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SHORT CONTRIBUTION

Effect of Resource Allocation Policies on Urban Transport Diversity

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Abstract: *Maximizing transport diversity is critical to the equitable achievement of stakeholder needs. Resource allocation policies help planners decide when and how to invest transportation infrastructure and services. However, policies for improving transport diversity are difficult to design, implement, and quantify because of the uncertainty, feedback interaction, and complexity of system relationships. This study proposes a hybrid model integrating system dynamics, cognitive maps, and a sensitivity model to tackle the problems. The model application is illustrated through an empirical study to enhance the managerial implications in the Taipei metropolitan area.*

1 INTRODUCTION

Transportation systems consist of infrastructure, modes, and stakeholders. Different transport stakeholders with diverse demands have different needs for transportation infrastructure and services, resulting in a diversity of needs. In fact, in transportation planning, transport policy makers must simultaneously consider the tradeoff between the differences in the supply of transport infrastructure or modes and the various needs of stakeholders. Feng and Hsieh (2009) suggested the concept of transport diversity, defined as different levels of satisfaction within stakeholder needs and measured using the variations in achievement among needs, to assess the urban transportation performance. The two approaches to improve transport diversity are goal setting (demand side) and resource management (supply side). If demand-side parameters are given, the critical issue for decision makers is how to allocate finite resources to realize greater transport diversity, thus denoting more equitable stakeholder need achievement.

Resource allocation is the main tool used to influence transportation performance, while the quantity and capacity of resources are finite and either expensive or difficult to increase. Applying inappropriate investments to given needs causes bias, which reduces equity and wastes resources that could otherwise be utilized more efficiently (Senouci and Adeli, 2001; Shohet and Perelstein, 2004). The efficient and effective resources allocation offers a realistic management opportunity for improving transportation performance. Several sources proposed optimization models to allocate the asset of the magnitude and scheduling of maintenance and rehabilitation (Adeli and Karim, 1997; Karim and Adeli, 1999; Kuhn and Madanat, 2006; Dridi et al., 2008) as well as to illustrate the allocation of social infrastructure (Bigotte and Antunes, 2007) and facilities (Castillo et al., 2008; Fan and Machemehl, 2008) via exact and heuristic methods. Moreover, Chu and Durango-Cohen (2008) introduced a time-series model for supporting the resource allocation to preserve infrastructure facilities.

Resource allocation policies impact system performance. However, few studies have explored resource allocation policies because of the difficulty of designing, implementing, and quantifying system relationships, owing to the associated uncertainty, feedback interaction, and complexity (Kang and Jae, 2005). The policies of resource allocation are complicated by iteration and by delays in implementing allocation decisions (Udwadia et al., 2003). Iteration creates a closed workflow in which interactive or interdependent relationships between parameters can be traced and checked for

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optional change requirement. Accordingly, this study proposes a systematic model to simulate the effects of resource allocation policies on transport diversity. The decision support model for resource allocation policies can help planners decide when and how to invest transportation infrastructure and services. The definition of transport diversity is illustrated in the next section, followed by the research approaches. The construction of the decision support model is then discussed in Section 4, followed by the application and results.

2 TRANSPORT DIVERSITY

Transport diversity refers to the satisfied level, which is measured as the gap between expected goal and present values, of stakeholder needs in the form of the entropy to tackle the issue of how to equitably satisfy diverse stakeholder needs. When the stakeholders and their needs are determined, minimizing the need gaps, the remainder of the needs achievement, between the expected goals and the present values (as shown in Equation (1)) is a key objective.

$$m_i = \frac{O_i^{\text{Max}} - V_i}{O_i^{\text{Max}} - O_i^{\text{Min}}} \tag{1}$$

$$H = -\sum_i \frac{n_i}{\sum_i n_i} \times \ln \frac{n_i}{\sum_i n_i} \tag{2}$$

where m_i denotes the normalized gap of need i, O_i^{Max} and O_i^{Min} represent the expected goal and minimum threshold of need i, respectively, V_i is the present value of need i, and H is the value of diversity. The normalized value prevents need gaps resulting from the differences in unit scale. Meanwhile, n_i denotes the positive remainder of the gap of needs, namely, the achievement. Moreover, transport diversity deals with the equal satisfaction of stakeholder needs, the other critical objective of transportation planning, in the form of the entropy presented in Equation (2). Greater diversity indicates that as the distribution between compartments becomes more equitable, the gradients between compartments reduce and larger numbers of compartments come to be involved in the system.

3 RESEARCH APPROACH

Resource allocation for systems in which diverse variables are linked by rich interactions offers various macro benefits (Simon, 1996). The interactions among system elements are crucial for understanding and managing the behavior and performance of transport systems. However, effectively explaining and controlling system evolution over time is difficult (Lee et al., 2007). To overcome the weakness of traditional techniques, including the inability of traditional tools to explain compounding effects as well as the inability to handle uncertainty, feedback loops, and iterative processes (Nguyen and Ogunlana, 2005), system simulation approaches have been introduced to model complex and uncertain behavior and performance of systems (Ulker et al., 2008). Simulated outputs are inadequate for optimizing policy decisions but useful for discussing allocation policies and performances (Wang et al., 2008). System dynamics, one of the primary established tools for system analysis, can address the rationality in system management (Lane, 2000). Quantitative methods are adopted in system dynamics; for example, the travel speed shown in Figure 1a is calculated precisely as trip distance divided by travel time.

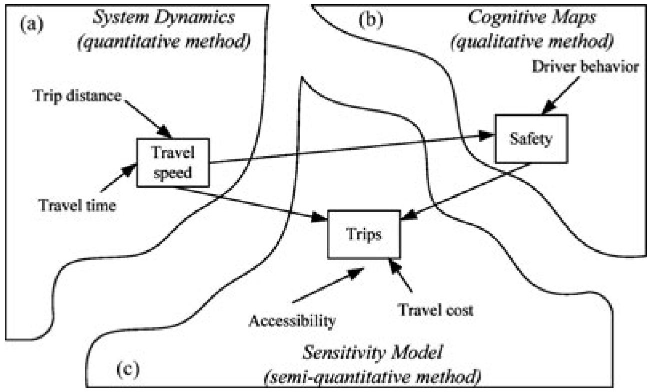

Fig. 1. Torn system approaches.

However, the precise relationships between factors might be unavailable, owing to the complexity of systems (Stylios and Groumpos, 2000). System dynamics emphasize process, data, and exact cause–effect relationships, whereas cognitive maps imply that decision makers make sense of reality and decide what they should do to forecast how the world would be more preferable in the future (Eden and Ackermann, 2004). For instance, the impacts of driver behavior and travel speed on safety, shown in Figure 1b, are identified via the qualitative cognition of experienced experts. Moreover, Kwahk and Kim (1999) identified the features of cognitive maps as understanding causal relationships, facilitating system thinking, and promoting the identification of opportunities and threats. A major difficulty of cognitive maps lies in determining relationship intensity with a qualitative feature reflecting the cognitive condition of individuals, something that cannot be directly measured. Some researchers indicated relationships using weighted connections; that is, simple additive weighting and analytic hierarchy process (Georgopoulos et al., 2003; Kwahk and Kim, 1999). Carbonara and Scozzi (2006) suggested that a collective map representing the consensus should be created by analyzing the maps of participants in a decision-making group.

The most severe challenge of the cognitive maps refers to the algorithm of multiplying an input vector with an adjacency matrix. This implies that the relationships between all factors are linear and addible, while the impact intensions are constant. The sensitivity model is thus employed, which includes system thinking, fuzziness, and simulation of semiquantitative data. The sensitivity model focuses on pattern recognition and feedback mechanism rather than on mono-causal relationship and enabling analysis of complex systems possible via fuzzy logic (Adeli and Karim, 2000; Karim and Adeli, 2002a; Adeli and Jiang, 2003), which provides a systematic method in which systems can be understood without detailed precision but accurate ordinal parameters (Chan and Huang, 2004). The relationship between variables is identified as the adjustment factors. For example, the variation in trip patterns over time (Figure 1c) is influenced by the levels of cost, accessibility, safety, and speed via a semiquantitative connection. Consequently, to obtain different kinds of relationships that fit a real-world situation, a hybrid model integrating system dynamics, cognitive maps, and a sensitivity model is described in the next section.

4 DECISION SUPPORT MODEL

A decision support model is developed to help decision makers understand system behavior and make investment decisions in relation to urban transportation systems. The decision support model is suitable for any spatial scale that is considered a holistic system of transportation planning regardless of individual stakeholder needs. The Taipei metropolitan area provides the empirical study to discuss the managerial implications of the model. Owing to the dynamic interactions between the various elements, systems seem to be misinterpreted by excessive insistence on a specific sector without consideration of the interrelationships. Therefore, the simplified interactions in the urban transportation system are represented in Figure 2.

The model comprising various items and equations is divided into four subsystems, namely, mass rapid transit (MRT), bus, passenger car, and motorcycle. Shared parameters, such as congestion, safety, and so on, interrelates these subsystems. Feedback loops are then built with all of the variables and connections. Furthermore, the subsystems of pedestrians and bicycles as well as parking and the land-use patterns are assumed as the external factors.

The MRT subsystem (Figure 3) describes both the supply of infrastructure and the needs of MRT users. The crowd phenomenon and subsidy strategy involve two balancing feedback loops, whereas several growing feedback loops are involved in stakeholder needs. The subsystem is capable of self-adjustment because of

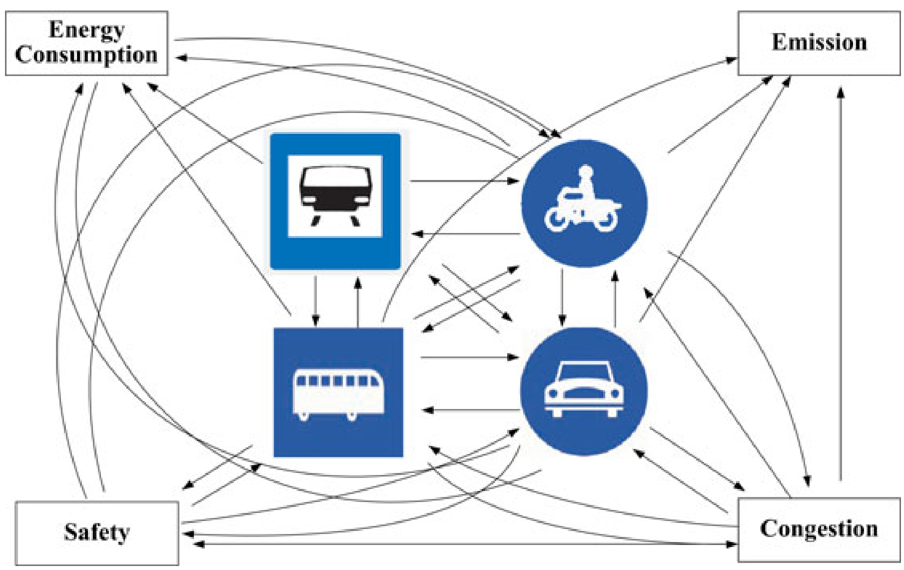

Fig. 2. Simplified interaction in the urban transportation system.

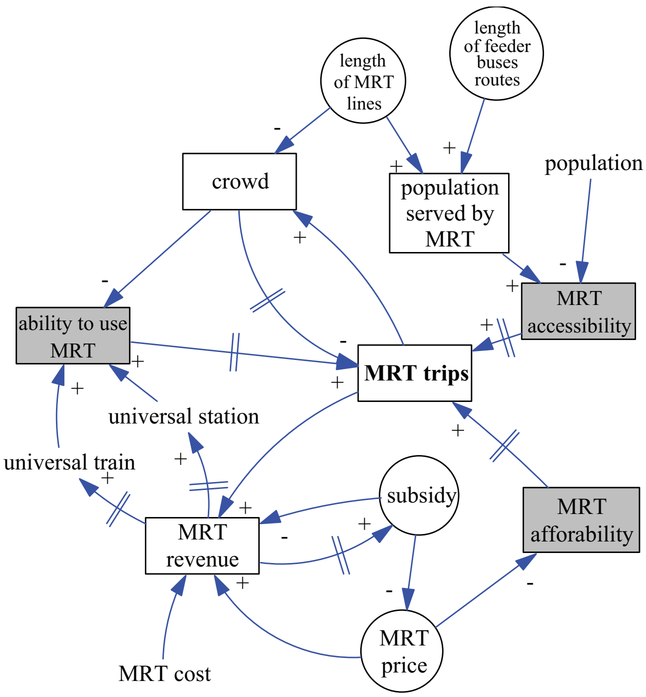

Fig. 3. Feedback structures in MRT subsystems. →: a causal relationship, with + (−) signs indicating a positive (negative) effect; signs on the arrows represent the delay effect; ▭: variables reflecting stakeholder needs; ○: policy variables.

the negative feedback loops. The negative feedbacks also make the subsystem independent from quantitative growth. The common management instruments for attracting people from other modes, such as infrastructure investment, pricing, and subsidy, are taken into account in the subsystem.

The feedback structures of other subsystems, shown in Figure 4, resemble the MRT subsystem described above. These subsystems consider the policies including infrastructure building, road space allocation, pricing, subsidy, regulation, and tax and fees to improve urban transportation systems (European Commission, 2006). The model maps the causality of transportation behaviors and resources allocation. The interactions among the components represent the use of information and managerial policies to impact system progress.

This study utilizes experimental approaches to examine the relationships between resource allocation policies and transportation system performance. Many critical inputs are obtained by data mining and expert discussion during pattern identification, model construction, and system simulation. Open participatory meetings emphasize communication, cooperation, and compromise among different participants with the objective of building consensus regarding system behavior. Experts fully understanding the information of transportation in Taipei, including planners, government, and scholars, are invited to build consensus. This process is relatively time-consuming but provides a significant incentive for group learning.

The decision support model integrates the algorithms of system dynamics, cognitive maps, and a sensitivity model. Different equation types are applied to distinct interactions according to the various attributes linking different elements. For example, the MRT accessibility in Figure 3 is defined as the ratio of the population served by the MRT and feeder buses to the total population. This is a precise quantitative relationship and is represented by Equation (3).

$$ac_t^{MRT} = \frac{P_t^{MRT}}{Pop_t} \tag{3}$$

where ac_t^{MRT} denotes the accessibility of the MRT at time t, P_t^{MRT} represents the population served by the MRT and feeder buses, and Pop_t refers to the total population. Additionally, some linear addible parameters are simulated in the form of cognitive maps. For example, the service population of the MRT comprises the population served by the MRT and feeder buses, and the served population should be related to the length of the MRT and feeder bus routes. However, it is difficult to obtain the exact relationships between the length of operating routes and the served population. The method of regression is used here and is shown in Equation (4).

$$P_t^{MRT} = \beta_t^{f-bus} L_t^{f-bus} + \beta_t^{MRT} L_t^{MRT} \tag{4}$$

$$\beta_t^{MRT} = 15 - 2 \times \ln \frac{L_t^{MRT}}{30} \tag{5}$$

where L_t^{f-bus} and L_t^{MRT} imply the operation length of feeder bus routes and the MRT lines at time t, respectively, and β_t^{f-bus} and β_t^{MRT} represent the influence intension of the lengths of feeder bus routes and the MRT lines on the population served by feeder buses and the MRT, respectively. In Taipei, the regression coefficient β_t^{MRT}, revealed in Equation (5), differs from a constant in past research of cognitive maps. All the estimated coefficients are statistically significant ($p < 0.05$), and R^2 of Equation (5) reaches 0.92.

$$trip_t^{MRT} = f_{af}^{MRT} f_{ac}^{MRT} f_{ab}^{MRT} f_{cr}^{MRT} trip_{t-1}^{MRT} \tag{6}$$

Besides, the sensitivity model is applied to formulate interactions acting as the adjustment coefficient. For example, Figure 3 shows that the MRT trips are impacted by MRT accessibility, affordability, crowdedness, and ease of use and are presented as Equation (6). The parameter $trip_t^{MRT}$ denotes the MRT trips at time t, and

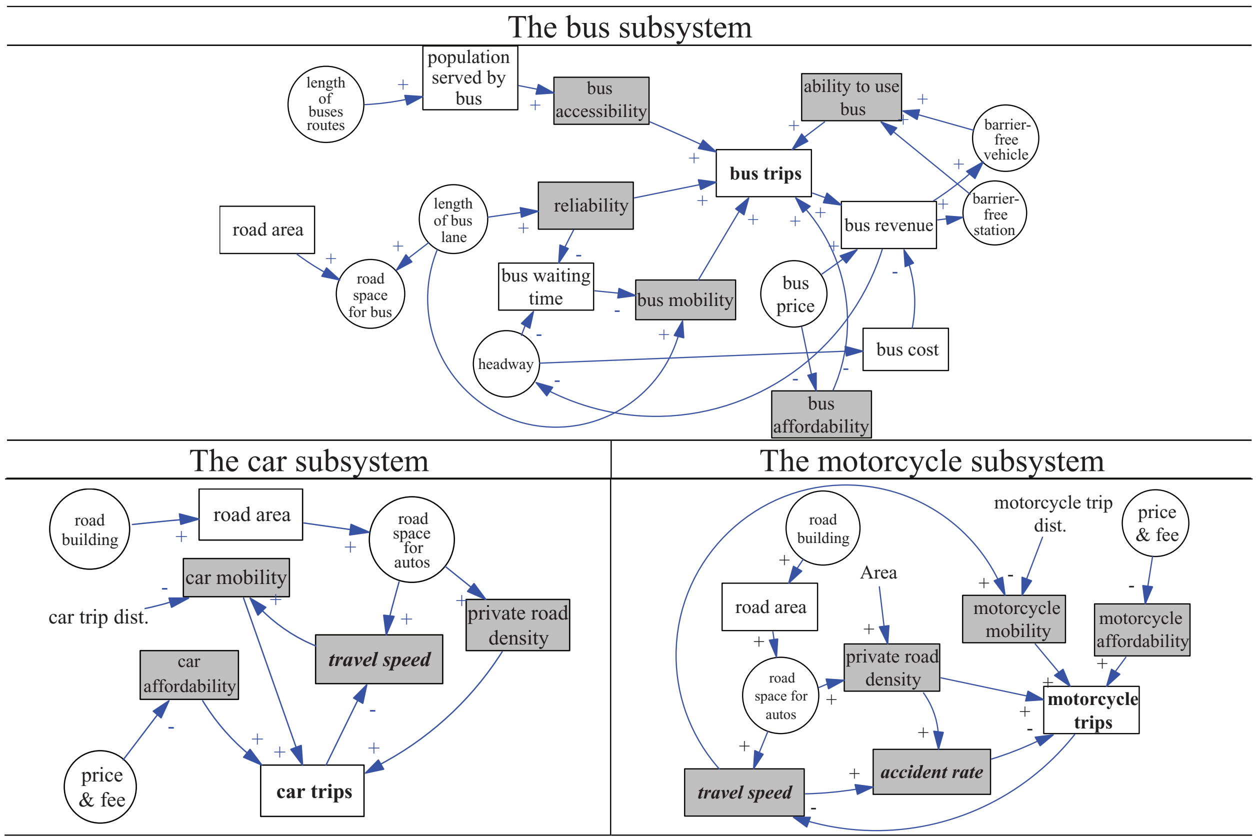

Fig. 4. Feedback structures in subsystems. →: a causal relationship, with + (−) signs indicating a positive (negative) effect; ▭: variables reflecting stakeholder needs; ○: policy variables.

f_{af}^{MRT}, f_{ac}^{MRT}, f_{ab}^{MRT}, and f_{cr}^{MRT} indicate the adjustment factors between the MRT trips and MRT affordability, accessibility, ease of use, and crowdedness, respectively. The functions of these adjustment relationships are defined such that the horizontal axis is the status value of the influencing variable and the vertical axis is the percent change of the affected variable. Figure 5 illustrates the effect of MRT affordability, defined as the ratio of monthly spending on MRT travel to disposable income on MRT trips. When the value of MRT affordability is below 0.1, the MRT trips increase by approximately 3%. The value of the MRT trips diminishes exponentially when MRT affordability exceeds 0.1. If the value of MRT affordability is greater than 0.4, over 95% of MRT trips transfer to other modes.

5 APPLICATION AND RESULTS

The validation of the proposed model is tested via boundary adequacy tests. Many methods of system assessment are used in the model formulation such as structure diagrams, inspection of model equations, and expert opinions. All structures are first verified by scholars and professionals experienced in urban transportation planning. The structure of the model is thus able to illustrate the real urban transportation system well. Besides, the constructed model has two features that

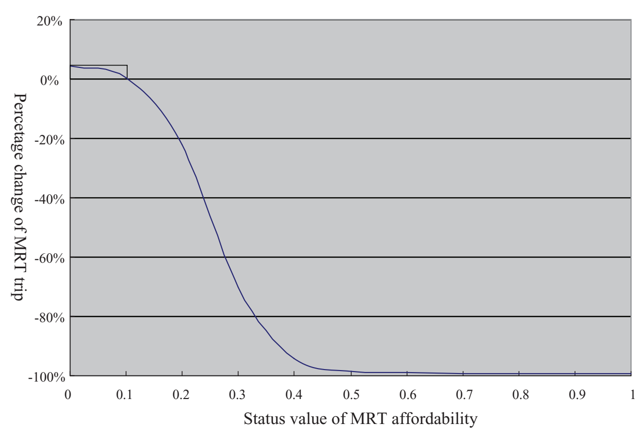

Fig. 5. Function of interaction between MRT affordability and MRT trips.

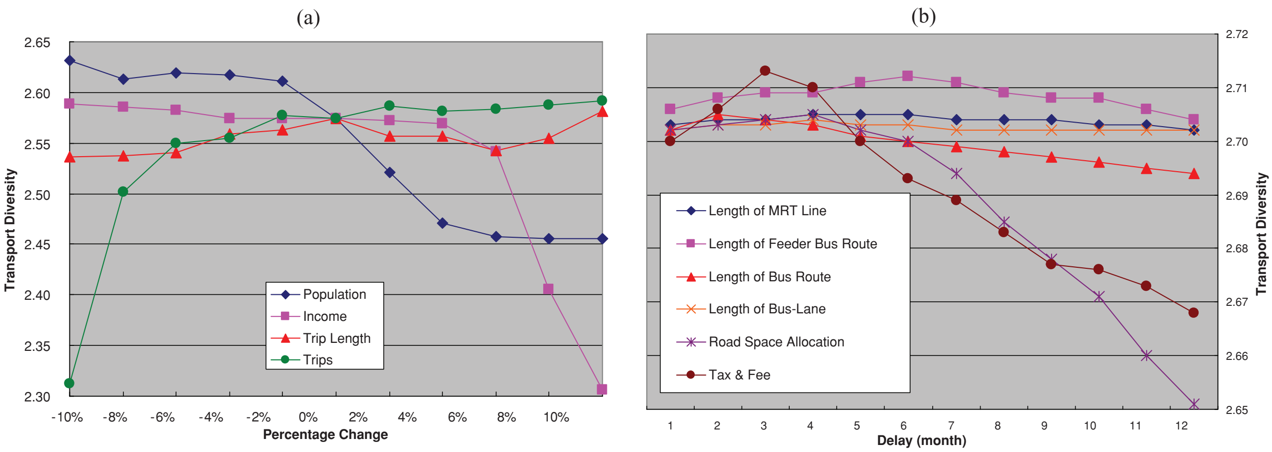

Fig. 6. Sensitivity analyses of socioeconomic factors and policy implementation delay.

significantly impact resource allocation policies: (1) sensitivities of external factors, such as population, income, etc., and (2) policy delay size and uncertainty. Transport diversity under different conditions is explored to understand the influence of uncertainty on policy effectiveness. Scenarios that might impact system behavior and the efficiency of policies are undertaken in this analysis. Different amounts of uncertainty about the impact of policy implementation delays on system behavior are also modeled to reflect levels of managerial implication.

To investigate external conditions involving different levels of socioeconomic factors from the present situation, system behaviors are simulated, with the change percentage ranging from −10% to 10%. Figure 6a shows the result of a sensitivity analysis of external factors. The variations in transport diversity vary from 2% (average length of trips) to 11% (income and amount of trips per month). Diversity is slightly inversely proportional to total population, while all parameters are fixed except the changes of served population because consideration of more stakeholders implies the need to satisfy more diverse needs and thus brings lower diversity. Notably, travel behavior varies with increasing disposable income, suggesting that the increased disposable income can enhance the affordability of private modes and then increase the emission, energy consumption, and accident rate and lower the diversity. In comparison, the reduction of disposable income does not transfer trips from private modes to public transit. Moreover, decision makers cannot control delays in implementation of policies of resource allocation that impact the system behaviors. The delays in effects of the strategies experienced for policy implementation in Taipei from 1 to 12 months are simulated to discuss the impact of delay durations on system behavior. The effects of delay size and adopted policy on transport diversity are illustrated in Figure 6b. The relationship between the delay sizes and the diversity is consistently concave, suggesting that improving resource allocation policies by adjusting the delays does not simply involve reducing delay sizes. However, reductions in diversity vary slightly from 0% to 1.8%. Impacts of delays in strategy implementation on system behavior are insignificant and thus delay sizes might not be an important feature of resource allocation effectiveness. Consequently, the model is a robust replication of resource allocation policies for transportation systems.

To obtain a baseline, a 5-year simulation without policy intervention is conducted for the Taipei metropolitan transportation system. The results of the baseline simulation are shown in Figure 7. Figure 7a is the simulation of transport diversity and summation of the normalized gaps. It shows that transport diversity is approximately negatively related with the gaps between stakeholder needs. The baseline result of the modal trips is illustrated in Figure 7b. This figure shows that car trips rise smoothly after the 16th month, most of which are transferred from motorcycle and bus trips. Besides, the gaps in Figure 7a are closely related to car trips in Figure 7b, providing evidence that controlling car trip growth significantly impacts the reduction in gaps of stakeholder needs. These baseline simulations demonstrate possible problems for Taipei if there is no effective policy to implement. Moreover, decision makers are supported via the baseline simulation in deciding when and how to adopt strategies.

To improve the performances shown in the baseline simulation above, some feasible policies subject to the budget are proposed by gathering information from the previous discussions. Figure 8 shows the results of simulation of policies invention. To curb the excessive

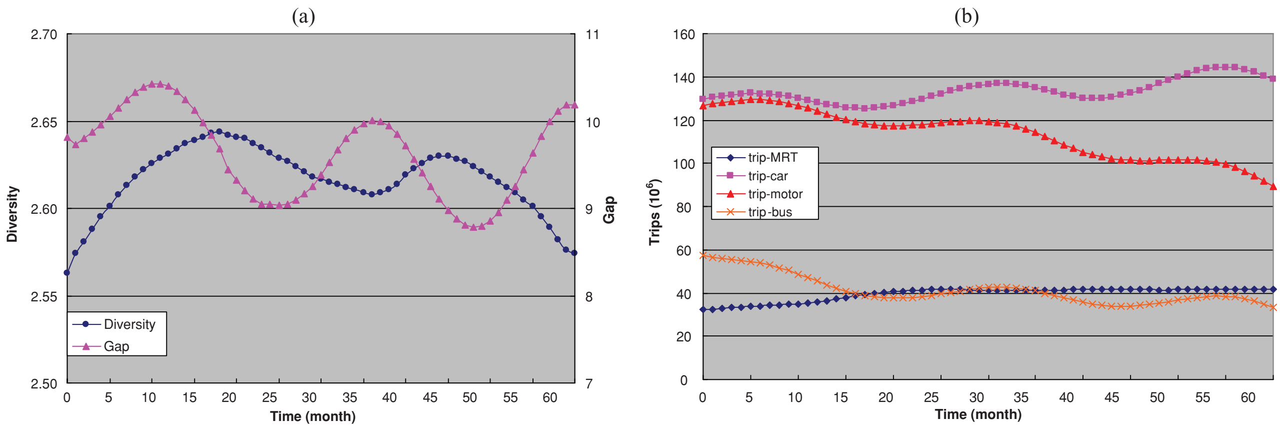

Fig. 7. Baseline simulation.

growth of car trips, strategies including levying taxes, restricting car entry, and gradually reallocating road space were introduced in periods 5, 21, and 23, and Figure 8b shows a lower average number of car trips than Figure 7b. The new MRT infrastructure operates at period 30, in which transport diversity increases sharply and the gap is bridged (Figure 8a). However, the MRT trips do not go up with a leap because MRT accessibility remains low and MRT capacity does not increase significantly. Travel speed (Figure 8d) causes the previous trend to move upward and the average accident rate to decline by more than 25% (Figure 8c) as a result of the

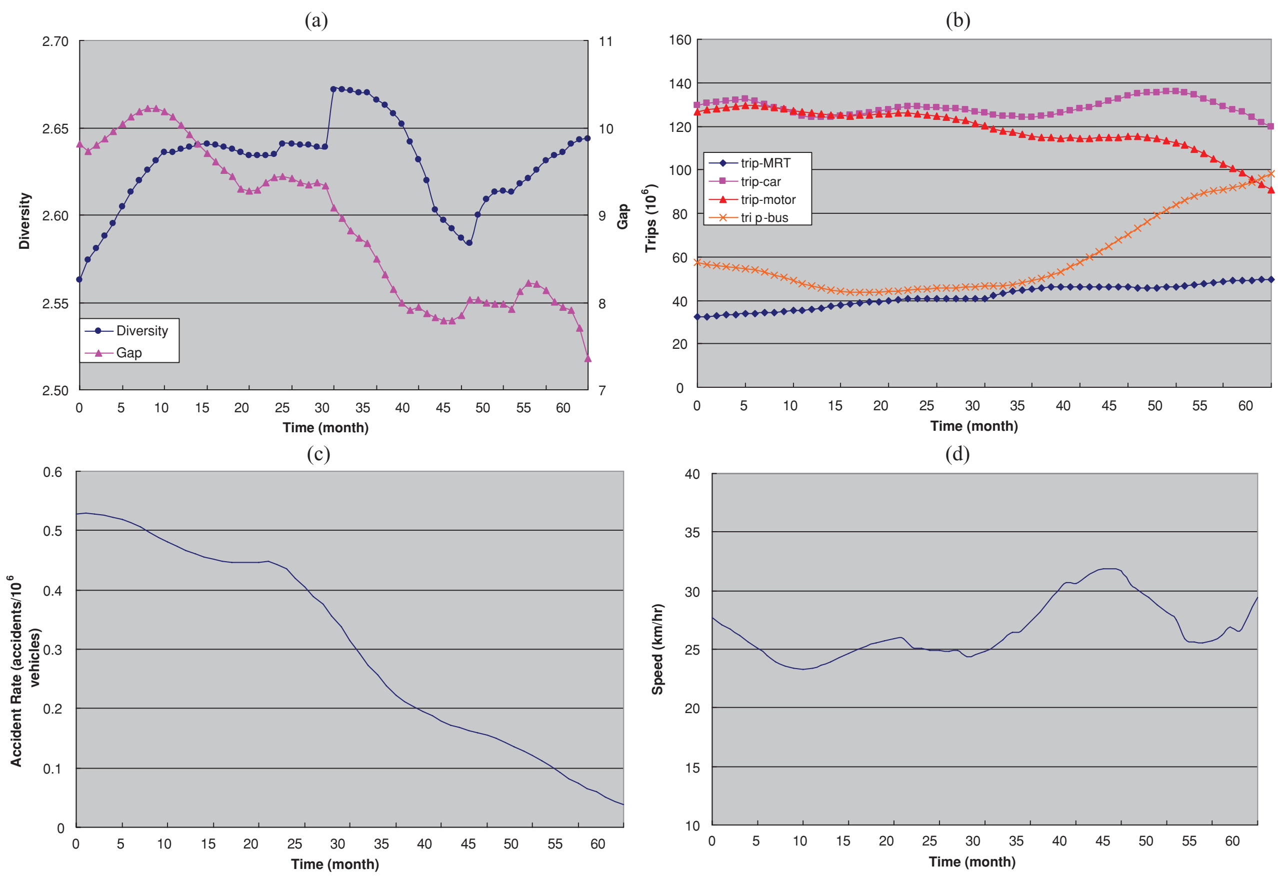

Fig. 8. Simulation of policies invention.

decreasing number of motorcycle trips because of the policies.

6 CONCLUSIONS

Traditionally, there has been little discussion of transportation system behavior, and decision makers lack specific and operational methods for clearly representing "what-if" scenarios in urban transportation system behavior. A hybrid model is introduced to help decision makers obtain a comprehensive understanding of transportation system behavior and to investigate the influence of resource allocation policies on transport diversity, representing the degree to which different stakeholder needs are satisfied. A hybrid model integrating system dynamics, a quantitative method, cognitive maps, a qualitative approach, and a sensitivity model, a semiquantitative tool, provides a practical solution for dealing with the complex relations among variables. The results of the sensitivity analysis reveal that the increase in private vehicle trips reduces transport diversity because of the increased energy consumption, emissions, and accident rate. However, tuning policy implementation delays does not significantly impact system performance through managerial choices of resource allocation in Taipei.

This study contributes to systems research on transportation by establishing a practical model for formulating and evaluating policies designed to improve system performance. The model presented in this article has application in and can be integrated in an advanced traveler information system to be used in intelligent transportation systems (Samant and Adeli, 2000; Karim and Adeli, 2002b, 2003a, 2003b; Jiang and Adeli, 2003, 2005; Ghosh-Dastidar and Adeli, 2003, 2006; Dharia and Adeli, 2003).

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