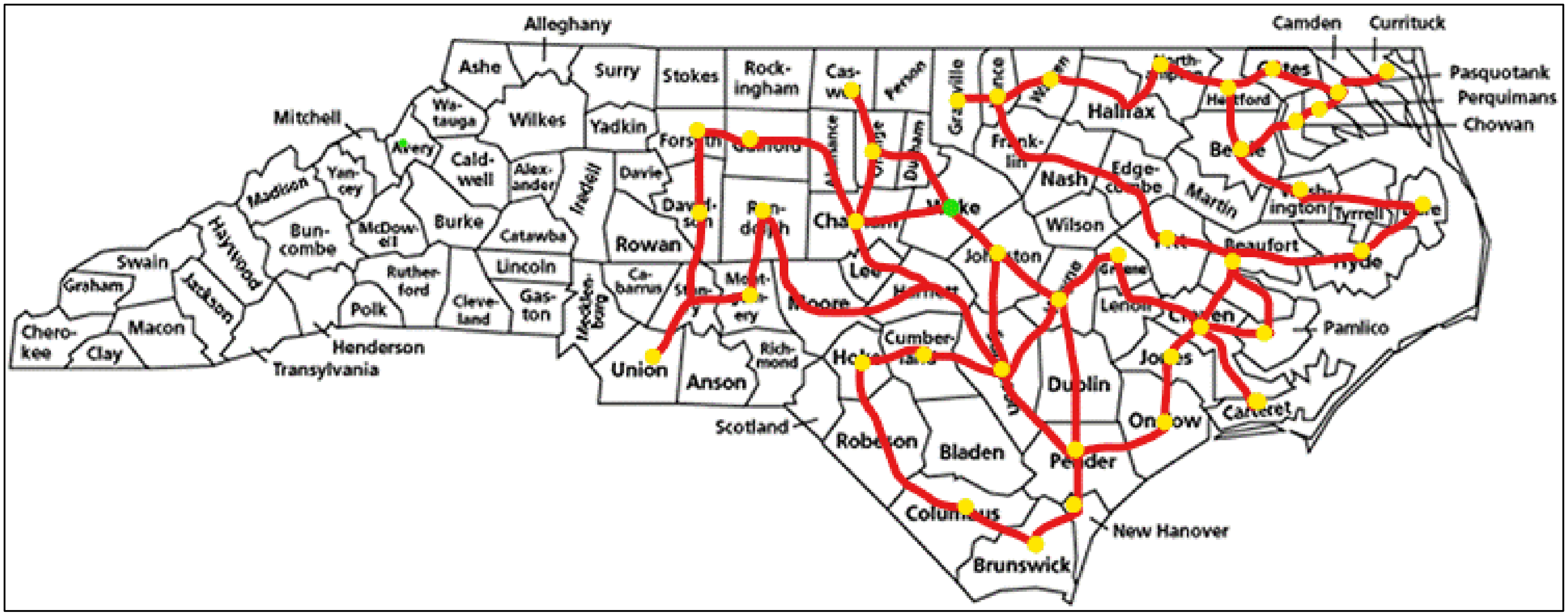

Figure 11. Route of one vehicle in static network.

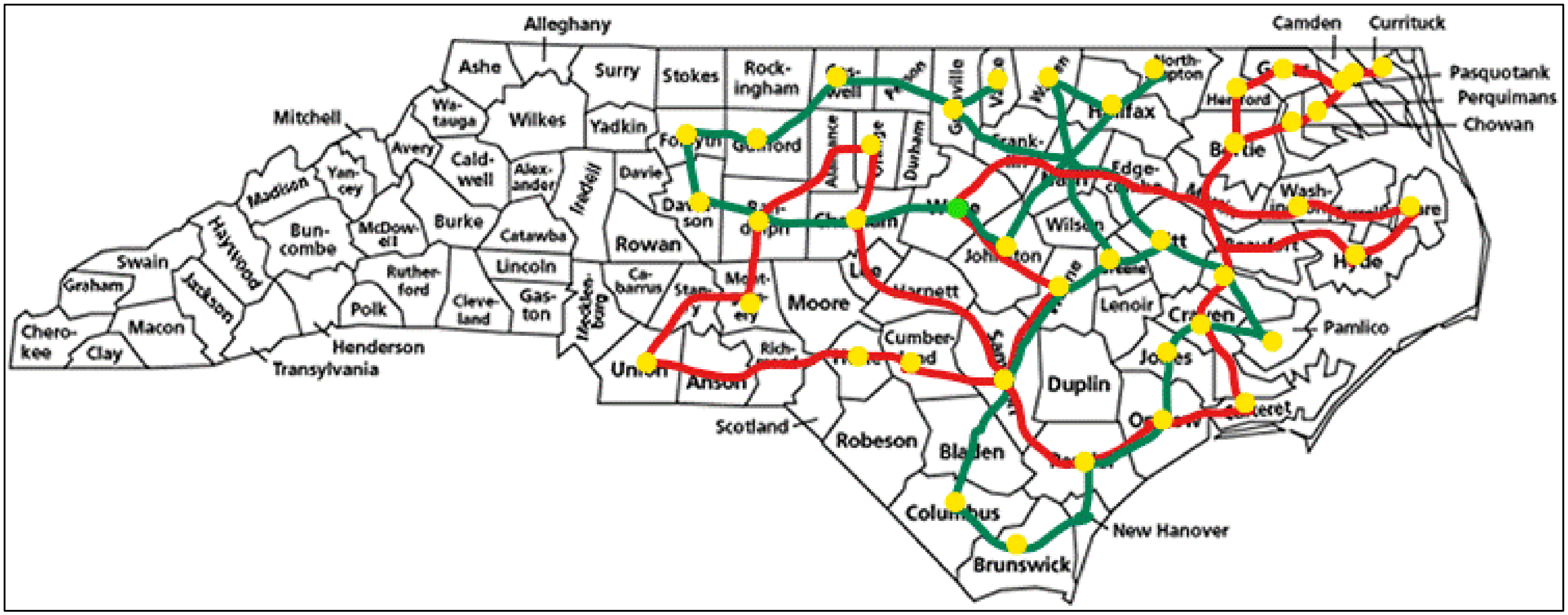

Figure 12. Route of two vehicles in static network.

5.3 Setting II: Dynamic Network Without Route Updating

In Setting II, we consider that the routing decisions are made after analyzing the predictions of weather and road and traffic conditions. The new routes found by ACO are in Tables 21 and 22.

Table 21
Route of one vehicle under dynamic network conditions without updating

Move	Path	Move	Path
1 - 14	1 - 14	22 - 20	22 - 45 - 25 - 20
14 - 31	14 - 31	20 - 40	20 - 40
31 - 33	31 - 33	40 - 27	40 - 27
33 - 19	33 - 19	27 - 26	27 - 43 - 26
19 - 16	19 - 16	26 - 24	26 - 24
16 - 30	16 - 47 - 52 - 30	24 - 36	24 - 36
30 - 28	30 - 62 - 28	36 - 29	36 - 54 - 29
28 - 17	28 - 17	29 - 21	29 - 21
17 - 32	17 - 32	21 - 41	21 - 29 - 54 - 1 - 14 - 31 - 41
32 - 15	32 - 17 - 58 - 57 - 14 - 64 - 15	41 - 11	41 - 48 - 11
15 - 4	15 - 4	11 - 9	11 - 9
4 - 5	4 - 5	9 - 7	9 - 7
5 - 8	5 - 4 - 8	7 - 13	7 - 9 - 13
8 - 35	8 - 35	13 - 2	13 - 2
35 - 3	35 - 3	2 - 10	2 - 10
3 - 38	3 - 35 - 38	10 - 6	10 - 6
38 - 12	38 - 55 - 4 - 12	6 - 34	6 - 60 - 16 - 44 - 34
12 - 18	12 - 5 - 15 - 55 - 38 - 18	34 - 23	34 - 51 - 23
18 - 37	18 - 37	23 - 39	23 - 39
37 - 25	37 - 25	39 - 1	39 - 23 - 51 - 29 - 54 - 1
25 - 22	25 - 45 - 22		

Table 22
Routes of two vehicles under dynamic network conditions without updating

Route IIA			Route IIB	
Move	Path		Move	Path
1 – 19	1 - 57 - 19		1 - 14	1 - 14
19 - 34	19 - 57 - 44 - 34		14 - 31	14 - 31
34 - 29	34 - 29		31 - 26	31 - 64 - 63 - 26
29 - 23	29 - 51 - 23		26 - 24	26 - 24
23 - 39	23 - 39		24 - 36	24 - 36
39 - 32	39 - 32		36 - 21	36 - 56 - 21
32 - 28	32 - 28		21 - 17	21 - 51 - 17
28 - 30	28 - 62 - 30		17 - 16	17 - 58 - 16
30 - 33	30 - 52 - 47 - 16 - 19 - 33		16 - 6	16 - 60 - 6
33 - 11	33 - 53 - 11		6 - 10	6 - 10
11 - 15	11 - 48 - 15		10 - 2	10 - 2
15 - 38	15 - 55 - 38		2 - 13	2 - 13
38 - 40	38 - 40		13 - 9	13 - 9
40 - 18	40 - 18		9 - 7	9 - 7
18 - 37	18 - 37		7 - 5	7 - 5
37 - 25	37 - 25		5 - 12	5 - 12
25 - 22	25 - 45 - 22		12 - 4	12 - 4
22 - 20	22 - 45 - 25 - 20		4 - 8	4 - 8
20 - 27	20 - 40 - 27		8 - 3	8 - 3
27 – 1	27 - 43 - 59 - 1		3 - 35	3 - 35
			35 - 41	35 - 4 - 15 - 41
			41 - 1	41 - 31 - 14 - 1

The planned travel time of the route with one (Route II) and combined routes of two vehicles (Route IIA and IIB) are 36.91 and 28.64 hours respectively, whereas in the actual network conditions, the travel time will be 36.71 and 29.82 hours respectively. Route II is highlighted in Figure 13 whereas Route IIA (red) and IIB (green) are illustrated in Figure 14.

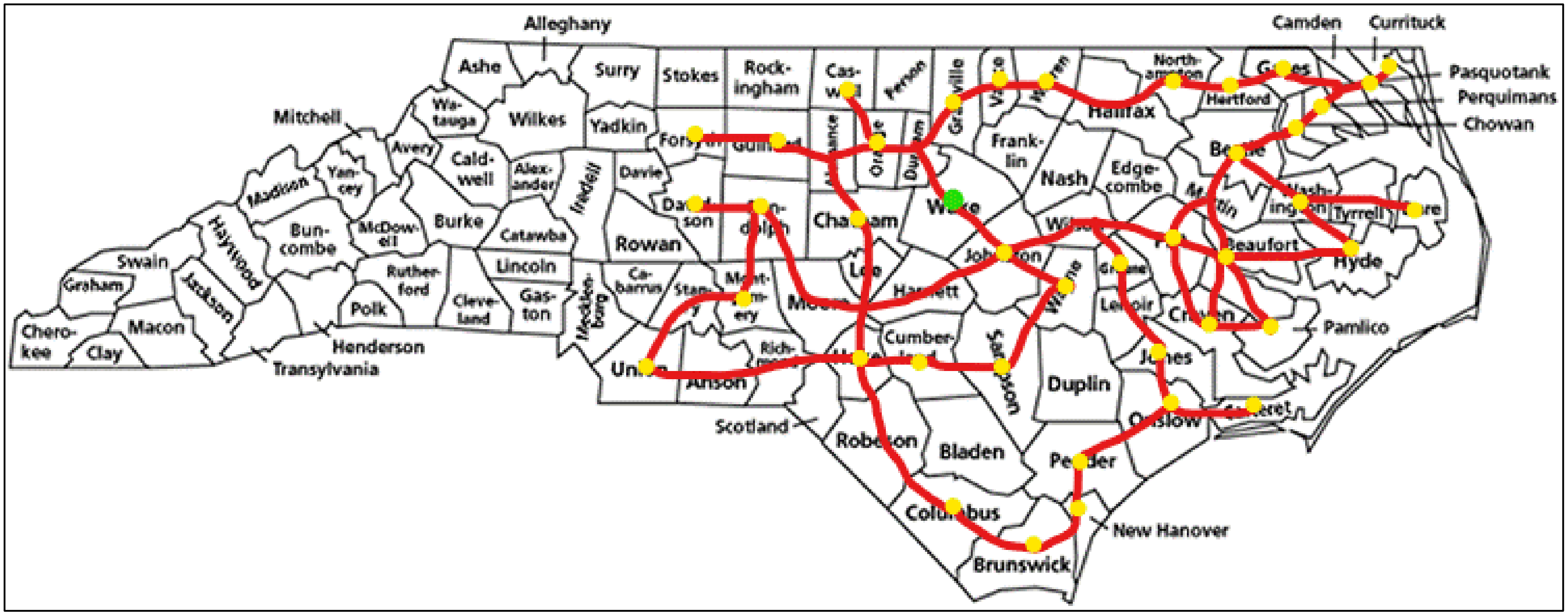

Figure 13. Route of one vehicle in dynamic network.

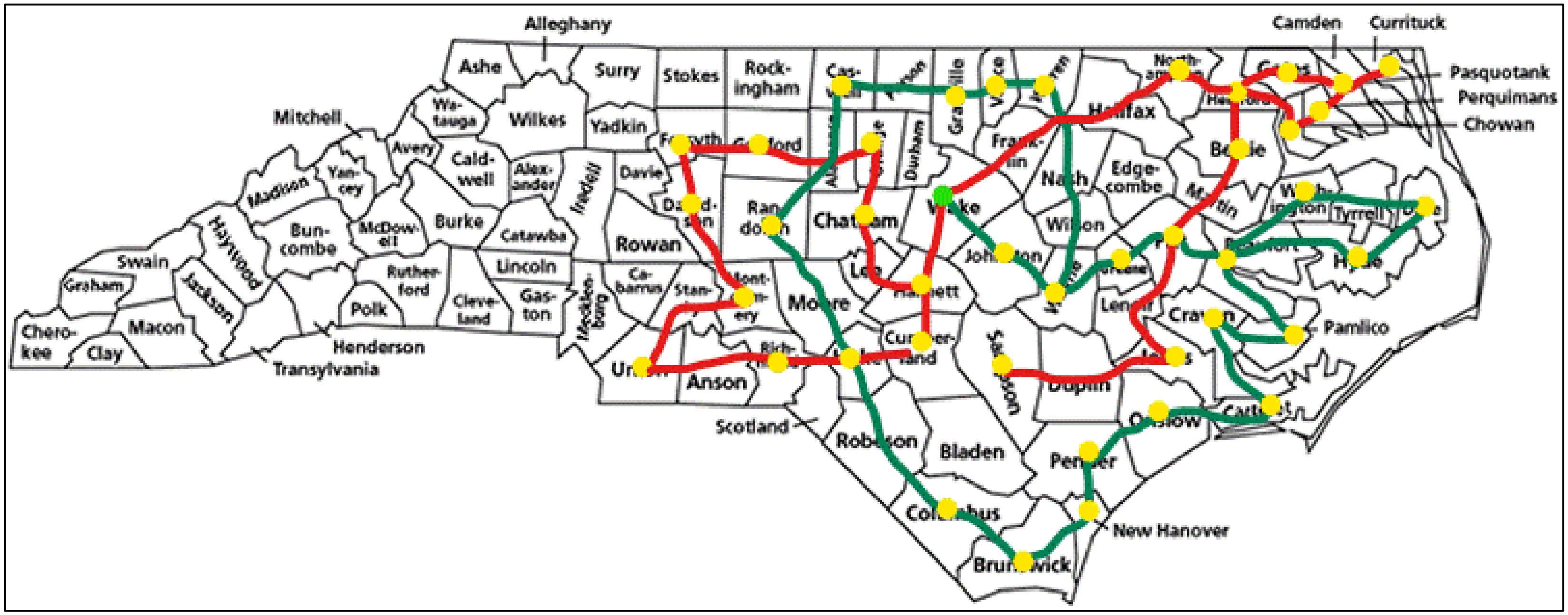

Figure 14. Route of two vehicles in dynamic network.

5.4 Setting III: Dynamic Network with Route Updating

While executing Route II, IIA and IIB and after visiting each of the primary nodes, the actual travel speed of the vehicle in the arcs it passes is collected as samples. 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. An example is shown in Table 23. The move has been specified in the updated route with a block. The rest of the steps are included in Appendix C. Since the vehicle does not pass zone 1 or 2 for this move, the distribution remains unchanged in those zones.

Table 23
Update of error ϵ_h, route and time

Move	Path	Zone 1		Zone 2		Zone 3		Updated route
19 - 17	19 - 16 - 58 - 17	n	-	n	-	n	3	1 14 31 33 11 5 12 7 9 13 2 10 6 16 19 17 30 28 32 39 23 21 24 8 $\boxed{35 \quad 3}$ 20 18 37 25 22 4 26 41 15 38 40 27 29 34 36 1
		μ	-	μ	-	μ	-0.05	
		σ^2	-	σ^2	-	σ^2	0.0013	
		μ'	-	μ'	-	μ'	-0.1	
		σ'^2	-	σ'^2	-	σ'^2	0.005	
		μ''	-	μ''	-	μ''	-0.054	
		σ''^2	-	σ''^2	-	σ''^2	0.0004	

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. Then the vehicle comes back to the depot at node 1. The new best routes we obtain in this situation, (Route III with one vehicle and Route IIIA and IIIB with two vehicles) are presented in Tables 24 and 25 respectively.

Table 24
Route of one vehicle under dynamic and uncertain network conditions (with updating)

Move	Path	Move	Path
1 - 14	1 - 14	21 – 36	21 – 56 – 36
14 - 31	14 - 31	36 – 24	36 - 24
31 - 33	31 - 33	24 – 26	24 - 26
33 - 11	33 – 53 – 11	26 – 38	26 – 43 – 38
11 - 5	11 - 5	38 – 18	38 - 18
5 - 12	5 - 12	18 – 37	18 - 37
12 - 7	12 – 5 – 7	37 – 25	37 - 25
7 - 9	7 - 9	25 – 22	25 – 45 – 22
9 - 13	9 - 13	22 – 20	22 – 45 – 25 – 20
13 - 2	13 - 2	20 – 40	20 - 40
2 - 10	2 - 10	40 – 27	40 - 27
10 - 6	10 - 6	27 – 35	27 – 38 – 35
6 - 16	6 – 60 – 16	35 – 3	35 - 3
16 - 19	16 - 19	3 – 8	3 – 35 – 8
19 - 17	19 – 16 – 58 – 17	8 – 4	8 - 4
17 - 28	17 - 28	4 – 15	4 - 15
28 - 30	28 – 62 – 30	15 – 41	15 - 41
30 - 32	30 – 62 – 32	41 – 34	41 – 31 – 14 – 57 – 44 – 34
32 - 39	32 - 39	34 – 29	34 - 29
39 - 23	39 - 23	29 – 1	29 – 54 - 1
23 - 21	23 - 21		

Table 25
Routes of two vehicles under dynamic and uncertain network conditions

Route IIIA		Route IIIB	
Move	Path	Move	Path
1 - 19	1 – 57 – 19	1 - 14	1 - 14
19 - 16	19 - 16	14 - 31	14 - 31
16 - 6	16 – 60 – 6	31 - 41	31 - 41
6 - 10	6 - 10	41 - 15	41 - 15
10 - 2	10 - 2	15 - 11	15 – 48 – 11
2 - 13	2 - 13	11 - 5	11 - 5
13 - 33	13 - 33	5 - 9	5 – 11 – 9
33 - 38	33 – 41 – 15 – 55 – 38	9 - 7	9 - 7
38 - 35	38 - 35	7 - 12	7 – 5 – 12
35 - 3	35 - 3	12 - 4	12 - 4
3 - 8	3 - 8	4 - 18	4 – 55 – 38 – 18
8 - 24	8 – 4 – 15 – 42 – 63 – 59 – 24	18 - 37	18 - 37
24 - 36	24 - 36	37 - 25	37 - 25
36 - 21	36 – 56 – 21	25 - 22	25 – 45 – 22
21 - 23	21 - 23	22 - 20	22 – 45 – 25 – 20
23 - 39	23 - 39	20 - 40	20 - 40
39 - 32	39 - 32	40 - 27	40 - 27
32 - 34	32 – 17 - 34	27 - 26	27 – 43 – 26
34 - 1	34 - 1	26 - 29	26 – 24 – 36 – 54 – 29
		29 - 17	29 – 51 – 17
		17 - 30	17 – 62 – 30
		30 - 28	30 – 62 – 28
		28 - 1	28 – 58 – 44 – 1

The duration of Route III is 25.38 hours and the total duration of Route IIIA and IIIB combined is 29.55 hours. Route III is highlighted in Figure 15 and Route IIIA (green) and IIIB (red) in Figure 16.

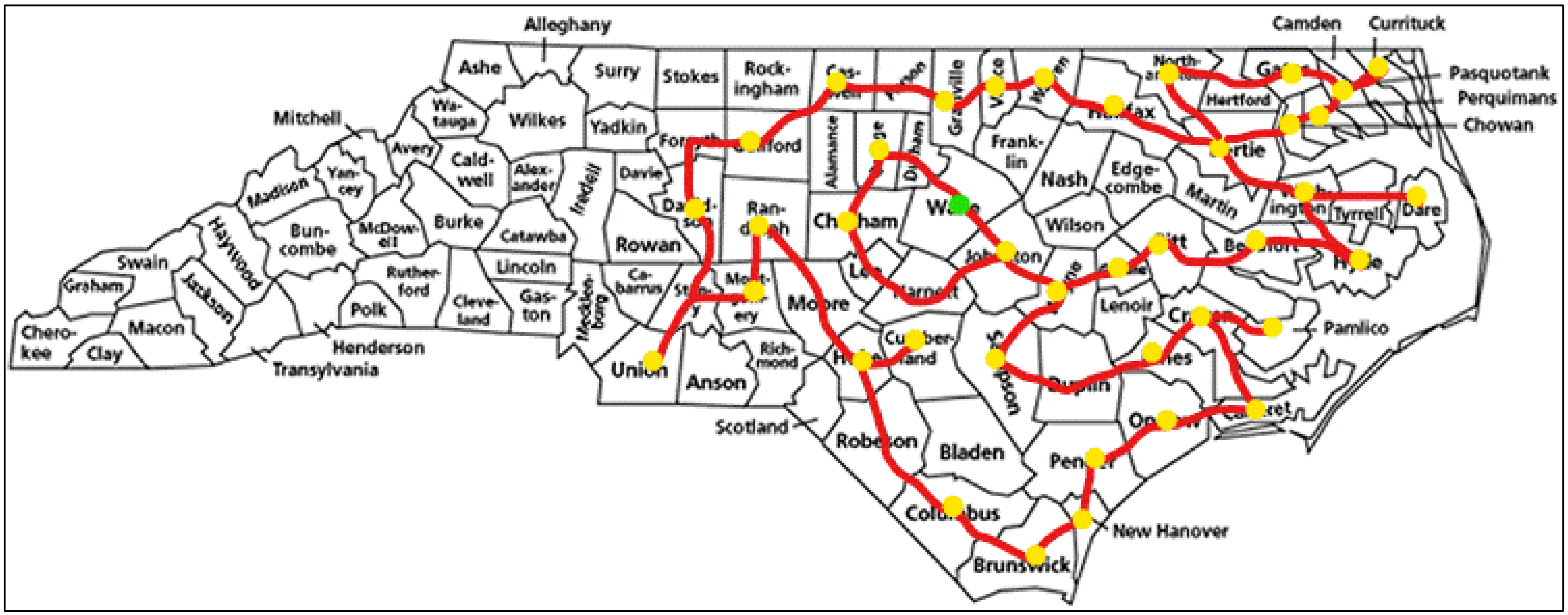

Figure 15. Route of one vehicle in dynamic and uncertain network.

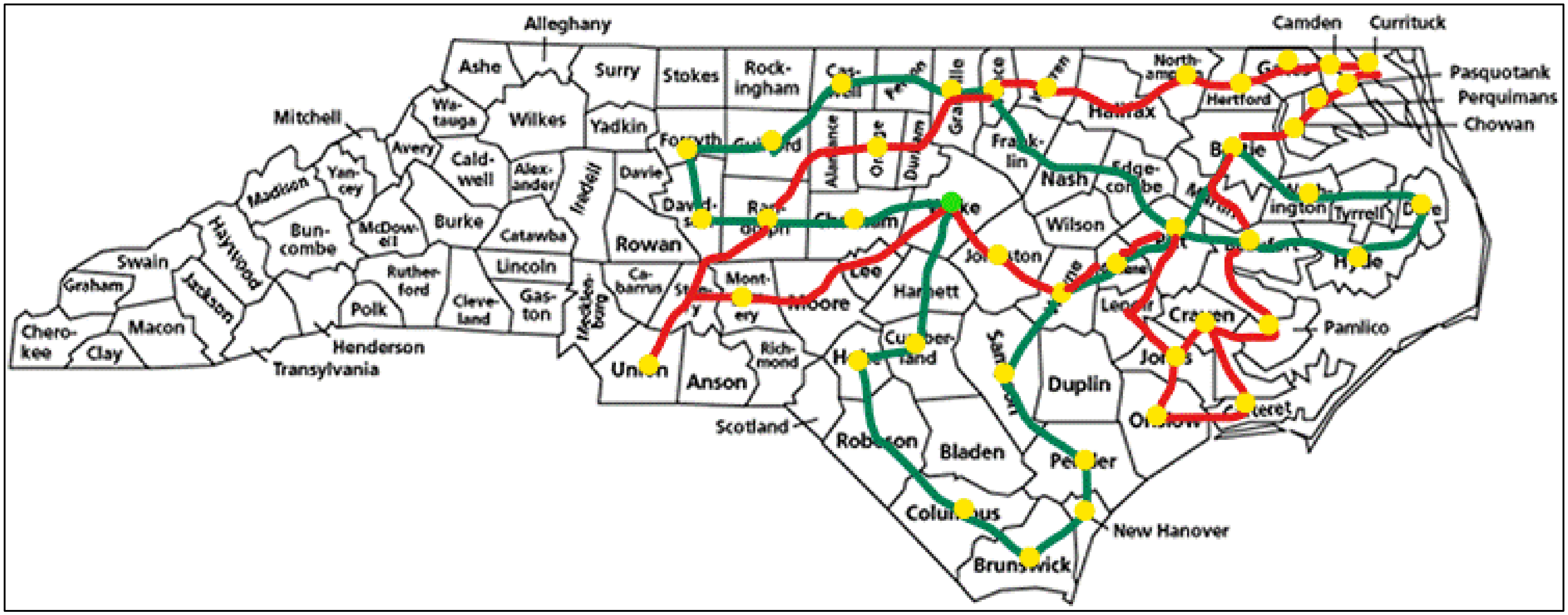

Figure 16. Route of two vehicles in dynamic and uncertain network.

5.5 Result Analysis

To compare the routes with one vehicle (Table 26), we compute the travel times of Route I in Settings II and III. We also compute the travel time of Route II in Setting III. By comparing Route I and Route II in Setting II, we see that we can save 2.94 hours by considering the dynamic network conditions. On the other hand, by comparing Routes II and III in Setting III, 11.33 hours can be saved by updating the dynamic network conditions while executing Route II. Similarly, with two vehicles, we compare the routes in Setting III (Table 27). We can save 8.79 hours by considering the dynamic network conditions and 0.27 hour if we update the dynamic network conditions while executing Route IIA and IIB comparing routes in Setting III.

Table 26
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

Table 27
Comparison among routes in different settings with two vehicles

	Setting I	Setting II	Setting III
Route IA and IB	17.73 + 15.45 = 33.18	18.66 + 15.45 = 34.11	18.38 + 20.23 = 38.61
Route IIA and IIB		13.93 + 14.71 = 28.64	14.32 + 15.50 = 29.82
Route IIIA and IIIB			14.22 + 15.33 = 29.55

5.6 Discussion

The results of this case study show that increasing number of vehicles does not always guarantee better result in reducing travel duration. But irrespective of number of vehicles or cases, the actual duration of the travelled route always improves routes compared to the planned ones. With a larger and more complex network compared to the previous one, this case study makes a stronger point about the importance of updating network forecast and routes to make more effective routing decisions.

CHAPTER 6

CONCLUSION AND FUTURE WORK

In the research, we have characterized the network to be dynamic and changing over time due to the combined effect of external factors. We have developed the methodology for solving the Traveling Salesman Problem with single vehicle and Vehicle Routing Problem with multiple vehicles 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 them to one hypothetical and one simplified 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. In both the case studies, the duration of the final executed route was observed to be significantly better than the actual duration of the planned routes irrespective of number of vehicles in consideration, which fulfills the objective of the study.

Immediate extension of this research should refine 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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APPENDIX A

ACCURACY OF ACO

To demonstrate the performance of Ant Colony Optimization algorithm used in this study, 30 small hypothetical networks were created each with n primary nodes and $2n$ secondary nodes. For the first 10 networks, $n = 4$, for next 10 networks, $n = 7$ and for the last 10 networks, $n = 10$. The co-ordinates have been generated with random numbers with MATLAB. The distances were calculated between every two nodes and corresponding travel duration was calculated considering the velocity to be 80mph. ACO algorithm was applied with only 20 iterations to find the best route with one vehicle covering all primary nodes. After that the optimal route was found with brute-force comparing all possible routes. The result gap = $\frac{ACO\ result - Optimal\ result}{Optimal\ result}$ was calculated along with the mean and standard deviation of the result gap. The results are summarized in Table 28.

With this study, we can safely state that this ACO algorithm can produce optimal decision when working with a small problem. Hence, we can assume that though the optimal solution is not guaranteed with a large problem like the case study of hurricane Florence, the model will converge well enough to a near-optimal result.

Table 28
Comparison of ACO result and optimized result

	Total number of nodes	Result from ACO	Optimal Result	Result Gap (%)	Mean (%)	Standard deviation (%)
n = 4	12	4.3278	4.3278	00.00	5.05	5.37
		3.2210	2.9389	9.60		
		4.1850	4.185	00.00		
		3.5191	3.0049	17.11		
		3.8495	3.5378	08.81		
		3.1714	3.1246	01.50		
		3.8116	3.4774	9.61		
		2.5613	2.5613	00.00		
		2.9911	2.8794	3.88		
		3.0738	3.0738	00.00		
n = 7	21	2.5311	2.3748	06.58	5.76	5.38
		3.1965	3.1965	00.00		
		2.9017	2.8836	00.63		
		4.0062	3.6188	10.71		
		3.2779	3.2641	00.42		
		2.9442	2.9142	01.03		
		3.5036	3.3162	05.65		
		2.3774	2.261	05.15		
		3.7041	3.4166	08.42		
		4.168	3.5029	18.99		
n = 10	30	4.4248	4.0618	08.94	4.56	4.16
		3.3438	2.9891	11.87		
		3.2293	2.9239	10.45		
		3.1726	2.9844	6.31		
		3.2046	3.1833	00.67		
		2.9512	2.9512	00.00		
		4.1106	3.9326	04.53		
		3.6696	3.6696	00.00		
		3.2454	3.2454	00.00		
		3.8522	3.7461	02.83		

APPENDIX B

DATA AND CALCULATION FOR HYPOTHETICAL CASE STUDY

Table 29
Arc lengths for hypothetical case study

(i,j)	L_{ij}	(i,j)	L_{ij}	(i,j)	L_{ij}	(i,j)	L_{ij}
(1,11)	93.6	(5,13)	127.3	(9,10)	68.6	(17,18)	63.4
(1,12)	101.2	(5,15)	79.9	(9,21)	139.7	(18,19)	78.1
(1,13)	176.8	(5,20)	62.3	(9,31)	34.7	(19,20)	52
(1,33)	305.2	(5,21)	84.3	(9,34)	137.6	(19,25)	72.3
(2,12)	83.6	(5,33)	46.9	(10,30)	82.7	(20,21)	58.8
(2,13)	72	(6,23)	54.6	(10,31)	63.3	(20,25)	40
(2,14)	63.2	(6,24)	65	(10,32)	53.6	(21,34)	149.5
(2,15)	69.9	(6,26)	68	(10,34)	172.6	(22,24)	77.6
(2,18)	78.5	(6,27)	49.1	(11,12)	70.7	(23,24)	46.5
(3,16)	105.7	(6,28)	76.2	(11,14)	81.4	(23,27)	89
(3,22)	35.9	(6,29)	93.7	(11,16)	121.8	(24,26)	91
(3,23)	79.1	(7,9)	83.9	(12,13)	89	(25,26)	52.7
(3,24)	86.3	(7,20)	88.1	(12,14)	79.4	(26,29)	52.9
(3,27)	167.3	(7,21)	52.3	(13,15)	70.7	(27,28)	59.8
(3,35)	79.1	(7,25)	71.7	(14,16)	65.5	(27,35)	169.1
(4,16)	169	(7,26)	77	(14,17)	59.9	(28,29)	40.9
(4,18)	62.2	(7,29)	71.6	(14,18)	103.7	(28,30)	74.4
(4,19)	52.9	(8,27)	68.3	(15,18)	89.3	(29,31)	81.5
(4,22)	107.2	(8,28)	54.9	(15,19)	50.1	(30,31)	36.1
(4,24)	59.6	(8,30)	72.7	(16,17)	45.9	(30,32)	40.4
(4,25)	61.6	(8,32)	100.3	(16,22)	86	(33,34)	212.8
(4,26)	84.5	(8,35)	233.3	(16,35)	169.3		

Table 30
Calculation analysis of Route III in hypothetical case study

Move	Path	Zone 1		Zone 2		Zone 3		Zone 4		Updated route
1 → 5	1 → 13	n	1	n	1	n	-	n	-	1 → 13 → 5
	→ 5	μ	0	μ	-0.2	μ	-	μ	-	→ 21 → 7 → 9
		σ^2	0	σ^2	0.02	σ^2	-	σ^2	-	→ 10 → 32 → 8
		μ'	0	μ'	0	μ'	-	μ'	-	→ 27 → 6 → 23
		σ'^2	0	σ'^2	0	σ'^2	-	σ'^2	-	→ 3 → 22 → 4
		σ''^2	0	σ''^2	0.02	σ''^2	-	σ''^2	-	→ 18 → 2 → 12
		μ''	0	μ''	-0.2	μ''	-	μ''	-	→ 1
5 → 7	5 → 21	n	-	n	-	n	2	n	-	1 → 13 → 5
	→ 7	μ	-	μ	-	μ	-0.08	μ	-	→ 21 → 7 → 9
		σ^2	-	σ^2	-	σ^2	0.002	σ^2	-	→ 10 → 32 → 8
		μ'	-	μ'	-	μ'	0	μ'	-	→ 27 → 6 → 23
		σ'^2	-	σ'^2	-	σ'^2	0	σ'^2	-	→ 3 → 22 → 4
		σ''^2	-	σ''^2	-	σ''^2	0.001	σ''^2	-	→ 18 → 2 → 12
		μ''	-	μ''	-	μ''	-0.075	μ''	-	→ 1
7 → 9	7 → 9	n	-	n	-	n	-	n	1	1 → 13 → 5
		μ	-	μ	-	μ	-	μ	-0.15	→ 21 → 7 → 9
		σ^2	-	σ^2	-	σ^2	-	σ^2	0.011	→ 10 → 32 → 8
		μ'	-	μ'	-	μ'	-	μ'	0	→ 27 → 6 → 23
		σ'^2	-	σ'^2	-	σ'^2	-	σ'^2	0	→ 3 → 22 → 4
		σ''^2	-	σ''^2	-	σ''^2	-	σ''^2	0.011	→ 18 → 2 → 12
		μ''	-	μ''	-	μ''	-	μ''	-0.15	→ 1
9	9 → 10	n	-	n	-	n	-	n	1	1 → 13 → 5
→ 10		μ	-	μ	-	μ	-	μ	-0.1	→ 21 → 7 → 9
		σ^2	-	σ^2	-	σ^2	-	σ^2	0.001	→ 10 → 32 → 8
		μ'	-	μ'	-	μ'	-	μ'	-0.15	→ 27 → 6 → 23
		σ'^2	-	σ'^2	-	σ'^2	-	σ'^2	0.011	→ 3 → 22 → 4
		σ''^2	-	σ''^2	-	σ''^2	-	σ''^2	0.001	→ 18 → 2 → 12
		μ''	-	μ''	-	μ''	-	μ''	-0.105	→ 1
10	10 → 32	n	-	n	-	n	-	n	2	1 → 13 → 5
→ 8	→ 8	μ	-	μ	-	μ	-	μ	-0.045	→ 21 → 7 → 9
		σ^2	-	σ^2	-	σ^2	-	σ^2	0.004	→ 10 → 32 → 8
		μ'	-	μ'	-	μ'	-	μ'	-0.105	→ 35 → 3 → 23
		σ'^2	-	σ'^2	-	σ'^2	-	σ'^2	0.001	→ 6 → 24 → 4
		σ''^2	-	σ''^2	-	σ''^2	-	σ''^2	0.001	→ 18 → 2 → 12
		μ''	-	μ''	-	μ''	-	μ''	-0.082	→ 1

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Table 30 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Zone 4		Updated route
8 → 3	8 → 35 → 3	n		n		n	2	n	-	1 → 13 → 5 → 21 → 7 → 9 → 10 → 32 → 8 → 35 → 3 → 23 → 6 → 24 → 4 → 18 → 2 → 12 → 1
		μ		μ		μ	-0.05	μ	-	
		σ^2		σ^2		σ^2	0.003	σ^2	-	
		μ'		μ'		μ'	-0.1	μ'	-	
		σ'^2		σ'^2		σ'^2	0.002	σ'^2	-	
		σ''^2		σ''^2		σ''^2	0.001	σ''^2	-	
		μ''		μ''		μ''	-0.071	μ''	-	
3 → 6	3 → 23 → 6	n		n		n	2	n	-	1 → 13 → 5 → 21 → 7 → 9 → 10 → 32 → 8 → 35 → 3 → 23 → 6 → 24 → 4 → 19 → 15 → 2 → 12 → 1
		μ		μ		μ	-0.03	μ	-	
		σ^2		σ^2		σ^2	0.001	σ^2	-	
		μ'		μ'		μ'	-0.071	μ'	-	
		σ'^2		σ'^2		σ'^2	0.001	σ'^2	-	
		σ''^2		σ''^2		σ''^2	.0002	σ''^2	-	
		μ''		μ''		μ''	-0.042	μ''	-	
6 → 4	6 → 24 → 4	n		n		n	2	n	-	1 → 13 → 5 → 21 → 7 → 9 → 10 → 32 → 8 → 35 → 3 → 23 → 6 → 24 → 4 → 19 → 15 → 2 → 12 → 1
		μ		μ		μ	-0.065	μ	-	
		σ^2		σ^2		σ^2	0.004	σ^2	-	
		μ'		μ'		μ'	-0.042	μ'	-	
		σ'^2		σ'^2		σ'^2	.0002	σ'^2	-	
		σ''^2		σ''^2		σ''^2	.0002	σ''^2	-	
		μ''		μ''		μ''	-0.044	μ''	-	
4 → 2	4 → 19 → 15 → 2	n	1	n	1	n	1	n	-	1 → 13 → 5 → 21 → 7 → 9 → 10 → 32 → 8 → 35 → 3 → 23 → 6 → 24 → 4 → 19 → 15 → 2 → 12 → 1
		μ	-0.1	μ	-0.1	μ	0	μ	-	
		σ^2	0.005	σ^2	0.005	σ^2	0.001	σ^2	-	
		μ'	0	μ'	-0.2	μ'	-0.05	μ'	-	
		σ'^2	0	σ'^2	0.02	σ'^2	.0002	σ'^2	-	
		σ''^2	0.005	σ''^2	0.004	σ''^2	.0002	σ''^2	-	
		μ''	-0.1	μ''	-0.12	μ''	-0.037	μ''	-	
2 → 1	2 → 12 → 1	n	2	n	-	n	-	n	-	1 → 13 → 5 → 21 → 7 → 9 → 10 → 32 → 8 → 35 → 3 → 23 → 6 → 24 → 4 → 19 → 15 → 2 → 12 → 1
		μ	-0.13	μ	-	μ	-	μ	-	
		σ^2	0.015	σ^2	-	σ^2	-	σ^2	-	
		μ'	-0.1	μ'	-	μ'	-	μ'	-	
		σ'^2	0.005	σ'^2	-	σ'^2	-	σ'^2	-	
		σ''^2	.0003	σ''^2	-	σ''^2	-	σ''^2	-	
		μ''	-0.08	μ''	-	μ''	-	μ''	-	

Table 31
Route III in actual condition in hypothetical case study

Arc	Distance	Zone	k (Actual)	Actual time	Cumulative actual time
1 - 13	176.8	1	1	2.21	2.21
13 - 5	127.3	2	0.8	1.989063	4.199063
5 - 21	62.3	3	0.7	1.1125	5.311563
21 - 7	88.1	3	0.7	1.573214	6.884777
7 - 9	83.9	4	0.45	2.330556	9.215332
9 - 10	68.6	4	0.245	2.485507	11.70084
10 - 32	53.6	4	0.163	4.110429	15.81127
32 - 8	100.3	4	0.163	7.691718	23.50299
8 - 27	68.3	4	0.163	5.23773	28.74072
27 - 6	49.1	3	0.43	1.427326	30.16804
6 - 23	54.6	3	0.39	1.75	31.91804
23 - 3	79.1	3	0.35	2.825	34.74304
3 - 22	35.9	2	0.6	0.747917	35.49096
22 - 4	107.2	3	0.35	3.828571	39.31953
4 - 18	62.2	3	0.21	3.702381	43.02191
18 - 2	78.5	2	0.48	2.044271	45.06618
2 - 12	83.6	1	0.8	1.30625	46.37243
12 - 1	101.2	1	0.8	1.58125	47.95368

Table 32
Route I in actual condition in hypothetical case study

Arc	Distance	Zone	k (Actual)	Actual time	Cumulative actual time
1 - 12	101.2	1	1	1.265	1.265
12 - 2	83.6	1	1	1.045	2.31
2 - 18	78.5	2	0.8	1.226563	3.536563
18 - 4	62.2	3	0.7	1.110714	4.647277
4 - 22	107.2	3	0.7	1.914286	6.561563
22 - 3	35.9	2	0.8	0.560938	7.1225
3 - 23	79.1	3	0.63	1.569444	8.691944
23 - 6	54.6	3	0.59	1.15678	9.848724
6 - 27	49.1	3	0.55	1.115909	10.96463
27 - 8	68.3	4	0.45	1.897222	12.86186
8 - 32	100.3	4	0.245	5.117347	17.9792
32 - 10	53.6	4	0.163	4.110429	22.08963
10 - 9	68.6	4	0.163	5.260736	27.35037
9 - 7	83.9	4	0.063	16.64683	43.99719
7 - 21	88.1	3	0.21	5.244048	49.24124
21 - 5	62.3	3	0.21	3.708333	52.94957
5 - 13	127.3	2	0.48	3.315104	56.26468
13 - 1	176.8	1	0.8	2.7625	59.02718

APPENDIX C

DATA AND CALCULATION FOR FLORENCE CASE STUDY

Table 33
Arc lengths belonging to zone 1 of Florence case study

(i,j)	L_{ij}	(i,j)	L_{ij}	(i,j)	L_{ij}	(i,j)	L_{ij}
(2,10)	22.3	(4, 12)	42	(5, 12)	22.5	(9, 11)	33.5
(2,13)	25.2	(4, 15)	21.5	(6, 10)	49.7	(9, 13)	35.0
(3, 8)	68.5	(4, 35)	52.7	(6, 13)	55.5	(10, 13)	47.8
(3, 35)		(4, 55)	23.9	(6, 46)	23.8	(11,48)	21.2
(4, 5)	38.1	(5, 7)	37.3	(7, 9)	40.5	(13, 53)	33.5
(4, 8)	51.9	(5, 11)	21.5	(7, 11)	50.7		

Table 34
Arc lengths belonging to zone 2 of Florence case study

(i,j)	L_{ij}	(i,j)	L_{ij}	(i,j)	L_{ij}	(i,j)	L_{ij}
(1, 14)	35.8	(15, 55)	26.5	(25, 37)	17.7	(38, 43)	53.4
(5, 15)	44.0	(15, 64)	43.4	(25, 45)	5.5	(38, 55)	14.5
(5, 48)	33.0	(16, 60)	27.2	(26, 43)	37.6	(41, 48)	16.1
(6, 60)	34.9	(18, 20)	31.2	(27, 38)	44.8	(41, 64)	29.4
(8, 35)	45.5	(18, 37)	12.8	(27, 40)	32.2	(42, 43)	35.8
(9, 53)	38.3	(18, 38)	24.3	(27, 43)	18.5	(42, 55)	31.5
(11, 53)	40.0	(18, 40)	34.8	(31, 33)	37.2	(42, 63)	25.9
(13, 33)	44.9	(19, 33)	37.7	(31, 41)	19.6	(42, 64)	28.6
(13, 46)	50.1	(19, 46)	39.1	(31, 48)	26.2	(43, 55)	49.4
(14, 31)	24.1	(19, 57)	27.9	(31, 53)	36.4	(46, 60)	30.4
(14, 33)	41.0	(19, 60)	37.2	(31, 64)	26.8	(48, 53)	34.0
(14, 64)	29.7	(20, 25)	27.5	(33, 46)	34.5	(50, 60)	29.5
(15, 41)	24.9	(20, 37)	27.5	(35, 38)	45.2	(63, 64)	20.2
(15, 42)	24.5	(20, 40)	25.3	(35, 55)	51.8		
(15, 48)	33.5	(22, 45)	13.5	(38, 40)	23.7		

Table 35
Arc lengths belonging to zone 3 of Florence case study

(i,j)	L_{ij}	(i,j)	L_{ij}	(i,j)	L_{ij}	(i,j)	L_{ij}
(1, 34)	39.3	(17, 39)	46.5	(28, 32)	43.9	(36, 56)	26.3
(1, 36)	42.2	(17, 51)	42.5	(28, 47)	34.0	(36, 59)	27.7
(1, 44)	49.0	(17, 58)	36.7	(28, 52)	33.2	(39, 49)	41.1
(1, 54)	25.5	(17, 62)	37.4	(28, 58)	30.9	(39, 61)	25.6
(1, 57)	35.9	(21, 23)	38.5	(28, 62)	22.5	(43, 59)	46.8
(1, 59)	30.7	(21, 29)	29.3	(29, 34)	29.4	(43, 63)	38.1
(14, 57)	32.5	(21, 49)	29.1	(29, 51)	20.1	(44, 57)	24.1
(14, 59)	45.3	(21, 51)	25.7	(29, 54)	14.6	(44, 58)	18.0
(14, 63)	45.8	(21, 56)	21.5	(29, 56)	24.9	(47, 50)	22.2
(16, 19)	24.7	(23, 32)	34.2	(30, 52)	30.0	(47, 52)	18.8
(16, 44)	45.4	(23, 39)	29.1	(30, 62)	35.3	(47, 58)	40.5
(16, 47)	40.1	(23, 49)	26.5	(32, 39)	20.9	(49, 51)	32.8
(16, 50)	22.0	(23, 51)	23.9	(32, 62)	38.6	(49, 61)	32.0
(16, 57)	48.3	(23, 61)	41.4	(33, 57)	45.9	(50, 58)	42.3
(16, 58)	31.9	(24, 26)	19.8	(34, 44)	18.3	(52, 62)	31.1
(17, 23)	32.5	(24, 36)	9.2	(34, 51)	31.3	(54, 56)	30.1
(17, 28)	23.6	(24, 59)	22.0	(34, 54)	28.0	(57, 58)	40.1
(17, 32)	28.1	(26, 59)	24.5	(34, 58)	34.2	(59, 63)	24.0
(17, 34)	38.6	(26, 63)	36.9	(36, 54)	29.9		

Table 36
Calculation analysis of Route III in Florence case study

Move	Path	Zone 1		Zone 2		Zone 3		Updated route
1 - 19	1 - 57 - 19	Sample size	-	Sample size	2	Sample size	1	
		Sample Mean	-	Sample Mean	0	Sample Mean	0	
		Sample Var	-	Sample Var	0	Sample Var	0	
		Prior mean	-	Prior mean	0	Prior mean	0	
1 - 14	1 - 14	Prior Var	-	Prior Var	0	Prior Var	0	
		Posterior mean	-	Posterior mean	0	Posterior mean	0	
		Posterior Var	-	Posterior Var	0	Posterior Var	0	
		Sample size	-	Sample size	1	Sample size	-	1 19 32 39 6 10 2 13 7 5 30 28 17 23 21 8 24 36 29 41 1
		Sample Mean	-	Sample Mean	0	Sample Mean	-	
		Sample Var	-	Sample Var	0	Sample Var	-	
		Prior mean	-	Prior mean	0	Prior mean	-	
14 - 31	14 - 31	Prior Var	-	Prior Var	0	Prior Var	-	1 14 31 33 35 25 37 18 38 22 20 40 27 26 34 11 9 12 15 4 3 16 1
		Posterior mean	-	Posterior mean	0	Posterior mean	-	
		Posterior Var	-	Posterior Var	0	Posterior Var	-	
19 - 16	19 - 16	Sample size	-	Sample size	1	Sample size	1	1 19 16 25 5 7 9 27 8 35 20 24 21 29 28 30 32 17 23 39 1
		Sample Mean	-	Sample Mean	0	Sample Mean	0	
		Sample Var	-	Sample Var	0	Sample Var	0	
		Prior mean	-	Prior mean	0	Prior mean	0	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
31 - 41	31 - 41	Prior Var	-	Prior Var	0	Prior Var	0	1 14 31 41 15 12 11 4 22 3 37 18 36 40 38 26 2 10 6 13 33 34 1
		Posterior mean	-	Posterior mean	0	Posterior mean	0	
		Posterior Var	-	Posterior Var	0	Posterior Var	0	
		Sample size	-	Sample size	1	Sample size	-	1 19 16 34 9 3 35 8 12 5 21 17 33 13 2 10 6 1
		Sample Mean	-	Sample Mean	0	Sample Mean	-	
		Sample Var	-	Sample Var	0	Sample Var	-	
41 - 15	41 - 15	Prior mean	-	Prior mean	0	Prior mean	-	1 14 31 41 15 38 18 37 11 4 40 22 25 20 27 26 36 29 23 39 32 24 30 28 7 1
		Prior Var	-	Prior Var	0	Prior Var	-	
		Posterior mean	-	Posterior mean	0	Posterior mean	-	
		Posterior Var	-	Posterior Var	0	Posterior Var	-	
16 - 6	16 - 60 - 6	Sample size	-	Sample size	2	Sample size	-	1 19 16 6 10 2 23 34 21 28 26 36 17 32 29 39 30 1
		Sample Mean	-	Sample Mean	-0.1	Sample Mean	-	
		Sample Var	-	Sample Var	0.005	Sample Var	-	
		Prior mean	-	Prior mean	0	Prior mean	-	1 14 31 41 15 4 38 12 5 11 33 13 9 7 8 3 35 18 20 27 40 37 25 22 24 1
		Prior Var	-	Prior Var	0	Prior Var	-	
		Posterior mean	-	Posterior mean	-0.1	Posterior mean	-	
		Posterior Var	-	Posterior Var	0.0025	Posterior Var	-	
		Sample size	1	Sample size	1	Sample size	-	1 19 16 6 10 2 9 26 12 5 7 33 34 36 39 28 23 21 32 24 1
		Sample Mean	-0.05	Sample Mean	0	Sample Mean	-	
		Sample Var	0.00125	Sample Var	0.005	Sample Var	-	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
15 - 11	15 - 48 - 11	Prior mean	0	Prior mean	-0.1	Prior mean	-	1 14 31 41 15 11 13 38 20 40 27 18 37 25 22 4 8 35 3 29 30 17 1
		Prior Var	0	Prior Var	0.0025	Prior Var	-	
		Posterior mean	-0.05	Posterior mean	-0.067	Posterior mean	-	
		Posterior Var	0.00125	Posterior Var	0.0017	Posterior Var	-	
6 - 10	6 - 10	Sample size	2	Sample size	-	Sample size	-	1 19 16 6 10 2 13 9 24 36 29 39 32 34 17 28 30 23 27 38 37 22 25 18 1
		Sample Mean	-0.08	Sample Mean	-	Sample Mean	-	
		Sample Var	0.0005	Sample Var	-	Sample Var	-	
		Prior mean	-0.05	Prior mean	-	Prior mean	-	
11 - 5	11 - 5	Prior Var	0.00125	Prior Var	-	Prior Var	-	1 14 31 41 15 11 5 12 8 35 3 20 26 40 21 33 7 4 1
		Posterior mean	-0.075	Posterior mean	-	Posterior mean	-	
		Posterior Var	0.00021	Posterior Var	-	Posterior Var	-	
		Sample size	2	Sample size	-	Sample size	-	1 19 16 6 10 2 7 12 37 18 4 22 38 3 25 20 8 35 1
		Sample Mean	-0.05	Sample Mean	-	Sample Mean	-	
		Sample Var	0.0003	Sample Var	-	Sample Var	-	
5 - 9	5 - 11 - 9	Prior mean	-0.075	Prior mean	-	Prior mean	-	1 14 31 41 15 11 5 9 13 33 34 29 21 23 28 39 27 40 26 24 36 30 17 32 1
		Prior Var	0.00021	Prior Var	-	Prior Var	-	
		Posterior mean	-0.0605	Posterior mean	-	Posterior mean	-	
		Posterior Var	8.7E-05	Posterior Var	-	Posterior Var	-	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
10 - 2	10 - 2	Sample size	1	Sample size	-	Sample size	-	1 19 16 6 10 2 7 12 8 38 40 20 22 25 18 27 34 23 39 17 28 30 21 1
		Sample Mean	-0.1	Sample Mean	-	Sample Mean	-	
		Sample Var	0.0008	Sample Var	-	Sample Var	-	
		Prior mean	-0.0605	Prior mean	-	Prior mean	-	
		Prior Var	8.7E-05	Prior Var	-	Prior Var	-	1 14 31 41 15 11 5 9 13 33 4 36 37 3 35 26 24 32 29 1
		Posterior mean	-0.0644	Posterior mean	-	Posterior mean	-	
		Posterior Var	7.9E-05	Posterior Var	-	Posterior Var	-	
2 - 13	2 - 13	Sample size	1	Sample size	-	Sample size	-	1 19 16 6 10 2 13 33 36 24 26 27 20 12 4 8 35 37 38 25 22 18 40 1
		Sample Mean	-0.05	Sample Mean	-	Sample Mean	-	
		Sample Var	0.0001	Sample Var	-	Sample Var	-	
		Prior mean	-0.0644	Prior mean	-	Prior mean	-	
		Prior Var	7.9E-05	Prior Var	-	Prior Var	-	1 14 31 41 15 11 5 9 7 29 34 39 32 17 28 30 23 21 3 1
		Posterior mean	-0.058	Posterior mean	-	Posterior mean	-	
		Posterior Var	4.4E-05	Posterior Var	-	Posterior Var	-	
		Sample size	1	Sample size	-	Sample size	-	1 19 16 6 10 2 13 33 3 35 8 27 40 38 22 28 17 23 1
		Sample Mean	-0.05	Sample Mean	-	Sample Mean	-	
		Sample Var	0.00003	Sample Var	-	Sample Var	-	
9 - 7	9 - 7	Prior mean	-0.058	Prior mean	-	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 20 25 37 18 36 24 26 29 30 34 39 32 21 1
		Prior Var	4.4E-05	Prior Var	-	Prior Var	-	
		Posterior mean	-0.0533	Posterior mean	-	Posterior mean	-	
		Posterior Var	1.8E-05	Posterior Var	-	Posterior Var	-	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
13 - 33	13 - 33	Sample size	-	Sample size	1	Sample size	-	1 19 16 6 10 2 13 33 34 29 28 17 32 36 39 23 21 4 26 24
		Sample Mean	-	Sample Mean	0	Sample Mean	-	
		Sample Var	-	Sample Var	0.0023	Sample Var	-	
		Prior mean	-	Prior mean	-0.067	Prior mean	-	1 14 31 41 15 11 5 9 7 12 38 40 20 25 22 37 18 3 35 8 27 30 1
		Prior Var	-	Prior Var	0.0017	Prior Var	-	
		Posterior mean	-	Posterior mean	-0.039	Posterior mean	-	
		Posterior Var	-	Posterior Var	0.001	Posterior Var	-	
		Sample size	2	Sample size	-	Sample size	-	1 19 16 6 10 2 13 33 36 21 29 34 17 27 40 20 26 24 23 32 30 1
		Sample Mean	-0.05	Sample Mean	-	Sample Mean	-	
		Sample Var	0.0001	Sample Var	-	Sample Var	-	
7 - 12	7 - 5 - 12	Prior mean	-0.0533	Prior mean	-	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 38 18 37 25 22 3 35 8 28 39 1
		Prior Var	1.8E-05	Prior Var	-	Prior Var	-	
		Posterior mean	-0.0524	Posterior mean	-	Posterior mean	-	
		Posterior Var	1.3E-05	Posterior Var	-	Posterior Var	-	
33 - 38	33 - 31 - 41 - 15 - 55 - 38	Sample size	-	Sample size	5	Sample size	-	1 19 16 6 10 2 13 33 18 37 8 35 3 39 32 21 1
		Sample Mean	-	Sample Mean	0	Sample Mean	-	
		Sample Var	-	Sample Var	0.0008	Sample Var	-	
		Prior mean	-	Prior mean	-0.039	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 38 40 20 25 22 27 26 24 29 34 17 28 30 23 36 1
		Prior Var	-	Prior Var	0.001	Prior Var	-	
		Posterior mean	-	Posterior mean	-0.005	Posterior mean	-	
		Posterior Var	-	Posterior Var	0.0001	Posterior Var	-	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
		Sample size	1	Sample size	-	Sample size	-	1 19 16 6 10 2 13 33 38 26 37 18 20 25 22 40 24 36 21 39 23 34 1
		Sample Mean	0	Sample Mean	-	Sample Mean	-	
		Sample Var	0.0014	Sample Var	-	Sample Var	-	
		Prior mean	-0.0524	Prior mean	-	Prior mean	-	
12 - 4	12 - 4	Prior Var	1.3E-05	Prior Var	-	Prior Var	-	1 14 31 41 15 11 5 9 7 12 4 35 8 3 27 30 17 28 32 29 1
		Posterior mean	-0.0519	Posterior mean	-	Posterior mean	-	
		Posterior Var	1.3E-05	Posterior Var	-	Posterior Var	-	
		Sample size	1	Sample size	2	Sample size	-	1 19 16 6 10 2 13 33 38 40 8 35 3 24 17 21 34 1
		Sample Mean	-0.05	Sample Mean	0	Sample Mean	-	
		Sample Var	0.00001	Sample Var	0.0001	Sample Var	-	
4 -18	4 - 55 - 38 - 18	Prior mean	-0.0519	Prior mean	-0.005	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 18 25 22 37 20 27 26 36 23 39 32 30 28 29 1
		Prior Var	1.3E-05	Prior Var	0.0001	Prior Var	-	
		Posterior mean	-0.0508	Posterior mean	-0.001	Posterior mean	-	
		Posterior Var	5.7E-06	Posterior Var	4E-05	Posterior Var	-	
38 - 35	38 - 35	Sample size		Sample size	2	Sample size	-	1 19 16 6 10 2 13 33 38 35 8 3 27 24 23 17 34 29 26 1
		Sample Mean		Sample Mean	0	Sample Mean	-	
		Sample Var		Sample Var	0.0001	Sample Var	-	
		Prior mean		Prior mean	-0.001	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 36 32 39 30 28 21 1
		Prior Var		Prior Var	4E-05	Prior Var	-	
		Posterior mean		Posterior mean	-8E-04	Posterior mean	-	
		Posterior Var		Posterior Var	2E-05	Posterior Var	-	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
		Sample size		Sample size	1	Sample size	-	1 19 16 6 10 2 13 33 38 35 3 8 27 24 36 29 28 30 1 0
		Sample Mean		Sample Mean	0	Sample Mean	-	
		Sample Var		Sample Var	0.0001	Sample Var	-	
18 - 37	18 - 37	Prior mean		Prior mean	-8E-04	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 18 22 25 37 20 40 26 34 21 23 39 32 17 1
		Prior Var		Prior Var	2E-05	Prior Var	-	
		Posterior mean		Posterior mean	-7E-04	Posterior mean	-	
		Posterior Var		Posterior Var	2E-05	Posterior Var	-	
		Sample size		Sample size	1	Sample size	-	1 19 16 6 10 2 13 33 38 35 3 8 40 36 34 32 39 1
		Sample Mean		Sample Mean	0	Sample Mean	-	
		Sample Var		Sample Var	0.0001	Sample Var	-	
37 - 25	37 - 25	Prior mean		Prior mean	-7E-04	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 27 26 24 29 21 23 28 30 17 1
		Prior Var		Prior Var	2E-05	Prior Var	-	
		Posterior mean		Posterior mean	-6E-04	Posterior mean	-	
		Posterior Var		Posterior Var	1E-05	Posterior Var	-	
35 - 3	35 - 3	Sample size	1	Sample size	2	Sample size	-	1 19 16 6 10 2 13 33 38 35 3 8 40 27 26 36 17 28 34 1
		Sample Mean	0	Sample Mean	-0.03	Sample Mean	-	
		Sample Var	0.0013	Sample Var	0.0004	Sample Var	-	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
25 - 22	25 - 45 - 22	Prior mean	-0.0508	Prior mean	-6E-04	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 24 29 21 23 39 30 32 1
		Prior Var	5.7E-06	Prior Var	1E-05	Prior Var	-	
		Posterior mean	-0.0506	Posterior mean	-0.003	Posterior mean	-	
		Posterior Var	5.6E-06	Posterior Var	1E-05	Posterior Var	-	
3 - 8	3 - 8	Sample size	1	Sample size	-	Sample size	-	1 19 16 6 10 2 13 33 38 35 3 8 34 17 32 39 23 21 1 0
		Sample Mean	0	Sample Mean	-	Sample Mean	-	
		Sample Var	0.0013	Sample Var	-	Sample Var	-	
		Prior mean	-0.0506	Prior mean	-	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 36 24 29 28 30 1
		Prior Var	5.6E-06	Prior Var	-	Prior Var	-	
		Posterior mean	-0.0504	Posterior mean	-	Posterior mean	-	
		Posterior Var	5.6E-06	Posterior Var	-	Posterior Var	-	
		Sample size	-	Sample size	3	Sample size	-	1 19 16 6 10 2 13 33 38 35 3 8 28 39 32 30 17 1
		Sample Mean	-	Sample Mean	0	Sample Mean	-	
		Sample Var	-	Sample Var	0.0001	Sample Var	-	
22 - 20	22 - 45 - 25 - 20	Prior mean	-	Prior mean	-0.003	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 24 36 34 23 21 29 1
		Prior Var	-	Prior Var	1E-05	Prior Var	-	
		Posterior mean	-	Posterior mean	-0.002	Posterior mean	-	
		Posterior Var	-	Posterior Var	1E-05	Posterior Var	-	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
8 - 24	8 - 4 - 15 - 42 - 63 - 59 - 24	Sample size	2	Sample size	3	Sample size	2	1 19 16 6 10 2 13 33 38 35 3 8 24 34 17 28 30 1
		Sample Mean	0	Sample Mean	-0.05	Sample Mean	0	
		Sample Var	0.0013	Sample Var	0.0012	Sample Var	0	
20 - 40	20 - 40	Prior mean	-0.0504	Prior mean	-0.002	Prior mean	0	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 36 29 21 23 39 32 1
		Prior Var	5.6E-06	Prior Var	1E-05	Prior Var	0	
		Posterior mean	-0.05	Posterior mean	-0.003	Posterior mean	0	
		Posterior Var	5.6E-06	Posterior Var	1E-05	Posterior Var	0	
40 - 27	40 - 27	Sample size	-	Sample size	1	Sample size	-	1 19 16 6 10 2 13 33 38 35 3 8 24 21 23 39 32 34 1
		Sample Mean	-	Sample Mean	0	Sample Mean	-	
		Sample Var	-	Sample Var	0.0001	Sample Var	-	
		Prior mean	-	Prior mean	-0.003	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 36 29 17 30 28 1
		Prior Var	-	Prior Var	1E-05	Prior Var	-	
		Posterior mean	-	Posterior mean	-0.003	Posterior mean	-	
		Posterior Var	-	Posterior Var	9E-06	Posterior Var	-	
27 - 26	27 - 43 - 26	Sample size	-	Sample size	2	Sample size	-	1 19 16 6 10 2 13 33 38 35 3 8 24 29 28 30 1
		Sample Mean	-	Sample Mean	-0.05	Sample Mean	-	
		Sample Var	-	Sample Var	0.0011	Sample Var	-	
		Prior mean	-	Prior mean	-0.003	Prior mean	-	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 36 21 23 39 32 17 34 1
		Prior Var	-	Prior Var	9E-06	Prior Var	-	
		Posterior mean	-	Posterior mean	-0.003	Posterior mean	-	
		Posterior Var	-	Posterior Var	9E-06	Posterior Var	-	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
24 - 36	24 - 36	Sample size	-	Sample size	-	Sample size	1	1 19 16 6 10 2 13 33 38 35 3 8 24 36 21 23 39 32 17 34 1
		Sample Mean	-	Sample Mean	-	Sample Mean	0	
		Sample Var	-	Sample Var	-	Sample Var	0	
		Prior mean	-	Prior mean	-	Prior mean	0	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 29 30 28 1
		Prior Var	-	Prior Var	-	Prior Var	0	
		Posterior mean	-	Posterior mean	-	Posterior mean	0	
		Posterior Var	-	Posterior Var	-	Posterior Var	0	
26 - 29	26 - 24 - 36 - 54 - 29	Sample size	-	Sample size	-	Sample size	4	1 19 16 6 10 2 13 33 38 35 3 8 24 36 21 23 39 32 17 34
		Sample Mean	-	Sample Mean	-	Sample Mean	-0.05	
		Sample Var	-	Sample Var	-	Sample Var	0.0013	
		Prior mean	-	Prior mean	-	Prior mean	0	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 29 30 28 1
		Prior Var	-	Prior Var	-	Prior Var	0	
		Posterior mean	-	Posterior mean	-	Posterior mean	-0.05	
		Posterior Var	-	Posterior Var	-	Posterior Var	0.00033	
36 - 21	36 - 56 - 21	Sample size	-	Sample size	-	Sample size	2	1 19 16 6 10 2 13 33 38 35 3 8 24 36 21 23 39 32 17 34 1
		Sample Mean	-	Sample Mean	-	Sample Mean	0	
		Sample Var	-	Sample Var	-	Sample Var	0.0013	
		Prior mean	-	Prior mean	-	Prior mean	-0.05	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 29 30 28 1
		Prior Var	-	Prior Var	-	Prior Var	0.000325	
		Posterior mean	-	Posterior mean	-	Posterior mean	-0.0333	
		Posterior Var	-	Posterior Var	-	Posterior Var	0.00022	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
		Sample size	-	Sample size	-	Sample size	2	1 19 16 6 10 2 13 33 38 35 3 8 24 36 21 23 39 32 17 34 1
		Sample Mean	-	Sample Mean	-	Sample Mean	-0.05	
		Sample Var	-	Sample Var	-	Sample Var	0.0001	
29 – 17	29 - 51 - 17	Prior mean	-	Prior mean	-	Prior mean	-0.0333	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 29 30 28 1
		Prior Var	-	Prior Var	-	Prior Var	0.00022	
		Posterior mean	-	Posterior mean	-	Posterior mean	-0.0469	
		Posterior Var	-	Posterior Var	-	Posterior Var	4.1E-05	
21 – 23	21 – 23	Sample size	-	Sample size	-	Sample size	1	1 19 16 6 10 2 13 33 38 35 3 8 24 36 21 23 39 32 34 1
		Sample Mean	-	Sample Mean	-	Sample Mean	-0.1	
		Sample Var	-	Sample Var	-	Sample Var	0.0014	
		Prior mean	-	Prior mean	-	Prior mean	-0.0469	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 29 17 30 28 1
		Prior Var	-	Prior Var	-	Prior Var	4.1E-05	
		Posterior mean	-	Posterior mean	-	Posterior mean	-0.0484	
		Posterior Var	-	Posterior Var	-	Posterior Var	3.9E-05	
		Sample size	-	Sample size	-	Sample size	2	1 19 16 6 10 2 13 33 38 35 3 8 24 36 21 23 39 32 34 1
		Sample Mean	-	Sample Mean	-	Sample Mean	-0.1	
		Sample Var	-	Sample Var	-	Sample Var	0.0013	
17 - 30	17 - 62 - 30	Prior mean	-	Prior mean	-	Prior mean	-0.0484	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 29 17 30 28 1
		Prior Var	-	Prior Var	-	Prior Var	3.9E-05	
		Posterior mean	-	Posterior mean	-	Posterior mean	-0.0513	
		Posterior Var	-	Posterior Var	-	Posterior Var	3.7E-05	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
23 - 39	23 - 39	Sample size	-	Sample size	-	Sample size	1	1 19 16 6 10 2 13 33 38 35 3 8 24 36 21 23 39 32 34 1
		Sample Mean	-	Sample Mean	-	Sample Mean	-0.05	
		Sample Var	-	Sample Var	-	Sample Var	0.0001	
		Prior mean	-	Prior mean	-	Prior mean	-0.0513	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 29 17 30 28 1
		Prior Var	-	Prior Var	-	Prior Var	3.7E-05	
		Posterior mean	-	Posterior mean	-	Posterior mean	-0.051	
		Posterior Var	-	Posterior Var	-	Posterior Var	2.7E-05	
39 - 32	39 - 32	Sample size	-	Sample size	-	Sample size	1	1 19 16 6 10 2 13 33 38 35 3 8 24 36 21 23 39 32 34 1
		Sample Mean	-	Sample Mean	-	Sample Mean	-0.05	
		Sample Var	-	Sample Var	-	Sample Var	0.0001	
		Prior mean	-	Prior mean	-	Prior mean	-0.051	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 29 17 30 28 1
		Prior Var	-	Prior Var	-	Prior Var	2.7E-05	
		Posterior mean	-	Posterior mean	-	Posterior mean	-0.0508	
		Posterior Var	-	Posterior Var	-	Posterior Var	2.1E-05	
32 - 34	32 - 17 - 34	Sample size	-	Sample size	-	Sample size	4	1 19 16 6 10 2 13 33 38 35 3 8 24 36 21 23 39 32 34 1
		Sample Mean	-	Sample Mean	-	Sample Mean	-0.05	
		Sample Var	-	Sample Var	-	Sample Var	0.0001	
30 - 28	30 - 62 - 28	Prior mean	-	Prior mean	-	Prior mean	-0.0508	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 29 17 30 28 1
		Prior Var	-	Prior Var	-	Prior Var	2.1E-05	
		Posterior mean	-	Posterior mean	-	Posterior mean	-0.0504	
		Posterior Var	-	Posterior Var	-	Posterior Var	1.2E-05	

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Table 36 (continued)

Move	Path	Zone 1		Zone 2		Zone 3		Updated Route
34 - 1	34 - 1	Sample size	-	Sample size	-	Sample size	4	1 19 16 6 10 2 13 33 38 35 3 8 24 36 21 23 39 32 34 1
		Sample Mean	-	Sample Mean	-	Sample Mean	-0.05	
		Sample Var	-	Sample Var	-	Sample Var	0.0001	
28 - 1	28 - 58 - 44 - 1	Prior mean	-	Prior mean	-	Prior mean	-0.0504	1 14 31 41 15 11 5 9 7 12 4 18 37 25 22 20 40 27 26 29 17 30 28 1
		Prior Var	-	Prior Var	-	Prior Var	1.2E-05	
		Posterior mean	-	Posterior mean	-	Posterior mean	-0.0503	
		Posterior Var	-	Posterior Var	-	Posterior Var	7.9E-06	