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Multistage System Planning for Hydrogen Production and Distribution

March 2011

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ABSTRACT. Hydrogen is an energy carrier that has the potential to improve the sustainability of transportation fuels and reduce oil dependence. This paper presents a stochastic dynamic programming model for sequentially building a hydrogen production and distribution system. The decision variables are the sequence and locations of the central production sites and the corresponding distribution systems from supply to demand sites. A case study based on the geographic setting of Northern California is included, in which the hydrogen is produced via coal gasification and transported from plant to city gates (demand sites) by cryogenic liquid hydrogen trucks. Future demands for hydrogen are modeled as uncertain parameters, with an assumption that hydrogen fuel cell vehicle (HFCV) market penetration rate increases from 1% to 25% over a 20-year period. This model provides multistage decision support for long term transportation energy planning at national and regional levels.

Keywords: multistage processes, energy infrastructure system planning, stochastic dynamic programming, hydrogen transition

INTRODUCTION

Seeking environmentally friendly and sustainable alternative fuels for transportation is important for the U.S. economy from both environmental and energy security perspectives. Hydrogen, as one of the alternative fuels, has received considerable attention in recent years for two reasons: (1) hydrogen is a clean energy carrier which can significantly reduce greenhouse gas emissions, and (2) it can be manufactured from a variety of primary energy resources, such as natural gas, coal, wind, nuclear, etc (National Research Council and National Academy of Engineering 2004).

Although the advantages of hydrogen have been well recognized, the success of a hydrogen-based economy relies on its cost competitiveness relative to other fuels. During the transition to a hydrogen economy, an entirely new infrastructure system would be required for producing and distributing gaseous fuels. The cost of developing such an infrastructure system is a potential barrier to the deployment of hydrogen. Several studies have attempted to quantify the steady-state costs of various infrastructure components in the entire energy supply chain system (DOE 2006; Freppaz et al. 2004; National Research Council and National Academy of Engineering 2004; Parker 2007). As components of the entire supply chain, hydrogen production and

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distribution facilities have been specifically analyzed in (Ogden and Yang 2006) and (Yang and Ogden 2007), where several ways of reducing the cost of production and distribution were proposed using engineering-economic models.

However, previous studies considered only steady state conditions and assumed deterministic and time-invariant demands, resource supplies, and other model parameters. This treatment may not be appropriate for the design of a hydrogen system where infrastructure is deployed over a long time period (planning horizon). In particular, there is considerable uncertainty regarding the growth in hydrogen demand over time. Hence, a model with an additional dimension for handling uncertainties and dynamics is required. The present paper addresses this void.

The problem of gradually building a hydrogen production and distribution system falls within the general category of a dynamic location problem, which is one of the major research interests in location and logistics science. In a recent review article by Melo et al. (2006), it was pointed out that few realistic models consider stochasticities and dynamics and thus more research is needed in this area. Some existing studies based on multistage deterministic or stochastic programming (Chardaire et al. 1996; Dias et al. 2007; Kelly and Marucheck 1984; Sheppard 1974; Wesolowsky and Truscott 1975) have shed light onto our work, even though we approach the problem mainly from a dynamic programming viewpoint. In the later part of this article, we will discuss how the choice among different modeling techniques may affect the computational complexity of the problem.

In this paper, a multistage stochastic dynamic programming model (Bellman and Kalaba 1965; Bertsekas and Tsitsiklis 1996; Dreyfus and Law 1977) is established to optimize the process of building and operating hydrogen production facilities during the transition to a hydrogen-based transportation system. Future demand for hydrogen is treated as the major source of uncertainty, and is assumed to increase over time. The location and sequence of production facilities represent the basic spatial and temporal dimensions of the problem. These are strategic planning decisions that are usually made over a long planning period and cannot be easily modified once implemented. In addition, there are operational decisions, such as the production quantities and the deliveries between plants and demand centers, which are examined more frequently and can be adjusted according to newly acquired information. This special feature of the problem leads to our choice of a stochastic dynamic programming model with a master- and sub- problem structure. The master-problem model focuses on the total expected system cost over the entire planning horizon while the sub-problem model focuses on the single-stage operational cost. The master and sub-problem models pass information between each other and are solved together iteratively. The details of this model structure will be provided in the next section.

A case study based on the geographic setting of Northern California is included, in which the hydrogen is produced via coal gasification and transported from plant to city gates (demand sites) by cryogenic liquid hydrogen trucks. The demand for hydrogen is assumed to increase as the hydrogen fuel cell vehicle (HFCV) market penetration rate increases from 1% to 25% over a 20-year period (Miller et al. 2005). Sensitivity analyses were conducted to identify important model parameters and to analyze their impacts on the design and cost-effectiveness of hydrogen infrastructure systems.

METHODOLOGY

Problem description

Before we formulate the problem, let us first describe the spatial and temporal dimensions of the problem and discuss the possible tradeoffs between different cost components of the system, which justify the need for a system approach.

Cost components:

The entire system cost includes the following components:

- fixed capital cost of building production plants, which depends on the number and sizes of the plants, and the land values of the plant locations;
- operational cost associated with fuel production, which is proportional to the production quantity;
- operational cost associated with fuel transportation, which depends on the quantity of fuel and the distance that it needs to be transported between the plants and demand sites; and
- operational cost associated with the penalty associated with the fuel shortage. This is a modeling choice. The cost may be considered as the cost of outsourcing if the penalty cost is chosen equivalent to the imported fuel cost, or it may be considered as a soft constraint for satisfying demand if the penalty cost is set high.

The objective of the model is to minimize the total system cost over the entire 20-year horizon.

Spatial dimension of the problem:

The geographic layout of the production plants is critical to the efficiency of the entire system. On the one hand, building centralized production plants in remote areas may reduce cost by taking advantage of economies of scale and lower land values. On the other hand, transporting hydrogen can be expensive because it is a low-density gaseous fuel (DOE 2006). Therefore, accessing demand sites, most of which are in populated areas, from those remote and centralized production plants may become expensive. The spatial dimension of the system causes tradeoffs between the capital cost of plants and the transportation cost of hydrogen, which need to be considered in the planning process.

Temporal dimension of the problem:

During the transition of the system over a long planning period, building and operational decisions are likely to be made sequentially. Therefore, we divide the entire planning horizon into multiple decision stages to incorporate the time-dependent feature of those decisions. Choice of time stage interval depends on frequency of the decisions. In this problem, decisions are made annually. Therefore, the planning horizon is divided into 20 decision stages. Regarding the construction of plants, the following assumptions are made:

- plant construction decisions are made at the beginning of each year;
- at most one new plant can be built in each time interval;
- construction of a new plant requires two years to complete; and
- once opened, a plant will not be shut down during the entire planning horizon.

Due to the 2-year construction lag, planning decisions for building new plants should only be made in the first 18 years of the 20-year planning period. Operational decisions are made yearly for those constructed plants. The 2-year construction lag also explains the lag in the operational costs associated with under-construction plants in our model formulation. Demand is assumed to be uncertain with an increasing trend over the planning period. Given time dynamics and demand uncertainty, there may be tradeoffs between the current cost of building and operating plants and the potential future cost of a fuel shortage. In the later part of this paper, we will use a case study to examine the impact of imperfect information of model parameters on system cost and to highlight the value of a stochastic model compared to its deterministic counterpart.

Mathematical model

<u>Basic structure of the model:</u>

A k-year multistage process can be considered as a process of the first k-1 years plus the last k^{th} year. Given a known initial system state at the beginning of year 1, let $f_k(s_k)$ be the minimum system cost as the system transits from year 1 to the state s_k in year k. By this definition, the minimum system cost as the system transits from year 1 to the state s_{k-1} in year k-1 is $f_{k-1}(s_{k-1})$. Let x_k denote the decision variable to be made at the beginning of the k^{th} stage, which transforms the system state from s_{k-1} to s_k. Let r_k be the cost realized in the k^{th} stage, which is usually a function of x_k and s_{k-1}. In the simplest manner, the relation between the unknown functions f_k and f_{k-1} can be formulated using dynamic programming as:

$$f_k(s_k) = \min_{x_k}\{ f_{k-1}(s_{k-1}) + r_k(x_k, s_{k-1})\},\ k = 2, 3, \ldots, K, \qquad (1)$$

where K is the entire planning horizon. The boundary condition $f_1(s_1)$ can be easily obtained based on the initial state.

Now let us add a little more complication to the above equation. Suppose there are two types of decision variables to be made in each stage, a planning decision denoted as x_k and an operational decision denoted as y_k. Equation (1) should be modified as:

$$f_k(s_k) = \min_{x_k, y_k}\{ f_{k-1}(s_{k-1}) + r_k(x_k, y_k, s_{k-1})\},\ k = 2, 3, \ldots, K. \qquad (2)$$

Under certain condition when y_k does not affect the transformation from s_{k-1} to s_k, using the concept of projection (sometimes also known as partitioning (Geoffrion 1970)), Equation (2) can be decomposed to a master problem and a sub problem represented in equation (3a) and (3b), respectively:

$$f_k(s_k) = \min_{x_k}\{ f_{k-1}(s_{k-1}) + g_k(x_k, s_{k-1})\},\ k = 2, 3, \ldots, K, \qquad (3a)$$

where

$$g_k(x_k, s_{k-1}) = \min_{y_k}\{ r_k(x_k, y_k, s_{k-1})\}. \qquad (3b)$$

Equations (3a,b) provide the basic structure of the proposed model, as illustrated in Figure 1.

Decomposition can provide some computational advantages especially if the dimensions of the decision vectors are high. It may not be common to have a decomposed structure in classic dynamic programming. However, decomposition techniques based on the concept of projection are widely used for solving mixed-integer and stochastic programming problems, for example, the well-known Benders decomposition (Benders 1962; Geoffrion 1972) and L-shaped method (Van Slyke and Wets 1969).

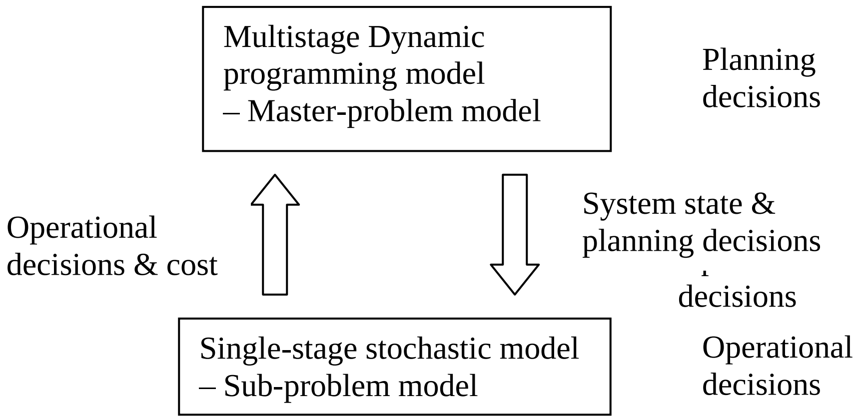


Figure 1. Structure of the decomposed stochastic dynamic programming model

<u>Mathematical formulation:</u>
The basic structure of the proposed model formulation is similar to Equations (3a, b), with some modifications to incorporate the uncertainty in demand and the 2-year construction lag.

The notations used in the master-problem model are defined as following:

- J: index j, set of candidate plant sites;
- λ: plant construction time/lag (i.e., two years in this study);
- z_j^k: planning decision variable made in stage k. It equals 1 if a new plant starts construction at location j at the beginning of time stage k; and 0 otherwise. This new plant becomes operational at the beginning of stage $k+\lambda$. Note that the index k denotes the year in which plant construction decisions are made and k can only be valued from 1 to 18;
- $S_k \subseteq J$: state variable at stage k. It is the set of all chosen plants by time stage k. The initial state of the system is given as S_0;
- F_j: annualized capital cost of a plant at location j;
- $H_{k+\lambda}(S_k)$: the total capital cost of the constructed plants at time stage $k+\lambda$, given system state at stage k as S_k;
- $O^*_{k+\lambda}(S_k)$: the minimum expected operational cost at time stage $k+\lambda$ including production cost, distribution cost and penalty cost, given system state at stage k as S_k. This value will be computed by the stochastic model in the sub-problem model and passed to the master-problem model;
- $f_k(S_k)$: the minimum cumulative expected total system cost from the beginning of the planning horizon until the end of time stage $k+\lambda$, given system state at stage k as S_k. Note that under-construction plants do not impact the minimization of system operating costs during their construction time.

The complete master-problem model is included in equations (4) to (6):

$$f_k(S_k) = \min_{j \in \{S_k \cup \phi\}} \{\lambda F_j z_j^k + H_{k+\lambda}(S_k) + O^*_{k+\lambda}(S_k) + f_{k-1}(S_{k-1})\}, \ k = 2, 3, \ldots, 18 \qquad (4)$$

$$S_{k-1} = \begin{cases} S_k & if \quad j \in \phi \\ S_k - \{j\} & if \quad j \in S_k \end{cases} \tag{5}$$

Boundary condition:

$$f_1(S_1) = \sum_{k=1}^{\lambda} \left(H_k^*(S_1) + O_k^*(S_1) \right) \tag{6}$$

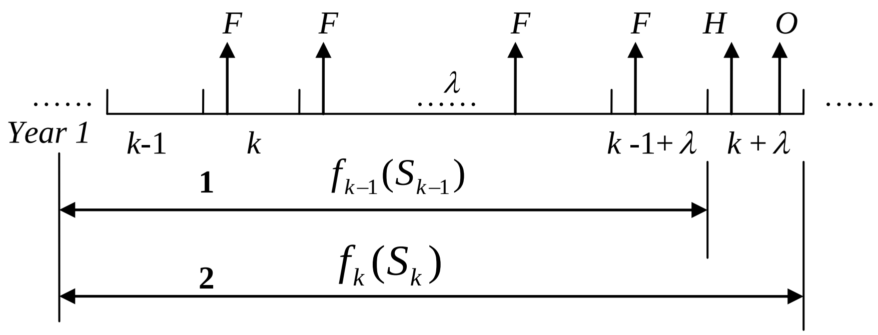


Figure 2. Recursive relations between time stage *k* and *k*-1

Equation (4) defines the recursive relation between time stages *k* and *k*-1. Figure 2 helps to illustrate this relation. The double arrow 1 represents $f_{k-1}(S_{k-1})$, the minimum expected total system cost from the beginning of year 1 until the end of stage k-1+λ given system state at stage k-1 as S_{k-1}. Consider a feasible decision at state *k* as to build a new plant at location (x_k=j). This decision causes three additional cost terms:

- capital cost of this under-construction plant between the k^{th} year and the $(k-1+\lambda)^{th}$ year (denoted by upward arrows *F*s in Figure 2, and summed as $\lambda F_j z_j^k$ in Equation (4));
- the operational cost of this new plant (denoted by arrow *O* in the figure and $O_{k+\lambda}^*(S_k)$ in the equation), since this new plant becomes operational at stage $k+\lambda$; and
- capital cost of all operational plants (denoted by arrow *H* in the figure and $H_{k+\lambda}(S_k)$ in the equation).

The optimal value function $f_k(S_k)$, represented by the double arrow 2 in Figure 2, should take the minimum value of the sum of the costs associated with x_k and $f_{k-1}(S_{k-1})$. The minimization in Equation (4) is taken with respect to all possible $j \in \{S_k \cup \phi\}$, where ϕ means that no new plant is introduced at time stage *k*.

Equation (5) defines the state transition between the $(k\text{-}1)^{st}$ stage and the k^{th} stage, which explains two possibilities. If there is no new plant from stage *k*-1 to stage *k* (i.e., $j \in \phi$), the state variable does not change so that $S_{k-1} = S_k$. Otherwise, the state variable at stage *k* (i.e., S_k) is formed by adding the new plant *j* to the existing S_{k-1} of stage *k*-1. The boundary condition is given in Equation (6), which is a single-stage optimization problem. The initial system state, S_0, is assumed to be an empty set. The first-year building decision is obtained from boundary condition (6). This plant is assumed to be operational immediately.

The complete sub-problem model is depicted in Equations (7-9), which returns the minimum expected operational cost O^* in stage k.

$$O_k^*(S_{k-\lambda}) = \min_{q,x} E_\omega \left(\sum_{j \in S_{k-\lambda}} \sum_{i \in I} \left(CP_j x_{ji}^k(\omega) + C_{ji} x_{ji}^k(\omega) \right) + \sum_{i \in I} \alpha q_i^k(\omega) \right) \quad (7)$$

Subject to

$$D_i^k(\omega) - \sum_j x_{ji}^k(\omega) = q_i^k(\omega) \qquad \forall i \in I, \omega \in \Omega \quad (8)$$

$$\sum_{i \in I} x_{ji}^k(\omega) \le cap_j^p \qquad \forall j \in J, \omega \in \Omega \quad (9)$$

where:

I:	index i, set of demand centers;
Ω:	index ω ,set of demand scenarios;
CP_j:	hydrogen production cost at plant j (\$/tonne);
C_{ji}:	delivery cost between plant j and demand center i, which includes the truck fixed and variable cost (\$/tonne);
cap_j^p:	plant production capacity at plant j (tonne);
α:	penalty level (i.e., cost of importing hydrogen from elsewhere) (\$/tonne);
$D_i^k(\omega)$:	the hydrogen demand from center i at time stage k (tonne);
$x_{ji}^k(\omega)$:	the amount of hydrogen delivered from plant j to the demand center i at time stage k (tonne);
$q_i^k(\omega)$:	the amount of hydrogen shortage at demand center i at time stage k (tonne).

The decision variables include the quantity of the hydrogen shortage at each demand center $q_i^k(\omega)$ and the amount of hydrogen delivered between plants and demand centers $x_{ji}^k(\omega)$ at each stage and under each demand scenario. The objective function (7) is to minimize the expected operational cost at time stage k, given that plants belonging to set $S_{k-\lambda}$ are operational at stage k. Equation (8) defines the amount of unsatisfied demand (q_i^k) at city i at time stage k. Constraint (9) imposes a hydrogen production limit based on the capacity of each plant j at time stage k.

<u>Solution procedure:</u>

This stochastic dynamic programming model is solved iteratively as follows:

Step 1: Solve boundary condition (6) and obtain $f_1(S_1)$.

Step 2: Repeat for each time stage k=1 to 18:

Solve $f_k(S_k)$ in equation (4), where $O_{k+\lambda}^*(S_k)$ is computed using the sub problem. The detailed procedure for computing $f_k(S_k)$ for a given S_k is illustrated in Table 1, using S_k ={1,2,3} as an example.

Step 3: At the final planning stage k=18, choose the minimum $f_k(S_k)$, and this $f_k(S_k)$ is the minimum cumulative expected total system cost throughout the entire 20 years. The planning decisions (i.e., the building sequence of production plants) can then be retrieved backward from S_{18}, S_{17}, …, to S_1.

Note that the iteration of the algorithm is carried over system stages. The algorithm starts from the boundary condition, which is a single stage problem that can be solved exactly. Then from the boundary condition, every time as the algorithm moves forward, one more time period is added. The problem in the new stage can still be solved exactly, because the previous stage problem is already solved. The algorithm continues to move forward until the end of the planning horizon is reached. This forward dynamic programming structure is an exact algorithm, not a heuristic procedure.

Table 1. Computation procedure from (k-1)st to k^{th} stage for a specific S_k

S_k	j	S_{k-1}	$F_j z_j^k$	$O^*_{k+\lambda}(S_k)$	$H_{k+\lambda}(S_k)$	$f_{k-1}(S_{k-1})$		$f_k(S_k)$
{1,2,3}	ϕ	1,2,3	0	O	H	g_1	$F_1 = O+H+g_1$	$\min\begin{Bmatrix} F_1 \\ F_2 \\ F_3 \\ F_4 \end{Bmatrix}$
	1	2,3	C_1	O	H	g_2	$F_2 = O+C_1+H+g_2$	
	2	1,3	C_2	O	H	g_3	$F_3 = O+C_2+H+g_3$	
	3	1,2	C_3	O	H	g_4	$F_4 = O+C_3+H+g_4$	

*The details of the computation process are interpreted as follows. Given S_k ={1,2,3}, there are four possible j values (2nd column) that could transform the system from state S_{k-1} (3rd column) to S_k. The three costs associated with each j are given in columns 4, 5, 6. The value of $f_{k-1}(S_{k-1})$ for each S_{k-1} is given in the 7th column. As a result, for each possible j, the total system cost is updated from stage k-1 to k in the 8th column. The minimum value of the four Fs is $f_k(S_k)$ (last column), and the corresponding j that minimizes the total system cost is an optimal planning decision for the state S_k.

The iterative solution procedure in the master problem was implemented in MatLab and AMPL/CPLEX (Fourer et al. 2003) were used to solve the sub-problem model at each stage. The complexity of this solution algorithm is dominated by the total number of stages (K) and the number of candidate locations (N). There are three layers of iterations, which correspond to the stage index, possible states in each stage, and possible decisions at each stage. These three layers result in a complexity no worse than $K \times N^2$. Note that the sub-problem model could be solved for all possible states before running the master-problem model, or be called when it is needed during the computation procedure of the master-problem model.

In general, the complexity of a dynamic programming model depends on the size of the decision tree, while the complexity of a stochastic programming model is dominated by the size of the scenario tree. Note that three demand scenarios are assumed in each decision stage, thus forming a total of 3^{20} possible random scenarios to be considered in this problem. If a stochastic programming framework is chosen for modeling this problem, then it has to handle 3^{20} branches in the scenario tree, which will cause a major numerical challenge. In a dynamic programming framework, only the random scenarios in a single-stage are considered at a time, and the combined possibilities of the remaining process are packaged in the unknown optimal return function $f_k(S_k)$ for $k = 1, 2, \ldots, K$.

CASE STUDY

Data Preparation

This paper examines a case study in Northern California in which it is assumed that the HFCV market penetration rate increases from 1 to 25% over twenty years, as shown in Figure 3 (Miller et al. 2005). Given a market penetration rate in each year, a demand model was used to identify the locations and magnitudes of demand for those areas in which there is sufficient demand to warrant infrastructure investment (Johnson et al. 2005). However, under uncertain conditions, demand in each area is randomly chosen between three demand levels in each year as shown in Table 2. Random demands at different locations are assumed to be independent of each other (i.e., no geographic correlation between them is considered).

Table 2. Three demand levels and associated probabilities

	Median	*High*	*Low*
% difference from median	0	+25%	-25%
Probability	2/3	1/6	1/6

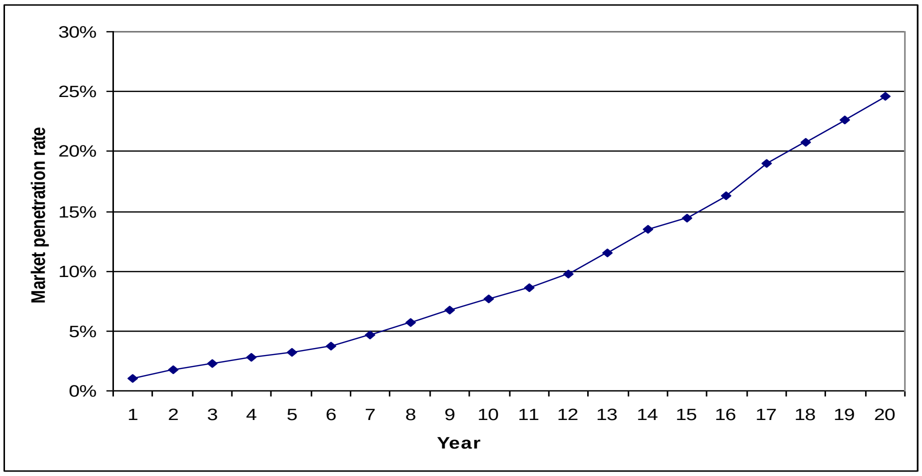


Figure 3. Market penetration growth rate

The size and number of demand centers grow as the market penetration rate increases from 1% to 25% as illustrated in Figure 4. There are five potential locations for hydrogen production sites. These sites are constrained by the locations of existing large power plants within the study area (USEPA 2002). A geographic information system (GIS) was used to identify the shortest path truck routes connecting each of the candidate production facilities to all of the demand centers. These routes form a candidate fuel delivery system. The model takes these data as inputs to identify an optimal facility building sequence that minimizes the total expected production and distribution costs.

The plant fixed cost includes both capital and operation and maintenance (O&M) costs associated with the coal gasification plant, hydrogen liquefier, truck terminal, and on-site storage. The production capacity of each plant is set to be 500 tonnes/day based on DOE recommendations (DOE 2006). Cost modeling conducted by H2A (DOE 2006) and Kreutz et al. (Kreutz et al. 2005) was used to estimate plant fixed costs. These costs were then annualized and converted to 2005 dollars assuming a real discount rate of 10% and a plant lifetime of 40 years. The capital cost of a plant was estimated to be $281 million per year.

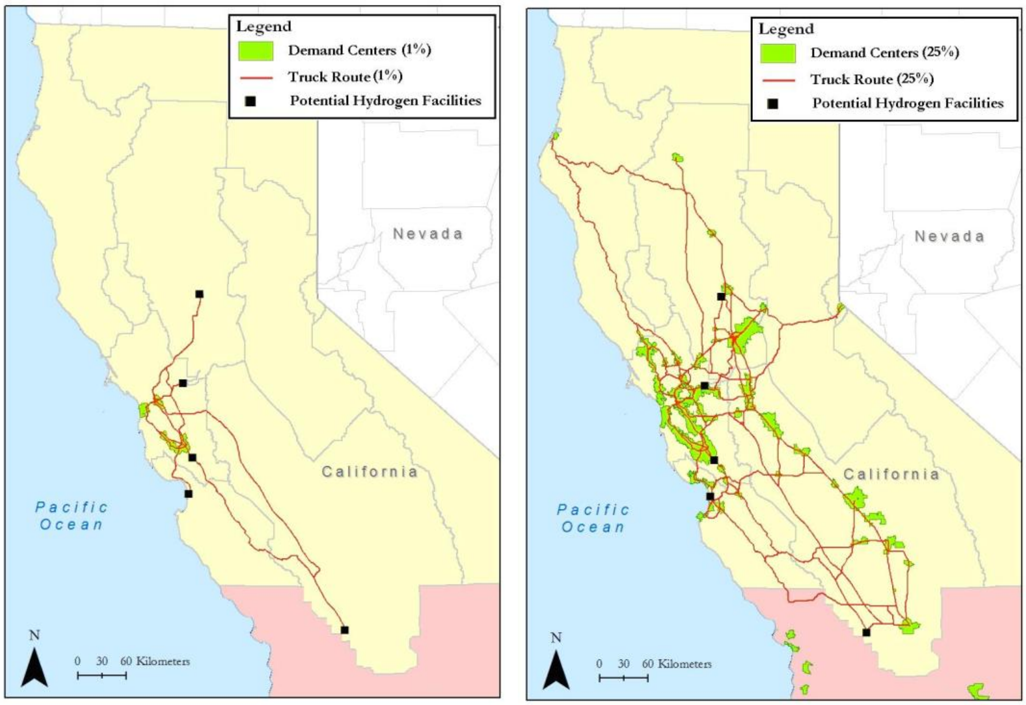


Figure 4. Demand centers and potential production facilities and truck routes at 1% and 25% market penetration rates

The plant variable cost includes the coal feedstock cost, electricity cost for liquefaction, and revenue from co-production of electricity. Assuming a coal-to-hydrogen efficiency of 57%, the amount of coal required to produce a kg of H_2 is 0.198 mmBtu/kg (Chiesa et al. 2005). This number is multiplied by the price of coal ($1.29/mmBtu) to calculate the feedstock cost, which is estimated to be $0.26/kg H_2. The electricity cost is calculated assuming that 9.25 kWh/kg H_2 is required for liquefaction and the electricity cost is $0.05/kWh (DOE 2006). The estimated cost of electricity in all cases is $0.46/kg H_2. The electricity revenue is calculated assuming that 2% of the coal input is converted to electricity and that the electricity is sold for $0.05/kWh (Chiesa et al. 2005). With these assumptions, the electricity revenue is estimated as $0.06/kg H_2. Therefore, the total plant variable cost after accounting for both costs and revenue is $0.66/kg H_2.

For hydrogen distribution via liquid trucks, it is assumed that the truck capital cost is $104,792 per year and truck capacity is 9,000 kg. The truck variable cost ($/km) is a function of fuel, labor, and fixed O&M costs. Assuming that the trucks are diesel-operated and achieve a fuel economy of 10 km per gallon, the fuel cost is calculated by dividing the fuel price ($2/gallon) by the fuel economy. As a result, the fuel cost is estimated as $0.20/km/truck. The labor cost is calculated by identifying the time it takes to travel one km (assuming an average truck speed of 60 km per hour) and multiplying this quantity by the wage ($20/hour). In addition, overhead is assumed to be 50% of labor. Therefore, the labor cost (including overhead) is estimated to be $0.50/km/truck. The fixed O&M cost includes truck maintenance and is given as $0.18/km/truck (DOE 2006). Therefore, the total distribution variable cost is $0.88/km/truck.

A transport cost matrix was developed for the shortest paths between potential production facilities and all demand centers at 25% market penetration. Since the number of trucks required along each route will differ at each market penetration level, the desired cost metric is dollars per truck. The shortest distances provided by the GIS were converted to costs by multiplying each one-way distance by two to get a roundtrip distance and then multiplying these distances by the fuel delivery variable cost. Since the delivery variable cost is in $/km/truck, the units of the resulting transport cost matrix is $/truck.

Results and Sensitivity analyses

In this section, the results of the case study are summarized and discussed. First, the results under baseline assumptions are reviewed. Then, sensitivity analyses are conducted in which key parameters are varied in order to see how changes in these parameters impact the system layout and costs.

Baseline case

The baseline scenario is defined as follows:

- all hydrogen plants have a maximum capacity of 500 tonnes H_2/day even though the actual production quantity is determined by the model;
- plant capital cost varies depending on location (Table 3) (e.g., plants near the San Francisco Bay Area are assumed to be 20% more expensive to build due to higher land and labor costs); and
- the penalty cost for demand shortages is $10/kg $H_{2,}$ which is set significantly high to ensure sufficient instate hydrogen production.

Table 3. Plant capital costs (M$/year)

Plant	*Location*	*Capital Cost (500 tonnes/day)*
Plant 1	Kern County	$ 281.3
Plant 2 (+20%)	San Jose	$ 337.6
Plant 3 (+10%)	Moss Landing	$ 309.5
Plant 4 (+20%)	Pittsburg	$ 337.6
Plant 5	Yuba City	$ 281.3

The complete results of the baseline scenario are summarized in Table 4. The first column contains the planning years and year zero denotes the time stage before the beginning of the first year. At the beginning of year 1, the plant building decision is determined by the boundary condition. The plant location pattern in each year is represented in the second column. For example, a plant at Yuba city (location ID 5) is built at the beginning of year 1 and this location pattern remains the same until the end of year 10 (or the beginning of year 11), when a new plant in Kern County (location ID 1) is built. Since it then takes two years to complete construction of a new plant, the second plant will become operational at the beginning of year 13. During construction, the model assumes that capital payments begin on the new plant even though it is not yet operational. These additional capital costs are recorded in the third column. The fourth column contains the capital costs of the operational plants. The annual operational costs, the expected hydrogen production quantity, and expected demand shortage are summarized in columns five, six and seven, respectively. The annual expected total system cost is stored in column eight, which is the summation of plant capital costs (including both under-construction and operational plants), operational costs, and shortage costs. The average cost of hydrogen ($/kg) is identified in column nine and is computed by dividing the total annual cost by the quantities of annual production and shortage together. Column ten records the percentage of the total system cost that results from penalties.

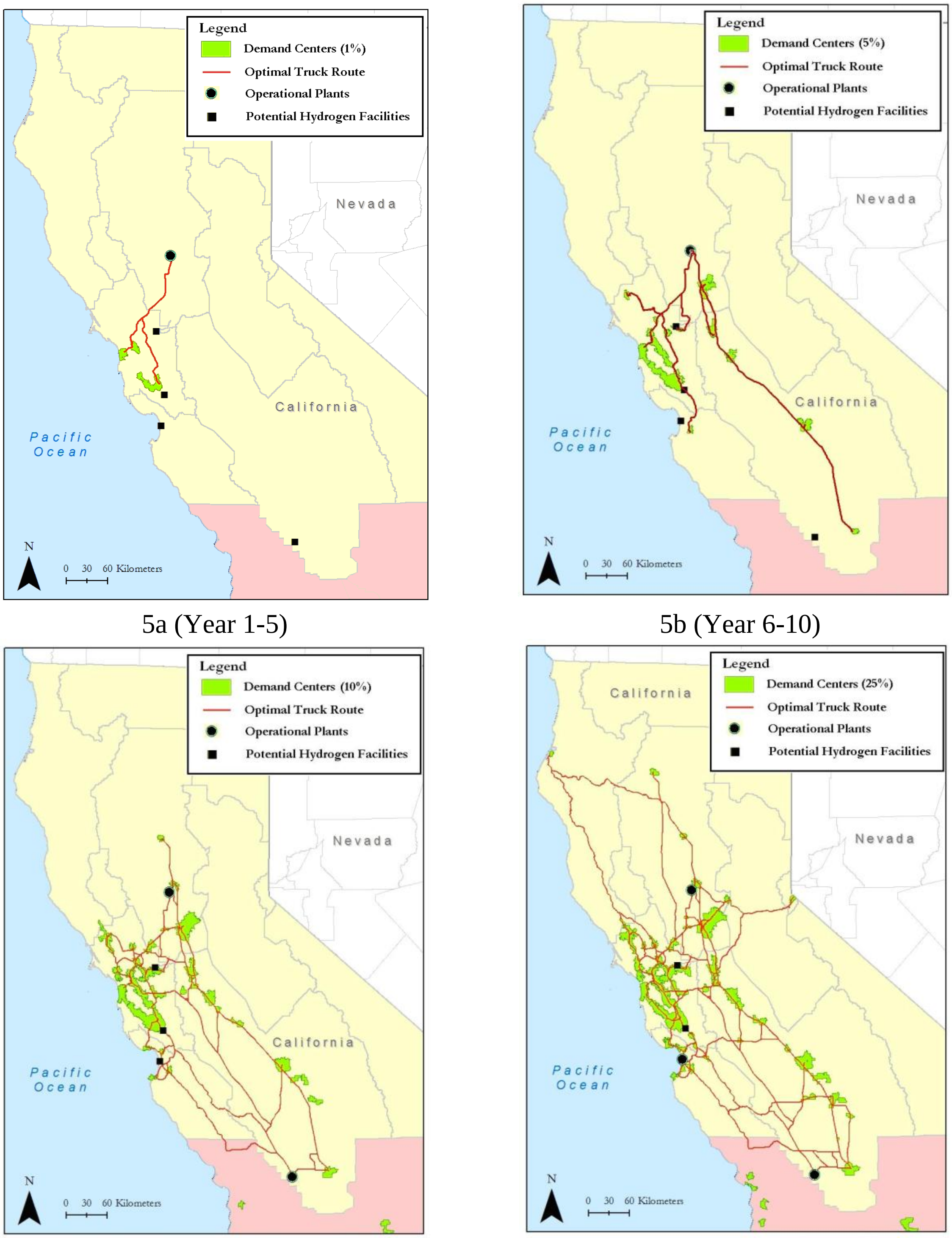
Table 4 indicates that the plant capital cost is significantly larger relative to the O&M costs. Since we vary the capital costs by location, the model minimizes the total system cost by choosing the plants with the lowest capital cost first. In fact, these low cost plants are selected even though they are distant from the demand centers (as shown in Figure 5), which indicates that delivery costs are less important compared to plant capital costs. For example, a single plant at Yuba City is operational from year 1 to 10. As shown in column 9 of Table 4, this plant is underutilized at the beginning, resulting in high average hydrogen costs of $24.48/kg and $12.88/kg in the first two years. However, as hydrogen demand increases and the plant becomes better utilized, the average cost decreases to $2.77/kg in year 10. The model chooses to build an additional plant at Kern County in year 11 because the penalty cost on fuel shortage outweighs plant capital and fuel delivery costs by year 13. In the base model, capital costs are the main drivers in selecting plant locations and determining hydrogen costs.

The sequence of building the hydrogen infrastructure system is illustrated in Figure 5, with results aggregated into four 5-year periods to save space. Although the choice of plants is the same in Figure 5(a) and (b), additional truck routes are needed to support the delivery of fuel to more demand centers.

Table 4. Baseline results summary

Year	New plant location (plant ID)	Capital cost of under-construction plants (2005$ million/year)	Capital cost of operational plants (2005$ million /year)	Operating cost (2005$ million/year)	Production (tonnes/year)	Shortage (tonnes/year)	Annual total system cost (2005$ million/ year)	Average H2 cost (2005$/kg)	penalty cost (%)
1	**5***		$281	$ 9	11,864		$ 290	$ 24.48	
2			$281	$ 18	23,217		$ 299	$ 12.88	
3			$281	$ 21	27,148		$ 302	$ 11.13	
4			$281	$ 30	39,350		$ 311	$ 7.91	
5			$281	$ 34	44,486		$ 315	$ 7.09	
6			$281	$ 44	57,798		$ 326	$ 5.63	
7			$281	$ 58	75,395		$ 339	$ 4.49	
8			$281	$ 73	96,187		$ 355	$ 3.69	
9			$281	$ 92	120,103		$ 373	$ 3.11	
10			$281	$107	140,506		$ 389	$ 2.77	
11	**1&5**	$281	$281	$145	155,957	2,620	$ 708	$ 4.37	4%
12		$281	$281	$214	174,964	8,073	$ 777	$ 3.98	10%
13			$563	$168	221,216		$ 731	$ 3.30	
14			$563	$199	261,142		$ 762	$ 2.92	
15			$563	$213	279,883		$ 776	$ 2.77	
16	**1,3 &5**	$310	$563	$289	311,329	5,089	$1,161	$ 3.57	4%
17		$310	$563	$464	350,416	19,578	$1,336	$ 3.26	15%
18			$872	$304	404,575		$1,176	$ 2.91	
19			$872	$350	444,073	1,597	$1,222	$ 2.72	1%
20			$872	$450	473,273	9,285	$1,322	$ 2.74	7%

Note: * Plant ID can be referred to Table 3 for its corresponding plant location.



5a (Year 1-5) 5b (Year 6-10)

5c (Year 11-15) 5d (Year 16-20)

Figure 5. Hydrogen production and delivery system design during four 5-year periods

In an uncertain-decision environment, a stochastic modeling method that considers the entire range of possible random scenarios often produces a more reliable solution than its deterministic counterpart that considers the expected value of random parameters. For comparison, solutions are obtained from a stochastic model and a deterministic model that use only the expected demands of the 20-year period. These two different solutions are then evaluated under an identical set of 1000 samples of demand scenarios randomly generated using Monte Carlo simulation based on the probability distribution given in Table 2. Figure 6 shows the performance of the two solutions generated from stochastic and deterministic models under the 1000 demand scenarios. The two curves indicate the cumulative probabilities of not exceeding a certain system cost, resulting from the stochastic (pink curve) and the deterministic (blue curve) solutions, respectively. For example, one may read that the probability of not exceeding a total system cost of 2005$14 billion is 90% following the stochastic solution and about 80% following the deterministic solution. It is clear that the stochastic solution provides better reliability on the higher end of cost thresholds, which is usually favored by risk-averse system planners especially if the system is large-scale and expensive. The stochastic solution also provides a better robustness in the worst case, with 2005$15.25 billion following the stochastic solution and 2005$16.25 billion following the deterministic solution.

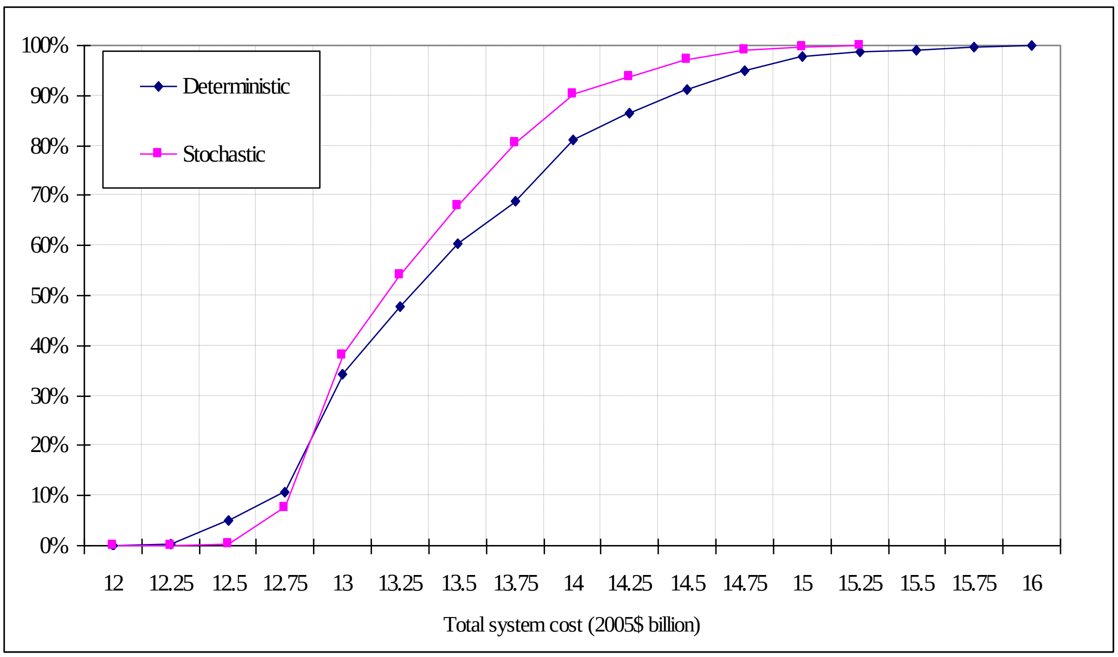


Figure 6. Comparison between stochastic and deterministic methods

<u>Sensitivity analyses</u>

Two sensitivity analyses are conducted to evaluate the impacts of basic energy feedstock (electricity, coal, and diesel) prices and the penalty cost on the system layout and the total system costs.

(1) Impact of feedstock prices

The cost of hydrogen production and distribution is dependent on the costs of several energy feedstock types that are used in the process. This section analyzes the impact of changes in these feedstock costs on the model results. Three feedstock types are examined: electricity, coal and diesel fuel. Coal is gasified to produce hydrogen while significant electricity is required to liquefy hydrogen for truck transport. Finally, diesel is used to fuel the trucks that transport the hydrogen to demand centers. The impacts of changes in the prices of these feedstocks on hydrogen system costs (capital and operational) are summarized in Table 5.

The results suggest that changes in feedstock prices do not affect the system capital cost. However, the system operational cost is sensitive to changes in feedstock prices. For instance, doubling the electricity cost results in about a 50% increase in the operational cost and a 12% increase in the total system cost. Compared to the electricity price, the changes in coal and diesel fuel prices have negligible impacts on the total system cost.

Table 5. System costs when feedstock costs are varied

Scenarios	*Total system cost (2005$ billion)*	*Capital cost (2005$ billion)*	*Operating cost (2005$ billion)*
Electricity price (2005$kWh) increase from 0.05 to 0.10 (100%)	$14.85 (+12%)	$9.99 (0%)	$4.86 (+48%)
Coal price (2005$/mmbtu) increases from 1.29 to 1.50 (16%)	$13.43 (+1%)	$9.99 (0%)	$3.44 (+5%)
Diesel fuel price (2005$/gal) from 2.00 to 4.00 (100%)	$13.30 (+0%)	$9.99 (0%)	$3.31 (+1%)
Baseline scenario	$13.27	$9.99	$3.28

(2) Impact of penalty cost

The penalty cost (i.e., imported hydrogen cost) was varied from $10 to $2 per kg of H_2 to examine its impact on the quantity of imported hydrogen to meet demand shortages.. It was found that if the imported fuel can be obtained for less than $2/kg, then all the demand over the 20-year planning horizon should be served by imported hydrogen. As the imported hydrogen cost increases to $4/kg, in-state production increases to 60% of the in-state demand. When the imported cost exceeds $8, it is most efficient to have all the demand satisfied by in-state production.

CONCLUSIONS AND FUTURE WORK

This paper presents a stochastic dynamic programming model to optimize the sequence of building hydrogen production facilities and simultaneously determine optimal production and delivery decisions in each time stage, under demand uncertainty. The proposed model integrates dynamic programming and stochastic programming methods to improve the effectiveness and flexibility of planning and operational decisions. This problem could also be formulated as a multistage stochastic programming model, as in several previous studies on the dynamic location problem mentioned in the introduction. However, the proposed model may provide some modeling flexibility such as integrating a computer simulation in the single-stage sub-problem model. It may also have computational advantages when the size of the scenario tree is the main cause for numerical difficulties.

A case study based on the geographic setting in Northern California was also examined in this paper. Numerical experiments show a clear advantage for stochastic modeling techniques in producing more reliable and robust design solutions under a highly uncertain decision environment. Based on the case study results and sensitivity analyses, some important policy implications have been identified. In general, we found that the capital cost was the major cost driver of the total system cost and varying the electricity price could change the operational cost significantly. Sensitivity analyses on the penalty cost revealed that optimal in-state production levels correspond to different hydrogen import costs. California is currently implementing low-carbon standards that may mandate certain levels of clean fuel to be produced within the state. Results from this study can provide information to support the formation of such policy.

An immediate extension of this work would be to consider plant capacity as a planning decision variable. The dimension of planning decisions would be increased to three: location, time, and size. Also, intermediate storage facilities can be introduced into the system to store excess produced hydrogen in order to mitigate fluctuations in production cost due to changes in the supply and prices of feedstocks. These modifications would have an impact on the complexity of the problem. Developing an efficient solution algorithm for the extended work is the focus of our ongoing efforts.

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