Prediction of a service demand using combined forecasting approach

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Abstract. Forecasting facilitates cutting down operational and management costs while ensuring service level for a logistics service provider. Our case study here is to investigate how to forecast short-term logistic demand for a LTL carrier. Combined approach depends on several forecasting methods simultaneously, instead of a single method. It can offset the weakness of a forecasting method with the strength of another, which could improve the precision performance of prediction. Main issues of combined forecast modeling are how to select methods for combination, and how to find out weight coefficients among methods. The principles of method selection include that each method should apply to the problem of forecasting itself, also methods should differ in categorical feature as much as possible. Based on these principles, exponential smoothing, ARIMA and Neural Network are chosen to form the combined approach. Besides, least square technique is employed to settle the optimal weight coefficients among forecasting methods. Simulation results show the advantage of combined approach over the three single methods. The work done in the paper helps manager to select prediction method in practice.

1. Introduction
Short-term demand forecasting is significant for a logistic service provider. Not only can it facilitate effective resource allocation but also establish better marketing strategies. Practically service demand is estimated by schedulers based on their own 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 Method
Broadly, there are two categories of forecasting methods: combined approach versus single one. Inconsistency among different forecasts gives rise to a thought of combining forecasts of different technology [1]. Combined approach depends on several forecasting methods simultaneously, instead of a single method. It can offset the weakness of a forecasting method with the strength of another, which could improve the precision performance of prediction [2]. Therefore rather than to try to select a method which is the most appropriate, it may be better to try to combine the forecasts obtained by different methods. Up to now combined forecasting has been applied for various applications [3], [2]. Considering a relatively high demand on prediction precision in logistic industry, here combined approach will be considered.

3. Combined Forecasting Approach
During a combined prediction, each component of method provides different ways of useful information for the whole prediction. Main issues during combined forecast modeling are how to select methods for combination, and how to find out weight coefficients among methods.
3.1. Selection of Method
The principles of method selection include that each method should apply to the problem of forecasting itself, also methods should differ in categorical feature and underlying concept as much as possible [1].

Generally forecasting approaches can be grouped into quantitative approach vs. qualitative one, while quantitative approach further consists of time series method, regression[4], and intelligent methods such as Neural Network[5] [6] etc. Here only quantitative approach will be considered as qualitative one replies on subjective human judgment and doesn’t be suitable for short-term forecasting as well [4].

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 [7]. 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 [8]. However, LTL service providers mainly serve regional clients, and the regional demand and supply cannot 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 [9]. Hence time series approaches instead of regression one will be taken into account.

Time series forecasts are those which are the result of extrapolating past data into the future [4]. There are two benchmark linear time series approaches --- single exponential smoothing and ARIMA [10]. Single exponential smoothing is a naive method in time series prediction, which involves weighting past data with weights that decrease exponentially with time [4]. It is often considered a simple and practical forecasting technique, since adaptations of the model can be made to account for changing conditions. Autoregressive Integrated Moving Average (ARIMA) is a flexible and efficient time series method with a solid basis of statistical theory. For all practical purposes, Box-Jenkins methodology can fit an ARIMA/ARMA model to all kinds of data patterns [11]. With automatic computer-based procedures, the usefulness of ARIMA method has been increased remarkably. Up to now, it has achieved a wide level of acceptance in many forecasting situations [12], [13].

Moreover intelligent approach is also a means to build short-term forecasting model. Among various intelligent tools, Neural Network excels at nonlinear approximation and self-adaptation in the process of prediction [14], [15].

Summarily, based on the two principles of suitability and differentation during selecting methods, exponential smoothing, ARIMA and Neural Network are chosen to form a combined approach.

3.2. Determination of Weight Coefficients
The second issue of combined forecasting is to find out weight coefficients among methods. Generally, least square technique can be used to fix the optimal weight coefficients among forecasting methods, where the objective function is minimal of the sum of forecasting error at all relevant periods [1]. Then combined approach is implemented based on the optimal weight vector. In fact, optimal weight coefficients decide the extent of which each method influences the output of overall forecast.

4. Simulation and Results
The figure below shows the monthly transport demand of company Schmidt Transport from January 2006 to December 2010. 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. Validation sets is specifically used for the evaluation and selection of NN model; while ARIMA and exponential smoothing don’t need a separate validation set, we use the first 54-month data for their identification and estimation; obviously the identification of combined model relates to the testing set of the original data.

In order to determine the value of adjustable parameter $a$ [9] in the single exponential smoothing model, we use grid search which increases $a$ with a step 0.1 in the range [0, 1] and then find the optimal value of $a$ based on that the model with this $a$ have the minimal error for training sets. Here the optimal value of $a$ is 0.7.

Revised automatic model searching is used to identify ARIMA model; the ARIMA model (as in equation 1) has been found as the optimal one for the sample data.

$$y_t = y_{t-12} + 53.4364 + 0.2328(y_{t-1} - y_{t-12}) + 0.0063(y_{t-2} - y_{t-14}) + 0.0810(y_{t-3} - y_{t-16}) + 0.2261(y_{t-4} - y_{t-18}) + 0.1600(y_{t-5} - y_{t-20}) - 0.2102 y_{t-36},$$  

(1)

Neural Network’s architecture adopted is a three-layer MFNN. Here deseasonalization and detrending are adopted for the performance improvement [16]. 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 [17]. The hidden nodes in the 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 [14]. The maximum training epochs are 1000. Furthermore mean absolute percentage error (MAPE) is considered for the performance comparison. Table 1 records the optimal NN structure which has 6 lag numbers (lag1–lag6) of input and has 14 hidden number.

| Data type                   | Lag number | Hidden number |
|-----------------------------|------------|---------------|
| Deseasonalization + Detrending | 6          | 14            |

Table 2 shows the performance of combined forecasting, NN, ARIMA and exponential smoothing under each sample sets. ARIMA model has 4.5% (MAPE) in training sets while 5.6% (MAPE) in testing set; correspondingly Exponential smoothing has an error of 7.5% in training sets while 6.0% in testing sets; NN model has a testing error of 4.5%, with training error 1.4% and validation error 1.8%. Comparatively, combined forecasting has the smallest testing error (4.1%).

![Figure 1. Original demand time series of five-year period](image-url)
| Month | Actual | NN Forecast | ARIMA Forecast | Exponential Smoothing Forecast | Combinational Forecast |
|-------|--------|-------------|----------------|-------------------------------|-----------------------|
| 1.    | 4050.0 | 0           | 0              | 0                             | 0                     |
| 2.    | 3850.0 | 0           | 0              | 0                             | 0                     |
| 3.    | 4400.0 | 0           | 0              | 0                             | 0                     |
| 4.    | 4000.0 | 0           | 0              | 0                             | 0                     |
| 5.    | 4150.0 | 0           | 0              | 0                             | 0                     |
| 6.    | 4000.0 | 0           | 0              | 0                             | 0                     |
| 7.    | 4010.0 | 0           | 0              | 0                             | 0                     |
| 8.    | 3600.0 | 0           | 0              | 0                             | 0                     |
| 9.    | 4150.0 | 0           | 0              | 0                             | 0                     |
| 10.   | 4750.0 | 0           | 0              | 0                             | 0                     |
| 11.   | 4500.0 | 0           | 0              | 0                             | 0                     |
| 12.   | 3550.0 | 0           | 0              | 0                             | 0                     |
| 13.   | 3850.0 | 0           | 0              | 0                             | 0                     |
| 14.   | 3890.0 | 0           | 0              | 0                             | 0                     |
| 15.   | 4550.0 | 0           | 0              | 0                             | 0                     |
| 16.   | 4650.0 | 0           | 0              | 0                             | 0                     |
| 17.   | 4200.0 | 0           | 0              | 0                             | 0                     |
| 18.   | 4000.0 | 0           | 0              | 0                             | 0                     |
| 19.   | 4100.0 | 0           | 0              | 0                             | 0                     |
| 20.   | 3650.0 | 0           | 0              | 0                             | 0                     |
| 21.   | 4090.0 | 0           | 0              | 0                             | 0                     |
| 22.   | 4250.0 | 0           | 0              | 0                             | 0                     |
| 23.   | 4300.0 | 0           | 0              | 0                             | 0                     |
| 24.   | 3850.0 | 0           | 0              | 0                             | 0                     |
| 25.   | 3860.0 | 0           | 0              | 0                             | 0                     |
| 26.   | 4600.0 | 0           | 0              | 0                             | 0                     |
| 27.   | 4150.0 | 0           | 0              | 0                             | 0                     |
| 28.   | 4000.0 | 0           | 0              | 0                             | 0                     |
| 29.   | 4350.0 | 0           | 0              | 0                             | 0                     |
| 30.   | 4150.0 | 0           | 0              | 0                             | 0                     |
| 31.   | 3850.0 | 0           | 0              | 0                             | 0                     |
| 32.   | 3800.0 | 0           | 0              | 0                             | 0                     |
| 33.   | 4000.0 | 0           | 0              | 0                             | 0                     |
| 34.   | 4000.0 | 0           | 0              | 0                             | 0                     |
| 35.   | 4750.0 | 0           | 0              | 0                             | 0                     |
| 36.   | 4500.0 | 0           | 0              | 0                             | 0                     |
| 37.   | 4150.0 | 0           | 0              | 0                             | 0                     |
| 38.   | 4550.0 | 0           | 0              | 0                             | 0                     |
| 39.   | 5250.0 | 0           | 0              | 0                             | 0                     |
| 40.   | 5000.0 | 0           | 0              | 0                             | 0                     |
| 41.   | 4550.0 | 0           | 0              | 0                             | 0                     |
| 42.   | 4600.0 | 0           | 0              | 0                             | 0                     |
| 43.   | 4350.0 | 0           | 0              | 0                             | 0                     |
| 44.   | 4300.0 | 0           | 0              | 0                             | 0                     |
| 45.   | 4900.0 | 0           | 0              | 0                             | 0                     |
| 46.   | 4750.0 | 0           | 0              | 0                             | 0                     |
| 47.   | 5150.0 | 0           | 0              | 0                             | 0                     |
| 48.   | 4350.0 | 0           | 0              | 0                             | 0                     |
| 49.   | 4600.0 | 0           | 0              | 0                             | 0                     |
| 50.   | 4650.0 | 0           | 0              | 0                             | 0                     |
| 51.   | 4550.0 | 0           | 0              | 0                             | 0                     |
| 52.   | 5000.0 | 0           | 0              | 0                             | 0                     |
| 53.   | 4900.0 | 0           | 0              | 0                             | 0                     |
| 54.   | 4750.0 | 0           | 0              | 0                             | 0                     |
| 55.   | 4900.0 | 0           | 0              | 0                             | 0                     |
| 56.   | 4550.0 | 0           | 0              | 0                             | 0                     |
| 57.   | 5250.0 | 0           | 0              | 0                             | 0                     |
| 58.   | 5400.0 | 0           | 0              | 0                             | 0                     |
| 59.   | 5250.0 | 0           | 0              | 0                             | 0                     |
| 60.   | 4850.0 | 0           | 0              | 0                             | 0                     |

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

It is concluded that:
- Combined modeling has the best forecasting performance in testing sets; while exponential smoothing/ARIMA the worst and NN somewhere between.
Among NN, exponential smoothing and ARIMA, NN needs longest modeling time while it exhibits the relatively better forecast results; nevertheless exponential smoothing needs probably the shortest modeling time while shows the weakest precision; and ARIMA is somewhere between NN and exponential smoothing.

- Obviously combined modeling needs even a bit longer modeling time than NN, however it shows an outstanding performance in prediction.
- Forecasting facilitates the operation and management in logistics companies. Accurate forecasts can save operational and management costs which accounts for the large part of whole costs. Considering the importance of forecasting precision, combined forecasting is regarded as the best choice for the case studied.

5. 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, combined modeling is selected mainly on account of its feasibility and applicability. And the forecasting performance of combined model is further compared with three benchmark time series method --- ARIMA, exponential smoothing and NN. It is found that combined forecasting exhibit the most satisfactory performance in out-of-sample testing.

Obviously the results got will facilitate the final decision of forecasting approach selection for the logistic manager in practice.

6. References
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