

The Value of Manufacturing Simulation

An Honors Thesis

by

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A handwritten signature in cursive script, reading "Alan M. Leduc", is written over a horizontal line.

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Manufacturing Simulation

The purpose of this project is to illustrate the usefulness and limitations of computer simulation in predicting the performance of manufacturing systems. The SimFactory manufacturing simulation program, produced by CACI Products Company, was used in this study, and was compared and contrasted with traditional mathematical models used to predict manufacturing system performance. It is intended that this text will serve as a guide for use in determining what types of problems are best analyzed using simulation software, and what types of problems are best addressed using manual computational techniques.

Using manual techniques, engineers combine data from the production line with quantitative expressions to predict manufacturing system performance. The mathematical models thus created often provide powerful tools to engineers and managers interested in optimizing a given system. However, if the assumptions upon which the model is based are incorrect, the model will fail to properly represent the real-world situation (Riggs, 8-9). Large systems also present problems when manual analysis techniques are used, as the final impact of small errors on a model can be much larger than the value of the individual errors themselves.

SimFactory manufacturing simulation software predicts the performance of manufacturing systems by allowing the user to construct a computer model of the production process and run simulated parts through simulated processes. Like other mathematical models, SimFactory models fail to represent the real-world situation if the assumptions used to set up the models are incorrect. The main difference between SimFactory and manual mathematical models is that SimFactory can

incorporate statistical fluctuations into the model, rather than using simple averages. This allows SimFactory to use variance which is more representative of real world conditions.

The Simulated Factory

The imaginary plant we are going to model in SimFactory uses a job-shop production system. This production system was chosen because it is the most common type of production system used in American manufacturing. Job-shops usually produce a wide variety of parts in relatively small numbers using general purpose equipment (Groover, 18). This requires the employment of skilled workers and careful supervision and planning (Riggs, 307).

This job-shop also uses batch production, where orders may be broken up into more than one batch. Each batch is then processed as a separate entity, allowing work to be performed on batches from different orders according to demand (Groover, 19). Batch sizes are determined by the size of the order, the size of the factory, the nature of the work to be performed, and the factory's existing workload.

To keep our manual calculations manageable, we will depart from reality and assume that our factory is "caught up," and has no work to do other than that which we are modeling.

Predicting Manufacturing Lead Time

One of the most important measures of the performance of a manufacturing system is the manufacturing lead time (MLT) of the system (SimFactory uses the term "Product Make Span" instead of MLT.). MLT is the time that the system requires to process a given product through the plant (Groover, 30). It is used in predicting the time necessary to process an order to ensure that the order will be completed when promised. Once the MLT is known, it is easy to determine when work should begin on an order by working backwards from the order's due date (Riggs, 544). Traditionally, MLT has been expressed mathematically using the following formula:

$$MLT = \sum_{i=1}^{n_m} (T_{su_i} + QT_{o_i} + T_{no_i})$$

- Where:
- T_{su_i} = The average setup time for a given machine "i".
 - Q = The quantity of parts to be produced.*
 - T_{o_i} = The average time required by machine "i" to produce one part.
 - T_{no_i} = The average non-operating time expected during the run and associated with machine "i" – machine breakdowns, maintenance, transport, etc.

*In our calculations, Q represents the number of parts *per batch*, not the total number ordered. The MLT value obtained using these calculations is thus the MLT for *each batch*, not for the entire order, unless there is only one batch in the order.

Let's say our plant just received an order for 20 metal spacers. To produce each part, four operations must be performed:

- (1) The sides of a metal block must be made square and even.
- (2) Four mounting holes must be drilled in the block.
- (3) The top and bottom of the block must be ground smooth.
- (4) The finished spacer must be inspected.

Each of these operations requires a different machine or station, and requires a batch setup time and average operating time which we know from past experience:

Operation:	Setup Time per Batch:	Operation Time per Part:
1	10 min.	10 min.
2	30 min.	8 min.
3	20 min.	12 min.
4	5 min.	2 min.

In order to simplify our calculations and the SimFactory model, we will assume that the non-operating time (T_{no_i}) for all the operations is zero.

Entering these values into the MLT formula gives the following result:

$$MLT = \sum_{i=1}^{n_m} (T_{su_i} + QT_{o_i} + T_{no_i})$$

$$MLT = (1): (10 + 20*10) = 210 \text{ min.}$$

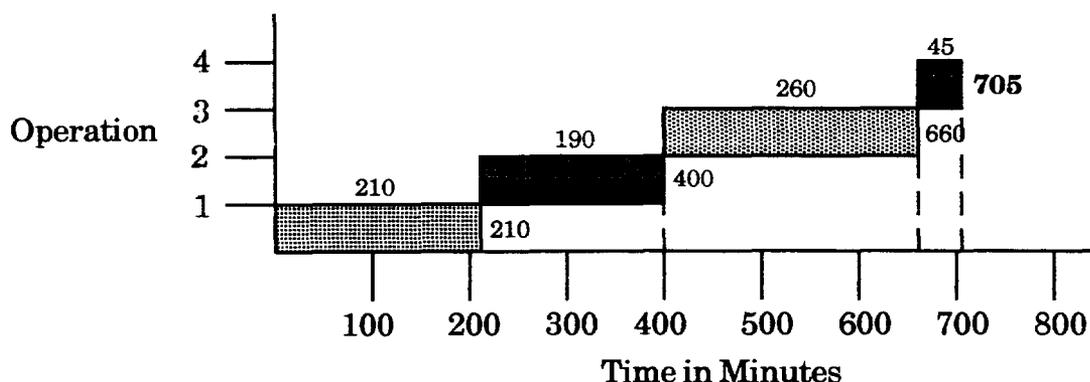
$$(2): (30 + 20* 8) = 190 \text{ min.}$$

$$(3): (20 + 20*12) = 260 \text{ min.}$$

$$(4): (5 + 20* 2) = 45 \text{ min.}$$

$$\text{Total MLT} = 705 \text{ min.}$$

Represented graphically, the MLT looks something like this:



Since 705 minutes \approx 12 hours, we calculate that work on the order should begin no later than 12 working hours before the order is to be shipped.

SimFactory, when given the same information and in the absence of variation, will calculate the same values. This is shown in the Operation Summary of the Replication Node/Operation Report for simulation MLT-1:

----- Operation Summary -----						
Name	Type	Count	Pct.	Total Time	Pct.	
DRILL FOUR H	Prt Setup	1	12.5	30.00	4.3	
FINAL INSPEC	Prt Setup	1	12.5	5.00	0.7	
FINISH GRIND	Prt Setup	1	12.5	20.00	2.8	
SQUARE UP BL	Prt Setup	1	12.5	10.00	1.4	
DRILL FOUR H	Processing	1	12.5	160.00	22.7	
FINAL INSPEC	Processing	1	12.5	40.00	5.7	
FINISH GRIND	Processing	1	12.5	240.00	34.0	
SQUARE UP BL	Processing	1	12.5	200.00	28.4	
Totals		8	100.0	705.00	100.0	

This information can also be found in summary form in the Final Products section of the Replication Part Status Report:

----- Final Products -----					
Part Name	Number Made	Minimum	Average	Std Dev	Maximum
INSPECTED	20	705.00	705.00	0.00	705.00

Introducing random variation into a system changes the results markedly, however. The values used to calculate processing times in the previous example were averages based on past experience. Specifying the distribution of the data causes SimFactory to produce radically different results. The distributions for the operations are shown in the following chart:

<u>Operation:</u>	<u>Distribution:</u>	<u>Mean:</u>	<u>Std. Dev.:</u>
(1) Square up Blocks	Exponential	10	10
(2) Drill four Holes	Normal	8	1.5
(3) Finish Grind	Normal	12	6
(4) Inspect	Normal	4	1.5

Below is the Final Products section of the Replication Part Status Report for simulation MLT-2. This simulation uses the same average values and processes the same number of parts as in our manual model and simulation MLT-1, but takes the distribution of the data into account as it simulates the manufacturing process.

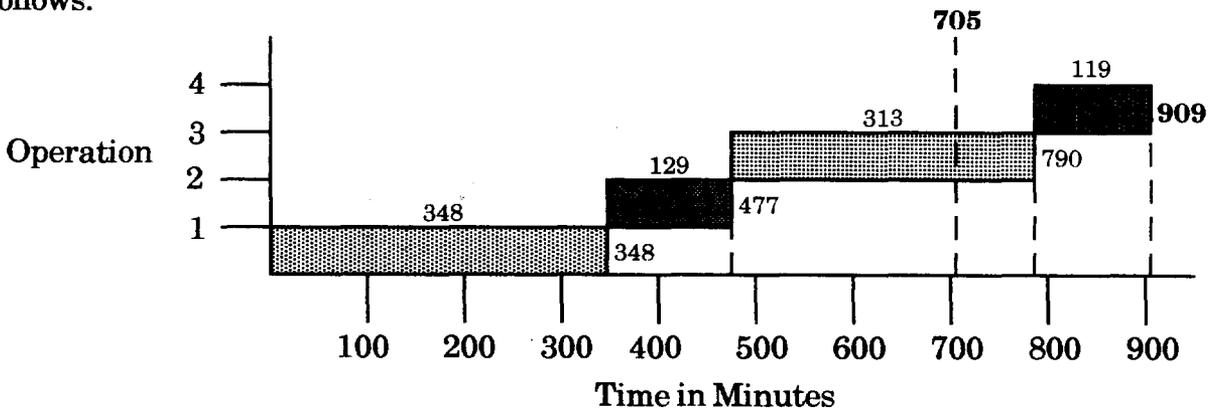
----- Final Products -----					
Part Name	Number Made	Minimum	Average	Std Dev	Maximum
INSPECTED	20	909.00	909.00	0.76	909.00

For a more in-depth look at what actually happened during the production run, we can check the Replication Node/Operation Report to see where the extra time came from:

Node Name	Op Name	Type	--- Count ---		----- Time -----	
			Num	(Pct)	Actual	(Pct)
DRILL PRESS	DRILL FOUR H	Processng	2	50.0	99.46	87.2
	DRILL FOUR H	Prt Setup	2	50.0	30.00	12.8
GRINDER	FINISH GRIND	Processng	2	50.0	293.27	94.9
	FINISH GRIND	Prt Setup	2	50.0	20.00	5.1
INSPECTION	FINAL INSPEC	Processng	2	50.0	113.42	95.4
	FINAL INSPEC	Prt Setup	2	50.0	5.00	4.6
ROUGHING MIL	SQUARE UP BL	Processng	2	50.0	337.85	97.1
	SQUARE UP BL	Prt Setup	2	50.0	10.00	2.9

Represented graphically, the true lead time to process the order is shown as

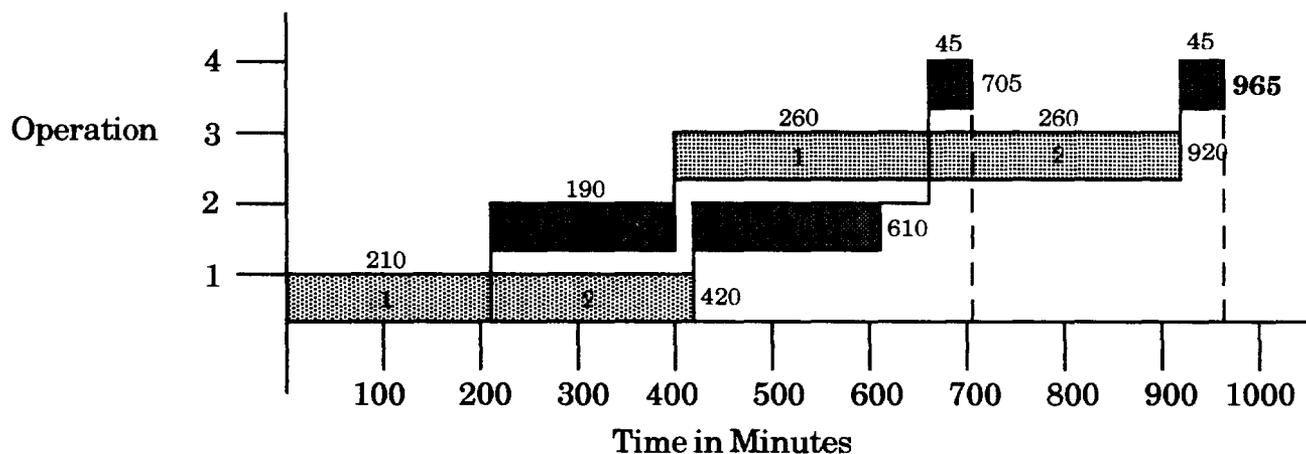
follows:



As shown above, three operations required more time than expected, while one required less. The total time required to process 20 blocks through the same four stations operating at the same speeds required 909 minutes, for a total increase of 204 minutes, or almost thirty percent! The production run will actually require 15 hours and 9 minutes to complete, rather than the 12 hours originally projected.

Perhaps the situation can be improved by increasing the number of parts produced, since larger sample sizes usually lead to in more reliable results. To check this hypothesis, a second batch of 20 parts is run through our simulated manufacturing system. To keep things simple, we will assume that a second setup is needed for tool changing and maintaining proper alignment of the equipment. Using manual calculations, we would expect the following results:

<u>Batch 1</u>	Elapsed Time	<u>Batch 2</u>	Total Elapsed Time
MLT = (1): $(10 + 20 \cdot 10) = 210$ min = 210 min.		(1): $210 + 210 =$	420 min.
(2): $210 \text{ min.} + (30 + 20 \cdot 8) = 400$ min.		(2): $420 + 190 =$	610 min.
(3): $400 \text{ min.} + (20 + 20 \cdot 12) = 660$ min.		(3): $660 + 260 =$	920 min.
(4): $660 \text{ min.} + (5 + 20 \cdot 2) = 705$ min.		(4): $920 + 45 =$	965 min.



According to the manual calculations and the accompanying graph of our production activity, we should expect two batches of 20 parts each to require 965 minutes, or just over 16 hours. Note that this is only about 51 minutes more time than our system actually required to process one batch of parts with statistical variation.

Using the same SimFactory model with statistical variation and increasing the number of batches from one to two, we obtain the following data:

SFII.5 (v.4.20) MLT-3 Replication Node/Operation Report
(From 0. Minutes to 1480.0 Minutes)

Node Name	Op Name	Type	--- Count ---		----- Time -----	
			Num	(Pct)	Actual	(Pct)
DRILL PRESS	DRILL FOUR H	Processng	2	50.0	353.15	85.5
	DRILL FOUR H	Prt Setup	2	50.0	60.00	14.5
GRINDER	FINISH GRIND	Processng	2	50.0	737.27	94.9
	FINISH GRIND	Prt Setup	2	50.0	40.00	5.1
INSPECTION	FINAL INSPEC	Processng	2	50.0	205.34	95.4
	FINAL INSPEC	Prt Setup	2	50.0	10.00	4.6
ROUGHING MIL	SQUARE UP BL	Processng	2	50.0	674.99	97.1
	SQUARE UP BL	Prt Setup	2	50.0	20.00	2.9

----- Final Products -----					
Part Name	Number	----- Product Make Span -----			
	Made	Minimum	Average	Std Dev	Maximum
INSPECTED	40	1035.75	1070.39	35.08	1105.03

In this simulation, Product Make Span (MLT) increased even further, to an average of 1070.39 minutes, or 17.8 working hours per batch. The production system required more time to finish the first batch than we expected it to use in producing two batches. Unfortunately, SimFactory does not report the time at which each batch enters and leaves a station, but this is only a minor concern. The more important question is: "Why are our manual calculations so inaccurate when we use the same data?" The answer lies in a very important statistical phenomena that the MLT formula fails to address.

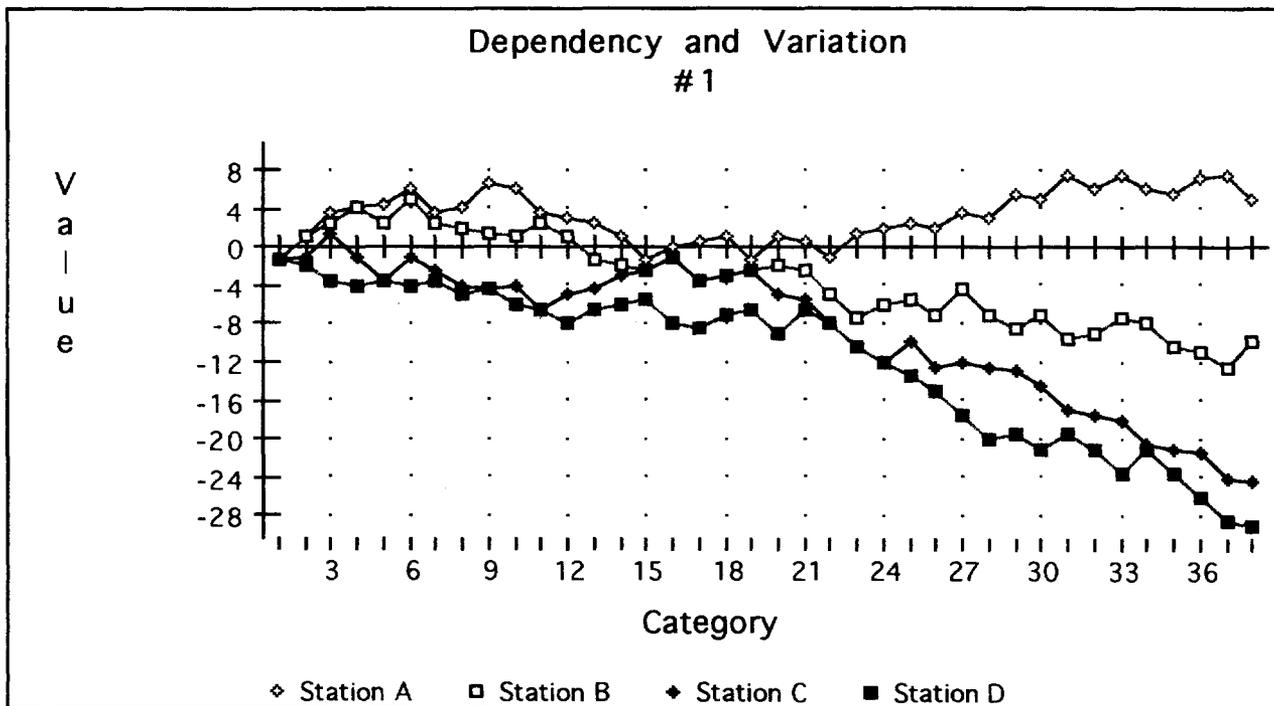
Inside a Simulation:

Is Variation the Key?

The MLT formula is indifferent to statistical variation, assuming that the use of averages for setup, operating, and non-operating times is sufficient. What if this assumption is incorrect, and variation plays a more important role in determining the behavior of manufacturing systems than the MLT formula indicates? To test this theory, we will perform some experiments that will allow us to observe the effects of variation as it is incorporated into a system.

We will begin with a simple system that processes parts through four stations, labeled A, B, C, and D. This time, however, we will use stations that all have exactly the same capacity so it is easier to manually predict our results (Goldratt, 105-112). To simplify calculations further, we will use parts per hour as the unit of measure, rather than minutes or hours per part. To determine how many units each station will produce per hour, we will roll a fair six-sided die. Each station will produce a minimum of one unit and a maximum of six units per hour. Therefore, the system should produce an average of three and one-half units per hour. Parts will be moved from station to station once an hour, with unfinished parts remaining in queues to be worked on in subsequent hours.

The following chart, Dependency and Variation #1, graphically illustrates the production activity for thirty-eight hours of simulated production, and is followed by an in-depth description of the first three hours of production activity. The horizontal line labeled 0 represents 3.5 units of production per hour, and the performance of the four stations is graphed in relation to this line. Work-in-process (WIP) is directly proportional to the vertical distance between a data point and that of the preceding station. Whenever two or more data points occupy the same position, there is no WIP between those points.



Our first roll for station A is a 2, so station A begins 1.5 units below average production levels. For station B, we get lucky and roll a 6. Unfortunately, because station A only completed two units in its first hour, station B can only produce a maximum of two parts in its first hour, no matter how high the roll. Therefore,

station B also begins at 1.5 units below average. Rolls for stations C and D are 4 and 3, leaving all four stations and the entire system 1.5 units short of our predicted average production.

Our second roll for station A is a 6, so station A produces 2.5 more units than expected, raising station A's total to 8 units, 1 more than predicted for two hours' production. We roll a second 6 for station B, so it also produces 2.5 more units than expected, also moving to 1 part ahead. Station C gets a 4, moving it up by .5 units to just 1 unit behind, and leaving 2 units in WIP, to be completed in the future. We roll a 3 for station D, so it loses another .5 units, falling two units behind and leaving a unit unfinished in its WIP queue. Keep in mind that although A and B are a unit ahead, the *system* is now two units behind.

On the third roll for station A, we get lucky again and roll another 6, moving station A another 2.5 units ahead, for a total of 3.5 more units produced than expected in three hours. Station B gets a 5, moving its total up to 3 units "ahead," and leaving one unit in WIP. Station C gets a 6 this time, and moves into positive territory, producing a total of 1.5 units more than expected while leaving one unit in WIP, since it received 5 units from B, and already had 2 units in WIP. D, however, falls farther back with a 2, leaving 4 more units in WIP for a total of 5. The first three stations have all produced more than required, yet the *system* is 3.5 units (one full hour) behind, even though all had the same capacity and the same random technique

was used to determine performance of all!

Because we already know that the average production rate for this factory is 3.5 units per hour, we can simply divide this rate into the desired amount of production to determine our MLT. This shortcut only applies when the production rate for the system is known. If an order for 20 units has been received, we simply divide 20 units by 3.5 units per hour to get 5.714 hours (rounded up to 6 hours since materials are moved on the hour). If we check the chart at six hours, however, we find that the system is already 4 units behind (See appendix A for exact values).

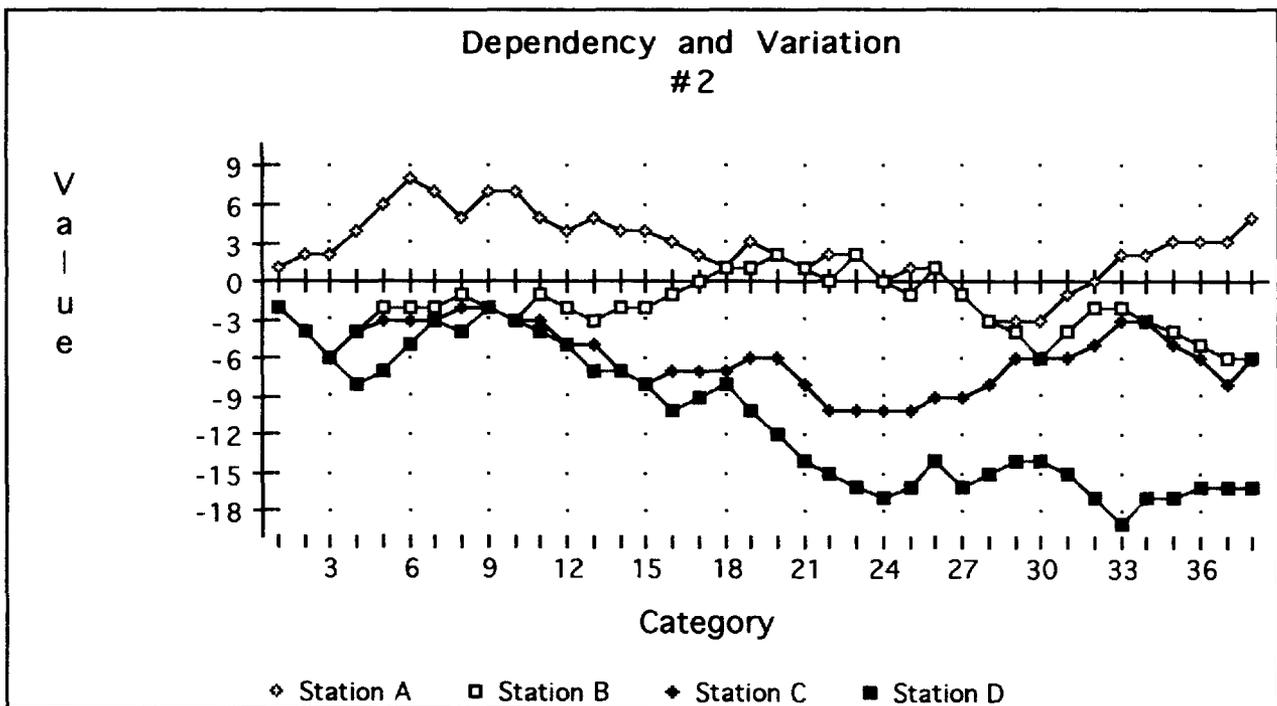
Even though all four stations had the same capacity, the amount of output dropped steadily from station to station, resulting in the system being a full 29 units behind after 36 hours, even though station A is 5 units ahead. Rather than 3.5 units per hour, the actual production rate for the system has fallen to about 2.7 units per hour. How does this relate to our earlier SimFactory and MLT calculations?

Each time we have performed a simulation with variation, our manual calculations predicting system performance have been shown to be grossly inaccurate. Statistical variation, however, is not the only cause of our problems. Returning to the chart Dependency and Variation #1, we can see that Station A has actually produced more units than expected, though the trend for Station A is relatively flat over the long-term. The reason the trends for the other stations go downward is that statistical variation is combined with another factor, dependency.

The Effects of Dependency

In every production system involving more than one step, dependency exists. In the previous example, the production process involved four steps, each taking place at a different station. Though all stations had the same theoretical capacity, they were actually limited by the production of the station ahead of them. This results in a passing along of the effects of variation at one station to those that follow.

This is clearly illustrated in Dependency and Variation #1 in the previous chapter and in the following chart, Dependency and Variation #2. D & V #2 was prepared using a random number table (see Appendices B and C) to choose production values from 1 to 5. The average production rate is therefore 3 units per hour, rather than 3.5. Although the system described by D & V #2 is not as far behind after 38 hours as the system in D & V #1, it is actually producing fewer units per hour, because the stations in D & V #2 have one-sixth less capacity than the stations in D & V #1.



The two charts clearly illustrate the effects of dependency on a system. Note that it is impossible for a data point from one station to rise above the data point for the previous station during the same hour. For this to occur, following stations would have to process parts that the preceding station had not yet finished. In addition, when stations A, B, or C experience positive variation in excess of that experienced by those which follow, the production gained is transformed into work-in process inventory, not finished goods. When A, B, and C experience negative variation during periods when there is no WIP to absorb these variations, their negative impact is passed on to the stations which follow. When this negative impact reaches station D, it results in a loss of production for the whole system in excess of that which can be compensated for by the normal variations in station D's performance. Because of dependency, the maximum variation exhibited by a preceding station is the minimum variation that the station which follows will exhibit (Goldratt, 113).

The Value of Computer Simulation

The weaknesses of using manual calculations in general and the MLT formula in particular to predict manufacturing performance have been made clear in the preceding chapters. These weaknesses were exposed through the use of manually-performed simulations that established the hidden importance of statistical variation and dependency. Manual simulations were performed because using manual calculations to prove these points is all but impossible. Unfortunately, there are limits to the usefulness of manual simulation as well.

Both the simulation using the die and the one using the random number table were unrealistic in important ways. In each simulation, the four stations had flat production distributions, either one to six or one to five. While changing the minimum and maximum number of units per hour is relatively easy, manually simulating a more realistically shaped distribution is not. We also began both simulations with empty, "caught up" production systems, something that only happens in the real world in plants that have just opened or just closed. Obviously, a computerized method of simulating production systems is needed. SimFactory manufacturing simulation software fills that need.

SimFactory allows the user to specify a "warm-up" period so the simulation does not begin with an empty production system, and the program can use any shape curve to model the performance of a station. For users who aren't certain what curve best describes a station's behavior, SimFactory provides a utility that will determine the shape of a station's performance curve when the raw data for that station's performance is entered. The program can keep track of products that follow different

routings through a plant, and model stations like furnaces or plating tanks that process several parts at once. Most importantly, SimFactory can simulate any size or type of production system. The only real limit to the program's ability is the validity of the assumptions upon which the model is based. Just as in the manual calculations and simulations, improper assumptions lead to erroneous conclusions.

Using SimFactory does have its drawbacks, however. The program itself is tremendously expensive - about \$20,000, and it requires the use of a relatively powerful desktop computer, adding to the cost if none are available. It is also difficult to work with. Many of the terms used by the program to describe its features and functions are not self-explanatory, and can be confusing to beginning users. When problems are encountered while a simulation is running, SimFactory either stops processing parts and waits for the simulation's time to run out, or it crashes and must be restarted. In both cases, the program gives few if any indications about the cause of the problem, leaving the user to either puzzle out the solution on his or her own or call CACI's offices in California for assistance.

These drawbacks limit the program's usefulness for many companies to the evaluation of major capital improvements or the designing of new plants and production lines. For this type of decision-making, SimFactory and other simulation software programs are invaluable, as they can provide a company's executives and officers with information that in the past could only be obtained by implementing a change and waiting to see what happened.

The decision to purchase and use SimFactory or another manufacturing simulation program should be based on the value of the decision at hand. Purchasing a twenty-thousand dollar computer program to help make a ten-thousand dollar

decision is not exactly cost-effective, but failing to use the same program to help make a five million dollar decision is taking an unnecessary risk, especially when the simulation may reveal a less-expensive way of achieving the company's goals. Once the program has been purchased and the models set up, however, the program may be used to help make as many decisions of any size as the company's officers and executives see fit.

Appendix A
Dependency and Variation #1

Hour	Station A	Station B	Station C	Station D
1	-1.5	-1.5	-1.5	-1.5
2	1	1	-1	-2
3	3.5	2.5	1.5	-3.5
4	4	4	-1	-4
5	4.5	2.5	-3.5	-3.5
6	6	5	-1	-4
7	3.5	2.5	-2.5	-3.5
8	4	2	-4	-5
9	6.5	1.5	-4.5	-4.5
10	6	1	-4	-6
11	3.5	2.5	-6.5	-6.5
12	3	1	-5	-8
13	2.5	-1.5	-4.5	-6.5
14	1	-2	-3	-6
15	-1.5	-2.5	-2.5	-5.5
16	0	-1	-1	-8
17	0.5	-3.5	-3.5	-8.5
18	1	-3	-3	-7
19	-1.5	-2.5	-2.5	-6.5
20	1	-2	-5	-9
21	0.5	-2.5	-5.5	-6.5
22	-1	-5	-8	-8
23	1.5	-7.5	-10.5	-10.5
24	2	-6	-12	-12
25	2.5	-5.5	-10	-13.5
26	2	-7	-12.5	-15
27	3.5	-4.5	-12	-17.5
28	3	-7	-12.5	-20
29	5.5	-8.5	-13	-19.5
30	5	-7	-14.5	-21
31	7.5	-9.5	-17	-19.5
32	6	-9	-17.5	-21
33	7.5	-7.5	-18	-23.5
34	6	-8	-20.5	-21
35	5.5	-10.5	-21	-23.5
36	7	-11	-21.5	-26
37	7.5	-12.5	-24	-28.5
38	5	-10	-24.5	-29

Appendix B
Dependency and Variation #2

Hour	Station A	Station B	Station C	Station D
1	1	-2	-2	-2
2	2	-4	-4	-4
3	2	-6	-6	-6
4	4	-4	-4	-8
5	6	-2	-3	-7
6	8	-2	-3	-5
7	7	-2	-3	-3
8	5	-1	-2	-4
9	7	-2	-2	-2
10	7	-3	-3	-3
11	5	-1	-3	-4
12	4	-2	-5	-5
13	5	-3	-5	-7
14	4	-2	-7	-7
15	4	-2	-8	-8
16	3	-1	-7	-10
17	2	0	-7	-9
18	1	1	-7	-8
19	3	1	-6	-10
20	2	2	-6	-12
21	1	1	-8	-14
22	2	0	-10	-15
23	2	2	-10	-16
24	0	0	-10	-17
25	1	-1	-10	-16
26	1	1	-9	-14
27	-1	-1	-9	-16
28	-3	-3	-8	-15
29	-3	-4	-6	-14
30	-3	-6	-6	-14
31	-1	-4	-6	-15
32	0	-2	-5	-17
33	2	-2	-3	-19
34	2	-3	-3	-17
35	3	-4	-5	-17
36	3	-5	-6	-16
37	3	-6	-8	-16
38	5	-6	-6	-16

(Riggs, 707)

APPENDIX C TABLE OF RANDOM NUMBERS*

03 99 11 04 61	93 71 61 68 94	66 08 32 46 53	84 60 95 82 32	88 61 81 91 61
38 55 59 55 54	32 88 65 97 80	08 35 56 08 60	29 73 54 77 62	71 29 92 38 53
17 54 67 37 04	92 05 24 62 15	55 12 12 92 81	59 07 60 79 36	27 95 45 89 09
32 64 35 28 61	95 81 90 68 31	00 91 19 89 36	76 35 59 37 79	80 86 30 05 14
69 57 26 87 77	39 51 03 59 05	14 06 04 06 19	29 54 96 96 16	33 56 46 07 80
24 12 26 65 91	27 69 90 64 94	14 84 54 66 72	61 95 87 71 00	90 89 97 57 54
61 19 63 02 31	92 96 26 17 73	41 83 95 53 82	17 26 77 09 43	78 03 87 02 67
30 53 22 17 04	10 27 41 22 02	39 68 52 33 09	10 06 16 88 29	55 98 66 64 85
03 78 89 75 99	75 86 72 07 17	74 41 65 31 66	35 20 83 33 74	87 53 90 88 23
48 22 86 33 79	85 78 34 76 19	53 15 26 74 33	35 66 35 29 72	16 81 86 03 11
60 36 59 46 53	35 07 53 39 49	42 61 42 92 97	01 91 32 83 16	98 95 37 32 31
83 79 94 24 02	56 62 33 44 42	34 99 44 13 74	70 07 11 47 36	09 95 81 80 65
32 96 00 74 05	36 40 98 32 32	99 38 54 16 00	11 13 30 75 86	15 91 70 62 53
19 32 25 38 45	57 62 05 26 06	66 49 76 86 46	78 13 86 65 59	19 64 09 94 13
11 22 09 47 47	07 39 93 74 08	48 50 92 39 29	27 48 24 54 76	85 24 43 51 49
31 75 15 72 60	68 98 00 53 39	15 47 04 83 55	88 65 12 25 96	03 15 21 91 21
88 49 29 93 82	14 45 40 45 04	20 09 49 89 77	74 84 39 34 13	22 10 97 85 08
30 93 44 77 44	07 48 18 38 28	73 78 80 65 33	28 59 72 04 05	94 20 52 03 80
22 88 84 88 93	27 49 99 87 48	60 53 04 51 28	74 02 28 46 17	82 03 71 02 68
78 21 21 69 93	35 90 29 13 86	44 37 21 54 86	65 74 11 40 14	87 48 13 72 20
41 84 98 45 47	46 85 05 23 26	34 67 75 83 00	74 91 06 43 45	19 32 58 15 49
46 35 23 30 49	69 24 89 34 60	45 30 50 75 21	61 31 83 18 55	14 41 37 09 51
11 08 79 62 94	14 01 33 17 92	59 74 76 72 77	76 50 33 45 13	39 66 37 75 44
52 70 10 83 37	56 30 38 73 15	16 52 06 96 76	11 65 49 98 93	02 18 16 81 61
57 27 53 68 98	81 30 44 85 85	68 65 22 73 76	92 85 25 58 66	88 44 80 35 84
20 85 77 31 56	70 28 42 43 26	79 37 59 52 20	01 15 96 32 67	10 62 24 83 91
15 63 38 49 24	90 41 59 36 14	33 52 12 66 65	55 82 34 76 41	86 22 53 17 04
92 69 44 82 97	39 90 40 21 15	59 58 94 90 67	66 82 14 15 75	49 76 70 40 37
77 61 31 90 19	88 15 20 00 80	20 55 49 14 09	96 27 74 82 57	50 81 69 76 16
38 68 83 24 86	45 13 46 35 45	59 40 47 20 59	43 94 75 16 80	43 85 25 96 93
25 16 30 18 89	70 01 41 50 21	41 29 06 73 12	71 85 71 59 57	68 97 11 14 93
65 25 10 76 29	37 23 93 32 95	05 87 00 11 19	92 78 42 63 40	18 47 76 56 22
36 81 54 36 25	18 63 73 75 09	82 44 49 90 05	04 92 17 37 01	14 70 79 39 97
64 39 71 16 92	05 32 78 21 62	20 24 78 17 59	45 19 72 53 32	33 74 52 25 67
04 51 52 56 24	95 09 66 79 46	48 46 08 55 58	15 19 11 87 82	16 93 03 33 61
83 76 16 08 72	43 25 38 41 45	60 33 32 59 83	01 29 14 13 49	20 36 80 71 26
14 38 70 63 45	80 85 40 92 79	43 52 90 63 18	38 38 47 47 61	41 19 63 74 80
51 32 19 22 46	80 08 87 70 74	88 72 25 67 36	66 16 44 94 31	66 91 93 16 78
72 47 20 00 08	80 89 01 80 02	94 81 33 19 00	54 15 58 34 36	35 35 25 41 31
05 46 65 53 06	93 12 81 84 64	74 45 79 05 61	72 84 81 18 34	79 98 26 84 16
39 52 87 24 84	82 47 42 55 93	48 54 53 52 47	18 61 91 36 74	18 61 11 92 41
81 61 61 87 11	53 34 24 42 76	75 12 21 17 24	74 62 77 37 07	58 31 91 59 97
07 58 61 61 20	82 64 12 28 20	92 90 41 31 41	32 39 21 97 63	61 19 96 79 40
90 76 70 42 35	13 57 41 72 00	69 90 26 37 42	78 46 42 25 01	18 62 79 08 72
40 18 82 81 93	29 59 38 86 27	94 97 21 15 98	62 09 53 67 87	00 44 15 89 97
34 41 48 21 57	86 88 75 50 87	19 15 20 00 23	12 30 28 07 83	32 62 46 86 91
63 43 97 53 63	44 98 91 68 22	36 02 40 08 67	76 37 84 16 05	65 96 17 34 88
67 04 90 90 70	93 39 94 55 47	94 45 87 42 84	05 04 14 98 07	20 28 83 40 60
79 49 30 41 46	52 16 29 02 86	54 15 83 42 43	46 97 83 54 82	59 36 29 59 38
91 70 43 05 52	04 73 72 10 31	75 05 19 30 29	47 66 56 43 82	99 78 29 34 78

*The random numbers in this appendix were developed by the Rand Corporation.

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