Chapter 10

Hydrogen station location analysis and optimization: Advanced models and behavioral evidence

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1. Introduction

This chapter aims to provide an insightful reference on hydrogen refueling station (HRS) location modeling for researchers, students, industry, and policy makers. In this literature review, we synthesize three main strands of research that are essential to planning a network of HRSs for light-duty fuel cell electric vehicles (FCEVs):

i. Social and behavioral data and research underlying early adoption, travel, and refueling tendencies.
ii. Geographic information system (GIS) models and tools for analyzing where to locate HRSs.
iii. Operations research (OR) models for combinatorial optimization of a network of HRSs.

A basic understanding of all three research areas is invaluable for HRS location modeling. Different models require different types of data that each assumes certain types of underlying consumer behavior. GIS and OR models have complementary strengths and weaknesses and can be integrated in different ways to develop effective models.

In Sections 2–4, we review behavioral, GIS, and OR research on HRS location. In Section 5, we discuss different ways that GIS and OR are integrated to produce more realistic and powerful models; these methods are not always included in scholarly publications, so we draw extensively on personal

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experience here. In Section 6, we conclude with some general recommendations for HRS network planning that can be adapted to different regions depending on data availability, geographic scale, modeling capabilities, etc. We also highlight some directions for future research.

Before beginning, it is important to clarify the three foundations of HRS modeling. First, the social and behavioral research and data section cover data from the following: consumer surveys and interviews; census, transportation agencies, vehicle rebate programs, and other secondary sources; and automated data collection devices in vehicles and stations. These data are tabulated and analyzed statistically and geographically to understand the stated and revealed preferences and behaviors of drivers that the stations aim to serve. Second, we view GIS as a system of hardware, software, data, and skills that combines a computerized map with multiple layers of geographically referenced features, a database of attributes of those features, and a wide variety of tools for spatial, logical, and numerical analysis within and across different map layers and to create new layers. Third, by "operations research" we refer to mathematical optimization of a system of HRS locations using linear and integer programming or heuristic algorithms.

A useful distinction is that OR models for HRS location (a) express their optimization criteria in purely mathematical terms and (b) have methods for solving for the optimal (or near-optimal) *combination* of locations without testing each and every possible combination. GIS models cover a much broader spectrum but generally facilitate highly detailed geographical analysis and visualization of a large number of factors. While GIS models can perform a wide variety of mathematical analyses of HRS combinations over geographic space, they generally test those combinations one at a time … *unless* they have OR tools built into them to perform combinatorial optimization. Another distinction is that most OR approaches to HRS location require a discrete pregenerated set of candidate sites, which may consist of all junctions in a network or a set of distinct candidate sites such as existing gasoline stations. GIS methods may or may not require predetermined candidate sites but can assess the suitability of locations across continuous space.

Finally, it is important to outline what is *not* covered in this chapter. To date, FCEV deployment and the supporting studies and models have focused more on the privately owned light-duty vehicle (LDV) market. This chapter is similarly focused on LDVs. Momentum has recently grown for FCEV deployment in the medium- and heavy-duty vehicle markets, but to date, the analyses of HRS location have not been nearly as robust and deployment of commercial vehicles in these segments is not expected for a few years. Some of the concepts demonstrated for the LDV market may apply to the medium- and heavy-duty cases, but readers should be aware that modifications and novel considerations would likely be necessary. Also not covered are supply chain factors such as fuel delivery trucks, pipelines, and onsite hydrogen generation. Models and behavior for battery electric vehicles (BEV) drivers and charging stations are sometimes reviewed here if applicable to FCEVs and no equivalent study exists for HRSs. In general, Levels 1 and 2 charging behavior and station modeling do not apply to HRSs because of the long charging times and the associated parking-based behavior, but models and behavior for fast charging are generally relevant to FCEVs and HRSs.

2. Social and behavioral data and findings for driving, purchasing, and refueling FCEVs

Each method or model that recommends the "best" locations for HRSs typically does so to locate stations conveniently for early FCEV adopters. This focus is motivated by the nearly unanimous finding that a lack of a convenient refueling infrastructure is the primary barrier to FCEV adoption [1]. What, precisely, constitutes convenience of stations for FCEV adopters and which kinds of convenience should be prioritized is therefore critical to any HRS location modeling approach, and one of the key dimensions in which HRS models differ from one another.

A station's convenience is almost always evaluated by drivers *relative to* another location such as their home or work or commonly traveled route. For location models to produce the best results, it is therefore essential to know where prospective or likely FCEV adopters live, work, and travel to understand where demand for refueling is likely to be. This in turn requires careful consideration of what kinds of data to collect to represent this demand. Several different kinds of data have been used to inform our understanding of how best to locate stations, and the types of data and data collection methods have evolved since researchers began modeling HRS locations.

Research on HRS location models predated the rollout of FCEVs, but until FCEVs came to market in the last few years, behavioral data on actual FCEV refueling by actual early adopters at actual HRSs did not exist, and creative approaches were required to fill this void. Most of the past work in this area, then, relied on *stated preference* surveys to understand where prospective adopters would want HRSs in order to feel comfortable adopting one, e.g., Brey et al. [2], or analyzed existing travel data to site HRSs conveniently relative to current travel patterns, e.g., Kang and Recker [3]. Others analyzed the driving and refueling behavior of drivers of BEVs, compressed natural gas vehicles (CNGVs), diesel vehicles, and even conventional gasoline cars, noting which findings might be most transferable to hydrogen. Once FCEVs were sold to initial adopters, however, it finally became possible to collect *revealed preference* data on actual FCEV adopter locations, travel habits and destinations, and refueling stations used.

In summary, there is considerable social and behavioral research that carries important implications for HRS station location modeling. Data have been collected on social and behavioral aspects of FCEV adoption and travel, and at different spatial scales, including primary and secondary data. We chronicle and organize this section according to the data collected and describe some of the subsequent methods employed, summarizing the key findings from each primary approach.

2.1 Identifying FCEV adopters

Understanding *who* is interested in adopting an FCEV is the first step in identifying where hydrogen refueling demand may be in a geographic area. As a helpful starting point, we highlight an influential early effort to estimate possible demand for refueling and recommend HRS locations from the US National Renewable Energy Laboratory (NREL). Based on three sets of rankings from (i) a literature review, (ii) expert interviews, and (iii) a focus group, Melendez and Milbrandt [4] identified several demographic characteristics that reflect common characteristics of likely early FCEV adopters that could be readily mapped, providing a first fine-scale glimpse at the geographic distribution of future demand. These maps used data available from the US Census and showed where high household income, households with two or more vehicles, commute distance, and high levels of education were distributed geographically. Together with other data more regional in nature—air quality, presence of state incentives or sales mandates, whether the city was part of the Clean Cities Coalition—and hybrid vehicle registration data from a third party, they weighted these characteristics and overlaid them in GIS to identify the likely locations of early adopters. They then used these maps of projected demand to recommend HRS locations to serve those demands: see Section 3.2 for how GIS methods were used to recommend station locations in this landmark study.

After the NREL study, work continued on trying to understand who is—or may be—willing to adopt a zero-emission vehicle [5–8], including studies on drivers who would prefer FCEVs over other options [9,10]. Characteristics of the vehicle—such as FCEV performance, cost, aesthetic, and storage—are critical to the adoption decision, as are individuals' attitudes and perceptions regarding technology, the environment, and social status [9–11]. Others have found that experience with using an FCEV in a trial or driving one for work positively influences willingness to consider one [12–15]. Other factors influencing FCEV adoption include tax credits, rebates, or HOV lane access [16], comfort, safety, and ease of use [17] and station reliability, which has proven to be a challenge and frustration for early FCEV adopters [11,18–20].

We next review the kinds of data collected by those researching travel and refueling behavior, along with preferences of known or prospective FCEV adopters, in the next section.

2.2 Travel, refueling data, and stated preference studies

The late 1980s saw the first efforts to explicitly study refueling behavior to inform alternative fuel station location planning. By conducting intercept surveys of 107 drivers of diesel vehicles and over 1500 gasoline drivers while they refueled at stations throughout northern California, and comparing their responses, Sperling and Kitamura [21] found that diesel drivers—treated as an analog population for how future AFV drivers would adapt to a sparser refueling network—prioritized convenience to home, work, or school substantially more than gasoline drivers did. Gasoline drivers instead tended to more often prioritize fuel price when choosing a station at which to refuel, while they also found that diesel drivers refueled at fewer stations overall. They estimated that a refueling network only 10% of the size of the current gasoline station network would be sufficient "to relegate refueling concerns to a relatively insignificant role in the vehicle-purchase decision" (p. 15).

Additional work on the survey data collected from gasoline drivers found that refueling entailed balancing several priorities and that attitudes and experience traveling throughout the area had a greater influence on station consideration than sociodemographic characteristics did [22,23]. Given that station convenience to locations such as home and work emerged as important to refueling station consideration, focus shifted to understanding what kinds of convenience drivers prioritized. Kitamura and Sperling's [23] work in particular is often cited in terms of how important refueling trips are relative to home, because home was either the stop immediately before or after the refueling event for about 75% of gasoline drivers. Most also refueled within 10 min of either their origin or destination. Another study of gasoline refueling conducted around this same time in Minnesota found that price and accessibility were the primary drivers of station choice and that drivers living in the same neighborhood do not necessarily share the same "choice set" of gasoline retailers they consider or include their nearest station to home in their choice sets [24]. How transferable these findings about gasoline and diesel drivers were to AFV refueling, however, remained a question.

By the mid-2000s, in anticipation of the initial rollout of FCEVs, researchers began to refocus their efforts on how to plan for a network of HRSs by incorporating consumer travel and refueling behavior into their recommendations. When developing station location methods, some work in this period referred to the diesel and gasoline refueling studies described in the previous paragraph when prioritizing locating initial stations convenient to the home and work locations of likely early adopters [25–27]. These findings were supplemented by incorporating input from local stakeholders interested in hydrogen rollout when making their recommendations to locate stations in initial clusters in California [28]. In analyzing retail gasoline sales from stations across Sacramento, however, Nicholas [29] found that the strongest correlation was not with the nearby population or traffic volumes but with a concept he called "population traffic," which measures the population in the buffer of paths to freeway entrances (Fig. 10.1). The findings suggest that drivers most often refuel near home but specifically where they enter and exit

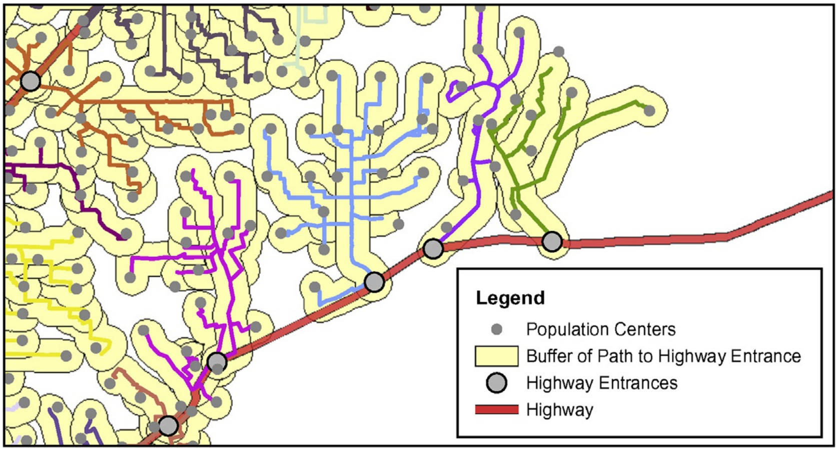

FIG. 10.1 Traffic "basins" that access their nearest freeway via the same exit, for calculation of Nicholas' "population traffic" measure, which correlates most strongly with gasoline sales. *(Credit: M.A. Nicholas, Driving demand: what can gasoline refueling patterns tell us about planning an alternative fuel network? J. Transp. Geogr. 18 (2010) 738–749.)*

freeways. Reminiscent of hydrologic drainage basins, these buffers are a different way of representing the spatial distribution of refueling demand and suggest that freeway exits may be "good" locations for initial HRS stations.

Still, without empirical data on the travel and refueling behavior of actual FCEV adopters or from an analog population of fast-fueling AFV drivers, there remained some uncertainty about the transferability of these findings to HRS station planning. As a result, stated preference studies that prompted people to consider AFV adoption and refueling station preference were helpful to the process of developing station planning methods. These provided some insight into who likely early AFV adopters were and what they found appealing about the vehicles [17,30,31], though much of this work was focused on BEV adoption, with limited transferability to HRSs. Others turned to simulations, primarily to recommend locations for BEV charging infrastructure, using observed travel behavior of drivers of gasoline vehicles collected from travel surveys [32,33] or using GPS data that tracked vehicles during a study period [34,35]. A key limitation to the transferability of the findings from the BEV studies that evaluated promising places for public charging infrastructure to HRS network planning was that the bulk of the recharging demand is met at home by early BEV adopters [36]. In general, though, the stated preference studies frequently found that drivers wanted stations near their homes, with less willingness to refuel or recharge on the way, so many of the scenario-type approaches reported convenience to likely home locations of adopters accordingly. One criticism of these findings, however, is that respondents often answer stated preference questionnaires based on their gasoline and diesel driving experience, where the high density of stations ensures there are several stations that are both near their home and on their way regardless of which direction they are headed [37].

Empirical data on fast-fueling AFV drivers' behavior came via a series of studies on drivers of compressed natural gas vehicles (CNGVs) in Southern California. Like Sperling and Kitamura's work in the 1980s, intercept surveys of drivers of CNGVs and those refueling with gasoline at nearby stations were collected while drivers refueled [38–40]. They interviewed 256 CNGV drivers at five different stations throughout greater Los Angeles, along with 267 drivers of conventional vehicles refueling at the closest gasoline stations to the CNGV stations. Similar to Kitamura and Sperling [23], both groups of respondents were asked about their travel before and after refueling to determine how the refueling event corresponded with home, work, shopping destinations, or other trip purposes. Using network GIS analysis, they compared CNGV driving and refueling patterns to that of gasoline drivers.

One critical distinction these studies provided was to identify if drivers refueled at the station nearest to their home or the one most conveniently on the way. Focusing on the drivers who refueled at a station that satisfied only one of criteria (but not both or neither) CNGV drivers refueled at stations that were objectively revealed to be most on the way, but not closest to home, by a surprisingly large 10:1 margin [39]. These studies also determined another key metric: CNGV drivers consistently tolerated up to about a 6-min deviation out of their way to refuel. This was higher than for gasoline drivers, who rarely deviated beyond 2 min, and CNGV drivers were also found to refuel nearer to the middle of their trip than the beginning or end, in contrast to their gasoline driver counterparts [40]. This was one of the first attempts to identify *which* type of convenience drivers were revealed to prioritize in a sparse fast-fueling AFV refueling network.

Stated preference and simulation approaches provided other useful insights for locating HRS stations around this time. Kang et al. [41] applied the simulation approach on travel survey data to measure how far drivers of gasoline vehicles would need to deviate from their current travel patterns to reach the proposed 68 hydrogen stations in California. Survey responses collected from those renting cars when visiting Orlando, Florida, USA found that 80% of those willing to rent an FCEV would travel at least one mile out of their way to refuel one at a hypothetical hydrogen station [42]. Brey et al. [43] found that the majority of their 601 survey respondents in Andalusia, Spain typically refuel near home when selecting a gasoline station and recommend maintaining this convenience for HRSs. Another survey of 230 residents of Seville, Spain found that drivers specifically asked about adopting an FCEV said they would prioritize HRSs based on proximity to home, followed by stations conveniently on the way, and noted station characteristics (such as price, reliability, and a convenience store) would factor into drivers' decisions regarding where to refuel [2].

The question of *how many* stations would be needed in an area to ensure sufficient coverage has been another area where stated preference and simulation approaches have been used. Studies generally show that between 5% and 20% of the number and locations of existing gasoline stations would be enough to meet early adopters' demand for refueling [26,44–46]. This approach typically relies on selecting a subset of HRSs from a comprehensive dataset of existing gasoline station locations, and/or evaluating coverage to home, work, or commute routes. Using a different approach, Melaina et al. [47] asked possible early adopters to evaluate hypothetical maps of multiple stations in an attempt to understand how many station drivers would need in a region to feel comfortable adopting one *and* how they would like them arranged.

Still, without actual data on FCEV adopters and their travel and refueling behavior, it remained uncertain what would transfer from this whole body of research to the revealed behavior and preferences of known adopters.

2.3 Hydrogen adopter and refueling data

Empirical data on travel and refueling behavior and preferences of actual FCEV adopters only became available soon after the first FCEVs were sold or leased in California late in 2014 and drivers began using the initial network of stations. This made it possible to collect and analyze data from actual FCEV adopters instead of relying on analogous populations, simulations, or stated preference approaches. Currently, the few published studies on *revealed* FCEV adopters' refueling behavior have provided valuable insight on a number of topics of interest for station planners, including: where early adopters reside, where and how often they refuel, and why they use certain stations.

The California Clean Vehicle Rebate Project (CVRP) provides the most comprehensive publicly available dataset on the home locations of FCEV adopters [9,20,48]. These data are aggregated to geographic scales as fine as the census tract level or ZIP codes but have two limitations. First, only those who received a rebate through this program are represented. Second, the data reflect where the person lived when they got the FCEV, which may have changed since then.

Another California-specific dataset has been useful in assessment of both FCEV adoption and station network use. As part of California Assembly Bill 8 passed in 2013, the California Air Resources Board (CARB) must produce an annual report about station network status and use, FCEV uptake, planned or proposed future stations, and the amount of hydrogen produced from renewable sources each year. These annual evaluations on FCEV deployment and hydrogen fuel station network development typically also report drivers' desire for more stations, but its 2018 report in particular highlights that early FCEV adopters considered proximity of a station to home as the most important aspect of the refueling station network, followed by having a station along a commuting route [49]. Stations on the way to errands or to a long-distance or vacation destination were considered "very" or "extremely" important less often. This in part corroborated the long-held notion that stations near home would effectively encourage FCEV adoption, given that the majority of actual FCEV adopters surveyed said having a station convenient to home was "Extremely Important" in their evaluation of the refueling station network. Over half of drivers refueled at multiple stations in this sparse refueling network. While not particularly surprising given how often most drivers rely on multiple stations for refueling needs, it did raise questions about how drivers considered different stations in the refueling network.

A series of studies on California FCEV adopters provided valuable insight into how drivers both subjectively and objectively prioritized HRSs in a refueling network *at the time they decided to adopt the vehicle* [48,50–52]. Using a web-based survey that included interactive web maps of available HRSs by quarter-year, they asked FCEV adopters to provide information on where they lived and traveled at the time they got the FCEV and up to five stations they were planning to use at that time. Analysis revealed that: (1) while proximity to home was indeed important for many, a single station near home was neither necessary nor sufficient for most FCEV adopters, (2) the travel times to stations that drivers felt were subjectively "near" home, work, and other location types exhibited substantial variability but did decay beyond 90 min (Fig. 10.2), and (3) 82% of early adopters compiled a "portfolio" of multiple stations that enabled them to satisfy various criteria of importance to them in different ways [50,51].

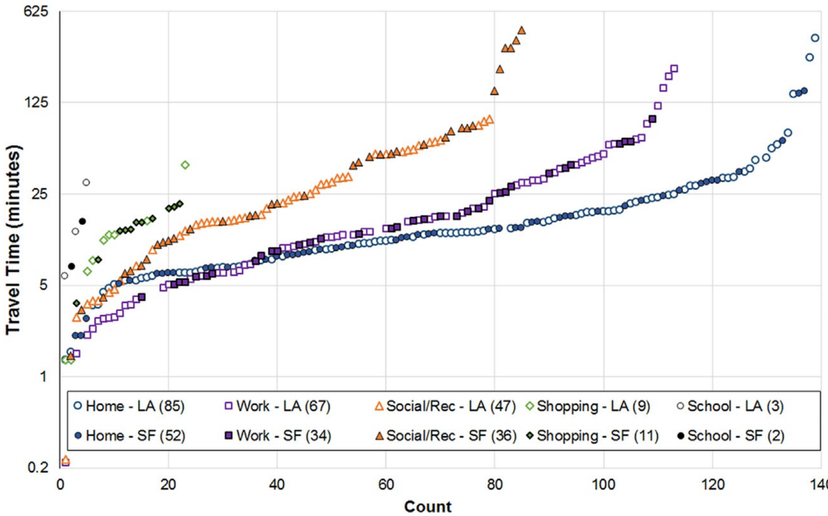

FIG. 10.2 Rank-ordered estimated travel times between stations, home, and frequent locations by respondents, if respondent subjectively considered the station to be geographically "near" that location for any reason. *(Credit: S. Kelley, A. Krafft, M. Kuby, O. Lopez, R. Stotts, J. Liu, How early hydrogen fuel cell vehicle adopters geographically evaluate a network of refueling stations in California. J. Transp. Geogr. 89 (2020a) 102897.)*

This research also considered the relative importance of stations to drivers, and the subjective and objective ways that these stations aligned with various criteria. By both subjective and objective measures, proximity to home is most important for primary stations, followed by stations near work and stations on the way (i.e., with the shortest deviations to reach). Secondary stations are still convenient to these locations but to a lesser degree and with less consistency between subjective and objective measures, while their third-fifth most important stations align more with social or recreational destinations. Drivers tend to use their primary stations both on weekdays and weekends, in contrast to their lower-ranked stations. Long-distance travel, considered to be a factor that might dissuade prospective adopters, did not prominently appear as a reason until either their fourth or fifth most important station. This is consistent with CARB's 2018 Annual Report [49], where convenience to a vacation destination was listed as the least important factor of the options listed.

Furthermore, when considering how station usage changed since adopters first got their FCEVs, 40% of these same respondents indicated that they had changed the stations they initially intended to use. The stations they did not initially consider but later switched to were significantly farther from home and required short deviations to reach [52]. However, drivers with stations already near home, work, and along frequently traveled routes were less likely to change their list of initial stations. This provided a first glimpse at how station network usage changes after adoption and also suggested that convenience priorities change after a bit of experience.

Studies employing more qualitative research methods corroborated many of these findings. Using ethnographic decision modeling based on interviews with California residents that either got an FCEV or seriously considered one before deciding against it, Stotts et al. [53] found that most wanted a primary refueling station near home, but nearly two-thirds of adopters that did not have a station near home were still willing to adopt the vehicle and rely on a station near work or on the way to work or other regular destination. Most drivers required a convenient backup station and also had some way to complete long-distance trips. In this study, no drivers decided *not* to get a vehicle on account of concern about the vehicle's range.

Station reliability has emerged as one of the most prominent issues facing greater FCEV diffusion. Ramea [20] surveyed 100 FCEV adopters in California and asked about drivers' most and least preferred stations in the HRS network there. Proximity to home and station reliability were the top two reasons listed for the most preferred station, while station unreliability was the most cited reason for their least preferred station, substantially more so than any measure of geographic inconvenience. Unreliability has been a prominent point of concern in interviews with early adopters, with most reporting that they have a "backup" station that can satisfy refueling demand in case they one they want is not operational [11]. In addition to being a source of frustration for early FCEV adopters and not something current gasoline drivers have to worry about, this topic in particular presents a critical gap in the HRS station location modeling literature at the moment.

2.4 Summary of implications for station planning

We conclude by summarizing some of the key implications for HRS station modeling from research that now spans three decades on social and behavioral aspects of FCEV adoption and refueling. Virtually every study, regardless of research method, has corroborated the long-held notion that having an HRS near home is important for FCEV adoption and therefore should be incorporated into station planning approaches. However, it is also evident that a station near home is neither necessary nor sufficient by itself to encourage adoption and meet refueling needs for many drivers. Other considerations are also important, including stations that are: on the way to frequently visited locations, near work or social and recreational locations, and in particular, reliable. In fact, drivers generally gravitate to stations that satisfy more than one of these criteria if they have access to them [48,50,51], and in the 2018 CARB report all of the criteria asked about were "Very" or "Extremely" important to at least some drivers. Further, if drivers have access to stations that satisfy several criteria, they are less likely to stop using them in favor of other stations in the network [52]. Some drivers are willing to adopt an FCEV without any station subjectively or objectively near home, so long as one is near or on the way to work or another frequently visited location [50,51,53]. Most importantly, station planners should be aware that drivers assemble a "portfolio" of stations in order to meet their diverse refueling needs (Fig. 10.3). In short, recent research on FCEV adopters has highlighted that a "one-size-fits-all" approach to planning stations by focusing on a single criterion is unlikely to succeed in facilitating widespread adoption. Still, modelers may wonder precisely how these measures of convenience should be represented and parameterized in HRS planning methods.

Drivers do indeed value a convenient station near home, but how close does a station need to be to be "close enough"? Of course, there is no single definitive answer to this question, but there are several helpful findings from the literature. The initial NREL study considered distances of 3, 5, and 10 miles from home when recommending station locations and assessing coverage [4]. Stated preference approaches have reported prospective adopters would prefer at least one station within a 10-min drive of home [15,43]. In Kelley et al. [50,51], only about 55% intended their primary station to be the one objectively nearest to home (though 80% listed their primary station as one of their nearest three). For the 139 stations drivers listed as objectively "near" their home, 40% were within 10 min and 75% were within 25 min under free-flow travel conditions. This reflects the variability of what drivers consider "near" to home and suggests that the narrower 10-min band found in some stated preference studies may be too restrictive. Conversely, over half of these adopters decided to get

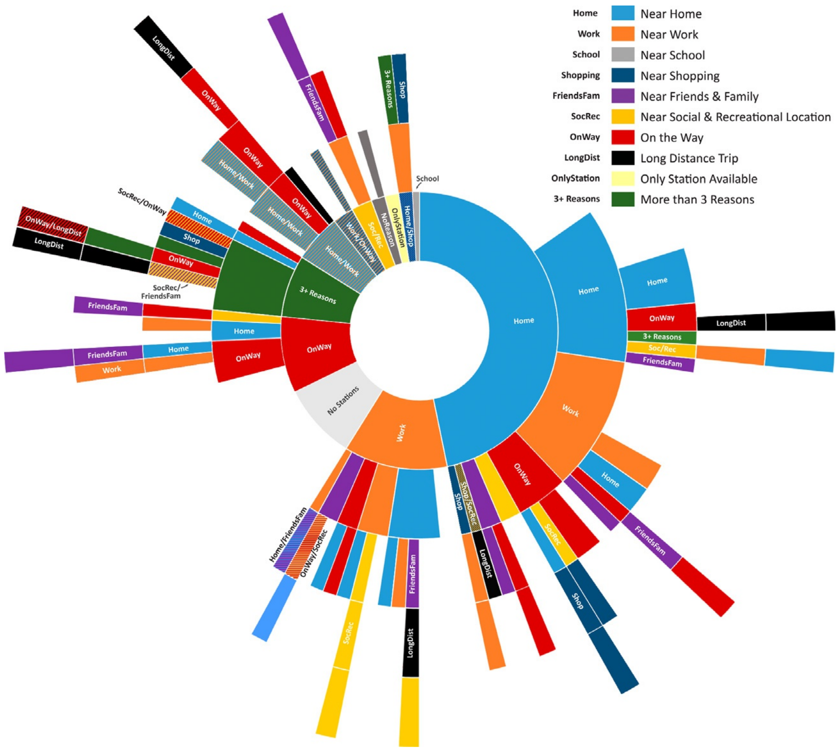

FIG. 10.3 The inner ring represents the main reason given for the respondent's first ranked station, continuing up to their fifth station listed on the outer ring. Each radial wedge represents one respondent. Wider wedges represent multiple respondents who identified the same ranking of station and reason. For interpretation, at the "3 o'clock" position, a respondent with a portfolio consisting of Home1-Home2-OnWay3-LongDist4-LongDist5 stations is visible. *(Credit: S. Kelley, A. Krafft, M. Kuby, O. Lopez, R. Stotts, J. Liu, How early hydrogen fuel cell vehicle adopters geographically evaluate a network of refueling stations in California. J. Transp. Geogr. 89 (2020a) 102897; S. Kelley, M. Kuby, O.L. Jaramillo, R. Stotts, A. Krafft, D. Ruddell, Hydrogen fuel cell vehicle drivers and future station planning: lessons from a mixed-methods approach. Johnson Matthey Tech. 64 (2020b) 279–286.)*

an FCEV without an HRS near home, but virtually all had one station within no more than a 6-min deviation between home and one of their frequently visited locations [48]. Of course, these findings should be corroborated elsewhere before generalization, but they do provide a helpful starting point for station network planning purposes.

Given that both stated and revealed preference studies have demonstrated the importance of stations being conveniently on the way for FCEV drivers, we review similar metrics for deviations. The simulation based on HRS coverage of the actual 68 planned hydrogen stations in California relative to current travel patterns suggested that drivers could expect to deviate between 2.5 and

9.6 min to reach a convenient station [41]. That was consistent with the revealed 6-min deviation observed by Kelley and Kuby [39] from their analysis of CNGV driving and refueling behavior, and corroborated by Kelley et al. [50,51] studies on the revealed spatial relationships between actual FCEV drivers' frequently traveled routes and stations. Kelley et al. [50,51] though found that the deviation depended on whether the station was primary, secondary, or third-fifth most important. The median deviation required by FCEV drivers to reach HRSs that they intended to use at the time of adoption was 3.4 min for primary stations, 7.1 for secondary stations, and 11.0 for those third-most important or beyond. After experience, a significant predictor of a driver switching to a station that they did not initially intend to use was a deviation of 3 min or less. Again, these should be examined elsewhere wherever possible but do offer some empirical measures for modelers to use when accounting for stations' convenience on the way.

In addition, revealed convenience between workplaces and stations considered to be "near" work is shown to decay more slowly than other nonhome location types in Kelley et al. [50,51] study, with 75% of these stations within 25 min of a work location. Drivers are willing to call stations "near" social or recreational destinations even when they are objectively farther away than other location types, as about 50% of stations are considered to be "near" these locations while they are actually more than 30 min away from them.

How station planners decide to incorporate the idea of "backup" stations, though, remains an open question. Given how prominent this topic has been in surveys and interviews with FCEV adopters, it would seem that a combination of either ensuring more reliable performance of stations and providing multiple stations near home or near or on the way to work or a regularly traveled route might help alleviate this concern. Ensuring a reliable and convenient infrastructure is essential: Krafft [54] interviewed 16 FCEV owners in California and found that most intend to keep their FCEVs after their lease expires, but for those not interested in leasing again, the process of refueling was one of their reasons why. This parallels the recent finding from Hardman et al. [55], who report that nearly 20% of both BEV and PHEV owners discontinued ownership of those vehicles and returned to a conventional one, often due to dissatisfaction with charging.

3. Geographic information system (GIS) models for HRS location

The development of HRS networks inherently raises questions of spatial location. Ideally, stations within an HRS network are well-located to meet the demands of potential fueling customers, providing multiple fueling options to support their day-to-day commutes and errands, occasional recreational activities, long-distance drives, and vacation or sight-seeing travel. At the same time, individual stations may need to be located such that they contribute to overall network health by adding redundancy, expanding market opportunities for FCEV deployment, or potentially increasing local fueling capacity to meet rising demand as the vehicle market grows. These questions of location are evaluated in the context of the physical world, with real impacts on the experience of FCEV drivers and the financial viability of HRSs. Stations that are conveniently located for drivers imply greater sales (with all other market competition forces being equal), and thus a more viable business. As a result, HRS location models that analyze real world, spatially resolved data are often utilized to understand where new HRS may be needed to support the growth and expansion of the FCEV market.

Much of the analysis to do so is carried out using geographic information system (GIS) platforms, such as ESRI's ArcGIS software or the freeware QGIS. These platforms are powerful tools for researchers and analysts to bring together multiple geospatial data sets, perform comparative analyses, and develop recommendations for new HRS locations. In recent years, high-resolution, high-fidelity spatial data have become increasingly available, enabling GIS models to become increasingly sophisticated and leading to high-precision recommendations for HRS location, HRS daily fueling capacity, and even in some case the sequential development of individual HRSs within network-buildout scenarios. GIS models have been applied to several pursuits, from theoretical research to practical application and use for private ventures and public support programs that cofund HRS development. In this section, we discuss the common features of GIS models for HRS location, introduce several recent models that have been influential in the literature and practice, and discuss the insights and limitations that have been made apparent through these efforts.

3.1 Overview of GIS model fundamentals

GIS models are explicitly intended to serve as representations of the real world. In the context of HRS networks, GIS models are often applied to analyze the geographic distribution of opportunity or need for new station development. Given that these models often rely on the built environment and data collected from residents, businesses, and other stakeholders located or traveling in the region of interest, there is often a tendency to consider GIS models as exact predictors. However, just like any model, GIS models are themselves simplified representations of reality, subject to certain sets of assumptions, conceptual frameworks, goals and objectives of the modelers, and limitations of imperfect data inputs, which themselves may have come from other models.

In practice, GIS models rely heavily on operations known as spatial overlays. Spatial overlays compare multiple data inputs mapped onto the geography of a region. These overlay functions may be additive or subtractive with respect to one another. For example, a GIS model that seeks to quantify the spatial distribution of potential FCEV adopters might assume that the likelihood of FCEV adoption correlates directly with household income and prior AFV ownership. Such a model may then overlay these two indicators such that the total market possibility is evaluated as the sum of the indicators. On the other hand, a GIS model built to evaluate the need for new hydrogen fueling stations may include a function that estimates the geographic distribution of hydrogen fuel demand. These spatial demand data may be considered in the model alongside data representing the distribution of available hydrogen fueling supply provided by built and/or planned HRS. These data inputs would then be compared in a subtractive overlay, such that the need for new fueling capacity is defined by the difference between demand and available supply.

The operations of spatial overlays are relatively simple in formulation and execution, but treatment of the input data for GIS models must be carefully considered. GIS models often consider spatial data available from a variety of sources, each potentially with its own spatial resolution, geometry, and attribute data types for each record. For example, an analysis may consider household income available at the census tract level in conjunction with vehicle registration data available at the resolution of ZIP codes. These geometries do not spatially align. A given ZIP code may be divided among several census tracts. Spatial misalignment between datasets is often resolved by applying an evaluation grid to GIS models. As with many other GIS model considerations, the appropriate method (averaging, summing, or other) for summarizing input data values into grid cells will depend on the intent and structure of the model.

In addition, even within a single dataset, each individual data entry may belong to geographic areas of widely varying size, e.g., urban vs rural census tracts. In addition, it is often appropriate to apply some form of normalization to the data to account for the spatial variation in data resolution and for comparison to other variables. For example, in a model that considers the count of households within each census tract that own multiple vehicles, the variable could be expressed as a proportion of all households within the census tract or in quintiles of all census tracts. Alternatively, a GIS model may consider the spatial density of such households, transforming the input data into an indicator like households per square mile. While it is commonly best practice to employ some form of normalization, the ultimate decision is usually led by consideration of the model goals.

In addition to overlay functions, GIS models often rely on more advanced functions to build a more fully informed representation of demand and supply. When spatial data used in GIS models may not completely cover the region, geospatial interpolation may be utilized to estimate areas not covered by source datasets. In the context of GIS, values of spatially resolved data may change systematically in some fashion as the distance grows from their point sources. For example, local concentrations of pollutant emissions generally decrease as one moves farther away from an emissions source according to a power-law function, while travel times from an HRS increase in an irregular fashion according to the speed of travel and route directness on the surrounding road network. Modern GIS platforms offer additional models for data interpolation with varying degrees of complexity and different methods for fitting the functions statistically or observationally. The choice of the appropriate method often depends on suitability of the method to the available data and the known geospatial relationships that may be available from outside sources.

Finally, given the transportation context, network analysis processes are often employed in GIS models to evaluate the convenience of fueling options provided by built and planned HRS. While many GIS models may use a simplified evaluation based on Euclidean distance from HRS station(s), others rely on evaluation according to drive times to or from stations or detours from shortest (or fastest) routes. To accomplish this analysis, the GIS model requires a spatially resolved and topologically correct network dataset. GIS models may employ road network data of varying fidelity; some models only consider highways or major arteries, while others consider all roadways within a region(s) of interest. Some models also use assumptions of travel speeds or posted speed limits based on roadway classification, while others use observed travel speed or leverage local planning organizations' traffic models. Network analyses are also often used to generate service areas, defined as the area around a station within one or more maximum drive times or travel distances. These can be used to define metrics that quantify the spatial correlation between known or projected need for HRS and the locations of stations (and even their daily fueling capacities) within the network.

3.2 Example GIS models for HRS location

This section reviews some of the prominent GIS models that have played a critical role in developing perspectives on HRS network development and strategies used in actual implementation. The majority of these models are from efforts within the United States, and particularly in California, but some models from other countries are presented as well. While not exhaustive of all models in the literature, this review provides perspective on some modern GIS models that have helped shape HRS location strategies that are in use today. While each model is built from common fundamentals of GIS, each model is unique, driven by differences in model intent, the framework adopted for evaluating FCEV driver adoption and infrastructure needs, geographic scope and scale of the model, and the available or assumed input data.

In the early 2000s, the US Department of Energy accelerated its research efforts in the area of hydrogen and fuel cell technologies. Development of hydrogen fueling infrastructure technology, analysis tools, and system-level insights has since become major pillars of this federal effort. Several studies of potential HRS network strategies have emerged from this program. One of the earliest GIS models is the nationwide analysis by NREL's Melendez and Milbrandt [4]. This foundational work helped identify the major urban markets across the United States with the greatest FCEV adoption potential. The model also provided spatial insights at multiple resolutions.

On the national level, Melendez and Milbrandt evaluated potential FCEV deployment on a 20×20-mile grid, illustrating the spatial variation of market opportunities across the states. This model demonstrated multiple concepts that have since become common features of other GIS analyses. First, as described in Section 2.1, key input parameters of the market evaluation included population metrics (household income, vehicle ownership, commute distance), incentives and supporting state or local policies, and environmental factors (such as whether the metropolitan area had a Clean Cities Coalition or was designated as a non-attainment area for National Ambient Air Quality Standards). Second, the study devised a numerical classification system that combines ranges of input data values into a limited number of classes representing “low” to “high” values, a step that is often necessary for both qualitative and quantitative data parameters, especially when their values may be subject to individual interpretation. Third, the study also introduced sensitivity analysis of the input variables via Monte Carlo analysis, expanding the model into the realm of scenario analysis. Fourth, scenario analysis was further expanded in the study through quantifying the total hydrogen demand in each 20×20-mile grid cell for various nationwide FCEV deployment scenarios (Fig. 10.4). For these analyses, vehicles were distributed across the evaluation cells according to each cell’s relative market strength and the relative size of each region’s observed vehicle sales to the national total.

A follow-up study at the subregional scale enabled higher resolution analyses of demand at the census-tract level, which were then used to evaluate potential optimal locations of individual HRS placement within several regional markets [4,56]. The GIS analysis to recommend station locations to serve these projected demands considered criteria informed by literature and focus groups, including: proximity to major shopping centers, placement along road segments with traffic volumes higher than the mean for the area, and along interstate highways to support longer distance travel, along with “balanced station coverage” within a geographic area. Their approach directly reflects the various geographic criteria that drivers consider when deciding where to refuel and those weighing the decision of whether or not to get an FCEV. Evaluations of service areas provided by each station were included and have since become a cornerstone concept in other GIS models.

These two early NREL studies are excellent examples of three key steps that have proven essential to most subsequent HRS station modeling: (i) choosing how to represent where the demand for refueling might be, (ii) identifying where that demand can be found in a particular geographic area, and (iii) deciding how to locate stations conveniently relative to that demand. Virtually every HRS station planning effort begins from this point. Of course, each GIS analysis is tailored to the region, client, and rollout stage and thus takes different approaches and uses different data. Identifying the necessary data to address

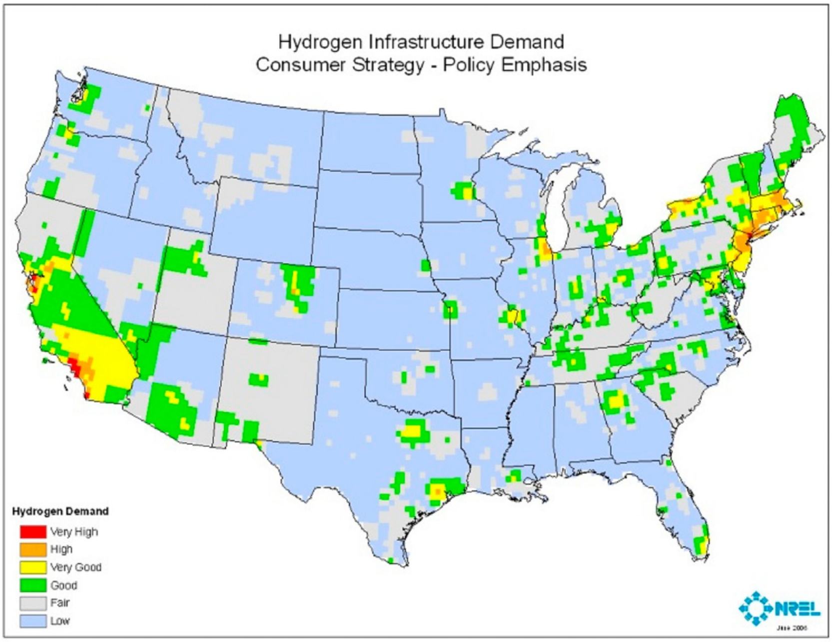

FIG. 10.4 Estimated hydrogen demand for a 20×20 mile raster grid for NREL's Consumer Strategy/Policy Emphasis Scenario. *(Credit: M. Melendez, A. Milbrandt, Geographically Based Hydrogen Consumer Demand and Infrastructure Analysis. National Renewable Energy Laboratory, Golden, CO (2006). Nationwide infrastructure evaluation for a policy-driven FCEV adoption scenario.)*

each of the three considerations can be a challenging task, as illustrated in subsequent GIS analyses in the United States and around the world, reviewed below.

The US Department of Energy has continued to develop its modeling tools over the years and has since introduced the Scenario Evaluation and Regionalization Analysis (SERA) model [57–59]. The model has become a platform for studying infrastructure and vehicle deployment for multiple AFV types, including FCEVs and BEVs. SERA is a powerful and complex scenario analysis tool with GIS functionality available at many geographic resolutions. Today, the tool even considers upstream hydrogen production and distribution infrastructure, evaluates finances along the hydrogen fuel chain, and uses these features in optimizing HRS and hydrogen production facility location. SERA achieves this because it is built from, or incorporates, functionalities similar to other US Department of Energy models, including H2A (hydrogen production analysis) [57–59], HRSAM and HDSAM (hydrogen refueling station and delivery models) [60], and H2FAST (hydrogen station financial evaluation) [57–59]. FCEV adoption is modeled in SERA through an Early Adopter Metric, which has evolved over the years but recent publications adopt a weighted evaluation based on HEV, PHEV, and BEV adoption (50%), luxury vehicle adoption (25%), and household income (25%).

As implied by its name, SERA is a powerful tool for scenario analysis. Because each component of SERA (market evaluation, station costs, etc.) has its own detailed model, the tool has significant flexibility to explore HRS network development concepts. For example, SERA has been used to explore the implications of HRS network strategies with varying emphasis on station clustering and density, as opposed to scenarios that aim for more expansive geographical coverage [61]. Other scenarios investigated variations in future station capacity and emphasis on high-capacity stations. In 2018, SERA was applied to national HRS network development in multiple scenarios of FCEV adoption rates as part of the public-private collaboration called H2USA. The scenarios for potential nationwide network growth included 8000 to 21,000 HRSs supporting 23–61 million FCEVs by 2050 [62]. The analysis also presented strategies for the sequence of markets to activate and the order of stations to be built in each market (Fig. 10.5).

To date, the vast majority of HRS network development in the United States has occurred in California. Over the years, several concepts have been investigated, from Governor Schwarzenegger's proposed Hydrogen Highway to today's more flexible public-private co-funding strategy administered by the California Energy Commission's Clean Transportation Program [18]. Three sources of modeling have been particularly influential in the state, including several modeling efforts by researchers at the University of California, Davis (UC Davis), the Spatially and Temporally Resolved Energy and Economy Tool (STREET) developed at the University of California, Irvine (UC Irvine), and the California Hydrogen Infrastructure Tool (CHIT) developed at the California Air Resources Board (CARB).

Early GIS investigations by researchers at UC Davis investigated questions that arose as the State of California began developing and implementing a plan to co-fund the development of an HRS network. One key insight was to identify minimum network sizes to initiate FCEV adoption [63]. In terms of coverage (or access to a station within convenient drive times), they demonstrated that the gasoline fueling network greatly exceeds the need for stations necessary to satisfy most drivers' requirement for basic geographic convenience. A viable early hydrogen network could be achieved with relatively few HRSs, especially at metropolitan scales.

Ogden and Nicholas [64] demonstrated that clustered HRS development in regional networks could more quickly enable FCEV deployment while minimizing costs (Fig. 10.6). These clustered developments would be focused in smaller areas identified by auto manufacturers as having high market potential, which provides the benefit of potentially rapid growth in vehicle adoption and station utilization. Station location within the clusters could also be optimized to minimize either the drive between stations and adopters' homes or the diversion

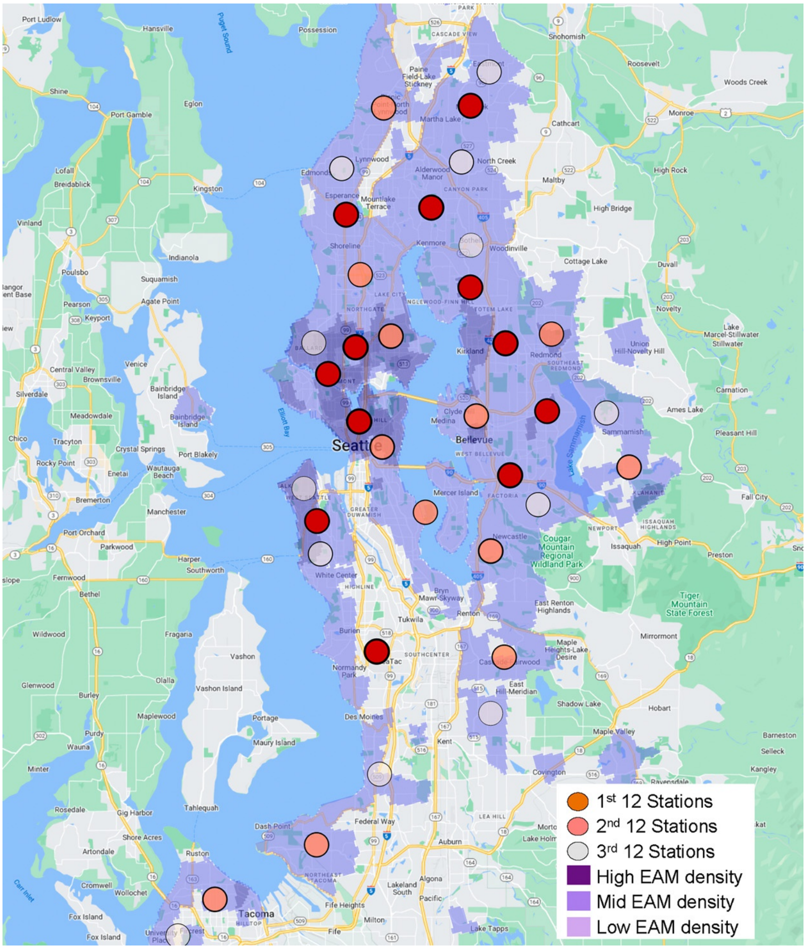

FIG. 10.5 SERA network analysis demonstration for greater Seattle region. *(Credit: M.W. Melaina, B.W. Bush, M. Muratori, J. Zuboy, S. Ellis, National Hydrogen Scenarios: How Many Stations, Where, and When? No. NREL/TP–5400-71083 (2018) 1461868. https://doi.org/10.2172/1461868.)*

from typical driving routes. UC Davis analyses are also unique in advancing a case for mobile refuelers to address a portion of hydrogen fueling demand [65]. While no retail mobile fuelers have been deployed in California, the concept has gained traction in Japan, where several mobile fuelers are available for limited times each day at several locations within a city.

UC Davis studies also advanced a strategy of small-station (around 100 kg/day capacity) development in early years to contain costs while the vehicle market grew. However, researchers also noted that while the early costs are higher for networks with larger stations (around 1000 kg/day capacity), it could lower costs and prices paid by consumers in the long run. Later investigations

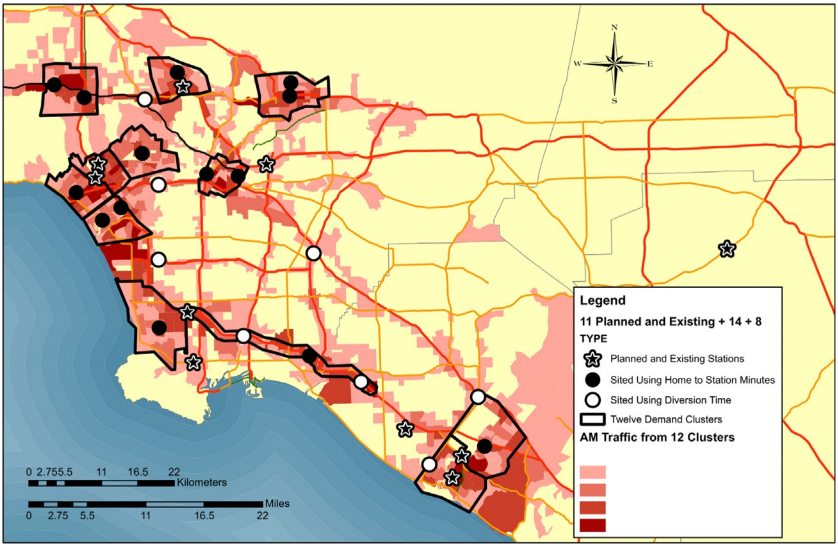

FIG. 10.6 UC Davis evaluation of HRS locations in clusters around southern California. *(Credit: M. Nicholas, J. Ogden, An Analysis of Near-Term Hydrogen Vehicle Rollout Scenarios for Southern California. University of California, Institute of Transportation Studies, Davis, CA (2010).)*

also combined GIS analysis of vehicle adoption, network strategies, and hydrogen production scenarios to model the complete hydrogen fuel infrastructure chain in markets across several states. These scenarios demonstrated the possibility of catalyzing FCEV sales in "lighthouse cities" to minimize the cost of producing, distributing, and selling hydrogen fuel.

The STREET model developed by Stephens-Romero and Samuelsen [66] at UC Irvine has similarly proven influential in California's strategy for HRS network development. Based on GIS analysis of gasoline fueling networks in Southern California communities, they found that a 6-min drive time to an HRS would provide similar convenience to the experience provided by today's gasoline station network [67]. This metric has since been adopted (among other drive times) in subsequent evaluations of California's HRS network development. STREET also incorporates spatial and temporal emission and air quality modeling [66,68].

STREET incorporates aspects of both GIS and operations research (OR) modeling. The OR aspects will be presented later in this chapter; here, we focus on the GIS side. The model relies on a combination of data provided by auto manufacturers on potential FCEV early adopters, the spatial distribution of HEV adopters, and residential land use to develop high-resolution areas for targeted network development (Fig. 10.7). The STREET model was used to develop an initial statewide network development plan of 64 HRSs as described in the California Fuel Cell Partnership's *Roadmap* [28]. The 64 stations were

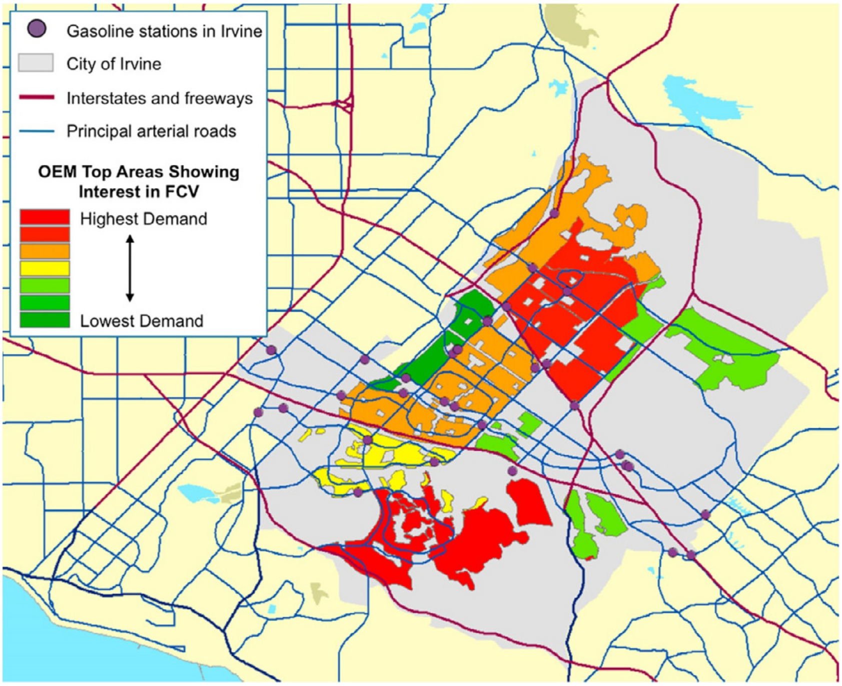

FIG. 10.7 STREET evaluation parameters demonstrated for city of Irvine, CA. *(Credit: S.D. Stephens-Romero, T.M. Brown, J.E. Kang, W.W. Recker, G.S. Samuelsen, Systematic planning to optimize investments in hydrogen infrastructure deployment. Int. J. Hydrogen Energy 35 (2010) 4652–4667.)*

primarily located in 5 regional clusters: West Los Angeles/Santa Monica, Torrance, Coastal and South Orange County, Berkeley, and the South San Francisco Bay Area. Auto manufacturer input identified connector stations to facilitate long-distance and intercluster travel and destination stations to enable vacation and leisure travel. The STREET model's findings refined the cluster model and directly guided state cofunding of early grant solicitations.

As interest in California's HRS cofunding opportunities grew, the needs for location evaluation tools evolved. Station developers participating in the state programs often encountered difficulties that could not easily be captured or anticipated by a modeling tool. In California, the vast majority of HRSs are constructed on leased land that is the property of existing gasoline stations. While some local areas may seem attractive for HRS location based on GIS evaluations of FCEV market potential, station developers often have difficulty finding or maintaining station owner interest in hosting hydrogen fueling infrastructure on their property. Other times, local factors (concerns or additional requirements suggested by residents, the business community, or even the permitting process) make a proposed location financially or practically unviable. These issues only become apparent once a station developer begins the process of engaging the site owner and community about the proposed HRS location.

A newer modeling platform with greater flexibility was needed to evaluate the HRS locations proposed by station developers rather than confining their possibilities to locations determined a priori. To address this need, CARB launched the California Hydrogen Infrastructure Tool (CHIT) [69]. In contrast with models like STREET, SERA, and the UC Davis tools, CHIT requires additional analysis or interpretation of the results to develop or assess a full network strategy. CHIT was instead developed with the intent to provide a basis to compare multiple locations proposed by multiple station developers within a consistently applied evaluation framework. In CHIT, all evaluations are completed using a high-resolution quarter-mile evaluation grid, and the roadway network represents all roads in California with estimated peak-traffic travel speeds based on observational and modeled data from local planning authorities.

In its first iteration, CHIT evaluated the relative need for new stations by comparing the coverage of the existing and funded hydrogen fueling network to the home locations of modeled first adopters (Fig. 10.8). First adopters were estimated using household income, education, luxury vehicle adoption, the sales of vehicles with prices similar to FCEVs, and the adoption rates of HEVs

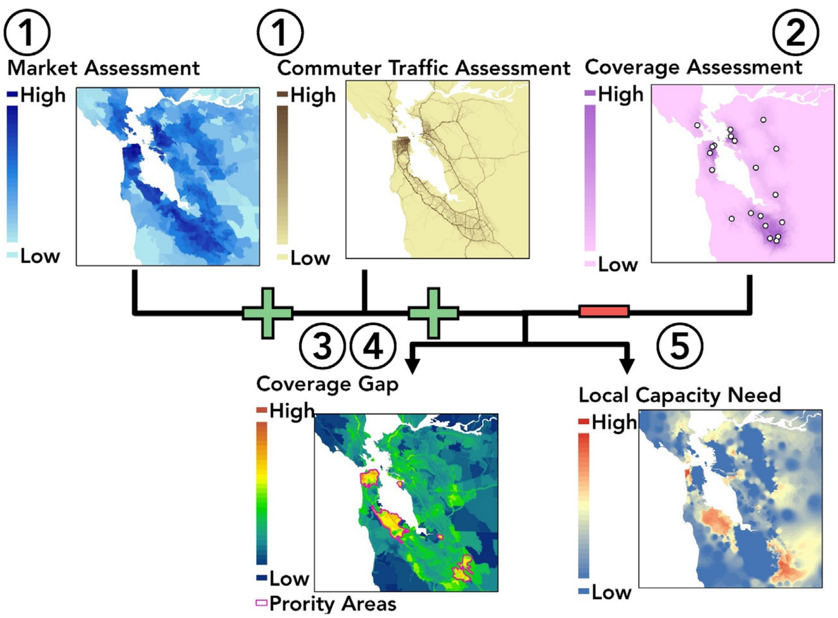

FIG. 10.8 CHIT evaluation process. *(Credit: California Air Resources Board. 2021 Annual Evaluation of Fuel Cell Electric Vehicle Deployment & Hydrogen Fuel Station Network Development. California Air Resources Board, Sacramento, CA (2021a).)*

and PHEVs. BEV adoption was intentionally not considered in CHIT because, unlike hybrid and fuel cell options, BEVs represent a vastly different relationship between driver and fueling infrastructure compared with conventional technologies. In the 2017 CHIT update, commuter traffic patterns were added as a consideration for where the hydrogen fueling market may be located [70].

CHIT was also unique in its evaluation of coverage provided by the existing and funded network. Prior models tended to evaluate coverage as binary; either coverage existed (to some distance or drive time away from a station) or not. In CHIT, coverage is instead quantified based on the number of stations within the area of coverage and the drive time to each station. Thus, CHIT evaluates varying degrees of coverage, which enables analysts to identify the need for redundant or closely clustered stations if local FCEV market potential is strong enough (and capacity needs are large enough). CHIT identifies the local need for new fueling capacity based on the known hydrogen fueling network projects and exogenously defined statewide projections of future fuel vehicle deployment.

Since it was introduced, CHIT has been integrated into planning and proposal evaluation in California's HRS cofunding program and annual evaluations of the current status and future outlook for HRS network development and FCEV deployment [19,71]. With the addition of separate scenario evaluation tools, CHIT has been leveraged to define and evaluate a vision toward 1000 HRSs supporting 1 million FCEVs by 2030 [72]. This methodology was later expanded and combined with a station economics model to evaluate the potential need for future state funding programs beyond those already in statute and helped demonstrate strategies that lead to a financially self-sufficient HRS network [71]. These scenario analyses have provided insight into location prioritization and expansion of the HRS network into new markets.

Interest in HRS network development has also grown in the northeast region of the United States. Although not yet open, development has begun on a small network of 12 HRS across the northeast. Further expansion from this initial HRS network is explored in plans developed for eight northeast states (e.g., [73]). The Northeast Electrochemical Energy Storage Cluster (NEESC) plans differ from the previous models in several ways. First, the GIS evaluations consider both LDVs and transit buses. The LDV market considers the location of households with estimated first adopters (based primarily on income) and the locations of known commercial fleets. These data are combined to map out the potential FCEV fleet density across each state (Fig. 10.9). However, the GIS modeling in these plans stops short of recommending specific locations for HRS development. Rather, it serves more as a resource for interested stakeholders to make their own informed decisions about potential new HRS locations.

Comparatively less information is available for GIS modeling efforts that have guided HRS network development outside of the United States. In Germany, a GIS model incorporates extensive information about the German

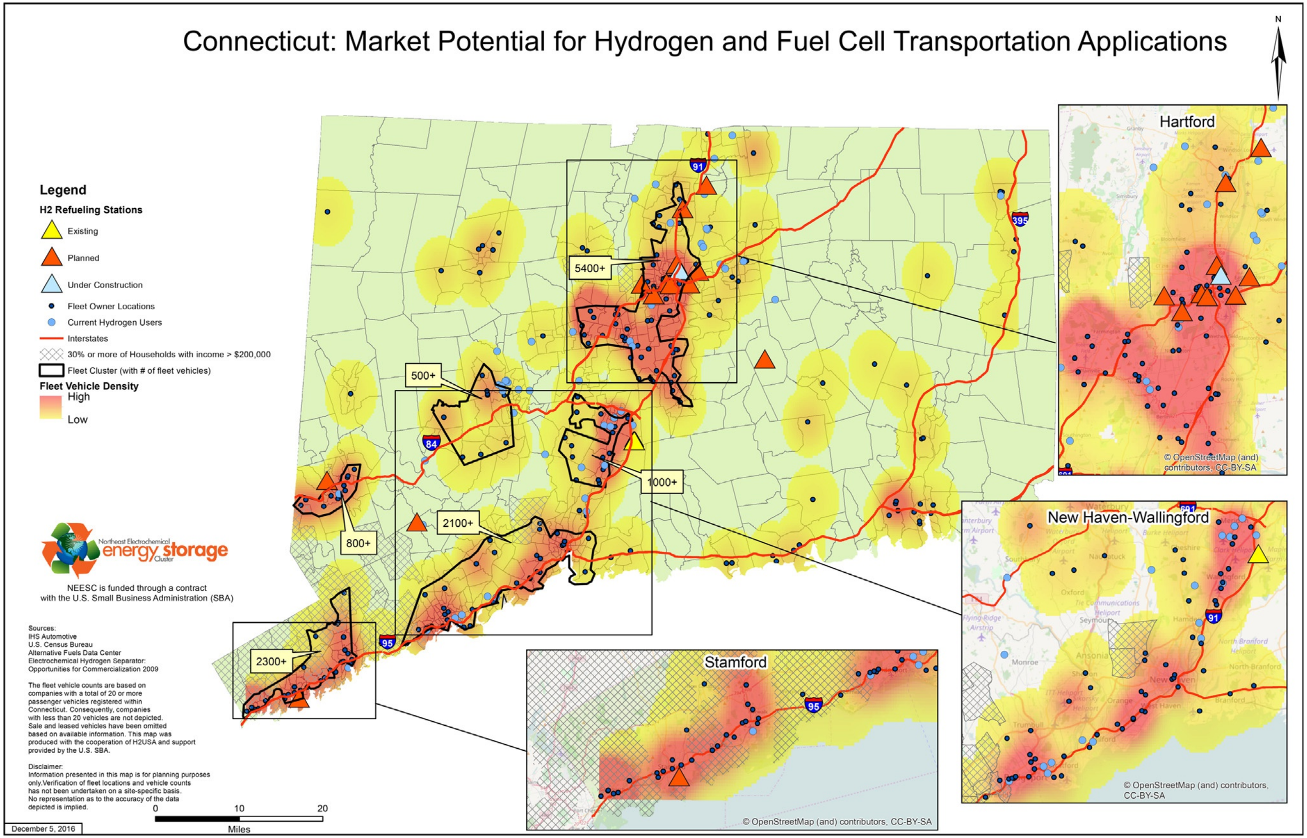

FIG. 10.9 Evaluation of HRS potential in Connecticut based on fleet and private vehicle locations. *(Credit: NEESC, J.M. Rinebold, A.C. Barton, Hydrogen and Fuel Cell Development Plan "Roadmap 2020". Connecticut Hydrogen Fuel Cell Coalition, East Hartford, CT (2020).)*

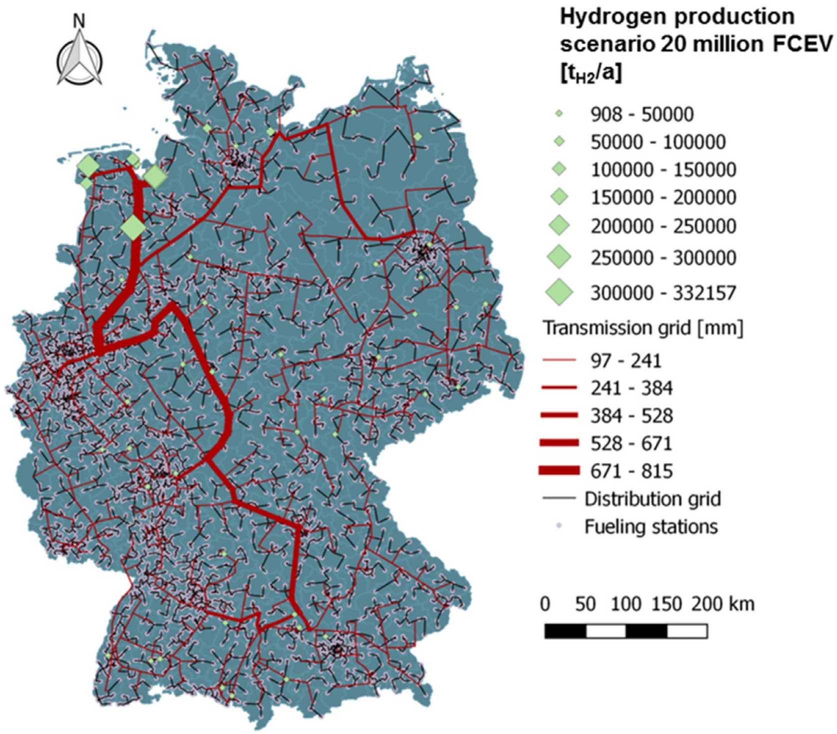

FIG. 10.10 Full infrastructure buildout scenario for 20 million FCEVs in Germany. *(Credit: M. Robinius, J.F. Linßen, T. Grube, M. Reuß, P. Stenzel, K. Syranidis, P. Kuckertz, D. Stolten, Comparative Analysis of Infrastructures: Hydrogen Fueling and Electric Charging of Vehicles. Schriften des Forschungszentrums Jülich, Julich, Germany (2018).)*

energy sector, including the electricity grid and potential hydrogen production and distribution infrastructure [74]. This GIS model has been used to identify priority locations for HRSs (Fig. 10.10) and also to evaluate scenarios and costs of deployment of zero-emission vehicle technologies. For instance, the model has demonstrated that within the context of Germany's current energy infrastructure, the development of charging infrastructure to support BEV deployment is cheaper than HRS network development in the early market (up to approximately 10 million vehicles) [75]. For larger market transformation, however, HRS network development may be 20% less costly than EV charger network development.

Japan's 2019 Strategic Road Map cites the need to optimize HRS location for FCEV adoption, following a strategy focusing on four major metropolitan areas and major transportation corridors [76]. Optimized locations are identified by the public-private Japan Hydrogen Mobility, relying on an OR model (see Section 4). However, GIS-based models have also been used to model station placement. Japan's HRS network is somewhat unique in that it incorporates several mobile fuelers that are available at various locations in a city at different times of day. Fuse et al. [77] later evaluated mobile refuelers using GIS and found benefits for the first-adopter phase. The model uses HEV adoption as a surrogate indicator for FCEV market potential (Fig. 10.11A) and identifies preferred station locations (Fig. 10.11B) based on maximizing coverage of market potential and, uniquely, fueling station locations with sufficient area lot size to meet hydrogen storage safety standards.

Brey et al. [25] developed a GIS model to investigate the sequential rollout of HRSs in Spain. The model adopts a nodal perspective, evaluating regions as a whole for their FCEV market potential and HRS needs. FCEV market potential is estimated based on regional renewable energy availability, kilometers of roadway, number of registered vehicles, pollution, and per capita income. Nodes are selected in sequence based on scenario-defining parameters of the rate of FCEV deployment, the associated portion of the population that needs hydrogen fueling access, and the desired maximum distance between nodes. The methodology considers stations intended to meet local market fueling needs and those needed to enable long-distance travel. The model then determines how many stations should be developed in each node in sequential time frames, with the FCEV population and maximum distance parameters specified in each time frame (Fig. 10.12).

3.3 Insights from GIS model implementation

As these models illustrate, the frameworks, goals, and applications of GIS models for HRS network development vary greatly. Over time, GIS models have increasingly expanded their scope beyond the market-based approach of siting HRS to meet customer demand and convenience metrics. The examples above include environmental evaluation, economic evaluation, and supply chain modeling. This is partially because each new set of answers to early questions raises an even larger set of new questions, expanding the scope of GIS applications. Analysts continue to refine the models as new experience in the nascent HRS development industry helps to better inform the needs for HRS models. In California, models have moved away from high specificity to greater flexibility. This has been largely due to the need to address the experiences of a wide array of stakeholders and the difficulty of modeling or predicting some aspects of physical infrastructure.

In addition, the FCEV adopter market is still relatively small, with only tens of thousands of vehicles deployed worldwide by the end of 2021. Many of the models above identify potential vehicle adopters based on assumptions of defining characteristics. As shown, there are many thoughts regarding the appropriate metrics. As the FCEV market grows, in-depth studies will be required to validate these assumptions or develop new understanding. As Section 2 demonstrated, we are only beginning to understand FCEV adopters' and nonadopters' decisions and drivers' behaviors when presented with an actual network

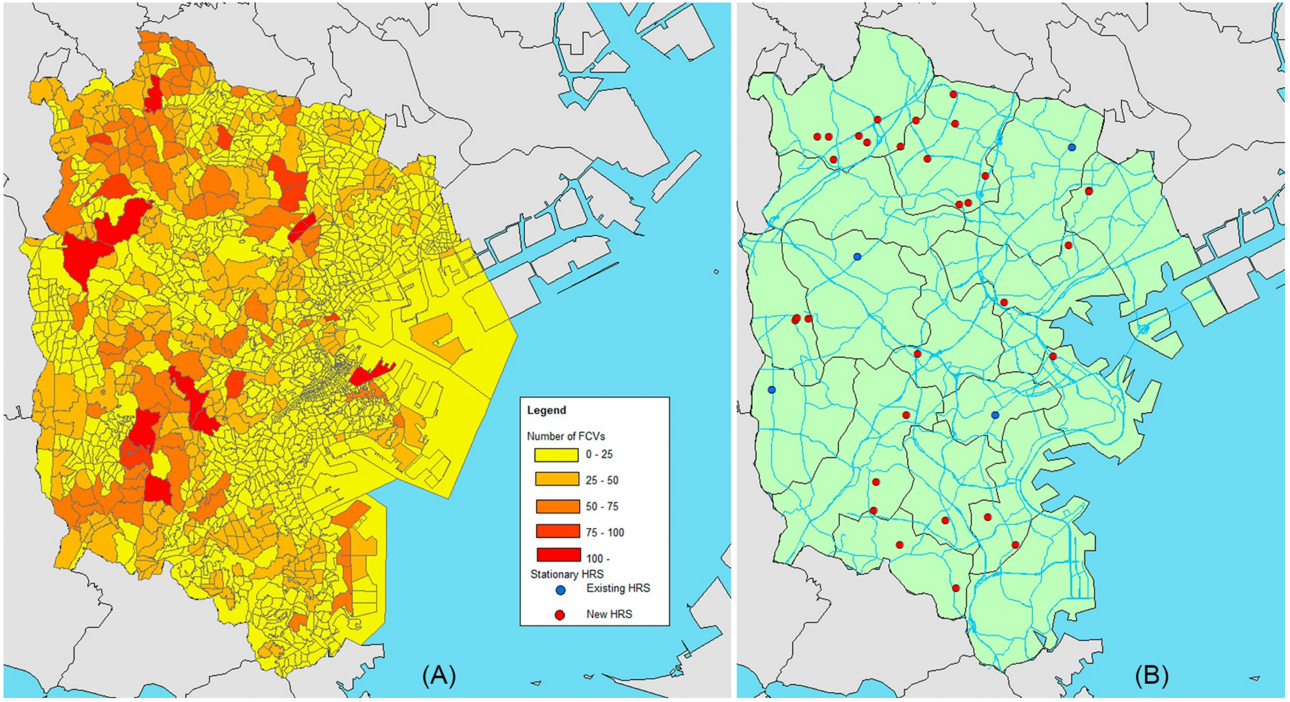

FIG. 10.11 Optimistic scenario evaluation of FCEV market potential (A) and HRS location needs (B) in Yokohama. *(Credit: M. Fuse, H. Noguchi, H. Seya, Near-term location planning of hydrogen refueling stations in Yokohama City. Int. J. Hydrogen Energy, ICHS 2019 Conference 46 (2021) 12272–12279.)*

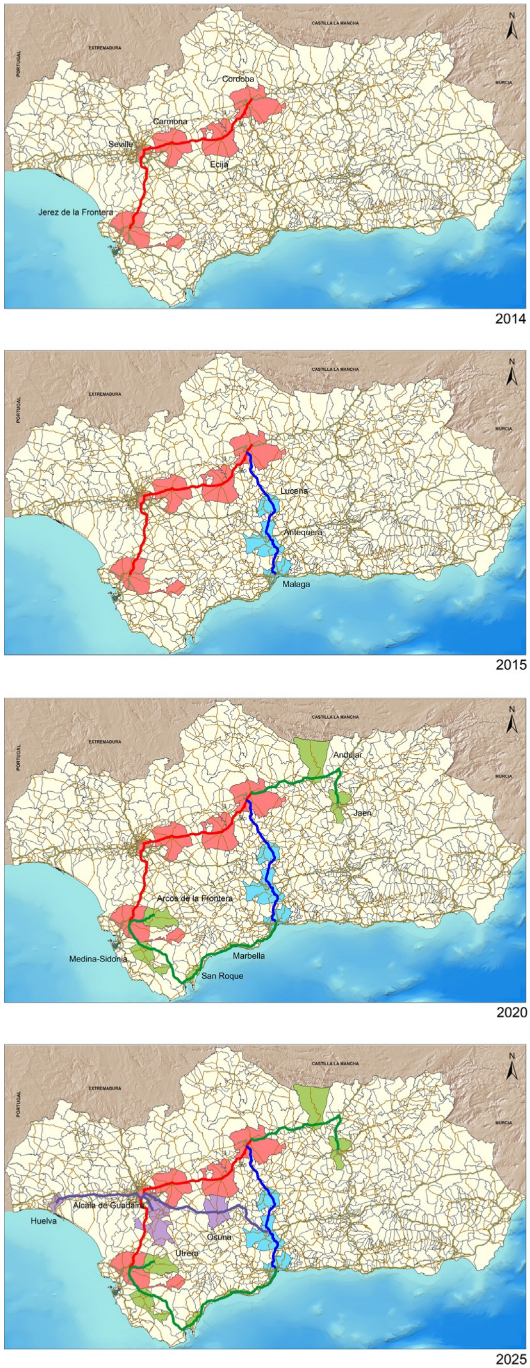

FIG. 10.12 Sequential HRS development in Spain's Andalusia region. *(Credit: J. Brey, A. Carazo, R. Brey, Analysis of a hydrogen station roll-out strategy to introduce hydrogen vehicles in Andalusia, Int. J. Hydrogen Energy 39 (2014) 4123–4130.)*

with multiple HRS options, given that all HRS networks around the world are relatively sparse. GIS modeling can help elucidate refined models of driver refueling choices.

As zero-emission vehicle (ZEV) technology becomes more commonplace, governments have begun to more closely evaluate the equity implications of deployment strategies, especially when supported by public funds. This is especially important for ZEV adoption, given the higher purchase price and total cost of ownership compared with conventional vehicle options. While ZEVs offer climate, environmental, and health benefits, some of these are localized to the associated fueling infrastructure and/or the vehicle driving routes. Thus, a careful balance must be achieved to ensure the benefits are equitably shared among communities. In addition, there could be incremental burdens (such as increased traffic due to infrastructure location) that must be understood, as well as any need for additional station subsidies to support potentially underutilized stations. This area of study is relatively new, but GIS-based models and evaluations may be a key component to ensure equitable zero-emission infrastructure development.

4. Operations research (OR) models for HRS location

The field of optimal facility location models using OR methods began in earnest in the 1960s with the development of mixed-integer programming (MIP) models and heuristic algorithms for the plant location and the *p*-median problems. From the 1970s to 1990s, researchers introduced new fundamental problems and extensions, developed faster solution methods, and applied the emerging methods to many kinds of facilities [78]. Yet until the early 2000s, almost no papers were published on optimal location of refueling stations. It is unknown whether oil companies used OR methods in-house, or whether the dearth of papers was due to the saturation of the landscape with competing gas stations at the same intersections. In fact, the earliest application of OR to fuel stations that we know of dealt with rationalizing the network of gas stations while sacrificing as little accessibility as possible [79]. It took the advent of more environmentally friendly fuels and vehicles to spark the development of this literature. The next earliest paper we have found aimed at locating stations to sell unleaded gasoline in India [80]. Neither of these early works cited any earlier OR applications for locating fuel stations. Interestingly, rather than starting with a basic approach, both were multiobjective models.

More optimal alt-fuel station location models were introduced in the 2000s, and the literature grew rapidly in the 2010s as natural gas, electric, biofuel, and hydrogen vehicles and stations were commercialized. Station location models are solved on a network consisting of arcs (road segments) and nodes (road junctions). In this section, we classify the models mainly in terms of how demand is expressed geographically, as nodes, arcs, origin-destination paths, and round-trip tours on a network. Note that each of these types of models implies certain assumptions about the refueling behaviors reviewed in Section 2. We then highlight some multiobjective models that combine these kinds of demands and conclude with some papers that have attempted to compare these methods against each other in terms of some type of common metric.

Throughout this section, we use the terms "shortest," "nearest," and "closest" interchangeably to represent the lowest "travel impedance" between two locations, which can be measured in terms of distance, travel time, or other generalized cost. In some cases, this could be a function of Euclidean or rectilinear grid distance, but ideally should be a function of fastest network travel time on a network where travel speed varies from arc to arc. Most models use speeds based on off-peak free-flow posted speed limits, but some explicitly account for network congestion. When driving range is included in a model, best practice calls for generating likely routes based on travel *time* while measuring the driving range against the *distance*. A few models have attempted to account for topography, wind, and other factors in estimating energy consumption that is not strictly a linear function of distance. Likewise, we use the term "weight" to describe the amount of demand at each node, which could be operationalized as resident population, households, likely customers, spending power, number of vehicles, or other measure of potential demand in a zone, which also relates back to the behaviors and data reviewed in Section 2.

4.1 Node-based models

Most classic approaches to optimal location of many kinds of public and private facilities aim to serve demands represented as points or nodes. Usually, the demand weight is the aggregated total for the surrounding zone, while the node itself serves as the point from which distances and travel times are measured. In node-based models, demand is assumed to be served by the nearest available station or a station within a certain distance. The literal interpretation of this assumption is that drivers travel from home to their nearest fuel station and back with no additional stops in order to refuel, which we know accounts for fewer than 10% of refueling trips [23] and possibly as few as 1% [40]. A more liberal interpretation is that drivers prefer stations near home, are more likely to patronize stations near home, and are more likely to purchase an FCEV if there is a station near home, all of which are true.

4.1.1 p-*Median models*

The p-median model [81] is probably the most widely applied location model across all kinds of facilities. It locates a given number of facilities p and allocates demand nodes to their nearest facility in order to minimize the total weighted travel time or distance in terms of person-miles or person-hours of driving to reach the nearest facility. Hakimi proved that the search for an optimal median solution can be restricted to the nodes of a network, eliminating the need for considering candidate sites on arcs. Revelle and Swain [82] first formulated the p-median problem as an MIP:

p-Median Model Formulation

$$\text{Min} \sum_i \sum_j a_i t_{ij} Y_{ij} \tag{10.1}$$

subject to:

$$\sum_j Y_{ij} = 1 \ \forall \ i \tag{10.2}$$

$$Y_{ij} \leq X_j \ \forall \ i,j \tag{10.3}$$

$$\sum_j X_j = p \tag{10.4}$$

$$Y_{ij} \in \{01\} \ \forall \ i,j \tag{10.5}$$

$$X_j \in \{01\} \ \forall \ j \tag{10.6}$$

where $X_j = 1$ if an HRS is opened at j, 0 otherwise (decision variable); $Y_{ij} = 1$ if demand node i is allocated to HRS j, 0 otherwise (decision variable); a_i = demand weight of node i (e.g., number of people, cars.); t_{ij} = travel time from demand node i to HRS j (e.g., minutes); and p = number of HRSs to open.

Objective function (10.1) minimizes total travel time for all demand weight to reach its nearest station. Since the total demand is a constant, this also minimizes average travel time. Constraint (10.2) states that all demand nodes i must be allocated to a station. Constraints (10.3) prevent nodes i from allocating to a station j unless the station at j is open, while (10.4) constrains the total number of stations opened to p. Eqs. (10.5) and (10.6) define the decision variables as 0–1 binaries, meaning no fractional allocations or station openings.

Nicholas and Ogden [27] were one of the first to site HRSs using the p-median model, which they applied to four metropolitan areas in California. They used existing gasoline stations as candidate sites, populations as demand weights, and driving times using a national database of major roads. By varying the number of stations p, they generated a declining curve showing the reduction in average travel time as a function of the percentage of gasoline stations outfitted with hydrogen pumps, and thus estimated how many stations would be necessary to achieve average access times between 3 and 7 min.

Itaoka [13] applied the p-median model at the national scale in Japan to develop an HRS rollout plan for 100–400 stations, which continues to serve as their blueprint for a national backbone of stations. Demand weights were estimated in several ways, including by middle-class and luxury car buyers. Lin et al. [83] generated data for the demand weights in a p-median model from

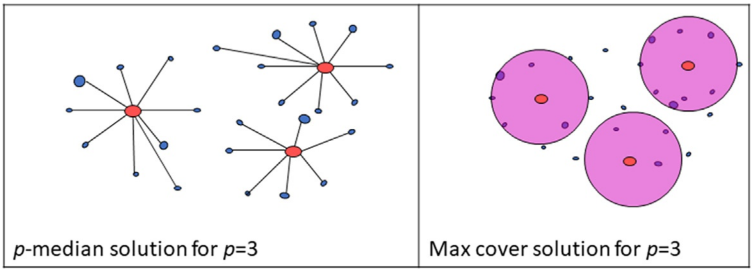

FIG. 10.13 Location-allocation (median) vs covering models. *(Credit: Authors.)*

economic, demographic, and traffic data. Islam et al. [84] measured their median objective in terms of total cost of energy lost getting to charging stations.

4.1.2 Covering models

Covering models are the next most popular model across all kinds of facilities but have greater potential to be misapplied. The word "cover" has a specific meaning in OR that is not synonymous with "serve" or "allocate." A demand node is covered if it is located within a threshold service distance or critical travel time requirement of a facility (Fig. 10.13). Covering models are ideal for service defined by a legal, physical, physiological, or widely accepted all-or-nothing standard, such as cell towers or warning sirens or emergency services such as fire stations and ambulance depots. Covering models also make sense when access or satisfaction can be characterized on a graph by a plateau with a sharp drop-off to nearly zero.

There are two main versions of covering models, both of which have been applied to HRSs. The Location Set Cover Problem (LSCP) minimizes the number of facilities (10.7) needed to cover every demand node i (10.8) [85].

Location Set Covering Model Formulation

$$\text{Min} \sum_j X_j \tag{10.7}$$

subject to:

$$\sum_{j \in N_i} X_j = 1 \ \forall \ i \tag{10.8}$$

$$X_j \in \{01\} \ \forall \ j \tag{10.9}$$

where N_i = the set of candidate sites j that can cover node i.

In cases where complete coverage is an unrealistic goal in terms of budget, the maximum cover problem maximizes the sum of demand weight covered (10.10) subject to a constraint on how many facilities p can be built (10.11). Constraints (10.12) ensure that a demand node i is covered ($Y_i = 1$) only if one of the facilities capable of covering it is opened [86].

Max Cover Model Formulation

$$\text{Max} \sum_{i} a_i Y_i \tag{10.10}$$

subject to:

$$\sum_{j} X_j = p \tag{10.11}$$

$$\sum_{j \in N_i} X_j \geq Y_i \; \forall \, i \tag{10.12}$$

$$X_j \in \{01\} \; \forall \, j \tag{10.13}$$

$$Y_i \in \{01\} \; \forall \, i \tag{10.14}$$

where $Y_i = 1$ if an HRS is opened within covering distance of demand node i, 0 otherwise (decision variable).

In either covering model, if the fixed cost of stations varies significantly from one location to another, the set cover objective (10.7) or max cover budget constraint (10.11) can be expressed in dollars instead of a count of facilities. Because most station rollouts are limited by their budget, the max cover model has been more popular for HRS applications.

In the HRS literature, the critical threshold can be defined based on desired goals, current gas-station service levels, or revealed or stated preference survey research. Stephens-Romero et al. [67] solved LSCPs for driving times of 2–5 min. In another example, Itaoka et al. [13] did a postoptimization evaluation of their p-median results to see how much demand in Japan would be covered using a 15-min driving time standard. Comparing to models in the BEV charging station literature, Asamer et al. [87] used a max cover model with a service standard of 5 min or 8 min of drive time from home. In contrast, for public BEV charging stations where drivers park and charge their cars and then walk to work, shopping, or other activities, covering models have been based on walking distances, such as 500 m by Efthymiou et al. [88] and 1 km by Bouguerra and Layeb [89]. Frade et al. [90] assumed 400 m for full coverage but gave credit for partial coverage up to 600 m and also consider both nighttime residential demand and daytime demands based on building types and employment. Defining the service standard based on driving range, however, is not recommended. For instance, a cover distance equal to half of the vehicle range would imply that half of the range can be expended to get from a covered node to the station and the other half to get back, with no fuel to accomplish anything else.

In choosing between median and covering models for node-based demands, there are a few points to keep in mind. When an all-or-nothing maximum travel time or distance cannot be reasonably assumed or agreed upon, a median approach may make more sense because there is no reasonable cutoff, just an increasing penalty with increasing distance. Be aware, however, that the p-median model will allocate all demand nodes to their nearest station regardless of how far away that is, which may be equally unrealistic. Various hybrid models have been developed in the OR literature to address these issues.

Both classic node-based models can be solved in numerous ways. In addition to the MIP formulations, researchers have developed many heuristic algorithms and meta-heuristics to solve larger problems faster to near-optimal solutions, including greedy, neighborhood search, exchange, genetic, Tabu search, Lagrangean relaxation, and particle swarm/ant colony heuristics [78].

4.2 Arc-based models

Arc-based models generally use road segments as the network features that generate the demand for fuel, as a function of the link's traffic count (average annual daily traffic, AADT) or vehicle-miles traveled (AADT × length). The behavioral concept behind them is that where people drive more is where they need refueling more. One of the best-known arc-based models for HRSs is the Fuel Travel Back model of Lin et al. [91]. The name derives from the behavioral simplification that when a vehicle's fuel tank or battery drops to a certain level, the driver leaves the arc, travels to the nearest station, fills up, and "travels back" to the same arc to continue the trip. The likelihood of vehicles reaching that level while on a given arc is proportional to the arc's VMT. The Fuel Travel Back model operationalizes this by placing a demand node at the arc centroid, weighting the nodes by the arc's VMT, and solving a p-median model.

Boostani et al. [92] define an Arc Demand Coverage Problem for completely covering a hierarchy of arcs using some fractions of the vehicle driving range as the coverage distance. In this model, higher level arcs (e.g., highways) can cover lower level arcs (arterial streets) but the reverse is not allowed. Sathaye and Kelley [93] model travel corridors and determine the necessary charging station density on these long arcs. Other arc-based models use the traffic volume of the arc(s) on which the candidate site is situated [2,79,94]. Other studies used the VMT of all arcs within a given neighborhood or buffer. However, summing AADT across multiple arcs in a zone risks double-counting the same vehicles as they pass over multiple arcs. To address this problem, Zhong et al. [95] developed a method to approximate the number of unique vehicles passing through a station's service area, which was then used in a max cover model for serving long-distance CNG trips.

In general, arc-based models do not explicitly test whether long-distance trips on shortest paths can be completed without running out of fuel, but a few models address the issue in other ways. In Boostani et al.'s Arc Demand Coverage Problem, if the cover distance is set to no more than half the driving range, then it will be possible to get from anywhere to anywhere by relaying from one station to another, but the resultant routes might zigzag inconveniently. Csiszár et al. [94] use a greedy-adding "oil stain" algorithm to optimize fast-charging stations for EVs using distance-based penalty or credit functions to discourage stations being too close or too far away. Zhong et al. [95] proposed that it is possible to achieve long-distance connectivity in an arc-based model by (a) including only arcs and candidate sites on interstate highways, (b) setting a large enough inter-station separation distance so that stations will be useful as "stepping stones" on long trips, and (c) adding more and more stations until they are forced close enough together to not exceed the driving range. Ultimately, however, the challenges of ensuring that origin-destination trips can be completed without running out of fuel leads to the next category of OR model: flow-based models.

4.3 Flow-based models

Flow-based models require an origin-destination (O-D) trip matrix as the geographic demands to be served. The behavioral concept is that drivers stop for fuel on their way between origins and destinations, and the models optimally locate stations to intercept these trips and refuel them. Many metropolitan areas generate O-D trip matrices as part of their travel demand modeling (it is the output of the trip distribution step of the standard 4-step travel demand model). An increasing number of departments/ministries of transportation are generating long-distance O-D trip matrices for their statewide, nationwide, or EU modeling. GPS and cell phone companies are a newer source of O-D trip matrices [96], and trip tables can be estimated using spatial interaction (gravity-type) models [97] or reverse-engineering techniques from arc volumes [98]. In addition, flow-based models require a topologically correct network and a set of candidate sites, which can be limited to a subset of the network nodes. Finally, flow-based models require generating the shortest/fastest travel path(s) for each O-D pair.

In the OR literature, Hodgson [99] and Berman et al. [100] developed the flow-capturing (or intercepting) location model (FCLM/FILM) to maximize the captured flow volumes (10.15) subject to opening only p stations (10.16). Structurally, the model is identical to the max cover model, except that the index q is introduced to represent O-D pairs, and in the cover constraints (10.17), the cover sets N_q consist of all candidate sites along the shortest path for pair q.

Flow Capturing Location Model (FCLM) Formulation

$$\text{Max} \sum_{q} f_q Y_q \tag{10.15}$$

subject to:

$$\sum_j X_j = p \tag{10.16}$$

$$\sum_{j \in N_q} X_j \geq Y_q \ \forall \ q \tag{10.17}$$

$$X_j \in \{01\} \ \forall \ j \tag{10.18}$$

$$Y_q \in \{01\} \ \forall \ q \tag{10.19}$$

where $Y_q = 1$ if any HRS is located along O-D pair q's shortest path, 0 otherwise (decision variable); $f_q =$ flow volume on O-D pair q (e.g., number of trips); $N_q =$ set of stations located along O-D pair q's shortest path; and $p =$ number of HRSs to open.

To extend the flow-based approach to locating fuel stations for AFVs, Kuby and Lim [101] developed the flow-refueling location model (FRLM) to handle trips where multiple stations may be needed along a path to enable trips to be completed without running out of fuel. The original model created a new index h representing each unique *combination of stations* that are capable of covering (refueling) an O-D round trip given an assumed driving range of vehicles. The original FRLM also depended on a preprocessing step to generate all possible combinations of stations along each path, cross-reference these combinations across paths, and remove redundant combinations to improve computation. To simplify the problem, it introduced the standard simplifications to assume symmetry of energy consumption in both directions, to aggregate O-D and D-O round trips, and to ensure the refuelability of round trips by requiring one-way trips to start or end with at least a half tank of fuel so that the trip can be retraced and refueled in the opposite direction. A regional example of an FRLM model solution is shown in Fig. 10.14.

Several other methods for solving the basic FRLM have been developed to avoid generating large numbers of facility combinations while accounting for vehicle driving range, which Kchaou-Boujelben [102] labels the (i) state of charge (SOC) tracking, (ii) path-segment, and (iii) arc-covering approaches. Wang and Lin [103] formulated the first SOC-tracking MIP with continuous variables that ensure that the tank level never exceeds 100% or drops below 0%. MirHassani and Ebrazi [104] introduced the path-segment approach based on three interrelated changes. First, they added artificial segments from each candidate site on a path downstream to each other candidate site within the max driving range. Second, they incorporated the MIP formulation of the shortest path problem into the station location problem for each O-D pair. Third, for an endogenously generated path to be covered, there must be a station at every node along the way. The artificial segments flexibly allow the generated paths to bypass the nodes without stations while ensuring that the next station along the way is within the driving range of the previous station.

The third category that avoids generating facility combinations is the arc-covering formulation [105]. In constraints (10.22), an O-D pair q is covered if all the directional arcs a_{jk} on its round trip are individually covered, and an arc is covered if any of the upstream facilities within the driving range are opened.

Arc-Covering FRLM Formulation

$$\text{Max} \sum_{q} f_q y_q \tag{10.20}$$

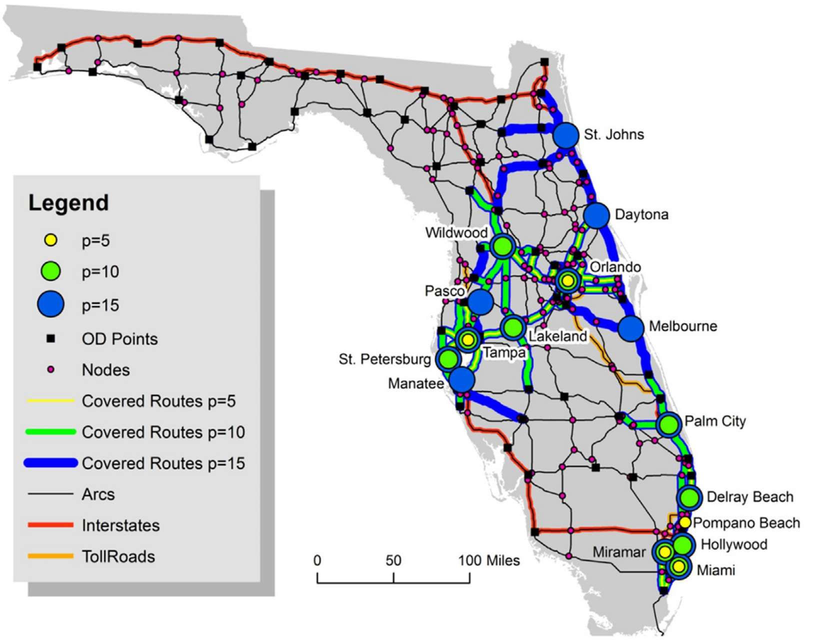

FIG. 10.14 FRLM solutions for 5, 10, and 15 optimal stations for the state of Florida for maximizing VMT (trips × length) that can complete trips on their shortest paths for a driving range of 100 miles, based on the data in Kuby et al. [97]. Note that 4 of 5 stations optimal for $p = 5$ remain optimal when resolving for 10 or 15 stations, and all top 10 stations remain optimal for 15 stations. There was no constraint requiring the model to connect Miami, Tampa, Orlando, and Jacksonville, or to cluster stations in the Miami-Palm Beach corridor or Tampa-Orlando region—it resulted from trying to serve the heaviest and/or longest flow volumes and locating stations at funnel points where many trips start, end, turn, or pass through. *(Credit: Authors.)*

subject to:

$$\sum_i X_i = p \tag{10.21}$$

$$\sum_{i \in K_{jk}^q} X_i \geq y_q \ \forall \ q \in Q, \ a_{jk} \in A_q \tag{10.22}$$

$$X_i \in \{01\} \ \forall \ i \tag{10.23}$$

$$Y_q \in \{01\} \ \forall \ q \tag{10.24}$$

where jk = the directional arc from node j to node k; A_q = the set of directional arcs jk on the round trip for O-D pair q; K_{jk}^q = the set of HRS candidate locations capable of refueling an FCEV and ensuring it can travel completely across directional arc jk without running out of fuel.

The most important feature researchers have added to the FRLM to make it more realistic is to allow detours from shortest paths to refuel. Kim and Kuby [106] developed a greedy-substitution algorithm that could generate all possible deviation paths within the model. Yıldız et al. [107] and Kınay et al. [108] developed very fast DFRLM solution methods using the path segments, branch-and-price, Bender's decomposition, and valid inequalities. Hosseini et al. [109] developed a heuristic that generates deviation paths that go through promising nodes *i* that do not exceed a given maximum deviation. Honma and Kuby [110] develop a simpler deviation model specifically for urban areas in which refueling by a single station is sufficient for any trip. Lin and Lin [111] minimize the maximum percentage deviation for any trip on the network.

Other extensions of the FRLM have included, for example:

- Set cover versions that minimize the number of stations or budget required (e.g., [103,109,112,113]).
- Station type, sizing, and costs [103,112–114].
- Multiple or uncertain driving ranges [115–117].
- Demand uncertainty [93,118].
- Highway/station congestion/queueing (e.g., [119]).
- Divided highways and complex freeway interchanges [120,121].
- Origin nodes are considered covered (i.e., consumers willing to purchase FCEVs) only if a critical threshold share of their O-D trips can be completed using the opened stations [122].
- Equitable coverage of different regions' trips [123].
- Integration with diffusion models [124].

4.4 Tour-based models

In tour-based models, the geographic demands are trip chains or tours, which could be for a single chain from home, a full day, or a set of days. These models recognize that drivers do not have to refuel their AFVs on every trip, especially short ones, but need to fit in a refueling event every so often or before the vehicle runs out of fuel. The data for these models consist of a series of stop locations and the distance between them, derived from trip diaries or GPS recordings, and in some cases timestamps. If GPS did not record the exact route taken between stops, shortest path algorithms are applied to estimate them [125]. For slow-charging of BEVs, the duration of the stops is also important, but for fast-filling FCEVs, it is less important to treat tours as time-space paths.

Kang et al. [41] analyzed the minimum deviation from daily travel patterns of California drivers in order to visit one of 68 proposed HRS at some point during a day assuming drivers' itineraries do not change. Cavadas et al. [126] analyzed slow EV charging location in the context of driver tours with two stops, allowing charging demand transference between the two stops. Wu and Sioshansi [125] use trip chains without timestamps from 1.3 million light-duty vehicles in Central Ohio to optimize BEV charging stations, which demonstrated that the data and computation for large-scale tour-based modeling are feasible. Examples of optimal location using timestamped activity-based tours are Kang et al. [127] for HRS siting, which simultaneously optimized tour construction, and Dong et al. [128] for BEV charging using multiday tours.

4.5 Other constraints, objectives, and model features

4.5.1 Facility capacity and costs

Several papers have commented that the earliest rollout of stations should be designed for maximizing geographic coverage to make it feasible for as many first adopters to purchase vehicles as possible [129–131]. As market penetration picks up, however, station crowding and capacity become an issue. Capacity constraints have been added to several types of station location models.

Capacity constraints are fairly straightforward to add to *p*-median and tour-based models, but become more challenging for node-covering, flow-intercepting, and flow-refueling models, which, like covering models generally, often lack variables that allocate demand to stations explicitly. Examples of how this is overcome include Upchurch et al. [132], Miralinaghi et al. [119], and Yıldız et al. [118].

Researchers have incorporated simple or complex station cost functions into most of the model types, either in a minimum cost objective or a budget constraint. Cost factors include land costs [105], electricity supply [133], and facility type [134].

4.5.2 Station separation

Regardless of whether demand is represented as points, arcs, O-D pairs, or tours, the stations themselves are represented as points. Most models rely on the main objective function to adequately space the stations away from each other by making stations as accessible as possible to as many different demands as possible. When station capacities are implemented, however, stations may be needed near to each other to handle a concentration of demand. Several papers have explicitly modeled station separation or dispersion. Brey et al. [135] included a penalty coefficient in the objective function when stations are located in municipalities that are too close together. Baouche et al. [136] and Zhong et al. [95] add a proximity constraint requiring that the separation distance between any pair of open facilities exceed some predefined minimum length. Kim et al. [137] combine a median objective with a maximum dispersion objective that maximizes the sum of all interfacility distances. Brey et al. [2] proposed a constraint that allows for more HRSs to be located on the same arc as a function of how many gas stations (a measure of potential demand) exist on the arc, which creatively combines capacity and separation considerations.

4.5.3 Multiple time periods (expansion planning)

Models have been extended to include multiple time periods and the decision of where *and when* to open HRSs for a coordinated rollout over time. Examples include Kuvvetli [138] for minimizing cost and risk and maximizing coverage for HRSs in Turkey, Chung and Kwon [139] for a multiperiod FRLM for BEVs in Korea; and Kim et al. [137] for HRS using the *p*-median and maximum dispersion model, Fuse et al. [77], Anjos et al. [140] employed a rolling-horizon approach to make their multiperiod model computationally tractable. Others include Hosseini and MirHassani [141] and Davidov and Pantoš [115].

4.5.4 Combination models—Single and multiple objectives

Many papers have recognized that station location is a multifaceted problem and combined different types of geographic demands into a single model using one or more objectives. An appealing single-objective combination is median models with a covering-like max-distance limitation (e.g., Chen et al. [142] for EV charging; Chen et al. [134] for electric scooter charging). Anjos et al. [140] located fast-charging stations (which can be considered similar to HRS) to maximize the number of EVs adopted at the end of each time period, where adoption depends on satisfying a zone's local node-based demand as well as their long-distance flow-based demand. Dong et al. [128] developed a max cover model with demand based on population density, traffic, and points of interest (POI) density in grid squares.

The key difference between the single and multiobjective optimization models is that the multiobjective approach recognizes that different objectives may be measured in incommensurate units (e.g., miles of travel and number of trips captured) and there is no single agreed-upon weight to convert one to the other [143]. Multiple objective models keep the different objectives in their native units of measurement, iterate systematically through a spectrum of weights, and generate a set of nondominated/non-inferior/Pareto-optimal solutions that together form a Pareto-optimal tradeoff curve or frontier. A sample of multiobjective models for fuel station location is cross-tabulated by objective type in Table 10.1.

4.6 Node vs flow model comparisons

While many OR studies focus on developing faster solution methods capable of solving larger problems or add a new feature to a classic model, only a few studies have systematically compared the performance of different classes of models in terms of the accessibility of the infrastructure plans. In the HRS literature, two studies have compared the performance of node-based and flow-based models in serving the public. Upchurch and Kuby [148] applied the FRLM and the *p*-median model to real-world networks for the state of Florida and the metropolitan area of Orlando. Their research question was which model

TABLE 10.1 Examples of multiobjective models.

	Min distance (median)	Max cover or set cover	Min cost (fixed charge)	Arc traffic	FCLM or FRLM	Other
Min distance (median)			Badri-Koohi et al. [144] *+Arc traffic* Chen et al. [134] *Electric scooter charging* Islam et al. [84] + *Substation energy loss*	Brey et al. [2] and Goodchild and Noronha [79] *Gasoline*	Capar and Kuby [112]	Kim et al. [137] *Dispersion*
Max cover or set cover			Kuvvetli [138] *+ Min risk* Wang and Wang [145]		Capar and Kuby [112]	
Min cost (fixed charge)					Ghorbani et al. [146] *CNG*	
Arc traffic						
FCLM or FRLM						Brey et al. [135] *Max suitability/max dispersion*
Other						Tafakkori et al. [147] *Min cost, min pollution, max jobs, max accessibility*

produces a system of stations that also performs well on the other model's objective. They answered this question by solving each model, plugging its optimal locations into the other model, and evaluating the other model's objective function. Two strong findings emerged from this analysis. First, the locations chosen by the FRLM performed better on the *p*-median model's objective function than the *p*-median's locations do on refueling flows—by a substantial margin at the urban scale and even more so at the statewide scale (Fig. 10.15). This is partly because the FRLM, without allowing for route deviations, is less forgiving than the *p*-median model. However, it is also because network nodes with heavy flow volumes passing to, from, or through them also tend to be near areas where population, jobs, and activities are concentrated, making the FRLM's flow-intercepting locations perform decently on the *p*-median's VMT from homes to stations objective. The *p*-median model, especially at the statewide scale, essentially carves the state up into separate service areas and places a station centrally to serve each service area, which may or may not correspond with a network location with heavy flow volumes.

The second major insight from this study is that the FRLM's optimal locations (network nodes with extremely heavy flows that capture different sets of

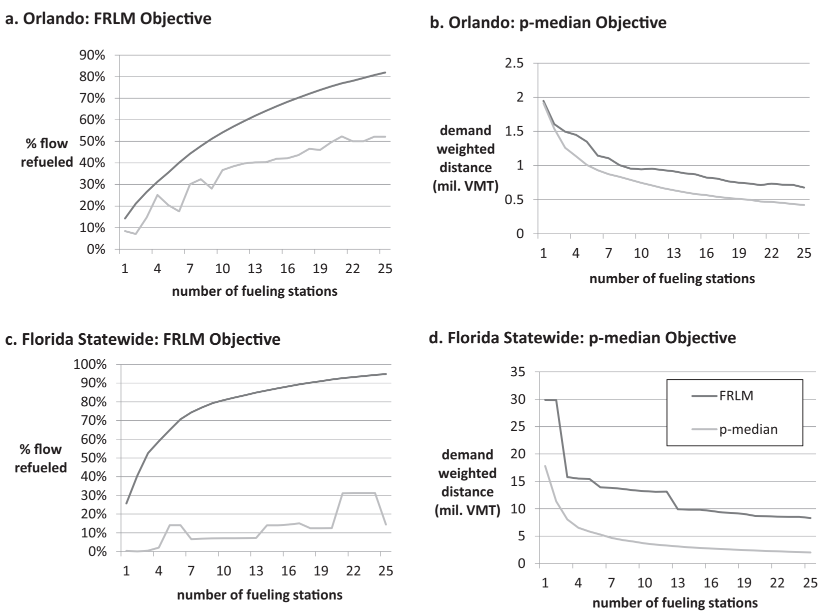

FIG. 10.15 Graphs showing the performance of *p*-median and FRLM optimal solutions on their own and the other model's objective functions at two different geographical scales. Note the smaller gaps between the two curves in the right column compared with the left column. *(Credit: C. Upchurch, M. Kuby, Comparing the p-median and flow-refueling models for locating alternative-fuel stations. J. Transp. Geogr. 18 (2010) 750–758.)*

flows than the other station locations) are highly stable: as more stations are added, the original locations usually remain optimal, with only a few stations shifting to different locations to minimize cannibalization of another station's flows or to satisfy a driving range "stepping stone" purpose. This is decidedly not the nature of median solutions, which can be visualized easily by envisioning the best location for one station (right in the dense central area), two stations (divide the region into two zones and place a station centrally in each zone, abandoning the center), and so on. The arc-based fuel-travel back median model might produce more stable locations than a population-based median model because traffic volumes are more naturally concentrated than population, but this has not been tested, and we expect that optimal locations would still jump around a lot.

A second study by Honma and Kuby [110] compared node-based and flow-based models by a different method. The paper formulated versions of the p-median and flow-capturing models for urban refueling to compare the accessibility of their optimal solutions on as level of a playing field as possible. Both models were required to cover all demands with the minimum amount of "wasted" or "extra" travel time by drivers and without exceeding a specified standard of "inconvenience" or running out of fuel. The models were tested on two networks, including the Orlando network from the previous study and an idealized city network. In the modified FCLM, extra travel time was measured by the deviations necessary to reach stations, while for the modified p-median it was measured by travel time to stations outside of a driver's residential zone. For the Orlando network, there were an average of eight gasoline stations per demand zone, meaning that for the modified p-median refueling (PMP-R) model, travel time to a station was considered extra or wasted only if a driver could not fill up at one of their eight nearest stations, roughly speaking. For the modified FCLM that allows deviations from shortest paths (DFCLM-R), every additional minute caused by detouring counted as extra travel time.

The Orlando network was solved for maximum inconvenience of 5-, 10-, 15-, 20-, and 40-min maximums. Fig. 10.16 maps the results of each model for optimally locating four stations with a 15-min limit on inconvenience. In the flow-based solution, 40% of O-D flows are infeasible (deviations would exceed 15 min) and the covered flows average 2.1 min of deviation. In comparison, in the node-based, 66% of node demand is uncovered and the extra travel time averages 5.4 min. The maps help illustrate why.

In the upper figures, the flow volumes that are intercepted by or deviate to one of the four stations (for the flow-based model) often originate from far away from the station, while the nodes served by the node-based model are limited to the immediate area around each station. In both models, every station is located on at least one freeway (indicated by the green flows), but in the DFCLM-R results three of the four optimal stations are at a confluence of multiple freeways. The DFCLM-R locates stations farther apart in order to reduce the

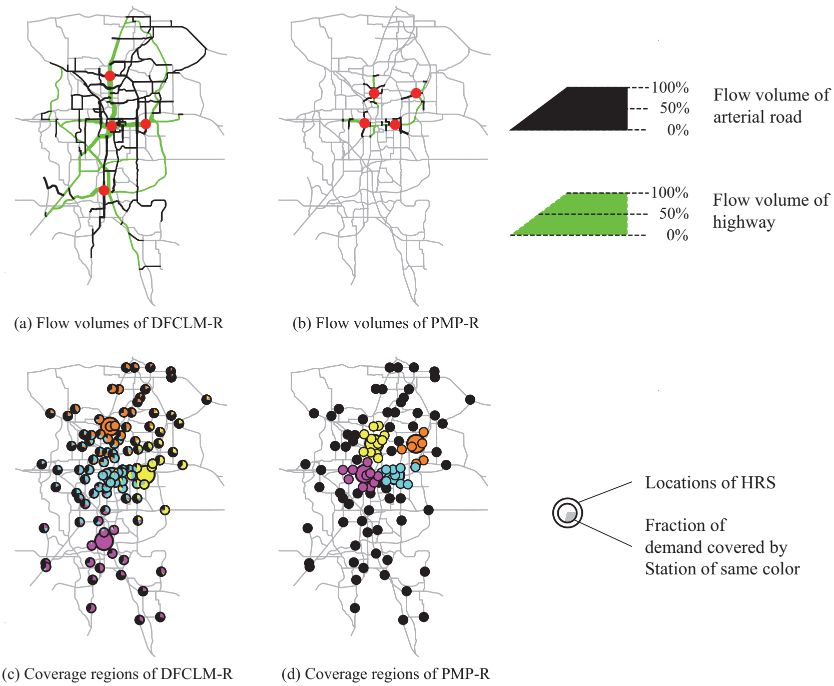

FIG. 10.16 Optimal locations and flow volumes covered (A and B). Nodes' flow demand partially covered (C) and node demand covered or not (D). *(Credit: Y. Honma, M. Kuby, Node-based vs. path-based location models for urban hydrogen refueling stations: comparing convenience and coverage abilities. Int. J. Hydrogen Energy 44 (2019) 15246–15261.)*

overlap of the sets of O-D flows that they capture. In contrast, the node-based model locates stations in the four most densely populated, nonoverlapping node clusters.

The two lower figures illustrate another inherent advantage of flow-based modeling. The large colored circles indicate one of the 4 optimal station locations. The smaller circles are demand nodes, which are colored according to which station serves them, with black indicating infeasible demand exceeding the 15-min limit on extra travel time. In the node-based model, stations serve only the surrounding 15-min drive-time buffer, and demand nodes are served by only one station. In the flow-based model, any demand node's trips for work, shopping, school, or other activities can be served by any station that it can pass by or detour through, which means that any zone's trips can be partially or fully served conveniently by one or more stations that may be near or far from that zone, as shown in Fig. 10.16C. Flow-based models can capitalize on the travel that drivers are already doing (especially on freeways) by adding a refueling stop to the trip, which extends the reach of stations and wastes less time for drivers. The lower maps also illustrate an equity implication embedded in a flow-based approach to station planning, where service is not planned based only on a targeted local early-adopter population but also considers the ability of more distantly located drivers, whose neighborhoods do not fit the classic early adopter profile, to conveniently access stations on their way to or through other neighborhoods.

Table 10.2 summarizes some of the main strengths and weaknesses of the four categories of station location optimization models.

TABLE 10.2 Strengths and weaknesses of the four main types of station location optimization models.

	Strengths	Weaknesses
Node-based *models*	+ Focus on locating stations near where people live, which increases likelihood of early adoption for most drivers + Stations close to home are usable on weekdays and weekends + Zone population and demographic data are generally available and easy to work with + Median and covering models are built into ESRI's ArcGIS Desktop and Pro + Simpler to communicate to decision-makers and public	– With few stations, it is impossible to place stations near everyone's home – Drivers rarely refuel on single-purpose round trip home-station-home – Some drivers with no station near home are still willing to purchase vehicles while relying on stations near work or on way to frequented destination – As number of stations increases, earlier locations often do not remain optimal – Inability to model long-distance trips and ensure they can be completed given driving range restrictions – More stations needed to cover the same percentage of total demand compared with flow-based models – *Covering models*—no agreed-on time or distance standard; drivers vary greatly in what they consider "close to home" – *Median models*—every neighborhood allocated to nearest station, regardless of how far away that is or whether it is in a direction someone might travel

TABLE 10.2 Strengths and weaknesses of the four main types of station location optimization models—cont'd

	Strengths	Weaknesses
Arc-based models	+ Drivers mostly refuel while out driving for other trip purposes + Data on arc traffic volumes are often available and relatively easy to work with + Gasoline station demand is correlated with neighborhood traffic flows to freeway exits	– Limited ability to accurately check the refuelability of long-distance trips – Prone to double-counting of same vehicles traveling on different nearby arcs
Flow-based models	+ Able to model local and long-distance flows in a single model + Considers both local demand and more distant demand for each station + Able to check whether longer round trips can be completed given driving range limitations + Avoids double-counting of same vehicle traveling over multiple arcs + Drivers mostly refuel on the way while driving for other trip purposes + Research shows some tendency for FCEV drivers to switch to stations on their way over time + Stations located at high-flow intersections tend to remain optimal as number of stations increase + Tends to locate stations where they also perform fairly well for node-based objectives	– Detailed O-D flow matrices are more difficult to obtain, especially for long-distance travel – Requires more difficult data processing with O-D flow matrices, shortest paths, and in some cases deviation paths – Specialized software needed for solving – Assumes drivers are equally willing to refuel farther from home if station is on their regular routes – Assumes drivers are willing to purchase FCEV with no station near home – Special care needed for modeling high-volume freeway interchanges
Tour-based models	+ Conceptually appealing idea that every trip does not need refueling but drivers must be able to refuel at some point during a multistop trip chain + Allows for placing stations where the trip chains of many drivers overlap, such as at downtown locations, major shopping and office concentrations, and near major freeway interchanges + Able to consider long-distance tours, range constraints, and avoid double-counting of same vehicle	– Tour data very hard to obtain, subject to availability and privacy issues, and may need to be synthesized – Most computationally difficult data to work with – Few real-world applications of these models

5. Integration of GIS and OR models

GIS and operations research are frequently used in combination and are much more powerful and realistic when integrated. In some cases, it is nearly impossible to classify an approach as either one or the other, and in the preceding sections, we have proposed the distinction that it's OR if the objective is stated mathematically as a maximization or minimization function and there is an exact or heuristic method for combinatorial optimization.

5.1 Strengths and weaknesses of GIS and OR

Table 10.3 summarizes the main strengths and weaknesses of GIS and OR approaches for HRS network planning. The greatest strength of GIS is its detailed and flexible representation of geographic space. This includes its abilities to: merge disparate data sets from disparate sources; represent different phenomena as points, lines, polygons, and raster cells; overlay these different data layers; and perform an incredibly wide range of spatial and mathematical operations across these layers and link these together in flexible ways. Humans have evolved an inherent ability to understand spatial relationships visually—an advantage that should not be underestimated. GIS can be integrated with almost any kind of quantitative technique and online platform. For the purpose of HRS system planning, however, its greatest limitation is its inability to consider all possible combinations of locations, unless it has OR methods built into it, in which case there is a tendency for GIS analysts to limit their models to those that can be constructed around the software's available OR problem options.

In many ways, the advantages and disadvantages of OR are the opposite of GIS. The main strength of OR is its ability to do combinatorial optimization. For problems that choose p stations out of n candidate sites, the number of combinations is $\frac{n!}{p!(n-p)!}$. In most real-world problems, this is far too many possible combinations to solve by testing each one in GIS (we will spare you the usual examples!). In problems without a given number of facilities (p), such as the LSCP, the number of combinations is many times larger than that. Given the high costs of HRSs, however, the ability to refuel the same number of trips with just 1–2 fewer HRSs through combinatorial optimization can save many millions of dollars. The ability to express requirements in terms of constraints that are applied to all nodes, arcs, O-D pairs, tours, candidate sites, and time periods simultaneously, with their complex interactions enforced mathematically, is another major strength. Variables linked across various constraints create, in essence, a domino effect, and thus an MIP model may have millions of domino effects all happening simultaneously. The main weaknesses of OR, of course, lie in the oversimplification of goals, factors, and geographic detail needed to create a tractable mathematical model.

TABLE 10.3 Strengths and weaknesses of GIS and OR for HRS infrastructure planning.

	Strengths	Weaknesses
GIS	+ Level of detail of geographic representation + Can represent many different data layers and use both raster (continuous) and vector (discrete) data + Site suitability considering multiple layers + Modeling flexibility by sequencing geoprocessing and spatial analysis steps + Visualization ability + Dealing with nonlinearities + Using big data and machine learning techniques + Comprehensive evaluation of a proposed new station + Can build interactive, easy-to-use platforms to collect data from non-experts	– Lack of robust built-in combinatorial optimization methods – Trial and error method may not succeed in finding optimal set of stations – Hard to evaluate interrelated effects
Operations research optimization models	+ Combinatorial optimization for finding the very best coordinated set of stations to maximize or minimize a mathematically stated goal + Ability to evaluate interrelated effects of multiple constraints and ensure they are feasible + Ability to perform multiobjective optimization and generate Pareto-optimal tradeoff curve	– Less detail of geographic representation – More mathematically complex – Need specialized staff or training – More difficult to communicate to decision-makers – Lacks visualization capability – Challenging to consider more than two objectives

Both methods are highly flexible and powerful in the hands of experienced analysts, and even more so when they are combined, which we discuss next.

5.2 OR tools built into GIS

Numerous OR tools are built into GIS software packages. For example, the most powerful and popular GIS software, ESRI's ArcGIS Desktop has a suite of OR tools in its Network Analyst module, starting with the ability to generate optimal shortest paths (including vehicle routing and traveling salesman problems) based on distance or time (or any other attribute) using the Dijkstra algorithm. Based on the shortest path capability, Network Analyst can generate service areas (e.g., buffers or polygons) around points, lines, and polygons based on Euclidean distance, network distance, or network travel time. Finally, based on the paths and buffers, its location-allocation tool can solve a limited number of OR models heuristically. These include set cover, max cover, *p*--median, distance-constrained *p*-median, capacitated coverage, maximize attendance (based on gravity model attractions), and max/target market share (given competitor locations). All of these problems can be converted into a *p*-median type formulation following Hillsman [149], which are then solved with the Teitz and Bart [150] substitution algorithm. Finally, shortest paths and service areas can also be generated using raster grid cells, where each cell can be assigned an impedance for passing through it relative to any of its eight neighboring cells—a powerful tool that facilitates optimal routing across a combination of continuous and network space, which could be important for hydrogen-powered ships, drones, and aircraft.

In addition to these "canned" OR tools, it is much easier now to write custom computer programs within GIS or called by GIS. Thus, any kind of heuristic OR algorithm can be implemented in a GIS environment, for example, the greedy algorithm for the DFRLM in Kim and Kuby [106].

5.3 GIS pre- and postprocessing for OR models

OR models greatly benefit by using GIS for spatial processing of their inputs and outputs. In terms of inputs, GIS can generate highly realistic travel times for a *p*-median model, coverage areas for a MCLP or LSCP, and shortest paths for an FRLM. Unavailable or expensive data, such as location of existing gasoline stations or POIs, can be crowd-sourced from OpenStreetMap or scraped from GoogleMaps for generating candidate sites. Stephens-Romero et al. [67] used GIS to select as candidate sites only the gasoline stations on road sections in the upper 90% of AADT traffic density, which reduced the number of candidate sites from 34 to 14. Many OR models have used GIS to develop weighting systems to prioritize populations, arc traffic, or trips in or from areas with higher likelihood of FCEV early adopters. For instance, Kuby et al. [97] used suitability analysis to weight the trip volumes by the demographic characteristics of the origin zones based on the GIS analysis of FCEV consumer demand by Melendez and Milbrandt [4] at NREL (see Sections 2 and 3). In another example, Zhao et al. [121] combined the strengths of OR and GIS to recommend HRS station locations at freeway intersections in the Hartford, Connecticut region. Freeways carry high volumes of passing traffic and are therefore attractive sites to flow-based models, but it is infeasible to build an HRS directly at a freeway interchange. They incorporated a GIS method developed by Kelley [151] to find the best location on the local street network at which to build a station that can conveniently be reached by drivers passing through the interchange in all possible directions (Fig. 10.17).

After OR models are solved, their results can be transferred to GIS for visualization and presentation to decision-makers. Automating this step can help ensure that results of different scenarios are visualized easily. Visualization is important, not only for communicating to decision-makers choosing among solutions, but for detecting errors in the input data or model.

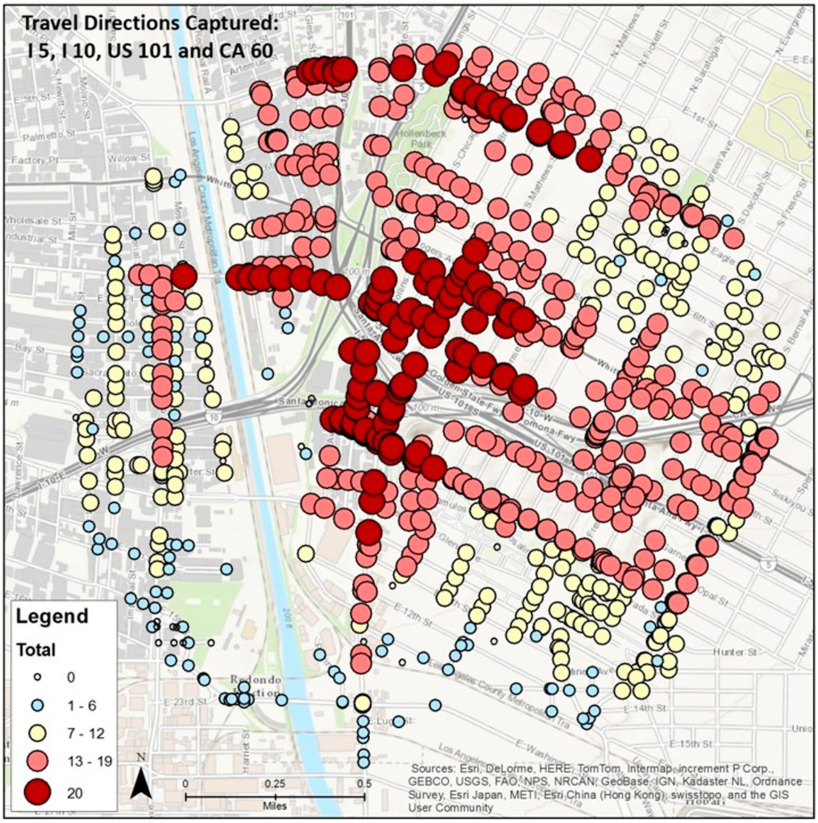

FIG. 10.17 This map of Kelley's [151] Traffic Freeway Capture Metric shows the accessibility of every street intersection within a 1-mile buffer around the intersection of four freeways in downtown Los Angeles, through which about 1 million vehicles travel each weekday. Specifically, the dot size and color indicate the number of freeway travel directions (e.g., US-101 southbound to I-10 eastbound) on which a driver could exit the freeway, detour to the street intersection to refuel, and return to their through-trip with no more than 6-min deviation from their direct route. The *large red dots* (dark gray in the print version) are locations accessible via all 20 possible freeway routes through the complex interchange. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.) *(Credit: Authors.)*

6. Discussion and conclusions

6.1 Conceptual model

The different kinds of planning tools and travel/behavior data reviewed form the basis for exploring the potential future scenarios for HRS location (Fig. 10.18). Three fundamental kinds of factors are needed for any GIS or OR modeling effort. First, future spatial representations of FCEV travel demand based on current behavior and assumptions about the shift to FCEVs are necessary. The home location of future FCEV owners, for example, can be derived from the home locations of current vehicle owners using a variety of tools to forecast who will be the early adopters and who might come later. The driving and refueling behavior of FCEV owners can also be derived from current behavior—ignoring future technological change such as shared autonomous FCEVs. Second, a set of discrete candidate sites are needed in most approaches, often based on current gas-station locations. California's Hydrogen Infrastructure Tool (CHIT), however, is an example of a GIS model that does not use discrete candidate sites but instead takes a heat-map approach to highlighting promising areas. Third, policy goals inform both the data and the model, considering the stage of the HRS/FCEV rollout, the rollout strategy, geographic scale, equity, budget, and other factors.

The modeling tools reviewed in this chapter are not suggested as a substitute for planning and policy process for developing a hydrogen refueling network, but as additional tools that improve the geographic decision-making process when used within the limitations of the tool assumptions and capabilities. Nevertheless, the research into these models yields a set of recommendations for models as well as planners and decision-makers.

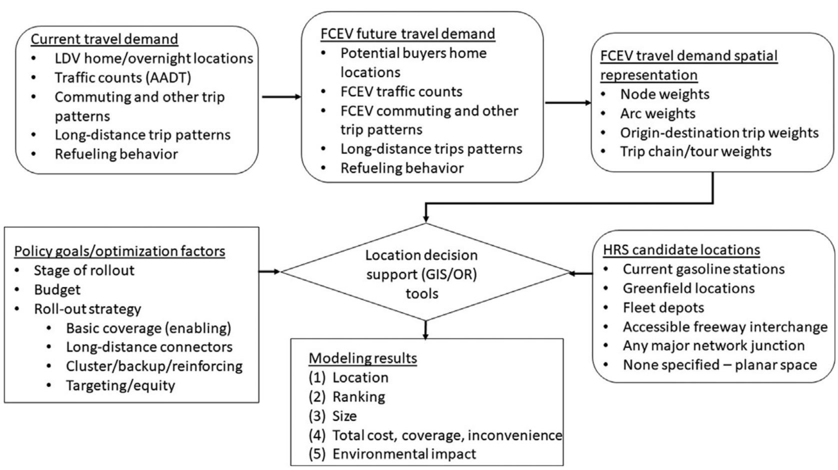

FIG. 10.18 Conceptual diagram of the HRS location modeling process. *(Credit: Authors.)*

6.2 Recommendations

Whether GIS, OR, or both are used to build a station planning tool, we feel confident in recommending some principles to follow. From the behavioral studies in Section 2, we know that, with nearly ubiquitous gasoline stations, drivers become accustomed to refueling near home but do not usually need to go out of their way to do so, and gasoline sales correlate well with the catchment areas of freeway exits closest to people's homes. It is not surprising, therefore, that drivers respond to stated preference studies that they would most prefer to have an HRS located near their home: this is typical of the experience that ICE drivers bring to the FCEV adoption decision. However, when that lifetime experience of gasoline refueling is transplanted to dealing with an extremely limited network of HRSs, we also now know that a substantial percentage of FCEV early adopters purchase a vehicle without *any* station near home, stating that they did so planning to rely on stations near work or on the way for their everyday needs. Furthermore, what early adopters subjectively label as near home was objectively farther away than what is assumed in GIS and max-cover models. We know that a large majority of adopters planned on using a portfolio of stations that are convenient for different kinds of trips or access and that this portfolio can change over time to prioritize stations farther from home. The portfolio approach is also important to FCEV drivers due to concerns about station reliability, backup stations, and long-distance trips. A key takeaway from the portfolio concept is that one driver's station near home is another driver's station near or on the way to work, school, or shopping. One town's local station is another town's long-distance destination or refueling "stepping stone." Once a station is built and added to GPS mapping apps, it is there for drivers to use it in ways that the location model may not have considered.

Based on these behavioral tendencies and an understanding of the different models, here are some location principles for planning a network of stations using either GIS or OR approaches:

1. Every region in the world is either in the very early stage of HRS development or has not started at all, and budgets for building HRSs are limited. The most important thing guiding any location modeling effort is to decide what the top priorities are, because a complete network cannot be built at once. The prioritization and phasing-in strategy needs to be carefully considered before modeling begins.
2. In our view, the primary objective for near-term HRS planning in nearly all regions should be to *enable* more drivers to adopt FCEVs by providing them with some basic level of coverage or service. This emphasizes expansion into new markets, regardless of whether demand is represented in terms of nodes, arcs, routes, or tours. Making the network more convenient, adding more capacity, and providing additional backup stations to existing markets should be supplemental and/or subsequent priorities.

3. There may be exceptions though, especially for stations that play specialized network roles, such as "connector" stations that are necessary to enable long-distance travel between regions. The emphasis or prioritization among these considerations may depend on the phase of network development. Initially, expansion into new markets may receive priority while at other times it may be more important to build fueling capacity and support expanding the volume of FCEV deployment potential in markets that may already have stations. The priority considerations may vary across space and with time but will typically be evaluated alongside the context of broader network-wide needs.
4. The number of stations needed to provide early adopters with some kind of basic geographic accessibility to a station is far less than the number of current gasoline stations. At the same time, this number varies significantly based on which behavioral assumptions are included or prioritized in the HRS location model. More stations will be needed to provide a given level of basic geographic coverage when modeling with point-based demands that assume a maximum covering distance or travel time than with flow-based models that can intercept local and nonlocal O-D trips. Put differently, the same number of flow-based stations will provide potentially convenient service to a higher percentage of total demand than point-based models.
5. Due to concerns about reliability, fuel availability, and refueling anxiety, FCEV drivers need a backup station that is convenient in some way. During the initial HRS rollout, however, there may be more efficient ways to do so than by placing multiple stations in the same neighborhood. In keeping with #2 above, backup stations for previously enabled drivers should also enable more new drivers to adopt with a basic level of single-station service.
6. In general, a good location for adding a new HRS to a coordinated network of stations should increase some aspect of overall network utility to current and/or potential future FCEV drivers. One or multiple considerations may be at play when evaluating the added utility of a new station; in general, evaluation of a given location should be more favorable as more considerations are applicable to that location. Considerations for siting each new location may include:
   a. Convenience to a "new" set of potential adopters who do not already have a station within reasonable proximity of their homes, potentially enabling new FCEV adoption by residents in neighboring communities.
   b. Expanding fueling capacity within an "activated" market to ensure that the total volume of available hydrogen fuel is well-matched to current demand and ahead of potential local FCEV population growth in the near-term.
   c. Expanding fueling opportunities within a region with the goal of increasing the convenience of utilizing the hydrogen station network, increasing fueling capacity, and/or expanding the number of backup

fueling options such that drivers have one or more conveniently located secondary stations for when their primary fueling station may become unavailable.

d. Addressing multiple modes of driver demand to provide convenient access not just to nearby residents but also to people who work, go to school, shop, and do other activities nearby, and assist drivers in developing a portfolio of hydrogen station options matched to multiple activities in their daily lives.

e. Providing stations conveniently accessed from busy "funnel" points where hundreds of thousands of daily trips pass through, turn left or right to continue their journey, or start or end at.

f. Spacing stations to provide refueling "stepping stones" for long-distance, intercity, and tourism travel routes that also enable basic service to new markets.

g. Making stations visible from freeways or arterial streets to increase exposure of the expanding hydrogen economy to the general public.

7. Some specific examples of locations that meet many of the criteria above include:

a. Shopping malls and office parks near intersections of multiple freeways.

b. Downtown locations with easy freeway access.

c. Locations convenient to automobile dealerships—which tend to cluster in order that car shoppers can comparison-shop, and which are often located near popular big-box retail outlets—so prospective FCEV buyers can experience hydrogen refueling.

8. Regardless of which type of model is used, certain data assumptions should be followed:

a. Convenience should always be measured in terms of travel time:

i. For node-based models, this will favor locations with good freeway access.

ii. For flow-based models, this will produce more realistic shortest paths and detours.

b. Travel speeds should account for the different speeds of different road segments.

c. For long-distance trips:

i. Station spacing should be evaluated by distance or energy consumption, not travel time.

ii. Long-distance connector stations should not be separated by more than half of a conservative FCEV driving range, in case a station on the corridor is not operational.

iii. Planning should consider the peak demand on weekends and holidays.

d. Point-based demand should ideally factor in jobs as well as residents, since jobs can also proxy for shopping and services.

9. While demographic groups that fit the classic early-adopter profile make sense for locating the very first round of stations to get from 0% to 1%–5% of market penetration, it is important to begin incorporating other groups soon after for equity reasons.

In terms of the decision whether or not to adopt an FCEV, we can think of the refueling infrastructure an extension of the car itself. Car buyers may view HRSs for occasional use as analogous to needing a car with extra storage space, additional passenger seats, or all-wheel drive for occasional use. In this sense, a portfolio of available and convenient stations is part of a larger portfolio of features of the automobile. It is helpful for location modelers to keep this idea in mind when designing a modeling approach, as it affects the location strategy, number of stations, and order/prioritization of an ideal HRS network.

6.3 Future research needs

In this chapter, we summarize decades of research on social and behavioral studies that inform HRS planning, review prominent GIS and OR models developed and applied to plan HRS networks, and provide recommendations for HRS network planning based on this body of literature to date. As we noted in the previous section, though, there is nowhere in the world beyond the very early stages of HRS network development, with most regions yet to even begin. Therefore, much of the focus in the literature to date relates to early or prospective adoption in a select few regions around the world. As adoption expands, new strategies, methods, and models will almost certainly be required to inform how best to do so.

One of the first research needs is therefore a more comprehensive set of revealed behavioral studies in different regions, and at different levels of market penetration, where and when there are opportunities to do so. Findings from the geographic regions highlighted in this chapter may not translate well to other parts of the world, and different priorities and considerations may emerge from a broader range of studies in the world. A mixture of quantitative and qualitative methods should also be applied by researchers, too, to better analyze and elucidate these potential differences, and better understand local barriers or promising incentives.

More work on how prospective drivers evaluate FCEVs relative to other ZEVs, and how they balance the possible refueling or recharging challenges they would face, is also important. For example, the lack of reliable access to a charging location at one's home, particularly in multifamily housing units, is a barrier for BEV adoption that might be a relative advantage for FCEVs. Further analysis on the appeal, role, or niche of these competing ZEVs, or other ways that FCEV refueling may be advantageous or not relative to other ZEVs is an area needing more research attention.

So far, models have yet to explicitly incorporate or address the potentially competing needs of building new stations to support current drivers vs the needs of building new stations to attract new FCEV drivers in existing hydrogen markets. More explicit analysis of the tradeoffs, which may require inclusion of upstream considerations like hydrogen production and distribution, could be helpful in managing expansion of an initiated network. Social and behavioral research on the refueling behavior of those who are no longer classified as early adopters will therefore be needed to build an infrastructure that tailors to the needs of early adopters, while ensuring that the network remains sufficiently useful and does not discourage people from abandoning their FCEVs.

The need to better measure and monitor station reliability and how it impacts refueling demand, and how to incorporate this into station planning, is another priority research need. Reliability becomes a question due to station equipment down-time and supply chain bottlenecks and breakdowns, especially in the industry's early stages. Therefore, reliability might be site-specific but may also be a shared concern among groups of stations with the same fuel provider. Due to the dynamic and/or random nature of stations going offline or becoming operational again, this is difficult to incorporate into traditional GIS and OR approaches and may require more robust integration of temporal components in these models. Reliability is also directly related to the concept of backup stations that has emerged from recent work on FCEV adoption, and how to better incorporate them into station planning models is an area of need.

Other types of models to be developed are those that explicitly aim to serve both local and long-distance trips with the same set of stations. Some have suggested that median and covering models are better suited for the local demands and flow-based or station spacing models are better suited for long-distance connectors, but the behavioral evidence and model comparison analyses suggest that may be too simplistic. There is a need for GIS models that better incorporate O-D flow data and check O-D paths for long-distance, multistop connectivity, but do so on a general network with intersecting flows and not just lengthwise on a linear corridor. The literature has also just scratched the surface with arc-based OR models that explicitly check for long-distance, multistop connectivity. In summary, there is no shortage of opportunity for new model development that addresses the current research gaps in HRS network planning.

While OR methods have been applied to many commercial transportation applications, (e.g., [123]), there has not been an exhaustive investigation of how to leverage GIS modeling methodologies for to medium- and heavy-duty goods movement. Fundamental functions (spatial overlays, network analysis, and traffic analysis) will likely be similar to the light-duty vehicle example, but the formulation of locating hydrogen fuel demand and location-specific suitability for HRS will likely involve considerations specific to commercial goods movement. Likewise, as the market develops, the need to continue to refine and implement hydrogen supply information into GIS models may become more prevalent.

Finally, there is now considerable attention being devoted to the concept of equity in AFV adoption and infrastructure planning, and better methods and metrics are needed to help assess equity for HRS network planning. To date, most efforts simply evaluate how many stations are placed in, or near, disadvantaged communities, such as those identified by California's CalEnviroScreen tool. However, there is essentially no research into whether or how that benefits the residents of those communities, what constitutes convenience for them, and what impacts may result from emphasizing this in station planning strategies. The following is a list of example research questions related to equity that need attention:

i. Infrastructure may be present, but can the neighboring communities even use it, if ZEV are still financially out of reach? What kinds of incentives may appeal to those living nearby in order to address this?
ii. Does the presence of stations draw additional traffic and congestion that would not have been there otherwise? Would building stations in disadvantaged communities bring additional traffic from wealthy neighborhoods into low-income or environmentally impacted neighborhoods?
iii. ZEVs have no tailpipe emissions, but there is ongoing research and recognition of other environmental impacts, such as tire wear that is dispersed into the air. Does locating the infrastructure in burdened areas contribute to well-known issues related to environmental justice?
iv. Many equity considerations involve micro-level engagement with the community, which is an aspect that is not often included in models, and difficult to quantify or operationalize in models. How can we incorporate community thoughts and desires into models?
v. Are there workforce and job opportunity impacts (positive or negative) within the community brought about by ZEV infrastructure?

Considering equity in HRS location planning will be a sign of the industry achieving a new level of growth and maturity.

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