# The Effects of Schedule Volatility on Supply Chain Performance

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**Abstract**

Schedule volatility is an unfortunate fact of life facing most suppliers of both products and services. In this paper we are concerned with establishing the magnitude of the problem faced and the resultant effects on supply chain performance. Empirical data collected from fifty-nine value streams is statistically analysed to investigate the negative effects of volatile customer schedules on performance. The evidence has been acquired predominantly via the rigorous site-based Quick Scan Audit Methodology. For each value stream the forecast error is evaluated, and confirms the excessive volatility of the orders placed by many customers. A comparison between the automotive and non-automotive supply chains is conducted to assess the generic nature of the resultant relationships. We have concluded that volatility is a universal problem not confined to particular industries. Hence it strengthens the viewpoint that solutions initially proposed for the automotive sector may well find successful application elsewhere.

**Keywords**: Supply chain management, empirical case investigation, schedule volatility, automotive vs. non-automotive, performance evaluation.
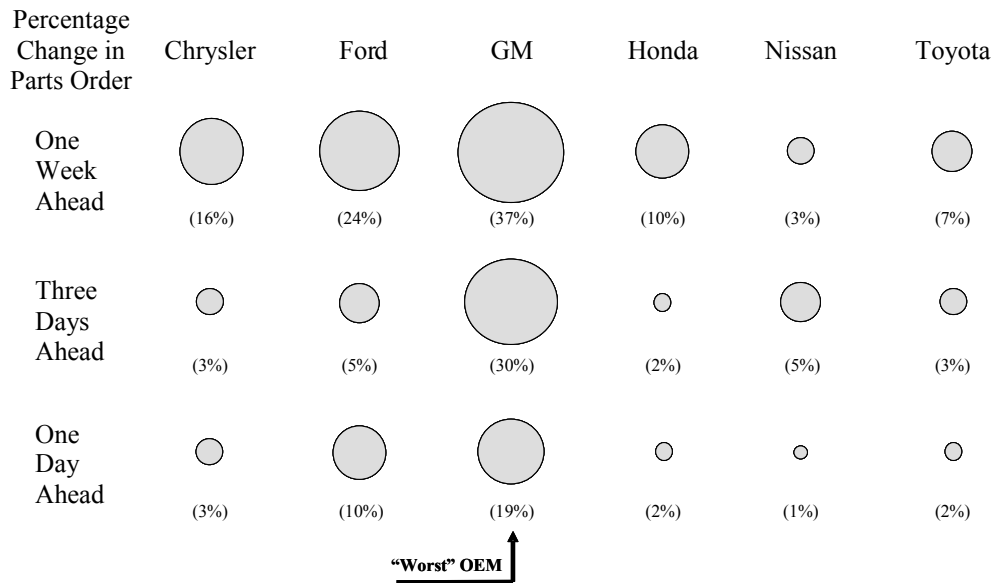
## 1 Introduction

Schedule volatility is a particular case of the bullwhip effect in which production orders are subject to more lively behaviour than the incoming customer demand (Childerhouse et al., 2006). However, although demand amplification has been studied via simulation (Forrester, 1958), using OR type analysis (Lee et al., 1997, who in passing coined the "bullwhip" phrase), and utilising transfer function modelling (Dejonckheere et al., 2002), there have been relatively few industrial studies to promulgate and exploit this knowledge. Notable exceptions are the in-depth case studies described by Harrison (1995) and Towill and McCullen (1999). Unusually, the latter paper also evaluated the impact of system design changes via an effective real-world BPR programme on bullwhip. They were able to provide substantial evidence on the simultaneous achievement of damping down volatility and reducing average stock levels in a global supply chain. Thus the system was effectively re-engineered to avoid the detrimental "vicious circles" which often plague production planning and control.

The earlier Case Studies by Harrison (1996) clearly illuminated the magnitude of the problems caused by schedule volatility. An extensive and very relevant horizontal survey was conducted by Liker and Wu (2000) comparing US and Japanese automotive OEMs. The data of particular interest to our research is portrayed in Figure 1. Clearly, the "Lean" principles invoking level scheduling (Suzaki, 1987) practised by the three Japanese automakers have resulted in far less volatility for their suppliers, especially in the short term. On that evidence there is an order of magnitude difference in forecast-ability to be overcome if the US auto suppliers are to achieve parity. Since the same marketplace is targeted by both groups of OEM, it is obvious that the material flow systems must generate this schedule volatility internally.

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| Percentage Change in Parts Order | Chrysler | Ford | GM | Honda | Nissan | Toyota |
|---|---|---|---|---|---|---|
| One Week Ahead | (16%) | (24%) | (37%) | (10%) | (3%) | (7%) |
| Three Days Ahead | (3%) | (5%) | (30%) | (2%) | (5%) | (3%) |
| One Day Ahead | (3%) | (10%) | (19%) | (2%) | (1%) | (2%) |

"Worst" OEM

**Figure 1: Summary of schedule volatility induced by US and Japanese implant automakers via their late order changes (Liker and Wu, 2000)**

It is also well established that production scheduling in any business serving many customers with many products is a very complex task. Algorithmic decision support systems provide only part of the answer. The practicalities to be faced include capacity constraints, efficiency of component/material/sub-assembly suppliers, shop floor problems, and a volatile marketplace (Olsmats et al., 1988). In some industries, this situation is much exacerbated by customers changing orders at very short notice. For example, the Liker and Wu (2000) study on US automakers established that in a particular company, the orders placed on their component suppliers change by 37% three days ahead, and by 19% one day ahead. But as far as the production schedulers involved in the vendor companies are concerned, this is just one more annoying source of volatility to be coped with, superimposed on that from every other customer. It is not surprising to find that there is a danger of a wrong reaction by the scheduler faced with such a complicated scenario. Unintended consequences within the enterprise include generation of the "Flywheel Effect" (Houlihan, 1984), and interacting "Vicious Circles" (Hoover et al., 1996).

Metters (1997) has shown via simulation that bullwhip can generate significant on-costs in the supply chain. Hence, appropriate production scheduling is a key factor in business strategy. Of course, the real-world range of possible schedule dynamics is very wide. At one end of the spectrum the aim is to level schedule, which, in effect, is making to stock even if the target is adjusted periodically in the light of sales trends. This approach is heavily dependent on customer collaboration if the delivery process is to be sufficiently smooth (Towill, 2006). At the other end of the spectrum, orders fluctuate much more widely than the incoming demand. In this paper the goal is to use the site-based Quick Scan Audit Methodology (Naim et al., 2002) to generate the necessary data to test for significant system variables resulting from schedule volatility. Both automotive and non-automotive sectors are included herein. A number of the 59 value streams are inter-linked, thus enabling an extended investigation of the knock-on effects of schedule volatility along the supply chain.

## 2   Contribution of the present paper

Understanding schedule volatility is extensively underpinned by what may be regarded as "hard" theory (Wikner et al., 1991). This is, of course, subject to how appropriately the expected real-world scenario has been represented prior to simulation or mathematical analysis. It is our view that considerable insight into system behaviour is generated via such approaches. Salient results have already been published (Childerhouse et al., 2008). In the present paper the five categories of scheduler strategy output identified have been used to classify the dynamics of the 59 real-world value streams. We show that all of the posited behaviours are encountered within the scope of our QSAM studies.

The term 'value stream' has been popularised by Womack and Jones (1996), and is defined as "the special activities required to design, order, and provide a specific product, from concept to launch, from order to delivery, and from raw materials into the hands of the customer". In many respects 'supply chain' and 'value stream' are synonymous. A practical interpretation is that a supply chain consists of a bundle of multiple value streams.

As befits the process engineering approach used herein, the QSAM is linked to the specific block diagram structure shown in Figure 2 (Mason-Jones and Towill, 1998). It is readily traceable to a systems engineering tautology (Parnaby (1979). The focus is on identifying and codifying in an informative and repeatable manner the four major uncertainties associated with the value stream under audit (Towill and Childerhouse, 2006). These are respectively due to "Our Process"; "Our Suppliers"; "Our Customers"; and the overarching "Control Systems". Furthermore, the patterns determined by such an audit can then be used to classify a particular value steam as "traditional", "typical", or "exemplar". In the latter case, further scrutiny of QSAM results can highlight the actions which enable such "best practice" (Childerhouse and Towill, 2004).
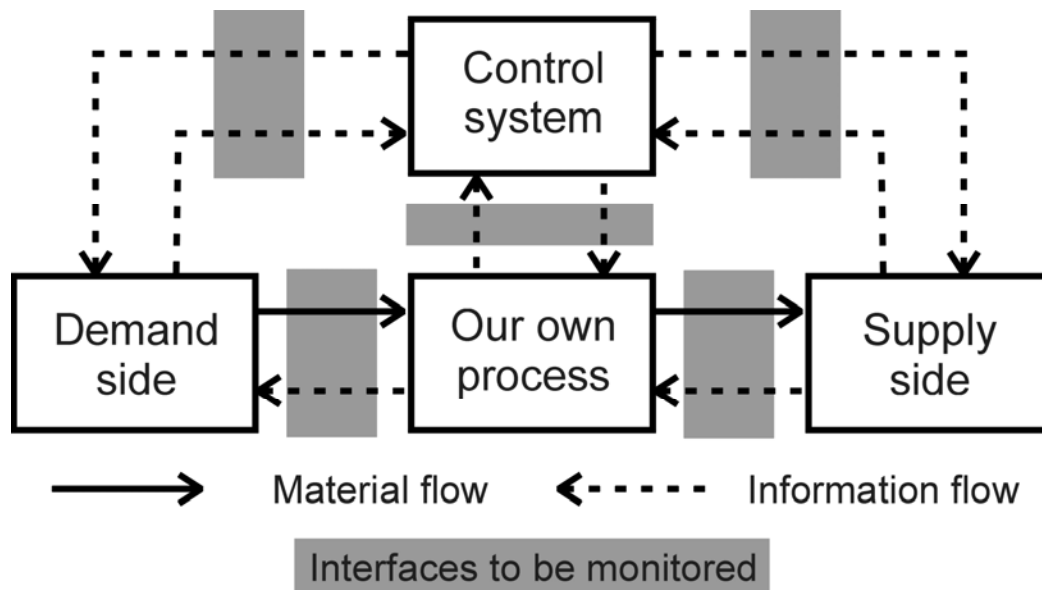


**Figure 2: Value stream representation underpinning the uncertainty circle**
**(Mason-Jones and Towill, 1998)**

Our aim is manifestly to increase the knowledge base on schedule volatility observed in real-world value streams. The novel contribution is the study across a sample of enterprises so that the phenomenon can be evaluated on a comparative basis. In particular, we study the schedule volatility induced in both automotive and non-automotive value streams. The results confirm that previously identified "best practice" companies minimise schedule volatility in order to avoid costly ramifications. Attention has been concentrated on the performance impact of the production scheduler strategy. This is based on an earlier in-depth Case Study in the UK automotive industry (Olsmats et al., 1988). That paper included simulation modelling to demonstrate the possible behaviour in response to various demands, a procedure already exploited to explore the range of experienced scheduler responses (Childerhouse et al., 2008).

## 3  Scheduler strategies

Production Schedulers are rarely concerned with managing just one product, and the task is therefore to perform a delicate balancing act between the demands for different items and between different customers (Olsmats et al., 1988). Also, the multi-product scenario can be somewhat different from aggregate statistics, requiring considerable care in subsequent analysis (Fransoo and Wouters, 2000). Certainly, there is some industrial evidence to support the view that schedulers may reasonably balance conflicting demands even if, as a consequence, the individual value stream volatility may be somewhat increased (Potter et al., 2005). Note that in these instances the bullwhip

consequently increased, but within acceptably set bounds.  Furthermore, in complex supply chain scenarios, the scheduler may be reasonably aware of what is actually happening at the marketplace despite demand amplification being induced by downstream players as identifiable within a European confectionary supply chain (Holmström, 1997).

There is a range of operating paradigms which the busy production scheduler can adopt in this situation.  Some will be manifestly more successful than others in terms of adherence to the schedule, annual stock turns, and customer service level.  Indeed in volatile situations just avoiding creating a chaotic situation on the shop floor and in dealings with second tier suppliers would be an achievement.  However the "best" scheduler decisions are highly particularised.  It is possible to develop a classification schema which will cover the range of expected responses (Childerhouse et al., 2008).  This approach will be further exploited herein.

At one extreme is where chaotic behaviour exists, and where progress chasers are much in evidence endeavouring to expedite "their own" particular clients' orders.  At the other end of the spectrum is level scheduling, which is an outcome of the "Smooth is Smart" philosophy (Towill, 2006).  Intermediate between these limiting strategies is the "Pass on Orders" (PoO) philosophy in which customer demand is sent straight on to the shop floor.  "Let them sort it out as they have the required up-to-date knowledge of local conditions" is the associated mantra.  The five categories we have selected follow directly from Childerhouse et al. (2008).  They are, in order of increasing volatility:

- Level scheduling (i.e. the output is unaffected by the input);
- Demand smoothing (i.e. a deliberate attempt is made to filter out the worst peaks and troughs);
- Pass-on-orders (i.e. output and input are aligned);
- Demand amplification (i.e. the output is somewhat more volatile than the input);
- Chaotic (i.e. seemingly excessive random volatility).

Note that the last phenomenon, in the specific sense defined by Burger and Starbird (2005), is easily self-induced.  For example, the doubly volatile scenario shown in Figure 3 result from a *planning and inventory vicious circle*, and a *quality driven vicious circle*.  Hence, the production scheduler must avoid actually making matters worse when seemingly taking action to improve this very complex situation.
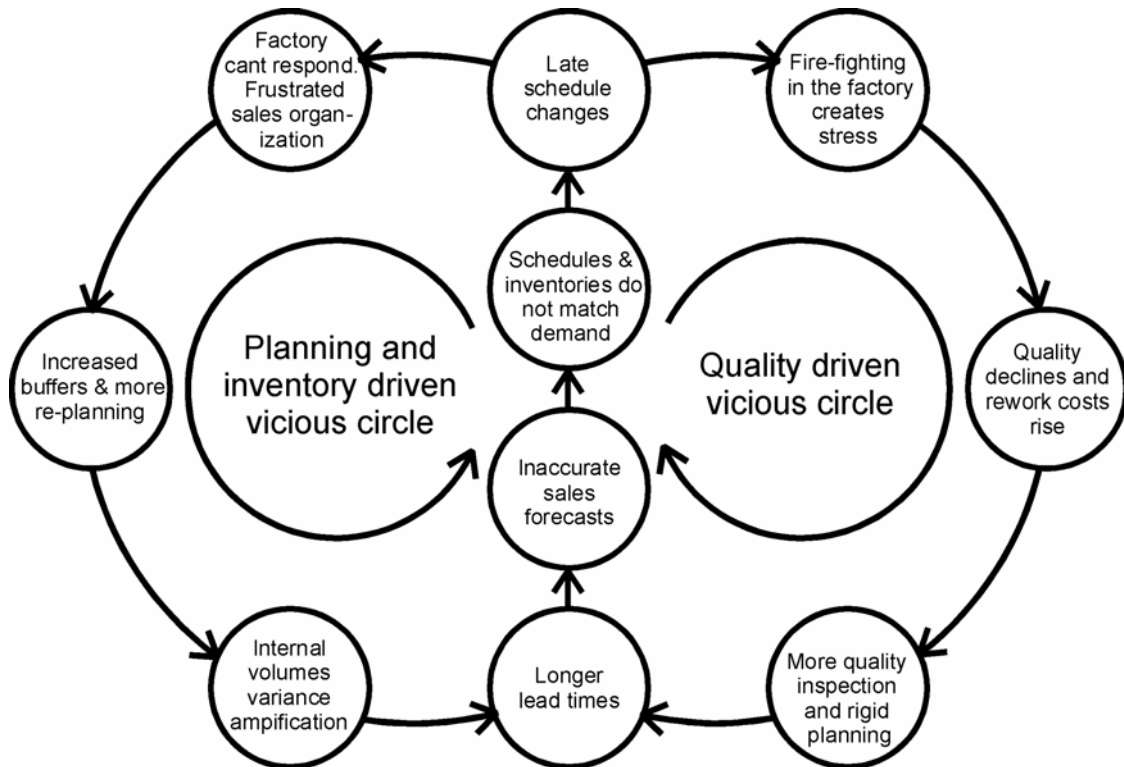
**Figure 3: Chaotic behaviour in the supply chain caused by self-enhancing feedback loops forming two "Vicious Circles"**

**Source: Authors, based on Hoover et al. (1996)**

Surprisingly, under such circumstances PoO can be a serious contender for scheduler strategy. For example, in the maybe somewhat artificial atmosphere of the "Beer Game", Sterman (1989) has shown that PoO performance can be used as a realistic benchmark for judging decision-making efficacy. He analysed the performance of some 2000 "players" involved in this popular management business game. The objective was to determine how many of them had bettered PoO. This was evaluated using a particular cost function which balanced inventory costs and order volatility. The conclusions reached were extremely interesting. Only 25% of this large sample of players actually bettered the PoO standard. From this result we might conclude that PoO is a reasonable strategy to adopt. "Only partially" is the further explanation, because within this select group were a few players (about 10%) whose performance was much superior to pass on orders. Hence, the challenge to provide the production scheduler with algorithmic decision support systems which will be consistently optimum in some sense (Disney et al., 2005).

Control theory underlines the importance of the production scheduler accessing as many system states as possible (Ashby, 1956). Considerable benefits arise from understanding the significance of such data, especially when it is timely, noise and bias free, and preferably includes product flow rates and inventory levels (Chatfield et al., 2004). However, it is still the scheduler's responsibility to decide when any individual decision support system (DSS) recommendation will be overridden in the light of other information available (Olsmats et al., 1988). Obviously any production scheduler may quite consciously adopt a different paradigm for dealing with various products, or indeed various customers. For example, Holmström, (1997) studied the bullwhip effect visible in the transmission and demand amplification of orders in a European confectionary supply chain, starting at the market place and tracking back to the factory. What happened during the consequential chain of decision-making depended very much on the product concerned. Bullwhip occurred at most echelons for both product types. However, at the factory, the production scheduler considerably smoothed the demand for the high-volume, low profit margin confectionary. In contrast, his decisions regarding the low-volume, high profit margin products were quite different, with a volatile schedule placed on the shop-floor. Trading bullwhip levels between products can thus be an acceptable way to proceed. But again this is helped if customer strategy is known. Planning can then proceed with confidence (Potter et al., 2005).

A summary of ways of coping with the problem are shown in Table 1 (Gilliland and Prince, 2001). Statistical forecasting is of restricted use when supplying "awkward" customers. In any event, our research methodology is based on identification and subsequent reduction of uncertainty. This is covered in depth by Childerhouse and Towill (2004), as is the necessary associated re-engineering by Towill and McCullen (1999). But, in our view, collaboration needs to extend both up and down the supply chain. Information quality as well as information quantity is essential for seamless operations (Chatfield et al., 2004).

| Approach | Characteristics | Possible Downside |
|---|---|---|
| Statistical Forecasting | Efficient and cheap to run: capable of automatic updating | Accuracy more dependent on volatility than sophistication: data has to be reliable |
| Supply Chain Engineering | Minimises reliance of business on forecasts, exploits "Rapid Response" modes | Need to carefully match pipelines to marketplace: responsiveness increases costs |
| Demand Smoothing | Identification of internal and external causes of uncertainty: re-engineer supply chain to minimise uncertainty | Customers may be unwilling to work with suppliers: customers may not be able to forecast demand |
| Collaboration with Customer | Emphasis on communicating and building, relationships, IT developments for collaboration | Difficult, protracted, expensive and time consuming for management |

**Table 1: Approaches suggested for coping with "unforecastable" demand**
**Source: Authors, based on Gilliland and Prince (2001)**

## 4 Research methodology

Empirical data was collected via the rigorous site-based Quick Scan Audit Methodology (QSAM) as outlined by Naim et al., (2002). This has been specifically developed to minimise the disturbance to the host organisation(s) whilst still acquiring an accurate performance and operations assessment of the supply chain. In total, it takes four researchers (plus appropriate company staff inputs) one week to fully audit the supply chain of a medium-sized organisation. During this period, only half of this time is spent on-site disrupting the host managers. However, it is important to note that QSAM is team based, and we stress the inclusion of players from the host organisation. So both parties contribute considerable effort and expertise to the audit programme.

The QSAM utilises the four well-honed investigative techniques of questionnaire analysis, process mapping, semi-structured interviews, and modelling from numerical data. The process-mapping phase is of prime importance, and enables flows to be determined across internal supply chains and interfaces involving both customers and suppliers. This procedure includes the identification of both value-added and non-value added processes. During the off-site stage of the QSAM a number of brainstorming sessions are then held so as to triangulate data from all sources, identify gaps in knowledge requiring further investigation, and also to resolve any inconsistencies. Rigorous analysis of the information allows key problem areas and issues to be highlighted. The output is thus a clear assessment of the current status of the company and its supply chain, together with the maturity of its practices and processes and their ability to meet current and future customer needs.

The depth of knowledge obtained from each individual Quick Scan mirrors the large investment in time by the researchers conducting the analysis. Inevitably, the understanding is not as great as the comprehensive knowledge obtained via detailed Case Study analysis. However, a far greater in-depth understanding of an individual value stream is gained via the QSAM than by using telephone or

postal surveys. Figure 4 illustrates this critical point in relation to the balance between the resultant depth of knowledge and number of companies analysed.
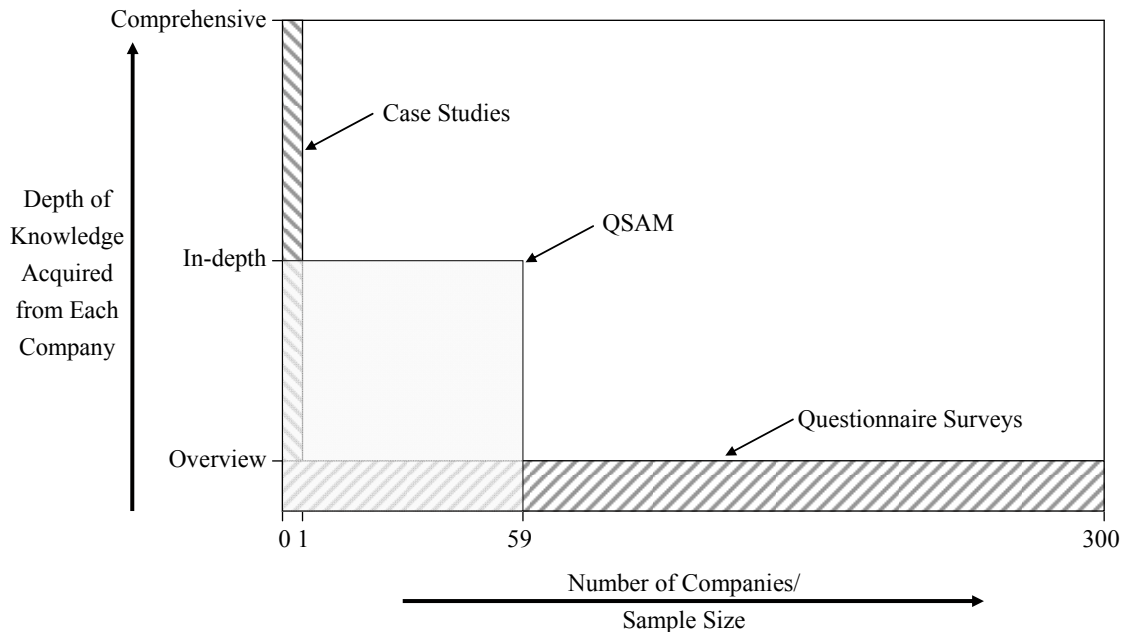


**Figure 4: Comparative scope and depth of understanding gained via QS analysis**
**Source: Childerhouse and Towill, 2003**

The key QSAM elements that result in successful supply chain evaluations are:

- A team of four researchers can ensure *investigator* triangulation.
- The use of four comprehensive data collection methods provides *methodology* triangulation.

Achieved via:

- The application of a refined, repeatable, systematic and hence holistic methodology.
- The considerable skills and knowledge of the QSAM team.
- The buy-in obtained from the win-win situation of the provision of improvement opportunities and gathering of rigorous research data.

Initially, the audit methodology was conducted solely in the European automotive sector, resulting in information relating to 22 value streams. The majority of these value streams were however based in the UK, with some elsewhere in Europe. They involved both OEM system and component suppliers. More recently, the QSAM has been adapted to evaluate other industrial sectors and has been successfully applied in Thailand and New Zealand. This has resulted in detailed information pertaining to a further 37 non-automotive value streams. Appendix A provides descriptive information of the value stream sample, it can be seen that they come from a range of market sectors including FMCG, telecommunications, heavy engineering and aerospace and cover a wide spectrum of value adding activities.

QSAM uses the investigative resources available to establish "new knowledge" via shop-floor studies. Importantly it additionally compares the "health" of a group of value streams via statistical significance testing (Childerhouse and Towill, 2003). This procedure enables trends to be observed, clusters of supply chains detected, and exemplars highlighted. Further and deeper examination of the site-acquired data then enables characteristics of "poor practice", "good practice", and "best practice" to be identified and cross-checked. Furthermore, because a battery of investigative techniques is exploited via QSAM, triangulation of data is commonplace.

## 5 Sector schedule volatility comparison

There is an on-going usage of the automotive sector somehow being "different", with impossible customers to deal with, ineffective processes, poor end products and macho personality conflict at all levels. This, of course, is not necessarily the case, as the study by Liker and Wu (2000) amply demonstrated. Much "good practice" has definitely existed for many years, typically in Japan (Suzaki, 1987) Germany (Warnecke and Huser, 1995), USA (Liker and Wu, 2000), and the UK (Parnaby, 1998 and 1995). Nevertheless, the current competency situation is extremely patchy, as our previous research has shown (Childerhouse et al., 2006). Hence, although the Toyota Production System ~ TPS (Ohno, 1988) and its European equivalent "Managing-By-Projects" (Parnaby 1988; Parnaby et al., 2003) is promulgating these practices throughout the industry, diffusion is actually taking a very long time (Spear and Bowen, 1999). As the latter authors have argued, a high success rate for TPS transfer is certainly not guaranteed, even amongst Toyota suppliers when assisted by internal consultants from the host company.

The definitions used in this section are linked in Table II. Our estimate of input volatility is based on the accuracy of one month ahead forecasts when compared to actual call-offs on the day for specific products. In the automotive sector the one month ahead forecast is typically provided by the customer (OEM) and can be considered a rough estimate of scheduled demand. Our average customer-induced volatilities are calculated from six months of recorded time series data for each particular product. The process of calculating the inaccuracy is straightforward. Once the two columns of data (forecast and actual) have been input to a spreadsheet, the forecasts are aligned to the actual result for each corresponding day and hence the average difference between the two calculated.

| Terminology | Definition |
|---|---|
| Input volatility (demand placed on the scheduler) | Changes in actual orders from the customer One-month-ahead schedule forecast. |
| Output volatility (demand placed on the shopfloor) | Orders for products (on the shop floor and elsewhere) placed by the production scheduler. |
| Scheduler Induced Volatility (relationship between input & output volatility) | "bullwhip"/smoothing induced by the decision making of the production scheduler. |

**Table 2: Definitions Used in Inter Market Sector Scheduler Induced Volatility Analysis**

Figure 5 is a frequency distribution graphs of input for the two sample groups. There is a very large spread of results for the schedule volatility as estimated via this process. However, for the automotive sector plotted in Figure 5a, half of our sample lies within the 20% range (27+23). Both Japanese implants studied are located within a few percentage points. This high level of consistency is to be expected as it agrees with previous conclusions reached by Harrison (1996) and Liker and Wu (2000) for such enterprises. Figure 5b shows the results of the same calculations performed on the non-automotive sample. Again, there is a significant spread of value streams. What is surprising at first sight is that this variability is so comparable with that estimated for the automotive sector.

(a) European automotive value stream sample       (b) None-automotive value stream sample
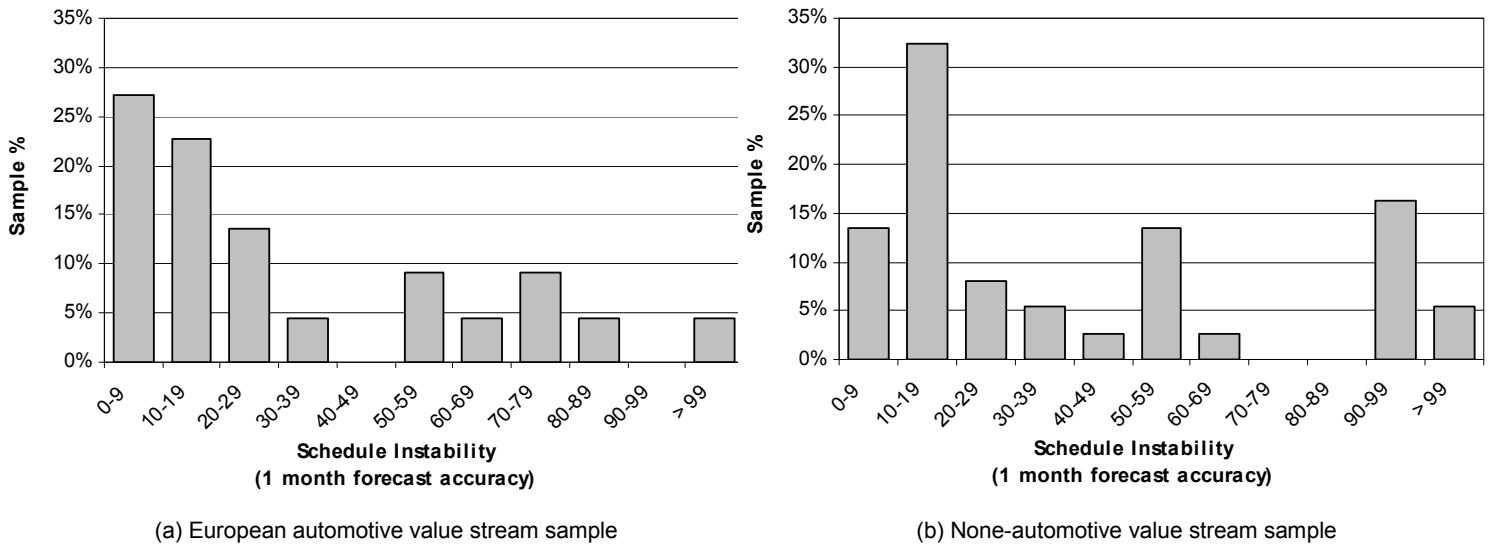
**Figure 5: Input volatility histograms**

The average one-month input volatility for the 22 automotive sample mean is 31% and the non-automotive is slightly higher at 38%. This small difference is not statistically significant with a t-value of 0.82. Yet the common perception is that the former is different from the supposed relatively staid behaviours anticipated in other market sectors. On this evidence it is not. This misconception is perceived to be due to even more pressure by OEMs demanding JIT deliveries which are often distinctly different from forecasts initially sent to supplies. So the impression persists that "automotive" is an unreasonable business in the extreme. Our results substantially beg to differ. Schedule volatility does not appear to be market sector specific. Hence, the ten bullwhip solutions previously proposed in the literature (Geary et al., 2006) may well be applicable across a wider range of industries than first thought.

## 6   Real world scheduler strategies

The previous section highlighted the input volatility a real-world production scheduler actually has to cope with when matching supply and demand. Data on the output volatility resulting from his actions was also collected and collated for the 59 value streams. A wide range of data was collected during each of the quick scans (see Naim et al., 2002) and overall measures for process and control uncertainty determined. This was necessary because data inconsistencies, different organisational procedures and a wide range of product types made it impossible to directly compare the empirical cases. To overcome this problem both process and control uncertainty were codified for the 59 value streams and a resultant measure of output volatility developed. Mapping these two variables together allows us to correspondingly position the five scheduler strategies and then evaluate the range of real world scenarios. Hence Figure 6a illustrates the automotive samples spread of scheduler strategies (note the numbers identify the value stream IDs).
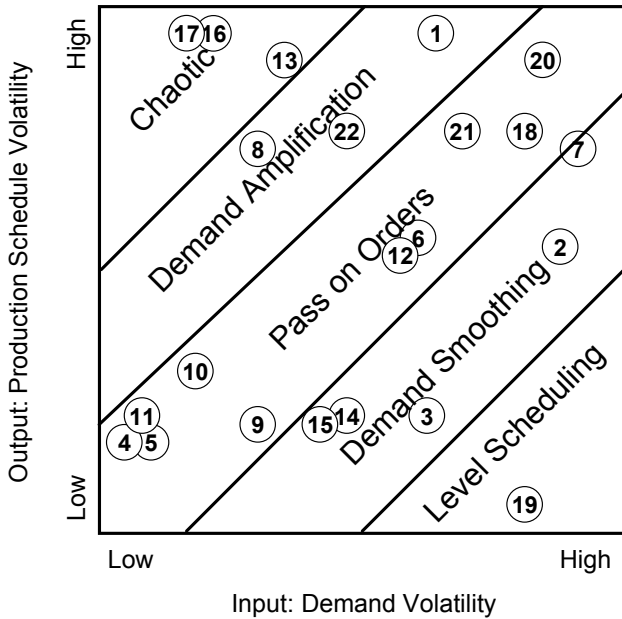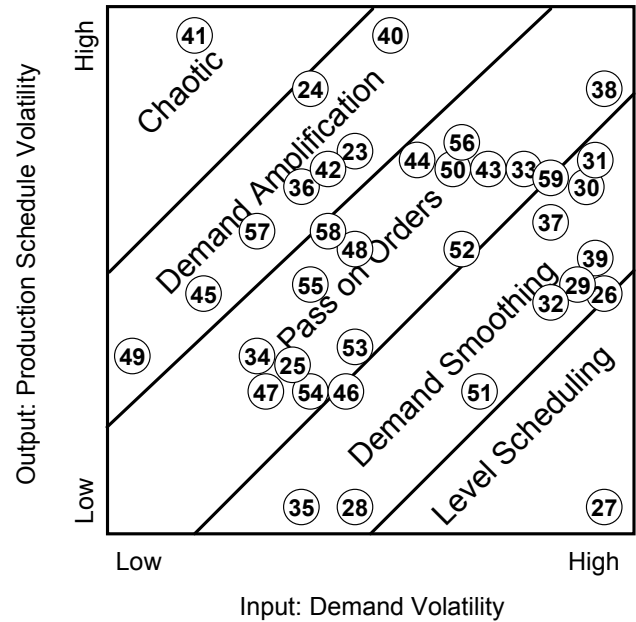
(a) European automotive value stream sample          (b) None-automotive value stream sample

**Figure 6: Factory scheduler strategy in real-world value streams**

The top left scenario is chaotic as the customer demand volatility is low but the output variance from the scheduler is far higher.  Demand amplification is nearly as bad for the system as this still has a significant gearing up of input-to-output volatility.  The central band in Figure 6a relates to the simple case of passing-on-orders where the input and output volatilities are approximately the same.  In some cases, it is possible to actually reduce the input volatility as shown in the demand smoothing area of Figure 6a.   The bottom right scenario goes one step further and provides level schedules for production and suppliers, thereby substantially decoupling the demand volatility from production processes altogether.  In other words "Smooth is Smart" (Towill, 2006).

The automotive sample in Figure 6a shows a relatively random scatter of input and output volatilities.   The correlation coefficient for the inter-relationship is 0.082, which is certainly not statistically significant.  For comparison Figure 6b illustrates the non-automotive sample mapped on to our research model.  Once again, the relationship between input and output volatility is minimal with another statistically non-significant correlation coefficient of 0.079.   These results are somewhat disconcerting, but not surprising.  Clearly, in many instances the incoming demand signal is being substantially manipulated before it hits the shop floor.

The distribution of the five scheduler strategies is reasonably similar for the two sample groups as highlighted in Table 3.  Both samples have relatively small "tops" and "tails", i.e. there are a minimal number of cases of either the chaotic or the level scheduling strategies.   Both sample groups also have approximately the same proportion of production schedulers utilising the simplest possible strategy of passing on orders.  Table 2 also provides anecdotal evidence from one or two automotive cases in each of the strategy types.   These help interpret the results associated with particular scheduler strategies.

| Scheduler Strategy | Non-automotive sample % | Automotive sample % | Comments on Specific Automotive QSAM examples |
|---|---|---|---|
| Chaotic | 3% | 14% | Value stream 17 has both internal and external customers: the process has variable yield rates and expediting product is commonplace. |
| Demand Amplification | 22% | 14% | Value stream 1 has relatively stable OEM customer demand but places highly variable demand on most of its suppliers. |
| Pass on Orders | 41% | 45% | Value streams 4 and 5 serve Japanese implants: the demand is level and the supply is co-ordinated by the customers. |
| Demand Smoothing | 32% | 23% | Value streams 14 and 15 are forging processes with the raw material common for many products, hence smoothing is feasible. |
| Level Scheduling | 3% | 5% | Value stream 19 is a third party logistics provider and levels its automotive customer's demands before placing them on the automotive parts supplier. |

**Table 3: Sample distribution of production scheduler strategies**

Level scheduling may be practiced for many reasons. For example a production scheduler with a clear view of downstream activities may be able to cut a swathe through bullwhip potentially induced by "players" over/under ordering. If he expects the average demand to be a relatively smooth trend line then he can ignore such fluctuations and considerably smooth orders onto the shop floor. Holmström, (1997) has shown this happening to high volume product supply in the European retail sector. However, conceptually there is little difference in implementing level scheduling as Make-to-Sell or as Sell-then Make (Hopp and Spearman, 2004). In the first instance the stock level fluctuates, in the second case the backlog fluctuates as capacity is deliberate".

## 7 The effects of schedule volatility

During the Quick Scan Audit, a large amount of quantitative data is collected. This facilitates the further performance evaluation of the alternative scheduler strategies. Due to the small number of chaotic and level scheduling instances for this particular extended purpose, the scheduler strategies have been aggregated into three broad categories:

- *Amplify*, those schedulers that increase the variability of demand (chaotic plus demand amplification);
- *Pass-on*, those schedulers that simply pass the demand variability upstream (pass-on orders); and
- *Dampen*, those schedulers that dampen the demand signal (demand smoothing plus level scheduling).

Analysis of variance (ANOVA) applied to these groupings is illustrated in Table 4 for each category against seven commonly used performance variables. The mean values and the resultant p-value is provided against each of the performance variables together with a description, scalar and the direction of good performance.

| Variable | Description | Scalar | Performance | Amplify (n=15) | Pass-on (n=25) | Dampen (n=19) | ANOVA p-value |
|---|---|---|---|---|---|---|---|
| Inventory levels | Large pools of inventory throughout the system | % presence of symptoms | > worse | 93% | 48% | 53% | **0.01** *** |
| Cycle time compression | Streamline material flow and minimise throughput time | % adherence to rule | < worse | 1.9% | 2.0% | 2.8% | **0.02** ** |
| Variety | Number of alternative product variants | Single units | < worse | 7 | 17 | 1196 | **0.05** ** |
| Time separated causality | Casual relationships often well separated in time | % presence of symptoms | > worse | 86% | 45% | 58% | **0.05** ** |
| Manufacturing lead time | Manufacturing lead time | Days | > worse | 18.7 | 9.8 | 5.1 | **0.06** * |
| Variable customer service | Variable performance to similar order patterns | % presence of symptoms | > worse | 83% | 59% | 54% | 0.25 |
| Profitability | Profit margin | % | < worse | 13.2% | 12.9% | 6.3% | 0.28 |

Notes: Statistically significant at the * = 90% level, ** = 95% level and *** = 99% level

**Table 4: Statistical Analysis of the Effects of Schedule Volatility**


The seven performance variables in Table 4 have been deliberately placed in order according to the statistical significance of the ANOVA results. Inventory levels have the most statistically significant result with the mean values of the three categories significantly different at the 99% level. The presence of large pools of inventory throughout the system is most common for the amplified value streams. This result is expected because increased buffers are required for situations with amplified demand. The lack of focus on cycle time compression is statistically significant at the 98% level for the mean value of the three categories. The result could indicate the expected benefit that planners that dampen demand facilitate streamlined material and information flows.

The third result in Table 4 is much more difficult to explain. Here the number of product variants statistically significant correlates at the 95% level with the three strategies. But those value streams with damped demand have far greater product variants, so perhaps these value streams are so designed to facilitate the offering of more product variety to customers (Scala et al, 2006). Time separated causality also has a p-value that is significant at the 95% statistical level. The amplified value streams have a far greater instance of time separated causality, indicating how much harder it is in the real-world to align cause and effect when demand signals are distorted. This result would certainly accord with the generic conclusions by Forrester (1958) but based in that instance only on simulation results. The category average manufacturing lead time decreases stepwise from "amplified" through "pass-on" to "dampen". This result is statistically significant at the 94% level. This is as expected, because time always acts as multiplier of demand amplification and often elapsed time is incorrectly used as a strategy to buffer demand volatility.

The penultimate variable in Table 4 is customer service. This result is not significant at the 90% level, although the mean values are much as expected. Those value streams with amplified demand are performing the worst in this respect. The profit margin mean values for the three categories are counterintuitive as they are expected to drop for those value streams with amplified demand; however,

this variable is not statistically significant.  However they are quite possibly due to chance.  Also profitability is affected by a large range of factors, and not just the performance of the supply chain.


## 8  Discussion

What impact might the four approaches listed by Gilliland and Prince (2001) have in such situations as those we have studied via QSAM?  We have previously shown in Figure 3 how a vicious circle erupts if internal communication is fragile.  Also "negotiated" demand smoothing, if possible, is extremely helpful to all players in the system (Towill, 2006).  Indeed, it is a key factor in the Toyota Production System (TPS) as emphasised by Suzaki (1987).  Competency in supply chain engineering clearly has an important benefit since it enables us to deliver the right quantity at the right time.  Some of our automotive QSAM sample has achieved this goal (Childerhouse and Towill, 2004).  This leaves the statistical forecasting mode, a process entirely within company control; except that, unfortunately, the forecast effectiveness critically depends on the flow and quality of information from system players (Hariharan and Zipkin, 1995; Chatfield et al., 2004; Hayya et al., 2006).  Unless, of course, the production scheduler argues that "history will repeat itself" and gambles on smoothing the flow of particular products (Holmström, 1997).  But, as demonstrated by Buffa, (1969) this may, on occasion, require excessive inventories to be kept, which simply shifts the on-costs from shop floor to storeroom.


The current research project outputs a number of effects which clearly emerged as being significantly related to production scheduler volatility.  Some of these properties are established at a very high confidence level.  These particular results indicate system weaknesses where business process improvement (BPI) programmes may have the greatest possible positive impact on seamless material flow.  The latter is a highly desirable property of most, if not all, supply chains.  Hence, in this investigation we have generated new knowledge on the effective engineering of value streams pertinent to a wide range of businesses.


It is inevitable that our sample of value streams is neither random nor necessarily representative of all possible real world scenarios.  Hence, the findings need to be further investigated to demonstrate the degree of similarity between the automotive and other industrial sectors.  If this is indeed the case, then there should be a "rich picture" emerging as to exactly why this is so.  Indeed some case studies exist which support our contention have already been published elsewhere by Liker, (2004).  The proposed five strategy model also needs further investigation to validate our theoretical subdivision on the basis of input and output volatility.  Currently, we are researching the obstacles and enablers of the alternative scheduler strategies and this has knock-on effects on sequential links in a supply chain.  Further research is also currently on-going to determine the exact conditions for the existence and specific nature of other self-inducing volatility feedback loops.


It is an interesting research question to investigate whether the pressures imposed on production schedulers are industry specific.  Our previous studies of European automotive supply chains have established the posited wide range of decision-making "level scheduling" to "chaotic" as actually being observed in real-world practice.   It is, therefore, natural to further progress this project to the stage where the following questions may reasonably be asked:

- Does the production scheduler face a similar set of problems irrespective of the market sector?
- Are a similar set of responses observable, irrespective of market sector?
- Can a scenario of the various possible effects of scheduler volatility be established which is also independent of market sector?
- Can previously posited phenomenon such as positive feedback loops/accelerator loops be associated with production scheduler induced volatility?
- Can general conclusions be reached on the "best" algorithmic DSS?
- Does the position of the decoupling point and the interplay of customer, supplier and manufacturing leads times radically effect the performance ramifications of the scheduler behaviour?

The managerial implications of our exploratory study are significant if still yet to be comprehensively verified. Schedule volatility and the bullwhip effect are not sector specific, hence managerial practices to enhance performance, such as time compression total cycle (Towill, 1996) should also be generic. The analysis shows that the decisions of production schedulers' affect the wider supply chain in relation to the upstream order volatility and hence act as a barrier to seamless operations. The consequence is poor customer service and higher inventories throughout the pipeline. The clear message from this scenario is that scheduler behaviour has significant knock-on effects and hence should be resourced sufficiently. This is in stark contrast to virtually all of the value streams studied, where advanced DSS and production scheduler expertise was not perceived as an important area for investment in resources.

## 9 Conclusions

The throughput controlling decisions made by a production scheduler can be broadly classified into five alternatives. These approaches have been verified via simulation and literature review. In this paper we have proposed a simple model to evaluate which one of these strategies are currently in use in any particular real-world value stream by measuring input and output volatility. This paper is researched via site-based QSAM investigations on a sample of value streams across a wide range of industries. However, it is then possible to compare the automotive supply chain cluster with the remainder businesses cluster. This exercise establishes that there is reasonable correlation between production scheduler volatility scenarios in automotive and non-automotive sectors. Hence, the conclusion is reached that this complex problem is not confined to automotive value streams. In fact, it is much more commonly encountered elsewhere than may be generally realised. But, on the positive side, this discovery means that generic solutions developed in one particular market sector may be readily transferred to others.

To summarise, our view is that irrespective of market sector, best practice companies minimise their schedule volatility. In other words the goal is to ensure that any order volatility is *not* further amplified as it passes upstream: "Smooth is Smart" (Towill, 2006). This reduces the significant ramp-up and ramp-down costs for their suppliers and hence the supply chain as a whole. *Contrary to some perceived wisdom, the schedule volatility phenomenon is not unique to the automotive industry.* Hence we have established a consequential "new management theory" likely to pass the transferability test proposed by Micklethwait and Woolridge (1996). It therefore follows that posited bullwhip solutions are unlikely to be market sector specific. That being the case, the ideas put forward by Geary et al. (2006) may turn out to be of universal applicability once particular value stream causes have been identified.

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**Appendix A: Value stream sample**

| Value Stream ID | Organisation ID | Nationality | Industry Sector | Major value adding | Decoupling point |
|---|---|---|---|---|---|
| 1 | A | UK | Automotive | Machining and Assembly | MTS |
| 2 | A | UK | Automotive | Assembly | MTS |
| 3 | B | UK | Automotive | Assembly | MTS |
| 4 | B | UK | Automotive | Assembly | ATO |
| 5 | B | UK | Automotive | Assembly | ATO |
| 6 | C | UK | Automotive | Assembly | MTO |
| 7 | D | UK | Automotive | Machining | MTS |
| 8 | E | UK | Automotive | Heat Treatment | MTO |
| 9 | E | UK | Automotive | Heat Treatment | MTO |
| 10 | F | UK | Automotive | Machining and Assembly | MTS |
| 11 | F | UK | Automotive | Machining and Assembly | MTS |
| 12 | G | UK | Automotive | Machining and Assembly | MTS |
| 13 | G | UK | Automotive | Machining and Assembly | MTS |
| 14 | H | Germany | Automotive | Forging | MTS |
| 15 | H | Germany | Automotive | Forging | MTS |
| 16 | I | UK | Automotive | Assembly | ATO |
| 17 | I | UK | Automotive | Assembly | ATO |
| 18 | J | Germany | Automotive | Machining | MTO |
| 19 | K | UK | Automotive | 3rd Party Logistics | MTO |
| 20 | L | UK | Automotive | Assembly | MTS |
| 21 | M | UK | Automotive | Machining and Assembly | ATO |
| 22 | O | UK | Automotive | Machining and Assembly | MTS |
| 23 | N | UK | Utilities | Water provision | MTS |
| 24 | Q | UK | Heavy Engineering | Design and Assembly | MTS |
| 25 | Q | UK | Heavy Engineering | Design and Assembly | MTS |
| 26 | P | UK | Construction | Assembly | MTO |
| 27 | P | UK | Construction | Assembly and Insulation | MTO |

| 28 | R | UK | Telecommunications | Assembly | MTS |
|----|-----|-------------|--------------------|--------------------------|-----|
| 29 | S | UK | Lighting | Assembly | MTS |
| 30 | S | UK | Lighting | Design and Assembly | ETO |
| 31 | S | UK | Lighting | Assembly | MTO |
| 32 | S | UK | Lighting | Assembly | ATO |
| 33 | T | UK | Telecommunications | Assembly | MTO |
| 34 | U | UK | Food | Food Processing | MTS |
| 35 | V | UK | Aerospace | Cutting and Sticking | MTO |
| 36 | W | UK | Aerospace | Assembly | MTO |
| 37 | X | UK | Steel | Melting and Shaping | MTS |
| 38 | Y | New Zealand | Food | Pasteurisation & bottling | ATO |
| 39 | Y | New Zealand | Food | Pasteurisation & Packing | MTS |
| 40 | Y | New Zealand | Food | Packaging & Distribution | MTO |
| 41 | Z | New Zealand | Light Engineering | Machining and Assembly | ATO |
| 42 | Z | New Zealand | Light Engineering | Machining and Assembly | ATO |
| 43 | AA | New Zealand | Food | Pasteurisation & Packing | MTS |
| 44 | AA | New Zealand | Food | Pasteurisation & Packing | MTS |
| 45 | AB | UK | FMCG | Food Processing | MTS |
| 46 | AC | Thailand | Construction | Mixing and Delivery | MTO |
| 47 | AD | Thailand | Telecommunications | Assembly | ATO |
| 48 | AE | Thailand | Manufacturing | Assembly | ATO |
| 49 | AF | Thailand | Manufacturing | Assembly | ATO |
| 50 | AG | Thailand | Telecommunications | Machining and Assembly | MTO |
| 51 | AG | Thailand | Telecommunications | Machining and Assembly | MTO |
| 52 | AH | Thailand | Steel | Rolling and Cutting | MTS |
| 53 | AI | Thailand | Service | Scanning | ETO |
| 54 | AJ | Thailand | Furniture | Assembly | MTS |
| 55 | AK | New Zealand | Heavy Engineering | Deign and Assembly | ETO |
| 56 | AL | Thailand | Rice Oven | Assembly | MTO |
| 57 | AM | New Zealand | Food | Storage and Chilling | MTO |
| 58 | AN | UK | Steel | Casting and Rolling | ATO |
| 59 | AO | UK | Steel | Rolling and Cutting | MTO |

Note: ATO = assemble to order, MTS = make to stock, MTO = make to order, ETO = Engineering to order