



## AGILE FORECASTING OF DYNAMIC LOGISTICS DEMAND

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Received 2 July 2007; accepted 20 November 2007

**Abstract.** The objective of this paper is to study the quantitative forecasting method for agile forecasting of logistics demand in dynamic supply chain environment. Characteristics of dynamic logistics demand and relative forecasting methods are analyzed. In order to enhance the forecasting efficiency and precision, extended Kalman Filter is applied to training artificial neural network, which serves as the agile forecasting algorithm. Some dynamic influencing factors are taken into consideration and further quantified in agile forecasting. Swarm simulation is used to demonstrate the forecasting results. Comparison analysis shows that the forecasting method has better reliability for agile forecasting of dynamic logistics demand.

**Keywords:** logistics, forecasting, supply chain management, dynamic influencing factors, agility, hybrid algorithm, Swarm, computer simulation.

### 1. Introduction

Forecasting results of dynamic logistics demand is essential to managers' decision-making. Firms that offer rapid delivery to their customers will tend to force all competitors in the market to keep finished goods inventories in order to provide fast order cycle times. As a result, every organization tends to manufacture according to the forecasting of future demand. The ability to accurately forecast logistics demand in agile manner also affords the firm opportunities to control costs through coordinating its manufacture, rationalizing its transportation, and optimizing its replenishment.

The improvement of supply chain efficiency is also closely connected with matching supply and demand. Matching supply and demand requires the reduction of uncertainty within supply chains, so as to facilitate a more predictable logistics demand, that was investigated by Rudnicki (2001). However, in many markets, it is becoming impossible to remove or ignore sources of turbulence and volatility. Hence, supply chain managers must accept uncertainty, but still need to develop a strategy that enables them to match supply and demand at an acceptable cost. The ability to achieve this has been termed supply chain agility, that is presented by White *et al.* (2005). Agility is needed in today's supply chains to counter the uncertainty and complexity in the decision process, that is investigated by Agarwal *et al.* (2006). Rapid response manufacturing is a new manufacturing pattern that can be used to implement the concept of agile design and

manufacturing. Generally, agility of a company is understood as the ability to operate in uncertainty whilst maintaining stable level of productivity and appropriate external product availability, see researches by Kidd (1994), Goldman *et al.* (1995) and Gunasekaran (1998).

In general practice, accurate demand forecasts lead to efficient operations and high levels of customer service, while inaccurate forecasts will inevitably lead to inefficient, high cost operations and/or poor levels of customer service. In many supply chains, the most important action to improve the efficiency and effectiveness of the logistics process is to improve the quality of the logistics demand forecasts. Modern logistics is characterized as agility, just in time and exactness; therefore, accurate logistics demand forecasting is necessary for the sake of the agile-oriented requirements.

The usual quantitative forecasting models for logistics demand are exponential smoothed method, gray system method, ANN method and so on. But a single forecasting model always has its limitations in assumptions and application range. Chu *et al.* (2004) analyzed the influencing factors of logistics demand, and utilized regression analyses, gray forecasting and neural network respectively to construct a single forecasting model to demonstrate their limitations; and then, the combination forecasting model brought forward in their paper shows considerably improvements in precision. Tang and Fu (2003) brought forward a forecasting model for logistics demand with periodical tendency and the fore-

casting was realized by the assistance of Matlab software. Laboratoire (2005) presents a short-term forecasting model based on a neuro-fuzzy method, but the time unit of the short-term in his paper is defined as day, that is to say his model is not suitable for the forecast of logistics demand variation in shorter time and is not good at taking dynamic or uncertain factors into modeling. Generally speaking, it is hard for ordinary approaches to forecast logistics demand agilely and hard for them to characterize so many dynamic influencing factors. While the hybrid algorithm applied in this paper can forecast logistics demand agilely and can also depict the relationship between logistics demand and some dynamic influencing factors.

## 2. The characteristics of dynamic logistics demand

Dynamic logistics demand varies according to different dates while a similar variation law is present in the whole day; the variation law is still different according to working days and general holidays; the demand further varies with season and weather.

Although there is a certain law, the precise forecasting is uneasy. First, the forecasting should be based on historical data analysis; therefore, the stochastic factors and disturbance cannot be precisely predetermined. Second, some complex factors, such as temperature variations in different seasons, even if their influences have been known, are hard to be quantitatively depicted.

To sum up, dynamic logistics demand has not only a certain law but also strong uncertainty. The demand in certain future time is usually related to the past demand level, the current demand situation, the weather and the date type of the day. Therefore, the forecasting model should reflect the following basic aspects:

- the periodical variation of logistics demand with season, date type and timetable;
- the inherent laws of logistics demand variation;
- the external influence such as temperature, sunlight, weather and so on;
- the demand variation in near time should have greater influence on the forecasting result than the previous data;
- different forecasting models should be applied according to different date types.

## 3. Relevant theory of the hybrid forecast algorithm

### 3.1. Merits and drawbacks of ANN forecasting

ANN (Artificial Neural Network) has the merits of approaching discretionary nonlinear function and simulating multi-variable problem soundly without pre-knowing the function relation between each independent variable and dependent variable.

The forecasting of dynamic logistics demand is a large-scale multi-mapping problem and the forecasting model is difficult to be determined. Through the training of data input and output, the mapping relation between input and output can be obtained, and the ANN model

can conveniently express the factors such as temperature, sunlight and date type.

The classical method for training a multi-layer feed-forward artificial neural network is the BP algorithm. Although it is successfully used in many cases and has been improved continuously, the BP algorithm suffers from a number of shortcomings. One of the shortcomings is the slow convergent rate, and the other is that the convergence may be local. These shortcomings have not been got over radically. While the EKF (Extended Kalman Filter) by Ngan and Fung (2001) training algorithm estimates the weights according to the rule of minimum root mean squared covariance, it needs less iteration than BP algorithm. Further more, not involving convergent parameters made it easier to apply methods by Wu and O’Grady (2004), and Wang and Papageorgiou (2005). Therefore, the EKF-ANN learning algorithm is applied for agile forecasting of dynamic logistics demand in this paper.

### 3.2. Theory of EKF-ANN algorithm

Through the BP algorithm, we know the learning process of the feed-forward ANN is the network power regulating process under the determined input and output samples. Therefore, the training of feed-forward ANN can be seen as nonlinear state estimate process. The basic idea of EKF learning algorithm is to regard the learning process of link power, which exists between every pair of neural units, as the state vector of EKF, so as to carry through optimal estimation. As the EKF-ANN algorithm presents approximately the least variance estimation of link power, the iterative convergence rate is faster than steepest-descend method. Furthermore, the method, by Park *et al.* (1991), doesn’t involve adjusting parameters that determine convergent ability, which makes its application quite convenient.

### 3.3. Deduction of systematic recursive filter for ANN

Suppose there is a  $N$  layer feed-forward ANN, and the number of neural units in each layer is  $L_k, k = 1, 2, \dots, N$ . Let the input layer be as the first layer and the output as the  $N$  layer. The connection weights between layers  $L_k$  and  $L_{k+1}$  is  $w_{ij}^{L_k}$  ( $i = 1, 2, \dots, L_k, j = 1, 2, \dots, L_{k+1}$ ). In order to convert the calculation of the connection weight  $w_{ij}^{L_k}$  to the filter recursion estimation form, all the connection weights constitute state vector:

$$W = [w_{11}^1 \cdots w_{L_1 L_2}^1 \quad w_{11}^2 \cdots w_{L_2 L_3}^2 \quad \cdots \quad w_{11}^{N-1} \cdots w_{L_{N-1} L_N}^{N-1}]^T.$$

The state vector  $X$  is composed of all the weights with linear arrangement, and its dimension can be calculated by formula:

$$N_x = \sum_{i=1}^{N-1} L_i L_{i+1}. \tag{1}$$

The system state equation and observation equation can be denoted as follows:

$$W(k+1) = W(k), \tag{2}$$

$$\begin{aligned} Y_e(k) &= h(W(k) + X(k) + k) + V(k) = \\ Y_r(k) &+ V(k). \end{aligned} \quad (3)$$

Here,  $X(k)$  is the input vector, while  $Y_r(k)$  is the corresponding factual output, and  $Y_e(k)$  is the corresponding expected output;  $V(k)$  is the stochastic white noise.

Its statistical character is:

$$E[V(k)] = 0, E[V(k)V^T(k)] = R(k). \quad (4)$$

For any given ANN, suppose there are  $M$  samples, which are  $(x_k, y_k)$  ( $k = 1, 2, \dots, M$ ); then for the  $j$  unit in the  $l$  layer, the output of  $l-1$  layer is  $O_i^{l-1}$ . When the number of input samples is  $k$ , the output of  $j$  unit in the  $l$  layer is:

$$O_{jk}^l = \sum_i w_{ij}^{l-1} O_{ik}^{l-1}. \quad (5)$$

Let the nonlinear function  $h(\cdot)$  denote the nonlinear mapping relation between inputs, outputs and weights.

Based on formula (11), suppose the output of  $j$  unit in the  $l$  layer for the  $k$  iterative calculation is:

$$O_j^l(k) = f_j^l[w_j^l(k), O^{l-1}(k)]. \quad (6)$$

Then:

$$\begin{aligned} Y_e(k) &= h(W(k) + X(k) + V(k)) = \\ &F^N(W^{N-1}(k), F^{N-1}(W^{N-2}(k) \dots \\ &F^1(W^2(k), X(k))) + V(k). \end{aligned} \quad (7)$$

Expand expected output by Taylor series and leave out quadratic upward items:

$$\begin{aligned} Y_e(k) &= h[\hat{W}(k|k-1) + X(k)] + \frac{\partial h}{\partial W} \Big|_{W(k)=\hat{W}(k|k-1)} \\ &[W(k) - \hat{W}(k|k-1)] + V(k). \end{aligned} \quad (8)$$

Let:

$$\begin{aligned} \frac{\partial h}{\partial W} \Big|_{W(k)=\hat{W}(k|k-1)} &H(k)h[\hat{W}(k|k-1) + X(k)] + \\ \frac{\partial h}{\partial W} \Big|_{W(k)=\hat{W}(k|k-1)} &\hat{W}(k|k-1) = C(k). \end{aligned} \quad (9)$$

Then the observation equation is:

$$Y_e(k) = H(k)W(k) + C(k) + V(k). \quad (10)$$

Formulas (2) and (6) constitute the simplified EKF model, and its filter recursion formulas are shown as follows:

$$\begin{aligned} \hat{W}(k+1|k+1) &= \hat{W}(k+1|k) + \\ K(k+1) &\left\{ Y'(k+1) - h[\hat{W}(k+1|k), X(k)] \right\}, \end{aligned} \quad (11)$$

$$\hat{W}(k+1|k) = \hat{W}(k|k), \quad (12)$$

$$\begin{aligned} K(k+1) &= P(k+1|k)h^T(k+1) \times \\ &[h(k+1)P(k+1|k)h^T(k+1) + R_{k+1}]^{-1}, \end{aligned} \quad (13)$$

$$P(k+1) = [I - K(k+1)h(k+1)]P(k). \quad (14)$$

Carry through singular value decomposition on variance  $P$  and obtain the systematic recursive filter formulas (Ngan, Fu 2003):

$$\begin{aligned} \hat{W}(k+1|k+1) &= \hat{W}(k+1|k) + \\ K(k+1) &\left\{ Y'(k+1) - h[\hat{W}(k+1|k), X(k+1)] \right\}, \end{aligned} \quad (15)$$

$$\hat{W}(k+1|k) = h[\hat{W}(k|k), X(k)], \quad (16)$$

$$\begin{aligned} K(k+1) &= U(k+1|k+1)D^2(k+1|k+1)U^T \times \\ &(k+1|k+1)H^T(k+1)R_{k+1}^{-1}. \end{aligned} \quad (17)$$

Here, the  $U(k+1|k+1)$  and  $D(k+1|k+1)$  are singular value decomposition matrix of error covariance  $P$ .

#### 4. The forecasting model

It is important to choose appropriate sample sets for the dynamic forecasting and thus to enhance the training speed and forecast precision. If the sample filter is carried out before each forecasting, selecting samples that have similar weather with the forecasting date, then much training time can be economized and interference from unrelated samples can be avoided. In this way, according to different forecasting dates, different forecasting training sample sets can be determined, and different weights and thresholds can be trained. However, mapping relation and sample sets vary with time, and the training sample should be re-determined for each time, which is hard to realize for the slow training, difficult converging ANN algorithm. The EKF-ANN algorithm is faster in calculation and feasible in choosing dynamic samples and forecast models.

Logistics demands in the continuous dates have certain relation and are affected by temperature, humidity, weather type and date intervals, therefore, the similar degree between the forecasting date and the date  $K$  can be defined as follows:

$$\begin{aligned} S(k) &= \alpha \left[ (T_{\max} - T_{\max}^K)^2 + (T_{\min} - T_{\min}^K)^2 \right] + \\ \beta &\left[ (RH_{\max} - RH_{\max}^K)^2 + (RH_{\min} - RH_{\min}^K)^2 \right] + \\ \gamma &(W - W^K)^2 + \delta \Delta D^k. \end{aligned} \quad (18)$$

The  $T_{\max}$ ,  $T_{\min}$ ,  $RH_{\max}$ ,  $RH_{\min}$  and  $W$  respectively denote the highest temperature, the lowest temperature, the maximum relative humidity, the minimum relative humidity and the weather type in the forecasting date; the  $T_{\max}^K$ ,  $T_{\min}^K$ ,  $RH_{\max}^K$ ,  $RH_{\min}^K$  and  $W^K$  respectively denote the above corresponding index in the date  $K$ ;  $\Delta D^k$  denote the date interval between forecasting date and date  $K$ ;  $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\delta$  are the coefficients that reflect the influence of temperature, humidity, weather type and date interval on logistics demand. The meteorological factors  $W$  and  $W^K$  can be quantitatively disposed as in Table.

If the  $S(k)$  is smaller, the similarity will be higher. Based on the meteorological data of the forecast date,

Quantitative disposal factor

Weather condition	Sunshine	Cloudlet	Cloudy	Rain
Quantitative value	1	2	3	4
Weather condition	Median rain	Thunder storm	Light snow	Heavy snow
Quantitative value	5	6	7	8

calculate in turn the similar degree between the previous date and the forecast date. The samples that correspond to smaller  $S(k)$  are chosen as dynamic training sample set.

The most important aspect of ANN forecasting model is how to choose the input variable. There is no general law and it should be determined according to concrete situations. Here logistics demands in the continuous dates are considered as having certain relation.

Arrange the resultant sample in time series and denote as follows:

$$X = [X_1 \ X_2 \ X_3 \ \dots \ X_M].$$

$X$  is the total sample set,  $X_i$  ( $1 \leq i \leq M$ ) is a vector in the sample, the elements in it are the historical demand data, weather condition data and date type data.  $M$  is the total number of resultant samples.

According to experience, the number of hidden layers is generally chosen as  $(IN \times ON)^{1/2}$ .  $IN$  and  $ON$  are the number of units in the input layer and output layer respectively.

The historical demand data in the resultant sample, the weather information in the forecast date and the date type are taken as network input, the output is the forecasted demand of 24 hours in the forecast date.

5. Example analysis by Swarm simulation

The Swarm platform developed by the Santa Fe Institute supports a kind of tools that can validate the above model. It is a collection of software libraries that can provide support for ANN simulation programming. It is implemented through the Object-Oriented Programming language, Objective-C, that was presented by Johnson and Lancaster (2004).

Information inadequacy often puzzles the operation of a complex huge system. The theory of Swarm is that through the transmission of signals entities determine its income by receiving the signals and further adjust their strategies. This process is carried out by simulation of evolution algorithm other than simultaneous equations. Besides, the systematic environment variables will obtain reasonable revision through the self adaptive process of microcosmic entity, which makes Swarm require less of the external initial variables. It can be seen that Swarm simulation suits for handling agile forecasting of dynamic variation.

The implementation of Swarm program is based on the Model Swarm and the Observer Swarm. The former, as a core, initiates, groups and schedules the simulation objects. The latter observe and analyze the behavior during the simulation, and drive data collection to read those numbers out of the model and draw them on a graph.

Fig. 1 is the operational menu of Model Swarm for Swarm simulation on dynamic forecasting of beverage

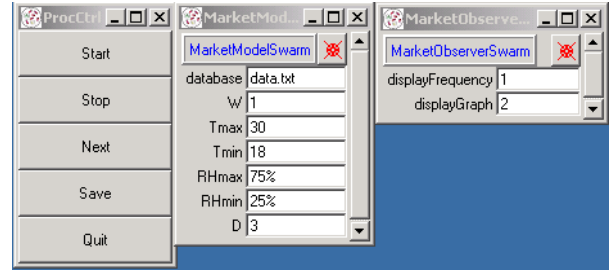


Fig. 1. Operational menu of Swarm simulation

demand on a summer day. The meanings of parameters and variables in the Model Swarm are listed as follows:

Database: historical demand data, the *data.txt* is the training samples set.

- $W$ : weather, the number 1 denotes sunshine.
- $T_{max}$ : the highest temperature on the forecasting day.
- $T_{min}$ : the lowest temperature on the forecasting day.
- $RH_{max}$ : the maximum relative humidity of the forecasting day.
- $RH_{min}$ : the minimum relative humidity of the forecasting day.
- $D$ : date type, the number 3 denotes Wednesday

Fig. 2 shows the difference between forecasting values and real values. Fig. 3 presents a vivid error

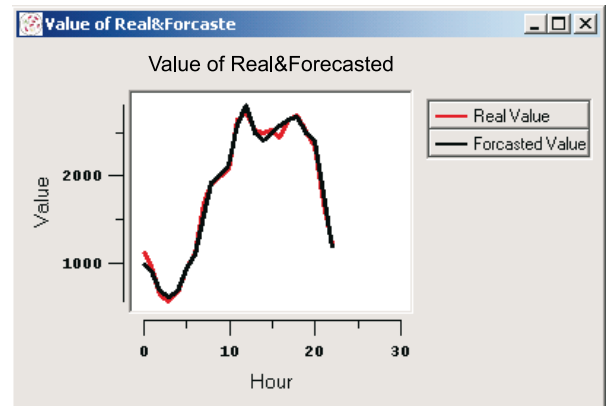


Fig. 2. Comparison of real value to forecasted value

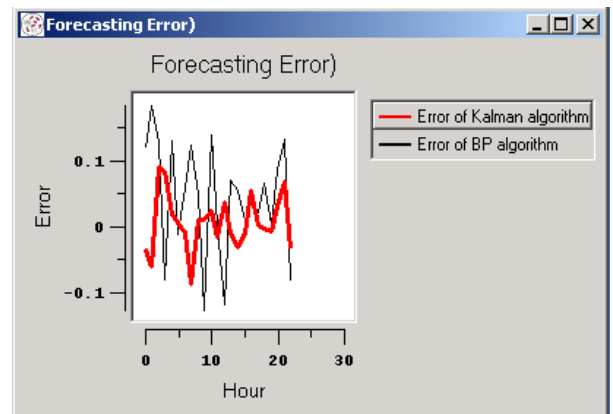


Fig. 3. Error contrast between EKF-ANN and BP-ANN

contrast between EKF-ANN forecasting algorithm and BP-ANN forecasting algorithm.

From the above comparison analysis, we believe that the forecast result is relatively better and the EKF-ANN forecasting algorithm is, to some extent, superior to traditional BP-ANN forecasting algorithm. In a sense, the EKF-ANN forecasting algorithm may be relatively accurate for agile forecasting while taking some dynamic influencing factors into consideration.

## 6. Conclusions

1. Modern logistics call for lean production, just in time distribution and agile supply chain management. Operations in logistics system will be characterized as flexibility, exactness and agility.

2. Agility-oriented forecasting method of dynamic logistics demand is a crucial approach to satisfy high level operational requirements of logistics in uncertain supply chain environment.

3. The hybrid algorithm for agile forecasting may take many dynamic factors into consideration and thus make the dynamic forecasting accurate and practical. Although the dynamic influencing factors considered in this paper are not comprehensive, this approach gives some insights into quantificational expression of dynamic factors in agile forecasting and can be seen as an example for managing the uncertainty in supply chains based on the agility paradigm.

4. The theoretical foundation of Swarm is non-equilibrium, random and dynamic. Its simulation model is non-linear that makes the system itself have self adaptability and simulation results approaching reality. Swarm simulation platform can be seen as a good tool for agile forecasting researches.

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