Freight generation and freight trip generation modeling

学位名	博士（工学）
学位授与機関	東京海洋大学
学位授与年度	2019
学位授与番号	12614 博甲第555号
URL	http://id.nii.ac.jp/1342/00001893/

[課程博士]
Doctoral Course

博士学位論文内容要旨
Abstract

専　攻 Major	応用環境システム学専攻	氏　名 Name	LIDASAN AL HANZ SEIJI BASA
論文題目 Title	**FREIGHT GENERATION AND FREIGHT TRIP GENERATION MODELING**		

Freight volume generation and freight trip generation have known to be modeled using the classical method of regression with the desired output such as freight volume or freight vehicle volume as the dependent variable, and socio-economic variables as independent variables. Practical models that exists mainly differ in the functional structure of the linear model such as whether there is an intercept or not, and the type of socio-economic variables that are included in the linear equation. However, they mostly still follow the classical linear regression method. This poses problems of underfitting and mostly of overfitting. Underfitting is when the model doesn't get enough information from the data in order to properly represent the relations of the socio-economic variables to freight volume and freight trip generation. On the other hand, overfitting, is when the model learns too much from the data and becomes too sensitive that it performs poor when it comes to forecasting. The overfitting problem is more common in freight models because practitioners tend to want to include as much variables as they can to improve the fit of the data but too much fit to data comes at a price of having poor performance in prediction. A method of estimating as varying intercept model was presented in chapter 3 which deals with the overfitting issue. The varying intercept models had the best out-of-sample cross-validation performance which shows that a varying intercept model is better for prediction than a model with a lot of dummy variables.

Another issue with modeling freight trip generation is that freight trip generation are not independent from other factors such as the location of freight related facilities. In the context of determining where and how much freight trips are produced; freight trips are a product of the decision of where logistics facilities are located and the socio-economic and locational variables. In addition, due to the limitations posed to where logistics facilities can locate, a natural spatial distribution of logistics facilities occur. In the case of Tokyo

Metropolitan Area, logistics facilities are relocating to the suburbs, near expressway interchanges in the fringes of Tokyo Metropolitan Area, or around Tokyo Bay. In the Kansai region, a similar observation can be seen of freight trips being concentrated around Osaka Bay. This has implications to freight trip generation as the spatial distribution of logistics facilities have now an effect on freight trips generated especially when trying to determine where freight trips are generated. Modeling freight trip generation through simple linear regression will fail to consider the unobserved effects of the spatial distribution of logistics facilities and will lead to poor forecasts. For the issues of spatial factors in freight trip generation modelling, chapter 4 showed how to consider the location choice of logistics facilities in estimating freight trip generation. Chapter 4 presented a two-step approach of first modelling location choice and floor area, and using the estimated parameter for logistics floor area, the truck trips generated can be estimated. Chapter 5 compared the lasso penalty for sparse regression and stepwise regression for variable selection. It was shown that the sparse regression framework is the better overall model for modeling freight trip generation in Tokyo Metropolitan Area in terms of number of parameters estimated, the MSE, and the computation time. The application of Fused Lasso was also explored in comparing the freight trip generation of 2016 and 2017. Because the number of trucks installed with digital tachometers is increasing through the years, a direct comparison cannot be made. However, it was shown that the Fused Lasso model can estimate the calibrated coefficients for both years and convert the 2017 to be comparable to 2016. Thus, the difference in freight trip generation from 2017 to 2016 was highlighted and it was confirmed that there was an increase especially in the western regions of Tokyo Metropolitan Area.

In chapter 6, a two-step approach to modelling truck trip generation was presented. To efficiently estimate the spatial regression model, variables that will be used as input variables by estimating a penalized regression model. The penalized regression model results showed that the Lasso penalty provides that best model and was used as basis for variable selection. From a total of 330 independent variables, the penalized regression (Lasso) have estimated 144 nonzero coefficients for both East and West Japan for the year 2018 which is less than half of the original 330 independent variables. This indicates that only less than half of the independent variables influences truck trip generation. The results show that for both East and West Japan, an SLM with a neighborhood structure of 12 nearest neighbors and an inverse distance weights matrix had the highest adjusted coefficient of determination. However, estimated coefficients cannot be directly interpreted due to the feedback effects of the spatial lags of the dependent variable in the model so total impacts must be calculated. Finally, using total impacts to forecast the 2030 truck trip generation for the East Japan case resulted in more realistic values as compared to only considering direct impacts which is akin to forecasting truck trip generation using an ordinary least squares (OLS) model.

This study tackles the problems of overfitting of freight volume generation and freight trip generation, the dependence of freight trip generation to the location of logistics facilities, and the issues of unobserved spatial effects to freight trip generation. The organization of the contents are as follows: Chapter 1 introduces the study, Chapter 2 presents the literature review of freight generation and freight trip generation models, Chapter 3 aims to solve overfitting problem in freight volume generation by applying a Bayesian varying (random) intercept model for national freight volume in Japan. Chapter 4 presents a method to consider location choice and location variables of logistics facilities to freight trip generation. Chapter 5 introduces sparse regression methods as an alternative to the classical regression method to deal with overfitting for freight trip generation. Chapter 6 shows how unobserved spatial variables can be considered for modeling freight trip generation through regression that considers spatial autocorrelation. Chapter 7 summarizes, concludes, and discusses the implications.