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The Hydrogen Infrastructure Transition (HIT) Model and Its Application in Optimizing a 50-year Hydrogen Infrastructure for Urban Beijing

by

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Abstract

Beijing could be an attractive region to initiate a hydrogen infrastructure for transportation. Air quality is poor, oil imports are soaring, and there is a desire to introduce innovative responses for the 2008 Olympics. If Beijing were to proceed to build hydrogen infrastructure before and after 2008, how they might proceed has not been addressed empirically or theoretically. We introduce the Hydrogen Infrastructure Transition (HIT) model and apply it to urban Beijing. HIT is a dynamic programming model, which generates the spatial and temporal infrastructure buildup decisions that minimize the net present value of capital and operating costs, carbon externalities, and refueling travel time disbenefits over time. HIT incorporates regionally specific spatial data to find optimal strategies for meeting an exogenously specified market penetration over time. Input assumptions can be varied to study how the optimal strategy depends on technological evolution, feedstock prices, carbon tax, and market penetration rate.

We find that: 1) regional spatial features have a significant impact on cost; 2) faster market penetration could make a better business case because scale economies in production and delivery can be taken advantage of earlier; 3) internalization of carbon costs should keep pace with market penetration to avoid high GHG emissions from coal gasification plants without carbon capture technology; 4) a rate of return of 12% is possible for the base case for hydrogen priced at \$3.52/kg from 2010 through 2019, \$2.17/kg from 2020 through 2059, and \$1.51/kg from 2060 onward; and 5) free hydrogen during the early stage could be a financially feasible solution to stimulate hydrogen 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 hydrogen infrastructure (H2I) 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*). Hugo and Rutter (*6*) provides a brief review of some H2I analyses using the static approach. The static approach, with or without optimization, is inaccurate because it ignores the financial effect of evolving factors (such as demand and technologies) on the supplier. 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 hydrogen infrastructure 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? (This is a simpler question than treating demand as endogenous, which we hope to investigate in the future.) We plan to address some other important questions, such as: how trade-offs are made between consumer convenience and supply cost, and environmental impact and cost? What are the hydrogen pricing alternatives responding to the optimal decisions? What if the technologies improve faster? What if the FCV penetrates faster? What if feedstock costs increase in the future?

There have been some simulation studies trying to solve a similar problem in other regions. HyTrans (*7*) has similar modeling goals to our approach, although it is intended for a national perspective without as much attention to the spatial details. HyTrans focuses more on consumer behavior and vehicle choice, but has fewer details on infrastructure in terms of technology choices, infrastructure design, station expansion, and technology competition. Hugo and Rutter (*6*) uses *mixed integer linear programming* to identify the optimal investment strategy by looking at an idealized network composed of 6 cities as demand clusters and 6 central production sites, but does not consider details of refueling station locations inside a city. Hugo and Rutter do not explore the trade off between consumer convenience and supply chain costs. And it remains unknown whether or not their model could handle a more complicated network. Nicholas et al (*8*) develop a GIS-based method to handle the station siting problem, but without much consideration on dynamics.

We also review the relevant efforts in the field of operations research. The target modeling question for HIT falls into the general category of resource allocation problems. Static resource allocation problems consider fixed demand and resource in a single decision period, and are usually formulated using linear or combinatory programming (*9*). The static problem is one of the foundational problems in the field of operations research, and has been studied extensively over the last fifty years (*10*). Static models are simple and easily implemented. However, it assumes that all the resource assignment can be done within single time window and does not consider future changes in demand and resources.

The dynamic resource allocation problem extends the static problem to find out which resource should be allocated to which demand at each time period so that the total benefit over the entire planning horizon is maximized. Some recent work (*11-13*) treats the dynamic resource allocation problem as a sequence of static problems, which is often referred as "*online*" algorithms. The algorithms are conceptually simple and easily implemented at a real-time basis. However, online algorithms are basically myopic models and do not take into account any anticipation for the future (*14*). Techniques based on *multi-stage linear programming* have also been proposed (*15-16*). However, these algorithms often face challenges of enumerating the entire solution space, and sometimes are difficult to be implemented in an online and dynamic fashion, such as (*17-18*). Techniques based on *DP* (*dynamic programming*) (*19*) take advantages of the natural integrality of dynamic resource allocation problems and incorporate both anticipated and real-time information into consideration, but sometimes may face the problem of dimensionality. Combining approximation methods and traditional *DP* is an on-going effort to improve the applicability of *DP* based resource allocation models to large size problems (*20-28*).

We have developed HIT and applied it to study the H2I transition process in an urban area. HIT is a *DP* model. It generates the spatial and temporal infrastructure buildup decisions that minimize the net present value of capital cost, operating cost, carbon tax, and refueling travel time disbenefit during a specified transition time. HIT 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 study how the strategy depends on technological evolution, feedstock prices, carbon tax, and market penetration rate.

In this paper, we first lay out the external data interface and internal structure of HIT. We then show the data we collected or estimated for the urban Beijing case study. The focus of this paper is on HIT, i.e. how we obtain the optimal decisions (output) from the data (input), rather than on how we collect or estimate the inputs (for example, demand). However, we do the best to describe the way we determine the key inputs. Then we show and interpret the results. Readers should be aware that the key output of the model is the optimal decisions. All other results, such as hydrogen pricing strategy, are simply obtained by engineering economics calculation based on the optimal decisions. Finally, we list some thoughts on our future work.

2. MODEL

2.1. Model External Interface

FIGURE 1 shows the external interface of HIT. Given the input data including demand (expressed as a growing market fraction over time), road network, traffic flow, facility unit cost for H2I, time value function (monetary cost of travel time), CO2 cost, and discount rate, HIT generates the optimal sequential spatial decisions via a *DP* algorithm. Many useful results such as the transition pattern and hydrogen pricing strategy could be obtained via further analysis of the optimal decisions.

In the following, we discuss each input and how the inputs are used inside the model.

Hydrogen demand D(t) is measured by kilograms of hydrogen per day (kg/d). Any H2I configuration at time t of capacity smaller than D(t) is considered infeasible. This rule helps to filter infeasible solutions and improves the computational efficiency of our model.

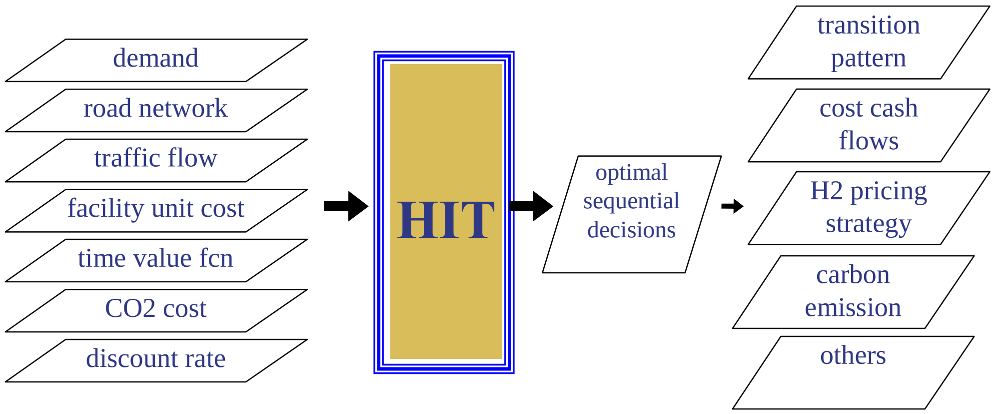

FIGURE 1: HIT External Data Interface.

The input description of the road network includes the spatial coordinates of and the distance between the connected nodes of the regional representative network. Traffic flow information is represented by traffic counts along the road network. For any node A at time t, there are usually 4 inflow segments, each of which is attributed with a distance between node A and each of the four adjacent nodes in kilometers and a traffic count in vehicles per day. These two sets of data for inflow segments are then translated into an aggregated Daily Vehicle Kilometers Traveled to Node A ($DVKT_A$). This allows us to ascribe an aggregated hydrogen demand d_A in kg/d to the node A. We define $f_A(t)= d_A(t)/ D(t)$ as the demand distribution ratio at node A at time t. This ratio represents the priority of building refueling stations at or near node A. We use $d_A(0)$ and D(0) to obtain $f_A(0)$ for the current stage (t=0), assume that $f_A(t)$ is constant over time, and then obtain $d_A(t)$ over time based on the given D(t). With $d_A(t)$, we can obtain refueling demand (in number of refueling trips per day) at node A by assuming fuel economy and DVKT per car. This process is conducted for every node. Then for a given configuration of refueling stations, assuming consumers always choose the nearest refueling station, we can calculate the total refueling travel time (disbenefit) in minutes per day.

To understand the trade-off between cost and consumer convenience, we need to attach a monetary value to refueling travel time. We use a nonlinear utility function to describe the relation between a travel time and its monetary value.

Another trade-off to be considered is between cost and environmental disbenefit due to carbon emissions, which can be estimated via a carbon tax over time. A predefined carbon tax is used instead of a CO2 damage cost, as the latter is usually not available for particular regions. In fact, the inclusion of a carbon tax is meaningful not only from the industry perspective (what is the optimal reaction of the industry under a given carbon tax policy over time?), but also from the regional social planning perspective (how to maximize the regional social surplus in a given carbon trading context?).

Carbon tax can be adjusted to reflect various levels of competition between coal (with and without CO2 sequestration), electrolysis, and natural gas reforming as hydrogen production technologies, as they have different well-to-wheel CO2 emission factors and different costs. A higher carbon tax implies more incentives for the industry or the region to adopt more lower carbon emitting technologies, which are usually more expensive.

Facility unit costs for hydrogen infrastructure include capital cost, the annual fixed cost, and annual feedstock variable cost of one facility at pre-defined size.

The discount rate is essentially used to measure the relative importance of the same magnitude of benefit/revenue or disbenefit/cost at different times. Although we use 12% in our case study, we keep in mind that we need to conduct sensitivity analysis on discount rate and think about inter-generation equity (*29*).

2.2. Model Internal Structure

2.2.1. Internal Structure of HIT

The core technique of HIT is *DP*, with the underlying reasoning being Principle of Optimality (*30*): 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.

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

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

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

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, feedstock variable cost V_t, travel time disbenefit T_t, and evnvironmental disbenefit E_t;

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.

Note that ideally, the decision variables X_t should include the number of plants and refueling stations and their optimal locations. We introduce aggregation and approximation techniques to reduce the dimensionality of the decision variables. In the HIT model, X_t represents only the number of plants and stations. Their optimal locations are obtained in an approximation manner by using the Station Engineer Model (see Section 2.2.3). We adopt 4 constraints in HIT: 1) for each stage, the total refueling capacity of the infrastructure must meet or exceed the demand at that stage. Insufficient production capacity is allowed, but by-product or inter-regional hydrogen must be purchased to match the balance; 2) optimized later configurations of more refueling stations is used as the transition target for any earlier optimized configuration of fewer refueling stations; 3) any infrastructure facility, once built, will stay in use forever; 4) however, refueling stations can expand in size, and onsite stations can be converted to pipeline-connected refueling stations, and coal central hydrogen plants can be upgraded by adding CO2 sequestration capability.

HIT is organized in terms of several sub-models. In the following several sections, we describe: how we use the Cost Capacity Sub-Model to estimate the facility unit costs based on cost data from (*3*) in order to obtain C_t, F_t, and V_t; how we use the Station Engineer Sub-Model to calculate T_t from any spatial configuration of refueling stations; how we use the Pipeline Engineer Sub-Model to determine the shortest pipeline from any spatial system configuration and the pipeline costs; and how we use the Environmental Engineer Sub-Model to calculate the CO2 emission cost E_t.

2.2.2. Cost Capacity Sub-Model

The cost-capacity method can be found at many engineering economics textbooks, e.g. (31). It can be used to estimate the capital cost of a facility based on the capital cost of another similar facility with a different size. For example, in (*3*), the total capital cost of one coal gasification plant at size of 1,200 ton/day is $1152 million. The component costs and cost/size factors are also given. For example, its Texaco coal gasifier costs $173 million with cost/size factor 0.85. So we can estimate the Texaco coal gasifier for one plant at 1,500 ton/day (adopted in the case study) as $209 million (=173*(1500/1200)^0.85). Similarly we estimate the other component capital cost. Using the same percentage numbers for general facilities, contingencies, and so on, we obtain the total capital cost for one plant at 1,500 ton/day at $1378 million. Fixed annual cost is 83 million $/yr, 6% of the total capital cost. Feedstock variable cost is 158 million $/yr, accounting for coal and electricity. However, the actual feedstock variable cost is proportional to the actual output.

2.2.3. Station Engineer Sub-Model

The Station Engineer Model is another component of HIT. It optimizes and predefines the spatial build-up process of refueling stations. The model begins with the “end-state”, e.g. it find the number and layout of refueling stations that would be optimal, if all the vehicles in Beijing used hydrogen (100% market penetration). The number of stations is estimated to be 800, based on peak hydrogen demand in Beijing and assuming a maximum station size of 5000 kg/d. We first optimize the locations of these 800 refueling stations. Then, working backwards to find an optimization for smaller demands, it optimizes the locations of 799 stations with the constraint that they must be built at the optimized 800 station locations. This process is conducted for successively fewer stations until we reach 1 station. This approach assumes that stations are built in locations that will someday be part of the optimized “end-state” layout or equivalently, that we do not close existing stations when more stations are added. The average travel time versus the number of stations is plotted on FIGURE 2. We can see that the travel time is about the same from 200 stations on. However, because we set a size cap of 5000 kg/d for refueling stations, more stations must be built to meet the demand without contribution to travel time reduction. This suggests an interesting topic to be investigated: whether or not giant refueling stations (e.g. 3-4 times in size of the current biggest gasoline station) are possible.

The Station Engineer Model calculates the total travel time disbenefit in million $/yr for a given siting configuration of refueling stations. The Station Engineer Model is composed of two parts: network-wide siting and node-wide siting. For network-wide siting, each intersection node on the network is attributed with a hydrogen demand quantity, which is calculated based on vehicle-kilometers traveled by the vehicles heading for the node from the adjacent nodes.

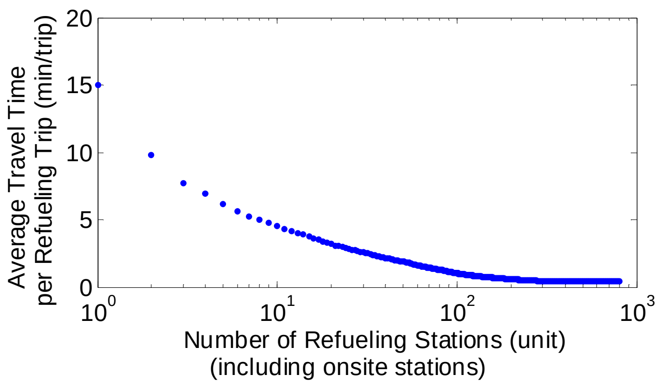

FIGURE 2 Average Refueling Travel Time.

Multiple refueling stations at the same node also help reduce travel time, which is realistic and reflected by the node-wide siting algorithm. The algorithm allocates the multiple stations evenly along the adjacent road segments, with the first station at the node. This is an approximation to the reality that multiple stations are sited along the local roads (not part of the representative network). One can imagine that the approximation will become more accurate by adding more nodes, certainly with computation time also increased. Integrating both node- and network-wide siting allows allocating more than one station to busy nodes (with large accumulated hydrogen demand) while some other nodes are still empty.

For any given configuration of refueling stations on the network, the total travel time cost can be calculated by assuming each of these hydrogen demand quantities is served by the nearest refueling station. Thus, the locations of any given number of refueling stations can be optimized so that the total travel time cost is minimized.

2.2.4. Pipeline Engineer Sub-Model

The Pipeline Engineer Model is used to obtain the pipeline costs, as part of C_t, F_t, or V_t. The core technique of the Pipeline Engineer Model is the minimum spanning tree method, which is available in most operations research textbooks, such as (*10*). The method is used to minimize the total pipeline length, which is the most significant factor of pipeline cost (*32*). Capital cost of one unit length of pipeline is also from (*3*); however, the operating cost is calculated based on real flow rate, as opposed to the constant flow rate assumption in (*3*), which tends to overestimate the operating cost.

2.2.5. Environmental Engineer Sub-Model

For any decision X_t, the real output of every facility unit can be determined. Using the CO2 emission factors from (*3*), the Environmental Engineer Model calculates the total CO2 emissions of the infrastructure system. Based on the predefined carbon tax policy at stage t, the total CO2 cost or environmental disbenefit E_t is calculated. Similar to carbon tax and facility unit cost, the emission factors (e.g. from hydrogen production) also change over time, reflecting technology improvement.

2.2.6. Period-end Future Cost Sub-Model

We assume that at the end of the specified transition period, the infrastructure has assumed a stable "end-state" form that will not change further over time. We defined the cost of hydrogen from this end-state system as the "period-end future cost". This is defined as the NPV of the infinite cash flows after the end of the study period, and is incorporated to reflect the need for a sustainable transition. Each period-end infrastructure configuration has its cost implication for the future generations after the transition study period (2010-2059 in this case study). Without consideration of period-end future cost, the infrastructure could end up being one with very high operating costs (including environmental cost), even though the transition cost is minimized. With the concept of period-end future cost, trade-off can be made between costs during 2010-2059 and after 2059. This allows us to assure that the optimal configuration is also a sustainable one---it takes the future into account.

Hence, strictly speaking, HIT considers not only the transition study period, but also the infinite horizon with a stable infrastructure configuration, assuming the configuration at the end of transition study period will exist forever. This does not mean that capital cost of rebuilding at the end of facility life is ignored or that facility life is infinite. HIT model incorporates facility life by converting the reoccurring capital cost at each facility life end into equivalent periodic fixed cost. An equivalent explanation to this is that more fixed cost makes the facility work forever. This approach eliminates the need to record facility life and thereby greatly reduces the computational time.

3. CASE STUDY DATA

In this section, we address the preparation of the input data for HIT in the urban Beijing case study, trying to be as transparent as we can.

3.1. Hydrogen Supply Options

In our case study for Beijing, we consider several options for hydrogen supply:

- Onsite production of hydrogen at the refueling station by small-scale steam reforming of natural gas
- Central production of hydrogen by water electrolysis
- Central large scale production of hydrogen from coal with CO2 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

In future work, we will expand this set of options to consider other supplies.

3.2. Four Scenarios

It should be noted that one goal of HIT is to provide application flexibility in hydrogen economy analysis. It aims at answering the question "what is the optimal transition strategy if…" In addition to the base case (Base), we investigate three more scenarios: NG, FastR&D, and FastMarket, with the following definition:

- Base: the prices of electricity at 0.045 $/kWh, coal at 1.22 $/MM Btu (high heating value), and natural gas at 6.5 $/MM Btu (high heating value) are all constant over time (as the same assumptions in (*3*)). Facility unit costs evolve over time as shown in FIGURE 5.
- 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. We assume no effect of natural gas price increase on electricity cost with the assumption that the power industry will stabilize the electricity price by seeking other generation technologies if natural gas price is too high.
- FastR&D: facility cost decrease to the lowest in 2035, as opposed to 2060 in Base case.
- FastMarket: full penetration occurs in 2035, as opposed to 2060 in Base case.

The transition study period is from 2010 to 2059. Time step is 5 years, so there are 10 stages with 2010-2014 as the first stage and 2055-2059 as the last stage. According to the convention of engineering economics, capital cost is charged at the beginning of each stage, while any other type of cost is charged at the end of the stage.

3.3. Demand

Based on information from Beijing Transportation Master Plan (*33*), the Beijing Municipal Commission of Population and Family Planning (*34*), and Zhu (*35*), we first project the vehicle population of light duty gasoline vehicles, light duty trucks, heavy duty gasoline vehicles, heavy duty diesel vehicles, and motorcycles. There are currently about 65,000 taxis and 11,400 buses (*36*). We assume there will be 18,300 fuel cell taxis and 2000 fuel cell buses by year 2010 based on Beijing's experience in natural gas buses and taxis (*37*). Assuming 411 km/day for one taxi and 151 km/day for one bus (*36, 33*), we estimate that hydrogen demand is 80.39 ton/day in 2010 (we validated the taxi daily travel distance by interviewing 10 Beijing taxi drivers. Most of the interviewees told us more than 60% of the taxis in Beijing are co-operated by two drivers, one in daytime and one in nighttime. It is normal for these two-shift taxis to drive for 200,000 km per year. 300 km/day is commonly cited elsewhere, which we believe is for one-shift taxis.). It is assumed that, with the existence of some refueling stations serving these two types of fleets, private hydrogen fuel cell vehicles (FCVs) begin to penetrate from year 2015. Based on reasonable assumptions on fuel economy and DVKT of each vehicle category (*38*), we estimate the hydrogen demand over time as shown in FIGURE 3.

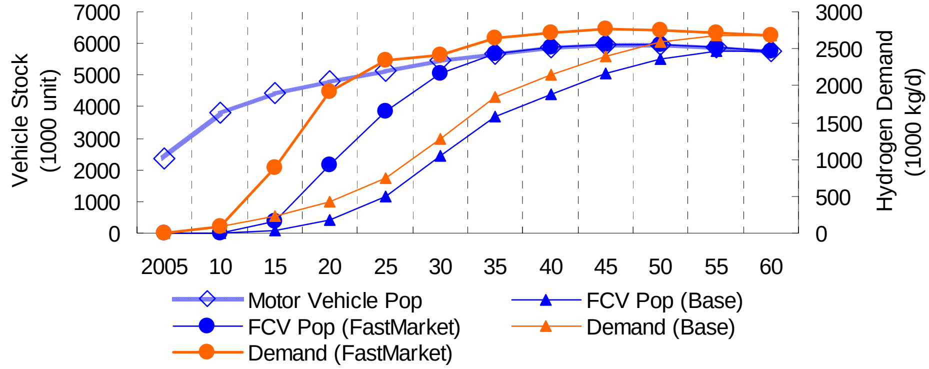

FIGURE 3 Vehicle Population And Hydrogen Demand.

3.4. Road Network and Traffic Flow

BUEWN (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. BUEWN consists of 4 ring roads and 15 rapid connecting roads (4 of the 15 rapid connecting roads are still under construction). Due to lack of GIS data, the coordinates of 64 nodes and distances of each road segment were measured by hand from commercial electronic map. Traffic count data are obtained from (*33, 39*).

With the road segment distance and traffic count data, we calculate the demand distribution factor for each node, plotted as green dot on FIGURE 4. The size of the green dot is proportional to the value of the demand distribution factor.

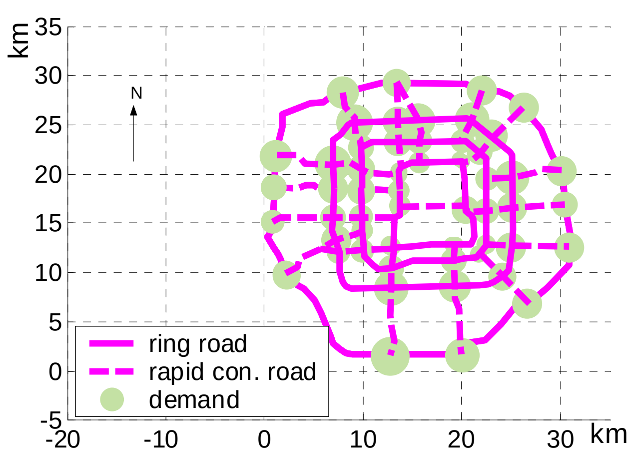

FIGURE 4 Representative Network.

3.5. Facility Unit Cost

FIGURE 5 shows the facility unit capital costs adopted in the Beijing case study, as well as the size of each facility unit. We consider 5 facilities and 3 pathways. For example, for the Base case, the capital cost of one coal gasification central plant without CO2 sequestration at size of 1.5 million kg/d in year 2035 is about 80% of that in year 2005 (0.8 from the square blue curve in

FIGURE 5). The right part of FIGURE 5 shows the capital cost of this plant in 2005 is $1377.60 million, which means that the capital cost in 2035 is $1102.1 million (=1377.60*0.8). Other capital cost data in both Base case and FastR&D case could be calculated in a similar way. Fixed cost is just a certain percentage of capital cost and therefore is not plotted. Feedstock variable cost is proportional to output. The 2005 cost and 2060 cost (in Base case) are inferred from "current technology" cost and "future optimism" cost in (*3*) using cost capacity model. Other costs in between those given points are obtained through quadratic interpolation.

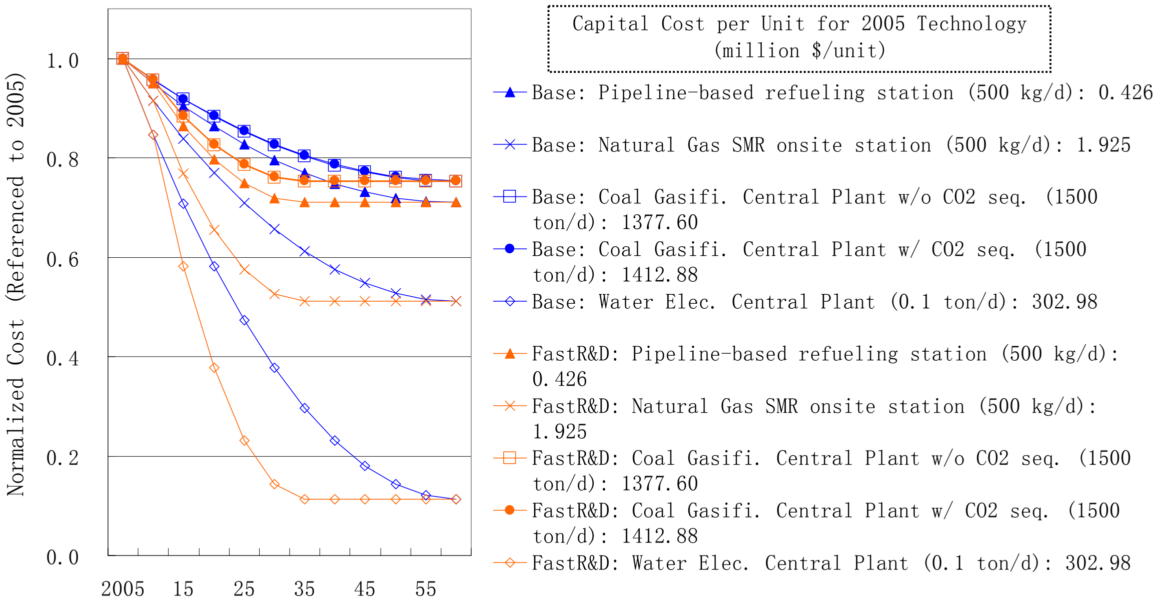

FIGURE 5 Facility Unit Cost Evolution.

For the distribution cost for transporting by-product or inter-regional hydrogen via tanker trucks, we adopt the $1.8/kg from (*3*), which is for a distance of 210 km. We assume tanker trucks are rented at this rate, so there is no capital cost investment for tanker trucks. We assume a distance of 170 km from Beijing to Changzhou, a city providing by-product hydrogen. The byproduct hydrogen is priced at $2/kg up to a purchase amount of 20,780 kg/d, beyond which the byproduct price increases rapidly. This is to prevent a large byproduct hydrogen purchase, which is not realistic.

It is assumed that the first 500 kg/d refueling station (base station) module will be built on a big lot of land and it will be expanded by adding 500 kg/d modules on the same land lot. Cost data for expansion modules (not shown) are similar to those for base stations, except that the capital cost is smaller (e.g. no need to purchase the land again).

One should be careful about the applicability of the facility unit cost data, estimated for the United States, to Beijing. The costs tend to be overestimated if we consider labor and feedstock price and underestimated if we consider technology importation (*40*). The impact of some other factors remains uncertain, such as productivity and permitting. It is too difficult for us to consider all these factors at this research stage. Another reason to use the U.S. facility unit cost data is to keep our analysis transparent by avoiding partial obscure adjustments. Although we don't know whether the facility unit cost estimations are too high or too low for Beijing, readers should be aware of this data flaw in the paper.

3.6. Value Function for Refueling Travel Time

We use an exponential function to estimate the monetary disbenefit of refueling travel time. Ideally, a behavioral survey should be conducted to determine the parameters of the exponential function or even the function structure. In this paper, the exponential function is calibrated by the assumptions: 1) 2 minutes per refueling trip 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 U.S. average hour rate (to be consistent with the U.S. facility unit costs); 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 FIGURE 6.

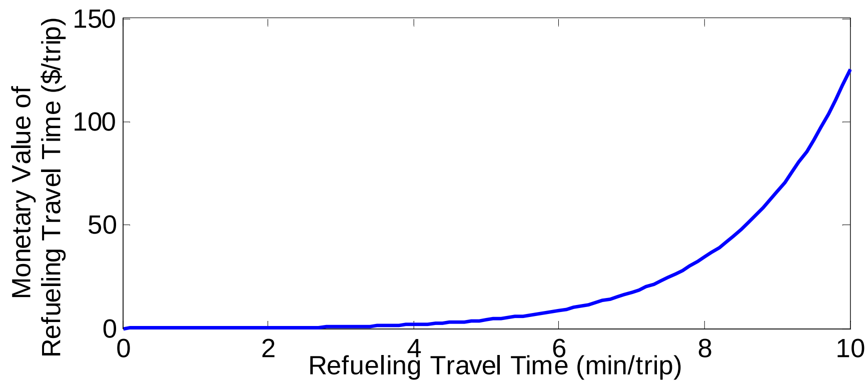

FIGURE 6 Travel Time Value Function.

3.7. CO2 Emission Factor and Carbon Tax

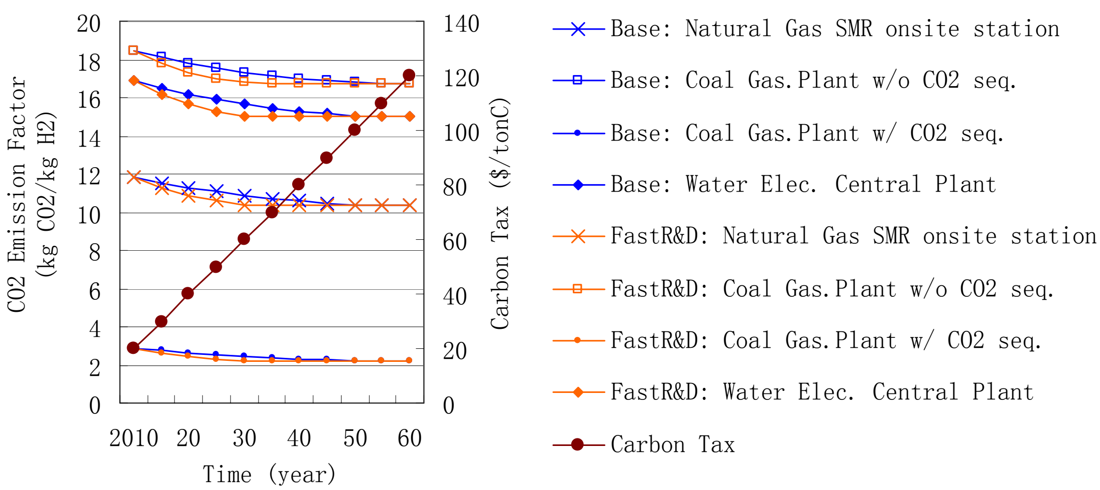

FIGURE 7 Carbon Tax And CO2 Emission Factors.

The carbon tax policy over time, as well as the emission factors for each of the production technologies, taken from (*3*), are plotted in FIGURE 7. As shown, the smallest emission factor occurs in 2035 in the FastR&D case. At present, the emission factors associated with electricity use are based on the U.S. average grid mix, but in future work, we will incorporate data appropriate to Beijing's electricity supply. For example, if we employ coal for hydrogen production (with or without CO2 sequestration), an analogous system might be used for electricity production.

3.8. Discount Rate

We adopt a 12% discount rate in the Beijing case study, as adopted in (*3*).

4. RESULTS

4.1. Optimal Decisions

TABLE 1 Optimal decisions

Case	H2I Component	2010	2015	2020	2025	2030	2035	2040	2045	2050	2055	2060-∞
Base	pipeline refueling station (#)	0	0	0	0	300	420	570	600	600	600	600
	(ton/day/station)	0	0	0	0	4.3	3.6	3.8	4.1	4.4	4.5	4.5
	NG SMR Onsite Station (#)	30	60	90	150	0	90	0	0	0	0	0
	(ton/day/station)	3	4	4.8	5	0	3.7	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	0	1	1	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	150	240	420	600	600	600	600	600	600
	(ton/day/station)	0	0	3	3.2	3.1	3.1	3.6	4.1	4.4	4.5	4.5
	NG SMR Onsite Station (#)	30	60	0	0	0	0	0	0	0	0	0
	(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	0	270	390	540	540	600	600	600
	(ton/day/station)	0	0	0	0	5	4	4	4.5	4.5	4.5	4.5
	NG SMR Onsite Station (#)	30	60	90	150	0	90	0	0	0	0	0
	(ton/day/station)	3	4	5	5	0	4	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	0	1	1	2	2	2	2	2
	0.1mkg/d, water electro. (#)	0	0	0	0	0	0	0	0	0	0	0
FastMarket	pipeline refueling station (#)	0	300	390	480	510	540	570	570	570	570	570
	(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
	(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

As shown in FIGURE 1, the optimal decisions (for each of the 4 scenarios) are the core output for deriving other useful results. They are shown in TABLE 1 for reference as we will need it in later discussions. We plot the period-end configuration in FIGURE 8, which is the same for Base, NG, and FastR&D (The period-end configuration of FastMarket has 30 stations fewer from that of any other, but overall has a similar spatial layout.). It should be noted that the local pipeline circles do not mean the exact locations of refueling stations. They illustrate how many refueling stations should be located near each node.

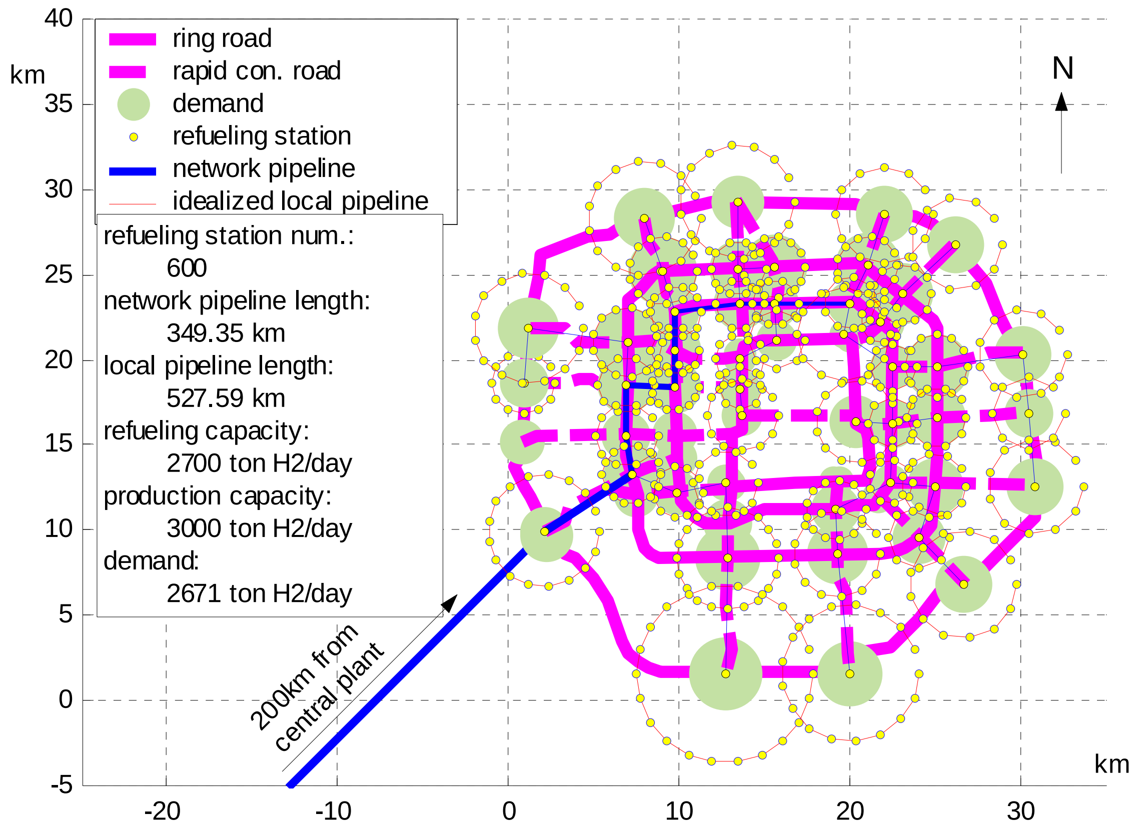

FIGURE 8 Period-end Spatial Configuration (Base, NG, FastR&D).

4.2. Production Technology

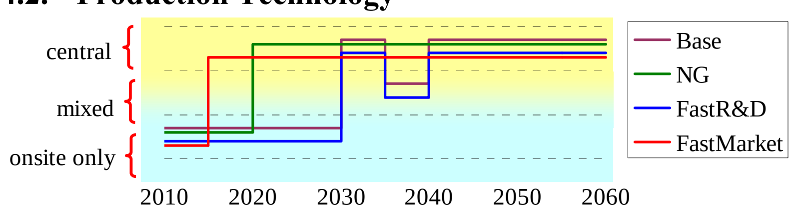

FIGURE 9 Production Technology Adoption.

In general, there is a transition from distributed hydrogen production (via small onsite natural gas steam reformers located at refueling stations) to centralized production of hydrogen with pipeline distribution. The transition happens at different times depending on the scenario. FIGURE 9 shows the production technology adoption during 2010 to 2060 for each of the four scenarios. Comparing the transition patterns among the four scenarios, we can observe that: 1) central production begins earlier when hydrogen vehicles penetrates faster or when the natural gas price increases over time. Faster market penetration drives the system toward central production earlier because coal gasification production becomes more competitive due to economy of scale. As we will see later, this can result in serious environmental impact. Even without faster market penetration, central production could occur earlier if natural gas price increases over time, adding the feedstock variable cost of onsite production and making onsite production less competitive; 2) during the middle years of a transition, onsite production could coexist with central production. This is because the temporal demand increment is too small to justify building another central plant. When demand goes high enough, another central plant is built and the temporarily built onsite stations are converted into refueling stations without production capability.

The average station size increases over time, but is "capped" by an assumed maximum of 5000 kg/d at each station. Larger station size gives scale economies, and also limits the extent of the infrastructure required (because fewer refueling sites are needed). In all cases, we approach the largest allowed station size in the end-state.

4.3. Cost Cash Flows

The cash flows of capital costs, operating costs (fixed and variable), carbon tax, and travel time disbenefit are plotted in FIGURE 10. We can see the big investment for central production occurs earlier in the NG and FastMarket cases, which is consistent with our earlier discussion. Note the frequency of large capital cash flows, which is due to the 15 year facility life assumption. Also note that the bigger carbon tax cash flows and the higher travel time disbenefit during early stages for the FastMarket case, which will be discussed later.

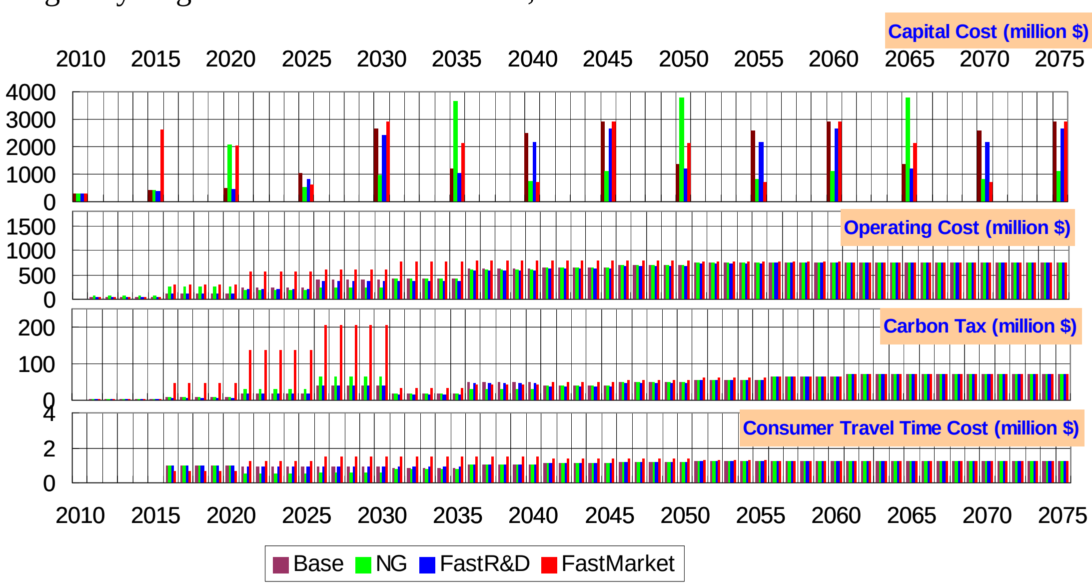

FIGURE 10 Cost Cash Flows.

4.4. Hydrogen Pricing

It is a little confusing to ask for the levelized delivered cost of hydrogen, because we are looking at a dynamic system rather than one with static size. However, we can explore the same question by asking: what could be the hydrogen price over time in order to achieve a 12% rate of return at each stage of infrastructure development? We explore different hydrogen pricing strategies, with the aim of identifying strategies that allow the infrastructure builder to "break even" on the investment. There are two dimensions of the pricing strategy: time required to reach breakeven and hydrogen price, i.e. we can breakeven the cost earlier by charging more on hydrogen. Based on the optimal decisions in TABLE 1, we obtain some feasible hydrogen pricing curves, shown in FIGURE 11, for each case (Base case, NG Case, FastR&D and FastMarket) and for 3 different "breakeven years" (2020, 2040 and 2060). Note the color for each case and the three pricing constrains explained by the following examples:

- Base 2020: For the base case assumptions, we plot the set of hydrogen prices over two time periods (2010 to 2019 and 2020 to 2059) required to allow the first "breakeven" in 2020, the second in 2060. From 2060 onward, we set a long term price that supports the "end-state infrastructure with a 12% rate of return";
- NG 2040: For the natural gas case, we set prices to allow the first breakeven in 2040, and the second in 2060. As before, from 2060 onward, we set a long term price that supports the "end-state infrastructure with a 12% rate of return;
- FastR&D 2060: For the FastR&D case, we set the first breakeven in 2060.

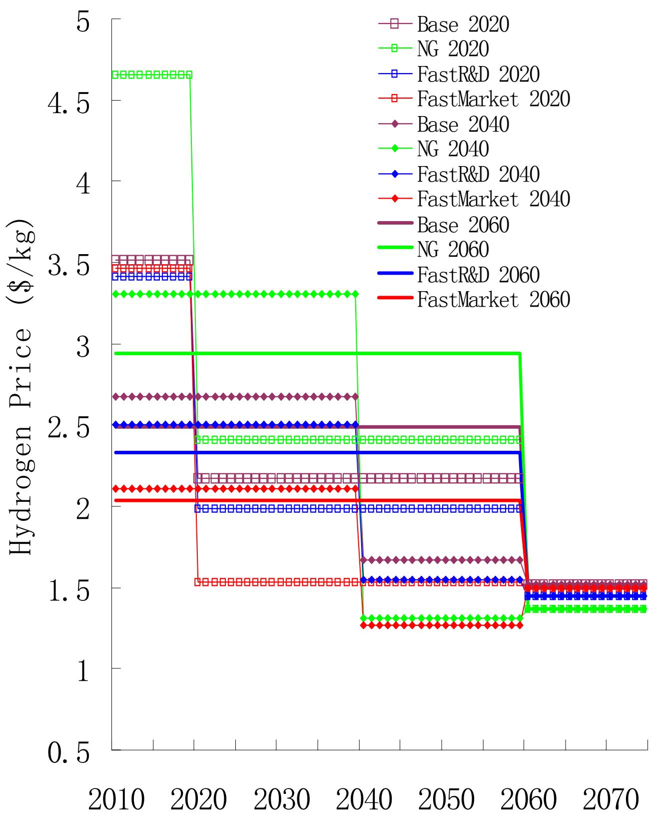

FIGURE 11 Hydrogen Pricing Strategies for 12% ROR.

We can see that any business case is a trade-off between time to achieve cost breakeven and the hydrogen price. If the investor can tolerate a breakeven time in 2060 in the Base case, the hydrogen price could be as low as $2.5/kg during 2010 to 2059 for 12% ROR.

The hydrogen prices in FIGURE 11 seem a little lower than the static estimates in (*3*). This could be due to several factors: 1) the high density of the urban Beijing allows a compact distribution system; 2) the pipeline length is minimized in our study, as opposed to non-optimized 600km assumption in (*3*); 3) we consider varied pipeline flowrate, as opposed to the constant 1.2 million kg/day flowrate assumed in (*3*).

For any time of breakeven, the NG case is the worst case from the investor perspective. Although many studies find natural gas an attractive feedstock for near term (note that the natural gas onsite production is also a near term technology in the optimal decisions) based on static study, we might need to rethink the issue, if we believe natural gas price growth rate at 50% per 5 years.

If we look at the three cases other than the NG case, we find that, for about \$3.5/kg, we could breakeven on infrastructure investments in just 10 years at 12% ROR, which seems an attractive business case. Assuming a hydrogen FCV has a fuel economy twice of that of conventional gasoline cars, (and knowing that 1 kg of hydrogen contains about the same energy as 1 gallon of gasoline), this hydrogen price is equivalent to about \$1.75 per gallon gasoline (the recent gasoline retail price in Northern California is about \$2.8 per gallon). Although we can not conclude that it is time to build a hydrogen infrastructure now, as FCVs are still very expensive, we can certainly explore another question: is it possible for the hydrogen industry (by itself or with assistance) to offer incentives to the FCV industry to achieve a win-win situation for both industries? If yes, by how much?

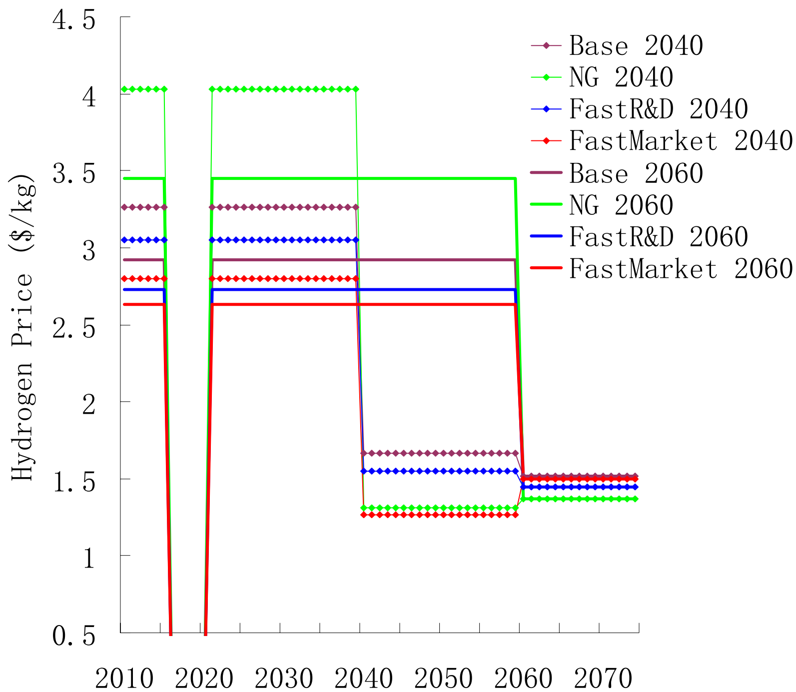

FIGURE 12 Hydrogen Pricing Strategies for 12% ROR (Free Hydrogen for 5 years).

How about free hydrogen during the initial introduction of hydrogen cars? In our base case, we assume that private FCVs enter the market in 2015. Could the hydrogen industry afford to provide free hydrogen during 2015 to 2019? We show the pricing strategies in FIGURE 12. Use the Base case as an example, the 12% ROR with a 2040 breakeven could be realized with

$3.26/kg from 2010 to 2014, $0/kg from 2015 to 2019, $3.26/kg from 2020 to 2039. The 2040 breakeven price $3.26/kg is higher than the counterpart in the no-free-hydrogen situation (see $2.67/kg in FIGURE 11), but this difference might be acceptable and the 5 years of free hydrogen could certainly stimulate the market growth. However, 5 years of "free hydrogen" would eliminate the possibility of an early breakeven (2020) at relatively low hydrogen prices seen in FIGURE 11. To fully explore this idea in future work, we plan to incorporate a model of how hydrogen price impacts demand growth for private FCVs.

4.5. Carbon Emission

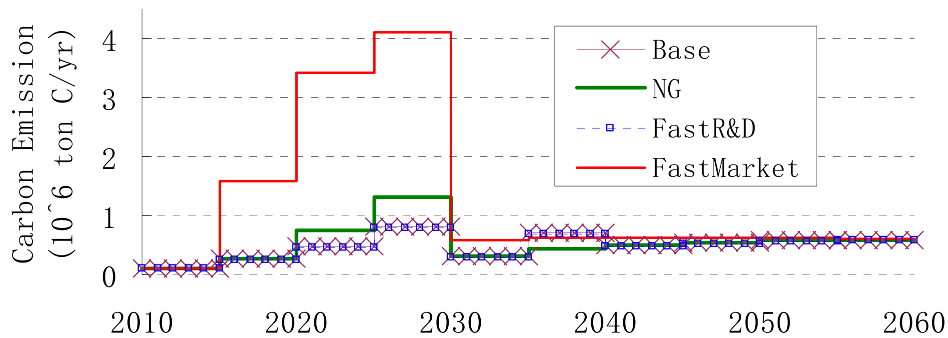

FIGURE 13 Well-to-Wheel Carbon Emission.

FIGURE 13 shows the annual carbon emissions over time for each of the four scenarios. As we showed earlier, the natural gas price growth and faster market penetration drive early adoption of central production, which begins with coal gasification without carbon capture, as shown in TABLE 1. Therefore, as shown in FIGURE 13, early central production adoption can create more carbon emission, as shown in the FastMarket case. This occurs due to the low carbon tax during early stages, as shown in FIGURE 7. As the carbon tax grows to a certain level, the central production is upgraded with carbon capture technology. Although it makes a better business case in the FastMarket case in terms of pricing to defer the upgrade to carbon sequestration, the environmental impact is more serious. 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, assuming carbon sequestration technology proves feasible.

4.6. Consumer Convenience

FIGURE 14 shows the average refueling travel time over time for each of the 4 scenarios. The higher the demand, the more refueling trips, the more travel time disbenefit if the average travel time per trip is constant. This is why the "investor" in the FastMarket case is more motivated to build more refueling stations during early stages so as to reduce the travel time per trip, as shown in FIGURE 14. Even with lower average travel time, the total travel time disbenefit in the FastMarket case is still higher than other cases during early stages, as shown in FIGURE 10.

4.7. Start-up Funding

One might be interested in how much money we need to build up and operate the hydrogen infrastructure. However, this is not a straightforward question, as the answer depends on: 1) whether or not revenue is taken into account? If yes, what is the pricing strategy? 2) the minimum rate of return (MRR), and 3) the time scope.

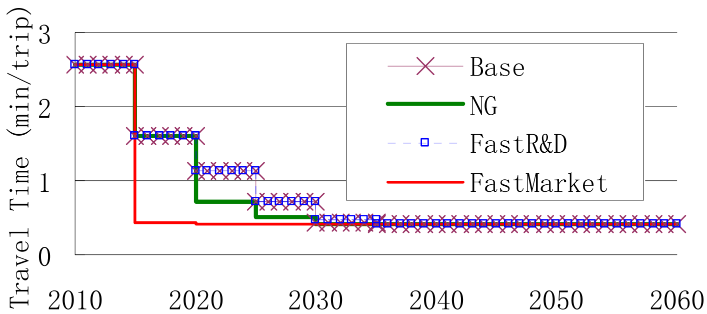

FIGURE 14 Refueling Travel Time for 4 Scenarios.

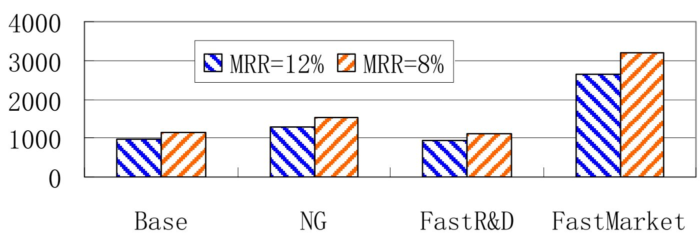

FIGURE 15 NPV of Costs 2010 to 2019 (million $).

We show the NPV of 10 years of costs in FIGURE 15 for two MRR and without using the revenue to balance the costs. Because revenue is not included, one safe conclusion is that we need less than $975.67 million (the exact number in FIGURE 15) in the Base case if we are guaranteed a 12% MRR for our money. However, it is dangerous to say that, in the FastMarket case, we need more start-up funding for the first 10 years. Although it is true that we will build the central plant earlier in the FastMarket case, more revenue due to higher demand might drive down the necessary start-up funding.

5. FUTURE WORK

Some thoughts on future work regarding the HIT methodology:

- 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.

And some thoughts on future work regarding HIT application:

- Obtain better data for the Beijing case study;
- 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 what hydrogen price would be needed over time to assure a 12% rate of return throughout the entire transition period. For the base case, the pricing policy of $3.52/kg from 2010 through 2019, $2.17/kg from 2020 through 2059 and $1.51/kg from 2060 onward could achieve a 12% rate of return.
- It could remain an acceptable business case even if free hydrogen is offered for several years.
- Innovative hydrogen pricing strategies could create a “win-win” situation for both energy and automotive industries.

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