Introduction to and calibration of a conceptual LUTI model based on neural networks

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Abstract

This paper deals with Land-Use-Transport-Interaction *(LUTI)* and presents the background and the calibration of a conceptual data driven LUTI modeling tool which is based on neural networks. A literature survey reveals the opinion of experts on the state of the art LUTI models: currently used land use transport models are too aggregate in substance to match travel demand models. Therefore research is conducted into the refinement of the models; resulting in comprehensive models. Unfortunately lack of theoretical frameworks results in these models not being operational on a large scale.

This paper looks for an alternative approach and therefore addresses the following questions: (i) what are solution methods to make LUTI models more applicable; (ii) is there a sound way to put into operation these solution methods; (iii) what modeling technique is suitable to be used in this context; (iv) how does the conceptual LUTI then look like; and finally (v) can we calibrate and test this model.

This leads to a conceptual model with three building blocks; (i) accessibility; (ii) household location choice; and (iii) employer location choice. Based on the demands and the previously mentioned lack of clear theories, it is concluded that a data driven approach, using Artificial Neural Networks (*ANNs*), is suitable to fit the framework. The auto calibration of ANN(s) ensures that complex relationships are found without a theoretical framework.

The calibration of the ANNs in the model shows good results. Further research has to result in the actual implementation of the model.
Keywords: LUTI, transport planning, neural networks, household location, employer location, accessibility.

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1 Introduction

This paper deals with Land-use – Transport - interaction *(LUTI)* and presents the conceptual design and the calibration of a LUTI modeling tool based on *empirical data*. LUTI models help to improve forecasting of land-use transport developments, by extending *traditional transport planning* with a land-use component. Internalising these land use transport interactions in traditional transport planning makes planning consistent; land use interacts with transport and vice versa. Clearly, most transport planning tools comprehend only a one-way relationship between land use and transport and therefore lack this consistency. The dynamic interaction between land use and transport determines on a strategic level the autonomous development of transport and land use systems. The interaction between land-use and transport *(LUTI)* is a widely accepted but still not generally (theoretical) understood topic. Therefore, as a logical step, traditional transport planning and modeling has not yet embraced the land-use topic.

This paper looks for an alternative approach and therefore addresses the following questions: (i) what are feasible solution methods to make LUTI models more (generally) applicable; (ii) is there a sound way to operationalise these feasible solution methods (iii); (iii) what modeling technique is suitable to be used in this LUTI context; (iv) what does the conceptual LUTI look like; and finally (v) can we calibrate and test this model. These questions will be answered in the following sections.

2 Towards more general applicable LUTI models

The development of LUTI models into applicable models for planning purposes is very difficult. Wegener [2] formulates the process until 1994 in the following words: 'After a period of stagnation in the development and use of integrated models, mainly triggered by Lee's "Requiem" [4,5], nowhere in the world have large-scale urban models become a routine tool of metropolitan plan making. If one considers the enormous range of planning problems facing a typical metropolitan area in industrialised countries today, the spectrum of problems actually addressed with current LUTI models is very narrow.'

In general as a response to this observation two opposite approaches to enhance LUTI models are introduced in literature:

- Increase of complexity and add more comprehensiveness [1,2,3]
- Decrease of complexity, add less comprehensiveness [5]

But what level of comprehensiveness does a LUTI model really need and is it necessary to choose between either an increase or a decrease in complexity, or can both approaches be combined? Is it possible to bring the best of both approaches into a new approach by combining them? A combination of both approaches seems possible. However, an approach to do this involves a paradigm shift in thinking about LUTI modelling: from theory- driven to data-driven modeling.

3 Operationalise the feasible solution method using data-driven modeling

A data-driven approach focuses more on creating relationships by using empirical data sets than on using sound theoretical frameworks. Rodrigue [6] states that the urban structure and its evolution must not be considered as given but as the result of complex interactions. It is precisely over these aspects that most of the operational land-use transport models are deficient. Lack of theory prevents models to become standard. Rodrique introduces the possibility of creating a self-adaptable spatial model.

An example of a data driven self-adaptable techniques are Artificial Neural Networks (ANNs). ANNs are basically very simple modeling structures that fit Lee's [5] framework of incomprehensive modeling. In addition, these simple modeling structures can be calibrated using very comprehensive data sets and therefore fit Timmermans' [3] remarks. When we look at both increasing and decreasing complexity and we couple this to the data driven approach we get the following:

- Incomprehensive modeling; data driven techniques need only simple modeling structures. Artificial Neural Networks are built up by only a number of simple structures, named layers. From a pure modeling point of view this results in a very simple and understandable modeling structure in which only the necessary number of variables is used.
- Comprehensive modeling; the modeling structure of the neural network models is very simple. However, the real level of comprehensiveness is obtained by the data. By using very disaggregate data of many disaggregate variables, the overall model will be far more comprehensive as when disaggregate data is used.

In short, using neural networks could fit both frameworks. The basic structure however, is very dependent on the variables to integrate in the model. The next section goes deeper into the question why neural networks are suitable to model the land use transport interactions.

4 The modeling technique: Can artificial neural networks model LUTI?

Recent developments in parallel distributed processing have enabled geographers and regional planners with new tools and methodologies to simulate complex urban dynamics with the usage of neural networks. As a pattern and process associator, a neural network enables to transform the structural relationships between its elements and thus provides a self-adaptable model. This approach will be able to overcome a number of important deficiencies in the currently used models. The theory behind the models lies within the conceptual model. Because a neural network model is self-adaptable, self-calibrating the absence of clear basis of theory is less important because the model seeks its own relationships out of data; a data-driven approach.

However, increasing the understanding of the relationship and building theory is therefore difficult when using neural networks. This is in contrast to the traditional approach. It is difficult to make a model based on sound theories, when theories are not yet developed to a satisfying level. The data driven models seem to fit in Lee's framework; avoiding the trap of more detail, but using the detail in the data to get a grip on the relationships. Data driven, empirically based, models have been proposed, but not yet developed. Despite the lack of research the empirical approach is a promising one.

5 Introduction of a new model approach based on neural networks

This section we present a conceptual model based on neural networks incorporating land use relationships. The objective of developing a new LUTI model was in this case: 'The development and evaluation of an empirically based neural network transport-planning model that internalises the principles of land-use transport interaction and thereby overcoming problems of theory driven approaches'.

Both estimation of transport system performance in a current and future state is regarded important, more than detailed forecasting of the land use patterns and market mechanisms. This leads to a model that internalises, transparent, less extensive land use relationships into a more traditional transport-planning model. Based on the discussion above, the conceptual model will look like Figure 1.

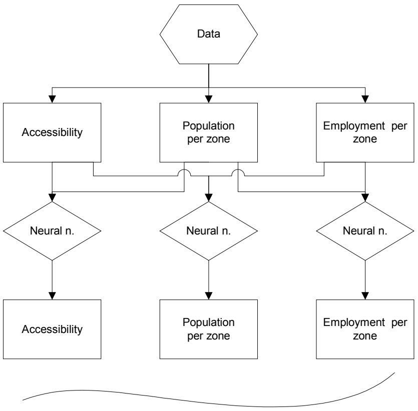


Figure 1: Conceptual model.

The model changes from state 1 to state 2 as a result of changes in the system, amongst others capacity changes in the availability of dwelling units/employment locations and capacity changes in the transport system.

6 Calibrating and testing the conceptual model

The previous section showed the conceptual LUTI model. In the proposed model, accessibility is connected to two land use parts; employment location and household location choice. This section presents the calibration and testing of the *individual* neural networks of the conceptual model. The calibration of the model is based on data of neighbourhoods in the Netherlands. The testing is based on data of a small region in the Netherlands, called Twente.

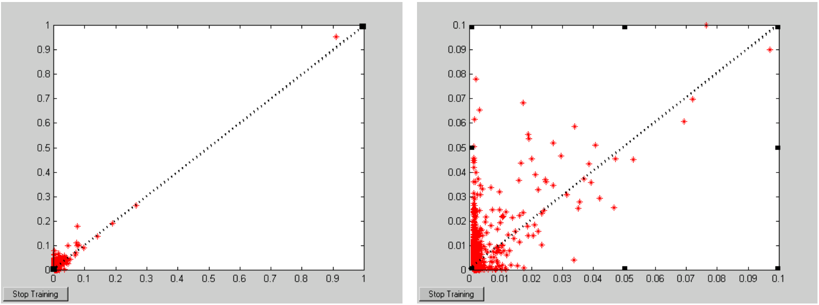
Before the model is tested the model has to be calibrated. This section gives the results of the calibration of the model parts. Calibration means the training of the neural networks. The total data set of the Netherlands is used for calibration. The modeling parts are tested with the data of Twente. This calibration answers the following general questions:

– can the models be calibrated using data of the Netherlands;
– is a calibrated model capable of producing the right results for Twente.

The calibration is started with the accessibility model, followed by the household location choice model and the employment location choice model.

6.1 Calibrating accessibility

In general the expectations are that the results of calibrating the accessibility part of this model are similar to the good results shown before [7,8]. The calibration is to a large extent comparable to that research.

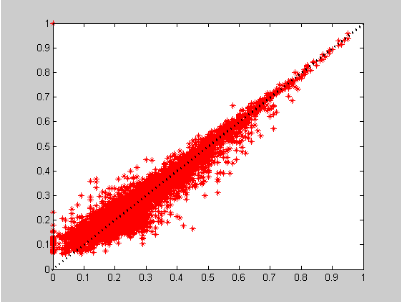


(a) (b)

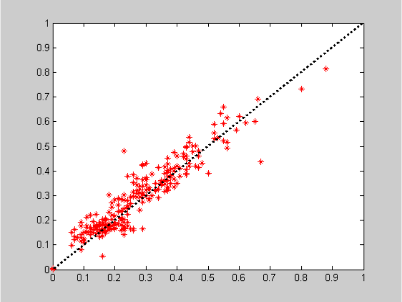
Figure 2: Calibration result OD estimation, total (a) and zoom (b).

Figure 2 (a,b) gives the results of the calibration of the neural network. The first part of the figure shows the calibration results for all tested values. There are a number of interesting observations to be made in this figure. First of all there is a large concentration of values at the origin. This is reviewed in figure 2b. Secondly, the figure shows that the points in a range 0.1-0.9 all lie very close to the 45-degree line. This shows a perfect calibration for the OD pairs with a higher number of trips. However, when we look at the second part of figure 2, we see that the differences between the 45-degree line and the calibrated results are large. The figure shows that when there is only a small amount of trips between OD-pairs the absolute differences are large.

The most important reason for this is that probably the calibration process of the neural network is focused on reproducing both high and low values. However, the incentive to reproduce high values better than lower values is higher; the absolute error made in not calibrating on higher numbers is bigger than not rightly calibrating on the very low numbers. Future neural networks have to be improved to fit both high and low numbers.



(a)

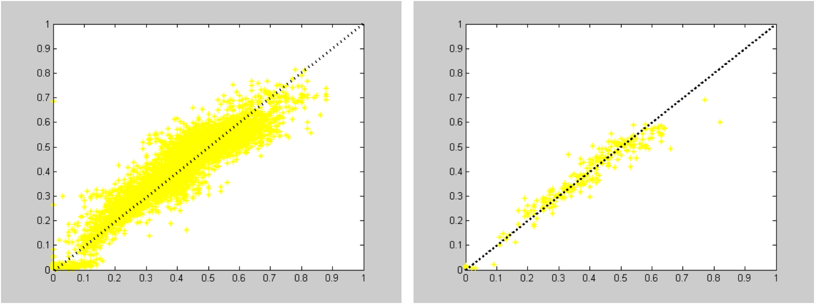


(b)

Figure 3: Calibration result single person households, The Netherlands (a) and Twente (b).

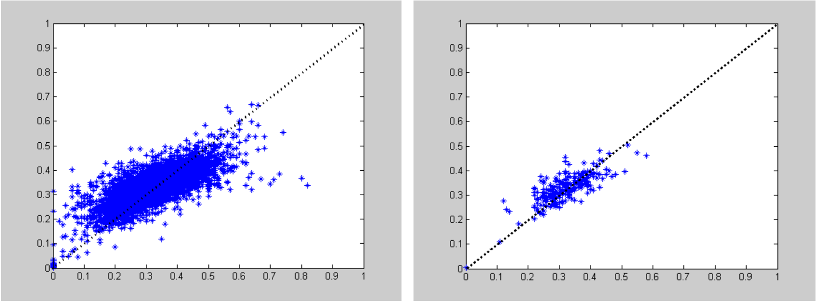
6.2 Calibrating household location choice

The second calibration deals with household location choice. The calibration is split up into two parts: (i) calibration for the household class distribution, and (ii) the total number of households. The first calibrated model gives four different outputs. Firstly the share of households without children is forecasted by the model, secondly the share of households with and thirdly households without children. Finally, the model gives the results for the total number of households in a specific neighbourhood. The model is calibrated using the data of the Netherlands. Figure 3 shows the calibration results when we look at households without children. The left hand side (3a) of the figure shows the results of the calibration using the total data set without Twente (approx. 10.000 zones). The right hand side (3b) shows the results of the testing the calibrated model with the use of the Twente data. Figure 4 shows the calibration results when we look at households without children. The left hand side (4a) of the figure shows the results of the calibration using the total data set without Twente (approx. 10.000 zones). The right hand side (4b) shows the results of testing the calibrated model with the use of the Twente data. The final household type is the household without children, when the household size is greater than 1. Figure 5 shows the results of forecasting the households without children. The last figure shows that again both the calibration and the test give a satisfying result.



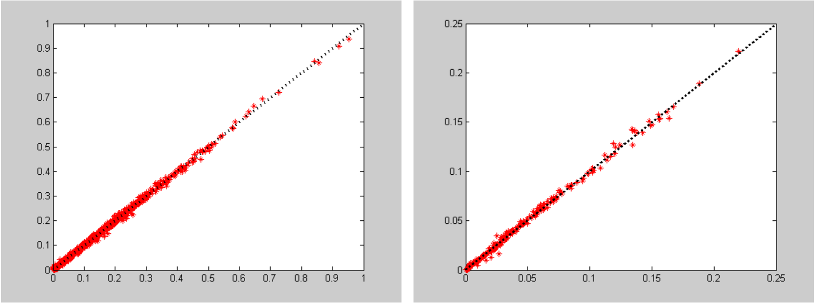
(a) (b)

Figure 4: Calibration result households with children, The Netherlands (a) and Twente (b).



(a) (b)

Figure 5: Calibration result households without children, The Netherlands (a) and Twente (b).



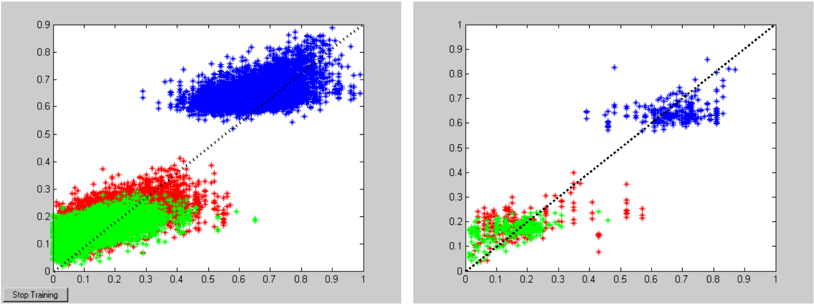
(a) (b)

Figure 6: Calibration result number of households, The Netherlands (a) and Twente (b).

The calibrated model delivers one more input: the number of households in a neighborhood. This is easier than the determining the distribution, because of the fact that only one output is requested. Figure 6 shows the result of the total number of households based on the data set of the Netherlands. The model seems to have no difficulties at all to reproduce the number of households per neighbourhood as the calibrated model reproduces the input data very well.

6.3 Employment location choice

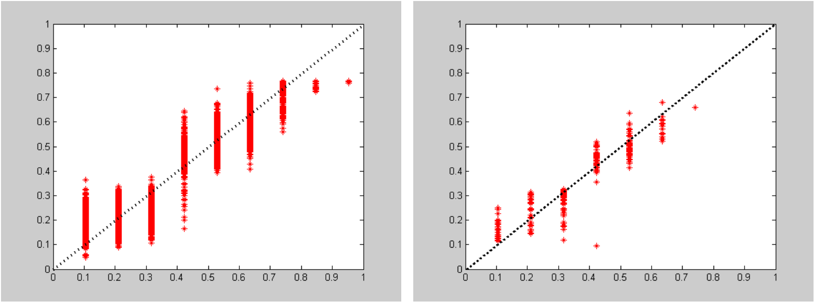
The final calibration deals with employment location choice and is to a large extent comparable with calibration of household location choice: (i) calibration for the employment class distribution, and (ii) calibration for the number of firms in a zone. The first calibrated model delivers three different outputs. Firstly the share of firms in the industrial sector is forecasted by the model, secondly the share of firms in commerce and finally the share of other employment sectors. The model is calibrated using the data of the Netherlands. Figure 7a shows the calibration result for the total data set without Twente (approx. 10.000 zones). Again the 45-degree line is the perfect calibration result. A number of interesting observations can be made. Firstly, there is a distinct difference between the three types of firms; the three different clouds of dots. The share of commercial firms in the Netherlands is overall the largest; the dots are placed highest in the figure. The share of commercial firms is followed by the industry sector share.



(a) (b)

Figure 7: Calibration result employment distribution, The Netherlands (a) and Twente (b).

Secondly, the clouds of dots are not of the same size, whereas the number of dots in a cloud is the same. Especially the cloud of the commercial firms seems to be bigger. This fact corresponds to the real data set in which the number of commercial firms in an area fluctuated more (in absolute numbers) than the number of firms in the industrial sector or the other sectors. This makes it harder to forecast, as can be seen by the less centralized position of this cloud of dots around the 45-degree line, which is the third observation. All clouds of dots are situation around the 45-degree line. This shows that the model did not make really big misjudgements. It is obvious that the calibration did not result in a perfect match between the calibrated model outputs and the real data set. However, the model performs quite well as proven by the centralized position around the 45-degree line. In short, this means that at least the data can be reproduced to a satisfying level. The second test is to test the model using the dataset of twente, 264 neighbourhoods (figure 7b). This figure shows the results of testing the calibrated model in the Twente case. The test of the model shows quite a similar pattern as in the case of the whole data set. Again there is a difference between the share of the different firm types and the sequence from small to large is the same. Of course there are fewer points in the figure, 264 against approximately 10.000 in the whole test set, which makes the figure clearer. Again the 45-degree line is the perfect calibration line. The calibrated model gives results that lie around this line, which is a fairly good result.



(a) (b)

Figure 8: Calibration result number of firms, The Netherlands (a) and Twente (b).

The second calibrated model delivers one input namely the number of firms in a neighbourhood. This calibration is easier than the first calibration, because of the fact that only one output is requested. Figure 9 shows the result of the calibration of the total number of firms model, based on the data set of the Netherlands (8a) and the test set of Twente (8b)

A number of interesting observations can be made. Firstly, we see that the calibrated model gives discrete values. This corresponds with the fact that the number of firms is really a discrete value. Secondly, it can be seen that on average the results lie on the 45-degree line, which in fact is not a real line because of the discrete values. The figure shows furthermore that in general a low number of firms and a higher number of firms are more difficult to reproduce using the calibrated model. This is in fact easy to explain, because the number of cases in which a high or low number of firms is situated in a neighbourhood is lower than the number of cases in between. Finally, the figure shows that the data set has a lot of corresponding neighbourhoods that have different amounts of firms. This is shown by the vertical situated dots. A calibrated neural network tries to find patterns in the data; in this case a pattern in the neighbourhood data. When corresponding neighbourhoods have different number of firms, the neural network has difficulties to explain these differences.

7 Discussion and conclusions

This paper presents a conceptual LUTI model that is based on neural networks. The state of the art in LUTI modeling shows that the currently used models are not widely applicable and have to large extent theoretical drawbacks. Modeling less comprehensively was proposed as acceptable when modeling land use is done in a transport planning framework. The aim is to use a data driven approach in order to overcome the problems of very comprehensive modeling as assumed necessary. The model has to be built around at least three components; (i) accessibility; (ii) household location choice; and (iii) employment location choice. This still not overcomes the problem of the lack of theory.

Data-driven, empirical models, based on neural networks are introduced as an alternative to the theoretically based models. In general, these models are not very suitable to form new theories due to the black box character. However, when calibrated soundly, these models can make transport planning consistent and they give an insight in the influence of the relationship between land use and transport.

The calibration shows that LUTI model building blocks are successfully trained with the data of the whole of the Netherlands as calibration data. Testing the individual parts of the model using test case data of Twente gives satisfying results.

The most important aspect of future research is the test of the complete model.

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