Using GAs to Minimise the Bullwhip Effect in a Supply Chain

T. O'Donnell[1], L. Maguire[2], R. McIvor[1], P. Humphreys[1]
[1] Faculty of Business and Management, University of Ulster, N. Ireland
[2] ISEL, School of Computing and Intelligent Systems, Faculty of Engineering, University of Ulster, N. Ireland
Corresponding Author: m.odonnell1@ulster.ac.uk

Abstract

This paper presents a genetic algorithm (GA) that is employed to eliminate the bullwhip effect in the beer distribution game. The authors demonstrate that the genetic algorithm can determine the optimal ordering policy for each member of the supply chain (SC) when facing deterministic and random customer demand. The approach is demonstrated using the MIT beer distribution game.

Keywords: Bullwhip effect; Beer game; Genetic Algorithms

1. Introduction

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, the greater the variability of the orders. 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 [1,2,3].

Possibly the best known illustration of the bullwhip effect is the MIT beer distribution game [4]. It is a replica system for producing and distributing a single brand of beer. The SC consists of five members: Customer, Retailer, Warehouse, Distributor and Factory. No communication is allowed and decisions are based only on orders from the next downstream player. Each player makes ordering decisions based on locally available information. The beer distribution game is completely deterministic. There are no random elements in the model. If demand does not change, the system will continue forever in complete equilibrium.

This paper discusses how GAs are used to investigate the optimum ordering policy to minimize the bullwhip effect in a SC. Section 2 provides a review of the relevant literature. Section 3 describes the application and the design of the GA. The results from a number of experiments are presented in Section 4. Finally, Section 5 provides a summary of the research.

2. Literature Review

Many researchers have investigated different approaches to eliminating the bullwhip effect but few have applied artificial intelligence techniques to the problem. The authors have reviewed the relevant literature which is summarised in table 1.

Artificial intelligence techniques present an alternative approach to classical management techniques. These techniques provide a powerful approach to reducing or eliminating the bullwhip effect. A major gap is present in the current literature with respect to the application of AI techniques to minimise the bullwhip effect. Current research into reducing the bullwhip effect has mainly comprised of classical management techniques.

AI Technique	Supply Chain Management Area		
	Bullwhip Effect	**Inventory Scheduling Distribution**	**Modeling**
GA	[5]	[7], [8], [9]	[13]
FL	[6]	[10]	[14], [15]
ANN		[11]	
GA and ANN		[12]	

Table 1: AI Techniques in Supply Chain Management

3. Methodology and Implementation

The main aim of this research is to investigate if GAs can eliminate 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, eliminating the bullwhip effect and reducing cost.

In the MIT beer game, a one week delay between orders being sent by one member and received by the next upstream member. Delays are used to represent information and physical lead-time that is present in SCs. 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….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 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 entire SC of N players, after M weeks/periods [5] is:

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

where $C_i = (INV_i(t) \times H_i) + (UFD_i(t) \times B_i)$

A model of the MIT beer game was created based on Stermans simulated beer game [4]. The ordering and inventory levels of each player are shown in Figure 1(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 GA determines the ordering policy for each member which is best suited to the customers orders throughout the duration of the game. The GA evaluates the chromosome based on the cost function and assigns a fitness value. The beer game calculates the total cost using the equation stated above. This process is repeated until the maximum number of generations is reached. The chromosome that has the highest fitness value is carried on to the next generation by elitism.

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}]. 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 01101 can be interpreted as 13. i.e. if demand is x then order x_{ij}+13. 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 x 6 = 24. (4 players with 6 bits for each player). i.e. 2^{24}.

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. The GA has a population size of 20 with a crossover rate of 0.6 and a mutation rate of 0.1.

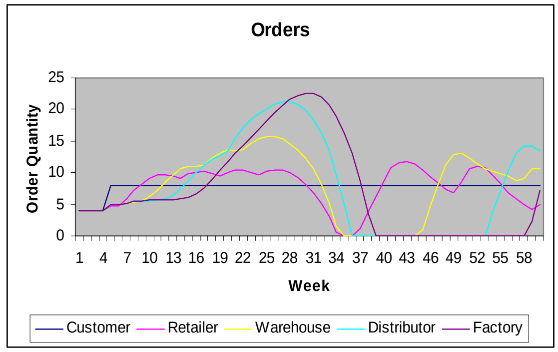

Fig 1(a): Ordering Levels of Simulated Beer Ga*me*

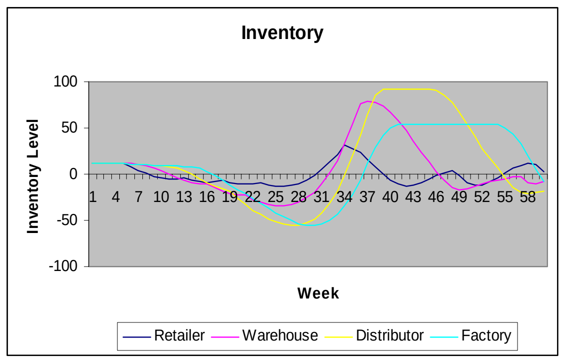

Fig 1(b): Inventory Levels of Simulated Beer Game

4. Experiments

This section provides the results to tests carried out on the beer distribution game using the GA. The aim of the experiments is to minimize cost by obtaining the optimal ordering policy. The following experiments are based on the work reported in [5].

4.1 Experiment 1

The first experiment was designed to test the performance of the beer game under deterministic demand and lead-time, i.e. order 4 units until week 5 and then a step change occurs when orders are ramped up to 8 and continues until the end of the game. The beer game was run for 35 weeks to provide a comparison with previous work of [5] and the GA determined the optimal policy that eliminated the bullwhip effect. The result was the 1-1 policy as can be seen in figure 2 and the associated cost is £360.

The game was then extended to 100 weeks to determine if the GA could discover a different ordering policy based on the number of weeks and the results did not change. The agents found the 1-1 policy as the optimal policy. The game is in complete equilibrium, no matter how many weeks the game is played for as there is no stock being held and all backorder costs are accumulated in the first few weeks because of the information and physical lead-time delays. These results are identical to those reported by [5].

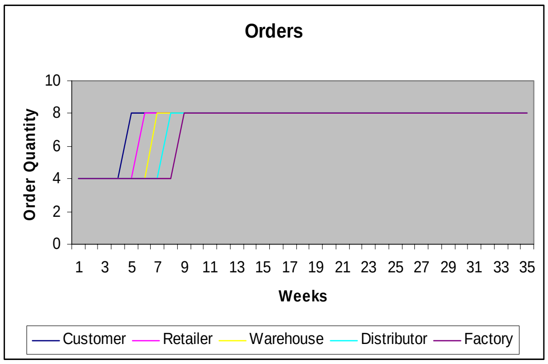

Fig 2: Results for Experiment 1.

4.2 Experiment 2

This experiment tested known stochastic demand [5], in the range of [0, 15]. The goal was to examine if the GA could find the optimal ordering policy with information delay remaining 1 week and physical lead-time at 2 weeks. The GA found a better policy than 1-1 policy by using x_{ij}+1 rule. The ordering strategies found by the agents [x_{12}, x_{23}+1, x_{34}+1, x_{45}+1] eliminate the bullwhip effect and the SC has a cost of £1926. The 1-1 policy has a cost of £2736 which is much higher. The ordering quantity of each player is shown in figure 3.

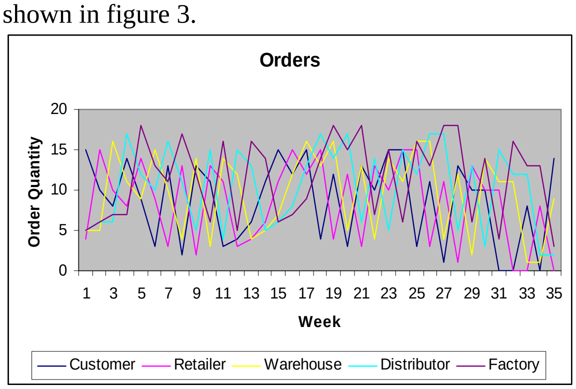

Fig 3: Results for experiment 2.

The game period was increased from 35 weeks to 100 weeks to see if the agents could learn a different ordering policy based on the number of weeks. The agents did find a different ordering policy [x_{12}, x_{23}, x_{34}, x_{45}] at a cost of £8474. This proves that the 1-1 policy is best suited for this set of values and number of weeks. A longer time frame allows the GA to fully exercise the search space and determine an optimum ordering policy. When running the best ordering policy [x_{12}+1, x_{23}, x_{34}+1, x_{45}] stated by [5] in the beer game, the cost is £11404 which is much higher than the 1-1 policy.

Further experiments were performed using differing random sequences for the 35 week period to determine which ordering policy was the most effective and at what cost. The results are listed below in table 2. The GA was run for 50 sets of random values and the optimum ordering policy that occurred most frequently was the 1-1 policy with a mean cost of £1554.85.

Order Policy Found by GA	Rate of Occurrence	Mean Cost
x_{12}, x_{23}, x_{34}, x_{45}	13	1554.85
x_{12}, x_{23}, x_{34}+1, x_{45}	8	1707.75
x_{12}, x_{23}+1, x_{34}, x_{45}	6	1833.67
X_{12}, x_{23}+1, x_{34}, x_{45}+1	4	1882
x_{12}+1, x_{23}, x_{34}, x_{45}	2	1897
x_{12}+1, x_{23}, x_{34}+1, x_{45}+1	2	1991.5
x_{12}, x_{23}, x_{34}, x_{45}+1	2	2049.5
X_{12}+1, x_{23}, x_{34}, x_{45}+1	4	2100.75
X_{12}+1 x_{23}+1, x_{34}, x_{45}	1	2219
X_{12}, x_{23}, x_{34}+1, x_{45}+2	1	2276
X_{12}, x_{23}+1, x_{34}, x_{45}+1	2	2346.5
x_{12}+1, x_{23}+1, x_{34}+1, x_{45}	1	2431
x_{12}+1, x_{23}, x_{34}+2, x_{45}+1	1	2438
x_{12}, x_{23}, x_{34}, x_{45}+5	1	4104
X_{12}+3, x_{23}, x_{34}, x_{45}+1	1	4227
x_{12}, x_{23}, x_{34}+8, x_{45}	1	6411

Table 2: Optimal Ordering Policies found by the GA for Random Values

Even though the 1-1 policy has the highest rate of occurrence and has the lowest mean cost, it may not be the best ordering policy for every set of random values.

Other experiments were carried out on unknown random values for 100 weeks. The same results as running the beer game for 35 weeks occurred. The 1-1 policy occurred the most frequently with a mean cost of £4020.

4.3 Experiment 3

This is a continuation of experiment 2. The same set of known random values are used but a physical lead-time of 0-4 weeks distributed through each stage in the SC, i.e. delay of 2 weeks between warehouse and retailer and delay of 4 weeks for the factory production line. The beer game was run for 35 weeks and the GA found an ordering policy better than 1-1 policy again. The best ordering strategy [x_{12}, x_{23}, x_{34}+1, x_{45}+1] gives a cost of £1875 which is much better than 1-1 policy that costs £3914. The ordering quantity of all members is shown in figure 4.

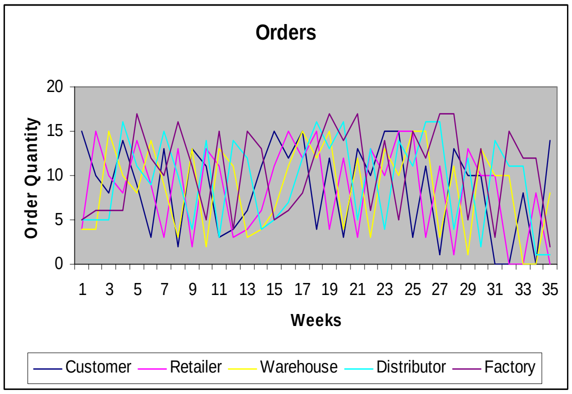

Fig 4: Results for experiment 3.

The time period was increased from 35 weeks to 100 weeks to test if the same results occurred but the GA found a different ordering policy [x_{12}, x_{23}, x_{34}+1, x_{45}] that has a cost of £8740 which is much lower than that of 1-1 policy which has a cost of £12012.

5. Conclusion and Further Research

This study has proved that the bullwhip effect can be eliminated by applying GAs to the beer game. Various experiments were carried out to compare results with that of [5]. The GA designed outperformed that of [5] by lowering cost and proving that no single ordering policy is suitable for every set of random customer orders.

Further experiments will be carried out to compare results with that of [5], which include members facing stochastic demand and lead-time. Extending the SC to more than five members will be examined to determine the effect of extra members on cost and the bullwhip effect.

6. References

[1] Lee, Hau L. Padmanabhan, V. and Whang, Seugjin, "The Bullwhip Effect in Supply Chains," *MIT Sloan Management Review*, Vol. 38, No. 3, pp 93-102, 1997.

[2] Lee, Hau L. Padmanabhan, V. and Whang, Seugjin, "Information Distortion in a Supply Chain: The Bullwhip Effect," *Management Science*, Vol. 43, No. 4, pp 546-558.

[3] Chen, Frank, Ryan, Jennifer K. and Simchi-Levi, David, "Impact of Exponential Smoothing Forecasts on the Bullwhip Effect," *Naval Research Logistics*, Vol. 47, No. 4, pp 269-286, 2000.

[4] Sterman, John D, "Modelling Managerial Behaviour: Misperceptions of Feedback in a Dynamic Decision Making Experiment," *Management Science*, Vol. 35, No. 3, pp 321-339, 1989.

[5] O Kimbrough, Steven, Wu, D.J. and Zhong, Fang, "Computers Play the Beer Game: Can Artificial Agents Manage Supply Chains?" *Decision Support Systems*, Vol. 33, No. 3, pp 323-333, 2002.

[6] Carlsson, Christer and Fuller, Robert, "A Position Paper on the Agenda for Soft Decision Analysis," *Fuzzy Sets and Systems*, Vol. 131, No. 1, pp 3-11, 2002.

[7] Damrongwongsiri, Monti and Chingping, Han, "A Genetic Algorithm Based Supply Chain Inventory and Distribution Cost Reduction Model," *Proceedings of the 7th Joint Conference on Information Sciences (JCIS '03).*

[8] Disney S.M., Naim, M.M. and Towill, D.R, "Genetic Algorithm Optimisation of a Class of Inventory Control Systems," *International Journal of Production Economics*, Vol. 68, No. 3, pp 259-278, 2000.

[9] Jahangirian, M. and Conroy, G.V, "Intelligent Dynamic Scheduling System: The Application of Genetic Algorithms," *Integrated Manufacturing Systems*, Vol. 11, No. 4, pp 247-257, 2000.

[10] Liu, Boading, "Fuzzy Criterion Models for Inventory Systems with Partial Backorders," *Annals of Operations Research*, Vol. 87, pp 117-126, 1999.

[11] Bruzzone, Agostino and Orsoni, Alessandra, "AI and Simulation Techniques for the Assessment of Supply Chain Logistics," *Proceedings of 36th Annual Simulation Symposium: AI and Simulation*, pp 154-164, 2003.

[12] Shervais, S., Shannon, T.T. and Lendaris, G.G, "Intelligent Supply Chain Management Using Adaptive Critic Learning," *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*, Vol. 33, No. 2, pp 235-244, 2003.

[13] Lee, Y.H., Jeong, C.S. and Moon, C, "Advanced Planning and Scheduling with Outsourcing in Manufacturing Supply Chain," *Computers and Industrial Engineering*, Vol. 43, pp 351-374, 2002.

[14] Petrovic, Dobrila, Roy, Rajat and Petrovic, Radivoj, "Supply Chain Modelling using Fuzzy Sets," *International Journal of Production Economics*, Vol. 59, pp 443-453, 1999.

[15] Wang, Juite and Shu, Yun-Feng, "Fuzzy Decision Modelling for Supply Chain Management," *Fuzzy Sets and Systems*, Vol. 150, No. 1, pp 107-127, 2005.