#### PROCESS CONTROL IN AGILE SUPPLY CHAIN NETWORKS

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# ABSTRACT

The work comprises a new theoretical development applied to aid decision making in an increasingly important commercial sector. Agile supply, where small volumes of high margin, short life cycle innovative products are offered, is increasingly carried out through a complex global supply chain network. We outline an equilibrium solution in such a supply chain network, which works through limited cooperation and coordination along edges (links) in the network. The links constitute the stochastic modelling entities rather than the nodes of the network. We utilise newly developed phase plane analysis to identify, model and predict characteristic behaviour in supply chain networks. The phase plane charts profile the flow of inventory and identify out of control conditions. They maintain quality within the network, as well as intelligently track the way the network evolves in conditions of changing variability. The methodology is essentially distribution free, relying as it does on the study of forecasting errors, and can be used to examine contractual details as well as strategic and game theoretical concepts between decision-making components (agents) of a network. We illustrate with typical data drawn from supply chain agile fashion products.

**Keywords**: Agile Supply Chain, Inventory, Process Control, Push and Pull Strategies, Bullwhip Effect.

**Topic**: Supply Chain Management, Design and Organization of Supply Chains, Supply Chain Performance Assessment.

### **1. INTRODUCTION**

For businesses to compete in the commercial sector where markets are increasingly more volatile, and unpredictable demands create uncertainty, their supply chains have needed to adapt to respond to such unpredictability. This capability a supply chain has of becoming flexible is referred to as *agility* ([1]; [2]) and some of the conditions in which an agile approach is best suited can be described by the following characteristics: (i) short life cycle products; (ii) high product variety in the face of unpredictable demand; (iii) small volumes and higher profit margins; (iv) competition based on product specification. With this agility the supply chain more frequently operates in a global context and there is an increasing trend to outsource the supply and manufacturing overseas, through a complex supply network ([2]; [3]; [4]), to reduce costs.

The global fashion industry is a prime example, particularly in the high end of the fashion market, in which businesses are competing in a fickle, volatile and unpredictable market where high-variety, high margin, short-life products are being sourced globally ([3]; [4]). Fashion retailers exploit this unpredictable market by introducing new products to their stores as frequently as possible, where product life cycles, from first offering in a store to discounting, average six weeks. There can be few industries where there is a greater need for a more responsive and rapid design/manufacturing/delivery lead-time throughout a complex global supply chain ([3]).

Using the fashion industry as a case study, this paper aims to introduce a new theoretical development ([7]; [8]; [9]) to aid agile supply chain decision making under uncertainty. The approach we adopt makes use of the concept of a decision frontier, which occurs between two components of a supply chain network ([6]). We uncover a duality between networks as knowledge structures

and networks as decision-making structures. We introduce a network transformation which opens up analysis using phase planes, which allows the investigation of changes in variability and network structure both at a global and local level. The local phase plane addresses the way in which decision-makers coordinate their decisions in conditions of increasing variability and uncertainty. The global phase plane reveals changes in variability as the volume of trade increases or decreases. The local phase plane is associated with key endogenous variables such as costs and contractual agreements between decision-makers. On the other hand the global phase plane is associated with exogenous variables such as pricing and promotion strategies. The phase planes each have associated efficient frontiers, which arise from the constrained optimisation problem. This new conceptual framework enables us to extend the previous work of, for example, Box and Lucerno ([14]) by applying methods of statistical process control such as feedback mechanisms to any forecasting method rather than just simple exponential smoothing.

The remainder of the paper is structured as follows. We first describe the agile global fashion industry supply chain in more detail and highlight some of the key decisions, in particular for the retailers, whilst exploring the relevance of some earlier research and literature. We then outline the modelling approach and an equilibrium solution in such a supply chain. The methodology of prediction capability using phase plane analysis is then illustrated with an example from the agile fashion industry making use of simulation. The paper ends with a conclusion and details of further research and collaborative work in progress.

# 2. THE AGILE FASHION INDUSTRY

In attempts to exploit the unpredictable UK market, high fashion retailers introduce new products to their stores as frequently as possible that in most cases requires global sourcing. Figure 1 illustrates their key decisions throughout this process of introducing new products, from the start of a season to the final product phase.

The process begins with the UK retailer's product design conception at the start of a season. Market trends will be continuously monitored and once the retailer has made a decision on fabrics, colours and trends (**Decision 0**) that he anticipates will be fashionable for a forthcoming season, the production and logistics are pre-booked. This relates to a tactic known as postponement, which is based on the principle of early product design and the delaying of final production until the final market destination and/or customer requirement is known ([1]). In this case postponement allows for any changes the retailer wants to make to the product specification before its introduction into the market. The pre-booking is predominantly done through overseas intermediaries who are agents with no manufacturing capabilities or assets (if they do own assets it is normally major logistics capability), but have access to an appropriate supplier network, which their role is to manage. At this stage, before the product definition and launch, the intermediary would select preferred fabrics and suppliers.

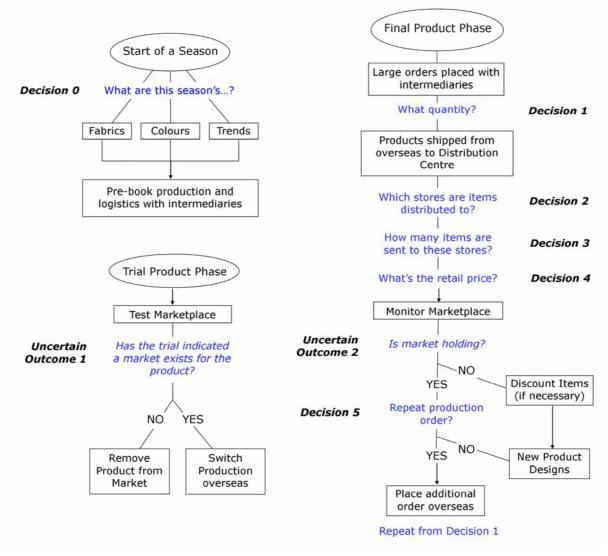


Figure 1. Key Retailer Decisions

Once the product design is complete it may go through a trial period in the retailer's flagship store (this is not always the case). At the trial stage the product can often be sourced and produced locally in small quantities (<20 items). The outcome of the trial (**Uncertain Outcome 1**) determines whether the production is switched overseas in large volume (>500 items) or the product is removed from the market.

When the production is switched overseas a large order is placed with an intermediary (**Decision 1**) who is responsible for sourcing the product at the lowest cost and lead-time possible. The most common approach to sourcing ([3])

is through competitive auctions, organised by the intermediary, for garment manufacturing by passing product specifications and volume requirements to approved manufacturers in the supply network base. Manufacturers send back an "offer package" based on price and lead-time and the best "offer" would be selected. The finished products would undergo quality checks by the intermediary and then dispatched to the retailer's distribution centre.

The remaining decisions the retailer has to make are when the finished product has been delivered, regarding its distribution amongst the stores and complete introduction into the market (**Decisions 2-4**). The average time such products exist in the market is 6-9 weeks, but can be as short as 3 weeks. During this time if customer feedback indicated the market was holding for the new product (**Uncertain Outcome 2**), a repeated order may be placed (**Decision 5**). Otherwise the products are discounted or sold through less fashion conscious outlets toward the end of its 6-9 week life cycle ([3], [5]).

# 3. MODELLING APPROACH

The approach adopted in this paper firstly recognises the distinction between the specialist skills of forecasting and those acquired by decision makers in operations management. Given an environment in which customer demand is increasingly uncertain, errors in forecasts are expected and when these errors are acknowledged and shared, real strategic progress can be achieved. The methods we use identify phenomena of practical interest, such as push and pull effects which occur in manufacturing systems, and the bullwhip effect, whereby variability is pushed upstream through a variety of transactional strategies and agreements ([7]).

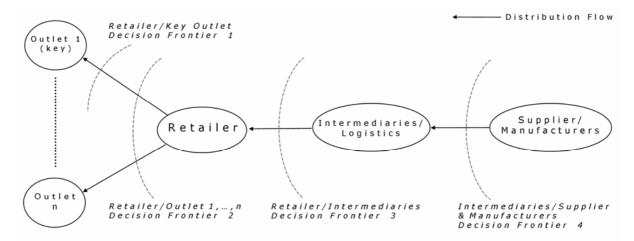


Figure 2. Decision Frontiers for a Typical Agile Supply Chain Network

The problem type, which is a specific case of a general type of mathematical problem, the two-echelon (primal-dual) problem, is illustrated in Figure 2 where the distribution of new products in the agile fashion industry (from the base of suppliers to the retailer) is divided by one of four possible decision frontiers. Each decision frontiers acts as a line cut and divides the connected network into two components, which can be treated as primal or dual ([6]). There can be as many decision frontiers as there are line cuts in the graph representing the network. Each line-cut generates a decision frontier and a set of efficient frontiers. For instance, the two-echelon problem is defined on *Decision Frontier 3*, where an intermediary determines the cost to charge a retailer, and a retailer determines the amount of inventory to order through the intermediary and the retail price.

In order to specify the model in more detail we now define some terms used. We let *C* be *the* unit wholesale price (which the intermediary charges the retailer), *V* the credit/unit paid by the intermediary to the retailer for unsold units returned by the retailer,  $V_e$  the product's unit salvage cost obtainable by the retailer from the open market at the end of the selling season, Q the retailer's order quantity, and *R* the unit retail price (which the retailer charges his

customers). According to the classical two-echelon problem applied to decision frontier 3 an intermediary attempts to determine the cost to charge a retailer under certain contractual obligations such as the discount for large orders, flexible quantity ordering ([12]), lead time for delivery or the credit/unit to pay for unsold units returned. A retailer determines the amount of inventory to order from the intermediary and the retail price to charge the customer, as well as negotiating the contractual obligations. Both the intermediary and the retailer attempt to maximise their profit. The traditional decision variables such as *C*, *V*, *Q*, *V*<sub>e</sub> and *R* influence the mean demand ( $\mu_D$ ) and supply ( $\mu_Q$ ) levels. The primal-dual transformation is applied, where the real decisions are about coordinating overage and underage (mix) between the primal and dual operators and deciding on the optimal total (global) output.

The objectives in this problem are to increase profit, reduce waste and improve customer service in a coordinated way under current business practice. At *Decision Frontier 3*, for example, this requires a profit maximizing solution to the decision set { $\mu$ , $\eta$ , $\sigma_e(\mu,\eta)$ }, which is derived from the variables  $\mu_D$  (the mean demand) and  $\mu_Q$  (the mean supply) by applying the primal-dual transformation, i.e.  $\mu = \mu_Q - \mu_D$ ,  $\eta = \mu_Q + \mu_D$ , and  $\sigma_e$  is the standard deviation of the combined forecasting errors for the demand and supply. The following formulation is based on the model described in detail in Pearson ([9]), which assumes that unbiased demand and supply fitting or forecasting techniques are already applied and the prediction errors are normally distributed. The primal-dual objective is to maximise:

E{Profit} = E{Contribution from captured demand – Costs of overage

– Costs of underage}

$$= \mu_D c_p - \{(\varphi(k) - k(1 - \varphi(k)))(c_{u_1} + c_{o_2} + c_p) + (k\varphi(k) + \varphi(k))(c_{o_1} + c_{u_2})\}\sigma_e \quad (1)$$

subject to:  $\mu - k\sigma_e = 0$ , (Newsvendor Constraint)

where  $\varphi(k)$ ,  $\varphi(k)$  are normal distribution density and cumulative distribution functions, respectively, for safety factor, k. The contribution to profit is  $c_{\rho}$ , which includes the contributions from the retailer and intermediary. The overage and underage costs of the retailer are  $c_{o_1}$  and  $c_{u_1}$ , respectively, while for the intermediary they are  $c_{o_2}$  and  $c_{u_2}$ . An interesting feature of the problem and the way it is formulated is that the retailer's (primal) overage is the same as the intermediary's (dual) underage, though they may have different attitudes to these phenomena resulting in unequal costs.

The equilibrium solution under conditions of constant variability is described by the following equation ([9]):

$$\Phi(k) = \frac{C_{u_1} + C_{o_2} + C_p}{C_{o_1} + C_{u_1} + C_{o_2} + C_{u_2} + C_p}$$
(3)

The equilibrium solution under conditions of changing variability is described by the following equations ([9]):

$$\Phi(k) + \frac{\partial \sigma_e}{\partial \mu} \varphi(k) = Const \left\{ = \frac{C_{u_1} + C_{o_2} + C_{p}/2}{C_{o_1} + C_{u_1} + C_{o_2} + C_{u_2} + C_{p}} \right\}$$
(4)

$$\varphi(k)\frac{\partial \sigma_e}{\partial \eta} = Const \left\{ = \frac{c_p}{2(c_{o_1} + c_{u_1} + c_{o_2} + c_{u_2} + c_p)} \right\}$$
(5)

Equation (4) is the 'mix' (overage/underage) solution, which tracks the way partners across decision frontiers synchronize their efforts to reach optimality, and equation (5) is the 'global' (volume) solution. Together they form a dynamic system of stochastic differential equations, which trace the optimal solution in circumstances where uncertainty increases or decreases over time and with relation to differing contractual and marketing strategies.

(2)

The model outlined here fulfils many of the requirements of modern agile supply chain networks. Some of the requirements are the incorporation of nondeterministic demand, lead-time and supply mechanisms into the modelling methodology ([10]). The patterns identified in such contexts frequently do not match deterministic assumptions, which are more generally associated with periods of stable operation. The complexity of events occurring in a local context is particularly difficult to express in a simple model. Nilsson et. al. ([10]) describe the need for complex adaptive systems (CAS) and agent-based modelling (ABM). Our approach to the study of network flow uncovers a duality between networks as knowledge structures and networks as decision-making structures ([11]) across naturally occurring decision frontiers ([6]). The approach also identifies through the use of phase planes the way in which two decision makers (agents) coordinate their efforts to achieve capable solutions in environments experiencing changing variability and increasing uncertainty ([7]; [8]). Patterns in the 'local' phase plane reflect the way in which endogenous variables, such as negotiated costs and contractual agreements between agents ([12]; [13]), affect the optimal solution. Patterns in the 'global' phase plane reflect the way in which exogenous variables (such as pricing promotion strategies and quality of forecasting in the global market) affect the optimal solution. The two phase planes are significantly uncorrelated ([7]). Each phase plane has an efficient frontier derived from the solution of the stochastic differential equations (Equations (4) and (5)). This is now demonstrated in the following section.

## 4. ILLUSTRATIONS

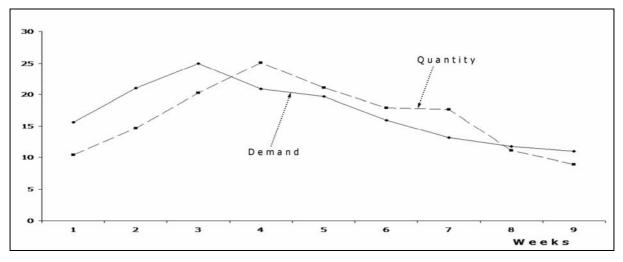


Figure 3. Time series life cycle of high fashion product over 9-week period

We illustrate the use of prediction capability and phase plane analysis at *Decision Frontier 1* with an example representative of a high fashion product, which has been introduced for the first time into the market, such as a woman's camisole or vest top. The contribution to profit is  $c_p = 6$ , and  $c_{o_1} = 5$ ,  $c_{u_1} = 0$ ,  $c_{o_2} = 0$ ,  $c_{u_2} = 1$ . The equilibrium solution is found to be k = 0 (derived from Equation (3)). Simulation is used to demonstrate the strategies employed in the marketing of high fashion clothing and data was simulated based on this illustrative example using a Java program. In this simulation the forecast demand is calculated simple using exponential smoothing with smoothing constant 0.2 and the forecast supply is calculated using the coordination constraint,  $\hat{Q} = \hat{D} + k\sigma_e$ , with k = 0. The demand, D, is randomly generated from the standard normal distribution whose mean increases for the first three weeks and decreases for the remaining six, and similarly for the supply, Q. This is presented in Figure 3 for a 9-week period, which is representative of an average life cycle for a high fashion product in a retail outlet, where sales peak in weeks 3-4 ([5]).

From Figure 3 the supply for this example product displays a lag behind the demand. This describes a common approach in marketing a new product, whereby the retailer attempts to generate demand for a high fashion garment in the early stages of it's life cycle, pulling the quantity amount up gradually, and branding the product as exclusive, then in the latter stages of the life cycle as the demand drops it pulls the quantity along with it, after a delay. Associated with this is the product's profile illustrated by the global and mix phase planes in Figures 4 and 5 respectively. The global phase plane identifies changes in the error variability,  $\sigma_e$ , to the expected volume,  $\eta$ , of trade as new markets are investigated and the mix phase plane identifies the way in which two decisionmakers (agents) coordinate their efforts to achieve capable solutions in environments experiencing changing variability and increasing uncertainty.

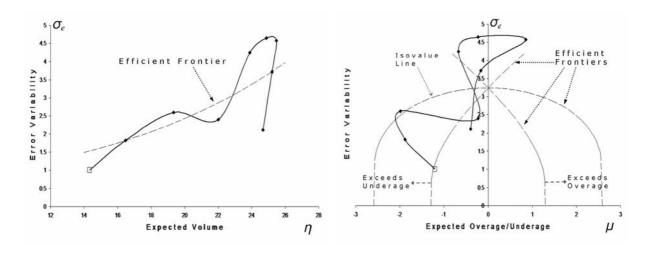


Figure 4. Global phase plane (k = 0) Figure 5. Mix phase plane (k = 0)

The profile in Figure 4 displays a typical increase in variability as volume increases. The efficient frontier for optimal allocation of stock volume can be derived from the 'global' solution, given in Equation (5) and mapped onto this phase plane. Market operation along this efficient frontier ensures maximum profit levels for a desired area of risk. Figure 5 illustrates the relationship between the two operators functioning across decision frontier 1 (Figure 2) by mapping the changes in error variability,  $\sigma_{e_r}$  against the expected overage/

underage,  $\mu$ . So in this example it shows how well the retailer and the outlets coordinate the flow of the product upstream in the supply chain network and the way in which error variability (and hence risk) varies through this process. The variability we speak of here is not just demand variability, but the joint variability experienced by both operators on either side of the decision frontier. The path of variability in Figure 5 (bold line), where a different marker shows the beginning of the path, displays a mild overall clockwise movement, indicating a 'pull' effect, which corresponds to the description for this product's life cycle presented in Figure 3. Also mapped onto the mix phase plane are three efficient frontiers. The isovalue line shows, using k as a parameter, the efficient frontier for solutions which have the same profit level as that obtained by the maximum profit solution (at k=0) which achieves the desired target levels of overage and underage. The other two efficient frontiers, which are derived from parametric equations given constant overage and underage targets ([9]), plot the area of capable optimal solutions using k as a parameter again. The optimal solution occurs at the point where all three efficient frontiers meet, so that agreed targets on customer service and overproduction match the maximum profit achievable in the area of market uncertainty for which the product is retailed.

This example considers a safety factor of k = 0 and yields the following target percentages for availability, overage and underage given in Table 1.

Table 1

Target Percentages for k = 0

Target Availability	50.00%
Target Overage	9.44%
Target Underage	9.44%
Percentage of Captured Demand	90.56%

These results are derived from the *availability*, *overage and underage theorems*, ([9]), which respectively state that if the target availability,  $\tau_a$ , is exactly met in prediction then

$$\tau_a = 100 \Phi(k) ; \qquad (Availability Theorem) \qquad (6)$$

if the target overage,  $\tau_{o}$ , is exactly met in prediction then

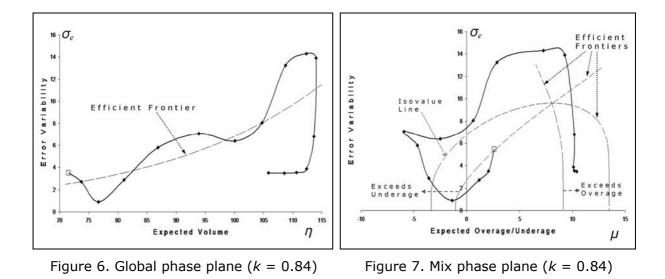
$$\tau_o = 100 \,\beta(\varphi(k) + k\Phi(k)); \qquad (Overage Theorem) \qquad (7)$$

and if the target underage,  $\tau_{u}$ , is exactly met in prediction then

$$\tau_{u} = 100 \,\beta(\varphi(k) - k(1 - \Phi(k))), \qquad (Underage \ Theorem) \qquad (8)$$

where *k* is the safety factor and  $\beta = \sigma_e / \mu_D$  is the error coefficient of variation.

The results in Table 1 display only 50% availability with equal percentage values for overage and underage. This reflects the symmetries of the efficient frontiers displayed in Figure 5, and a relatively low percentage of captured demand at 90.56%. Most retailers, however, would seek to capture 97.5% (or more) of the customer demand, which implies a target underage,  $\tau_u$ , of about 2.5% (or less). Therefore, using Equation (8) with  $\beta \approx 0.2$ , this would lead to a change of policy by setting the decision variable, k, to about 0.84. Figures 6 and 7 illustrate this change in policy with regard to the targets agreed when setting this value of k and they represent the associated phase planes for another randomly generated set of demand and supply data, where k = 0.84, for a product with a longer life cycle of 16 weeks. In this example, the contribution to profit is  $c_p = 8$ , and  $c_{o_1} = 1.5$ ,  $c_{u_1} = 0$ ,  $c_{o_2} = 0$ ,  $c_{u_2} = 0.5$ , which produces an equilibrium solution of k = 0.84 (derived from Equation (3)).



The profile in Figure 6 also displays a typical increase in variability as volume increases. Previously, in Figure 4, k=0 which indicated a lower customer service level. In Figure 6 the safety level, k, has been increased to 0.84 indicating an increase in customer service and the efficient frontier is mapped onto this phase plane to show the desired area of risk for ensuring maximum profit levels in the corresponding objective function (Equation (1)). In Figure 7 the coordination of flow of the product upstream in the supply chain network through the retailer and outlet (Decision Frontier 1, Figure 2) is once again illustrated, along with the way in which the error variability changes throughout this process. The path of variability against expected overage/underage, shown in Figure 7 by the bold line where a different (square) marker indicates the beginning of the path, this time clearly displays a clockwise movement, which implies a more prominent 'pull' effect. The three efficient frontiers, which are again mapped onto the phase plane in Figure 7 using k as a parameter, show a shift from the symmetry displayed by those in Figure 5 from the previous example when k = 0. The isovalue line in this case, where k = 0.84, shows the efficient frontier for solutions which have the same profit level as that obtained

by the maximum profit solution (at k = 0.84), which achieves the desired target levels of overage and underage.

The three efficient frontiers will meet at the same point if, and only if, the solution is an equilibrium solution for that decision frontier in the supply chain network. The efficient frontiers shown in Figure 7 meet at the same point indicating that k = 0.84 is an equilibrium solution. This may not happen ([6]) since either the (downstream) retail outlets or the (upstream) retail distributor might decide to adopt his own solution based on knowledge acquired in his own part of the network (i.e. node), rather than shared with the decision partner established across the decision frontier.

We now further investigate the possible changes in solutions that may occur across the decision frontier between a retail distributor and an outlet. The retail outlet will have a limit on how much it can display of a particular product in store which will influence its decision on the size of the delivery order from the retail distributor for that product, while the distributor may have to make decisions about promotional policy of the company which tend to determine the demand for the product.

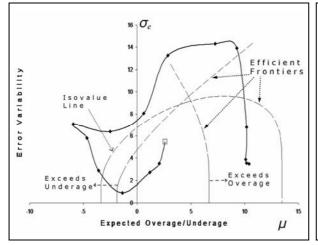


Figure 8. Mix phase plane with change in policy (k = 0.5)

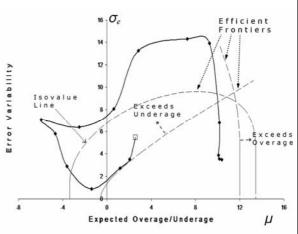


Figure 9. Mix phase plane with change in policy (k = 1.2)

In order to limit wastage and use shelf space more efficiently, the retail outlet may prefer to set the safety factor at a lower level. This scenario is demonstrated in Figure 8, where the retailer's (sub) optimal solution would be to supply a lower level of produce by using a safety factor of k = 0.5. However, this would be done at the expense of the retailer given the present levels of uncertainty and variability associated with predicting demand and supply. Alternatively, the retail distributor may wish to adopt a 'push' strategy in order to promote the product on the shelves, setting the safety factor at a higher level than the outlet might prefer. This scenario is demonstrated in Figure 9, where the retailer's (sub) optimal solution would be to supply at a higher level of produce by using a safety factor of k = 1.2. Likewise, this would be done at the expense of the retail outlet given the present levels of uncertainty and variability. Table 2 shows the affect these changes of policy have on the target percentages. By setting the safety factor at k = 0.5, the target overage decreases to a more desirable level for the retail outlet at the expense of the retailer since the target availability decreases and the target underage increases (hence reducing the percentage of captured demand). Conversely, by setting the safety factor at k =1.2, the target underage decreases and the target availability increases to a more desirable level for the retailer at the expense of the retail outlet since the target overage increases.

#### Table 2

Target Percentages for k = 0.84 and the two changes in policy

	<i>k</i> = 0.5	<i>k</i> = 0.84	<i>k</i> = 1.2
Target Availability	69.15%	79.95%	88.49%
Target Overage	14.67%	20.02%	26.41%
Target Underage	4.16%	2.35%	1.18%
Percentage of Captured Demand	95.84%	97.65%	98.82%

#### 5. CONCLUSION

Typically many western organisations now focus on marketing and product design activities while outsourcing the manufacture and delivery of products to the developing world. This global supply activity has been mainly focused on predictable 'functional' markets where there is a stable demand for longer lead time, lower margin, lower variety products and where low cost, or what is called lean supply, are the key competitive supply chain parameters. What is now however becoming increasingly important is that global supply chains are also being used to supply much higher profit margin, fast moving, 'innovative' markets where there is a volatile and unpredictable demand for short life cycle, high variety products, and where supply chain flexibility and responsiveness (called agile supply) are the key competitive elements. Agile supply chains are also characterised by complexity, because of the extended networks of different overseas suppliers required for the high product variety, so much so that the management of these supply chains is typically left to foreign intermediaries who take complete responsibility for managing the supply chain ([2]; [3]; [4]). In such a regime, where besides the fickle and uncertain marketplace, retailers typically may not even know who makes their products (as evidenced by occasional child labour scandals for major UK clothing retailers) and there are inherently high levels of uncertainty and risk.

Much research has, in fact, been carried out in lean supply chain networks but relatively little quantitative work has been done in agile networks. Agile supply chain networks operate within high-risk levels and there is therefore a requirement for more suitable decision-making models as management tools to monitor and audit, as well as improve, supply chain performance. The decisionmaking model we have developed maps the path of the variability against

changes in local and global performance measured across key decision frontiers. This was illustrated across the decision frontier between retailer and outlets and can be applied to any of the decision frontiers in Figure 2. The monitoring and improvement of performance is assisted by the use of feedback mechanisms such as adaptive target control and the use of a target gain function. These are implemented when the process drifts out of the control zone described in [7] and [8]. The control zone is an area of the mix phase plane where operation remains within acceptable targets described by the efficient frontiers. The model incorporates non-deterministic demand, lead times and supply mechanisms into the methodology fulfilling many requirements of agent-based modelling (ABM) and complex adaptive systems (CAS). It identifies the non-linear behaviour of the product's market area and the relationship between operators in the supply chain network across explicitly defined decision frontiers, which can be used to enhance the decision-making for businesses operating in such volatile markets. The methodology we have proposed can be applied in both the lean and agile contexts. The innovative facility to map changes in variability is a key feature, which should enhance research and understanding of the mechanisms occurring in such supply chains. The next stage of research will involve developing a commercial model through collaborative work, which will aid decision-making throughout the whole process of introducing a new product into the market.

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