Engineering Applications of Artificial Intelligence 26 (2013) 1044–1051

Contents lists available at SciVerse ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

A grey approach for forecasting in a supply chain during intermittent disruptions

Avinash Samvedi, Vipul Jain *

Department of Mechanical Engineering, Indian Institute of Technology Delhi, New Delhi—110016, India

ARTICLE INFO

Article history:
Received 7 December 2011
Received in revised form
25 September 2012
Accepted 3 December 2012
Available online 16 January 2013

Keywords:
Supply chain risk management
Grey prediction method
Bullwhip effect
Forecasting
Simulation

ABSTRACT

The supply chains today have become vulnerable to frequent disruptions, and with continuing emphasis on efficiency, lacks robustness to deal with them. A part of the solution lies in forecasting the disruption beforehand and the other part in knowing which policies will suit such disrupted conditions best. Accurate and immediate forecasts are a must in a supply chain and hence play a huge role in stabilizing. This study compares the performance of three established forecasting methods (moving average, weighted moving average and exponential smoothing) as well as grey prediction method, during disruptions and stable situations. The experiments are performed in the form of discrete event simulation, on a four stage beer game settings. The results show that moving average and weighted moving average methods become incompetent during disruptions, and are useful only during stable times, when the demand hovers around a predefined mean value. Exponential smoothing and grey method seems to give better results during disruptions and also during stable times in upstream tiers. Grey prediction method in particular is the best method when the disruption frequency is high and also when the disruption impact is gradual rather than sudden.

1. Introduction

The mad rush to make the supply chains better, faster and cheaper is making the chain increasingly complex, interdependent and risky. Since the early 1990s, many firms have implemented various supply chain initiatives to increase revenue, to reduce costs, and/or to reduce assets. This single minded focus on improving efficiency is having adverse impact on the fragility and vulnerability of supply chains (Craighead et al., 2007; Wagner and Bode, 2006). All this has made managing supply chain risks a challenge that it was never before. It is worth mentioning that today supply continuity is the single biggest business driver, whereas in the past, supply chain managers were mainly concerned with reducing cost, reducing purchase price variance, and managing inventory. This is due to the frequent disruptions a supply chain encounters on a regular basis. Supply chain disruptions are "unplanned events that may occur in the supply chain which might affect the normal or expected flow of materials and components" (Svensson, 2000). Disruption does not only halt the supply chain operations, but without preparation and precaution it takes time for the affected system to recover (Sheffi and Rice, 2005; Hendricks and Singhal, 2005). To effectively deal with these risks, there have been calls for "resilience" (Sheffi and Rice, 2005) or "robustness" (Tang, 2006).

The impact of supply chain disruptions has led to a growing interest in the area of supply chain risk and its management, as evidenced in the number of industry surveys, practitioner conferences and consultancy reports devoted to the topic (McKinsey, 2008). Adding to situation is strong evidence that catastrophic events such as earthquakes, floods, tornadoes etc. are becoming more frequent (Coleman, 2006). Elkins et al. (2005) observed that there has been an increase both in the potential for disruptions and in their magnitude. Supply chain executives in IBM believe that supply chain risk management (SCRM) is the second most important issue for them (IBM, 2008). Also, the research by AMR in 2007 reported that 46% of the executives believe that better SCRM is needed (Hillman and Keltz, 2007). However, as evident from (McKinsey, 2008), few companies have taken commensurate actions.

Risks occur because we can never know exactly what will happen in the future. We can use the best forecasts and do every possible analysis, but there is always uncertainty about future events (Waters, 2007). 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; Wang, 2002). Today, companies spend billions of dollars annually on software, personnel and consulting fees to achieve accurate demand forecasts (Aiyer and Ledesma, 2004). From a broader supply chain perspective, accuracy of a firm's demand forecast is important not only for itself but also for its partners because the quality of forecasts often affects the performance of the entire supply chain, including vertical partners as well as horizontal

* Corresponding author.
E-mail address: vjain@mech.iitd.ac.in (V. Jain).

0952-1976/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.engappai.2012.12.002

competitors (Chen, 2003). This work is an effort towards making the supply chain resilient by studying the robustness of different forecasting methods under stable and disruption situations. The methods considered here are moving average (MA), weighted moving average (WMA), exponential smoothing (ES) and grey prediction method (GPM). Although there are several other sophisticated methods available, the first three methods have been picked up because of their extensive use in the industry, simply because of their ease of use. The last method GPM has never been tested in the supply chain disruption situation, even though it has been used in similar situations before Wang (2002), Hsu (2011). This made the method an exciting prospect for this study.

The rest of the paper is organized as follows. Section 2 describes the problem being considered here and also reviews the literature on supply chain disruptions and different demand forecasting methods, specifically the grey prediction method. Section 3 gives a brief introduction to the preliminaries of grey theory and grey prediction method. Section 4 describes the simulation set-up used for the current study. Section 5 analyses the results obtained from the simulation runs and discusses their significance in detail. Finally, Section 6 concludes the paper with future research directions.

2. Problem description

A significant feature of the rapidly evolving business climate spurred on by significant technology shifts, innovation, communication technologies and globalization, is the increasing prevalence of risk in almost every aspect of our lives (Wu and Blackhurst, 2009). This has led to a significant increase in the risks faced by the supply chains today. These risks are further enhanced by the outsourced production to overseas locations, extended supply chains, the number of nodes increased, and the increasing complexity of the networks. This results in supply chain players becoming increasingly more coupled, in the sense that decisions taken by one firm in a supply chain directly affects the performance of other firms. One very important aspect of coupling in the context of supply chain is the forecast developed by various parties in the supply chain. Reduction in forecasting errors, at any stage of a supply chain, helps in vastly improving the demand supply matching (Zhu et al., 2011). From the literature, studies of combined statistical methods have shown better results than individual methods for both forecast accuracy improvement and lower forecasting risk (Hibon and Evgeniou, 2005). In Smith and Wallis (2005), analysis of combining methods using a simple average was explored, where combined methods showed better results than individual methods (Clemen, 1989). Colloby and Armstrong (1992) proposed a rule-based forecasting technique that analyzes time series by combining four extrapolation methods based on some predefined rules. This technique improved the forecast accuracy.

Overcoming the challenges involved in creating a credible forecast is an incredibly daunting task for most forecasters. There is a constant flow of new products, promotions and changing channels of distribution (Helms et al., 2000). Most of traditional methods for dealing with the predictive problems include simple regression, multivariate regression, time series analysis, etc. Although these models have the advantage of accurately describing the phenomenon of long-term trends, they have the limitation of requiring at least 50, and preferably 100 or more observations in order to construct the model. Due to the requirements of our society and the rapid innovation in new technologies, we usually are able to make only a few observations within a short time span to forecast future situations in order to formulate a "quick response" (Wang and Hsu, 2008b). The same requirement arises during the disruption situations as the firms have very little data of the situation and the forecasts should be made using them. Also the forecasting methods are severely tested during disruption situations and forecasting accuracy takes a hard hit. In recent years, to overcome these shortcomings, artificial intelligence was proposed to amend traditional forecasting methods.

Artificial intelligence analysis including the artificial neural network (Liang, 2007), fuzzy theory (Lee et al., 2007; Wang and Hsu, 2008a) and grey theory (Huang et al., 2007) are often used to solve traditional forecasting methods. Grey forecasting theory is an important technique in the grey theory, and it uses approximate differential equations to describe future tendencies for a time series. It has the advantage that it can be used in circumstance with as few as four observations in a prediction process (Chen and Chang, 1998). Grey theory, a non-traditional forecasting technique based on scarce and fuzzy information, was proposed in 1982 by J.L. Deng. The first-order one-variable grey model, GM (1, 1), is the most widely used and is successfully demonstrated in many applications such as electricity demand forecasts (Huang et al., 2007), stock market prediction (Wang, 2002), tourism forecast (Yu and Schwartz, 2006), integrated circuit industry output forecasts (Hsu and Wang, 2007), and optoelectronics industry output forecasts (Chang, 2005). In order to increase the grey model accuracy of forecast, many improved versions of GM (1, 1) model were established (Hsu and Wang, 2007; Hsu, 2009; Huang and Wang, 1997).

3. Grey prediction method

Grey theory is a truly multidisciplinary and generic theory that deals with systems that are characterized by poor information and/or for which information is lacking. The fields covered by grey theory include systems analysis, data processing, modeling, prediction, decision making and control. Grey forecasting models have been extensively used in many applications. The GM (1, 1) is one of the most frequently used grey forecasting model. This model is a time series forecasting model, encompassing a group of differential equations adapted for parameter variance, rather than a first order differential equation. Its difference equations have structures that vary with time rather than being general difference equations (Chen, 2003).

Prediction is an action based on discussions and studies of the past to tell about the future. Grey prediction is based on some theoretical treatment of the original data and establishment of grey models of the data to discover and to control the development laws of the system of interest so that scientific quantitative predictions about the future of the system can be made (Liu and Lin, 2006). A grey system is a system with characteristics between white and black ones (Deng, 1982). This implies that the grey system has the characteristics to deal with situations where only partial information is available. The grey model (GM) is one of the best features in the grey system theory. Generally, the grey model is written as GM (m, n), where m is the order and n is the number of variables of the modeling equation. GM (1, 1) and GM (1, N) models are more commonly used in the forecast model. Conventional modeling techniques use the given data directly to construct a model to approximate the output behavior of the system. The grey system, however, is based on the accumulated data to establish the model (Huang and Wang, 1997; Deng, 1989).

The most commonly used grey model is the GM (1, 1) model, which indicates one variable and one order grey forecasting model. The general procedure for a grey forecasting model is derived as follows (Hsu, 2011).

Step 1: Establish the original data sequence from observed data

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n))$$

Step 2: Generate the first-order accumulated generating operation (AGO) sequence $x^{(1)}$ based on the original data