AN INTEGRATED MULTI-OBJECTIVE MODEL FOR MAXIMIZATION OF *MOBILITY* AND EQUITY UNDER ENVIRONMENTAL CAPACITY CONSTRAINTS

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ABSTRACT:

This paper proposed an *Integrated Model* which serves a multi-objective optimization problem: the maximization of *mobility* and *Spatial Equity* under the constraint of quantitatively specified *environmental capacity*. As an extension of the *Integrated Model* suggested previously, this model incorporates equity as an additional optimization objective. The multi-objective model is evaluated by a vector of Pareto-optimal solutions using Dalian city as a case study. To compare model's performance, models with the single objective of equity maximization and *mobility* maximization are implemented, respectively. The multi-objective model results in less equity than the equity maximization model and a lesser *mobility* level than the *mobility* maximization model. Results verified that the proposed multi-objective model can be applied to trade-off between the maximization problems of equity and *mobility*. Calculated car ownership and emissions at the zonal level provide meaningful references for decision making in environmental evaluation and *mobility* management.

Keywords: Integrated Model, Multiobjective Optimization, Mobility, Spatial Equity, Accessibility, Environmental Capacity

1. INTRODUCTION

The expansion of car ownership and the rapid increase of car dependency have been the main reasons accounting for various urban problems in different regions. Among the externalities induced by road traffic, environmental pollution has caught the attention of many policy makers around the world. Given planned scenarios of land use and network development, changes in car ownership contribute to spatial variations in traffic pollution, zonal a*ccessibility*, etc. Giving the common expectation that increasing *mobility* levels will result in heavy environmental pollution, while equitable a*ccessibility* 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 differences in zonal *accessibility* seems to be important.

One commonly adopted approach in *mobility* management aimed 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 can be considered 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 propose a *multiobjective integrated model* to maximize *mobility* and equity under a quantitatively specified *environmental capacity* constraint. This model is an extension of the i*ntegrated model* previously suggested by Feng et al. (2010) by incorporating equity as an additional optimization objective. A bi-level programming model based on a network assignment representation is employed. The upper level problem is formulated by a multi-objective optimization model subject to the *environmental capacity* constraint, and the lower level problem represents a traffic assignment model. An inter-zonal aggregate modal split model is used to represent the impact of the trip matrix on variation in *mobility*. An efficiency theory based model is developed to specify the named *environmental capacity*. To verify the performance of the proposed model, a case study is carried out based on real data collected for 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 multiobjective optimization is designed for the model application. A case study is 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 using *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 solution which relates to a vector of zonal car ownerships is obtained at the upper level subject to the constraint that the environmental load should not be larger than the corresponding *environmental capacity*. The obtained 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. 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 this modeling process is depicted in Figure 1:

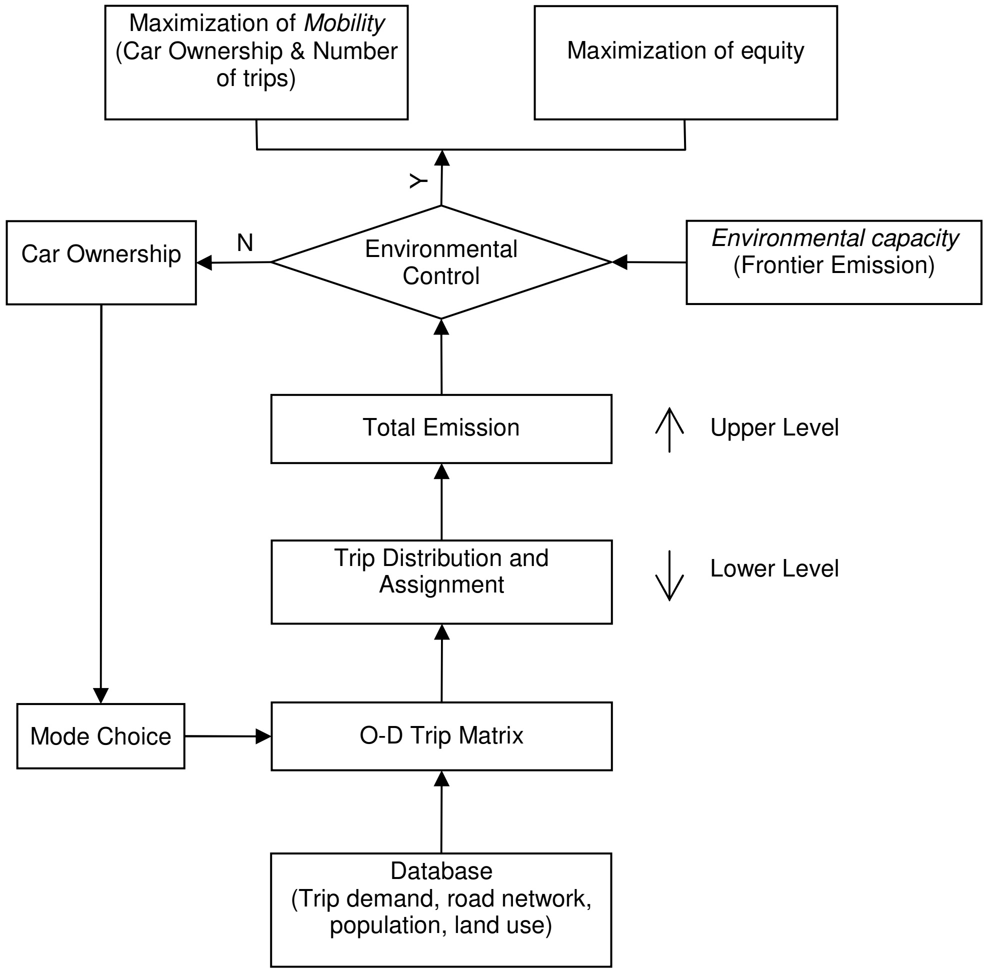

Figure 1 Flowchart of the *Integrated Model*ing system

2.1 Upper level problem: Multi-objective optimization on *mobility* and equity

As indicated in Figure 1, the bi-level model is composed of two levels of problems named the upper level problem (ULP) and lower level problem (LLP). The ULP is a multiobjective optimization problem with the objective of maximizing the sum of zonal car ownership and total number of trips by car and non-car modes, and the maximization of *spatial equity*. It can be mathematically represented 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:

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

Subject to:

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

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

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

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 from zone *i* to 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 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 off 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 $\overline{\phi}_{ij}^c$ 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 $\overline{\phi}_{ij}^c$ 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). 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). Thus, the only difference is that income is replaced with zonal *accessibility*. Consequently, this factor 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 measuring *accessibility*-based equity.

Accessibility can be defined at either the individual level or the zone 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. The disadvantage of individual-based *accessibility* is 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 zones 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 above BL programming approach. This limit was introduced in the model based on 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:

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

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

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 equal to:

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

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

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 from zone i to 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 zonal 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 current 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 shown 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 result of the traffic assignment. The emission factors are based on the existing literature. The emission E_i from zone i equals 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 attempt to define EC in terms of emissions. More specifically, the theory of efficiency analysis is used to specify the emission capacity by assuming there is no inefficiency in the ideal transportation system. Here, we adopt the stochastic frontier analysis (SFA) model (Kumbhakar and Lovell, 2000) with multiple inputs and single output. We use the logarithm form of Cobb-Douglas equation 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 Algorithm

In the field of transportation, various algorithms have been proposed to solve the bilevel programming problem. Algorithms suffer from the difficulty in finding the optimal solution theoretically because of the inherent non-convex characteristics associated with bilevel programming problem (details can be found in 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 addressing bilevel programming problems (e.g., Leblanc, 1975; Feng, et al., 2008).

Considering the characteristics of multiobjective bilevel optimizations, a multiobjective GA is specifically adopted. Even though there is no single best solution with respect to both objectives in this study, 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

The data we used in the case study was collected in Dalian City, which is located in the Northeastern 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.

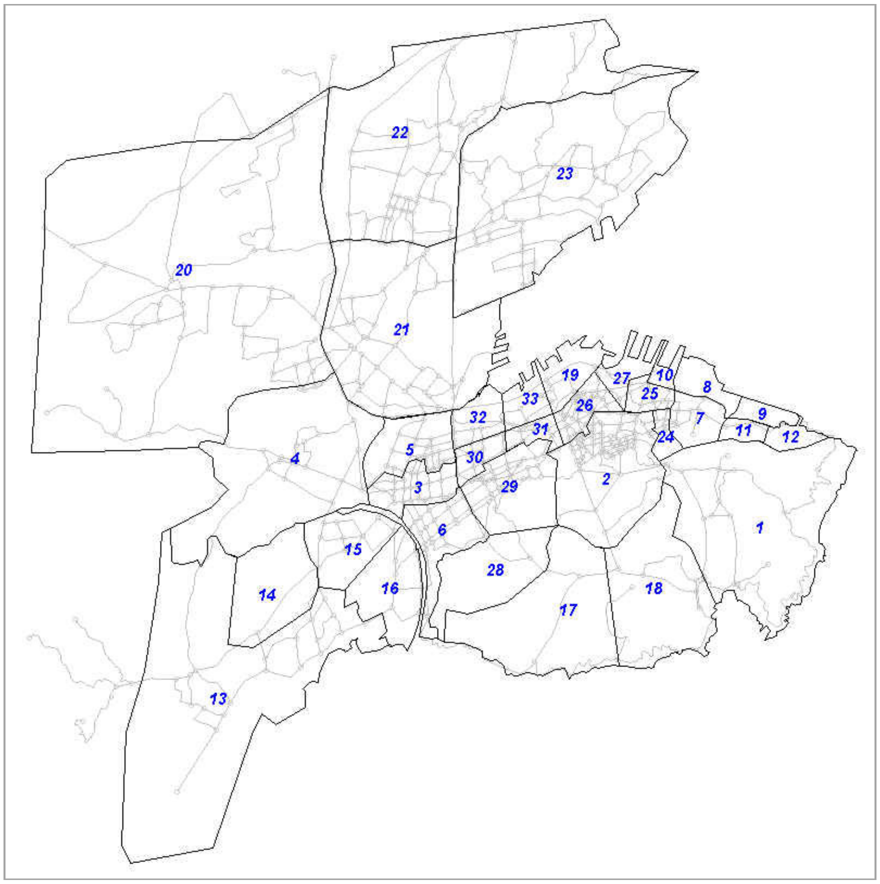

Figure 2 Road network of Dalian City

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 calibration, 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.

For the specification of EC, we adopted the Millennium Cities Database (Kenworthy and Laube, 2001) because it is hard to get historical zone 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 EC at zones.

The modal split model is estimated using the PT survey data. Inter-zonal travel times were calculated using the shortest path under current trip demand. Due to the available data, only two types of land-use patterns, industry ($indu_i$) and commercial ($comm_i$), 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:

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

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

4. RESULTS AND ANALYSES

In order to implement the integrated model, it is necessary to calculate in advance the environmental capacity of zones and inter-zonal mode choice. These estimations have been specified in previous study (Feng et al., 2010), and here we take the estimated results into the calculation of proposed multi-objective model. Results of the Pareto-optimal solutions are shown in Figure 3. Here the mobility levels are presented by total number of car ownership considering that the weight parameters associated with travel demand were set as 0.5. The designed algorithm finds the minimum of equity value and maximum of mobility value.

The results indicate that mobility increases with decreasing equity. The Pareto-optimal solution can be used to specify the trade-offs between mobility and equity for policy makers who can decide on the best solution considering their specific situations.

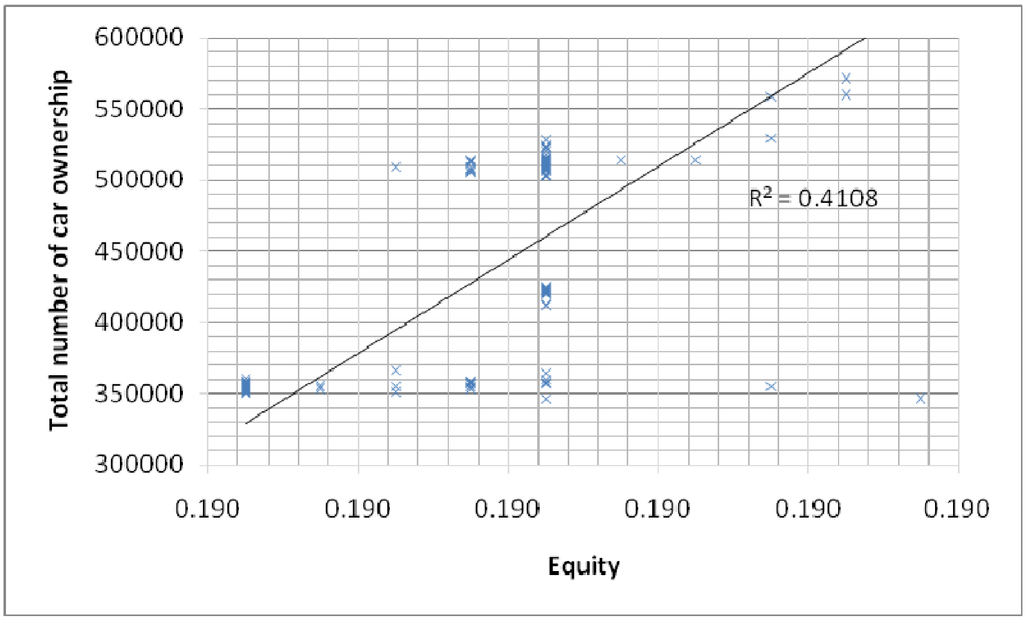

Figure 4 **Pareto-optimal solutions for multi-objective optimization**

Figure 3 also shows that the differences in values are significant for mobility but very small for equity (the 7th unit after the decimal point). This is understandable because values of mobility and equity are in different scales. When calculation is closed to the convergence, a small improvement on equity level may require the large decrease of mobility. Moreover, in case of the small differences among equity values, one of the reasons might be due to the fact that the pattern of total trip demand between zones is fixed and only the probability of car travel varies in terms of variations in car ownership. Additionally, estimation results on the modal split model in the previous study indicated that the mode choice probability of car trips was not significantly sensitive to variation in car ownership. Therefore, the consequent variation in the trip matrix is limited within a particular range which leads to similar patterns of accessibility and equity. This is partially attributed to the quality of the data for model estimation. A better modal split model may also change this finding.

In order to identify the performance of proposed multi-objective model (Case 3), we additionally calculate the model with the single objective of maximizing spatial equity (Case 2). This model differs from Case 3 only because of the elimination of the mobility objective. The results associated with the model of mobility maximization (Case 1) which has been specified in a previous study are directly included in this study for comparison.

Considering that zonal car ownership is the decision variable in this integrated model, we analyze the results associated with car ownership instead of the sum of trips. The results related to equity, total car ownership and total emission calculated from the three cases are reported in Table 2.

Table 3 Comparative results for three cases

	Equity	Total car ownership
Case 1: equity maximization	0.18989926	—
Case 2: mobility maximization	—	**649,692**
Case 3: multiobjective optimization	**0.18989931**	**508,958**

Note that the Pareto-optimal solution represented in Table 4 is confirmed based on the medium level as a example among the vector of solutions from both equity and mobility viewpoints (as shown in Figure 2, point B). As expected, Case 1 yields the best equity level and Case 2 yields the maximum mobility, while Case 3 yields the less car ownership than Case 2 and less transport equity than Case 1. This means the model with single objective can only deal with the problem of maximization or minimization of specific target, which may induce negative effects on others.

Expecting that an equitable accessibility distribution would contribute to environmental conservation, and high level of mobility would induce high pollution, we compare the results of total emission from the three cases. As shown in Table 2, Case 1 and Case 2 result in the lowest and highest total emission, respectively. The Pareto-optimal solution has a result less than that of Case 2, but higher than Case 1, which is interrelated to its levels of equity and car ownership. This also implies that decision makers can take the total emission induced to evaluate the trade-offs between equity and mobility.

Figure 4 represents the differences between zonal emissions and environmental capacities associated with the Pareto-optimal solutions which are calculated based on the multiobjective model. Results show that there are different levels of emission distribution across the zones. Emissions at most of the all zones are significantly less than or closed to their capacities. The fact that the distance between emission and capacity cannot be zero is accounted by network topology, distributional pattern of travel demand, and the requirement of multi-objective optimization.

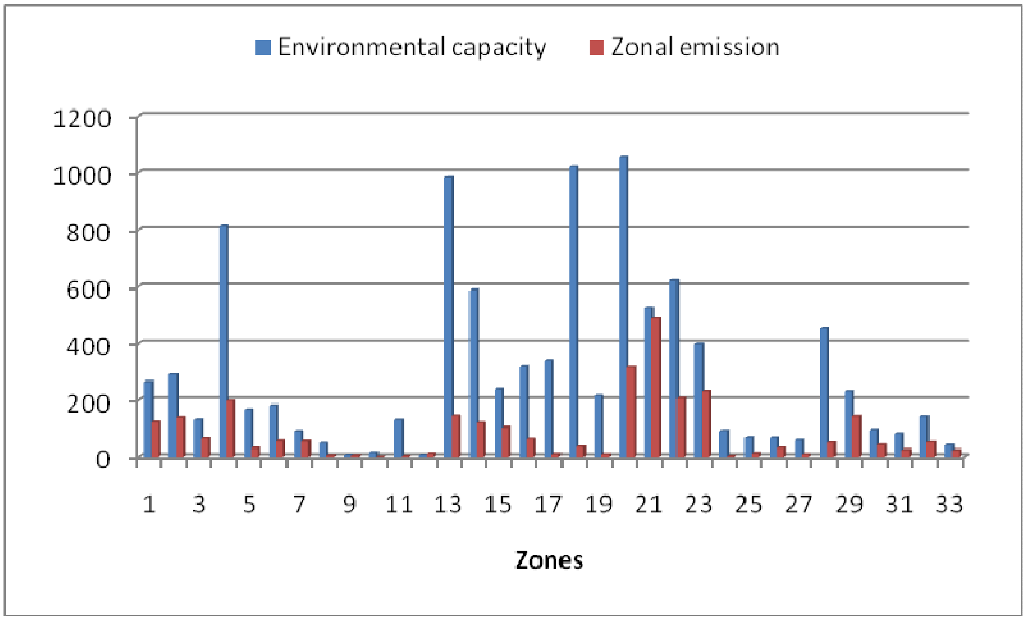

Figure 5 Results of zonal emission and environmental capacity calculated by multiobjective model

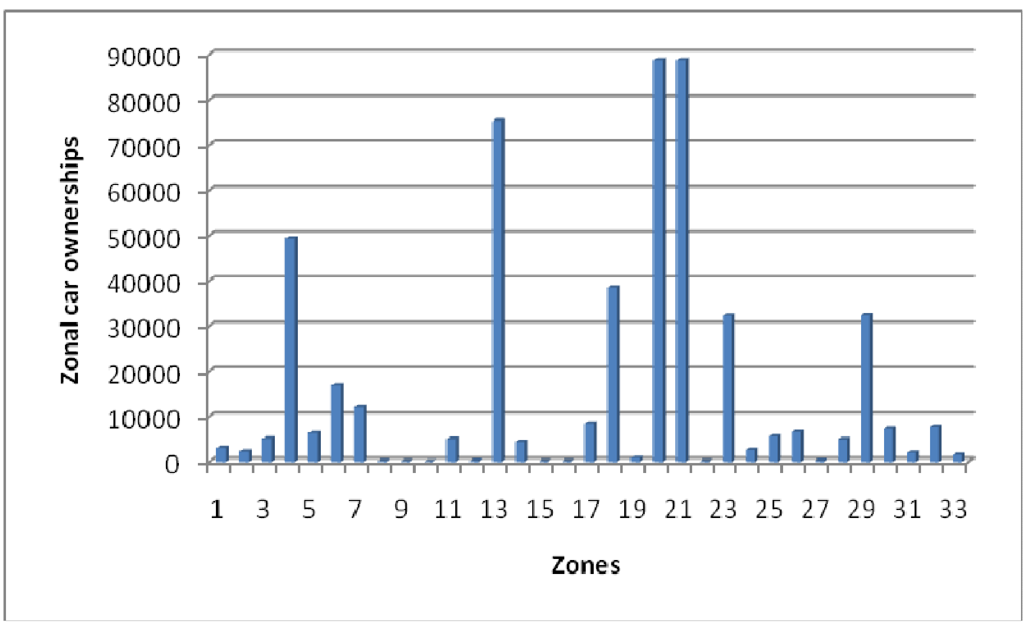

Figure 6 Zonal car ownerships calculated by the multi-objective model

The results of zonal car ownership calculated by multi-objective optimization model are shown in Table 5. It shows that the car ownerships get significant increases in different zones. This means an optimal distribution of zonal car ownership can be specified with the purpose of equity and mobility maximization. The difference between current car ownership and optimal level gives a meaningful indication to regional mobility management.

5. SUMMARY AND DISCUSSION

In decision making process related to urban strategic planning and infrastructure investment, policies should be designed consistent with the requirement of a sustainability framework. Regarding 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 multiobjective optimization between *mobility* maximization and equity maximization under a quantitative specified *environmental capacity* constraint. A bi-level programming approach is adopted for model development. The upper level problem represents the trade-offs for policy makers between *mobility* and *accessibility*-based equity, while the lower level problem deals with the problem of traffic flow distribution. Considering the distribution of travel demand among zones, the lower level problem adopted a combined distribution and assignment model. In addition, an aggregate modal split model and stochastic frontier model were estimated to identify the inter-zonal mode choice probability of car travel and zonal *environmental capacity*, respectively. The model was finally implemented in the context of a case study of Dalian City.

Results verify that the proposed integrated multi-objective model can be applied to trade-off between *mobility* and *accessibility*-based equity for policy decision making. To verify the performance of proposed model, two models which have a single optimization objective for each, *mobility* maximization or equity maximization, were additionally carried out. The model of *mobility* maximization and equity maximization yield the highest and lowest level of car ownership, respectively. Comparative results showed that the Pareto-optimal solutions provide a group of alternatives which can be adopted by planners in terms of their specific requirements. Calculation results also showed different distribution patterns of zonal emission and zonal car ownership among three cases, which can be taken as a reference for environment evaluation and *mobility* management.

The proposed *integrated model* incorporates multiple model specifications. The interconnection problem between different components 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 results by using more advanced choice models.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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