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# Eliminating bullwhip effect in supply chain stock systems using smart controllers

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***Abstract*---** Several alternative approaches have been proposed for supply chain modeling majority of which steady-state models. These models cannot adequately deal with dynamic characteristics of supply chain system affected by lead time, demand fluctuation, sale prediction and so forth. Static models in particular cannot describe, analyze and provide solutions for a key issue in supply chains called bullwhip effect. The bullwhip effect is information deviation from one end of the supply chain to the other which intensifies fluctuation and change in demand from downstream to upstream. This issue leads to major deficiencies. One of the approaches used to cope with dynamic issues is control systems approach. In present study, a predicting model controller was developed to minimize the bullwhip effect in supply chain. In addition, a prediction methodology is integrated into predicting model control framework to predict uncertainty in distorting demand behavior. Integration of a prediction methodology in predicting model control framework improved the controlling system's performance. The main feature of demand signal used in model design is its fluctuation and distortion. One of the main factors behind bullwhip effect is demand signals processing and in fact, the predicting model used. The prevailing predicting model in present models is the exponential smoothing model which is proved to be diagonal, particularly in predicting distorted demand prediction. Based on non-linear and fluctuating behavior of distorted demand, instead of classical predicting models such as exponential smoothing, neural networks were used to model and predict distorted demand behavior.


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***Keywords*---**supply chain, bullwhip effect, predicting control, neural network, pharmacy Education.

## 1. Introduction

Arrangement of a supply chain is in a way that suppliers provide raw materials to the manufacturer and the manufacturer produces final products which are delivered to wholesalers. Then, wholesalers deliver products to retailers for sale and retailers provide consumers with final products. In this arrangement, along with physical downstream flow of products, there is an upstream flow of information in which only retailers have accurate information on consumers' demand. Demands observed by wholesalers, manufacturers and suppliers are not real demands for products. This is due to the fact that the orders they receive are moderated by some predicting techniques or ordering policies used by the next direct node downstream. In most supply chains, it is observed that changes in ordering patterns increase in upstream flow, i.e., toward the manufacturers and suppliers. Lee, Padmanabhan, & Whang (1997) called this phenomenon bullwhip effect. Effective supply chain management leads to lower production, stock and transportation costs and increased level of customer services at every stage of supply chain (*Hoseini SA, et. al., 2020; Jaghoubi S, 2019: Wahba AA., 2021*). There have been many alternative approaches proposed to model supply chains. According to Beamon (1998), these approaches can be classified into four categories:

- Definitive models in which all parameters are known
- Random models with at least one unknown parameter while the parameters follow a probability distribution
- Game theory based economic models
- Simulation based models which assess different performance strategies for supply chain (Beamon, 1998).

Most of these models are steady-state models and are based on stable situations or average performance while static models fail in coping with dynamic features of supply chain systems due to lead time, demand fluctuations, sales prediction and so on. These models fail in explaining and analyzing the bullwhip effects and providing solutions (Sarimveis, Patrinos, Tarantilis, & Kiranoudis, 2008). Obviously, dynamic features consideration in supply chain systems modeling proposes a competitive advantage which concentrate on alternatives for supply chain dynamicity modeling. These models are classified as: continuous time differential equations modeling, discrete time differential modeling, discrete event modeling and classical operational research modeling. One of the main approaches to solve dynamic problems is control system engineering. The control theory provides sufficient mathematical tools for designing and simulating supply chain management systems based on dynamic models. Control theory, in particular, can be used in assessment and finding a solution for bullwhip phenomenon (Sarimveis et al, 2008). Demand processes, stock policies, time intervals for delivery and predictive techniques have a significant impact on bullwhip effect. Among these models, the predicting models, stock policies and, to some extent, the lead times are controllable; therefore, it is desirable to make decisions to minimize bullwhip effects using these models (Agrawal, Sengupta, & Shanker, 2009). Lee et al. (1997) introduced five main factors in bullwhip effects:

- Non-zero lead time
- Demand signals processing (demand prediction)
- Price change
- Supply insufficiency
- Orders categorization

Among different bullwhip creators, predicting models are the most important ones because the stock system of supply chain is directly affected by predicting models. That is why many researchers have worked on the effects of predicting models on bullwhip effect (Duc, Luong, & Kim, 2009). They observed that Control Theory is one of the main approaches to solve dynamic problems. Employing classical controlling techniques in supply chain dates back to early 1950s when Simon (1952) applied Continuous Time Servomechanism Theory to manipulate production rate in a simple system. The idea of using control theory was developed by Vassian (1955) in discrete time models. Vassian proposed a stock control framework based on Z transformation methodology. Forster (1961) created a revolution by proposing industrial dynamicity, but the need for a new framework development which can be used as a basis for controlling rules search or new feedback methods in production/stock system. Towill (1982) proposed a production control system based on stock and order as a block diagram. This system developed by Coil was based on new control rules and feedback models in production/stock systems. Some improvements and some moderations in the systems such as its development to discrete time systems led to creation of a group of production control systems model based on order and stock (Sarimveis et al., 2008).

Present study aims to model and analyze the optimization problem in supply chain and minimize bullwhip effect using control engineering approach. The proposed model is based on production control system model according to the stock and order. In this context, comparing several predicting models, the best system, namely the non-diagonal estimator, was used. Also, based on novel approaches in control theory, especially predicting model control approach, the desirable controller was designed for stock systems. It is claimed that modeling approach proposed in this study is novel and the designed controller can determine the optimal order rate in response to demand change, particularly customers' distorted demand behavior which in turn minimizes the bullwhip effect.

Rest of paper organized as follows: In the second part of this study the model is introduced and formulated. In the third part the proposed controlling models are addressed. Next, the simulation results are presented and finally, the concluding remarks are provided.

## 2. Proposed model

The conceptual model of this study is presented in the following figure as a block diagram of node j in supply chain:

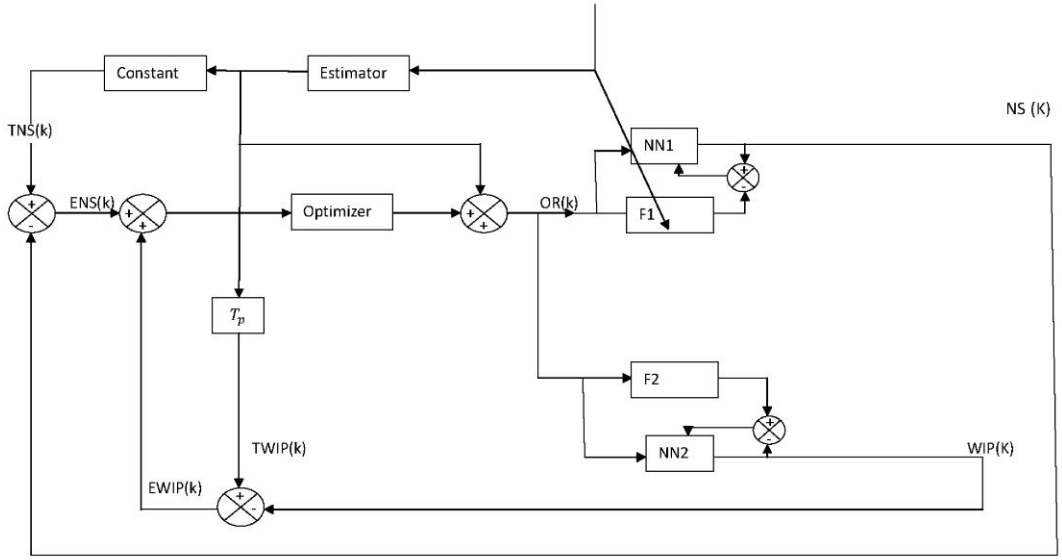


Figure 1. Block diagram of the proposed model

First, it is necessary to describe the block diagram's controlling symbols. Each arrow means transmission of an imperative signal transmitted in a block in one direction. Each rectangle indicates a conversion function which will be explained later. Moreover, in some cases it is observed that signal values are summed up or deducted. In the diagram, the downstream node demand determines the system regulation points and controlling signal, i.e. the order rate in each time period. The upstream node demand is exogenous and has to be estimated optimally. *F1* and *F2* represent equations for the first and second processes and *NN1* and *NN2* show two neural networks which will be designed for the first and second dynamic learning. The system performing logic will be detailed below. The indices used in modeling are:

$NS_j(k)$: Real net stock of node $j$ at time k and $j \in \{P, W, D, R\}$

$TNS_j(k)$: Target Net Stock for node $j$ at time $k$

$TWIP_j(k)$: Target work in progress during the target production at time $k$

$WIP_j(k)$: Work in progress during the real production at time $k$

$ENS_j(k)$: Error in the net volume of node $j$ at time $k$

$EWIP_j(k)$: Error in work in progress at time $k$

$_j(k)$: Order rate or volume of node $j$ at time $k$

$T_P$: Physical production delay

*G*: Controlling interest

$R_j(k)$: Received or completion rate of commodity at time $k$

$Y_{jk}(k)$: The amount of commodity delivered at time $k$ by upstream node $j$ to downstream node $k$.

$$jk \in \{PW, WD, DR, RC\}$$

$D_{kj}(k)$: The order supplied by downstream node $k$ at time $k$ to upstream node $j$

$$jk \in \{\wp, DW, RD, CR\}$$

$\hat{D}_{kj}(k)$: Estimation of $D_{kj}(k)$ approximated by a non-diagonal predicting system

$BO_j(k)$: The amount of bullwhip effect of node $j$ at time $k$

$I_j(k)$: Available stock of node $j$ at time $k$

Objective functions: Broadly speaking two objectives are followed simultaneously. First, minimizing production matching costs, and second, minimizing the stock maintenance costs along the chain. Therefore, the system would be designed to minimize the matching costs due to increase or decline in production to meet the system needs as well as to minimize stock maintenance costs. The matching costs may be due to bullwhip behavior and production order rate costs are varying. Maintenance costs are due to reduction of hits and their effects through stock position. Maintained stock plays the role of impact absorber against the demand fluctuations. The production matching costs may include employment, firing, overwork, maintaining additional raw material, loss of capacity and obsolete stock.

The objective is simultaneous minimization of the stock and orders (bullwhip) variance. It is desirable to suppose that there is interaction between stock and demand fluctuations. For example, there is a spectrum of designs which, at one end, the demand is considered precisely with minimum stock information available and pass on orders, or, at the other end, absorb demand fluctuations at stock and maintain the order rate level (as surface plan). Due to lead time, this interaction assessment is difficult. Moreover, in order issuance, the best policy may be attracting a part of fluctuations and work on a part of demand change.

**2-1- Bullwhip measure**

As mentioned earlier, several measures are provided for bullwhip effect and the following equation has been proved:

$$VR=\frac{\sigma^2_{Output}}{\sigma^2_{Input}}=\frac{1}{\pi}\int_0^{\pi}\left|F(j\omega)\right|^2 d\omega=\frac{W_n}{\pi}=\sum_{n=0}^{\infty}f^2(n)$$

(1)

As discussed earlier, this destructive effect in supply chain system in control sciences is recognized as a disturbing input. So, this effect has to be mathematically formulated. Equation (2-3) indicates that bullwhip effect consists of output variance/input variance ratio whose discrete function would be obtained by mapping it into the frequency space by Fourier transformation.

2-2- Differential equations of the system for node $j$:

$$ENS_j(k) = TNS_j(k) - NS_j(k)(2)$$
$$EWIP_j(k) = TWIP_j(k) - WIP_j(k)(3)$$
$$WIP_j(k) = WIP_j(k-1) + \quad {}_j(k-1) - R_j(k)(4)$$
$${}_j(k) = \hat{D}_{kj}(k)(5)$$
$$NS_j(k) = NS_j(k-1) + R_j(k) - Y_{jk}(k)(6)$$
$$TNS_j(k) = G * \hat{D}_{kj}(k)(7)$$
$$TWIP_j(k) = T_p * \hat{D}_{kj}(k)(8)$$
$$R_j(k) = \left(k - T_p - 1\right)(9)$$
$$NS_j(k) = I_j(k) - BO_j(k)(10)$$
$$BO_j(k) = D_{kj}(k-1) - Y_{jk}(k)(11)$$

This dynamic model explains the supply chain systems accurately. This model takes demand $D_{kj}(k)$ as input and calculates it based on controlling works and lead time, order rate and supply or production. The unreliability factor is prediction of demand in upstream node at time $k$ which has to be estimated in some way.

**2-3- Target stock determination**
After estimating the demand through a suitable predictive system, the value of target stock has to be determined. Target stock is the inventory playing the role of impact absorber against demand fluctuations. In this model, target net stock at each time is a function of average estimated demand for that time; that is$TNS_j(k) = G * \hat{D}_{kj}(k)$. This value is a function of time. It means the target is mobile and this is a distinctive aspect of the proposed model.

**2-4- Determining order in progress value**
In this system, the feedback loops of work in progress in production (order in progress) are active. The order in progress value, like production control system model, is based on order and stock which is obtained from estimated demand coefficient at lead time, i.e. $TNS_j(k) = G * \hat{D}_{kj}(k)$.

**2-5- Received rate at each time period**
The order issued by node $j$ at time $k$ is received at time $k + T_p + 1$due to $T_p$ units of physical delay in production and one unit of order processing and administrative works delay; therefore, received or produced level at time $k$ equals order rate at$k - T_p - 1$, i.e. $R_j(k) = \left(k - T_p - 1\right)$.

**2-6- Real net stock at each time period**
Real net stock at time $k$ in node $j$ is $NS_j(k) = NS_j(k-1) + R_j(k) - Y_{jk}(k)$ that means at each time period $k$ after receiving or production the value is $R_j(k)$ and it is $Y_{jk}(k)$ after meeting the downstream node demand in a period before and delivery to it. The residual value is added to the previous period's net stock.

**2-7- Real order in progress at each time period**
The order in progress at period $k$ in node $j$ is:

$$WIP_j(k) = WIP_j(k-1) + \quad _j(k-1) - R_j(k)(12)$$

It means that at each time period $k$ the value of $R_j(k)$ units are received; therefore this is output of the order cycle. On the other hand, an order issued at previous time period $_j(k-1)$, would be added to the previous time period order in progress $WIP_j(k-1)$based on lead time of order processing and administrative works of the order in progress loop.

**2-8- Order rate at period $k$**
In designed model, it is aimed to find an optimal input signal to the system as the controlling signal or order rate. The optimal signal is one for which the system error is minimized. This signal is generated following the logic in production control system model family which is based on order and stock. At each $k$, first the net stock error (the difference between real net stock and target net stock) and error of order in progress (the difference between real order in progress and target order in progress) is calculated and these errors are inputs of optimizer. Instead

of error values, error generating singles are inputs of optimizer. The optimizer output is summed up with estimated demand at $k$ and generates the order rate signal.

Equation $BO_j(k) = D_{kj}(k-1) - Y_{jk}(k)$ means the delay value at $k$ in node $j$ is equal to value of demand in downstream node $k$ from upstream node $j$ at period $k$-*1* that cannot be supplied by $j$ at time $k$ and is passed to the next period. These equations are not introduced to the system dynamic generator equations directly and are merely referred to for defining the net stock.

**3. Proposed models**

**3-1- Predicting controller design**

In these controllers at sampling time $k$, a control horizon $ch$ of future manipulated variable changes is selected such that the predicted respond during the predicting horizon would be of desirable and certain features. This process is fulfilled by minimizing an objective function which includes future controlled variables deviation from desirable reference path along $ph$ and controlling energy along the $ch$. Optimizing predicting model control for an assumed horizon is conducted by control replacing and only the first replacement is accomplished. The problem is solved again at time it+1 with measured output as a new start point. In production/stock planning problem, present and future order rates$(k+j|t), j = 0, \dots, ch$, are manipulated variables.

Of course, order rate is obtained from sum of optimizer output signal and demand estimation. While the net stock predicted value $NS(k+j|t), j = 1, \dots, ph$ and working levels during the production or predicted order in progress $WIP(k+j|t), j = 1, \dots, ph$ are controlled variables. Net stock value predictions and order in progress value predictions are calculated by the following equations:

$$NS_j(k) = NS_j(k-1) + R_j(k) - Y_{jk}(k) (13)$$

$$WIP_j(k) = WIP_j(k-1) + \quad _j(k-1) - R_j(k) (14)$$

Prediction model's control limitations are

- Balance equation of net stock and order in progress along prediction horizon
- Up and down bounds on manipulated variables and control movements along control horizon
- Zero control movement along $ch$
- Continuous excitation condition along $ch$

Prediction model's control elements are:
Prediction model: The process or system output is predicted by this model for time *T*. This is an exogenous model which runs parallel to the real model which is assumed to be unknown to some extent.
Target path: The control aims to move the output vector along a desirable path which is *r(k)* toward the final desirable point *d(k)*. This path, *r(k)*, is called the reference path. In most of cases, it is assumed that future desirable output of the process is unknown. If future target point was unknown, a predictor can be used to predict the desirable path which has to be traced by system output. This is an

important future feature for complex goals management which may vary in response to some unpredicted events dynamically. Controlling rule organization: The predicted output $Y_p(k+j), j = 1, \dots, T$ depends on assumed control input $u(k+j), j = 0,1 \dots, T$. A major objective of prediction process is calculating prediction errors. The algorithm attempts to minimize the difference between $Y_p(k+j)$ and $r(k+j)$.

**3-2- Neural Networks application in proposed model**

This is important to note that it is proved that multilayer perceptron networks (MLP) with a latent layer and sigmoid conversion functions in the middle layer and linear conversion functions in the output layer can approximate all functions (functions with integral square) with any approximation degree provided that they have sufficient neurons in latent layer. Accordingly, the approximated functions have to be piece-wise continuous and the number of middle layers cannot be selected as infinite. This is called global approximation theorem. Following, how the network architecture is designed will be explained.

Number of layers: A bilayer perceptron network with a latent layer was selected.
Number of neurons in each layer: In layer zero, neurons are equal to inputs. The number of neurons in the output layer is equal to network outputs. The number of neurons in the middle layer had to be calculated. The more complicated the system, the more neurons are needed for its nonlinear writing. As a rule of thumb, if the neurons are more than 40, one more layer has to be added.

Actuator function: Actuator function $f$ can be linear or non-linear. An actuator function is selected based on the particular need for solving a problem which is supposed to be solved by neural network. In practice, limited number of actuator functions can be used. For this research prediction problem, in the latent layer, the sigmoid non-linear layer was used and in the output layer, the linear function.

Network learning: It means regulating parameters or weight matrices and bias vectors. The network is ready to learn after initiation of weights and network biases. In present study, the network has to be trained for prediction of distorted demands. Learning process needs a set of sound network behaviors such as inputs $p$ and target outputs $t$. During the learning process, weight matrices and bias vectors of the network are iteratively regulated so that network performance function is minimized. The general performance function for forerunning networks is the mean square error (mean square error between network outputs $a$ and target outputs $t$). Here, the post-propagation learning model was used (Levenberg-Marquardt algorithm). First, an initial value was assigned to network parameters. These values were selected randomly. Obviously, a sound selection can provide the algorithm rapid convergence and incorrect selection leads to trapping into the local minima in vector space for the network parameters at the start point of the network. Therefore, different random start points were selected. Second, new weights and biases are reselected, and this is iterated until the end condition is satisfied.

Classification of data to test and learning: There have to be three subsets in development of neural networks:
Training: Data which belong to problem domain and are used in training level for neurons updating.
Test: This data is used during learning process to assess the network response to unlearned data.
These two sets of data should be separated but both considered as learning data.
Credit data: After selecting the best network, before system running, there have to be examples of two different subsets to measure system accuracy. In this study, test and credit data is similar. There are no particular rules for measurement of subsets size.
Data normalization: Data has to be normalized in a particular interval like [0,1]. A technique for making the input/output $z_i$ non-scaled is to use the following function:

$$z_i n = 2\left(\frac{z_i - z_i^{min}}{z_i^{max} - z_i^{min}}\right) - 1 \tag{15}$$

$z_i n$ is the normalized value. Using this transmission, all data are normalized at [-1,1].

Learning rate determination ( ) in post-propagation error: High learning rate increases the training speed since from one iteration to the other, the weights vector changes, but it may fluctuate at error level and never converge. In contrast, lower rates reach absolute minimum, but at a lower speed. Learning rate is a value between 0 and 1. Here, the value is 0.01.

End condition and momentum term: Momentum means weights updating in line with escaping the local optima and reducing the instability. High momentum increases local minima while low momentum reduces the learning speed. Momentum can be considered constant or adaptive and the value of momentum can be determined based on the problem type. Momentum term was considered 0.7. In the network designed in this study, the end command is issued after certain epoch or when the error tolerance reaches 0.01. Learning error for learning data is calculated from the MSE and at each period for test data it was calculated from mean absolute precipitance error (MAPE).

### 3-3- Minimization algorithm for Asexual Reproduction Optimization (ARO)

There are diverse techniques inspired by asexual reproduction. ARO algorithm is inspired from the Budding technique in asexual reproduction. In ARO, in the first version, each individual is indicated with a binary strand. This is exactly the same as binary reflection in evolutional algorithms. A decision variable vector $x$ is an individual in optimization problem $X = (x_1, x_2, \dots, x_n)$ as $X \in R^n$ and each decision variable $x_i$ is a chromosome consisting of some bits called genes. A chromosome with length of $L$ is considered. In this chromosome first bit indicated the variable sign. $L_1$ of the first bit indicates the decision variable while $L_2$ of the last bit indicates the decimal part of decision variable. It is obvious that the larger the bits of the $L_2$ decimal part, the more accurate the decision variable would. Consequently, each chromosome's length is $l = l_1 + l_2 + 1$and length of each individual is $n * L$ (Hiller ……, 2011). It is assumed that each response in search space ($S$) is a creature in its natural environment and in fact, if we consider the search space (S), this space is comparable to the environment in which the creature lives, grows and reproduces. For example, search space $R^2$ for variable $X = (x_1, x_2)$ is an environment in which the individual (like a particular worm which reproduces) lives. Also, there are limited resources in the environment and only most capable individuals can survive and live. First, the algorithm starts with a random individual in a specific domain S. Then, this individual reproduces a child with particular operator called reproduction mechanism. The parent and child compete based on a performance index or fitness for survival function. If the child called wind wins the competition, its parent is excluded. Therefore, the parent is substituted by the child who will be a new parent. If the parent wins, then wind is excluded. The algorithm iterates this process to meet the end condition. The pseudo-code of algorithm is:

**Pseudo code of ARO**

```
Begin
t = 1;
P = Initialize (L,U); % Parent Initialization between lower and upper bound
Fitness_P = fit(P); % Fitness of P is calculated
While stopping conditions are not met % Stopping Criteria
Bud(t) = Reproduce(P); % P reproduces a Bud
Fitness_Bud(t) = fit(Bud(t)); % Fitness of Bud(t) is calculated
If Fitness_Bud(t) is better than Fitness_P
P = Bud(t); % Bud(t) is replaced with P
Else
clear Bud(t); % Bud(t) is discarded
end
t = t + 1;
End
End
```

Actually, the above pseudo-code will be placed as ARO algorithm in figure 1 as optimizer block. Selecting a suitable reproduction operator is crucial. In ARO, the reproduction operator is only the change operator while most of evolutionary algorithms use different operators to conduct the search in space and use previous information based on traditional control theory. In ARO, in each chromosome, there is a randomly selected gene for reproducing a sub-strand with $g$ bits. It is necessary to note that $g$ has uniform distribution in [1, L]. $L$ is the maximum number of bits (genes) of a chromosome. Therefore, bits of each sub-strand are mutated such that 1 replaces 0 in each selected gene and vice versa. In fact, the strand which is called larvae is a mutated form of its parent. A larva desirably searches in the space but not for the previous generation information employment; whereas based on optimization theory, both search and application operators are needed. Therefore, to increase the algorithm's optimization power, an application mechanism is also added to it such that larvae and its parent can integrate their information. As a result, child would be reproduced similar to its biological model. Using this instrument, one can make sure that both mechanisms of search and application are used. The mutation occurs in cross-section.

**ARO steps**

Reflection: Reflection in ARO is binary.
Primary response: An integer number is generated in the intended interval as a parent.
The fitness of this parent is measured by objective function.
The parent reproduces a wind using reproduction operator.
Before fitness, justification of the wind is tested. If it was not justified, it is repaired by a mechanism and then justification is measured. Comparing objective function value for the parent and the wind, the one with higher fitness is selected for next generation production. This is iterated until reaching the end condition.

## 4. Simulation

In order to investigate and compare the effectiveness of different prediction models, a real dataset consisting of 1000 supply chains of Food&Drug Company was collected. The data shows daily demand for a particular Drug part. The particular feature of this dataset is its distortion and fluctuating behavior which complicates prediction and increases unreliability. About 10% of demand data is zero and changes in demand values in different periods are high. The data is demonstrated in figure 2.

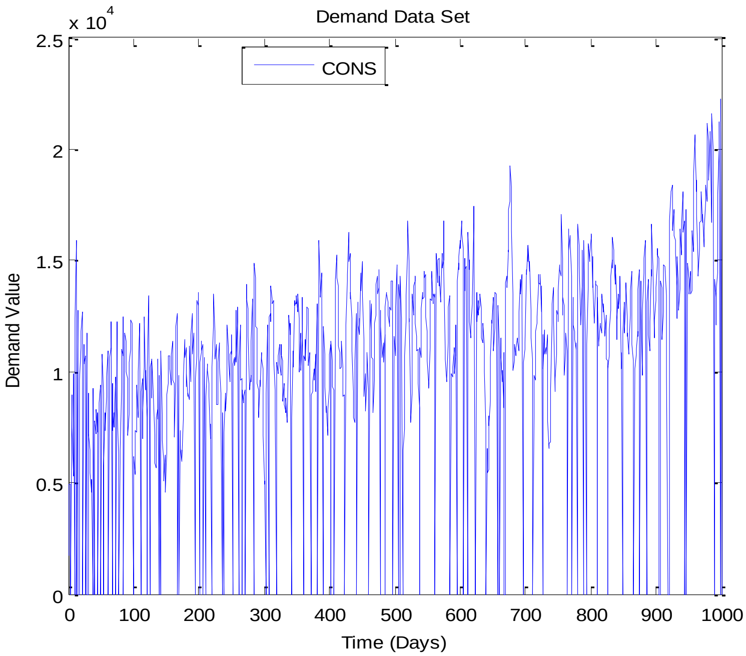


Figure 2. Schematic of demand time series data

As you can see, data behavior is distorted and non-linear. Some statistical features are presented in table 1.

Table 1. Demand time series statistical features

| SD | Mean | Min. value | Max. value | Domain | Non-zero data | Number (n) |
|---|---|---|---|---|---|---|
| 4522 | 10680 | 0 | 22230 | 22230 | 900 | 1000 |

The data show a cyclic increasing behavior. Fortunately, the amount of data is sufficient to predict using neural networks. Iterative neural networks model is similar to neural network. The only difference is that each neuron in the latent layer has reversible connections which are returned in the next level into all neurons in that layer. This provides the reversible neural networks with learning some patterns over time.

**Finding the best network architecture**

Table3 lists the best network architectures for three different datasets. As mentioned before, the optimal architecture was selected based on minimum error of assessment using the test data.

Table 3. The best network architectures for different datasets

| Number of optimal neurons in the middle layer | Multiple perceptron | | Reversible network | |
|---|---|---|---|---|
| | I | J | i | j |
| Dataset 1 | 20 | 40 | 1 | 16 |
| Dataset 2 | 20 | 19 | 1 | 9 |
| Dataset 3 | 11 | 10 | 1 | 17 |

i (i=1,2,...20) is the number of network parameter selections and i (i=1,2,...,40) is the number of neurons in the middle layer.

**Error criterion selection**

To compare different prediction models, MAPE was considered as a general criterion. Since in distorted demands, demand level is zero at some periods, the main definition of MAPE with terms in form of $\frac{|E_t|}{D_t}$ in which $D_t$ and $E_t$ are real demand and prediction error at time $t$ respectively, they are not practically used since the denominator for some time periods would be zero. Therefore, instead of the traditional definition of MAPE, an alternative definition is used:

$$MAPE = \frac{\sum_{t=1}^{n}|E_t|}{\sum_{t=1}^{n} D_t} (16)$$

For the sake of comparisons stability, error criterions other than MAPE had to be considered. A research by Armstrong and Collopy (1992) assessed the error comparison criteria between 90 annual time series data and 101 seasonal time series data. They concluded that if possible prediction errors were large; MAPE should not be selected as assessment criterion because MAPE tends to lower predictions. They also concluded that while Route Mean Square Error (RMSE) is used frequently, it is not reliable. They suggested using Median absolute percentage error (MdAPE) when there are many time series data as the best technique for prediction, but using MdAPE calculation for distorted demand data is also difficult since there are zero demand periods. Of course, there are other error criteria such as 'Percentage Better' that have been suggested in literature to compare different prediction models of distorted demand. So, here only the MAPE is used to compare different prediction models. Table 3 compares four models used for prediction based on MAPE.

Table3. Different prediction models comparison

| MAPE (%) | naive | Exponential smoothing | synthetos | Multilayer perceptron | Reversible network |
|---|---|---|---|---|---|
| Dataset 1 | 43.17 | 34.15 | 26.12 | 21.61 | 21.28 |
| Dataset 2 | 41.11 | 33.47 | 25.96 | 21.53 | 21.21 |
| Dataset 3 | 44.89 | 34.99 | 29.56 | 25.65 | 26.67 |

Based on this table, the synthetos model clearly outperforms other classical models such as naive and exponential smoothing. Neural networks generally outperformed the classical prediction models for all three datasets. Also, in comparing the two networks, the reversible neural networks, while needing higher computations is not different in term of performance from multilayer perceptron model. All five prediction models used performed best on dataset two.

**ARO optimization algorithm implementation**

Running times ($T_{max}$) is 1000 and number of decision variables is equal to prediction horizon which is five. Minimum value of weight vector is zero and maximum value is two times more than estimated demand value. As mentioned earlier, in this algorithm, first the parent randomly selects a value in interval between the upper and lower bounds. Actually, this value is the primary justified respose. Here, the lower bound is zero and the upper bound is two times more than demand value. Since the number of decision variables is five, then there are five values for order rate along the prediction horizon which are selected randomly as the parent's values. Then, the parent's fitness value is calculated. The parent produces a child and then the child's fitness value is calculated. If the child's value is better than that of the parent, the parent is substituted by the child; otherwise, the child will be excluded. This iterates until reaching the end condition.

**ARO algorithm validation**

To validate optimization algorithms, there are well-known functions used whose optimal values are certain and are used to test the speed and accuracy of these algorithms. The result of optimization for 10 dimensions and its comparison to standard genetic algorithm are listed in table 4.

Table 4. Comparing proposed optimization to algorithm GA

| مقایسه بین GA و ARO بعد10در | | | | | |
|---|---|---|---|---|---|
| Function | Objective function | ARO | | GA | |
| | | Mean | SD | Mean | SD |
| Rastrigin | 10e-10 | 59.95 | 1.23 | 86.156 | 0.263 |

**Model validity**

To determine the model's validity, real data of demand is used. The designed model is implemented with real data and optimal control signal determination, or order rate, was conducted online. One controlling performance criteria is that real values and system outputs be able to track the target outputs or reference values and, as a result, system error is minimized. As mentioned above, there are two processes in the designed model. The goal of controller is to determine the control signal or order rate such that at each time period, the signal tracks real net stock, target stock and order in progress signal, and target order in progress. Figure3 represents the target net stock and real net stock values at sampling periods.

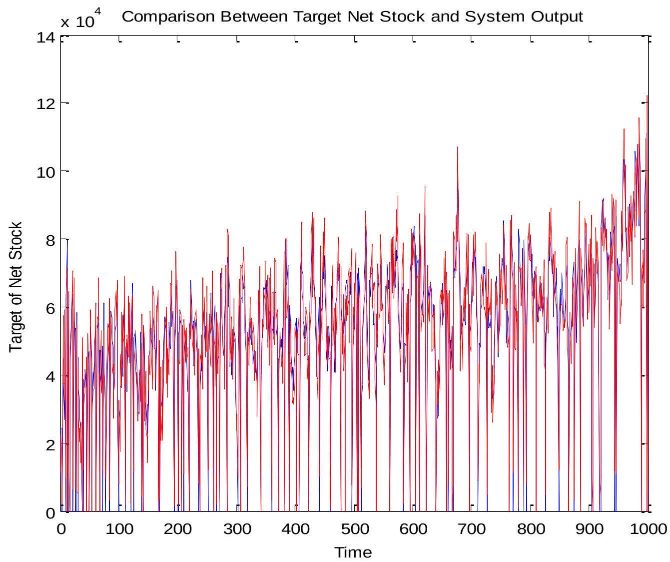


Figure 3. Real and target net stock values

In this figure, the target net stock is in red and system output or real net stock at each time period is in blue. As you can see, after running the ARO algorithm and dynamic learning by neural network, real stock value approaches the desirable output, i.e. the target net stock. Figure 4 shows the value of desirable order in progress and the real order in progress for the sampling periods.

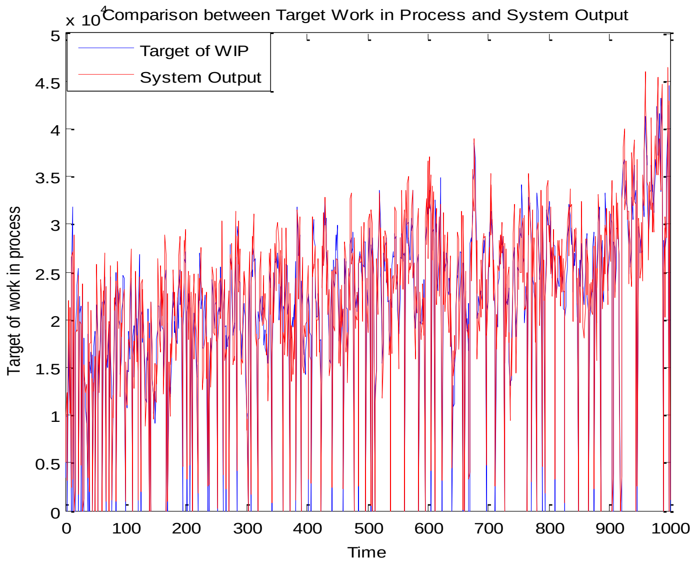


Figure 4. Real and target order in progress values

As you can see, after running the optimization algorithm of asexual reproduction (ARO) and dynamic learning of neural networks, the system output which is the real order in progress at each time period, approaches the desirable output, target order in progress value. Tendency of the output of both processes to desirable outputs ensure error minimization. This, in turn, leads to a situation in which order rate signal is equal to estimated demand signal.

**Bullwhip effect**

As mentioned before, bullwhip effect is intensification of the demand fluctuations in moving towards upstream nodes in supply chain. Prediction model controller's design makes it difficult to extract transformation functions and depict frequency response vectors. Therefore, the bullwhip's general measure, variance ratio, is used:

(17)

Where $\sigma^2_{0\mathrm{R}}$ =2665.9 and $\sigma^2_D$=4521.8; therefore, variance ratio or bullwhip effect is 0.5896. Figure5 shows order rates in sequential periods.

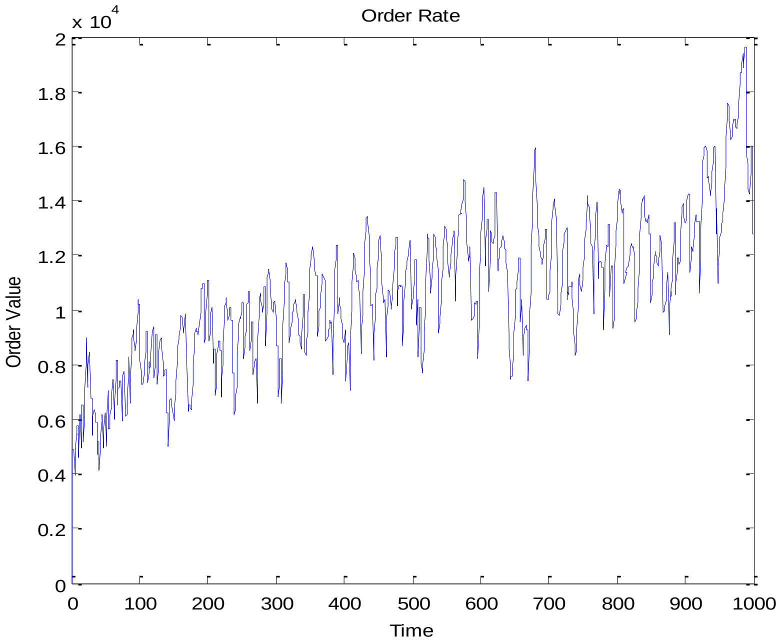


Figure 5. Order rate at different periods

This figure refers to 1000 sampling periods and obtained values are in fact values of controller estimation of order rates at each time period. It is observed that as time periods increase, the order rates increase as well. Figure 6 indicates the asexual reproduction optimization algorithm convergence:

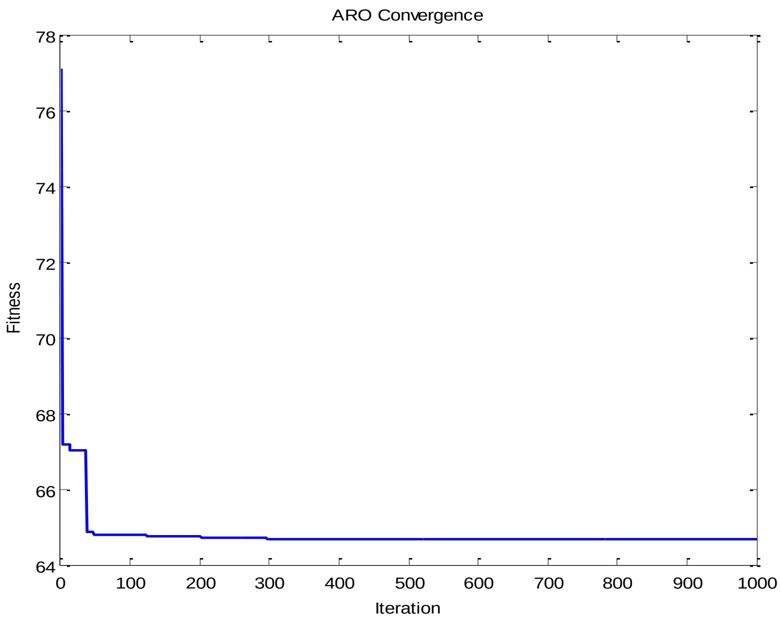


Figure 6. Convergence diagram of asexual reproduction optimization algorithm

**5. Conclusion**

Prediction model control has been used in supply chains and the results were satisfactory, but proposed systems did not have future demand information. Integrating a prediction methodology into the model prediction control framework could improve the controlling system performance. In this study, first a prediction system was used in a customer's demand prediction model. The customer's demand is distorted and fluctuating; that is, fluctuations are high and in relatively diverse periods, this demand is zero. Real time series data of demand for an part in Drug Company was collected to predict uncertainty in distorted demand behavior, classical and smart prediction models were used. One of the common demand prediction models in scientific literatures is exponential smoothing model, while Croston (1972) indicated that this is a diagonal prediction model. This is more obvious particularly when the demand is distorting. To design the desirable prediction system, first more advanced demand prediction models such as neural networks, reversible neural networks, integration of wavelet and neural networks with classical models like naive, exponential smoothing and synthetos model were compared in a real time series and then, the new controlling design and framework was proposed. In the new control design, the best demand prediction model was used. It was expected that more advanced models such as intelligent ones outperform the classical ones because advanced models introduce non-linear models; therefore, they can outperform linear models and based on non-linear and fluctuating behavior of distorted demands, neural networks were better in modeling and predicting them compared to classical models such as exponential smoothing and synthetos.

At first, it seemed that noise reduction improves distorted data prediction. To this end, using data filtering model before insertion into the neural networks and noise elimination were desirable. Wavelet analysis is one of the most powerful filtering and noise elimination tools in this context. Therefore, different wavelets such as Meyer, Morlet, and Mexican Hat etc. were investigated. Noise elimination did not influence the data behavior and it was concluded that data doesn’t have noise and generally speaking, you cannot assume that wavelet and neural network integration can outperform in predicting time series compared to neural networks since the networks are noise-tolerable. Five different prediction models, naive, exponential smoothing, synthetos, neural networks and reversible neural networks were compared based on MAPE defined in the study. Neural networks outperformed other classical models mentioned. The output of this predictive model, i.e. estimation of future periods demand for downstream nodes, is the regulation points or target values of controlled processes, feedback loop of the net stock and feedback loop of order or production flow. In addition, estimated demand plays a role in generating the order rate controlling signal at each time period. A control system consisting of an optimizer and two perceptron neural networks with a latent layer was designed. The control system’s goal is to find optimal control signal at each time period so that the real output deviation of both processes from regulation or reference path points is minimized. Neural networks are responsible for dynamic learning of the process and predicting several periods ahead values of the process based on present control signal value as the process input. The functions constituting the processes dynamics and system equations were extracted based on the production planning problem’s logic. After the training of neural networks, real output of the two feedback processes were introduced into the optimizer along with networks' prediction values which were responsible for dynamic learning of these processes. The optimizer had to solve a conditioned dynamic nonlinear optimization problem defined by the objective function and problem limitations were explained to determine the optimal controlling signal which is the order rate at each time period. To solve the minimization problem, a meta-heuristic algorithm ARO was used. Through minimizing the overall system error, the optimizer made the control signal closer to the estimated demand signal. This ensured minimizing the bullwhip effects. Implementation of the proposed design with a real dataset of distorted demand brought about satisfactory results.

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