# Forecasting Short Term Trucking Rates

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**Summary:** This study develops a forecasting model that predicts both contract and spot rates for truckload transportation on individual lanes for the next seven days. This study considers several input variables, including lagged values of spot and contract rates, rates on adjacent routes and volumes. This study uses a neural network based on Nonlinear Autoregressive Models with eXogenous input (NARX) models. Traditional time series models, including autoregressive integrated moving average (ARIMA), are also used and results from different models are compared. Results show that the NAR model provides better short-term forecasting performance for spot rates than the ARIMA model.

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## KEY INSIGHTS

1. The model's prediction of contract rates is much more accurate and has much less forecasting variability than spot rates. A high forecasting accuracy can be achieved for contract rates either using NARX or ARIMA models. However, spot rates are difficult to forecast due to high variability.
2. Neural network has better short-term forecasting performance than ARIMA for spot rates (6% lower RMSE).
3. There exists no short-term information transmission between spot and contract rates.

## Introduction

Transportation costs constitute an important part of total logistics costs and have a dramatic impact on all kinds of decisions across the supply chain. Accurate estimation of transportation costs can help shippers make better decisions when planning transportation budgets and can help carriers estimate future cash flows.

The objective of this study is to develop a forecasting model that predicts both contract and spot rates for truckload transportation on individual lanes for the next seven days. Shippers can cover their freight transportation requirements by two types of services: through long-term contracts or on the spot market. Shippers in most cases use contract carriers to haul their truckload products. The contract is typically a one-year commitment, which consists of origin/destination, service requirement, volume and any other factors that affect the price. On occasions when the contract rate fails, when a tender is not accepted, the lane/rate does not exist in the route guide or there is a surge in freight volume not covered sufficiently under the long-term contracts, the shipper needs to go to the spot market to obtain a rate. The rate is decided based on the market condition at the time of the transaction.

This study considers several input variables, including lagged values of spot and contract rates,

rates on adjacent routes and volumes. The architectural approach to short-term forecasting is a neural network based on Nonlinear Autoregressive Models with eXogenous input (NARX) models. NARX models are powerful when modelling complex, nonlinear and dynamic systems, especially time series. Traditional time series models, including autoregressive integrated moving average (ARIMA), are also used and results from different models are compared. This study uses one high-volume lane as a sample lane for forecasts. However, the same methodology can be applied to all different lanes.

## Methodology

In this study, different models are proposed to forecast both contract and spot rates, specifically neural networks and traditional time series models.
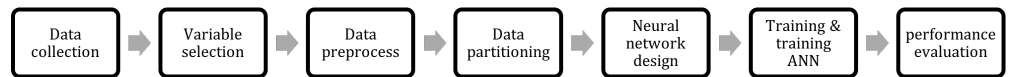
Initially, univariate Autoregressive integrated moving average (ARIMA) and Nonlinear autoregressive (NAR) neural network models are used to forecast both TL contract and spot market rates. Then, new variables are added (including volume and rates on adjacent trading routes), Nonlinear autoregressive with exogenous inputs (NARX) neural network models are used. The forecasting performance of each model will be compared and the best predictive model will be selected.

*Nonlinear autoregressive (NAR) and Nonlinear autoregressive with exogenous inputs (NARX) models*

NAR and NARX models are capable of modelling complex, dynamic and nonlinear real-word time series data, thus providing a powerful tool for time series analysis and predictions. The NAR model is constructed to predict the value of an observation $y_i$ based on the past observations of $y$. The function can be expressed as:

$$y(t + 1) = f\big[y(t), \dots y\big(t - d_y + 1\big)\big],$$

where $y(t)$ represents output of network at discrete time $t$. $d_y \geq 1$ is the memory delay. $d_y$ defines how far back past values will be included in the model.

The NARX model builds upon NAR model and further incorporates past values of exogenous variables. the function is defined as

$$y(t + 1) = f\big[y(t), \dots y\big(t - d_y + 1\big); u(t), u(t - 1), \dots u(t - d_u + 1)\big],$$

where $u(t)$ and $y(t)$ represent input and output of network at discrete time $t$. $d_u \geq 1$, $d_y \geq 1$ and $d_u \leq d_y$ are memory delays.

The nonlinear mapping $f(\cdot)$ can be approximated by a standard back-propagation algorithm. Then, the resulting connected architecture is called NARX network.

*Process to build an ANN*

A proper process has to be followed to build an ANN model. This study follows the procedures as listed out in Figure 1.

Figure 1: ANN model process flow

Data collection → Variable selection → Data preprocess → Data partitioning → Neural network design → Training & training ANN → performance evaluation

***Data collection***: The dataset used in this paper contains the daily contract and spot cost per mile (CPM), and volume information for each origin region to destination region over a one-year period (1 Apr 2016 to 31 Mar 2017), obtained from Chainalytics. Specifically, contract and spot dry van rates on one region to region corridor (Georgia Central (GA_C) to Florida Central (FL_C)) are used as an empirical example for forecasting. Figure 2 plots the spot and contract rates for this route. Contract rates are very stable, while spot rates are more volatile and fluctuates around contract rates.

Figure 2: GA_C|FL_C daily spot vs contract CPM
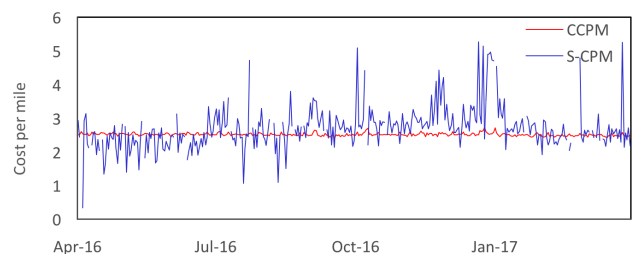


***Variable selection***: The primary rule for variable selection is that input variables shall be as predictive as possible. To select the appropriate variables and the number of delays (lags), the autocorrelation coefficient of output variables and

the cross-correlation coefficient of input and output variables are calculated.

Using the past knowledge of the trucking industry, a few variables are identified as the potential candidates to be included in the forecasting model:

- The past values of contract/spot rates to account for autocorrelation of the time series;
- The past values of spot rates for contract rates forecasting and vice versa, to account for interactions between spot and contract rates;
- The past values of contract/spot rates on adjacent routes to account for the interaction of rates between adjacent routes, and regional supply/demand dynamics. Specifically, in this case, all routes with origin GA_C are selected and then the routes adjacent to GA_C to FL_C are chosen as candidates. Here, routes from GA_C to FL_N (Florida north), FL_S (Florida south) and SC_C (South Carolina south) are selected as potential candidates.

Based on the autocorrelation and cross-correlation analysis, the potential input variables are further refined. For contract rate forecasting, the potential variables include the lagged values of contract rates, spot rates, contract rates for GA_C to FL_S and volumes. On the other hand, the potential variables for spot rates include lagged values of spot rates and contract rates.

**Data pre-processing:** The input and target values are normalized to keep them within the interval [-1,1]. This help to simplify the problem of potential outliers for the network.

**Data Partitioning:** The data is split into training, validation and testing data, with a spilt ratio of 70:15:15 based on time sequence.

**Neural Network design:** The neural network uses NAR and NARX architecture as described above.

**Training and testing ANN:** During training, the real values of $y(t)$ are used as the input for the feed forward network, instead of the estimated ones. During testing, the predicted outputs in this network are fed back to the input of the feedforward neural network.

**Performance evaluation:** The metrics used to evaluate performance are the Mean Squared Error (MSE) for model selection and Root Mean Squared Error (RMSE) for model comparison.

*ARIMA models*

Autoregressive integrated moving average (ARIMA) model is a common and popular tool to model time series. The model uses past values of a univariate time series to analyse the trend and forecast future cycles. An ARMA$(p, q)$ process for a stationary series $Y_t$ can be defined as:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + a_t + \theta_1 a_{t-1} + \cdots + \theta_q a_{t-q}$$

where $a_t$ is a white noise.

**Results and Discussions**

The RMSE results for the best NAR and ARIMA models for both spot and contract rates is shown in Table 1. RMSEs for the testing set (which includes 53 day forecasts) and for 7-days rolling forecasting have been calculated.

For spot rates, the best NAR(X) model is NAR model with seven days feedback delay. The best ARIMA model is ARIMA (6,0,2). Adding additional information, such as past values of contract rates and volumes, does not improve the model's performance. All these results indicate that spot rates contain high levels of noise, and the resulting neural network is unstable.

Table 1: RMSE comparisons between NAR and ARIMA models

| Rate type | Model type | Best model | RMSE for testing set (53 days) | RMSE for 7 days (rolling forecast) |
|---|---|---|---|---|
| Spot | NAR(X) | NAR with $d_y$=7 | 0.58864 | 0.56511 |
| | ARIMA | ARIMA (6,0,2) | 0.56472 | 0.60167 |
| | % Difference | | 4% | -6% |
| Contract | NAR(X) | NARX with $d_y$=7, $d_u$=7 | 0.03302 | 0.03286 |
| | ARIMA | ARIMA (7,0,1) | 0.03860 | 0.03082 |
| | % Difference | | -14% | 7% |

Note: % Difference is calculated as $(\text{RMSE}_{\text{NAR(X)}} - \text{RMSE}_{\text{ARIMA}})/\text{RMSE}_{\text{ARIMA}}$ , as a way to measure relative performance of two types of models.

For contract rates, the best NAR(X) model is the NARX model with seven days feedback delay and seven days input delay of volumes. The best ARIMA model is the ARIMA (7,0,1) model.

Generally speaking, the NAR model provides better short-term forecasting performance for spot rates than the ARIMA model, while the ARIMA model and NAR model have almost equally accurate performance for contract rates. However, for a longer-term forecast, the NARX model provides better results for contract rates.

The model's prediction of contract rates is much more accurate and has much less forecasting variability than spot rates. A high forecasting accuracy can be achieved for contract rates either using NARX or ARIMA models. However, spot rates are difficult to forecast due to high variability. For 7-day rolling forecasts, the spot error is around $0.565 per mile over a $2.7 per mile average using the NAR model, with a coefficient of variation (COV) of 0.209. On the other hand, the contract error is around $0.031 per mile over a $2.5 per mile average using the ARIMA model and $0.033 per mile using the NARX model. The COVs are 0.012 and 0.013 using ARIMA and NARX models respectively, indicating almost equally sound performance of the two models.

Last but not least, results show that there exists no short-term information transmission between spot and contract rates. This can be due to the fact that contract rates are often negotiated for a one-year period, which reflects future market expectation at the time of contract negotiations. On the other hand, spot rates often reflect current market supply/demand dynamics.

**Conclusions**

This study has developed a forecasting model that predicts both contract and spot rates for truckload transportation on individual lanes for the next seven days. The model used is a neural network model based on NARX model. This study considers several input variables, including lagged values of spot and contract rates, rates on adjacent routes and volumes. The best NAR(X) models for spot and contract rates are selected based on highest forecasting accuracy on the validation set. The NAR(X) model is also compared with traditional time series models (ARIMA).

Results show that overall speaking, contract rates have much higher forecasting accuracy and less forecasting variability compared to spot rates. Furthermore, for spot rates, the NAR model has better short-term forecasting results compared to the ARIMA model, while for contract rates, NARX and ARIMA models provide almost equally good forecasting results. For a longer-term forecast, the NARX model is more accurate than the ARIMA model for contract rates.

This study has made several contributions. First, this research has made methodological advancements by introducing the hybrid neural network and time series model (NAR and NARX) into the transportation forecasting field. The model is shown to have better short-term forecasting abilities for spot rates, as well as accurate forecasts for contract rates in both shorter (seven days) and longer terms (two months). Second, the results from this study can be applied to industrial players for their own forecasting. These results provide guidelines for both shippers and carriers regarding how to select input variables, what model to use, and what forecasting error is normally expected from the model.

Limitations of this study exist. The classifications between spot rates and contract rates in the dataset are reported by various companies. However, some rates can be misclassified, thus resulting in higher modelling errors. In addition, this study only considers one year of data, which makes it hard to model in monthly seasonality effects. In the future research, it is interesting to see whether a classification technique could be used to automatically classify a new rate (either spot or contract), based on rate behaviour rather than self-reported. Furthermore, it is also worthwhile to investigate seasonal effects (for example, the month of the year effect) on spot rate forecasting using data that lasts for a longer period.