Industrial Management & Data Systems

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Received 9 July 2014
Revised 15 October 2014
5 December 2014
Accepted 20 December 2014

Abstract

Purpose – The purpose of this paper is to test the effectiveness of fuzzy time series (FTS) forecasting system in a supply chain experiencing disruptions and also to examine the changes in performance as the authors move across different tiers.

Design/methodology/approach – A discrete event simulation based on the popular beer game model is used for these tests. A popular ordering management system is used to emulate the behavior of the system when the game is played with human players.

Findings – FTS is tested against some other well-known forecasting systems and it proves to be the best of the lot. It is also shown that it is better to go for higher order FTS for higher tiers, to match auto regressive integrated moving average.

Research limitations/implications – This study fills an important research gap by proving that FTS forecasting system is the best for a supply chain during disruption scenarios. This is important because the forecasting performance deteriorates significantly and the effect is more pronounced in the upstream tiers because of bullwhip effect.

Practical implications – Having a system which works best in all scenarios and also across the tiers in a chain simplifies things for the practitioners. The costs related to acquiring and training comes down significantly.

Originality/value – This study contributes by suggesting a forecasting system which works best for all the tiers and also for every scenario tested and simultaneously significantly improves on the previous studies available in this area.

Keywords Simulation, Forecasting, Supply chain risk management, Fuzzy time series forecasting

Paper type Research paper

1. Introduction

Supply chains are becoming more and more complex and prone to disruptions because of the globalization. Business Continuity Institute (2011) performed a survey of 559 companies represented by 62 countries and 14 industry sectors and found out that "85 percent of companies reported at least one supply chain disruption in the last 12 months." Such disruptions are unexpected and large deviations from the normal operations of the supply chain, resulting from a plethora of external and internal factors. Supply chain managers are aware that the company's reputation, consistency in earning and ability to increase shareholder returns are increasingly dependent on their capabilities for managing supply chain disruptions (Hendricks and Singhal, 2005). Adopting proactive approaches in dealing with changing supply chain risks and vulnerabilities can secure supply chain systems (Asbjørnslett, 2009). But to be effective in being proactive needs a better forecast of the future. Uncertainty about future can

The work described in this paper was supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. PolyU 15201414); and a grant from The Natural Science Foundation of China (Grant No. 71471158). The authors also would like to thank The Hong Kong Polytechnic University Research Committee for financial and technical support.

Industrial Management & Data Systems
Vol. 115 No. 3, 2015
pp. 419-435

0263-5577
DOI 10.1108/IMDS-07-2014-0199

lead to risky event outcomes (Wieczorek, 2012). In such uncertain times the goal of firm's management efforts should not necessarily be to eliminate risks, but to become more risk informed. Keeping the performance at an acceptable level during disruptions is one of the top most concerns for the managers in a supply chain today. Also, because a supply chain is only as secure as its weakest link, all the tiers in the chain should be given their due importance and should be proactively guarded against any disruptions. This pro activeness is only possible with the help of timely and accurate forecasts.

An accurate forecasting system can prove to be an invaluable asset to a supply chain. The performance of supply chains is greatly affected by the forecasting accuracy, as forecasts help managers to make operational, tactical as well as strategic decisions. A number of studies in the past have studied different forecasting systems on a supply chain but there are very few studies which test the performance of the forecasting systems in disruption settings in a supply chain. Samvedi and Jain (2013) is one such study, which tests gray prediction system under disruptions scenario. The study shows that this system is good in some scenarios and also only for particular tiers. But what is proven again by them is the fact that it is useful to use techniques such as gray and fuzzy which are better in dealing with uncertain situations and disruption scenarios is full of such uncertainty. Fuzzy time series (FTS) is another such forecasting technique which breaks down the entire range of numbers in a time series into many fuzzy sets. This causes losing some information but retaining the most important part of it, its position in the entire range. This information is enough to make a rough forecast quickly and speed is desperately needed in such scenarios. Also the forecast itself is a range of numbers and it can be left to the manager's discretion on which number to choose from that range. FTS has been successfully used to deal with various problems such as enrollment prediction (Song and Chissom, 1993a), stock index forecasting (Yu, 2005), temperature forecasting (Wang and Chen, 2009), hydrometeorology forecasting (Wang *et al.*, 2012), etc. This study tests its performance in a supply chain experiencing disruptions. This study tries to fill this gap in literature by testing a very promising forecasting system in such scenario. This is done by running simulation tests on a popular linear supply chain game known as beer game.

In supply chain management, the beer distribution game developed at MIT about 50 years ago is still one of the most popular tools to simulate a linear supply chain. It helps students and practitioners both to get a grasp on the workings of a supply chain and also help them understand important aspects such as the bullwhip effect, effects of information sharing, effects of using a particular system in the chain, etc. (Lee *et al.*, 2004; Geary *et al.*, 2006). It also helps managers to understand the intricate workings of their supply chain and also the effect of some policy decisions on the long run. Through a system simulation, managers can gain insight into the dynamics of the entire system and not just the individual parts. It helps them to make predictions about the future and also provides them with sufficient information to confidently take their decisions. The general purpose of these games is threefold: to create awareness and insight from experiencing the interplay of different sections and functions; to teach by creating understanding and knowledge on the basis of try-outs of different planning principles; and to train by providing practical know-how from planning a handling job (Morecroft and Sterman, 2000).

This paper is further organized as follows. Section 2 discusses the relevant literature on supply chain risk management (SCRM), FTS forecasting and on use of beer game as well. The procedure for the methodology used is detailed out in the Section 3. Section

4 discusses the experimental setup. Evaluation of the performance of FTS methodology against other well-known forecasting systems is discussed in detail in Section 5. Section 6 concludes with managerial implications of this research followed by the scope of future work.

2. Literature review

As global supply chains expand to more and more countries, their supply lines become longer, the issues affecting the supply chain gets bigger and its management gets trickier. This leads to the increased importance of SCRM and this increase happens almost at the same rate as the globalization happens. This also led to the increased activity in this research field and led to a sudden eruption of large number of quality articles in this area. Therefore, disruption risks, lying in different processes of the supply chain as well as in the external environment, began to receive increased attention. Jüttner *et al.* (2003) outlined a research agenda for SCRM research, for which they presented a literature review and also an empirical study. Kleindorfer and Saad (2005) showed how traditional operational risks are joined with disruption risks arising from natural hazard, terrorism and political instability. Tang (2006) developed a unified framework for classifying SCRM articles and, by highlighting the gap between theory and practice, identified directions for future research. Craighead *et al.* (2007) relate the design characteristics of the supply chain, including the complexity, to supply chain disruptions. By conducting an empirical research, the authors prove the hypothesis that supply chain disruption is a result of complexity. Wagner and Bode (2008) explored practices and tools for risk identification, assessment and mitigation. Sodhi and Tang (2009) and Samvedi *et al.* (2013) developed quantitative models to manage the risks of modern supply chains. Marsden and Docherty (2013), present an analysis on how disruptive events can be seen as an opportunity to construct and accelerate policy changes which are commonly slow and incremental over long periods of times. Sodhi *et al.* (2012) argue most global companies lack a formal process to estimate the probability of catastrophic events and also the capability to accurately forecast them. In fact not being able to forecast accurately the future business scenarios is the first reason why it is difficult to deal with the disruptions in a supply chain.

Fueled by an increasingly dynamic business environment and growing availability of advanced software and tools, demand forecasting has gained an elevated importance among practitioners in recent years (Hsu and Wang, 2007). Today, companies spend billions of dollars annually on software, personnel and consulting fees to achieve accurate demand forecasts (Aiyer and Ledesma, 2004). It is a well-known fact that a chain can only be as strong as its weakest link. Hence what is required is not a good forecast at one level but at all the tiers of the chain. Most of the traditional methods work well for one scenario or the other. But what is required is to have a system which consistently performs better than others in every scenario. Also the requirement to work with very little data is a constraint for most of the traditional methods. Samvedi and Jain (2013) tested the performance of gray prediction method (GPM) in such situation and concluded that although this method has the ability to work with very little data, it works well only for few scenarios. This study was an effort in the right direction but presented only a partial solution. The current study builds on that and goes one step further by testing and proving that FTS forecasting system works best for all tiers and in all scenarios. FTS forecasting system also performs better than gray prediction in the scenarios where it performed better than other methods.

The FTS method has strengths in analyzing a short time series with limited past observations (Wu and Chau, 2010; Fu, 2011). The method was first defined by Song and Chissom (1993a). They proposed the definitions of FTS and methods to model fuzzy relationships among observations. The method deals with those time series where the entries are linguistic expressions and not numbers. The research was expanded and they went ahead to develop time-invariant and time-variant models (Song and Chissom, 1993b; Tsaur *et al.*, 2005; Singh and Borah, 2013). Besides the above researchers, Chen (1996) proposed another method to apply simplified arithmetic operations in forecasting algorithm rather than the complicated max-min composition operations presented in Song and Chissom (1993a). However, in time series model, when unexpected conditions happen, the historical data cannot respond to the fluctuations immediately. This would probably results in terrible inaccurate forecast. To deal with the problem, a group decision-making method was employed to integrate the subjective forecast values of all decision makers. Fuzzy weighted method was then combined with subjective forecast values to produce the aggregated forecast value. Besides, Huarng (2001) pointed out that the length of intervals affects forecast accuracy in FTS and proposed a method with distribution-based length and average-based length to reconcile this issue. This method applied two different lengths of intervals to Chen's model and the conclusions showed that distribution-based and average-based lengths could improve the accuracy of forecast. Although the forecasting performance of Huarng's method is excellent, it creates too many linguistic values to be identified by analysts. It becomes apparent that the major drawback of these methods is the lack of consideration in determining a reasonable universe of discourse and the length of intervals.

FTS has been used for supply chain forecasting in the earlier studies also (Tozan and Vayvay, 2008; Tozan and Vayvay, 2009). But none of those studies compared the performance with other established methods. Also important was to check the performance in disruptions scenario at all tiers of the chain. The performance of FTS is compared with GPM and auto regressive integrated moving average (ARIMA) forecasting methods. GPM is a technique in the gray theory that uses approximate differential equations to forecast in a time series. The main advantage of this method is its capability to be used in circumstances with as few as four observations (Chen and Chang, 1998). Its performance has been successfully demonstrated in many applications such as electricity demand forecasts (Huang *et al.*, 2007), stock market prediction (Wang, 2002) and supply chain disruptions (Samvedi and Jain, 2013). ARIMA on the other hand is the method of choice for a large number of supply chain researchers (Bandyopadhyay and Bhattacharya, 2013; Duc *et al.*, 2008). ARIMA (p,d,q) model was given by Box Jenkins in 1970, and hence is also sometimes known as Box Jenkins model. The model has three parts to it namely auto regression (AR), integration (I) and moving average (MA). The three values p, d and q denote the orders of each of these parts, respectively. The complete algorithm consists of five steps namely identification, estimation, diagnostic check, model construction and forecasting (Box *et al.*, 1994).

3. FTS

In this section, we briefly review the concept of FTS. The content of this section is common knowledge among researchers in this field and is part of almost every other published research study. The authors have consulted Song and Chissom (1993a, b), Huarng (2001) and Wang *et al.* (2012). The main difference of FTS and traditional time series is that the values of FTS are represented by fuzzy sets rather than real values. All the fuzzy sets considered in this study have triangular membership functions.

3.1 FTS basics

Let U be the universe of discourse, where $U=\{u_1, u_2, u_3, \ldots, u_n\}$, where u_i's are the crisp values in the time series. A fuzzy set defined in the universe of discourse U can be represented as:

$$A = \mu_A(u_1)/u_1 + \mu_A(u_2)/u_2 + \mu_A(u_3)/u_3 + \ldots + \mu_A(u_n)/u_n \tag{1}$$

The "+" sign in the above notation is not a mathematical operator but shows that how many different crisp numbers of the time series fall in the considered fuzzy set "A." Also μ_A denotes the membership function of fuzzy set A, μ_A: $U \to [0, 1]$ and $\mu_A(u_i)$ denotes the degree of membership of u_i belonging to the fuzzy set A, and $\mu_A(u_i) \in [0, 1]$, and $1 \leqslant i \leqslant n$.

Definition 1: FTS

Let $Y(t)$ ($t=\ldots, 0, 1, 2, 3, \ldots$), a subset of real numbers is the universe of discourse on which fuzzy sets $f_i(t)$ ($i=1, 2, 3, \ldots$) are defined. If $F(t)$ is a collection of $f_i(t)$ ($i=1, 2, 3, \ldots$), then $F(t)$ is called a FTS on $Y(t)$ ($t=\ldots, 0, 1, 2, 3, \ldots$). The variable t denotes time.

Definition 2: first order fuzzy relation

If there exists a fuzzy relationship $R(t-1, t)$, such that $F(t)=F(t-1)\times R(t-1, t)$ where$\times$represents an operator, then $F(t)$ is said to be caused by $F(t-1)$. The relationship between $F(t)$ and $F(t-1)$ is denoted by $F(t-1)\to F(t)$.

If $F(t-1)=A_i$ and $F(t)=A_j$, the logical relationship between $F(t)$ and $F(t-1)$ is denoted by $A_i \to A_j$, where A_i is called the left hand side and A_j the right hand side of the fuzzy relation. Note the right hand side of the fuzzy relation represents the future fuzzy set (forecast). Its crisp counterpart is denoted as $Y(t)$.

Definition 3: N-order fuzzy relations

Let $F(t)$ be a FTS. If $F(t)$ is caused by $F(t-1)$, $F(t-2), \ldots, F(t-n)$, then this fuzzy relationship is represented by $F(t-n), \ldots. F(t-2), F(t-1) \to F(t)$ and is called an n-order FTS. N-order-based FTS models are referred to as high-order models.

Definition 4: time-invariant FTS

Suppose $F(t)$ is caused by $F(t-1)$ only and is denoted by $F(t-1)\to F(t)$, then there is a fuzzy relationship between $F(t)$ and $F(t-1)$ which is expressed as the equation:

$$F(t) = F(t-1) \times R(t-1, t) \tag{2}$$

The relation R is referred to as a first order model of $F(t)$. If $R(t-1, t)$ is independent of time t, that is, for all times t_1 and t_2, $R(t_1-1, t_1)=R(t_2-1, t_2)$, then $F(t)$ is called a time-invariant FTS. Otherwise it is called a time-variant FTS.

Definition 5: fuzzy relationship group

Relationships with the same fuzzy set on the left hand side can be further grouped into a relationship group. Suppose there are relationships such that:

$$A_i \to A_{j1},$$
$$A_i \to A_{j2},$$
$$\ldots,$$
$$A_i \to A_{jn},$$

then they can be grouped into a relationship group as follows:

$$A_i \rightarrow A_{j1}, A_{j2}, \ldots, A_{jn}$$

The same fuzzy set cannot appear more than once on the right hand side or the relationship group.

3.2 Forecasting with time-invariant FTS

Stepwise procedure is described as below:

Step 1: define the universe of discourse U for the historical data. First, we find the minimum data $D_{\min}$ and the maximum data $D_{\max}$ individually in the historical time series data, and then we define the universal discourse U as $U=[D_{\min}-D_1, D_{\max}+D_2]$, where D_1 and D_2 are two proper positive numbers.

Step 2: partition the universe of discourse into intervals of equal length $u_1, u_2, \ldots$. The number of intervals will be in accordance with the number of fuzzy sets $A_1, A_2, \ldots, A_n$ to be considered.

Step 3: define the fuzzy sets A_i on universe of discourse U in Step 2. If there are fuzzy sets $A_1, A_2, \ldots, A_n$, then the fuzzy sets A_i, $\forall i=1, 2, 3, \ldots, n$ can be described as:

$$A_i = \mu_{A_i}(u_1)/u_1 + \mu_{A_i}(u_2)/u_2 + \mu_{A_i}(u_3)/u_3 + \ldots + \mu_{A_i}(u_n)/u_n \quad (3)$$

For example, the linguistic variable can be described as fuzzy sets $A_1=$ (not many), $A_2=$ (not too many), $A_3=$ (many), $A_4=$ (many many), $A_5=$ (very many), $A_6=$ (too many), $A_7=$ (too many many). Thus, all the fuzzy sets are expressed as follows:

$$A_1 = 1/u_1 + 0.5/u_2 + 0/u_3 + 0/u_4 + 0/u_5 + 0/u_6 + 0/u_7$$

$$A_2 = 0.5/u_1 + 1/u_2 + 0.5/u_3 + 0/u_4 + 0/u_5 + 0/u_6 + 0/u_7$$

$$A_3 = 0/u_1 + 0.5/u_2 + 1/u_3 + 0.5/u_4 + 0/u_5 + 0/u_6 + 0/u_7$$

$$A_4 = 0/u_1 + 0/u_2 + 0.5/u_3 + 1/u_4 + 0.5/u_5 + 0/u_6 + 0/u_7$$

$$A_5 = 0/u_1 + 0/u_2 + 0/u_3 + 0.5/u_4 + 1/u_5 + 0.5/u_6 + 0/u_7$$

$$A_6 = 0/u_1 + 0/u_2 + 0/u_3 + 0/u_4 + 0.5/u_5 + 1/u_6 + 0.5/u_7$$

$$A_7 = 0/u_1 + 0/u_2 + 0/u_3 + 0/u_4 + 0/u_5 + 0.5/u_6 + 1/u_7$$

Step 4: fuzzification is the process of identifying associations between the historical values in the dataset and the fuzzy sets defined in the previous step. Each historical value is fuzzified according to its highest degree of membership. If the highest degree of belongingness of a certain historical time variable, say $F(t-1)$, occurs at fuzzy set A_k, then $F(t-1)$ is fuzzified as A_k.

Step 5: determine fuzzy logical relationships, which are required for forecasting using FTS. Establishing the fuzzy logical relations of various orders as given as follows:

(1) for first order models, if for year n–1 and n the fuzzified arrivals are A_i and A_j, then the first order fuzzy logical relationship is represented as $A_i \rightarrow A_j$;

(2) for second order models, if for year n–2, n–1 and n, the fuzzified arrivals are A_{i1}, A_i and A_j, respectively, then the second order fuzzy logical relation is represented as $A_{i1}, A_i \rightarrow A_j$; and

(3) for third order models, if for year n–3, n–2, n–1 and n, the fuzzified arrivals are A_{i2}, A_{i1}, A_i and A_j, respectively, then the third order fuzzy logical relation is represented as $A_{i2}, A_{i1}, A_i \rightarrow A_j$.

In a similar way we can find the fourth, fifth, sixth, seventh, eighth and other higher order fuzzy logical relations.

Step 6 (defuzzification): based on the fuzzy logical relationships, which are formed in Step 5, the forecasts are made by extrapolating the FTS, using the following principle:

- If the jth order fuzzified historical arrivals for year i are A_{ij}, $A_{i(j-1)}$, …, and A_{i1}, where $j \geqslant 2$, and if there are the following fuzzy logical relationship in which the current state is A_{ij}, $A_{i(j-1)}$, …, A_{i1}, shown as follows:

$$A_{ij}, A_{i(j-1)}, ..., A_{i1} \rightarrow A_{j1}$$

$$A_{ij}, A_{i(j-1)}, ..., A_{i1} \rightarrow A_{j2}$$

$$A_{ij}, A_{i(j-1)}, ..., A_{i1} \rightarrow A_{jp}$$

where A_{ij}, $A_{i(j-1)}$, …, A_{i1}, A_{j1}, A_{j2}, A_{jp} are fuzzy sets, the maximum membership values of A_{j1}, A_{j2}, …, and A_{jp} occur at intervals u_1, u_2, …, *and* u_p, respectively, and the midpoints of the interval u_1, u_2, …, *and* u_p are m_1, m_2, …, and m_p, respectively, then the forecasted arrivals the ith year is $(m_1 + m_2 + ... + m_p)/(p)$.

This completes the process of FTS forecasting system. The next section details out the experimental setup which is used for testing the performance of this system against few other well-established forecasting systems.

4. Experimental setup

Experiments are useful for investigating behavior in supply chains for a number of reasons. Experiments allow us to gauge the extent to which behavioral factors cause empirical regularities. In an experiment, we can control the environment each firm faces. The beer distribution game provides such an environment (Croson and Donohue, 2002). This game is a role-playing simulation of an industrial production and distribution system. In use for nearly six decades, the game has been played all over the world by thousands of people ranging from high school students to chief executive officers and government officials (Croson and Donohue, 2002, 2006). The four-stage problem of the beer game is a single-product supply chain that includes a retailer, a wholesaler, a distributor and a manufacturer. The system is depicted in the Figure 1. The customer places his demand at the retailer who in turn places its demand at the wholesaler and thus it proceeds to the end of the chain. Similarly the supply line comes from upstream to downstream and ends at the retailer which handles the customer. Demand disruptions are realized at the retailer end because this is the point where customer demands come. These disruptions can be of two types namely increase or decrease in customer orders. If the orders decrease then the chain has an oversupply and thus has more stock than desired at every point of the chain. On the other hand the increase in customer orders causes shortage in the chain and the shortages usually carry more cost than the oversupply, as also is the case in the cost structure of the beer game. The other type of disruptions come from the supply side, but is not the subject of this study.

What makes such studies with beer game so interesting and appealing is the fact that the data generated from these games is considered to be equivalent to the real time data. This has been proven time and again by many researchers. Croson and Donohue (2006) found that there were not many differences in the performance among undergraduate, MBA, or PhD students, and senior executives. Through the use of an internet version of the beer distribution game, Machuca and Barajas (2004) found there were not significant differences in results between students and executive in the decision-making processes of these groups. Such studies opened up the possibility of using the data from such games for research studies. Therefore many such behavioral laboratory studies, using beer game, are conducted at universities and several of these studies attempt to include elements of real-life situations through the creative use of software simulation applications (Scandura and Williams, 2000).

The Sterman (1989) model, which automates the entire process using few mathematical equations is a popular method (Laugesen and Mosekilde 2006; Hwarng and Xie, 2008). Such an automated method is mainly required in conditions where the quantity of data required is huge, i.e. for a longer period. In such situations it is mostly not possible to have live beer game sessions with human players and thus require an automated process. This in turn requires having algorithms which can take ordering decisions. Sterman (1989) model is one such popular model and is given below.

The amount ordered in period t (O_t) is non-negative:

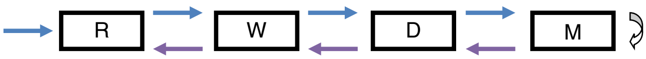
$$O_t = \max(0, IO_t) \tag{4}$$

$$IO_t = L_t'' + \alpha_s(S_t{}^* - S_t) + \alpha_{sl}(SL_t{}^* - SL_t) \tag{5}$$

$$L_{t+1}'' = \theta L_t + (1-\theta)L_t'' \tag{6}$$

where IO_t is the indicated order rate; L_t, the goods shipped; L_t'', the expected shipment; S_t, the actual stock on hand; $S_t{}^*$, the desired stock; SL_t, the actual outstanding orders; $SL_t{}^*$ the desired outstanding orders; α_s, the stock parameter; α_{sl}, the outstanding orders parameter; and θ, the exponential smoothing factor.

The simulation is run five times, each with duration of 1,000 periods, and we report averaged forecasting errors. The supply lead time has been taken as two weeks and



Source: Samvedi and Jain (2012)

Figure 1.
A four-level single product supply chain

order processing time also as two weeks. In each set of simulation runs, the standard values have been used for the parameters in the above model. We used:

$$S^* = 50, \;\; SL^* = 150, \;\; S_0 = 40, \;\; SL_0 = 120, \;\; L_0 = 40, \;\; \theta = 0.25,$$

$$\alpha_s = 0.4, \;\; \alpha_{sl} = 0.136$$

These standard values have been picked up from the literature and some have been suitably modified for the current scenario. These small modifications were required because the demand stream at the retailer level is not the same as the basic beer game (where the game starts with a demand of four units and after few periods' moves on to eight units). There are in total three test scenarios here. The demand at the retailer level in normal scenario is uniformly distributed in the range [40, 60]. To get disruptions effect, the demand interval is raised five times to [200, 300]. This can be done in two different ways, each important from the analysis viewpoint. The first way is to suddenly switch the retailer demand to the disruptions mode (sudden disruptions) and the other way is to have a gradual increase (smoothened disruptions). Both of these scenarios exist in real life and hence were necessary to check the performance under both scenarios. The smoothening effect is obtained by raising the demand gradually in five periods.

5. Results and analysis

This section details out the results achieved, of performance of competing forecasting systems, for different operating scenarios. The mean absolute percentage error (MAPE) is used as the forecasting performance criterion. The FTS system is compared with two other systems namely GPM and ARIMA. These methods have been chosen because of their widespread use by practitioners and researchers alike. Many studies claim them to be the best of the lot and hence they provide a solid benchmark values to compare with. In this study GPM uses the same setup that of Samvedi and Jain (2013). ARIMA method on the other hand has different orders at different levels and hence been referred only as ARIMA, rather than with their orders. The results clearly show that the FTS forecasting system is far superior to all other systems compared. This is true for all the tiers in the supply chain as well as for any environment, i.e. normal scenario, sudden disruption scenario and also smoothened disruption scenario. This shows how the system adapts successfully to the situation in hand and is able to give better forecasts. This is important because most of the systems work best in one scenario or the other. Having a system which is best for all the scenarios simplifies things.

Starting with the normal scenario, Table I shows the forecasting performance in terms of MAPE values. It clearly shows how the FTS system outperforms the other systems at all tiers. Another observation from Table I is that the second order FTS performs better than the first order FTS. GPM method is the least desirable in all as it

Forecasting type	Mean absolute percentage error (MAPE)			
	Retailer	Wholesaler	Distributor	Manufacturer
GPM	6.5044	7.1827	10.5378	18.6195
ARIMA	5.8259	6.5082	8.8582	12.1347
FTS	5.2363	5.9385	9.4777	14.5032
FTS2 (order 2)	4.9513	5.4981	7.5261	10.3230

Table I. Forecast errors for different forecast types in normal operations fails at every tier against the other two. On the other hand it can be seen that the performance of ARIMA starts matching that of FTS as we move upstream. But this can be easily countered by increasing the order of FTS.

These values can be better understood by looking at Figures 2 and 3. Figure 2 shows a part of the simulation run for the retailer level. It can be easily seen that the FTS1, i.e. first order FTS runs quite close to the mean demand line. On the other hand other systems show a little more variance. Out of all GPM is the one which has the highest variance because of its tendency to try to match out every demand value. Although it succeeds in following the demand trail, more closely than others, it also ends up with the least forecast accuracy. ARIMA and FTS2 can be seen to be less vigorous than GPM in following the demand trail but also are a little more active than the FTS1. But in the end FTS2 ends up scoring the best performance.

Figure 3 also provides a similar insight to the simulation runs but at the distributor level. ARIMA model beats FTS1 at this level and can also be seen from the figure to be running close to FTS2. A hint of bullwhip effect can also be seen from it. FTS1 still is far better than GPM which again succeeds in following the demand trail better but with a huge time lag. This affects its performance and even FTS1, which silently follows the demand trail without trying to accurately match it, beats it.

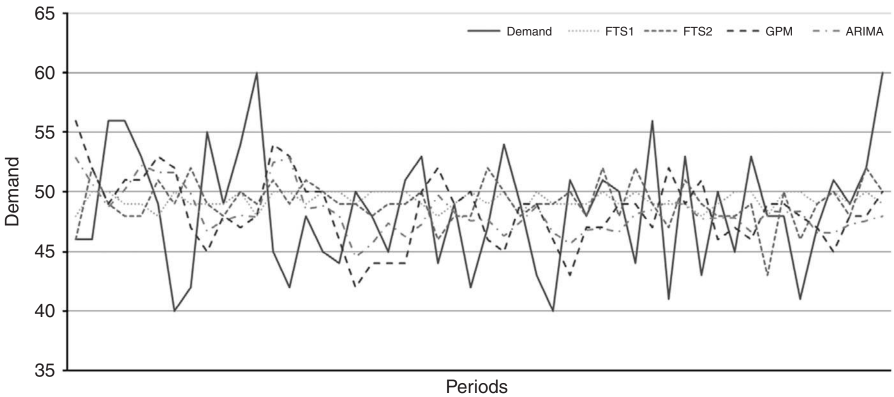


Figure 2.
Forecasting performance at retailer for normal scenario

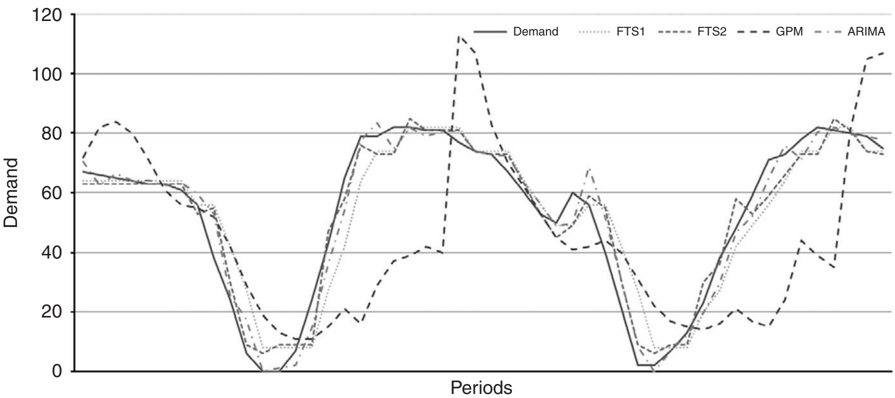


Figure 3.
Forecasting performance at distributor for normal scenario

The real test of the system comes when disruptions are pictured in. The next test is conducted for sudden disruption scenario when the mean demand is suddenly increased five times, few times in the total run duration. As this happens, the forecasting systems try to keep up with the new demand pattern. What is required of the systems here is the flexibility to immediately change over to this new demand pattern. As can be seen in Table II, the MAPE values are far more than what we had in Table I. This is because of the disruption scenario. As the demand values have increased, so has the errors in its estimate. Also contributing is the fact that this change in demand levels is done suddenly, leaving very less time for the systems to react. The insight to sudden disruptions is provided by Figure 4, which is for the retailer level.

The next test is performed for the smoothened disruption scenario. This is important because in practice most of the times the disruptions come in a gradual manner rather than in sudden nature. This helps the forecasting systems by giving them time to adapt to the new scenario. The results from the test runs are provided in Table III.

Forecasting type	Retailer	Mean absolute percentage error (MAPE) Wholesaler	Distributor	Manufacturer
GPM	12.5159	23.1550	47.8125	94.8960
ARIMA	9.9525	20.8830	39.6468	72.4170
FTS	8.7359	18.5283	40.8899	77.8681
FTS2	8.2598	15.9456	37.0420	71.3116

Table II. Forecast errors for different forecast types, under sudden disruptions scenario

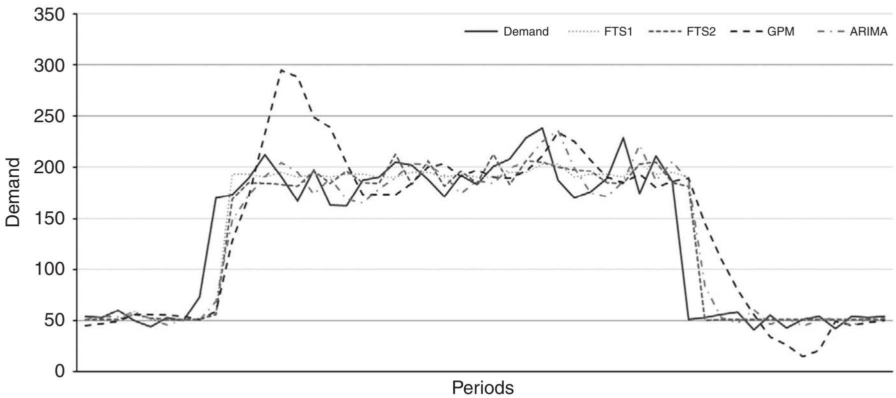


Figure 4. Forecasting performance at retailer for sudden disruption scenario

Forecasting type	Retailer	Mean absolute percentage error (MAPE) Wholesaler	Distributor	Manufacturer
GPM	10.1670	22.6241	45.4840	94.4564
ARIMA	9.2573	20.3276	36.9024	70.3276
FTS	8.7445	18.1204	36.6927	76.9977
FTS2	7.9825	16.2576	33.7111	70.2986

Table III. Forecast errors for different forecast types, under smoothened disruptions scenario

The values in Table III almost match up with the values in Table II. This is contrary to what is expected because smoothening helps forecasting systems to adapt and hence the performance should have been better. This can be explained by the fact that the gradual steps added are responsible for this. These steps have more than normal demand and hence have bigger errors. The details of this are provided by Figure 5, which shows the gradual climb up.

Table IV clearly shows how the accuracy of the FTS system is improved when we increase the number of fuzzy intervals. These tests are done for smoothened disruptions. This is on the expected lines because by increasing the number of fuzzy intervals we shorten their range and consequently increase the accuracy of the representation of a demand value by its interval. Also to be observed is the fact that incremental improvement for every increase falls to negligible levels as the number of intervals reach higher values.

One aspect which has to be kept in mind here is that increasing number of intervals increases the time of running the program and also the memory required is huge. Thus although the accuracy get better with increasing intervals, we need to draw the line somewhere because of memory storage and speed constraints. It depends on which tier you are, to decide on minimum number of intervals required. It is advised to go with a bigger number if it is possible. Similar results are produced when this test is performed on higher order FTS. The results are given in Table V.

The results and discussion here show beyond any doubt that FTS is actually the best forecasting method for all scenarios and also for all the tiers in the chain. The accuracy which can be achieved though depends on the number of intervals used and which

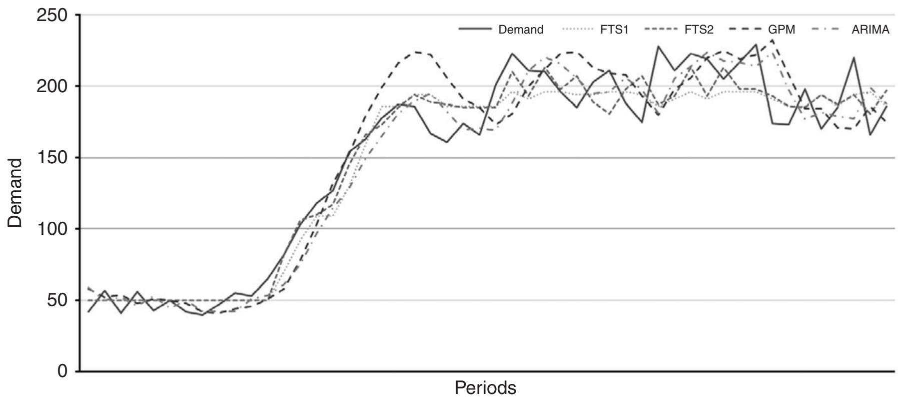


Figure 5. Forecasting performance at retailer for smoothened disruption scenario

Table IV. Effects on forecast errors with increasing number of intervals

Forecasting type	Retailer	Wholesaler	Distributor	Manufacturer
	Mean absolute percentage error (MAPE)			
FTS5	12.6571	17.1270	68.8395	149.6424
FTS10	8.1674	14.9675	37.7153	74.0414
FTS20	7.4448	9.9172	22.1089	42.1753
FTS50	5.4809	7.8560	17.1355	26.9537
FTS100	5.2476	7.4803	16.3175	25.8041

order FTS is used and hence indirectly depends on the computing power available. But even for small interval numbers and an order as less as 5, a decent forecasting accuracy can be achieved and hence FTS system of forecasting should be readily deployed as the forecasting system of choice. The computing times for different FTS order are shown in Figure 6.

It can be clearly observed, from Figure 6, that the time increases with increasing number of intervals and also with increasing FTS order. This increase is more pronounced for number of intervals and the difference in time between different FTS order decreases to almost negligible at higher number of intervals. This shows that it is better to improve the forecast accuracy by increasing the FTS order or number of intervals.

6. Conclusion

Risk management has become an integral part of a holistic SCM ideology. Terrorism, local politics, uncertain weather conditions, natural disasters and various other issues effect the supply chain from outside. On the other hand there are many other issues such as trade union strikes, quality problems, maintenance issues and supplier problems, which affect the chain internally. In today's growing supply chains, this has become a fact of life. The mad rush to make the supply chains better, faster and cheaper is making the chain increasingly complex, interdependent and risky. Companies are also responding to these challenges by undergoing major changes and are implementing new operations strategies and technologies. The larger a supply chain, the more difficult it is to cope with uncertainty, both upstream and downstream, and protect

	Mean absolute percentage error (MAPE)			
Forecasting type	Retailer	Wholesaler	Distributor	Manufacturer
FTS	9.2162	16.1613	38.0940	78.1193
FTS2	8.5160	14.2408	35.0765	72.0801
FTS3	7.7148	13.2245	34.6315	70.4973
FTS5	5.7445	12.4983	33.3549	69.8205
FTS7	5.3859	12.0592	33.3163	69.6565
FTS10	5.3623	11.7043	33.1923	69.5623

Table V. Effect of increasing FTS order

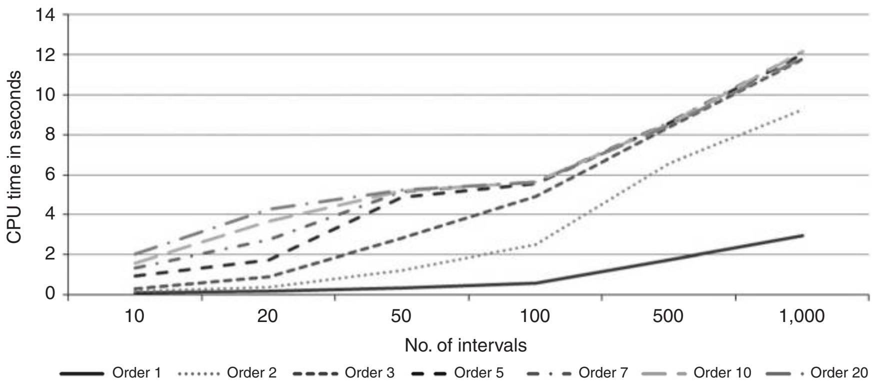


Figure 6. Computing time for different orders of FTS

every link. There is overall an understanding among the researchers that it is better to be prepared to some extent than to wait for the disruptions to happen and then react. Although it is agreed by all that it is almost impossible to predict the disruptions with certainty, the importance of better forecasts is universally recognized. This study is an effort in that direction and successfully tests the better performance of FTS system when compared to others. The results clearly prove the superiority of FTS forecasting system to the others.

There are huge managerial implications of this study in the sense that armed with better forecasts of the future the managers can make better decisions for their supply chain. As we have seen, the study holds good for all the tiers in the chain and thus avoids confusion of checking the tier at which you operate and then choose the forecasting system. Also the study shows that FTS is the best system even in no disruption scenario and this makes things simpler for the managers because now they do not need to change the forecasting system on the change of business environment. This makes things simpler for the managers and also gives them time to take better decisions. Also important from the research viewpoint is the fact that a fuzzy technique has performed so well against other established technique ARIMA. This should certainly increase the interest in less traditional fuzzy techniques. As the results suggested, depending on the computing power available the firm can choose to be more and more accurate with FTS. The same can be done by using other modifications of FTS, which have been proven in the literature to work in other fields. The same can be tested for the supply chains forecasting. This holds a good scope for the future research in this topic.

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