MANUFACTURING COMPLEXITY – HOW EXTERNAL COMPLEXITY INFLUENCES THE EFFECTS OF INTERNAL COMPLEXITY

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ABSTRACT

This effort extends our previous research into the elements of the design of manufacturing systems and seeks to separate the effects for the internal elements (those due to system design) from the basic elements of external complexity – order variation (frequency and size). Simulation experiments were conducted that included two levels of the external complexity to determine the significance and effect of ten elements of complexity resulting from managerial decisions relative to the design of the manufacturing system. The results show that the external complexity elements dominate the cause of system unpredictability. We also confirm the findings from our previous research while discovering the difference in effects of the internal complexity factors based upon the amount of variation in the order arrival rate.

INTRODUCTION

Even small production systems are complicated necessitating active management to ensure achieving quality and delivery promises that satisfy customers while ensuring profitability. How a firm designs it manufacturing system is based upon its understanding of market demand and the firm's competitive strategy. There are many aspects of a system's design that must be established prior to starting production. Additionally, a system's design may need to change over time. These design decisions will likely affect the "complicatedness" of the production system, which, in turn, affects the performance of the system and the firm.

Complexity is a notion synonymous with something being complicated. It can be a result of the number of things (Lofgren, 1977; Klir, 1985; Flood 1987), e.g. machines and products. It could also be the number and types of relationships between items in the system (Pippenger, 1978; Simon, 1962). We recognize manufacturing systems are complex by these notions. The general effect of complexity is unpredictability (Casti, 1979). For manufacturing systems, this might be seen, for example, in the inaccuracy of promised dates. The variety of products in the system, which changes from one period to another, and the different product flows for these products, are part of the complexity that leads to unpredictability. Management often employs time-tested interventions like forecasting, holding inventories, or overstating lead times to hedge against this unpredictability.

Hence, an understanding of the how the choices made in the key elements of a system's design affects complexity is relevant. It is important for managers to recognize the lasting impact their decisions can have on performance so they can make the best decisions about the design as well as incorporate other management actions needed to achieve the desired performance that satisfies their customers. The results of this study will have practical and theoretical value. We hope to elucidate the magnitude of the key structural decisions in the design and management of a manufacturing system. By understanding these determinants of complexity, managers can better design systems and make critical operational decisions. Theoretically, the results may point to factors that are consequential to incorporate in the burgeoning study of supply chain management.

In this research, we examine the effects of several elements of a manufacturing system's design in the context of two forms of external complexity. We do this using a simulation of a batch manufacturing system. Following is a brief theoretical background followed by a description of the simulation design, the statistical analysis, and concluding with a discussion of the results.

BACKGROUND

In our previous research, eight different elements of internal complexity related to the design of a manufacturing system were studied. These elements, listed in Table 1, were identified from research literature as developed in Gabriel (2013). Generally, past research identifies these complexity attributes individually, but little has been done to study their effect on performance with more than one at a time. Recent examples include Park and Kremer (2015) who studied the complexity caused by product variants, Wan et al. (2012) researching the impact of the product variety, and Smunt and Ghose (2016) who evaluated the effects routing commonality.

We again study the effects of the eight elements that we previously tested and include two additional internal manufacturing complexity items – unit run-time differences and set-up time (see Tables 1 & 2). We do this, in part, because, in our previous effort, the effect of the number of work centers in a system was significant, but appeared to function the reverse of what was anticipated. It was hypothesized that a batch manufacturing system with more work would have a greater amount of routings to be managed, making the system more susceptible to having greater variation in flow time, thus greater variation in order lateness and tardiness. This unpredictability would be considered the negative effect of the added complexity due to having to manage the additional work centers and the greater variety of routings through the system. We fathom that the reversed effect could be due to other factors including the extent of the difference in run times among the various items produced in the system as well as how significant the amount of set-up time is compared to the unit run time. We, therefore, add two additional system factors – set-up time and the differences is part-processing times.

In practice, set-up time has received the particular focus of those espousing Just-in-Time and lean manufacturing principles. As a recent example, Phan and Matsuhi (2010) found correlation between set-up time reduction and performance factors like on-time delivery, manufacturing cost and flexibility, depending on the national context. Set-up time has also been a variable commonly included when studying manufacturing systems because it consumes capacity and occurs intermittently thereby disrupting process flow. Two recent examples are Djassemi (2005) and Garavelli (2001). In his study of cellular manufacturing, Djassemi (2005) recognized the potential impact of set-up times by using three levels of set-up times depending on product similarity. Garavelli (2001), in his study simulating a batch production system, incorporated a ratio-based set-up time (0 or 30% of processing time). He found that the benefits from system flexibility are significantly different depending on the length of set-up times. Systems with high set-up times benefitted less from having additionally flexibility. Since we see that the size of the set-up time is a relevant factor that can affect system performance, we incorporate set-up time ratio in this study to further our investigation into the results found in our previous study. The Set-up Time Ratio (STR), similar to Garavelli (2001), is the amount of set-up time for a batch of a manufactured item as a ratio to the unit run time for that item. We do this because it may be possible that the predictability of flows is different when set-up time is large relative to unit run time than when set-up time is short relative to the unit run time. This may also contribute to the unexpected effect on the number of work centers shown in our prior study.

Table 1
Elements of Internal Manufacturing Complexity with Definitions

Internal Complexity Element	Definition
Product Mix	The number of end-products produced in a manufacturing system.
Product Mix Ratio	The proportion of production volume attributed to the largest volume end-product.
Product Structure Depth	The number of levels in a product structure for an end-product.
Product Structure Breadth	The maximum number of manufactured items at a single level in an end-product's product structure.
Component Commonality	A measure of the shared used of components.
Number of Routing Steps	Number of distinct manufacturing operations that items require based upon their manufacturing routing.
Number of Work Centers	The number of work centers in a manufacturing system.
Routing Commonality	A measure of the degree of similarity of routing sequences among manufactured items in a system.
Run Time Difference	The difference in per unit run time between one manufactured item to a different manufactured item. This simply means that one item will consume more work center capacity than a different item.
Set-up Time Ratio	The amount of set-up time for a batch of a manufactured item as a ratio to the unit run time for that item.

The second internal complexity factor that has been added to this study is the variation in part-processing times between the different items processed in the system. Jarrahi and Abdul-Kader (2015) found that differences in processing times among products as a key contributor of variability in a production system when modeling a production line. Likewise, when developing formulae to estimate production throughput on production lines, Dhouib et al. (2008) also incorporate processing time differences among products because they have been shown to cause starving and blocking in such systems thereby affecting throughput rate. Similarly, we have included Run Time Difference (RTD) - the difference in per unit run time between one manufactured item and a different manufactured item. In conjunction with the reasoning of Jarrahi and Abdul-Kader (2015) and Dhouib et al. (2008), we conjecture that when run times are similar, then the flow of goods may be less complex, that is, more predictable, because flow times may be more similar. Because we did not control for this in our previous study, these differences in run times may have added noise to the effect of the number of work centers, thus confounding the effects.

Table 2
Elements of Internal Manufacturing Complexity with References

Internal Complexity Element	Literature Source
Product Mix	Park & Kremer (2015), Wan et al. (2012), Huang & Inman (2010), Bozarth, Warsing, Flynn & Flynn (2009)
Product Mix Ratio	Kotha and Orne (1989)
Product Structure Depth	Orfi, Terpenny, & Sahin-Sariisik (2011), Fry, Oliff, Minor, & Leong (1989), Benton, W. C. and R. Srivastava (1985, 1993);
Product Structure Breadth	Orfi, Terpenny, & Sahin-Sariisik (2011), Fry, Oliff, Minor, & Leong (1989), Benton, W. C. and R. Srivastava (1985, 1993);
Component Commonality	Huang & Inman (2010), Song & Zhao (2009), Wacker & Miller (2000), Vakharia, Pamenter, & Sanchez (1996)
Number of Routing Steps	Deshmukh, Talavage and Barash (1998)
Number of Work Centers	Deshmukh, Talavage & Barash (1998), Calinescu et al. (1998), Frizelle & Woodcock (1995)
Routing Commonality	Smunt & Ghose (2016), Orfi, Terpenny, & Sahin-Sariisik (2011), Monahan & Smunt (1999), Bozarth & Edwards (1997)
Run Time Difference	Jarrahi and Abdul-Kader (2015), Dhouib, Gharbi & Ayed (2008)
Set-up Time Ratio	Phan and Matsuhi (2010), Djassemi (2005), Garavelli (2001)

Additionally, we introduce two forms of external complexity associated with the variation related to customer ordering – order arrival rate variation and order size variation.

These are included in this study to explore how they might influence the effects that the elements of internal complexity have on production system performance. The variation in order arrival rate and the variation in order size is considered external complexity because is not under the direct control of the management of a manufacturing operation, but these may change how the system design elements affect system performance. In recent literature, we see the relevance of arrival rate variation. Disney et al. (2006), as they study their proposed inventory ordering policy, recognize that reducing the order variability will enable a supplier to be able to offer shorter lead-times. This is because the factory can better plan the utilization of its resources from period to period. Balakrishnan et al. (2004) develop and test supply chain policies predicated on the deleterious effect that customer order variability has on supplier costs where they suppose that buffer capacity is required to avoid extended lead times or substantial safety stock holding costs. When studying the productivity of manufacturing systems, van Ooijen (2003) recognizes that changes in the order arrival rate generally lead to a change in throughput where increased arrival rates equate to increased throughput. In their study of the impact of order decisions in a two-echelon supply chain, Boute et al. (2007) concluded that a smooth order pattern leads to shorter and less variable lead times.

The variation in order size is not only a reality that manufacturers encounter, but, logically, will also affect system performance by changing the capacity demanded to fill the orders. System capacity is inflexible in the short-term, so when a series of higher than average orders arrive, throughput will be reduced as utilization of capacity approaches or exceeds its design capacity. We recognize that supply chain interactions with consumer demand can lead to substantial variation in customer-to-supplier order sizes, as demonstrated in the bullwhip effect. Therefore, it was logical to also include this factor in our study.

METHODOLOGY

A simulation of the same generic batch-type manufacturing operations as in our prior research was used to obtain a sample of data on system performance when the experimental factors were altered. It was believed that batch shops would be more likely to experience a wider range of the complexity elements that were being investigated.

In this situation, there were 12 experimental factors. Since our goals were to determine if the internal manufacturing complexity elements have an effect when the two external complexity factors changed, we used only two levels for all factors. Even by limiting the design to two levels for each factor, this would have required 4096 experiments to have a full factorial analysis. Since this was not practical to conduct, a fractional factorial experiment was undertaken. The result was a design requiring 256 experiments. Each experiment was replicated 15 times using the batch means method to obtain independent samples (Schmeiser, 1982; Pritsker, 1986).

To measure systems performance, the same five measures were used as in the previous effort (see Gabriel, 2013). These were the means of lateness and tardiness and the standard deviations of flow time, lateness and tardiness. Using mean lateness and tardiness captures a firm’s concerns about completing orders too early or late (lateness), and the customer’s desire not to have late orders (tardiness). The measures involving standard deviation cope with the general notion that complexity causes unpredictability (Casti, 1979).

Table 3 summarizes the levels used for each experimental factor. The same settings were used for those complexity elements included from the previous research. Products, manufactured items, and their associated product structures and routings were generated to achieve the system experimental parameters. Refer to Gabriel (2013) for details. Figure 1 presents three product structures as examples of the setting for product structure breadth and depth.

In the case of run time difference (RTD), a uniform distribution with the mean unit run time of 0.20 hours was used. For the "low" complexity, the distribution had endpoints of 0.15 and 0.25 hours. For the "high" complexity situations, the endpoints were 0.05 and 0.35 hours. The set-up time ratio (STR) for the "low" complexity cases was set to 0.40 hours, being only twice the average per unit run time. The STR high complexity setting was to be 10 time the average unit run time, resulting in a 2 hour set-up time.

As for the external complexity factors, the customer orders arrival rate variation was set at two substantially different coefficients of variation, 0.10 and 1.00. The prior study used the exponential distribution, but this may have induced large variation that inhibited the analysis from detecting variation caused by the experimental factors. In this study, the arrival rate was based on a truncated normal distribution (truncated to prohibit negative times). Since the arrival rate for each experiment needed to be set "fairly", the mean arrival rate was set for each experiment such that, after conducting pre-trial runs, each had a bottleneck work center with an average utilization of 95%.

Order size variation was set such that there was no variation at the "low" complexity setting. In these runs, the order size was always 200 units. For the "high" setting, the target for the mean order size was 200 with a standard deviation of 35 using a truncated normal distribution (where 0 would be the minimum). Then, the order quantity for each product varied based on the number of products (P) and the product mix ratio (PMR) to achieve a coefficient of variation of 0.175 (35/200) for the entire order.

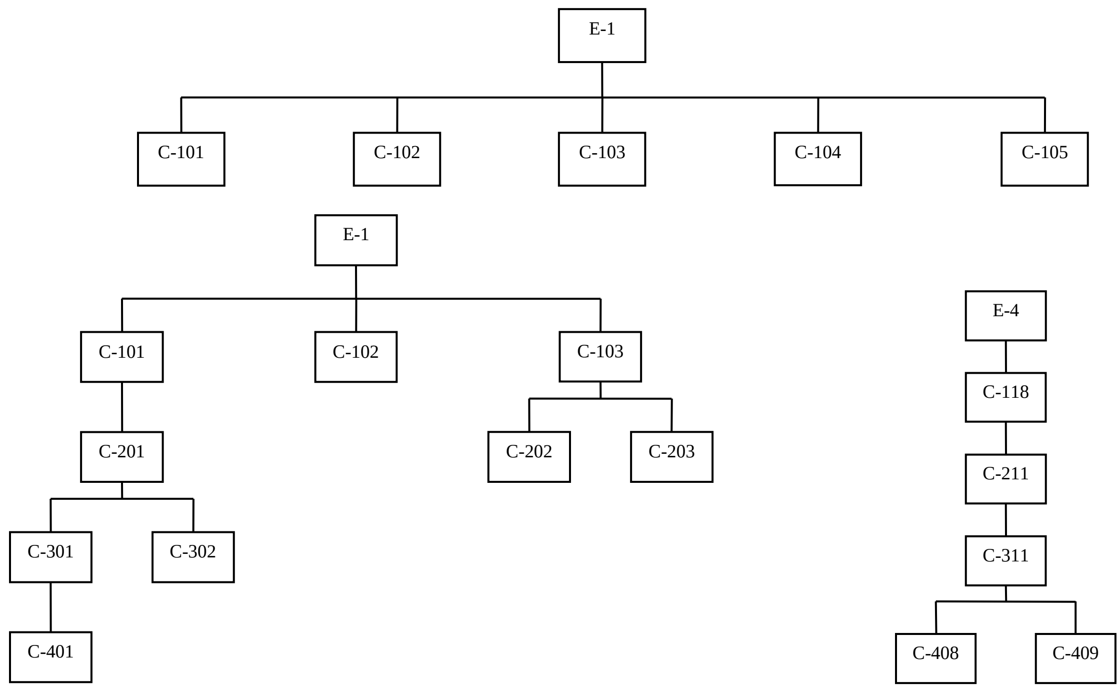
Table 3
Experimental Levels for the Complexity Factors

	Levels	
Complexity Factor	High Setting	Low Setting
Products – (P)	5	2
Product Mix Ratio (PMR)	All equal	1 Dominant/Others equal
Product Structure Depth (D)	5	2
Product Structure Breadth (B)	5	2
Component Commonality (CC)	0 %	~30 %
Number of Routing Steps (RS)	10	4
Number of Work Centers (WC)	10	4
Routing Commonality (RC)	0 %	~50 %
Run-time Difference (RTD)	Max. = 0.2 hrs/unit	Max. = 0.1 hrs/unit
Set-up Time Ratio (STR)	10:1	2:1
Order Arrival Rate Variation (ARV)	cv = 1.0	cv = 0.10
Order Size Variation (OSV)	cv = 0.175	None – Constant Order Size

One non-experimental factor that could influence system performance was the due date tightness factor, because it will affect the amount of lateness and tardiness produced by a system. Due dates were set using TWKCP, total work content for the critical path, which incorporates a due date tightness factor, k. TWKCP is the sum of all the operation times in the longest chain of the product structure. The due date tightness factor, k, was established in trial runs for the manufacturing system in the experiment that was deemed to be the "simplest". The value for k was set such that, after the warm-up period, approximately 30% of the orders were tardy.

For each experimental system to be compared fairly, each end-product was assigned a specific random number stream to be used in all experimental runs. This would maintain the identical order sequence and quantity for each end-product for experiments having the same settings of P and PMR.

Figure 1 Examples of the Simulated Product Structures



The total work content (TWK) method (Goodwin and Goodwin, 1982) was employed to calculate the release dates when each order arrived in the simulation. The order release for the lowest level component on the critical path of a product structure occurred immediately as the order arrived. Parent items in the product structure were released at the time that the last order for the required children items was completed. This gave the manufacturing orders for parent items an opportunity to be released early or late, thus providing clearer evidence of the impact of system complexity on performance.

The earliest order due date (EDD) rule was used for scheduling orders at work centers with ties broken using the order of arrival to the work center (FCFS). EDD was shown to perform well compared to other rules (Fry et al., 1989), and by using EDD, the primary reason for late order completion should be due to the system complexity.

Other important ystems paraments included the following. All items in a manufacturing order remained together for each processing step meaning no “batch-splitting” occurred. No loss of product occurred, e.g., quality failures, so that every order was completed for its entire order quantity. Transfer time for moving manufacturing orders between work centers was ignored in the simulation. Each work center contained a single server (i.e. machine). There was an unlimited maximum queue size at a work center.

The fictitious batch manufacturing shop was simulated using AWESIM according to the design attributes just described. This is the same simulation used in the prior study except for the changes to the arrival rate distribution (as stated earlier) and the addition of the new complexity elements.

Data for every order was automatically captured in a database. To determine the number of orders in a replication for all experiments, trial runs were conducted using the “worst case”, or most complex, system. It is a common to establish the replication size as the length of time needed to clear the transient period. This was then converted to the number of orders by multiplying that time by the average orders per hour. In preliminary simulation runs, the average orders per hour were determined in the steady state period. Doing this ensures that the same number of orders was evaluated for every replication in every experimental run. To guarantee a long enough observation period, the replication size was set to 2000 orders. For each experiment, data was collected beginning with order 2001 and ending with order 4000. An interval equal to one replication was left between batches where statistics were not collected to maintain independence of batches. Hence, for orders 4001 to 6000, data was ignored. Data collection resumed beginning at order 6001 through 8000, and so on until 15 replications of data had been obtained for each of the 256 experiments. The statistics were accumulated for 2000 consecutive orders to avoid censoring data (Blackstone et al., 1982). For example, data was recorded for order 4000 even if orders 4001, 4002 and 4003 were completed prior to order 4000.

RESULTS

After completing the 256 experiments, there were 3840 sets of data, each containing 2000 production orders. The performance measures for each order were calculated and analyzed. An initial review of the data revealed that the near normality requirement of ANOVA techniques was not met. Transformation techniques were evaluated for each performance measure. The LOG transformation was deemed the best choice for all measures, individually. Similar to the previous study, the correlations between the five performance measures, with or without transformation, were all very high, all above 0.89. Principle components analysis using SPSS statistical software extracted a single factor from the transformed DVs explaining 93.6% of their variation. As in the prior study, this factor was named MFGPERF, denoting it as a summary measure for total system performance.

Using MFGPERF as the dependent variable, an ANOVA analysis was performed to “screen” the significant effects. Table 4 presents the results. Only three of the complexity elements (CC, RS, and CC) were not statistically significant at 0.05 significance. The effect size was measured using η^2. Although η^2 may be distorted by not using a full-factorial model, it is still a way to measure relative effect size. In the omnibus model, ARV, arrival rate variation, had the greatest effect (0.902), far more than that of the second highest item, D, depth of product structure, (0.297). OSV (0.264), B (0.224) and WC (0.211) also had appreciable effect sizes. PMR (0.038) and P (0.018) had marginal effect sizes, whereas RTD (0.009) and STR (0.002) had no meaningful effect.

Table 5 displays the results of the ANOVAs for each transformed performance measure excluding the three complexity elements that were not significant in the omnibus test. Universally, ARV has the highest effect size regardless of the dependent variable. RTD, and STR have no practical significance in any case, having η^2 values all below 0.010. Beyond these three, the relative effect size for the other complexity elements varies based on the performance measure. OSV, the second measure of external complexity, has a consistently high effect size for the three performance measures involving variation – the standard deviations of flow time (S_{FT}), of lateness (S_L), and of tardiness (S_T). It had much less effect on mean tardiness (T_{MEAN}) and substantially less on mean lateness (L_{MEAN}).

Table 4
Omnibus ANOVA Results

Source	Type III Sum of Squares	df	Mean Square	F	Significance	η2	Sig.
Corrected Model	4,377.33	9	486.37	1,129.87	0.000		
Intercept	0.00	1	0.00	0.00	1.000		
P	6.15	1	6.15	71.24	0.000	0.0180	*
D	139.36	1	139.36	1,613.88	0.000	0.2970	*
B	95.16	1	95.16	1,102.04	0.000	0.2240	*
PMR	12.92	1	12.92	149.63	0.000	0.0380	*
CC	0.33	1	0.33	3.82	0.051	0.0010	N. S.
RS	0.33	1	0.33	3.82	0.051	0.0010	N. S.
WC	88.63	1	88.63	1,026.43	0.000	0.2110	*
RC	0.03	1	0.03	0.34	0.561	0.0000	N. S.
RTD	3.13	1	3.13	36.30	0.000	0.0090	*
STR	0.51	1	0.51	5.93	0.015	0.0020	*
ARV	3,043.43	1	3,043.43	35,245.00	0.000	0.9020	*
OSV	118.54	1	118.54	1,372.77	0.000	0.2640	*
Error	330.47	3827	0.09				
Total	3,839	3,840					
Corrected Total	3,839	3,839					

Adjusted R Squared = .914

Lacking results for a full factorial experiment, the effect sizes are difficult to compare fairly. In order to get some idea of the relative effect sizes among the complexity elements, the rank order of effect sizes was made for each performance measure as shown in Table 6. Items in bold denote that η^2 is well below 0.100. One noteworthy generalization from the ranked ordering is that P and PMR rank at or near the bottom for the five performance measures. P never has an η^2 above 0.066. B, D, WC, and PMR have effect sizes very close to each other for T_{MEAN}, ranging from 0.125 to 0.159. Another generalization is that D ranks relatively high for most performance measures – either ranked 2 or 3 with the exception of L_{MEAN}, where it is ranked 4.

The marginal means (see Table 7) for each performance measure were evaluated to better understand the size and the direction of the effects. Combing these results with those in Table 6, we conclude that increased variability in the order arrival rate (ARV) substantially adds to the unpredictability of system outcomes, that is, it increases complexity. This is clearly reflected in the relative increase in size of all of the measures of variation, S_{FT}, S_L, and S_T. Similarly, we observe that increased variability in order size (OSV), the other external complexity element, leads to greater unpredictability. These were followed by two elements of system design complexity - product structure depth (D) and breadth (B). Systems with product structures that are wider and/or deeper demonstrated poorer performance (in L_{MEAN} and T_{MEAN}) and well as greater unpredictability (in S_{FT}, S_L, and S_T).

Table 6
Rank Ordering by Effect Size

Rank	S_{FT}	L_{MEAN}	S_L	T_{MEAN}	S_T
1	ARV	ARV	ARV	ARV	ARV
2	OSV	B	D	B	OSV
3	D	WC	OSV	D	D
4	B	D	WC	WC	WC
5	WC	**P**	B	PMR	B
6	**P**	**PMR**	**PMR**	OSV	**P**
7	(none)	**OSV**	**P**	**P**	**PMR**

Values in bold are occurrences where the direction of the effect is opposite of what was anticipated. As in the case of our prior research, the number of work centers in the system, WC, universally had the opposite effect as would be anticipated. As the number of work centers increased, the unpredictability lessened. Not only did the mean lateness and tardiness improve, there was also smaller variation of flow time, lateness and tardiness. For the number of products, P, there were some mixed results. When there were more products being produced by the system, the variation in flow time and tardiness shrank, yet the variation in lateness increased. However, when there were more end-products, performance worsened (in L_{MEAN} and T_{MEAN}) as anticipated. For PMR, it also showed having an opposite effect on $S_{FT.}$ Based upon the prior analysis of the effect size using η^2, the difference for PMR is considered not practically significant.

Table 7
Marginal Means by Performance Measures

		Performance Measure				
Factor	Setting	S_{FT}	L_{MEAN}	S_L	T_{MEAN}	S_T
P	Few	**2,106**	1,983	2,015	2,046	**1,982**
	Many	**1,927**	2,065	1,868	2,070	**1,864**
D	Shallow	1,431	1,451	1,397	1,483	1,382
	Deep	2,602	2,597	2,486	2,633	2,465
B	Narrow	1,563	1,435	1,484	1,484	1,460
	Broad	2,470	2,613	2,399	2,632	2,386
PMR	Dominant Product	**2,038**	2,009	1,913	2,010	1,912
	Equal volumes	**1,995**	2,039	1,970	2,107	1,934
WC	Few	**2,498**	**2,605**	**2,432**	**2,630**	**2,417**
	Many	**1,535**	**1,443**	**1,450**	**1,486**	**1,430**
RTD	Small	1,996	1,974	1,920	2,013	1,901
	Large	2,037	2,073	1,962	2,103	1,946
STR	Short	1,964	1,970	1,887	2,003	1,869
	Long	2,069	2,078	1,996	2,113	1,977
ARV	Small	305	167	180	223	157
	Large	3,729	3,881	3,702	3,893	3,690
OSV	none	1,849	1,987	1,849	2,028	1,833
	Some	2,184	2,061	2,034	2,088	2,014

One of the key questions to be addressed was the impact of the external complexity elements, arrival rate variation (ARV) and order size variation (OSV). To do this, ANOVAs were analyzed when these factors were excluded and the adjusted R^2 were then compared. Table 8 reports the results of the different combination of models with and without each external complexity element. When no external complexity is included in the model, the internal complexity factors only explain 8.8% of variation in MFGPERF as compared to 91.4% when both ARV and ORV are included. This indicates that external complexity plays an extremely large role in system performance and unpredictability. If only ORV is included, adjusted R^2 increased to 0.119, explaining only 3% more variation than the internal complexity factors. Introducing ARV without ORV into the model increased adjusted R^2 to 0.883, explaining over 79% more variation in MFGPERF. This is a clear indication that the arrival pattern of customer orders can have a considerable impact on system performance.

Table 8
Model Comparisons

Model	Significance	Adjusted R^2
Model without Ext. Complexity Factors	< 0.001	0.088
Model with Order Size Variation only	< 0.001	0.119
Model with Arrival Rate Variation only	< 0.001	0.883
Full model	< 0.001	0.914

Finally, since ARV had such a huge effect, we wanted to discover how it might influence the way the other complexity elements affect performance and unpredictability. Table 9 displays the effects from ANOVA models when the results for high ARV were split from the results for low ARV. Interpretation of these results must also be guarded because the experiment was fractional factorial. Yet, we believe there is value in making some observations at this point. Note that based upon adjusted R^2, the models explain close to the same amount of variation in MFGPERF. The largest change observed is for ORV. When variation in arrival rate was low, order size variation has a very large effect on performance, both relative to the other factors and relative to when ARV is high. When ARV is high, P, the number of end-products, had no effect on performance, but a low amount (η^2 = 0.103) when ARV is low. This occurs similarly for RTD, the routing time differences from item to item, but the effect size is small (η^2 = 0.033) when ARV is low. Likewise, the product mix ratio, PMR showed a greater and substantially more sizeable effect (η^2 = 0.208) at the low level for ARV than at the high level where it had no meaningful effect on performance. However, when there was greater variation in arrival rate of orders, the product structure elements – breadth (B) and depth (D) – as well the number work centers (WC), had a substantial increase in their effect on performance.

Table 9
Effects of Complexity Factors when Arrival Rate Variation is Held Constant

Factor	Effect (η^2 - upper/p-value - lower) ARR Rate CV Low	ARR Rate CV High	Change in Effect
P	**0.103** (0.000)	**n. s.** (0.067)	↓
D	**0.393** (0.000)	**0.487** (0.000)	↑
B	**0.258** (0.000)	**0.455** (0.000)	↑
PMR	**0.208** (0.000)	**0.008** (0.000)	↓
WC	**0.234** (0.000)	**0.451** (0.000)	↑
RTD	**0.033** (0.000)	**0.003** (0.020)	↓
STR	**n. s.** (0.710)	**0.014** (0.000)	↑
OSV	**0.640** (0.000)	**0.002** (0.089)	↓
Adjusted R^2	0.777	0.724	

DISCUSSION

The purpose of this research was to discover how the complexity elements related to a manufacturing system's design affect system performance in the context of differing levels of external complexity. First and foremost, we find that external complexity in the form of the variation in customer order arrival rate (ARV) and order size (OSV) dominates the explanation of manufacturing performance and system unpredictability. Arrival rate variation had, by far, the largest effect. When systems cannot anticipate the timing of new orders, the manufacturing system's innate ability to cope with this variation is low, thus affecting predictability of outcomes. Additionally, when order sizes vary, this leads to more unpredictability in the results. The results from changes in the amount of variation for either (or both) of these showed increased lateness and tardiness. We also see more unpredictability as measured by the standard deviation of lateness and tardiness. When a firm experiences more variation in lateness, they can be excessively delinquent in their delivery to customers or end up frequently holding finished goods in inventory until the contracted ship date. When orders complete early, in essence, they had used system capacity at a time that was sooner than necessary, possibly preventing other items from utilizing resources when needed so that those orders could complete on time. Alternatively, it may mean that there is excess capacity that has to exist in order to cope with the unpredictability caused by customer order rates and sizes. For practicing managers, in order to moderate the impact of this external complexity, they must employ other management interventions like expediting, holding inventories, or using safety stock, all of which increase a firm's costs. Here is the value for adopting top-tier ERP systems that incorporate sophisticated algorithms, which are now accommodated by the availability of affordable modern computing power. In addition, the results regarding external complexity lend credence to the continuation of research into order planning, order release, scheduling, and batch-sizing. Further study of how these effects can be mitigated through integrated supply chain planning is also justified by our results because suppliers will need to be prepared to cope with the same unpredictability that is due to the external complexity because that will naturally flow to them.

Additionally, when controlling for external complexity, we confirmed which of these system complexity elements influence performance. The main things for managers of firms to consider are the depth and breadth of their product structures, and to a much lesser degree, the number of products they offer and the mix of products. This concurs with our previous results. The depth of a product structure is a result of the amount of backward integration a firm commits to do. The negative impact to performance of the local system by producing items deep into the end item's product structure (backward integration) may justify outsourcing. In this research, we did not study the affect that supplier deliveries might have, but an alternative to backward integration is to outsource to external suppliers. It also confirms to managers that there is a tradeoff. Backward integration grants more control of supply to a firm, but may require firms to invest in "buffer" capacity as the additional complexity necessitates this extra capacity in order to maintain lead times and meet delivery promises. This comes at additional costs.

As far as the breadth of the product structure, again, this is problematic when a firm is committed to produce such a number and variety of items internally that eventually get assembled into their end items. Outsourcing some manufactured items can reduce the effects to performance that results from having so many items competing for system resources. We also observed that the potential for product structure breadth and depth to negatively affect performance and increase unpredictability is exasperated by variability in order arrival rates. Meaning that managers cannot neglect to consider this aspect of customer demand when making insource/outsource decisions. This is also something for researchers to consider as they study areas related to system design.

In addition, component commonality and routing commonality showed no meaningful effect on system performance. This is also in-line with our previous research, now confirmed after accounting for external complexity.

This research sought to identify attributes of a system that management controls that have an impact on system performance excluding most common interventions by management. We excluded using forecasting, holding inventory, including safety stock or safety lead time, as well as advanced methods to schedule orders. Clearly, the purpose of these is to allow a system to cope with external (and internal) sources of variation to lessen their effect on performance, especially as experienced from customers These must be employed to operate viably in a competitive environment.

Even after this second research into the system elements of complexity, there is no obvious reason for the effect observed for the number of work centers. Having a greater variety of work centers for processing the variety of manufactured items, while attempting to hold utilization constant, seemed like something that would lead to more variation in performance. It was expected that the standard deviations of flow time, lateness or tardiness would increase when greater variety of work centers existed. It did not function as expected even when controlling for the external complexity items (order arrival rate and order size variation) and for routing time differences (RTD) and set-up time ratio (STR). Recall, these were included, in part, to try to account for this unexpected result. That did not occur. In fact, routing time differences and set-up time ratio has no practical effect while the number of work center has a sizeable effect on performance in the opposite direction. No obvious explanation is available for this.

From these results, we have now identified, through confirmation, the primary strategic and tactical elements in manufacturing systems that affect performance to the customer through longer lead times or late deliveries. At the same time, we noted items that appear to have little impact (for batch-type manufacturing systems). This gives direction as research continues in strategic supply decisions like insourcing versus outsourcing by the effects demonstrated especially by the breadth and depth of products structures.

CONCLUSION

A study was conducted to investigate the proposed elements of internal manufacturing complexity under two levels for two attributes of external complexity – variation in order arrival rate and variation in order size. The results indicate that the amount of variation in the order arrival rate has the largest effect on the performance measures included in this research. The variation in order size also played a very significant role in system performance and unpredictability. Additionally, the findings from the prior research effort regarding the relevant elements of internal complexity were confirmed. The breadth and depth of the product structure are important concerns for a firm to reflect upon when evaluating causes of performance variation.

The generalization of the findings, of course, is limited by the research design. A batch-type system was simulated, so these conclusions might not be true for assembling line or machine shop type of systems. Additionally, only two levels of each factor were simulated because it was impractical to be able to perform all possible permutation of experiments even by confining the study to having two levels for each. Also, the high settings for number of products was relatively low. Yet, there was statistical significance. We believe this is an indication that this factor is something important as a firm considers expanding their product line. Another limitation was that a full factorial ANOVA was not used. Due to the extraordinary number of simulations that would have been required, a fractional factorial design was used. Some of the analysis, especially when focused on evaluating numerical effects, is susceptible to error due to lacking a complete set of combinations of factors. It also eliminated the opportunity to evaluate interactions among factors. These are significant limitations that might be addressed in future research.

Further research into the effect of the number of products in a portfolio is recommended, since five was the largest considered herein. It may be that this has a more dramatic effect than was estimated in this research. The interactions among factors, especially with the external complexity factors could be considered. In addition, rooting out the reason for the reverse effect of the number of work centers is of interest.

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