Journal of Quality Engineering and Production Optimization

Vol. 7, No. 2, Winter & Spring 2022

http://jqepo.shahed.ac.ir

Research Paper

DOI: 10.22070/JQEPO.2021.14110.1179

The Impact of Time and Time Delay on the Bullwhip Effect in Supply Chains

Sajjad Aslani Khiavi*[1], Simin Skandari Dastghiri[2]

[1] *Department of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran*
[2] *Department of Management, Meshkinshahr Branch, Islamic Azad University, Meshkinshahr, Iran*

**** Corresponding Author:** Sajjad Aslani Khiavi (Email: sajjadaslani8@gmail.com)*

***Abstract** – Modeling and measuring the demand variance propagation from the initial hours of the supply chain (SC) to the final hours is one of the most important challenges facing the logestics experts. Factors such as time delay increase demand fluctuations over the time in SC networks. This problem often referred to the Bullwhip Effect (BWE) in production systems. In this paper, a flight scheduling network as a supply chain are designed using Inverse Data Envelopment Analysis (IDEA). The effects of the arrival time of the aircraft (landing time) to the airport, as well as the delayed flights (depart time with delay) to the next destination on the demand variance were examined. The results show that demand fluctuations increased significantly by delaying flights in the closing hours. Also, the bullwhip effect due to landing time, at the beginning of the day are more than the final flight hours. This means that due to the higher demand during office hours (beginning of the day), there are many fluctuations in the variance of orders. Comparing the results with the control engineering approach, we found that the proposed method shows the hidden points (effect of flight shifts on involuntary oscillations) of the size of the bullwhip effect. While these hidden points have not been identified in previous methods.*

***Keywords**– Supply Chain, Network IDEA, Relative Bullwhip Effect, Time Delay, Airport Network*

I. INTRODUCTION

The advent of air transport in recent decades has caused significant problems in air traffic in the world. In this regard, flight delays, cancellation costs in recent years have been about several billion dollars in different countries. Of these costs, it was about 25% for airlines. Compared to countries around the world, the total revenue of the US aviation industry over the past four years is more than $ 5 billion. As a result, setting up and managing delays has become a top priority for air navigation service managers.

Until the early 1990s, main aerial traffic delays occurred at a relatively small case of aerial transportation network. Until early 2007, as the worst year for airline delays, demand at many US airports, and to some extent in Europe, for several hours a day, as well as in hot seasons, was close to or above airport capacity. So, not only were flight delays at airports dependent on different hours of the day, especially on bad weather days. As a result, congestion on such days and hours can quickly cause air traffic problems and affect many level of the SC network. In fact, at least one company has experienced pilot "delays" (Beatty et al., 1998). The net cost of delay in this network is very high. Estimates for the United

Manuscript Received 1- May -2022 & Revised: 13- June -2022 & Accepted: 30- July -2022
ISSN:2423-3781

States in 2007 ranged from $ 12 billion (Aviation Association, 2009) to $ 41 billion, including direct delays for airlines and their demand. Also, the indirect and inductive costs that these delays have brought to airlines are an important issue for the airline network.

In this regard, Wu et al. (2018) Due to aviation activities at airports, weather conditions and air traffic are dependent on flight delay orders. They used a tool to find the release of the delay and study its effects. Using factual information from an Asia-Pacific airline, it has been determined that flight delays can be transmitted to airports / downstream airlines, where delay power is reduced or increased. Considering the effects of increased latency under the control of air traffic or aviation agents, the concepts that regulate flight schedules with additional buffer time were examined. Wu et al. Showed that by increasing the buffer time efficiently, flight schedules can be made more reliable. In the case of dynamic modeling, several system-level transactions take place during the trading time, and it is recommended to use the optimal strategy for the human Mars exploration architecture. Intended transactions include transactions between in resource utilization and propulsion technologies as well as circuit and warehouse location selection over time (Hu et al., 2014).

Consider an integrated manufacturing system that returns products after major repairs or special cycles for major repairs. This model maximizes profits by considering the costs of production, reconstruction and inventory, using the integer linear programming model. These models were tested through a set of experimental data (Hashemi et al. (2014)). An analytical model of network queuing and analysis developed by Pyrgiotis et al. (2013) was used to investigate the complex phenomenon of delay propagation in a large network of large airports. They referred to the "bullwhip effect" that led to the further release of these delays. Such phenomena are particularly evident at hub airports, where some flights (with reduced delays) may benefit from changes in the planned demand profile due to delays. On the other hand, two inconsistent analyzes were examined. With the delays caused by the proposed model, anyone can continue to create a discrete-continuous econometric model in creating long delays. The results of the analysis showed that the published delay produces a newly formed delay from each time. Also, by analyzing their flight schedules, different airlines can be informed to reduce the amount of flight delays (Kaffel et al. 2016).

A very important study discusses the similarities between the aviation system and the beer distribution system (Olivia et al. (2009)) and conducts a detailed and comparative study of performance measurements and constraints in both systems. They gave. Based on the proposed comparison as well as previous research on supply chain modeling, they define an equivalent supply chain framework and define appropriate performance metrics for the aviation system.

Due to the sense of competition in the market, supply chain issues have become more important. (Asif et al., 2012). SCM may be a chain of relationships between suppliers, manufacturers, distributors, and retailers that converts raw materials into end products (Lee et al., 2014). To model and regulate such a chain, all factors must be considered (Disney et al., 2003). SCM has recently been considered by most experts in the industrial and control system (Payne et al., 2004). The spread of variance of orders, from downstream to upstream, is considered BWE. Dejunkir et al. (2003) began the analysis of this phenomenon by amplifying the variance.

The study and research of demand variance in supply networks was proposed by Forrester (1958). He was the first to research BWE and described it as an increase in demand. He stated that this issue can be optimized by reducing the time delay. Forrester (1958) introduced four topics for the phenomenon of demand fluctuations: demand data processing, quota games, order classification, and price fluctuations. This was not a new issue, and many researchers have been interested in working on it. As such, uncertain demand is one of the most important reasons for BWE. Other factors such as random demand, random noise (Sajjad Aslani et al. 2019, 2021) and forecasting method are also important in influencing the efficiency of SCM.

Many studies have been done in recent years to measure and adjust this. Studies such as control theory, mathematical programming, and statistics were among these methods. (Dejonckheere et al., 2003; Disney and Twill, 2003; Dejonckheere et al., 2004; Kim et al., 2006; Duke et al., 2008a; Duke et al., 2008b; Fu et al., 2008). Some studies that support data envelopment analysis (DEA) on BWE measurements, although DEA has the ability to achieve the relative performance of DMUs of decision units (DMUs), But is not able to study internal processes for DMUs.Cao and Huang (2008) considered the secret relationship between two sub-processes and showed that the overall performance of DMU is the efficiency of two sub-processes.Lee et al. (2012) a two-shift model Envelopment data were presented by testing the method (Liang et al.) Moreno and Lozano (2014) also used the DEA network model to measure the performance of NBA teams.

Khalili et al. (2015) created an uncertain network with unpleasant data to investigate the performance of power generation and transmission networks. The researchers introduced the DEA network to determine the performance of power generation and distribution processes. In the first phase, power plants used forces such as oil and gas to generate energy. In the transition phase, regional generators transfer and distribute electricity to consumers in homes, industries and agriculture. They evaluated the final performance of DMUs and sub-DMUs using the multi-feature decision making (MADM) method.

Using aspects of SCM (Constantino et al., 2015; Disney & Lambrecht, 2008; Fu et al., 2015), it can be assumed that BWE examines SCM performance. BWE creates a number of adverse events including unacceptable production scheduling, warehousing leading to huge costs, low level of service for all nodes in the production chain, immediate effect on setting and shutting down machinery, upstream inventory, barriers Production schedule and schedule are predicted. It also leads to weak supplier-customer relationships (Cannella et al., 2013; Disney et al., 2007; Wang & Disney, 2016). Amir Rezaei et al. (2015) investigated the performance of seven production chains including suppliers, manufacturers, transmitters and consumers using the DEA aspect. In another work, Amir Teymouri et al. (2011) examined the DEA model to quantify the performance of suppliers and manufacturers in the supply chain.

Accordingly, Aslani et al. (2021) developed a new network IDEA model with adverse outputs for RBWE calculation. In Aslani et al.'s research, to measure the effect of bull whip, each separate time period was considered as a decision unit. Demand fluctuations do not occur for no reason. But certain cases cause the production and dissemination of this variance. As a result, in this study, by presenting a network model of inverse DEA and introducing the effect of uncertainties in a production network, the relative score and the effect of these factors on supply chain fluctuations were studied. In fact, time and latency variables are unfair because the BWE value automatically increases over time. The dependence of fluctuations on time and latency variables should be considered in the BWE score. By adding the effect of these factors on the BWE score, we get a fair score and define these new scores as relative BWE.

The rest of this paper is summarized as follows: The proposed time-delayed airline network is formulated with the IDEA network in Section 3, which provides an illustrative example of a time-delayed supply chain system to confirm the advantage of the proposed strategy. . Our conclusion is presented in Section 4.

II. DESINNING THE PROPOSED AIRLINE NETWORK AS A SUPPLY CHAIN

In fact, by developing the IDEA approach with the desired goals, a way can be obtained to measure the acceptable magnitude of demand fluctuations from the downstream to the upstream. As mentioned, time delay in the process of requesting goods and supply is one of the factors that affect the issue of fluctuations in demand variance. The quantification of this relative magnitude must be checked if there is a time delay. IDEA alone cannot be useful for planning this internal factor. IDEA network structures enable scientists to advance this. In addition to scoring the overall whipping effect for a supply chain, the IDEA network examines the internal process and performance of airport chain stages. Figure 1 shows the proposed IDEA network model for quantifying the size of demand fluctuations at the airport in the presence of time delays and eventual flight cancellations.

To use a dynamic network, we divided flight corridors into several units at a given time and defined each flight interval as a decision unit (airports). In fact, one decision unit in different shifts becomes several decision units of the proposed model. This partitioning introduces a dynamic supply chain for an airport flight. All decision-making units have one type of consumer goods and one type of manufactured goods. Because delay is an unpleasant phenomenon and because experts want to reduce output per unit, the reverse DEA is used.

$$t = \{t_0 = 6, t_1, \dots, t_{n-1}, t_n = 24\}$$

For the every $0 \le j \le n$, we suppose that:
DMU_j is a decision making unit in $[t_j, t_{j+1}]$:

$$DMU_j = [(x_{1j}, \dots, x_{mj}) = inputs, (y_{1j}, \dots, y_{sj}, l_{1j}, \dots, l_{sj}) = outputs]$$

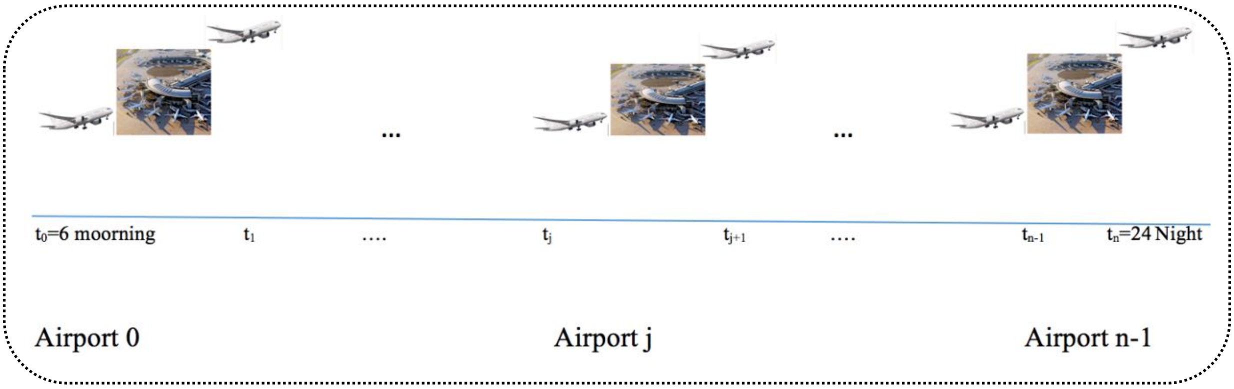

Fig 1. A schematic representation of the operation of the proposed Network IDEA model.

The proposed model (Figure 2) was a network IDEA method in two phase; in the first phase, demand ($x_{ij}: i = 1, \dots, m$), and time (t_j) are the inputs. Outputs from the first phase included current orders ($y'_{rj}: r = 1, \dots, s$) that were intermediate orders for the second stage. The decision process caused delay in sending orders. In fact, time delay was considered as an inappropriate input in the step 2. In this model, time intervals were a decision making unit. So, as mentioned the absolute score of this phenomenon become so large through the time (unfairly). Indeed, time is an unfair factor for comparing the two absolute sizes of the demand propagation in different periods. To this end, in this model, we considered the time duration of each decision making unit as an input to be fairly considered in the relative score of this phenomenon.

Fig 2. Conceptual scheme of a aerial transportation network as a DMU.

As seen in fig 2, each fly shifts (DMU) includes two forward connected sub-DMUs, i.e., stage 1 and stage 2. In stage 1 demands are receiving and after manager processing, orders were sending in stage 2. Time delay take place among this process. Tab. 1 shows the notation of the inputs, intermediates and outputs variable.

Table I. Inputs and Outputs

Variables	*Notations*
$t_j; j = 1, \dots, n$	Landing time in jth airport (supposed as an input, to probe the effective of the time)
$t_{j+1}; j = 1, \dots, n$	Take Off time in jth airport
$x_{ij};\ i = 1, \dots, m, j = 1, \dots, n$	Demands for ith destination in jth airport (input for stage 1)
$y'_{ij};\ i = 1, \dots, m, j = 1, \dots, n$	The number of airplane that are available and predicted to ith destination in jth airport (intermediate variable:)
$y_{ij};\ i = 1, \dots, m, j = 1, \dots, n$	The number of airplane that finally allocated to ith destination in jth airport (output of stage 2)
$L_{ij};\ i = 1, \dots, m, j = 1, \dots, n$	Delays that take place from prediction process time until allocation time in jth airport to ith destination (inputs for stage 2). Such as taxi out time, Repairs, technical defects, passenger boarding, runway congestion and ...
$j = 1, \dots, m$	Airport Number
$i = 1, \dots, n$	Destination Number

A. The network IDEA model for evaluating overall delay propagation in the SC

To begin with, we note that based on the theoretical aspects of the work of Khalili et al. (2015), a model can be developed for its purpose. In the proposed model, both desirable (intermediate measures) and undesirable (time delay) inputs were also considered. As it is preferred to probe the effect of undesirable inputs (time delay) in the relative score of the bullwhip effect, these inputs were considered as outputs in the second phase. The following notations were used in this regard. Suppose that $\mathrm{RBWE_o}$, $\mathrm{RBWE_o^1}$ and $\mathrm{RBWE_o^2}$ are the relative size of the total demand oscillation, the relative size of the first fly shift (with time) and the relative size of the demand oscillation of the second phase (with time delay), respectively. Using a constant return to the scale and input-axis model, we can write Equation (2):

$$
\begin{aligned}
& RBWE_o = min\ \frac{\sum_{r=1}^{s} u_r y_{ro} + \sum_{r=1}^{s} u''_r l_{ro}}{\sum_{i=1}^{m} v_i x_{io} + \sum_{i=1}^{m} v_i t_o} \\
& s.t \begin{cases} \dfrac{\sum_{r=1}^{s} u'_r y'_{rj}}{\sum_{i=1}^{m} v_i x_{ij} + \sum_{i=1}^{m} v_i t_j} \geq 1; j = 1, \dots, n \\ \dfrac{\sum_{r=1}^{s} u_r y_{rj} + \sum_{r=1}^{s} u''_r l_{rj}}{\sum_{r=1}^{s} u'_r y'_{rj}} \geq 1, j = 1, \dots, n \end{cases} \\
& u_r, u'_r, u''_r, v_i \geq 0; i = 1, \dots, m, r = 1, \dots, s
\end{aligned}
\tag{2}
$$

Model (2) ، is a relative nonlinear model for measuring demand fluctuations that can be converted to a linear model (4) using Equation (3).

$$
\frac{1}{\sum_{i=1}^{m} v_i x_{io} + \sum_{i=1}^{m} v_i t_o} = t \tag{3}
$$

We can rewrite:

$$
\begin{aligned}
& RBWE_o = min\ \sum_{r=1}^{s} u_r y_{ro} + \sum_{r=1}^{s} u''_r l_{ro} \\
& s.t \begin{cases} \sum_{i=1}^{m} v_i x_{io} + \sum_{i=1}^{m} v_i t_o = 1 \\ \sum_{r=1}^{s} u'_r y'_{rj} - \sum_{i=1}^{m} v_i x_{ij} - \sum_{i=1}^{m} v_i t_j \geq 0; j = 1, \dots, n \\ \sum_{r=1}^{s} u_r y_{rj} + \sum_{r=1}^{s} u''_r l_{rj} - \sum_{r=1}^{s} u'_r y'_{rj} \geq 0, j = 1, \dots, n \end{cases} \\
& u_r, u'_r, u''_r, v_i \geq 0; i = 1, \dots, m, r = 1, \dots, s
\end{aligned}
\tag{4}
$$

Theorem 1: The linear programming model (4) in the presence of time effect and delays, to obtain the relative size of the BWE in a airport of the airport network chain, is possible and the optimal value is greater than or equal to 1.

Proof: See Apendix

Definition 1: Optimal solution of the model (4) is relative magnitude of time and delay effect on demand variance in total network of a airport chain.

B. N-IDEA model for evaluating landing time effect (stage 1) on the demand oscillation

Model (7) is nonlinear programing method to evaluate RBWE in stage 1:

$$RBWE_o^1 = min \frac{\sum_{r=1}^{s} u'_r y'_{ro}}{\sum_{i=1}^{m} v_i x_{io} + \sum_{i=1}^{m} v_i t_o}$$
$$s.t \begin{cases} \sum_{r=1}^{s} u_r y_{ro} + \sum_{r=1}^{s} u''_r l_{ro} = RBWE_o^* \\ \frac{\sum_{r=1}^{s} u'_r y'_{rj}}{\sum_{i=1}^{m} v_i x_{ij} + \sum_{i=1}^{m} v_i t_j} \geq 1; j = 1, \dots, n \\ \frac{\sum_{r=1}^{s} u_r y_{rj} + \sum_{r=1}^{s} u''_r l_{rj}}{\sum_{r=1}^{s} u'_r y'_{rj}} \geq 1, j = 1, \dots, n \end{cases} \tag{7}$$
$$u_r, u'_r, u''_r, v_i \geq 0; i = 1, \dots, m, r = 1, \dots, s$$

Model (7) can be converted to a linear model (9) using equation (8).

$$\frac{1}{\sum_{i=1}^{m} v_i x_{io} + \sum_{i=1}^{m} v_i t_o} = t \tag{8}$$

We can rewrite:

$$RBWE_o^1 = min \sum_{r=1}^{s} u'_r y'_{ro}$$
$$s.t \begin{cases} \sum_{r=1}^{s} u_{ro} y_{ro} + \sum_{r=1}^{s} u''_r l_{ro} \geq RBWE_o^* \\ \sum_{i=1}^{m} v_i x_{io} + \sum_{i=1}^{m} v_i t_o = 1 \\ \sum_{r=1}^{s} u'_r y'_{rj} - \sum_{i=1}^{m} v_i x_{ij} - \sum_{i=1}^{m} v_i t_j \geq 0; j = 1, \dots, n \\ \sum_{r=1}^{s} u_r y_{rj} + \sum_{r=1}^{s} u''_r l_{rj} - \sum_{r=1}^{s} u'_r y'_{rj} \geq 0, j = 1, \dots, n \end{cases} \tag{9}$$
$$u_r, u'_r, u''_r, v_i \geq 0; i = 1, \dots, m, r = 1, \dots, s$$

Theorem 2: linear programming model (9), to obtain the proposed size of the BWE in a airport of the airport network chain, is always possible and the optimal value is greater than or equal to 1.

Proof: See apendix

Definition 2: Optimal solution of the model (9) is the flight time effect on demand variance in the airport network transportation.

C. N-IDEA model for evaluating take off delays effect (stage 2) on the demand oscillation

Model (12) is nonlinear programing method to evaluate RBWE in stage 2:

$$RBWE_o^2 = min \frac{\sum_{r=1}^{s} u_r y_{ro} + \sum_{r=1}^{s} u''_r l_{ro}}{\sum_{r=1}^{s} u'_r y'_{ro}}$$
$$s.t \begin{cases} \frac{\sum_{r=1}^{s} u_r y_{ro} + \sum_{r=1}^{s} u''_r l_{ro}}{\sum_{i=1}^{m} v_i x_{io} + \sum_{i=1}^{m} v_i t_o} \geq RBWE_o^* \\ \frac{\sum_{r=1}^{s} u'_r y'_{rj}}{\sum_{i=1}^{m} v_i x_{ij} + \sum_{i=1}^{m} v_i t_j} \geq 1; j = 1, \dots, n \\ \frac{\sum_{r=1}^{s} u_r y_{rj} + \sum_{r=1}^{s} u''_r l_{rj}}{\sum_{r=1}^{s} u'_r y'_{rj}} \geq 1, j = 1, \dots, n \end{cases} \tag{12}$$
$$u_r, u'_r, u''_r, v_i \geq 0; i = 1, \dots, m, r = 1, \dots, s$$

Model (12), can be converted to a linear model (14), using equation (13).

$$\frac{1}{\sum_{r=1}^{s} u'_r y'_{ro}} = t \tag{13}$$

So we can write:

$$RBWE_o^2 = \min \sum_{r=1}^{s} u''_r l_{ro} + \sum_{r=1}^{s} u_{ro} y_{ro}$$
$$s.t \begin{cases} \sum_{i=1}^{m} u_r y_{ro} + \sum_{i=1}^{m} u''_r l_{ro} - RBWE_o^* \sum_{i=1}^{m} v_i x_{io} - RBWE_o^* \sum_{i=1}^{m} v_i t_o \geq 0 \\ \sum_{r=1}^{s} u'_r y'_{rj} = 1; j = 1, \dots, n \\ \sum_{r=1}^{s} u'_r y'_{rj} - \sum_{i=1}^{m} v_i x_{ij} - \sum_{i=1}^{m} v_i t_j \geq 0; j = 1, \dots, n \\ \sum_{r=1}^{s} u_r y_{rj} + \sum_{r=1}^{s} u''_r l_{rj} - \sum_{r=1}^{s} u'_r y'_{rj} \geq 0, j = 1, \dots, n \\ u_r, u'_r, u''_r, v_i \geq 0; i = 1, \dots, m, r = 1, \dots, s \end{cases} \tag{14}$$

Theorem 3: linear programming model (14) in presence of time delays, to measure the relative score of the bullwhip effect in a airport of the dynamic airport network, is always possible and the optimal value is greater than or equal to 1.

Proof: See Apendix

Definition 3: Optimal solution of the model (14) is delay propagation magnitudes.

III. CASE STUDY AND NUMERICAL ANALYSIS

A. Demand variance in real airport

In this study, shahid madani international airport in tabriz was considered as a real airport network. The test run time was 18 hours. To use the proposed method, we divided a day into 9 equal flight shifts. Therefore, the raw data obtained from 6 to 8 were considered as the first flight shift and decision units 2 to 9 were considered accordingly. Table 2 shows the network inputs and outputs. As shown in the table, all this data was normalized.

Table II. Inputs, outputs and time delays

DMU_j	Time $[t_j, t_{j+1}]$	Input1: demand for destination 1 (x_{1j})	Input2: demand for destination 2 (x_{2j})	Input3: Demand for destination 3 (x_{3j})	Output1: Sending order (predicted airplanes to destination 1) (y_{1s})	Outout2: Sending order 1(predicted airplanes to destination 2) (y_{2s})	Output3: Sending order 1(predicted airplanes to destination 3) (y_{3s})	Delay1 in proparing airplanes (l_{1s})	Delay2 in proparing airplanes (l_{2s})	Delay3 in proparing airplanes (l_{3s})	y'_{1j}(allocation the airplanes to destination 1)	y'_{2j} (allocation the airplanes to destination 2)	y'_{3j} (allocation the airplanes to destination 3)
1	[6-8]	0.1	0.1	0.8	0.6	0.6	0.58	5 min	5 min	5 min	0.1	0.1	0.8
2	[8-10]	4	2	0.25	6.5	6.5	6.6	5 min	5 min	5 min	6	6	6.1
3	[10-12]	10	2	2	2.5	1.3	1.3	5 min	5 min	5 min	2	0.8	0.8
4	[12-14]	3	3.8	3.1	5.5	5.5	5.6	5 min	5 min	5 min	5	5	5.1
5	[14-16]	1.25	2	1	4.5	6.5	9.6	5 min	5 min	5 min	4	6	9.1

6	[16-18]	4.4	5	5	2.5	2.5	3	5 min	5 min	5 min	2	2	2.5
7	[18-20]	1.3	5	5	3.8	6	5	5 min	5 min	5 min	3.3	5.5	4.5
8	[20-22]	0.5	1.1	1.1	6	6	7	5 min	5 min	5 min	5.5	5.5	6.5
9	[22-24]	3.6	5	5	4	3	3.25	5 min	5 min	5 min	3.5	2.5	2.75

Table 3 shows the relative size of the BWE at the phase 1, 2, and in the total network. It should be mentioned that the size of the BWE in the proposed method was a relative magnitude.

Table III. Flight demands propagation using the proposed network IDEA

DMU_j	*Time* $[t_j, t_{j+1}]$	*RBWE in stage1 (Impact of landing time on oscillation)*	*RBWE in stage2 (Impact of take off delays on oscillation)*	*RBWE in Network*
1	[6-8]	1	1	1.4098
2	[8-10]	6.0959	1	6.0959
3	[10-12]	1	1	1
4	[12-14]	3.0493	1.0151	3.0993
5	[14-16]	3.6201	1	3.6201
6	[16-18]	1	1.114	1.114
7	[18-20]	1.538	1	1.6142
8	[20-22]	3.191	1	3.191
9	[22-24]	1	1	1

The results in Table 3 shows that with the shift working attitude for the airport demands, the demand propagation on the initial shif of flights were large. By assuming time as the input, the proposed method could examine dynamic effects on relative score in a fair way. This feature is visible in Table 3 at the first stage. Time delay is one of the important factors for the effect of the BWE. The investigated approach reveal that the demand propagation occurred at the second phase of the chain with delay. Due to the similarity of time delay in the solved case study, these relative scores had low variances. The results of the relative method in Table 3 showed that the effect of the bullwhip phenomenon produced in the entire network had different relative scores.

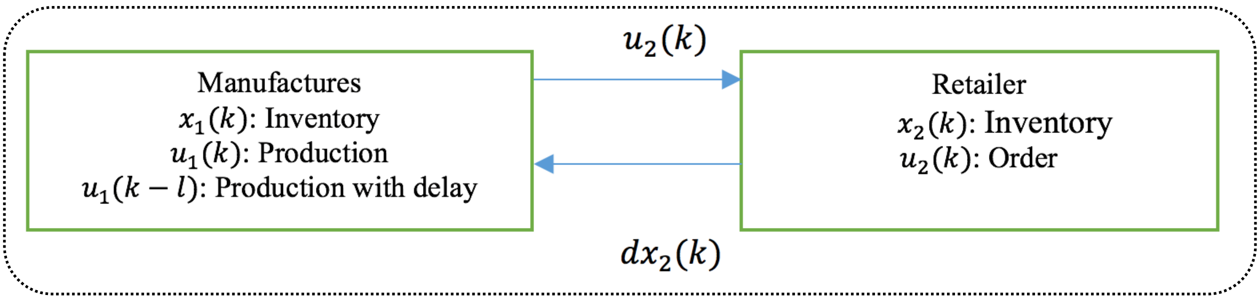

Fig 3. Airport network

B. Comprative evaluation

In the following, we compare the relative value of the bullwhip effect that measured by the proposed method and the frequency response method. To do this, we designed a state-space model of a two echelon allocation airport network with time delay in the ordering (allocation) process. Figure 3 demonstrates an airport network that consisting of two eccheton. Airplane landed node as downstream node and where airplane take off with delay assumed as a upstream node.

The state space model of supply chain is as follow:

$$\begin{cases} x_1(k+1) = x_1(k) + u_1(k) + u_1(k-1) - u_2(k) + dx_2(k) \\ x_2(k+1) = x_2(k) + u_2(k) - dx_2(k) \end{cases}$$

To measure the bullwhip effect using the frequency response method, we must take z transformation of state space equations:

$$ZX_1(z) = X_1(z) + U_1(z) - U_2(z) + Z^{-1}U_1(z) + dX_2(z)$$

$$ZX_2(z) = X_2(z) + U_2(z) - dX_2(z)$$

We can write:

$$\left|\frac{U_1(z)}{U_2(z)}\right| = \left|\frac{z-1+2d}{(z-1+d)(1+z^{-1})}\right|$$

The BWE can happen if the size of transfer function in the Bode diagram becomes more than zero. So, simulation scores reveal that fly shifts leads to the BWE in the presence of delays. In this systems, with increasing delays, the sizes of the BWE increases.

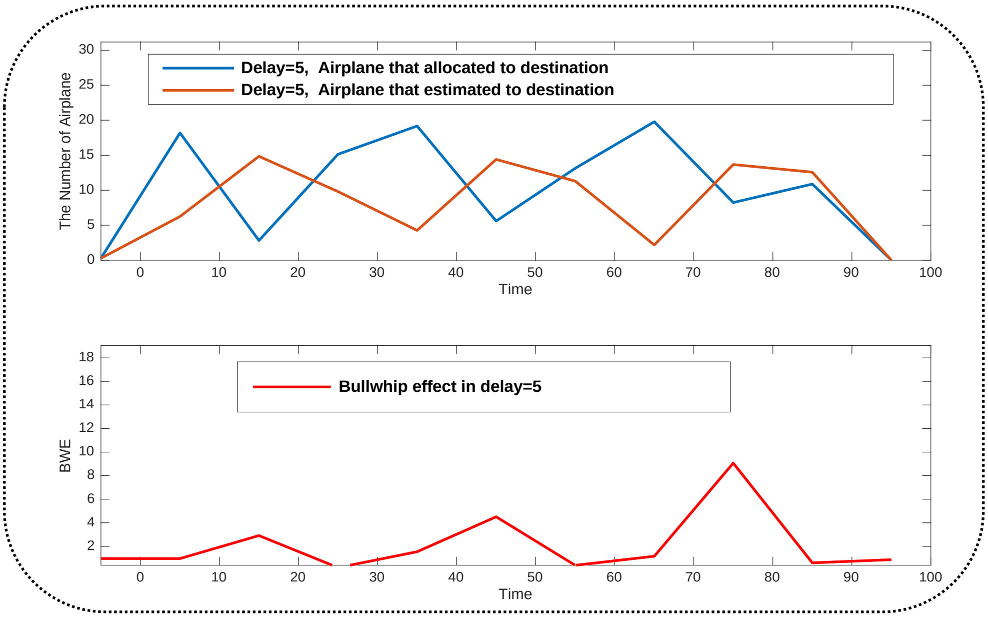

Fig 4. The bullwhip effect scores using control theory

Figure 4 shows that in the initial times, no bullwhip effect was observed in the downstream nodes. After the fifth intervals, the bullwhip effect occurred and this phenomenon continued until the final time. The magnitude of this bullwhip effect was 2. So, we can say that in initial times the demand oscillation was not occur. These results are against of airports report and proposed method results. Fig. 5 reveal the score of the demand oscillation, using the control engineering method and proposed network DEA model

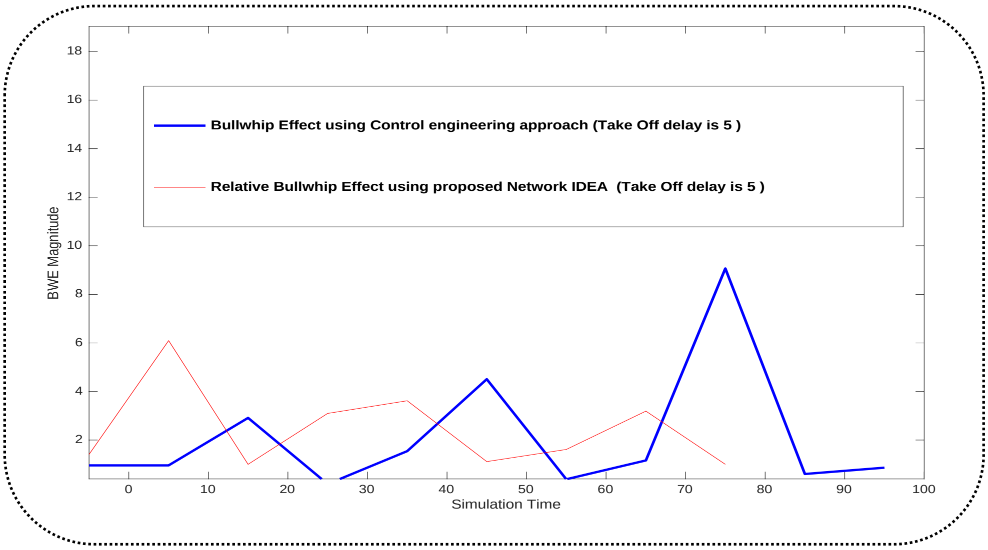

Fig 5. The size of the BWE using the control engineering method and proposed network IDEA model

However, the proposed method gave a relative score (relative importance) to the bullwhip effect. According to the results presented in Figure 5, the bullwhip effect occurred at all times examined, especially at initial times.

IV. CONCLUSION

In this paper, using a network inverse DEA, a relative measurement method was proposed for the delay propagation, taking into account landing time and take off delays. In the proposed airport network, two important factors, namely time factors (different shifts) and undesirable factors (time delay), were considered in the calculations. For probe the eefect of time on the demand variance, the supply chains node was considered at different times as decision-making units. To add the effects of time delay on the bullwhip effect, the network inverse DEA was used. So that, in the second stage, time delay was considered as an undesirable input. Some related theorems such as feasibility and optimality were proved for the proposed IDEA model. Finally, for the validation of the relative method, a real airport network as a supply chain was used. The proposed network were compared with the achievements of the frequency response method, using numerical case study.

Fluctuations in flight demand during the day are transferred from the early hours of the day to the late hours of the night, and magnification occurs in flight delays and demand. In the old formats, the relative causes and internal factors of the aviation network components are not mentioned. Therefore, experts do not consider the relative effects of time and ambiguous processes in dealing with the effect of demand fluctuations that cause significant errors. In this study, by entering effective latent factors (over time), we were able to provide an acceptable quantification of the spread of demand fluctuations. The effect of flight time on the magnitude of demand fluctuations in the network in turn can provide important information for managers. We used a time frame for unspecified demands and extended this perspective across the air network. This perspective allows airport managers to identify the impact of different flight shifts on demand fluctuations and time delays, and to plan each shift carefully.

Poropsed system help airport experts to experiment the fly shift impact of BWE on airport allocation SC. The hidden strengths and weaknesses are revealed at this stage. So, a case study shows that the size of demand propagation in the first phase (landing time) is greater than the second phase (effect of take-off delays). Therefore, airport managers should focus more on the difference between flight shifts. It can be said that demand fluctuations (dynamics) are more sensitive at the beginning of the day.

One of the most important features of the proposed method was the division of overnight into consecutive flight shifts. With this solution, we were able to consider different flight shifts as a decision unit. This solution, while ensuring the dynamics of the transportation system, revealed the effect of flight shifts on the magnitude of demand fluctuations. Specialists can benefit from the findings of this modeling style for various day-to-day scheduling tailored to flight courses. In contrast to the old methods, the magnitude of the fluctuations obtained for RBWE was greater at the beginning of the day than at night. The method used in this study revealed gaps that were hidden in the old methods.

REFERENCES

Amirteioori, A., Khoshandam, L. (2011). A Data Envelopment Analysis Approach to Supply Chain Efficiency. Advances in Decision Sciences. V. 2011, 608324, 8 pages, doi:10.1155/2011/608324.

Asif F M, Bianchi C, A, Rashid & Niclescu C, M. (2012). Performance analysis of the closed - loop supply chain. Journal remanufacturing.vol.2, no.1, pp.1-21.

Aslani Khiavi, S., Skandari, S. (2021). The Design of Inverse Network DEA Model for Measuring the Bullwhip Effect in Supply Chains with Uncertain Demands. Journal of Optimization in Industrial Engineering, 14(2), 203-214.

Aslani Khiavi S, Khaloozadeh H, Soltanian F. (2021) Regulating Bullwhip Effect in Supply Chain with Hybrid Recycling Channels using Linear Quadratic Gaussian Controller. IJIEPR; 32 (1) :13-27.

Beatty, R., Hsu, R., Berry, L., Rome, J., (1998). Preliminary Evaluation of Flight Delay Propagation through an Airline Schedule. In: Proceedings of the 2nd USA Europe Air Traffic Management R &D Seminar, Orlando, Fl.

Cannella, S., López-Campos, M., Dominguez, R., Ashayeri, J. and Miranda, P.A., (2015). A simulation model of a coordinated decentralized supply chain. International Transactions in Operational Research, 22(4), pp. 735-756.

Costantino, F., Di Gravio, G., Shaban, A. and Tronci, M., (2015). The impact of information sharing on ordering policies to improve supply chain performances. Computers & Industrial Engineering, 82, pp.127-142.

Dejonckheere, J., Disney, S., Lambrecht, M, N., Towill, D, R. (2003). Measuring and avoiding the bullwhip effect: A control theoretic approach. European journal of operational research, vol.147, pp.567-590.

Disney, S, M., Towill, D, R. (2003). On the bullwhip and the inventory variance produced by an ordering policy. Omega. vol. 31, pp.157-167.

Dejonckheere, J., Disney, S.M., Lambrecht, M.R. and Towill, D.R., (2004). The impact of information enrichment on the bullwhip effect in supply chains: A control engineering perspective. European Journal of Operational Research, 153(3), pp. 727-750.

Duc, T.T.H., Luong, H.T. and Kim, Y.D., (2008a). A measure of bullwhip effect in supply chains with a mixed autoregressive-moving average demand process. European Journal of Operational Research, 187(1), pp. 243-256.

Duc, T.T.H., Luong, H.T. and Kim, Y.D., (2008b). A measure of the bullwhip effect in supply chains with stochastic lead time. International Journal of Advanced Manufacturing Technology, 38(11-12), pp. 1201-1212.

Fu, D., Ionescu, C., Aghezzaf, E.H. and De Keyser, R., (2015). Quantifying and mitigating the bullwhip effect in a benchmark supply chain system by an extended prediction self-adaptive control ordering policy. Computers & Industrial Engineering, 81, pp.46-57.

Forrester, J.W. (1958). Industrial Dynamics, A major breakthrough for decision makers, Harvard Business Review, pp. 67-96.

Goodarzi, M., Farzipoor, R, (2018). How to measure bullwhip effect by network data envelopment analysis? Accepted in Computers & Industrial Engineering https://doi.org/10.1016/j.cie.2018.09.046.

Hashemi, V., Chen, M., Fang, L. (2014). Process planning for closed-loop aerospace manufacturing supply chain and environmental impact reduction. Computers & Industrial Engineering, 75; 87–95.

Ho, k., Weck, O., Hoffman, J., Shishko, R. (2014).Dynamic modeling and optimization for space logistics using time-expanded networks. Acta Astronautica, 105; 428–443.

Kao, C., Hwang, S.N. (2008). Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan, European Journal of Operational Research, 185, 418–429.

Kao, C., Liu, S.T. (2011). Efficiencies of two-stage systems with fuzzy data. Fuzzy Sets and Systems, 176, 20–35.

Kafle, N., Zou, B. (2016). Modeling flight delay propagation: A new analytical econometric approach. Transportation Research Part B, 93; 520-542.

Khalili, K., Shahmir, Z., (2015). Uncertain network data envelopment analysis with undesirable outputs to evaluate the efficiency of electricity power production and distribution processes. Computers & Industrial Engineering, http://dx.doi.org/10.1016/j.cie.2015.06.013.

Kim, J.G., Chatfield, D., Harrison, T.P. and Hayya, J.C., (2006). Quantifying the bullwhip effect in a supply chain with stochastic lead time. European Journal of Operational Research, 173(2), pp. 617-636.

Li, Y., Chen, Y., Liang, L., Xie, J. (2012). DEA models for extended two stage network structures, Omega. 40(5), 611–618.

Khiavi, S.A., Khaloozadeh, H., Soltanian, F. (2019). Nonlinear modelling and performance analysis of a closed-loop supply chain in the presence of stochastic noise. Mathematical and Computer Modelling of Dynamical Systems 25 (5), 499-521.

Khiavi, S.A., Hashemzadeh, F., Khaloozadeh, H. (2021). Sensitivity analysis of the bullwhip effect in supply chains with time delay, International Journal of Systems Science: Operations & Logistics, DOI: 10.1080/23302674.2021.1968064.

Khiavi, S.A., Khaloozadeh, H. & Soltanian, F. (2021). Suboptimal sliding manifold For nonlinear supply chain with time delay. J Comb Optim 42, 151–173. https://doi.org/10.1007/s10878-021-00733-1.

Li T & Ma J (2014) Complexity analysis of the dual-channel supply chain model with delay decision. Nonlinear Dyn, 78, 2617–2626.

Liang, L., Cook, W.D., Zhu, J. (2008). DEA models for two-stage processes: game approach and efficiency decomposition, Naval Research Logistics, 55, 643–53.

Moreno, P., Lozano, S. (2014). A network DEA assessment of team efficiency in the NBA. Annals of Operations Research, 214 (1), 99-124.

Olivia, J, P. and Fry, K. (2009). The Air Transportation System as a Supply Chain, AIAA Guidance, Navigation, and Control Conference, Chicago, Illinois. 10 – 13.

Pin-Ho, L., Shan-Hill, D., Shi, Shang, J. (2004). Controller design and reduction of bullwhip for a model supply chain system using z-transform analysis. Journal of process control, vol.14, pp.487-499.

Pyrgiotis, N., Malone, K., Odoni, A. (2013). Modelling delay propagation within an airport network. Transportation Research Part C, 27; 60–75.

Rezaiei, A, H,. Adressi, A. (2015). Supply chain performance evaluation using DEA. Vol. 2. 2. 748-458.

Wang, X. and Disney, S.M., (2016). The bullwhip effect: Progress, trends and directions. European Journal of Operational Research, 250(3), pp. 691-701.

Wu, W., Cheng-Lung, Wu., Feng, T., Zhang, H. and Qiu, Sh. (2018). Comparative Analysis on Propagation Effects of Flight Delays: A Case Study of China Airlines, Journal of Advanced Transportation. Volume 2018, Article ID 5236798, 10 pages.

APENDIX

Proof theorm1: Suppose that θ, λ_j^1 and λ_j^2 $(j = 1, \dots, n)$ are dual variables with first, second and third inequality, respectively. Thus, we can write:

$$
\begin{gathered}
Max\ \theta \\
s.t \begin{cases}
(x_{io} + t_o)\theta - \sum_{j=1}^{n}(x_{ij} + t_j)\lambda_j^1 \le 0; i = 1, \dots m \\
\sum_{j=1}^{n} l_{rj}\lambda_j^2 \le l_{ro}; r = 1, \dots, s \\
\sum_{j=1}^{n} y'_{rj}\lambda_j^1 - \sum_{j=1}^{n} y'_{rj}\lambda_j^2 \le 0 \\
\sum_{j=1}^{n} y_{ij}\lambda_j^2 \le y_{ro}; r = 1, \dots, s
\end{cases} \\
\theta\ free, \lambda_j^1, \lambda_j^2 \ge 0; j = 1, \dots, n
\end{gathered}
\tag{5}
$$

One feasible solution to Problem (5) is as follows:

$$\lambda_j^1 = \lambda_j^2 = 0, \forall j \ne o, \quad \lambda_o^1 = \lambda_o^2 = 1 = \theta \tag{6}$$

Obviously, the equation (6) is feasible for the dual problem (5) and the optimal value for the objective function is 1. So, primal model (4) also is feasible. In this case: $1 \le \theta^{\max}$. We know that any solution to the minimization problem is greater than or equal to the optimal solution of the dual problem (maximization). If k be the optimal solution from primal (4), then $1 \le \theta^{\max} \le K$.

Proof theorm 2: Suppose that θ_1, θ_2 , λ_j^1 and λ_j^2 $(j = 1, \dots, n)$ are dual variables with first, second, third and fourth inequality, respectively. So we can write:

$$
\begin{aligned}
&\qquad\qquad Max\ \ \theta_1+\theta_2\\
&s.t\begin{cases}
(x_{io}+t_o)\theta_1-\sum_{j=1}^{n}(x_{ij}+t_j)\lambda_j^1\le 0; i=1,\dots m\\
l_{ro}\theta_2+\sum_{j=1}^{n}l_{rj}\lambda_j^2\le 0; r=1,\dots,s\\
\sum_{j=1}^{n}y'_{rj}\lambda_j^1-\sum_{j=1}^{n}y'_{rj}\lambda_j^2\le 0\\
y_{ro}\theta_2+\sum_{j=1}^{n}y_{ij}\lambda_j^2\le 0; r=1,\dots,s
\end{cases}\\
&\qquad \theta_1\ free, \theta_2, \lambda_j^1, \lambda_j^2\ge 0; j=1,\dots,n
\end{aligned}
\tag{10}
$$

One feasible solution to model (10) is as follow:

$$\theta_2=\lambda_j^1=\lambda_j^2=0, \forall j, \quad \lambda_o^1=1=\theta_1 \tag{11}$$

Obviously, the equation (11) is feasible for the dual problem (10) and the optimal value for the objective function is 1. So, primal model (9) also is feasible. In this case: $1\le\theta^{max}$. We know that any solution to the minimization problem is greater than or equal to the optimal solution of the dual problem (maximization). If k be the optimal solution from primal (9), then $1\le\theta^{max}\le K$.

Proof theorm 3: Suppose that θ_1, θ_2 , λ_j^1 and λ_j^2 $(j=1,\dots,n)$ are dual variables with first, second, third and fourth inequality, respectively. So we can write:

$$
\begin{aligned}
&\qquad\qquad Max\ \ \theta_1\\
&s.t\begin{cases}
-RBWE_o^*(x_{io}+t_o)\theta_2-\sum_{j=1}^{n}(x_{ij}+t_j)\lambda_j^1\le 0; i=1,\dots m\\
y_{ro}\theta_2+\sum_{j=1}^{n}y_{rj}\lambda_j^2\le y_{ro}; r=1,\dots,s\\
l_{ro}\theta_2+\sum_{j=1}^{n}l_{rj}\lambda_j^2\le l_{ro}; r=1,\dots,s\\
y'_{ro}\theta_1+\sum_{j=1}^{n}y'_{rj}\lambda_j^1-\sum_{j=1}^{n}y'_{rj}\lambda_j^2\le 0; r=1,\dots,s
\end{cases}\\
&\qquad \theta_1\ free, \theta_2, \lambda_j^1, \lambda_j^2\ge 0; j=1,\dots,n
\end{aligned}
\tag{15}
$$

One feasible solution to problem (15) is as follow:

$$\theta_2=\lambda_j^1=\lambda_j^2=0, \forall j, \quad \lambda_o^2=1=\theta_1 \tag{16}$$

Obviously, the equation (16) is feasible for the dual problem (15) and the optimal value for the objective function is 1. So, primal model (14) also is feasible. In this case: $1\le\theta^{max}$. We know that any solution to the minimization problem is greater than or equal to the optimal solution of the dual problem (maximization). If k be the optimal solution from model (14), then $1\le\theta^{max}\le K$.