Determination of a Desirable Time Step for QuasiDynamic Urban Model on Sapporo Test Bed

Chapter 5

Determination of a Desirable Time Step for Quasi-Dynamic Urban Model on Sapporo Test Bed

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Abstract: This paper presents an application of the Sapporo GIS based Test Bed, which has been built to support urban model testing and development. It briefly describes TRANUS Sapporo model, which has been calibrated both at one time point and for a time interval. The model is quasi-dynamic, which runs its land-use and transportation submodels sequentially with time lag. In this study, Sapporo Test Bed was an efficient tool to identify the inputs and parameters that are the main cause of uncertainty of the model results. The uncertainty is accumulated by the quasi-dynamic structure, which is a usual structure of the most existing urban models. Moreover, this paper has proposed a heuristic approach to determine a desirable time step for quasi-dynamic urban model. This is achieved by a simplified Monte Carlo simulation technique. Uncertainty in the model output is evaluated from various statistical indexes. It is found that a time step of 3.3 years is most desirable by trading off between uncertainty and accuracy. However, a 3.3-year time step may not be desirable from a practical viewpoint, we evaluated that a time step of 5 years is also acceptable compared with 3.3 years based on our simulation results.

1. INTRODUCTION

In the past few years, research interests are recently given to consider uncertainty in urban modeling even though most of them have falled in the transportation modeling only (Pradhan and Kockelman, 2002; Rodier and Johnston, 2001; Zhao and Kockelman, 2001). Although extensive consideration of uncertainty in the modeling is not recent for the professional practice, very few realizations in the practical modeling could be found. Mehndiratta et al. (2000) concluded that, while most Metropolitan Planning Organizations (MPOs) believe uncertainty to be pervasive in their transportation planning activities, the vast majority do not try to quantify it. Two reasons for this are addressed. Firstly, because their model is complicated enough, MPO desire not to deal with more complication. Secondly, there is no legislative mandate to force them to evaluate uncertainty in the results. Likewise, Rodier and Johnston (2001) recently emphasized the importance of acknowledging major areas of uncertainty in travel demand analysis, and they suggested such acknowledgement is necessary in order to maintain the credibility of transportation modeling. Moreover, Pradhan and Kockelman (2002) argued that since many MPO are now moving towards integrated land use-transportation models (largely in response to federal legislation), it is important to understand the uncertainty propagation in these very complex models. These are the existing researches about uncertainty in land-use/transportation modeling, which are very few indeed. Nevertheless, they primarily have objectives to investigate the model behavior rather than to find the implication of the analysis results. Therefore, the present study has goal to present an implication of uncertainty analysis of operational urban model. The discussion in this paper is based on the empirical results of the TRANUS model application to Sapporo Metropolitan of Japan. Simulation for the uncertainty analysis has been conducted on the Sapporo Test

Bed.

The remainder of this paper is structured as follows. Section 2 briefly describes Sapporo Test Bed as well as TRANUS Sapporo model. Section 3 presents uncertainty analysis of TRANUS Sapporo model in which the sensitivity analysis approach is employed. Section 4 presents an implication of the uncertainty analysis to determine a desirable time step for the quasi-dynamic urban model. Finally, Section 5 concludes the paper.

2. SAPPORO TEST BED FOR URBAN MODELS

Conceptually, Sapporo Test Bed has goals to be a test machine' in the field of urban modeling with the following specific objectives. The system is designed to be easily implemented for different study area by only replacing the associated database. The database is maintained to be main data resource for developing urban model because comprehensive database is not always available for real modeling practice. The test bed is to provide an efficient technique to prepare data. The method is theoretically sound and at the same time operationally feasible. It provides GIS environment to aid visualization of the operations. It is also designed to be flexible enough for a wide range of applications as well as various user groups. This is achieved by specifying a connectivity standard that is applicable to common computer programs, which include the database and GIS packages. It is also to provide an interface module to connect with external programs and urban model as well as to allow possibility for further development, which can be done without changing the original code of the system. Moreover, the test bed is to bridge the gap between urban model, which are usually complicated and the model user who have less theoretical specialization. This is accomplished by user-friendly environment with Graphical User Interface so that users can prepare their necessary data in a way that is theoretically sound, and also users can test the model with less complication of the operation.

Overview of the test bed system is shown in Figure 12.

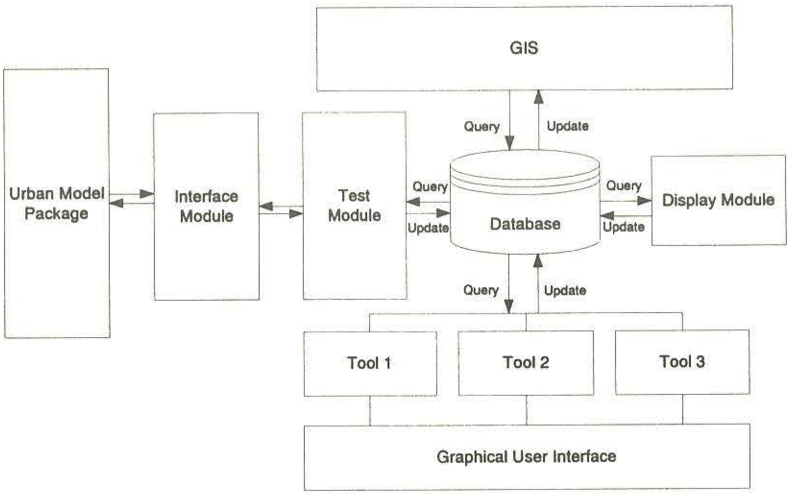

Figure 12 Overview of Test Bed

There are three main parts: the urban model to be tested, the interface module model, and the test machine. Firstly, the urban model, which is client of the system. It is the existing operational urban models (Wegener 1994, 1999; US EPA 2000; TMIP 1998), which are being used in the real application around the world. Each of these models include different component of the urban system. Usually they model land-use, transportation, and the environment. Secondly, the interface module. It links the urban model, which is to be tested to the main system. The module operates the transfer of data between the two components in a systematic way. Thirdly, the inter-connected program modules.

These are comprised of various components such as the GIS-based database, graphical user interface, analysis tools, and test modules, etc. The test module currently available is the uncertainty analysis module that is presented in this paper. The system has become a tool to test the existing urban model by means of various analysis approaches. Presently, a prototype system has been built for Sapporo Metropolitan area of Japan where various kinds of data are available (Hokkaido Development Bureau, 1985, 1991, 1995). The present paper presents a test of TRANUS Sapporo model by utilizing various functions of Sapporo test bed.

2.1 TRANUS Model of Sapporo

Developed by De la Barra (1989), TRANUS is one of the existing operational models that have been and being used in real applications (see, for example, US EPA, 2000; Wegener, 1994, etc). TRANUS is similar to MEPLAN (ME&P, 1995) in the way to represent the spatial interaction among urban activities by using input-output model framework. The main feature that distinguishes TRANUS from MEPLAN is the concept of 'scaled utilities' in TRANUS's logit model to allocate activities to different zones. Since TRANUS is a general model framework, a certain design must be specified for each application of the model for a study area. In the present study, we applied TRANUS to Sapporo Metropolitan area of Japan, which is located in its northern main island. It is markedly monocentric with about two millions population. Public transportations are well provided with several commuter railway lines (JR lines) and three subway lines. Zoning system in TRANUS Sapporo is the one used in the real transportation planning of Sapporo, which is consisted of 73 zones. Although the following paragraph briefly describes TRANUS Sapporo, interested readers are recommended to consult De la Barra (1989) for specific detail of TRANUS.

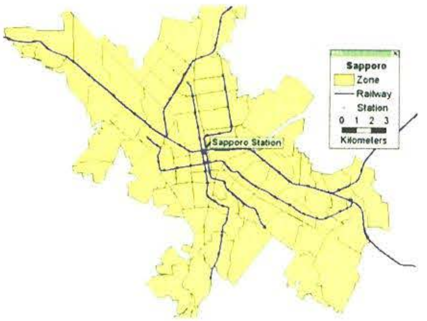

Figure 13 Study Area of TRANUS Sapporo

In one time period, there are three modules to model land-use and transportation interaction, i.e., activity (land-use) model, interface model, and transportation model. Firstly, the activity model (or so-called land-use model) operates with three groups of sectors namely resident, business (employment), and land sectors. In TRANUS Sapporo, residents are represented in terms of household. We have only one sector of household in our model due to the fact that social segregation is not evident in the Japanese society nowadays. It is, however, worth noting that most of the applications of TRANUS or MEPLAN models have several classes of household classified by income. Business is represented by three groups of worker namely primary, secondary, and tertiary employment sectors. This categorization was also used in the real analysis in Sapporo transportation planning. The primary and secondary employment sectors are exogenous (or given) while the tertiary sector is endogenous (or to be determined by the model). Land sector is represented by two types of land namely residential (Res land) and commercial land (Com Land). The growth of land development is constrained by total developable land (Dev Land). Relationship among these economic sectors are represented by 'Social Accounting Matrix' as shown in Table 1.

Table 1 Social Accounting Matrix of TRANUS Sapporo

	Producing						
Consuming	Primary	Secondary	Tertiary	Household	Res Land	Com Land	Dev Land
Primary				f 1			
Secondary				f 1			
Tertiary				f 1		e1	
Household			f 2		e2		
Res Land							1
Com Land							1
Work				c1			
Private			c2				

The relationships among sectors are either fixed or elastic. The fixed relationship is represented by the fixed coefficient (f), which is the fixed consumption of producing sectors by consuming sectors. This is similar to technical coefficient in input-output model. Specifically, workers (of all three employment sectors) consumption of household is represented by the average number of worker per one household (f1). Similarly, household consumption of service of tertiary sector is represented by ratio of the number of tertiary sector by the number of household (f2). The elastic relationship is represented by the elastic coefficient, which is price-elastic (e). That is, e1 and e2 represent the price-elastic consumption of land by household and tertiary sectors.

Secondly, the interface model makes linkage between the land-use (activity) model and the transportation model. In the SAM, the interface module is shown by the small matrix below the large matrix in Table 1. That is, c1 and c2 represent conversion of interzonal/sectoral flow from the activity model (in household or worker units) into travel flow for the transportation model, by trip categories: work and private trips. The work trip is derived by workers in the household going to work while the private trip is derived by tertiary workers providing service to residents (or household).

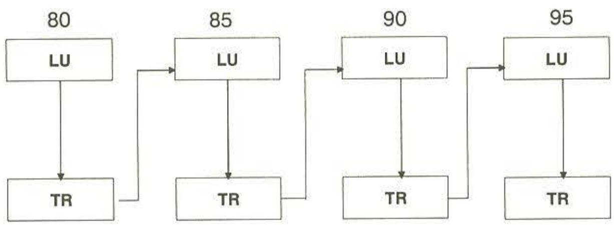

Figure 14 Quasi-Dynamic Structure

Thirdly, the transportation module determines the last two part of typical four-step transport model, i.e., mode split and assignment. Changes in transportation during 1980 to 1995 modeled in TRANUS Sapporo are the major projects such as new subway, highway, railway stations, etc. These three modules determine equilibrium in the land and transportation markets by repeating the model runs until convergence. Next, the model moves forward to the next time period by the incremental model, which specifies the growth of economic sectors.

The growth is modeled by a fixed rate of growth in the exogenous sectors. The model base year is 1980 and run with five-year step to 1995, shown in Figure 3.

The model has been calibrated at the base year and the residual has been compensated. Figure 4 illustrates that, after residual compensation, the base year forecast of household in 1980 is exactly equal to the real value. However, only base year calibration is not enough to model the change of the urban system in a quasi-dynamic model. Therefore, a so-called interval calibration has been conducted for the period 1980 to 1985. Result of the interval calibration is shown in Figure 5. The result is satisfactory with R^2 (coefficient of determination) of 0.6161. Moreover, in order to evaluate the calibrated model, it is used to forecast the household distribution in 1995.

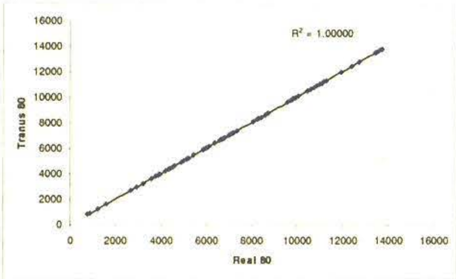

Figure 15 Base Year Calibration Result

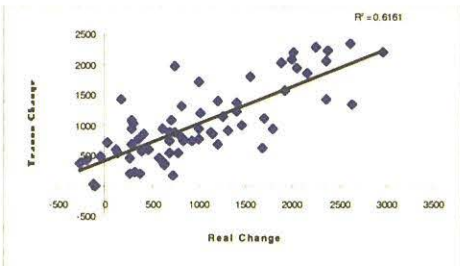

Figure 16 Interval Calibration Result

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Figure 17 Validation Forecast

Comparison of the real change of household from 1985 to 1995 and the change forecasted by the model is shown in Figure 6. It can be evaluated that the model can represent the change satisfactorily with R^2 value of 0.6116. Therefore, the satisfactorily calibrated and validated model is used for the further analysis presented in the subsequent sections.

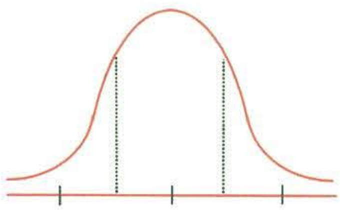
3. UNCERTAINTY IN QUASI-DYNAMIC MODEL

In science, the word error does not carry the usual connotations of the terms mistake or blunder (Talylor, 1997). Error in a scientific measurement means the inevitable uncertainty that attends all measurements. Error is inherent in all models since they are abstractions of real world behavior;

simplifications of reality are unavoidable in order to make the models usable and practical. Of many possible sources of error in travel and emission models, the most important ones are thought to be natural uncertainty, uncertainty in model design and structure, data uncertainty and calibration errors, and uncertainty in socioeconomic projections and other model inputs. Pradhan *et.al.* (2002), natural uncertainty includes the uncertainty due to quantities that are random even in principle and quantities that are random because of the effort and cost involved in precise measurement. The structure of the mathematical model used to represent urban behavior is also a key source of uncertainty, because models are necessarily simplified representations of the phenomena being studied. In addition, models valid in one portion of the input space may be completely inappropriate for making predictions in other regions of the input space, or in the same portion at a different point in time. Data uncertainty and calibration errors include measurement errors due to imprecision, systematic biases, estimation of parameters using small samples, and estimation of parameters using non-representative samples. Uncertainty in socioeconomic projections and other inputs are possibly the greatest source of uncertainty in any model. They are especially significant since modelers can do very little to reduce the errors due to these sources (Barton-Aschman, 1997). The relative importance of error sources can be judged based on the sensitivity of forecasts to input errors and the magnitude of forecast errors. These relationships are measured by input variation elasticity and coefficients of variation respectively. Since the quasi-dynamic framework involves running model sequentially, the uncertainty will accumulate larger and larger over time. This makes the final result less reliable. Among many sources of uncertainty that arise in the model, this study is focused on the uncertainty in model input and parameters, which are the sources that is quantifiable easily. The ways to represent these uncertainties are discussed as follows.

3.1 Uncertainty of TRANUS Sapporo

A sensitivity and uncertainty analysis is presented with a case study of TRANUS Sapporo model. It is necessary in this study to run TRANUS model in a reasonably limited number due to time and effort limitation. In similar to Pradhan *et.al.* (2002), the factorized design approach of Monte Carlo simulation is employed. The input distribution is divided into three equal-probability bins, and the mid-percentile point of each bin is chosen as the sample point, as illustrated in Figure 4. It is



considered to be an efficient way of obtaining well-distributed inputs.

Figure 4 Representative Points of Input Uncertainty

The present analysis has focused on the uncertainties that are generated by four parameters, i.e., the economic growth input and three model parameters. The economic growth input considered is the growth of the secondary employment sector for each time period, which controls the total employment (worker) in the study area. It is varied into three values: 15%, 19%, and 25%. The three model parameters are volume factor, logit parameter, and trip generation elasticity. The volume factor is used to convert the resulting trade flow from land-use model to the demand for travel used in the transport model. It is varied into three values: 1, 1.4, and 1.8. It represents the number of person trip that is derived by one unit of economic flow in the land-use model. The logit model parameter is the dispersion parameter used in the allocation of spatial activities in the land-use model. It is varied from 0.5 to 1 where the default calibrated value is 0.8. Lastly, the elasticity parameter in the trip generation model is also varied into three values of 0.5, 0.8 and 1 respectively. The parameter variation is summarized in Table 2.

Table 2 Variation in Input and Parameters

Input or Parameter	Low	Mid	High
Secondary employment control total (SndInc)	15%	19.154%	25%
Volume factor (VolFac)	1	1.4	1.8
Logit parameter of the land use model (Logit)	0.5	0.8	1
Trip generation elastic (TripElas)	0.5	0.8	1

Therefore, a total of $3 \times 3 \times 3 \times 3 = 81$ uncertainties are generated by varying these input and model parameters. These are fed to TRANUS Sapporo, so that 81 corresponding model outputs are obtained. The analysis of these simulations is presented in the next section.

3.2 Sensitivity and Uncertainty Analysis

In order to observe behavior of the model under simulated uncertainty, two kinds analysis were conducted, i.e., sensitivity analysis and uncertainty analysis. Generally, sensitivity analysis studies how the variations in the model output can be apportioned, quantitatively or qualitatively, to different sources of variation, i.e., how model behaves depends on information input, Crosetto (2001). Uncertainty analysis allows assessing the uncertainty associated with the model output as a result of propagation through the model of errors in input and uncertainty inherent in the model itself, as was discussed in the earlier sections. Firstly, sensitivity analysis is presented. Many approaches to do sensitivity analysis includes break-even analysis, regression analysis, analysis of variance, scatter plots, etc. (Frey et.al., 2002). The present study employs multivariate sensitivity analysis, which identifies the degree to which the model outputs are affected by changes in the model inputs. Different variation in the model input is generated by the simulation technique described earlier. Outputs of the land-use model that we focused are the tertiary sector employee (Worker), household (HH), residential land (Res.), commercial land (Com), and developed urban land (Urban). Results of the regression analysis indicate impact of variation in an input on each model output. The impact may be measured by two indicators: regression coefficient and p-value. However, in order to eliminate dimensions or units, a standardized coefficient is used instead of the original regression coefficient. It represents the change in the dependent variable (measured in multiples of its standard deviations) caused by a change of one standard deviation in the independent variable, see Equation (1).

$$a_x^{std} = a_x \times \frac{\sigma_x}{\sigma_y} \qquad (1)$$

where a_x^{std} is standardized regression coefficient, a_x is regression coefficient, σ_x is standard deviation of the independent variable, and σ_y is standard deviation of the dependent variable. It measures the number of standard deviations in the output one may expect from a single standard deviation's increase in input x. On the other hand, p-value indicates level of significance for a two tailed t-test of the hypothesis that the variable has no impact on the dependent variable (i.e., its regression coefficient is zero). A variable with a p-value of less than 0.05 is considered very statistically significant.

By employing a tool available in Sapporo Test Bed, the sensitivity analysis was performed for each zone individually by using the tools provided in Sapporo test bed. As an example, Figure 5 shows the result of zone 23 in year 1995.

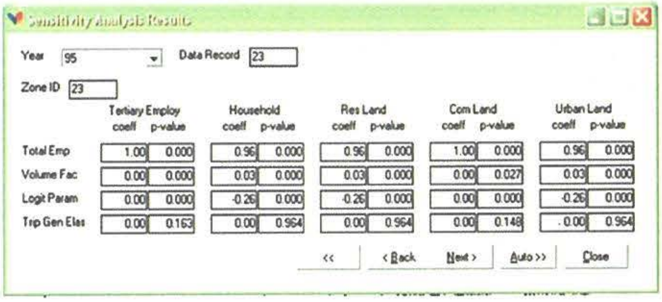


Figure 5 Tool to Observe Sensitivity by Zone by Year

However, presenting results of all zones separately are less encouraged and difficult for presentation, zone-average value of each three forecast years (1985, 1990, and 1995) are presented instead, as shown in Table 3 a) to c) respectively. Large standardized coefficients and small p-value for the secondary employment control total (SndInc) mean that uncertainty in employment control total has an impact that is both statistically and practically significant to uncertainty in the model outputs (HH, Worker, Res, Com, and Urban). Some parameters are statistically significant but, however, are not practically significant. For example, the logit model parameter is statistically significant as indicated by small p-value but is not practically significant to uncertainty in the tertiary sector worker as indicated by very small standardized coefficient. Similar interpretations follow for the other parameters as well. In conclusion, uncertainty in the employment control total is the major source of uncertainty of all of model outputs; uncertainty in logit model parameter causes uncertain household forecast and uncertain residential land use; and uncertainty in the trip generation elasticity parameter does not exhibit significant impact to all of the land-use related outputs that we observed in this analysis.

Table 3 a), b), c) Sensitivity Analysis Results

1985	SndInc		VolFac		Logit		TripElas	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Worker	1.000	0.000	0.000	0.014	0.000	0.000	0.000	0.415
HH	0.959	0.000	-0.013	0.036	-0.013	0.000	0.000	0.947
Res	0.947	0.000	0.002	0.023	-0.013	0.000	0.000	0.949
Com	1.000	0.000	0.000	0.128	0.000	0.005	0.000	0.860
Urban	0.953	0.000	0.003	0.023	-0.019	0.000	0.000	0.949

1990	SndInc		VolFac		Logit		TripElas	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Worker	1.000	0.000	0.000	0.068	0.000	0.004	0.000	0.307
HH	0.944	0.000	0.004	0.036	-0.011	0.011	0.000	0.964
Res	0.926	0.000	0.003	0.016	-0.005	0.012	0.000	0.963
Com	1.000	0.000	0.000	0.223	0.000	0.025	0.000	0.613
Urban	0.936	0.000	0.004	0.016	-0.013	0.013	0.000	0.963

1995	SndInc		VolFac		Logit		TripElas	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Worker	1.000	0.000	0.000	0.113	0.000	0.015	0.000	0.293

HH	0.946	0.000	0.005	0.015	-0.022	0.000	0.000	0.963
Res	0.904	0.000	0.002	0.014	-0.054	0.000	0.000	0.963
Com	1.000	0.000	0.000	0.254	0.000	0.036	0.000	0.517
Urban	0.926	0.000	0.003	0.014	-0.061	0.000	0.000	0.962

Next, result of the uncertainty analysis is presented. In this study, the degree of uncertainty in the model outputs is measured by the coefficient of variation (COV), which is defined as the standard deviation of a variable divided by its mean. Uncertainty propagation in the model results is shown in Figure 6.

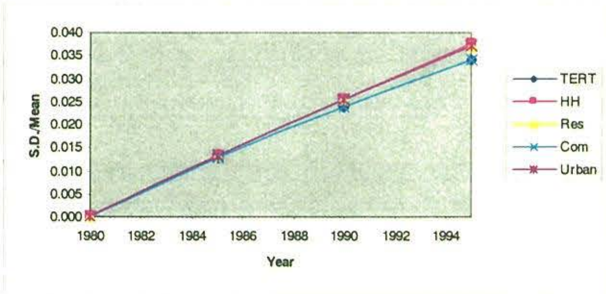


Figure 6 Uncertainty Propagation

It is obvious that the uncertainties accumulate through quasi-dynamic structure of the model; that is, larger uncertainty in the later years: from 0 in 1980 to about 0.03 in 1995. It is interesting that the graph can be seen into two groups. The ones with higher variation (or COV) are relating to residents, i.e., household and residential land. The one with lower variation are relating to employment, i.e., tertiary worker and commercial land. Higher uncertainty in household and residential land sector is caused by the external input of residential land development that is required at every model period in the incremental model.

4. TRADE-OFF BETWEEN ACCURACY AND UNCERTAINTY

We have known that many of the existing land-use/transportation models including TRANUS has quasi-dynamic structure in which land-use and transportation interacts each other by sequentially running the model with a time-lag. The quasi-dynamic structure is generally preferable than a simple projection (or sometimes called a static model) because it represents the lagged interaction. As a consequence, one of the key determinants of accuracy of the model result is time step of the model. The existing operational models usually use five-year time step. This is due to the availability of data such as census survey data, which is usually collected every five years. If we, however, remove this limitation of data availability, we may imagine increasing the model accuracy by shortening the time step, probably as small as one year. A very short time step will require larger number of model run, which in turn render the propagated uncertainty as discussed in the previous section. With this uncertainty consideration in mind, the researcher might think to minimize uncertainty by prolonging the time step, probably as long as 20 years or even ignore quasi-dynamic and use a static model instead. Unfortunately, a very coarse modeling structure will loss detail of urban structure. Therefore, it becomes a trade off between accuracy and uncertainty to select an appropriate time step for the model.

4.1 Accuracy of Static and Quasi-Dynamic Models

In this section, accuracy of static and quasi-dynamic models are evaluated with empirical results. TRANUS model, which has been calibrated for the time interval of 1980 and 1985, is used to forecast the number of household in 1995. From 1985, two configurations are built as shown in Figure 7. The first one (so-called static model) is to directly forecast the household in 1995 while the second (so-called quasi-dynamic model) takes one intermediate step in 1990 before making the 1995 forecast.

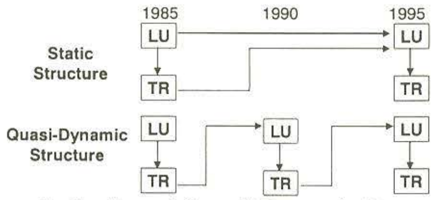


Figure 7 Static and Quasi-Dynamic Structures

Goodness of fit of the forecast made by the two model structures are shown in Figure 8 a) and b) respectively. Each figure shows the change of the number of household during 1985 and 1995. The coefficient of determination (r^2) shows that the quasi-dynamic model produces more accurate forecast than the static model.

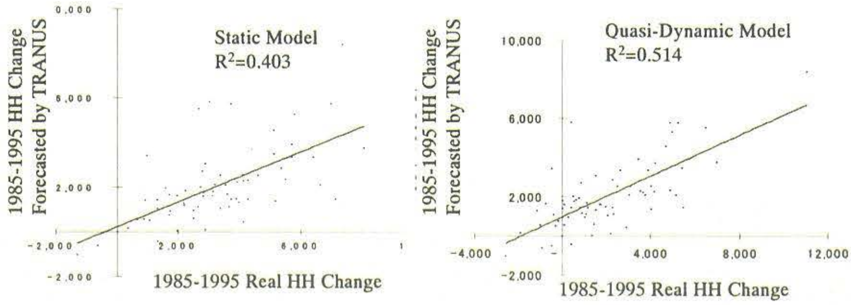


Figure 8 a), b) Precision of Static and Quasi-Dynamic Structures

Based on the result presented, we may say that quasi-dynamic model is more preferable due to the gaining accuracy. However, with presence of uncertainty, the model results are contaminated with the propagated uncertainty through the quasi-dynamic structure. The magnitude of propagation depends heavily on the number of time steps used in the modeling. Therefore, choosing an appropriate time step will be a compromised solution for uncertainty and accuracy, the next section presents a heuristic approach to determine a desirable time step under possible simulated uncertainties.

4.2 Desirable Time Step for Quasi-Dynamic Model

The simulation approach for uncertainty analysis presented in Section 3 is employed as a tool to simulate uncertainty in the following analysis. Since we have known from Section 3.2 that which model input and parameters are significant to cause uncertainty in the model output, the insignificant input is no longer considered, i.e., TripElas is discarded. To repeat again, a time step in a quasi-dynamic model is an important factor to control the creditability of the model results. An appropriate time step should not be so long that the model loss the urban structure, but at the same time should not be so short that the propagated uncertainty is beyond reliability level. This section presents a heuristic approach to determine an appropriate (or desirable) time step for a quasi-dynamic model while possible uncertainties are simulated and input to the model. Our idea is illustrated in Figure 9. It is to run the urban model several times with different time steps. At one value of time step, the model is under the simulated uncertainty in the same was as discussed in Section 3.1. Again, we evaluate the model result by using two indicators: the coefficient of variation (COV) for uncertainty and the coefficient of determination (r^2). By repeating the simulation with the other different time steps, the desirable value of time step can be obtained by break-even evaluation. In the other words, it is to weigh the resulting uncertainties and the resulting accuracy and choose the time step that give acceptable uncertainty and accuracy.

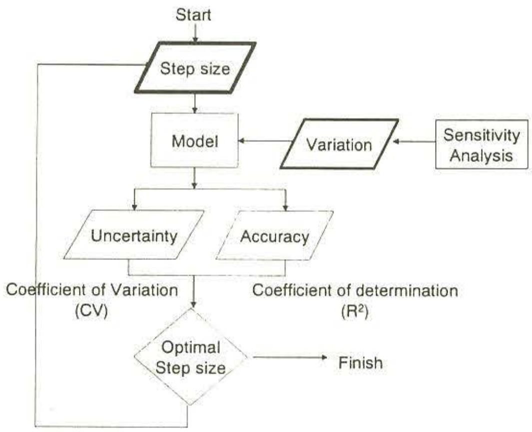


Figure 9 Heuristic Approach to Determine a Desirable Time Step

An experiment with TRANUS Sapporo is conducted. It is based on the results obtained in Section 3 that which indicates three input and parameters (the employment control total, logit model parameter, and volume factor) being significant to generate uncertainty in the land-use related outputs. As a consequence, the simulation of uncertainty in this section is performed by varying only the three significant parameters. Table 4, again, summarizes the variation in these model input and parameters.

Table 4 Significant Sources of Uncertainty

Input or Parameter	Low	Mid	High
Secondary employment control total (SndInc)	15%	19.154%	25%
Volume factor (VolFac)	1	1.4	1.8
Logit parameter of the land use model (Logit)	0.5	0.8	1

TRANUS Sapporo, which is calibrated for 1980 and 1985, is used to forecast the number of household in 1995. As shown in Figure 10, we considered five configurations of the model with different time steps during the forecast period of 10 years: namely a step time of 10 years, 5 years, 3.3 years, 2.5 years, and 2 years respectively. Since either 3.3 or 2.5 years of time step may sound unfamiliar in the real modeling practice, each model configuration is referred to by the number of intermediate step instead of length of the time step, i.e., 0 step, 1 step, 2 steps, 3 steps, and 4 steps respectively.

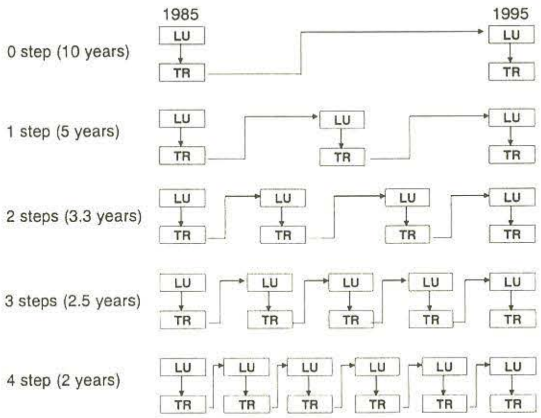


Figure 10 Five Model Configurations with Different Time Steps

The resulting uncertainty and accuracy of the 1995 household forecast of different time steps are shown in Table 5 and 6 respectively. In case of COV, three summary-results of the zonal household forecast are shown as the minimum, maximum, and the average values.

Table 5 Simulation of Different Time Steps: Uncertainty

	Cofficient of Variation				
	0 step	1 step	2 steps	3 steps	4 steps
min	0.0007	0.0009	0.0009	0.0009	0.0010
max	0.0672	0.0782	0.1200	0.1364	0.1416
avg	0.0086	0.0102	0.0105	0.0116	0.0129

Table 6 Simulation of Different Time Steps: Accuracy

Coefficient of determination (r^2)				
0 step	1 step	2 steps	3 steps	4 steps
0.1966	0.3995	0.4867	0.4977	0.5198

Firstly, let consider the index of uncertainty (COV), the uncertainty in the results is increased as the number of time step increase. The rate of increment is relatively monotonic. This is basically due to accumulation of the uncertainty at every model run. It is expected that the uncertainty will be higher if the number of step increases more. Secondly, let consider the index of accuracy (r^2), the results show an increase in goodness-of-fit of the household forecast as the number of step increases. It is observed that the fit is improved substantially when the number of step is increased from 0 to 1 step. An addition of a step to 2 steps still shows the improvement in the model accuracy; however the rate of improvement is not as large as before. Further addition of one step (to be 3 and 4 steps) shows improvement of accuracy with smaller rate of improvement. It is therefore expected that even though we increase the number of step, the model accuracy will be improved but in a very small increment.

Considering both COV and r^2, a desirable number of steps for this example become a trade-off between uncertainty and accuracy, which may result in 2 steps for the forecast during the ten-year period, i.e., 3.3 years as a time step. This is because larger number of steps than 2 will result in large uncertainty accumulation but with small accuracy improvement. This has shown, with empirical result, that the conventional time step of 5 years is not very desirable from either viewpoint of accuracy or uncertainty. A careful determination of this factor (time step) in general quasi-dynamic model, which is normally overlooked, must give us higher creditability of the result. However, a time step of 3.3 years may not sound appropriate in real application, possibly because the necessary data is mostly available at 5-year period (or with 1 time step). Therefore, from the above numerical example, 1 step may be also acceptable from the practical viewpoint in operational modeling since the simulation result of the 1 and 2 steps are not very different. In conclusion, this section has presented to determinate a desirable length of time step for quasi-dynamic urban model. The example is shown with TRANUS model of Sapporo. Since the result presented is specific to the worked model under the specific situation and assumptions, similar analysis must be done with this idea for the other models and applications to in order determine their appropriate length of time step.

5. CONCLUDING REMARKS

This paper has presented an approach to deal with uncertainty in the urban modeling. The technique to represent uncertainties presented in Section 3 and 4 is a very simple since we intended to minimize the computing effort in this demonstrative project. A more general simulation technique such as full Monte Carlo simulation should be conducted in real application so that full correlation in input uncertainty can be accommodated. In the second part, a heuristic approach to determine a time step in quasi-dynamic model is presented. An example with TRANUS Sapporo has shown that 3.3-year is more desirable under the situations simulated. Although a 3.3-year time step does not make much sense in real application, at least it proves that the 5-year time step is still valid for our TRANUS Sapporo model. This result is based on our experiment with the present version of TRANUS Sapporo only, so it is not applicable to other specific model. Instead, the researcher or practitioner should conduct a similar analysis to her model. This is important in the real modeling if the modeler would like to evaluate their model results with respect to possible uncertainty.

Moreover, the work presented in this study is very effort and time consuming although the idea is very simple. We took many advantages of Sapporo test bed. The sensitivity analysis of model output at zone level does not exist, simply because the amount of work is too large to be handled usually. In the previous studies, for example, sensitivity analysis was conducted only for a few numbers of variables such as, total vehicle mile travel, average population density, etc. In contrast, this study had performed a sensitivity analysis for variables at zone level such as zonal household and employment. With a study area of 70 zones and 3 time steps and 81 scenarios of simulation, we need to do the tedious works for $70 \times 3 \times 81 = 17010$ times: run the urban model, read the model result, cut and paste to do sensitivity analysis, store the result in some time. This amount of work is very not attractive for manual operation, if not impossible. Therefore, the tool available in the test bed was made such detailed analysis possible. Other applications of Sapporo test bed are ongoing and will be presented in subsequent papers.

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