Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Direct Neural Network Based Service Level Control in RFID-enabled Supply Chain

Seong Rok Hong*, Jang Sun Yoo*, Jong Myoung Ko*
Chang Ouk Kim*

**Department of Information and Industrial Engineering, Yonsei University*
Seoul, Republic of Korea {Tel: 82-10-2441-4290, e-mail:cornicherok@yonsei.ac.kr, staryoo7@yonsei.ac.kr, jmko@yonsei.ac.kr, kimco@yonsei.ac.kr}

Abstract: In recent supply chain management, as the online use of inventory data becomes available with the development of Radio Frequency Identification (RFID) technology, it is now possible to monitor the performance measures in a timely fashion. Customer service level is a key performance measure that can be computed as the percentage of times that customer orders electronically received are fulfilled by on-hand inventory. Online monitoring of the service level enables the management paradigm to progress toward the closed loop based control which keeps revising the operation policy to reach a target service level. This paper proposes a closed loop supply chain control based on a direct neural network controller. Simulation based experiments were performed to test the performance of the controller against two kinds of unstable customer demand curves.

1. INTRODUCTION

In recent supply chain management, as the online use of inventory data becomes available with the development of Radio Frequency Identification (RFID) technology, it is now possible to monitor the performance measures in a timely fashion. Customer service level is a key performance measure that can be computed as the percentage of times that customer orders electronically received are fulfilled by on-hand inventory. Online monitoring of the service level enables the management paradigm to progress toward the closed loop based control (McFarlane, 2002) which keeps revising the operation policy (i.e. set of decision variables) to reach a target service level.

In this paper, we propose a direct neural network controller for the closed loop based supply chain management. Until now, the neural network based control has been applied in mechanical system control areas such as robot, aircraft, and ship controls (Abdelhameed, 1999; Argiriou, Bellas-Velidis, Kummert, & Andre, 2004; Daosud, Thitiyasook, Arpornwichanop, Kittisupakorn, & Hussain, 2005; Sato & Ishii, 2006). It has a strength that it can be applied to unstable customer demands which rapidly change over time. Moreover, the direct neural network controller does not need the step to acquire the learning data in advance. The data required for the direct neural network are just those of the actual service level computed online during the operation of supply chain, possibly using the RFID technology. As shown in fig. 1, the direct neural network controller includes a multilayer neural network model as an intelligent decision maker and a real supply chain as the control subject. The controller continues adjusting decision values in order to make the actual service level keep close to the target. The actual service level may fluctuate severely if sudden customer demand change occurs. The error between the actual and the target is then propagated to the network learning and the neural network makes its effort to minimize the error in a short time. This sense-and-quick response mechanism is repeated for the operation stage of the supply chain.

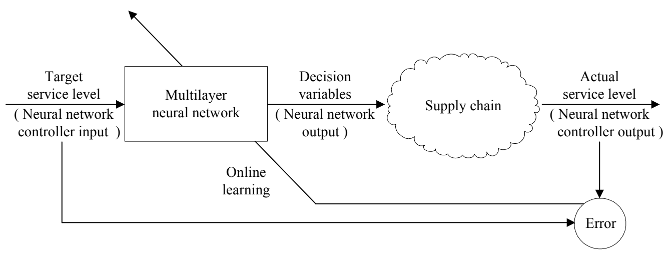

Fig. 1. Architecture of direct neural network controller.

2. DIRECT NEURAL NETWORK CONTROLLER

2.1. Three-stage supply chain model

We consider a well-known three-stage supply chain model. The operational logic of the supply chain model is established based on the beer game model (Macal and North, 2003). The most upstream stage consists of three suppliers which produce different parts and supply them upon the order request of manufacturer. The manufacturer is the intermediate stage and uses a stock replenishment policy that determines order quantity per period based on the difference between a desired safety stock level and current safety stock level, the amount of backorders, and forecasted customer demands. In a manufacturing shop, products are assembled according to a fixed rate. The most downstream stage consists of three wholesalers and they use the same stock replenishment policy as the manufacturer.

The customers of the wholesalers are retailers, and they usually issue orders through the Internet. Unsatisfied orders are treated as lost sales. The actual service level of a wholesaler during period t can be computed using the on-hand stock data that can be checked accurately using product RFID data (Wang and Liu, 2005) and customer order data stored in the wholesaler database. Finally, there is a transportation lead time between any two stages.

The variables of the supply chain are classified as follows:

•Decision variables: The elements which can be controlled by the supply chain manager. They are the manufacturing rate, desired safety stock, transportation time, etc.

•External variables: The elements which are influenced by the external environment such as the customer demand and supply rate. They cannot be controlled by the supply chain manager.

•Target variables: The performance measures of the supply chain such as the customer service level.

A target variable is the output of a complex and nonlinear function of the decision variables and the external variables. The variables which constitute the three-stage supply chain model are described in table 1.

Table 1. Variables

Type	Variable name
Decision variables	Desired product safety stock at wholesaler *i* (*i* = 1, 2, 3)
	Desired product safety stock at manufacturer
	Desired safety stock for part *j* at manufacturer (*j* = 1, 2, 3)
	Transportation time from manufacturer to wholesaler *i* (*i* = 1, 2, 3)
	Transportation time from supplier *j* to manufacturer (*j* = 1, 2, 3)
	Manufacturing rate
External variables	Customer demand at wholesaler *i* (*i* = 1, 2, 3)
	Supply rate *j* (*j* =1, 2, 3)
Target variable	Customer service level

2.2. Direct neural network controller

The configuration of the direct neural network controller is shown in fig. 2. The multilayer neural network consists of an input layer, a hidden layer and an output layer. The input layer consists of one input node which takes a real-valued target service level. A network output node produces the learned value of a decision variable of the supply chain. The set of the output values is then reflected to the operation of the supply chain and an actual service level is acquired after a time period.

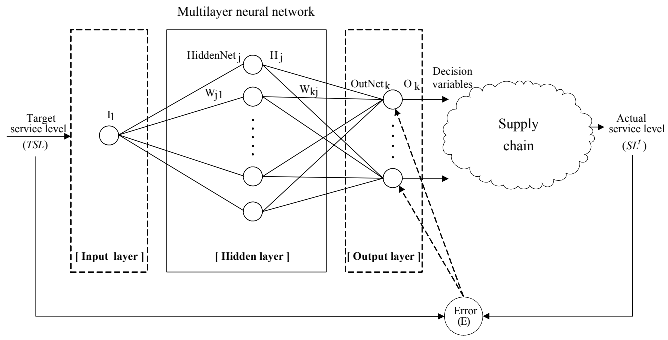

Fig. 2. Learning model of direct neural network controller.

As shown in equation (1), O_k^t , the output of the *k*th node in the output layer at period *t*, is obtained by applying the sigmoid function to $OutNet_k^t$ which is the weighted sum of the output values H_j^t of the hidden layer as in equation (2).

$$O_k^{\,t} = f(OutNet_k^{\,t}) = \frac{1}{1+\exp^{-OutNet_k^{\,t}}} \tag{1}$$

$$OutNet_k^{\,t} = \sum_j H_j^{\,t} W_{kj}^{\,t} \tag{2}$$

The backpropagation algorithm (Haykin, 1998) is applied for the online neural network training. The training data are the differences between the target service level and actual ones which are periodically obtained during the supply chain operation. The squared error (E^t) between the target service level (*TSL*) and the actual service level (SL^t) at period *t* is defined as

$$E^t = \frac{1}{2}(TSL - SL^t)^2 \tag{3}$$

The backpropagation algorithm uses the incremental (or stochastic) gradient descent rule to minimize the error *E*. At each time of collecting an actual service level, the network weights are updated by equation (4) where η is a positive constant called the learning rate and its range is (0, 1].

$$W_{kj}^{\,t+1} = W_{kj}^{\,t} - \eta \frac{\partial E^t}{\partial W_{kj}^{\,t}} \tag{4}$$

To implement the incremental gradient descent rule, the chain rule is applied to the partial derivative $\partial E^t / \partial W_{kj}^{\,t}$ in equation (4) for rewriting it as

$$\begin{aligned}\frac{\partial E^t}{\partial W_{kj}^{\,t}} &= \frac{\partial E^t}{\partial O_k^{\,t}} \cdot \frac{\partial O_k^{\,t}}{\partial OutNet_k^{\,t}} \cdot \frac{\partial OutNet_k^{\,t}}{\partial W_{kj}^{\,t}} \\ &= \frac{\partial E^t}{\partial SL^t} \cdot \frac{\partial SL^t}{\partial O_k^{\,t}} \frac{\partial O_k^{\,t}}{\partial OutNet_k^{\,t}} \cdot \frac{\partial OutNet_k^{\,t}}{\partial W_{kj}^{\,t}}\end{aligned}$$

$$= (SL^t - TSL) \cdot \frac{\partial SL^t}{\partial O_k{}^t} \cdot f'(OutNet_k{}^t) \cdot H_j{}^t \qquad (5)$$

In the case of the direct neural network controller, however, the error backpropagation for the weight learning cannot be directly applied. In equation (5), the partial derivative $\partial SL^t / \partial O_k{}^t$, which means the amount of service level change to a small perturbation of the decision variable O_k, is not analytically computable, because the input-output relationship of the supply chain is quite complex and is usually a unknown stochastic function. To overcome the difficulty, Zhang *et al*. (1995) suggested the use of a unit value (1 or -1) as the approximated value by employing the sign function as

$$\begin{aligned} &If \quad \frac{\partial SL^t}{\partial O_k{}^t} \geq 0,\ sign\left(\frac{\partial SL^t}{\partial O_k{}^t}\right) = 1 \\ &If \quad \frac{\partial SL^t}{\partial O_k{}^t} < 0,\ sign\left(\frac{\partial SL^t}{\partial O_k{}^t}\right) = -1 \end{aligned} \qquad (6)$$

where $\frac{\partial SL^t}{\partial O_k{}^t} \approx \frac{SL^t - SL^{t-1}}{O_k{}^t - O_k{}^{t-1}}$

However, according to the results of a simulation based test, even when equation (6) is used for the learning, it took too much time for reaching the target service level. As for the supply chain, the error defined in equation (3) should be drastically reduced in a few on-line executions. Slow discovery of the best decision values is not acceptable in the supply chain operation from the viewpoint of time and cost.

To achieve the purpose, we add an error amplification function in equation (5) as

$$\frac{\partial E^t}{\partial W_{kj}{}^t} = \frac{\partial E^t}{\partial SL^t} \cdot \frac{\partial O_k{}^t}{\partial OutNet_k{}^t} \cdot \frac{\partial OutNet_k{}^t}{\partial W_{kj}{}^t} \cdot sign\left(\frac{\partial SL^t}{\partial O_k{}^t}\right) \cdot B^t \qquad (7)$$

The error amplification function is defined as

$$B^t = \frac{(TSL - SL^t)}{\alpha} \qquad (8)$$

where α is an amplification parameter and its range is (0, 1]. In this equation, the amplification value B^t is proportional to the error between TSL and SL^t. Also, the less the α value is, the more the amplification effect occurs. Accordingly, if a big error of TSL-SL^t is generated, the B^t value which is greater than the error is reflected in equation (7) and, as the result, the weight in equation (4) is also modified greatly.

3. EXPERIMENTS

In this section, we perform simulation based experiments for testing the performance of the direct neural network controller. In all experiments, random numbers between -0.5 and 0.5 were assigned as the initial weight values of the neural network and the learning rate was set to 0.3. The multilayer neural network is configured with one hidden layer and five hidden nodes. The simulation was implemented using the ARENA 7.0 software. The α was set as 0.05. The performance measure is the average of the actual service levels of the three wholesalers.

It is assumed that, at every period, the demand at a wholesaler follows a certain normal distribution. However, the mean demand changes over time. The standard deviation is assumed as 5% of the mean demand. Two scenarios of the mean demand change were created. The one is the step demand case and the other is the S-curve demand case. How to generate the two demand cases will be explained in detail in the following subsections. The target service level is 90% and the entire simulation period is 1400 days.

3.1 Step demand case

This is the case where the mean demand is constant during a certain time interval, jumps up or down suddenly, and keeps the changed value again. This change pattern is repeated until the end of the simulation time. This demand process is appropriate for modelling periodic demand variation or sudden economic impacts on the demand. In this paper, the step demand process was generated with two parameters: change cycle that is the mean change interval and fluctuation amount that determines the changed mean value. To consider different nonstationary levels, five scenarios were generated using the two parameters as in table 2, where the uniform distributions determine the fluctuation amount probabilistically. The initial mean customer demand and standard deviation are 200 and 10, respectively.

Table 2. Five step demand scenarios

Scenario	Mean demand change cycle	Fluctuation amount
1	350	Uniform(190,210)
2	280	Uniform(180,220)
3	233	Uniform(170,230)
4	200	Uniform(160,240)
5	175	Uniform(150,250)

The fluctuation of the actual service level is reported in fig. 3. For the five scenarios, the average errors between the actual service level and the target during the entire simulation time are 1.94, 1.96, 1.98, 1.88, and 2.58, respectively, and these errors are considerably small. If the direct neural network controller cannot reflect the demand changes to its decision making in a short time, the average errors would be significantly high. Based on the analysis of the result, we conclude that the performance of the direct neural network controller is reliable on average. . In addition, the controller was verified to have the capability of adapting to the step demand changes very fast although the fluctuation of the actual service level increases as with the nonstationary level of the demand.

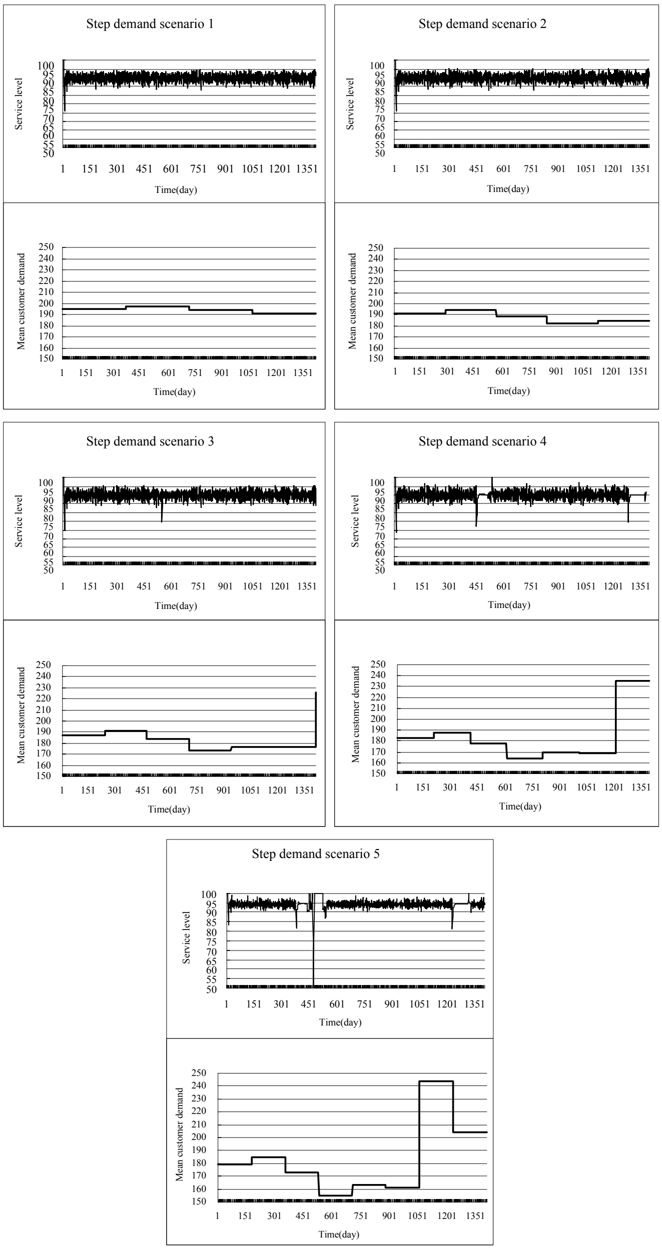

Fig. 3. Actual service levels for five step demand scenarios

3.2 S-curve demand case

In general, the mean demand curves of products with short life-cycles show S-shape patterns - in the early stage of the sales, the demands grow up to peak levels, remain in the levels steadily for a while, and shrink gradually as new competitive products are introduced in the market. This research uses the sign function as in equation (9) to create the S-shape demand curves.

$$Mean\ demand_t = a + b\sin\left(\frac{\pi}{n} \times x_t\right) \quad (9)$$

$$x_{t+1} = x_t + Uniform(1,2) \quad (10)$$

In equation (9), a is a baseline value and it was determined using a uniform distribution (100, 200) in this experiment. The parameter b is the variation range of the mean demand and three demand scenarios were created by using different b values, which are 50, 100, and 200. The parameter n is the total demand forecasting time and it was set to 1400 days. The variable x_t is the factor to determine the shape of the mean demand curve. x_0 was determined according to a uniform distribution (0, n/10), and x_t (t>0) is recursively computed by equation (10) to remove the symmetric feature from the demand curve.

The fluctuation of the actual service level is shown in fig. 4. In particular, as for the scenarios 3, the direct neural network controller did not follow the mean demand change for a fairly long time; spent the time for the weight learning. However, as shown in the middle part of the scenario 3, the actual service level during the learning time does not deviate from the target distantly - the service level stays between 80 and 100, except one case where the service level drops below 65. The average errors of the three scenarios are 1.52, 1.87 and 3.45, respectively, and they are very small over all.

In summary, throughout the simulation based experiments with the two nonstationary demand patterns, it was verified that the direct neural network controller is capable of making the actual service level reach the target service level in a short time and remain around the target with small average errors.

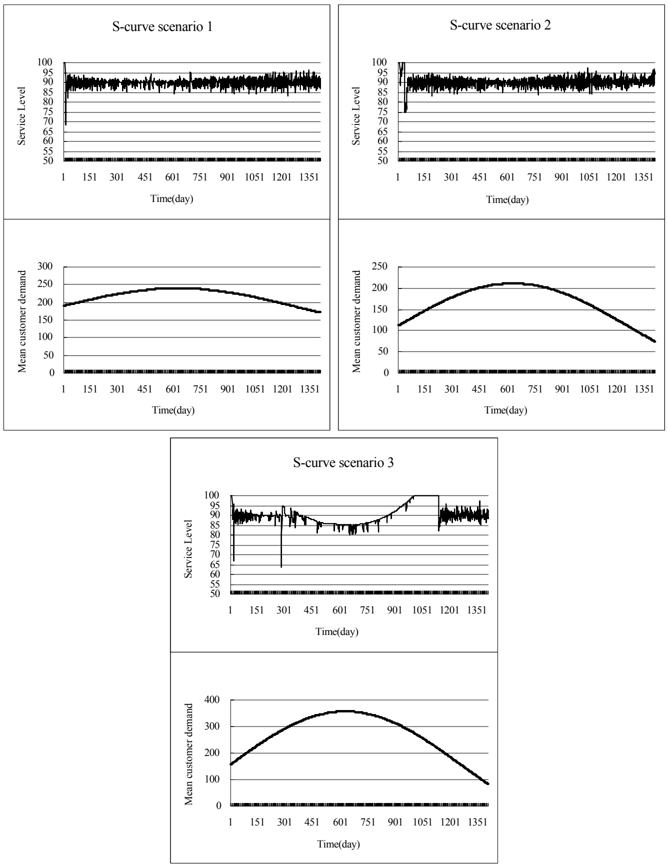

Fig. 4. Actual service levels for three S-shape demand scenarios.

4. CONCLUDING REMARKS

In this paper, we proposed the direct neural network controller that detects the significant change of customer demand indirectly by the change of customer service level that is measurable online through the RFID technology, and generates appropriate decisions for maintaining the target service level by adjusting the network weights. As an improvement point, it is common that the costs required for the unit change of each decision variable are different. Therefore, the study on controlling customer service level with the consideration of the unit change costs is worthy of investigation in the future.

ACKNOWLEDGEMENT

This work was supported by grant No. R01-2006-000-10014-0 from the Basic Research Program of the Korea Science & Engineering Foundation.

REFERENCES

Abdelhameed, M. (1999). Adaptive neural network based controller for robots. *Mechatronics*, **vol.9**, 147-162.

Argiriou, A., Bellas-Velidis, I., Kummert, M., and Andre, P. (2004). A neural network controller for hydronic heating systems of solar buildings. *Neural Networks*, **vol.17**, 427-440.

Daosud, W., Thitiyasook, P., Arpornwichanop, A., Kittisupakorn, P., and Hussain, M. (2005). Neural network inverse model-based controller for the control of a steel pickling process. *Computers & Chemical Engineering*, **vol.29**, 2110-2119.

Haykin, S. (1998) *Neural networks: a comprehensive foundation* (2nd ed.). Prentice Hall.

Macal, C., and North, M. (2003) Effects of global information availability in networks of supply chain agents. *In Proceeding. Agent 2003: Conference on Challenges in Social Simulation*, pages. 235-252.

McFarlane, D. (2002) Auto-ID based control. Auto-ID Center White Paper CAM-AUTOID-WH-004, Cambridge University, UK.

Psaltis, D., Sideris, A., & Yamamura, A. (1998). A multilayered neural network controller. *IEEE Control Systems Magazine*, **vol.8**, 17-21.

Sato, M., and Ishii, K. (2006). A neural network based controller for a wheel type mobile robot. *International Congress Series*, **vol.1291**, 261-264.

Wang, F., and Liu, P. (2005) Temporal management of RFID data. *In Proceedings of the 31st VLDB Conference*, pages 1128-1139.

Zhang, Y., Sen, P., and Hearn, G. (1995) An on-line trained adaptive neural controller. *IEEE Control Systems Magazine*, **vol.15**, pages 67-75.