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A study on the cost of operational complexity in customer–supplier systems

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Abstract

This paper reports on the application of the operational complexity index [Frizelle, G., Woodcock, E., 1995. Measuring complexity as an aid to developing operational complexity. International Journal of Operations and Production Management 15(5), 26–39]. The aim is to address what is the relationship between costs and the complexity index. The investigation carried out measurements on two types of supplier–customer systems in the UK. One is make-to-stock with low product variety but high volume, while the second is make-to-order with high variety but low volume. The research found some evidence that inventory costs are associated with operational complexity. Moreover, while the index is generic to both case studies, there seemed to be a direct link between the index value and cost only in the make-to-stock case.

Keywords: Complexity; Entropy; Operational cost; Simulation; Supply chain

1. Introduction

Manufacturing industry is suffering from an increasing requirement for more flexibility and agility to deal with the variety and uncertainty in the markets it serves. The effects of uncertainty and unpredictability are also manifest at the interfaces between customers and suppliers, i.e. along the supply chain. In order to adapt to uncertain and unpredictable changes from customers, manufacturers and suppliers need to be flexible in the product range they offer and in the volumes they supply. Lee (2004) studied top-performing supply chains and identified the keys to success to be agility to deal with sudden changes, adaptability over time as market structures and strategies evolve, and alignment of all the firms in the supply network to optimise their interests. Specifically, many manufacturing managers view product range flexibility as a core competence for competitive success (De Meyer et al., 1989).

A few researchers found the level of flexibility to influence the choice of one or more performance measures, although others found the contrary. Banker et al. (1990) observed that product complexity (defined as number of moving parts in the mould) had a significant impact on the cost of supervision, quality control, and tool maintenance.

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Kekre and Srinivasan (1990) reported that significant increases in market share and company profitability were associated with broadening product variety, but the widely believed association of production costs to variety were not supported by empirical results. MacDuffie et al. (1996) studied 70 assembly plants and concluded that the impact of product variety on performance is much less than is generally assumed. In contrast, it was found product complexity to have a persistent impact on productivity. Guimaraes et al. (1999) utilised replies to a questionnaire sent to 500 plant managers to test the impact of manufacturing system complexity on performance. They defined manufacturing system complexity as comprising system complexity, operator task complexity, operator behaviour complexity, supervisory task complexity, training effectiveness, and man–machine interface effectiveness. They measured nine variables such as productivity, turnover, manufacturing costs and quality. The survey showed man/machine interfaces to be a significant contribution in reducing the negative effect of systems complexity. Randall and Ulrich (2001) investigated the bicycle industry and found that some types of product variety incur high investment costs and high logistic costs in order to achieve the required flexibility. The authors refer to these as "market mediation costs", because of uncertainty of demand. Their empirical results suggest that the firms that match their supply chain structure to the product variety type outperform the firms that fail to do so. Chandra et al. (2005) modelled a major automotive company in terms of capacity planning, flexibility, and part commonality. The experimental results showed that increasing level of flexibility and part commonality yielded improvements in production profitability.

Although flexibility or agility is widely accepted as a core competence in coping with variety and uncertainty, being flexible is not, by itself, the whole answer to coping with the variety and uncertainty inherent in a supply chain. It was observed that 40% of flexibility-improvement projects were unsuccessful due to "failure to identify precisely what kind of manufacturing flexibility was needed, how to measure it, or which factors most affected it" (Upton, 1995, 1997), or "what level the and type of flexibility do we require" (Hill, 1991). Jordan and Graves (1995) found that offering limited flexibility yielded most of the benefits to be had from being flexible. In order to achieve this, a measure of how well a supplier adapts to changes of demand is needed, Simply being flexible in an unspecific way is insufficient. Adaptability is also achieved through implementing appropriate planning and scheduling procedures.

Failure of production planning and scheduling to cope with customers' requirements for product and volume variety also exposes the limitations of undifferentiated flexibility. Lauff and Werner (2004) addressed complexity of scheduling problems in dealing with variety and uncertainty. Uncertainty comes not only from the customer, but also from the shop floor and suppliers. Shop floor disturbances make scheduling very difficult in practice, exacerbated by the dynamic nature of the environment. The disturbances and the complexity of scheduling cause deviations from a plan that is often overoptimistic (Stoop and Wiers, 1996).

Three points emerge from this literature. First there is a need for a clearer understanding of the nature of the complexity created by the performance of a plant or supply chain. Are all forms of complexity equivalent or does one need to be more specific? For example what, if anything, do system complexity, operator task complexity, operator behaviour complexity, and supervisory task complexity have in common (Guimaraes et al., 1999)? Is it possible to identify a "footprint of complexity"? Second if there is no obvious common mechanism, are there common consequences that arise from the presence of these forms of complexity? Finally, if the answer to either is "yes", does this lead to the development of a suitable measure?

However, so far there is no satisfactory and generally admitted definition of complexity (Perona and Miragliotta, 2004). In manufacturing and supply chain management, complexity implies number of elements or subsystems, degree of connectivity and interaction among the elements, unpredictability, uncertainty, and variety in products and in system states. Some researchers applied the metrics approach to measure individual aspects of a complex system (Perona and Miragliotta, 2004; Lauff and Werner, 2004; Blecker et al., 2005). For instance, Perona and Miragliotta (2004) proposed three indices, such as a supply relationship index to measure type and stability of connectivity, the number of components and products to measure product variety, and the annual quantity production orders to measure information and planning complexity. Another approach to answering above questions is to take an information-theoretic view. Frizelle, Woodcock and Suhov (Frizelle and

Woodcock, 1995; Frizelle and Suhov, 2001) defined an information-theoretic measure to quantify what they referred to as "structural complexity" and "operational complexity" in manufacturing systems. The structural complexity index measures complexity of the system configuration, while the operational complexity index measures operational (dynamical) aspects when the system is running. Based upon the theory, methodologies for analysing the operational complexity were developed (Calinescu et al., 2000 and Sivadasan et al., 2002; Sivadasan et al., 2002).

It is widely believed that operational costs increase as the system becomes more complex. The literature cited earlier highlighted possible mechanisms that may contribute. George and Wilson (2004) even regarded complexity as "the silent killer of profits and growth". Frizelle (1998) proposed a linkage between sources of cost and operational complexity. However, while the links he suggested appear plausible, no formal justification was given. Moreover, the emphasis on inventory queues suggest that the linkage is, at best, only partial. For example, it is difficult to see a direct link between supervisory task complexity and finished goods and/or raw material stocks. Further, even where inventories are involved, one intuitively expects very agile companies to generate less inventory in their chains than their more leaden footed competitors.

This paper therefore sets out to investigate the relation between operational complexity and supply chain costs. It will address two related questions. The first is what cost generators, if any, can be associated with operational complexity. The second is whether a relationship can be adduced between the values taken by a complexity index (see below) and specific cost generators.

The remainder of the paper is structured in four sections. The first section looks at a theoretical model that not only suggests categories of cost that might be associated with different forms of complexity but also gives a rationale as to why there could be a link between the index and cost. The second section covers the methodology and falls into two broad subsections. The first describes the gathering of data from the field in two major UK manufacturing companies and their suppliers. The second subsection explains the role of simulation in the exercise. Section three discusses the results and conclusions are drawn in the concluding section.

2. Theoretical background

There are three parts to the theoretical background. The first two recount the basic ideas that led to the development of an index and how the index relates to queues. The third develops the link to costs and shows why there is reason to believe that increasing index values may be related to increasing costs.

2.1. Complexity indices

Complexity index measures (Frizelle and Woodcock, 1995; Frizelle and Suhov, 2001) were developed originally to measure complexity for a manufacturing system, which can be viewed as comprising two parts: a structural and an operational part. The structural part is relatively stable and reflects the structure of the system. The operational part mirrors aspects of the dynamics of the system. In particular, it reveals how the system deals with disturbances during operation.

Structural complexity is thus defined as the expected amount of information (entropy) necessary to describe the state of a planned system. In a manufacturing system, the data required for calculating the structural complexity can be obtained from the production schedule.

Operational complexity is defined as the expected amount of information necessary to describe the state of the system's deviation from the schedule. The calculation involves measurement of the difference between actual performance of the system and the expected performance predicted in the schedule. The operational complexity index measure hence reflects variety and uncertainty coming from the customer and the supplier, goodness of the planning and scheduling adaptable to the uncertainty, and level of flexibility of the process which restricts the planning or scheduling in dealing with the variety and uncertainty.

These ideas can be extended to a supply chain system with a single supplier supplying a single product to a single customer. In such a system, structural complexity can be determined either by reference to the schedules involved or through observing the profiles of policy stock. Operational complexity appears either as the variation from schedule actually observed, or as the variation of the policy stock profile from what was predicted.

2.2. A queuing model

In a supply chain, the product flow across a supplier–customer interface can be viewed as an input–output system, where the arrivals are Poisson and the service rate is negative exponential. The entropy of the queue $H(\pi)$ can be expressed as (Frizelle and Suhov, 2001)

$$H(\pi) = -L \log L + (L+1)\log(L+1), \tag{1}$$

where L is the mean length of the queue.

It can be shown that the derivative of the entropy to the mean length of the queue is positive for any $L>0$. Therefore, it can be concluded that the entropy, i.e. the operational complexity, is monotone increasing with the mean length of the queue. If the queue length represents the stock of inventory, the average stock thus rises as the complexity (which is indicated by the fluctuation of the stock) increases, as illustrated in Fig. 1. As a higher level of stock implies higher cost, the operational complexity is thus associated with cost.

There is one other useful consequence of the monotonicity of operational complexity with queue length. It means that for any resource in the chain where a queue has accumulated, there is a unique value of the entropy. This fact is used as the basis for developing simulations. It means that if the entropy calculated for the queues in the simulation equals the values determined by direct observation then, in a statistical sense, the behaviour of the simulated queues should match those of the observed queues. Of course, this will not hold true if the dynamics of queue formation are not those of the real system.

2.3. Costs of complexity

The costs of complexity are the costs involved in running a system, analysed in terms of its complexity. As with the complexity index, the costs of complexity can be divided into two categories, i.e. costs of structural complexity and costs of operational complexity.

For a supply chain, the structural complexity costs include all costs resulting from the production and shipping of a single item in planned circumstances. These might be thought of as costs emanating from the existence of tolerated states—what might be called tolerated costs (although we shall not use that terminology). They include the capital and revenue costs of the plant, equipment and people needed to make, store and ship the product, plus overheads (Frizelle, 1998). The revenue costs are typically found from the operating budgets of the supplier and the customer.

The costs of structural complexity can therefore be calculated as the expected costs for scheduled production over a period of time. In the study described in the following section (Case 2), the supplier supplied more than one product to the customer. Therefore, following the definition above, a network of chains was involved. Suppose the network comprises n chains. Then we may write the

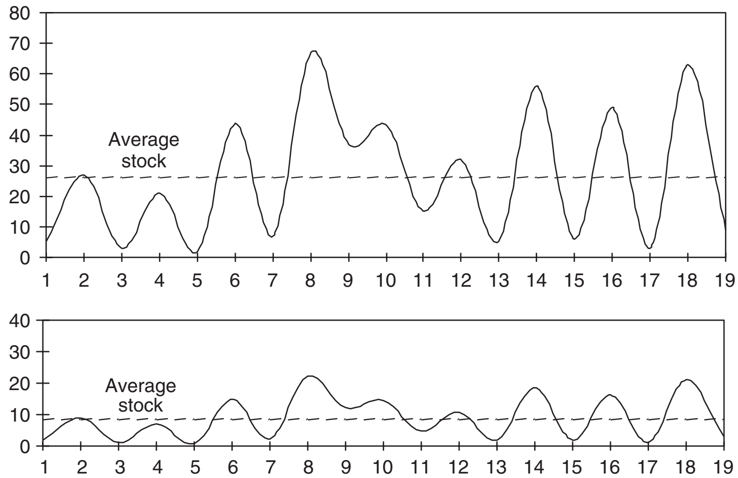

Fig. 1. An illustration of the relation between fluctuation and average stock.

structural cost as

$$C_S = \sum_{i=1}^{n} \sum_{j=1}^{m_i} \sum_{k=1}^{s_{ij}} p_{ijk}^S C_{ijk}^S + h, \tag{2}$$

where n is the number of product types (chains), m_i the number of independent resources on which a process/operation is required by product i, s_{ij} the number of scheduled states of product i on resource j, p_{ijk}^S the probability of product i on resource j being in scheduled state k and, $\sum_{k=1}^{s_{ij}} p_{ijk}^S = 1$, for any $j = 1, 2, \cdots, m_i$; $i = 1, 2, \cdots, n$, C_{ijk}^S is the manufacturing cost of product i on resource j being in scheduled state k,[1] h is the transport cost, i, j, and k are indices of product, resource, and scheduled state, respectively.

The sum in the first item on the left of the equation reflects the *expected* conversion costs, i.e. the conversion costs in the budget. On the other hand, the conversion costs C_{ijk}^S can be categorised as variable costs and fixed costs. That is,

$$C_{ijk}^S = q_{ijk} c_{ijk}^S + f_{ijk}^S, \tag{3}$$

where q_{ijk} is the quantity of product i at resource j being in scheduled state k, c_{ijk}^S the cost of processing a unit of product i at resource j being in scheduled state k, and f_{ijk}^S the fixed cost of product i at resource j in scheduled state k.

As fixed costs, f_{ijk}^S normally do not change with the states and note that $\sum_{k=1}^{s_{ij}} p_{ijk}^S = 1$, we have,

$$C_S = \sum_{i=1}^{n} \sum_{j=1}^{m_i} \left(\sum_{k=1}^{s_{ij}} p_{ijk}^S q_{ijk} c_{ijk}^S + f_{ij}^S \right) + h. \tag{4}$$

The following example demonstrates the states and the probabilities in the equation above. Since costs accumulate across resources and product mix, to make it simple, it is assumed that one product is manufactured at a machine. The scheduled daily production rates vary between 6 units and 9 units, which represent 4 states, with the percentages (probabilities) of 20%, 40%, 30%, and 10%, respectively. The direct variable cost for a unit product is £200 and the machine needs one set-up each day, which involves a fixed cost of £300. The company works 250 days per annum. It is hence expected that in a year the production rates are 6 units per day for 50 days, 7 units for 100 days, 8 units for 75 days, and 9 units for 25 days. Therefore, the total annual cost can be calculated to be £440,000. This can be considered as an approximation to the structural complexity cost, that is the cost that is tolerated, within the plant, in order to maintain the structure of the chain. Such figures are typically found in a budget.

The costs of operational complexity include the extra costs caused by variation of the actual state from the predicted state. These costs can also be classified into two categories: capital items and revenue items. The capital items include the fixed costs of holding excess storage, excess plant and equipment, additional IT, etc. They are difficult to estimate. On the other hand, the revenue costs are very real. They include excess inventories, labour charges, rectification costs, revenue loss, warranty payments, excess overhead, etc. (Frizelle, 1998). Again the revenue element of the operational complexity costs correspond to the "actual" column of a cost control statement. The variational element, the difference between what is expected and what has been achieved, appears in the variances reports.

As we are only interested how the cost changes between different scenarios, we can ignore the budgeted (predicted) element of the cost, and consider only the cost at every possible state that deviates from the scheduled states or deviates from the tolerated range of states when computing the operational complexity cost (referred to as a non-tolerated state below). This greatly simplifies matters. For example, as the transhipment costs are unaltered between scenarios, they are not included. It can be expressed as an equation as follows:

$$C_D = \sum_{i=1}^{n} \sum_{j=1}^{m_i} \sum_{k=1}^{n_{Sij}} p_{ijk}^D C_{ijk}^D, \tag{5}$$

where n is the number of product types (chains); m_i the number of independent resources; n_{Sij} the number of non-tolerated states; p_{ijk}^D the probability of product i at resource j being in non-tolerated state k; C_{ijk}^D the cost of product i at resource j being in non-tolerated state k; i, j, and k are indices of product, resource, and non-tolerated state, respectively.

Similarly, it can also be categorised as variable costs and fixed costs:

$$C_D = \sum_{i=1}^{n} \sum_{j=1}^{m_i} \sum_{k=1}^{n_{Sij}} (p_{ijk}^D q_{ijk}^D c_{ijk}^D + f_{ijk}^D), \tag{6}$$

[1] As one is usually only interested in cost savings resulting from reduced structural complexity, this term can often be simplified to include only the items that are going to change, such as inventory levels. The comment equally applies to the terms h and f_{ijk}.

where q^D_{ijk} is the quantity deviating from scheduled quantity q_{ijk} of product i at resource j being in non-tolerated state k, c^D_{ijk} the cost of processing per volume of product i at resource j being in non-tolerated state k, and f^D_{ijk} the fixed cost of product i at resource j in non-tolerated state k, e.g. a fixed cost for backlog when stock-out happens.

Assume that the scenario in the forementioned example is in a JIT environment, without stock. The unpredictable daily demand varies randomly between 6 and 9 units with the same probability distribution as the production schedule. However, in the case of scheduled daily production of 6 units, the company may take the risk of loss or backlog of sales. In the case of scheduled daily production of 9 units, on the other hand, the company may have unsold stock. There will hence be three non-tolerated states for unsold stock and three for loss of business (queuing effects, which involve more states, can be included in simulations). It is assumed in the example that shortages incur losses of £50 per unit product and a one-off cost of £30 is charged for relieving a unit of stock (thus for simplification purposes there is no queuing effect). It is also assumed that there is no fixed cost for shortage or excess stocking. The annual costs due to the variational element of the operational complexity would therefore be £22,300.

In this exercise, we are predominantly interested in the costs that may be expected to change over the time span of a schedule and reflect some aspect of operational complexity. In line with our definition of a supply chain, we consider first the cost of manufacture a single product line, at the supplier plus the cost of its transportation. We deliberately ignore the cost of raw materials either at the customer or at the supplier, because that encompasses a range of other costs, including costs to the supplier of his upstream chain. Specifically, we take the cost of manufacture as a conversion cost i.e. the product cost less its raw material cost. This will therefore include operational overheads. We use this to value finished goods inventory. To that will be added a single overhead representing transport cost as this tends to be a fixed unit cost between a specific supplier and customer, in line with our definition of a supply chain. This latter will be used to value raw material inventory at the customer's site. Menkhorst (2003) considers that inventory carrying costs alone account for up to 39% of running a chain followed by transport (12%) and warehousing (8%).

3. Methodology

The exercise was carried out in two distinct stages. Ideally, all data should be collected from the field to populate the operational complexity and cost equations. However, it is apparent that this would only furnish one data point unless the parameters governing the behaviour of the chains changed radically. Since such parameters include the structure of the chains, the products involved, the ways of doing business and so on, radical changes during the period of observation were unlikely to happen. To get around the problem, a second stage was initiated where alternative scenarios could be generated synthetically by simulation. The two stages will now be described in some detail.

3.1. *Stage one: data collection from the field—the industrial studies*

In order to calculate the complexity indices, two categories of data were required: planned states and unplanned states. The first category of data was obtained from plans, schedules and order patterns. The second is calculated by difference from the actual (observed) production or inventory levels. The probabilities, which are used for calculating the complexity indices and the costs, are estimated by the data collected. In practice, most recent data can be used for the purpose. It is hence assumed that the statistical data, i.e. probabilities, are relatively stable.

Two supply chains were studied. One chain involves the supplier making to stock and the customer holding a relatively small raw material stock as a buffer. The chain is characterised as having low product variety but high volume. The second chain involves making to order with high variety but low volume. In this case, the variety precludes the supplier from being able to make to stock. It allows one to see if a link between operational complexity and supply chain cost exists in two very different types of chain. In each of the two chains, two companies were involved, referred to as the supplier and the customer. So, for example, there were no intermediate stages such as a distribution centre. Moreover, the geographical distances in each case were relatively short so that the effects of transport could be ignored.

The stage one comprised two phases: familiarisation and data collection. The first phase builds the understanding of people, process, and plant by interviews and shop floor visits. In this phase, the key processes and flows are mapped. The second phase records observations on orders, schedules, production, inventories, and deliveries, supplemented by archival data. Teams of researchers worked simultaneously at the supplier and at the customer sites over a 3-week period. Each team typically consisted of three people. The findings were checked by interviews. A full discussion of the approach taken can be found in Sivadasan et al. (2002).

The first case study (Case 1) was carried out at a Unilever detergent plant in the fast-moving consumer goods business. The supply chain comprised a vendor supplying plastic bottles to a manufacturer of household chemicals. The manufacturer (the customer) scheduled his filling lines with a weekly rolling plan (referred to as Initial Plan in Table 1 in the next subsection) using an MRP system, which took its demand from a downstream distribution warehouse that placed daily orders. A specified safety stock is considered in the production plan. The plan is rescheduled according to daily demands under the limitation of production capacity. In this case, 9 weeks data of customer requests, plans in different stages, scheduled production, actual production, scheduled delivery, actual delivery, and costs data were collected. The production comprises 6 lines for a range of more than 50 products including different bottle sizes. The cost of operational complexity was identified to be the operating cost, consisting mainly of the costs for inventory stocking and shortage.

The second case study (Case 2) came from one of the suppliers of BAE Systems. Here the vendor supplied the customer with printed circuit boards. The chain was characterised by the fact that the customer rarely ordered the same board twice. This meant that the supplier had both to design and then to manufacture the board. This prevented the supplier from holding stock, although in practice there was a residual finished goods stock as he had to make in excess of the order quantities to allow for shortages and wastage. The chain was further defined by frequent small deliveries direct to the customer. In this case, 6 months data of customer orders, initial production, actual production, and delivery were collected. The major cost generators for operational complexity were excess production and scrap due to defect.

3.2. Stage two: generating additional scenarios through simulation

Stage two can be divided into distinct phases: modelling the system, "tuning" and validating the model, and carrying out "what if" analysis in different scenarios.

The skeleton structure of the simulation models consists of three submodels, an operational model, a scheduling model, and a control model, representing the three basic functions in the supply chain operation. First, the customer sends his requirements to the supplier. This is simulated in the control model, using Visual Basic for Applications (VBA). Then the supplier schedules his manufacturing operation, simulated in the scheduling model using Microsoft Excel. Finally, the product is manufactured, simulated in the operational model by Arena software. The VBA model controls the production in Arena based on the requirements and provides a bridge to link Arena and Excel for data transfer. Given the very different nature of the two

Table 1
Comparison between the daily volumes of real and simulated systems in Case 1

	Initial plan		Actual delivery		Production		Stock	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Real system	33.3833	41.8095	24.5407	37.5324	24.4719	25.5347	96.9174	59.0126
Simulated system	33.1713 (3.40)	43.5870	24.4983 (4.43)	37.1626	24.2763 (4.24)	21.7805	93.8087 (23.61)	54.3574
Difference	−0.2120	1.7775	−0.0424	−0.3698	−0.1955	−3.7532	−3.1087	−4.6552
Percentage	0.64%	4.25%	0.17%	0.99%	0.80%	14.70%	3.21%	7.89%
95% Confidence interval	−0.74	−9.86	−1.20	−6.74	−0.99	−0.24	−3.50	−6.32
	1.16	6.03	1.28	6.87	1.38	7.69	9.72	13.77

Note: 1. The mean values are the average of the daily figures in the monitored period (60 days). 2. The values of the simulated system are the average of 50 replications and the figures in brackets are the standard deviation.

studies, they were modelled separately as Model 1 and Model 2 corresponding to Case 1 and Case 2, respectively. The simulation of the manufacturing process in Model 1 is shown in Fig. 2 and the information and the materials flows in Model 2 are shown in Fig. 3.

Although the simulation models were built to reflect as much of the detail found in the structural and operational elements of the chain as possible, some differences cannot be avoided. When simulating customer changes, for example, the model generates variations on the pattern of demand using a distribution similar to that observed. Combining this variation with the original order may result in a negative final request, which is of course inadmissible and has to be corrected. However, the correction skews the resulting distribution from the actual. In consequence, it was necessary to "tune" the model.

"Tuning" slightly changes the distribution parameters of inputs in the simulation so that the both inputs and outputs are statistically similar. After the simulated system of Case 1 is tuned, the daily volumes at the different stages from the simulated system and from the real system are compared in Table 1. Table 1 shows that the mean values of the initial plan, the actual delivery, and the actual production were tuned to have a difference of less than 1% with low standard deviation from those in the real system. The mean of the average daily stock in the simulation, as an output of the system, is also very close to that in the real system, although the standard deviation (shown in brackets) is relatively high. The reason for the high standard deviation of daily stock is that stock accumulates the effects of disturbances in the period of test. This accumulation causes the stock level to differ from one run to the next. Statistical tests were also used for validation of the simulation model. The difference between the mean values was tested by a z-test and the difference between the standard deviations by an F-test. None of the items is rejected with a significance level of 0.05. The 95% confidence interval, as shown in Table 1, implies that the error between the value of the real system and that of the simulated lies within the interval with a probability of 0.95. Therefore, it can be concluded that the two systems are similar in both input information and production behaviours.

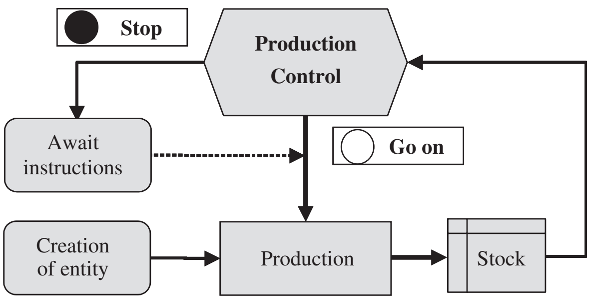

Fig. 2. Modelling the production line in Case 1. An entity in the model (Arena) represents a daily production batch.

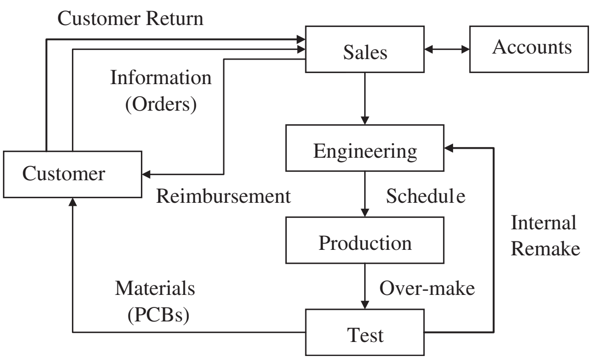

Fig. 3. Modelling the flows in Case 2.

Table 2 shows the data from the "tuned" simulated system in Case 2. Although two items are statistically rejected, it can still be seen that the mean values are very close.

A number of scenarios were generated by changing the input or internal uncertainty from the tuned model above, referred to as "Simulated Current". In Model 1, the first scenario, called "Timely Information", assumes that the manufacturer (customer) sends the Confirmed Request 1 day earlier than in the current situation (immediately despatch after received the order). In this scenario, the manufacturer has more time to schedule the demand. A second scenario, called "Better Adherence", assumes that the forecast more closely reflects the actual demand both in terms of the average level and in the deviation about the mean. A third scenario, "Eliminated Uncertainty", eliminates all uncertainties in customer demand, in raw materials supply, and in production.

In Model 2, variations are considered in the demand, the overload, and the failure in production. The scenarios, apart from "Simulated Current", are "Increased Demand", "Halved Overload", "Halved Failure", "halved both failure rate and overload" (Halved F&O), "Eliminating

Table 2
Comparison between the real and simulated systems in Case 2

Test Items		Request Qty	Loaded Qty	Finished Qty	Delivered Qty	Scrap Qty	Stock Qty	Price £	Required Qty	Production days
t-test of mean values	Real	69.55	89.68	74.40	62.77	15.28	11.63	113.10	27.33	20.13
	Simulated	71.10	88.81	73.22	61.95	15.51	11.19	112.42	26.78	19.90
	Lower limit	−3.37	−2.44	−1.56	−1.63	−1.19	0.07	−1.75	0.14	−0.03
	Upper limit	2.13	4.17	3.91	3.28	0.73	0.80	3.11	0.96	0.50
	Test results	√	√	√	√	√	×	√	×	√
	Real	151.53	175.03	157.72	141.37	55.33	37.82	250.35	22.64	18.22
F-test of standard diviations	Simulated	154.51	180.43	144.15	124.84	74.39	29.55	221.01	21.79	19.71
	Lower limit	0.73	0.73	0.82	0.85	0.56	0.96	0.85	0.7770	0.6910
	Upper limit	1.38	1.36	1.54	1.59	1.04	1.80	1.59	1.4586	1.2972
	Test results	√	√	√	√	√	√	√	√	√

Overload'', ''Eliminating Failures'', and eliminating both failure and overload (''Eliminating F&O'').

4. Experimental results and discussion

4.1. Complexity of the simulated systems

Operational complexity is calculated in the Excel model. In Case 1, two types of complexity were studied, referred to as flow complexity and stock complexity. The flow complexity is the information generated by the variation between the initial and the actual demand. The flow complexity can be viewed as the complexity input from the customer. The stock complexity is the information in the difference between the scheduled stock and actual stock. The stock complexity reflects the complexity of the system (Frizelle and Suhov, 2001). The flow complexity index and the stock complexity index calculated from the real data and from the data obtained by simulation are shown in Fig. 4. The complexity indices obtained from simulation are the averages of 50 replications of running the model. The differences between the real values and the simulated averages are less than 6%. The standard deviation of the flow complexity indices and the standard deviation of the stock complexity indices are also drawn in the figure by the short bars above and below the average.

In Case 2, the operational complexity indices between three interfaces were calculated, both in the ''tuned'' system and the real system. These are the complexity indices between required quantities and produced quantities, between produced quantities and despatched (allocated) quantities, and between despatched quantities and requested quantities. The values of the complexity indices are illustrated in Fig. 5. The largest difference between the values of the real and the simulated indices is less than 12%.

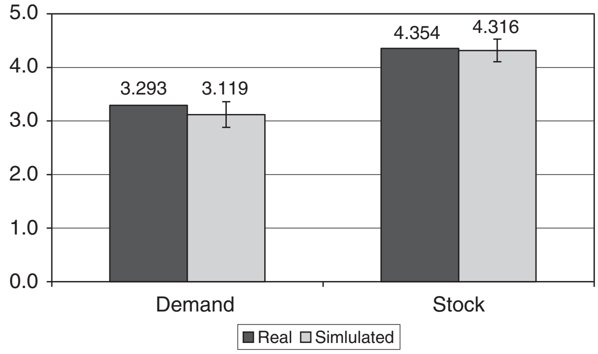

Fig. 4. Complexity indices in Case 1: real compared with simulated.

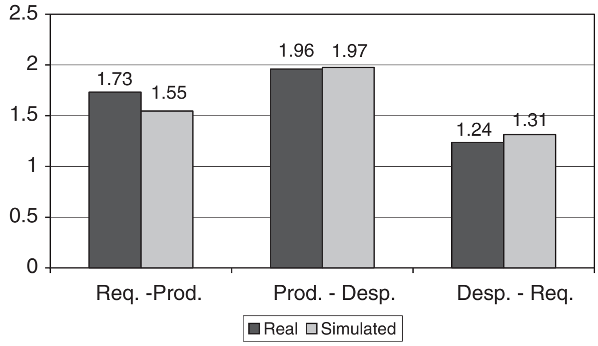

Fig. 5. Complexity indices in Case 2: real compared with simulated.

The coincidence of the complexity indices between the real and the simulated systems shows that the operational complexity index does not rely on a certain set of data and thus it is a generic measure. In similar systems with the same categorisation of states, the complexity indices measured should be the same or close.

4.2. Complexity and costs

Fig. 6 shows the results of the comparison between the costs and the complexity indices obtained from the simulation under the differing scenarios created in Case 1. The figure shows that there is close coincidence between the complexity indices and the operational costs under these scenarios. The simulation experiments also show that when the customer sends timely information to the supplier, the supplier has a better chance to control the inventory and to fulfil the customer demand. This results in the reduction of the complexity and the costs. The experiments confirm that the reduction or elimination of uncertainty will improve the operational performance.

In the simulation of Case 2, the simulation results for the costs and the operational complexity indices are shown in Fig. 7. It can be seen that increased number of orders (increased demand), which makes costs (and sales) increase proportionally, does not strongly affect the value of the complexity index. When the initial overload is reduced, the defects in production will cause the increase of remake and thus cause the complexity index to increase. In the scenarios with reduced overload, the costs are

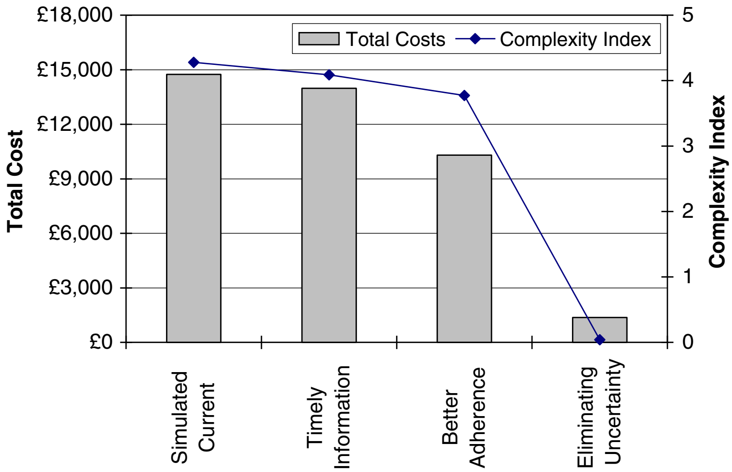

Fig. 6. Complexity indices and costs for four scenarios in Case 1. (The costs have been rescaled to preserve confidentiality.)

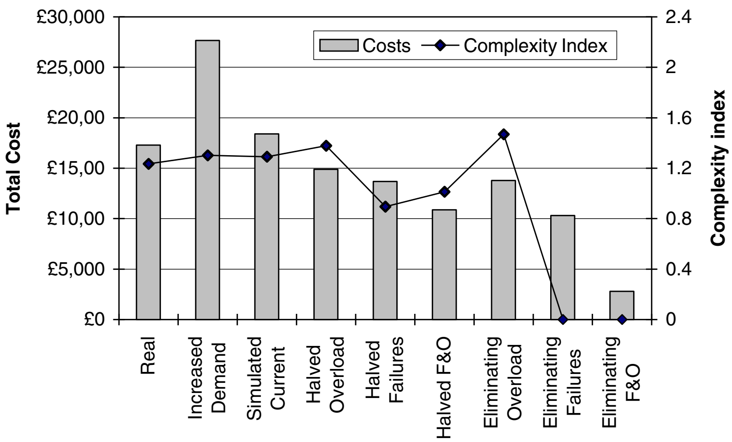

Fig. 7. Complexity indices and costs for eight scenarios in Case 2. (The costs have been rescaled to preserve confidentiality.)

reduced by reduction of the excess production although remaking and delivery delay increase. In Model 2, remaking is taken as an additional order (internal remake order) as it was in the real world. Since they are difficult to be calculated, the costs of remaking production batches and the delivery delay due to remake were thus not included. The cost could be significant and there was a possibility of loss of the customers (That is why the company had an initial overload.). In this sense, the operational complexity index provided a better measure to address the problem. The extent of the increase will, of course, be dictated by the specifics of the situation. Therefore, it can be concluded that, in this make-to-order case, the costs depends on their own specifications and are not necessarily associated with the complexity indices.

This finding for Case 2 is unsurprising and in line with the predictions made above. Thus, operational complexity's stress on queues emphasises inventory costs of supply chains. In this particular case, the need to make specifically to order means a near absence of stock in the chain.

The demand pattern and the complexity index in Case 1 shows that the bullwhip effect took place in this supply chain as the demand for detergent by final customers should be smooth in average (although there could be a seasonal fluctuation). Thus, it can be concluded that the complexity is endogenous which is possibly reduced by management of complexity and the operating costs could be reduced. The simulation confirmed this point. The company realised from this study that prompt information sending to its supplier could benefit not only the supplier but also itself to get in time what needed. However, in practice, manufacturers often send their request when every thing is confirmed and settled and overlook the importance of prompt information.

In case 2, the management also overlooked the endogenous complexity caused by the process capability as the product quality is finally achieved by overproduction and inspection process. The endogenous complexity could cost the company in sales price up to 20% of revenue.

5. Conclusions

The investigation on the relationship between operational complexity and its costs has been carried out through a theoretical queuing model and the simulation of two types of industrial supply chain. It has shown that both the queuing model and the simulation support the first question posed at the start of the paper; that operational complexity is indeed associated with the operational costs of running a supply chain. Moreover, these costs can be apportioned between those associated with the structure of the chain and those generated by departures from what was planned.

However, a second question was also asked; can a relationship be adduced between costs and the operational complexity index? More specifically, will a reduction in the index lead to a reduction in costs? It was clear from the fieldwork, supported by the simulations, that a clear relationship existed in the make-to-stock case study. By contrast no such relationship could be inferred in the make-to-order case.

Closer examination suggests that the second conclusion needs to be clarified. What was established is that inventories generated through deviation from schedule, do not fall with a reduction in the index. This is hardly surprising as no policy inventories should exist in a make to order environment. Indeed this finding was predicted.

It raises the question, however, about why no attempt was made to quantify the costs of the structural element of operational complexity, nor to calculate the corresponding indices. After all, financial figures can be gleaned from company budgets. Moreover one would expect policy stock to represent a far higher investment than inventory fluctuations arising from operational complexity. Indeed the question was a major topic of discussion with the industrial sponsors. The answer is that the second research goal was to see if the entropy index varied with costs. A budget represents a single data point. To generate further points would have required mining data from earlier budgets. Apart from the fact that such an enquiry would have taken the work beyond the scope of the project, there was no guarantee that the relevant entropy values could have been calculated.

Even with this qualification, the literature shows that operational complexity is not the only type of complexity in a supply chain. Were it possible to ascribe a cost to all of the complexities cited, then they might indeed reduce with lower levels of overall complexity. For example, to be agile usually requires holding spare manufacturing capacity. This usually includes a fixed element of structural cost that might be reduced by simplifying the chain, as reducing variety would free up capacity.

The research does show that operational complexity is a major source of costs. It should therefore be of major concern to a manufacturing enterprise and deserves more attention. The work has also shown that the operational complexity index defined by Frizelle and Woodcock (1995) is a generic measure, i.e. similar systems will have close values of the index. The index provides another dimension in performance measurement of a manufacturing enterprise or a supply chain. The work has developed a way to ''tune'' simulation studies by comparing entropy values taken from the field to those calculated for the simulation model. Finally, this study confirms, from a new standpoint, that further/shared information can reduce the variety of non-tolerated states and results in the reduction of costs.

Many questions remain. The most obvious is if cost can be used as a measure of complexity in a build-to-order system? A second is. would the same results be replicated with different companies? The findings in this paper are limited by the number of industrial cases undertaken. A third is what impact other forms of complexity have on costs and is it possible to generate an exhaustive list. There is scope for further investigations into these matters and using the complexity indices as a diagnostic tool is also a direction for future research.

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