Optimizing the Regional Hydrogen Transition with Exogenous Demand:

Tool Development and Empirical Study

by

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DEDICATION / 献辞

谨以此论文献给

5.12 四川地震中遭受苦痛的同胞和所有奉献爱心的人

去世的爷爷和正在跟病痛斗争的奶奶

爸爸林伟词，妈妈陈舜真，弟林旭天和妹林晓燕

小姨，二伯，二姑夫，小叔，堂兄

昔日好友奕兆，孟杰，翰铭，喜强，耿雄，纲郁，吴宁，德新，等

以及一直陪伴左右的爱妻叶琳和即将出生的儿子 Alex

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ABSTRACT

Hydrogen as an alternative fuel promises reduction of greenhouse gas, pollutants and oil consumption from transportation. However, the barriers to a hydrogen economy are multi-dimensional, significant and complex. Existing studies, mostly addressing these barriers separately, are limited in providing an integrated understanding of hydrogen transition. Built on welfare economics, mathematical programming, and existing hydrogen infrastructure models, this dissertation develops a dynamic programming model to optimize the hydrogen transition based on social welfare maximization. Simplified by exogenous hydrogen demand and regional scope, the model identifies the optimal sequence of infrastructure configurations in terms of when, where, by what technology and at what size to build up each facility while minimizing the net present value of social cost, including technology, environmental, and fuel accessibility costs. Empirically, the optimal 2010-2060 sequence specifically for Southern California reveals several technology trends: industry hydrogen toward distributed toward central production, trucking toward pipeline distribution, open CO2 emission toward carbon capture and sequestration (CCS), and natural gas toward biomass toward coal on feedstock. Water electrolysis is considered but does not enter the optimal sequence. Economic analysis shows that the hydrogen industry in Southern California can potentially balance investment in 10 years by charging \$4.59 per kg or gain a 7.67-billion-dollar profit by charging \$4/kg for 50 years, and the long-term average hydrogen cost can be only \$1.886/kg, outperforming the DOE goal of "\$2.00-\$3.00/gge at the pump". These optimistic

results are achieved through optimization coupled with system dynamics and regional spatial details. The optimal sequence is also analyzed regarding capital and variable cost, technology competition and supplementation, fuel accessibility, station location and number, and CO2 mitigation. Sensitivity analysis is conducted with respect to externality discount rate, carbon tax rate, biomass availability, natural gas and coal prices, price and carbon intensity of electricity, and timing of adopting CCS. A higher carbon tax rate can motivate early adoption of CCS, as also found by the urban Beijing case study (attached in the appendix). Policy recommendations are made with respect to policy signal, industry hydrogen, government subsidy, industry cross-subsidy, compensation for early refueling inconv``enience and carbon policy.

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LIST OF ACRONYMS/ABBREVIATIONS

ACRONYM	Definition of acronym
BDT	bone dry tonne
C-BIO	central production via biomass gasification
C-BIOCCS	central production via biomass gasification with CCS
C-COALCCS	central production via coal gasification with CCS
CCS	carbon capture and sequestration
C-ELE	central production via water electrolysis
CO2	carbon dioxide
C-SMR	central production via natural gas SMR
C-SMRCCS	central production via natural gas SMR with CCS
D-ELE	distributed production via water electrolysis
D-SMR	distributed production via natural gas SMR
FCV	fuel cell vehicle
HPTG	Hydrogen Pipeline Tree Growth
ICE	internal combustion engine
kg	kilogram
kgC	kilogram of carbon
kgCO2	kilogram of carbon dioxide
kgH2	kilogram of hydrogen
LTAHC	Long-term average hydrogen cost
PEM	Polymer Electrolyte Membrane
REFSTA	non-production refueling station
SMR	steam methane reforming
VMT	vehicle-mile-traveled

1 INTRODUCTION

Motor vehicles, as a major petroleum consumer, criteria air pollutant emitter and carbon dioxide (CO2) emitter, contribute to the risks of energy insecurity, air pollution and climate change. In the United States, about 230 million motor vehicles[1] are in use, almost all powered by petroleum fuels, accounting for 50% of total petroleum consumption, 55% of total carbon monoxide emissions, 35% of total nitrogen oxide emissions, 30% of total volatile organic compound emissions, and 25% of total CO2 emissions in the United States (ORNL, 2006). Aiming at mitigating these adverse impacts, a wide range of solutions with respect to travel demand management, vehicle efficiency improvement, and alternative vehicle fuels have been proposed, implemented or continuously discussed.

Hydrogen as an alternative to gasoline, coupled with its end-user, the fuel cell vehicle (FCV), has been proposed to simultaneously reduce oil consumption, air pollution, and CO2 emissions (Ogden and Williams, 1989; Dunn, 2002; Sperling and Cannon, 2004; NRC, 2004; Solomon and Banerjee, 2006). On the one hand, FCVs emit only pure water at the tailpipe (Larminie and Dicks, 2003), meaning no distributed emissions of air pollutants and CO2. On the other hand, hydrogen can be made from a wide range of energy sources, such as natural gas, coal, wind, sunlight, biomass and nuclear (Ogden, et al., 2004a; NRC, 2004), promising energy diversity

[1] Including both cars and trucks, see (ORNL, 2006) for Table 3.3

and security. Depending on the type of energy source and technology, hydrogen production could emit more, less or zero air pollutants and CO2 (Ogden, et al., 2004a; NRC, 2004). Additional possible benefits of FCVs are being investigated, such as synergy with grid electricity (Kempton and Tomic, 2005a; Kempton and Tomic, 2005b; Williams and Kurani, 2007) and vehicle design flexibility (Ogden, Steinbugler and Kreutz, 1999; Rousseau and et al., 2004; Kromer and Heywood, 2007).

Despite all the appealing social benefits of hydrogen as a vehicle fuel, consensus has yet to be achieved concerning when, how and even whether the current gasoline-based vehicle-fuel system should be transformed into a hydrogen-FCV system. A hydrogen transition will likely reduce the social costs[2] caused by gasoline consumption, but on the other hand will also sacrifice the resources already invested on the current gasoline system, complicating the worthiness of a hydrogen transition. The overarching question is whether such a transition should move toward (certainly including the option of keeping the status quo) where should it occur and how to navigate such a transition with full consideration of transition barriers.

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[2] Throughout this dissertation, social costs refer to all kinds of costs imposed on any member of the region of interest and include both direct economic costs and external costs.

Conceptually, a hydrogen transition can be defined as a temporal process where an exogenous travel demand, measured by the total vehicle miles traveled (VMT) by the consumers in a given economic system, is served by a changing mix of gasoline, hydrogen and the corresponding vehicle technologies, supplied by fuel producers and automakers. Although the hydrogen infrastructure can be built based on proven technologies, the costs can be in scale of billions of dollars (NRC, 2004; Thomas et al, 2003; Romm, 2006), daunting although not necessarily much higher than those needed to maintain the current gasoline-based fuel system (Plotkin, 2007). Concerns have also been raised regarding the limited environmental benefits of hydrogen, if it is produced from fossil fuels and carbon capture and sequestration is not adopted. On the vehicle side, FCVs are still much more expensive than conventional gasoline vehicles (Ogden, 2004b; Ahluwalia and Wang, 2008), with on-board hydrogen storage and fuel cell technology still awaiting substantial improvement or cost reduction. Consumer acceptance is a critical issue for early commercialization, and it is still unclear how much the early consumers are willing to pay for FCVs and how much fuel accessibility they are willing to sacrifice. And probably the most challenging question for policy makers is how to overcome the "chicken-egg" dilemma that consumers are unwilling to buy fuel cell vehicles unless there is easy access to hydrogen fuel and private entities are unwilling to invest in building hydrogen infrastructure unless there is a substantial demand for hydrogen. These barriers, associated with technology readiness, costs, environmental impact, consumer acceptance and policies, are largely intertwined with each other and therefore an integrated analytical approach, although difficult, is desirable.

The concept of economic efficiency from the field of welfare economics (Pigou, 1932) provides an overarching perspective allowing us to sort out and analyze many transition barrier issues. In contrast to income distribution—another central concept of welfare economics that concerns allocation of social welfare ("the pie") to individual players within the economic system—economic efficiency concerns about how to maximize the social welfare (i.e. making the pie as large as possible). For simplification, the light-duty transport sector is viewed in this dissertation as having only conventional gasoline vehicles and FCVs as fuel end users and other alternative vehicles such as hybrid vehicles and bio-fuel vehicles are not considered. Then, a hydrogen transition can be seen an evolving process of hydrogen replacing gasoline while the exogenous transport demand is served. The economic efficiency issue can then be treated as maximization of social welfare of all the players operating a possibly growing FCV fleet, a possibly diminishing gasoline vehicle fleet, a possibly growing hydrogen infrastructure, and a possibly diminishing gasoline fuel system. In this dissertation, optimizing a hydrogen transition has the same meaning of maximizing the social welfare of a hydrogen transition.

An optimized hydrogen transition has important policy implications. First, by knowing the potential maximum social welfare of the hydrogen transition, the policy maker is able to decide whether it is worth abandoning the current gasoline fuel system and moving toward a hydrogen system from a realistic dynamic context instead of based on a static vision. And even if a hydrogen transition is worthy, another practical issue may be whether the resulting net gain in social welfare is significant enough to overcome the transaction cost (such as the social cost to inform, convince, and even compensate stakeholders) of initiating the transition. More net gain of social welfare resulting from a hydrogen transition suggests more economic incentives are potentially available for motivating oil companies, automakers, new ventures, and consumers to participate in the hydrogen transition. Second, the revealed optimal transition can be different from the "the faster the better" intuition pushed by the social burden of the current state and motivated by the envisioned benefits of the static end-state. It is responsible to consider the interests of both the future and current generations and make a temporal tradeoff in transition strategy. This is related to the issue of so-called dynamic efficiency or intergenerational equity and similar to what economists have proposed as one economic interpretation of sustainability (Asheim et al, 2001; Pezzey et al, 2001; Stavins et al, 2003). Third, most importantly, policies not aiming at the optimal transition, because the optimal transition is unknown, will likely navigate the transition in a sub-optimal path, resulting in intergenerational inequity and waste of social resources.

Although little effort has been made to directly address the economic efficiency issue of a hydrogen transition, the basis allowing us to do so has been formed by multidisciplinary efforts on alternative vehicle modeling, assessment of social costs of gasoline consumption, hydrogen infrastructure studies, mathematical programming techniques and advanced computation technologies. Obviously, the economic efficiency issue of a hydrogen transition can be extremely complex. Given the resources for this dissertation, two simplifications, represented by exogenous hydrogen demand and the regional scope, are adopted.

The assumption of an exogenous hydrogen demand can greatly reduce problem complexity without sacrificing too much research significance. In the hydrogen transition context, although the total transport demand represented by VMT served by both gasoline and hydrogen is exogenous, there can be two treatments of hydrogen demand—as endogenous decision or as exogenous information. The penetration of hydrogen-FCV, represented by hydrogen demand over time, results in social costs of providing hydrogen and FCVs as well as social benefits from avoiding the social costs associated with the substituted gasoline fuel and vehicles [3]. If the hydrogen demand is endogenous, i.e. tuning the hydrogen demand scenario (among other decisions) to maximize the social welfare of hydrogen transition, it then becomes necessary to quantify social costs of gasoline, hydrogen, gasoline vehicles, and FCVs, greatly adding to problem complexity. But if the hydrogen demand is treated as exogenous information, the quantities of FCVs and social costs associated with FCVs and the substituted gasoline fuel and vehicles are also exogenously determined and the decision set can be narrowed down to how to design the hydrogen infrastructure efficiently so as to minimize the social costs associated with hydrogen supply. That is, with exogenous hydrogen demand, the

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[3] Strictly speaking, part of the benefits result from transport demand being served. This type of benefits can be viewed as exogenous since the total VMT is assumed to be exogenous. That is, we do not consider VMT reduction.

hydrogen transition process can be optimized by simply minimizing the social costs of supplying hydrogen over time. Certainly, exogenous hydrogen demand is a constraint that can lead to sub-optimal hydrogen transition. This can be solved by repeated optimization for different hydrogen demand scenarios, a possible extension of this dissertation.

In addition to exogenous hydrogen demand, a regional scope is a necessary simplification to incorporate spatial details. Many studies have suggested that the spatial design of hydrogen infrastructure can differ across regions, and therefore hydrogen infrastructure modeling has been advanced from spatial parameter judgments (e.g. making assumptions on station locations and pipeline length) to idealized layout (Paster, 2006; Yang et al, 2006; Mintz, 2007; Chang, 2007; Yang and Ogden, 2007a and 2007b). However, no study has been conducted to incorporate region-specific spatial details into hydrogen transition dynamics. This is because most transition analyses are focused on the national or international context, where consideration of spatial details can be extremely difficult due to data needs and computation time. A regional scope allows representation of real road network and spatial distribution of hydrogen demand. Besides, regional studies with spatial details can provide empirical knowledge basis for hydrogen transition analyses in a national or international context, where geographic regions are usually highly aggregated.

Thus, this dissertation aims at optimizing regional hydrogen transition by minimizing social costs of hydrogen supply for exogenous hydrogen demand during a given study period. Intended contributions are both tool development and empirical analysis. Figure 1-1 shows the methodology boundary and framework adopted in this dissertation.

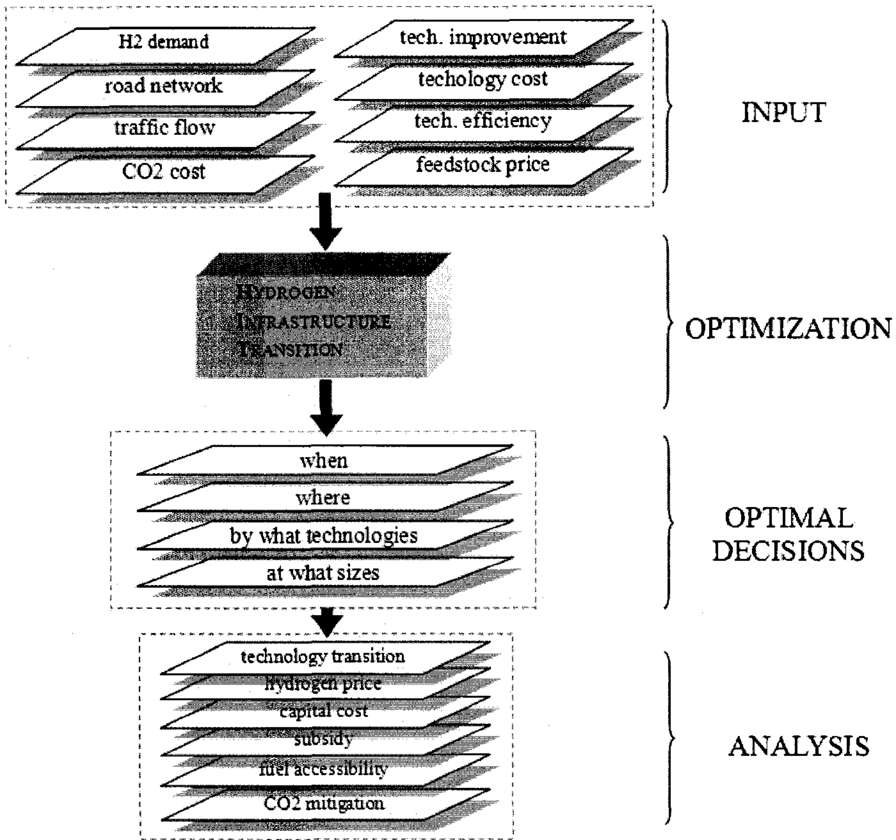


Figure 1-1: Study Boundary and Framework

First, a dynamic optimization model, called HYDROGEN INFRASTRUCTURE TRANSITION (HIT), is developed to minimize the social costs of regional hydrogen supply during a transitional period for an exogenous growth scenario of hydrogen demand. As shown in Figure 1-1, with the foreseen hydrogen demand and other information (such as technology improvement and carbon policy), the HIT model identify the optimal sequence of infrastructure buildup decisions by aiming at such a question: for a given region, when, where, by what technologies and at what sizes to build up the hydrogen infrastructure in order to minimize the net present value (NPV) of social costs of supply hydrogen? Carbon emissions and refueling travel time are assessed in dollars to enable tradeoffs with technology costs. Road network and traffic flow information are used to derive the spatial distribution of hydrogen demand. Demand growth and technology improvement describe the dynamic context. Therefore, the cost estimate based on such the optimal sequence of buildup decisions reflects considerations of regional details, dynamic context, technology competition and supplementation, spatial design, temporal strategy, and social tradeoff.

The second objective of this dissertation is to draw some empirical observations by applying the HIT model to two regions, urban Beijing and Southern California. The urban Beijing case study has been published as a conference paper at the 2006 National Hydrogen Association annual conference and the paper is included as an appendix to this dissertation (see "APPENDIX B: THE URBAN BEIJING CASE STUDY OF THE HIT MODEL"). The main body of this dissertation focuses on the Southern California case study. After the optimal hydrogen transition, represented by the optimal infrastructure buildup sequence, is found, this dissertation analyzes the optimal sequence with respect to technology transition patterns that reflect technology competition and supplementation; delivered hydrogen price that balances costs and indicates the competitiveness of hydrogen transition; capital costs that indicate risks for private sectors and needs for policy insurance; subsidy that the hydrogen industry may demand from the government or may provide for FCV purchase; fuel accessibility that is especially critical for early commercialization; CO2 mitigation that a hydrogen transition can potentially achieve; and some other issues. Sensitivity analysis is conducted for several sequences with respect to externality discount rate, carbon tax rate, coal price, electricity price, natural gas price, and electricity carbon intensity. It is hoped that the empirical observations drawn from the Southern California case study can be used to either confirm or re-examine the previous understandings of hydrogen transition and generate new hypotheses for further research.

The organization of this dissertation is as follows. Chapter 2 provides an overview of hydrogen technologies and transition issues and reviews some concepts of welfare economics as a theory tool to sort out hydrogen transition issues. This chapter then reviews several existing hydrogen cost models and mathematical programming techniques relevant to infrastructure modeling. Chapter 3 develops the HIT model using dynamic programming. Data are also presented for the Southern California case study. Chapter 4 focuses on analysis of the case study results. The final chapter summarizes the key findings and discusses the policy implications.

2 LITERATURE REVIEW

The social aspects of hydrogen transition discussed by most studies include technology cost and performance (e.g. what technologies should be adopted), fuel accessibility (e.g. how many refueling stations and how to locate them), and environmental impact (e.g. air pollution, CO2 emissions, and oil use) associated with the hydrogen infrastructure. These social aspects are often intertwined with each other and the problem complexity is amplified by spatial design, system dynamics and the diversity of hydrogen technologies. This chapter first provides an overview of technologies and issues associated with hydrogen as an alternative vehicle fuel.

The concepts of economic efficiency and income distribution from the welfare economics provide a powerful theoretical framework to sort out a wide range of hydrogen transition issues. The economic efficiency of a hydrogen transition can be optimized via maximizing its social welfare. Such an optimization can be informative but complex if system dynamics and spatial details are taken into account. Very few efforts have been made to optimize hydrogen transition by considering both system dynamics and spatial details. The second part of this chapter briefly reviews the economic efficiency and income distribution concepts from the field of welfare economics and uses these two concepts to review the hydrogen transition issues. Existing hydrogen transition and infrastructure models are also reviewed from such a welfare economics perspective.

Fundamental analysis of hydrogen technologies is the basis for modeling and assessing a hydrogen infrastructure system. The third part of this chapter reviews some important models that assess economic and environmental aspects of various hydrogen technologies.

Due to the great diversity of hydrogen technologies and consideration of system dynamics and spatial details, possible sequences of hydrogen infrastructure buildup decisions can be numerous, pointing to the need for some appropriate optimization technique. The forth part of this chapter reviews some relevant efforts in the field of mathematical programming.

2.1 Hydrogen as Vehicle Fuel

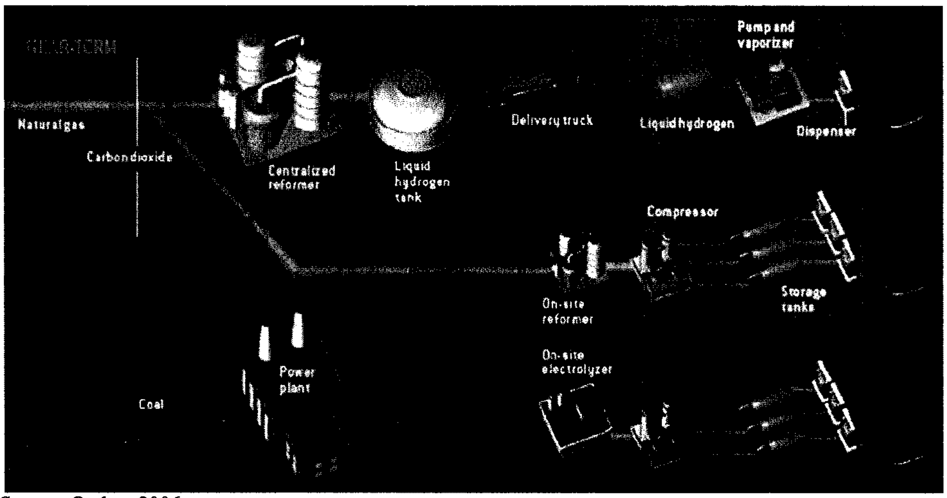
Hydrogen serves as a vehicle fuel mainly via one of two chemical processes – combustion with oxygen in a modified internal combustion engine (ICE) and electrochemical reaction with oxygen in a Polymer Electrolyte Membrane (PEM) fuel cell. A hydrogen ICE converts chemical energy stored in hydrogen via combustion into mechanical energy and powers the vehicle. A PEM fuel cell converts chemical energy of hydrogen into electric energy which is then converted by the electric motor into mechanical energy (Larminie and Dicks, 2003). This dissertation limits discussion to PEM FCVs fueled by onboard compressed gaseous hydrogen dispensed from hydrogen refueling stations.

FCVs are more efficient than conventional gasoline vehicles, meaning that the energy from fuel required for the same driving distance is less for FCVs than gasoline vehicles. It also means that a higher fraction of the total exogenous VMT served by FCVs will reduce energy input to the transport system. Unlike gasoline vehicles that emit criteria pollutants and GHGs, FCVs emit only pure water at the tailpipe. However, hydrogen production, depending on technology, can have more or less CO2 emissions than gasoline production, so comparison of only tailpipe emissions can be misleading and a life-cycle comparison is often more appropriate.

At the current technology level, FCVs based on mass production are still substantially more expensive than gasoline vehicles (Ogden, 2004b; Ahluwalia and Wang, 2008). FCVs could have some unique advantages over gasoline vehicles, such as synergy with grid electricity (Kempton and Tomic, 2005a; Kempton and Tomic, 2005b; Williams and Kurani, 2007) and vehicle design flexibility (Ogden, Steinbugler and Kreutz, 1999; Kromer and Heywood, 2007; Rousseau and et al., 2004); but in other aspects such as reliability and driving range, FCVs are not yet ready to compete against gasoline vehicles (von Helmolt and Eberle, 2007).

Hydrogen is supplied by the hydrogen infrastructure. A hydrogen infrastructure consists of one or multiple pathways (see Figure 2-1, Figure 2-2), where a pathway is a minimum chain of facilities that can collectively and logistically perform three supply functions: hydrogen production, distribution and dispensing. Figure 2-1 shows a possible near-term hydrogen infrastructure consisting of three pathways:

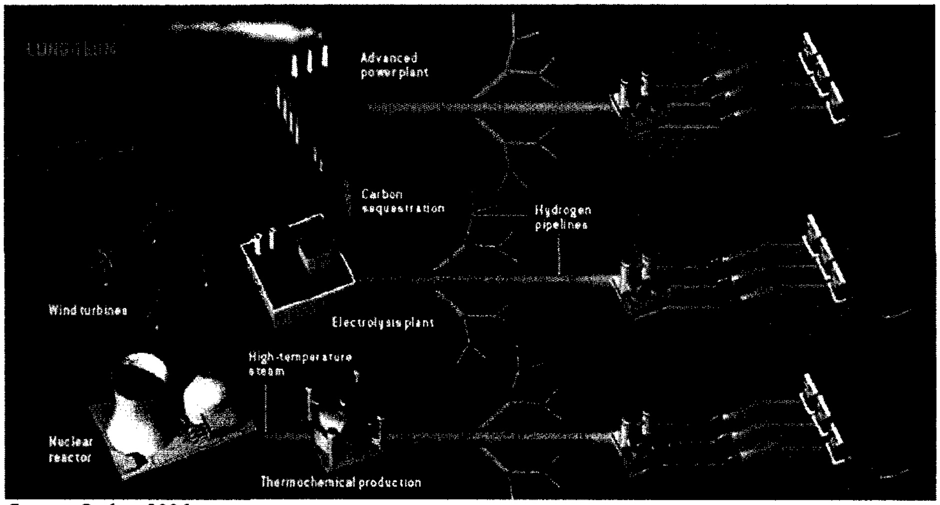
hydrogen produced via central steam reforming of natural gas and distributed to refueling station via trucking, hydrogen produced onsite via steam reforming of natural gas, and hydrogen produced onsite via water electrolysis. Figure 2-2 shows a possible long-term hydrogen infrastructure of three central pathways: coal gasification, water electrolysis based on wind electricity, and thermochemical reaction based on nuclear power, all with pipeline for hydrogen distribution. A more detailed introduction of hydrogen technologies can be found in various studies (Ogden, 2004a; NRC, 2004; Thomas et al, 2000).



Source: Ogden, 2006

Figure 2-1: Possible Near-term Hydrogen Infrastructure

These technologies differ in costs, scales, feedstock availability, sustainability, improvement potential, and GHG emissions and no technology can prevail in all aspects. For example, coal gasification appears to be a low-cost technology for hydrogen production, but it can emit a large amount of CO2 if carbon capture and sequestration (CCS) is not adopted and coal as a fossil fuel is not a sustainable resource.



Source: Ogden, 2006

Figure 2-2: Possible Long-term Hydrogen Infrastructure

A successful transition to a hydrogen-FCV system may need to overcome several kinds of barriers. One question often asked is whether FCVs can become cost-competitive with gasoline vehicles or how much the consumers are willing to pay for environmental friendliness and the unique features of FCVs. It is important to understand how consumers perceive the differences between FCVs and gasoline vehicles, on which some studies (Kurani et al., 1994; Turrentine and Kurani, 2007) have been conducted. For fuel refueling, a desirable level of fuel accessibility to trigger early market penetration may be needed and suggest a dispersed refueling network (Sperling and Kitamura, 1986; Greene, 1998; Kurani, 1992; Melaina, 2003). Such a requirement for a large infrastructure in early commercialization stages, when demand is low and revenues are small, adds to the economic difficulty of initialing a hydrogen transition.

On the fuel side, one common question is whether hydrogen can be cost-competitive against gasoline. Some estimates of hydrogen cost suggest that hydrogen is more expensive than gasoline in the near term but could become cost-competitive in the future due to technology improvement and economy of scales (NRC, 2004; Singh et al, 2005; Ogden, 2006). One on-going research topic is how to design a low-cost hydrogen infrastructure by optimizing spatial parameter such as station number, pipeline length and facility location. The infrastructure design objective can also be expanded to include less dependence on fossil fuel and more CO2 reduction, but conflicts among design objectives are likely. For example, coal gasification may be cheaper but cause more adverse environmental impact than water electrolysis based on renewable electricity. Other relevant issues include feedstock availability, policy constraints (such as renewable portfolio standard), and impacts on electricity supply (especially when water electrolysis is considered). And one question related to commercialization is how the industry will perceive the risks and profitability of participating in a hydrogen economy.

Then, these two sets of research agendas, one on FCV and the other on hydrogen, seem to suggest that FCVs separately compete against gasoline vehicles and hydrogen separately against gasoline, probably due to the implicit assumption that the structure and behavior of the future vehicle-fuel industries will be similar to what we currently observe. One way to avoid such an assumption is to compare the two vehicle-fuel systems with a life-cycle basis (Wang, 2002; Ogden et al, 2004b; Delucchi, 2004), such as comparing the life-cycle performance of per vehicle mile traveled by a FCV and a gasoline vehicle.

Life-cycle analyses are generally a static approach with no consideration of transition context or spatial details. Also, the current life-cycle models are mostly limited to isolated aspects of social costs, such as private cost, energy use, criteria pollutants, and greenhouse gases. One way to integrate these social impacts is to monetize them and use a single social cost metric. The foundation to do so is being built by research on social costs of transport, such as Broadman (1986) on social costs of imported oil; Wang, et al (1994) on monetizing costs of motor vehicle air pollutants in various U.S. regions; Small and Kazimi (1995) on costs associated with air pollution caused by motor vehicles; Delucchi (2000) reviewing estimates of external costs of motor vehicles and instructing application of these estimates; Vermeulen, et al (2004) providing an overview of social costs associated with transport; and Greene (2005) on costs of oil dependence. Also, Life-cycle approaches ignore player behavior or their reaction to polices, ignore distribution of costs and benefits among stakeholders, and are unable to address the "chicken-egg" problem.

Several hydrogen transition models and general energy transition models with hydrogen representation have been developed to simulate disaggregated stakeholder behavior with respect to exogenous policy inputs (Leiby et al, 2006; Greene et al, 2007; Wood, 2006; ETSAP, 1978). Disaggregate transitional models are very important for policy testing. It is possible to adjust the policy inputs to explore the policies that can lead to the optimal hydrogen transition, but it should be noted that any exogenously specified behavior (such as consumers do not buy FCVs unless there are a certain number of stations) or system structure setting (such as a given level of stakeholder aggregation) may inherently constrain system performance (such as social welfare) and lead to sub-optimal solutions.

Another possible improvement of the existing transitional models is incorporation of spatial details. If spatial parameters are assigned with average values (such as pipeline length) or based on simplified rules of thumb (such as station number proportional to population density), these average values or rules of thumb should still be based on empirical studies that considers spatial details. Since such kinds of regional studies are few, it is necessary to include spatial details in the transition model.

Overall, the barriers to hydrogen transition, associated with technology readiness, costs, environmental impact, consumer acceptance and policies, are largely intertwined with each other and therefore an integrated analytical approach is desirable. On the other hand, an integrated approach seems to face difficulty in reconciling some modeling issues, as previously discussed. To sort out these barrier and modeling issues and clarify the policy implications of any particular exogenous information and endogenous decision, some welfare economics concepts can be helpful, as to be discussed next.

2.2 Hydrogen Transition: a Welfare Economics Perspective

Welfare economics is concerned with the economic efficiency of an economic system as well as the income distribution among stakeholders (e.g. consumers and producers) within the system (Pigou, 1932). Economists have developed different measurements of economic efficiency improvement, and one classical one is social welfare maximization, where social welfare can be defined as the total net benefit of a given system. Such a system can be static or dynamic; if the system is dynamic, the net benefit can be represented by the net present value (NPV) of benefit and cost cash flows. In some sense, benefit-cost analysis is one application of welfare economics, although conclusions based on some types of benefit-cost analysis (such as maximization of benefit-cost ratio) may not be consistent with those based on social welfare maximization.

Although what should constitute social welfare is problem-specific and subject to measurement ability, maximum social welfare is, at least theoretically, an appealing situation, because no stakeholder in the system with maximum social welfare can be better off (i.e. gaining individual net benefit or welfare) without making any other worse off (i.e. causing loss of individual net benefit). Such a condition is also known as Pareto efficient (Persky, 1992). Theoretically, changing the system into the state of maximal social welfare from otherwise can always be an improvement in the sense that at least one stakeholder can gain more net benefit without hurting any other. It also means that social welfare maximization can lead to a win-win situation for all stakeholders (Samuelson and Nordhaus, 2004).

Certainly, social welfare maximization does not say anything about the equity issue, i.e. how the total net benefits are allocated among stakeholders, referred to as the issue of income distribution. There are three important issues associated with income distribution. The first is about transaction cost of distribution. A system that has maximal social welfare is always Pareto efficient, but a Pareto efficient system has maximal social welfare only if there is no substantial transaction cost associated with the process of income distribution. In reality, there are many types of transaction costs, such as the costs associated with convincing the stakeholders to accept the maximal social welfare situation or the costs to influence the public on perceiving the external costs. Apparently, transaction costs are common in reality and can be substantial, suggesting the practical limitation of the notion of social welfare maximization. This can indeed be resolved by including the transaction costs, if they can be measured, as part of the total social welfare to be maximized. The second is about the equity issue. As Sen (1970) points out, a Pareto efficient system can still be highly inequitable. Lack of equitable income distribution can be attributed to lack of assigning a welfare value to equity and the existence of transaction costs. If there are no transaction costs, a system with maximal social welfare can also achieve equitable income distribution. And if equity is properly valued and integrated, social welfare maximization will lead to equitable income distribution. The third issue is about internal trade, such as one stakeholder (e.g. consumers) purchasing goods from another stakeholder (e.g. fuel producers). The price of internal trade helps distribute net benefits within the system but does not affect the total net benefits, which means it is not necessary to control internal trade price while maximizing social welfare. This does not necessarily apply to internal trade quantity, as the system net benefit may be affected by consumption.

The concepts of economic efficiency and income distribution are originally discussed in a static context, but have been extended to dynamic problems. Stavins (et al, 2003) proposes a framework of social welfare maximization as an economic treatment of sustainability, where the discounted social welfare of an economic development path is maximized. From such a perspective, the economic system consists of not only players from different sectors, but also same-sector players at different times. As such, income distribution is concerned with allocating the social welfare both among players and across generations.

The above notions of welfare economics can be used to sort out the many hydrogen transition issues as previously discussed. The social welfare of hydrogen transition includes benefits and costs for consumers, gasoline providers, hydrogen providers, FCV makers over time, and other possible players (such as carbon auditors). For convenience, the social benefits of a hydrogen transition associated with oil dependence, air pollution and climate change can be viewed as the avoided costs associated with these social aspects of the replaced gasoline[4]. Then it can be assumed that the only social benefit of hydrogen transition results from satisfaction of the total travel demand (hydrogen and gasoline combined). And since travel demand is exogenous, the resulting social benefit is not controllable and can also be viewed as exogenous, even though difficult to measure or simply unknown. The resulting convenience is that social welfare maximization for hydrogen transition can be treated as minimization of social costs associated with consumption of gasoline, gasoline vehicles, hydrogen and FCVs.

Thus, a hydrogen transition is defined as optimal when it achieves the maximal social welfare or when the total social costs to serve the total travel demand are minimized. It should be noted that benefits and costs are net present value and discounting rates[5] are used to weigh benefits and costs over time. Such a social welfare maximization coupled with discounting reflects what Stavins (et al, 2003) calls as "dynamic efficiency".

The policy implication is that the optimal hydrogen transition is how social resources are most efficiently allocated in serving travel demand, as far as the system boundary can be defined by the exogenous travel demand and the availability of only

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[4] The hydrogen supply can also cause social costs on these aspects (e.g. hydrogen based on fossil energy), which will be counted.

[5] However, choosing a proper discount rate for a long term issue or for external costs is still a controversial issue.

two fuel options, gasoline and hydrogen. Certainly, the framework can be expanded to include more fuel types and even fuel efficiency technologies. Another policy implication is that all stakeholders in the optimal hydrogen transition can be at least not worse off than in any other non-optimal transition including business as usual (but before we know the optimization result, business as usual should still be viewed as possible to be the optimal transition). This is important since the main goal of the government is to promote the welfare of individuals and avoid wastefulness of social resources (Stavins et al, 2003).

In minimizing the social costs of hydrogen transition, there are a wide range of variables that can possibly be treated as controllable, i.e. decisions. One example of decision set is how to build up the infrastructure while representing tradeoff among technology, environmental impact, and fuel accessibility. Another important decision is when and by how much the hydrogen sector penetrates the fuel market, as faster hydrogen penetration may earlier reduce social costs of gasoline consumption while requiring earlier investments in hydrogen infrastructure, representing a temporal tradeoff of costs. If hydrogen penetration or hydrogen demand is controllable, it becomes necessary to measure the social costs of gasoline, gasoline vehicles, hydrogen and FCVs. This would greatly add to problem complexity, although a rich body of literature on social costs of vehicles and fuels are available, as previously reviewed.

Another consequence of endogenous hydrogen demand is the need for stakeholder behavior modeling. If hydrogen demand is treated as a decision variable in the optimization model, it does not mean that the government can directly control hydrogen demand in reality. In reality, hydrogen demand is indirectly affected by policy settings such as economic incentives for consumers to purchase FCVs. Therefore, if hydrogen demand is controllable and policy testing is included, it is necessary to model stakeholder behavior. Disaggregating stakeholders and representing their behaviors are also important from the income distribution perspective. An optimal hydrogen transition does not guarantee equitable distribution of the maximized social welfare. By modeling stakeholder behavior, we can simultaneously maximize the social welfare and determine the income distribution. If the income distribution turns out to be unpleasant (e.g. consumers bear too much cost and oil companies receive too much profit), we can then tune the policy settings to hopefully reach a more equitable situation.

There are some transition models with stakeholder disaggregation, allowing income distribution under specified policy settings. Developed by the Energy Information Administration (EIA) of the U.S. Department of Energy (DOE), the National Energy Modeling System (EIA, 2003; Wood, 2006), or NEMS, is a general equilibrium economic model representing the U.S. energy market. NEMS disaggregates the fuel supply markets, production sectors, and consumption sectors of the energy system. In NEMS, an integrated module is built to communicate with each sector or market and reach a solution by calling each supply, production, and consumption module in sequence until the price and quantity of each energy trade between sectors are converged.

Originally developed in the late 1970s at Brookhaven National Laboratory and later overseen by Energy Technology and Systems Analysis Program (ETSAP) of the International Energy Agency (IEA), the MARKet ALlocation model (MARKAL) is an energy-economic optimization model of a region over a time span of several decades (ETSAP, 1978). The U.S. Environmental Protection Agency (US EPA) applies the MARKAL framework by developing the EPA National MARKAL Database (EPANMD) (Shay et al, 2006), which represents the US national economy through hundreds of life-cycle flows of material and energy within and across sectors. Driven by EPANMD, the US EPA MARKAL as a linear programming model solves for the least-cost energy solution in meeting sector energy demands under the constraint of flow conservation of material and energy. Other constraints of US EPA MARKAL include maximum introduction rate of new technologies, resource availability, energy use goals and emission goals. Costs are usually represented as unit cost (such as million USD per megawatt of power plant) without spatial representation. The US EPA MARKAL treats the United States as a single region, but is being expanded to represent different U.S. regions and include more fuels such as hydrogen for transportation (Delaquil et al, 2007).

Developed by the U.S. DOE, The Hydrogen Transition Model (Leiby et al, 2005; Leiby et al, 2006; Greene et al, 2007), or HyTrans, is a market equilibrium simulation model with a focus on hydrogen transition. HyTrans disaggregates the market into hydrogen producers and retailers, vehicle manufacturers and consumers and simulates the behavior and decisions of these stakeholders, assuming each stakeholder as a rational entity. HyTrans maximizes social welfare with stakeholder disaggregation. HyTrans is a dynamic, multi-period optimization model, covering the period from 2005 to 2050. For spatial representation, HyTrans disaggregates the United States into three geographic regions and three fuel density demand regions within each geographic region.

The National Renewable Energy Laboratory researchers developed a dynamic model called HyDive to understand the "chicken and egg" problem for initiating a hydrogen refueling infrastructure (Welch 2006, 2007). HyDive disaggregates stakeholders into consumers, fuel suppliers, and policymakers and uses systems dynamic methods to model their decisions. The model uses GIS data with consumer attributes to identify areas that could be early adopters of hydrogen and optimal locations for refueling stations.

More detailed reviews of the above transition models can be found at (Plotkin, 2007) and (Ogden, 2008).

The above transition models all aim at maximizing system efficiency and more or less disaggregate the system into different stakeholders, which allows representation of stakeholder behavior responding to policy settings. However, from the perspective of social welfare maximization, a potential downside of stakeholder is that the resulting hydrogen transition may not be optimal, because stakeholder grouping and behavior representation are essentially constraints that can possibly prevent full cooperation of stakeholders that is required for social welfare maximization without stakeholder disaggregation. Such full cooperation may seem unlikely compared to what we are observing from the gasoline vehicle system, but since the hydrogen transition is usually a long-term process and innovative policies may take place to reshape the industry structure and consumer behavior, it is important to explore the full potential of system performance enabled by stakeholder full cooperation. For example, a model that assumes consumers accept FCVs only when they are not more expensive than gasoline vehicles would exclude the scenario where consumers pay extra for FCVs because 1) they have perceived the external costs of gasoline vehicles and believed that these costs will eventually come out of their pockets in form of taxes to fund government projects in dealing with external impacts of gasoline; or 2) the government perceives the external costs of gasoline on their behalf and provides them FCV purchase subsidies that actually come from their own pockets. Such a scenario can possibly belong to the optimal transition and be excluded because of assumption of consumer behavior as a result of stakeholder disaggregation.

Besides the sub-optimality risk, stakeholder disaggregation requires representation of internal trades that may not be necessary for social welfare maximization. When stakeholders are disaggregated, there will be some trades between stakeholders, such as selling hydrogen from hydrogen producers to consumers. These trades are usually characterized by two variables: quantity and price. From the perspective of social welfare maximization, while the quantity of such a hydrogen trade is related to the quantity of gasoline being replaced and therefore affects social welfare, the price of trade does not affect social welfare because it only affects the distribution of social welfare, i.e. allocation of surplus to producers and consumers without affecting the total surplus. And because the quantity of such a hydrogen trade is already captured by inclusion of hydrogen demand as a decision variable, it becomes unnecessary, just from the perspective of social welfare maximization, to model the hydrogen trade between consumers and producers.

After the above discussions of concerns related to stakeholder disaggregation, the next question naturally becomes whether social welfare maximization without stakeholder disaggregation will lead to an optimal but unrealistic hydrogen transition. If being unrealistic is based on some kinds of cost or benefit not included (but note that it is impossible to capture all possible cost or benefit aspects) in the model, then it is possible that the so-called optimal hydrogen transition is unrealistic or realistically sub-optimal because, for example, the maximized social welfare will be substantially offset by the transaction cost, not included in the model, to convince oil companies to accept the optimal transition. But this is due to coverage of cost and benefit aspects, not due to the notion of social welfare maximization. When an optimization model is used to maximize the social welfare of hydrogen transition, the model user must acknowledge that the real world has been simplified and represented by the cost and benefit items in the model. By including sufficient important cost and benefit items, social welfare maximization can lead to the optimal and executable hydrogen transition scenario.

2.3 Hydrogen Cost Estimation

To optimize hydrogen transition by maximizing social welfare, it is important to reduce the social cost of hydrogen infrastructure, not just in its end state but also during the transition period. Many important studies have attempted to model the hydrogen infrastructure from various perspectives and estimate hydrogen cost based on a hypothetical representation of hydrogen infrastructure. These studies provide rich information for hydrogen transition analysis.

To understand the existing efforts in modeling hydrogen infrastructure and estimating hydrogen costs, it is important to know how a hydrogen infrastructure is commonly represented. A hydrogen infrastructure can be treated as a system whose logistical boundary is defined as major feedstock (such as coal, natural gas, water, etc), industry hydrogen and electricity as inputs and delivered hydrogen and emitted CO2[6] as outputs (see Figure 2-3). Such a system boundary definition is commonly adopted by existing hydrogen cost models (Ogden, 1999b; NRC, 2004; H2A, 2008).

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[6] Some CO2 may be captured and sequestrated. If so, only the emitted CO2 is considered having environmental impact.

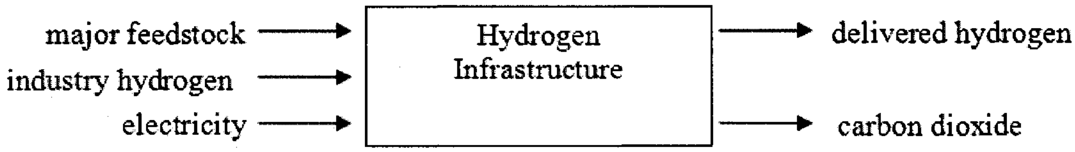

Figure 2-3: System Boundary

As previously stated, a hydrogen infrastructure consists of one or multiple pathways, where a pathway is a minimum chain of facilities that can collectively and logistically perform three supply functions: hydrogen production, distribution and dispensing. As mostly discussed in the literature (Ogden, 1999b; NRC, 2004; H2A, 2008), a hydrogen pathway usually takes one of the three forms: central, distributed (or onsite), and industry hydrogen.

- In a central pathway, a feedstock (such as natural gas, coal or biomass) is converted at a central plant into hydrogen, which is then transported through a distribution route (pipeline or trucking) to a refueling station and then delivered to consumers.
- In a distributed pathway, hydrogen is produced from a feedstock (natural gas or electricity) and dispensed at the same facility called an "onsite station". For onsite hydrogen production, there is no need for hydrogen distribution.
- In an industry hydrogen pathway, hydrogen is purchased as a commodity from outside the system, and then transported to a refueling station. There is a large quantity of hydrogen being produced for the petroleum and chemical industries

and some fraction is distributed through the merchant hydrogen system (Ogden, 1999b).

There are a number of issues to be considered in modeling a hydrogen infrastructure.

Hydrogen Demand

Demand for hydrogen equals system hydrogen output, as insufficient supply is not considered in this dissertation. Because the future demand for hydrogen is highly uncertain, if not impossible to project, hydrogen demand for the purpose of hydrogen cost estimation has been based on scenario analysis instead of projections of future demand.

The National Research Council hydrogen study (NRC, 2004) uses the Excel spreadsheet model developed by Simbeck and Chang (2002) to estimate hydrogen cost. The NRC study includes a comprehensive assessment of hydrogen cost. It estimates hydrogen cost for three demand levels: 1080 and 21.6 tonnes per day for central pathways and 432 kg per day for distributed pathways (for reference, a single FCV can consume about 0.5 kgH2 per day. So a central production facility with an output of 1080 tonnes per day could serve 2.16 million FCVs). In the NRC study, different pathways are modeled to operate at a constant load factor of 90% for the period of facility life. Hydrogen cost is estimated based on the resulting cash flows over the same period.

Since 2003, the US DOE convened a team of government, industry and academic analysts as the H2A (Hydrogen Analysis) group to develop a comprehensive set of cost and performance data for hydrogen energy technologies with the aim of improving the transparency and consistency of hydrogen analysis. The resulting database model is called the H2A model (H2A, 2007). The model estimates hydrogen cost for a wide range of hydrogen pathways and has been applied for several demand levels: 1500 kg/day and 100 kg/day for steam methane reforming (SMR) onsite stations, 1500 kg/day and 100 kg/day for water electrolysis onsite stations, 50 tonne/day for central electrolysis using wind electricity, 341 tonne/day for central SMR and 277 tonne/day for central coal gasification. Similar to the NRC study, the H2A model also assumes hydrogen demand to be constant over the period of facility life. In fact, such a static treatment of demand has been a common practice in hydrogen cost community, as evident by several other studies (Ogden, 1999b; Ogden 1999c; Johnson et al, 2005; Linnemann and Steinberger-Wilckens, 2006; Yang and Ogden, 2007b; Chang et al, 2007).

Although these studies differ in demand level, they all assume the demand to be constant over the time of facility life. Such a static demand perspective is reasonable for modeling a small part of a mature economy. For example, the owner of a new onsite station in a future mature hydrogen economy can reasonably assume the sales of the station to be constant over 20 years and then analyze the resulting cash flows. However, we are more interested in social welfare maximization by viewing the hydrogen infrastructure development as a system in a transitional context. During the hydrogen transition period, the demand growth over a facility lifespan (e.g. 20 years for stations or 40 years for central plants) may be significant enough to affect the infrastructure buildup decisions. Therefore, given the transition context, a dynamic representation of demand is desirable.

Optimization

Optimization has rarely been adopted by existing hydrogen cost models. Mostly, pipeline length, station number, station locations and facility utilization are based on assumptions rather than treated as a series of dynamic and spatial decisions. More importantly, hydrogen cost is estimated for each individual pathway rather than for the whole infrastructure system where different pathways compete and supplement (to be further discussed later) with each other and reach an optimal system configuration. Optimization has been applied to some infrastructure components, such as station siting (Nicholas, et al., 2004) and hydrogen distribution (Shayegan et. al., 2006; Johnson et al. 2005; Parker 2007; Yang and Ogden, 2007a).

The HyTrans model is probably the first model to apply optimization to simulate market response to hydrogen technologies and policies. HyTrans is a dynamic, non-linear optimization model (Greene, et al., 2007), where market agents (hydrogen producers, distributors, and retailers, and vehicle manufactures, purchasers and users) are assumed to "rational, optimizing economic agents with full information and foresight" (Greene, et al., 2007, p3). The model is intended for policy testing where market agents are disaggregated to reflect income distribution guided by policies.

System Dynamics

System dynamics as applied to modeling hydrogen infrastructure considers two issues: 1) how the infrastructure should be built up with foresight of technology improvement, policies, and demand growth and 2) how the status of infrastructure at a given time affects further buildup decisions. The dynamic demand perspective discussed above is indeed related to system dynamics. Similarly, the essential reason to consider system dynamics is that we are more interested in modeling hydrogen infrastructure in the transitional context and the changes of technologies, policies and demand are too significant to be ignored in relative to the facility lifespan.

While some transition models, such as MARKAL (ETSAP, 1978), HyTrans (Greene et al, 2007) and EICOMP (Gether, 2004), incorporate foresight of information into the optimization, most of the hydrogen cost models assume static hydrogen demand and ignore system dynamics. However, some static models are extended to consider the effect of changing factors on hydrogen cost. For example, the NRC (2004) study estimates hydrogen cost for both "current technology" and "future optimism" settings, attempting to create an estimation range. Such an estimation range is informative, although it is unable to directly provide an estimate of hydrogen cost resulting from an infrastructure that evolves from the time of "current technology" to that of "future optimism". Instead of explicitly estimating future hydrogen cost, the H2A model incorporates Tornado diagram and Monte Carlo simulation for sensitivity analysis.

Technology Assessment

There are many known technologies for hydrogen production, including steam methane reforming (SMR) of natural gas, coal gasification, biomass gasification and water electrolysis. Water electrolysis technologies are further categorized by the source of electricity and the existing literature covers solar, wind, hydraulic, nuclear and grid electricity. Among these technologies, natural gas SMR and water electrolysis are viewed as most viable for onsite production. Technologies for hydrogen distribution mainly include gaseous high-pressure hydrogen via pipeline, gaseous high-pressure hydrogen via trucking, and liquid hydrogen via trucking.

The NRC study covers almost all the technologies listed above, while the application of the H2A model has covered not as many technologies but provides a more detailed characterization of each technology it covers. The HyTrans model identifies several production, distribution and dispensing technologies and allows combinations of these facilities, resulting in tens of possible hydrogen pathways (Greene, et al., 2007). Yang and Ogden (2007a) compares the above three modes of hydrogen distribution with an idealized layout context to determine the lowest-cost mode with respect to demand density and geographic size.

A broad coverage of technologies is important as it allows not only a thorough comparison but also technology competition and supplementation.

Technology Competition

In some circumstances, one technology is preferable to another by contributing less to the net present value of total social cost and therefore becomes part of the optimal solution. This refers to technology competition. Such a relative preference may change with circumstances. For example, in early stages when demand is low, trucking may be more attractive than pipeline and is part of the optimal solution. When demand grows, pipeline may become more competitive due to economy of scale. As a result, pipeline may gradually replace trucking in the optimal solution. When a broad range of technologies are available, assembling the least-cost infrastructure over time requires the hydrogen cost model to allow competition among technologies.

From the infrastructure system perspective, it may be unnecessary to look at technology competition in the facility operation level, such as choosing the optimal hydrogen pressure in a pipeline segment. However, it may be oversimplified to compare technologies in the pathway level, i.e. comparing a limited number of pre-defined hydrogen pathways and choosing the best one. For example, in the NRC (2004) study, the several 1080 tonne/day central pathways are all with pipeline distribution, while the several 21.6 tonne/day central pathways are all with trucking distribution. When these pathways are compared based on average delivered hydrogen cost, what are ignored are the possibilities of pipeline serving the 21.6 tonne/day central plants and trucking serving the 1080 tonne/day central plants. Pre-defining hydrogen pathways is a method to simplify the analysis, but the downside is preventing competition of facility technologies and creation of an innovative pathway or system especially in a dynamic context. Such a pathway pre-definition approach can also be observed in several other studies (Ogden, 1999b; Sheyegan, 2006; H2A, 2008). The HyTrans model allows facilities to freely match each other and form the optimal pathway and therefore inherently incorporate facility-level technology competition.

It should be noted that deciding on the level of details to represent technology competition is still more art than science. I believe facility-level technology competition (as in Greene, et al., 2007) is more desirable than pathway pre-definition at present because hydrogen infrastructure design has not been adequately understood.

Technology Supplementation

Minimizing the system cost requires not only technology competition but also technology supplementation, i.e. multiple pathways coexisting to reduce costs. For example, biomass gasification can be the most competitive production technology if carbon tax is high enough, but may need to co-exist with the second best technology in meeting the system demand because of biomass resource availability. Pipeline distribution may be selected for highly concentrated demand areas, but its coexistence with trucking serving some dispersed rural areas may be better than an exclusive pipeline distribution system, at least at some certain levels of demand. Parker (2007) has explored this concept in a study of biomass hydrogen where natural gas-based hydrogen is a back-stop technology. To my knowledge, technology supplementation is a missing attribute in virtually all existing hydrogen cost models.

Fuel Accessibility

Fuel accessibility refers to the ease for FCV motorists to access hydrogen refueling stations. Fuel accessibility can be improved by adding refueling stations or effectively locating refueling stations or both. Fuel accessibility is not free and can be costly in the early stages of infrastructure development, and thus several studies have been conducted to understand the desired level of fuel accessibility from the consumer perspective (Sperling and Kitamura, 1986; Kitamura and Sperling, 1987; Greene, 1989; Kurani; 1992; Greene, 1998). Melaina (2003) proposes three approaches in estimating sufficient station number based on percentage of existing stations, closeness to residents of metropolitan area, and closeness to roads of high traffic density. These studies provide critical basis for understanding refueling need and behavior. However, these studies mostly treat fuel accessibility as an ordinal variable, e.g. "unacceptable" and "desirable" and are unable to reveal tradeoff between fuel accessibility and other costs on consumers. For examples, how much fuel accessibility would consumers sacrifice if they are offered 50% discount on fuel price?

Because there is no meaning for difference between ordinal values, treating fuel accessibility as an ordinal variable imposes difficulty for integrated analysis where fuel accessibility is intended to trade off with other system objectives, such as technology costs. Imagine two extremely unrealistic (because it is intuitively undesirable) situations: 1) fuel accessibility is maximized by building refueling stations everywhere, and 2) technology costs are minimized by building only one centralized (with enough capacity) refueling station. The former situation is too expensive and the later is too inconvenient and a natural hypothesis is existence of an intermediate situation where an optimal tradeoff can be achieved. The key issue is how to quantify fuel accessibility and integrate it into social welfare framework (i.e. monetary benefits and costs) to enable optimization.

Nicholas (et al, 2004; et al, 2006) estimates how many hydrogen stations are needed to reach the current gasoline accessibility for hydrogen by effectively siting hydrogen stations at existing gasoline station locations. His model calculates refueling travel, which can be monetized for social tradeoff.

Spatial Layout

Spatial layout is mainly concerned with refueling station locations that affects fuel accessibility and pipeline length and trucking distance that affect hydrogen distribution cost. The NRC study assumes 438 stations and 600 kilometers of pipeline for each 1200 tonne/day central pathway, and 9 stations and 150 kilometers of trucking routes for each 24 tonne/day central pathway. These parameters are not based on spatial layout and therefore their region applicability is unclear. The H2A model also derives station number based on demand and station size, but takes a further step by using an idealized layout reflecting population density and region area (Paster, 2006; Mintz, 2007). The idealized layout approach also appears in several other studies (Chang, 2007; Yang and Ogden, 2007a and 2007b). Yang (et al, 2006) compares idealized and real-world city station citing models. Some other researchers (Ogden 1999b; Melaina, 2005; Shayegan et al., 2006) investigate the sensitivity of distribution cost to delivery distance. Some studies investigate spatial layout of hydrogen or feedstock distribution system. For example, Parker (2007) studies supply of biomass for hydrogen production and optimizes the spatial layout of biomass distribution based on spatial details of northern California. Johnson (2005) studies hydrogen infrastructure in Ohio and optimizes a hydrogen pipeline network based on minimum-spanning tree algorithm (Cormen, 2001).

Specifically with respect to station location, the two key issues are on how to determine the optimal station number and the optimal station locations. By examining alternative fuel experiences in the United States (Sperling and Kitamura, 1986; Kitamura and Sperling, 1987; Melaina, 2003), New Zealand (Kurani, 1992), Canada (Greene, 1989), these studies attempt to estimate a sufficient number of stations, in terms of percentages of existing gasoline stations, for a successful alternative fuel vehicle fleet, but do not explicitly consider spatial details or implicitly treat station location as a black-box function.

In the mathematical programming community, the station siting problem has often been treated as that of facility location on a network of roads (Hakimi , 1964;

Hooker, et al., 1991; Church and ReVelle, 1974; Bapna, et al., 2002) or as a subset of the existing gasoline station network (Nicholas, et al., 2004). These facility location models explicitly or implicitly assume the fixed nodes, mostly home or workplace, as the origins of refueling travel.

Hodgson (1990) and Berman (et al., 1992) question this origin assumption and argue that many facilities, such as convenience stores, automated teller machines, and gasoline stations, serve demand in form of the passing traffic flows. In other words, visiting these facilities is a secondary trip purpose and therefore setting a fixed node as the trip origin is not reasonable. Both Hodgson and Berman propose a flow-capture model, where a traffic flow is considered captured if it passes a station and the objective is to maximize the number of captured flows by locating a give number of stations. Since their work, the flow-capture model has been improved and extended, for example, with respect to combining both fixed origins and passing flows (Hodgson and Rosing, 1992), trip deviation (Berman, et al., 1995), one flow captured by multiple facilities (Hodgson and Berman, 1997), and consideration of vehicle range (Kuby and Lim, 2005).

Overall, the station location problem has generally been formulated either as a fixed-origin network location problem or as a flow-capture problem. Both approaches have merits and drawbacks. As previously discussed, the flow-capture approach has an important merit of reflecting the secondary nature of refueling trips. However, the approach inevitably ignores the difference of capturing long and short trips. For example, consider two trip routes, where one is 20 mile long and another is only 1 mile long. If both routes have the same flow volumes and each route passes one and only one station, the flow-capture approach would not tell the difference, but intuitively, motorists on the one-mile route will have better fuel accessibility. An even more serious drawback is no reflection of inconvenience suffered by motorists making un-captured flows. Two solutions with the same number of captured flows would then be considered having the same performance, even though they could in fact differ significantly in the number of un-captured flows. The third drawback lies in the difficulty to convert number of captured flows into dollars to enable tradeoff between station costs and refueling convenience. Such a tradeoff is important where station location is just part of a broader system context, such as the hydrogen infrastructure problem considered in this dissertation. The fourth drawback of the flow-capture approach is on data needs, as detail travel data are often difficult to collect. Although not capturing the secondary nature of refueling travel, the fixed-origin network location approach allows monetization of solution performance based on travel time value, and generally has lesser data needs.

In general, the spatial layout of hydrogen infrastructure based on geographic details has not been adequately integrated into the hydrogen transition context. Such integration can reveal two possible infrastructure development behaviors: 1) optimal expansion of refueling network driven by demand growth and tradeoff between technology costs and fuel accessibility cost; 2) optimal expansion of pipeline network causing diminishing trucking service. Last but not the least, integration of spatial layout into an optimization model can lead to more accurate estimates of infrastructure parameters, including station number, pipeline length and trucking distance, and therefore a more accurate estimate of hydrogen cost.

Geographic Scope

Probably the most important motivation of estimating hydrogen cost is to assess the cost-effectiveness of hydrogen in addressing national or global issues. Ideally, for hydrogen cost estimation, a regional scope as large as spatial details can be handled should be used. With sufficient regional case studies providing empirical findings, the cost-effectiveness of hydrogen as a nationwide fuel can be adequately assessed. Although not necessarily considering spatial details and a dynamic context, some excellent region-specific case studies on hydrogen cost have been conducted, such as the pioneering work done by Ogden (1999b) on Southern California, the comprehensive NRC study on hydrogen cost estimation in the United States, Altmann (et al., 2004) on modeling European hydrogen infrastructure, Johnson (et al., 2005) on coal-based hydrogen infrastructure in Ohio, Yang (et al, 2006) on hydrogen supply for four urban areas of California, Melendez and Milbrandt (2006) on various U.S. metropolitan areas, Melaina and Bremson (2006) on various U.S. cities, Shayegan (et al., 2006) on London, Wietschel (et al., 2006) and Keith Parks (2006) on the United States, Parker (2007) on northern California, Yang and Ogden (2007b) on an interactive Excel tool for modeling hydrogen supply in 73 U.S. urban areas, Tzimas (et al., 2007) on Europe, Chang (et al, 2007) on Beijing, and H2A (2008) allowing a drop-down selection of applicable regions.

When spatial details are not considered, as a simpler approach, hydrogen infrastructure is modeled by assuming region-wide average parameters, such as the assumptions of the NRC study on pipeline length, feedstock price, station number, etc. By interpreting the hydrogen cost estimates in a national context, the study implicitly assumes that these parameter assumptions represent the national average and more importantly, that such an average hydrogen infrastructure is developed nationwide simultaneously, which can be misleading. But on the other hand, the NRC study also acknowledges that "while it will be many years before hydrogen use is significant enough to justify an integrated national infrastructure … regional infrastructure could evolve sooner" (NRC, 2005, p4).

The regions that adopt hydrogen sooner will likely be ones with hydrogen-friendly attributes, such as high gasoline price, high and concentrated travel demand, aggressive environmental and energy policies, etc. Estimating hydrogen cost with a regional scope can help identify these hydrogen-friendly regions and develop a national geographic phase-in strategy for hydrogen.

Summary

There is a significant knowledge gap in understanding regional hydrogen cost in a transitional context. Such a knowledge gap can be narrowed by estimating hydrogen cost based on an infrastructure optimized spatially and over time. Such an optimization can be further improved by having broad technology coverage and allowing technology competition and supplementation and tradeoffs among system objectives. Spatial optimization results in the constraint of geographic scope due to computation time. Optimization over time leads to system dynamics and requires foresight of information, such as demand growth and technology improvement, and carbon policy evolvement.

2.4 Mathematical Programming

As previously stated, the modeling task of this dissertation is to optimize the regional hydrogen transition with exogenous hydrogen demand. And this task is previously translated into minimization of social costs of hydrogen supply over time for a given demand scenario. Dynamic context, spatial details and technology diversity all add to problem complexity. So it is necessary to review the relevant literature in the mathematical programming community in order to choose an appropriate optimization framework.

The objective function of the intended model is minimization of total social cost while deciding where, when, by what technologies and at what sizes to build and operate the hydrogen facilities. From the mathematical programming perspective, consideration of multiple technologies and facility sizes suggests increasing the size of the problem, but what really categorize the hydrogen infrastructure design problem are the "where" and "when" components.

For the "where" component, what are relevant from the mathematical programming community are the rich literature in facility location models. These models are common in that they all pertain to locating facilities to meet demand in some form of spatial distribution. Facility location models can be broadly classified based on optimization objective (such as maximum geographic coverage or minimum total travel time) or parameter assumption (such as deterministic or stochastic). More relevantly, based on spatial characteristics, facility location models can be grouped into continuous location models, where facilities can be located on every point in the plane, and network location models, where facilities can only be located on the nodes or along the arcs of a given network. Discussion of continuous locations models can start from the Webber problem (Wesolowsky, 1993) and cover extensions in terms of algorithms (e.g. (Rosing, 1992) on column generation algorithm) and problem attributes (e.g. (Krarup and Pruzan, 1979) on minmax location problems).

Network location models are more relevant to this dissertation, as formulating the hydrogen infrastructure problem in a network facility location context has three merits. First of all, the traffic flow data that describes the demand distribution is intuitively based on network of roads instead of a continuous plane. Second, a network context allows discrete representation and is more convenient to be solved numerically. Third, results presented on a network are easier to interpret.

Static network location models consider location decisions once or for one representative period, while dynamic network location models reflects temporal change of information (demand, cost, policies) and decisions. Although dynamic models are capable of addressing more realistic and important issues, much more attention has been devoted to static models because of two possible reasons. First, historically, static models are the basis and dynamic modes are the extension, and hence improving static models may benefit dynamic models. Second, some of the static deterministic problems are already very difficult to solve (Owen and Daskin, 1998). Researchers have covered a great variety of static network location problems, including p-median (e.g. Hakimi (1964, 1965) on reducing solution set; (Beasley, 1982) on solution methods), p-center (e.g. (Handler, 1979) on transforming the p-center problems into covering problems), discrete ordered median (e.g. Boland, et al., 2006), uncapacitated facility location (e.g. (Efroymson and Ray, 1966) on analytical solution; (Erlenkotter, 1978) on branch-and-bound algorithms with dual ascent methods), aggregate capacity plant location (e.g. (Klose, 1998) on exact algorithms), maximum covering location (e.g. Daskin 1995), and capacitated facility location (Harkness and ReVelle 2003). More literature information on static facility models are provided by review papers such as Owen and Daskin (1998), Klose and Drexl (2005), ReVelle and Eiselt (2005), and ReVelle and Eiselt (2008).

In the hydrogen infrastructure context, we need to consider when to adopt certain hydrogen technologies while foreseeing the evolving factors. This makes dynamic network location models more relevant.

Dynamic programming (DP) is a natural and powerful modeling framework for dynamic network location problems. The philosophy of dynamic programming is called Principle of Optimality, as discovered by Bellman (1957). It is implemented through the definition of a value function at each stage which represents the cost from that stage through the end of the time horizon. The structure of the value function is usually unknown, but it is possible to solve the dynamic programming model by using recursive algorithms and boundary conditions. The beauty of dynamic programming is that it breaks a large problem into a sequence of simpler optimization sub-problems (Cervellera 2006).

Ballou (1968) applies dynamic programming to a hypothetical small-scale dynamic single-facility location problem based on potential location sites, which are determined by static optimization for each time step. This approach can theoretically guarantee only the sub-optimal solutions, as recognized by Ballou (1968). Sweeney and Tatham (1976) improves Ballou's approach by proving that, to yield a global optimal solution, only the R_t best alternatives for time step t, generated via mix-integer programming (MIP), need to be included in the state space in the dynamic programming procedure. Scott (1971) uses dynamic programming to consider multiple facilities located one at a time with the constraint of no facility close-down. Wesolowsky and Truscott (1976) relaxes this constraint by allowing facilities to be relocated in response to demand changes with both integer programming and dynamic programming formulations.

As a popular formulation tool for dynamic network location problems, dynamic programming has however rarely been computationally implemented due to the curse of dimensionality (Bellman, 1957). That is, the size of state or decision space increases exponentially with additional state or decision dimensions. The curse of dimensionality is prevalent even for simplified, medium-scale supply networks (Sarimveis, 2007). Therefore, in applying dynamic programming to the hydrogen infrastructure development problem, we will likely face a serious computation challenge.

The main trend, if not the only, in tackling the curse of dimensionality is by approximation techniques, as has been explored by many researchers (Sutton and Barto, 1998; Tsitsiklis and Van Roy, 1999; Secomandi, 2000). An approximation algorithm is usually demonstrated in a specific case study where the approximate solution is benchmarked by exact optimal solution separately obtained. However, it is unclear whether or not the demonstrated proximity will be achievable in other case studies. Furthermore, the variation in the approximate solution in response to parameter variation is usually difficult to interpret

Often forgotten is the simple idea of enumeration. By definition, optimization is finding the best from a set of alternative or feasible solutions. Enumerating and evaluating all the feasible solutions seems natural but is often impractical because of the enormous time required for enumeration. This is why most optimization research is focused on solution procedures as alternatives to enumeration. However, enumeration can become more practical when computation technologies improve, the model users can tolerate more computation time (such as a planning context rather than a real-time traffic control context), and the size of feasible set can be reduced. In attempt to applying enumeration to global optimization problems, Asic and Kovacevic-Vujcic (1991) develops a set reduction procedure, where a sequence of logical tests are applied to eliminate a substantial portion of the solution set and enumeration is applied to the remaining "interesting" solutions.

Applying such enumeration thinking to dynamic programming has not been studied theoretically or empirically. Therefore, such an attempt is still highly experimental. It will require in-depth understanding of the problem context so that problem-specific constraints can be used to create set-reducing logical tests.

3 METHODOLOGY

As previously established, the modeling task of this dissertation is to develop a dynamic optimization model, called HYDROGEN INFRASTRUCTURE TRANSITION (HIT), which minimizes the social costs of regional hydrogen supply during a transitional period for an exogenous scenario of hydrogen demand. As commonly agreed, an optimization model can be described in terms of the simplified problem that captures the relevant and manageable elements of the reality; the exogenous factors whose values serve as the inputs for optimization; the decision variables whose values, also called outputs, are endogenously determined by optimization; the optimization objective in the form of a function of exogenous factors and decision variables; the model formulation including both the objective function and the constraints that describe the relationships of factors and decisions; and the solution procedure, or called algorithm, that is followed by manual calculation or implemented with a computer software to reach the optimal values of the decision variables.

In the first section of this chapter, the above aspects of the HIT model are described. The HIT model is supported by several sub-models that prepare some inputs or perform some off-line optimization procedures. The second section describes these sub-models. One of the sub-models, the Station Location sub-model, optimizes the locations of refueling stations and is described separately in the third section due to its complexity and details. The forth section shows the data that describes the inputs of the Southern California case study.

3.1 The HYDROGEN INFRASTRUCTURE TRANSITION Model

3.1.1 Problem Simplification and Assumptions

A clear description of how the hydrogen transition problem in reality is abstracted into a mathematical model is critical for further communication. Describing the abstraction will inevitably define the system boundary and clarify what elements in reality are included or not. Such an abstraction or simplification is necessary for generation of useful information due to always limited intelligent and computing resources, but is inherently imperfect in simulating the real world and therefore demands appropriate interpretation of results.

In this dissertation, hydrogen transition is seen as the system configuration changing over time during the study period T, which is divided into several time steps. A configuration is a static snapshot of the infrastructure during a specific time step, as illustrated in Figure 3-1. The change of configuration is represented by exogenously evolving factors, such as demand growth, and decisions on incremental development of the hydrogen infrastructure, such as a central plant added to increase total hydrogen production capacity or a pipeline segment added to connect a refueling station (so that hydrogen can be transported via this pipeline segment to the station).

When the configuration changes from one to another or operates during one specific time step, the resulting social costs[7] are registered. Therefore, a hydrogen transition can be viewed as a sequence of configurations resulting in a series of social cost cash flows over time (Figure 3-1).

On the other side, selling hydrogen to consumers (FCV motorists) result in a revenue cash flow (Figure 3-1) in proportion to the hydrogen demand and price. In this dissertation, a hydrogen price is determined not by maximizing the profit, but by equating the net present values of revenue and social cost cash flows for a given discount rate within a given period[8]. Since the demand is exogenous, such a cost-balancing hydrogen price provides a simple metric to characterize the social costs. In fact, minimization of the net present value of social costs also leads to minimization of the hydrogen price for the same period.

As previously stated, given the exogenous hydrogen demand, the social welfare of a hydrogen transition can be maximized by minimizing the net present value of these social cost cash flows.

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[7] In the HIT model, the social cost includes technology cost (capital, fixed and variable costs), carbon external cost, and fuel accessibility cost. This will be clearly defined in the section "3.1.3 Objective Function".

[8] This given period starts from the beginning of the study period but can be any subset of the study period, depending on discussion interest.

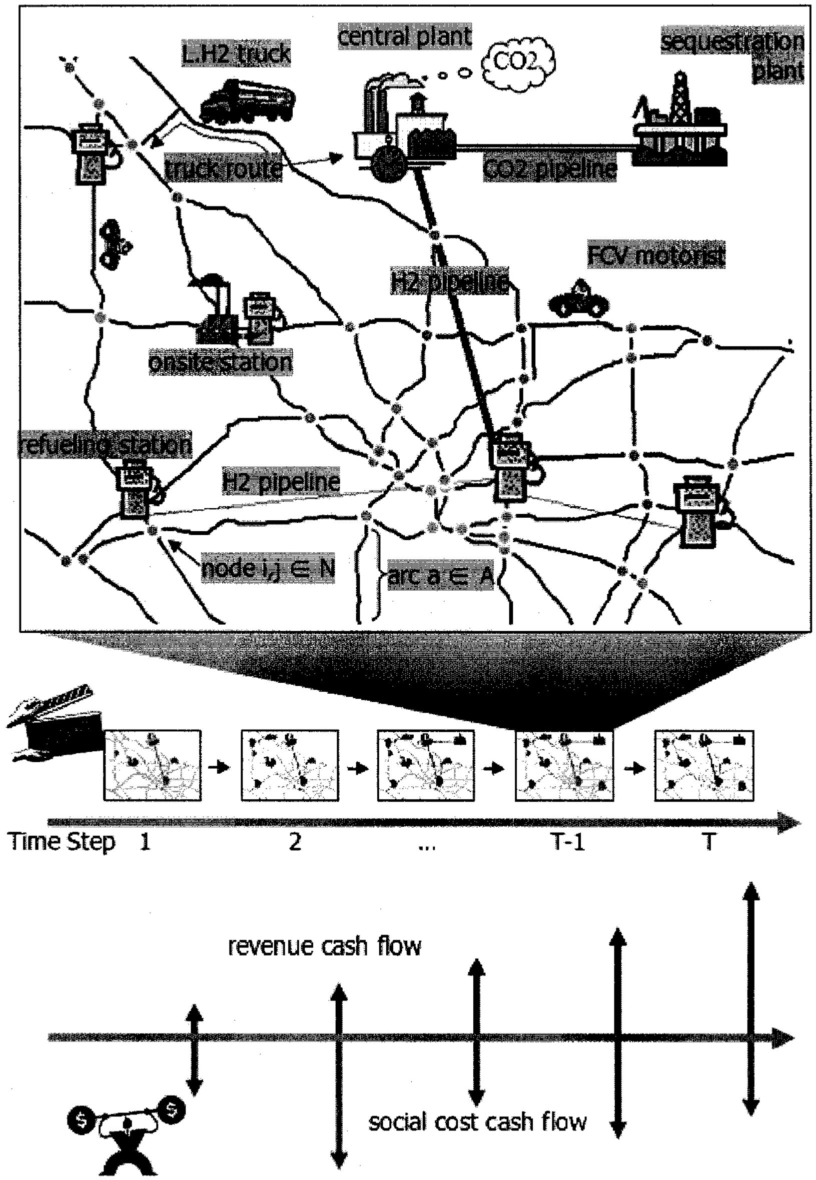

Figure 3-1: Hydrogen Transition Problem

The system configuration is composed of road network, FCV motorists, and some facilities for hydrogen supply and CO2 disposal, where the term "facility" has a strict definition and one facility refers to one of the following:

- one central hydrogen production plant with or without the carbon capture component
- one carbon capture component including CO2 compressor, as an upgrade component for central plant originally without the carbon capture component
- one CO2 pipeline segment connecting central plant and sequestration plant
- one CO2 sequestration plant
- renting service by liquid hydrogen truck
- hydrogen pipeline segment connecting one central plant with one refueling station or connecting two refueling stations
- one refueling station module (one or multiple modules make up a refueling station)
- one onsite station (one or multiple modules make up an onsite station)

These facilities can further be differentiated by technology. For example, one onsite station can be one based on water electrolysis or one based on natural gas SMR. Each facility in the configuration is represented by some exogenous attributes (such as capacity and capital cost) and some endogenous decisions (such as the location and output), which are discussed in the sections "3.1.2 Exogenous Factors and Decision Variables". When all the exogenous factors and decision variables are determined, the system configuration is uniquely defined. During any specific time step, by assumption, the system configuration operates without changing any decision variable, referred to as configuration invariability. If configuration invariability is unrealistic relative to the length of time step (e.g. 5 years), we can always shorten the time step to make the configuration invariability assumption more reasonable.

One important distinction of the above problem simplification from other studies is the resolution of system or level of details. In this dissertation, one facility is the smallest physical component to be modeled. This means each facility is treated as a black box in a sense that some facility characteristics, such as hydrogen pressure or type of compressor, do not affect the optimization and are therefore irrelevant in the problem context. Before the optimization, it does take steps to fundamentally model the facility, such as a central coal gasification plant at 1400 tonne/day, based on other studies (such as the NRC (2004) study and the H2A (2007) model), but only several attributes of the facility are seen or controlled by the HIT model, such as capital cost and CO2 emission rate. Therefore, in this dissertation, technology competition is between facilities, different from comparison between pre-defined pathways as adopted in the NRC (2004) study.

3.1.2 Exogenous Factors and Decision Variables

The HIT model takes exogenous factors as inputs and determines the optimal values of decision variables as outputs. Here we cover the exogenous factors and decision variables associated with network, motorists (users or consumers), and facilities. All exogenous factors and decision variables can be viewed as of a time dimension, even though some do not change over time.

Consider a directed surface network, $G = (N, A)$, where N and A are the sets of nodes and arcs, respectively (Figure 3-1). Each node i or j has two exogenous factors, the two coordinates on the two-dimensional plane. Each arc a_{ij} has four exogenous factors: the IDs of the two end nodes i and j, the real distance l_{ij} from i to j along a_{ij}, and the traffic volume v_{ij} along a_{ij} in terms of average annual daily traffic (AADT) of FCV motorists. By assumption, the connectivity of network G is assumed not to change over time, but the traffic volume v_{ij} will increase over time in proportion to hydrogen demand. Existing traffic volume v_{ij} and their projected growth rates can be acquired from federal and regional planning agencies.

There is no decision variable associated with the surface network or the motorists, which are seen by the HIT model as a relevant but uncontrollable part of the system configuration. The traffic volume on the network G reflects the spatial distribution of hydrogen demand and affects locations of refueling stations. The process of linking spatial distribution of FCV motorists with station locations is covered by the section "3.3 *Station Location Sub-model*".

For central plants, onsite station module, and refueling station module, the exogenous factors of each facility are:

- capacity/size: the designed maximum hydrogen output of the facility, usually in kgH2 per day. For onsite or refueling stations, the capacity of each module is exogenous, but the total capacity of a station is a decision variable and is controlled through the number of modules contained in a station.
- capacity factor: the percentage of the capacity that is considered as available under normal circumstances. The capacity and capacity factor attributes are used to determine the number of the same facility needed in satisfying the hydrogen demand.
- efficiency: the consumption rate of each type of feedstock or energy, such as MMBtu coal per kgH2 or kWh electricity per kgH2. When the facility output is determined, the efficiency attributes are used to determine the quantities of feedstock and energy.
- CO2 emission rate: the rate of emitted CO2 in terms of kgCO2 per kgH2.
- CO2 capture rate: the rate of captured CO2 in terms of kgCO2 per kgH2. This factor only applies to non-electrolysis central plants.
- capital cost: the cost to construct the facility, represented by a lump sum amount occurring at the beginning of the facility life period
- fixed O&M cost: the operating cost that is independent of facility output

- life: the length of time for the facility to operate. After life, the facility retires or is rebuilt at the then level of costs. A shorter life indicates more often does the facility need rebuilding and hence more capital cost.

Carbon capture components and sequestration plants have the same exogenous factors, although the capacity is related to CO2 instead of hydrogen. And they do not have CO2 emission rate.

For central plants, onsite station module, and refueling station module, the decision variables of each facility are:

- location: the facility location is also represented by spatial coordinates. The location of one facility often affects the decisions of other facilities. For example, the location of one refueling station may affect the length of pipeline segment connecting the station.
- output: the facility output indicates the facility contribution to satisfaction of hydrogen demand and is also used to determine the quantities of feedstock and CO2 emission.
- status: when one facility is built, its status is active until it retires. When one facility has an active status, it operates, resulting in costs, feedstock consumption and emission.
- facility number: the number of the same type facility is just an alternative decision variable for facility status. For example, we can suppose ten

central SMR plants with a same size. Building four plants is equivalent to activating the status of four plants.

Carbon capture components and sequestration plants have the same decision variables, although the out is related to CO2 instead of hydrogen.

The decision variables associated with hydrogen or CO2 pipelines include connectivity and size in terms of diameter. The length and diameter attributes are used to calculate the capital cost and fixed O&M cost of pipeline.

Trucking service is represented as a rental service charged in terms of dollars per kgH2 per mile. The L.H2 trucking service has two exogenous factors: rental rate in terms of dollars per kgH2 per mile and electricity efficiency in terms of kWh per kgH2 liquefied. This rental rate already includes the cost of electricity for hydrogen liquefaction but does not include carbon tax from electricity generation. The electricity efficiency is used to calculate electricity consumption for hydrogen liquefaction so as to calculate the CO2 emission and carbon tax from electricity generation.

The decision variables associated with trucking service are the truck route and quantity of delivery. The shortest distance between a hydrogen source and a specific refueling station is computed in a sub-model and supplied to the optimization model as input data.

Other exogenous factors used in the HIT model include:

- industry hydrogen supply curve: it shows how the marginal price or average price of industry hydrogen as a function of quantity.
- equivalent carbon tax rate: this is used to describe the social cost of CO2 emission. The CO2 social cost is a damage cost rather than a tax collected by the government, but when the damage is caused, it can been seen as if a dummy agency from outside the system is collecting tax from within the system. When a higher carbon tax rate is adopted, the real meaning is that the policy maker or the user of the HIT model believes in a larger damage cost of one unit CO2 emitted.
- feedstock and energy prices: prices of coal, biomass, natural gas, and electricity are used to calculate variable cost.
- CO2 emission rate for grid electricity: this rate is used to calculate the CO2 emission from any process that involves electricity consumption. This dissertation does not consider a dedicated wind power plant for hydrogen production. It is believed that renewable electricity will be part of the electricity market. Therefore, the consideration of renewable electricity should be reflected by the decrease of CO2 emission rate of grid electricity and the increase or increase of grid electricity price. So hydrogen based on renewable electricity is an issue of sensitivity analysis regarding grid electricity price and CO2 emission factor rather than an issue of technology coverage.

- refueling travel time value: this time value is based on the approach that transportation engineers use to estimate the cost of travel time. It is used to monetize the time for FCV motorists to travel to the refueling station.
- discount rate: the nature of discounting is a rule to weigh costs and benefits at different times. It should be noted that there has not been a consensus on the choice of discount rate for long-term (e.g. over 50 years) project assessment.

The only decision variable not directly related to facilities is the quantity of industry hydrogen purchased and transported by L.H2 trucks to refueling stations. CO2 emission associated with production of industry hydrogen is not considered.

Strictly speaking, feedstock, assessment of carbon externalities, and value of travel time are characterized by exogenous factors, but they are related to price of material or impact directly affecting social cost assessment and therefore are covered in the section "3.1.3 Objective Function".

All the above exogenous factors have a time dimension, suggesting the model user foreseeing these factors. Such a foresight of factors can be based on projections of future by other studies or just scenario setting. It is commonly called "perfect foresight" when the point estimates of these exogenous factors throughout the study period are adopted as model inputs. However, it should be note that the descriptive "perfect" by no means indicate that the model user is absolutely confident with the information or is blind to the uncertainty of these exogenous factors. Perfect foresight (probably should be called "pretended perfect foresight") is essentially a "what-if" thinking. Uncertainty can be addressed by stochastic modeling or Monte Carlo simulation. Although these approaches do not require perfect foresight of point values of the factor, they still have to pretend perfectly foreseeing the probability distribution (or the distribution of distribution or some other attributes) of the factor. Uncertainty can also be addressed by sensitivity analysis with different values, but still perfectly foreseen, of the exogenous factors. Thus, in my view, the notion of perfect foresight is an inevitable element in modeling a dynamic system.

Somewhat related to uncertainty, some researchers criticize the notion of perfect foresight with respect to length of planning period. That is, even with a long-term study period, the decision maker may still only look into the near future in making the near-term decisions. Therefore some researchers propose imperfect foresight or myopic foresight based on the reason that no one can predict a long future and myopic foresight is more realistic. However, when decisions are made based on myopic foresight up to a time shorter than the study period, the implicit assumption is that the impact of the "unknown" information beyond that time point is ignored (mathematically, the corresponding benefits or costs beyond that time point are multiplied by zero) or assumed to be in some form of trajectory (e.g. flat or extrapolation) beyond that time point. Whatever the implicit trajectory is, it joins the myopic foreseen information and forms a perfect foresight. By saying that a myopic foresight is superior, it is assuming that the implicit trajectory is more superior to a perfectly foreseen one, which can be misleading.

3.1.3 Objective Function

The objective function is usually a real function of both exogenous factors and decision variables. It is the value of the function that measures the desirability of the decisions. Optimization is the process of finding the set of decisions that maximize (or minimize) the objective function.

The objective of the HIT model is to minimize the social cost net present value of hydrogen transition. By definition, the social cost as concerned in this dissertation consists of technology cost, environmental cost, and fuel accessibility cost, as shown in Figure 3-2. Specifically, technology cost includes capital cost, fixed O&M cost, and variable cost of building and operating facilities. Environmental cost in this dissertation refers to the carbon tax for emitting CO2 into the atmosphere, although if necessary in future study, it can also include costs of criteria pollutant emissions. Fuel accessibility cost includes refueling travel time cost, although if necessary in future study, it can also include cost of time on refueling, as FCV motorists may experience more hydrogen refueling trips and longer refueling time at the station.

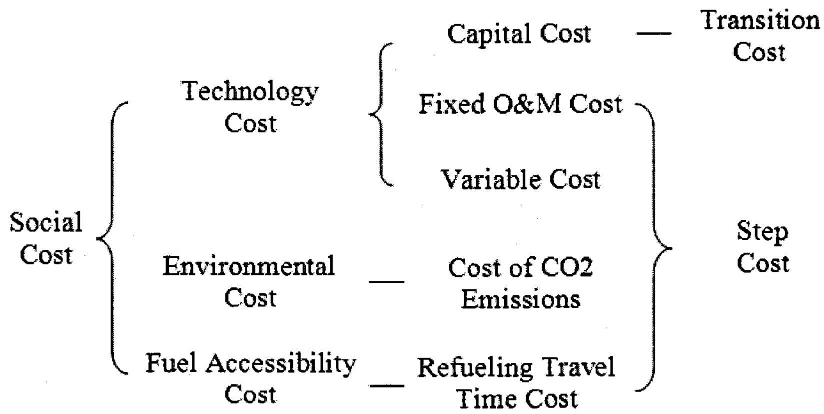

Figure 3-2: Relationship of Cost Items

From the mathematical perspective, these cost items can be grouped into transition costs that occur due to incremental change of system configuration and step costs that occur due to operation of system configuration during a time step. That is, transition cost includes only capital cost, and step costs include CO2 emission cost, refueling travel time cost and the other technology costs—fixed OM cost and variable cost. The relationships of these cost items are illustrated by Figure 3-2.

3.1.4 Dynamic Programming Formulation

As already illustrated in Figure 3-1, a hydrogen transition can be seen as a temporal sequence of hydrogen system configurations resulting in social cost cash flows. Such an abstraction is again illustrated below in Figure 3-3, where some mathematical terms, to be defined and explained, are also illustrated. By defining these terms, we can reach the dynamic programming formulation for the HIT model.

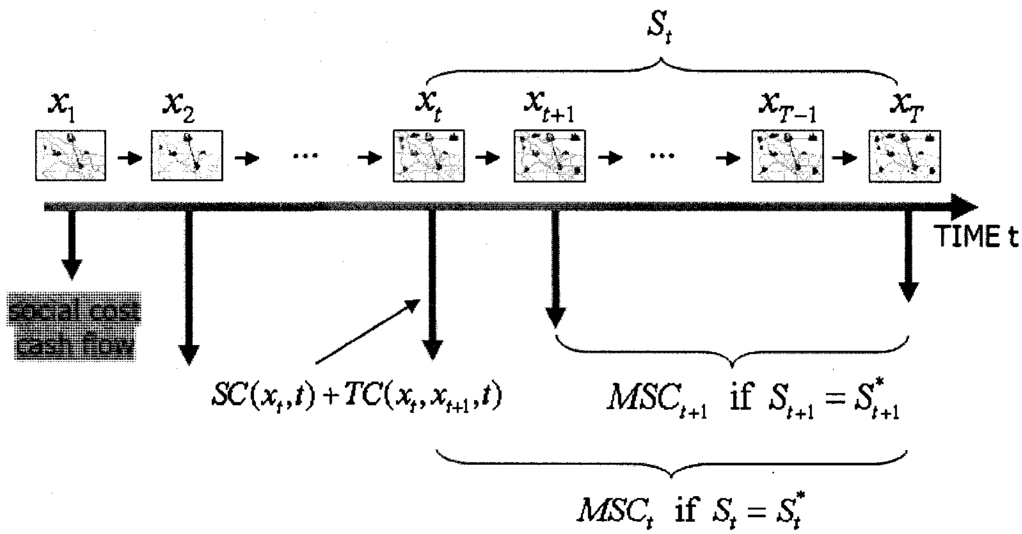

Figure 3-3: Dynamic Programming Formulation

Suppose a configuration x_t is inherited at the beginning of time step t and will be operated during time step t. Let S_t represent a sequence of configurations starting from t through the study period T.

$$S_t = \{x_t, x_{t+1}, x_{t+2} \dots x_T\} \tag{3-1}$$

Different S_t results in different social cost cash flows from t to T. Let S^*_t represent the optimal sequence that minimizes the discounted value (see model formulation for explanation on discount factor) of these social cost cash flows and let MSC_t (symbolizing the minimum social cost) represent such a discounted value. As known, any discounted value must be associated with the time at which the cash flows are discounted to[9]. For convenience, $MSC_t(x_t)$ is assumed to be associated with the end of time step t. In brief, the discounted value of the total social cost cash flows from the beginning of time t to the end of study period T is MSC_t, given that the system configuration at the beginning of time t is x_t and that the optimal sequence S_t^* is followed (see Figure 3-3).

For a given x_t, S_t^* is usually unique; different x_t could result in different S_t^*. Thus, the optimal sequence S_t^* can be treated as a function of x_t, as represented by $S_t^*(x_t)$. The resulting MSC_t can also be treated as a function of x_t, as symbolized by $MSC_t(x_t)$.

As consistent with the above definitions, x_0 represents the system configuration just before the study period, such as no existence of hydrogen infrastructure assumed in the case study of this dissertation. The begining-of-first-time-step [10] minimum discounted value of social costs can then be represented by $MSC_0(x_0)$.

Now we are ready to reach a dynamic programming formulation to establish the recurrence relationship between $MSC_t(x_t)$ at different *t*. Let $SC(x_t, t)$ be the step

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[9] For example, although rarely explicitly stated, net present value is indeed the discounted value with respect to the beginning of the time horizon.

[10] the end of "time step zero" is the same as the beginning of time step one.

cost (see the previous section "3.1.3 Objective Function" for definition of step cost) of operating x_t during time step t and $TC(x_t, x_{t+1}, t)$ be the transition cost (capital cost) from x_t to x_{t+1}. For convenience of discounting calculation, both $SC(x_t, t)$ and $TC(x_t, x_{t+1}, t)$ are also with respect to the end of time step t. Although it appears that x_t is assumed to instantaneously change into x_{t+1} at the end of time step t (or the beginning of time step $t+1$), the time required to construct the facility has already been reflected in the capital cost, as explained in the section "3.2.5 Technology and Environmental Costs". Let r be the effective discount rate for one time step. Thus, the formulation as in equation (3-2) holds.

$$\begin{aligned} MSC_t(x_t) = \min_{x_{t+1}} \{ & SC(x_t, t) + TC(x_t, x_{t+1}, t) \\ & + (1+r)^{-1} \cdot MSC_{t+1}(x_{t+1}) \} \end{aligned} \tag{3-2}$$

The equation (3-2) is a typical formulation reflecting the "making the best next step" philosophy of dynamic programming (Bellman, 1954). When x_t is inherited as a system state, the "decision maker" concerns which is the next configuration x_{t+1} to minimize the bracket "{ }" of equation (3-2). The "decision maker" wishes he could just know every MSC_{t+1} for all possible x_{t+1} so that he could just compare all the possible values of within the bracket "{ }" of equation (3-2) and choose the x_{t+1} that minimizes the bracket value.

It is in fact impossible to solve equation (3-2) alone for $MSC_t(x_t)$, simply because the function structure or value of $MSC_{t+1}(x_{t+1})$ is unknown. However, a solution to equation (3-2) can be reached via recursive algorithms based on known boundary conditions at the end of study period. The boundary condition employed here is based on the assumption that the hydrogen system (infrastructure configuration, demand, technology costs, etc) at the last time step T are continued and unchanged beyond the time scope. After time t, the step cost is constant and occurs once every time step, but the transitional cost for rebuilding facilities is not constant for each time step because of different facility lives and timing of construction. However, the transition cost will repeat itself for every lease common multiple of facility lives. Let h be the number of time steps that constitute such a lease common multiple and $SC_{LCM}(x_T)$ be the equivalent value of all the transitional and step costs during the first h time steps. Thus, based on the concept of capitalized cost from engineering economics, the minimum discounted value of social cost with respect to end-of-T can be calculated as in equation (3-3). Note that the end-of-T configuration x_T is not pre-determined. It will be part of the sequence being optimized.

$$MSC_T(x_T) = \frac{SC_{LCM}(x_T)}{(1+r)^h - 1} \tag{3-3}$$

As an alternative, the boundary condition in (3-4) suggests ignorance of any costs beyond the time scope.

$$MSC_T(x_T) = 0 \tag{3-4}$$

The key difference between the two boundary conditions is that the first one explicitly considers the interest of future generations beyond the time scope. Although the costs in tens of years can become insignificant due to discounting, a structural inclusion of costs for future generations is deemed more suitable for long-term issues and enables broader discussion (e.g. sensitivity analysis of discount rate). Thus, the boundary condition in (3-3) is adopted in this dissertation.

The two formulas, expressed in (3-2) and (3-3), form the HIT model framework for this dissertation to obtain the minimum social cost $MSC_0(x_0)$ and the associated optimal buildup sequence S_0^*.

3.1.5 Constraints and the State-filter Algorithm

During the optimization, the constraints that represent relationships among exogenous factors and decision variables must be complied with. For example, the sum of refueling facility capacity multiplied by capacity factor must equal or exceed total hydrogen demand, because insufficient refueling capacity is not allowed, or mathematically equivalently speaking, the penalty for insufficient refueling capacity is set infinite. From the modeling perspective, constraints characterize the causalities and correlations that the modeler observes from the real world and believes as relevant, or that the modeler assumes to narrow down the problem scope.

In this dissertation, when all the decision variables of a given time step are determined, the system configuration at the time step is uniquely defined. If the decision variables and exogenous factors comply with all the constraints, the corresponding configuration x_t is considered feasible, but not necessarily optimal. All the feasible configurations for a given time step t make up the so-called solution set, decision space or state space $X_t = \{x_t\}$. These names are interchangeable for X_t because a configuration x_t can be viewed as a state when it represents what the system is changing from, or can be viewed as a decision (as like a collection of decision variables) when it represents what the system is changing into.

As indicated in the HIT formulation in equation (3-2) and (3-3), the optimization process in nature is to compare all feasible configurations x_{t+1} in the state space X_{t+1} and identify the best one x^*_{t+1} for each time step. Because of the large number of feasible configurations, the optimization is computationally time-consuming. One way to reduce computation time is to reduce the size of state space $|X_{t+1}|$ by introducing more problem-specific constraints.

From the mathematical programming perspective, constraints are rules for judging whether or not a configuration is feasible. A constraint can be any relevant logical condition in form of inequality, equality or membership. There are many constraints to be considered. Solutions are tested against the entire constraints sequentially[11]. Solutions contradicting with the first constraint are discarded and those passing the first constraint will continue for test against remaining constraints until all constraints are exhausted. Apparently, each constraint makes contribution in reducing the number of feasible configurations, i.e. the size of state space $|X_{t+1}|$, and can result in reduction of computation time. This is a critical perspective in designing the algorithm for solving the HIT model. I call it as the state-filter algorithm, as if each constraint serves as a filter through which infeasible configurations are removed.

There are several reasons for confidence with the state-filter algorithm. First, each state filter, at least when implemented as matrix operation in Matlab[12], can be very fast, and more importantly, can be conducted off-line. The total computation time of the HIT model is below four hours and this is achieved with an ordinary personal computer with 1.2GHz CPU and 1GB RAM. Second, more state-filters can always be created to further reduce state space size $|X_{t+1}|$. Thus, unlike in many other optimization techniques where more constraints increase the difficulty of solving the problem, with the state-filter algorithm, more constraints may reduce the feasible solution set thus make the problem easier to solve.

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[11] It does not matter how the constraints are ordered.

[12] Matlab is the software platform for the implementation of the HIT model, created and owned by the MathWorks, Inc.

The following state-filters are adopted in the Southern California case study.

- State-filter #1, flow conservation. For each node of hydrogen or CO2 flows, the net inflow plus output equals the net outflow plus hydrogen demand or sequestrated CO2.

- State-filter #2, pipeline capacity conservation. When hydrogen travels from one segment to another, it travels from an upstream segment to a downstream one. An upstream segment relative to one segment maybe a downstream one relative to another segment. For any node on hydrogen pipeline network, the capacity of the upstream pipeline must equal the sum of all the adjacent downstream pipelines.

- State-filter #3, logistic connectivity. Any configuration includes connections of hydrogen facilities. The HIT model only considers realistic logistic connections, For example, hydrogen pipeline always originates from a central plant. A hydrogen flow from a central plant or industry hydrogen source can only be absorbed by a refueling station, but not by an onsite station. No pipeline or trucking route is connected to an onsite station. A central plant must be connected with a hydrogen pipeline or trucking route; that is, no plants are built to be idling without output. The CO2 sequestration plant, pipeline and the capture component must exist and be connected together.

- State-filter #4, no insufficient capacity. All the possible configurations with insufficient production or refueling capacity are considered irrelevant and therefore filtered out.

- State-filter #5, optimal station location. Station locations must be optimized. All the possible configurations with station locations inconsistent with those determined by the Station Location sub-model (see "3.3 *Station Location Sub-model*") are eliminated. The number of stations is determined online by the HIT model.

- State-filter #6, optimal pipeline network. Pipeline network must be optimized. All the possible configurations with pipeline segments that are not part of the optimal pipeline network optimized by the HPTG model (see "3.2.3 Hydrogen Pipeline Tree Growth") are filtered out.

- State-filter #7, central plant locations. Locations of central plants are limited to 9 potential locations close to industrial zones (see Figure 3-12).

- State-filter #8, discreet facility construction. At the beginning of each time step, the HIT model determines the incremental number of facilities added to the configuration. For central plants, the incremental facility number is a common multiple of one. For refueling stations, the incremental number is a common multiple of 5 modules (500 kg/day each module), which means either zero or at least 2500 kg/day of system-wide refueling capacity increase. For each pipeline network associated with a central plant, three possibilities are considered: none, half or all of the pipeline segments are built.

- Stage-filter #9, not too much redundant capacity. With consideration of capacity factor, all the configurations with a combining production or refueling capacity exceeding some demand threshold (such as the 2060 demand level in the Southern California case study) are considered irrelevant and therefore eliminated from the state space.

- Stage-filter #10, facility transformation constraint. The number of onsite stations that are transformed into non-production refueling stations can not exceed the number of the onsite stations that have been built. A similar constraint is imposed with regard to upgrading a central plant with a carbon capture component.

- Stage-filter #11, no central production unless refueling stations exist. Because we assume that centrally produced hydrogen is supplied only to non-production refueling stations, whether or not they are originally built or transformed from onsite stations, central production will not appear until non-production refueling stations exist. Otherwise, we can always delay the occurrence of central production and achieve lower NPV because of decreasing technology costs and non-negative discount rate. However, it should be noted that non-production refueling stations can occur before central production, as industry hydrogen will be transported to these non-production refueling stations.

- Stage-filter #12 capacity limit for refueling or onsite stations. The maximum station size is set to 5000 kg/day. That equals the capacity of ten station modules

- State-filter 13: no facility close-down. Once a facility is built, it cannot be closed down during the later stages, but an onsite station can be converted into a refueling station by removing the production component within the onsite station and a central plant originally without a carbon capture component can be upgraded by adding one.

- State-filter 14: onsite station location. When a configuration has a mix of onsite and refueling stations, the later are located close to central plants and onsite stations are located further. This is because the location of an onsite station does not affect the objective, but by locating refueling stations near central plants (also where industry hydrogen is produced if there is no central plant), the costs of either pipeline or trucking rental can be reduced.

With these state-filters, the state space size is reduced to the extent that enumeration of the remaining feasible configurations can be conducted with a reasonable amount of computation time for each time step. As a result, the total run time for the HIT model is about four hours achieved by a personal computer with 1.2GHz CPU and 1GB RAM.

While more constraints lead to a smaller state space, a natural skepticism is that the original problem may be changed by adding more constraints as state-filters. Such a concern can be resolved by ensuring that the additional constraints do not eliminate the configurations that are interesting to the model user. For example, for the time step of 10% hydrogen penetration, the model user can apply a state-filter that eliminates those configurations with total production capacity larger than the demand level at 50% penetration and still be confident that the optimal one is still left.

Each state-filter has a clear meaning and represents the assumption or simplification in defining a relevant problem scope. The resulting optimal sequence can be claimed as globally optimal with respect to such a problem scope. From another perspective, the model represented by equation (3-2) and (3-3) can be seen as formulating a larger problem that covers the interesting problem scope in the mind of the model user as well as many unwanted solutions that simply add to computation time.

3.2 Sub-models

3.2.1 Hydrogen Demand

Hydrogen demand is a critical exogenous factor. At any time step, a feasible configuration must have sufficient production and refueling capacity to meet the demand. Otherwise, we would need to quantify the penalty of insufficient supply, which is difficult and beyond our scope. After the optimal sequence is obtained, the resulting social cost can be calculated and levelized by hydrogen demand to reach the average cost estimate, which is another computational usage of hydrogen demand. With these being said, hydrogen demand is not used to select any infrastructure technologies. For example, we do not make judgments such as: because hydrogen demand is so high, only central production is considered; or, because hydrogen demand is still small, only onsite production is considered. Instead, any configuration with sufficient supply capacity is a possible part of the optimal sequence, and the only criterion is the social cost net present value.

Hydrogen demand is calculated based on regional vehicle population, vehicle age distribution, fuel cell vehicle market penetration, vehicle usage, and fuel economy.

$$\begin{aligned} DH2(Yr) = \sum_{Age} \big[& VPop(Yr) \cdot ShrByAge(Age) \cdot FCVSaleShr(Yr - Age) \\ & \cdot DayVMTbyAge(Age) / FCVMPG \big] \end{aligned} \tag{3-5}$$

In equation (3-5), $DH2(Yr)$ represents hydrogen demand in kg per day by all the FCVs that operate during year Yr. $VPop(Yr)$ represents the number of all light-duty vehicles operating during year Yr. $ShrByAge(Age)$ represents the percentage of vehicles that are Age years old. $FCVSaleShr(Yr - Age)$ represents the vehicle sale share or market penetration of FCV in year ($Yr - Age$). $DayVMTbyAge(Age)$ represents the average daily miles traveled by one Age -years-old vehicle, as newer vehicles are usually driven more than older vehicles . $FCVMPG$ represents the average fuel economy of FCV in miles per gallon equivalent. In this dissertation, $ShrByAge(Age)$, $DayVMTbyAge(Age)$, and $FCVMPG$ are assumed to be constant over time. The data of all the inputs to equation (3-5) are provided in the section "3.4.2 Demand".

3.2.2 Fuel Accessibility Cost

When the fuel is produced, transported and stored at the refueling station, the fuel becomes available but not necessarily easy for the consumer to access from where she needs the fuel when she needs it. A FCV motorist, especially of the early hydrogen market, may need to know where the hydrogen refueling stations are located, drive a long why to the station, refuel the FCV carefully and patiently and even follow some extra safety procedures. All these probably unpleasant experiences may result in stress and loss of money and time and are considered as deteriorating fuel accessibility. Due to limited knowledge in measuring refueling experience, this dissertation limits the scope of fuel accessibility to refueling travel time. Therefore, fuel accessibility cost in this dissertation refers to the monetary value of refueling travel time of all FCV motorists traveling to a refueling station. The details on how to calculate and monetize refueling travel time are provided in the section "3.3.1 Measuring Fuel Accessibility".

As indicated in the section "3.1.3 Objective Function", the social cost of hydrogen transition includes technology cost, environmental cost, and fuel accessibility cost. From the spatial perspective, more refueling stations can reduce refueling travel time and therefore reduce fuel accessibility cost, but on the other side increase technology cost. So the introduction of fuel accessibility cost is to enable the social trade-off between refueling accessibility and station number. From the temporal perspective, more hydrogen demand, as a result of more FCV motorists and more hydrogen refueling trips, leads to more fuel accessibility cost, which suggests the need to build more stations. So the introduction of fuel accessibility cost is also to simulate the expansion of refueling network in response to demand growth.

These conceptual understandings are captured by equation (3-6). Fuel accessibility cost, represented by $AccessCost$, is a function of hydrogen demand ($DH2$) and station number $StaNum$. Higher hydrogen demand leads to more refueling trips and therefore more fuel accessibility cost. More stations leads to less average refueling travel time ($ARTT$)[13], less total refueling travel time and therefore less fuel accessibility cost.

$$AccessCost(DH2(Yr), StaNum) = \frac{C_{time}}{C_{fpr}} \cdot DH2(Yr) \cdot ARTT(StaNum) \tag{3-6}$$

Fuel accessibility cost is also associated with two exogenous factors, C_{time} and C_{fpr}. The time value factor C_{time} converts travel time into dollars and is set as corresponding to 50% of the regional wage rate. The fuel tank factor C_{fpr} is defined as the average amount of hydrogen pumped into tank for each refueling. The data of these two factors are provided in the section "3.4.7 Fuel Accessibility".

A Station Location sub-model has been developed to establish the relationship between average refueling travel time ($ARTT$) and number of stations ($StaNum$). The sub-model is based on the following assumptions.

- The mobile-origin notion "where you drive more is where you more likely need refueling". Specifically, the probability of a location being the origin of a refueling trip is proportional to the frequency of a random motorist passing the location.

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[13] The term, average refueling travel time ($ARTT$), is defined as the expected refueling travel time by a random FCV motorist. It is fully discussed in the section "3.3.1 Measuring Fuel Accessibility".

- Motorists always refuel at stations closest to where they need refueling.
- Stations are located so that the average refueling travel time for a random regional motorist is minimized.

Because of its complexity, the Station Location sub-model is explained in detail by the dedicated section "3.3 *Station Location Sub-model*". In summary, the Station Location sub-model generates the optimal station roll-out scheme that minimizes the average refueling travel time ($ARTT$) for each incremental station while maintaining location logistic continuity between adjacent time steps. This location optimization process takes into account travel behavior, traffic flow, and regional road network. The sub-model then calculates the average refueling travel time as corresponding to station number under the optimal station roll-out scheme. These region-specific $ARTT$ - $StaNum$ data are then used for function fitting. The fitting $ARTT$ - $StaNum$ equation for Southern California is as below.

$$ARTT(StaNum) = 46.99 \cdot StaNum^{-0.4886} \qquad (3\text{-}7)$$

In equation (3-7), $ARTT$ is in minutes per one-way refueling trip.

Although the HIT model only uses the $ARTT$ - $StaNum$ equation from the Station Location sub-model, it should be noted that station location information is also a by-product output of the sub-model. Thus, after the optimal sequence of hydrogen transition is found, the station location can also be found from stored information.

product output of the sub-model. Thus, after the optimal sequence of hydrogen transition is found, the station location can also be found from stored information.

3.2.3 Hydrogen Pipeline Tree Growth

The cost associated with hydrogen pipeline is related to pipeline length, diameter, flowrate, and land use. As an alternative to the idealized layout approach which ignores spatial details and diameter variation, the Hydrogen Pipeline Tree Growth (HPTG) sub-model is developed in order to derive the information of pipeline length by diameter while optimizing the pipeline network.

Unlike the Station Location sub-model which optimizes station locations for each incremental station, the HPTG model optimizes the could-be final pipeline network. If pipeline enters the optimal sequence, the HIT model expands the pipeline network into this could-be final pipeline network. Specifically, based on the maximum hydrogen demand and the capacity limit for a refueling station, we can determine the number of refueling stations in meeting the maximum demand. The locations of these stations are determined by the Station Location sub-model and then serve as nodes to be possibly connected by pipeline. The HPTG sub-model generates a pipeline network that connects all these stations, but this pipeline network is only a could-be situation and only serves as an input to the online optimization of the HIT model. The generation of such a could-be final pipeline network does not suggest any assumption on when or whether pipeline will be adopted. For any time step, the

HIT model can choose either no pipeline or a subset or the whole of the optimal could-be final pipeline network.

Given the stations location or nodes of the largest refueling network, the HPTG sub-model minimizes the total pipeline length while connecting each refueling station. The length of a pipeline segment between two station are based on straight-line distance, but some multiplier can be added to reflect right-of-way if such information is available. Each pipeline segment represents one-way hydrogen flow and each station has a capacity representing the hydrogen demand of each node.

The minimization of pipeline length is formulated as a minimum spanning tree model (Cormen, 2001). Let i, j be the member index of station set $Node_s$ or plant set $Node_p$. Let binary decision variable $IfLink_{i,j}$ represents building ($IfLink_{i,j} = 1$) or not building ($IfLink_{i,j} = 0$) a directional pipeline transporting hydrogen from i to j. When $IfLink_{i,j} = 1$, the pipeline length from i to j, $PLength_{i,j}$, is counted into total pipeline length, represented by $TotalLength$. Thus, the optimization objective can be described by equation (3-8).

$$\text{Minimize } TotalLength = \sum_{i,j \in Node_s \cup Node_p} IfLink_{i,j} \cdot PLength_{i,j} \tag{3-8}$$

$$IfLink_{i,j} = 1 \text{ or } 0 \tag{3-9}$$

$$\sum_{i \in Node_s \cup Node_p} IfLink_{i,j} = 1 \qquad \forall j \in Node_s \tag{3-10}$$

(3-11)

$$Source_j = Source_i \quad \text{when} \quad IfLink_{i,j} = 1$$
$$\forall j \in Node_s, \forall i \in Node_s \cup Node_p$$
$$Source_j = j \quad \forall j \in Node_p \tag{3-12}$$
$$Source_j \in Node_p \quad \forall j \in Node_s \tag{3-13}$$

Several constraints supplement the objective function to formulate the HPTG sub-model. The decision variable $IfLink_{i,j}$ is restricted as binary by equation (3-9). There must be one and only one inflow pipeline for each station, which is represented by equation (3-10). With $Source_j$ representing the plant that supplies hydrogen to station or plant j, equation (3-11) ensures that the hydrogen of any two interconnected stations comes from the same plant. Equation (3-12) means that the hydrogen of any plant comes from itself and equation (3-13) means that hydrogen of any station must come from one of the plants. When any hydrogen flow travels from one pipeline segment to another, it is called from an upstream segment to a downstream one. A segment can be both upstream relative to some and downstream to others. The equation (3-13) also ensures an upstream pipeline segment is always connected before its any upstream segment being connected. That is, any interconnected pipeline network must has a hydrogen source—a central plant.

In the Southern California case study, the could-be all-station-connected pipeline network is divided into 9 sub-networks associated with 9 central plant locations (Figure 3-12). These plant locations are identified based on GIS information of existing power plants, railroad, natural gas facilities, biomass availability and population. Each pipeline sub-network grows from its associated plant as the root and gradually covers more downstream stations until either the capacity of the plant is used up or the HIT model determines that it is better off to stop growing.

The HPTG sub-model then records the location and length each pipeline segment. The pipeline capacity changes from one segment to the next downstream one, reflecting absorption of capacity by the node. Thus, based on the flow conservation principle, the flowrate capacity of each pipeline segment can be obtained. The diameter of a pipeline segment can then be calculated based on length and flowrate capacity according to the Panhandle B Pipeline equation (Crane Co., 1998) as also adopted by the H2A (2007) model. Another attribute of a pipeline segment is land use, here represented by urban or rural area based on the census data (US Census, 2002). Pipeline length and diameter are two critical parameters in calculating costs of each pipeline segment. As previously stated, each pipeline segment is viewed as a facility unit by the HIT model.

3.2.4 Truck Route

Because each individual refueling station can be supplied with hydrogen via either pipeline or trucking, trucking distance for each station must be determined for the HIT model to calculate the rental cost and CO2 emission from diesel truck. To calculate the trucking distance for each station, the trucking route from each individual station to its nearest plant is identified via the Truck Route sub-model.

Plant locations are treated as the source nodes and station locations are treated as the sink nodes. The Truck Route sub-model determines the route between each pair of plant and station by solving the shortest path problem, which is covered by some operations research textbooks (Ahuja, et al., 1993) and not further explained here.

3.2.5 Technology and Environmental Costs

The HIT model considers building, replacing, rebuilding, and operating hydrogen facilities including plants, refueling stations, onsite stations, hydrogen pipelines, CO2 pipelines, and CO2 sequestration plants. In the online optimization process, the technology and environmental costs of these facilities are retrieved from a separate cost data database. These facility costs data are prepared offline via an Engineering Economic sub-model. Although different facilities are modeled differently, the common approach is to rely on data or equations from existing studies such as the H2A model (H2A, 2007) and the NRC study (NRC, 2004).

a. Central plants, Refueling Station Module and Onsite Station Module

A central plant, a refueling station module or an onsite station module is treated as a processing unit composed of several process components (e.g. gasifier, compressor). The capital cost of a facility is estimated based on data of a reference facility, including the cost and scale factor of each process component, and percentage parameters that reflect costs of general facilities, land, contingencies, and other factors, as shown in equation (3-14) and (3-15). The fixed O&M cost is modeled as a certain percentage of the capital cost as in equation (3-16). As in equation (3-17), the variable cost is the sum of costs of all kinds of feedstock, such as natural gas, coal, electricity, and so on, whichever is applicable. The environmental cost is represented by the carbon tax for CO2 emissions due to both hydrogen production and electricity generation as shown in equation (3-18).

$$UV\_H2Fclt = UV\_Factor \times \sum_i \left(\frac{H2FcltSize}{H2FcltRefSize} \right)^{a_i} \times CRef\_Part_i \tag{3-14}$$

$$UV\_Factor = (1 + GF + EPS + CT + WLM) \times SSF \tag{3-15}$$

$$FC\_H2Fclt = FP\_H2Fclt \times UV\_H2Fclt \tag{3-16}$$

$$VC\_H2Fclt = \sum_l (H2Out \times 365) \times FSK_j \times FPrice_j / 10^6 \tag{3-17}$$

$$EC\_H2Fclt = (H2Out \times 365) \times (ConvC + FSK_e \times GridC) / 10^3 \times CTax / 10^6 \tag{3-18}$$

UV_H2Fclt : capital cost of a facility (station module or plant), million $

$H2FcltSize$: output capacity of the facility, kgH2/day

$H2FcltRefSize$: output capacity of a reference facility, kgH2/day

α_i : scale factor for component i

$CRef\_Part_i$: capital cost of reference component i, million $

UV_Factor : ratio of facility capital cost to process unit capital cost (PUC). PUC is the sum of all component capital costs

GF : percentage of PUC for general facilities

EPS : percentage of PUC for engineering permitting and start-up

CT : percentage of PUC for contingencies

WLM : percentage of PUC for working capital, land and misc.

SSF : site specific factor

FC_H2Fclt : fixed O&M cost, million $/year

FP_H2Fclt : percentage of capital cost as fixed O&M cost

VC_H2Fclt : variable cost, million $/year

$H2Out$: hydrogen output, kgH2/day

FSK_j : flow rate of feedstock j, unit feedstock/kgH2

$FPrice_j$: price of feedstock j, $/unit feedstock

EC_H2Fclt : environmental cost with plants or stations, million \$/year
$ConvC$: carbon emission rate of H2 production, kgC/kgH2
FSK_e : flow rate of electricity, kWh/kgH2
$GridC$: carbon emission rate of electricity, kgC/kWh
$ConvC$: carbon emission rate of hydrogen production, kgC/kgH2
$CTax$: carbon tax rate, \$/ton C

The size of facility (plant or station module), $H2FcltSize$, is given as an assumption in the case study. Central plants, independent of production technology, are assumed to have the same size of 1,400 ton hydrogen/day[14]. Any individual refueling station or onsite station is modeled as a base module plus zero, one or multiple expansion modules. Each base module or expansion module has a size of 500 kgH2/day, so the size of a refueling or onsite station is always a common multiple of 500 kgH2/day, but subject to a 5000 kg/day upper limit. A base module is built to begin the operation of the station and expansion modules are stacked to the base module to represent capacity expansion. Although the size is the same, a base module is more expensive than an expansion model due to more costs on general facilities, permitting, and land.

The facility output, $H2Out$, is determined endogenously by the HIT model. For a specific time step, hydrogen demand distribution determines the output of each individual refueling station or onsite station by the principle that hydrogen demand

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[14] The NRC (2004) study assumes 1,200 ton/day for central plants. The plant size assumed in this dissertation may be too large for biomass gasification. But for simplication, we adopt a uniform plant size.

at a specific location is satisfied by the nearest station (see "3.3 *Station Location Sub-model*"). If a refueling station is connected via pipeline or trucking to a plant, the station output is accounted as part of the plant output; if there is not enough central production capacity or simply no central plant, the refueling station output is accounted as industry hydrogen from the nearest plant location[15]. As such, when the hydrogen source of each refueling station is determined, so is the output of each plant (or the amount of industry hydrogen).

The carbon tax rate, $CTax$, is given as assumption to represent carbon damage cost and can be seen as if a dummy agency from outside the system is collecting tax from within the system. When a higher carbon tax rate is adopted, the real meaning is that the policy maker or the user of the HIT model believes in a larger damage cost of one unit CO2 emitted. Because an explicit carbon tax policy does not exist in California at the time of writing and it is beyond our study scope to construct a carbon tax policy likely to be adopted in California, the carbon tax policy assumed in the case study is highly hypothetical, although some relevant literature on carbon tax are reviewed beforehand. The accuracy of such an assumed carbon tax rate is subject to more discussion. At this point, it is mainly a modeling technique to enable

[15] We do not explicitly investigate the location of industry hydrogen source. Instead, each central plant location in this dissertation is treated as an industry zone providing industry hydrogen.

tradeoffs between technology cost and environmental cost. As a remedy, a sensitivity analysis with respect to carbon tax is conducted later in the case study.

Except for facility size $H2FcltSize$, facility output $H2Out$, and carbon tax rate $CTax$, all the other values of input parameters in (3-14)-(3-18) are from the H2A (2007) model and the NRC (2004) study. These values for the Southern California case study are presented in the section "3.4 *Base Scenario*".

b. Liquid hydrogen Trucks

Liquid hydrogen trucks are modeled as a rental service in terms of dollar per mile per kgH2, so the technology costs associated with liquid hydrogen trucks only include the rental fee that supposedly pays back all the costs (plus some profit margin) on the truck rental company, including cost of electricity for hydrogen liquefaction[16]. The truck rental cost, $Cost\_Truck$, is proportional to trucking distance, hydrogen quantity being transported, and rental rate, as in equation (3-19). Liquid hydrogen trucks serve refueling stations that are not connected via pipeline. Trucking distance, $Dist\_tk$, is from a given refueling station to the nearest plant with available capacity or to the nearest industry zone (plant location) if not enough central production capacity is available. The distance is obtained via the Truck Route sub-model. When a refueling station is served by truck, its output becomes the quantity transported by truck, $H2\_tk_k$.

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[16] The rental fee already reflects the regional electricity price.

$$Cost\_Truck = \sum_k Dist\_tk_k \times H2\_tk_k \times Rate\_tk \times 365/10^6 \tag{3-19}$$

$$EC\_Truck = \sum_k (Dist\_tk_k \times H2\_tk_k \times DsUse \times DsC + H2\_tk_k \times EleLquf \times GridC)/10^3 \times CTax \times 365/10^6 \tag{3-20}$$

$Cost\_Truck$: cost of renting liquid trucks, million \$/day
$Dist\_tk_k$: distance of trucking from station k to its source, mile
$H2\_tk_k$: hydrogen transported by truck to station k, kgH2/day
$Rate\_tk$: rental rate of liquid truck, \$/mile/kgH2
EC_Truck : environmental cost with liquid H2 trucks, million \$/year
$DsUse$: diesel consumption, gallon/(mile. kgH2)
DsC : carbon emission rate for diesel, kgC/gallon
$EleLquf$: electricity consumption for H2 liquefaction, kwh/kgH2
$GridC$: carbon emission rate of electricity, kgC/kwh
$CTax$: carbon tax rate, \$/ton c

Environmental cost associated with liquid hydrogen trucks includes carbon tax for CO2 emissions from both diesel consumption and hydrogen liquefaction, as shown in equation (3-20).

Except for trucking distance $Dist\_tk_k$, trucking flowrate $H2\_tk_k$, and carbon tax rate $CTax$, all the other values of input parameters in (3-19) and (3-20) are from the NRC (2004) study.

c. Hydrogen Pipeline

The capital cost of the pipeline is broken down into costs of right of way, material, labor and miscellanea, each of which is estimated based on equations from the H2A model (H2A, 2007) and Parker (2004), as shown in equations (3-21)-(3-25). Like plants and stations, fixed O&M cost is modeled as a percentage of the capital cost, as in equation (3-26).

$$UV\_HPL = LUInd \times (Row\_hpl + Mtrl\_hpl + Lbr\_hpl + Misc\_hpl)/10^6 \tag{3-21}$$

$$Row\_hpl = 1.1 \times (577 \times Dpl^2 + 29788) \times Lpl + 40000 \tag{3-22}$$

$$Mtrl\_hpl = 1.1 \times (330.5 \times Dpl^2 + 687 \times Lpl + 26960) \times Lpl + 35000 \tag{3-23}$$

$$Lbr\_hpl = 1.1 \times (343 \times Dpl^2 + 2074 \times Dpl + 170013) \times Lpl + 185000 \tag{3-24}$$

$$Misc\_hpl = 1.1 \times (8417 \times Dpl + 7324) \times Lpl + 95000 \tag{3-25}$$

$$FC\_HPL = FP\_HPL \times UV\_HPL \tag{3-26}$$

UV_HPL : cost of a pipeline segment, million \$
$LUInd$: land use indicator
Row_hpl : right of way cost, \$
$Mtrl\_hpl$: material cost, \$
Lbr_hpl : labour cost, \$
$Misc\_hpl$: miscellaneous cost, \$
Dpl : diameter of the pipeline segment, inch
Lpl : length of the pipeline segment, mile
FC_HPL : fixed o&m cost of hydrogen pipeline, million \$/year
FP_HPL : percentage of capital cost as fixed o&m cost

When optimizing the pipeline network, the HPTG sub-model also records the diameter, Dpl, and length, Lpl, of each pipeline segment. The land use indicator, $LUInd$, is intended to reflect the pipeline cost difference due to variation in land cost, construction difficulty, and land use policy. In the case study, the indicator is set to 130% for urban area and 100% for rural area.

Except for pipeline diameter Dpl and length Lpl, all the other values of input parameters in (3-21)-(3-26) are from the H2A (2007) model.

d. CO2 Pipeline

Capital and fixed O&M costs of CO2 pipeline are estimated in the same way as hydrogen pipeline, as shown in equations (3-27)-(3-32). All CO2 pipelines are assumed to be built in rural areas and so the land use indicator is 100% for all CO2 pipelines.

The CO2 pipeline length refers to the straight-line distance from the plant to the CO2 sequestration site. If more information is available, the straight-line assumption should be modified with some distance multiplier to reflect the real pipeline length. In the Southern California case study, the border between California and Nevada is assumed to be the CO2 sequestration site based on a published study by Dahowski (et al., 2004)[17]. So there are 9 possible CO2 pipelines connecting the 9 plant locations to the CO2 sequestration site, resulting in 9 possible values for the pipeline length parameter $Lcpl$. Three different types of central plants with carbon capture are considered: coal gasification, biomass gasification and natural gas SMR. Each technology has a different maximum CO2 capture rate, i.e. the CO2 flowrate into the CO2 pipeline when the plant operates at its maximum capacity. Thus, for the same plant location, there will be 3 possible CO2 design flowrate and therefore 3 pipeline

[17] Recent studies (e.g. http://www.westcarb.org) shows abundant carbon storage capacity in other areas of California.

diameter, depending on which technology is adopted for the plant. So in the HIT model, there are 27 possible combinations of length and diameter to be considered for CO2 pipeline.

$$UV\_CPL = (Row\_cpl + Mtrl\_cpl + Lbr\_cpl + Misc\_cpl)/10^6 \tag{3-27}$$

$$Row\_cpl = 1.1 \times (577 \times Dcpl^2 + 29788) \times Lcpl + 40000 \tag{3-28}$$

$$Mtrl\_cpl = 1.1 \times (330.5 \times Dcpl^2 + 687 \times Lcpl + 26960) \times Lcpl + 35000 \tag{3-29}$$

$$Lbr\_cpl = 1.1 \times (343 \times Dcpl^2 + 2074 \times Dcpl + 170013) \times Lcpl + 185000 \tag{3-30}$$

$$Misc\_cpl = 1.1 \times (8417 \times Dcpl + 7324) \times Lcpl + 95000 \tag{3-31}$$

$$FC\_CPL = FP\_CPL \times UV\_CPL \tag{3-32}$$

UV_CPL : Cost of a pipeline segment, million $
Row_cpl : Right of way cost, $
$Mtrl\_cpl$: Material cost, $
Lbr_cpl : Labour cost, $
$Misc\_cpl$: Miscellaneous cost, $
$Dcpl$: Diameter of the pipeline segment, inch
$Lcpl$: Length of the pipeline segment, mile
FC_CPL : Fixed O&M cost of hydrogen pipeline, million $/year
FP_CPL : Percentage of capital cost as fixed O&M cost

e. CO2 Sequestration Plant

The capital cost $UV\_CO2SeqPlant$ of a CO2 sequestration plant is estimated in reference to a known estimate, which refers to the capital cost, $UV\_SeqPlantRef$, estimated somewhere else for a sequestration plant (the reference sequestration plant) with a known size, $SeqPlantRefSize$, as shown in equation (3-33).

As previously stated, all central plants are assumed to have the same size of 1400 ton hydrogen/day, which is also applicable to the input parameter *H2PlantSize* in equation (3-33).

$$UV\_CO2SeqPlant = \frac{H2PlantSize \times RSeq\_CO2}{SeqPlantRefSize} \times UV\_SeqPlantRef \qquad (3\text{-}33)$$

$UV\_CO2SeqPlant$: capital cost of sequestration plant, million \$
$H2PlantSize$: capacity of hydrogen central plant, kgH2/day
$RSeq\_CO2$: CO2 sequestration rate, ton CO2/kgH2
$SeqPlantRefSize$: size of the reference sequestration plant, ton CO2/day
$UV\_SeqPlantRef$: capital cost of a reference sequestration plant, million \$

f. Construction Time

When construction time is not considered or assumed to be zero, it is equivalent to paying the capital cost and finishing the construction at the same time. When construction time is considered, some capital cost must be paid earlier than the completion of construction. Because of value of time, such an early payment of capital cost suggests higher cost. By assuming the construction time, the original capital cost can be treated as a series of periodic uniform payments over the period of construction. Construction time assumptions are presented in the section "3.4.5 Technology Cost".

3.3 Station Location Sub-model

In the "3.2.2 fuel accessibility cost" subsection, it is briefly mentioned that the Station Location sub-model generates the $ARTT$ - $StaNum$ equation from traffic and network data. In spite of the simplicity of its role in the HIT model, the Station Location sub-model involves a systematic approach to linking refueling behavior, traffic and network data, and station location. This section describes how the sub-model starts from traffic and network data to reach the $ARTT$ - $StaNum$ equation while reasonably considering refueling behavior.

Driven by a mobile-origin notion that "where you drive more is where you more likely need refueling", this dissertation develops a new approach to siting station. Instead of the home or workplace, any point along the road network is a possible refueling trip origin, with the probability quantified by the distribution of VMT or fuel consumption. Then, station siting is treated as a network transportation problem.

In the following sections, a brief explanation of the mobile-origin notion is provided and followed by formulating the average refueling travel time ($ARTT$) as the measurement of fuel accessibility. By minimizing $ARTT$, a mixed-integer-programming (MIP) model is used to locate refueling stations. The method is described together with a case study in Southern California.

3.3.1 Measuring Fuel Accessibility

Fuel accessibility is defined as the easiness for a random motorist to access a station from where the motorist has a refueling need. The following paragraphs address these questions.

- Who is this random motorist? Or, what is the probability of a specific motorist being selected? Is it a uniform $1/|V|$ or weighted by VMT, income, or something else?
- Where are the origins of refueling trip? Home, workplace, shopping mall, school, fun route, or anywhere?
- How the easiness is measured? What does it mean to optimize the station locations by maximizing fuel accessibility?

Consider a directed graph, $G = (N, A)$, where N and A are the sets of nodes and arcs, respectively. Let $i, j \in N$ be node i and j, and $a_{i,j} \in A$ be a directed arc from node i to j. Let $s = s_{a,m\cdot\Delta} \in S$ denote a small segment on arc $a_{i,j}$, with a fixed small length of Δ, and with a distance of $m \cdot \Delta$ from node i ($\mathrm{m} = 1, 2, \ldots$). Set S contains all the small segments on arcs. These notations are illustrated in Figure 3-4. Let V denote the set of all motorists traveling along G and $v \in V$ be any particular one of them.

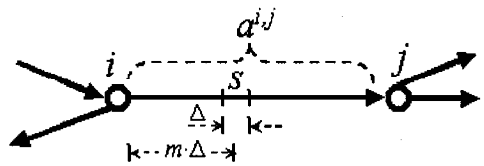

Figure 3-4: Network Element Notation

A refueling node is a node with one or multiple stations. Let $N^f \in N$ be the set of refueling nodes. Now consider a random motorist $v^* \in V$ driving on G to assess the fuel accessibility of N^f. One proper measurement of fuel accessibility of N^f is the expected value of travel time for v^* to travel from where v^* need a refueling to the nearest station, defined as average refueling travel time ($ARTT$). There are two sources of randomness here. One involves the probability of v^* being any particular motorist v, defined as p^v. The other involves the probability of this particular motorist v having a refueling need at a particular location s, defined as p^{vs}. Once these two probabilities as well as the travel time from s to the nearest station, defined as $t^s = t^s(N^f)$, are identified, $ARTT$ can be formulated as in equation (3-34).

$$ARTT = \sum_{v \in V} \sum_{s \in S} t^s \cdot p^v \cdot p^{vs} \tag{3-34}$$

For a given set of station locations N^f, ts can be calculated. Both p^v and p^{vs} are independent of N^f and need further formulation. Formulating p^v involves the equity issue, that is, which motorists have relative more power to influence station siting. Formulating p^{vs} involves some understanding of refueling behavior. Another consideration is that the formulations should ideally have low data requirements.

For simplicity, a time frame of one year is assumed. Let f^{vs} be the number of times per year v passing s, fv be the total number of visits by v to everywhere in S, fs be the total number of all motorists V to a specific location s, and f be the total number of visits by all motorists V to everywhere in S. The relationship among these frequency terms is as below.

$$f^{v} = \sum_{s \in S} f^{vs} \tag{3-35}$$

$$f^{s} = \sum_{v \in V} f^{vs} \tag{3-36}$$

$$f = \sum_{v \in V} f^{v} = \sum_{v \in V} \sum_{s \in S} f^{vs} \tag{3-37}$$

The attributes of s that contribute to a large f^{vs} could be closeness to v's home, workplace, or favorite shopping center, or just belonging to v's most enjoyable route. Whatever the reasons, f^{vs} aggregately reflect v's travel behavior caused by the network, perception, budget, etc. Intuitively, where one drive more is where the one more likely need refueling, so a larger f^{vs} implies a larger p^{vs}, which, as an assumption, is represented by equation (3-38). When v at s has a refueling need, s becomes the origin of the refueling trip. The understanding of refueling behavior here is referred to as the mobile-origin notion, because the location of origin can be anywhere on the network.

$$p^{vs} = f^{vs} / f^{v} \tag{3-38}$$

As another assumption, the probability of v^* being a particular motorist v is weighed by v's relative travel frequency, as in equation (3-39). The implication of this assumption is that frequent drivers have more votes on deciding where stations should be located.

$$p^{v} = f^{v} / f \tag{3-39}$$

Combining equations (3-34) through (3-39), we can obtain another form of $ARTT$ as in equation (3-40), which is important in that the index v disappears and therefore it is no need to obtain disaggregate travel data.

$$\begin{aligned} ARTT &= \sum_{v \in V} \sum_{s \in S} t^{s} \cdot f^{vs} / f \\ &= \sum_{s \in S} t^{s} \cdot \sum_{v \in V} f^{vs} / f = \sum_{s \in S} t^{s} \cdot f^{s} / f \end{aligned} \tag{3-40}$$

To understand the data needs for equation (3-40), one more transformation of equation (3-40) is needed. Define Ts as the aggregate VMT by all motorists V at s and T as the total VMT by all motorists V over S. Define Cfe as the average fuel economy. Define $FUEL^{s}$ and $FUEL$ as the fuel consumption due to VMTs and VMT, respectively. And also note that every s has a uniform length of delta. Thus, the final transformation of $ARTT$ is obtained as in equation (3-41). Equation indicates the needed data is the spatial distribution of VMT, which is usually not difficult to obtain. The equation provides another perspective: spatial distribution of fuel consumption. And because the total fuel consumption $FUEL$ is a constant term, minimizing $ARTT$ is equivalent to minimizing $ARTT \cdot FUEL$. A resulting interpretation of t^s in equation is the time for $FUEL^s$ to "travel back" from where it is burned to the nearest station. Thus, when a set of stations N^f results in a set of t^s that minimize $ARTT$, the expected refueling travel time of a random motorist, it also minimize $ARTT \cdot FUEL$, the total time for all the fuels to hypothetically travel from where they are burned to the nearest station, as shown in equation (3-43).

$$ARTT = \sum_{s \in S} t^s \cdot \frac{f^s \cdot \Delta}{f \cdot \Delta} = \sum_{s \in S} t^s \cdot \frac{T^s}{T} \tag{3-41}$$

$$ARTT = \sum_{s \in S} t^s \cdot \frac{T^s / C_{fe}}{T / C_{fe}} = \sum_{s \in S} t^s \cdot \frac{FUEL^s}{FUEL} \tag{3-42}$$

$$ARTT \cdot FUEL = \sum_{s \in S} t^s \cdot FUEL^s \tag{3-43}$$

3.3.2 Station Siting as a Transportation Problem

The previous sub-section finds that the problem of siting stations can be seen as "fuel traveling back", as in equation (3-43). However, the application of equation is not convenient because it considers everywhere along the each road segment of the network. This sub-section explains how the "fuel traveling back" problem can be treated as a well-studied transportation problem.

For any s on a directed arc a_{ij}, because $FUEL^s$ must first arrive at j, then all the $FUEL^s$ along a_{ij} must "gather" at node j into $FUEL^j$ before they further "travel" to the nearest station. Let l^j, called average node-wide travel time, be the average time from s to j and t^j be time from j to nearest station. Thus, equation (3-43) is transformed into (3-44).

$$\begin{aligned} FUEL \cdot ARTT &= \sum_{j \in N} (t^j + l^j) \cdot FUEL^j \\ &= \sum_{j \in N} t^j \cdot FUEL^j + l \\ l &= \sum_{j \in N} l^j \cdot FUEL^j \end{aligned} \tag{3-44}$$

Note that the everywhere index s disappears in equation (3-44). Instead, located is indexed by node j. Now the problem changes: any node $j \in N$ is attributed with an aggregated fuel demand $FUEL^j$ and a set of refueling nodes N^f are to be selected to minimize the total travel time for these aggregated "fuel groups" to travel back to the nearest stations. This fits perfectly into the transportation problem context which has been widely studied in the field of operations research, and so the optimization model can be easily formulated as in equation (3-45).

$$\begin{aligned} &\text{Minimize:} \\ &FUEL \cdot ARTT = \sum_{j,i \in N} (t^{ji} + l^j) \cdot flow^{ji} \\ &\text{Subject to:} \\ &\sum_{i \in N} flow^{ji} = FUEL^j \qquad (\forall\, j \in N) \quad \text{(a)} \\ &\sum_{j \in N} flow^{ji} \le Mnum \cdot build^i \qquad (\forall\, i \in N) \quad \text{(b)} \\ &\sum_{i \in N} build^i = \left|N^f\right| \qquad \text{(c)} \\ &build^i = \begin{cases} 1 & i \text{ is refueling node} \\ 0 & \text{otherwise} \end{cases} \end{aligned} \tag{3-45}$$

For model (3-45), $build^i$ and $flow^{ji}$ are the decision variables. Quantity $flow^{ji}$ represents the amount of fuel "traveling" from j to i. Constraint (a) ensures satisfaction of all demands, as if forcing all fuel to travel back to stations. Constraint (b) ensures fuel can only travel back to a refueling node and $Mnum$ is an arbitrarily big number merely for programming purpose. Constraint (c) limits the number of refueling nodes to be $|N^f|$.

3.3.3 Some Practical Aspects

For applying the model in equation (3-45), there are three practical issues: location continuity, starting number of refueling nodes, and multiple stations for one node.

The term $|N^f|$ in equation (3-45) represents the total number of refueling nodes. If we apply the model independently to different values of $|N^f|$ and obtain a corresponding station location scheme for each $|N^f|$, we are in nature ignoring the spatial relationships among these schemes or assuming it is free of cost to move a station from one location to another. For example, if optimizing $|N^f| = 10$ and $|N^f| = 20$ refueling nodes leads to two location schemes SL_{10} and SL_{20} and two performance values $ARTT_{10}$ and $ARTT_{20}$, respectively, there is no guarantee that the locations of SL10 is a subset of those of SL20. Thus, if we proceed and state that "if the refueling network grows from 10 refueling nodes to 20, the average refueling travel time decreases from $ARTT_{10}$ to $ARTT_{20}$", we either ignores the relationships between the SL_{10} locations and SL_{20} locations or assume there is no cost to move any refueling node in SL_{10}, but not in SL_{20}, to SL_{20}. Apparently, this is inappropriate. This is referred to as the location continuity issue, which is important because we are interested in the dynamic growth instead of a static refueling network.

Related to the location continuity issue is the issue of starting number of refueling nodes. It is about how many refueling nodes to be simultaneously sited. For example, we can optimize the location of one refueling node independently, then optimize the location of the second refueling node by holding the location of the first refueling node, and so on. We can also simultaneously optimize 10 refueling nodes and add one refueling node a time from the 11th refueling node and delete one refueling station a time from the 9th refueling node. There are many other options, leading to many possible roll-out schemes. Which one is the best?

The third issue is related to the possibility of multiple stations on a single refueling node. Due to limited data availability and the purpose of reducing computation time and data processing time, the total number of nodes $|N|$ is often much smaller than the possible maximum number of stations to be considered. This means the possibility of building multiple stations in a single refueling node. Note that the distance between two adjacent nodes can be miles, so multiple stations per node here does not mean multiple stations around an intersection like 4-corner gas stations in real life, but multiple stations within a local area around a node. So how to model the benefit of siting multiple stations? And how to trade off between building multiple stations and opening another refueling node? This is referred to as the issue of multiple stations for one node.

When all these issues are addressed, an optimal station roll-out scheme is generated. The optimal station roll-out scheme shows where new stations are added as the refueling network grows. It does not include the time dimension, although it is assumed that a larger refueling network occurs sometime later than a smaller one. But it is up to the HIT model to determine how long it takes for the refueling network to grow, e.g. from 20 stations to 200 stations. As previously mentioned, the key information provided by the Station Location sub-model to the HIT model is the $ARTT$ - $StaNum$ equation.

We use the Southern California case study to illustrate how the model in equation (3-45) is applied and how the two practical issues are addressed. The flowchart in Figure 3-5 shows the detailed process from traffic data to obtain the optimal station roll-out scheme. Particularly, the Step 9 deals with the multiple stations per node issue and deserves more details, as shown in Figure 3-6.

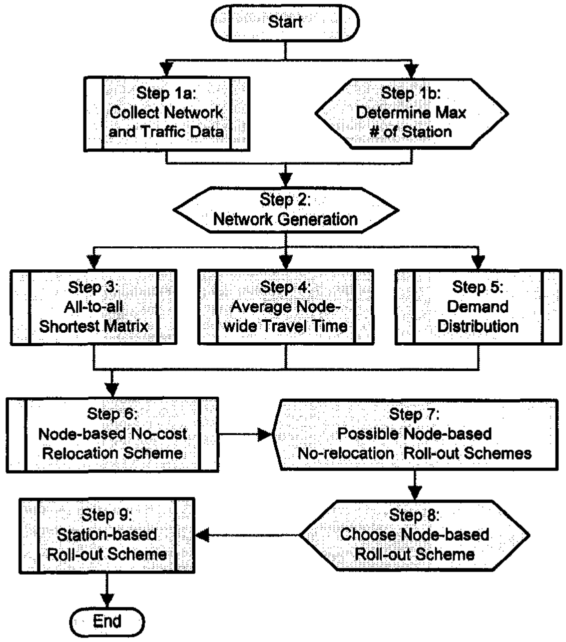

Figure 3-5: Siting Approach Flowchart

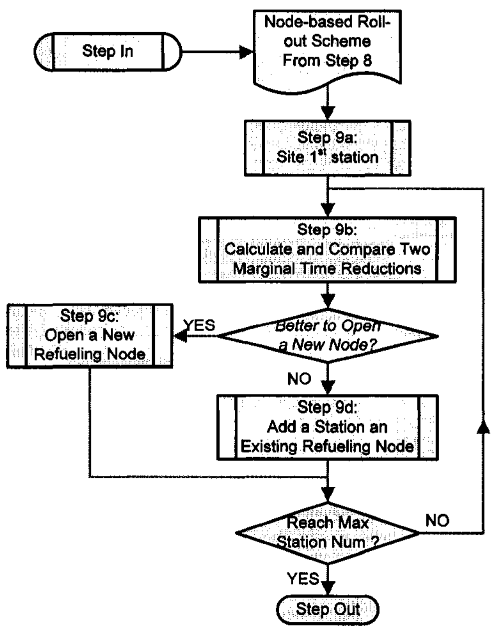

Figure 3-6: Step 9 Flowchart

Based on the spatial scale, traffic density distribution and data availability, 168 nodes (most are intersections) on major roads (including freeways) are selected to form the network G (Step 2). The all-to-all shortest matrix is generated via the Floyd-Warshall algorithm (Cormen, et al., 1990) based on real distances (Step 3). The average node-wide travel time, l^j as in equation (3-44), is also calculated (Step 4). The spatial distribution of demand, represented by $FUEL^j / FUEL$ for any node j, is also calculated (Step 5) and illustrated by the circle size in Figure 3-7.

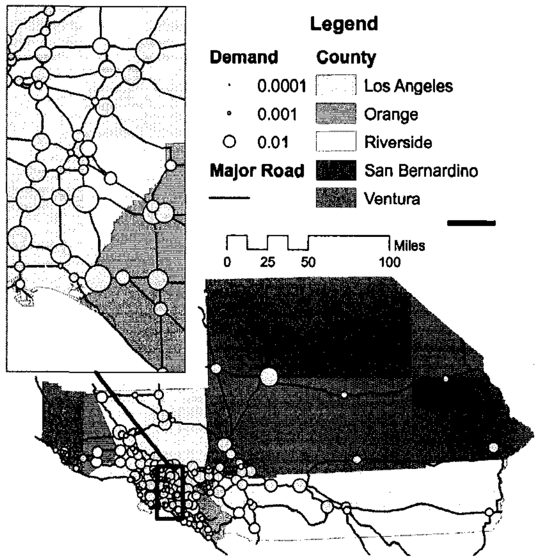

Figure 3-7: Network with Demand Distribution

By applying model (3-45) to any $|N^f| = \{1, 2 \ldots 168\}$, 168 optimal independent selections of N^f and the corresponding values of $ARTT$ are obtained (Step 6). However, as these 168 N^f are each independent, the assumption must be made of ignoring station relocation cost if the 168 N^f are to be used as a rollout scheme. Though this is not realistic, these $ARTT$ values form a theoretical lower bound of $ARTT$ for any no-relocation roll-out scheme.

Assuming one refueling node increment and using each of the 168 N^f as the starting refueling network, we can derive 168 no-relocation roll-out schemes (Step 7), but need to select the best one. Since the $ARTT$ values of 168 independent N^f provides a theoretical lower bound, we use $ARTT$ deviation from the bound as a selection criterion.

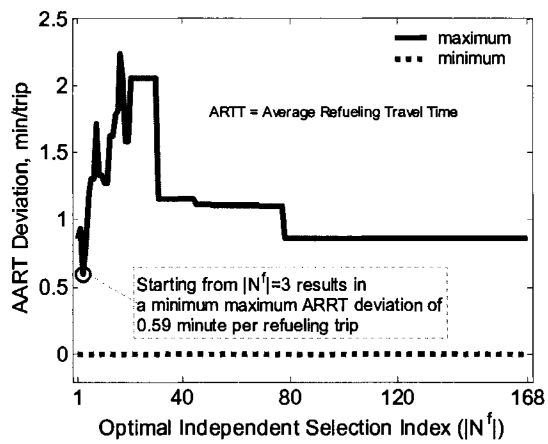

Figure 3-8: ARTT Deviation

The $ARTT$ deviations (maximum and minimum) of the 168 no-relocation schemes are plotted in Figure 3-8. The minimum $ARTT$ deviation is zero for any no-relocation scheme (Figure 3-8). This is logical in that by definition, any no-relocation scheme must have at least one selection of refueling nodes also belonging to the *168* independent nodes N^f.

The maximum deviation (Figure 3-8) indicates the performance of the no-relocation scheme. The maximum deviation varies considerably with range of 0.63-2.41 min/trip or 0.69-2.6 mile/trip. This suggests that a no-relocation scheme should be carefully selected to ensure a better siting strategy. Based on maximum *ARTT* deviation, the no-relocation roll-out scheme under location constraint of 3 refueling nodes is the best (Step 8).

The decision variable $build^i$ in model (3-45) is about choosing refueling nodes, but not how many stations on each node. With a maximum of 1500 stations[18] on 168 nodes, multiple stations per node must be considered.

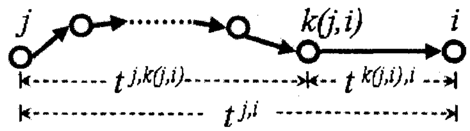

Figure 3-9: Last Arc Travel Time

Consider splitting $t^{j,i}$ in (3-45) into $t^{j,k(j,i)}$ and $t^{k(j,i),i}$ as in Figure 3-9, where $k(j,i)$ is the second last node along the shortest path from j to i. Conceptually, more stations on i should reduce the average of last-arc travel time $t^{k(j,i),i}$ as these stations could be spread out and $FUEL^j$ does not always have to reach i to find a station. This effect is approximately reflected by equation (3-46), where n^i is the number of stations around i, based on the assumption that multiple stations on the same node are located with the priority order of "1st station on node", "closeness to roads", and "spreading out around node".

[18] in the Southern California case study, hydrogen demand grows and more than 1500 stations will be needed. The fitted ARTT-StaNum below will be extended for more stations. This is deemed reasonable, given the obvious trend in Figure 3-10.

$$t^{*i} = \frac{4}{n^i + 3} \cdot \frac{\sum_{j \in N, y^{ji} > 0} t^{k(j,i),i} \cdot FUEL^j}{\sum_{j \in N, y^{ji} > 0} FUEL^j} \tag{3-46}$$

When a no-relocation scheme is obtained, two marginal $ARTT$ reductions can be calculated: one due to opening a new refueling node and the other as the maximum marginal $ARTT$ reduction due to adding a station to an existing refueling node. These two marginal reductions are compared to decide whether to open a new node or just add a station to an existing refueling node. This process is reiterated and more and more stations are added, resulting in more refueling nodes and reduction of $ARTT$. The $ARTT$ - $StaNum$ equation can then be fitted (Figure 3-10). Then an optimal station roll-out scheme can be found (Step 9).

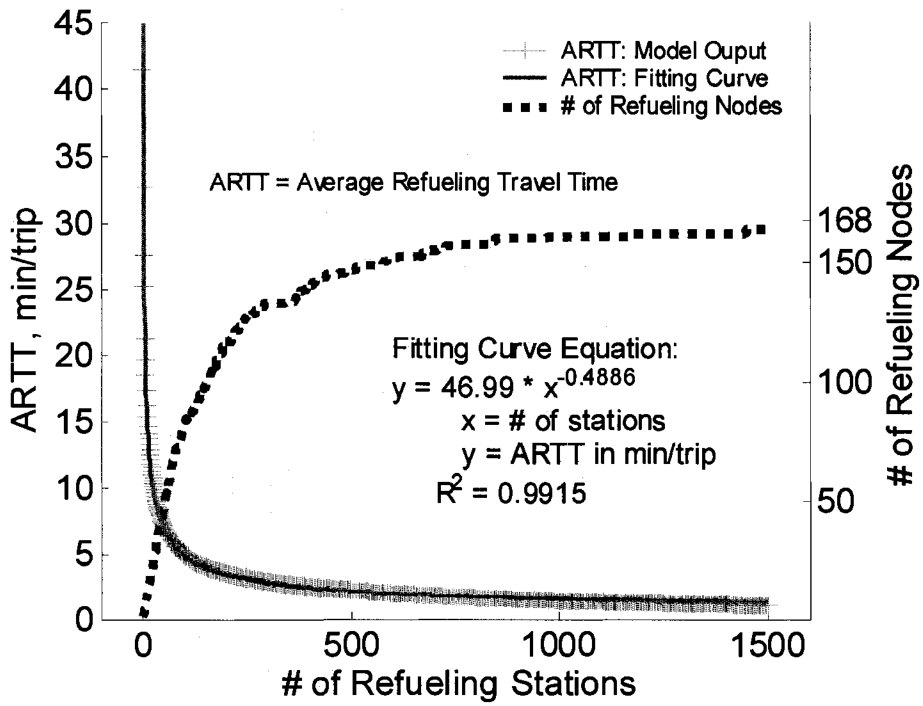

Figure 3-10: Average Refueling Travel Time vs. Station Number

3.4 Base Scenario

3.4.1 Study Scope

California has long been a leader in regulating vehicle emissions and promoting clean vehicle technologies. In April 2004, the California governor Arnold Schwarzenegger signed Executive Order S-7-04 as the vision for a "California Hydrogen Highway Network". The Hydrogen Highway vision has since stimulated many research, development, and demonstration activities on understanding and promoting hydrogen and FCV technologies for California. Particularly, Southern California has received much attention from hydrogen-related stakeholders partly due to the large vehicle fleet, high population concentration, and severe air quality in the region. The potential of Southern California to be one of the first in the world in adopting hydrogen fuel has motivated some serious discussions and studies (Ogden 1999b; Bunch and Kazimi, 1996; Lipman et al, 2004; McCarthy et al, 2008; Nicholas and Ogden, 2006; Cunningham et al, 2008).

For these reasons, Southern California is selected in this dissertation as the study region for the case study of the HIT model. The study region includes 5 counties: Los Angeles, Orange, San Bernardino, Riverside and Ventura with the regional attributes in Table 3-1. We assume a time scope of 2010-2060 with 5 years per time step. We consider two onsite production options: natural gas SMR (D-SMR) and electrolysis (D-ELE); six central productions: water electrolysis (C-ELE), natural gas SMR with (C-SMRCCS) and without CCS (C-SMR), biomass gasification with (C-BIOCCS) and without CCS (C-BIO), and coal gasification with CCS (C-COALCCS); and industry hydrogen. Central plants and industry hydrogen must be coupled with refueling stations (REFSTA) that do not have production capability. We consider two hydrogen delivery modes: gaseous hydrogen via pipeline and liquid hydrogen via tanker truck.

Table 3-1: Southern California Overview (2005)

Population	17.6 million
Area	33,953 sq. mi.
Density	517/sq. mi.
Transport demand	154 billion VMT
Fuel Consumption	8.47 billion gallon
Vehicle Stock	11.4 million

3.4.2 Demand

The total hydrogen demand $DH2(Yr)$, as appearing in the several previous equations, is an exogenous factor and estimated based on vehicle miles travelled (VMT) projected for Southern California. Total VMT is projected by extrapolating an existing 2030 projection conducted by California Department of Transportation (Caltrans, 2005). Daily per-vehicle VMT by vehicle age and vehicle population share by vehicle age, respectively symbolized by $DayVMTbyAge(Age)$ and $ShrByAge(Age)$ as in equation (3-5), are from the EMFAC2007 model developed by the California Air Resources Board (CARB, 2006). These three sets of data are used to project total vehicle population and annual total vehicle sales. By assuming the DOE Scenario 3 (Gronich, 2006), which envisions the number of FCVs for Los Angeles area for 2012-2025, and a 100% market penetration by FCV sale in 2060, annual FCV sales are projected for 2010-2060. Annual gasoline vehicle sale, total gasoline vehicle population, total FCV population, gasoline demand and hydrogen demand are then also derived. For simplification, we assume 27.5 mpg of fuel economy for new gasoline vehicles and 68.8 mpg for new FCV after 2010 and do not consider fuel economy improvement over time, which is a desirable improvement in the future study. All these data and intermediate results are presented in Appendix Table 1 and 2.

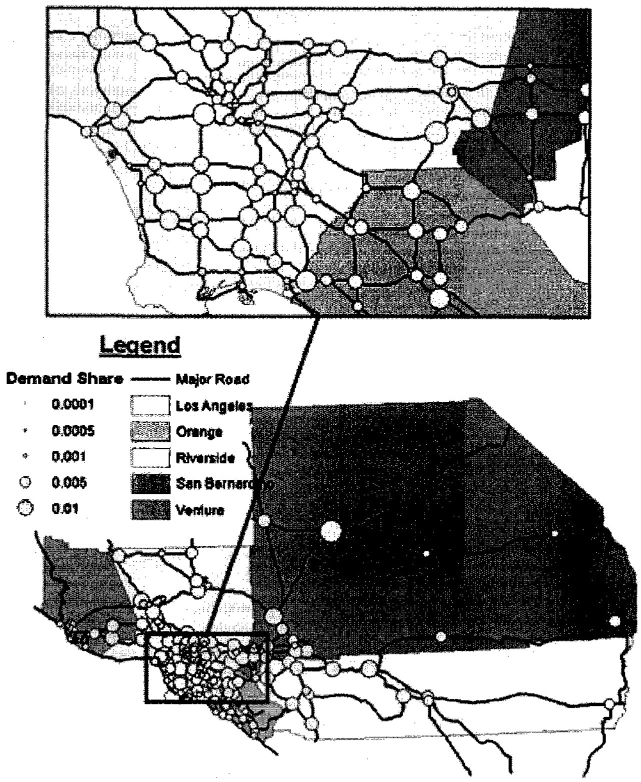

Figure 3-11: Network and Demand Distribution

3.4.3 Network

The study region is modelled as a network of 168 nodes connected by major roads, as shown in Figure 3-11. There are thousands of traffic flow monitors in the study region and the selected 168 nodes are mostly along the busiest roads, although several nodes along rural roads are also included to ensure good spatial coverage. The spatial distribution of total hydrogen demand is proportional to the VMT distribution and is represented by the demand share of each node.

3.4.4 Plant and CO2 Sequestration Location

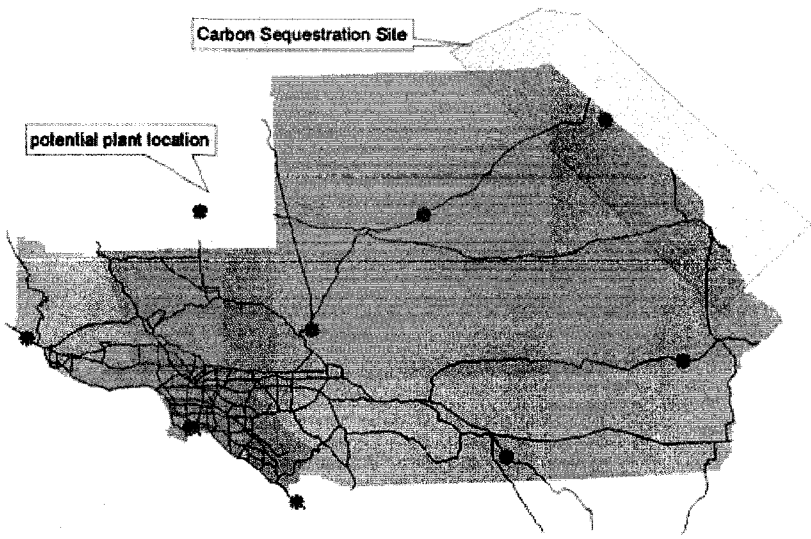

Figure 3-12: Plant and Carbon Sequestration Location

One estimate of the carbon storage capacity (saline formation) of the Basin & Range province is 889,055 MtCO2 (Dahowski, et al., 2004). The overlay of the province on the study region (Figure 3-12) is assumed to be the carbon sequestration and storage area. A total of 9 central plants are needed to meet the 2060 demand. The potential locations (Figure 3-12) for central plants are selected by considering proximity to population, railroad, industry zones, and carbon sequestration area.

3.4.5 Technology Cost

Technologies are represented by a facility characterized by size, activity, capital, fixed O&M and variable costs, efficiency and carbon emission, among which only activity is a decision variable and others are exogenous factors. Technology improvement is described by a decrease of costs and emission factors and an increase of efficiency over time.

The size of a central plant may very by production technology. However, assuming different sizes for central plants will substantially add to model complexity. As a compromise, a uniform size of 1,400 ton/day is assumed for central plants[19]. A stackable module size of 500 kg/day and a size upper limit of 5,000 kg/day are assumed for refueling, onsite SMR, and onsite electrolysis stations. A facility life of 20 years is assumed for refueling, onsite SMR, and onsite electrolysis stations, and 40 years for all central plants, pipelines and sequestration plants. These are summarized in Table 3-2.

[19] This plant size may be too large for biomass gasification. This issue may be addressed in future study.

Table 3-2: Facility Capacity and Life

refueling station	n*500 kg/d <= 5000 kg/d; n = number of 500 kg/d modules	20 years
onsite SMR		
onsite electrolysis		
central plant (any technology)	1400 metric ton/day	40 years
hydrogen pipeline segment	decision variable	
CO2 pipeline segment		
sequestration plant		

a. Facility Capital Cost

Facility capital costs for stations and plants for 2010-2014 are derived from the H2A model (H2A, 2007) according to the engineering-economic methods previously described. Because the H2A model does not provide future technology assessment at the time of conducting the case study[20], technology data for year 2060 are derived by using the ratios of "future optimism" and "current" assessments reported by the NRC study (NRC, 2004). Facility capital costs between 2010 and 2060 are derived via quadratic interpolation and shown in Appendix Table 3.

Capital cost of hydrogen pipeline is estimated at the level of trunk segment connecting into each of the 168 network nodes and the local delivery pipeline connecting from the node to a refueling station. Length, diameter, land type, and resulting capital cost of these pipeline segments are presented in Appendix Table 4.

[20] The H2A model now includes some cost assessments for year 2015.

There are 9 potential CO_2 pipelines being considered to connect the 9 central plant locations to the sequestration site, depending on whether the central plant has carbon capture capability. Although the length of each CO_2 pipeline is certain, its diameter has three possibilities depending on whether the plant is based on biomass gasification, coal gasification or natural gas SMR. This is because amount of CO_2 captured per unit of hydrogen output differs among technologies: 2.34 kgC/kgH2 for C-SMRCCS, 4.41 kgC/kgH2 for C-COALCCS and 7.04 kgC/kgH2 for C-BIOCCS, according to the NRC study (NRC, 2004). The lengths, diameters and resulting capital costs for 2010 for the 9 pipelines are shown in Appendix Table 5.

For both hydrogen and CO_2 pipelines, technology improvement is represented as a decreasing fraction of the 2010 capital cost based on the "future optimism" and "current technology" data for hydrogen pipeline from the NRC (2004) study, as shown in Appendix Table 6.

We estimate an installed cost of 1.39 million dollars for an injection well with injection capacity of 1,500 tons CO_2 per day and injection depth of 1,500 meters (Dahowski, et al., 2004). The number of injection wells is determined by the actual amount of CO_2 captured. Therefore, capital cost for sequestration plants is estimated with respect to technology type of central plants and is shown in Appendix Table 7.

Construction time is 1 year for hydrogen pipeline segments, and refueling, onsite SMR, and onsite electrolysis stations, and 3 years for central plants, CO_2 pipeline segments and CO2 sequestration plants. CO2 pipeline is usually much longer than hydrogen pipeline and therefore is assumed to require longer construction time. The effect of construction time is already reflected in the facility capital costs.

b. Facility Fixed O&M Cost

Fixed O&M cost in terms of million USD per year is calculated as a percentage of capital cost, as shown in equation (3-16) as an example. These percentages, also called fixed O&M cost factor, are cited from the H2A (2007) model and shown in Appendix Table 8.

c. Facility Variable Cost

Depending on technology, facility variable costs come from consumption of one or more of these types of feedstock: electricity (commercial and industry prices), natural gas (commercial and industry prices), coal, and biomass. We estimate 7.94 million BDT/year of biomass available in the study region (Jenkins, 2005), which can only support one central plant with the assumed size of 1400 ton/day. There is no representation of biomass supply curve in the model. Consumption rates and prices of feedstock (EIA, 2006; H2A, 2003) are shown in Appendix Table 9 through 11.

Tanker truck is represented as a rental service at a rate of \$1.80 per kgH2 per 210 kilometres (NRC, 2004). Hydrogen liquefaction consumes a large amount of electricity. The electricity consumption rate for hydrogen liquefaction is shown in Appendix Table 12. Electricity consumption for liquefaction is used to calculate the resulting CO2 emissions and carbon tax, but not electricity cost, which is already represented as part of trucking rent.

d. Industry Hydrogen Supply Curve

Based on Ogden's Southern California study (Ogden, 1999b), an industry hydrogen supply below 42,000 kg/day is available at a delivered cost of 2.80 \$/kg, adjusted by inflation and not including station costs. The marginal cost of more industry hydrogen is assumed to increase linearly to 10 \$/kg at 84,000 kg/day.

3.4.6 Carbon Tax

A carbon tax of 20 \$/tonC in 2010, aggressively increased by 20 \$/tonC per a 5-year time step, is assumed to represent the social cost of carbon emissions.

3.4.7 Fuel Accessibility

Two exogenous factors are related to calculation of fuel accessibility cost: time value factor C_{time} and fuel tank factor C_{fpr} as in equation (3-6) of the section "3.2.2 Fuel Accessibility Cost".

A time value of 0.33 \$/min, equivalent to 50% of 40 \$/hour wage rate (VTPI, 2006), is assumed to convert travel time into dollars.

The fuel tank factor C_{fpr} is assumed to be 4.08 kgH2 per refueling. This is based on the assumptions of 400 miles of driving range, 68.8 mpgge of fuel economy, and 70% emptiness of fuel tank for every refueling.

3.4.8 Discount Rate

An internal discount rate of 10% annually is assumed for technology costs including capital, fixed O&M, and variable costs. This means that a \$100 cost at a specific time has the same net present value of a one-year-later \$110 cost. An external annual discount rate of 10% is also assumed for environmental cost (carbon tax in this dissertation) and fuel accessibility cost (refueling travel time cost in this dissertation). All discount rates in this dissertation are real, as inflation is not considered. All dollar values are expressed in year-2000 dollar.

No consensus has been formed on a single right discount rate for long-term project analysis, and the choice of discount rate has been at the center of debate for a long time and involves complicated economic and equity issues. It is not the intention of this dissertation to discuss in depth the choice of a discount rate. Instead, a 10% discount rate, as also adopted by the H2A model, is selected for the BASE scenario. A separation of internal and external discount rates is intended as a model attribute to allow different valuation of future internal and external costs. A sensitivity analysis of the external discount rate is included in this dissertation, but the need for more sensitivity analyses on both discount rates is acknowledged.

3.4.9 Other

The California grid CO2 emission factor is assumed to be 0.275 kgCO2/kWh, according to the 1998-2000 average value reported by EIA (2002).

4 SOUTHERN CALIFORNIA CASE STUDY

This chapter covers results and discussions of the Southern California case study in several sections. The first section presents the optimal sequence of system configurations that the HIT model identifies to minimize the social cost net present value of the hydrogen transition in Southern California under the BASE scenario. The next sections discuss the economic, environmental and fuel accessibility aspects of such an optimal sequence. The final section shows some sensitivity analysis.

4.1 The Optimal Sequence of Configurations

4.1.1 Hydrogen Production

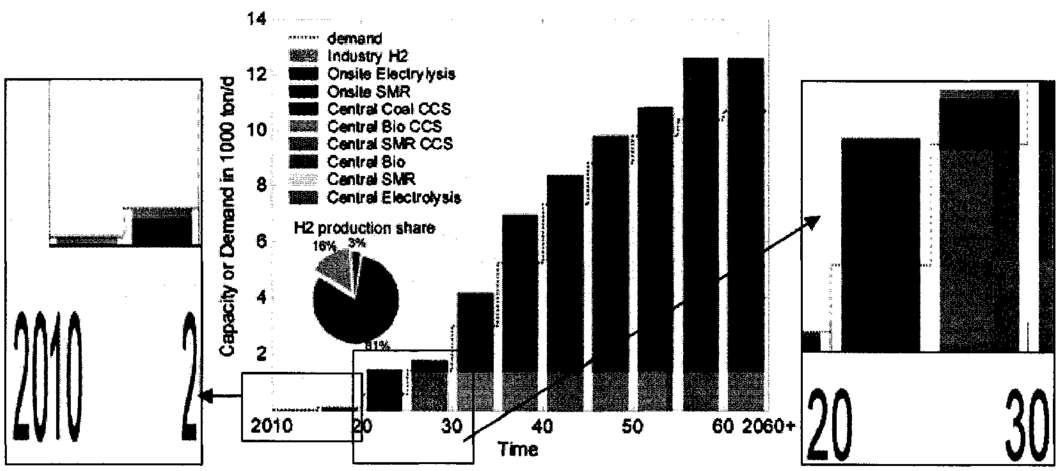

Figure 4-1: Cumulative Capacity by Technology

As shown in Figure 4-1, during 2010-2014, all hydrogen supply comes as industry hydrogen at a rate of 1,365 kg/day delivered via tanker truck to 4 refueling stations.

For 2015-2019, a supply of 44,795 kg/day industry hydrogen are delivered by tanker truck to 36 refueling stations, while 50 D-SMR stations are also built to meet the remaining demand of 62,215 kg/day. From 2020, central production enters the market and begins to dominate, although industry hydrogen and D-SMR also co-exist for some years help the system keep up with demand growth but avoid low utilization of central production.

Although C-COALCCS dominates during most of the study period, the first central plant, introduced in 2020, is by C-BIO, which is upgraded with CCS after 5 years to cut costs on carbon tax. The upgrade means that a carbon capture component is added to convert the C-BIO plant into C-BIOCCS, a CO2 pipeline is built and a CO2 sequestration plant is also built. Available biomass allows for one C-BIO or C-BIOCCS plant but is not enough for two[21]. Other technologies, D-ELE, C-ELE, C-SMR, C-SMRCCS, are not chosen as part of the optimal decisions.

4.1.2 Hydrogen Delivery

As shown in Figure 4-2, trucking is initially adopted to deliver industry hydrogen and later collaborates with pipelines to deliver hydrogen from central production. Pipelines expand around central plants and distribute hydrogen to the near refueling

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[21] The total available biomass is 7.94 million BDT per year. One plant in this dissertation requires 79% of the available biomass. More biomass could be utilized if a smaller plant size is assumed.

stations, while trucks distribute hydrogen to remote refueling stations, where demand levels are not high enough to justify further expansion of the pipeline network. While trucking continues to dominate hydrogen distribution for about the first 25 years, it gradually loses share to pipelines over time with demand growth.

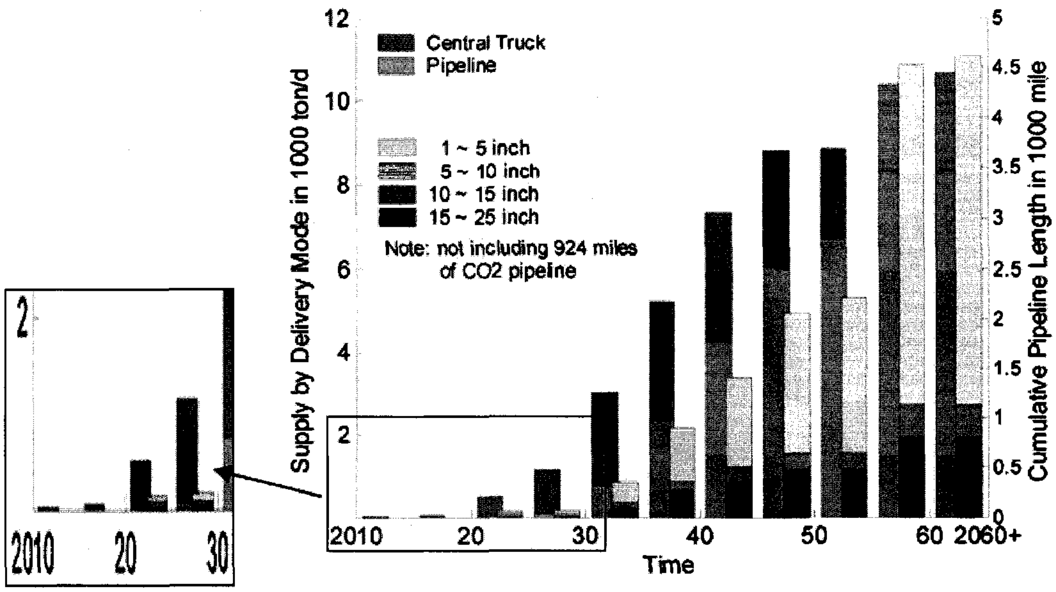

Figure 4-2: Hydrogen Distribution Technology

4.1.3 Hydrogen Refueling

Station location optimization enables a small refueling network to provide a desired level of fuel accessibility. The trade-off between travel time and station costs causes the refueling network to expand from 4 stations of an average size of 500 kg/day during 2010-2014 to 2376 stations of 5000 kg/day during 2055-2059, as shown in Figure 4-3, Figure 4-4, and Figure 4-5. The average refueling travel time with 2376 stations in 2060 is less than 50 seconds. The two figures, station number over time as in Figure 4-5 and average refueling travel time over time as in Figure 4-3, reflect the ARTT-StaNum function in equation (3-7), also shown in Figure 3-10.

The approximate locations of hydrogen stations are shown for four time steps in Figure 4-6. The locations of stations around a node reflect the assumption that multiple stations on the same node are located with the priority order of "1st station on node", "closeness to roads", and "spreading out around node", as explained in the section "3.3 *Station Location Sub-model*".

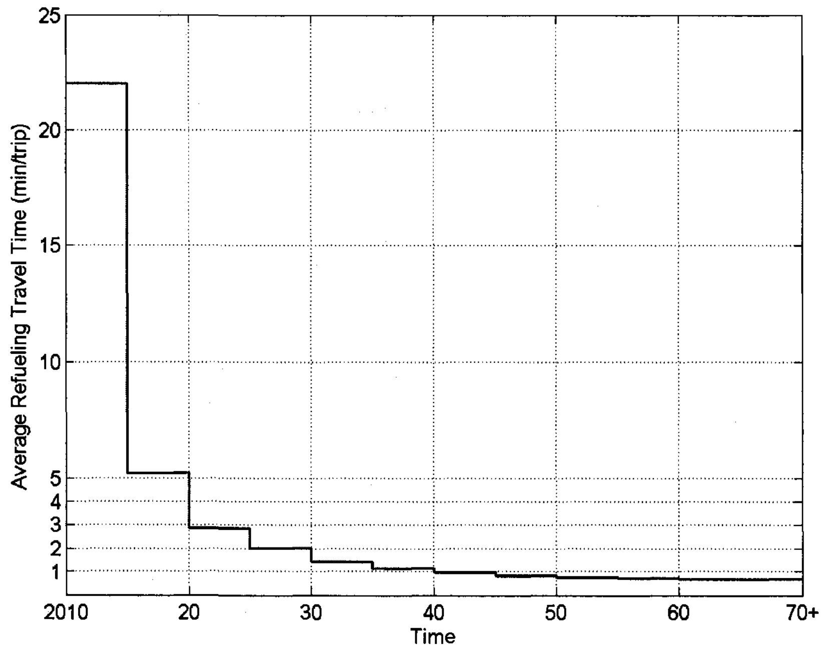

Figure 4-3: Average Refueling Travel Time

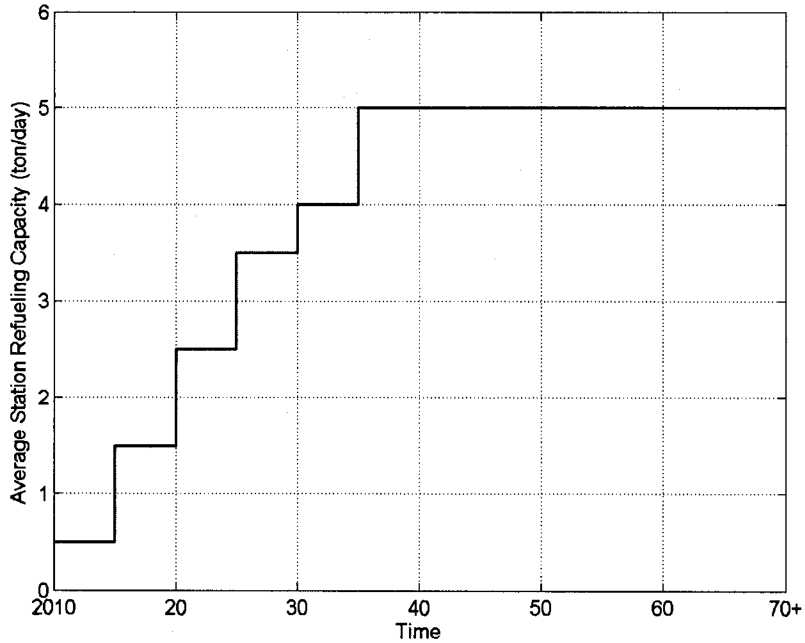

Figure 4-4: Average Station Capacity

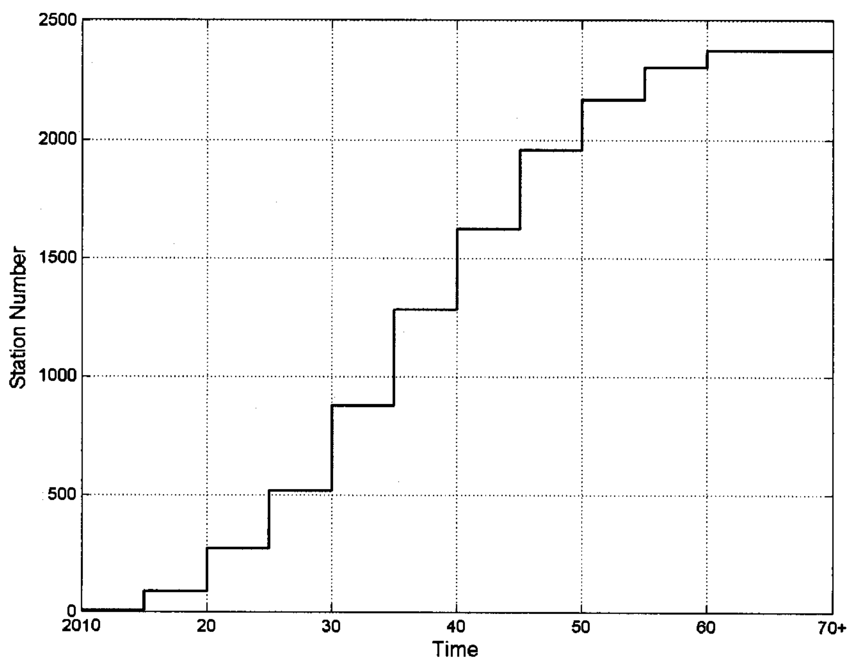

Figure 4-5: Station Number

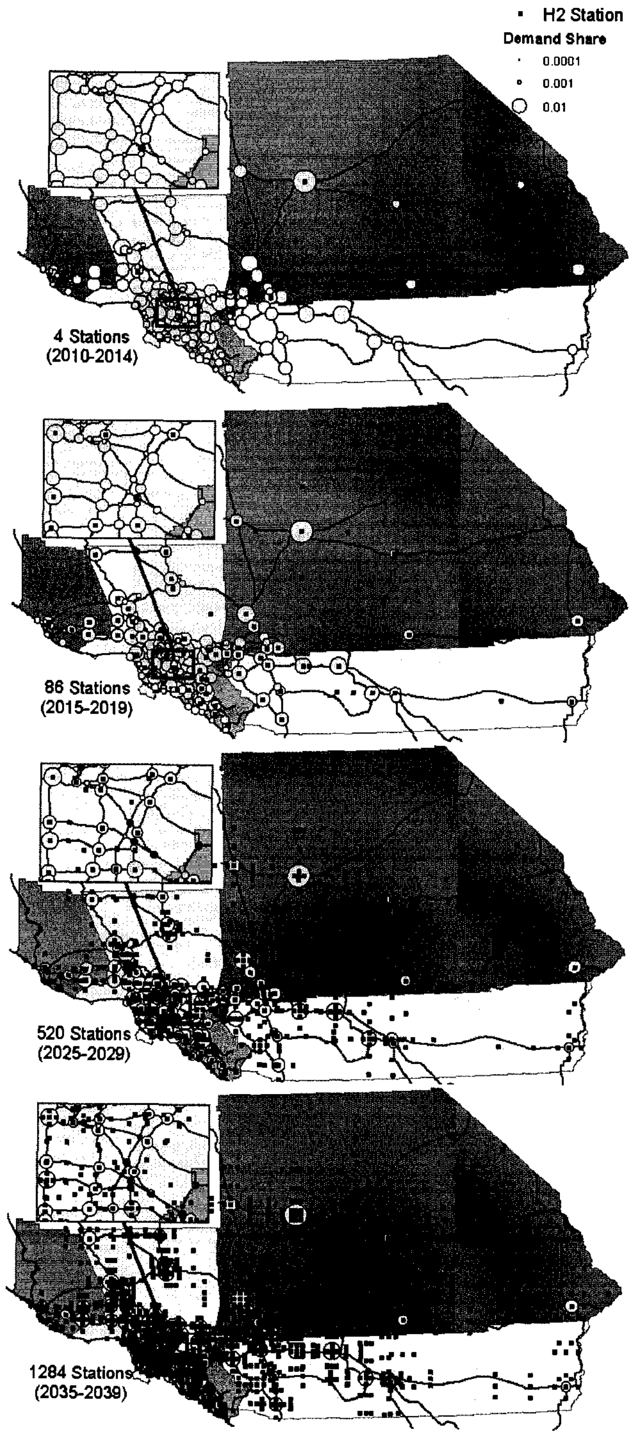

Figure 4-6: Station Location

4.1.4 Overview of Technology Transition

The optimal sequence exhibits three parallel trends:

- Production: industry hydrogen to distributed production (D-SMR) to central production (C-BIO to C-BIOCCS to C-COALCCS)
- Distribution: trucking to pipelines
- Dispensing: refueling stations to onsite stations to refueling stations

Industry hydrogen plays an important role in meeting a low demand at low costs and bridging a mature hydrogen industry. Although the low-cost industry hydrogen is available only up to 42,000 kg/day (see description of industry hydrogen supply curve in the section "3.4.5 Technology Cost"), the amount is more than enough to serve the demand during the first five years. With one tanker truck and four small refueling stations (500 kg/day of capacity), the system starts without massive capital investments. This is important because lower start-up capital needs imply lower risks and therefore smaller challenge for polices to stimulate industry participation.

Distributed production could collaborate with industry hydrogen to strengthen the bridging role. For example, during 2015-2019 when demand exceeds the limited amount of low-cost industry hydrogen but not to the extent to justify central production, distributed production comes into play.

Competition exists between industry hydrogen and distributed production and the key drivers[22] are demand, technology improvement and carbon tax. For example, during 2010-2014, industry hydrogen outperforms distributed production. However, over time, increase in carbon tax due to increasing carbon tax rate deteriorates industry hydrogen, where liquefaction process consumes a large amount of grid electricity[23] and causes CO2 emissions. On the other side, decrease in technology costs of distributed production[24] due to technology improvement and increase in utilization due to demand growth enhance the competitiveness of distributed production. As a result, the demand increment during 2050-2054 is served by distributed production instead of industry hydrogen by truck.

Likewise, distributed production competes as well as supplements with central production. In the optimal sequence, it appears that distributed production is replaced by central production when demand grows to a certain level, due to a comprehensive competition on technology and environment costs. However, it does not mean that distributed production is gone forever. As shown in the optimal sequence, onsite SMR comes back during 2050-2054, although soon replaced again by central production. This is because when the demand increment is large enough to exceed the available capacity of existing central plants but not big enough to justify

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[22] Feedstock prices are assumed to be constant over time, so their role in technology competition is beyond the examining capability of this case study.
[23] CO2 emission rate of grid electricity is assumed to be constant over time.
[24] Although trucking cost decreases over time, the supply curve of industry hydrogen is assumed to be unchanged over time.

building another plant, the model finds it better off to tackle the capacity crisis with small-scale distributed production and delay the online date of the new plant by 5 years. In other words, it is because the gains from postponing large capital investments exceed the loss of dumping the production equipments of distributed production[25].

Demand and carbon tax rate are the two key drivers for the introduction of central production. Increased demand augments utilization of central production, allowing the benefits of economies of scale to surmount high capital costs. The increasing carbon tax rate makes central production more favorable, because central production has the CCS option while neither industry hydrogen nor distributed production has the option.

For distributed production, natural gas SMR outperforms water electrolysis. The main reason is the relatively lower technology costs of SMR. Also, water electrolysis requires a large amount of electricity and therefore suffers high electricity cost and high carbon tax from electricity generation.

Without the constraint of biomass availability, biomass gasification could outperform any other central production technology, due to its low technology costs and ability to absorb CO2 through CCS and therefore earn carbon credits. However,

[25] Refueling equipments of distributed production are kept to form refueling stations.

the available biomass in Southern California is not enough to support two gasification plants. When demand grows far beyond the capacity of one plant, coal gasification enters the market. Coal availability is not restricted or priced as a supply curve, which partly explains the result that, once coal gasification is introduced, it locks out new central production technologies from entering the market. The natural gas price, the electricity price, the grid CO_2 intensity and the technology costs all play a part in holding back other central production technologies.

The trend of pipelines replacing trucking is driven mainly by demand growth and pipeline topology. One spatial consequence of demand growth is the increase in hydrogen flow between a connected pair of plant and station. The larger is the hydrogen flow from a plant to a refueling station, the more advantageous is connecting the plant and the station with pipelines than by truck. This explains the overall trend of pipeline replacing trucking as demand grows. However, a station can be connected with pipeline only if its upstream station is already connected with pipeline. A good example is the transition from the stage 2050-2054 to the stage 2055-2059, when there is a considerable expansion of the pipeline network. What happens is that a substantial number of onsite stations or truck-served refueling stations, still waiting during the stage 2050-2054 for their upstream stations to be pipeline-connected, are linked with pipelines in the stage 2055-2059 when the upstream stations are connected via bigger pipelines to two new coal plants.

4.2 Economic Analysis

4.2.1 Cost Overview

Cash flows of capital, fixed, variable, environmental and fuel accessibility costs for the optimal sequence are shown in Figure 4-7 through Figure 4-11.

Capital cost will be discussed later in detail. It should be noted that the capital cost for the CO2 sequestration plants totals only 161 millions dollars and is not very visible in Figure 4-7 because it is spread over time. For CCS, the capital cost of carbon capture and compression is the major component and is already included in the central plant capital cost. The total capacity of CO2 sequestration in 2060 is about 79.3 million metric ton CO2 per year.

Variable costs appear to have the largest magnitude. Refueling stations and coal plants contribute the most of capital and fixed costs. Electricity, coal and trucking rent contribute to most of variable costs. Environmental cost and fuel accessibility cost are relatively small compared to other cost components. When the biomass gasification plant is upgraded with CCS, it absorbs CO2, resulting carbon credit (represented by negative cost in Figure 4-10). With more coal gasification plants being built, the CO2 emission exceeds absorption[26] and the system is charged with

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[26] Most of CO2 from coal gasification are captured and sequestrated. Only a small portion (about 1%) of the total generated CO2 is emitted to atmosphere.

net environmental cost (Figure 4-10). Probably coincidentally, environmental cost per time step gets very close to fuel accessibility cost when the system approaches the final 2060 configuration.

A possibly important way to reduce the hydrogen cost of the optimal sequence is by reducing electricity cost. This is not only because the variable cost is the most significant cost component and the electricity cost represents the largest portion of the variable cost (even larger than coal in the 2060 configuration), but also because the BASE scenario adopts the 2005 electricity price the California, 9.55 ¢/kWh for plants and trucking and 11.92 ¢/kWh for refueling and onsite stations, which are higher than the national average. Long-term electricity price trends in California can significantly affect the hydrogen cost.

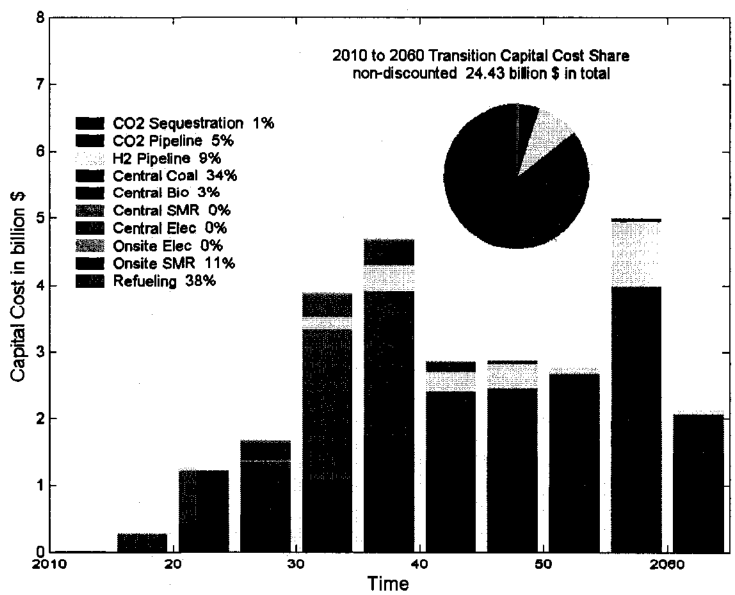

Figure 4-7: Capital Cost Cash Flow

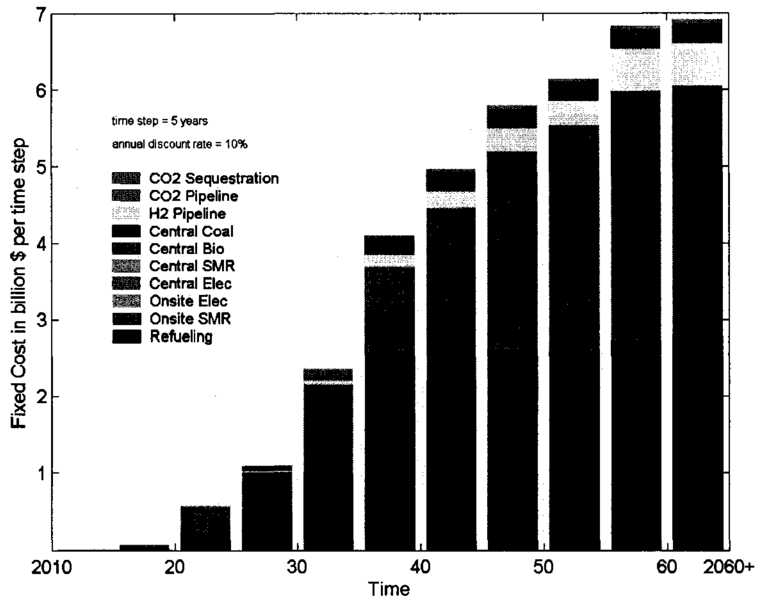

Figure 4-8: Fixed O&M Cost Cash Flow

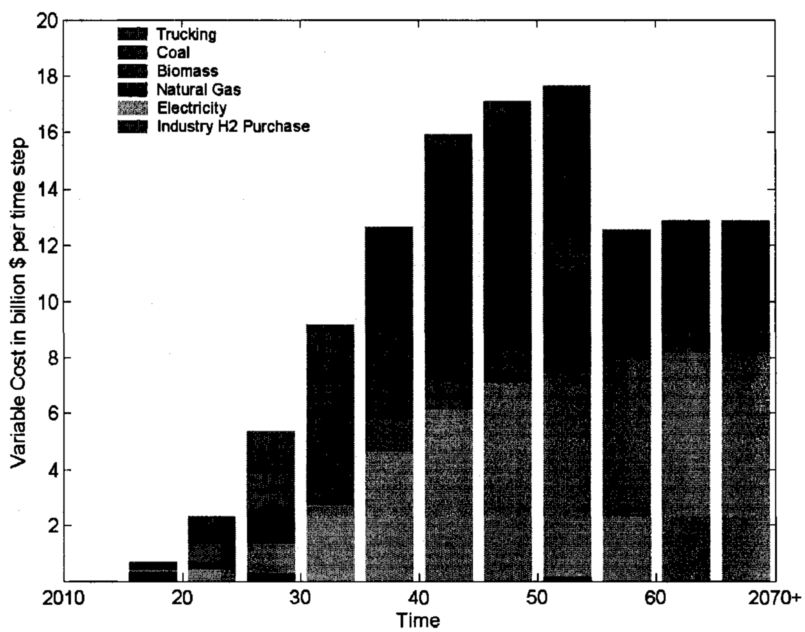

Figure 4-9: Variable Cost Cash Flow

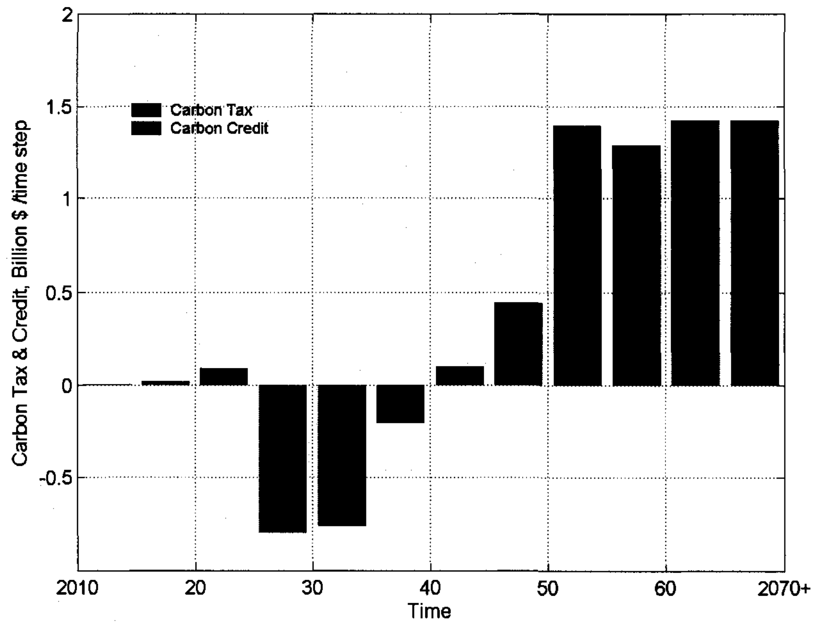

Figure 4-10: Environmental Cost Cash Flow

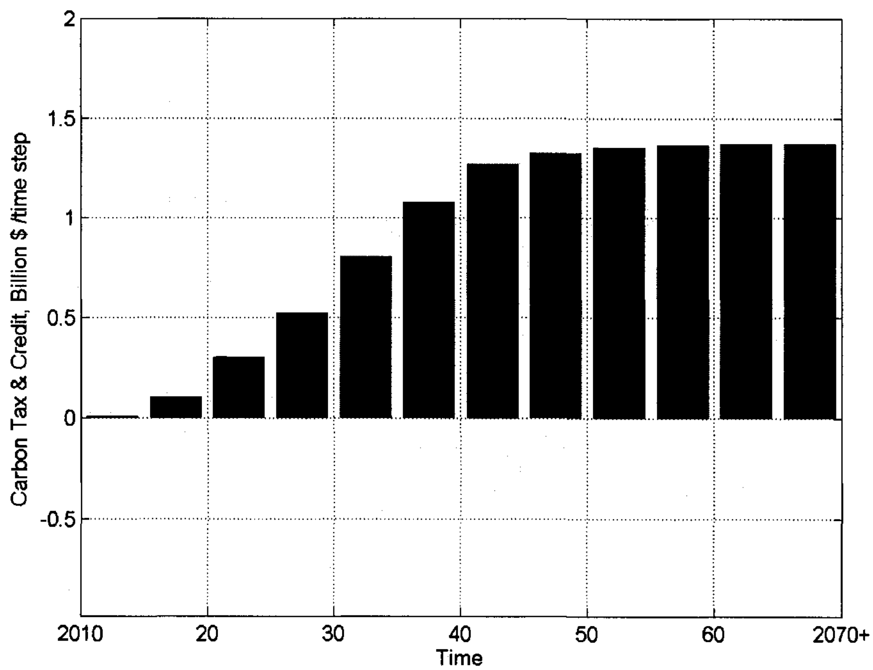

Figure 4-11: Fuel Accessibility Cost Cash Flow

4.2.2 Hydrogen Cost

Hydrogen cost estimation in this dissertation is conceptually different from that of many other studies. Conventionally, the average cost is estimated for a constant output and a single pathway. Although we can still average the costs throughout the entire study period over the total discounted hydrogen consumption, such a single average cost can only be achieved with a lengthy period of cost recovery and is not informative enough for those interested in transition barriers and investment risks.

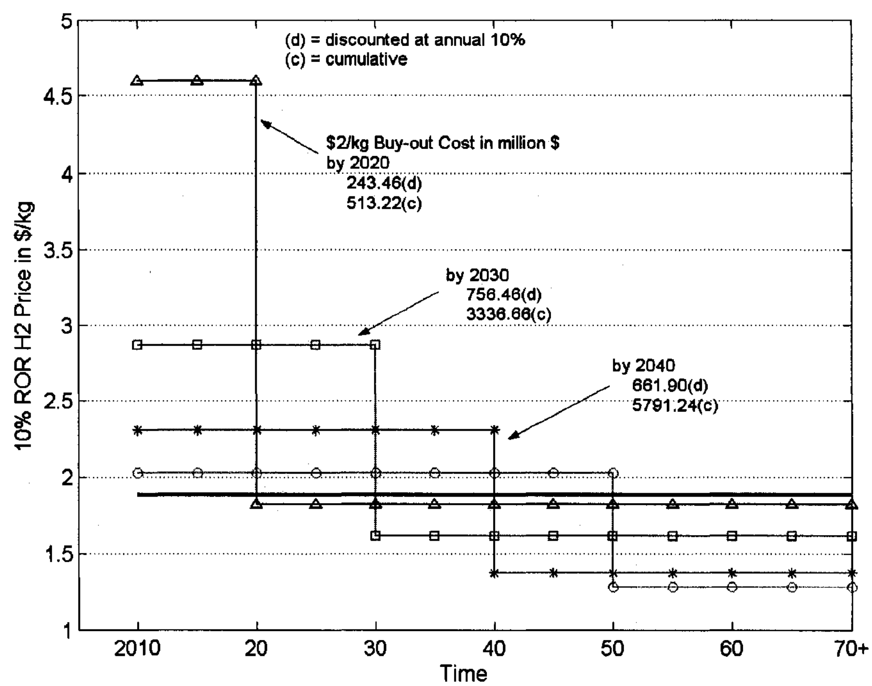

Figure 4-12: Hydrogen Cost

Alternatively, we can average the costs during a specific time period, such as the first 10 years, over the hydrogen consumption during the same period. As a result, a series of Z-shaped curves can be generated to convey more information on hydrogen cost, as shown in Figure 4-12. Each Z-curve consists of three attributes: breakeven time, transitional price and mature price. Their meanings can be explained as follows: under the optimal sequence and for the 10% real discount rate, if hydrogen is charged at a constant transitional price between 2010 and breakeven time (the short-term transition period), the revenues and costs during this same period balance each other; then if hydrogen is charged at the so-called mature price after breakeven time, the revenues and costs after breakeven time also balance each other. Under the optimal sequence, any given breakeven time leads to a unique transitional price, a unique mature price, and therefore a unique Z-curve. The length of time from 2010 to a breakeven time is also defined as the measurement of investor patience, because it quantifies how long the industry needs to wait for the first time to recover the costs. A breakeven time of year 2020 is equivalent to the 10-year investor patience.

For reference, when comparing hydrogen cost with gasoline price, we assume hydrogen fuel cell vehicles have twice fuel economy of gasoline vehicles and one kgH2 has the same amount of heat value as one gallon gasoline[27]. Thus, for the same driving distance, the fuel cost of hydrogen at $4/kg is equivalent to that of gasoline at $2/gal.

Under the optimal sequence, the 10-year investor patience requires a transitional price of $4.59/kg and results in a mature price at $1.82/kg. This appears to be economically attractive in the context that the gasoline price in California has reached $3.33 /gal at the time of writing (Dec 2007).

The mature price is always lower than the transitional price, reflecting the legacy benefits for future generations. The early generations bear early capital investments that are relatively more difficult to recover by revenues in early years. The mature price is lower also because of technology improvement over time and economies of scale with higher demand.

More investor patience leads to lower transitional price. The reason is that large capital costs generally precede large revenues enabled by high demand. With more time, the industry can harvest bigger revenues because of bigger sales occurring later so as to counterbalance the earlier burden of capital investments. As a result, the industry is able to recover the costs with a lower hydrogen price. Should a hydrogen system be pursued, a low transitional price would be desirable. One policy question would be how to enhance, through policies and political signals, the industry's confidence in anticipating a hydrogen economy and accepting some long-term risks, so that the industry could feel safe with longer process of cost recovery and therefore has the capability to supply hydrogen at lower price during the early years.

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[27] Strictly, the lower heat value (LHV) is 120.1 MJ/kg for hydrogen and 121.3 MJ/gallon for gasoline.

Although more investor patience enables a lower transitional price, the marginal effect decreases with investor patience. For instance, as shown in Figure 4-12, the first 10-year increase of investor patience leads to a drop of transitional price by \$1.73/kg, while the second 10-year increase of investor patience brings about only a decrease of \$0.56/kg. This suggests that transitional price is more sensitive to investor patience in earlier years. If any policies or subsidies were to assure industry investment, it is more important to focus on early years from the perspective of initiating a low-cost hydrogen transition.

More investor patience not only drives down the transition price, but also reduces mature price. In other words, if the hydrogen industry can tolerate longer process of cost recovery, hydrogen could become more affordable for both the early and future generations. However, investor patience is not free. It requires usage of social resources, in form of subsidy, regulation, or other policy instruments, to enhance the industry's confidence in longer-term investment. Also, longer process of cost recovery means that more generations of consumers bear transitional price, which is higher than mature price. Thus, if a hydrogen system is to be pursued, one policy question is that how much investor patience is the best for the society, considering usage of social resources and benefit tradeoff among early and future generations.

Theoretically, if the breakeven time is set at the infinite future, all the generations of consumers will bear the same hydrogen cost, i.e. the transitional price with infinite investor patience. This is represented by the no-marker black line in Figure 4-12,

$1.886/kg, which is obtained by averaging the net present value of all social costs over the discounted total hydrogen consumption. This hydrogen price is named as the long-term average hydrogen cost (LTAHC). Although a LTAHC is calculated based on infinite investor patience, it should not be interpreted as an unachievable target. This will be further explained in the next section.

4.2.3 Profitability

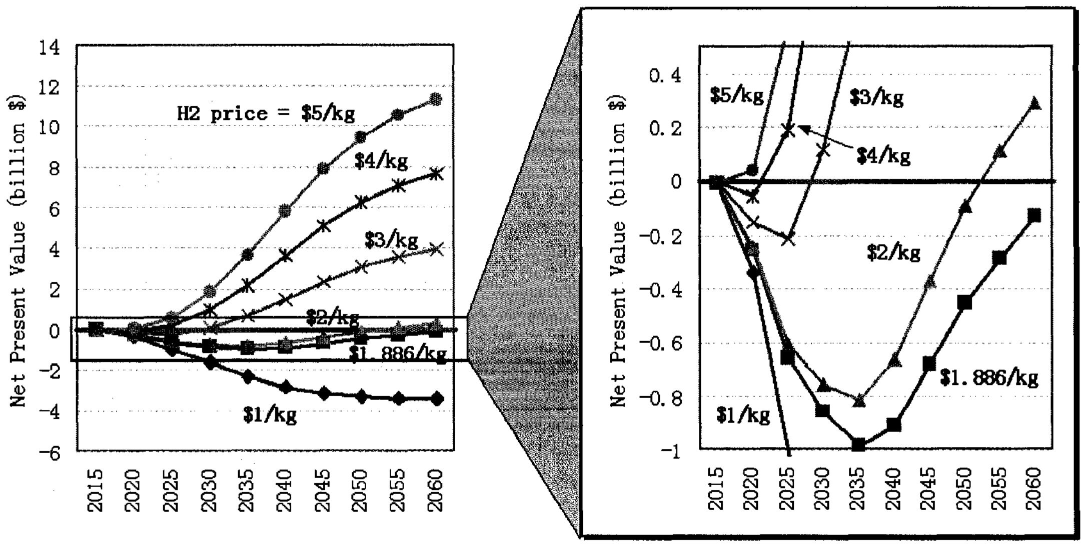

Figure 4-13: Profit NPV by Hydrogen Price

A hydrogen price constant over time determines the revenues over time because the hydrogen demand is exogenous. By discounting these revenues and the social costs of the optimal sequence, the resulting net present value can indicate how the system profit evolves over time with the given hydrogen price. As in Figure 4-13, each curve represents the profit net present value over time for each hydrogen price. The time when the curve meets the x-axis indicates how long it takes for the hydrogen revenues to balance the social costs. For example, if hydrogen is charged at \$2/kg, it takes about 40 years for Southern California to balance the social costs of a hydrogen transition under the optimal sequence. If it is \$3/kg, it takes less than 20 years.

In the previous section, the long-term average hydrogen cost (LTAHC) is based on infinite investor patience. That is, LTAHC is calculated by placing the time of cost-balancing in the infinite future. This might provide an impression that a breakeven price at LTAHC, \$1.886/kg with the optimal sequence in this case study, is practically meaningless. However, if hydrogen is charged at LTAHC, the profit net present value is quickly approaching the x-axis by 2060 (Figure 4-13), suggesting that just a little more than LTAHC could balance the costs by 2060. In fact, adding only \$0.114/kg to LTAHC can make the cost breakeven in about 2050.

It is not difficult to prove that any two price curves in Figure 4-13 will not intersect with each other. This means any price below LTAHC will not intersect the x-axis to result in a cost breakeven and any price larger than LTAHC will definitely intersect the x-axis hydrogen prices and result in a cost breakeven.

The net present value of profit always starts from near zero. For a hydrogen price below LTAHC, the net present value of profit will decrease over time, indicating a growing deficit. For a hydrogen price larger than LTAHC, the net present value of profit initially decreases, at some point returns to intersect the x-axis and then keep increasing. This means any hydrogen price over the LTAHC leads to a deficit-balance-profit process.

The net present value of profit also indicates the market potential within a certain period of time. For example, a hydrogen price at $4/kg over the 50-year period with the optimal sequence results in a 7.67 billion dollars net present value of profit for Southern California. In business language, this means a 40-year market with a size of 7.67 billion dollars.

4.2.4 Hydrogen Cost Breakdown

The long-term average hydrogen cost (LTAHC) is divided into three sources of contribution: capital, fixed O&M and variable (Figure 4-14). The capital cost and fixed O&M cost of LTAHC are further divided into sources by facility (Figure 4-15 and Figure 4-16) and the variable cost of LTAHC into sources by feedstock or services (Figure 4-17).

The capital cost is probably a more emphasized economic barrier for a hydrogen transition. This is not because of the magnitude of capital cost, as the magnitude of variable cost can be much higher as evidenced in Figure 4-14; the capital cost is more often talked about probably because it represents risks that deters private investors and is therefore more policy relevant.

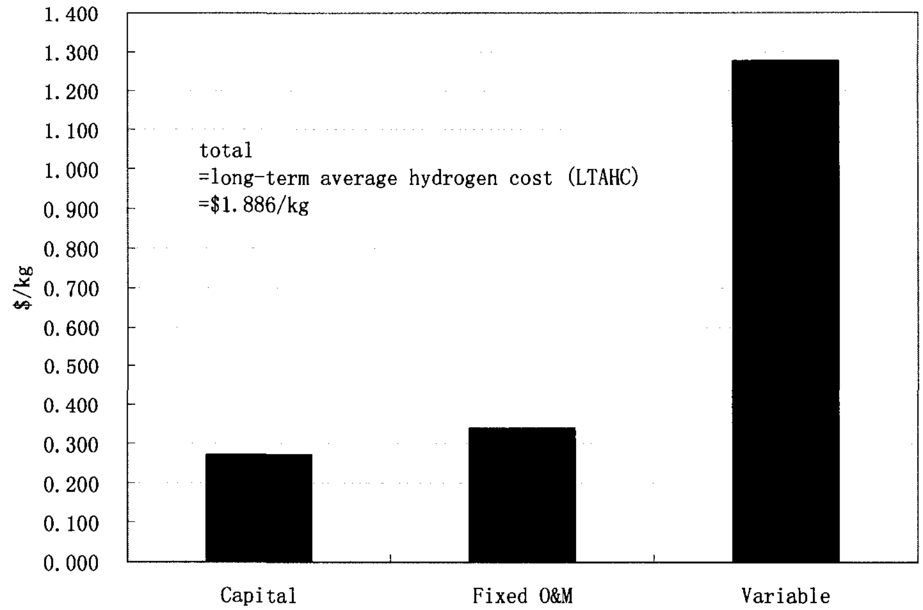

Figure 4-14: Breaking Down LTAHC

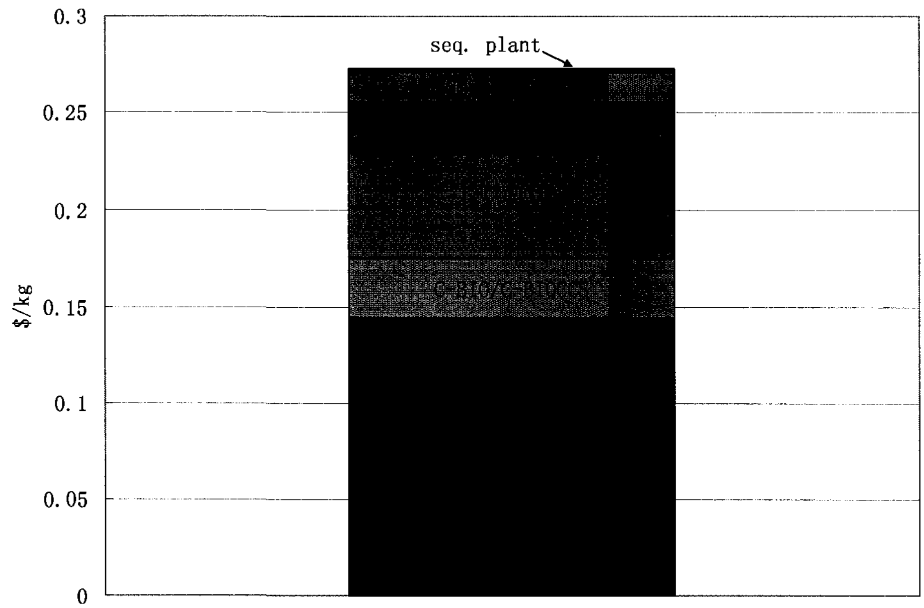

Figure 4-15: Capital Cost of LTAHC

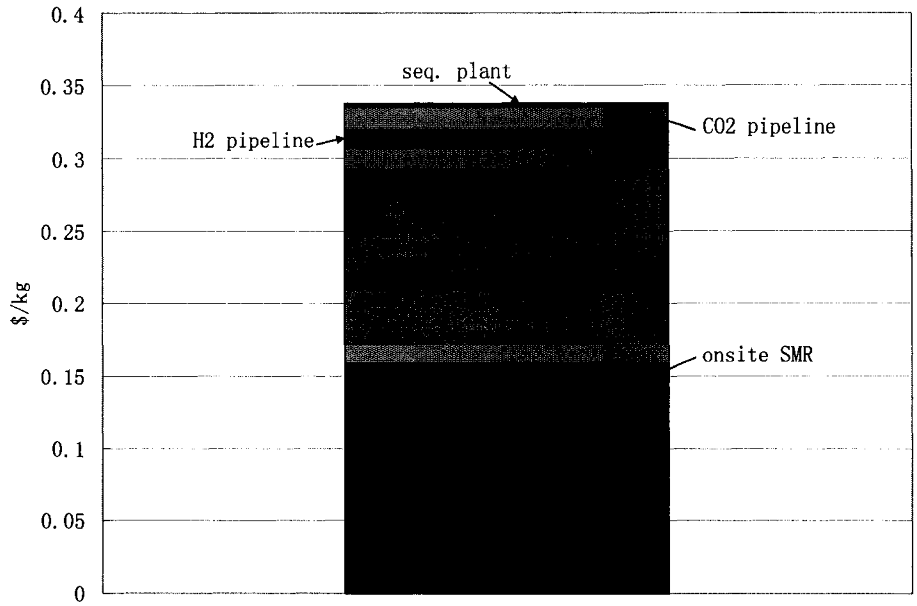

Figure 4-16: Fixed O&M Cost of LTAHC

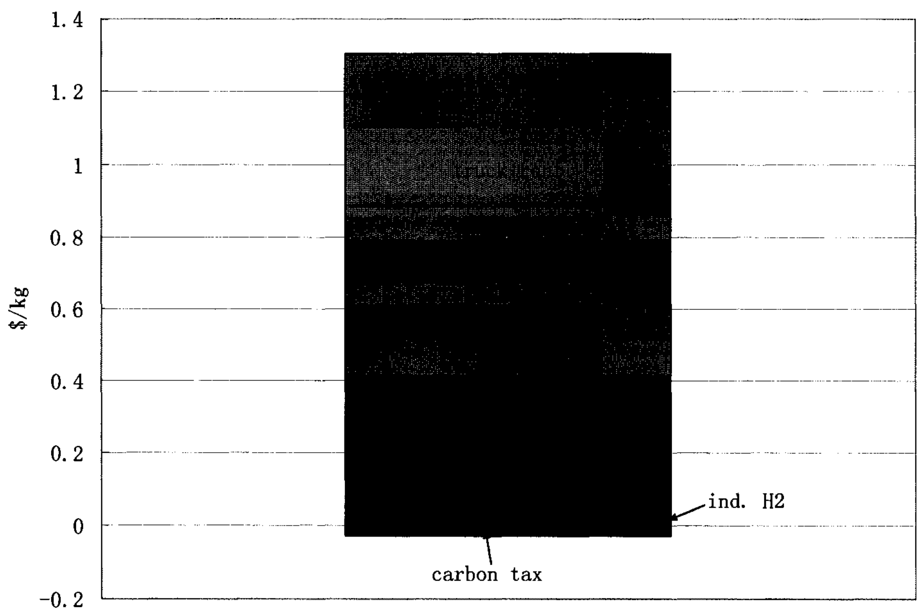

Figure 4-17: Variable Cost of LTAHC

The variable cost makes up nearly 70%, representing the largest component of LTAHC. Within the variable cost, 31% comes from the trucking rental fee, partly because trucking dominates the early distribution market (Figure 4-2) and the rental costs are discounted less heavily. The electricity cost makes up nearly 30% of the variable cost, as it covers electricity costs for all facilities. However, the electricity cost in Figure 4-17 does not include the cost of liquefaction electricity, which is included in the trucking rental fee[28]. This further emphasizes the significance of electricity cost. The carbon tax portion is negative, representing a carbon credit. This is because the carbon credit cash flows in early years are discounted less heavily and outweigh the later carbon tax cash flows (Figure 4-10).

For most facilities, the share of capital cost is consistent with the fixed O&M cost. For example, the refueling station contributes to a similar share of capital cost and fixed O&M cost. Such a relationship between the capital cost and the fixed O&M cost is because the fixed O&M cost is calculated as a percentage of the capital cost. However, the onsite SMR contributes to a much smaller share of fixed O&M cost than capital cost. This is because some onsite SMR stations are converted into refueling stations early in their lives. Once an onsite SMR station is built, its capital cost is registered and its fixed O&M cost is counted only against the years of service.

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[28] The liquefaction electricity cost accounts for about 28% of the truck rental fee.

4.2.5 Capital Cost

There are two reasons for a close look at capital costs. First, capital costs are a significant portion of the total social cost and can be reduced by technology improvement. Breaking down the capital costs by technologies could help us understand the R&D priorities for technology improvement. Second, from the perspective of cash flow analysis, capital costs generally occur much earlier than recovering revenues, which amplifies the influence of capital costs on the social cost NPV and also causes risks for the hydrogen industry. To accurately assess such risks, it is important to understand the temporal distribution of capital costs.

The distributions, over time and among technologies, of the capital costs with respect to the optimal sequence are shown in Figure 4-7. The cumulative non-discounted total of capital costs over the 50-year study period is $24.43 billion, which includes all the first-time and rebuild capital costs of refueling stations, onsite stations, hydrogen pipeline, CO2 pipeline, and CO2 sequestration plants. This amount should not be treated as the required start-up fund for a hydrogen transition, because it is distributed over time and can be recovered by hydrogen sales revenues.

More important is the timing of capital costs. Under the optimal sequence, big capital costs are avoided during the first 10 years by choosing industry hydrogen and distributed production. This significantly reduces the impact of capital costs of the first central plant on the social cost net present value.

There are three stages with large capital costs. The stages of 2030-2034 and 2035-2039, where demand grows the fast, each observe a construction of two coal plants and a significant expansion of refueling network. Although not the one with big demand increase, the stage of 2055-2059 experiences a construction of two coal plants and a big expansion of the pipeline network replacing a number of onsite stations waiting to be replaced during the previous stage. Part of the capital cost of this stage is the rebuild of some refueling stations that are originally constructed in 2035.

In terms of share by technology, refueling stations and central plants contribute to 37% (coal and biomass gasification plants combined) and 38% of capital costs (Figure 4-7). The share by hydrogen pipeline is only 9% due to minimization of pipeline length and consideration of pipeline diameter. Accounting for only 3% of hydrogen supply during the 50 years, onsite SMR however contributes to 11% of capital costs.

Figure 4-18 shows how the marginal and cumulative per-vehicle capital cost evolves over time. By 2060, the marginal per-vehicle cost, the ratio of capital cost and FCV sale during 2055-2059, is about $605 per vehicle.

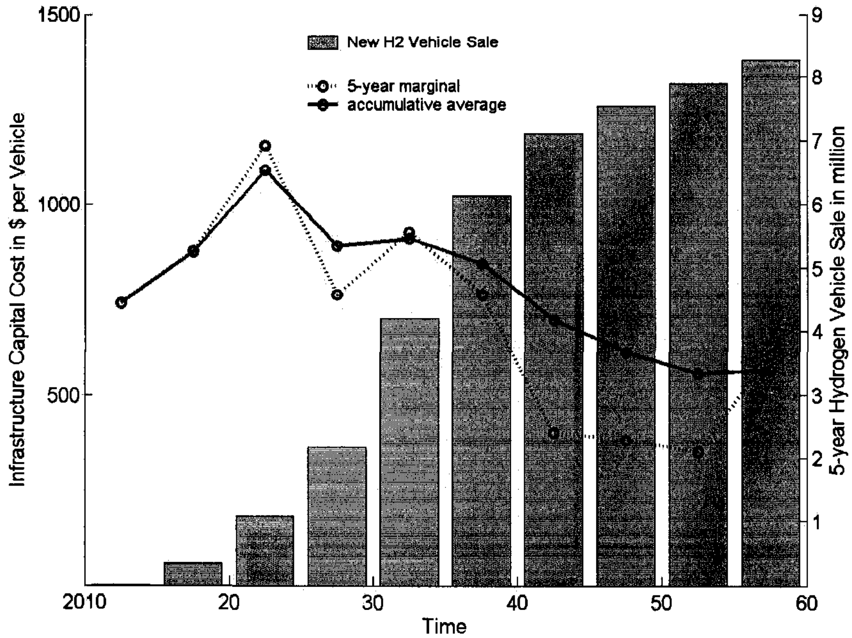

Figure 4-18: Non-discounted Per-vehicle Capital Cost

4.2.6 Subsidy Need

One way to describe the transition barrier is the subsidy need during the short-term transition period. Such a subsidy need exists when hydrogen is charged below the transitional price with respect to a given investor patience. Although the transitional prices in Figure 4-12 already seem low compared to the gasoline price at the time of writing, even cheaper hydrogen is still relevant from the perspectives of compensating expensive FCVs and helping market penetration of hydrogen.

Maintaining a matching subsidy for a 10-yr investor patience may cost the least public fund. It costs about $200 million (discounted) of subsidy to allow a $2/kg transitional price for a 10-year short-term transition period, but it costs more than double for the same transitional price for a 20-year short-term transition period. The big jump in subsidy need is due to the start of central production in 2020, right after the 10-year short short-term transition period.

The key observation here is that it may be most effective to subsidize during the early years of industry hydrogen and distributed production. Such a 10-year subsidy assumption creates an attractive transition scenario: a total subsidy of $200 million, a 10-year hydrogen price at $2/kg, cost recovery in 10 years for the industry, and a mature hydrogen price of $1.82 /kg from 2020 on.

4.2.7 Subsidization Capacity

When hydrogen is charged above transitional price, extra profits can be generated beyond cost recovery at 10% discount rate. If used to compensate FCV purchase, these extra profits represent the capacity of the hydrogen industry to subsidize the FCV industry.

The hydrogen industry can possess significant subsidization capacity if hydrogen is paid at equivalent gasoline price. The 2005 average gasoline retail price in California is $2.517/gallon, which is equivalent to 5.034 $/kgH2, assuming FCV has twice higher fuel economy. As of April 21 2008, the California gasoline retail price has risen to $3.846/gallon, equivalent to $7.692/kgH2. If consumers are willing to accept the equivalent hydrogen price during the whole study period, instead of the breakeven price of $1.886/kg (Figure 4-12), the hydrogen industry can have a subsidization capacity of $4,715 per FCV purchase for the 2005 gasoline price and $8,697 for the 2008 April gasoline price. That is, if during 2010-2060, all the FCV motorists pay for hydrogen at the equivalent 2008 April gasoline price, the hydrogen industry can offer a rebate of $8,697 for each new FCV sold during the 50 years while still maintaining a 10% rate of return. Such a per-FCV subsidy is substantial and may be enough for the fuel-vehicle system of hydrogen to compete with that of gasoline, as FCVs are projected to be $ 3600-6000 more expensive than gasoline vehicles in mass production (Kromer and Heywood, 2007). However, FCVs can be even more expensive during the early stages where FCV production is in small scale.

How to make the hydrogen industry agree to such a rebate is a policy design issue that is beyond the scope of this dissertation, although the rate-of-return regulation for the US electricity industry may have provided some insight.

4.2.8 Hydrogen-Gasoline Tie Curve

When the per-FCV subsidization capacity of the hydrogen industry, which results from FCV consumers paying the equivalent gasoline price for hydrogen as discussed in the section "4.2.7 Subsidization Capacity", equals the price difference between a FCV and a conventional gasoline vehicle, the fuel-vehicle systems of hydrogen and gasoline reach a tie situation, assuming all vehicle attributes other than first-purchase price to be the same between FCVs and gasoline vehicles. Under the optimal sequence for Southern California, a higher gasoline price results in a higher per-FCV subsidization capacity and therefore a higher FCV cost to tolerate in a tie situation. A tie curve between gasoline and hydrogen can be found by hypothetically changing the gasoline price, as shown in Figure 4-19. Any data point below the tie curve indicates a situation where the hydrogen-FCV system economically outperforms the gasoline system. The tie curve is based on the assumptions of a 100 kW vehicle with a glider cost of $20,000 for both FCVs and gasoline vehicles. Gasoline ICE drive-train is assumed to cost at $30/kW.

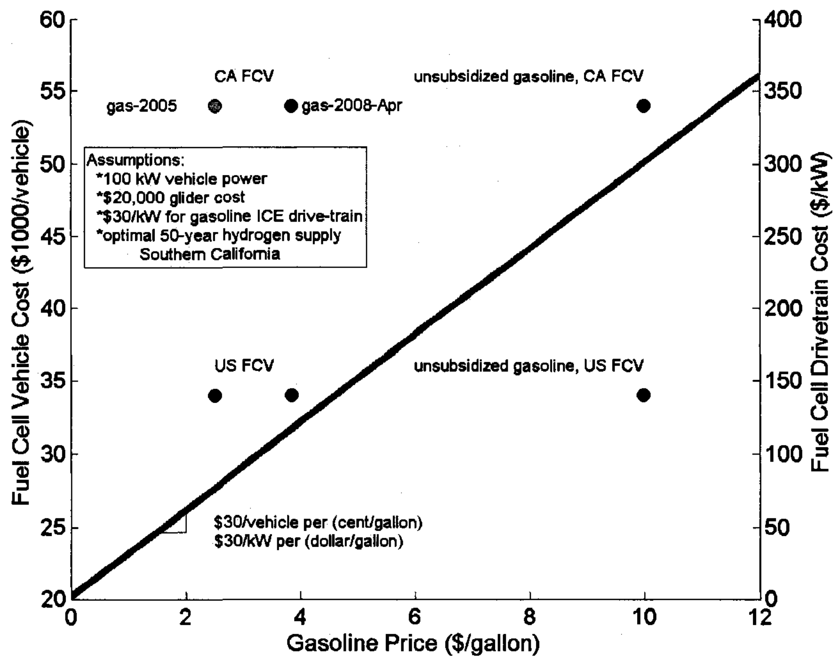

Figure 4-19: Hydrogen-Gasoline Tie Curve

In the BASE scenario, a total of about 5,000 FCVs are purchased during 2010-2014. According several studies (Tsuchiya and Kobayashi, 2004; Greene et al, 2007), the fuel cell drive-train cost can reach $340/kW for the first 5,000 FCVs, which results in a FCV at $54,000. This represents a situation where Southern California is the first place to adopt a hydrogen-FCV system at the scale of 5000 FCVs during 5 years. With the two gasoline retail prices in California history, $2.517/gallon (2005 annual average) and $3.846/gallon (April 21 2008), two status points can be obtained, as under "CA FCV" in Figure 4-19.

These two status points are still far above the tie curve, suggesting that a hydrogen-FCV system is not ready for Southern California if it is the only region to adopt hydrogen during 2010-2060. This is certainly too pessimistic if a hydrogen transportation system is pursued. In the extremely optimistic situation where the whole nation is adopting hydrogen in the same pace with Southern California, 85,511 FCVs will be produced during 2010-2014, driving down driving down the price of a FCV to about $34,000. For Sothern California, this results in two optimistic status points as shown under "US FCV" in Figure 4-19, which are quite close to the tie curve. It is easy to observe that the status point is quickly approaching the tie curve due to the gasoline price increase in recent years.

The social cost of gasoline may be much higher than the retail price. For example, the CTA (1998) report estimates the social cost of gasoline between $5.60 and $15.14 per gallon, which consider the health and economic costs and government subsidy to the oil industry. The social cost of gasoline is still subject for more research and debate and its accurate estimate is beyond the scope of this dissertation.

For a hypothetical real price of gasoline at \$10/gal, another two status points can also be obtained. The "unsubsidized gasoline, CA FCV" status point is also quite close to the tie curve, while the "unsubsidized gasoline, US FCV" status point is well below the tie curve. If Southern California will pursue hydrogen with the given demand scenario, it is likely that some other states will also follow, resulting the status point between "CA FCV" and "US FCV". The status point will move downward with more cumulative production of FCV and rightward with a rising gasoline price, both indicating an increasing competitiveness of the hydrogen-FCV system.

Apparently, how to assess the competition between hydrogen and gasoline for Southern California critically depends on how the society acknowledges the real gasoline price and how aggressively hydrogen will be adopted in the country. If the subsidized retail price of gasoline continues to be used as a comparison benchmark for alternative fuels and California is alone to bear the learning costs of FCV manufacturing, then hydrogen is probably not ready for Southern California. On the other hand, if a moderate estimate of real gasoline price is believed and a significant number of states implement hydrogen and share the learning costs, hydrogen can in the very near future be outperforming gasoline in meeting transport demand. Also, with more FCVs being produced, the FCV cost will likely drop and the status point in Figure 4-19 will then move downward.

The above discussion is based on the assumption that the 5000 FCVs during 2010-2014 are from the same production plan. This assumption may be too conservative. If a 10-year planning period is adopted by the FCV industry, the FCV cost can be lower and the competition as discussed above can work in more favor of the hydrogen-FCV system.

The tie curve indicates that a higher FCV price should be tolerated when the gasoline price increases or when a higher real gasoline price is acknowledged. For every cent of gasoline price increase, Southern California can accept a \$30 increase in the FCV price target. In other words, the price target of a fuel cell drive-train for Southern California should be adjusted by \$30/kW for every dollar of increase in gasoline price. Equivalently, for every dollar increase in gasoline price, an additional \$30/kW can be tolerated for the FCV drive train cost.

4.3 Refueling Network

As previously stated, the station location sub-model generates the ARTT-StaNum equation for the HIT model to calculate the fuel accessibility cost for any given station number. This section first reviews how fuel accessibility changes over time under the optimal sequence, and then examines the corresponding station locations by using geographic information system (GIS) and statistic analysis. The station number over time is also discussed, as the main purpose of optimizing station location is to maximize fuel accessibility for a given number of stations or, equivalently speaking, to minimize station number in achieving a given level of fuel accessibility. Early station siting is separately discussed because our results are contradictory to current knowledge.

4.3.1 Fuel Accessibility

Fuel accessibility, measured by average refueling travel time (ARTT), improves over time (Figure 4-3). Under the optimal sequence, average refueling travel time starts at about 22 minutes per trip during 2010-2014 and quickly drops to about 5 minutes per trip during 2015-2019. It keeps decreasing but at a slower pace until it is less than 1 minute per trip in 2060. However, even in 2060, there is a 10% of chance for a random FCV user in Southern California to drive over 6 minutes to access a hydrogen refueling stations (Figure 4-20).

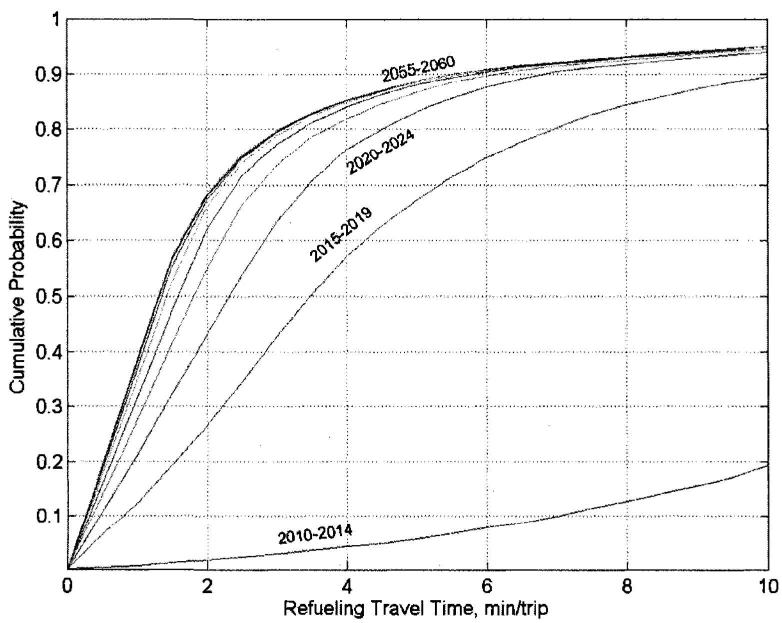

Figure 4-20: Refueling Travel Time Distribution

As in 2060, the average refueling travel time with 2376 stations is less than one minute, which is a significant improvement from the 1 min 36 s enabled by the existing 3850 gasoline stations in the study region (Nicholas, 2007). This may suggest the location sub-optimality of gasoline stations due to lack of central planning and reflect the inefficiency reality that multiple gasoline stations are built around the same intersection. Or it may reflect the difference in the method of measuring refueling travel time—Nicholas (2007) uses a fixed location as the refueling trip origin, while the Station Location sub-model in this dissertation is based on a mobile-origin notion (see the section "3.3 *Station Location Sub-model*").

Fuel accessibility improves with more stations. The ARTT-StaNum function, as in equation (3-7) and also shown in Figure 3-10, establishes the linkage between average refueling travel time (Figure 4-3) and station number (Figure 4-5). The function structure is consistent with the one found by Nicholas (2004), indicating the robustness of such a function structure. The ARTT-StaNum function indicates that, if station locations are optimized, the marginal improvement on fuel accessibility decreases as the refueling network expands. However, this does not mean one additional station is less important in a later stage, when a smaller improvement on fuel accessibility coupled with a higher demand can still bring about more reduction on fuel accessibility cost, according to the equation (3-6).

There are two motivations for increasing the number of stations. During 2010-2034 when the average station capacity is still below the assumed capacity limit 5000 kg/d, the motivation is to reduce average refueling travel time so as to partially offset the increase of fuel accessibility cost (total travel time cost as in Figure 4-11) due to demand growth. After 2035, this motivation combines with another one—because station size has already reached the maximum limit (Figure 4-1), increasing station number is the only way to accommodate the increasing demand.

Under the optimal sequence, when will FCV motorists in Southern California have the same level of fuel accessibility as with gasoline? Nicholas (2007) estimates that the average gasoline refueling travel time in the study region is about 1 min 36 s. From Figure 4-3, FCV motorists in Southern California can enjoy the current fuel accessibility as early as year 2030 when 877 stations are built and the average refueling travel time is about 1 min 28 s.

Is 22 minutes per refueling trip acceptable for the small number of FCV motorists during 2010-2014? Or, is their acceptance realistic? The short answer is positive under the model assumptions and the key explanation is that these motorists accept long refueling trips because their travel time costs can theoretically be reimbursed through some kind of income distribution mechanism. The HIT model certainly considers the option of building more stations during 2010-2014, but the resulting increase in technology costs (related to stations) is not worth the savings on travel time costs, partly due to the fact that there are only a few FCV motorists. It can be socially better off if the savings on technology costs are used to compensate the few FCV motorists for their travel time loss based on agreement on the time value function. The compensation burden will get heavier when demand grows and more FCV motorists appear, and then make it more attractive to build more stations.

4.3.2 Locating Early Stations

Among different stations siting schemes, one is deemed more efficient if it offers better fuel accessibility with the same number of stations or if it offers the same fuel accessibility with a smaller number of stations. The optimal station siting scheme embedded in the optimal sequence is based on optimizing fuel accessibility for any given number of stations and therefore can be deemed theoretically the most efficient one given the assumptions on some practical aspects discussed before. Since it is the most efficient one, the optimal siting scheme can be used to examine the efficiency of other siting propositions.

Many studies suggest that early stations should be located in close proximity to high-profile places, such as those associated with high income residents or shopping centers. In the context of this dissertation, a node with a high demand share can be treated as a high-profile place. Is the optimal siting scheme here consistent with the high-profile proximity proposition? This question is addressed by visualizing the siting scheme and quantifying the correlation between demand and station number.

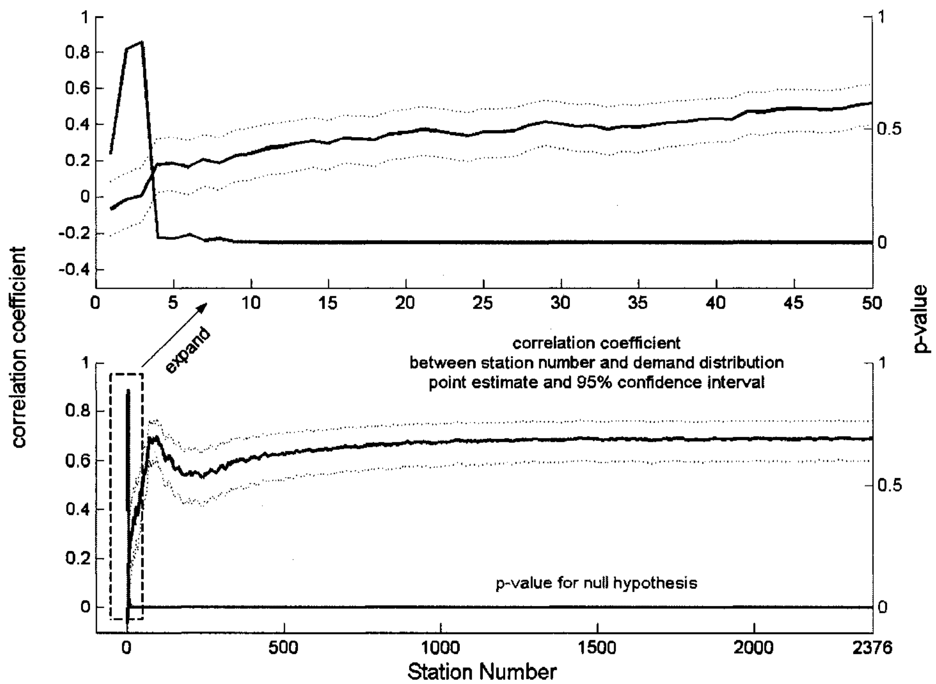

Figure 4-21: Demand and Station Number Correlation

The GIS visualization of the optimal siting scheme is shown in Figure 4-6. During 2010-2014, the 4 stations are located at nodes with a demand share of 2.30%, 0.83%, 0.79% and 0.26% respectively ranking 1st, 47th, 54th, and 128th by demand share among the 168 nodes. The GIS presentation (Figure 4-6) also confirms that not all 4 stations are located in high demand nodes. These appear to be contradictory to the high-profile proximity proposition. On the other hand, with more and more stations being built, it indeed can be observed from the GIS maps (Figure 4-6) that many more stations are located in the high-demand Los Angeles metropolitan area than in other less dense areas.

To further confirm the existence of this contradiction, we quantify the correlation between demand share and station number for each node. Each node is attributed with a constant demand share (even when the total demand grows). For a given total number of stations in the network, the number of stations around each node is given in the optimal siting scheme. So a correlation coefficient for each total station number between 1 and 2378 can be obtained by considering the 168 nodes as a sample group. The 95% confidence interval and the associated p-value are also shown in Figure 4-21. The correlation can be considered strong if the p-value is below 0.01.

As Figure 4-21 reveals, the correlation generally becomes stronger with station number. The correlation is not existent or very weak for up to 15 stations and does not appear to be strong until 50 stations. This strongly indicates that the efficient locations of early stations do not necessarily follow a high-profile proximity pattern.

The contradiction can be understood from the competition of high-profile nodes for early stations. Facing the fierce competition among high-demand nodes for hosting one of the very few stations, the model finds it socially better off to site a significant portion of these few stations at some intermediate nodes, instead of favoring some high-demand nodes while disregarding others. This leads to the observed weak correlation for early stations. The correlation actually becomes strong when most nodes have at least one station and the main effect of more stations is reducing node-wide average travel time (or improving local fuel accessibility).

But there are some situations where the high profile proposition seems intuitively reasonable and realistic. A station may be dedicated to a specific vehicle fleet and built, for example, at the site of a car rental company. Such a co-location of the station with a fleet can be extended to many circumstances, but the fundamental assumption of these circumstances is that an unlimited weight of attractiveness is placed on the high-profile place and zero weights are assigned for all other locations. This is suitable from the perspective of a private entity or a market segment. But the social perspective of this dissertation acknowledges the right of every location to attract a station. Therefore, the high profile proposition is more suitable for serving an isolated fleet, while the fuel-travel-back optimization approach in this dissertation is more relevant for social or system analysis.

4.3.3 Station Number

Current fuel accessibility of gasoline could be achieved with many fewer stations. For the current gasoline accessibility of 1 min 36 s (Nicholas, 2007), the needed number of hydrogen stations is only 1010 or 27% of gas stations in the study region. This indicates a lack of location optimality of gas stations due to lack of central planning (Nicholas, 2004 and 2007). The 27% estimate is for reaching the current fuel accessibility level and is even lower than the estimate of 30% reported by Nicholas (2004) which indicates the sufficient number of stations to initiate the market in the Sacramento County. This, if the Sacramento County is comparable to Southern California, indicates a significant improvement of station location, which is because Nicholas (2004) assumes the locations of current gas stations as the only possible locations for hydrogen stations. The implication is that, to achieve a certain level of fuel accessibility, more hydrogen stations are needed if they are restricted to gas station locations. Nicholas (2007) estimates the average travel time for gasoline refueling in the Los Angeles urban area as 3 min for 228 stations, while our ARTT-StaNum function, as in equation (3-7) and also shown in Figure 3-10, leads to 3 min 30 s for 228 stations. This is surprising because Nicholas (2007) considers only the current gasoline station locations and our model considers every node on the network. Without location restriction, our model is expected to have better location performance. The explanation may be on demand density: Nicholas (2007) only focuses on the Los Angeles urban area, while the study region of this dissertation is five counties including a large portion of rural areas.

To satisfying a given demand, fewer stations result in a bigger station size. If 708 stations, estimated above, are to serve the whole fleet in 2010[29], an average size of 10,600 kg/day is required, equivalent to about 2,800 fill-ups per day. Such a kind of super-large station is a possible way of utilizing economies of scale to reduce dispensing cost and provide better refueling service without sacrificing fuel accessibility. However, safety, permitting and possibly other unseen obstacles suggest further feasibility investigation.

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[29] Assuming all the passenger vehicles in 2010 are replaced with FCVs

While the required station number can be calculated for any desired ARTT, it remains an open question that which ARTT or which number of stations is a social optimum. Only looking at the ARTT curve, one might state that it makes no difference once the station number reaches a certain number, say, 500. While this statement is valid for a random motorist, it is socially incorrect, because when demand is high and ARTT is multiplied by total refueling trips, the total travel time could be very high and a small reduction of ARTT could still be very significant.

Time value (in $/min) and economies of scale are the two theoretical elements that drive our speculation on station number. Conceptually, if there was no value for refueling travel time, different numbers of stations would make no difference to the demand side; and if there were no economies of scale in building and operating stations (so opening a new station with 5000 kg/day capacity had the same cost of opening 500 stations each with 10 kg/day capacity), then it would not matter how many stations to build from the supply side. So from a social planning perspective, a theoretical framework to determine number of stations is to compare two variables: marginal time cost reduction (MTCR), the total reduction in refueling travel time cost in dollars due to adding one more station; and marginal siting cost (MSC), the cost difference between adding a new station and adding the same refueling capacity to the existing stations. MSC is purely due to the costs of a new site, such as land purchase and permitting but not including any part of process unit. Assuming 35% of process unit cost, 14% capital charge rate, and a ± 40% variability, the marginal siting cost (MSC) is estimated. For the marginal time cost reduction (MTCR), we assume 50% (VTPI, 2006) (100% for comparison) of wage rate \$30/hr, a driving range of 350 miles for a full tank of hydrogen and one refueling need per 70% of tank emptiness. MTCR is estimated for 6 cases of wage rate share, fleet share of FCV, and station number (Figure 4-22).

As a general rule, a MTCR larger than MSC suggests that it is socially better off to add another station, such as in case #2 and #5, while MTCR less than MSC indicates an excessive number of stations, such as in case #3 (Figure 4-22).

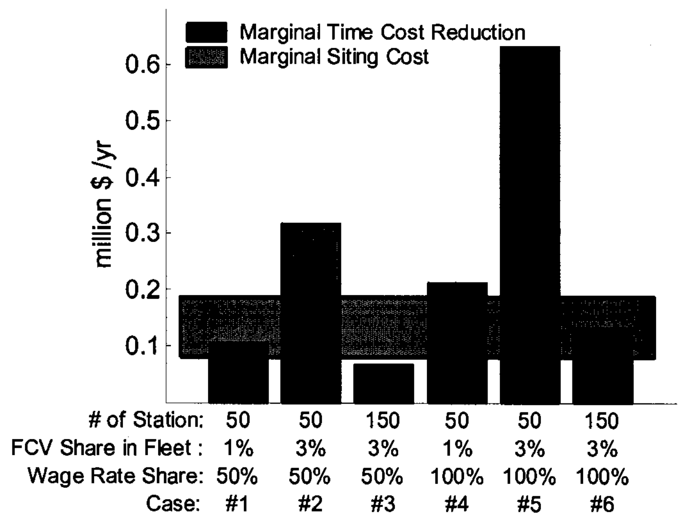


Figure 4-22: MTCR vs. MSC

Figure 4-22 shows that MTCR increases with value of time. If commuters are targeted as early FCV users, more stations are needed because commute travel time is usually assumed to have higher value (VTPI, 2006). The effect of time value also leads to a hypothesis for further investigation that more comfortable refueling and stronger symbolic sense of hydrogen could reduce refueling travel time disutility, lower MTCR and therefore reduce required number of stations.

Figure 4-22 shows that MTCR increases with FCV share in fleet, indicating station number should keep up with hydrogen demand (even not considering station size constraint). Resulting from the declining slope in the ARTT curve, MTCR decreases with station number, meaning that building more stations reduce the urgency of building more.

The MTCR for the 6 cases are comparable with MSC. This suggests that travel time cost should be incorporated into hydrogen infrastructure planning, although virtually no studies have done so.

Figure 4-22 also suggests a simple framework to choose the optimal number of stations: solving the equation MTCR = MSC. This is already reflected in the HIT model with the following logic, where N_t is the optimal station number during time step t and N_{st} is the optimal station number without the 5000 kg/day station size constraint. A capacity factor 90% is assumed.

$$Nt = \max(Nst, \frac{dmd(t)}{90\% \times 5000})$$

The optimal station number without station size constraint is estimated as a function of FCV share in the current fleet as shown in Figure 4-23. The range is due to the previous assumption of 40% variability in MSC.

The framework used to determine optimal station number from the social perspective can be extended to the industry perspective, if the industry is centrally planned or can be viewed as a monopoly. The hydrogen station industry, if viewed as a profit maximizer, is interested in adding more stations because with better fuel accessibility, consumers are willing to accept a higher hydrogen price or to consume more hydrogen, resulting in more profit. Therefore, the MTCR term should be interpreted or replaced by marginal profit due to adding one more station. How to quantify the marginal profit is beyond the scope of this paper.

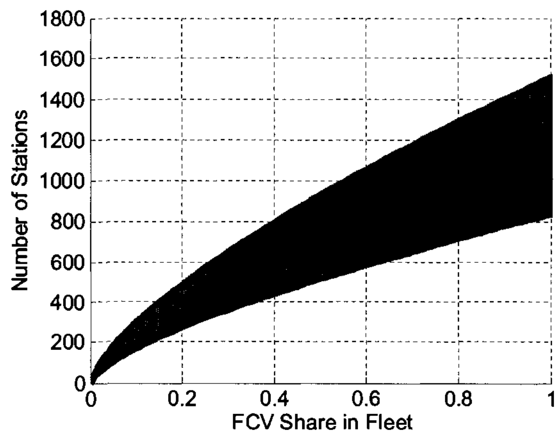


Figure 4-23: Optimal Station Number

4.3.4 Station Size and Utilization

The average station size grows over time as shown in Figure 4-4. It starts at 500 kg/day, the module size as well as the minimum station size allowed in the model, increases by 1 ton/day almost every 5 years, and reaches 5 ton/day in 2035. Such a trend of station size reflects relatively higher priority in early years on spreading out stations and later on utilizing economics of scales of large stations.

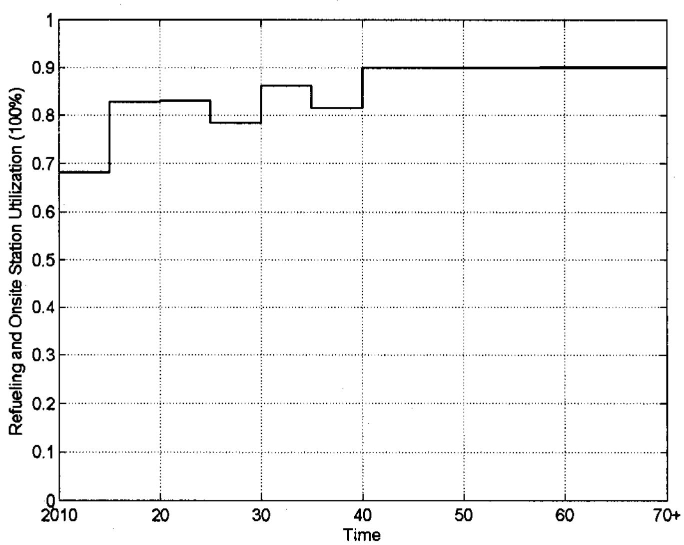


Figure 4-24: Station Utilization

By assumption, the capacity factor for both refueling and onsite stations is 90%, which also serves as the upper limit of utilization. Because supply security is not considered in this dissertation, a utilization factor smaller than capacity factor usually results from capacity discreteness. For example, the average station utilization factor during 2010-2014 is less than 70% with four 500 kg/day stations supplying 1365 kg/day (Figure 4-24). Should the station module size be set as 400 kg/day, four 400 kg/day stations would have been chosen to achieve a 85% utilization.

4.3.5 Pipeline Length

The total pipeline length increases as the pipeline network expands over time and reaches 4611 miles in 2060 serving 2376 refueling stations. This translates into an average of 1.94 mile pipeline per station. The total length is based on real distance and optimization and demonstrates a significant reduction from other estimates based on idealized layout. For example, the DOE/H2A model estimates a total pipeline length of 18,998 miles serving 4313 stations (4.40 mile pipeline per station) for a 100% penetration (current demand level) in the Los Angeles--Long Beach--Santa Ana region.

When the pipeline network is fully expanded in 2060, 76% pipelines are of diameter below 5 inches and serves as the final segment of hydrogen flow. Such a diameter differentiation attempts to capture pipeline design in reality and make improvement from idealized models that usually assumes uniform or 2 to 3 classes of pipeline diameter.

4.4 CO2 Mitigation

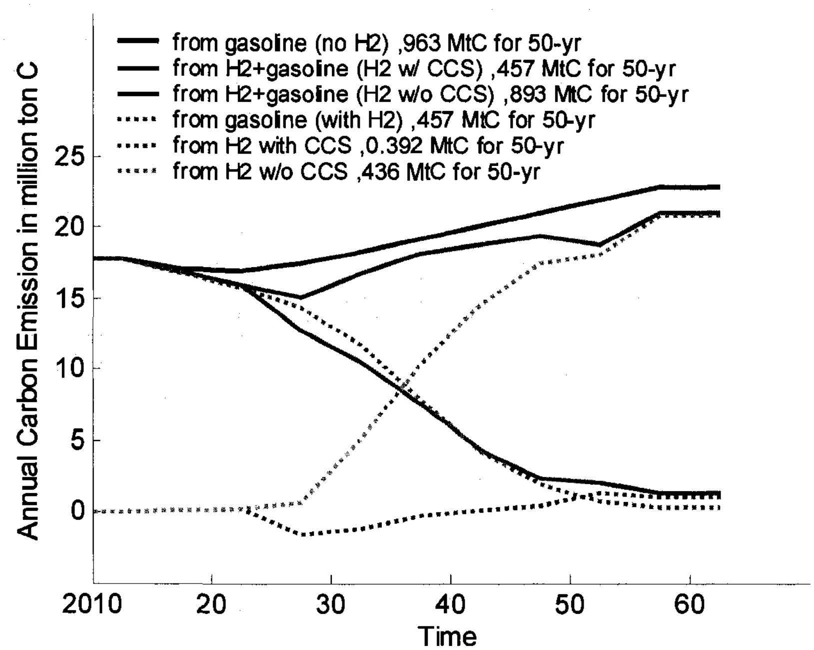


Figure 4-25: CO2 Emissions

If the 50-year travel demand is served solely by conventional gasoline vehicles, the resulting 50-year carbon emissions are estimated to be about 963 MtC (blue solid curve in Figure 4-25). As shown in Figure 4-1, C-BIO comes into play in 2020 and is upgraded with CCS five years later, followed by the dominance of C-CoalCCS. One of the driving force is the carbon tax rate as explained in the section "3.4.6 Carbon Tax". With the dominance of central plants with CCS, the hydrogen demand curve coupled with the optimal sequence could reduce annual CO2 emissions by about 99% and the 50-year cumulative emissions by about 50% (green solid curve in Figure 4-25). Sequestrating CO2 from biomass gasification results in negative contribution and offsets the CO2 emissions from other technologies. The outcome is only 0.302 MtC during the 50 years attributed to hydrogen supply (purple dot curve in Figure 4-25). If CCS is not adopted, the optimal sequence, dominated by coal gasification, provides positive but little CO2 mitigation potential (yellow dot line and red solid line in Figure 4-25). However, this is to support the argument that CCS technology is a must for hydrogen transition, because if CCS is not available, the optimal sequence may be a different one where coal gasification is not adopted at all.

4.5 Sensitivity Analysis

The HIT model generates the optimal sequence for a given set of exogenous factors. If a set of exogenous factors is called a scenario, the HIT model can be seen as a function that associates a scenario and a sequence. So far, this dissertation has focused on the BASE scenario as in the section "3.4 *Base Scenario*", and the corresponding optimal sequence.

One way to conduct sensitivity analysis is to define several scenarios and analyze the resulting variation in the optimal sequence. This kind of sensitivity analysis is covered in the urban Beijing case study of the HIT model as in "APPENDIX B: THE URBAN BEIJING CASE STUDY OF THE HIT MODEL".

This dissertation adopts a different approach of sensitivity analysis. Several scenarios are defined to reflect issues of interest. Then the optimal sequence based on the BASE scenario is modified to form several sequences. The purpose is to quickly examine the performance of these sequences (representing different hydrogen transition processes) under each scenario. For example, by comparing two sequences under different scenarios, we can identify which factor variation can make a sequence with more renewable hydrogen more attractive. The sequence modification is not based on running the HIT model and so what kinds of scenario make these modified sequences optimal are unknown.

4.5.1 Definition of Scenario and Sequence

The following 7 scenarios are defined. Note the key element in the scenario definition that is used to name the scenario.

Table 4-1: Definition of Scenarios for Sensitivity Analysis

Scenario Name	change from the BASE scenario as defined in the section "3.4 *Base Scenario*"
BASE	no change
E8%	the discount rate for environmental and fuel accessibility costs is changed to annual **8%** (10% in BASE)
CT70	carbon tax rates increases by \$5/tonC per time step from \$20/tonC in 2010 to **\$70/tonC** in 2060 (in BASE, by \$20/tonC per time step to \$220/tonC in 2060)
Coal35	coal price is **\$35/short** ton, 50% increase from BASE (\$23.30/short ton in BASE)
G138CO2	a **grid** electricity CO2 emission factor of **0.138 kgCO2/kWh**, representing 50% reduction from BASE (0.275 kgCO2/kWh in BASE)
ELE60%	industry **electricity** price at \$0.057/kWh, commercial elect. at \$0.072/kWh, both are **60%** of the BASE price (in BASE: \$0.096/kWh and \$0.119/kWh, respectively)
NG2001	year **2001 natural gas** prices, \$6.07 per 1000 cu.ft for industry price and \$4.93 per 1000 cu.ft for commercial price (year 2005 prices in BASE: \$10.69 and \$9.84 per 1000 cu.ft, respectively)

The 6 sequences for sensitivity analysis are designed to differ only in the technology of central plant and equal in all the other decisions, such as output, location, and distribution technology. For each sequence, the numbers and technology types of central plants are shown in Table 4-2.The name of a sequence is based on the technology type and number of central plants. Each sequence is also explained as below. In general “B refers to biomass and “C” refers to coal, “N” to natural gas and “E” to electrolysis. B1 means 1 biomass plant is built, and C8 means 8 coal plants are built.

Table 4-2: Definition of Sequences for Sensitivity Analysis

	time step	1	2	3	4	5	6	7	8	9	10	11
	start year	2010-	15-	20-	25-	30-	35-	40-	45-	50-	55-	2060-
sequence name	central plant technology	number of facility										
B1C8 or BASE optimal	C-BIO			1								
	C-BIOCCS				1	1	1	1	1	1	1	1
	C-COALCCS					2	4	5	6	6	8	8
B2C7 or Biomass Intensive	C-BIO			1								
	C-BIOCCS				1	2	2	2	2	2	2	2
	C-COALCCS					1	3	4	5	5	7	7
N1C8 or No Biomass	C-SMR			1								
	C-SMRCCS				1	1	1	1	1	1	1	1
	C-COALCCS					2	4	5	6	6	8	8
B1N8 or NG Intensive	C-BIO			1								
	C-BIOCCS				1	1	1	1	1	1	1	1
	C-SMRCCS					2	4	5	6	6	8	8
B1N8LC or Late CCS	C-BIO			1	1	1	1	1				
	C-BIOCCS								1	1	1	1
	C-SMR					2	4	5				
	C-SMRCCS								6	6	8	8
B1E2C6 or Electrolysis Intensive	C-BIO			1								
	C-BIOCCS				1	1	1	1	1	1	1	1
	C-ELE					2	2	2	2	2	2	2
	C-COALCCS						2	3	4	4	6	6

- **B1C8 or BASE Optimal**: this sequence is optimal with respect to the BASE scenario and has been extensively discussed in the previous sections. The name means that 1 biomass gasification plant (C-BIO and then C-BIOCCS) and 8 coal gasification plants (C-COALCCS) appear in succession, as also illustrated in Figure 4-1.

- **B2C7 or Biomass Intensive**: B stands for biomass and C for coal. In 2030, 1 C-BIOCCS and 1 C-COALCCS are built as opposed to 2 C-COALCCS in BASE Optimal. This sequence is in fact infeasible in the BASE scenario because of biomass availability (see the related assumption in the section "3.4.5 Technology Cost"). The purpose is to investigate the effect of relaxing the constraint of biomass availability.

- **N1C8 or No Biomass**: N stands for natural gas. The C-BIO in BASE Optimal is replaced by C-SMR and C-BIOCCS by C-SMRCCS. The purpose is to examine the effect of no biomass.

- **B1N8 or NG Intensive**: All C-COALCCS in BASE Optimal is replaced by C-SMRCCS. The purpose is to compare BASE Optimal and NG Intensive with variation in coal and natural gas prices.

- **B1N8LC or Late CCS**: LC stands for "late CCS". The first adoption of CCS is postponed for 20 years from 2025 in NG Intensive to 2045 in Late CCS. The purpose is to investigate how carbon tax rate affects the adoption of CCS.

- **B1E2C6 or Electrolysis Intensive**: E stands for water electrolysis. In 2030, 2 C-ELE (central water electrolysis) are built as opposed to 2 C-COALCCS in BASE Optimal. Water electrolysis is an important technology to realize renewable hydrogen. The purpose of including this sequence is to investigate what factors can be altered to make water electrolysis more attractive for hydrogen production.

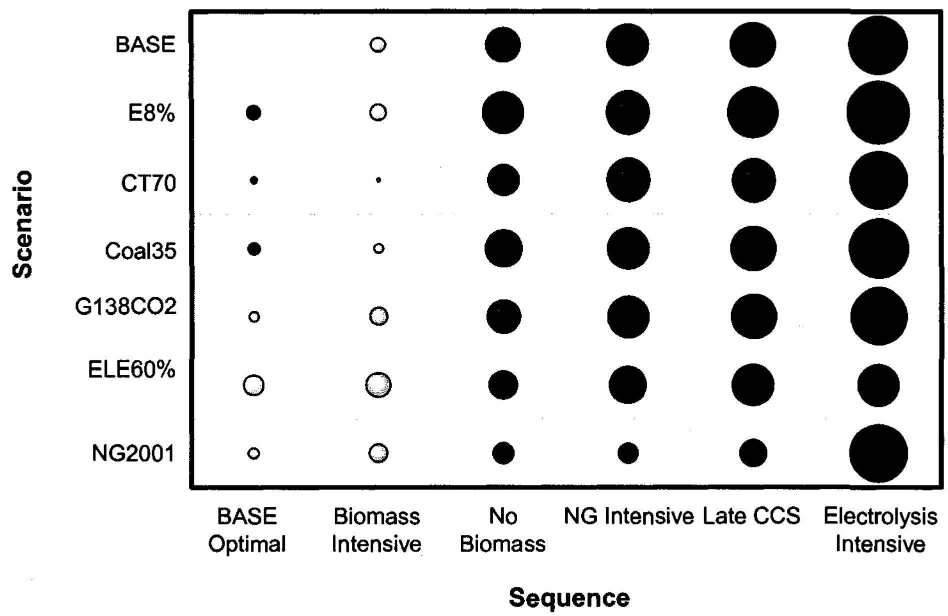
Table 4-3: LTAHC by Scenario by Sequence

Sequence	BASE Optimal	Biomass Intensive	No Biomass	NG Intensive	Late CCS	Electrolysis Intensive
Scenario	Long-term Average Hydrogen Cost (LTAHC), $/kgH2					
BASE	1.886	1.807	2.338	2.548	2.658	3.176
E8%	1.957	1.793	2.522	2.593	2.829	3.349
CT70	1.901	1.883	2.251	2.579	2.563	3.117
Coal35	1.943	1.853	2.395	2.548	2.658	3.207
G138CO2	1.852	1.774	2.304	2.516	2.628	3.075
ELE60%	1.738	1.663	2.192	2.416	2.541	2.518
NG2001	1.841	1.763	2.051	2.038	2.157	3.131

Table 4-4: 50-yr Cumulative CO2 Emissions by Scenario by Sequence

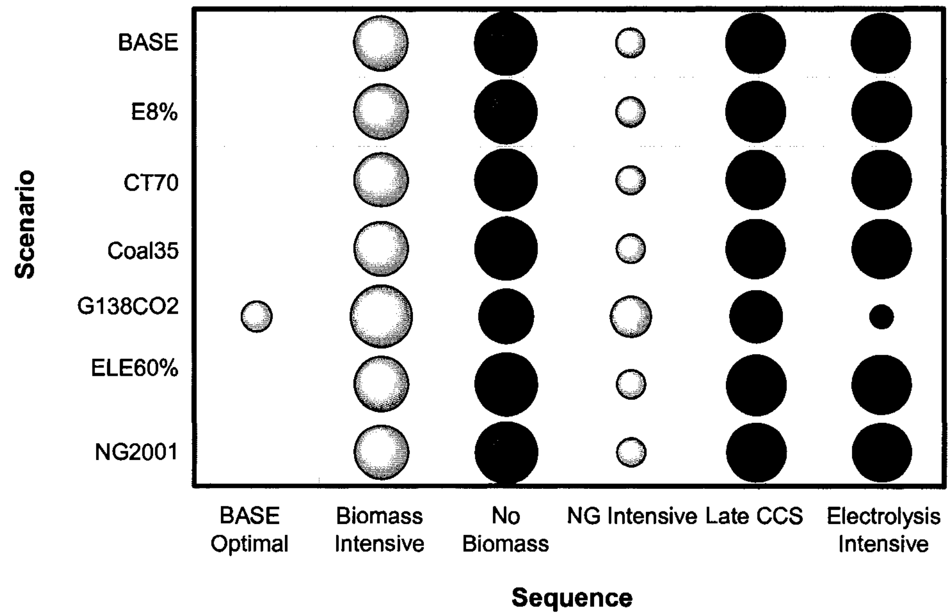
Sequence	BASE Optimal	Biomass Intensive	No Biomass	NG Intensive	Late CCS	Electrolysis Intensive
Scenario	50-yr cumulative CO2 emissions, MMT Carbon					
BASE	0.39	-61.10	81.89	-16.76	74.30	73.20
E8%	0.39	-61.10	81.89	-16.76	74.30	73.20
CT70	0.39	-61.10	81.89	-16.76	74.30	73.20
Coal35	0.39	-61.10	81.89	-16.76	74.30	73.20
G138CO2	-19.08	-80.28	62.42	-34.75	57.14	11.75
ELE60%	0.39	-61.10	81.89	-16.76	74.30	73.20
NG2001	0.39	-61.10	81.89	-16.76	74.30	73.20

To evaluate the performance of each sequence, the long-term average hydrogen cost (LTAHC) in dollar per kgH2 is selected as the economic metric and the 50-year cumulative CO2 emission in million metric ton of carbon (MMTC) is selected as the environmental impact metric. The values of these two metrics for each sequence by each scenario are presented in Table 4-3 and Table 4-4 and the variation caused by an alternative sequence or scenario is visualized in Figure 4-26 and Figure 4-27. The information contained in these two tables is analyzed with respect to several issues in the following sections. For each issue, an impact is represented as the numerical change of LTAHC or cumulative CO2 emission due to change of scenario or sequence. For example, for BASE Optimal, the LTAHC is \$1.886/kg for BASE scenario and \$1.841/kg for NG2001 scenario, so the impact of NG2001 scenario is \$-0.045/kg. For reference, every 1 cent of variation in LTAHC indicates a \$38 million change of social cost net present value, which is significant.



blue = positive value; white = negative value; empty = zero and no variation
size indicates variation of LTAHC from BASE Optimal in the BASE scenario

Figure 4-26: Hydrogen Cost Variation



blue = positive value; white = negative value; empty = zero and no variation
size indicates variation of 50-year CO2 emission from BASE Optimal in the BASE scenario

Figure 4-27: CO2 Emission Variation

4.5.2 BASE Optimal—the BASE Scenario Optimal Sequence

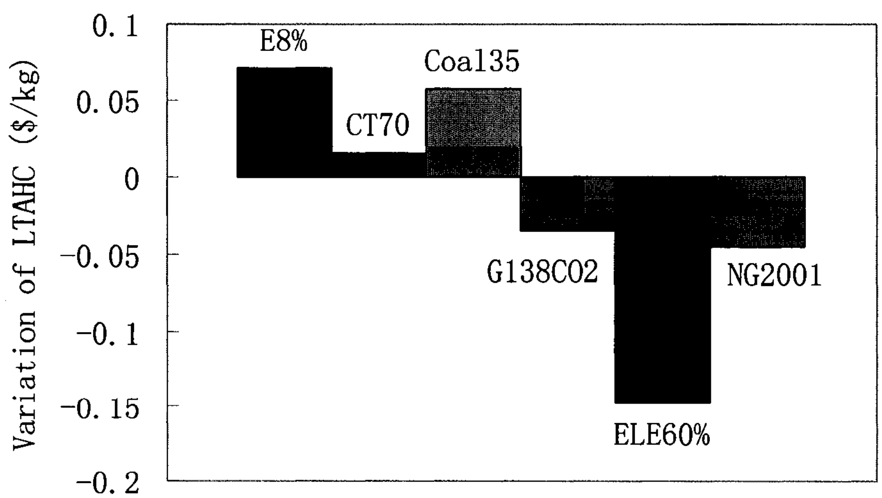


Figure 4-28: Sensitivity of the BASE Scenario Optimal Sequence

Figure 4-28 shows the impact on LTAHC by each non-BASE scenario. Regarding the direction of impact, the results show that a reduction of electricity price (ELE60%), natural gas price (NG2001) or CO2 emission factor of grid electricity (G138CO2) can lower hydrogen cost, while a reduction of externality discount rate (E8%) or carbon tax rate (CT70), or an increase of coal price (Coal135) can increase hydrogen cost.

The most significant impact is a reduction of LTAHC by $0.148/kg due to 40% reduction of electricity price. This is a consistent response to the result as in Figure 4-9 that electricity cost makes up the largest portion of the variable cost. This is certainly not to suggest that such a big drop of the electricity price in California is likely in the future, although according to EIA (2006), Oregon has an electricity price of $0.078/kWh, about 48% less than California.

A surprising outcome is that a lower carbon tax rate leads to a higher hydrogen cost. This is a little counterintuitive, since the cumulative CO2 emission of the BASE Optimal sequence is 0.392 MMTC, positive. The secret is that during 2020-2045, the system has a negative contribution of CO2 emissions due to biomass gasification coupled with carbon capture and sequestration, therefore earning carbon credits. Although the cumulative absorption is surpassed by the later cumulative emission, the carbon credits gained earlier are less heavily discounted than the later carbon taxes. A decrease of carbon tax rate affects both carbon credits and taxes, and the net effect is a net increase of hydrogen cost for the BASE Optimal sequence.

However, the impact of such a significant cut in carbon tax rate (from BASE to CT70) is much less significant than just a small change of externality discount rate (Figure 4-28), from 10% in BASE to 8% in E8%. The impact of E8% is \$0.071/kg in LTAHC, representing the largest increase of LTAHC among all the scenarios. It indicates the high level of sensitivity of cost-effectiveness of hydrogen transition to the externality discount rate. This can raise some serious issues regarding long-term discounting or intergenerational equity, as some even proposes a zero discount rate for environmental cost (Stern, 2007).

4.5.3 BASE Scenario

Figure 4-29 shows the LTAHC by sequence under BASE scenario. Any feasible sequence should have a higher LTAHC than BASE Optimal, because BASE Optimal is the optimal sequence under BASE scenario through the HIT model. In Figure 4-29, BASE Optimal has a lower LTAHC than any other except Biomass Intensive. This is because the sequence Biomass Intensive is an infeasible sequence under BASE scenario and an infeasible sequence can be better or worse than the optimal sequence. Therefore, the results in Figure 4-29 demonstrate the optimality of BASE Optimal as well as the appeal of more available biomass. That is, if more biomass is available, more biomass gasification plants should be built to substitute for coal gasification plants.

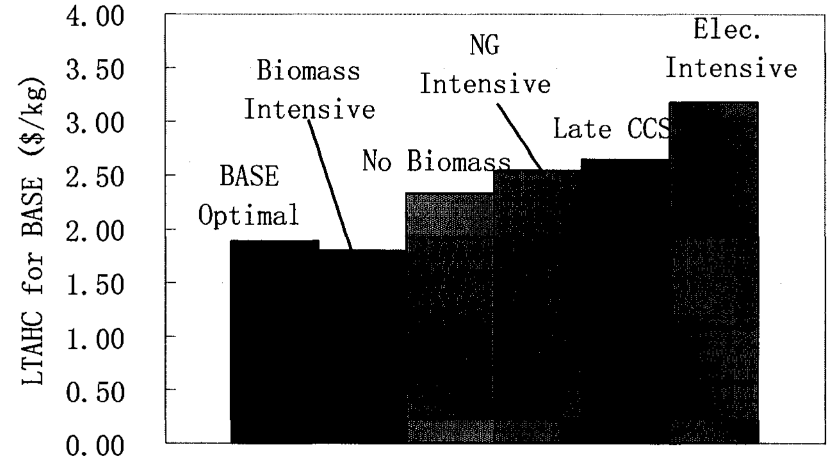


Figure 4-29: Hydrogen Cost by Sequence

By adopting only 2 C-ELE plants, the LTAHC jumps up to over $3/kg, suggesting the economic difficulty to adopt water electrolysis under the projected technology level, electricity price and carbon intensity of electricity.

4.5.4 Externality Discount Rate

As previously seen in Figure 4-28, a lower externality discount rate can make a sequence economically less favorable. Mathematically, this is because a lower discount rate amplifies the net present value of future costs. However, it should be noted that such a NPV amplification is also applied to a future revenue. As shown in Figure 4-30, a lower externality discount rate has an opposite impact on BASE Optimal and Biomass Intensive: making BASE Optimal worse while Biomass

Intensive better. Compared to BASE Optimal, the sequence Biomass Intensive has one more C-BIOCCS and therefore more carbon credit revenues, so Biomass Intensive actually welcomes a lower discount rate to amplify the NPV of these revenues. If biomass gasification coupled with carbon capture and sequestration proves to be sufficient and feasible for hydrogen production, a lower externality discount rate can actually play to the interest of the hydrogen industry.

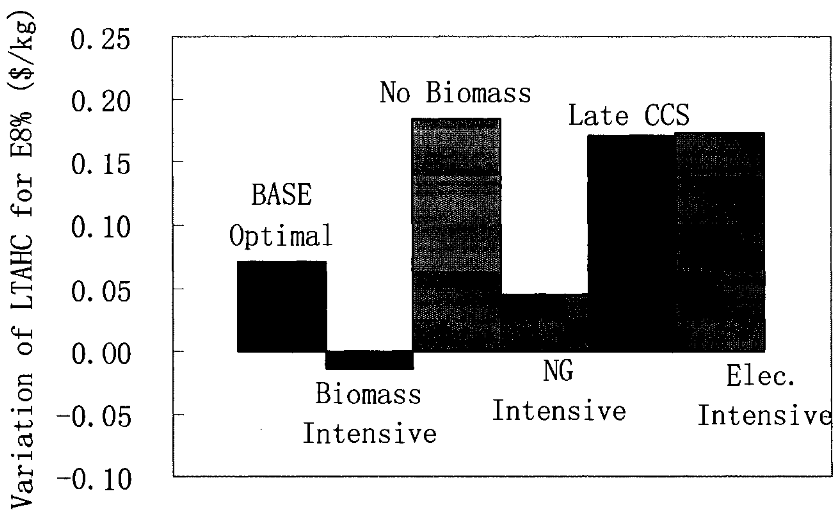


Figure 4-30: Externality Discount Rate on Hydrogen Cost

4.5.5 Carbon Tax Rate

Figure 4-31 shows the impact on hydrogen cost of a reduced carbon tax rate by each sequence. As already explained a lower carbon tax rate reduces carbon credits of BASE Optimal and therefore increase the hydrogen cost of BASE Optimal. The same explanation also applies to NG Intensive and Biomass Intensive. For Biomass Intensive, where more carbon credits are earned due to one additional biomass gasification plant, the adverse effect of a reduce carbon tax rate is much more significant.

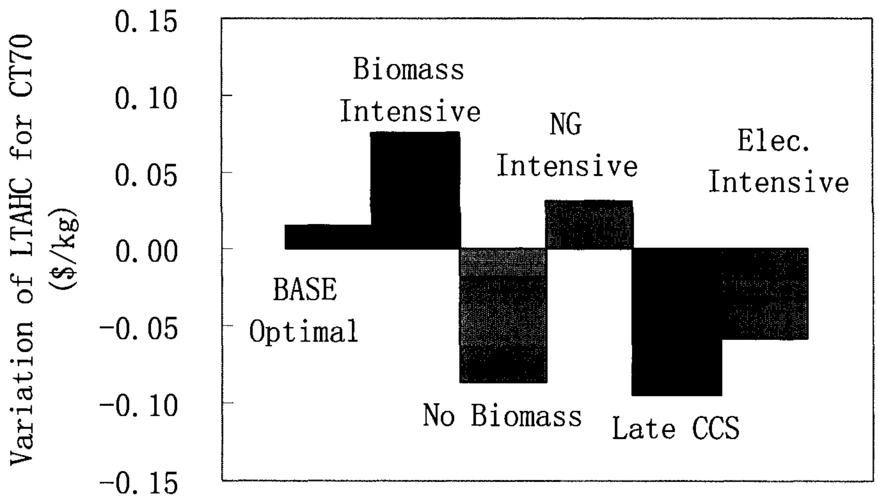


Figure 4-31: Carbon Tax on Hydrogen Cost

The opposite effect of a reduce carbon tax rate on NG Intensive and Late CCS is due to the delayed adoption of CCS. Because the adoption of CCS is 20 years later in Late CCS than in B1N8, NG Intensive earns some carbon credit revenues during these 20 years, while Late CCS has to pay carbon tax during these years. Combined with the discounting effect, a lower carbon tax rate turns out to economically favor Late CCS but hurt B1N8.

As NG Intensive and Late CCS only differ in the time of CCS adoption, the above analysis naturally motivates the hypothesis of carbon tax rate on promoting CCS adoption. As shown in Figure 4-32, under the BASE scenario where a more aggressive carbon tax rate is assumed, NG Intensive results in a lower LTAHC and is more attractive. But under the CT70 scenario where the carbon tax rate is lower, Late CCS is economically more appealing. That is, under CT70 scenario, the cost savings by delaying adoption of CCS exceeds the extra carbon tax from such a delay, but a higher carbon tax rate increase such an extra carbon tax and therefore promote earlier adoption of CCS. The similar effect of carbon tax rate on CCS adoption is also observed in the urban Beijing case study as in "APPENDIX B: THE URBAN BEIJING CASE STUDY OF THE HIT MODEL".

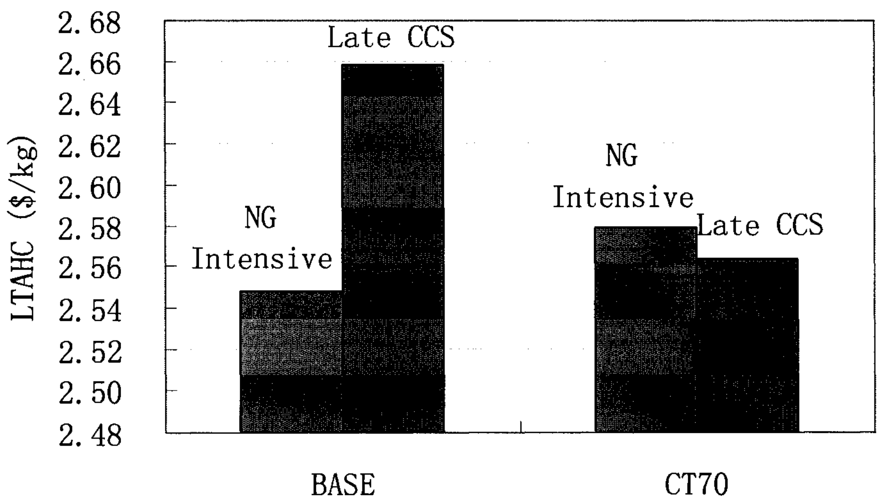


Figure 4-32: Carbon Tax on CCS

4.5.6 Coal Price

The Southern California case study does not reflect the reality that coal is not favored by the energy and environmental policies in California, but this is remedied by considering coal gasification with CCS. The unfavorable policies against coal can be represented by a higher coal price for coal consumers within California, so it is important to investigate how the coal price will affect the hydrogen transition. As opposed to the BASE scenario, a 50% increase of coal price in the Coal35 scenario leads to significant increase in hydrogen cost for BASE Optimal, Biomass Intensive, No Biomass and Electrolysis Intensive. No impact is evident in the other sequences, simply because coal gasification is not part of these sequences.

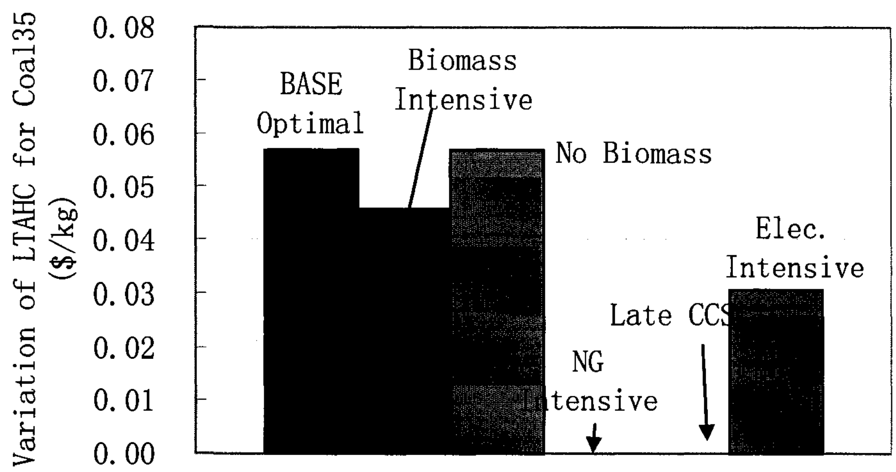


Figure 4-33: Coal Price on Hydrogen Cost

4.5.7 Electricity Price and Decarbonization

Figure 4-34 shows the impact on hydrogen cost by the ELE60% scenario, where the electricity prices is assumed to be 60% of the BASE scenario. Such a reduction of electricity price leads to significant drop in hydrogen cost for all sequences.

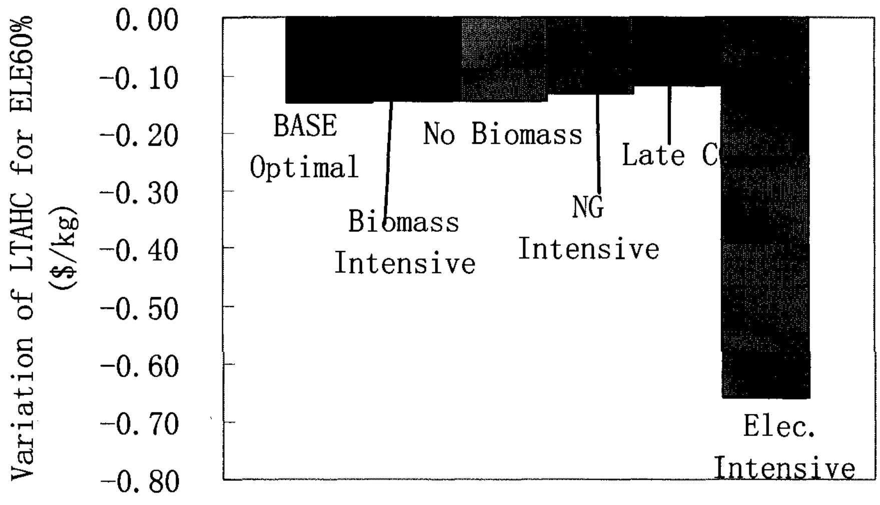


Figure 4-34: Electricity Price on Hydrogen Cost

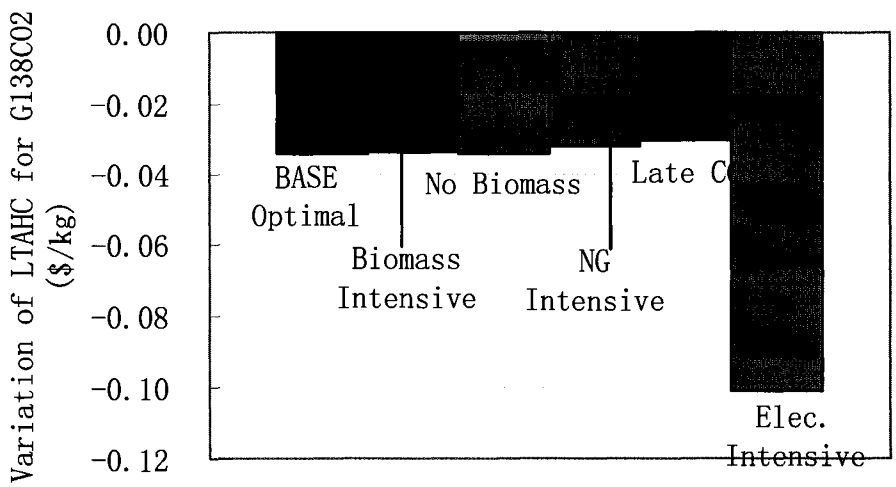


Figure 4-35: Electricity CO2 Emission Factor on Hydrogen Cost

Figure 4-35 shows the impact on hydrogen cost by the G138CO2 scenario, where the CO2 emission factor of California grid electricity is assumed to drop from 0.275 kgCO2/kWh in the BASE scenario down to 0.138 kgCO2/kWh. This also leads to significant drop of hydrogen cost for all sequences because of lower carbon externality.

Apparently, the hydrogen cost in scenario Electrolysis Intensive is the most sensitivity to electricity price and carbon intensity. Increasing the share of low-cost renewable electricity, such as wind, solar, or hydraulic electricity, can reduce carbon intensity of grid electricity and make water electrolysis more attractive. If renewable electricity can be obtained via low-cost technologies, renewable hydrogen can become more competitive.

4.5.8 Natural Gas Price

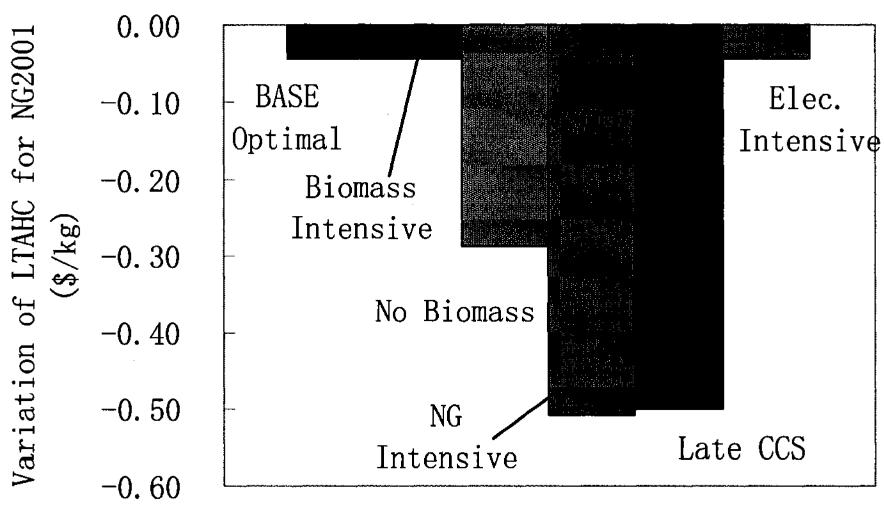


Figure 4-36: Natural Gas Price on Hydrogen Cost

In the BASE scenario, we use the 2005 natural gas price of California, which is the highest since 2000. Figure 4-36 shows the impact on hydrogen cost of the scenario NG2001, where the 2001 natural gas price in California is adopted, 43% lower than the 2005 price. The results show that a sequence using more natural gas for hydrogen production is more sensitive to natural gas. If central natural gas SMR dominates the central production as in NG Intensive or Late CCS, the resulting effect is about $0.50/kg drop in LTAHC. However, the future natural gas price could be volatile and increasing. Given the sensitivity shown in Figure 4-36, the trend of natural gas price should be an important factor in considering natural gas SMR for hydrogen production.

4.5.9 CO2 Emissions

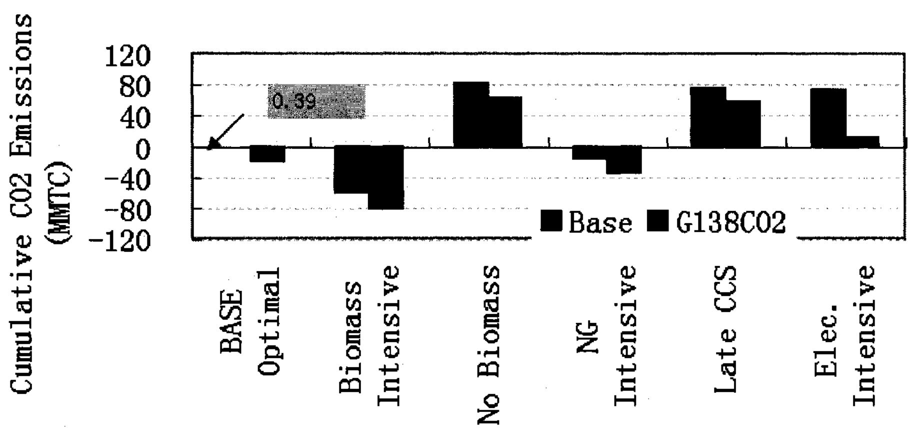


Figure 4-37 Cumulative CO2 Emissions by Sequence

Figure 4-37 shows the 50-year cumulative CO2 emissions in million metric tons of carbon for each sequence for the BASE and G138CO2 scenarios. Comparison between the two scenarios shows that a lower carbon intensity of grid electricity reduces CO2 emissions or increases CO2 absorption for all sequences. The magnitude of effect is very close among most sequences, because of similar amount of electricity consumption, except the Electrolysis Intensive sequence, which includes 2 water electrolysis plants. Water electrolysis requires a large amount of electricity and so its CO2 emission is very sensitive to the carbon intensity of electricity. Late CCS has similar CO2 emissions with Electrolysis Intensive but is less sensitive to variation of electricity carbon intensity, because compared to Electrolysis Intensive, Late CCS has a less share of CO2 emissions from electricity generation and higher share from natural gas SMR.

Although Figure 4-37 shows a significant advantage by BASE Optimal over Electrolysis Intensive on CO2 emissions and indicates the limitation of water electrolysis in CO2 mitigation, this should be related to the overall transportation context rather than based on absolute quantity comparison. As shown in the previous Figure 4-25, the cumulative CO2 emissions from the gasoline-only system are 963 MMTC. With the exogenous hydrogen penetration, the cumulative CO2 emissions from gasoline are reduced to 457 MMTC. While BASE Optimal emits only 0.39 MMTC under BASE scenario and results in a 52.5% reduction of cumulative CO2 emissions from all light-duty vehicles, Electrolysis Intensive emits 73.2 MMTC under BASE scenario and results a 44.9% reduction. Thus, the impact of substituting 2 C-COALCCS with 2 C-ELE is about 7 percentage points of increase in the 50-year cumulative CO2 emissions.

Biomass gasification with CCS has a large impact on the cumulative CO2 emissions, as evidenced by the comparison between Biomass Intensive and BASE Optimal in Figure 4-37. And by also looking at Figure 4-29, the observation is that if more biomass is available, the substitution of a coal plant with a biomass gasification plant, both with CCS, can not only lower hydrogen cost but also reduce CO2 emissions.

5 CONCLUSIONS

5.1 Summary and Policy Implications

Hydrogen as an alternative vehicle fuel promises the reduction of GHG and criteria pollutant emissions and oil consumption. Optimization of the hydrogen transition based on social welfare maximization fits the common policy goal of efficient allocation of social resources and an optimal hydrogen transition provides the basis for the policy maker to understand the worthiness of, potential of success of, and policy needs for a hydrogen transition.

This dissertation develops the Hydrogen Infrastructure Transition (HIT) to optimize the hydrogen transition with two simplifications: exogenous hydrogen demand and regional scope. The central modeling question is when, where, by what technologies and at what sizes to build up the hydrogen infrastructure in order to minimize the social cost NPV of hydrogen supply. The model is implemented in a dynamic programming structure but supported by several sub-models including a sophisticated station location sub-model. By including a broad spectrum of hydrogen technologies, allowing free combinations of facility technologies and monetizing fuel accessibility and GHG emissions, the model explicitly considers system dynamics, spatial details, technology competition and supplementation, and social objective tradeoff.

Specifically in the Southern California case study, the hydrogen infrastructure development is optimized for five counties and over the time scope of 2010-2060. Hydrogen technologies are represented by 6 central production technologies, 2 onsite production technologies and 2 distribution technologies. Industrial hydrogen is also considered. Carbon capture and sequestration is optional for central SMR, coal gasification and biomass gasification, required for coal gasification and not considered for water electrolysis. Capital, fixed O&M and variable costs as well as fuel accessibility cost and environmental cost are tradable with each other and the buildup sequence is optimized by minimizing the NPV of the sum of these three kinds of social costs during the study period.

The following findings are associated with the optimal buildup sequence resulting from the BASE scenario in the Southern California case study.

First, several general trends of technology transition are found and summarized in Table 5-1. Along with these general trends, there are some specific observations worth mentioning. The dominance of central production comes as early as in 10 years (i.e. in 2020). During the first 10 years, industry hydrogen and onsite production prevail against but help bridge central production. Biomass gasification is more attractive than coal gasification but constrained by biomass availability. Carbon capture and sequestration is adopted as early as in 15 years (i.e. in 2025). The infrastructure gradually expands into one with 4611 miles of hydrogen pipeline serving 2376 refueling stations. As pipeline network grows, the length share of small pipelines also increases. At the end, 76% in length of the hydrogen pipeline are of diameter below 5 inches.

Table 5-1: Technology Trends of Optimal Sequence

Perspective	Trend
Feedstock	industry hydrogen → natural gas → biomass → coal
Pathway	Industry hydrogen → distributed → central
Distribution	trucking → pipeline
CCS	central w/o CCS → central with CCS
Avg. station size	Increase over time
Station number	Increase over time

Second, the long-term average hydrogen cost (LTAHC) is only $1.886/kg, which represents a 10% discount rate and accounts for not only capital, fixed O&M and variable costs, but also fuel accessibility and environmental costs. The two major variable cost components of LTAHC are truck rental fee and electricity cost. On the other hand, if hydrogen is priced at $4.59/kg without government subsidy or $2.00/kg with $200 million of subsidy, the hydrogen industry is able to balance all the costs during the first 10 years. In general, hydrogen can be priced even lower if a longer breakeven time is assumed. For profitability, a 50-year constant price at $4/kg indicates a hydrogen market with a profit potential of 7.67 billion dollars Southern California, discounted. When the system approaches 2060 with a 100% hydrogen penetration, variable cost is the largest cost component, while electricity cost contributes most to the variable cost and coal cost comes in second. For investment risk, the 50-year non-discounted total of capital costs is $24.43 billion, with the 4 largest contributions from central plants (38%), refueling stations (37%), onsite SMR stations (11%) and hydrogen pipeline (9%). For industry cross-subsidy, if hydrogen is priced at the equivalent gasoline price (as of April 14 2008) throughout the study period, the hydrogen industry is able to subsidize FCV purchase by $8,697 per vehicle. In competing with the gasoline system, the hydrogen-FCV system can narrow the gap when either a FCV becomes cheaper or the gasoline price becomes higher or less subsidized. The results show that in narrowing the competitiveness gap, one cent increase of gasoline price has the same effect as $30 reduction of a FCV cost.

Third, fuel accessibility improves over time and the average refueling travel time decreases from 22 minutes in 2010, to 1 minute 28 seconds (current gasoline accessibility) in 2030, and to less than 1 minute in 2060. Such a gradual improvement is different from the threshold understanding and resulted from tradeoff between technology and fuel accessibility costs. The correlation between station number and demand distribution is weak and insignificant during early years, but becomes stronger with increase in demand and station number.

Fourth, the hydrogen demand curve coupled with the optimal sequence could reduce annual CO2 emissions by about 99% and the 50-year cumulative emissions by about 50%, but such a mitigation potential is based on the feasibility of CCS.

At last, the long-term average hydrogen cost (LTAHC) appears to be sensitive to electricity price, natural gas price, coal price, carbon tax rate, externality discount rate, and CO2 emission factor of grid electricity. If no biomass gasification is involved, a higher carbon tax rate or a lower externality discount rate generally increase the hydrogen cost. If biomass gasification is selected, then depending on how much hydrogen made from biomass with CCS, a higher carbon tax rate or a lower externality discount rate may increase or lower the hydrogen cost. More available biomass can reduce the hydrogen cost and can make the hydrogen industry favor a higher carbon tax rate or a lower externality discount rate. Another effect of a higher carbon tax is motivating early adoption of CCS. A lower price and a lower carbon intensity of grid electricity can significantly reduce the hydrogen cost and make water electrolysis more attractive for hydrogen production.

All these modeling results have several policy implications. First, the Southern California case study provides region-specific evidence showing that the Department of Energy's goal of "\$2.00-\$3.00/gge (delivered, untaxed) at the pump" (http://www1.eere.energy.gov/H2Andfuelcells/mission.html) for hydrogen cost is achievable and can even be outperformed by the region-specific optimization. Second, the Southern California case study in this dissertation is still one of the first to consider both system dynamics and spatial details of hydrogen transition and therefore its empirical findings require further examination before being generalized to a national or international context. More regional studies should be conducted to form the empirical basis for policy discussion on hydrogen as a solution for national issues. Third, hydrogen as a vehicle fuel is economically competitive for Southern California, although the relative competitiveness of a hydrogen+FCV system is restrained by the FCV cost and the subsidy for gasoline. Fourth, industry hydrogen and a small number of onsite stations can help bridge central production and alleviate capital cost burden. Fifth, to achieve the optimal hydrogen transition, a system-oriented cooperation is needed from different stakeholders including governments, fuel suppliers, car makers, and consumers.

If a hydrogen transition is to be pursued, the following policy instruments can be considered.

- Sending out strong policy signal on the long-term commitment to hydrogen transition. This can attract long-term investment and lower hydrogen cost.
- Effectively allocating some industry hydrogen for initiating the transition.
- Subsidizing the hydrogen industry in early stages and tax it in later stages.
- Compensating early FCV motorists for suffering limited fuel accessibility. Such a compensation fund can come from profits of the hydrogen industry during the later years when hydrogen demand is high.
- Subsidizing FCV purchase with the anticipated profits from the hydrogen industry.
- Using carbon tax or cap-and-trade system to encourage low-carbon technologies or carbon capture and sequestration.
- Either having a highly competitive market to promote technology competition and supplementation, or having a highly regulated industry with a least-cost planning.

- With the above policy instruments and the net gain in social welfare, negotiating with consumers, auto makers and fuel providers to break the chicken-and-egg dilemma.

5.2 Limitations and Contributions

This dissertation contributes to the state of the art of hydrogen transition analysis, hydrogen assessment and mathematical programming. First, the HIT model provides a new framework for hydrogen transition analysis in a dynamic context and incorporates several important attributes absent from previous models, such as demand growth, system dynamics, technology competition and supplementation, spatial details and social objective tradeoff. The Southern California case study results in important findings that improve the understanding of hydrogen transition. Second, the economic and environmental assessment of hydrogen in this dissertation is based on optimization spatially and over time, reflecting efficient allocation of social resources. Third, this is the first application of dynamic programming on hydrogen infrastructure development. The space-filter algorithm proves successful in dealing with the dimensionality problem associated with large-scale dynamic programming models. Several mathematical programming techniques are also applied as parts of the HIT model.

This dissertation has several limitations. First, hydrogen demand is exogenous. Whether such a hydrogen demand scenario is realistic and optimal for Southern

California and how to realize such a demand scenario are beyond the study scope. Second, the model identifies the optimal sequence, but does not address the required policies to navigate such a buildup sequence. Third, water electrolysis based on solar or wind energy is not explicitly covered. However, the penetration of solar or wind energy can be reflected by grid electricity price and carbon intensity. Fourth, although sensitivity analysis is provided, uncertainly is not fully addressed. Possible improvements can be accomplished through Monte Carlo simulation or stochastic modeling. Fifth, the model appears complicated and its user-friendliness is yet to be improved. Sixth, the time value function is based general travel context and may not be applicable to refueling travel. Seventh, the carbon tax rate assumed in this dissertation is still highly hypothetical due to lack of consensus on carbon tax rate in the literature. Finally, the empirical findings from this dissertation have unknown applicability to other regions.

Any of the limitations described above suggests room for improvement or extension. Probably more interesting, three possible future studies are discussed here. First, applying the model to more regions can strengthen the empirical basis for policy analysis. Second, we can change the demand scenario and estimate the corresponding hydrogen cost. If the benefits of different hydrogen demand scenario can be quantified, we will be able to select the optimal hydrogen transition scenario for the region. Third, more scenario studies can be conducted concerning, e.g. restriction of coal use and renewable portfolio standard.

BIBLIOGRAPHY

Ahluwalia, R. K. and X. Wang (2008). "Fuel cell systems for transportation: Status and trends." Journal of Power Sources 177(1): 167-176.

Ahuja, R. K., T. L. Magnanti, et al. (1993). Network Flows: Theory, Algorithms, and Applications, Prentice Hall.

Altmann, M., P. Schmidt, et al. (2004). Potential for Hydrogen as a Fuel for Transport in the Long Term (2020 - 2030). Ludwig Boelkow System Technik.

Asheim, G. B., W. Buchholz, et al. (2001). "Justifying Sustainability." Journal of Environmental Economics and Management 41(3): 252-268.

Asic, M. D. and V. V. Kovacevic-Vujcic (1991). "An implicit enumeration method for global optimization problems." Computers & Mathematics with Applications 21(6-7): 191-201.

Ballou, R. H. (1968). "Dynamic Warehouse Location Analysis." Journal of Marketing Research 5(3): 271-276.

Bapna, R., L. S. Thakur, et al. (2002). "Infrastructure development for conversion to environmentally friendly fuel." European Journal of Operational Research 142(3): 480-496.

Beasley, J. E. (1993). "Lagrangean heuristics for location problems." European Journal of Operational Research 65(3): 383-399.

Bellman, R. (1957). Dynamic Programming. Princeton, Princeton University Press.

Berman, O., M. J. Hodgson, et al. (1995). Flow intercepting models. Facility Location: A Survey of Applications and Methods. Z. Drezner. New York, Springer. 389-426.

Berman, O., R. C. Larson, et al. (1992). "Optimal Location of Discretionary Service Facilities." Transportation Science 26(3): 201-211.

Blank, L. T. and A. Tarquin (2005). Engineering economy. Boston, McGraw-Hill.

Boland, N., P. Dominguez-Marin, et al. (2006). "Exact procedures for solving the discrete ordered median problem." Computers & Operations Research 33(11): 3270-3300.

Broadman, H. G. (1986). "The social cost of imported oil." Energy Policy 14(3): 242-252.

Bunch, D. S. and C. Kazimi (1996). Analysis of the Future Household Market for Alternative Fuel Vehicles in Southern California Using a Microsimulation Forecasting System. Institute of Transportation Studies, University of California, Davis. Research Report UCD-ITS-RR-96-19

Bureau of Transportation Statistics. (2006). The Intermodal Transportation Database. (http://www.bts.gov/). Accessed in 2006

California Air Resources Board (CARB). (2006). The EMission FACtors (EMFAC) model. (http://www.arb.ca.gov/msei/onroad/latest_version.htm). Accessed in 2006

California Department of Transportation (Caltrans). (2005). California Motor Vehicle Stock, Travel and Fuel Forecast. (http://www.dot.ca.gov/hq/tsip/otfa/mtab/MVSTAFF.htm). Accessed in 2006

Chang, L., Z. Li, et al. (2007). "Pathways for hydrogen infrastructure development in China: Integrated assessment for vehicle fuels and a case study of Beijing." Energy 32(11): 2023-2037.

Church, R. and C. ReVelle (1974). "The maximal covering location problem." Papers in Regional Science 32(1): 101-118.

Cormen, T. H., C. E. Leiserson, et al. (1990). The Floyd-Warshall algorithm. Introduction to Algorithms, first edition, MIT Press and McGraw-Hill: 558 - 565.

Cormen, T. H., C. E. Leiserson, et al. (2001). Introduction to Algorithms, MIT Press.

Crane Co. (1998). Flow of Fluids Through Valves, Fittings, and Pipe, Crane Valves.

Cunningham, J. M., S. Gronich, et al. (2008). Why Hydrogen and Fuel Cells are Needed to Support California Climate Policy. Institute of Transportation Studies, University of California, Davis. Research Report UCD-ITS-RR-08-06

Dahowski, R., J. Dooley, et al. (2004). A CO2 Storage Cost Curve for North America. IEA Greenhouse Gas R&D Programme. Contract IEA/CON/02/82

Daskin, M. S. (1995). Network and Discrete Location: Models, Algorithms, and Applications. New York, John Wiley & Sons.

Delaquil, P., G. A. Goldstein, et al. (2007). US Multi-region MARKAL Modeling. ETSAP Semi-annual Workshop. Palo Alto, Stanford University, June 28, 2007.

Delucchi, M. A. (2000). "Environmental Externalities of Motor Vehicle Use in the US." Journal of Transport Economics and Policy 34(2): 135.

Delucchi, M. A. (2004). Conceptual and Methodological Issues in Lifecycle Analyses of Transportation Fuels. Institute of Transportation Studies, University of California, Davis. Research Report UCD-ITS-RR-04-45

Efroymson, M. A. and T. L. Ray (1966). "A branch-and-bound algorithm for plant location." Operations Research 14: 361–368.

Energy Information Administration (2002). Updated State-level Greenhouse Gas Emission Coefficients for Electricity Generation: 1998-2000.

Energy Information Administration. (2006). Annual Energy Price Statistics. (http://www.eia.doe.gov/). Accessed in 2006

Energy Information Administration (EIA) (2003). The National Energy Modeling System: An Overview 2003. the Energy Information Administration, the U.S. Department of Energy. Report #: DOE/EIA-0581

Erlenkotter, D. (1978). "A Dual-based Procedure for Uncapacitated Facility Location." Operations Research 26: 992-1009.

ETSAP. (1978). ETSAP website. (http://www.etsap.org/Tools/MARKAL.htm). Accessed in March 2008

Gether, K. (2004). Transition to Large Scale Use of Hydrogen and Sustainable Energy Services: Choices of technology and infrastructure under path dependence, feedback and nonlinearity. Energy and Process Engineering. Trondheim, Norwegian University of Science and Technology. PhD Dissertation.

Greene, D. (1989). "Fuel Choice for Dual-Fuel Vehicles: An Analysis of the Canadian Natural Gas Vehicles Survey." SAE Technical Paper(892067).

Greene, D. (1998). "Survey Evidence on the Importantce of Fuel Availability to the Choice of Alternative Fuels and Vehicles." Energy Studies Review 8(3): 215-231.

Greene, D., P. N. Leiby, et al. (2007). Integrated Analysis of Market Transformation Scenarios with HyTrans. Oak Ridge National Lab. ORNL/TM-2007/094

Greene, D. L. and S. Ahmad (2005). Costs of U.S. Oil Dependence: 2005 Update. Oak Ridge National Laboratory.

Gronic, S. (2006). Hydrogen & FCV Implementation Scenarios, 2010 - 2025. DOE 2010-2025 Scenario Analysis Meeting: August 9-10, 2006, Washington, DC.

Hakimi, S. L. (1964). "Optimum Locations of Switching Centers and Absolute Centers and Medians of a Graph." Operations Research 12(3): 450-459.

Hakimi, S. L. (1965). "Optimum Distribution of Switching Centers in a Communication Network and Some Related Graph Theoretic Problems." Operations Research 13(3): 0462-0475.

Handler, G. Y. (1979). Complexity and efficiency in minimax network location. Combinatorial Optimization. N. Christofides, A. Mingozzi, P. Toth and C. Sandi. New York, John Wiley & Sons: 281-314.

Harkness, J. and C. ReVelle (2003). "Facility location with increasing production costs." European Journal of Operational Research 145(1): 1-13.

Hodgson, J. M., K. E. Rosing, et al. (1996). "Applying the flow-capturing location-allocation model to an authentic network: Edmonton, Canada." European Journal of Operational Research 90(3): 427-443.

Hodgson, M. J. (1990). "A flow-capturing location–allocation model." Geographical Analysis 22: 270-279.

Hodgson, M. J. and O. Berman (1997). "A billboard location model." Geographical and Environmental Modeling 1: 25-45.

Hodgson, M. J. and K. E. Rosing (1992). "A network location-allocation model trading off flow capturing andp-median objectives." Annals of Operations Research 40(1): 247-260.

Hooker, J. N., R. S. Garfinkel, et al. (1991). "Finite Dominating Sets for Network Location Problems." Operations Research 39(1): 100-118.

Howarth, R. and R. Norgaard (1993). "Intergenerational Transfers and the Social Discount Rate." Environmental and Resource Economics 3: 337-359.

Hugo, A., P. Rutter, et al. (2005). "Hydrogen infrastructure strategic planning using multi-objective optimization." International Journal of Hydrogen Energy 30(15): 1523-1534.

Hydrogen Analysis Group (H2A). (2007). DOE H2A Analysis. U.S. Department of Energy. (http://www.hydrogen.energy.gov/h2a_analysis.html). Accessed in 2008

International Center for Technology Assessment (CTA) (1998). The Real Price of Gasoline. International Center for Technology Assessment (CTA). REPORT NO. 3

Jenkins, B. M. (2005). Biomass in California: Challenges, Opportunities, and Potentials for Sustainable Management and Development. California Energy Commission. Contract 500-01-016

Joffe, D., D. Hart, et al. (2004). "Modelling of hydrogen infrastructure for vehicle refuelling in London." Journal of Power Sources 131(1-2): 13-22.

Johnson, N., C. Yang, et al. (2005). Optimal Design of a Fossil Fuel-Based Hydrogen Infrastructure with Carbon Capture and Sequestration: Case Study in Ohio. National Hydrogen Association Annual Hydrogen Conference, Washington, DC.

Kempton, W. and J. Tomic (2005a). "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue." Journal of Power Sources 144(1): 268-279.

Kempton, W. and J. Tomic (2005b). "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy." Journal of Power Sources 144(1): 280-294.

Kitamura, R. and D. Sperling (1987). "Refueling behavior of automobile drivers." Transportation Research Part A: General 21(3): 235-245.

Klose, A. (1998). "A Branch and Bound Algorithm for An Uncapacitated Facility Location Problem with a Side Constraint." International Transactions in Operational Research 5(2): 155-168.

Klose, A. and A. Drexl (2005). "Facility location models for distribution system design." European Journal of Operational Research 162(1): 4-29.

Krarup, J. and P. M. Pruzan (1979). Selected families of location problems. Ann. Discrete Math. 5: 327--387.

Kromer, M. A. and J. B. Heywood (2007). Electric Powertrains: Opportunities and Challenges in the U.S. Light-Duty Vehicle Fleet. Massachusetts Institute of Technology. No. LFEE 2007-03 RP

Kuby, M. and S. Lim (2005). "The flow-refueling location problem for alternative-fuel vehicles." Socio-Economic Planning Sciences 39(2): 125-145.

Kurani, K. (1992). New Transportation Fuels in New Zealand: Innovation, Social Choice and Utility. Institute of Transportation Studies. Davis, University of California, Davis. PhD dissertation.

Kurani, K. S., T. Turrentine, et al. (1994). "Demand for electric vehicles in hybrid households: an exploratory analysis." Transport Policy 1(4): 244-256.

Larminie, J. and A. Dicks (2003). Fuel Cell Systems Explained (2nd Edition), John Wiley & Sons.

Leiby, P., D. Greene, et al. (2006). "Systems Analysis of Hydrogen Transition with HyTrans." Transportation Research Record 1983(-1): 129-139.

Leiby, P. N., D. L. Greene, et al. (2005). HyTrans: Hydrogen Transition Model Version 1.5. Center for Transportation Analysis, Oak Ridge National Laboratory.

Lin, Z., C.-W. Chen, et al. "The least-cost hydrogen for Southern California." International Journal of Hydrogen Energy In Press, Corrected Proof.

Lin, Z., J. Ogden, et al. "The fuel-travel-back approach to hydrogen station siting." International Journal of Hydrogen Energy In Press, Corrected Proof.

Linnemann, J. and R. Steinberger-Wilckens (2007). "Realistic costs of wind-hydrogen vehicle fuel production." International Journal of Hydrogen Energy 32(10-11): 1492-1499.

Lipman, T. E., D. M. Kammen, et al. (2004). An Integrated Hydrogen Vision for California. Institute of Transportation Studies, University of California, Davis. Research Report UCD-ITS-RR-04-43

Lloyd, A. C., J. H. Leonard, et al. (1994). "Fuel cells and air quality: a California perspective." Journal of Power Sources 49(1-3): 209-223.

McCarthy, R. W., C. Yang, et al. (2008). Assessing Strategies for Fuel and Electricity Production in a California Hydrogen Economy. Institute of Transportation Studies, University of California, Davis. Research Report UCD-ITS-RP-08-12

Melaina, M. W. (2003). "Initiating hydrogen infrastructures: preliminary analysis of a sufficient number of initial hydrogen stations in the US." International Journal of Hydrogen Energy 28(7): 743-755.

Melaina, M. W. (2005). Initiating hydrogen infrastructures: Analysis of technology dynamics during the introduction of hydrogen fuel for passenger vehicles, University of Michigan. PhD Dissertation.

Melaina, M. W. and J. Bremson (2006). Regularities in early hydrogen station size distributions. Energy in a World of Changing Costs and Technologies. 26th North American Conference. Ann Arbor, Michigan, International Association of Energy Economics.

Melendez, M. and A. Milbrandt (2006). Geographically Based Hydrogen Consumer Demand and Infrastructure Analysis. National Renewable Energy Laboratory. Technical Report NREL/TP-540-40373

Mintz, M. (2007). Modeling Infrastructure Expansion and H2A Delivery Pathways. presented at the IEA/IPHE Workshop: Building the Hydrogen Economy, Enabling Infrastructure Development. Detroit, MI, , April 3, 2007.

National Research Council (NRC) (2004). The Hydrogen Economy: Opportunities, Costs, Barriers, and R&D Needs. Washington, D.C., The National Academies Press.

Nicholas, M., S. Handy, et al. (2004). "Using Geographic Information Systems to Evaluate Siting and Networks of Hydrogen Stations." Transportation Research Record(1880): 126-134.

Nicholas, M. A. and J. M. Ogden (2007). "Detailed Analysis of Urban Station Siting for California Hydrogen Highway Network." Transportation Research Record 2006(1983): 129 - 139.

Office of Highway Policy Information Federal Highway Administration. Highway Performance Monitoring System. (http://www.fhwa.dot.gov/policy/ohpi/hpms/index.htm). Accessed in 2006

Office of Highway Policy Information Federal Highway Administration. Highway Performance Monitoring System. (http://www.fhwa.dot.gov/policy/ohpi/hpms/index.htm). Accessed in 2006

Ogden, J. (2006). High Hopes for Hydrogen. Scientific American. September, 2006.

Ogden, J. (2008). Review of Hydrogen Infrastructure Cost and Transition Models. Institute of Transportation Studies, University of California, Davis. (report forthcoming)

Ogden, J., D. Sperling, et al. (2004a). Where Will the Hydrogen Come From? System Considerations and Hydrogen Supply. The Hydrogen Energy Transition. Burlington, Academic Press: 73-92.

Ogden, J. M. (1999b). "Developing an infrastructure for hydrogen vehicles: a Southern California case study." International Journal of Hydrogen Energy 24(8): 709-730.

Ogden, J. M. (1999a). Prospects for Building a Hydrogen Energy Infrastructure. 24: 227-279.

Ogden, J. M., T. G. Kreutz, et al. (2000). "Fuels for fuel cell vehicles." Fuel Cells Bulletin 3(16): 5-13.

Ogden, J. M., M. M. Steinbugler, et al. (1999c). "A comparison of hydrogen, methanol and gasoline as fuels for fuel cell vehicles: implications for vehicle design and infrastructure development." Journal of Power Sources 79(2): 143-168.

Ogden, J. M. and R. H. Williams (1989). Solar Hydrogen : Moving Beyond Fossil Fuels. Washington DC, World Resources Institute.

Ogden, J. M., R. H. Williams, et al. (2004b). "Societal lifecycle costs of cars with alternative fuels/engines." Energy Policy 32(1): 7-27.

ORNL. (Annual Reports). Transportation Energy Book. Oak Ridge National Laboratories, U.S. Department of Energy. (www-cta.ornl.gov/data). Accessed

Owen, S. H. and M. S. Daskin (1998). "Strategic facility location: A review." European Journal of Operational Research 111(3): 423-447.

Parker, N. (2004). Using Natural Gas Transmission Pipeline Costs to Estimate Hydrogen Pipeline Costs. ITS-Davis. UCD-ITS-RR-04-05.

Parker, N. (2007). Optimizing the Design of Biomass Hydrogen Supply Chains Using Real-World Spatial Distributions: A Case Study Using California Rice Straw. Institute of Transportation Studies, University of California, Davis. Research Report UCD-ITS-RR-07-04

Parks, K. (2006). Hydrogen Deployment System Modeling Environment (HyDS ME) Documentation. National Renewable Energy Laboratory. Milestone Report NREL/MP-560-40763

Paster, M. (2006). Hydrogen Delivery Options and Issues. presented at USDOE Hydrogen Transition Analysis Workshop. Washington, DC, August 9-10, 2006.

Persky, J. (1992). "Retrospectives: Pareto's Law." The Journal of Economic Perspectives 6(2): 181-192.

Pezzey, J. C. V. and M. A. Toman (2001). Progress and problems in the economics of sustainability. International Yearbook of Environmental and Resource Economics 2002/2003. T. T.H. and H. Folmer. Cheltenham, Edward Elgar.

Pigou, A. C. (1932). The Economics of Welfare. London, Macmillan and Co.

Plotkin, S. E. (2007). Examining hydrogen transitions. Argonne National Laboratory ANL-07/09

Putsche, C. P. V. (1999). Survey of the economics of hydrogen technologies. National Renewable Energy Laboratory.

ReVelle, C. S. and H. A. Eiselt (2005). "Location analysis: A synthesis and survey." European Journal of Operational Research 165(1): 1-19.

ReVelle, C. S., H. A. Eiselt, et al. (2008). "A bibliography for some fundamental problem categories in discrete location science." European Journal of Operational Research 184(3): 817-848.

Romm, J. (2006). "The car and fuel of the future." Energy Policy 34(17): 2609-2614.

Rosing, K. E. (1992). "An optimal method for solving the (generalized) multi-Weber problem." European Journal of Operational Research 58(3): 414-426.

Rousseau, A. P., R. Ahluwalia, et al. (2004). Comparing Apples to Apples: Well-To-Wheel Analysis of Current Ice and Fuel Cell Vehicle Technologies. Fuel Cell Power for Transportation 2004, SAE International.

Samuelson, P. A. and W. D. Nordhaus (2004). Economics, McGraw-Hill/Irwin.

Scott, A. J. (1971). "Dynamic location - allocation systems: some basic planning strategies." Environment and Planning 3(1).

Secomandi, N. (2000). "Comparing neuro-dynamic programming algorithms for vehicle routing problem with stochastic demands." Computers and Operations Research 27(2000): 1201-1225.

Sen, A. K. (1970). Collective choice and social welfare, Holden-Day.

Shay, C., J. DeCarolis, et al. (2006). EPA U.S. National MARKAL Database: Database Documentation. U.S. Environmental Protection Agency, Office of Research and Development. EPA-600/R-06/057

Shayegan, S., D. Hart, et al. (2006). "Analysis of the cost of hydrogen infrastructure for buses in London." Journal of Power Sources 157(2): 862-874.

Simbeck, D. and E. Chang (2002). Hydrogen Supply: Cost Estimate for Hydrogen Pathways. SFA Pacific, Inc. Report to National Renewable Energy Laboratory, NREL/SR-540-32525

Singh, M. K., J. S. Moore, et al. (2005). Hydrogen Demand, Production and Costs by Region to 2050. TRB 2005 Annual Meeting, Washington, D.C., Transportation Research Board.

Small, K. A. and C. Kazimi (1995). "On the Costs of Air Pollution from Motor Vehicles." Journal of Transport Economics and Policy 29(1): 7.

Smith, L. A., N. Gupta, et al. (2001). Engineering and Economic Assessment of Carbon Dioxide Sequestration in Saline Formations. First National Conference on Carbon Sequestration. Washington D.C.

Solomon, B. D. and A. Banerjee (2006). "A global survey of hydrogen energy research, development and policy." Energy Policy 34(7): 781-792.

Southern California Association of Governments. Regional Data. (http://www.scag.ca.gov/resources.htm). Accessed in 2006

Sperling, D. and J. S. Cannon (2004). The Hydrogen Energy Transition, Academic Press.

Sperling, D. and R. Kitamura (1986). "Refueling and new fuels: An exploratory analysis." Transportation Research Part A: General 20(1): 15-23.

Stavins, R. N., A. F. Wagner, et al. (2003). "Interpreting sustainability in economic terms: dynamic efficiency plus intergenerational equity." Economics Letters 79(3): 339-343.

Stern, N. H. (2007). The Economics of Climate Change: The Stern Review Cambridge University Press.

Sutton, R. S. and A. G. Barto (1998). Reinforcement Learning (Adaptive Computation and Machine Learning), The MIT Press.

Sweeney, D. J. and R. L. Tatham (1976). "An Improved Long-Run Model for Multiple Warehouse Location." Management Science 22(7): 748-758.

Thomas, C. E., B. D. James, et al. (2000). "Fuel options for the fuel cell vehicle: hydrogen, methanol or gasoline?" International Journal of Hydrogen Energy 25(6): 551-567.

Tseng, P., J. Lee, et al. (2005). "A hydrogen economy: opportunities and challenges." Energy 30(14): 2703-2720.

Tsitsiklis, J. N. and B. V. Roy (1997). "An analysis of temporal difference learning with function approximation." IEEE Transactions on Automatic Control 42(5): 674-690.

Tsuchiya, H. and O. Kobayashi (2004). "Mass production cost of PEM fuel cell by learning curve." International Journal of Hydrogen Energy 29(10): 985-990.

Turrentine, T. S. and K. S. Kurani (2007). "Car buyers and fuel economy?" Energy Policy 35(2): 1213-1223.

Tzimas, E., P. Castello, et al. (2007). "The evolution of size and cost of a hydrogen delivery infrastructure in Europe in the medium and long term." International Journal of Hydrogen Energy 32(10-11): 1369-1380.

US Bureau of the Census (US Census) (2002). Economic Census.

Vermeulen, J., B. Boon, et al. (2004). The Price of Transport: Overview of the Social Costs of Transport. CE. Publication number: 04.4850.40

Victoria Transport Policy Institute (VTPI). (2006). Transportation Cost and Benefit Analysis. (http://www.vtpi.org/tca/). Accessed in 2006

von Helmolt, R. and U. Eberle (2007). "Fuel cell vehicles: Status 2007." Journal of Power Sources 165(2): 833-843.

Wang, M. (2002). "Fuel choices for fuel-cell vehicles: well-to-wheels energy and emission impacts." Journal of Power Sources 112(1): 307-321.

Wang, M. Q., D. J. Santini, et al. (1994). Methods of valuing air pollution and estimated monetary values of air pollutants in various U.S. regions. Argonne National Lab. ANL/ES/CP--83898

Welch, C. (2006). Lessons Learned from Alternative Transportation Fuels: Modeling Transition Dynamics. National Renewable Energy Laboratory. Technical Report NREL/TP-540-39446

Welch, C. (2007). Discrete Choice Analysis: H2FCV Demand Potential. USDOE H2Scenario Analysis Workshop. Washington, DC, January 31, 2007.

Wesolowsky, G. (1993). "The Weber problem: History and perspective." Location Science 1: 5-23.

Wesolowsky, G. O. and W. G. Truscott (1976). "The multiperiod location-allocation problem with relocation of facilities." Management Science 22(1): 57-65.

Wietschel, M., U. Hasenauer, et al. (2006). "Development of European hydrogen infrastructure scenarios--CO2 reduction potential and infrastructure investment." Energy Policy 34(11): 1284-1298.

Williams, B. D. and K. S. Kurani (2007). "Commercializing light-duty plug-in/plug-out hydrogen-fuel-cell vehicles: "Mobile Electricity" technologies and opportunities." Journal of Power Sources 166(2): 549-566.

Wood, F. (2006). Overview of NEMS-H2, Version 1.0. DOE Hydrogen Transition Analysis Workshop, January 26, 2006.

Yang, C., M. A. Nicholas, et al. (2006). Comparison of Idealized and Real-World City Station Citing Models for Hydrogen Distribution. National Hydrogen Association Annual Hydrogen Conference Long Beach, National Hydrogen Association.

Yang, C. and J. Ogden (2007a). "Determining the lowest-cost hydrogen delivery mode." International Journal of Hydrogen Energy 32(2): 268-286.

Yang, C. and J. Ogden (2007b). US Urban Hydrogen Infrastructure Costs Using The Steady State City Hydrogen Infrastructure System Model (SSCHISM). presented at the 2007 National Hydrogen Association Meeting. San Antonio, TX, March 18-22, 2007.

APPENDIX A: DATA TABLE

Appendix Table 1: Vehicle Population and VMT by Age

Age	Vehicle Population Share	Daily VMT
25	0.00%	21.8
24	0.00%	22.2
23	0.14%	22.5
22	0.52%	23.1
21	0.90%	23.6
20	1.29%	24.2
19	1.67%	24.6
18	2.05%	25.1
17	2.43%	25.7
16	2.82%	26.2
15	3.20%	27.1
14	3.58%	27.9
13	3.97%	28.8
12	4.35%	29.7
11	4.73%	30.6
10	5.11%	31.7
9	5.50%	32.9
8	5.88%	34.2
7	6.26%	35.7
6	6.64%	37.3
5	7.03%	39.3
4	7.41%	41.7
3	7.79%	44.7
2	8.17%	49.1
1	8.56%	56.4

Source: EMFAC2007 model (CARB, 2006)

Appendix Table 2: Vehicle Sale and Fuel Demand Projection

Year	Total Annual VMT (million VMT)[a]	Total Vehicle Pop (1000 unit)	Total Vehicle Sale (1000 unit)	Gas Vehicle Sale (1000 unit)	FCV Sale (1000 unit)[b]	Total Gas Vehicle (1000 unit)	Total FC Vehicle (1000 unit)	Gasoline Demand (million gallon/yr)	Hydrogen Demand (million gge/yr)
2010	164308	12151	1040	1040	0.0	12151	0	7584	0.0
2011	166378	12304	1053	1053	0.0	12304	0	7473	0.0
2012	168448	12457	1066	1065	1.0	12456	1	7377	0.3
2013	170517	12610	1079	1077	2.0	12607	3	7293	0.9
2014	172587	12763	1092	1090	2.0	12758	5	7222	1.3
2015	174656	12916	1105	1080	25.0	12887	30	7146	8.6
2016	176726	13069	1118	1078	40.0	13001	69	7073	19.3
2017	178795	13223	1132	1082	50.0	13106	116	7007	31.5
2018	180865	13376	1145	1060	85.0	13178	197	6929	52.7
2019	182934	13529	1158	1038	120.0	13219	310	6841	81.6
2020	185004	13682	1171	1011	160.0	13223	459	6743	118.8
2021	187074	13835	1184	994	190.0	13203	631	6644	160.4
2022	189143	13988	1197	987	210.0	13171	817	6551	203.1
2023	191213	14141	1210	960	250.0	13106	1035	6450	253.1
2024	193282	14294	1223	953	270.0	13030	1264	6356	303.4
2025	195352	14447	1236	936	300.0	12935	1512	6263	357.2
2026	197421	14600	1249	883	366.4	12786	1814	6143	425.1
2027	199491	14753	1262	833	429.6	12587	2166	6004	503.9
2028	201560	14906	1276	773	502.1	12333	2573	5843	595.2
2029	203630	15059	1289	706	582.2	12019	3040	5656	699.6
2030	205700	15212	1302	634	667.4	11643	3569	5437	817.3
2031	207769	15365	1315	560	754.4	11207	4158	5187	947.1
2032	209839	15518	1328	488	840.0	10716	4803	4912	1087.5
2033	211908	15671	1341	420	920.8	10178	5493	4616	1235.8
2034	213978	15824	1354	340	1014.4	9585	6240	4293	1395.1
2035	216047	15977	1367	268	1098.8	8949	7028	3953	1561.2
2036	218117	16130	1380	207	1173.1	8285	7845	3605	1730.4
2037	220186	16284	1393	157	1236.9	7608	8676	3258	1899.4
2038	222256	16437	1407	116	1290.9	6928	9508	2919	2065.4
2039	224325	16590	1420	84	1335.7	6258	10331	2592	2225.9
2040	226395	16743	1433	60	1372.4	5608	11134	2284	2379.3
2041	228465	16896	1446	44	1402.1	4986	11910	1997	2524.1
2042	230534	17049	1459	33	1426.0	4397	12652	1734	2659.6
2043	232604	17202	1472	27	1445.1	3847	13355	1495	2785.2
2044	234673	17355	1485	25	1460.2	3339	14016	1282	2900.7
2045	236743	17508	1498	26	1472.1	2877	14631	1094	3005.9
2046	238812	17661	1511	20	1491.5	2453	15208	924	3103.9
2047	240882	17814	1524	16	1508.9	2069	15745	773	3194.4
2048	242951	17967	1538	13	1524.7	1728	16239	641	3277.4
2049	245021	18120	1551	11	1539.2	1429	16691	528	3352.9
2050	247091	18273	1564	11	1552.7	1170	17103	431	3421.5
2051	249160	18426	1577	11	1565.4	951	17475	351	3483.6
2052	251230	18579	1590	12	1577.5	769	17810	286	3539.7
2053	253299	18732	1603	14	1589.2	622	18111	235	3590.4
2054	255369	18885	1616	16	1600.5	505	18381	195	3636.3
2055	257438	19038	1629	18	1611.5	416	18623	166	3678.0
2056	259508	19191	1642	10	1632.3	341	18851	139	3719.1
2057	261577	19345	1655	3	1652.9	277	19068	113	3759.6

2058	263647	19498	1669	0	1668.5	225	19272	91	3798.3
2059	265717	19651	1682	0	1681.6	185	19465	75	3835.1
2060	267786	19804	1695	0	1694.7	154	19649	62	3870.4

Source: a. 2010-2030 from California Department of Transportation (Caltrans, 2005); 2031-2060 based on extrapolation.
b. 2012-2025 from the DOE Scenario 3 (Gronich, 2006); else from projection based on 100% penetration in 2060.

Appendix Table 3: Facility Capital Cost (million USD)

Year	Station Site*	REFSTA	D-SMR	D-ELE	C-ELE	C-SMR	C-SMRCCS	C-BIO	C--BIOCCS	C-COALCCS
Size (kg/d)	5000	500	500	500	$1.4*10^6$	$1.4*10^6$	$1.4*10^6$	$1.4*10^6$	$1.4*10^6$	$1.4*10^6$
2010-14	0.602	0.325	1.494	1.922	1904	511	703	790	912	1336
2015-19	0.602	0.308	1.356	1.639	1584	484	661	753	869	1273
2020-24	0.602	0.292	1.232	1.386	1297	459	623	720	831	1218
2025-29	0.602	0.278	1.123	1.162	1044	438	589	691	798	1169
2030-34	0.602	0.266	1.028	0.969	824	419	560	666	769	1126
2035-39	0.602	0.256	0.948	0.805	639	403	536	645	744	1090
2040-44	0.602	0.248	0.882	0.671	487	390	516	627	724	1060
2045-49	0.602	0.241	0.832	0.566	369	380	500	614	708	1038
2050-54	0.602	0.237	0.795	0.492	284	373	489	604	697	1021
2055-59	0.602	0.234	0.773	0.447	234	369	482	598	690	1011
2060+	0.602	0.233	0.766	0.432	217	367	480	596	688	1008

* represents the capital cost of opening a site for adding up to modules

Source: 2010-2014 data from H2A (2006) model; ratio of 2060 vs 2010 from (NRC, 2004)

Appendix Table 4: Hydrogen Pipeline Data

		Trunk Pipeline Segment			Local Delivery Pipeline per Station		
Node	Land Type	Length mile	Diameter inch	Capital Cost million USD	Length mile	Diameter inch	Capital Cost million USD
1	Rural	1.93	4.75	1.02	1.62	1.50	0.82
2	Rural	13.79	14.75	10.54	1.36	1.50	0.79
3	Rural	1.84	10.50	1.34	0.29	1.25	0.44
4	Urban	1.45	10.00	1.44	1.33	1.50	0.99
5	Rural	3.64	7.25	1.88	1.19	1.50	0.71
6	Rural	2.51	5.50	1.28	0.55	1.25	0.51
7	Rural	4.97	11.50	3.24	0.75	1.25	0.58
8	Rural	17.80	16.50	15.22	1.38	1.50	0.80
9	Rural	32.98	17.25	29.34	2.76	1.75	1.27
10	Rural	22.04	17.25	19.72	2.75	1.75	1.26
11	Rural	16.60	7.00	7.18	3.69	1.75	1.46
12	Rural	34.16	5.75	13.12	5.27	2.00	1.93
13	Rural	11.55	11.50	7.07	2.59	1.75	1.16
14	Rural	2.55	3.25	1.15	1.99	1.50	0.92
15	Rural	16.60	8.00	7.72	0.84	1.50	0.60
16	Urban	2.53	11.25	2.33	1.26	1.50	0.97
17	Rural	5.47	8.00	2.78	0.55	1.25	0.52
18	Urban	11.11	15.25	11.50	1.02	1.50	0.89
19	Urban	1.59	4.50	1.16	0.00	0.00	0.46
20	Urban	2.93	3.75	1.69	0.65	1.25	0.70
21	Urban	1.20	3.50	0.96	0.42	1.25	0.62
22	Urban	0.69	8.00	0.86	0.43	1.25	0.63
23	Urban	0.29	2.25	0.57	0.50	1.25	0.64

24	Urban	0.52	3.00	0.67	0.39	1.25	0.60
25	Urban	1.55	3.00	1.08	0.29	1.25	0.57
26	Urban	4.48	11.25	3.78	0.59	1.25	0.70
27	Urban	2.59	4.50	1.61	0.40	1.25	0.61
28	Urban	4.22	7.50	2.80	0.43	1.25	0.63
29	Rural	4.12	11.75	2.79	0.66	1.25	0.56
30	Urban	3.11	11.50	2.81	0.67	1.25	0.73
31	Rural	1.09	2.50	0.68	0.56	1.25	0.51
32	Urban	1.22	1.50	0.91	0.28	1.25	0.56
33	Urban	3.71	3.75	2.02	0.58	1.25	0.68
34	Urban	50.85	20.00	70.11	0.44	1.25	0.65
35	Rural	63.56	21.50	73.93	1.55	1.50	0.88
36	Rural	9.45	5.50	3.82	1.27	1.50	0.72
37	Urban	13.23	13.25	11.85	0.81	1.50	0.79
38	Rural	7.03	13.25	5.01	0.84	1.50	0.62
39	Rural	10.79	13.75	7.77	0.84	1.50	0.62
40	Urban	3.30	10.00	2.69	0.53	1.25	0.67
41	Urban	1.88	10.25	1.75	0.77	1.25	0.77
42	Urban	8.75	13.25	7.99	1.12	1.50	0.92
43	Rural	3.26	8.00	1.80	0.55	1.25	0.52
44	Urban	5.27	7.00	3.28	0.78	1.25	0.76
45	Urban	3.85	4.50	2.17	0.85	1.50	0.78
46	Urban	1.36	2.00	0.97	1.03	1.50	0.84
47	Rural	0.93	8.50	0.79	0.88	1.50	0.62
48	Urban	3.56	11.25	3.10	0.73	1.25	0.75
49	Urban	7.77	5.25	4.10	1.06	1.50	0.86
50	Urban	4.23	9.75	3.26	0.40	1.25	0.62
51	Rural	64.71	18.75	63.23	0.60	1.25	0.55
52	Urban	3.04	4.25	1.79	1.07	1.50	0.86
53	Urban	1.44	2.50	1.02	0.51	1.25	0.65
54	Urban	2.12	3.50	1.34	0.46	1.25	0.63
55	Urban	3.02	7.00	2.07	0.38	1.25	0.61
56	Urban	1.06	3.25	0.89	0.40	1.25	0.61
57	Urban	3.68	6.50	2.35	0.00	0.00	0.46
58	Urban	1.80	8.50	1.54	0.00	0.00	0.46
59	Urban	1.02	5.75	0.96	0.54	1.25	0.66
60	Urban	1.37	8.25	1.27	0.00	0.00	0.46
61	Urban	1.56	4.50	1.15	0.88	1.50	0.79
62	Urban	2.66	4.25	1.62	0.74	1.25	0.73
63	Urban	3.58	2.50	1.84	1.12	1.50	0.87
64	Urban	1.25	8.00	1.18	0.62	1.25	0.70
65	Urban	2.47	5.50	1.64	0.37	1.25	0.60
66	Rural	4.73	12.75	3.37	0.41	1.25	0.48
67	Rural	21.53	11.75	13.10	2.15	1.75	1.03
68	Rural	29.95	14.75	22.46	2.62	1.75	1.20
69	Rural	2.79	10.25	1.83	0.66	1.25	0.55
70	Urban	0.64	3.00	0.71	0.25	1.00	0.55
71	Urban	1.27	6.00	1.09	0.38	1.25	0.60
72	Urban	5.01	7.25	3.19	0.49	1.25	0.65
73	Urban	0.23	4.50	0.56	0.46	1.25	0.63
74	Urban	2.15	8.25	1.73	0.37	1.25	0.60
75	Urban	2.89	5.25	1.81	0.50	1.25	0.65
76	Urban	4.34	9.00	3.17	0.76	1.25	0.76
77	Urban	3.93	3.75	2.11	0.61	1.25	0.69
78	Rural	74.74	22.50	92.33	1.07	1.50	0.72
79	Rural	4.72	3.25	1.83	1.67	1.50	0.83
80	Rural	2.33	11.00	1.66	0.66	1.25	0.56
81	Urban	4.78	12.25	4.28	0.00	0.00	0.46
82	Urban	1.34	9.75	1.34	0.59	1.25	0.69
83	Urban	0.99	9.00	1.08	0.00	0.00	0.46
84	Urban	5.55	13.00	5.15	0.66	1.25	0.73
85	Urban	1.64	3.75	1.15	0.38	1.25	0.60
86	Urban	1.76	5.00	1.27	0.48	1.25	0.64
87	Rural	14.15	13.25	9.72	1.09	1.50	0.70
88	Rural	6.23	11.75	4.04	1.21	1.50	0.73
89	Urban	1.98	5.25	1.39	0.34	1.25	0.59

90	Urban	7.03	11.00	5.57	0.86	1.50	0.80
91	Urban	3.35	4.75	1.97	0.49	1.25	0.64
92	Urban	0.28	2.25	0.57	0.34	1.25	0.59
93	Urban	4.99	4.50	2.67	1.19	1.50	0.91
94	Rural	3.13	10.25	2.01	0.74	1.25	0.58
95	Rural	17.88	9.75	9.44	1.07	1.50	0.68
96	Urban	2.26	5.50	1.54	0.53	1.25	0.66
97	Urban	1.82	7.75	1.49	0.46	1.25	0.64
98	Urban	5.61	10.25	4.31	0.58	1.25	0.69
99	Urban	6.06	12.25	5.30	0.83	1.50	0.80
100	Urban	1.59	4.75	1.18	0.35	1.25	0.59
101	Urban	2.47	10.25	2.16	0.39	1.25	0.61
102	Urban	1.30	4.50	1.04	0.56	1.25	0.67
103	Urban	3.30	9.25	2.56	0.37	1.25	0.61
104	Urban	3.15	4.00	1.81	0.53	1.25	0.66
105	Urban	4.02	8.75	2.92	0.00	0.00	0.46
106	Rural	2.78	11.50	1.97	0.51	1.25	0.51
107	Rural	1.76	2.50	0.88	0.82	1.50	0.59
108	Urban	3.07	8.50	2.30	0.97	1.50	0.84
109	Urban	2.57	10.00	2.19	0.30	1.25	0.58
110	Urban	2.19	7.75	1.70	0.29	1.25	0.57
111	Urban	5.97	7.00	3.65	0.42	1.25	0.62
112	Urban	2.62	4.50	1.62	0.61	1.25	0.69
113	Urban	14.90	10.50	10.89	0.47	1.25	0.65
114	Urban	1.02	9.00	1.10	0.38	1.25	0.61
115	Urban	3.95	3.00	2.04	0.99	1.50	0.83
116	Urban	8.75	11.25	6.95	0.65	1.25	0.72
117	Urban	6.98	5.50	3.79	0.60	1.25	0.68
118	Urban	2.69	8.00	2.01	0.46	1.25	0.64
119	Urban	2.10	3.50	1.33	0.48	1.25	0.64
120	Urban	0.86	6.25	0.90	0.00	0.00	0.46
121	Urban	2.58	4.50	1.60	0.39	1.25	0.60
122	Urban	1.63	2.75	1.10	0.45	1.25	0.62
123	Urban	4.99	11.25	4.16	0.39	1.25	0.61
124	Rural	1.54	2.00	0.80	0.81	1.50	0.58
125	Urban	4.70	10.25	3.69	0.50	1.25	0.66
126	Urban	1.08	7.75	1.07	0.35	1.25	0.60
127	Urban	2.18	3.50	1.36	0.47	1.25	0.63
128	Urban	0.75	7.75	0.89	0.26	1.00	0.56
129	Urban	2.63	3.75	1.57	0.47	1.25	0.64
130	Urban	2.17	4.00	1.39	0.50	1.25	0.65
131	Urban	2.15	4.50	1.42	0.42	1.25	0.62
132	Urban	2.68	4.75	1.67	0.47	1.25	0.64
133	Urban	2.26	5.50	1.54	0.37	1.25	0.60
134	Urban	6.03	6.25	3.50	0.55	1.25	0.67
135	Urban	3.12	3.25	1.73	0.54	1.25	0.66
136	Urban	1.26	7.00	1.13	0.35	1.25	0.59
137	Urban	1.21	5.00	1.02	0.50	1.25	0.65
138	Urban	2.72	9.50	2.23	0.41	1.25	0.62
139	Rural	5.90	11.75	3.85	0.70	1.25	0.57
140	Urban	5.83	12.75	5.29	0.56	1.25	0.69
141	Urban	5.46	10.50	4.28	0.64	1.25	0.71
142	Rural	5.76	11.00	3.57	0.55	1.25	0.52
143	Urban	3.30	2.50	1.73	1.05	1.50	0.85
144	Rural	1.47	9.50	1.09	0.34	1.25	0.46
145	Urban	2.68	3.50	1.57	0.78	1.25	0.75
146	Rural	5.10	12.25	3.49	0.87	1.50	0.63
147	Urban	3.63	2.50	1.86	1.25	1.50	0.92
148	Rural	17.67	13.75	12.49	1.54	1.50	0.84
149	Rural	3.94	6.25	1.88	0.95	1.50	0.63
150	Rural	5.34	3.00	1.99	1.82	1.50	0.87
151	Rural	14.88	6.75	6.35	1.94	1.50	0.93
152	Urban	20.61	14.25	19.54	0.99	1.50	0.87
153	Urban	0.72	2.25	0.73	1.45	1.50	0.99
154	Urban	1.88	1.75	1.15	0.32	1.25	0.58
155	Urban	1.85	8.00	1.53	0.60	1.25	0.69

156	Urban	2.29	4.75	1.50	0.47	1.25	0.64
157	Rural	2.41	3.25	1.11	0.82	1.50	0.59
158	Rural	70.06	18.25	66.21	5.33	2.00	2.15
159	Rural	51.74	5.25	18.98	4.86	2.00	1.80
160	Rural	71.98	22.50	88.93	3.62	1.75	1.61
161	Urban	1.81	6.75	1.41	0.26	1.00	0.56
162	Urban	2.41	8.25	1.88	0.38	1.25	0.61
163	Urban	2.36	6.50	1.68	0.63	1.25	0.70
164	Urban	3.87	3.00	2.00	0.87	1.50	0.78
165	Urban	3.44	4.00	1.93	0.67	1.25	0.71
166	Rural	20.62	6.50	8.51	1.60	1.50	0.83
167	Rural	5.01	13.00	3.61	1.73	1.50	0.90
168	Urban	4.57	7.00	2.90	0.71	1.25	0.73

Note: hydrogen pipeline inlet pressure is about 1000 psia according to (H2A, 2009)

Appendix Table 5: CO2 Pipeline Data

plant location index		1	2	3	4	5	6	7	8	9
length (mile)		160	158	119	205	84	130	48	20	0
diameter (inch)	C-BIOCCS	31.25	31.25	29.50	33.00	27.50	30.00	24.50	20.75	0.00
	C-COALCCS	26.00	26.00	24.50	27.25	23.00	25.00	20.50	17.25	0.00
	C-SMRCCS	20.25	20.25	19.25	21.25	17.75	19.50	16.00	13.50	0.00
capital cost in 2010 (million USD)	C-BIOCCS	317.96	313.99	216.61	443.41	137.77	242.72	66.81	22.45	0.00
	C-COALCCS	241.48	238.47	165.10	331.22	106.86	185.55	52.56	17.93	0.00
	C-SMRCCS	171.64	169.50	119.82	234.04	76.72	133.00	39.06	13.84	0.00

Note: CO2 pipeline inlet pressure = 1500 psia (Smith et al, 2001)

Appendix Table 6: Pipeline Technology Improvement Curve

year	capital cost (2010 = 1)
2010-14	1
2015-19	0.94968
2020-24	0.90466
2025-29	0.86494
2030-34	0.83051
2035-39	0.80138
2040-44	0.77754
2045-49	0.75901
2050-54	0.74577
2055-59	0.73782
2060+	0.73517

*applied to hydrogen pipeline and CO2 pipeline

Source: 2010-2014 data from H2A (2007) model; ratio of 2060 vs 2010 from (NRC, 2004)

Appendix Table 7: CO2 Sequestration Capital Cost (million USD)

Year	plant technology		
	C-SMRCCS	C-BIOCCS	C-COALCCS

		at 1.4*10^6 kgH2/d	
2010-14	11.16	33.57	21.03
2015-19	10.60	31.88	19.97
2020-24	10.09	30.37	19.02
2025-29	9.65	29.03	18.19
2030-34	9.27	27.88	17.46
2035-39	8.94	26.90	16.85
2040-44	8.67	26.10	16.35
2045-49	8.47	25.48	15.96
2050-54	8.32	25.03	15.68
2055-59	8.23	24.77	15.51
2060+	8.20	24.68	15.46

Source: Dahowski, et al., 2004; NRC, 2004

Appendix Table 8: Fixed O&M Cost Factor

Technology	percentage of capital cost as fixed O&M cost
REFSTA	8%
D-SMR	3%
D-ELE	7%
C-ELE	5%
C-SMR	6%
C-SMRCCS	6%
C-BIO	7%
C-BIOCCS	7%
C-COALCCS	6%
hydrogen Pipeline	4%
CO2 Pipeline	4%
CO2 Sequestration	6%

Source: H2A, 2007; NRC, 2004

Appendix Table 9: Electricity Consumption (kWh/kgH2)

Year	REFSTA	D-SMR	D-ELE	C-ELE	C-SMR	C-BIO	C-SMRCCS	C-BIOCCS	C-COALCCS
2010-14	2.00	2.26	53.68	53.99	0.71	1.60	1.81	2.24	3.74
2015-19	1.91	2.15	52.94	52.63	0.68	1.45	1.72	2.04	3.36
2020-24	1.82	2.06	52.28	51.41	0.66	1.31	1.63	1.86	3.03
2025-29	1.75	1.97	51.70	50.33	0.64	1.19	1.56	1.70	2.73
2030-34	1.68	1.90	51.19	49.40	0.62	1.09	1.50	1.56	2.47
2035-39	1.63	1.84	50.76	48.61	0.60	1.00	1.44	1.44	2.26
2040-44	1.58	1.79	50.41	47.97	0.59	0.92	1.40	1.35	2.08
2045-49	1.55	1.75	50.14	47.46	0.58	0.87	1.36	1.27	1.94
2050-54	1.52	1.72	49.95	47.11	0.57	0.83	1.34	1.22	1.84
2055-59	1.51	1.71	49.83	46.89	0.57	0.80	1.32	1.19	1.78
2060+	1.50	1.70	49.79	46.82	0.57	0.80	1.32	1.18	1.76

Source: H2A, 2007; NRC, 2004

Appendix Table 10: Major Feedstock Consumption Rate (MMBtu/kgH2)

Year	D-SMR	C-SMR	C-BIO	C-SMRCCS	C-BIOCCS	C-COALCCS
	natural gas	natural gas	biomass	natural gas	biomass	coal
2010-14	0.2106	0.1658	0.2406	0.1755	0.2406	0.1730
2015-19	0.2048	0.1643	0.2245	0.1729	0.2245	0.1703
2020-24	0.1997	0.1630	0.2101	0.1706	0.2101	0.1678
2025-29	0.1952	0.1618	0.1974	0.1686	0.1974	0.1657
2030-34	0.1913	0.1608	0.1864	0.1668	0.1864	0.1638
2035-39	0.1880	0.1599	0.1771	0.1653	0.1771	0.1622
2040-44	0.1853	0.1592	0.1695	0.1641	0.1695	0.1609
2045-49	0.1832	0.1586	0.1636	0.1632	0.1636	0.1599
2050-54	0.1817	0.1582	0.1593	0.1625	0.1593	0.1592
2055-59	0.1808	0.1580	0.1568	0.1621	0.1568	0.1587
2060+	0.1805	0.1579	0.1559	0.1620	0.1559	0.1586

Source: H2A, 2007; NRC, 2004

Appendix Table 11: Feedstock Price

Feedstock	Price	Used by	Source
commercial electricity	11.92 ¢/kWh	REFSTA, D-SMR,	EIA (2006)
industry electricity	9.55 ¢/kWh	C-SMR, C-BIO, C-SMRCCS, C-BIOCCS, C-COALCCS, D-ELE, C-ELE	EIA (2006)
commercial natural gas	10.69 $/kcf	D-SMR	EIA (2006)
industry natural gas	9.84 $/kcf	C-SMR, C-SMRCCS	EIA (2006)
coal	23.30 $/short ton	C-COALCCS	EIA (2006)
biomass	46 $/bdt	C-BIO, C-BIOCCS	H2A (2007)

Appendix Table 12: Electricity Consumption for hydrogen liquefaction

Year	electricity consumption kWh/kgH2
2010-14	11
2015-19	10.43
2020-24	9.92
2025-29	9.47
2030-34	9.08
2035-39	8.75
2040-44	8.48
2045-49	8.27
2050-54	8.12
2055-59	8.03
2060+	8

Source: H2A, 2007; NRC, 2004

APPENDIX B: THE URBAN BEIJING CASE STUDY OF THE HIT MODEL

This appendix contains a paper presented at the NHA conference on the application of the HIT model to urban Beijing. The citation information of the paper is as follows:

> Zhenhong Lin, Joan Ogden, Yueyue Fan, Daniel Sperling, "The Hydrogen Infrastructure Transition (HIT) Model - Case Study in Beijing," Proceeding of the National Hydrogen Association Annual Conference, Long Beach, California, March 2006.

********************PAPER BEGINS*********************

THE HYDROGEN INFRASTRUCTURE TRANSITION (HIT) MODEL ---- CASE STUDY FOR URBAN BEIJING

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Abstract

We introduce the Hydrogen Infrastructure Transition (HIT) model and apply it to Beijing, China. The HIT model is a dynamic programming model that generates the spatial and temporal infrastructure buildup decisions that minimize the net present value of capital and operating costs, carbon taxes, and refueling travel time disbenefits over time. The HIT model incorporates regionally specific spatial data about road networks, traffic flows and hydrogen demand distribution to find optimal strategies for meeting an exogenously specified market penetration over time. Input assumptions can be varied to test the sensitivity of strategies to technological evolution, feedstock prices, carbon taxes, and market penetration rates.

We consider 4 scenarios: base case, increasing natural gas prices, rapid technology improvement, and rapid market penetration. For each scenario, we show 1) the least-cost spatial and temporal decisions generated by the HIT model; 2) the optimal infrastructure layout; 3) levelized costs over time; 4) well-to-wheel carbon emissions over time.

Our findings are as follows: 1) the starting infrastructure configuration for all the 4 scenarios during 2010 to 2014 (beginning of the planning horizon) is 30 onsite steam methane reformer (SMR) stations with 3 ton per day per station. These stations serve only hydrogen taxis and buses (assuming the government will first introduce hydrogen taxis and buses) and provide a basis to attract the private fuel cell vehicle purchase, which is assumed to start from year 2015. 2) Regional spatial features

have a significant impact on cost. Using a spanning tree optimization algorithm, we find that the high vehicle density and ring road network in urban Beijing can be served by a compact pipeline network with a total length of several hundred kilometers. This is shorter than previously reported pipeline designs. 3) Faster market penetration could make a better business case because scale economies in production and delivery can be taken advantage of earlier. 4) Carbon policy would need to keep pace with market penetration to avoid high CO2 emissions from coal gasification plants without carbon capture technology. If demand increases rapidly, a higher carbon tax might be needed to drive the adoption of carbon capture technology. 5) Faster technology improvement lowers cost. 6) For each scenario, we examine the levelized cost over time for a 12% rate of return. For the base case, the pricing policy of $2.8/kg from 2010 through 2019, $1.8/kg from 2020 through 2059 and $1.1/kg from 2060 onward could achieve a 12% rate of return, ignoring the effect of price on demand.

1. Introduction

Hydrogen as an alternative transportation fuel offers the prospects of reducing pollution, greenhouse gas, and oil use. Various studies [1-4] have considered principles, status, and cost estimates of H2I (hydrogen infrastructure) technologies. To analyze the regional H2I transition process, an end-state "static" approach usually assumes a fixed hydrogen demand for a single pathway. The static approach is simple and therefore widely adopted, but has significant limitations for understanding implementation of new fuels [5]. The H2I transition problem gets more complicated if we want to consider the spatial details: for example, does the travel behavior and road network layout in the region of interest allow a H2I with very low hydrogen distribution cost?

We have developed a new modeling program HIT (Hydrogen Infrastructure Transitions) to understand the dynamics of H2I transitions. We define the target modeling question for HIT: given demand for hydrogen as vehicle fuel over time as an exogenous variable, how to make the optimal decisions in terms of where, when, at what sizes and by what technologies to build up the production, distribution and dispensing component facilities of the hydrogen transportation fuel infrastructure? Based on dynamic programming, the HIT model generates the spatial and temporal infrastructure buildup decisions that minimize the net present value of capital and operating costs, carbon taxes, and refueling travel time disbenefits during a specified transition time. HIT considers spatial details such as road networks, traffic flows and hydrogen demand distribution, and other regional attributes such as feedstock prices and labor cost. Input assumptions can be varied to study how the optimal transition process depends on technology evolution, feedstock prices, carbon taxes, and market penetration rates.

We have applied the HIT model to study the H2I transition process in urban Beijing. Four scenarios are defined to investigate the effect of technology improvement, natural gas price, and market growth. Based on the observations, another scenario is added to investigate the effect of carbon tax policy. Results include the optimal decisions, the optimal 2060 infrastructure layout, the levelized costs over time, and the well-to-wheels (WTW) carbon emissions.

This paper provides a brief introduction to the HIT model and focuses on the case study of urban Beijing.

2. Model

The HIT model is built to generate the optimal-sequential-spatial decisions for a given set of exogenous projections, such as demand, technology, and carbon tax. Several engineering-economic sub-models are also developed to derive more results from the optimal-sequential-spatial decisions, such as levelized cost and WTW annual carbon emissions. FIG. 1 shows the external interface of the HIT model.

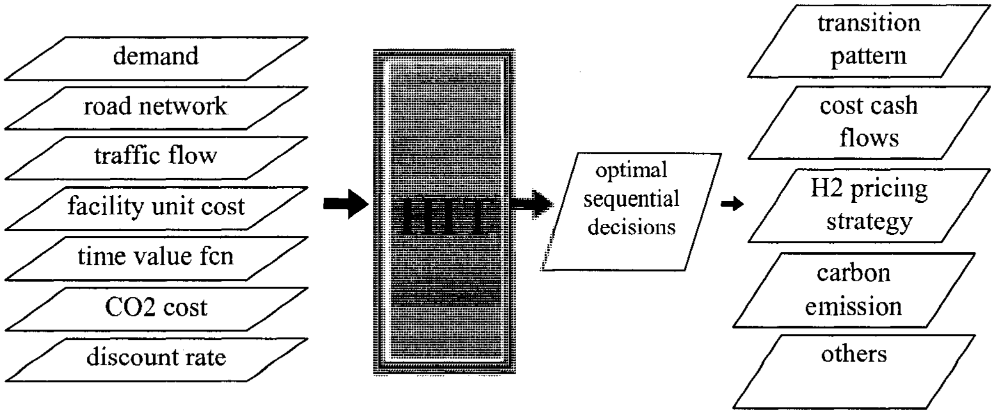

FIG. 1: HIT External Data Interface.

The core technique of HIT is dynamic programming, with the underlying reasoning being Principle of Optimality [6]: an optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state that is the same as the one resulting from the first decision.

The formulation of the HIT model is as follows. We consider several stages (time steps).

$$MNPV_t(S_t) = \min_{X_t} \left\{ TC_t(S_t, X_t) + SC_{t+1}(T(S_t, X_t)) + (1+r)^{-1} \cdot MNPV_{t+1}(T(S_t, X_t)) \right\}$$

$$MNPV_T(S_T) = SV(S_T)$$

$$SC_t = F_t + V_t + T_t + E_t$$

Where:

$MNPV_t$: the minimum cost from stage t to stage T (transition study period);

S_t : the system configuration at stage t;

TC_t: transition cost or marginal capital cost from stage t to $t+1$;

SC_{t+1}: stage cost or operating cost of stage $t+1$, sum of annual fixed cost F_{t+1}, feedstock variable cost V_{t+1}, travel time disbenefit T_{t+1}, and evnvironmental disbenefit E_{t+1};

X_t: decision variables at stage t on where, what sizes/how many, by which technology;

$SV(X_T)$: period-end future cost of the end configuration X_T. It is assumed that the system configuration keeps constant from stage T onward, so all the cost components (capital, operating, et al) will sum to periodic cash flows from stage T to infinite time. $SV(X_T)$ is obtained from these cash flows via capitalized cost method.

$T(S_t, X_t)$: transformation of the system state;

r: stage discount rate.

3. Case Study Data

3.1. Hydrogen Pathways

In the case study for Beijing, several options are considered for hydrogen supply:

- Onsite production of hydrogen at the refueling station by small-scale steam reforming of natural gas
- Onsite production of hydrogen at the refueling station by small-scale water electrolysis
- Central production of hydrogen by water electrolysis
- Central large scale production of hydrogen from coal with CO2 (carbon dioxide) vented to the atmosphere, and pipeline delivery of hydrogen to refueling stations
- Central production of hydrogen from coal with CO2 capture and sequestration with pipeline delivery of hydrogen to refueling stations

- Purchase of truck-delivered byproduct hydrogen from industrial operations

3.2. Four Scenarios

The transition study period is from 2010 to 2059. With 5 years per stage (time step), there are 10 stages with 2010-2014 as the first stage and 2055-2059 as the last stage. Four scenarios are identified to investigate the effect on the transition process of feedstock prices, technology improvements, and market growths. They are:

- Base: feedstock prices are assumed constant over time; 100% market penetration of hydrogen fuel cell vehicles occurs in 2060; technology improves over time; carbon tax rate change linearly from 20 USD/tonC (ton carbon) in 2005 to 120 USD/tonC in 2060.
- NG: natural gas price increase 50% per 5 years, affecting natural gas onsite station variable cost, as opposed to constant natural gas price in Base case.
- FastR&D: all the pathway technologies improve faster; facility cost decrease to the lowest in 2035, as opposed to 2060 in Base case.
- FastMarket: hydrogen demand grows faster; full penetration occurs in 2035, as opposed to 2060 in Base case.

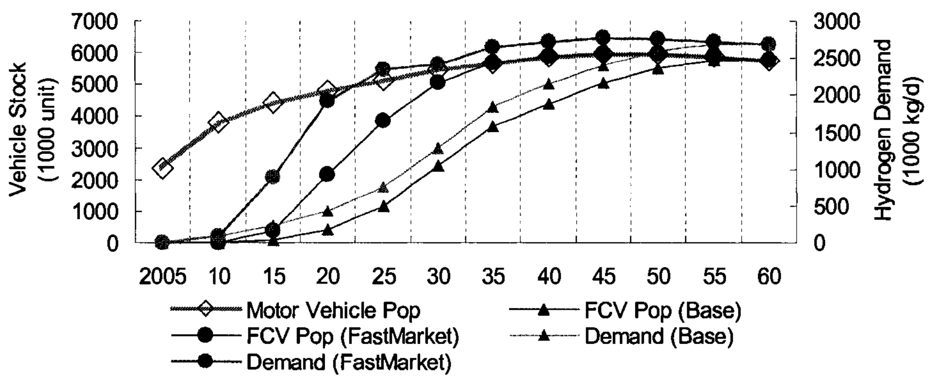

FIG. 2: Vehicle Population and Hydrogen Demand.

3.3. Demand

Based on information from Beijing Transportation Master Plan [7], the Beijing Municipal Commission of Population and Family Planning [8], and Zhu [9], we first project the vehicle population of light duty gasoline vehicles, light duty trucks, heavy duty gasoline vehicles, heavy duty diesel vehicles, and motorcycles. It is assumed that fuel cell buses and fuel cell taxes first enter the market, and private fuel cell cars then enter the market in 2015. The vehicle population and hydrogen demand are projected and shown in FIG. 2.

3.4. Road Network and Traffic Flow

The Beijing Urban Express Way Network is identified as the representative spatial transportation network of urban Beijing, as it serves 70%-80% of total motor vehicle traffic. It consists of 4 ring roads and 15 rapid connecting roads (4 of the 15 rapid connecting roads are still under construction), which are connected at 64 intersection nodes, as shown on **Error! Reference source not found.**. Each intersection node is attributed with a weight number that characterizes the relative priority of building refueling stations around the node. These weight numbers are calculated based on the road network structure and traffic distribution (traffic count data are obtained from [7, 10]), and denoted by the sizes of the green dots on FIG. 3.

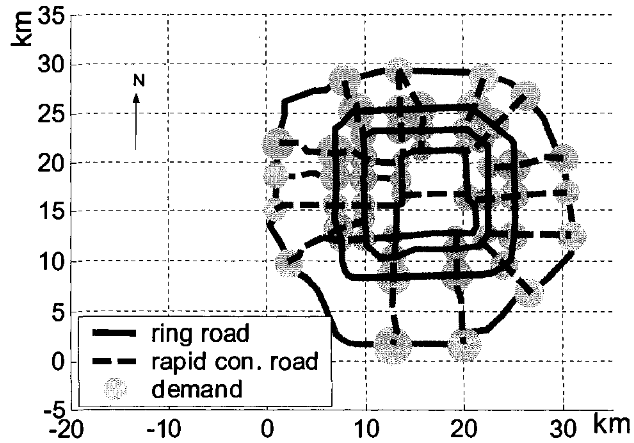

FIG. 3: Representative Network.

3.5. Facility Unit Cost

Technology improvement is quantified by decrease of facility unit cost over time, where facility unit is defined as an infrastructure component with a pre-defined size. Many of the available data on hydrogen infrastructure economics are based costs in the United States. For our case study in Beijing, the U.S. facility unit cost data from the National Academies Hydrogen Economy study (the NRC hydrogen study) [3] are adjusted to account for differing labor cost, productivity, material cost, and technology importation via a location factor of 0.7 [11], and listed in FORM 1. Facility unit costs decrease quadratically to the lowest in 2060 except for the FastR&D case, where facility unit costs decrease quadratically to the lowest in 2035 and then keep constant from 2035 to 2060. The capital costs over time for one coal plant are also plotted in FIG. 4 as an example.

We adopt a 12% discount rate in the Beijing case study.

3.6. Value Function for Refueling Travel Time

To consider trade-off between cost and consumer convenience, we use an exponential function to estimate the monetary disbenefit of refueling travel time. We calibrate he exponential function based on the assumptions: 1) 2 minutes per refueling trip (one way) is reasonable for consumers and therefore the refueling travel time could be treated as ordinary travel time; in this case, the disbenefit is calculated based on half of the average hour rate for a typical car owner in Beijing. Note that refueling time at the station is not counted; 2) if there is no travel time (an idealized case), then people don't mind a small increment in travel time, which means disbenefit per minute is zero if travel time is zero; 3) disbenefit per minute increases rapidly beyond some acceptable level (e.g. 10 minutes per trip). The calibrated travel time function is shown in FIG. 5.

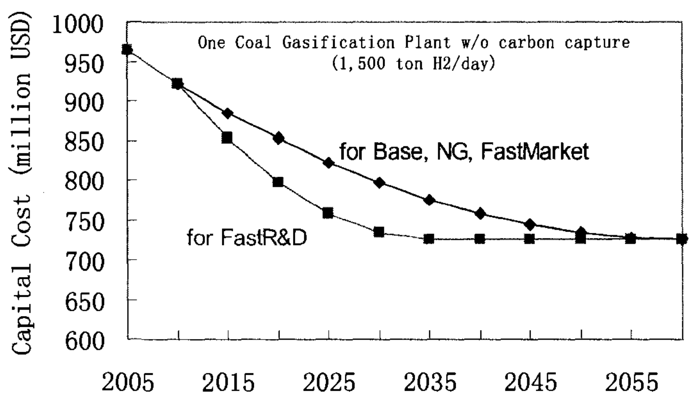

FIG. 4: Capital Cost Example

FORM 1 Facility unit capital cost

All in million USD (2000)	2010	2060 (2035 thru 2060 for FastR&D)
Pipeline-based Refueling Station (500 kg/d)	0.2982	0.2142
Ref. station with natural gas SMR onsite (500 kg/d)	1.3475	0.6965
Ref. station with water electrolysis onsite (500 kg/d)	1.8487	0.4277
Coal plant w/o C capture (1500 ton/d)	922.88	725.55

Coal plant w/ C capture (1500 ton/d)	946.89	746.27
Central plant via water electrolysis (100 ton/d)	179.47	24.154

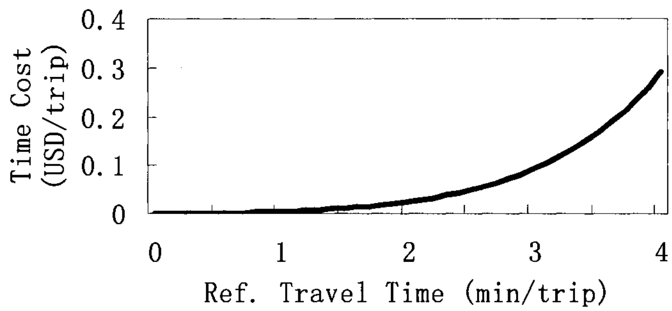

FIG. 5: Travel Time Value Function

3.7. CO2 Emission Factor and Carbon Tax

FORM 2 CO2 emission rates

All in kgCO2/kgH2	2010	2060 (2035 thru 2060 for FastR&D)
Ref. station with natural gas SMR onsite (500 kg/d)	12.96	10.60
Ref. station with water electrolysis onsite (500 kg/d)	45.56	22.22
Coal plant w/o C capture (1500 ton/d)	19.62	16.86
Coal plant w/ C capture (1500 ton/d)	4.77	2.47
Central plant via water electrolysis (100 ton/d)	44.88	22.00

The CO2 emission rates of hydrogen production for each technology from the NRC hydrogen study [3] are adjusted by the China average grid emission factor and shown on FORM 2. CO2 emission rates decrease quadratically to the lowest in 2060 except for the FastR&D case, where CO2 emission rates decrease quadratically to the lowest in 2035 and then keep constant from 2035 to 2060. To reflect the trade-off between environmental impact and economic costs, a carbon tax is assumed at 20 USD/tonC in 2010, increasing 10 USD/tonC per 5 years to 120 USD/tonC in 2060.

4. Results and discussion

4.1. Optimal Decisions

The optimal build-up processes for the 4 scenarios, previously defined, are generated by the HIT model and shown in FORM 3.

FORM 3 shows that for all the 4 scenarios, production shifts sometime during the transition period from onsite to central production. However, the time for such a technology shift is different among the scenarios. NG and FastMarket cases have relatively earlier shift to central production. For NG case, higher natural gas price makes onsite natural gas SMR production less attractive; for FastMarket case, higher demand makes central production more attractive due to scale economies in production and distribution.

FORM 3 also shows that non-sequestration coal plants only occur in the NG and FastMarket cases. This is because carbon tax rate is low in early stages. With carbon tax rate increasing, the non-sequestration coal plants are upgraded with sequestration technology. The additional costs of carbon sequestration are justified by the savings on carbon tax.

4.2. The 2060 Optimal Infrastructure Layout

FORM 3 shows that the 2060 configuration is similar for all the 4 scenarios, with 2 central plants and a similar number of refueling stations. Based on the algorithm of the HIT model, this implies the spatial layout of the infrastructure is also similar.

The 2060 layout for the NG case is shown in FIG. 6. As expected, the spatial distribution of the 600 refueling stations is similar to that of traffic, represented by the locations and sizes of green dots on FIG. 6. The implication is that more refueling stations should be built on traffic busy locations in order to maximize refueling convenience.

FORM 3 Optimal decisions

Case	H2I Component	2010	15	20	25	30	35	40	45	50	55	2060-∞
Base	pipeline refueling station (#)	0	0	0	150	270	390	450	510	540	540	540
	Avg size (ton/day/station)	0	0	0	5	5.0	5.0	5.0	5.0	5.0	5	5
	NG SMR Onsite Station (#)	30	60	90	0	0	0	0	0	0	0	0
	Avg size (ton/day/station)	3	4	5.0	0	0	0.0	0	0	0	0	0
	1.5mkg/d, Coal, non-Seq (#)	0	0	0	0	0	0	0	0	0	0	0
	1.5mkg/d, Coal, Seq (#)	0	0	0	1	1	2	2	2	2	2	2
	0.1mkg/d, water electro. (#)	0	0	0	0	0	0	0	0	0	0	0
NG	pipeline refueling station (#)	0	0	120	210	330	480	540	540	600	600	600
	Avg size (ton/day/station)	0	0	4	4.0	4.0	4.0	4.0	4.5	4.5	4.5	4.5
	NG SMR Onsite Station (#)	30	60	0	0	0	0	0	0	0	0	0
	Avg size (ton/day/station)	3	4	0	0	0	0	0	0	0	0	0
	1.5mkg/d, Coal, non-Seq (#)	0	0	1	1	0	0	0	0	0	0	0
	1.5mkg/d, Coal, Seq (#)	0	0	0	0	1	2	2	2	2	2	2
	0.1mkg/d, water electro. (#)	0	0	0	0	0	0	0	0	0	0	0
FastR&D	pipeline refueling station (#)	0	0	0	150	270	390	450	510	540	540	540
	Avg size (ton/day/station)	0	0.0	0.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	NG SMR Onsite Station (#)	30	60	90	0	0	0	0	0	0	0	0
	Avg size (ton/day/station)	3	4	5	0	0	0	0	0	0	0	0
	1.5mkg/d, Coal, non-Seq (#)	0	0	0	0	0	0	0	0	0	0	0
	1.5mkg/d, Coal, Seq (#)	0	0	0	1	1	2	2	2	2	2	2
	0.1mkg/d, water electro. (#)	0	0	0	0	0	0	0	0	0	0	0
Fast Market	pipeline refueling station (#)	0	300	390	480	510	540	570	570	570	570	570
	Avg size (ton/day/station)	0.0	3.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	NG SMR Onsite Station (#)	30	0	0	0	0	0	0	0	0	0	0
	Avg size (ton/day/station)	3	0	0	0	0	0	0	0	0	0	0
	1.5mkg/d, Coal, non-Seq (#)	0	1	2	2	0	0	0	0	0	0	0
	1.5mkg/d, Coal, Seq (#)	0	0	0	0	2	2	2	2	2	2	2
	0.1mkg/d, water electro. (#)	0	0	0	0	0	0	0	0	0	0	0

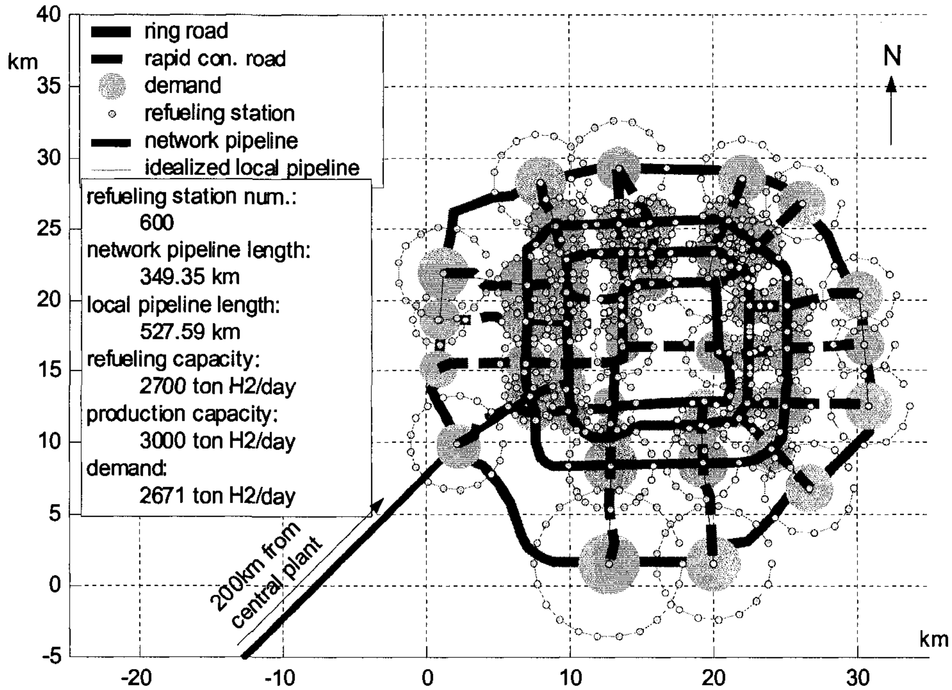

FIG. 6: 2006 Optimal Infrastructure Layout

Also in FIG. 6, the length and layout of the network pipeline (connecting coal plants and intersection nodes) are optimized by the HIT model via a spanning tree sub-model. The 349 km of network pipeline connects coal plants with all the 64 intersection nodes, while the 528 km of local pipeline transports hydrogen from these intersection nodes of the network pipeline to refueling stations. The ratio of pipeline length to demand is 0.32 km.day/ton in this optimal layout, lower than the 0.50 km.day/ton in the NRC hydrogen study [3], which does not use spatial optimization. Clearly, a more compact pipeline system could help reduce the levelized cost, as to be shown later. This implies that the regional spatial feature, when considered in the infrastructure planning, could significantly affect the transition cost.

4.3. Levelized Cost

The first 10 to 20 years of the transition period are more important from financial perspective, because the low revenues, due to low demand, make it hard to recoup the costs. FORM 4 shows the levelized costs over time for the 4 scenarios and for two breakeven constraints: 1st breakeven by 2020 and by 2030. Assuming no effect of price on demand, we can observe from FORM 4 that we can charge more for hydrogen to achieve earlier breakeven.

FORM 4 Levelized cost of optimal transition

Note: 1) assuming 12% discount rate; 2) all in USD/kgH2 delivered			
1st breakeven occurs by 2020			
Scenario	2010-2019	2020-2059	2060-infinite
Base	2.8	1.8	1.1
NG	3.9	1.9	1.2
FastR&D	2.7	1.6	1.1
FastMarket	2.7	1.3	1.3
1st breakeven occurs by 2030			
Scenario	2010-2029	2030-2059	2060-infinite
Base	2.6	1.3	1.1
NG	3.2	1.4	1.2
FastR&D	2.5	1.2	1.1
FastMarket	1.8	1.3	1.3

Levelized cost, when compared to the equivalent gasoline price, indicates how affordable the transition is. The gasoline price in Beijing is about 2.0 USD/gal in March 2006, which is equivalent to 4.0 USD/kgH2, assuming that the fuel economy of hydrogen fuel cell vehicles on average is twice of that of conventional gasoline vehicles. From FORM 4, the levelized cost for breakeven by 2020 ranges from 2.7 to

3.9 USD/kg, all below or close to the current gasoline price. This implies to some degree that a 12% rate of return for the first 10 years is achievable for hydrogen transition in Beijing.

As an implicit assumption, the infrastructure stays the same after 2060, so the levelized cost from 2060 onward is comparable with other static results. For a system by future optimism technologies consisting of 1 coal plant with carbon sequestration, 600 km pipeline, and 438 refueling stations, serving a demand of 1,200 ton/d, the NRC hydrogen study [3] estimates 1.64 USD per kg delivered hydrogen, which is higher than the after-2060 estimate of this study, 1.1-1.3 USD/kg. One implication is that dynamic-spatial optimization based on regional attributes could help identify a low cost transition process and a low cost system layout. Moreover, the capital cost and some operating costs of hydrogen equipments are assumed to be lower in Beijing than those in U.S.-based NRC hydrogen study.

If the effect of price on demand is ignored, the levelized costs in FORM 4 could also be viewed as the required hydrogen prices over time to achieve a 12% rate of return. Taking the Base case as example, the pricing policy of $2.8/kg from 2010 through 2019, $1.8/kg from 2020 through 2059 and $1.1/kg from 2060 onward could achieve a 12% rate of return.

4.4. Carbon Emission

WTW carbon emission is an important attribute of hydrogen pathway and transition analysis. FORM 5 shows the annual carbon emissions over time, resulting from the optimal transition processes shown in FORM 3, for the 4 scenarios. During 2015 to 2029, annual carbon emissions are higher in the NG and FastMarket cases than the Base and FastR&D cases. While higher natural gas price or higher demand could drive earlier adoption of central production, low carbon tax during early stages makes carbon sequestration technology temporally unattractive.

FORM 5 Well-to-Wheels carbon emission

	Annual Emission (MMT C/yr)										Total (MMT C)
	2010-14	**2015-19**	**2020-24**	**2025-29**	**2030-34**	**2035-39**	**2040-44**	**2045-49**	**2050-54**	**2055-59**	**2010-59**
Base	0.10	0.27	0.48	0.27	0.41	0.55	0.59	0.61	0.62	0.62	22.53
NG	0.10	0.27	0.73	1.25	0.41	0.55	0.59	0.61	0.62	0.62	28.71
FastR&D	0.10	0.26	0.45	0.21	0.32	0.42	0.48	0.54	0.58	0.60	19.73
FastMarket	0.10	1.56	3.31	3.94	0.78	0.78	0.75	0.71	0.67	0.63	66.10
FastMarket + Aggrsv Ctax*	0.10	1.56	2.03	0.83	0.78	0.78	0.75	0.71	0.67	0.63	44.17

* In this scenario, carbon tax increases by 20 USD/tonC per 5 years from 20 USD/tonC in 2010 to 120 USD/tonC in 2035 and keeps constant at 120 USD/tonC from 2035 to 2060; everything else is same as in the FastMarket scenario.

This suggests that carbon policy should keep pace with market growth or the carbon tax policy should be adjusted to encourage earlier adoption of carbon capture technology. To further explore this hypothesis, a new scenario is derived from the FastMarket case by only changing the carbon tax policy. Instead of peaking in 2060 at 120 USD/tonC as in the FastMarket case, the carbon tax in the new scenario increases by 20 USD/tonC per 5 years from 20 USD/tonC in 2010 to 120 USD/tonC in 2035 and keeps constant at 120 USD/tonC from 2035 to 2060. Since everything else is same as in the FastMarket scenario, the new scenario is named "FastMarket + Aggrsv CTax", described in FIG. 7.

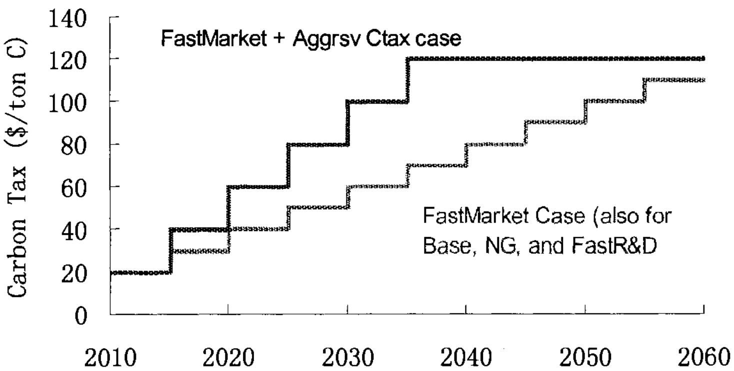

FIG. 7: Carbon Tax for FastMarket+Aggrsv CTax Case

The optimal decisions for the FastMarket+Aggsv CTax case is generated by the HIT model and shown in FORM 6 and the annual WTW carbon emission is shown in FORM 5. Comparing the optimal decisions and annual WTW carbon emission between the FastMarket case and the FastMarket+Aggsv CTax case, we can observe that the more aggressive carbon tax policy causes carbon sequestration technology being adopted 10 years earlier in the FastMarket+Aggsv CTax case, resulting in a reduction of carbon emission by 33% or 21.9 MMT carbon from the FastMarket case.

FORM 6 Optimal decisions for the FastMarket + Aggrsv CTax case

pipeline refueling station (#)	0	300	390	480	510	540	570	570	570	570	570
Avg size (ton/day/station)	0	3	5	5	5	5	5	5	5	5	5
NG SMR Onsite Station (#)	30	0	0	0	0	0	0	0	0	0	0
Avg size (ton/day/station)	3	0	0	0	0	0	0	0	0	0	0
1.5mkg/d, Coal, non-Seq (#)	0	1	1	0	0	0	0	0	0	0	0
1.5mkg/d, Coal, Seq (#)	0	0	1	2	2	2	2	2	2	2	2
0.1mkg/d, water electro. (#)	0	0	0	0	0	0	0	0	0	0	0

5. Future work

- Improve the model by including demand as an endogenous variable;
- Investigate alternative hydrogen pricing strategies, taking into account the impact of hydrogen price on market growth;
- Examine the possibility of integrating other approximation algorithms into the HIT model.
- Apply the HIT model to other cities or regions and identify the most attractive places to build up a hydrogen infrastructure;
- Conduct more sensitivity analyses (such as on discount rate and feedstock prices), and interpret the results in applicable contexts.

6. Conclusions

- Regional spatial features have a significant impact on cost.
- Faster market penetration could make a better business case because we are able to take advantage of scale economies in production and delivery earlier.
- Carbon policy should keep pace with market penetration to avoid high GHG emissions from coal gasification plants without carbon capture technology. If demand increases rapidly, a higher carbon tax might be needed to drive the adoption of carbon capture technology.
- For each scenario, we examine the levelized cost over time for a 12% rate of return. For the base case, the pricing policy of \$2.8/kg from 2010 through 2019,

$1.8/kg from 2020 through 2059 and $1.1/kg from 2060 onward could achieve a 12% rate of return, if the effect of price on demand is ignored.

7. Acknowledgements

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8. References

1. Ogden, Joan (1999). "Prospects for Building a Hydrogen Energy Infrastructure." Annual Review of Energy and the Environment 24: pp.227-279.

2. Solomon, Barry D. and Abhijit Banerjee (2005). "A global survey of hydrogen energy research, development and policy." Energy Policy. In Press, Corrected Proof.

3. National Research Council, and National Academy of Engineering (2004). The Hydrogen Economy: Opportunities, Costs, Barriers, and R&D Needs. Washington, D.C., the National Academies Press.

4. Padró, CEG and V. Putsche (1999). Survey of the economics of hydrogen technologies, National Renewable Energy Laboratory.

5. Sperling, Daniel (1988). New Transportation Fuels, A Strategic Approach to Technological Change. University of California Press, Berkeley, California. Publication No. UCD-ITS-RP-88-1.

6. Bellman, Richard (1957). Dynamic Programming. Princeton, Princeton University Press.

7. Beijing Transportation Committee (2004). Outline of Beijing Transportation Master Plan. Beijing, Beijing Transportation Committee.

8. Ma, Xiaohong and Yafei Hou (2004). "Study on 50 year population growth trend in Beijing." Market and Population Analysis 10(2).

9. Zhu, Songli and Keyuan Jiang (2002). "Energy Demand and Emissions of Beijing Urban Transport from Year 1998 to 2020." China Energy 2002(6).

10. Li, Bengang and Shu Tao (2004). "Influence of expanding ring roads on traffic noise in Beijing City." Applied Acoustics 65(3): 243-249.

11. Humphreys, Kenneth King (2005). Project and cost engineers' handbook. New York, Marcel Dekker Inc.

********************PAPER ENDS*********************