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Analysis on the feedback effect for the diffusion of innovative technologies focusing on the green car

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ABSTRACT

Previous studies of technical competitive relationship have mostly focused on the analysis of one-directional impact of the technical attribute on market share. However, there is a cyclical feedback effect between the technical attributes and market share, and that means the small difference of competitiveness at the early phase of technology diffusion can greatly affect the final market share. As such, this study presents the system dynamics model which can forecast sales of innovative technology considering the feedback effect of market share on technical attributes. For that, the causal loop diagram among the various variables was defined using the econometric model applied and proven in various studies of the Bass diffusion model, discrete choice model, etc. to reinforce the theoretical background of the causal relationship among the variables of the forecasting model. Furthermore, infrastructure building scenarios and feedback effect scenarios were applied to the developed forecasting model to present the implication for successful adoption of green car technology from the infrastructure development view point.

1. Introduction

Korea established green growth as its new national development paradigm to help to solve the problems of global warming, the energy crisis, etc. and to create a new growth engine and it has been investing in various efforts to accomplish this new goal (Presidential Commission on Green Growth [1]). As a part of these efforts, the government voluntarily announced on November 17, 2009 its target to reduce green house gas emissions by 30% compared with BAU (Business As Usual) by 2020. This 30% reduction target is the most aggressive target of the three originally proposed reduction scenarios and can be accomplished only when actively adopting the various green house gas reduction measures. Particularly, it will require the deployment of green cars such as electric vehicles (EV) and hydrogen fuel cell vehicles (HFCV), in addition to energy consumption saving through a strong demand management policy (Presidential Commission on Green Growth [2]). Therefore, the development and distribution of green car technology that can drastically reduce green house emissions in the transportation sector will be the key to accomplishing the green house gas reduction target.

However, EVs and HFCVs are still in the early phase of technology development and require many technical breakthroughs for them to be commercialized, thus uncertainty of their technology development continues to be high. Furthermore, they use a motor and battery or hydrogen fuel cell as their key power source and are completely different technology in feedstock from the conventional vehicles using internal combustion engines. Therefore, the technology cannot be widely deployed without the construction of a new recharging infrastructure first. As such, the hybrid electric vehicle (HEV), which uses a motor and battery in parallel with the internal combustion engine can thus be distributed without the requirement of a new recharging infrastructure, is gaining attention as the short-term alternative for the deployment of green cars. Eventually, the speed of market entry of green

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cars and the market share of the alternative technologies will be determined by the outcome of green car technology development and the degree of recharging infrastructure development.

This study attempts to envisage the future of transportation by developing the model which can forecast sales of green car alternative technology according to a dynamic change of factors such as fuel efficiency, feedstock cost, vehicle price and degree of infrastructure development that affects the vehicle consumer utility. There is a feedback effect particularly between the vehicle price/degree of infrastructure development and market share (Meyer [3]). This feedback effect shows that the market share increases when the price of a vehicle technology decreases or infrastructure development is promoted, and that increase of the market share accelerates the reduction of vehicle price and infrastructure development. Such feedback effects can cause a small competitive edge within a technology in the early distribution phase to result in a major difference of market share during the technology maturity phase. Therefore, analyzing the impact of the feedback effect on sales of new technology is an important part of forecasting sales of not only green cars but also other innovative technologies.

To consider how the feedback effect, mostly from green car technology, impacts sales of innovative technologies and competitive relationships among the technologies, Chapter 2 reviews the existing related studies while Chapter 3 studies the three key methodologies for market forecasting model development. Chapter 4 presents the developed sales forecasting model developed using the methodologies presented above and Chapter 5 studies the baseline data and parameters to apply the forecasting model to green cars. Chapter 6 deducts the sales forecasting results for the green car technologies based on the various scenarios and Chapter 7 summarizes the significance of this study and future study directions.

2. Literature review

The total market size of green car technology has mostly been quoted directly from the government's deployment target or technical prediction of manufacturers, or by using a qualitative method such as establishing the distribution scenario (The National Academies [4], EIA [5] and IEA [6]). However, there are few quantitative forecasting studies for future green car market size using the diffusion model based on the past time series data (Park [7]). The reason is because there are no sufficient data to estimate the future because innovative technology is not yet established in the market. Park's study used the hybrid vehicle sales volume data in the Japanese market, which is the pioneer in hybrid vehicle deployment, to forecast sales of green cars in Korea. But, it has the limitation of not being able to consider the competitive relationship of various alternative green car technologies.

While there is a shortage of studies forecasting the total green car market size, there have been many studies analyzing the impact of technical attribute changes on the market share of the technology (Golob [8], Ewing [9], Mau [10] and Axsen[11]). This is because most studies of technical competitive relation used the discrete choice model, which has the strength of easy availability of data for estimating the model parameters as it uses a consumer survey result. However, most studies of competitive relations had their own limitations on forecasting the deployment volume of each technology, as they only estimated the selective probability of the technology without consideration to the total market size.

Therefore, there is a need to integrate the diffusion model and discrete choice model to develop one that predicts the total market size while considering the competition among the technologies. Although Jun and Kim developed prediction models integrating the diffusion model and discrete choice model, they were limited in that they did not consider repurchase (Jun [12] and Kim [13]). Most diffusion models forecast the market distribution by considering only the initial purchase, but repurchase with consideration to the life of the technology needs to be considered also in order to recognize the transition among competing technologies through the integration of the discrete choice model. Jun presented an integrated model that includes both the diffusion model and discrete choice model with consideration to repurchase, but it was not a complete integrated model as the methodology merely applied the various models sequentially (Jun [14] and Jun [15]). Furthermore, it was based on the discrete choice model based only on the one-directional impact of technical attribute on probability of product purchase and was not able to analyze the feedback effect of the accumulated product purchase volume on the technical attribute.

The existing economic models are limited in analyzing the feedback effect between the technical attributes and product purchase probability. Therefore, the feedback effect studies have been using the system dynamics or agent based modeling (ABM) based on the complexity economic theory. Dogan and Patrick used the system dynamics technique to forecast sales of HFCV while Malte predicted the same with ABM (Keles [16], Schwoon [17], Schwoon [18] and Patrick [3]). Although the studies analyzing the feedback effect develop and utilize very detailed simulation models to consider the composite effects of the various factors affecting the market distribution of HFCV, its weakness is that it has a weak theoretical background of the causal relationship among the variables. Therefore, this study intends to supplement the weakness of the existing simulation model by deploying the system dynamics based on the simulation model integrating the diffusion model and discrete choice model with consideration to repurchase. Sales forecasting considering the diffusion model, repurchase, customer choice model, and feedback effect simultaneously is the method that was first proposed in this study.

3. Research methodologies

3.1. Diffusion model

This study forecasts the total green car market size using the Bass diffusion model. The Bass diffusion model, proposed by Bass in 1969, is the most widely used diffusion model. It defines the probability of a consumer adopting a new product at time T in terms of the innovator group's adoption probability and imitator group's adoption probability, called the innovation factor p and imitation factor q, respectively (Bass [19]). While the adoption probability of the innovator group remains the same as the innovation factor during the prediction period, the adoption probability of the imitator group is determined as the product of the imitation factor and cumulative adopter rate. Defining the innovation factor as p, imitation factor as q, density function of product adoption at time T as $f(T)$, cumulative density function of product adoption at time T as $F(T)$, the conditional probability of a consumer not adopting the product until time T to select the product at time T can be presented in the following mathematical form:

$$\frac{f(T)}{[1-F(T)]} = [p + qF(T)] \tag{1}$$

The Bass diffusion model well reflects the new product diffusion process showing an S-curve shaped distribution curve. As the purchase probability by the imitators increases when there are more adopters, the overall purchase probability decreases as the potential adopters decrease after the market saturates. Thus the product distribution speed will rapidly increase as the volume passes the critical mass, and it will rapidly decrease as the product market reaches the saturation point.

However, the Bass diffusion model has a limitation of assuming only the initial purchase of the product. In other words, it cannot consider the product repurchase after the product lifecycle and considers only the probability of the consumer, who has not purchased the product until that time, as newly purchasing the product. As such, there have been various studies to additionally consider repurchase in the Bass diffusion model (Lilien [20], Mahajan [21], Rao [22] and Wieringa [23]). However, the models by Lilien and Mahajan can only be accepted as a repeated purchase model rather than a repurchase one since they did not consider the competition with other products. Rao's model can also be considered more as a repeat purchase model than repurchase model since it does not include the competition with another product. Since Rao analyzes diffusion using aggregate data, there is a limitation on separating and identifying the new purchaser and repeat purchaser. Therefore, this study proposes a model that separates the new purchasers and those purchasing the product after the product lifecycle. In the model developed in this study, the new purchasers make the green car purchase decision according to the Bass diffusion model, while those who had already purchased a green car adopts one of the competing green car technologies according to the discrete choice model after the product passes its product life.

3.2. Discrete choice model

To estimate the market share of each green car technology, this study considers the impact of factors like fuel price, fuel efficiency, vehicle price and degree of infrastructure development on purchase probability of the product. Since the consumers make the choice to maximize utilities after considering various product attributes, the result of consumer choice is mainly the categorical variable with the discrete value. Therefore, using the conventional estimation method such as the least square method can cause an econometric problem like the violation of the basic assumption of IIA normal distributed error (Greene [24]). The discrete choice model is a statistical analysis method used when the dependent variable is a qualitative variable or categorical variable. In the discrete model, choosing from two reaction categories is called binary choice while choosing from multiple alternatives is called multinomial choice, and it includes ranking. Although there are various forms of the multinomial choice model like the multinomial logit model, probit mode and mixed logit model, the multinomial logit model is the most widely used because of ease of estimation. Like the discrete choice model, the multinomial logit model is based on the random utility model consisting of the deterministic term, which is the observation of the consumer utility and statistical stochastic term. The random utility model of the multinomial logit model can be expressed as follows (Train [25]):

$$U_{ni} = \beta x_{ni} + \epsilon_{ni} = V_{ni} + \epsilon_{ni} \tag{2}$$

Here, n means the consumer, i means the alternative, x means the product attribute vector, and β means estimation coefficient vector. In this case, the probability of a consumer n choosing an alternative j can be expressed as follows:

$$P_{nj} = \text{Prob}\Big(V_{ni} + \epsilon_{ni} < V_{nj} + \epsilon_{nj}, \forall i \neq j) = \text{Prob}\Big(\epsilon_{ni} < \epsilon_{nj} + V_{nj} - V_{ni}, \forall i \neq j) \tag{3}$$

Since this probability expresses the case of ε_{ni} less than $\varepsilon_{nj} + V_{ni} - V_{nj}$, the joint probability distribution function of the probability variable vector can be expressed as follows:

$$P_{nj} = \text{Prob}\Big(\epsilon_{ni} < \epsilon_{nj} + V_{nj} - V_{ni}, \forall i \neq j\Big) = \int_{\epsilon} I\Big(\epsilon_{ni} < \epsilon_{nj} + V_{nj} - V_{ni}, \forall i \neq j\Big) f(\epsilon_n) d\epsilon_n \tag{4}$$

Here, I means the indicator function.

Since the error term ε_{ni} in the above equation is a probability variable, the model will vary according to which probability distribution is assumed. As the multinomial logit model assumes the independent and homoscedastic type I extreme value distribution density function, the choice probability equation after a deduction like Train's (2003) can lead to the following equation.

$$P_{nj} = \frac{e^{V_{nj}}}{\sum_i e^{V_{ni}}} = \frac{e^{\beta' x_{nj}}}{\sum_i e^{\beta' x_{ni}}} \tag{5}$$

This is a mathematically calculable closed form, and the coefficients can be estimated by the maximum likelihood estimation.

However, the multinomial choice model has the weakness of not being able to use the difference of preference data among the alternatives not selected. Therefore, the rank ordered logit model is widely used to utilize the rank data that contain more information about consumer preference than the multinomial choice data. The theoretical basis of the rank ordered logit is basically the same as the multinomial logit model, and can be considered as the reiterated multinomial logit form. The choice probability of a ranked logit model can be expressed as follows (Hausman [26] and Train [25]):

$$P\left(r_1, r_2, \cdots, r_J\right) = \prod_{h=1}^{J-1} \frac{e^{V_h}}{\sum_{m=h}^{J} e^{V_m}} \tag{6}$$

In this study, the estimation coefficient vector estimated with the ranking ordered logit model developed by the Korea Energy Economics Institute in 2008 was applied to develop sales forecasting model for the green car.

3.3. System dynamics model

This study focuses on the feedback effect of the market share back on the technical attribute in addition to the impact of the technical attribute on the market share of the technology. The reason is that there are competing green technologies of HEV, EV, and HFCV and that there is no single technology that can claim absolute superiority with the current technical prediction. However, because of the characteristics of green car technology that require significant time and cost in developing a new recharging infrastructure, it will be difficult for EV and HFCV to mutually grow, thus the market share gap due to the nominal technical superiority of a technology at early market entry can drastically widen due to the feedback effect as the market grows. Such feedback effect cannot be analyzed by the regression method used to estimate the parameters of the Bass diffusion model or discrete choice model. System dynamics is widely used to analyze such dynamic behavior of a system through the feedback structure. System dynamics began with the concept of Industrial Dynamics by Forrester in 1961 and developed into system dynamics as its application expanded from the industrial sector to all areas of social science and then to the natural science and engineering fields (Forrester [27]). System dynamics express the complex causal relationship among the variables with the stock and flow in the diagram based programming language. The general structure and relationship between the stock and flow of a system dynamics expressed in the first-order linear positive feedback system, which is the simplest form of a feedback system, can be expressed as follows (John [28]) (Fig. 1):

$$\frac{dS}{dt} = \text{Net Inflow Rate} = gS \tag{7}$$

System dynamics enables modeling feedback loop, time delay and non-linearity through the causal loop diagram consisting of unit feedback systems shown above. This study developed a causal loop diagram by considering the Bass diffusion model, discrete choice model, repurchase, and feedback using the system dynamics methodology and applied it to forecast sales of green car technologies.

4. Model

To propose an integrated model considering all models, including the Bass diffusion model, discrete choice model, repurchase, and feedback, this study defined the state transition matrix as follows:

P_{ijt} Probability of a consumer owning *i* type of vehicle purchasing a *j* type of vehicle at time *t*

Applying the above state transition matrix to the forecasting model for the alternative green car technology such as HEV, EV, and HFCV, the following four system states can be defined and the state transition matrix can be deduced as shown in Eq. (8).

S_0 conventional vehicle
S_1 hybrid electric vehicle
S_2 electric vehicle
S_3 hydrogen fuel cell vehicle

$$P_{ijt} = \begin{bmatrix} p_{00t} & p_{01t} & p_{02t} & p_{03t} \\ p_{10t} & p_{11t} & p_{12t} & p_{13t} \\ p_{20t} & p_{21t} & p_{22t} & p_{23t} \\ p_{30t} & p_{31t} & p_{32t} & p_{33t} \end{bmatrix} \tag{8}$$

In this study, the integrated forecasting model was developed by defining each element of the above state transition matrix using the diffusion model and discrete choice model with some assumptions.

Assumption 1. Consumers select one of the existing vehicles or three alternative green car technologies.

$$\sum_{j=0}^{n} P_{ijt} = 1 \text{ for all } t \tag{9}$$

Assumption 2. After purchasing a green car, the consumer does not purchase internal combustion vehicles again.

$$P_{i0t} = 0 \text{ for } i > 0 \text{ and all } t \tag{10}$$

Assumption 3. The probability of a consumer owning an internal combustion vehicle who is purchasing a green car conforms to the Bass diffusion model.

$$1{-}P_{00t} = p + q \times \frac{Y(t)}{m} \tag{11}$$

p Innovation factor
q Imitation factor
$Y(t)$ Number of accumulated customers owning a green car at time t
m Potential market size of passenger vehicles

Assumption 4. Selecting which type of green car will conform to the discrete choice model.

$$P_{ijt} = \frac{e^{U_j(t)}}{\sum_{j=1}^{n} e^{U_j(t)}}, \text{j} = 1, 2, 3 \tag{12}$$

$$U_i(t) = V_i(t) + \varepsilon_i(t) \tag{13}$$

$$V_i(t) = \sum_{k=1}^{l} \alpha_k \times X_{ik}(t) \tag{14}$$

$U_i(t)$ Utility of i type of green car at time t
$V_i(t)$ Quantitative part of utility of i type of green car at time t
$\varepsilon_i(t)$ Probabilistic part of utility of i type of green car at time t
α_k Weight factor of the attribute k of a green car
$X_{ik}(t)$ Value of the attribute k of i type green car at time t

This study considered following three attributes for green car technologies.

k 1; fuel efficiency
k 2; vehicle price
k 3; fueling/recharging infrastructure

Assumption 5. The number of consumers purchasing a green car is calculated as the sum of number of consumers owning an internal combustion vehicle and purchasing a green car for the first time and the number of consumers owning a green car and repurchasing another green car.

$$N_i(t) = F_i(t) + R_i(t) \tag{15}$$

$$F_i(t) = (m{-}y(t{-}1)) \times (1{-}P_{00t}) \times P_{it} \tag{16}$$

$N_i(t)$ Number of consumers purchasing i type of green car at time t
$F_i(t)$ Number of consumers owning an conventional vehicle and purchasing i type of green car at time t
$R_i(t)$ Number of consumers owning a green car and purchasing i type of green car at time t

Assumption 6. The vehicle life of any type of green car is s.

$$R_i(t) = \sum_{j=1}^{n} N_j(t{-}s) \times P_{ji}(t) = \sum_{j=1}^{n} N_j(t{-}s) \times P_i(t) \tag{17}$$

Assumption 7. The market share of each type of green car has a negative feedback effect on the green car vehicle price and a positive feedback effect on the fueling/recharging infrastructure attribute.

$$X_{ik}(t) = X_{ik}^{exg}(t) + X_{ik}^{int}(t) \quad \text{for } i = 1,2,3 \text{ and } k = 2,3 \tag{18}$$

$$X_{ik}^{int}(t) = \beta_k \times \left(P_{it} - P_{i(t-1)}\right) \times \left(X_k^{\max} - X_{ik}(t-1)\right) \quad \beta_k < 0 \text{ if } k = 2, \beta_k > 0 \text{ if } k = 3 \tag{19}$$

$X_{ik}^{exg}(t)$ Value of k attribute of i type green car at time t externally determined by the technical prediction of experts
$X_{ik}^{int}(t)$ Value of k attribute of i type green car at time t internally determined by the impact of market share of i type green car
β_k Effect of market share of k attribute (coefficient)
$X_k^{\max}$ Maximum value for k attribute

By defining the variables and links of the system dynamics model with the developed mathematical model, this study can easily simulate the market diffusion process of the green car technologies according to the various scenarios of technical attributes such as the degree of infrastructure development, fuel efficiency, fuel price, and vehicle price. Furthermore, the system dynamics model has the strength of supplementing a theoretical backup of causal relationships of various factors. The developed causal loop diagram mainly consists of three parts (Fig. 1). A part expresses the Bass diffusion model in the causal loop diagram and deploys the process of the potential adopter of the green car technology using the existing internal combustion engine to adopt the green car technology with the innovation coefficient and imitation coefficient. B part deploys the process of the owners of the green cars past the lifecycle to repurchase a green car again. C part deploys the process of estimating the customer utility of each alternative technology according to the attribute of each technology such as the degree of infrastructure development, fuel efficiency, fuel price and vehicle price and calculating the market share of the technology based on the estimation. Then the feedback process of the technology attribute changing according to the change of the market share is deployed.

5. Data description

This study performed the empirical study of sales forecasting for green car technologies using the developed integrated forecasting model.

5.1. Diffusion model data

For the diffusion model, the innovation coefficient, imitation coefficient, and data on the potential market size are needed. In this study, the coefficient value, which is estimated in Park's study was used in order to forecast the overall sales of the green car (Park [7]). Park's study estimated the innovation coefficient and imitation coefficient based on the actual HEV sales result in Japan in order to estimate the total green car market size in Korea (Park [7]). It then compensated the imitation coefficient, which is more affected by customer inclination than the product's own attributes, using the results of Takada's study which estimated and compared the imitation coefficient of the durable goods in different countries (Park [7] and Takada [29]). The potential market size was estimated using the number of vehicles registered and disposed of in Korea between 1983 and 2004. Table 1 shows the result of the estimation of diffusion model parameter in Park's study.

5.2. Discrete choice model data

To apply the discrete choice model to forecast sales of the green car technology, the estimated weight factor (α_k) of the impact of each attribute of fuel efficiency, fuel cost, vehicle cost and level of infrastructure on consumer utility and predicted attribute value ($X_{ik}(t)$) of each green car technology in each year are needed. First, the estimated value by Ahn's study were used for the weight factor of each attribute (Ahn [30]). Ahn estimated the weight factor of attributes like the fuel, vehicle type, fuel efficiency, fueling accessibility, and purchase price through the conjoint analysis using rank ordered logit model (Table 2).

Table 1
Parameter estimates for HFCVs in Korea.

Parameters	P	q	m
Coefficients	0.0037	0.3454**	10,282,245*
Standard errors	(0.0036)	(0.1151)	(763363.4)

* $p<0.01$.
** $p<0.05$.

Table 2
Weight factor estimation for each technical attribute.

	Multinomial logit		Rank ordered logit	
	Coefficient	t-value	Coefficient	t-value
Fuel efficiency	0.0143*	11.08	0.0099*	15.00
Infrastructure	−0.0046**	−2.06	0.0008	1.46
Investment cost	−0.0018*	−16.36	−0.0011*	−37.25

* $p<0.01$.
** $p<0.05$.

Next, this study performed a long-term prediction on efficiency and investment cost of green car technologies based on the opinions of the most renowned experts in green car area. In this study, the empirical study was performed by applying the technical attribute prediction value of HEV, EV and HFCV, which are the specific technologies of the green car area (Table 3). However, since the prediction of fueling access for each technology was not performed, this study assumed that the recharging infrastructure of HEV was 100% by using the existing recharging infrastructure, while the scenario of the recharging infrastructure of EV and HFCV linearly increasing beginning in 2010 and reaching 100% in 2050 was used as the baseline scenario for the empirical study. Furthermore, the price prediction of each energy source used as the basic assumption of the long-term energy demand forecasting study performed by Kim in 2008 was used for the fuel price ([31]).

6. Results

6.1. Baseline scenario

The baseline scenario indicates that only HEV enters the market early to have the largest number of distributed vehicles by around 2035, while EV and HFCV will begin to appear in the market in around 2030 and will reach the accumulated number of distributed vehicles similar to that of HEV by around 2050 (Fig. 3). However, experts predict that the consumer utility of EV will be higher than that of HFCV and thus the market share of EV will be slightly higher than that of HFCV (Tables 2–4).

However, the analysis of the accumulated number of vehicles distributed does not give a clear idea of which technology is superior per year. The analysis of the diffusion of each green car technology in terms of the year-by-year market share indicates that the market share of HEV will gradually decrease from 100% in 2010, and then the decrease will accelerate from around 2030 when the distribution of EV and HFCV will be more active. EV and HFCV are expected to enter the market around 2015 and 2023, respectively. Near 2037, market shares of both EV and HFCV will surpass that of HEV to become the leading green car technologies (Figs. 1–5).

6.2. Infrastructure development scenario

Next is the analysis of the impact of infrastructure development on sales. The baseline scenario assumed that the construction of the EV and HFCV recharging infrastructure would begin in 2010 and have a sufficient level of infrastructure so that the EV or HFCF users would experience no inconvenience compared to the conventional internal combustion vehicles by around 2050. For the infrastructure development scenario, the year in which the hydrogen recharging stations reach 100% was reduced by 5 years each time from 2050 in the baseline to 2030 to analyze the HFCV diffusion curve (Table 4).

Table 3
Year-by-year technical attribute prediction.

Technology	Technical attribute	Unit	2010	2020	2030	2040	2050
HEV	Fuel price	$/GJ	48.53	74.74	79.45	85.25	91.96
	Efficiency	Km/l	15.8	28.0	32.0	34.0	36.0
	Investment cost	Thousand $	47.3	40.8	38.0	37.5	37.5
	Infrastructure	%	100.0	100.0	100.0	100.0	100.0
EV	Fuel price	$/GJ	30.90	32.35	32.56	32.80	33.06
	Efficiency	kWh/100 km	15.0	16.2	16.7	16.9	17.2
	Investment cost	Thousand $	81.9	54.7	50.8	41.3	38.3
	Infrastructure	%	–	25.0	50.0	75.0	100.0
HFCV	Fuel price	$/GJ	34.29	35.50	37.45	38.16	38.51
	Efficiency	Km/l	30.0	36.0	39.0	40.0	40.0
	Investment cost	Thousand $	150.0	60.0	40.0	30.0	30.0
	Infrastructure	%	–	25.0	50.0	75.0	100.0

Table 4
Infrastructure scenario (unit: %).

Recharging infrastructure saturation year	2010	2020	2030	2040	2050
Baseline (2050)	–	25.0	50.0	75.0	100.0
2045	–	28.57	57.14	85.71	100.00
2040	–	33.33	66.67	100.00	100.00
2035	–	40.00	80.00	100.00	100.00
2030	–	50.00	100.00	100.00	100.00

The Fig. 4 shows that, if the year of the level of the hydrogen recharging station development reaching 100% is moved up to 2030, the maximum accumulated number of vehicles distributed will reach 7.9 million units in around 2045. If it is moved up to 2040, the accumulated number of vehicles distributed in 2050 will be 5.9 million units.

6.3. Infrastructure development scenario with feedback effects

Next, the coefficient for infrastructure feedback was set to 1 and the simulation was performed according to the infrastructure development scenario to analyze the feedback effect between the market share and level of infrastructure development. If the

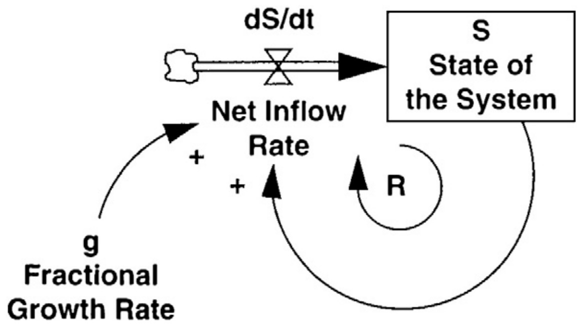

Fig. 1. First-order, linear positive feedback system.

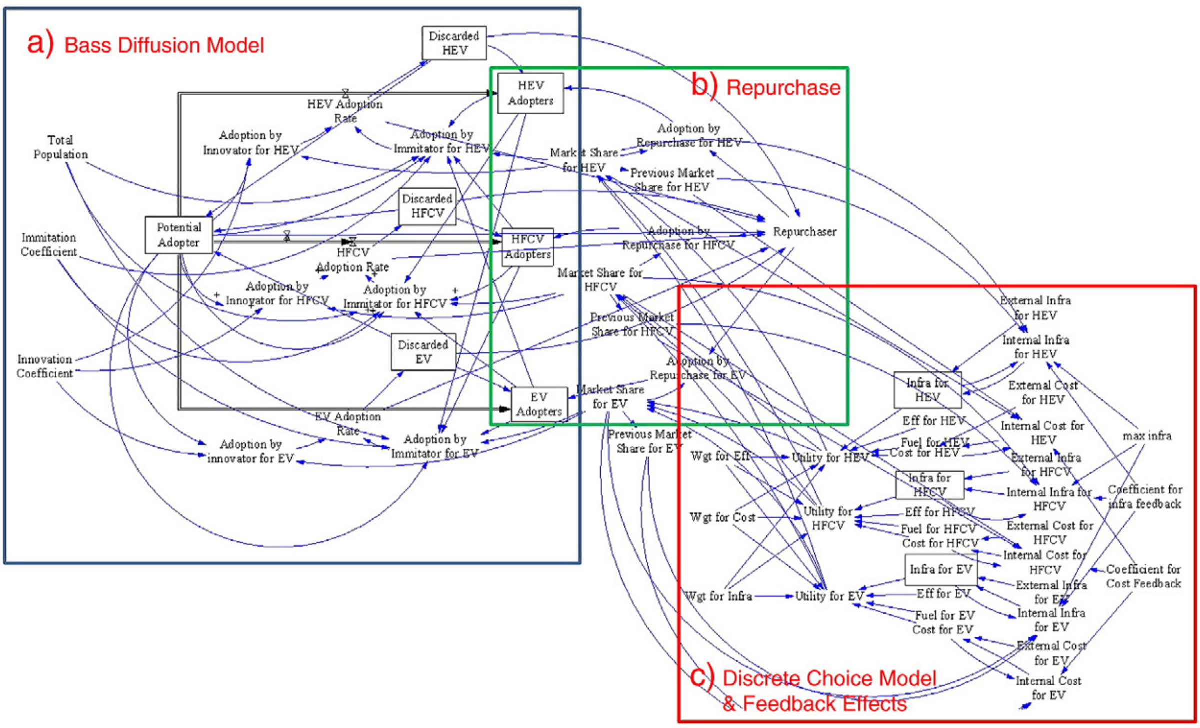

Fig. 2. Causal loop diagram for integrated forecasting model.

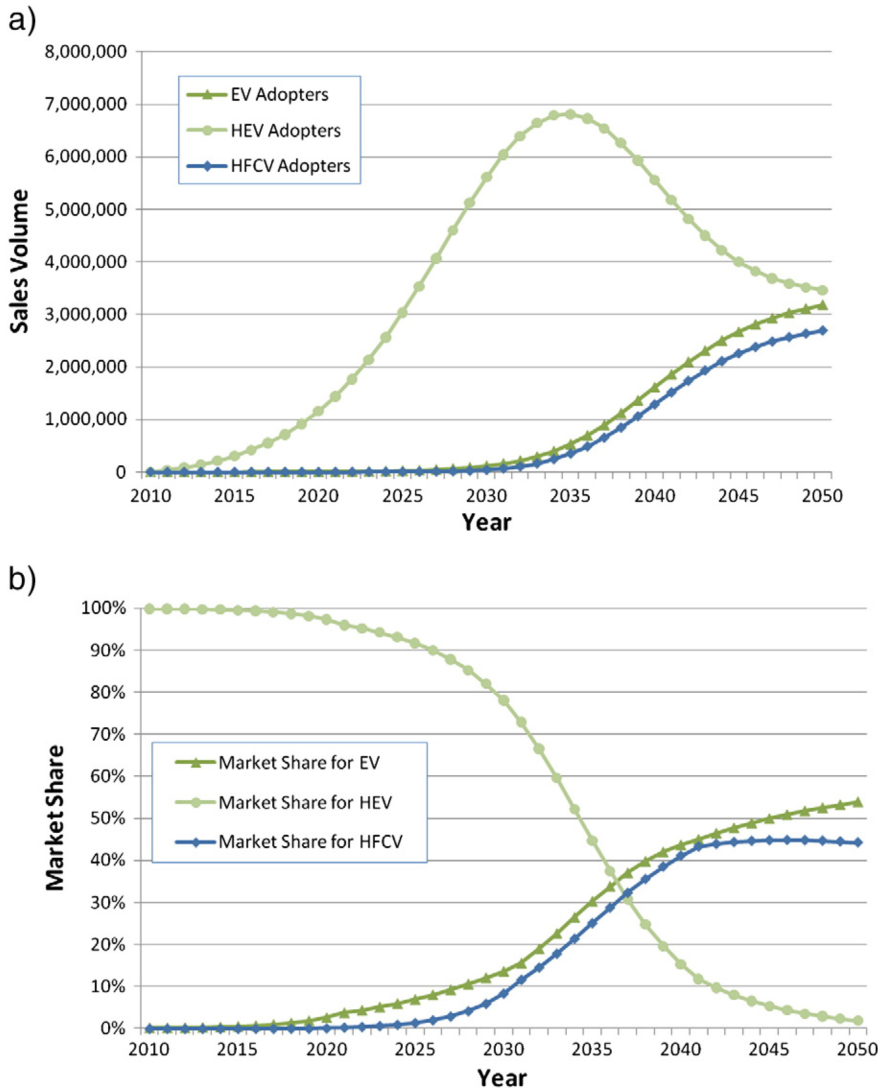

Fig. 3. Baseline scenario. (a) Accumulated number of green cars. (b) Market share of each green car technology.

saturation point of the hydrogen recharging infrastructure is moved up 5 years at a time from the baseline scenario, the simulation shows that the accumulated number of HFCV distributed will increase from the baseline scenario (Fig. 5). If it is moved up by 10 years to 2040, the HFCV will reach saturation around 2045. After that, as the year in which the hydrogen recharging infrastructure is completely developed is moved up by 5 years, the highest accumulated number of HFCV distributed would increase and the year the distribution of HFCV begins would also move up.

Lastly, the market shares of HFCV according to the infrastructure scenario with or without the feedback effect were compared. Assuming the coefficient for infrastructure feedback to be 1, the years of highest HFCV market share in the scenarios of infrastructure completely being developed in 2040 and 2035 were both 2040 if the feedback effect was not considered. However, if the feedback effect was considered, the years of highest HFCV market share in the scenario of 2040 being the year the infrastructure is completely developed and the scenario of 2035 being the year the infrastructure is completely developed would move up by 5 years and 10 years to 2035 and 2030, respectively. However, in the scenario of 2030 being the year the infrastructure is completely developed, there was not much difference between the case involving the feedback effect and the case where the feedback was not considered. The reason is because the scenario of completely developing the hydrogen infrastructure by 2030 is the same infrastructure development scenario that has the highest impact to the HFCV market share, thus the feedback effect was insignificant. However, this analysis showed that the feedback effect played the reinforcing role of amplifying the impact of infrastructure development on the product's market share, and thus it enabled a more detailed analysis of the impact of the initial infrastructure development, which tended to be underestimated in the existing economic model based only on the consumer choice theory on the product's competitive superiority.

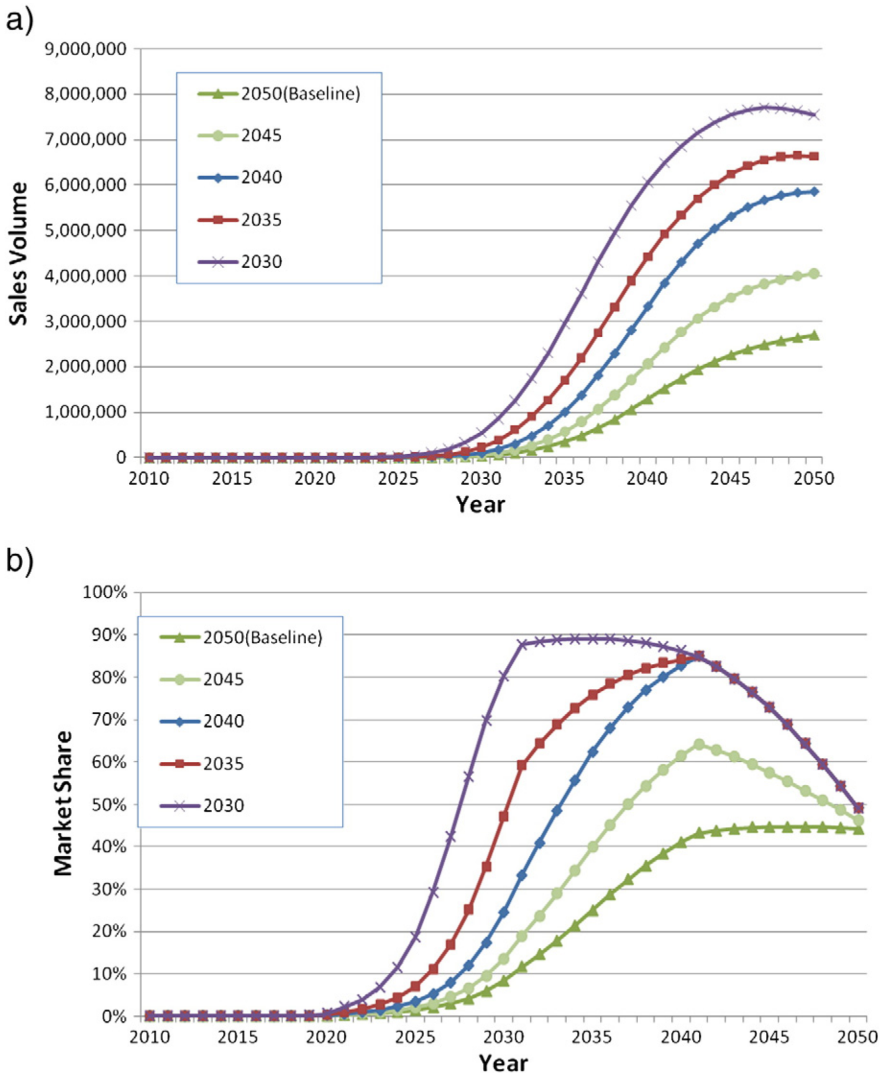

Fig. 4. Infrastructure scenario. (a) Accumulated number of green cars. (b) Market share of each green car technology.

7. Discussions and conclusions

This study developed the system dynamics based sales forecasting model to analyze the impact of the feedback effect on the diffusion of innovative technologies focusing on green car technology and the market share among the competitive technologies. To reinforce the theoretical background of causal relationships among the variables of the forecasting model, the causal loop diagram of the variables was defined using the proven econometric models such as the Bass diffusion model and discrete choice model.

By applying different technology development scenarios and feedback effect scenarios to the developed forecasting model, the various insights for sales of green car technologies were obtained. The baseline scenario, which applied the technology development prediction by the experts, predicted that while HEV will completely dominate the green car market initially, three green car technologies of HEV, EV and HFCV will have a similar number of accumulated sales volume by around 2050 as the EV and HFCV technologies are developed.

Next, the analysis of the year-by-year market share of each green car technology according to the infrastructure development scenario indicates that, unlike the change of technical attributes such as the hydrogen energy price and HFCV fuel efficiency, the level of infrastructure development is a factor that can change not only the highest market share but also the time to reach critical mass and to occupy the highest market share. In other words, it shows that the external factors like developing an infrastructure can have a higher impact on a technology securing competitive superiority then the technology development itself.

Lastly, there is an insight from the feedback scenario. In the case where the feedback effect is not considered, the years of the highest HFCV market share in the scenarios of infrastructure completely being developed in 2040 and 2035 are both 2040.

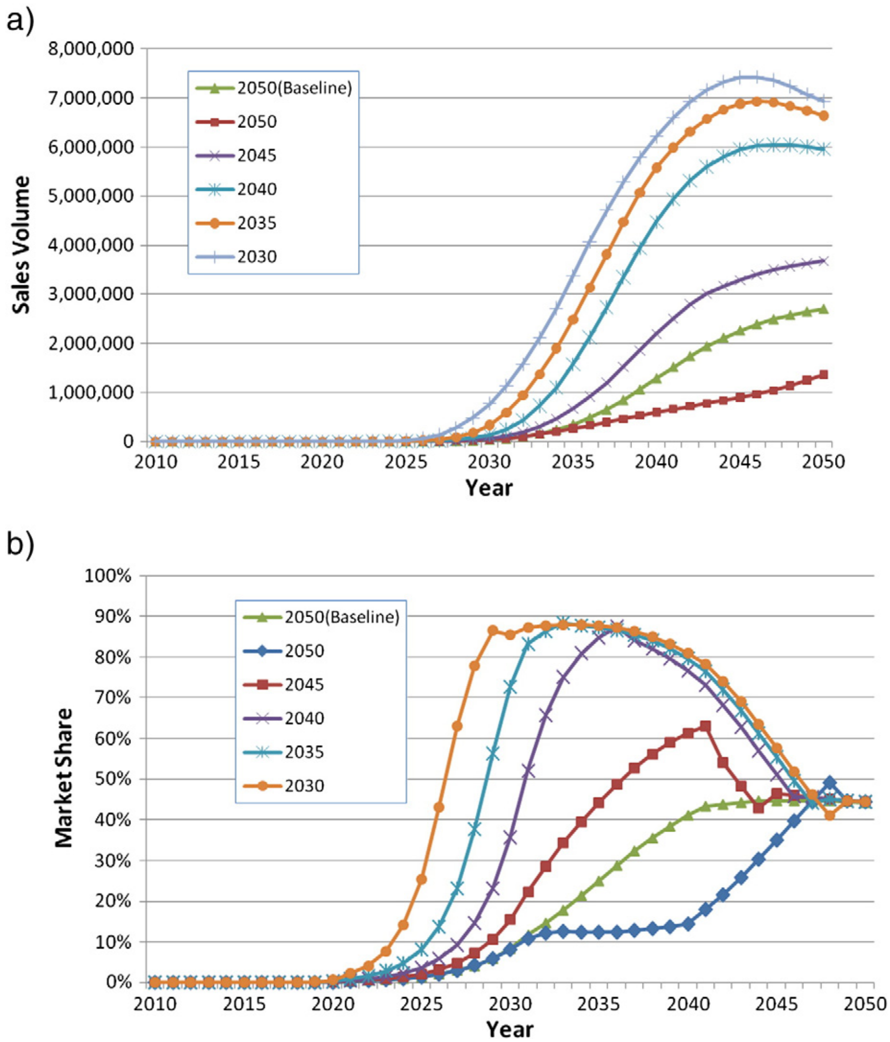

Fig. 5. Infrastructure scenario with feedback effect. (a) Accumulated number of green cars. (b) Market share of each green car technology.

However, if the feedback effect is considered, the years of highest HFCV market share in the scenario of 2040 being the year the infrastructure is completely developed and the scenario of 2035 being the year the infrastructure is completely developed would move up by 5 years and 10 years to 2035 and 2030, respectively. This analysis showed that the feedback effect played a reinforcing role of amplifying the impact of infrastructure development on the product's market share. Therefore, if the feedback effect is valid, the impact of the initial infrastructure development on the product's competitive superiority can be underestimated in the existing economic model based only on the consumer choice theory.

This study developed a new demand forecasting methodology by effectively integrating the econometrics model and system dynamics model. The developed forecasting model can consider the feedback effect that was difficult to be applied in the existing economics model through applying system dynamics methodology and can have a sound theoretical background by developing the causal loop diagram which is based on the proven economic model. Furthermore, the application of the developed model to the green car area led to a significant result in the R&D and infrastructure development viewpoint that can be used as a reference for successful deployment strategy of green car technologies.

The developed model can be applied in other studies of successful dissemination strategies or policies of innovative technologies. Furthermore, the result of this study can be more useful if the forecasting results can be used in the studies of social, economic, energy and/or environmental impact according to the diffusion of innovative technologies.

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