

A Threshold Coverage Flow-Refueling Location Model
to Build a Critical Mass of Alternative-Fuel Stations

by

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ABSTRACT

In order to address concerns about the dominance of petroleum-fueled vehicles, the transition to alternative-fueled counterparts is urgently needed. Top barriers preventing the widespread diffusion of alternative-fuel vehicles (AFV) are the limited range and the scarcity of refueling or recharging infrastructures in convenient locations. Researchers have been developing models for optimally locating refueling facilities for range-limited vehicles, and recently a strategy has emerged to cluster refueling stations to encourage consumers to purchase alternative-fuel vehicles by building a critical mass of stations. However, clustering approaches have not yet been developed based on flow-based demand. This study proposes a Threshold Coverage extension to the original Flow Refueling Location Model (FRLM). The new model optimally locates p refueling stations on a network so as to maximize the weighted number of origin zones whose refuelable outbound round trips exceed a given threshold, thus to build critical mass based on flow-based demand on the network. Unlike other clustering approaches, this model can explicitly ensure that flow demands “covered” in the model are refuelable considering the limited driving range of AFVs. Despite not explicitly including local intra-zonal trips, numerical experiments on a statewide highway network proved the effectiveness of the model in clustering stations based on inter-city flow volumes on the network. The model’s policy implementation will provide managerial insights for some key concerns of the industry, such as geographic equity vs. critical mass, from a new perspective. This project will serve as a step to support a more successful public transition to alternative-fuel vehicles.

DEDICATION

*This thesis is dedicated to my parents
for their endless love, support and encouragement*

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CHAPTER 1

INTRODUCTION

1.1 Background

The dominance of petroleum-fueled vehicles in the transportation sector has long raised concerns about energy security, sustainability, environmental protection, and public health. Most countries, including the United States, remain dangerously dependent on imported petroleum; crude oil imports accounted for 47% of U.S. petroleum consumption in 2011, among which 46% of the consumption was attributed to gasoline used in motor vehicles, while renewable energy made up only 9% of total primary energy consumption (U.S. Energy Information Administration 2013). Fluctuating oil prices also imposed a strong influence on the current oil-based transportation system, and further on the entire society (European Parliament et al. 2009). Therefore, the current status of the transportation industry signals a dangerously heavy dependence on a single finite resource that triggers serious and extensive concerns from perspectives of national security and sustainable development. In addition, the pervasive use of petroleum-fueled vehicles also leads to widespread concerns about environmental sustainability, climate change, and public health (Michaelis 1995).

With a number of detrimental impacts related to vehicles using petroleum fuels, the commercialization of alternative-fuel vehicle (AFV) started decades ago but a widespread diffusion of AFVs has not yet occurred. Broadly speaking, an AFV is a type of vehicle that runs on a fuel other than conventional petroleum fuels (either gasoline or diesel), using forms of energy such as compressed natural gas (CNG), liquefied petroleum gas (LPG, or propane), hydrogen, biodiesel, ethanol, and electricity that cannot

be refueled (note that the words ‘refueled’, ‘recharged’, and ‘served’ will be used interchangeably in this paper) at ubiquitous gas or diesel stations when running low. Even though in recent years AFVs on the market have started to gain popularity, the market share of AFVs is yet very limited: less than 0.5% of registered vehicles in the U.S. were alternative-fueled in 2011 (U.S. Department of Transportation 2015; U.S. Energy Information Administration 2013). Compared to conventional gasoline- and diesel-powered vehicles, the contemporary AFV industry faces many barriers, including a high initial investment cost, limited driving range, availability of AFVs, inconsistent public policy, and the scarcity of available stations for their refueling or recharging (U.S. Department of Energy 2012; Ramage and Agrawal 2004; Melendez 2006; Ogden 1999).

1.2 Problem Statement

Among the shortcomings associated with AFVs, the lack of refueling infrastructure has been identified by many as one of the most formidable barriers to the large-scale transition to AFVs (Melendez 2006; Romm 2006; Melaina, Bremson, and Solo 2013). The underlying chicken and egg problem – who will manufacture and purchase the AFVs if a fueling infrastructure does not exist and who will build the fueling network for vehicles that are not built yet – makes the initial locations of AFV refueling stations become decisive in order to break the gridlock (Melaina 2003; Romm 2006). In response to the question of how to build an effective AFV refueling network to attract the general public to purchase an AFV, studies suggested that (1) the number of AFV refueling stations should be at least 15% of all existing gas stations for the successful penetration of the household vehicle market (Melaina 2003); and (2) considering drivers refueling behavior, early AFV refueling infrastructures should

maximize convenience by serving the routes that drivers frequently travel, probably high-volume roads, rather than their home locations (Kelley and Kuby 2013).

Previous optimal location models on AFV's fueling infrastructure development mostly locate stations 'conveniently' either to maximize the traffic volume refueled or minimize the overall travel costs to the stations for the purpose of better serving AFV drivers. However, increasingly difficult to ignore is the fine line between serving current drivers and attracting potential buyers in terms of locating station. Therefore, some recent approaches attempted to locate "clusters" of stations in areas whose residents fit the classic profile of early AFV adopters: high purchasing power, high income and/or households with more than one vehicle (Tal and Nicholas 2013; Turrentine and Kurani 1995). Certainly, the idea of planning to achieve some kind of critical mass of stations to convince potential buyers to purchase a new AFV is promising because locally abundant AFV stations may increase public awareness and reduce range anxiety of potential buyers (Neubauer and Wood 2014). The station network should also put emphasis on long-distance trips that are long enough to trigger range anxiety and require multiple stations to refuel vehicles of limited driving range.

In terms of the strategy of clustering stations, the ideal model for planning refueling stations should decide the spatial pattern of clusters without exogenous intervention, for example, based on traffic flow on paths. Driven by the need to develop infrastructure to facilitate the early adoption of AFVs, this thesis introduces a new efficient formulation for the problem of locating a set of facilities to promote critical mass for refueling round trips between origin–destination (OD) pairs while considering the limited driving range of AFVs.

1.3 Organization

The thesis is structured as follows. Chapter 2 offers a literature review on existing models or methods of locating a network of refueling stations optimally. The model developed in this study and its formulation and variation are presented in Chapter 3. The data used in the numerical experiments of the model are briefly discussed in Chapter 4. The chapter that follows examines the results of the numerical experiments. A discussion about the limitations and application of the model is provided in Chapter 6. Finally, a summary of the findings of the thesis and possible directions for future research are presented in the last chapter.

CHAPTER 2

LITERATURE REVIEW

A considerable number of methods or models have been developed to locate a network of fueling stations optimally, and different classification schemes have been used by researchers, for example, based on the strategy the model used to deal with demand (Upchurch and Kuby 2010; MirHassani and Ebrazi 2012). In this chapter, optimal facility location problems on networks, particularly fuel station location problems, will be reviewed based on the spatial units to be served: nodes, arcs, paths (or routes, flows, trips), and tours (i.e., trip chaining or space-time path). In addition, a brief overview of “clustering” approaches will be presented at the end of this chapter.

2.1 Node-based Approaches

Nodes are the most commonly covered spatial units in optimal location models, and models using this approach are intended to locate a set of facilities and, in some cases, allocate node-based demand to those facilities. For example, the p -median model (Hakimi 1964; ReVelle and Swain 1970) is a location-allocation model that locates p facilities, and allocates demand nodes i to facilities j to minimize the total distance traveled by consumers to facilities. With its ability to site stations close to where most people live, the application of p -median model in locating refueling stations was appealing because early studies demonstrated empirically that consumers mostly prefer to refuel near their homes (Sperling and Kitamura 1986; Kitamura and Sperling 1987). Goodchild and Noronha (1987) were the first to use p -median as one of the objectives in a multi-objective programming model for rationalizing an existing gas station networks. For AFV stations specifically, the p -median model was used in studies by Nicholas,

Handy, and Sperling (2004) and Nicholas and Ogden (2006) and adopted by Oak Ridge National Laboratory for several major studies of transition to hydrogen vehicles (Greene et al. 2008). Variants of p -median were also utilized to locate refueling stations. For example, a structurally similar model was developed by Lin et al. (2008), called ‘fuel travel-back’ approach, with nodes weighted by the quantity of fuel consumed on segments pointing to demand node i (instead of population at nodes) and with travel time between demand nodes i and candidate facility location j substituted for distance. One of the advantages of using the p -median model is the minimal data requirements. Road network data and population data are largely available in GIS format from various sources (e.g., US Census Bureau, ESRI), and inter-node distances can be computed readily using custom programs (Upchurch and Kuby 2010).

Other well-known node-based problems include set cover (Toregas et al. 1971), maximum cover (Church and ReVelle 1974), fixed-charge models (Balinski 1965), and p -center problems (Minieka 1970). Like the p -median problem, all of them assume that demand is expressed at nodes while facilities can be placed at the nodes of the network or at points on arcs. With many other affecting factors ignored, the models only consider population or demand at aggregated nodes and the distance from nodes to facilities becomes the most critical factor. The underlying assumption is that customers make single-purpose refueling trips from home or work-place to the facility. Therefore, an obvious problem with the node-based approaches is the accuracy in representing complex real-world behaviors.

2.2 Arc-based Approaches

The second group of models aims to locate stations on high-traffic arcs trying to maximize the passing traffic. In a study of national hydrogen station network, Melendez and Milbrandt (2005) considered only roads with at least 20,000 vehicles per day as a basis for their GIS analysis to outline a continuous major traffic corridors across the U.S. Goodchild and Noronha (1987) developed a multi-objective model including a weighted p -median objective and a second objective that maximizes the traffic flows on roads passing by a station. The reasoning behind this is that many drivers tend to refuel on their way to somewhere else, also known as impulsive purchase en-route, which by definition does not affect a predetermined trip. The arc-based approach takes advantage of the great availability of traffic count data, but its disadvantages are twofold: (1) it double counts flows that pass over several arcs, and (2) it is unable to evaluate whether the entire path can be refueled, which is especially important for AFVs with limited range.

Bapna, Thakur, and Nair (2002) introduced a multi-objective approach called Maximum Covering/Shortest Spanning Subgraph Problem (MC3SP). The model tackles the vehicle range issue by enabling an arc by locating the required number of fuel stations on it so that an AFV of a standard range can traverse the arc. An enabled arc covered the population demands of its endpoints and all other nodes within specified distances. MC3SP minimizes the fixed cost of enabling arc (i.e., construction of stations) as well as the variable costs of traffic along that arc and maximize population coverage through a spanning subgraph between cities. Two main advantages of this model should be noted: (1) it maximizes coverage of population along enabled arcs instead of O–D flow volumes that can refuel along their shortest path; (2) the spanning subgraph approach may force

trips into unnecessarily long and rarely used paths based on the weights on the objectives (Kuby and Lim 2005). These approaches tend to locate stations on several adjacent links of a high-volume roads. As a result, arc-based methods are not ideal either, especially when same trips by the same drivers may be counted more than once if the trip travels multiple links, although drivers might refuel only once (Upchurch and Kuby 2010). This concern arc-based approaches more suitable to be a secondary objective, as in Goodchild and Noronha (1987).

2.3 Path-based Approaches

The third type of method locates refueling stations based on paths, typically maximizing passing flows or intercepting as many trips as possible by allocating one or a combination of stations to the nodes along the path. Instead of treating demands at stationary nodes or arcs as was done in previously mentioned approaches, Hodgson (1990) considered traffic flow passing by as the primary demand for businesses like gasoline stations or automatic teller machines because their customers do not conduct a single-purpose trip solely to consume this type of service. Hodgson (1990) then proposed a flow-capturing location-allocation model (FCLM) seeking to locate p facilities to intercept or capture maximal traffic flows at its starts, ends, or passing by an open facility, later termed the flow-intercepting location model (FILM) by Berman, Larson, and Fouska (1992). The essence of these models is the nature of path-based or flow-demand, and, therefore, a demand is considered served if a facility is located anywhere along the path. Owing to these characteristics, Upchurch and Kuby (2010) argued that FILM provides a behaviorally realistic basis for locating refueling stations; however, problems in applying the basic FILM to site refueling stations were twofold compared to the

conventional models. First, a matrix of traffic flows from origins to destinations is required that is burdensome to calculate and challenging to work with than node or arc data. Additionally, for a longer inter-city path, one station along the path may not be enough to sustain an AFV with limited driving range to complete the entire trip.

Adopting the idea of ‘flow capturing’ but extending it to address the second limitation mentioned above, Kuby and Lim (2005) developed the flow-refueling location model (FRLM), which counts a flow as refueled only if a series of stations exists on a path that is sufficient to refuel the round trip between the origin and destination, given the assumed driving range of vehicles. Wang and Lin (2009) advanced a set covering FRLM that imposes the range restriction by keeping track explicitly of the fuel remaining on each vehicle at each node on the path. Wang and Wang (2010) extended Wang and Lin (2009)’s previous work to a hybrid model by adding a classic set covering model, that considers the node-based population demand and path-based and seeks to serve long-distance travel as well as cover most of the short-distance travel. Another version of the FRLM is the deviation-flow refueling location model (DFRLM) developed by Kim and Kuby (2012), which allows deviations from the shortest path between a given OD pair. A flow can be refueled or not depends on whether the vehicle is able to stop at stations that are situated on or near the driver’s pre-planned paths. A reasonable deviation from planned routes to gas stations is usually acceptable to most drivers.

The solution methods for path-based approaches keep evolving as well. MirHassani and Ebrazi (2012) developed a new formulation of FRLM that could be solved faster in either flow-based set cover or maximum coverage form. The model satisfied the driving range assumption and implicitly indicated a valid combination of

fuel stations by applying a relaxed variable for implementing mass balance constraints. Another recently developed extension of FRLM is the arc cover-path cover (AC-PC) FRLM model presented by Capar et al. (2013) that introduced a more computationally efficient way of covering the arcs that comprise each path.

2.4 Tour-based Approaches

The most realistic approach from a behavioral standpoint is to relate demand to tours (or trip chaining, space-time path). Andrews et al. (2012) developed an optimization model for locating charging stations for electric vehicles that uses vehicle tours data as an input and minimizes the total distance travelled by all vehicles to access the selected charging stations for the entire time period assuming candidate locations are capacitated and each vehicle has a number of charging options at various periods and locations. Kang and Recker (2014) proposed a facility location problem considering full-day household scheduling and routing situations which used coverage model as a location strategy and household activity pattern problem as the scheduling and routing tool. Ji, Nicholas, and Tal (2015) used travel diary data of gasoline vehicles as input and scaled a proportion of the tours as battery electric vehicles (BEV) so as to evaluate the charging demand considering the limited driving range of BEVs. Together with the charging demand, they also used locations of existing fast-charging stations to identify the unserved charge windows and a greedy algorithm to place potential stations.

Tour-based approaches require sufficiently large number of drivers' travel diary data typically obtained from regional household travel surveys. A travel diary includes the respondent's trip information consisting of the location of origin and destination, departure and arrival time, trip mode, trip purpose, etc. of each trip on assigned survey

dates, which is challenging and costly to obtain compared to the volumes of OD flows or traffic counts on links. This significantly limits the application of tour-based models.

2.5 Clustering Approaches

Clustering strategies for developing AFV's refueling stations are emerging in the industry. The purpose is to provide a higher level of service to a geographically smaller but densely populated and polluted area, thus maximizing the number of potential buyers by building a critical mass. The California Fuel Cell Partnership (2012), which focuses on the infrastructure deployment strategy of Fuel Cell Electric Vehicle (FCEV) in California, argued that early "hydrogen communities" for passenger vehicles should be built as clusters of retail hydrogen stations within certain specific communities as illustrated on their roadmap. Existing hydrogen stations in California are clustered mainly in the Los Angeles and San Francisco-Sacramento regions (Figure 1). Outside of the U.S., electricity and CNG stations are planned to be built in urban/suburban and other densely populated areas in Europe by 2020, and then along the TEN-T core network and shore-side by 2025 (European Commission 2014).

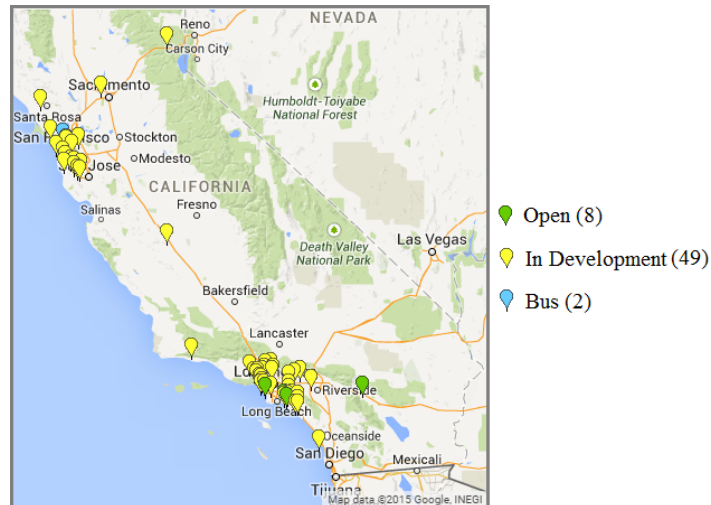


Figure 1. Maps of existing and planned hydrogen stations in California¹

Currently, location models that are designed for the clustering approach are yet very limited. Kuby et al. (2009) used FRLM to investigate rolling out strategies for an initial refueling infrastructure in two different scales: metropolitan Orlando and Florida statewide scales. A strategy of “clustering and bridging” was suggested for phasing in clustered and connecting stations in several stages or tiers, but the idea of clustering to achieve some kind of critical mass was not an explicit part of the model. Stephens-Romero et al. (2010) developed a node-based model for planning hydrogen stations in California which first identified hotspots of early adopters based on automakers’ opinions and used a set-covering formulation to locate stations based on the hydrogen communities recognized.

However, selecting hotspots or early AFV communities may in turn confine the scope of the model and prevent the infrastructure from serving a broader market when it is actually feasible to do so by organization station placement optimally. It also focuses

¹ Retrieved from California Fuel Cell Partnership (2015) on April 1, 2015. Note that 42 out of 49 stations under development will be operational by the end of 2015, and the rest is planned to be available by January 2016.

on local usage to the exclusion of medium and long distance trips. Rather than predetermining the hotspots exogenously, an efficient flow-based clustering approach for building critical mass to facilitate the initial AFV infrastructure development is needed based on origin-destination routes as the primary demand for vehicle refueling.

CHAPTER 3

METHODOLOGY

3.1 Model Formulation

Different from the original Flow Refueling Location Model (FRLM), which maximizes the total flow volume refueled, the objective of the model is to locate p refueling stations on a network to maximize the weighted number of origins for which the refueled outbound flows exceed a given threshold, thus to build critical mass based on flow-based demand on the network. The model is formulated based on assumptions that were commonly used in FILM/FRLM-related research (Hodgson 1990; Berman, Larson, and Fouska 1992; Kuby and Lim 2005; Capar and Kuby 2012; Capar et al. 2013): (1) the traffic between an origin-destination (OD) pair flows through a single path (typically the shortest or least-travel-time path), (2) drivers have full knowledge of location of fueling stations along their path and refuel as necessarily needed to successfully complete their round trips, (3) only nodes of the network are considered as potential locations of refueling stations, (4) vehicles have the same driving range, (5) fuel consumption is directly proportional to distance traveled, and (6) refueling (or recharging) stations are uncapacitated.

In line with the FRLM, an OD traffic flow is considered refueled if vehicles starting from the origin can reach the destination and return to the origin without running out of fuel. The original FRLM assumed vehicles start at the origin with a half tank, based on the reasoning that if a vehicle with a half tank is able to reach the first station on the path, it could fill up at the same station on the returning trip and arrive at the origin with at least a half tank, and be able to repeat the same or other similar trip afterwards.

AC-PC FRLM holds the same assumption by determining the starting fuel tank level based on the location of stations. If a station is built at the origin, the vehicles starting from the origin will be considered as having full tank. On the contrary, if there is no station built at the origin, vehicles will start with the remaining fuel from the last fill-up on the same path. As the energy consumed in both directions of each arc is symmetrical, the AC-PC FRLM will ensure that every trip starts with at least half a tank. The AC-PC FRLM formulation is adopted in the extension.

To formulate the model, the following model sets and parameters are defined first:

- N the set of nodes constituting the transportation network $N = \{1, 2, \dots, n\}$
- M the set of origin–destination nodes where $M \subseteq N$
- i, j, k indexes for potential facilities/candidate sites/nodes
- q the index for OD pairs (and the path between them)
- Q the set of OD pairs
- S_j the set of OD pairs originating from node j
- $a_{j,k}$ a *directional* arc starting from node j and ending at node k
- A_q the set of directional arcs on path q , sorted from origin to destination and back to origin
- $K_{j,k}^q$ the set of candidate sites, which can refuel the directional arc $a_{j,k}$ in A_q calculated based on the driving range R .
- R the driving range of vehicles
- f_q volume of traffic flow on path q
- p the number of stations to be located

T the threshold for the percentage of path flow volume originating from a node that must be refuelable to consider the node “covered” ($0 \leq T \leq 1$)

w_j the weight of the origin. E.g., the percentage of flow volume of paths originating

from node j relative to that of all paths: $w_j = \frac{\sum_{q \in S_j} f_q}{\sum_{q \in Q} f_q}$

The following decision variables are defined:

z_i binary variable; 1 if service station is built at node i , 0 otherwise

y_q binary variable; 1 if the flow on path q is refuelable, 0 otherwise

c_j binary variable; 1 if the percentage of path volume originating from j that are refuelable exceeds the threshold T , 0 otherwise

The model is formulated as follows:

Formulation 1. Threshold Coverage FRLM

Maximize $\sum_j w_j c_j$ (1)

s.t. $\sum_{i \in K_{j,k}^q} z_i \geq y_q, \quad \forall q \in Q, a_{j,k} \in A_q$ (2)

$\sum_i z_i = p$ (3)

$\frac{\sum_{q \in S_j} f_q y_q}{\sum_{q \in S_j} f_q} \geq T c_j, \quad \forall j \in M$ (4)

$z_i, y_q, c_j \in \{0, 1\}, \quad \forall q \in Q, i \in N, j \in M$ (5)

The objective (1) is to maximize the weighted number of origins whose refueled outbound flows exceed the given threshold T . The weight of an origin, w_j , can be based on the sum of trips from zone j to all destinations and/or socio-economic variables associated with adoption of more advanced, sustainable and expensive vehicles. In the case presented in the thesis, the percentage of flow volume of paths originating from node j relative to that of all paths is used as the weight for an origin.

Constraint (2), adopted from the AC-PC FRLM formulation, ensures that an OD flow q is refuelable only if each directional arc on a path q is travelable after refueling at one of the open stations. The set $K_{j,k}^q$ is the set of candidate nodes i that allows driving across the entire arc from node j to k if a driver completely refills their tank with range R at i , and j to k is one of arcs in path q . Details about generating these “cover sets” can be found in Capar et al. (2013). Constraint (3) limits the number of stations located to p .

The key innovation of this extension is introducing the idea of threshold coverage of an origin represented by decision variable c_j in the formulation. Constraint (4) makes sure that the node j is considered covered (i.e., c_j will be 1) only if the percentage of path volume originating from j that are refuelable exceeds the threshold T . The last set of constraints defines binary variables.

3.2 Multi-objective Version

As maximizing the amount of refuelable flow volume is no longer an objective in the new formulation presented above, the decision variable y_q may be 0 even though stations needed to refuel the round trip on path q are located. The optimization result may yield an inaccurate amount of refuelable flow volume and, furthermore, alternative optimal solutions may exist when the amount of refuelable flow volume can be increased without compromising the threshold coverage objective. Therefore, a multi-objective version of the new formulation is developed to address these issues. In order to ‘push’ y_q to 1 when applicable, a standardized volume coverage objective, $\frac{\sum_q y_q f_q}{\sum_q f_q}$, and a weight, W , for balancing two objectives are introduced into the objective. The second objective indicates the percentage of volume that are refuelable. The weight W then needs to be

carefully calibrated to be as small as possible to prevent flow volume coverage objective from taking over control of the model and marginalizing the threshold coverage objective, while still encouraging all covered flow variables y_q to be 1. The basic criteria to determine W is that the multi-objective formulation should yield the same level of threshold coverage objective as the optimal solution based on the single-objective formulation while maximizing the percentage of flow volume covered. The binary constraint imposed on the flow-coverage decision variables y_q is relaxed as shown in (11) which leads to a reduction of the number of the binary variables included in the formulation. As will be discussed in next section, among the three binary decision variables of the original formulation (i.e., threshold coverage c_j , flow coverage y_q , and site selection z_j), the number of flow coverage decision variables, y_q , is usually the largest because each OD pair has a traffic flow.

The multi-objective version is formulated as follows:

Formulation 2 . Multi-objective Threshold Coverage FRLM

$$\text{Maximize} \quad W * \sum_j w_j c_j + (1 - W) * \frac{\sum_q y_q f_q}{\sum_q f_q} \quad (6)$$

$$\text{s.t.} \quad \sum_{i \in K_{j,k}^q} z_i \geq y_q, \quad \forall q \in Q, a_{j,k} \in A_q \quad (7)$$

$$\sum_i z_i = p \quad (8)$$

$$\frac{\sum_{q \in S_j} f_q y_q}{\sum_{q \in S_j} f_q} \geq T c_j, \quad \forall j \in M \quad (9)$$

$$z_i, c_j \in \{0, 1\}, \quad \forall i \in N, j \in M \quad (10)$$

$$y_q \leq 1, \quad \forall q \in Q \quad (11)$$

CHAPTER 4

DATA

The numerical experiments are based on a real-world network of the Florida state highway (Figure 2) prepared by Kuby et al. (2009). The study area covered the entire state of Florida, and the road network was based on ESRI and Florida Department of Transportation's (FDOT) network including all interstate highway, toll roads, and U.S. highways, as well as selected important state highways for intercity trips. The data set focuses primarily on inter-city travels ranging from 7 to 781 miles (one way), which includes majority of trips that are long enough to trigger range anxiety. Shortest paths are determined by the minimum travel time based on the posted speed limits of freeways and a calibrated 15% time penalty on the posted speed limit for arterial streets. 4000 traffic analysis zones (TAZs) from FDOT were aggregated at county level, and most counties are represented by a single centroid, except for (1) six counties in the Miami, Tampa–St. Petersburg and Orlando areas that were subdivided into two or three nodes separately and (2) several sparsely populated counties that were combined into one. The OD nodes were initially located in major intersections and traffic generators. Based on inputs from researchers in Florida with local knowledge, the network and paths were calibrated as necessary to reflect the realistic situation by adjusting the speeds associated with different classes of roads, adding missing road links, or modifying OD nodes locations (Lines et al. 2007).

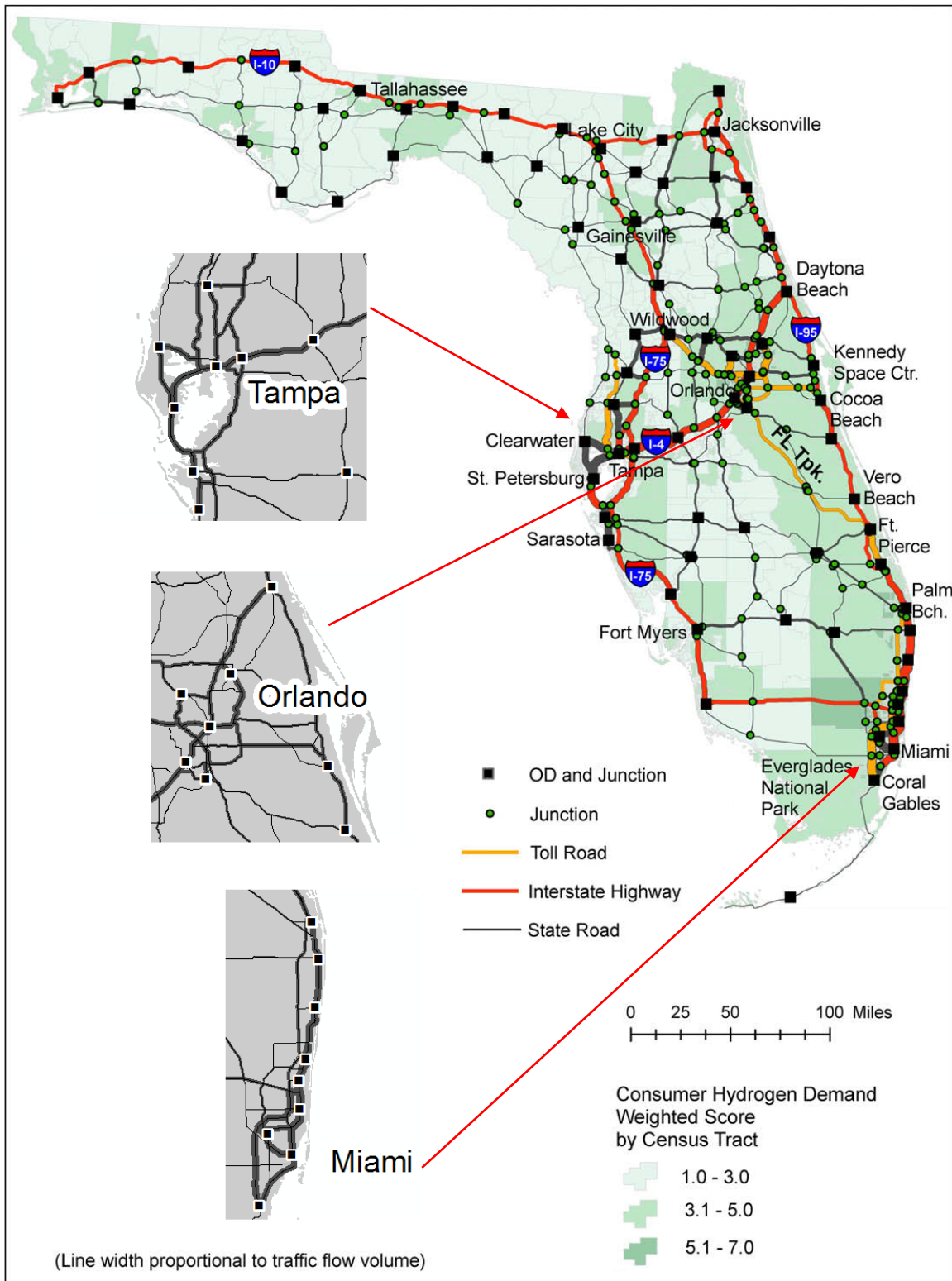


Figure 2. Florida state highway network used for numerical experiments²

² The map is modified from Kuby et al. (2009) with major metropolitan areas shown in greater detail.

In all, the data set contains 74 OD nodes, 2,701 OD flows (i.e., $74 \times 73 \div 2$), 52,236 arcs, and 302 junctions that are potential site locations. Short intra-zonal flows are excluded in the data set. Because FDOT does not maintain a statewide trip table for long-distance intercity trips, a gravity model (Equation 12) was used to estimate intercity flows (T_{ij}) based on the origin zone's aggregated population (P_i), the destination zone's aggregated population (P_j), and a friction function (Equation 13) for intercity home-based social-recreational and vacation trips from Michigan's statewide travel forecasting model recommended by a Federal Highways Administration guidebook (Center for Urban Transportation Studies, University of Wisconsin – Milwaukee and Wisconsin Department of Transportation 1999):

$$T_{ij} = P_i \times P_j \times FF_{ij} \quad (12)$$

$$FF_{ij} = 50 \times GG_{ij}^{-0.114} \times e^{-0.03GG_{ij}} \quad (13)$$

where GC_{ij} is the generalized cost between zones i and j , calculated as $0.75 \times \text{length in miles} + 0.5 \times \text{travel time in minutes}$, and the resulting T_{ij} values were then standardized to a percentage based on the statewide total volume and used as the intercity trip volumes f_q in the model. Additional details regarding data generation and collection can be found on Kuby et al. (2009) and Lines et al. (2007).

In order to evaluate the flow volumes estimated by the gravity model, Figure 3A aggregates all trip volumes on all paths passing through each link of the network, which is comparable to the actual traffic volume on major Florida roads from FDOT in Figure 3B. Despite of urban road volumes that are inflated by local traffic, focusing on the rural

roads and interstates reveals that the estimated inter-city traffic flows on the simplified network appear similar to the actual flows.

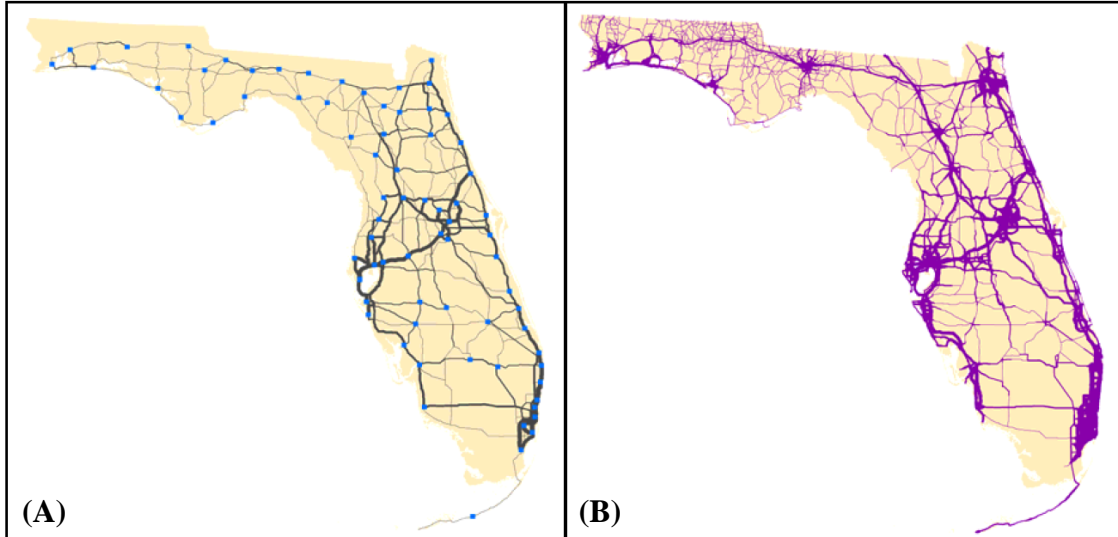


Figure 3. Comparison of (A) estimated flow volume of the state highway network based on the gravity model and (B) actual Florida traffic volume on road segments³.

Based on the estimated f_q , the weight of each OD node, i.e., the percentage of flow volume of paths originating from node j relative to that of all paths, is calculated using the equation: $w_j = \frac{\sum_{q \in S_j} f_q}{\sum_{q \in Q} f_q}$ (Figure 4). As expected, most of high-weight origins are located in Miami, Tampa, and Orlando metropolitan areas, and, in fact, the Miami area alone has the five highest weighted origins.

³ Retrieved from Florida Hydrogen Initiative final report (Lines et al. 2007).

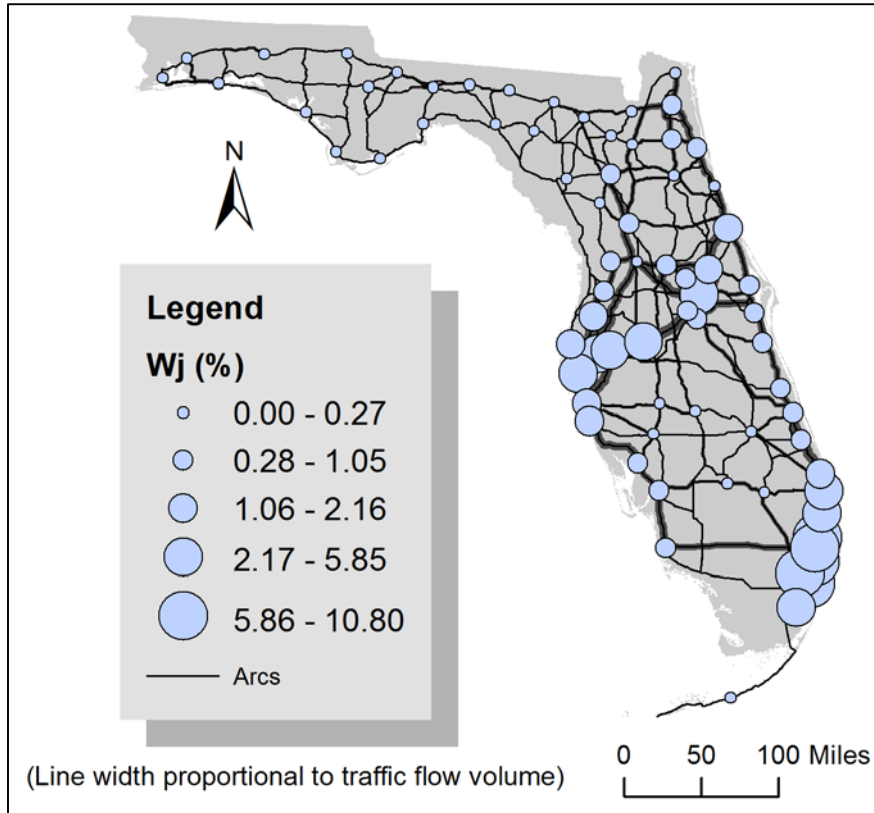


Figure 4. Map of weights of OD nodes

CHAPTER 5

NUMERICAL EXPERIMENTS

5.1 Setting and Computing Times

A variety of scenarios locating stations optimally for intercity trips within Florida was run for the numerical experiments to determine whether the model is functioning as intended. Scenarios varied by systematically changing three primary parameters of the model: threshold percentage ($T = 10\%$ - 90% with an increment of 10%), number of stations located ($p = 4$ or 15), and driving range ($R = 60$ or 200 miles). The mixed-integer programming model was generated using the Mosel modeling language. All problem instances are solved using FICO Xpress-IVE Version 7.8 on a computer with Windows 8.1 64-Bit OS, Intel Core™ i7 CPU at 2.4 gigahertz with 8.0 gigabyte of RAM. Xpress-MP was run for a maximum of 2 hours for each problem instance.

The model has 3,077 binary decision variables including 302 site-selection variable z_i , 74 binary threshold-coverage variable c_j , and 2,701 flow-coverage variables y_q . Theoretically, the number of constraints in the model is 104,472 including one constraint (3), 74 constraints (4) for each OD node, and 104,472 constraints (2) for each directional arc, regardless of the parameters given. In practice, however, it is noted that when the driving range is lower than the length of the longest arcs in the network (i.e., 88 miles in this case), the equations of constraints (2) for arcs that is longer than the driving range have an empty left-hand side because there is no node, not even its endpoints, can refuel this arc on the network, which leads to a reduction in the number of constraints depending on the driving range given.

Currently, various models of AFVs with different ranges are available in the market and the technological maximum range of the AFV vehicle is around 180 to 300 miles for today's prototypes, such as Tesla Model S has a 208 mile and 265 mile Environmental Protection Agency (EPA) driving range with 60-kWh and 85-kWh battery respectively (U.S. Department of Energy 2015). National Research Council (2004) considered vehicles that have at least a 300 mile driving range for the infrastructure development scenarios, and similarly U.S. DOE (2007) has outlined 300 miles driving range as the goal for 2015. For this study, the driving range of 200 miles was chosen as a reasonable or "safe" driving range that tolerates human error, suboptimal vehicle performance, improper filling, side trips, and deviation. A 60-mile driving range was also analyzed in the numerical experiments to represent low-range AFVs, e.g., the 2015 Nissan Leaf has an EPA range of 84 miles (U.S. Department of Energy 2015).

The running times of the model vary in different cases as summarized in Figure 5. When p equals to 4, the solver was able to solve all instances to its global optimum within two hours. However, decreasing the threshold percentage usually led to a significant increase in computing times especially when the driving range is 200 miles. When p equals to 15, it is noted that some instances, especially when the driving range is 60 miles, were not solved to optimality but the gaps are fairly small when the solver stopped. When the number of stations built is great, there are a lot more possible combinations of station selections, which require significantly more computing time for the solver to finish the global search and confirm the result is globally optimal.

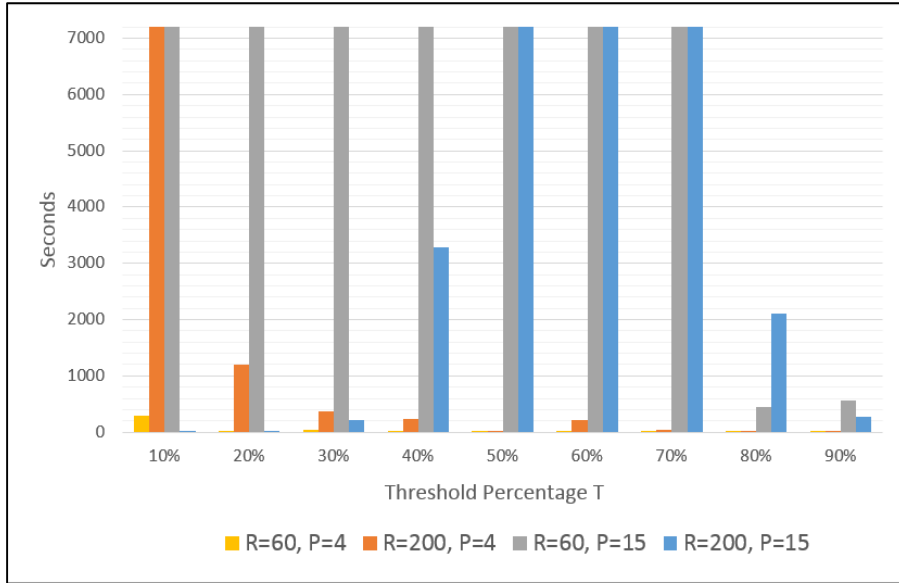


Figure 5. Computing times for different scenarios

5.2 Comparison of Objectives

The model is utilized to create tradeoff curves of objectives by systematically varying the threshold coverage percentage T from 10% to 90% in increments of 10% in different scenarios (Figure 6). The volume coverage objective is calculated for each case based on the solution given by the threshold coverage model. Two general trends are noticed pertaining to the threshold objective. First, the higher the threshold percentage (x axis), the lower the threshold coverage objective value because it gets harder to reach the threshold percentage and cover same amount of origins with a fixed number of stations. Second, holding range R and threshold percentage T constant, as the number of stations built increases, the threshold coverage objective increases. In addition, when the number of stations built is large enough (i.e., 15), the threshold coverage objective can steadily maintain a high value (70% or greater) even when the threshold percentage is extremely high.

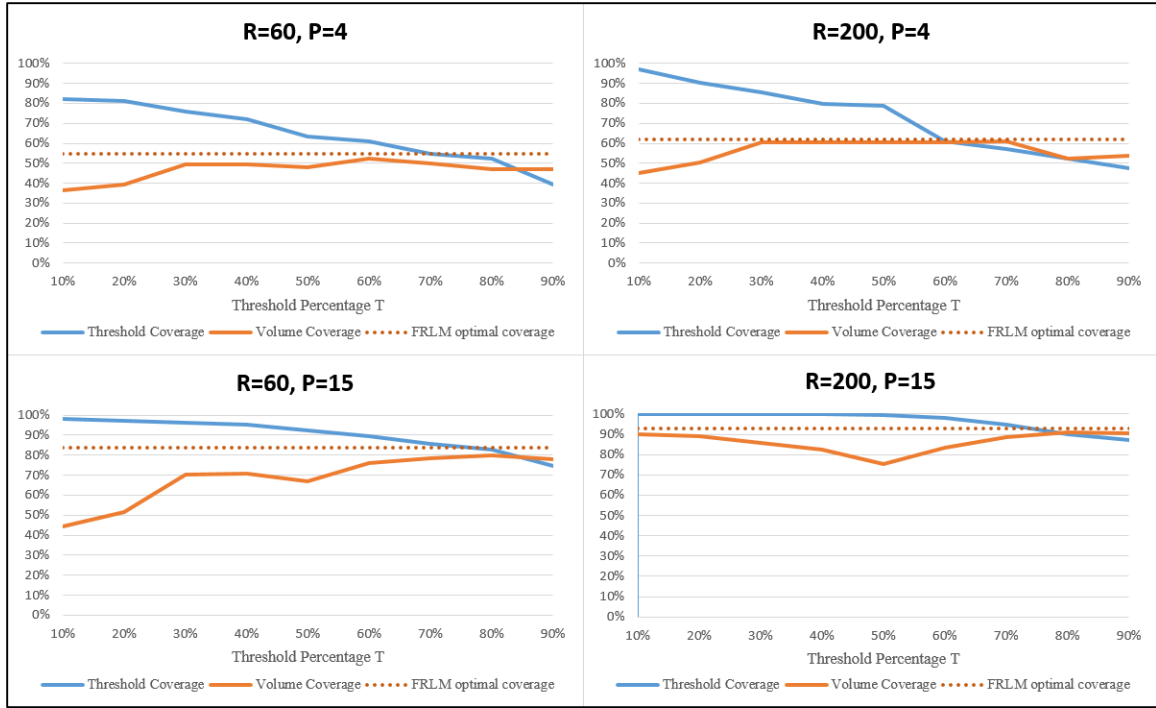


Figure 6. Comparison of objectives in different scenarios

In order to numerically compare the quality of the solutions in this research with the AC-PC FRLM formulation of Capar et al. (2013), the volume coverage objectives of the optimal solutions based on FRLM formulation in different cases are represented as straight dashed lines in Figure 6. In general, the volume coverage percentages of the new model do not show a unified pattern in terms of changing the p , range, and T parameters, but all values are less than the upper bound calculated by AC-PC FRLM. In some cases the volume coverage objective is relatively close to the upper bound from the traditional FRLM-AC-PC model.

5.3 Comparison of Station Locations

Two sets of maps are presented to visually demonstrate the solutions of the numerical experiments. The first set of maps (Figure 7) shows the results of the model with a range of 200 miles, $p = 4$ and $T = 10\%$, 50% , and 90% respectively as well as the

optimal solution of FRLM formulation with a range of 200 miles and $p = 4$ for comparison. Each map depicts the location of selected sites for AFV stations, routes that are refueled by these stations as a whole⁴, and covered origins whose percentage of outbound refueled flows exceed the given threshold. When $T = 10\%$ (Figure 7A), a surprising but reasonable pattern emerged when the model placed stations in four populated cities in Florida: Jacksonville, Tampa, Orlando, and Miami. The reason is when the threshold percentage is very low and the driving range is adequately high, locating stations in major cities can refuel many trips between these cities and ‘small’, surrounding origins and for these origins the volume to major cities is large enough to exceed a relatively low threshold percentage readily which leads to a number of nodes around major cities are covered.

As the threshold percentage increases, a notable pattern is observed that the locations of selected stations are clustering: when $T \geq 50\%$ (Figure 7B), a station in Jacksonville is ‘abandoned’ and there are now two stations in the Miami metropolitan area. When the threshold percentage is extremely high as 90% (Figure 7C), two additional stations are located in the Miami metropolitan area. This is in line with the spatial pattern of w_j illustrated in Figure 3 which shows that the Miami metropolitan area has most of high weighted origins. For comparison purpose, Figure 7D shows the FRLM solution with a vehicle range of 200 miles and four stations and the pattern is similar to threshold coverage solution with $T = 50\%$.

⁴ As routes overlap, it is not possible to differentiate exactly which routes are refuelable on these maps. In GIS, however, it is possible to select individual routes and visualize the result.

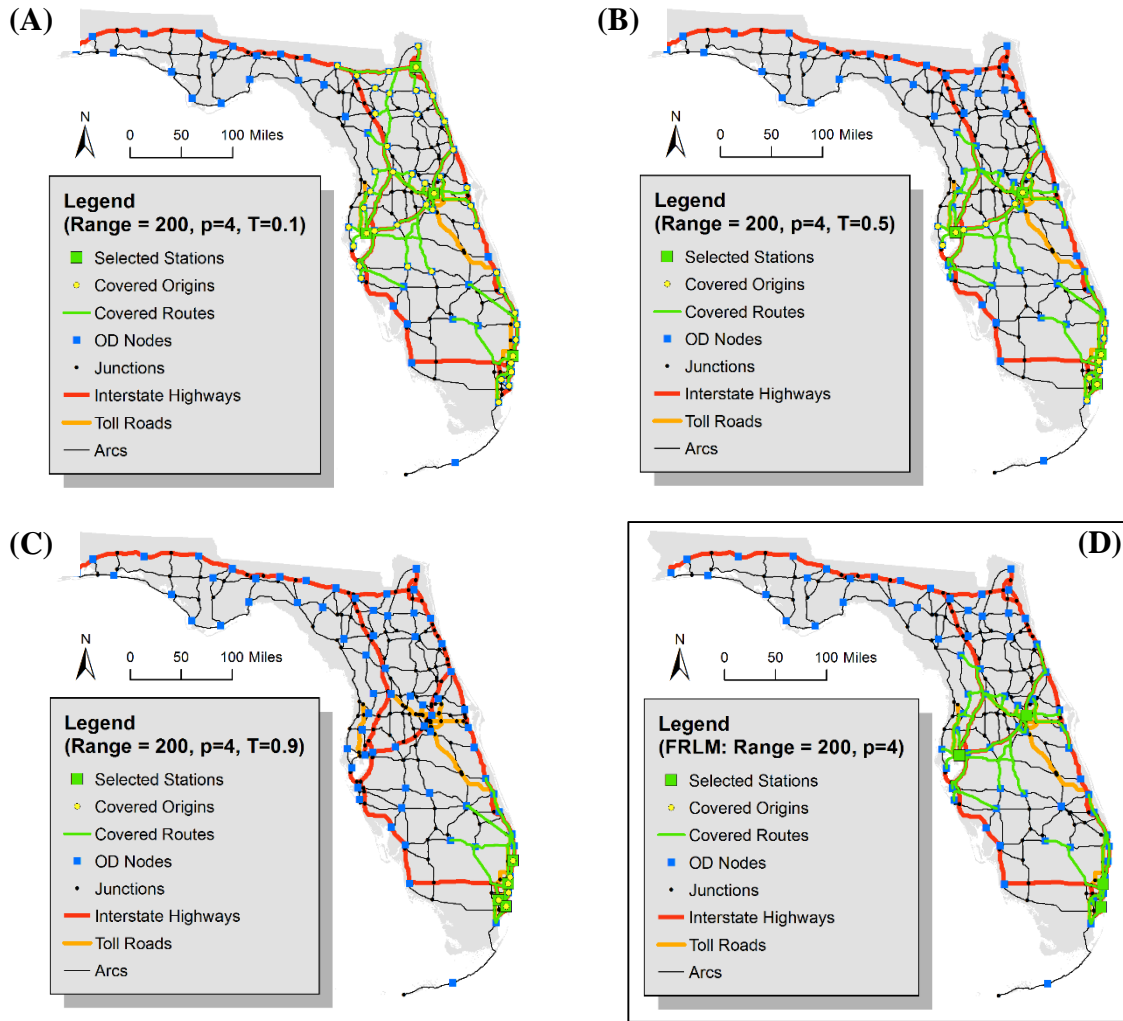


Figure 7. Location of selected stations, covered origin and covered routes with a range of 200 miles, $p = 4$, and $T = 10\%$ (A), 50% (B), and 90% (C) based on threshold coverage model as well as the optimal solution by FRLM model (D) for comparison ⁵

The second set of maps (Figure 8) shows the results of the model with a range of 200 miles, $p = 15$ and $T = 80\%$ and 90% respectively for comparison in the Orlando and Tampa area in central Florida. First of all, when $T = 80\%$ and $p = 15$ (Figure 8A), compared to the previous case when $p = 4$, the 11 additional fuel stations allow trips to be made among most of the routes within the area. As the threshold percentage increases to

⁵ Note: the original FRLM formulation covers only routes, not origin nodes.

90% (Figure 8B), three stations “moved” accordingly while the other stations in the area remained in the same locations. The number of covered origins decreases as T increases but two clusters of stations in Tampa and Orlando can be easily identified. Even though short intra-zonal trips are not included in the data, residents who live in or near Tampa and Orlando have more stations around them and the closer proximity to stations indicates an easy access to the AFV refueling infrastructure that is also able to capture a great proportion of short-distance *inter-zonal* trips.

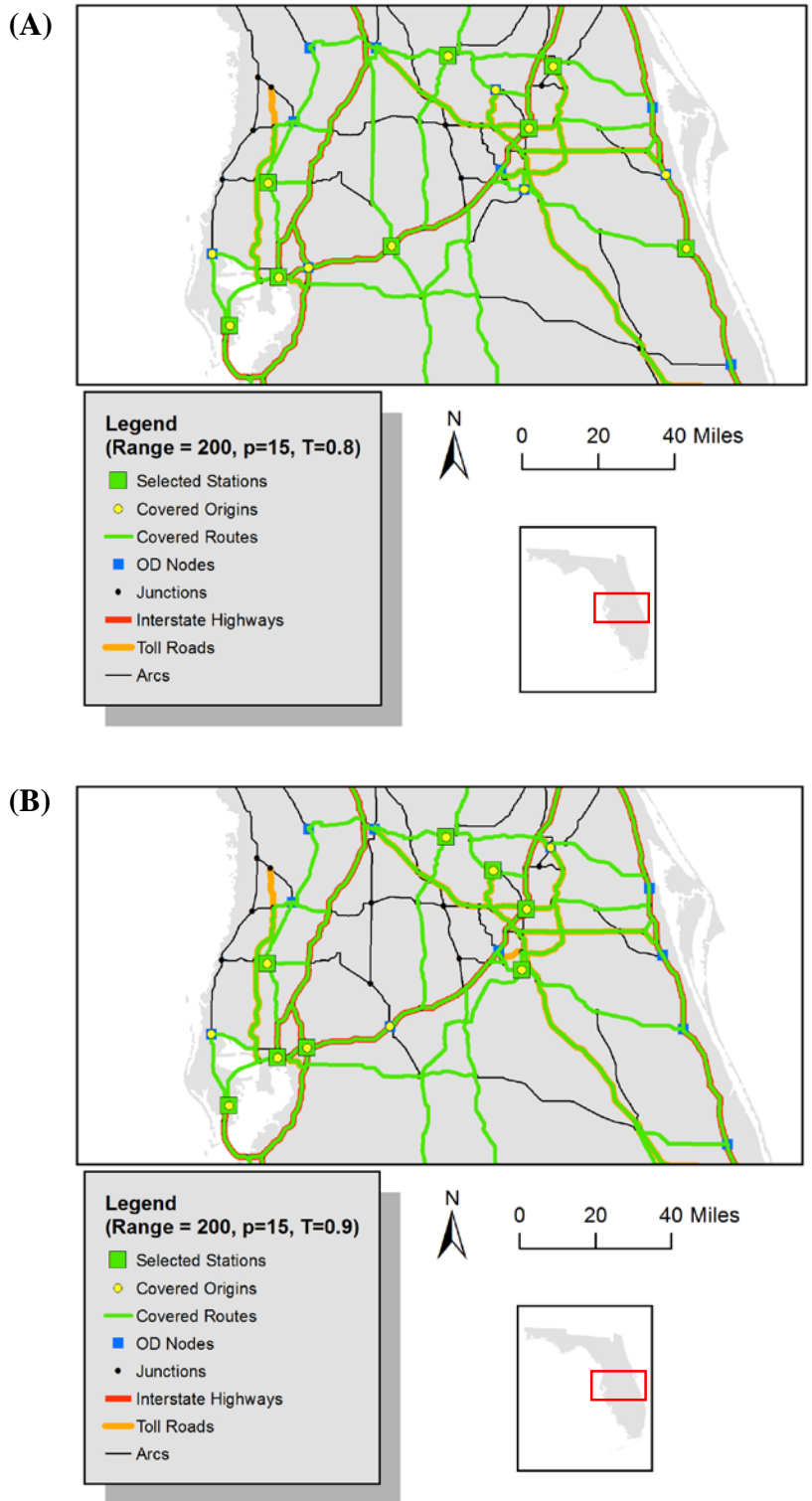


Figure 8. Location of selected stations, covered origin and covered routes with a range of 200 miles, $p = 15$, and $T = 80\%$ (A) and 90% (B) based on threshold coverage model.

CHAPTER 6

DISCUSSION

It should be noted that the numerical experiments presented in the thesis are a proof of concept used to assess whether the new formulation is working as intended. The Florida network data used in numerical experiments contains only mid-to-long-distance inter-city travels and short intra-zonal flows are not represented. The inter-zonal trips are usually long enough to trigger range anxiety of drivers. In addition, paths longer than the vehicle's driving range will require multiple stations along the path to make the path refuelable, which is necessary to test the implementation of flow refueling model. Lastly, volumes of short distance intra-zonal trips can be extremely large compared to that of inter-city trips especially when combining them in the same model. While the results indicate that the model passes the logical test of performing as expected, additional work is needed to better understand the ideal degree of spatial aggregation and parameter settings before the model can be directly implemented for the purpose of actual planning and policy making.

Second, an accurate and up-to-date OD flow matrix can be difficult to obtain for some geographies, compared to traffic volume counts on arcs or population counts in zones used in other types of models. For example, in this study, a spatial interaction or gravity model was used to estimate OD flows as the input because FDOT does not maintain a statewide trip table. In addition, solving the model to optimality requires a global search using branch and bound, which takes a huge amount of computing time even though the network used is simplified by excluding short intra-zonal trips and ODs are aggregated to a county level for most counties. Although a multi-objective version

was developed to mitigate the issue, it still cannot guarantee an optimal result and the weight needs to be carefully calibrated based on different scenarios.

That being said, however, the preliminary results in the numerical experiments did prove the clustering model works as intended. Furthermore, the essential purpose of the model is to encourage consumers to purchase AFVs. To further elaborate how the model can achieve that, take the sparsely populated Santa Rosa County in northwest Florida as an example. According to the numerical experiment results, when the driving range is 200 miles, the threshold coverage percentage is 50%, and the number of stations is 15 in the entire states, one of the 15 stations is placed in Escambia County (a regional population center) and, subsequently, Santa Rosa is “covered” because the route between Santa Rosa and Escambia is made refuelable by this station, which consist of more than 50% of outbound inter-city traffic volumes of Santa Rosa (Figure 9).

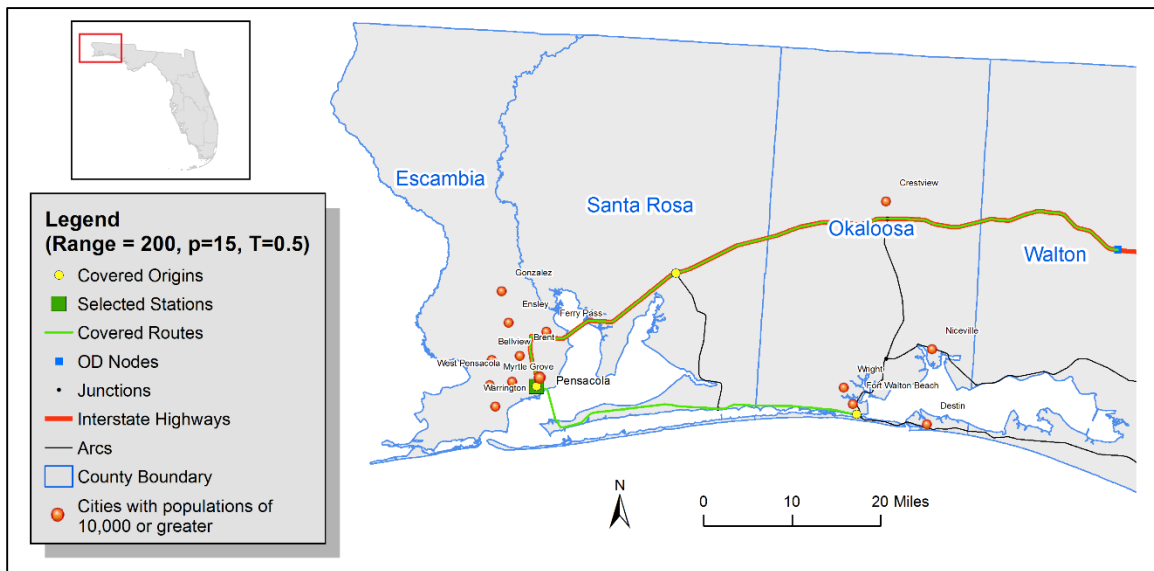


Figure 9. Santa Rosa Example (R=200miles, p=15, T=0.5)

The logic of this placement is, as discussed previously, when the threshold percentage is not high and the driving range is appropriate, locating stations in major

cities can refuel many trips between these cities and small surrounding origins and for these origins the volume to major cities is large enough to exceed a low threshold percentage easily. In daily life, potential AFV buyers living in Santa Rosa are likely to travel to Escambia for work or other purposes, who can simply incorporate the station as a refuel stop in the trip. The station in Escambia is then plausible to serve Santa Rosa's residents. One may still argue that with short distance intra-zonal trips omitted, Santa Rosa may not be covered by this station when there is no station within the county to serve short-distance trips. Therefore, future work is needed to investigate a strategy to integrate short- and mid-to-long distance coverages in a model. In addition, further testing on different scales and level of spatial aggregation of the new formulation is needed, such as applying to the metropolitan level.

At last, several significant insights about the application of the model in actual planning or policy making were found based on the results. There are a number of parameters input into the model including: vehicle driving range, the number of stations to be located, threshold coverage percentage, and weight for origins. The driving range is confined by the current technologies and types of alternative fuel used and the number of stations is limited due to budget or funds available for infrastructure development. Therefore, policy makers need to investigate what level of service in terms of covering an OD's outbound trips is desirable. The key parameter of the model, the threshold coverage T , may be determined by empirical studies about drivers or potential buyers driving and/or refueling behaviors in terms of AFV's purchasing decisions. When a coverage standard is determined, the model could be utilized to answer how many stations are needed for satisfying a region's inter-zonal trips by gradually increasing the

number of stations. Users can also define other factors that are associated with AFV's purchasing decisions as the weight of OD nodes, for example income level, number of vehicles per household, etc., instead of only using each node's percentage of total flow volume in the current implementation.

CHAPTER 7

CONCLUSION

In order to address concerns about the dominance of petroleum-fueled vehicles, the transition to alternative-fueled counterparts is urgently needed. As the lack of refueling infrastructure is recognized as one of the top barriers to a successful public transition to AFV, researchers have developed a variety of models to locate AFV refueling stations optimally considering their limited range. An effective AFV refueling network to attract potential buyers is essential to send the message that AFV infrastructures are ready. Therefore, clustering stations in high-profile communities to foster a critical mass for AFV market has recently emerged as a strategy favored by the industry and policy makers. A problem with this approach is that clustering stations within a community itself may focus too heavily on local trips and not serve the community's medium-to-long distance trips. A flow-based clustering approach that can fill in the gap was missing to satisfy the need. In this study, a threshold coverage formulation of FRLM model was developed, which maximizes the weighted number of origins whose refueled outbound flows exceed a given threshold, thus to build critical mass based on flow-based demand on the network. Unlike other clustering approaches, this model can explicitly ensure that flow demands "covered" in the model are refuelable considering the limited driving range of AFVs.

Numerical experiments on a statewide network in Florida with inter-city OD flows has proved the effectiveness of the new formulation in building the clusters of stations based on flow-based demands. In addition, characteristics of the model have been discovered based on the numerical experiments. First, the model tends to place stations in

OD nodes that generated a high volume of flows when the threshold percentage is relatively low. As the threshold percentage increases, the spatial pattern of stations gradually becomes clustered because more volumes need to be refuelable for an origin to be considered as “covered” and thus stations are located closer in order to maximize the weighted coverage objective. Last, when the threshold coverage percentage is close to the maximum, majority of stations are placed in and around the major cities.

The model’s policy implementation will provide managerial insights for some key concerns of the industry, such as geographic equity vs. critical mass, from a new perspective and will serve as a step to support a more successful public transition to alternative fuel vehicles. Directions for future research include: extending the model to investigate a roll-out strategy for AFV refueling station development; applying the model to multi-scale problem, e.g., integrating both regional and metropolitan level; designing different weighting mechanisms such as by incorporating other factors that influence the AFV buyers’ purchasing decisions; modifying the model to consider impacts of different types of charging infrastructures (i.e., home charging vs fast charging) instead of solely using vehicle driving range as a constraint; modifying the model to consider the different types of potential buyers (only-vehicle vs multi-vehicle household); and using constraint method in the multi-objective extensions of the threshold coverage model.

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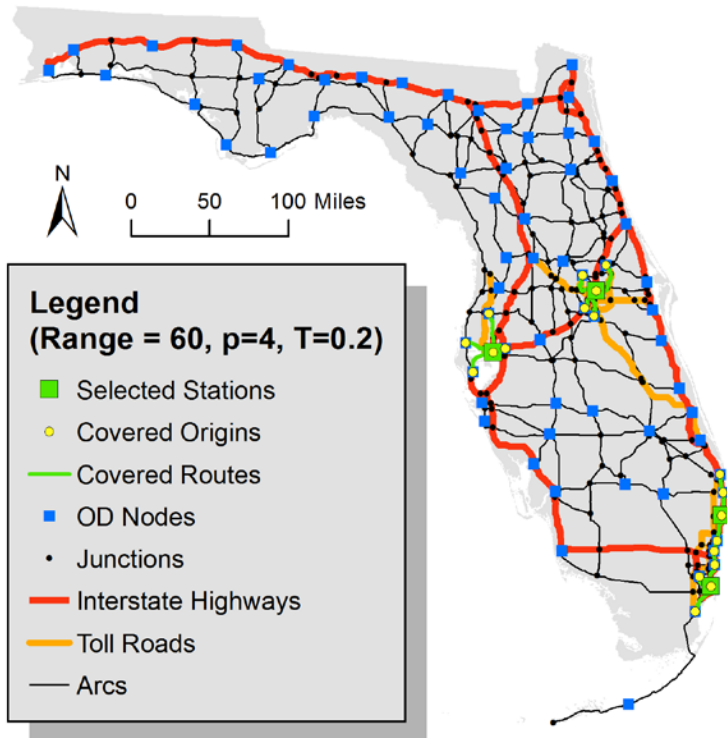
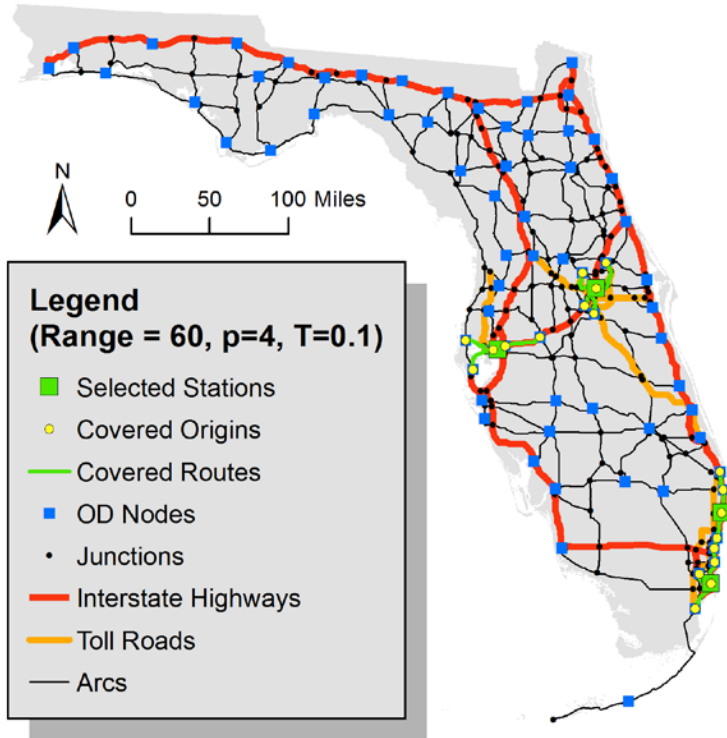
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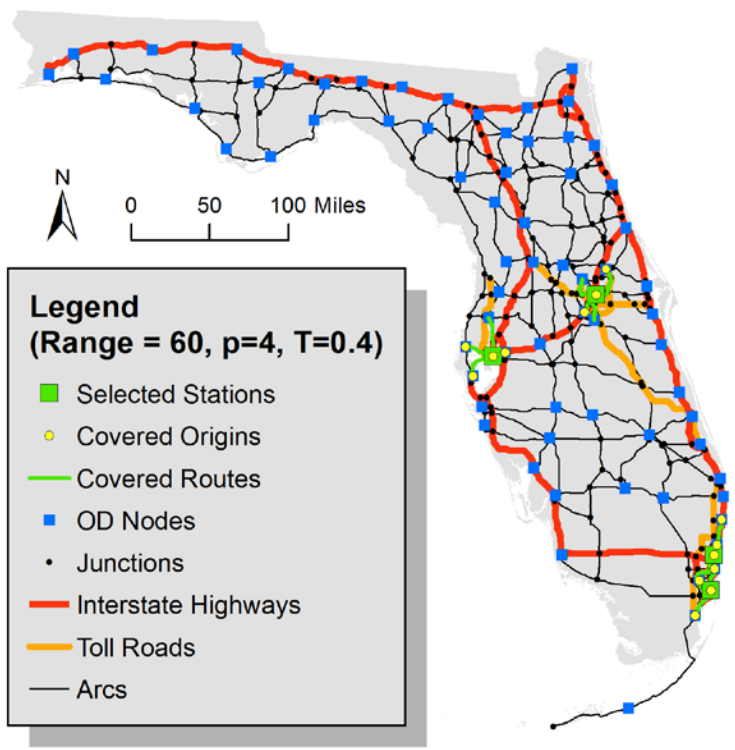
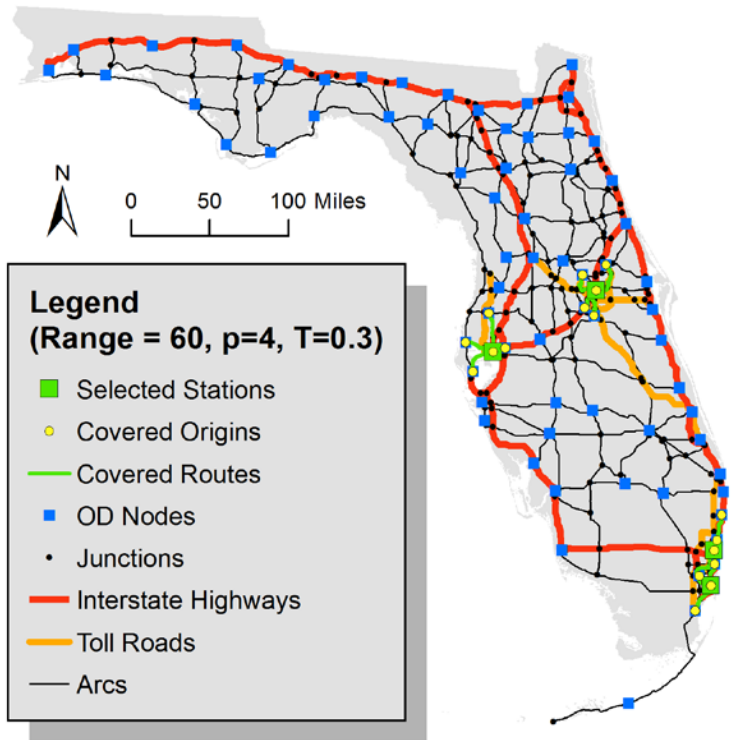
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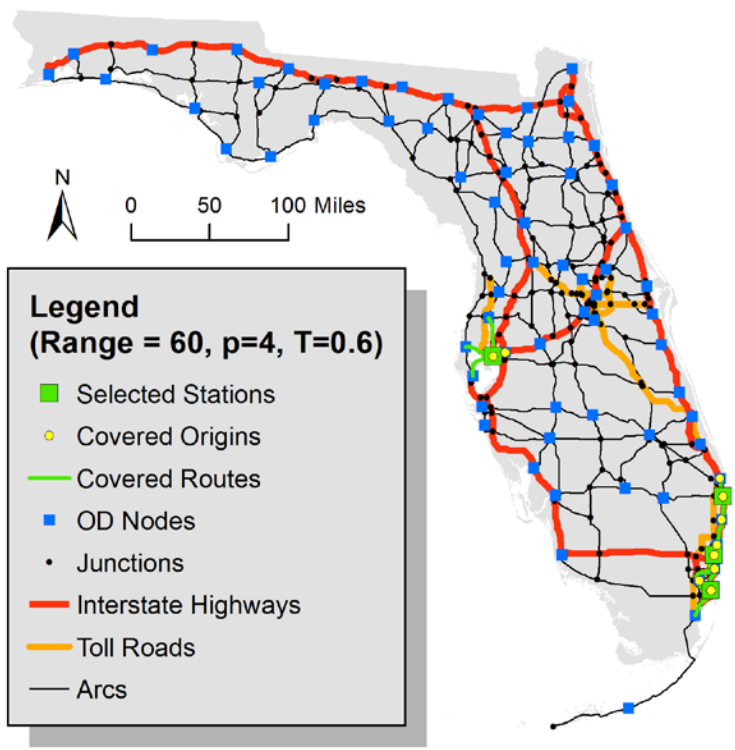
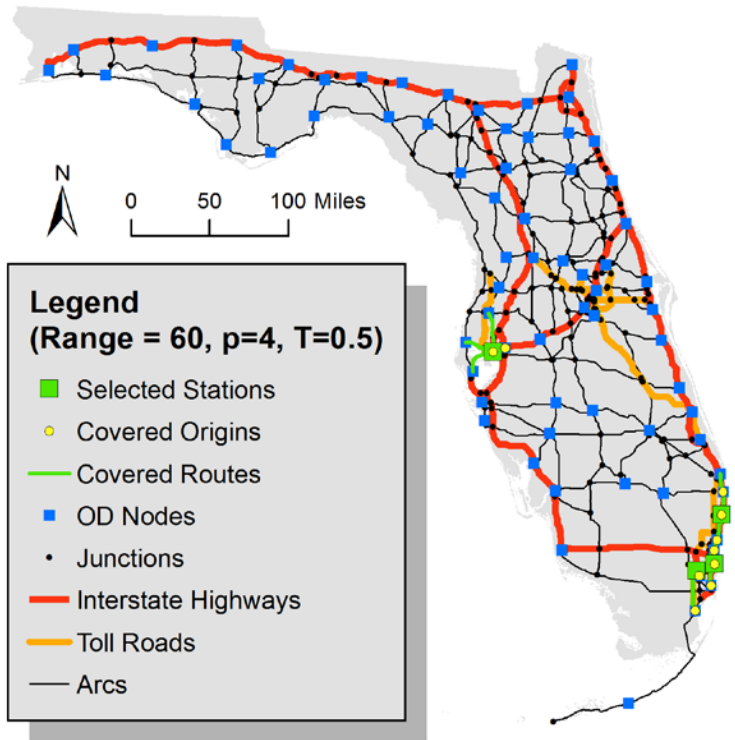
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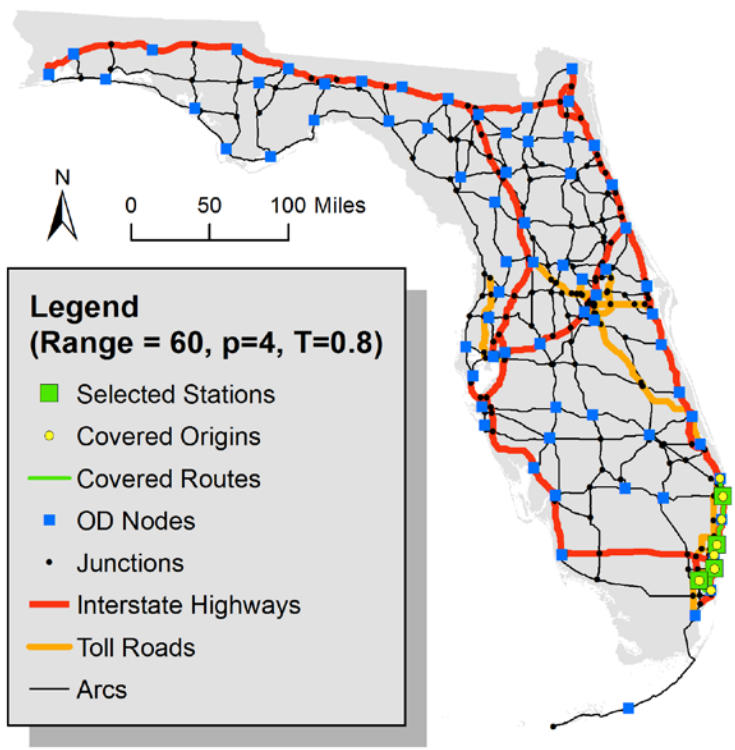
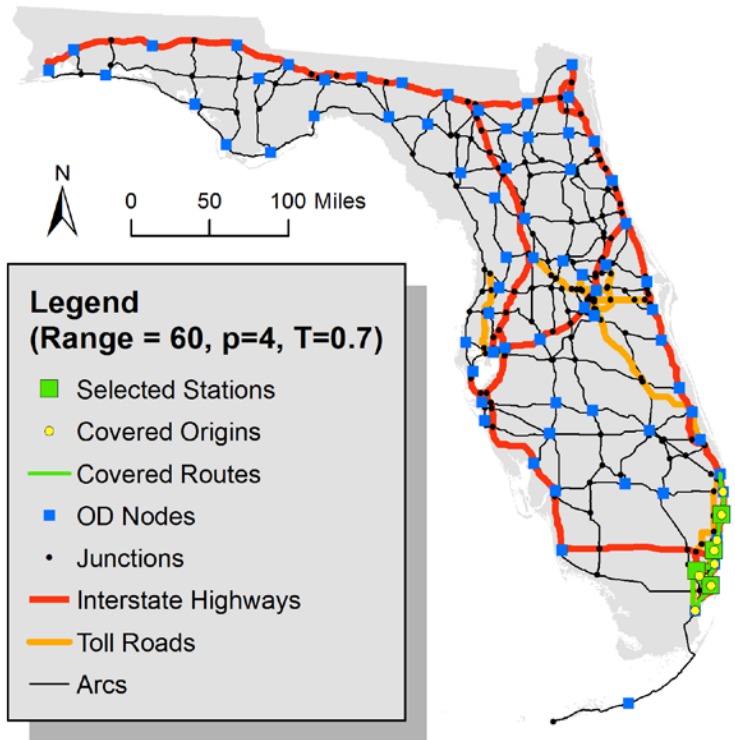
APPENDIX A

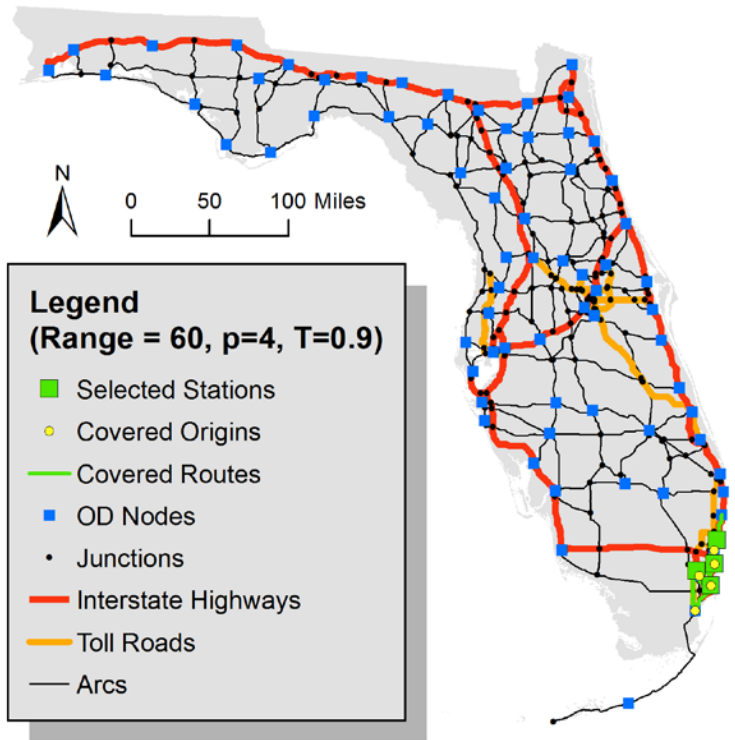
NUMERICAL EXPERIMENT RESULTS ($R = 60$, $p = 4$)





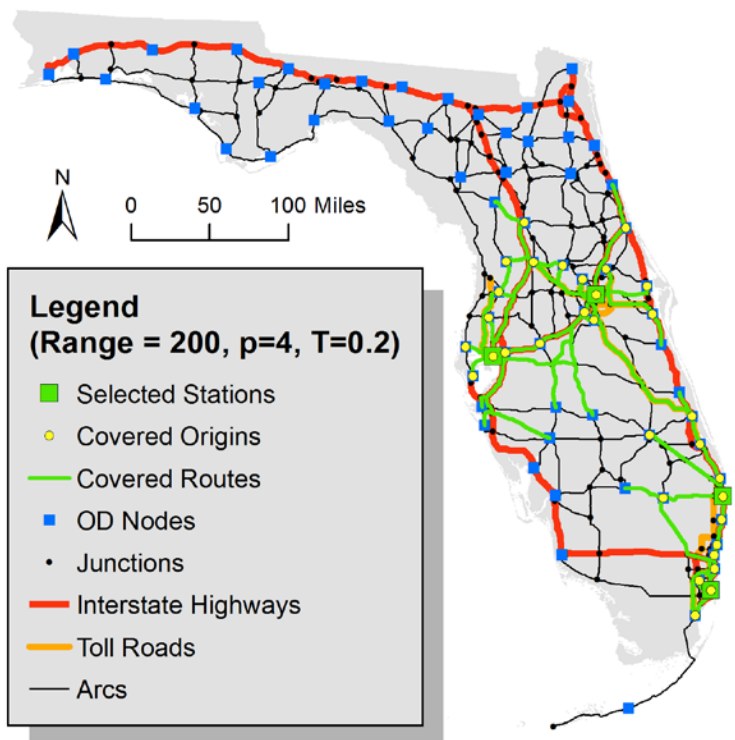
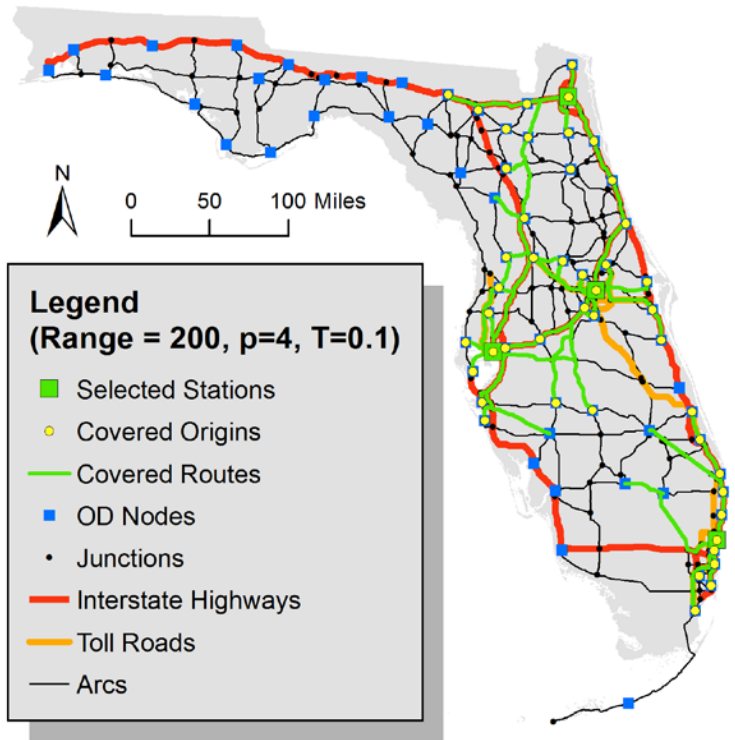


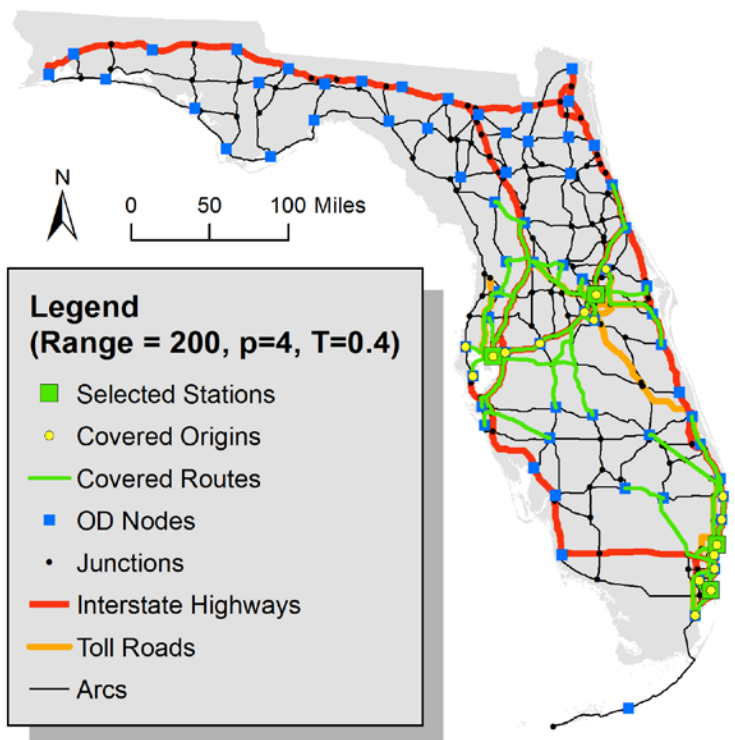
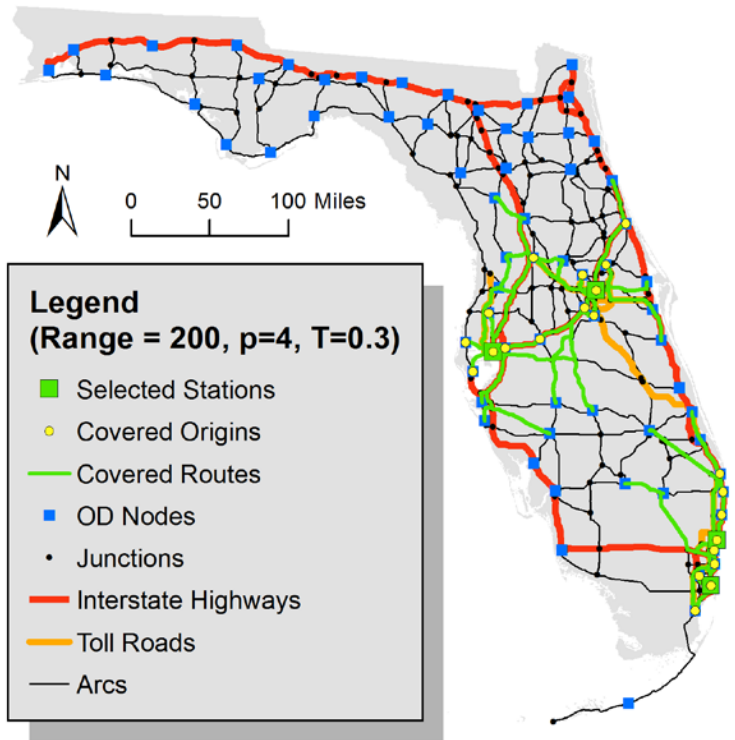


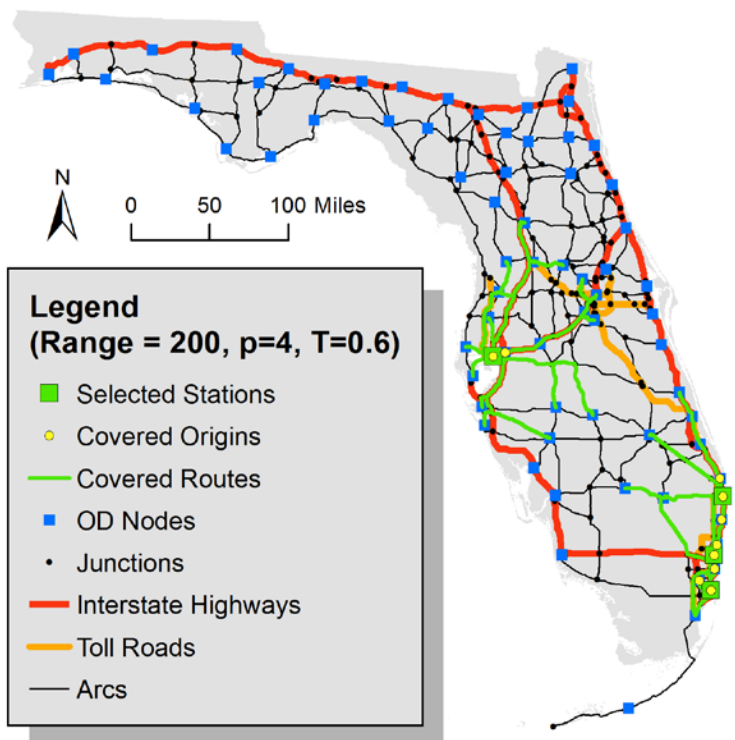
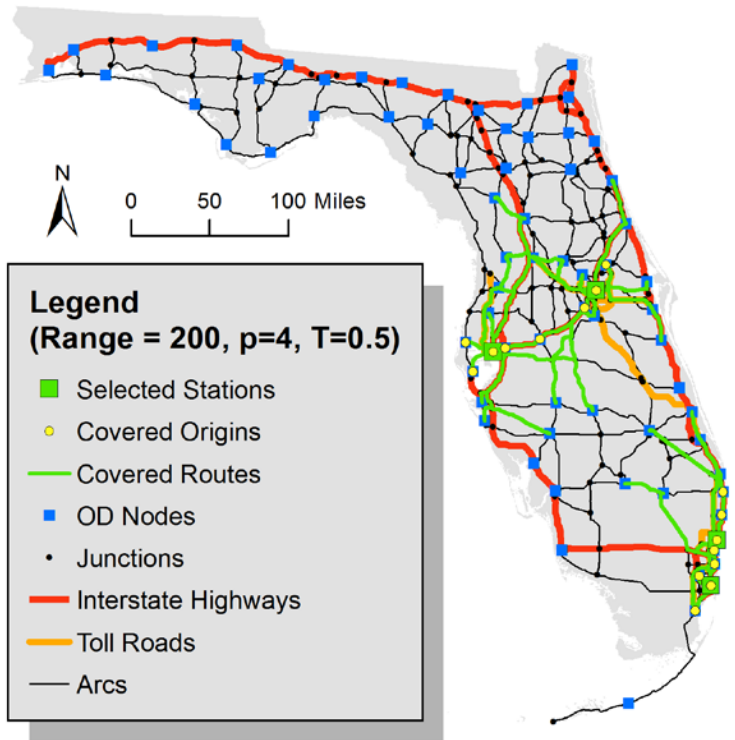


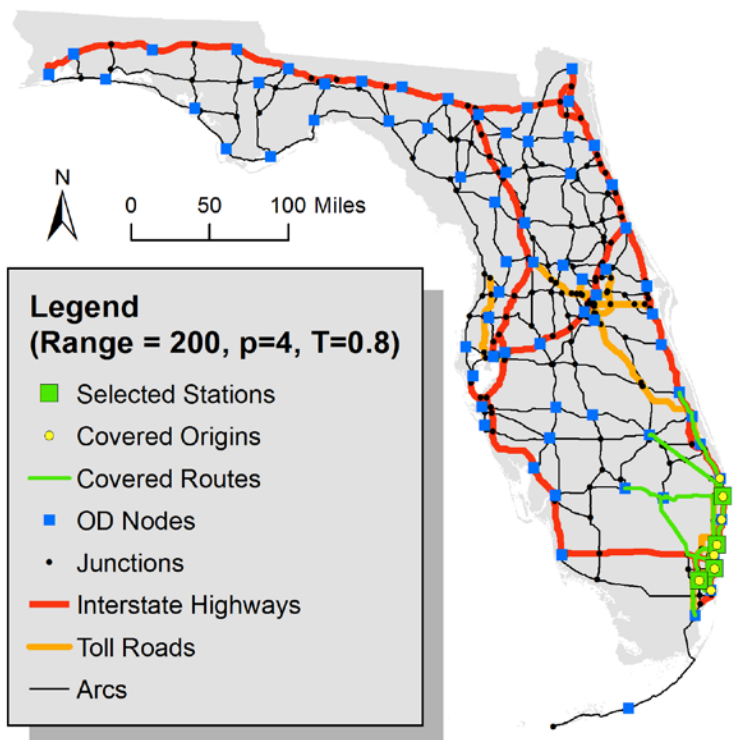
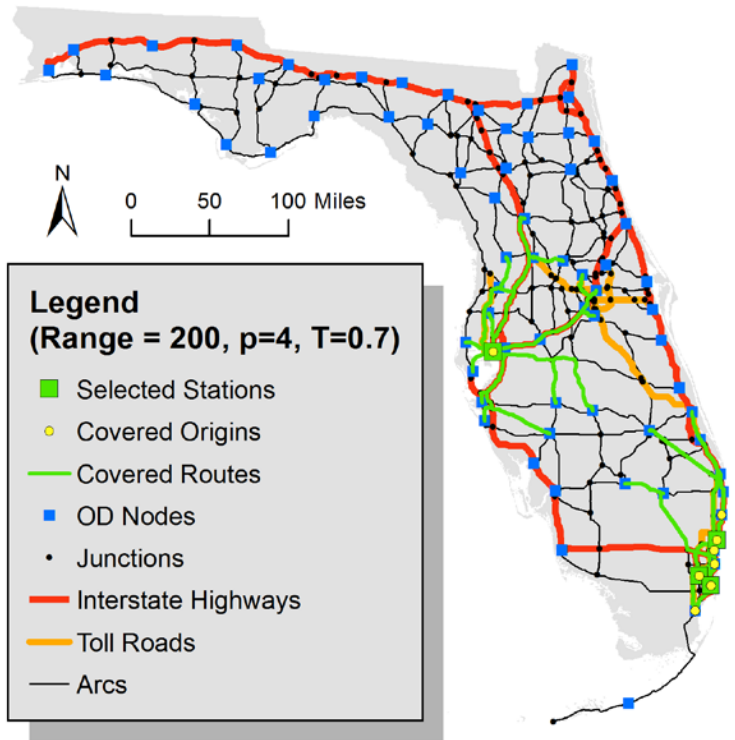
APPENDIX B

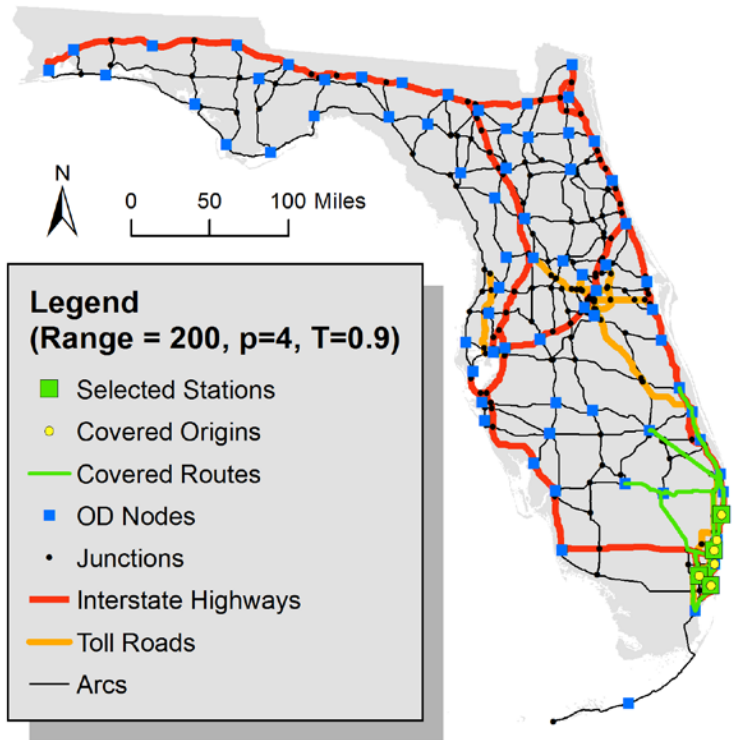
NUMERICAL EXPERIMENT RESULTS ($R = 200$, $p = 4$)





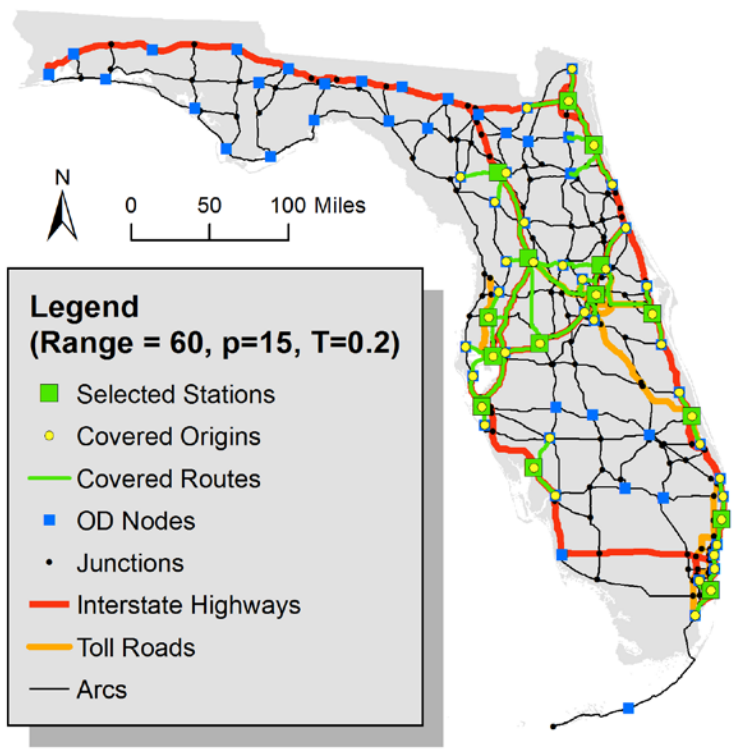
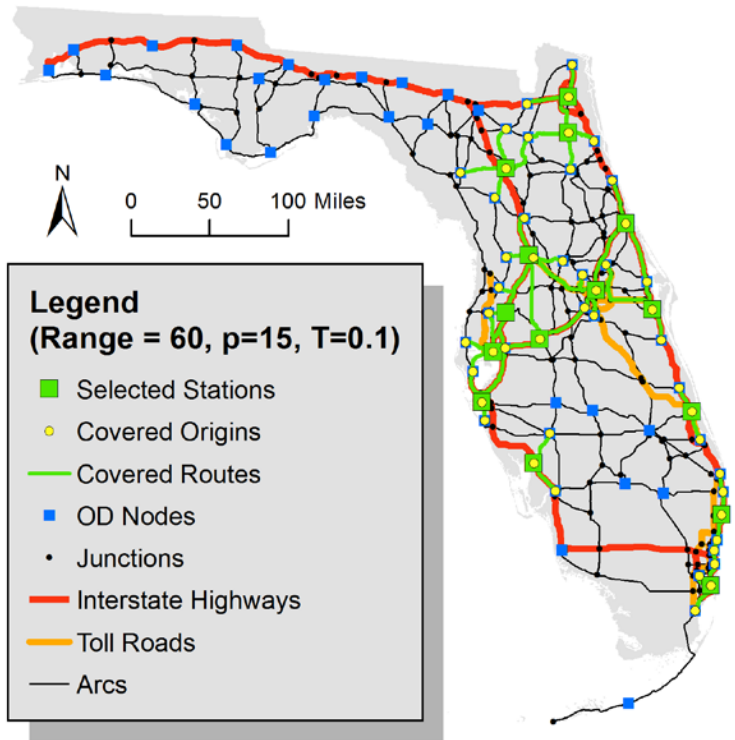


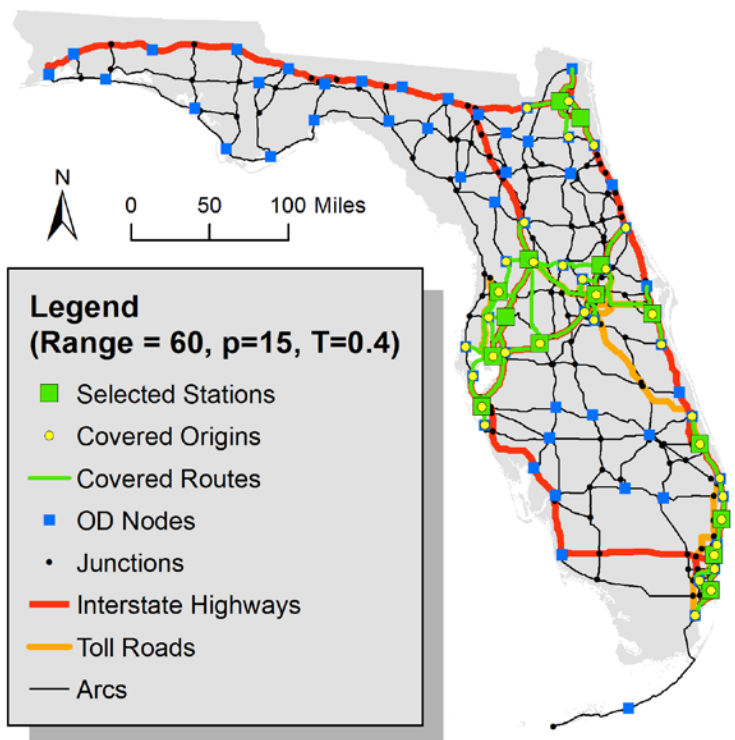
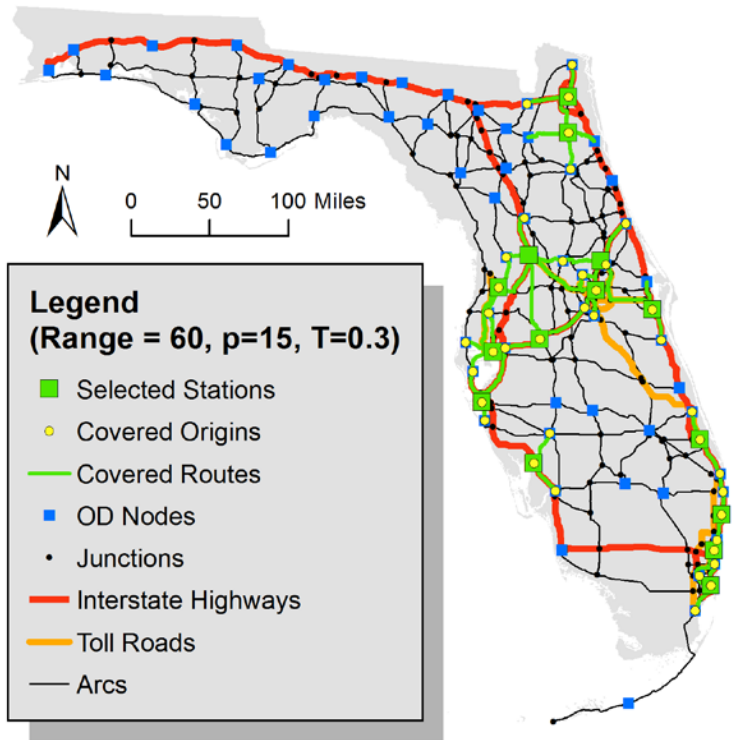


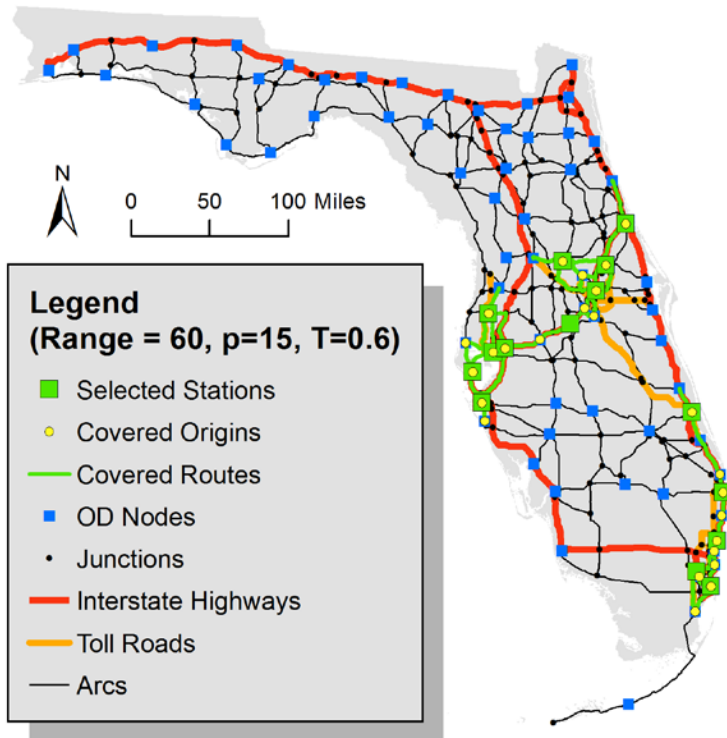
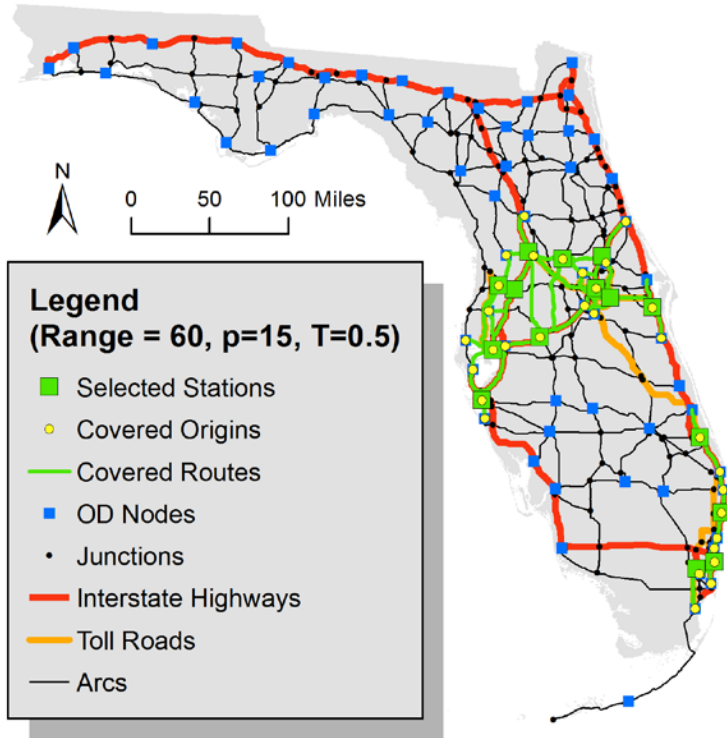


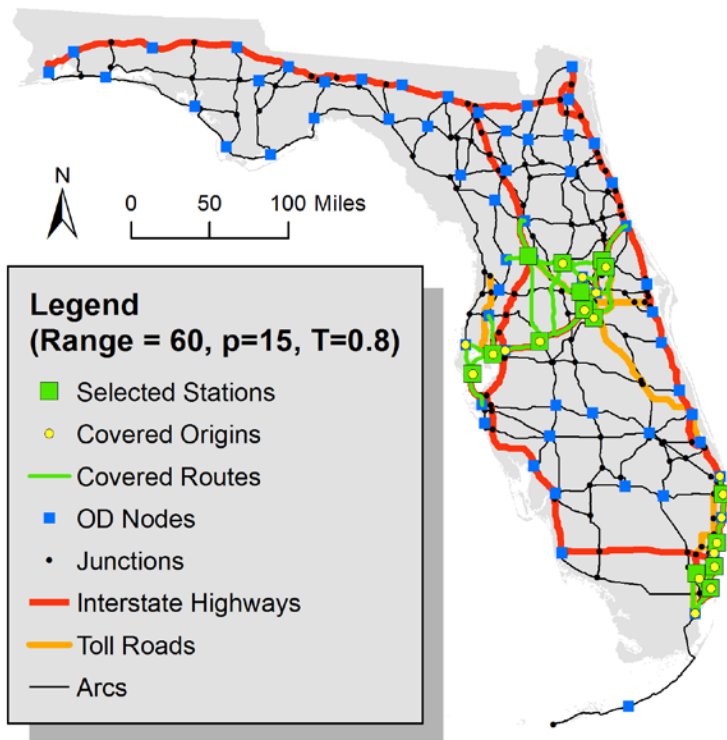
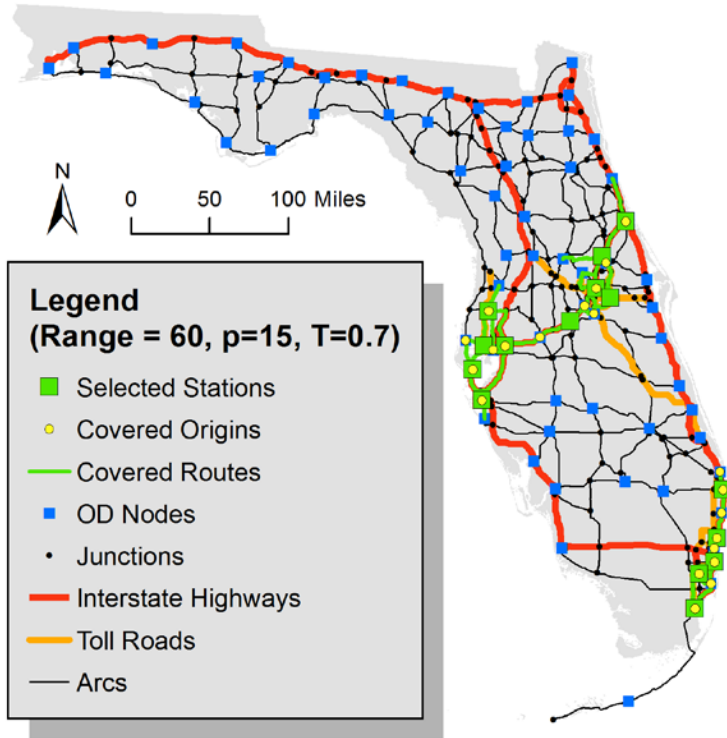
APPENDIX C

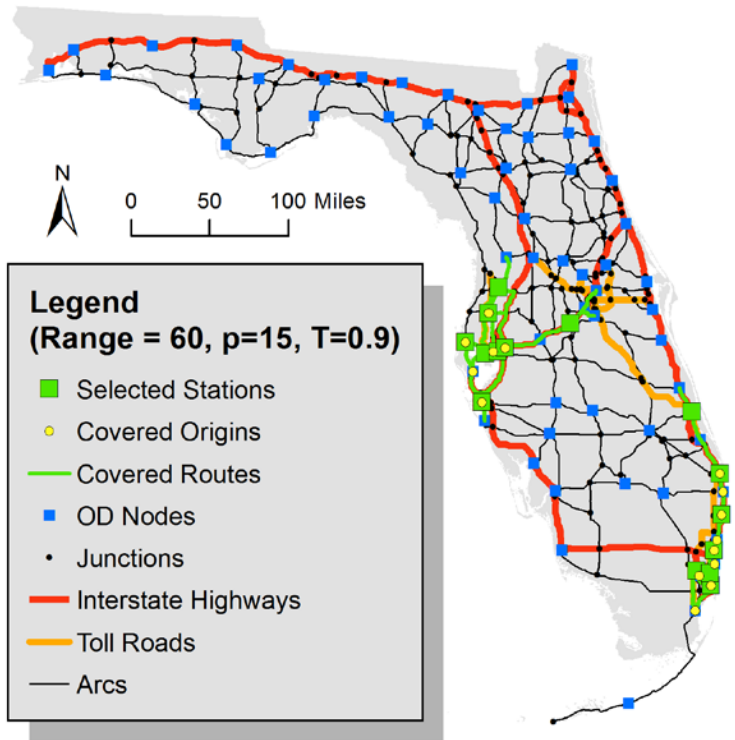
NUMERICAL EXPERIMENT RESULTS ($R = 60$, $p = 15$)











APPENDIX D

NUMERICAL EXPERIMENT RESULTS ($R = 200$, $p = 15$)

