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以運輸多樣性觀點建立都市永續運輸評估與資源分派模式

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中　華　民　國　98　年　5　月　31　日

一、中英文摘要

（一）中文摘要

要公平地滿足各不同運輸權益關係人之需求，如何極大化運輸多樣性成為關鍵之因素，正確的支援模式可協助規劃者了解系統行為，並據以決策何時及如何進行有限資源之配置。然而，由於系統中各項元素的關係存在許多不確定性、回饋機制與複雜性，要建立、執行及量化用以改善運輸多樣性之策略實為相當困難，為了克服上述課題，本研究提出一個複合模式整合了量化的系統動態模型、質化的認知圖法、及半量化的感受性模型，並利用台北都會區為案例分析，探討所建構模式的應用性及其管理意涵。

關鍵詞：運輸多樣性、系統行為、系統模擬

（二）英文摘要

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 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.

Keywords: transport diversity, system behavior, system simulation

二、報告內容

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 trade-off between differences in the supply of transport infrastructure or modes, as well as 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. Two approaches to improving 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 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 that reduces equity and wastes resources which 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 literatures proposed optimization models to allocate the asset of the magnitude and scheduling of maintenance, 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 due to the difficulty of designing, implementing, and quantifying system relationships owing to associated uncertainty, feedback interaction, and complexity (Kang and Jae, 2005). The policies of resource allocation is complicated by iteration and delays in implementing allocation decisions (Udwadia et al., 2003). Iteration creates closed work flow in which interactive or interdependent relationships between parameters can be traced and checked for 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.

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 how to equitably satisfy diverse stakeholder needs. When the stakeholders and whose needs are determined, minimizing the need gaps, the remainder of the needs achievement, between the expected goals and present values (as shown in Eqn. 1) is a key objective.

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

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

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 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 Entropy presented in Eqn. 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.

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 rationality in system management (Lane, 2000). Quantitative methods are adopted in system dynamics; for example, the travel speed shown in Fig. 1-A is calculated precisely as trip distance divided by travel time.

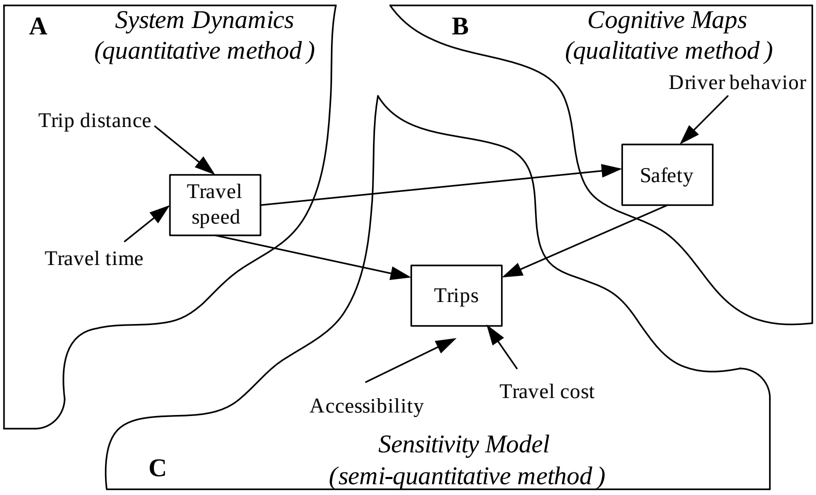


Fig. 1 Torn system approaches

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 Fig. 1-B, 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 which cannot be directly measured. Some researchers indicated relationships using weighted connections, i.e. 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 semi-quantitative data. The sensitivity model focuses on pattern recognition and feedback mechanism rather than 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, variation in trip patterns over time (Fig. 1-C) is influenced by the levels of cost, accessibility, safety and speed via a semi-quantitative connection. Consequently, to obtain different kinds of relationships that fit real world situation, a hybrid model integrating system dynamics, cognitive maps, and sensitivity model is described in the next section.

Decision Support Model

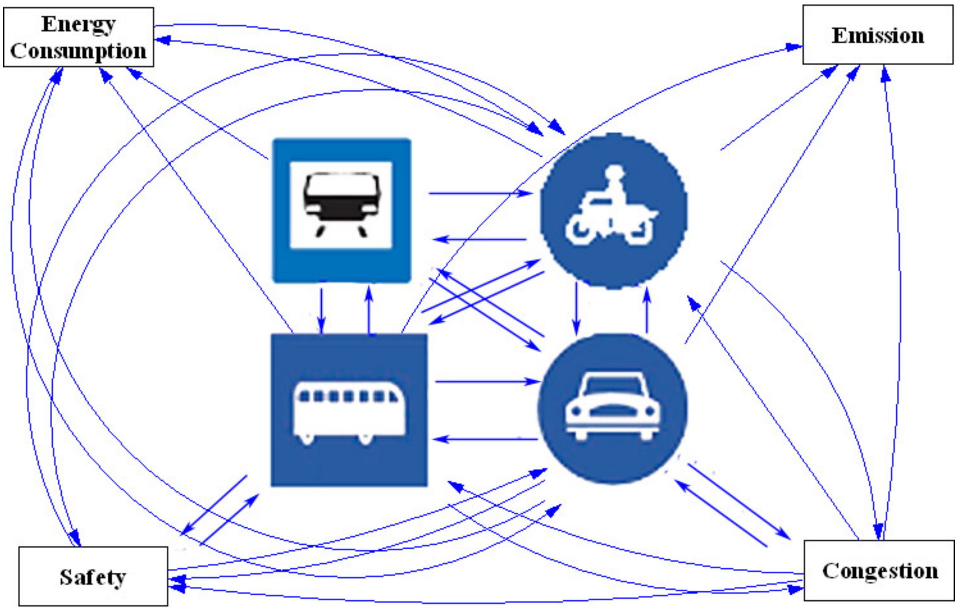
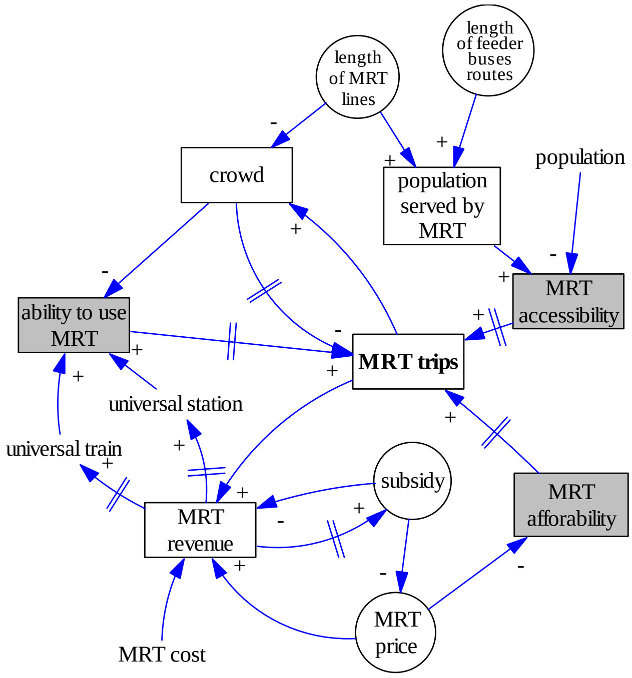


Fig. 2 Simplified interaction in the urban transportation system

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 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 inter-relationships. Therefore, the simplified interactions in the urban transportation system are represented in Fig. 2.



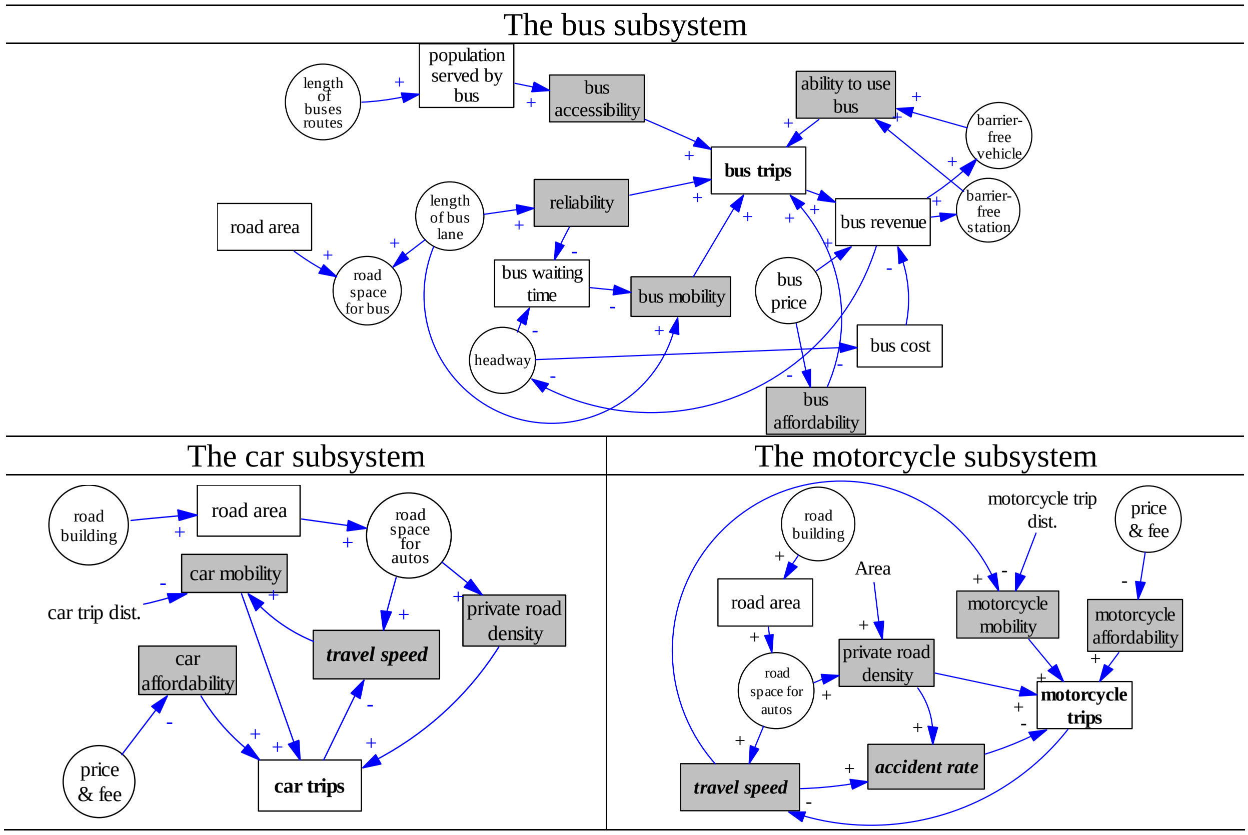
Legend:
⟶: a causal relationship with + (-) signs indicating a positive (negative) effect
// signs on the arrows represent the delay effect
▭: variables reflecting stakeholder needs; ◯: policy variables

Fig. 3 Feedback structures in MRT subsystems

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 (Fig. 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 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 Fig. 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.



Legend:
: a causal relationship with + (-) signs indicating a positive (negative) effect
: variables reflecting stakeholder needs; : policy variables

Fig. 4 Feedback structures in subsystems

This study utilizes experimental approaches to examining 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 to system behavior. The experts fully understanding the information of transportation in Taipei, including the 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 sensitivity model. Different equation types are applied to distinct interactions according to the various attribute linking different elements. For example, the MRT accessibility in Fig. 3 is defined as the ratio of the population served by MRT and feeder buses to the total population. This is a precise quantitative relationship and represented by Eqn. 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 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 served population. The method of regression is used here and is shown in Eqn. 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 MRT lines at time *t*, respectively, and β_t^{f-bus} and β_t^{MRT} represent the influence intension of the lengths of feeder buses routes and MRT lines on the population served by feeder buses and the MRT, respectively. In Taipei, the regression coefficient β_t^{MRT}, revealed in Eqn. 5, differ from a constant in past research of cognitive maps. All the estimated coefficients are statistically significant ($p<.05$) and the R^2 of Eqn. 5 reaches *.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, Fig. 3 shows that MRT trips are impacted by MRT accessibility, affordability, crowdedness, and ease of use, and presented as Eqn. 6. $trip_t^{MRT}$ denotes the MRT trips at time t, and f_{af}^{MRT}, f_{ac}^{MRT}, f_{ab}^{MRT} and f_{cr}^{MRT} indicate the adjustment factors between 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 percentage change of the affected variable. Fig. 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 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.

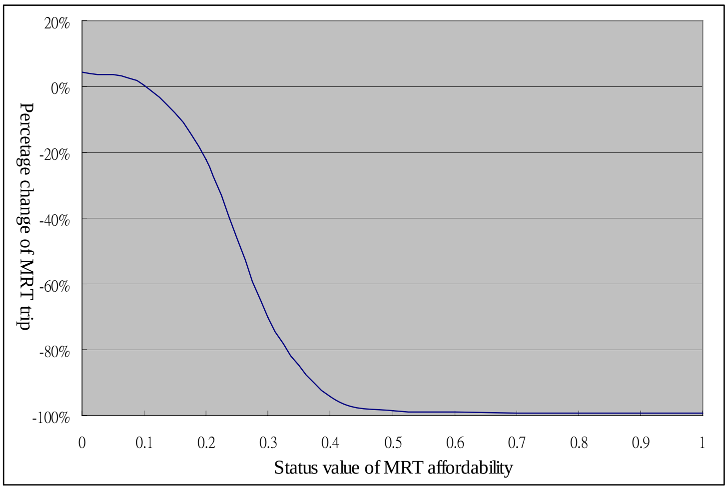


Fig. 5 Function of interaction between MRT affordability and MRT trips

Application and Results

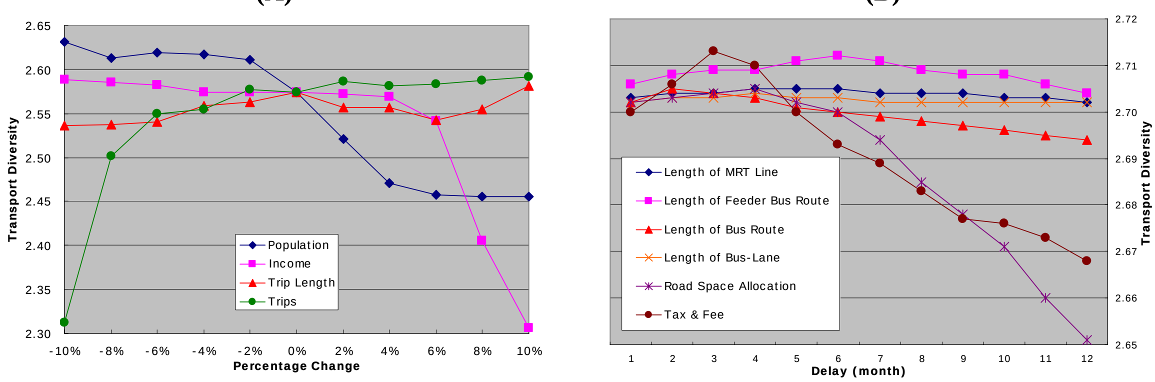


Fig. 6 Analyses of sensitivity and policy delay

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 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 which might impact system behavior and the efficiency of policies are undertaken in this analysis. Different amounts of uncertainty about the impact of policy delays on system behavior are also modeled to reflect levels of managerial implication.

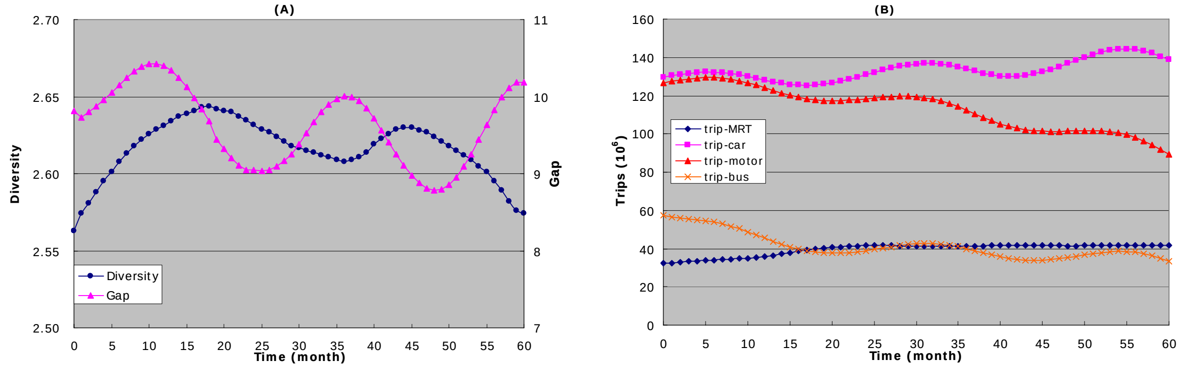


Fig. 7 Baseline simulation

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 Fig. 7. Fig. 7-A is the simulation of transport diversity and the 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 Fig. 7-B. 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 Fig. 7-A are closely related to car trips in Fig. 7-B providing evidence that controlling car trip growth significantly impact 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.

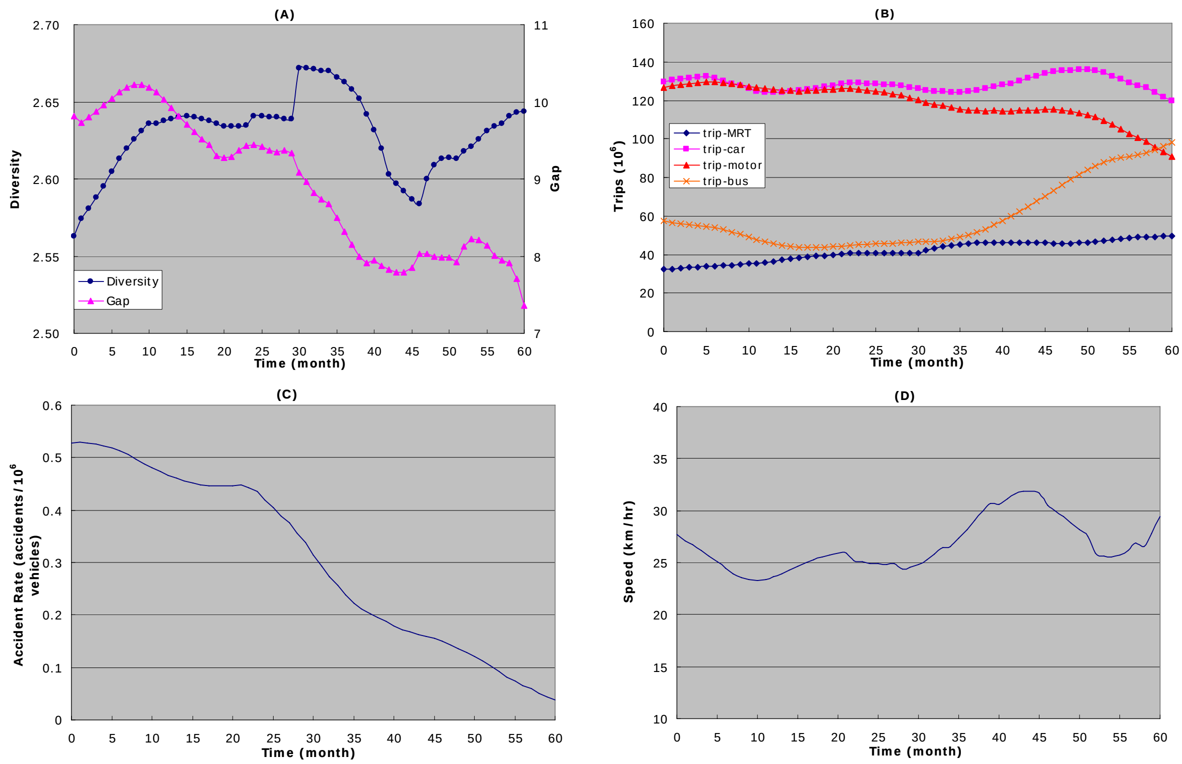


Fig. 8 Simulation of policies invention

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. Fig. 8 shows the results of simulation of policies invention. To curb excessive growth of car trips, strategies including levying taxes, restricting car entry, and gradually reallocating road space were introduced in, and Fig. 8-B shows a lower average number of car trips than Fig. 7-B. The new MRT infrastructure operates at period 30, in which transport diversity increases sharply and the gap is bridged (Fig. 8-A). 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 (Fig. 8-D) causes the previous trend to move upwards and the average accident rate to decline more than 25% (Fig. 8-C) as a result of decreasing number of motorcycle trips because of the policies.

Conclusion

Traditionally, there have been little discussion of transportation system behavior and decision-makers lack specific and operational methods for clearly representing of 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 for investigating 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 sensitivity model, a semi-quantitative tool, provides a practical solution for dealing with the complex relations among variables. The results of sensitivity analysis reveal that the increase in private vehicle trips reduces transport diversity due to the increased energy consumption, emissions and accident rate. However, tuning policy 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 paper 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&b; Jiang and Adeli, 2003, 2005; Ghosh-Dastidar and Adeli, 2003, 2006; Dharia and Adeli, 2003).

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三、計畫成果自評

本研究內容與原計畫相符，主要係根據第一年所建立之運輸多樣性概念，建立都市運系統中各項因果關係與回饋，內容元素包括權益關係人需求、運輸系統行為與運輸政策等，並據以建立整合系統動態模型、認知圖法與感受性模型演算方式之決策支援模式，用以評估各項策略對於同時考量多元與公平之運輸多樣性指標的影響及該決策支援系統所提供之資訊，並根據前述重要結論，分析系統模擬方法應用之限制及運輸多樣性評估之要件。至民國 98 年五月底前已達成預期之目標，完成第二年之工作項目。研究成果部份已投稿至 Computer-Aided Civil and Infrastructure Engineering 並獲接受刊登。

此外，依照第三年之工作預定進度表，由民國 98 年 8 月 1 日起，本研究將基於前二年度所建構之運輸多樣性架構及都會區運輸系統之因果關係，利用數學規劃方式建立都市大眾運輸之資源配置多目標最佳化模式，期以進一步驗證運輸多樣性於都會區大眾運輸系統之穩健性與可操作性外，並將藉由模糊規劃求解多目標問題，評估運輸資源配置對於系統運輸多樣性之影響。