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Modeling freight distribution using artificial neural networks

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Abstract

Studies about freight distribution modeling are limited due to the limitations in data availability. Existing studies in this subject, generally either use the conventional gravity models or the regression based models as modeling techniques. The present study, using the 1993 US Commodity Flow Survey Data, models inter-regional commodity flows for 48 continental states of the US with three different artificial neural networks (ANN). The results are compared with those of Celik and Guldmann's (2002) Box–Cox Regression Model. The ANN using conventional gravity model variables provides a slight improvement with respect to this Box–Cox model. However, the ANNs using theoretically relevant variables provide surprising improvements in comparison to the Box–Cox model. It is concluded that ANN architecture is a very promising technique for predicting short-term inter-regional commodity flows.

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1. Introduction

"Spatial Interaction Modeling" in transportation planning is used for modeling of passenger and freight distributions over space. Passenger flows have been studied more extensively than freight distribution due to the fact that the availability of suitable data for modeling the freight distribution has been more limited. While it is relatively easier to obtain data to model passenger flows through an O–D survey among relatively homogenous households at both the inter- and intra-city levels, data to model freight movements may involve many shippers and receivers in the form of firms (producers, wholesalers, and retailers) and households. This makes data gathering and tracking more difficult and costlier.

The movement of freight is also about more than the opportunities available at the origins and destinations in the form of employment, schools, and residences, as is the case of passenger movements. Since the flows of commodities are a reflection of all economic activities over space, not only transportation planners, but economists and geographers are also deeply concerned with the commodity flows over space and among industries. For this reason, commodity flows require establishing elaborate models that take account of the structure of the economy.

Taking the advantage of the 1993 Commodity Flow Survey data from the US Bureau of Transportation Statistics, this paper attempts to empirically model inter-regional commodity flows with an Artificial Neural Network (ANN), in connection with the theoretical spatial price equilibrium framework (Samuelson, 1952; Bröcker, 1989). Using the same framework, Celik and Guldmann (2002) have specified and estimated a flexible Box–Cox model with a set of explanatory variables that characterize the economic structures of the origins and destinations, and their spatial configurations. The present study extends this earlier work by inputting the same set of variables into two separate feed-forward Backprob ANNs for 15 commodity groups, and evaluates the performances of these new models using Celik and Guldmann Model, and a base ANN model using conventional Gravity Model variables (zonal totals and distance) as benchmarks.

The relevant literature is reviewed in the next section. Section 3 discusses the modeling methodology in terms of theoretical background, variables, and the structure of ANN models. Description of data is included in Section 4. Section 5 presents the results of the proposed model. The last section is devoted to conclusions and further research directions.

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2. Literature review

The flow of commodities over space has been studied by many researchers, ranging from regional scientists and geographers (Isard, 1951; Bon, 1984) to international trade theorists (Frankel and Wei, 1998; Krugman, 1980), transportation planners and spatial interaction modelers. Beyond intervening opportunities models, optimization models, and data-hungry general equilibrium models such as inter- and multi-regional input–output models, the movement of freight can also be modeled using two main techniques: conventional gravity models and regression based models. Gravity models, being heuristic in nature, are mainly concerned with replicating the observed flows between each and every pair of origin and destination with minimum error. In this family of models, the flow is a function of some proxy variables of the origin and destination magnitudes (in general, total zonal production of the origin and total zonal attraction of the destination), some measure of origin and destination accessibilities, and the distance, in either power or exponential form (Fotheringham and O'Kelly, 1989). Furthermore, it has been shown that it is possible to represent the geographic configuration of origins and destinations in the model by inclusion of two additional variables representing intervening opportunities and competing destinations (Fotheringham, 1983; Guldmann, 1999). In situations where the researcher is more concerned with the possible determinants of flow variations beyond pure replication, regression-based models may be preferable. This family of models may give decision makers the ability to control the flow since it may unveil the causative relationship of the flow with a set of policy variables. Furthermore, a well-specified regression model can also be used for predictive purposes. As it is mentioned earlier, there are relatively few commodity flow studies in the literature (Reed, 1967; Black, 1971, 1972; Chisholm and O'Sullivan, 1973; Ashtakala and Murthy, 1988), and they employ a basic gravity model focusing on best fit with little theoretical foundation. On the other hand, using a regression model, Celik and Guldmann (2002) determine significant sets of variables for each of the 16 commodity groups for 48 continental states of the US using the 1993 Commodity Flow Survey and the Box–Cox functional form. Reviewing all the above studies, it is possible to say that there are no uniformly good or bad models in replicating the flow of commodities. However, it is possible to say that the more homogenous the product group, the higher the goodness of fit of the models. This implies that, since it is not practically possible to obtain data with the desired level of disaggregation, there remains a lack of highly dependable forecasting methods for commodity flows.

Recent years have seen the evolution of a new and promising technique called "Artificial Neural Networks" (ANN). Within a relatively short period, ANN has outperformed many conventional computing methods in many disciplines, as well as in transportation planning and spatial interaction modeling. Dougherty (1995) gives a short list of ANN applications in transport, and urges a closer examination of the relationship between statistics and neural networks. Since then, the number of applications of ANN has been increasing geometrically, and it is not possible to present and discuss them exhaustively here.

From our point of interest, one of the pioneering studies of ANN (Black, 1995) modeled (a) seven groups of commodity flows between nine census regions of the US in 1977 and (b) 1965–1970 US migrations, and compared the results with those of a doubly constrained gravity benchmark model. Using zonal totals and distance as inputs into ANN, Black concluded that the prediction error with ANN is significantly lower than that of the counterpart benchmark model. In other words, ANN outperforms the conventional doubly constrained gravity model. A similar result in spatial interaction modeling is reported by Fisher and Gopal (1994). Using a logarithmic regression function as a benchmark model with three variables (two zonal magnitudes measured by gross regional products; and a friction variable), they conclude that the ANN outperforms the benchmark model. However, Mozolin et al. (2000) note the underperformance of ANN prediction in comparison to the maximum likelihood doubly constrained gravity models in spatial interaction modeling of passenger flows among counties of the Atlanta Metropolitan Statistical Area in 1990. According to Mozolin et al., even if the literature reports calibration superiority of ANN in comparison to conventional models, an ex-post prediction of the conventional gravity model outperforms those of ANN.

These variations in the results of ANN modeling of spatial interactions may stem from the very nature of the phenomena as well as from the different specifications of network architecture used in these studies. Unfortunately, we do not yet have enough empirical and theoretical studies to reach conclusive evidence about these variations since we are at the very outset of a new era of modeling.

Like conventional gravity models, ANN can also be considered quite heuristic, since it does not provide any insight in terms of causative relationship between the constituting parts of a system. Also it does not provide an elasticity as clear as from regression based models. It is of course possible to obtain a set of parameters in terms of weights; however, they are not as distinct as we are used to. As noted by many authors, ANN still suffer black-box phenomenon, and it stands as a good pattern-imitating algorithm.

3. Modeling methodology

3.1. Theoretical background

The Spatial Price Equilibrium Model developed by Samuelson (1952) provides a consistent theoretical framework for the flow of commodities in a multi-regional spatial configuration, where the flows take place from high-price regions to low-price regions until equilibrium is reached, with price differentials between regions equal to transportation costs. This basic principle is valid for all commodities among all regions as long as the regions are economically and geographically connected.

Despite its sound theoretical framework, Samuelson's, 1952 formulation presents three important practical problems: "first, the problem of specifying functional forms,...; second, the problem of estimating the model parameters with available data; and third, the problem of designing efficient algorithms for a numerical approximation of the equilibria" (Bröcker, 1989, p. 8). First and second problems are related to the specification of the excess supply functions of regions while the third problem is related to the solution of maximization of net social pay off among the regions.

Bröcker (1989) attempts to connect theory and empirical research in trade modeling and shows that all forms of the gravity model (constrained, unconstrained, and elasticity constrained) are reduced forms of spatial price equilibria of interregional trade, using a modified version of the Spatial Price Equilibrium (Samuelson, 1952). A spatial price equilibrium is characterized by prices and quantities satisfying supply and demand conditions corresponding to the explicit (or structural) form of the trade model, with both prices and quantities as endogenous variables. Eliminating prices leads to the reduced form of the model, where equilibrium flows are directly assigned to the vector of exogenous variables:

$$(\boldsymbol{s}, \boldsymbol{w}, \boldsymbol{d}, \boldsymbol{c}) = (s_1, \ldots, s_I, w_1, \ldots, w_I, d_1, \ldots d_j, c_{11}, \ldots, c_{ij})$$

where the vector $\boldsymbol{s}$ represents prices of other commodities; $\boldsymbol{w}$ measuring the supply characteristics influencing purchase choices; $\boldsymbol{d}$ measuring demand characteristics; and $\boldsymbol{c}$ the transportation costs between regions. Eventually, Bröcker (1989) shows that the generalized gravity form

$$x_{ij}(\boldsymbol{s}, \boldsymbol{w}, \boldsymbol{d}, \boldsymbol{c}) = \boldsymbol{a}_i(\boldsymbol{s}, \boldsymbol{w}, \boldsymbol{d}, \boldsymbol{c}) f(c_{ij}) \boldsymbol{b}_j(\boldsymbol{s}, \boldsymbol{w}, \boldsymbol{d}, \boldsymbol{c}) \tag{1}$$

is consistent with the trade equilibrium situation. Eq. (1) suggests that the origin and destination factors, $\boldsymbol{a}_i$ and $\boldsymbol{b}_j$, may be functions of the whole vectors $(\boldsymbol{s}, \boldsymbol{w}, \boldsymbol{d}, \boldsymbol{c})$, and not only of the components of these vectors associated with i or j, exclusively. It further requires the specification of relevant variables such as characterizing origins and destinations demand and supply conditions and the geography; and the specification of a best fitting functional form.

3.2. Variables

In accordance with the framework explained above, three groups of variables are used in this study: the variables characterizing supply and demand conditions at the origin, the variables characterizing demand conditions at the destination, and the variables specifying the geography.

3.2.1. Origin variables

(1) Sectoral employment, and (2) sectoral value-added in that product group are used as two proxy variables for sectorial production at the origin. To capture the effect of redistribution activities on commodity out-shipments, (3) wholesale employment is used as another origin variable. (4) The average plant size is intended to capture scale or diversification effects in the product group. Theoretically, as the plant scale of an industrial sector increases, total production and total out-shipments in that industry are supposed to increase due to increased production efficiency. It is estimated by dividing total sectoral employment by the total number of establishments in that sector. (5) Total population, and (6) personal income per-capita are two proxy variables of demand conditions at the origin. Even though the origins are supposed to be associated with supply conditions for commodity out-shipment, local final demand at origins may have significant effects. As local consumption increases, the out-shipment of the commodity may decrease.

3.2.2. Destination variables

Since the destinations are mainly demand points, the variables are expected to be proxies for commodity demand at intermediate and final levels. (7) Total manufacturing employment at the destination is used as a proxy variable for intermediate demand. (8) Personal income per-capita, and (9) total population are used to capture final demand effects at the destination. (10) Wholesale employment is again used to measure redistribution effects at the destination.

3.2.3. Geographical variables

(11) The average distance of all commodities shipped is used as the basic friction variable. Two additional variables are used to include spatial configuration of the study area: (12) competing destinations, and (13) intervening opportunities variables. The competing destinations variable measures the accessibility of a specific destination to all other destinations (Celik and Guldmann, 2002; Fotheringham, 1983), while the intervening opportunities variable defines the concept that flows to a destination decrease when the opportunities between the

origin and destination increase (Celik and Guldmann, 2002; Guldmann, 1999). Finally, three dummy variables are used to capture geographical effects better. (14) One of the dummy variables indicates if trading states share a common physical border. It is expected that trade flows between neighboring states increase because of better business information, cultural commonalities, etc. Two other dummy variables are used to capture the effects of international trade on inter-regional commodity flows. (15) If the destination state has a customs district, then some of the commodities moving to the destination state may be oriented to foreign export via that customs district. On the other hand, (16) some of the commodities originating from an origin state including a customs district may be generated by foreign import through that customs district.

The commodity flow between two points, can then, be written with the variables specified and numbered above, and may be expressed in the framework of Eq. (1) as follows.

$$F_{ij} = a_i(\text{origin variables})f_{ij}(\text{grographical variables}) \times b_j(\text{destination variables}) \tag{2}$$

where $\boldsymbol{a_i}$ is the supply point factor, $\boldsymbol{b_j}$ the demand point factor, and $\boldsymbol{f_{ij}}$ the interaction factor.

3.3. The Box–Cox model

Celik and Guldmann (2002) use a flexible Box–Cox regression equation as the functional form of Eq. (2) with the specified set of 16 variables. Their model is formulated as follows:

$$\frac{Y^{\theta} - 1}{\boldsymbol{\theta}} = a_0 + a_1 X_1 + a_2 \frac{X_2^{\lambda} - 1}{\boldsymbol{\lambda}} + \cdots + a_n \frac{X_n^{\lambda} - 1}{\boldsymbol{\lambda}} + \boldsymbol{\varepsilon} \tag{3}$$

where, θ, λ, and a_n are the parameters to be determined endogenously, € is assumed to be a normally distributed error term, with $E(\varepsilon) = 0$ and $E(\varepsilon\varepsilon') = \delta^2 I$. The Box–Cox transformation (3) is continuous at $\lambda = 0$, because X^{λ} tends toward LnX when $\lambda \to 0$. Thus, the linear and log-linear functional forms are simply specific points ($\lambda = 1$ and 0) on a continuum of forms allowing for different degrees of independence and interaction among the variables. In other words, with a maximum likelihood estimator, the Box–Cox formulation determines a best fitting functional form endogenously in any range between linear and log-linear functional forms (Box and Cox, 1964).

Celik and Guldmann's (2002) estimated model for 15 different commodity groups establishes the benchmark for the present study. For a complete list of estimated parameters and significant variables among the original variable set for each commodity group, see Celik and Guldmann (2002).

3.4. Artificial neural network

Given all the drawbacks just mentioned, this study attempts to fill a gap between regression based-models and the ANN by combining the strengths of the two approaches. Three different ANN models are specified in this study: (1) using three conventional gravity model variables (zonal totals and average distance); (2) using only the statistically significant variables, at the 95% confidence level among the set of variables identified by Celik and Guldmann's (2002) Box–Cox model of 15 commodity groups; (3) using all the 16 theoretically relevant variables used by Celik and Guldmann (2002). All three models use a Feed-Forward Backprob ANN Architecture with a supervised training and learning algorithm. The results are evaluated comparatively with respect to the benchmark Box–Cox model.

The purpose of a significant-variables ANN model is to see whether it performs better than a statistically estimated model using the same set of variables. Since ANN models still suffer from the so called "Black Box" phenomenon, it is possible to select the significant set of variables using a statistical procedure, then use this set as inputs to an ANN architecture, which is known to have a significant superiority in pattern recognition. In this way, the advantages of both procedures are combined. This is, in a sense, a sequential approach to modeling.

The purpose of the all-variables ANN model, on the other hand, is twofold: First, the benchmark model (Celik and Guldmann, 2002) uses the maximum likelihood estimation for determining the endogenous parameters. For this reason, eliminating the insignificant variables from the Box–Cox equation could cause significant prediction errors, as eventually predictions of the Box–Cox model are estimated using all the variables. Thus, to obtain a better comparative basis, an all variable ANN model is estimated. Furthermore, comparison of significant-variables ANN and all-variables ANN models could provide some insight about whether the additional insignificant variables improve model performance at the margins.

Finally, one more ANN model with three conventional variables is also estimated to serve as another benchmark model. These variables are the flow totals of the origin and destination, and the average distance between them. The purpose of this model is to compare the performance of the ANNs using conventional variables as input and that of the ANN using theoretically sounder variables.

ANN is, in a sense, a simulator of biological learning and cognitive processes. Neurons of a biological nervous system are represented by artificial neurons in the form of layers; the input of this neuron layer is the weighted sum of data. In matrix form:

$$\boldsymbol{I} = \boldsymbol{W}\boldsymbol{X} \tag{4}$$

where $\boldsymbol{I}$ is the input vector, $\boldsymbol{W}$ the weight matrix, and $\boldsymbol{X}$ the input data vector. Then, this weighted sum is fed into a transfer function producing an output.

$$Y = f(\boldsymbol{I}) \tag{5}$$

The estimated output is compared with the observed system data, and the error is back propagated through the ANN and new set of weights are obtained. This process continues iteratively up to the point where the error is at a minimum.

The numbers of layers and neurons in these layers, the form of the transfer functions, and the learning algorithms (which propagate the error back through the network) vary, depending on the network architecture. Since, there have been great many numbers of studies, explaining the basics of and advances in ANN, a detailed explanation of ANN is not included here. (see Munakata (1998), and Hagan et al. (1996) for basic and in-depth explanations of ANN).

A feed-forward backpropagation ANN with two hidden layers is employed in this study. The number of neurons in the first hidden layer is the same as the dimension of the input data vector for each commodity group (i.e. if we have nine variables determining the output, we use nine neurons in the first hidden layer). The transfer function for the first hidden layer is a nonlinear sigmoid function:

$$Y = 1/[1 + \exp(\boldsymbol{I})] \tag{6}$$

In the second hidden layer, only one neuron is employed. The transfer function of the second hidden layer is the same sigmoid function. The learning method is supervised learning, by which "an input is presented to one side of the feed forward network, and an output is computed. This is compared with the output desired for these inputs, and a global error function is computed. This is then, used to update the weights in order to move the outputs towards the desired output" (Dougherty, 1995, p. 249). The "Levenberg–Marquardt", learning algorithm is chosen to assure a fast convergence and save computer time (see Hagan et al., 1996, for details).

4. Data

Four main data sources are used: the 1993 Commodity Flow Survey, CFS, (Bureau of Transportation Statistics); the 1993 County Business Patterns; the 1992 Censuses of Manufactures (Bureau of the Census); and the Annual State Personal Income (Bureau of Economic Analysis). The CFS provides the data for the dependent (flow) and distance variables. The other sources provide the data for the independent variables.

Prior to 1993, the most recent commodity flow survey performed in the US was for the year 1977, with data difficult to access and not in electronic format. There has been a dearth of such data in other countries, as demonstrated by the very limited number of related empirical studies described earlier (e.g. India; Great Britain; Alberta, Canada). However, the Bureau of Transportation Statistics, a joint unit of the US Department of Transportation and the US Bureau of Census, has released the results of the 1993 and 1997 Commodity Flow Survey, making them widely available in electronic form. The structure of these data is very suitable for empirical origin-destination analyses of commodity flows, and makes it feasible to develop and test new empirical models aimed at explaining the variations of these flows. The 1993 CFS data with a 200,000 sample size is preferred for model calibration and training as the 1997 data used a different commodity classification system less consistent with the employment classification and a smaller sample of 100,000. The trained or calibrated model can be used for the 1997 CFS data as an ex-ante analysis of the model performance and a future study.

Data for the dependent variable are drawn from File 9 of the 1993 CFS, and measure the value (Million $) of out-shipments from each origin state to every other state, for each of 15 commodity groups (see Table 1), primarily defined at the two-digit SIC level (the highest level of disaggregation for O–D flows in the CFS). Missing observations are eliminated from the database. The geographical coverage is the 48 US continental states (Alaska, Hawaii, and District of Columbia are eliminated from the data set). Imported products shipments are included after they leave the importer's domestic location for another location. Export shipments are also included until they reach the port of exit from the US Shipments through a foreign country, with

Table 1
Commodity groups codes and definitions

Codes	Definitions
20	Food and Kindred Products
24	Lumber or Wood Products
25	Furniture or Fixture Products
26	Pulp, Paper, or Allied Products
28	Chemicals or Allied Products
30	Rubber of Plastics Products
32	Clay, Concrete, Glass or Stone Products
33	Primary Metal Products
34	Fabricated Metal Products
35	Machinery, excluding electrical, Products
36	Electrical Machinery Products
37	Transportation Equipment
38	Precision Instruments
39	Miscellaneous Freight Shipment
75	Textile, Apparel and Leather Products

both the origin and destination in the US, are included. Definitions of commodity codes are given in Table 1.

All the employment variables are drawn from the County Business Patterns (CBP) database, and include origin sectoral employment, origin wholesale employment, destination manufacturing employment, and destination wholesale employment. The origin average establishment size variable is estimated by dividing the origin sectoral employment by the number of establishments in that sector. The numbers of establishments are drawn from the CBP. The value-added variable is drawn from the 1992 Census of Manufactures. The state personal income per-capita variables and the state population variables are drawn from the Annual State Personal Income database of the Bureau of Economic Analysis (BEA). The distance variable is directly derived from the 1993 CFS as average hauled distance. File 9 in the 1993 CFS has both tonnage and ton-miles values for each commodity group. Dividing ton-miles by ton values, the average hauled distance for each commodity group between each O–D pair is estimated. The competing destinations variable and the intervening opportunities variable are estimated using distance and total employment (Celik and Guldmann, 2002; Guldmann, 1999; Fotheringham, 1983).

5. Results

The results of One Box–Cox Regression (BCM) and three ANN models; Conventional Variables (CVM); Significant Variables (SVM); and All Variables (AVM) models are compared and evaluated using the root mean squared error (RMSE) and the R^2 statistics. The RMSE is defined as

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad \text{for } i = 1, 2, \ldots, n \tag{7}$$

where y_i is the observed and $\hat{y}_i$ is the model-predicted value of flow. The other performance measure, the R^2 goodness of fit statistics is defined as

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad \text{for } i = 1, 2, \ldots, n \tag{8}$$

where $\bar{y}$ is the average of the observed flows.

The first question in this study is to test whether an ANN model using the three conventional gravity model variables outperforms the regression-based spatial interaction model of Celik and Guldmann (2002). The second question tested is that whether this performance can be improved by inputting only the statistically significant variables into another ANN. In the final step, all the theoretically relevant variables used in Celik and Guldmann (2002) are fed into an ANN. The performance measurements of these models are presented in Table 2.

The R^2 statistics for BCM varies between 0.247 for the commodity group 25 (furniture or fixture products); and 0.796 for the commodity group 20 (food and kindred products). With this level of performance, it can be said that Celik and Guldmann's model is comparable with previous studies in the literature. In general, goodness of fit for the CVM increases with respect to BCM. Its R^2 varies between 0.666 for the commodity group 39 (miscellaneous freight shipment); and 0.860 for the commodity group 33 (primary metal products). However, this increase in CVM is not absolute in the sense that BCM outperforms CVM for two products groups; 20 (food and kindred products), and 26 (pulp paper or allied products). SVM outperforms both BCM and CVM for each commodity group. Its R^2 statistics

Table 2
Models' goodness of fit measurements

Codes	BCM		CVM		SVM		AVM	
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
20	0.796	208.7	0.770	221.6	0.982	61.7	0.987	53.3
24	0.593	56.2	0.834	35.8	0.962	17.3	0.991	8.3
25	0.247	44.2	0.739	26.0	0.883	17.4	0.987	5.7
26	0.779	63.0	0.726	70.2	0.939	33.1	0.981	18.4
28	0.671	222.1	0.752	192.8	0.903	120.7	0.979	56.1
30	0.776	51.4	0.791	49.5	0.940	26.7	0.975	17.1
32	0.353	39.7	0.831	20.3	0.930	13.1	0.983	6.4
33	0.778	104.1	0.860	82.6	0.955	46.6	0.993	19.0
34	0.775	70.9	0.783	69.7	0.960	29.9	0.983	19.6
35	0.665	172.6	0.758	146.7	0.947	68.6	0.984	38.1
36	0.666	196.9	0.817	145.9	0.971	58.2	0.989	35.0
37	0.544	436.4	0.724	339.5	0.967	116.7	0.990	65.4
38	0.642	91.2	0.766	73.8	0.961	30.1	0.990	15.6
39	0.589	80.2	0.666	72.3	0.953	27.0	0.987	14.4
75	0.508	362.2	0.796	233.4	0.971	87.5	0.999	11.2

Table 3
Error reductions of the model with respect to BCM

Codes	CVM	SVM	AVM
20	−0.06	0.70	0.74
24	0.36	0.69	0.85
25	0.41	0.61	0.87
26	−0.11	0.48	0.71
28	0.13	0.46	0.75
30	0.04	0.48	0.67
32	0.49	0.67	0.84
33	0.21	0.55	0.82
34	0.02	0.58	0.72
35	0.15	0.60	0.78
36	0.26	0.70	0.82
37	0.22	0.73	0.85
38	0.19	0.67	0.83
39	0.10	0.66	0.82
75	0.36	0.76	0.97
Avg	0.18	0.62	0.80

are significantly improved and vary between 0.883 for the commodity group 25, and 0.982 for the commodity group 20. The performance of AVM is greatly improved, and it significantly outperforms all other models for each commodity group. Its R^2 vary between 0.975 for the commodity group 30(rubber and plastic products); and 0.999 for the commodity group 75 (textile apparel and leather products).

Table 3, which presents the error reductions of the models with respect to benchmark BCM, confirms the above findings. The maximum error reduction of CVM with respect to BCM is 49% for the commodity group 32, (clay concrete, and glass or stone products). The average error reduction for 15 commodity groups is 18% for CVM. This average is 62% for SVM with 76% for the commodity group 75, and 80% for AVM, with 97% the same group 75.

6. Conclusions

The theoretical framework outlined above states that with a fine level of product disaggregation, given supply and demand functions, and associated transportation costs for each O–D pair, one should be able to predict freight flows with a very acceptable level of accuracy. However, real-life applications do not allow researchers to work with such perfect information especially in the area of freight modeling. Depending on the policy perspective expected from a study, either determination of policy variables, or predictive accuracy of modeling (or both) may become important. The findings of this study suggest that ANN may improve the performance of the predictive models in freight distribution modeling, in the same way as they have for passenger flows. An ANN with conventional flow distribution variables may provide moderate performance improvement in comparison with a regression based statistical model or a gravity model as suggested by Black (1995), and Fisher and Gopal (1994). However, an ANN with statistically significant variables among a set of theoretically sound variables increases the model performance surprisingly. If all of the variables which are thought theoretically relevant in explaining the flows, are fed into the ANN, the performance of the model is greatly increased.

At this point, it could be claimed that increasing the number of variables in any model would improve the model performance. This fact stands as a mathematical property especially for the ordinary least square estimator. On the other hand, if there were no theoretical relevance between dependent and independent variables, this improvement resulting from increased number of independent variable set would remain only marginal. Evidently, this is not the case concerning the findings of this study. Even if the subsequent improvements in the ANN models tested here had been resulted from increased number of variables, the ANN proved immense calibration superiority with respect to a benchmark regression model using the same set of variables.

As it was stated earlier, the main limitation of ANN models is that it suffers from the so called "black-box" phenomenon. It fails to establish a causal relationship between the constituting parts of a system. Thus, it is not possible to select the significant policy variables among a set of hypothesized variables. Furthermore, the obtained weights for a variable do not provide a clear elasticity measure unlike regression models.

Another limitation of ANN for predictive purposes lies in very structure of the model; when new origin and destination pairs are added to the existing network for prediction, the model will not be able to obtain results for the extended part of the network since it would not have estimated parameters from the calibration phase. In other words, an ANN model is not flexible to network changes. This indicates a future research direction to obtain strategies to adopt network changes.

The results of this study indicate that a theoretically sound regression model (to select significant policy variables) and an ANN (to obtain a predictive superiority) can be combined successfully as a sequential modeling approach. An ANN using theoretically relevant variables as input is a very promising tool for short-term forecasting of interregional freight distribution modeling.

This sequential modeling framework can be used for any type of spatial interaction modeling such as telecommunication, shopping, migration, and input–output modeling. Beyond spatial interaction, ANN is a very promising technique in any type of pattern recognition. It can be used in trip/freight generation, mode choice, cost estimation, and project scheduling. Obviously, more elaborate studies are needed in all of these areas using ANN.

Of course, this improvement is obtained for replicating a set of observed flows, and this result does not necessarily suggest that ANN will produce superior results for prediction, as indicated by Mozolin et al. (2002). This issue obviously remains as another research question.

References

Ashtakala, B., Murthy, A.S.N., 1988. Optimized gravity models for commodity transportation. Journal of Transportation Engineering 114 (4), 393–408.

Black, W.R., 1971. The Utility of the Gravity Model and Estimates of its Parameters in Commodity Flow Studies. Proceedings of the Association of American Geographers 3, 132–143.

Black, W.R., 1972. lnter-regional commodity flows: some experiments with the gravity model. Journal of Regional Science 12 (1), 5–21.

Black, W.R., 1995. Spatial interaction modeling using artificial neural networks. Journal of Transport Geography 3/3, 155–166.

Bon, R., 1984. Comparative stability analysis of multiregional input–output models: column, row, and Leontief-Strout gravity coefficient models. The Quarterly Journal of Economics 99 (4), 212–235.

Box, G.E.P., Cox, D.R., 1964. An analysis of transformations. Journal of the Royal Statistics Society 26 (3), 211–243.

Bröcker, J., 1989. Partial equilibrium theory of lnter-regional trade and the gravity model. U Papers of the Regional Science Association 66, 7–18.

Celik, H.M., Guldmann J.M., 2002. Spatial Interaction Modeling of Interregional Commodity Flows, presented at the 42nd European Congress of the Regional Science Association, Dortmund, Germany.

Chisholm, M., O'Sullivan, P., 1973. Freight Flows and Spatial Aspects of the British Economy. Cambridge University Press, New York and London.

Dougherty, M., 1995. A review of neural networks applied to transport. Transportation Research Part C 3/4, 247–260.

Frankel, J.A., Wei, S.J., 1998. The role of history in bilateral trade flows. In: Frankel, J.A. (Ed.), The Regionalization of the World Economy. The University of Chicago Press, Chicago.

Fisher, M., Gopal, S., 1994. Artificial neural networks: a new approach to modeling interregional telecommunication flows. Journal of Regional Science 34/4, 503–527.

Fotheringham, A.S., O'Kelly, M.E., 1989. Spatial Interaction Models: Formulation and Applications. Kluwer Academic Publishers, Dordrecht/Boston/London.

Fotheringham, A.S., 1983. A new set of spatial-interaction models: the theory of competing destinations. Environment and Planning A 15, 15–36.

Guldmann, J.M., 1999. Competing Destinations and Intervening Opportunities Interaction Models of Inter-City Telecommunication Flows. Papers in Regional Science 78, 179–194.

Hagan, M.T., Demuth, H.B., Beale, M.H., 1996. Neural Network Design. Plus Publishing Co., Boston, MA.

Isard, W., 1951. Inter-regional and regional input–output analysis: a model of space economy. The Review of Economics and Statistics 33 (4), 157–169.

Krugman, P., 1980. Scale economies, product differentiation, and the pattern of trade. American Economic Review 70 (5), 950–959.

Mozolin, M., Thill, J.C., Usery, E.L., 2000. Trip distribution forecasting with multilayer perceptron neural networks: a critical evaluation. Transportation Research Part B 34, 53–73.

Munakata, T., 1998. Fundamentals of the New Artificial Intelligence: Beyond Traditional Paradigms. Springer, New York, NY.

Reed, W.E., 1967, Areal Interaction in India, Duke University Research Papers. Chicago, Illinois.

Samuelson, P.A., 1952. Spatial price equilibrium arid linear programming. American Economic Review 42, 67–93.

Data sources

Commodity Flow Survey, 1993 on CD-ROM CD-CFS-93-1, US Department of Commerce, Bureau of the Census, Washington, DC.

County Business Patterns, 1992–1993 on CD-ROM, US Department of Commerce, Bureau of the Census, Washington, DC.

Economic Census, Census of Manufacturing, 1992 on CD-ROM CD-EC92-1i, US Department of Commerce, Bureau of the Census, Washington, DC.

Annual State Personal Income Database, US Department of Commerce, the Bureau of Economic Analysis, Washington, DC. Available from <www.bea.doc.gov/bea/regional/spi>.