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Integrated Network Transport Simulator to Evaluate Transport Policy for Reduction of Carbon Dioxide Emission

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Abstract

Not only purchase of electric vehicle but also modal shift from vehicle traffic should be promoted for reduction of greenhouse gas emission. Effect of transport policies for reduction of carbon dioxide emission should be estimated properly with simulating vehicle traffic on a target road network. For the purpose, it is aimed that the integrated network transport simulator is developed based on the multi-agent simulation model to evaluate transport policies for reduction of CO_2 emission in the present study. The proposed integrated network transport simulator consists of the vehicle traffic simulation model, the travel mode choice model and the vehicle choice model. CO_2 emission is estimated with the vehicle traffic simulation model. The decision processes of the vehicle choice and the travel mode choice are respectively described considering with the social interaction. It is assumed that not only the conformity effect but also non-conformity effect should be considered as the social influence. Therefore, hierarchical Bayesian modeling is applied to describe the vehicle choice and the travel mode choice considering with heterogeneity and social interaction. The model parameters are estimated with the database of questionnaire survey in a local city of Japan and the proposed simulator is applied to estimate the effect of the carbon tax. The reduction of carbon dioxide emission as the effect of the policies is estimated using the proposed integrated network transport simulator. From the view point of CO_2 emission, it can be found that the effect of reducing CO_2 emissions with only the carbon tax is limited since the spread of low emission vehicles is hindered and the rate of sustainable transport mode goes down, although the EV will be popularized.

Keywords: greenhouse gas emission; multi-agent simulation; hierarchical Bayesian modeling; carbon tax;

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1. Introduction

Greenhouse gas emission by vehicle traffic should be reduced appropriately not only with innovation of automotive technology but also with modal shift to sustainable transport mode such as public transport or bicycle. Therefore, the modal shift from private vehicle to sustainable transport mode as well as the purchase of electric vehicle (EV) is regarded as the sustainable mobility shift in the present study. However, the practice of modal shift is not easy in the local city, where residents depend on automobiles in the daily life. Therefore, not only improvement of service of sustainable transport mode but also economic incentive policies is considered for sustainable mobility shift.

Some studies have focused on social interaction in travel behavior (Dugundji et al., 2005, 2011). For example, Carrasco and Miller (2006) have focused on the spatial distribution of ego networks. Furthermore, a social and spatial framework is presented that distinguishes between individual and aggregate interactions, and introduces the concept of a local field effect to represent the share of decision-makers within a defined reference group that choose a particular alternative (Dugundji and Gulya´s, 2008). The author modeled the mobility shift using the multi-agent simulation (MAS) considering with heterogeneity and local interaction to estimate the effect of transport policies in reducing carbon dioxide (CO_2) emissions, though heterogeneity in the vehicle choice cannot be considered (Okushima, 2015).

Particularly, it should be noted that social conformity has a strong influence on consumer behavior when consumers buy a new product (Rogers, 2003). Similarly, some studies have focused on the social conformity aspect in the choice behavior associated with types of low-emission vehicles. Axsen et al. (2009) estimate preference dynamics associated with the adoption of hybrid electric vehicles to improve the behavioral realism of the energy-economy model considering with the neighbor effect with joint SP-RP estimation techniques. Kuwano et al. (2013) take in account social conformity as well as choice set formation and heterogeneity over the sample set for decision-making process for choice of vehicle type. The author proposed the MAS model with local interaction to estimate the promotion process of EVs, though heterogeneity and policy related to economic incentives are not considered (Okushima, 2016).

Consequently, it is aimed that the integrated network transport simulator with the travel mode choice model and the vehicle choice model is developed to evaluate transport policies for reduction of CO_2 emission as well as traffic congestion in the study. Since the decision of mobility shift would be changed with influence of local community, local interaction should be described for estimation of carbon dioxide emission. Particularly, heterogeneity on local interaction should be described in the modeling of mobility shift. On the other hand, multi-agent simulation model is suitable to describe social interaction and heterogeneity of trip makers. Therefore, the multi-agent simulation model is applied to estimate effect of transport policies.

2. Integrated network transport simulation model

2.1. Structure of the integrated network transport simulation model

The proposed network transport simulation system consists of three interactive models such as the vehicle traffic simulation models, the travel mode choice model and the vehicle choice model considering social interaction. The outline of the proposed transport simulation system is illustrated in Fig. 1.

The vehicle traffic simulation model is developed as the dynamic and stochastic user optimal traffic assignment for road network with the macroscopic flow model. Decision process of trip makers consists of vehicle choice and travel mode choice. Local share of vehicle type or of travel mode is given as output of the decision process. On the other hand, it is assumed that vehicle choice and travel mode choice of trip makers are influenced by local share as the feedback considering social interaction.

2.2. Vehicle traffic simulation model

The vehicle traffic simulation model is composed of the vehicle departure model, the stochastic route search model and the macroscopic flow model. The stochastic route search method for individual vehicles and the route choice model at the departure time is integrated with the macroscopic flow model in order to estimate the traffic flow on the target network adequately.

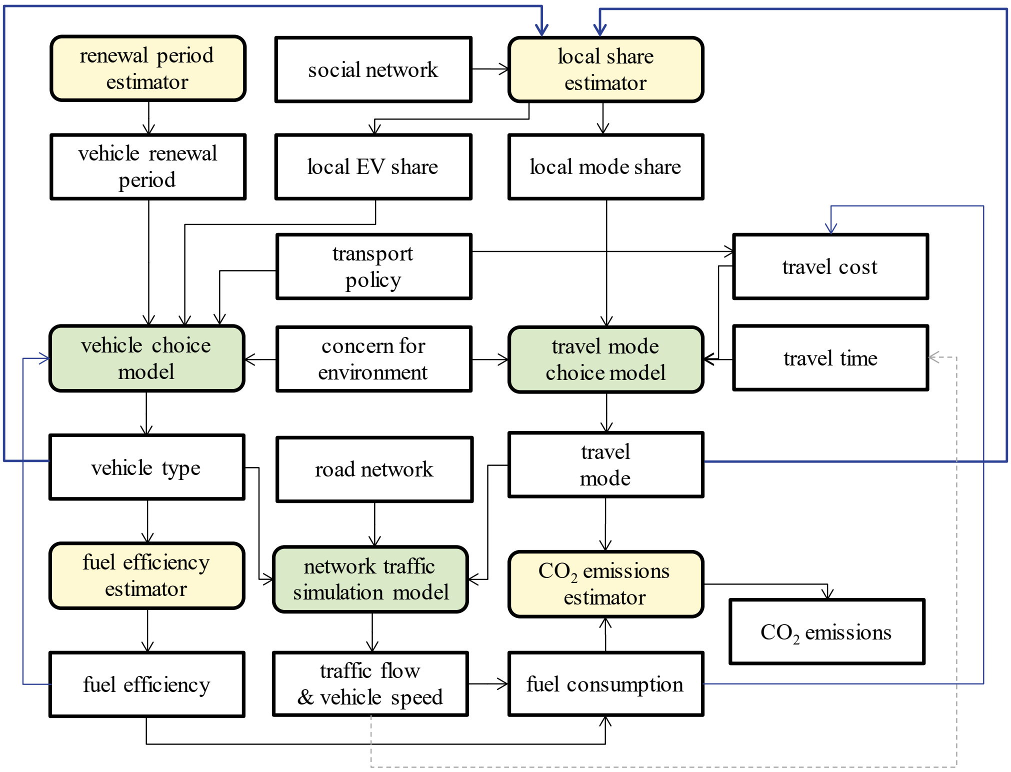

Fig. 1. structure of the integrated network transport simulation model

According to the vehicle departure model, the departure time of each vehicle is determined in the interval of one second. OD traffic volume in one hour and time distribution of generated traffic by zone in 15 minutes are given. It is assumed that intervals of departure time from each centroid are distributed according to exponential distribution model.

The route from the current link to the destination is stochastically searched on the target road network with the stochastic route search model. Dial method is used to probabilistically determine a link in the traveling direction at each node. Focusing on the structure of route data of individual vehicles, I adopt a route search algorithm using the minimum tree with the target point as the vertex. At each node every 5 minutes, the link choice probability for each destination is updated.

It is assumed that individual vehicles move between links according to the macroscopic flow model. In the macroscopic flow model, the expected outflow time from link j is estimated at the time t when the vehicle h flows into link j as follow;

$$eot_{j,[h]} = t + lt_j(0) + \frac{ns_j}{ca_j} \tag{1}$$

where $lt_j(0)$:travel time on link j with zero flow, ns_j: current number of vehicle on link j, ca_j : flow capacity of link j.

Actually possible outflow time of the vehicle h from link j also depends on the outflow time of the vehicle h' in front of the vehicle h as follow;

$$pot_{j,[h]} = \max\left(eot_{j,[h]} , aot_{j,[h']} + \frac{1}{ca_j} \right) \tag{2}$$

where $aot_{j,[h]}$: actual outflow time of the vehicle h' from link j.

On the other hand, inflow traffic to the link j is determined by inflow demand and traffic capacity as follow;

$$fin_j = \min\left(fd_j , ca_j , ns_j^{\max} - ns_j \right) \tag{3}$$

where fd_j: traffic demand of flow into link j, $ns_j^{\max}$: maximum number of vehicle on link j.

Therefore, actual outflow time is affected in the case of saturation on the downstream link.

2.3. Vehicle choice model

The vehicle choice model is developed to measure the effect of the promotion policy considering social interaction and the heterogeneity of the households. Therefore, the hierarchical Bayesian binary logit model is applied. Hierarchical Bayesian modeling was previously developed in the field of marketing science to describe household heterogeneity (Rossi et. al., 2005).

Vehicle types vary in the real market. Because it is difficult to describe vehicle choice in detail, vehicle types are classified into three categories such as EV, low emission vehicle (LV) and normal vehicle (NV). The vehicle choice process comprises two steps in the nested structure. In the lower step, the choice set consists of LV and NV. In the upper step, the choice set consists of EV and others, which includes LV and NV.

The deterministic components of the utility for EV are defined as follow;

$$V_{\mathrm{[h]}}^{\mathrm{EV}} = \beta_{les,[h]} les_{[h]} + \sum_{k} \beta_{k,[h]} x_{k,[h]}^{EV} \tag{4}$$

and the deterministic components of the utility for other vehicle (LV and NV) as follow;

$$V_{\mathrm{[h]}}^{\mathrm{other}} = \beta_{ct,[h]} ct_{[h]} + \beta_{\Lambda,[h]} \Lambda_{[h]} \tag{5}$$

where $x_{k,[h]}^{EV}$: explanatory variable k for EV at household h, $\beta_{k,[h]}$: coefficient of variable k at household h, $les_{[h]}$: ratio of EV owner in local community, $ct_{[h]}$: the monthly amount of the carbon tax, $\Lambda_{\mathrm{[h]}}$: log-sum variable for LV and normal vehicle (NV) at household h.

The coefficient of variable k is defined for individual household h using a specification of multiple liner regression, as follows;

$$\beta_{k,[h]} = \sum_{m} \Delta_{k,m} \cdot \mathrm{z}_{\mathrm{m,\ [h]}} + \varepsilon_{k,[h]} \tag{6}$$

where $\varepsilon_{k,[h]} \sim N(0, \sigma_k)$ (7)

and $\mathrm{z}_{\mathrm{m,[h]}}$: personal variable for attribute m, N( ) : normal distribution, σ_k : standard deviation of variable k, $\Delta_{k,m}$: coefficient of personal variable for attribute m for factor variable k.

2.4. Travel mode choice model

The hierarchical binary logit model is applied in the related study to describe the heterogeneity and social interaction in relation to commuting mode choice (Okushima, 2015). The deterministic components of utility in the present study are defined as follows:

$$V_{\mathrm{[h]}}^{\mathrm{car}} = \beta_{[h]}^{tt} tt_{\mathrm{car,[h]}} + \beta_{[h]}^{tc} tc_{\mathrm{car,[h]}}, \tag{8}$$

$$and\ V_{\mathrm{[h]}}^{\mathrm{stm}} = \beta_{[h]}^{tt} tt_{\mathrm{stm,[h]}} + \beta_{[h]}^{tc} tc_{\mathrm{stm,[h]}} + \beta_{[h]}^{lms} lms_{[h]} + \beta_{[h]}^{ms}. \tag{9}$$

where $tt_{m,[h]}$:travel time with mode m, $tc_{m,[h]}$:travel cost with mode m, lms: local mode share around trip maker h.

2.5. Local share estimator

Social interaction on social network is described with multi-agent modeling. The relation between trip makers like a social network of the real world is generated with a simple algorithm for the small world network (Watts and Strogatz, 1998). As a result, average number of links for an individual is 6.6. The local share of EV and the local share of sustainable transport mode for individual *h* are calculated using information from the direct linked individuals as follows:

$$les_{[\mathrm{h}]}(t) = \frac{\sum \delta_{[m]}^{EV}(t)}{M_{[h]}} \tag{10}$$

$$lms_{[\mathrm{h}]}(t) = \frac{\sum \delta_{[m]}^{stm}(t)}{M_{[h]}} \tag{11}$$

where $\delta_{[m]}^{EV}$: dummy variable for EV owner at the direct linked individual *m*,

$\delta_{[m]}^{stm}$: dummy variable for sustainable transport user at the direct linked individual *m*,

$M_{[h]}$: number of the direct linked individual for individual *h*.

2.6. Carbon dioxide emission estimator

Fuel consumption by vehicle *h* on link *j* is estimated with fuel efficiency according to vehicle type and vehicle speed on the link of the road network as follow:

$$fc_{j,[\mathrm{h}]} = \frac{fcv_{[\mathrm{h}]}}{fcv_{ave}} \cdot ld_j \cdot \left(\alpha_0 + \alpha_1 \frac{1}{lv_j} + \alpha_2 \cdot lv_j + \alpha_3 \cdot (lv_j)^2 \right) \tag{12}$$

where $fcv_{m,[h]}$:travel time with mode *m*, $tc_{m,[h]}$:travel cost with mode *m*, *lms*: local mode share around trip maker *h*.

Carbon dioxide emission by vehicle *h* on link *j* is estimated with fuel consumption and discharge rate of CO_2 according to vehicle type as follow:

$$ef_{j,[\mathrm{h}]} = fc_{j,[\mathrm{h}]} \cdot DRC \tag{13}$$

The discharge rate of CO_2 is fixed at 2.322 kg of CO_2 per liter of fuel consumption from normal size passenger vehicles and at 2.619 kg from large size trucks.

3. Data for analysis

The vehicle choice model and the transport mode choice model should be described using the data from the questionnaire survey.

The transport policy consists of demand response transit (DRT) system and economic incentive policies. It is assumed in the DRT system that the share transit is traveling directly from home to the nearest railway station or the nearest bus terminal every half hour. It means that the level of service in the public transport is improved remarkably. On the other hand, the targeted economic incentive policy is the carbon tax. The carbon tax is assumed to be charged for consumption of gasoline. The economic incentive policy is assuming to be implemented with the DRT system as substitute travel mode.

The intention of purchasing EV and travel mode change in case of transport policies implementation can be measured using the database of the questionnaire survey in a regional city of Japan. The change of travel mode corresponding to the transport policy is asked in stated preference survey. Simultaneously, the purchasing EV corresponding to the transport policy is asked.

Components of vehicle, such as purchase price, kilometer range between recharging, fuel operation cost, should be regarded as important factor for vehicle choice. On the other hand, the factors of travel mode choice are assumed as the social conformity in addition to the travel time and the travel cost. The toll for economic incentive is added to the travel cost. In terms of the carbon tax, the fuel efficiency of the vehicle should be considered according to the vehicle type.

The questionnaire survey was conducted using the web-survey monitors. The vehicle owners in the Tokushima city of Japan are targeted for the questionnaire survey. Responses to the questionnaires were collected through the survey website and 442 valid samples for analysis.

4. Bayesian estimation and verification of the model

The responses as the stated preference in case of transport policy are used for the explained variable of the travel mode choice and the vehicle choice. Therefore, the vehicle choice model and the travel mode choice model can be described with the data of the questionnaire survey. The parameters of the vehicle choice model and the travel mode choice model with the hierarchical Bayesian modeling are estimated with Markov chain Monte Carlo methods.

The posterior distribution of the coefficient parameter beta in the vehicle choice model is summarized in Table 1. As a result of appropriately limiting the variables, the log marginal likelihood is -1663 at the maximum. Many individuals have a positive coefficient of local share of EVs. Conversely, some individuals have a negative coefficient. Therefore, heterogeneity in the influence of local interaction should not be ignored in the analysis of EV choice.

Table 1. Posterior distribution of the coefficient parameters for the vehicle choice model.

variables	mean	std dev	min.	5%	25%	med.	75%	95%	max.
EV specific	4.006	11.966	-21.16	-14.63	-2.81	2.57	11.21	25.06	29.54
Difference between the purchase price [10^4 JPY]	-0.262	0.205	-0.75	-0.61	-0.46	-0.20	-0.09	0.00	0.00
Monthly amount of the carbon tax [JPY]	-0.046	0.082	-0.47	-0.25	-0.05	-0.02	0.00	0.00	0.00
Improvement of the crusing range [km]	0.081	0.108	0.00	0.00	0.00	0.03	0.14	0.30	0.60
Ratio of EV owner in local community	0.245	0.253	-0.27	-0.06	0.07	0.17	0.41	0.74	1.03
Dummy for various design of EV	6.742	1.949	2.32	3.39	5.58	6.65	8.00	10.08	11.96
Inclusive value for LV and NV (log-sum)	0.511	0.313	0.00	0.00	0.24	0.53	0.76	1.00	1.00

In terms of the travel mode choice model, the SP scale parameter is determined by maximizing the log marginal likelihood. When the SP parameter value is set as 0.82, the logarithm marginal likelihood is -1673 at the maximum. The posterior distribution of the coefficient parameter beta in the travel mode choice model is summarized in Table 2. It can be confirmed that every coefficient parameter is distributed in the reasonable range.

Table 2. Posterior distribution of the coefficient parameters for the travel mode choice model.

variables	mean	std dev	min.	5%	25%	med.	75%	95%	max.
Travel time [minutes]	-0.568	0.178	-1.19	-0.80	-0.67	-0.58	-0.48	-0.28	0.14
Travel cost [JPY]	-0.046	0.079	-0.41	-0.17	-0.09	-0.04	-0.01	0.11	0.19
Local mode share [%]	0.024	0.270	-0.63	-0.38	-0.22	0.04	0.19	0.48	0.64
Dummy for sustainable mode specific	9.012	9.874	-17.95	-7.49	0.51	11.39	16.30	24.55	29.52

As a result of the traffic simulation, the CO_2 emissions in the road network are shown in Fig. 2. It can be found that a large amount of CO_2 is discharged on the highways and the major arterial roads with heavy traffic.

The estimated link flows are compared with the observed link flows in the database of the road traffic census survey in Japan as shown in the Fig. 3. The RMS error is estimated as 8960 and the correlation is estimated as 0.866. As the p-value is calculated as 0.22 in the result of the two-sample Kolmogorov-Smirnov test, the estimation result of the link flows is validated statistically.

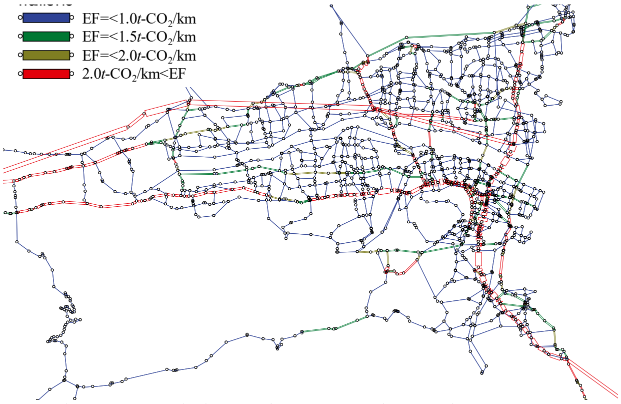

Fig. 2. CO_2 emission on the target road network.

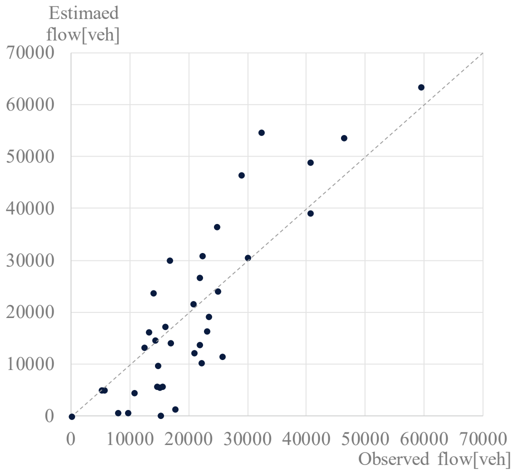

Fig. 3. Verification of the simulation result of link flows.

5. Simulation results

The reduction of carbon dioxide emission as well as the total travel time as the effect of the transport policy is estimated using the proposed network transport simulation system. The attributes of all trip makers are set up in the target city with duplicating samples in the road traffic census OD survey according to population. The coefficient values of the vehicle choice model and the travel mode choice model are given by formula (6) using the personal variable for attributes of each trip maker. It is simulated until ten years by a unit of one week with the proposed system. The time series changes of the number of travel modal shift and the estimated share of LV and EV are estimated.

As the result of the simulations in Fig. 4, the share of EV remains low 10 years later without the policy. In terms of travel mode choice, the travel mode share is influenced for both the conformity and non-conformity effects for local interaction between the heterogeneous trip makers. The share of EV increases gradually according to the amount of the carbon tax. Conversely, the rate of change to sustainable travel mode is reduced gradually according to the share of EV.

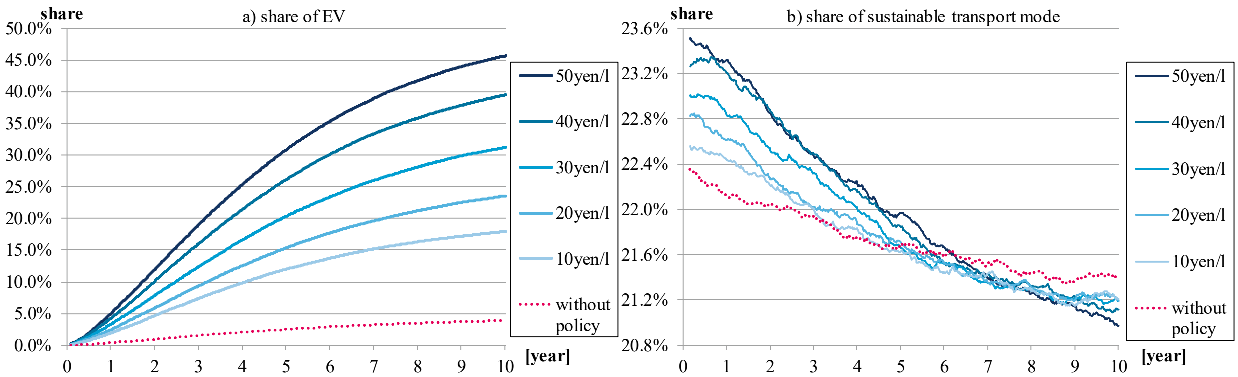

Fig. 4. (a) Time series change of share of EV; (b) Time series change of share of sustainable transport mode.

The reduction rates of CO_2 emissions for ten years in the case with the carbon tax are illustrated in Fig. 5. The reduction rate without the policy reaches 20% after 10 years, because the share of LV reaches 50%. However, since the share of LV reduces according to the share of EV, the reduction rate does not increase greatly even in the case that the carbon tax is 50 yen/l.

As a result of the traffic simulation in the case that the carbon tax is 50 yen/l, the reduction of CO_2 emissions in the road network are shown in Fig. 6. It can be found that the reduction of CO_2 emissions is large on the highway and the main arterial roads with heavy traffic.

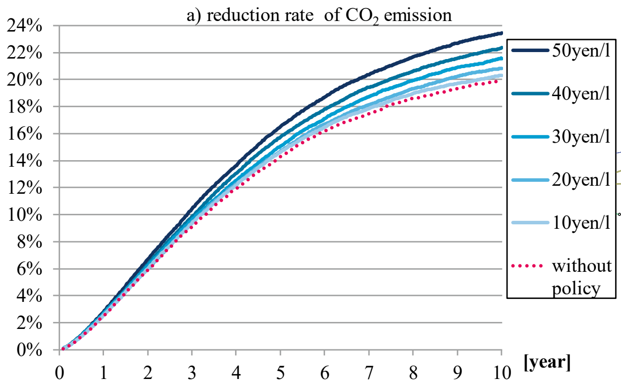

Fig. 5. Time series change of reduction rate of CO_2 emission.

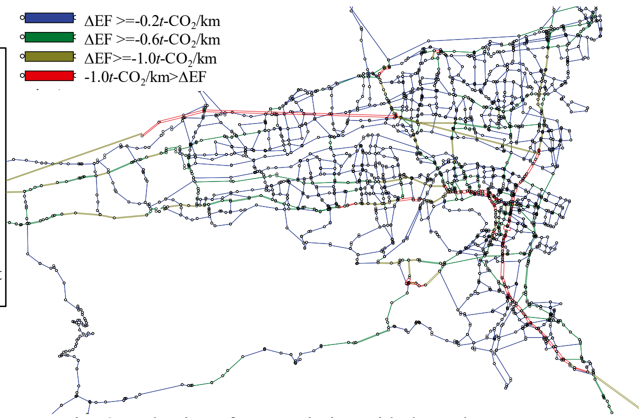

Fig. 6. Reduction of CO_2 emission with the carbon tax.

6. Concluding remarks

The integrated network transport simulator is developed based on the multi-agent simulation model to evaluate transport policies for reduction of CO_2 emission in this study. The study findings are summarized as follows:

[1] Considering social interaction as a factor related to transport mode choice and vehicle choice, a framework to measure the effect of reducing CO_2 emissions is constructed as multi-agent traffic simulation.

[2] The traffic simulator is combined with the MAS to consider traffic congestion, as the impact of traffic congestion on CO_2 emissions is significant.

[3] Taking into consideration changes in the share of EV and LV, the effect of reducing CO_2 emissions by only the carbon tax is not sufficient. Therefore, not only the carbon tax but also the appropriate combination of the locally transport polices should be combined adequately.

Acknowledgements

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