SHORT TERM DEMAND FORECASTING FOR A TYPICAL LOGISTICS SERVICE PROVIDER

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Abstract

Short-term demand forecasting is important for logistics service providers. Not only can it help making efficient resource plans, but also it can facilitate establishing better marketing strategies. The purpose of our work is to find feasible approach to forecast short-term demand for a Less-than-truckload (LTL) carrier. Through the comparison of possible forecasting methods, a benchmark linear time series method ARIMA is employed based on a revised "automatic model searching" strategy. Considering its capacity of nonlinear approximation, neural network (NN) is then used for the performance comparison. It is shown that NN built on data-deseasonalization and -detrending exhibits the most satisfactory performance in out-of-sample testing. Obviously the result facilitates practical application of service demand forecasting in LTL industry.

Key words: Demand Forecasting, Logistic Service, Time Series Forecasting, Neural Network, ARIMA

1. Introduction

Less-than-truckload (LTL) trucking company is an indispensable component of road transport industry. Generally it provides not only LTL service but also truckload (TL) service. LTL freight is contrasted with TL freight in which a shipper rents the entire cube space of a trailer. In LTL freight where a shipment normally ranges between 50 and 4500 kg (Powell and Sheffi, 1983), a shipper rents a portion of a trailer's space, along with other shippers (Kenneth, 1994).

Short-term demand forecasting is significant for a LTL service provider. Not only can it facilitate effective resource allocation but also establishing better marketing strategies. Practically schedulers estimate the service demand using their own manual experiences which often contain errors. The objective of this paper is to exploit service demand forecasting for a LTL trucking company. In the paper, sample data are provided by company "Schmidt Transport" locating in Ruhr industrial area of Germany, and this company is one of the largest-size partners in a national logistics network "CargoLine"which is constituted of 43 members and operates over 2395 tractors and 3168 trailers.

2. Selection of forecasting methods

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Time series forecasting and regression analysis are two important short-term forecasting methods. In regression modeling, we must find explanatory variables which have theoretical relationships with forecasted output (Babcock, et al., 1999).

For national TL trucking industry, their service demand reflects national economic conditions to a large extent, thus some published national macroeconomic indexes can be selected as explanatory indicators (Fite, et al., 2002). However, LTL service providers mainly serve regional clients, and the regional demand and supply can not represent national economic activities completely. So it may have no obvious correlation between the macroeconomic indexes and demand of LTL service providers. The viewpoint has been certified for the case investigated using correlation analysis (Zhou, et al., 2005). Considering the aim at short-term prediction, here time series forecasting method is adopted.

AutoRegressive Integrated Moving Average (ARIMA) is a flexible and widely used time series method. It has been successfully applied in traffic flow forecasting (Williams, 2003), also as a promising way for modelling different kinds of service demand (Bianchi et al. 1998; Babcock, et al., 1999). Similarly, NN with the capacity of nonlinear approximation also aroused plenty of practices in forecasting and pattern recognition. Burger et al. (2001) have demonstrated that it leads to better results for tourism demand forecasting comparing with traditional statistical approaches. These work motivated us to explore the feasibility of ARIMA and NN for the logistics demand forecasting.

3. Time series forecasting: ARIMA

Seasonal ARIMA (p, d, q) (P, D, Q) (Brockwell and Davis, 1996) has the form:

$$\phi(B)\Phi(B^s)\Delta^d\Delta_s^D Y_t = \theta(B)\Theta(B^s)e_t \tag{1}$$

Where Y_t = a time series; B= backshift operator defined by $B^a Y_t = Y_{t-a}$; s is periodicity of time series Y_t ; e_t is white noise process; Nonseasonal differencing operator: $\Delta^d = (1-B)^d$; Seasonal differencing operator: $\Delta_s^D = (1-B^s)^D$; Nonseasonal operator: $\phi(B) = 1-\phi_1 B - \cdots - \phi_p B^p$; $\theta(B) = 1-\theta_1 B - \cdots - \theta_q B^q$; Seasonal operator: $\Phi(B^s) = 1-\Phi_1 B^s - \cdots - \Phi_P B^{Ps}$; $\Theta(B^s) = 1-\Theta_1 B^s - \cdots - \Theta_Q B^{Qs}$; The parameter p and P represent the nonseasonal and seasonal autoregressive polynomial order respectively; q and Q represent the nonseasonal and seasonal moving average polynomial order respectively; d represents the order of regular differencing, while D represents the order of seasonal differencing.

The Box and Jenkins methodology (Box and Jenkins 1976) is an approach to build ARIMA model from time series data. It has an iterative procedure involving (a) identification of a tentative model, (b) estimation of model parameters, (c) diagnostic checking, and (d) forecasting.

One important base model of seasonal ARIMA model is ARMA (p, q): $\phi(B)X_t = \theta(B)e_t$. It means that any stationary time series X_t can be combined of autoregressive part and moving average part respectively (Brockwell and Davis, 1996); that is:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \tag{2}$$

Empirically time series only with trends may be transformed into stationary one after 1 or 2 regular differencing; and some seasonal time series may also be transformed into stationary one after 1 seasonal differencing.

3.1 Automatic model searching

The iterative procedure (Box and Jenkins, 1976) requires visual examination of intermediate results and the model is eventually developed based on expert judgement of the analyst (Liu et al., 2001). Very often this process is hard to be implemented on account of many ambiguities and the model got may not be the optimal solution. In order to solve this problem from a practicer point of view, "automatic model searching" is suggested by Cho (2003) and Cortez (2004), which automatically models time plot for all candidates within a certain wide range and then uses a measure of model evaluation to find the fit model with minimal measure. Based on the conclusion from Box and Jenkins (1976), Cho (2003) sets the range of all parameters between 0 and 2. Nevertheless, it is easy to find in the literature that some "big" models of ARIMA are identified for practical time series (Badescu, 2001; Babcock, et al., 1999; Bianchi, et al., 1998; Contreras et al., 2003; Kim and Moosa, 2005). In order to ensure the applicability of "automatic model searching", the range of relevant parameters should be modified. According to our investigation from literature, it is proposed that p/q between 0 and 10 and P/Q between 0 and 5 while d/D still from 0 to 2, since an extreme large number of models found in the literature belong to this range. Now computation costs of searching an optimal model is increased vastly; table1 shows that number of modelling increases from 729 by Vicho to 39204 in the new range.

Model	SARIMA(p,d,q)(P,D,Q) (Vicho)	SARIMA(p,d,q)(P,D,Q)	ARMA(p,q)
Number of modeling	3^6=729	$11^2*6^2*3^2$=39204	11^2=121
Range	All 0~2	$p/q \in [0,10]$, $d/D \in [0, 2]$, $P/Q \in [0, 5]$	

Table 1: Number of modelling under different searching range.

To reduce computation time, a revised searching process with a unit of "differencing" is proposed by authors (see figure1).

In the unit of differencing, 1~2 regular differencing or/and 1 seasonal differencing can be used; However the total number of all differencing should be less than 3(Box and Jenkins, 1976). Thus all the combination of differencing (d, D) are (1, 0), (2, 0), (0, 1), (1, 1). Here to avoid uncertainties, the original time plot is processed under four possibilities respectively, which produces four new time series. Suppose all of them are stationary, the maximal number of modelling will be 4×121=484 according to figure 1. The calculation costs are still much less than 39204 times in the range of SARIMA model.

Modelling in the searching algorithm (figure 1) contains estimation and diagnostic checking of Box and Jenkins (1976). The two ranges for ARMA and SARIMA model are defined in table 1. Moreover the same as in Box and Jenkins (1976), some information theory statistic such as Akaike´s Information Criterion (AIC) or Bayesian Information Criterion (BIC) instead of least fitting error by Cho (2003) is used to select optimal model order. These statistics include a penalty about model complexity in order to avoid overfitting while only least fitting error may result in model overfitting.

The reasons why differencing is adopted are as follows: (1) some practical time series only exhibit trends; usually only 1 or 2 regular differencing can make these time plots stationary (Box and Jenkins, 1976). (2) Even for some seasonal time plots, only 1 seasonal differencing can also make them stationary (Babcock et al., 1999; Zhou et al., 2005). (3) Simply ARMA (p, q) model can be built for any stationary time series (Brockwell and Davis, 1996); the searching of optimal model in the range of ARMA (p, q) saves much time comparing with that of seasonal ARIMA (p,d,q)(P,D,Q).

Apparently the new "discriminative" searching process enhances the efficiency in automatic model identification. Besides, the characteristics of ACF can be applied to determine the stationarity of time plot, which are relatively easy to deal with.

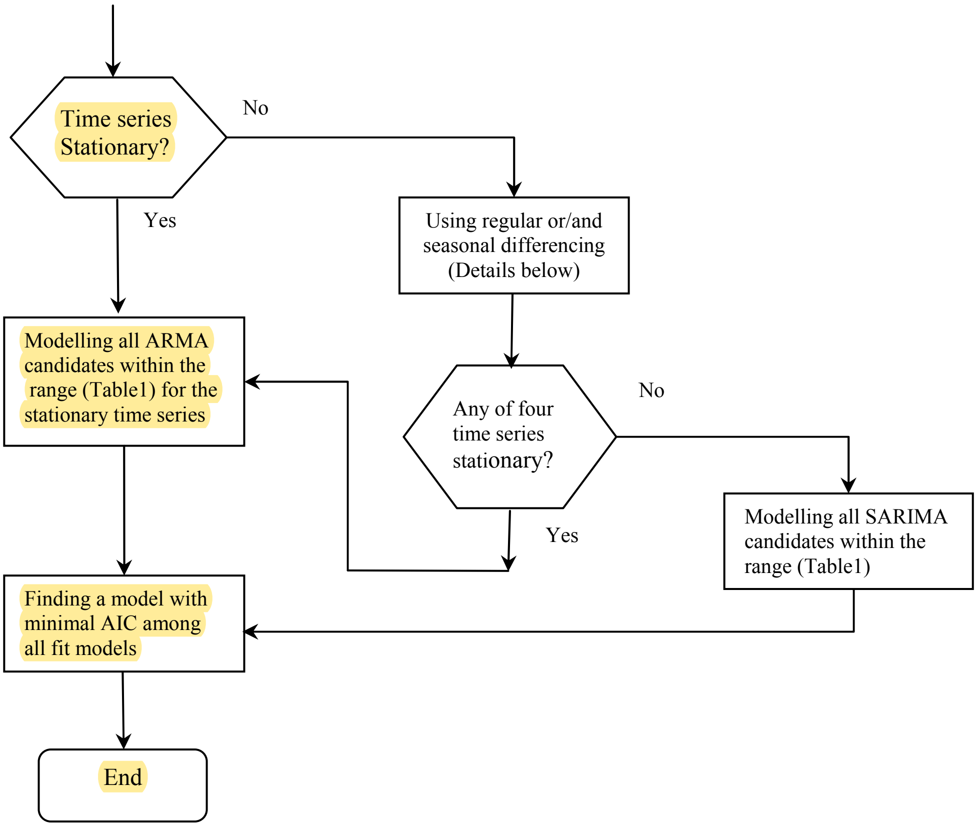

Figure 1: Revised automatic model searching

4. Time series forecasting: Neural Network

Sufficiently complex neural network is capable of approximating arbitrary function (Hornik et al., 1989). Empirically, it has been successfully adopted in different fields such as time series forecasting, and pattern recognition (Burger et al., 2001; Cho, 2003; Bansal et al., 1998).

Neural network (NN) is essentially a parameterized nonlinear model/ function that can be fitted to data for the purposes of prediction, classification, etc. The nonlinear model is mainly composed of many nonlinear elements called transfer functions. In neural network jargon, NN is constructed as "neurons" and "layers" (Nakamura, 2005). There are different kinds of network architecture. The most popular one for time series forecasting is the multi-layer feedforward neural network (MFNN).

The algorithms used to estimate NN are "training algorithms". Loosely speaking, the training algorithm is some kind of nonlinear optimization routine which iteratively adjusts the parameters of NN in the direction of the negative gradient of mean squared error (Nakamura, 2005). A standard training algorithm is levenberg-Marquardt algorithm which appears to be the fastest method for training moderate-sized feedforward neural network.

Up to now there are few practical guidelines for the identification of NN structure. Especially, how to define the number of input and hidden nodes is a key task in the NN time series forecasting. Usually the optimal architecture can be found based on performance comparison of some holdout data sets (Zhang et al., 2005). Generally data sets are divided into three parts as training sets, validation sets, and test sets which are used for model estimation, model selection, and performance evaluation respectively.

One of the problems that occur during neural network training is called overfitting. The error on the training set is driven to a very small value, but when new data is presented to the network the error is large. If the number of parameters in the network is much smaller than the total number of points in the training set, then there is little or no chance of overfitting. However, overfitting will be one crucial issue when the data is of a limited size. One method to improve network generalization is early stopping in which the training algorithm stops just when validation error begins to increase. To avoid local minima in the training, multiple random initial starts are preferred. Zhang and Qi (2005) conclude that data pre-processing measurements such as deseasonalization or/and detrending can improve forecasting performance for seasonal and trend time plots.

5. Simulation and results

The figure below shows the monthly transport demand of company Schmidt Transport from January 2000 to December 2004. To keep data confidentiality, here the unit of demand has been omitted. The plot reveals an upward trend from the 36th month to 60th month and a distinct seasonal pattern for which transport demand is relatively high in the third or fourth and tenth or eleventh month and relatively low in the eighth month. The total five-year data are divided into three parts: first four-year data for training, next six-month for validation and the last six-month data for testing. Note that ARIMA modeling doesn't need a separate validation set, therefore we use the first 54-month data for ARIMA identification and estimation.

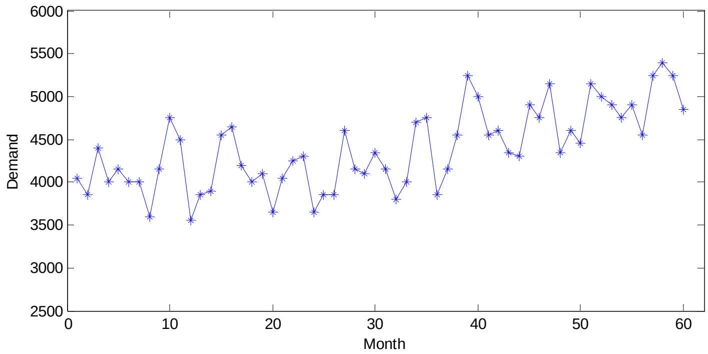

Figure 2: Original demand time series of five-year period

In the identification of ARIMA modelling, the original time plot $\{y_t\}$ is not stationary as the autocorrelation function of $\{y_t\}$ doesn't decrease quickly as t increases. Then four kinds of differencing are applied for $\{y_t\}$. According to the procedures of revised searching process, ARMA (5, 1) with 1 seasonal differencing is found to be the optimal model as it has minimal AIC among all fit models. When we check autocorrelation functions (ACF) and partial autocorrelation functions (PACF) of the series $x_t (x_t = y_t - y_{t-12})$, we can not find distinct characteristics of ARMA (5, 1) according to the identification measures by Box and Jenkins (1976). The model ARMA (5, 1) is:

$$x_t = 53.4364 + 0.2328\, x_{t-1} + 0.0063 x_{t-2} + 0.0810 x_{t-3} + 0.2261 x_{t-4} + 0.1600 x_{t-5} - 0.2102 e_{t-1} + e_t \qquad (3)$$

After introducing $x_t = y_t - y_{t-12}$ to equation (3), we get the forecasting model for monthly transport demand forecasting:

$$y_t = y_{t-12} + 53.4364 + 0.2328(y_{t-1} - y_{t-13}) + 0.0063(y_{t-2} - y_{t-14}) + 0.0810(y_{t-3} - y_{t-15}) + 0.2261(y_{t-4} - y_{t-16})$$
$$0.1600(y_{t-5} - y_{t-17}) - 0.2102e_{t-1} \quad (4)$$

NN architecture adopted is a three-layer MFNN. To find the suitable network structure, we use validation sets for the model evaluation and selection. Here deseasonalization and detrending are adopted for the performance comparison. The number of input nodes or the lagged observations used in the NN is often a more important factor than the number of hidden nodes for time series forecasting (Zhang, et al., 1998). The hidden nodes in our experiment vary from 1 to 14. For the deseasonalized series, the input nodes vary from 1 to 6; for the original data, we use 8 lag numbers: 1-4, 12-14, and 24. Levenberg-Marquardt algorithm is employed for the training. The early stopping is implemented to avoid the overfitting in small-size sample modeling. Considering the counteracting effect between overfitting and "oversaturation" from multiple random initial starts, here we initialize network 10 times randomly. The maximum training epochs are 1000. Furthermore mean absolute percentage error (MAPE) is considered for the performance comparison.

Table 2 records final NN structure used for different data type. The NN model based on original data needs 2 lag numbers as inputs (lag1,lag2), while NN model based on deseasonalization and detrending needs 6 lag numbers(lag1~lag6). Table 3 shows the performance of NN and ARIMA approaches under each sample sets. There is no obvious overfitting for both NN models as the error of validation set of both models is smaller or slightly bigger than that of training set (Table 3). ARIMA model has 5.6% MAPE in testing set; NN model with original data has bigger error (13.1%) in testing set; however, NN model with deseasonalization and detrending (called NN-dsdt) has the smallest testing error (4.0%).

It is concluded that

1) Between two NN models, NN model after deseasonalization and detrending is more suitable on account of its remarkably better forecasting precision;
2) Between ARIMA and NN-dsdt, NN-dsdt needs relatively longer modelling time. Nevertheless it exhibits relatively better forecast results with much less input numbers, both of which ensure lower costs of forecasting. Here NN with deseasonalization and detrending is considered as the suitable solution in the case study.

Data type	Lag number	Hidden number
Original	2	12
Deseasonalization + Detrending	6	14

Table 2: Best NN models under original, deseasonalization + detrending datasets

* Error means relative error which equals to (actual-forecast)/forecast*100.

Month	Actual	ARIMA			NN			NN-dsdt		
		Forecast	Error*	MAPE	Forecast	Error*	MAPE	Forecast	Error*	MAPE
1.	4050.0	0	_		0	_		0	_	
2.	3850.0	0	_		0	_		0	_	
3.	4400.0	0	_		4384.2	-0.4		0	_	
4.	4000.0	0	_		4550.6	13.8		0	_	
5.	4150.0	0	_		4099.6	-1.2		0	_	
6.	4000.0	0	_		4052.7	1.3		0	_	
7.	4010.0	0	_		4134.5	3.1		4072.1	1.5	
8.	3600.0	0	_		4052.7	12.6		3641.8	1.2	
9.	4150.0	0	_		4028.2	-2.9		4123.4	-0.6	
10.	4750.0	0	_		4550.6	-4.2		4696.7	-1.1	
11.	4500.0	0	_		4550.6	1.1		4538.2	0.8	
12.	3550.0	0	_		4099.6	15.5		3456.2	-2.6	
13.	3850.0	0	_		3923.8	1.9		3867.7	0.5	
14.	3890.0	0	_		4440.4	14.2		3871.8	-0.5	
15.	4550.0	0	_		4052.7	-10.9		4639.9	2.0	
16.	4650.0	0	_		4550.6	-2.1		4566.6	-1.8	
17.	4200.0	0	_		4052.7	-3.5		4146.1	-1.3	
18.	4000.0	4058.4	1.5		4099.6	2.5		3950.7	-1.2	
19.	4100.0	4144.4	1.1		4134.5	0.8		3979.0	-3.0	
20.	3650.0	3840.1	5.2		4052.7	11.0		3561.0	-2.4	
21.	4050.0	4291.0	6.0		4028.2	-0.5		4032.9	-0.4	
22.	4250.0	4745.1	11.6		4440.4	4.5		4265.6	0.4	
23.	4300.0	4356.7	1.3		4310.8	0.3		4425.5	2.9	
24.	3650.0	3559.4	-2.4		4052.7	11.03		3712.0	1.7	
25.	3850.0	3889.4	1.0		4028.2	4.6		3794.0	-1.5	
26.	3860.0	3790.5	-1.8		4310.8	11.7		3863.4	0.1	
27.	4600.0	4493.9	-2.3		4052.7	-11.9		4503.6	-2.1	
28.	4150.0	4727.8	13.9		4550.6	9.7		4209.0	1.4	
29.	4100.0	4029.5	-1.7		4099.6	-0.1		4104.7	0.1	
30.	4350.0	4039.1	-7.2		4637.7	6.6		4335.7	-0.3	
31.	4150.0	4265.6	2.8		4310.8	3.9		4098.7	-1.2	
32.	3800.0	3579.8	-5.8		4134.5	8.8		3837.7	1.0	
33.	4000.0	4110.7	2.7		4099.6	2.5		4261.0	6.5	
34.	4700.0	4336.7	-7.7		4310.8	-8.3		4685.7	-0.3	
35.	4750.0	4613.7	-2.9		4550.6	-4.2		4833.6	1.8	
36.	3850.0	3877.6	1.0		4052.7	5.3		3949.4	2.6	
37.	4150.0	3996.2	-3.7		3923.8	-5.5		4109.5	-1.0	
38.	4550.0	4147.1	-8.9		4310.8	-5.3		4536.0	-0.3	
39.	5250.0	5090.6	-3.0		4440.4	-15.4		5209.9	-0.7	
40.	5000.0	4534.2	-9.3		4550.6	-9.0		4970.5	-0.6	
41.	4550.0	4609.1	1.3		4134.5	-9.1		4537.7	-0.3	
42.	4600.0	4757.8	3.4		4099.6	-10.9		4554.5	-1.0	
43.	4350.0	4557.5	4.7		4052.7	-6.8		4477.7	2.9	
44.	4300.0	4190.6	-2.5		4099.6	-4.7		4285.1	-0.3	
45.	4900.0	4452.1	-9.1		4637.7	-5.4		4910.4	0.2	
46.	4750.0	5205.5	9.6		4550.6	-4.2		4738.3	-0.3	
47.	5150.0	4850.9	-5.8		5045.9	-2.0		5056.8	-1.8	
48.	4350.0	4277.7	-1.7		4440.4	2.1	Training set: 6.0	4447.7	2.3	Training set: 1.3
49.	4600.0	4625.1	1.0		4409.6	-4.1		4674.1	1.6	
50.	4450.0	4893.8	10.0		4310.8	-3.1		4491.8	0.9	
51.	5150.0	5328.7	3.5		5045.9	-2.0		5135.2	-0.3	
52.	5000.0	5205.5	4.1		4550.6	-9.0		4970.3	-0.6	
53.	4900.0	4733.3	-3.4		5045.9	3.0		4779.8	-2.5	
54.	4750.0	4811.2	1.3	Training set: 4.5	4637.7	-2.4	Validati-on set: 3.9	4964.9	4.5	Validatio-on set: 1.7
55.	4900.0	4402.0	-10.2		5045.9	3.0		4646.3	-5.2	
56.	4550.0	4599.4	1.1		4052.7	-10.9		4619.3	1.5	
57.	5250.0	5096.0	-2.9		4099.6	-21.9		5259.2	0.2	
58.	5400.0	5053.3	-6.4		4550.6	-15.7		4745.6	-12.1	
59.	5250.0	5598.5	6.6		4052.7	-22.8		5188.6	-1.2	
60.	4850.0	4530.5	-6.6	Testing set: 5.6	5045.9	4.0	Testing set: 13.1	4663.3	-3.8	Testing set: 4.0

Table 3: Model outputs using ARIMA, NN and NN-dsdt respectively.

6. Conclusion

The paper focuses on short term demand forecasting for a LTL carrier. Firstly multiply regression approach is not adopted considering not identifying suitable relevant influencing factors. Among time series forecasting methods, ARIMA and NN are selected mainly on account of their feasibility and applicability. In order to simplify the searching for optimal order of ARIMA model, so called “automatic modelling searching” is employed after revision. Based on the collected data, it is found that NN with data preprocessing measures exhibit the most satisfactory performance in out-of-sample testing. The results facilitate the final decision of forecasting approach selection in practice.

It is noticed that the results got is based on the data collected. Therefore one of tasks ahead of us is to verify forecast approaches under different period; also some “naive” forecast approaches （e.g. smoothing method） will be applied and further compared with the results got up to now.

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5. Biography

Ling Zhou studied control engineering at the Hohai University in China. Since 2003, she is a PhD candidate in the NRW graduate school of production and logistics at Dortmund University. Her research interests include demand forecasting in transport and logistics, application of soft computing approaches, etc.

Dr. Bernhard Heimann is deputy head of Institute of Transport and Logistics at Dortmund University. His interests mainly contain modeling and optimization of logistics system; up to now he has been involved in industry consulting projects for many international logistics companies.

Prof. Uwe Clausen is head of Institute of Transport and Logistics at Dortmund University and also director of Fraunhofer Institute of Material Flow and Logistics in Dortmund. He was manager in international parcel division of Deutsche Post and then European Operations Director at Amazon.com before 2001. His research interests include transportation network optimization and modelling of freight traffic etc.