Policy decision making for trade-offs between mobility and equity maximization under environmental capacity constraints

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Policy Decision Making for Trade-offs Between Mobility and Equity Maximization Under Environmental Capacity Constraints

A Case Study of an Integrated Multi-Objective Model

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Key words: Policy decision making; Environmental capacity; Mobility; Equity; Accessibility

Abstract: This paper investigates the trade-offs between mobility and equity maximization under environmental capacity constraints by proposing an integrated model for multi-objective policy decision making. The model specifically deals with two systematic objectives: maximization of mobility and equity, which are respectively formulated by the sum of total car ownership and number of trips, and the difference levels among zonal accessibilities. The environmental capacity constraint is specified based on efficiency theory in which the frontier emission under maximum system efficiency is taken as the capacity. To investigate the performance of the proposed model, three types of hypothetical policies (network improvement, population increase and urban sprawl) are designed and the effects of these policy scenarios are simulated using data of Dalian City, China. Results show that the proposed model can be used for representing the trade-offs between mobility and equity based on different policy interventions. Compaed with two extreme cases with a single objective, mobility maximization and equity maximization, the Pareto-optimal solutions provide more options in practice for decision makers. Taking the solution with the minimum car ownership as an example, the policy of urban sprawl yields the most significant improvement in both emission and accessibility among three scenarios.

1. INTRODUCTION

The rapid expansion of car ownership and the increase of car dependency have been one of the main reasons accounting for various urban problems in different regions worldwide. Under the planned scenarios of land use and network development, changes in car ownership would induce spatial variations in traffic pollution, congestion, accessibility, etc. Expecting that increasing mobility levels will result in heavy environmental pollution, while equitable accessibility would contribute to environmental conservation, it is necessary to further investigate the dynamics between mobility and air pollution, and mobility and accessibility or equity. More specifically, under the premise of transport environmental control, the issue of how to increase mobility levels while decreasing accessibility differences among zones seems to be important.

One commonly adopted approach in mobility management aiming at alleviating environmental load is to increase the cost of car use. Examples of this approach include policies such as road pricing, fuel tax, vehicle maintenance programs, etc. Planners in general do however not control vehicle purchases, but may influence excessive car use. They need to persuade people to use public transport modes for accommodating their travel. The level of car ownership and number of car trips are frequently used in practice for mobility evaluation. Considering mobility development from the viewpoint of environmental conservation, investigating the dynamics of mobility and environmental pollution would be extremely important, especially for developing countries where a dramatic increase in car ownership is to be expected in the near future due to fast economic development.

Another issue induced by mobility change is the distributional problem of impacts which results in the issue of equity or inequality. Equity has been discussed in different disciplines, and is of similar importance as economic development and environment conservation. It is commonly understood as fairness or justice of the distribution of the impacts (both benefits and costs) of an action on two or more subgroups (Litman, 2007). In the field of transportation, as pointed out by Yang and Zhang (2002), equity can be observed from either a social or spatial perspective. Social equity basically refers to differences in income or social welfare between individuals or certain population groups. Spatial equity commonly indicates differences in the spatial distribution of levels of transportation services (e.g., travel time, cost, distance, and number of transfers). Different from the social equity, spatial equity is a dynamic indicator which is affected by the zonal/regional mobility level, transport network conditions, inter-zonal mode choice, and land use topology. The equity discussed in this paper concerns the spatial equity which is specifically defined using a formal indicator based on zonal accessibility.

When looking at traffic demand at the aggregate level, the change in zonal car ownership will influence trip generation, which consequently determines traffic flow distribution, travel time, accessibility and emission. Under the condition of environmental control, to know the maximum level of mobility and equity is important to urban planning, strategic decision making and land use planning at the macroscopic level. Obtaining the Pareto solution for the trade-off between mobility and equity would also benefit policy development in mobility management.

The purpose of this study therefore is to investigate the trade-offs between mobility and equity maximization under environmental capacity constraints by proposing an integrated model for multi-objective policy decision making. The model specifically deals with two systematic objectives, maximization of mobility and equity, which are respectively formulated by the sum of total car ownership and number of trips, and the difference levels among zonal accessibilities. The environmental capacity constraint is specified based on efficiency theory in which the frontier emission under maximum system efficiency is taken as the capacity. To investigate the performance of the proposed model, three types of hypothetical policies, network improvement (NI), population increase (PI) and urban sprawl (URS), are designed and the effects of these policy scenarios are simulated using data of Dalian City, China.

The remainder of this paper is organized as follows: Section 2 represents the integrated model and details for associated components. A genetic algorithm for multi-objective optimization is developed for the model application. A case study and the relevant designed policy scenarios are introduced in Section 3. Results and analyses are given in Section 4. The paper is summarized and concluded in Section 5.

2. THE INTEGRATED MODEL

The proposed integrated model serves two optimization objectives: maximization of mobility which consists of the sum of car ownerships and number of trips in total, and maximization of spatial equity which is defined and measured using zonal accessibility. The modeling process is established using a bi-level programming method which follows an iterated calculation process to obtain the optimal solutions as long as the environmental load does not exceed the environmental capacity. The Pareto-optimal solutions here which relate to a vector of zonal car ownerships are obtained at the upper level subject to the constraint that the environmental load should not be larger than the corresponding environmental capacity. The obtained vector of zonal car ownership will be used to calculate the inter-zonal mode choice probabilities which are used to calculate the origin-destination (O-D) trip matrix. Consequently, the obtained O-D matrix will be assigned to the road network in lower level problem. It results in a traffic flow distribution and associated emission levels which provide the inputs for the upper level problem. A flowchart on the whole modeling process is depicted in Figure 1:

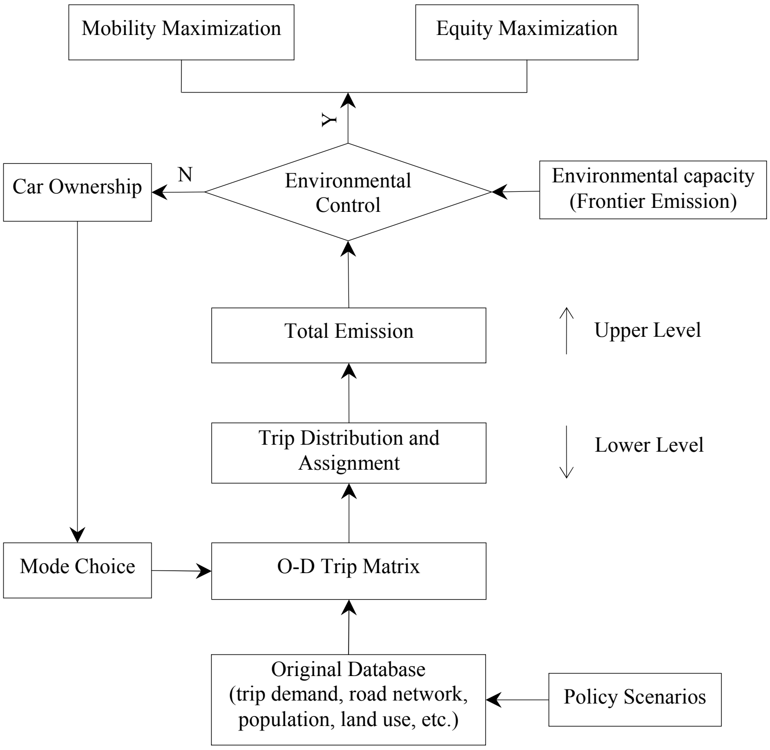


Figure 1 Flowchart of the integrated model system

2.1 Upper level problem: Trade-off between mobility and equity

As presented in Figure 1, the integrated model is composed of two levels of problems, named the upper level problem (ULP) and lower level problem (LLP). The ULP is a multi-objective optimization problem which can be formulated as below:

Maximize:

$$f_1(u_i) = \lambda_u \sum_{i \in I} u_i + \lambda_v \sum_i \sum_j (\varphi_{ij}^c \cdot q_{ij}^c + \overline{\varphi}_{ij}^c \cdot \overline{q}_{ij}^c) \tag{1}$$

Minimize:

$$f_2(u_i) = \frac{1}{2N^2 \overline{A}} \sum\nolimits_{j \in N} \sum\nolimits_{i \in N} \left| A_j - A_i \right| \tag{2}$$

Subject to:

$$E_i(u_i) \le E_{0i}\ ,\ i \in I \tag{3}$$

$$0 \le u_i \le u_{0i}\ ,\ i \in I \tag{4}$$

$$A_i = \sum\nolimits_{j \ne i} (P_j / t_{ij}(u_i)),\ i \in I \tag{5}$$

where f_1 and f_2 are two optimization objectives, representing the mobility and spatial equity, respectively; u_i represents the car ownership in zone i, and u_{0i} represents the maximum car ownership in zone i; q_{ij}^c and $\overline{q}_{ij}^c$ are trip demand between O-D pair (i, j) by car and public mode, respectively; $\lambda_u, \lambda_v, \varphi_{ij}^c$ and $\overline{\varphi}_{ij}^c$ are the pre-defined parameters relating to u_i and q_{ij}; N represents the total number of zones; E_i represents the total emission of zone i, and E_{0i} represents the emission capacity of zone i; A_k is the accessibility of zone k; P_j is the population of zone j and t_{ij} is the average travel time between zone i and zone j; I and A are the set of zones and links, respectively.

The objective functions are composed of maximization of mobility and equity. This multi-objective optimization problem implies that policy makers wish to maximize the mobility level (here, refers to the total number of car ownership and trips) on one hand, and maximize accessibility-based equity (decrease accessibility differences) on the other. The trade-off effects between two objectives can be measured by the set of Pareto-optimal solutions. Different from the optimal solution with single objective, the Pareto solution is not the absolute optimal for either of the objectives. The definition is based on the Pareto improvement which means that solution changes make one objective better without making others worse off. The named Pareto-optimal solution is only obtained when no further Pareto improvement can be made. Pareto-optimal solutions can be interpreted as a vector of solutions. Considering the conflicts between different system targets in practice, Pareto solutions provide policy makers information about the trade-offs between mobility and equity where various weighting schemes can be applied.

The mobility (f_1) is represented by the total of car ownership and number of trips by car mode and public mode. The parameters λ_u, λ_v, φ_{ij}^c, and $\overline{\varphi}_{ij}^c$ reflect different weights for policy goals which should be defined based on consensus building among all stakeholders related to the targeted policies. Larger values of $\overline{\varphi}_{ij}^c$ may result in more trips by public mode and less car trips while ensuring that the total number of trips reaches its maximum. Parameters λ_u and λ_v can also be used to reflect different emphasis between car ownership and trips.

Equity (f_2) is defined as a function of zonal accessibility (A_i). Here, we adopt the GINI coefficient to express equity, which is widely applied in the social sciences to measure income and welfare equity (further discussions on the comparison of related indicators have been discussed by Feng et al., 2009). Therefore, this indicator defined by accessibility indicates the level of distributional differences between zonal accessibilities across zones. The values of the GINI coefficient are between 0 and 1. Similar to the inherent meaning in evaluating social welfare, a lower GINI coefficient indicates a more equal accessibility distribution, while a higher number of indicative of a less equal distribution. The value “0” corresponds to perfect equity, meaning that each zone has the same level of accessibility, and “1” corresponds to perfect inequity, indicating that only one zone gets the accessibility, while other zones all have a zero accessibility level. The values of 0 and 1 are theoretically two extreme cases which are impossible to happen in practice in measuring accessibility-based equity.

It is obvious that the accessibility measurement needs to be specified for providing references of equity evaluation. Accessibility can be defined at either the individual level or the zonal level. Individual-based accessibility is concerned with the opportunities that an individual at a given location possesses to participate in a particular activity or set of activities (Odoki et al., 2001). Effects of spatial, temporal, and inter-personal constraints on accessibility can be evaluated based on individual-based accessibility, and as a result, such accessibility can be used to evaluate a wide range of policies. However, the individual-based accessibility has the disadvantage that it is data-intensive. For the current study, it would be more convenient and operational to adopt conventional location-based measures of accessibility associated with zone-based travel forecasting models. Such zonal accessibility is usually calculated based on gravity-type trip distribution models. Without loss of generality, in this paper, we define accessibility as a function of zonal population P_j and inter-zonal travel time, t_{ij}, as shown in Equation (5).

The optimization problem follows the constraint conditions that the emission in each zone i ($E_i(u_i)$) which is the function of zonal car ownership (u_i) is less than EC (E_{0i}). In addition, the decision variables, zonal car ownership (u_i) at zone i, are specified within the range of [0, u_{0i}]. The upper bound of the constraint (u_{0i}) is given by, for example, taking into account the actual limitations of the zonal population. This limit could be equal to or larger than the maximal car ownership derived from the bilevel model. This limit was introduced due to the assumption that car ownership per capita should be within a certain range. The number of trips can be calculated from the travel demand between O-D pairs (Q_{ij}) and mode choice probability (P_{ij}^c), which are shown as follows:

$$q_{ij}^c(u_i) = Q_{ij} \cdot P_{ij}^c(u_i) \tag{6}$$

$$\overline{q}_{ij}^c(u_i) = Q_{ij} \cdot (1 - P_{ij}^c(u_i)) \tag{7}$$

where Q_{ij} represents the total trips between O-D pair (i, j); P_{ij}^c represents the probability of choosing car mode from zone i to zone j.

Here, the mode choice probability between zone i and j is also a function of zonal car ownership. To link the lower and upper levels, an aggregate logit model is proposed to reflect the fact that mode choice probabilities are determined by car ownership levels at the origins, inter-zonal travel times and zonal land use characteristics. The probability of car trips between zones i and j is measured as follow:

$$P_{ij}^c(u_i) = \frac{\exp(V_{ij}^c)}{1 + \exp(V_{ij}^c)} \tag{8}$$

$$V_{ij}^c = b_0 + b_1 \cdot t_{ij}^c + b_2 \cdot u_i + b_3 \cdot indu_i + b_4 \cdot comm_i \tag{9}$$

where, V_{ij}^c and $\overline{V}_{ij}^c$ are deterministic term of the utility of choosing and not choosing the car from zone i to j, respectively; t_{ij}^c represents the travel time by car between zone i and j; $indu_i$ and $comm_i$ are dummy variables of land use for industry and commerce, respectively; b_0 and b_i are parameters need to be estimated.

Unlike disaggregate choice models that require choice data at the individual level, aggregate models are used to represent the accumulated results of individual choices at the zone level where the traffic analysis zones (TAZ) are taken as the choice alternatives. Consequently, the dependent variable of the aggregate model under study is the average modal share of different travel modes. Given the probability of a car trip, the trip probability by public mode can be simply obtained by using Equation (6). Note that we differentiate between car and public mode only because car trips make up a big share of the pollution. Traffic flows and emissions associated with public mode are not dealt with in this study. Thus, only the car trip matrix is incorporated in the traffic assignment in the lower level problem.

The emission from each link is calculated as the product of link length, traffic volume and emission factors that depend on the average driving speed on each link, which is calculated as follow:

$$E_i(u_i) = \sum_{a \in A_i} e_a,\ A_i \in A \tag{10}$$

$$e_a = \gamma_{ak} \times v_a \times l_a,\ a \in A, k \in K \tag{11}$$

where e_a represents the emission on link a; γ_{ak} represents the emission factor of category k on link a and k indicates travel speed category; v_a represents the link volume; l_a represents the length of link a.

Traffic volume (v_a) and average travel speed are the results of traffic assignment. The emission factors are based on the existing literature. The emission E_i from zone i equals to the sum of emissions from the links (e_a) which belong to zone i. Therefore, the area and spatial location of each zone affect the emission and concentration level. For instance, the zones within the central business district (CBD) mostly have a high density of road network and traffic flow, and consequently show high emission/pollution concentrations, although their areas are small. In contrast, suburban zones are usually large in scale, but have lower road network densities, and less pollution than CBD zones. Considering the complexity of pollutant diffusion and spatial differences, only emission constraints are included in this study.

Calculation of environmental capacity (EC) at the zonal level would be helpful to effectively control the environment pollution considering the specific characteristics of different areas. Although EC can be understood in terms of either emissions or concentrations, here we define EC by emissions. More specifically, the theory of efficiency analysis is used to specify the emission capacity by assuming there is no inefficiency in the ideal state of transportation system. Here, we adopt the stochastic frontier analysis (SFA) model (Kumbhakar and Lovell, 2000) with multiple inputs and single output. The logarithm form of Cobb-Douglas equation is adopted for measuring system efficiency:

$$\ln y_i = \theta_0 + \sum_{m \in M} \theta_m \ln x_{im} + \varepsilon_i \tag{12}$$

$$\varepsilon_i = \omega_i + \mu_i \tag{13}$$

where y_i represents the total amount of car emissions in city or zone i; x_{im} represents the m^{th} input variable in city or zone i; M represents the set of input variables; θ_0, θ_m are unknown parameters; ε_i is a composite error term; μ_i is the non-negative technical inefficiency component; ω_i is the two-sided random-noise component.

Different from the deterministic frontier model, here, the error term has two components. This makes it possible to measure the random effect outside of the control of producers. The noise component of ω_i is assumed to be distributed independently of u_i. Because we expect the emission to be lower giving the same level of inputs, the sign of μ_i in the error term is positive. The measure for environment efficiency CE_i is given by

$$CE_i = \exp(-\mu_i) \tag{14}$$

Here, CE_i reflects the grade of inefficiency with a value between zero and one. The smaller the value is, the more efficient the transportation system. Then, the frontier emission, EC_i, indicating environment capacity, can be calculated as

$$EC_i = y_i \cdot CE_i \tag{15}$$

The system inputs used in SFA are indicators of transport mobility and network density while the outputs are the observed car emissions. Then, the frontier emission calculated by current explanatory variables is regarded as EC. Thus, it is specified as the most efficient level rather than the maximum level. It means that the highest efficiency implies the worst performance of the system and the emission levels would be at their maximum. Therefore, the calculated maximum mobility will actually be the environmentally most efficient level.

3.2 Lower level problem: A combined distribution and assignment model

Given the updated O-D trip matrix, the traffic flow distribution can be observed by a traditional traffic assignment process. Due to the consideration that the O-D trip demand is fixed and trip distribution among zones, the lower level problem adopts a combined distribution and assignment model.

Minimize:

$$\sum_a \int_0^{v_a} c_a(x)dx + \frac{1}{\xi}\sum_i \sum_j (q_{ij}^c \ln q_{ij}^c - q_{ij}^c) \tag{16}$$

Subject to:

$$\sum_{h \in H} f_h = q_{ij}^c, i \in I, j \in J \tag{17}$$

$$\sum_{j \in J} q_{ij}^c = O_i, i \in I \tag{18}$$

$$\sum_{i \in I} q_{ij}^c = D_j, j \in J \tag{19}$$

$$v_a = \sum_{h \in H} f_h \delta_{ah}, a \in A, h \in H \tag{20}$$

$$f_h, q_{ij}^c \geq 0, h \in H, i \in I, j \in J \tag{21}$$

where, c_a represents the travel time on link a; f_h represents the traffic flow on path h; O_i represents the trip generation by car in origin zone i and D_j represents the trip attraction by car in destination j; ξ is the dispersion parameter for the trip distribution model; f_k represents the traffic flow on path k; J and H are the set of zones and paths, respectively.

The flow distribution is constructed by using an entropy model where the path flows can be any combination of traffic flows between O-D pairs and each combination is called a state. All states are equally likely to occur, and the flow with the highest occurring likelihood is the set with the maximum number of states. The model is a doubly constrained model in that both the total flow generated at origins and the total flow attracted to destinations are fixed and known. The solution of this model is a set of O-D trip rates and link flows which satisfy both the principle of user equilibrium and entropy maximization.

3.3 Solution method

Regarding the calculation method of bilevel programming problem, a number of algorithms have been proposed. Algorithms commonly suffer from the difficulty to ensure the optimal solution in theory because of the inherent non-convex characteristics associated with bilevel programming problem (Bard, 1999). Here, we adopt the genetic algorithm (GA) considering the simplicity in actual applications. The effectiveness of GA has been verified in many studies (e.g., Leblanc, 1975; Feng, et al., 2008).

Considering the characteristics of multi-objective bilevel optimizations, a multi-objective GA is specifically adopted. Even though there is no single best solution with respect to both objectives, the non-dominated solutions or Pareto-optimal solutions can be obtained. More specifically, we use the non-sorting genetic algorithm (NSGA-II) as the main calculation engine. The elitism in NSGA-II can speed up the performance of the GA significantly, and can also prevent the loss of good solutions once they are found (Deb, 2001). In addition, it can provide various Pareto-optimal solutions in a single run and consequently the burden of performing multiple runs for various values of weights can be reduced. NSGA-II also has the capability of constraint handling, which is useful to fit our calculation requirements. In the application of numerical example, a traffic assignment modular is embedded in the GA program to calculate the fitness values.

3. CASE STUDY

3.1 Data and parameter settings

The data was collected in Dalian City which is located in the North-East part of China. Among the three major economic bodies in China, Dalian is one of the central cities in the Ring-Bohai economic region. Belonging to Liaoning Province, Dalian is also the leading city in stimulating the economic development of the whole province. In recent years, Dalian has become the largest port in Northeast China and Inner Mongolia province.

Different from most Chinese cities, in the central area of Dalian City, more than seventy percent of daily trips are served by public transport modes such as bus, light rail and tram. Motorcycles are rare and few bicycles are used. As one of the cities in China with fast economic development, Dalian has significantly expanded its transportation system in recent years. Between 2002 and 2005, the disposable average income increased by 11.8%, while the normal price for a car decreased by 26.5% (DMBS, 2001-2005). The annual growth rate of private passenger cars increased fast, from 28% to 34.8%. Particularly in 2007, private passenger cars accounted for approximately 60% of the total increase in the number of vehicles.

Figure 2 shows the road network of the central urban area of Dalian City. The road network, which was simplified for the sake of model simulation, includes 33 zones, 895 links and 544 nodes. The central area with a dense road network shown by grey line covers a few zones, including zone 24, 25, 26 and 31. Recently, the region located near zone 5 has become another business center with road and building construction for multiple functions.

Except for the road network data, land use data and personal trip (PT) survey data were used for model estimation and application. These data were collected in 2004 in a research project about the comprehensive planning of the Dalian transportation system, funded by the Dalian government. The PT survey method is similar to widely adopted surveys in other countries.

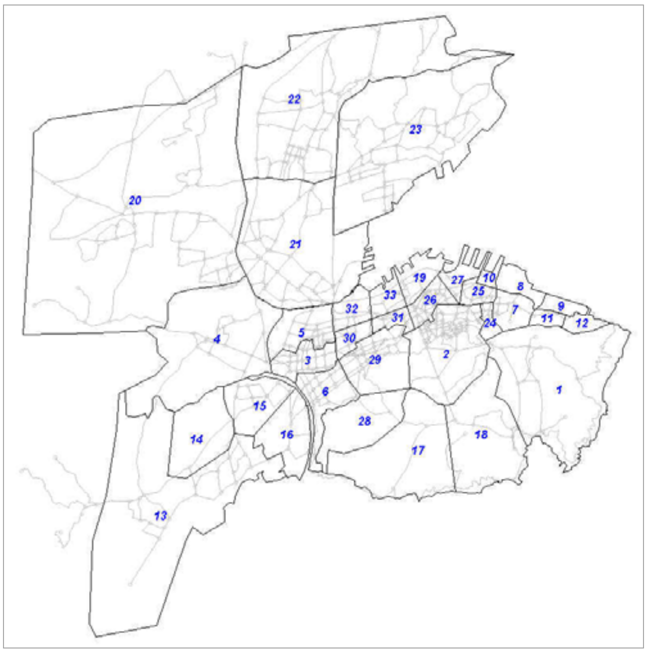


Figure 2 Road network of Dalian City

For the specification of EC, we adopted the Millennium Cities Database (Kenworthy and Laube, 2001) because it is hard to get historical zonal data for Dalian City. The database covers the data of 100 cities worldwide concerning demographics, economics, urban structure and a large number of transport-related data. These cities are selected from both developed and developing countries. Some of the developed cities served as benchmarks. Since the emission in this study is defined at the zonal level, whereas the database is at the city level, we validated the parameters in Equation (12) using city data and estimated the ECs for zones.

The modal split model is estimated using the PT survey data. Inter-zonal travel time is calculated using the shortest path under current trip demand.Due to the available data, only two types of land-use patterns, industry (*indui*) and commercial (*commi*), were included as independent variables in the model. The parameters of the logit model were estimated using maximum likelihood estimation method.

The trip matrix of car mode is assigned to the road network, ignoring non-car trips. The link impedance function in the traffic assignment is defined using the Bureau of Public Roads (BPR) function of the following form:

$$t_a\left(v_a\right) = t_0 \cdot \left\{1.0 + 0.15\left(\frac{v_a}{S_a}\right)^4\right\} \tag{22}$$

where t_a and t_0 are travel time on link a and travel time under free flow, respectively. S_a is the volume capacity on link a.

Regarding the various emitted pollutants from road traffic, only CO was taken into account in this research. It is responsible however for the largest share of urban pollution. The emission factors of CO were borrowed from the existing literature (Feng et al., 2003). The emission factor for each link varied with average travel speed, as shown in Table 1.

Table 1 Emission factors by travel speed (g/km)

Speed (*km*/*h*) / Pollutant (*g*)	γ<15	15≤γ>20	20≤γ>25	25≤γ>35	35≤γ>45	γ≥ 50
CO	84.7	58.8	51.6	40.1	29.8	26.2

Due to the consideration that there are theoretically a huge number of possible solutions, a restricted solution space is generated in advance for simulation purpose. Such a calculation scheme would ensure to find the global optimal solution in a limited range, while without loosing the generality of model performance investigation. A vector of possible solutions composed of integers with fixed intervals between two values for each variable associated with zones is generated randomly. The solutions for all zones are then combined together randomly without duplications. For comparison, two hundred sets of solutions are picked up in advance to check the model performances under policy interventions.

3.2 Policy design

Three aspects of policies are considered: population change (total population in zones), urban sprawl, and road network improvement, as shown in Table 2.

The first scenario S_1 which is the case without any policy intervention is used for reference in comparing with results by other scenarios. the scenario of S_2 relates to network improvement assumes that the capacity of each link will be increased by 20%. S_3 is assumed to increase the population in each zone by 10%. The scenario of urban sprawl (S_4) is designed based on the assumption that residents living in the central area move to suburban areas due to high land prices and costs of living in the city center. We assume a 30% decrease and 30% increase for downtown and suburban areas, respectively. Population in transitional zones between center and suburban areas is assumed without change.

Table 2 Design of policy scenarios

ID	Policy Scenarios
S_1	No policy;
S_2	Network improvement (*NI*);
S_3	Population increase (*PI*);
S_4	Urban sprawl (*URS*);

In order to evaluate the model performance, the key indicators have to be defined. Although a variety of outputs can be produced in the process of model implementation, such as travel time, average speed, accessibility, level of service, and trip distance, we are primarily concerned with variations in mobility and equity levels, and the associated traffic emissions and accessibilities. Therefore, the emissions, car ownership and accessibility are considered as the most relevant performance indicators.

Before carrying out the model under policy impacts, the models of environmental capacity and modal split model need to be validated additionally. Details on the specification of environmental capacity model have been presented by Feng et al. (2008). Here, because the quality of data for validation of the aggregated modal split model is not good enough, the estimated model based on PT data is not suitable for direct use in prediction. Alternatively, a simplified calculation procedure is adopted where the trip probability from zone i to zone j equals to the ratio between car ownership and population. This calculation method imposes an assumption that people having cars would definitely choose car mode for travel, ignoring the effects of possible traffic congestion.

4. RESULTS AND ANALYSES

Before investigating the performance of multi-objective model, two additional models with single objective, named mobility maximization and equity maximization, are first implemented respectively. These models are treated as two extreme cases comparing with the multi-objective model. Results of the models are compared in Table 3:

Table 3 Total car ownerships and GINI coefficients by three cases

Cases		Total car ownership	GINI coefficient
Case 1	Mobility maximization	**1,045,875**	0.19033
Case 2	Equity maximization	508,350	**0.18986**

The two models with single objective indicate the possible maximum mobility (Case 1) and the possible maximum equity, respectively. Results in Table 3 shows that, under environmental capacity constraints, the maximum car ownership is approximately double of that when equity maximization is taken as the optimization objective. In keeping the maximum equitable accessibility distribution, the relevant car ownership from Case 2 needs dramatic decrease than Case 1. It should be noted that the equity values calculated based on accessibility are only different at a small scale. Such type of indicator is highly sensitive to network performance, and can be even affected by the convergence criteria set in the traffic assignment process (Feng et al., 2008).

The proposed multi-objective model is implemented for each policy scenarios. The plot figures of Pareto-optimal solutions obtained by four scenarios are presented in Figure 2. Solutions show a similar correlation trend between equity and total car ownership where the total car ownership changes inversely with equity. Keeping the vertical values consistent, the points among four cases varied in terms of equity axis. The statistical results of GINI coefficients for all cases are presented in Table 4.

Table 4 Statistical results of GINI coefficients by different policy scenarios

Policy scenarios	Minimum	Maximum	Average
S_1: No policy	0.18986	0.19042	0.19010
S_2: Network improvement	0.18988	0.19024	0.19004
S_3: Population increase	0.18987	0.19032	0.19006
S_4: Urban sprawl	0.18830	0.18864	0.18846

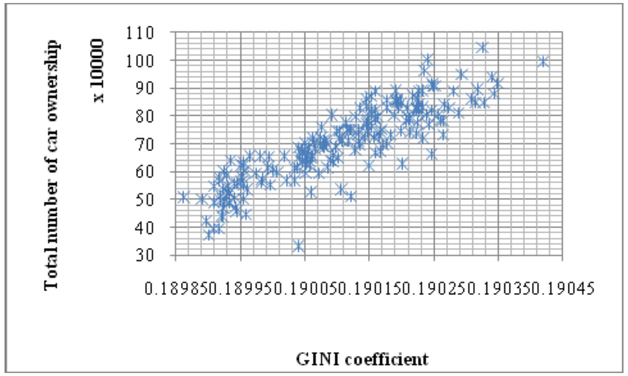
It shows that the average GINI coefficients with policy interventions become smaller than that without policy. Among all policy scenarios, the most significant improvement of transport equity is caused by urban sprawl where population are redistributed. Further, comparisons of the minimum equity values between S_2, S_3 and S_1 suggest that policy scenarios would not definitely result in a more equitable accessibility distribution than the original network state without policies. While a feasible design of policies may benefit to equity improvement in terms of the values in average.

In case of policy making in practice, decision makers need to determine the most feasible solution from the vector of Pareto-optimal solutions in terms of the trade-offs between mobility and equity. For the purpose of analysis, we choose, for example, the solution with the minimum equity value as the optimal solution in subsequent analyses. Relevant results of emission and accessibility are shown in Table 5.

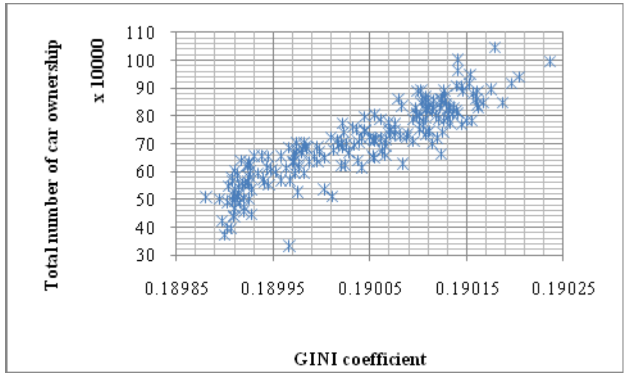
Table 5 Results of emission and accessibility by different policy scenarios

Policy scenarios	Emission		Accessibility	
	Average	Total	Average	Total
S_1: No policy	54	1771	233,734	7,713,223
S_2: Network improvement	54	1771	233,784	7,714,875
S_3: Population increase	49	1610	257,141	8,485,648
S_4: Urban sprawl	46	1532	260,508	8,596,748

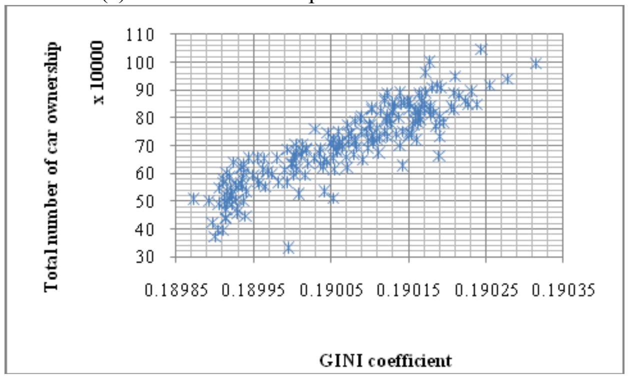
It is evident that S_4 (urban sprawl) yields the most significant improvements on traffic emission, and the biggest accessibility level among all scenarios. As a comparison with S_4, the population increase for all zones does not result in higher emission than S1. This can be attributed to the modal split model where the over increase of population associated to car increase would result in low level of OD trip matrix and other associated indicators. Moreover, the outputs related to emission by S1 and S_2 are same while the accessibilities are slightly different. This is probably because that the traffic condition on equilibrium is not so congested that network improvements could not significantly influence the traffic flow distribution and the relevant emission and accessibility.



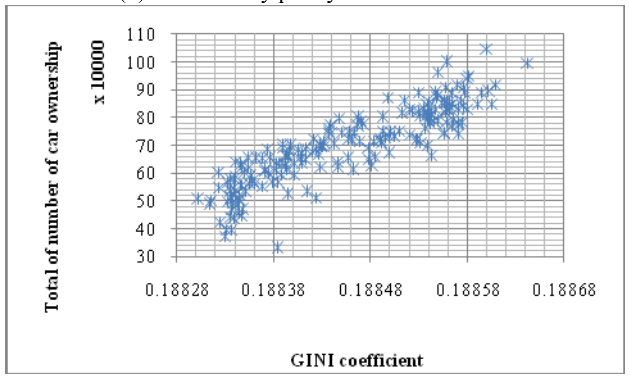
(a) Solutions without policies



(b) Solutions by policy of NI



(c) Solutions by policy of PI



(d) Solutions by policy of URS

Figure 2 Pareto-optimal solutions by different policy scenarios

5. CONCLUSIONS

In decision making process related to urban strategic planning and infrastructure investment, policies should be designed as consistent with the requirement of a sustainability framework. Regarding the environmental conservation associated with road traffic, mobility management policies need to be evaluated through a comprehensive modeling procedure which covers multi-facets of transport externalities. One of the problems is how to sustain the optimum main target without losing much from others. Since emphasizing only one objective may induce negative effects on others, specifying the trade-offs between multiple objectives is potentially very important to policy making.

Therefore, this paper proposed an integrated model which supports such kind of policy decision making with multiple concerns. The model deals with the issue of multi-objective optimization between mobility maximization and equity maximization under a quantitative specified environmental capacity constraint. In order to investigate the performance of proposed model under policy interventions, three hypothetical policies were designed, including network design problem, population increase and urban sprawl. The model was finally implemented in the context of a case study of Dalian City.

Results as discussed verified that the proposed integrated multi-objective model can be applied to trade-off between mobility and accessibility-based equity for policy decision making. The models which have single optimization objectives for each, mobility maximization and equity maximization, were additionally carried out, and yield the highest car ownership and equity level, respectively. Regarding the proposed multi-objective model, the Pareto-optimal solutions provide a group of alternatives which can be adopted by planners in terms of their specific requirements.

Simulation results on policy interventions showed that all policies obtained an improvement on network equity. Taking the solution with minimum equity as an example, urban sprawl yielded the most significant improvement on emission and accessibility among all policy scenarios. In addition, the policy of network improvement would not influence the emission and accessibility significantly when the traffic condition is not yet congested, while the urban sprawl obtained significant improvements on both aspects. The vector of Pareto-optimal solution can be taken as a reference in practice for policy makers for environment evaluation and mobility management.

The proposed integrated model incorporates multiple functions of model specifications theoretically. The interconnection problem between different components gives arises when it is applied to real cases. Limited by the data quality of personal trip survey in the case study, there are possibilities to obtain better calculation results. For instance, the more advanced mode choice model representing aggregated mode choice as well as good data would benefit to the improvements of results significance. In addition, the model can be further developed from several perspectives: 1) considering the deficiency of tradition traffic assignment mechanism, models at the lower level problem can be replaced by incorporating a dynamic assignment procedure; 2) improvement can also be the application of multi-agent simulation in representing the distribution of traffic flows. However, this would require a sufficient database; 3) future research may also address the dynamics issue of land use within this modeling framework.

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