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Minimising the Bullwhip Effect in a Supply Chain Using Genetic Algorithms

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Abstract

This paper presents a computational intelligence (CI) approach, which addresses the bullwhip effect in supply chains (SC). A genetic algorithm (GA) is employed to reduce the bullwhip effect and cost in the MIT beer distribution game. The GA is used to determine the optimal ordering policy for members of the SC. The paper shows that the GA can reduce the bullwhip effect when facing deterministic and random customer demand combined with deterministic and random lead times. The paper then examines the effect of sales promotion on the ordering policies and shows that the bullwhip effect can be reduced even when sales promotions occur in the SC.

Keywords: Bullwhip effect; Beer game; Genetic Algorithms; Sales Promotion

1. Introduction

A supply chain is an integrated process which includes all activities associated with the flow and transformation of goods from raw materials stage through to the end user. It also involves the integration of information which flows up and down the SC. Businesses today are not separate entities; they are all working together in one SC, which can improve the quality of goods and services across the SC. Each stage in the SC performs a different process and must interact with all other stages in the SC. The primary purpose of a SC is to satisfy the needs of the customer while generating profits. The SC activities begin with a customer order and end when a satisfied customer has paid for the purchase (Chopra and Meindl, 2004). Supply chain management (SCM) is a set of approaches utilised to efficiently integrate suppliers, manufacturers, warehouses and stores so that merchandise is produced and distributed at the right quantities, to the right locations and at the right time in order to minimise system wide costs while satisfying service level requirements (Simchi-Levi et al, 2002)

The bullwhip phenomenon refers to the amplifications in orders in a SC. Procter & Gamble were one of the first companies to discover the bullwhip effect when they examined the ordering patterns for one of their products. The retail demand was fluctuating slightly but when examining the upstream members of the SC; there was a greater variability of orders as shown in Figure 1. This distorted information from one end of the SC to the other can lead to inefficiencies, i.e. excessive inventory, quality problems, higher raw material costs, overtime expenses, shipping costs, poor customer service and missed production schedule (Lee et al. 1997a, 1997b; Chen et al. 2000). Industries with reliable demand forecasts waste millions of dollars every year because they are not able to match production to demand. The bullwhip effect is a major cause of this problem. As information - normally forecast data - is passed down the SC, most participants only have access to data from the business either directly above or below them.

This paper investigates whether the optimal ordering policies for each member of a SC can be found using a GA, to reduce the bullwhip effect and cost across the entire SC. This paper also examines the effect of sales promotions on the bullwhip effect by inserting a large upsurge in demand to represent a sales promotion. Sales promotions are a major cause of the bullwhip effect. If the price of a product is reduced, customers will buy in bulk therefore resulting in customers orders not reflecting true demand. This paper discusses how a GA is employed to obtain the optimal ordering policies to minimise the bullwhip effect in a SC. It also examines the effect of sales promotions on the ordering policy of the members. Section 2 provides a review of the relevant literature and computational intelligent techniques. Section 3 describes the design of the MIT beer game and the GA. The results from the various experiments are provided in Section 4. Section 5 is a discussion of results, which is followed by the conclusion and recommendations for further work.

2. Review

The bullwhip effect is not a new phenomenon; numerous researchers from different backgrounds have studied it. Forrester (1961) was the first to study the dynamic behaviour of simple linear SCs. He presented a practical demonstration of how various types of business policy create disturbance, which were often blamed on conditions outside the system. He stated that random, meaningless sales fluctuations could be converted by the system into apparently annual or seasonal production cycles thereby sub-optimising the use of capacity and generating swings in inventory. A change in demand is amplified as it passes between organisations in the SC (Cao and Siau, 1999). In industries where the entire SC can consist of numerous layers, this means the majority of information that managers use to make decisions is only available to a few participants and concealed from those further up and down the SC. Without a clear view of end user demand, companies must rely on only that information they have access to. Unfortunately, this information is usually distorted by multiple layers of forecasts and transactions (Factory Logic, 2003). This lack of coordination can cause multiple problems including increases manufacturing costs, inventory costs, replenishment lead times, transportation costs, labour costs associated with shipping and damages the level of product availability (Chopra and Meindl, 2004). The four main causes of the bullwhip effect have been identified by Lee et al. (1997a, 1997b), which are *Demand Forecast Updating*, *Order Batching*, *Rationing and Shortage Gaming* and *Price Variations*.

Increasing Variability of Orders up the Supply Chain

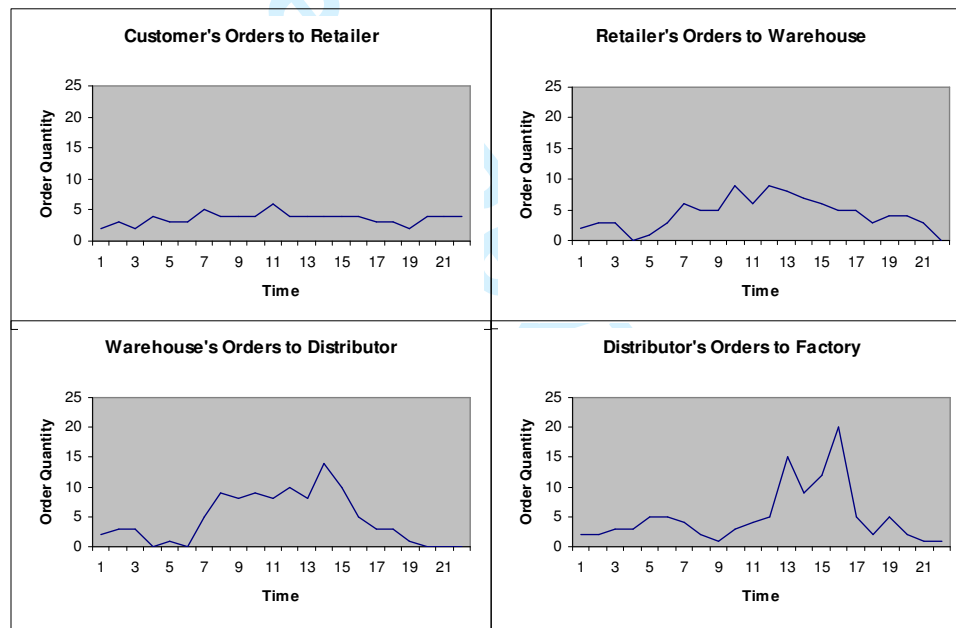


Fig 1. The Bullwhip Effect (Lee et al, 1997)

Demand Forecast Updating

Forecasting data used is normally based on the previous orders received by the company from its customers. The main reason for this problem is that the data is usually based on forecasted orders and not actual customer demand. As most companies are untrusting, this leads to companies not wanting to share information about demand, which leads to information distortion throughout the supply chain (Lee et al, 1997a, 1997b). Various methods of forecasting such as exponential smoothing or moving average forecasting have been employed by many companies to find the 'truest' demand. Unfortunately, any type of forecasting can cause the bullwhip effect (Chen et al. 1998). However, it is possible to reduce the bullwhip effect significantly by using centralised information and allowing only one member of the supply chain to place orders on behalf of all other members via Vendor Managed Inventory (VMI) and Continuous Replenishment Programs (CRP) (Lee et al, 1997a, 1997b).

Order Batching

Order batching has been identified as another major cause of the bullwhip effect (Lee et al, 1997a, 1997b; Chen et al, 1998, 2000). Order batching refers to a company ordering a large quantity of a product in one week and not ordering any for many weeks. The main reason for a company ordering in batches is it may prove to be less costly because of transportation costs or the company will get a discount if a large quantity is ordered in one period. Although this may reduce the cost for the company, the other members of the supply chain are likely to suffer. The impact of batch ordering is simple to understand. Where the retailer uses batch ordering, the manufacturer will observe a very large order, followed by several periods of no orders and then another large order etc. The manufacturer forecast demand will be greatly distorted as it will base future demand forecasts on orders rather than actual sales (Chen et al, 1998). One method of reducing the bullwhip effect is through ordering less and more frequently, which will allow the supplier to determine the true demand.

Rationing and Shortage Gaming

When a product demand exceeds supply, a manufacturer often rations its product to customers (Lee et al, 1997a, 1997b). Rationing schemes that allocate limited production in proportion to the orders placed by retailers lead to a magnification of the bullwhip effect (Chopra and Meindl, 2004). When this problem arises, many customers will exaggerate their orders to ensure that they receive a sufficient amount of the required product. This can cause major problems as when demand is not as high, the orders will stop and cancellations will begin to arise. This leaves the manufacturer with excess inventory and no customer orders. This also makes it difficult for the manufacturer to believe there is an increase in demand whereas customer demand is actually unchanged.

Price Variations/Sales Promotions

If the price of products changes dramatically, customers will purchase the product when it is cheapest. This may cause customers to buy in bulk, which also adds to the order-batching problem. Manufacturers and distributors occasionally have special promotions like price discounts, quantity discounts, coupons, rebates etc. (Lee et al, 1997b). All these price promotions result in price fluctuations and the customers ordering patterns will not reflect the true demand pattern. One method of avoiding price fluctuations is by stabilising prices (Lee et al, 1997b). If companies can reduce the price of their product to a single reduced price, the fluctuations in demand will not be as aggressive. Sales promotion is another major contributor to this problem. If the consumer purchases more of the product because of the promotion, this will cause a large spike to shown in demand and further upstream the supply chain. Despite the lowered price for consumers, this will have the opposite effect on the supply chain causing forecast information to be distorted and in effect causing inefficiencies, i.e. excessive inventory, quality problems, higher raw material costs, overtime expenses, shipping costs, poor customer service and missed production schedule (Lee et al, 1997b; Chen et al, 1998). Campbells Soup provides a useful illustration of how price promotions can cause an increase in the bullwhip effect (Fisher, 1997). With the use of Electronic Data Interchange (EDI) and shortened lead times, Campells became aware of the negative impact the overuse of price promotions can have on physical efficiency. When Campbells offered a promotion, retailers would stock up on the product. This proved inefficient for both the supplier and the retailer. The retailer had to pay to carry the excess inventory and the supplier had to pay for the increase in shipments (Fisher, 1997).

This illustration proves that a consistent low price should be employed by retailers and suppliers to avoid the increase in demand. This increase in demand is the main cause of the bullwhip effect as it causes demand information to get distorted and large 'one-off' shipments, which are extremely costly. Retailers use promotions to meet monthly quotas for products, which can result in the overuse of promotions. The result is an addiction to incentives that turn simple predictable demand patterns into a chaotic series of spikes that only add to cost (Fisher, 1997). No matter where a promotion occurs, whether it is a sales promotion to entice the consumer to buy a specific product or a discount for retailers from a manufacturer, it is more prudent to provide lower prices all year round and disregard promotional strategies altogether (Fisher, 1997). In an ideal world, companies would use everyday low pricing. Unfortunately this is not the case as companies compete with other competitors by using price promotions to increase profits and improve market share.

Techniques used to reduce the bullwhip effect

Classical management techniques are widely employed to reduce the bullwhip effect in supply chains. Information sharing has been examined by Yu et al (2001), Veloso and Roth (2003), Steckel et al (2004), Thonemann (2002), Gangopadhyay and Huang (2002), Disney et al (2004) and Seyedshohadaie et al (2004), and information distortion

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by Lee et al (1997a, 1997b, 2004). Information in relation to demand has been investigated by Zhang (2005), Bjork et al (2004), Wijngaard (2004) and Baganha and Cohen (1998). The effect of Vendor Managed Inventory (VMI) on the bullwhip effect has been examined by Zhang and Da (2004), Disney and Towill (2003), Jiang et al (2003) and Cetinkaya and Lee (2000). Lee et al (1997a, 1997b, 2004) state that a major factor of the bullwhip effect is demand forecasting and that it increases the bullwhip effect, this theory has been investigated by many researchers, Zhang (2004), Chen et al (2000a, 2000b, 1998), whereas Alwan et al (2003), Braun et al (2003) and Chatfield et al (2002) have presented new forecasting methods to reduce the bullwhip effect. Samuel and Mahanty (2003) have identified problems with shortage gaming, which is another major cause of the bullwhip effect as identified firstly by Lee et al (1997a). Control theory is another popular approach to examining and reducing the bullwhip effect. Decjonckheere (2003a) employ control theory to measure the bullwhip effect and Lin et al (2004a, 2004b) apply z-transforms to the problem whereas Deckjonckheere et al (2002) examines the bullwhip effect by using transfer function analysis. Deckjonckheere et al (2003b) take the approach of using control theory incorporated with information sharing to reduce the amplifications and McCullen and Towill (2001) investigate and present an approach through agile manufacturing. Production and inventory control has been examined using control theory by Disney et al (2004). Logistic problems have also been identified and many researchers have taken an interest in this sector. Sheu (2005), Kelle and Milne (1999), Pujawan (2004) and Cachon (1999) have all investigated scheduling problems. Inventory problems have been examined by Zhou et al (2004), Baganha and Cohen (1998), Daganzo (2004), Chen and Samroengraja (2004) and Holweg and Bicheno (2002). The artificial intelligence approach to reducing the bullwhip effect has been examined by a small number of researchers as stated previously. Carlsson and Fuller (2001, 2002) have employed fuzzy logic to supply chains to reduce the bullwhip effect and O' Kimbrough (2002, 2001) have created artificial agents by means of genetic algorithms to reduce the bullwhip effect.

Table 1 provides a summary of all the techniques employed to reduce the bullwhip effect. The main interest is on information and forecasting methods. These techniques are promising if members of a SC share information. However, the majority of companies are still reluctant to do this. Control theory presents a theoretical approach to reducing the bullwhip effect but is inappropriate for implementing in complex SCs. The logistics approach is beneficial in many ways but information sharing is a necessity for many applications. Vendor Managed Inventory (VMI) is an excellent method for reducing the bullwhip effect and has been employed by many international companies such as Procter and Gamble and Walmart (Lee et al. 1997a, 1997b). The principal problem associated with this method is the sharing of information between retailer and factory. CI techniques present an alternative approach to classical management techniques. CI techniques provide more computationally powerful algorithms, which provide the capability to exhaustively search complex situations. Classical management techniques may find the local optimum instead of the global optimum. CI approaches are more robust and have better generalisations, i.e. the technique employed can be easily modified to optimise a similar problem.

There are three main techniques that may be used in a CI approach as described below:

Fuzzy Logic

Fuzzy logic (FL) is modelled on the reasoning part of the human brain. Its main advantage is that it can deal with vague and imprecise data. Humans do not need precise numerical data to make decisions whereas computers do, FL is modelled on a similar principal. The outputs of the systems are not a precise mathematical answer but it is still a 'good enough' answer (Zadeh, 1973).

Artificial Neural Networks

An Artificial Neural Network (ANN) is an information processing paradigm inspired by the way biological nervous systems, such as the brain, process information and learns from experience. In other words, ANNs focus on replicating the learning process performed by the brain. Humans have the ability to learn new information, store it and return to it when needed. Humans also have the ability to use this information when faced with a problem similar to the one that they have learned from in the past (Haykin, 1999).

Genetic Algorithms

Genetic Algorithms (GA) are a class of algorithm, which are powerful optimisation tools that imitate the natural process of evolution and Darwin's principal of 'Survival of the Fittest'. In the process of evolution, weaker individuals tend to die off and stronger ones tend to live longer and reproduce. GAs optimise in a similar manner, by simulating the Darwinian evolutionary process and naturally occurring genetic operators on chromosomes (Davis, 1991) (Holland, 1992). GAs are used to solve extremely complex search and optimisation problems which prove difficult using analytical or simple enumeration methods. GAs do not examine sequentially but by searching in

parallel mode using a multi-individual population, where each individual is being examined at the same time (Goldberg, 1989).

The CI approach demonstrated in this paper allows for a similar effect as VMI but information sharing between members is not required. The only information required by the GA is customer demand. The GA will exhaustively search for the global optimum ordering policy and allocate this ordering policy to each member of the SC. GAs provide an efficient and robust method of obtaining global optimisation in difficult problems (Vonk, 1994). GAs do not require derivative information found in analytical optimisation. A GA works well with numerically generated data, experimental data or analytical functions and has the ability to jump out of local minimum, i.e. has the ability to find the global optimum. The GA approach presented in this paper provides an ordering policy for each member of the SC and does not require the sharing of information. The initial experiments are based on O'Kimbrough et al (2002) to prove the validity of the model. The other experiments are used to investigate if the GA has the ability to reduce the bullwhip effect and cost across the entire SC when facing random customer demand and lead times with sales promotions occurring in any given time period.

Information/ Forecasting	Quantifying/ Collaboration	VMI/ Logistics	Control/ CI
Lee et al (2004)	Moyaux et al (2003)	Zhang and Da (2004)	Carlsson and Fuller (2002)
Zhang (2004)	Metters (1997)	Disney and Towill (2003)	Carlsson and Fuller (2001)
Zhang (2005)	Donovan (2003)	Jiang et al (2003)	O Kimbrough et al (2002)
Chen et al (2000)	Wheatley (2004)	Cetinkaya and Lee (2000)	O Kimbrough et al (2001)
Bjork et al (2004)	Baliga (2001)	Sheu (2005)	Disney et al (2004)
Chen et al (1998)	Kleijnen and Smits (2003)	Zhou et al (2004)	Dejonckheere et al (2004)
Gangopadhyay and Huang (2002)	Moyaux et al (2004)	Baganha and Cohen (1998)	Dejonckheere et al (2003)
Lee et al (1997)	Hieber and Hartel (2003)	Cachon (1999)	Lin et al (2004)
Vojak and Suarez-Nunez (2004)		Daganzo (2004)	McCullen and Towill (2001)
Chatfield et al (2002)		Holweg and Bicheno (2002)	Dejonckheere et al (2002)
Wijngaard (2004)		Chen and Samroengraja (2004)	Lin et al (2004)
Li et al (2005)		Kelle and Milne(1999)	
Veloso and Roth (2003)		Pujawan (2004)	
Steckel et al (2004)			
Seyedshohadaie and Zhang (2004)			
Yu et al (2001)			
Samuel and Mahanty (2003)			
Braun et al (2003)			
Thonemann (2002)			
Alwan et al (2003)			
Disney et al (2004)			

Table 1: Techniques employed to reduce the bullwhip effect

3. Methodology and Implementation

The aim of this research is to investigate if GAs can reduce the bullwhip effect in a SC based on the MIT beer distribution game. The GA will determine the optimal ordering policy for each member of the SC, thereby significantly reducing the bullwhip effect and reducing cost. Sterman (1989) provided evidence of the bullwhip effect in the Beer Distribution Game, which is a classroom experiment used to teach SC management concepts (Moseklide et al 1991). This game is easy to understand but complex enough to be interesting. The majority of people who play the game find it difficult, if not impossible, to avoid the chaotic ordering policies that are the basis of the game.

The MIT beer distribution game is a replica of a system for producing and distributing a single brand of beer. The SC consists of five members including a Customer, Retailer, Warehouse, Distributor and Factory. No communication is allowed between players and decisions are based only on orders from the next downstream player. Customer demand drives the system. Customer orders are pre-determined but are only revealed period-by-period as the game progresses. This information is not revealed to anyone but the retailer. The customer places an order with the retailer who fills the order if there is enough beer in stock. When the retailer's inventory is low, the retailer orders beer from the warehouse to replenish its inventory. In a similar manner, the warehouse orders from the distributor and the distributor orders from the factory. The factory orders from itself, or generates a production request when it needs to replenish its inventory. An unlimited supply of raw materials is available to the factory. There is a one-period delay in the order being received and a two-period delay in items being shipped and reaching their destination. The factory has a three-period production delay. Initially, the SC is in complete equilibrium in terms of demand, orders, supplies and inventory. The beer game is completely deterministic. There are no random elements in the model. If demand does not change, the system will continue forever in a complete equilibrium (North and Macal, 2003).

Each player makes ordering decisions based on locally available information. Orders are based on the following factors:

- Current demand
- Expected demand
- Inventory
- Items in supply line
- Desired inventory
- Desired items in supply line

The players attempt to eliminate the gap between desired and actual inventory and supply line levels in terms of inventory and what is in the pipeline. The following equations are based on Mosekilde et al (1991) and are used to calculate the amount to order for each member of the supply chain.

$$Order_t = \max(0, \text{Indicated Order}_t)$$

where Indicated Order_t is the indicated order at time t.

$$Expected\ Demand_t = \theta * Demand_t + (1 - \theta) * Expected\ Demand_{t-1}$$

where Expected Demand_t is the demand expected at time t, Demand_t is demand from immediate downstream player at time t and θ ($0 \leq \theta \leq 1$) is a parameter controlling the rate at which expectations are updated.

Stock adjustments to inventory are determined as:

$$AS_t = \alpha_S * (DINV - INV_t)$$

Where AS_t is Stock adjustment at time t, the stock adjustment parameter α_S is a fraction of the difference ordered in each round. The participants lack the time and information to achieve the optimal inventory level, the desired inventory (DINV) is a constant value but it may vary from member to member and INV_t is the actual inventory level of the member at time t.

Stock adjustments to the supply line are determined as:

$$ASL_t = \alpha_{SL} * (DSL - SL_t)$$

Where ASL_t is the stock adjustments to the supply line, DSL is the desired supply line, SL_t is the amount in the supply line at time t and α_{SL} is the fractional adjustment rate. The ordering parameter $\beta = (\alpha_{SL}/\alpha_S)$ is the relative weight attached to the supply line versus the stock differences from desired levels.

$$Indicated\ Order_t = Expected\ Demand_t + AS_t + ASL_t$$

The generic expression for the indicated order rate becomes:

$$Indicated\ Order_t = Expected\ Demand_t + \alpha_S * (Q - INV_t - \beta * SL_t)$$

where Q is a measure of desired inventory relative to desired pipeline:

$$Q = DINV + \beta * DSL$$

By using these equations, a descriptive, behavioural decision model to represent humans playing the beer game is designed. (Sternan, 1987, Sternan, 1989). Each player incurs a holding cost and a penalty cost if there are backorders. The objective is to reduce cost across the entire SC. The following notations are used to derive the total cost of the SC: N = number of players, $i = 1 \dots N$. i.e. 4. $INV_{i(t)}$ = inventory of player i at week t . $UFD_{i(t)}$ = unfulfilled demand/backorders of player i at week t . $C_{i(t)}$ = cost of player C_i at week t . H_i = Inventory Holding Cost of player i per unit per week i.e. £1. B_i = Backorder Penalty Cost of player i per unit per week i.e. £2

The total cost for the entire SC of N players, after M weeks/periods is:

$$TC = \sum_{i=1}^N \sum_{t=1}^M C_{i(t)}$$

where $C_{i(t)} = (INV_{i(t)} \times H_i) + (UFD_{i(t)} \times B_i)$ (O' Kimbrough et al, 2002)

A model of the MIT beer game was created based on Sternans simulated beer game (Sternan, 1989). The ordering and inventory levels of each player are shown in Figure2(a, b). The further upstream the SC, the more significant are the amplifications in the ordering and inventory levels, i.e. the bullwhip effect.

The ordering policy of each member is based on the order received from the immediate downstream member, e.g. 1-1 policy means if the customer orders 4 units from the retailer, the retailer orders 4 units from the warehouse etc. and the overall chain representation of the order for the 1-1 policy is $[x_{12}, x_{23}, x_{34}, x_{45}]$ and $x_{12} = x_{23} = x_{34} = x_{45}$. The value x_{ij} represents the demand that each player j receives from the immediate downstream player i , i.e., x_{34} represents the demand received by the factory which is ordered by the distributor and so on.

Binary coding is used to represent the chromosomes. In the original simulated beer game, no member orders more than 30 cases in any week. As a result, a 5-bit binary string is used to represent how much to order, e.g. the representation 00101 can be interpreted as 5. i.e. if demand is x then order $x_{ij}+5$. The GA determines the additional order to satisfy demand. The maximum order is 31 with a 5-bit representation. One bit is added to the left hand side of the string to represent a '+' or '-' and the string is scaled to represent values between $[x_{ij}-31, x_{ij}+31]$. The length of the chromosome becomes $4 \times 6 = 24$. (4 players with 6 bits for each player), i.e. 2^{24}

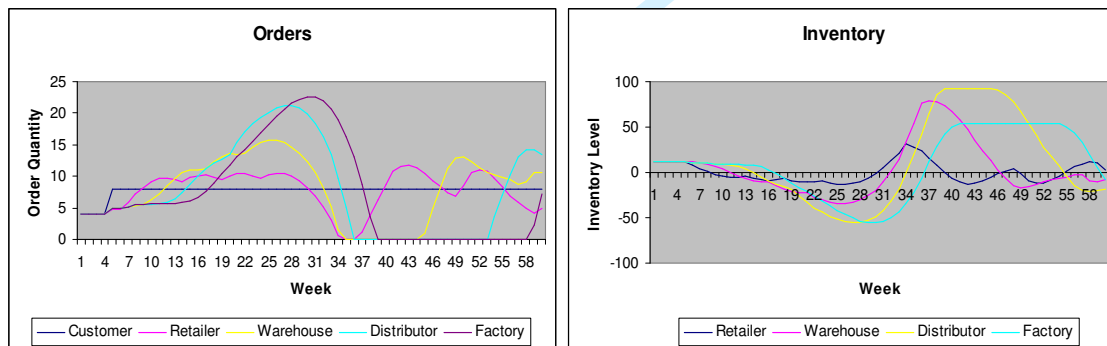


Fig 2(a & b): Ordering and Inventory of Simulated Beer Game

The members of the SC learn rules via a GA, where the absolute fitness function is the negative of the total cost (TC). Standard selection mechanism is used, which is proportional to fitness, as well as elitism, single point crossover and standard mutation operators.

4. Experiments

This section provides results of the tests carried out on the MIT beer distribution game using GAs. The initial experiments are based on the work of O'Kimbrough et al (2002) in order to prove that this model is valid. The aim of the experiments is to minimise cost by obtaining the optimal ordering policy for all members. The latter

experiments are to investigate if the GA has the ability to reduce cost and the bullwhip effect when a sudden spike, representing a sales promotion, is introduced into the demand and to determine if the GA can find the optimal ordering policy for each member of the supply chain.

4.1 Experiment 1

The first experiment was designed to test the performance of the beer game under both deterministic demand and lead-times, i.e. order 4 units until week 5 and then a step change occurs when orders are ramped up to 8 which continues until the end of the game. Figure 3(a) presents the order quantities of each member before the GA is employed. The beer game was run for 35 weeks to provide a comparison with previous work of O' Kimbrough (2002) and the genetic algorithm determined the optimal policy that eliminated the bullwhip effect. The result was the 1-1 policy as shown in figure 3(b) and the accumulated cost is £360.

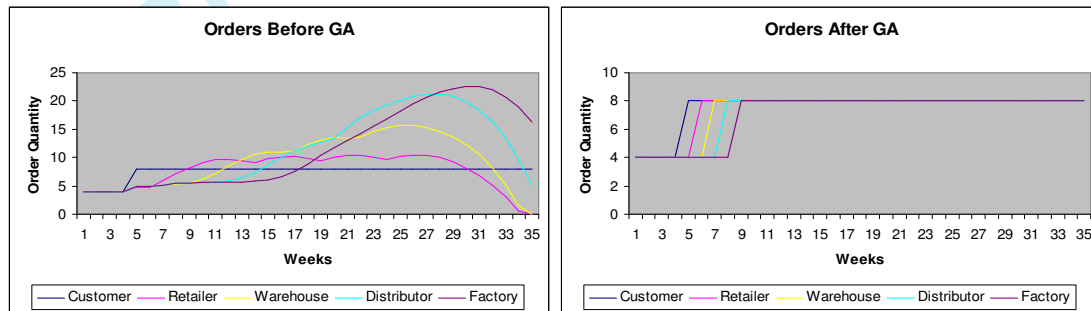


Fig 3(a & b): Results for experiment 1.

This experiment proves that the GA can eliminate the bullwhip effect and play the game without any amplification in orders occurring. These results are better than when humans play the beer game. These results are identical to those reported by O' Kimbrough (2002), therefore validating this approach.

4.2 Experiment 2

This experiment tested known stochastic demand (O' Kimbrough et al, 2002), in the range of [0, 15]. The goal was to examine whether the GA could find the optimal ordering policy. Figure 4(a) presents the ordering quantities for each member of the supply chain before the GA is employed. It demonstrates that the customer's orders cannot be tracked easily and amplifications are occurring in the orders. When playing the game for 100 weeks, the GA found the optimal ordering policy to be $[x_{12}, x_{23}, x_{34}, x_{45}]$, i.e. the 1-1 policy at an accumulated cost of £8474. The ordering policies of all members are shown in Fig 4(b). Employing the GA removes the major amplifications present in Fig 4(a) which has an order quantity scale of 0-60, and each member is able to track the customers demand effectively as presented in Fig 4(b) which has an order quantity range from 0-16. Using this ordering policy reduces the bullwhip effect significantly by eliminating amplifications in orders. This proves that this ordering policy is best suited to this set of random values and deterministic lead times. Further experiments were carried out to investigate if this ordering policy was robust for all random values in the range of [0, 15] and deterministic lead times. Various ordering policies were used with 50 sets of random customer orders to exhaustively search for the optimal ordering policy for each set. In this experiment when one of the random sets of values was generated by MATLAB, each different ordering policy was run to determine the accumulated cost. The lowest cost found would be the optimal ordering policy for that specific set of random values. This process was repeated 50 times. When all 50 sets of random values were examined, the results show that the 1-1 policy was optimal for every set.

This proves that if demand varies slightly between [0-15] and a supply chain has deterministic demand, the optimal ordering policy for the entire supply chain is the 1-1 policy, which reduces the bullwhip effect and has the lowest accumulated cost.

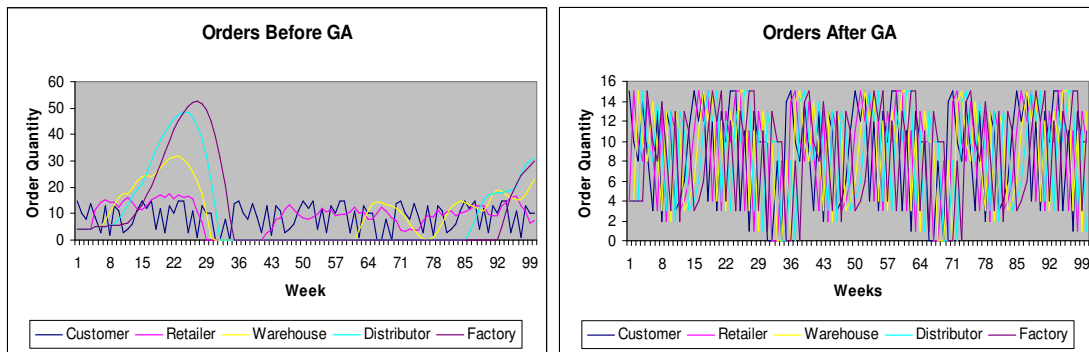


Fig 4(a & b): Results for experiment 2.

4.3 Experiment 3

This is an extension of experiment 2 by testing both known stochastic demand and lead time. The shipping lead time varied between 0-4 weeks in each time period. The game was run for 100 weeks and the GA found the optimal ordering policy $[x_{12}, x_{23}+1, x_{34}+1, x_{45}]$ at an accumulated cost of £11116. This is much lower than 1-1 policy that has an accumulated cost of £19703. This proves that this policy is optimal if faced with this set of random values and random lead times. The ordering quantity of all members is given in figure 5(b), which has a scale of 0-20, it shows that the members have the ability to track customer demand when facing random demand and random lead times and remove the amplifications present in figure 5(a), which has a order quantity scale of 0-50. Removing the amplifications and showing that the members have the ability to track demand clearly proves that the bullwhip effect is significantly reduced.

Further experiments were carried out to investigate if this ordering policy is robust for all random customer orders in the range of [0-15] and random lead times in the range of [0-4]. Random values representing customer orders and lead times for each time period were generated. Various ordering policies were used with 50 sets of random values to determine which policy occurred most frequently as in experiment 2. Table 3 shows the ordering policies that occurred most frequently and the associated mean costs.

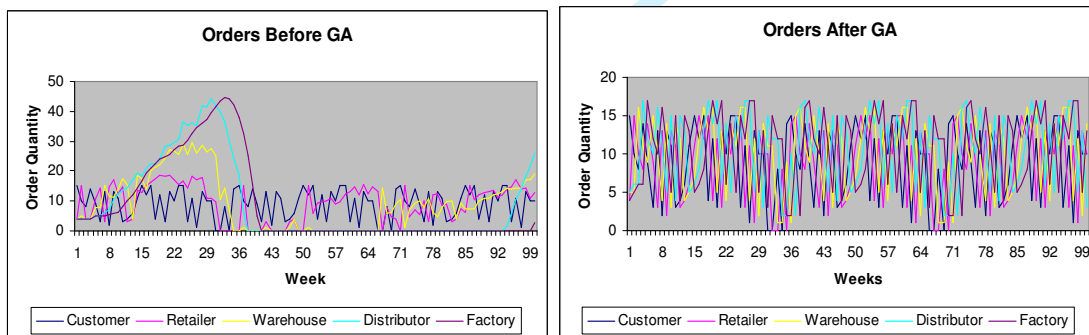


Fig. 5(a & b): Results for experiment 3

This experiment proves that the ordering policy found by the GA was not robust for every set of random customer orders in this range and random lead times. The ordering policy found by the GA is only optimal for the set of random customer orders and lead times used in the experiment. The probability of the ordering policy $[x_{12}, x_{23}, x_{34}, x_{45}]$ or $[x_{12}, x_{23}+1, x_{34}, x_{45}]$ being optimal for supply chains of this size with random customer orders and lead times is quite high. Therefore, if forecast or historical data were available, managers have the choice of choosing the ordering policy which occurs most frequently, [1-1 policy], or the ordering policy which provides the lowest cost, i.e. $[x_{12}, x_{23}+1, x_{34}, x_{45}]$.

Ordering Policy	Rate of Occurrence	Mean Cost
$X_{12}, X_{23}, X_{34}, X_{45}$	20	9616.48
$X_{12}, X_{23+1}, X_{34}, X_{45}$	18	9110.18
$X_{12}, X_{23}, X_{34+1}, X_{45}$	12	9322.5

Table 3: Optimal ordering policies found for random customer orders and lead-times

4.4 Experiment 4

Sales promotion can have a major impact on the bullwhip effect. This experiment was designed to investigate whether the GA had the ability to find the optimal ordering policy for the SC when an ordering spike was inserted into demand. The demand remained random in the range of [0-15] and had deterministic lead times. The spike in demand was used to represent a sales promotion and an increase in customer demand. The spike was represented as either 30, 45 and 60 customer orders in a single week period. The promotional strategy was placed at 10-week intervals to determine whether the week the promotion was held made any difference to the ordering policy. Figure 6(a) presents the ordering policies of each member when facing a sales promotion in week 50 representing 60 customer orders in a single week. The members cannot track demand without the help of the GA, as major amplifications are present during weeks 15-35 and members are unable to track when the promotion occurs. When employing the GA, it found the optimal ordering policy found to be $[x_{12}, x_{23}+1, x_{34}+1, x_{45}+1]$ for every 10-week interval. The same ordering policy was found when customer demand was reduced to 45 or 30 units in any week. Figure 6(b) shows the orders of each member. The bullwhip effect is reduced, as the members are able to track demand more easily.

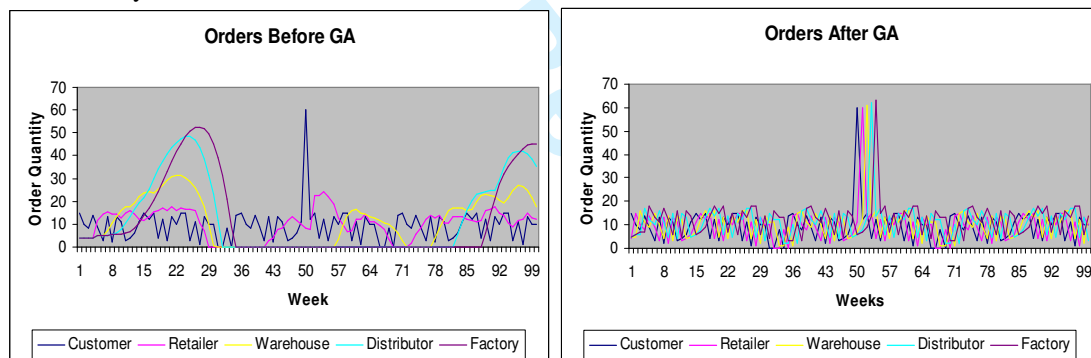


Fig 6(a & b): Results from experiment 4

The optimal ordering policy was $[x_{12}, x_{23}+1, x_{34}+1, x_{45}+1]$ for every week and demand sequence regardless of how much extra was ordered or what time period the promotion occurred. Further experiments were carried out to investigate if this ordering policy was robust for every promotional strategy in the range of [30-60] and random customer demand in the range of [0-15]. Various ordering policies were used with 50 sets of random values to determine which ordering policy occurred most frequently as in the previous experiments, with the exception of inserting a large spike into the demand sequence. The ordering policy that occurred most frequently was $[x_{12}, x_{23}, x_{34}, x_{45}]$, i.e. the 1-1 policy as it was optimal 94% of the sets tested.

This proves that the ordering policy found by the GA is not optimal for all sets of customer demand with sales promotions occurring. The probability of the 1-1 policy being optimal for any set of random values and deterministic lead time is quite high and this is the ordering policy that would be chosen for a SC of this size.

4.5 Experiment 5

This experiment is a continuation of experiment 4 and was carried out to determine whether the GA could find the optimal ordering policy for random demand with large spikes occurring in the demand and random lead times. The demand was in the range of [0-15]. Lead time varied between [0-4] in each time period and sales promotions spikes were represented by [60, 45, 30] units inserted into the customer demand sequence at 10 week intervals. There are major amplifications in the orders of the members before the GA is employed as shown in figure 7(a). The GA found the optimal ordering policy for all promotions occurring in any week to be $[x_{12}, x_{23}+1, x_{34}+1, x_{45}]$. This proves the ordering policy found by the GA is optimal for all increases in demand in this range for this set of known random customer demand and lead times. Figure 7(b) presents the ordering policies for the members when a spike of 60 is inserted into the sequence at week 30. The bullwhip is reduced as the amplifications occurring during weeks 10-40 in Fig 7(a) are eliminated and the members can easily track demand and where the promotion occurs.

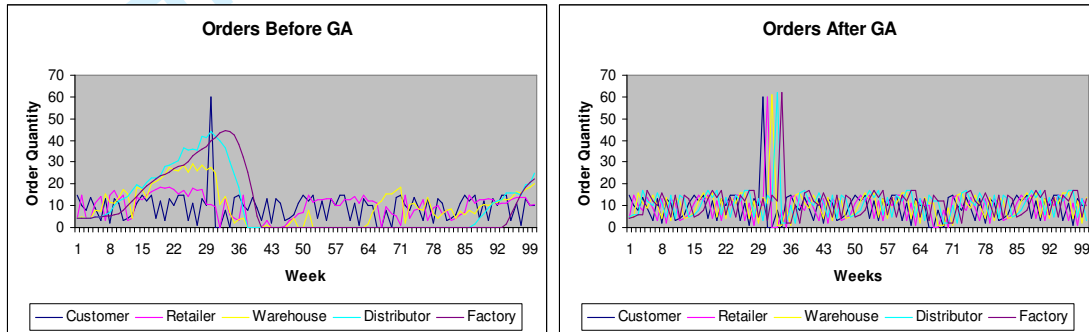


Fig. 7(a & b): Results from experiment 5

If members of the supply chain can track demand effectively, the bullwhip effect will be reduced as shown in figure 7(b). Further experiments were carried out to investigate if this ordering policy was robust for all sets of random customer orders and random lead times with a sales promotion occurring in the 100 week time period. Several different ordering policies were used against 50 sets of random customer orders to determine which policy occurred as optimal most frequently as in the previous experiment. The ordering policies found to be optimal are listed in table 4.

Ordering Policy	Rate of Occurrence	Mean Cost
$X_{12}, X_{23}, X_{34}, X_{45}$	7	12164.54
$X_{12}, X_{23}, X_{34}+1, X_{45}$	21	11167.84
$X_{12}, X_{23}+1, X_{34}, X_{45}$	15	10272.36
$X_{12}, X_{23}+1, X_{34}+1, X_{45}$	6	12991.82
$X_{12}+1, X_{23}, X_{34}+1, X_{45}$	1	11672.22

Table 4: Ordering polices found optimal for random demand and lead time with promotions

This proves that the ordering policy found by the GA is not optimal for every set of random customer orders and lead times. The highest occurring policies are $[x_{12}, x_{23}, x_{34}+1, x_{45}]$ and $[x_{12}, x_{23}+1, x_{34}, x_{45}]$. Companies that require an ordering policy for each member of the SC should choose one of these two ordering policies as the probability of these being the most optimal is very high. The manager can choose the ordering policy which is optimal most frequently $[x_{12}, x_{23}, x_{34}+1, x_{45}]$ of the ordering policy which will provide the lowest cost $[x_{12}, x_{23}+1, x_{34}, x_{45}]$. This section provides results to tests carried out on the MIT beer distribution game using GAs. The initial experiments are based on O'Kimbrough et al (2002) work to prove that this model is valid. The aim of the experiments is to minimise cost by obtaining the optimal ordering policy for all members. The latter experiments are to investigate if the GA has the ability to reduce cost and the bullwhip effect when a sudden spike, representing a sales promotion, is introduced into demand and can find the optimal ordering policy for each member of the supply chain.

5 Discussion

This paper presents a system that can reduce the bullwhip effect dramatically in SCs using CI techniques. The results show that the GA has the ability to find the optimal ordering policy for each member of the SC to reduce cost and the bullwhip effect. The GA found the optimal ordering policy each time when facing deterministic and random demands and lead times.

The initial experiments were developed as in O'Kimbrough et al (2002) to validate the approach by observing similar results and then extending the experiments. The first experiment was the MIT beer distribution game, i.e. deterministic demand and lead times. The GA found the optimal ordering policy to be the 1-1 policy. The second experiment tested random demand and deterministic lead times. The reason for this experiment was to investigate whether the GA can track random demand. In a practical environment, very few SCs face deterministic customer demand and fluctuations in orders normally exist. The next experiment was a continuation of the second experiment. Random demand and random lead times were used to determine if the GA had the ability to discover optimal ordering policies when facing two uncertainties. This is the most realistic scenario as most SCs have random customer demand and flexible shipping delays. Experiment 4.4 and 4.5 were used to determine whether the ordering policy differed when a large spike was introduced into customer demand to represent a sales promotion. The basis of this experiment was to investigate whether a SC has historical data and the effect of a sales promotion on ordering policies. Would a new ordering policy need to be implemented? When investigating random demand and deterministic lead times, a new ordering policy was required to ensure the members further upstream do not rapidly decrease their inventory levels, whereas when facing random demand and random lead times, a new ordering policy is not required. These results also prove that the ordering policies found in these experiments are not robust for all random orders and lead times, regardless of promotions occurring in the SC.

These experiments proved that by using historical data, the optimal ordering policy for a SC could be found by employing GAs. The more historical data provided, the easier it is for the GA to find the optimal ordering policy. On average, when facing stochastic demand and deterministic lead times, the 1-1 policy will be optimal whereas when facing stochastic lead times there are two ordering policies that may be optimal: $[x_{12}, x_{23}, x_{34}+1, x_{45}]$ and $[x_{12}, x_{23}+1, x_{34}, x_{45}]$. The results provide managers with a choice, by allowing them to decide what ordering policy is best for the company, i.e. the ordering policy which occurs optimal most frequently or the ordering policy which provides the lowest cost. By employing the ordering policies determined to be optimal will reduce the bullwhip effect in SCs. These ordering policies do not differ if sales promotions are inserted into customer demand in a single week. If a SC is required to choose an ordering policy for all the members, the ordering policies stated above would be most appropriate to use. The next step in this research is to determine whether the GA can determine the optimal ordering policy when the system is online, i.e. can the GA update the ordering policy each week and implement the new policies to reduce the bullwhip effect and cost across the entire SC.

This study has proved that the bullwhip effect can be reduced significantly by applying GAs to the MIT beer distribution game. It has shown that the GA has the capabilities to determine the optimal ordering policy for each member of the SC when facing stochastic or random demand and lead times and promotional strategies occurring at any point in the time period. One of the main problems associated with the bullwhip effect is sales promotions and the experiments prove that by employing GAs to the SC, promotions will not cause a major increase in the bullwhip effect, as the GA has the capability of finding the optimal ordering policy for each member.

Further work can be carried out to investigate whether the GA can determine the optimal ordering policy for an online model, i.e. a model which must be updated weekly. The type of promotion strategy employed by a company can significantly increase demand, e.g. price discounts, "2 for 1" offers etc. whereas other types of promotions e.g. extra points for a gift, has less effect on demand. Inserting various promotional strategies into demand and increasing it accordingly within the SC, the GA must be able to find the optimal ordering policy to reduce the bullwhip effect and cost across the entire SC. This model will be more realistic than the off-line model as it will be dynamic and the orders are changing weekly. Further research will be carried out to design an agile SC. This type of SC is the most complex as it needs to be responsive and efficient. Designing an agile SC and employing a GA to reduce the bullwhip effect during promotional strategies will also be examined.

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