USING SIMULATION TO EVALUATE ALTERNATIVE MANUFACTURING POLICIES

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Abstract

Many tools are available to the engineer involved with planning, optimizing, and structuring production environments and policies. One tool, digital simulation, offers the flexibility and power to quickly build and manipulate manufacturing models. This paper demonstrates that digital simulation is beneficial in comparing manufacturing policies and assigning resources. Simulation allows the engineer to build different manufacturing models, examine different polices, and investigate different resource assignments. Using a production line model, two manufacturing policies are examined. The time to build the first and last final assembly and the amount of time subassemblies wait in holding queues are analyzed and compared against policy candidates. Also shown is how simulation can aid in assigning an extra resource. The production model in this study has four people-driven workstations and starts with one person at each station. The model is used to show where an extra resource is and is not useful.

Introduction

Ideally, the impact of a policy changes on a production system should be well understood before implementation. Modeling is one approach that can be used to provide a production engineer with the means to evaluate policy changes prior to implementation. Modeling allows the system's performance to be analyzed. When issues arise, such as having to decide where to add more resources, the model is used to evaluate alternatives, eliminating options that reduce the performance of the system. Without the model, selecting between alternative policies may be based on heuristics and may result in decreases in system performance.

Resources are often limited, so analysis of policy impacts is difficult. We are often reacting to the impact of policy changes, rather than being proactive. Resources that could have been used to analyze policy impacts are then consumed dealing with emergencies. As long as the resources continue to focus on these emergencies, the system cannot effectively analysis policy impacts.

Many tools are available to model production systems. This study looked at four possible modeling approaches: Simulation, TABU Algorithms, Genetic Algorithms and the Program Evaluation and Review Technique / Critical Path Method (PERT/CPM). A non-compensatory multi-criteria decision analysis approach was used to select the approach that best supported the test bed used in this study; a manual production assembly line. While all four approaches can be used to support analysis of policy impact on a process, each was found to have different strengths and weaknesses that influence their effectiveness. The simulation approach was selected as the most appropriate modeling approach for this test bed. Alternative production policies were then analyzed using the simulation approach, and the results are reported in this paper.

Background.

Both the TABU and genetic algorithms are used for scheduling. The TABU algorithm starts with an existing schedule and works to improve it. A search methodology is used to determine and evaluate alternative schedules. The iterative approach compares possible schedule candidates and, using a predetermined criterion, either accepts it as better or rejects it. The end result is an optimum sequence in which jobs should be performed. Variability for each job is not considered with this algorithm.

TABU and genetic algorithms are similar. The TABU algorithm can generate multiple schedules, but only carries one schedule to the next iteration. A genetic algorithm performs an iterative search in which several schedules are generated and each is carried to the next step. Genetic algorithms are useful in cases where little is known about the system, so the algorithm will explore many different schedules at one time. One problem with genetic algorithms is they can use considerable computer resources and can be time consuming. As like with the TABU algorithm, the end result is a calculated job sequence. And like the TABU algorithm the variability associated with each job is not considered.

Using the TABU and genetic algorithms is more beneficial when job preemptions are allowed. It can become much simpler when a single machine is used for a non-preemptive sequence of jobs. (Pinedo and Chao, 1999)

The PERT/CPM method is a good way for determining which path in a sequence of paths will take the longest time. This path is called the critical path. PERT/CPM provides a systematic approach to build a schedule, identify possible bottlenecks and examine resource loading. Introduction to Operations Research describes the following procedure for the PERT/CPM. The PERT/CPM method first identifies the activities required to carry out the project. Next, the time required for each activity is estimated. A network is built showing the required sequence activities must occur. Once this sequence is established more information can be obtained about the manufacturing system than can be from either the TABU or genetic algorithms. The critical path can be identified, the expected start and ending times for the jobs can be calculated, and probabilities of completing the project within a certain time can be determined (Hillier and Lieberman, 2001).

Simulation is a powerful and flexible tool that can be used to analyze a system. Simulation imitates a real-world system – in our case, a manufacturing system. An artificial history is generated showing how the system behaves over time. Once a model is developed and validated, considerable information can be obtained regarding the system including: the throughput of the system, bottleneck locations, and time spent within queues. Changes can be made to the model and "what-if" questions answered such as, "What if resources are scheduled differently?" or, "What if an hour of overtime is worked?" (Banks, Carson, Nelson and Nicol, 2001)

Hypotheses

Tools such as the PERT/CPM method, genetic algorithms, and the TABU algorithm are useful in modeling a production system and should be considered when time and resources are available. When there are many unknowns and resources are limited, simulation is a valuable tool.

The test bed used in this study is one in which a new product is being introduced and the production run is expected to last up to a full year. Operators perform all tasks manually. Because the production system is machine paced, variability within the operation is significant. The current policy is to build sub-assemblies according to a work order. All sub-assemblies required are built to completion and the entire work order is closed. The sub-assemblies are moved as a single transfer batch to the next station. With large orders, sub-assemblies may be temporarily stored on the shop floor awaiting completion of the final assembly to close out the work order, while the next workstation is waiting on this sub-assembly.

There are issues to consider when implementing a manufacturing policy utilizing larger work order sizes and requiring order completion before proceeding to the next production stage. The first assemblies built are stored until the entire work order is complete and storage is not a value added operation. The next production stage needing this sub-assembly can sit idle while a required sub-assembly is available but cannot be "pulled" until its work order is complete.

The production line examined in this study has a fixed number of workstations with one person performing the labor. Adding workers to the workstation increases the manufacturing rate for that station. Once one worker is placed at each workstation and extra workers are available but there are not enough workers to place an equal number at each workstation, analysis is required to locate the better location to place the extra workers. With no analysis, the selection of worker placement reduces to a random or "best guess" process. It is conceivable that the placement of an extra worker could have no effect on the throughput.

The TABU algorithm, genetic algorithms, the PERT/CPM method, and simulation are examined to compare their value in addressing these manufacturing issues. When time and resources allow one manufacturing tool to be used, simulation provides useful information.

Methodology

To validate the value of simulation and its selection for the purpose of comparing manufacturing policies and assigning resources, it was compared against the other three selected tools. A non-compensatory decision analysis was applied. The following seven parameters were considered: the ability to assign resources, the ability to restrict sequences of events, the ability to identify bottlenecks, the ability to schedule start times, includes variability, is dynamic, and the ability to make statistical predictions. Each parameter was selected because of its usefulness in understanding the manufacturing system described. Because this procedure is unique to the environment and needs of the manufacturing facility, results will change with the workplace and engineering needs.

Exhibit 1. Summary of the Decision Analysis.

Attribute	TABU	Simulation	Genetic Algorithms	Pert / CPM
Assign Resources	No	Yes	No	Yes
Sequence Restrictions	No	Yes	No	Yes
Identify Bottlenecks	No	Yes	No	Yes
Schedule Start Times	Yes	Yes	Yes	Yes
Allow Variability	No	Yes	No	Yes
Dynamic	No	Yes	No	No
Prediction Capability	No	Yes	No	Yes

It can be seen that among the four tools being evaluated, simulation has more value for developing an initial working knowledge of the manufacturing system. The attributes selected were those applicable to the manufacturing environment described. For a different manufacturing environment with different needs, the selection of a different tool may be appropriate.

The model built simulates the production environment described previously. The dependent variable for this simulation is the manufacturing policy. Two manufacturing policies are considered. One policy allows sub-assemblies to be pulled whenever needed and available; the other policy states that the work order must be complete before the sub-assemblies may be issued.

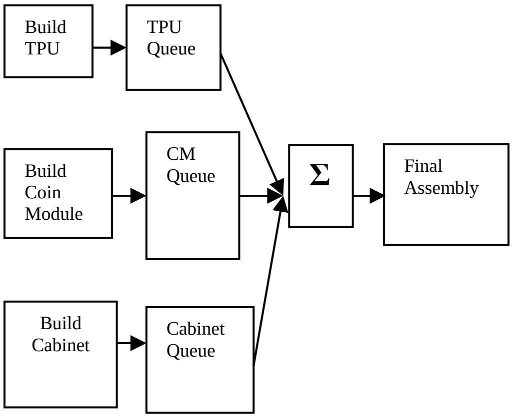
The independent variables for this simulation are the wait times for the assemblies and the build times for each sub-assembly and the final assembly. The work order batch size and number of resources were varied identically for the different policies.

A transit bus fare box production line was selected to model and analyze. The fare box accepts coins, tokens, or magnet fare cards and allows a passenger to ride the transit bus. A fare box consists of a coin module, a magnetic ticket module, and a cabinet with the operator interface installed. Manufacturing a fare box requires four processes: assembling the coin module; the ticket-processing unit; the cabinet; then combining the three in a final assembly. Estimates for each processing time were acquired. The expected, pessimistic, and optimistic process times were estimated. The simulation model consists of three independent processes – one for each subassembly and a process that models the final assembly. Each subassembly built is held in a queue. For the two cases considered here, one of two events occur. Either all of the required subassemblies are built and then the final assembly process begins, or as soon as the final assembly process needs a subassembly and the subassembly is in its queue, it may be pulled and used.

The number of people at each process was varied. Initially there was one person at each process. Systematically, one extra person was walked through each process. The last combination uses two people placed at each process. All of this is done for five different work order batch sizes: 1, 5, 10, 15 and 20. The time spent waiting in a queue and the throughput times were studied for these different work order sizes and for differing numbers of resources. Twenty replications were run for each combination of batch size and resource count.

ARENA version 5.0 (student version) was used to perform the simulation.

Exhibit 2. Simulation Model Logic Flow.



A triangular distribution, being a reasonable distribution to use when no data is available, was used to model each process (Law and Kelton, 2000).

Exhibit 3. Triangular Distribution Inputs.

Process Distributions			
Process	**Optimistic**	**Mean**	**Pessimistic**
Coin Module	3.75 hrs.	4.75 hrs	6 hrs
Ticket Unit	2.6 hrs.	3.72 hrs	5.6 hrs
Cabinet	5 hrs.	6.25 hrs	8 hrs
Final Assembly	18 min.	21 min	40 min

Initially, entities are dumped into the three-subassembly production lines. The number of entities corresponds to the batch size being built. A holding queue is used to hold the assemblies until needed. Variables are used to count the coin modules, ticket unit, and cabinets built. During the pull policy simulation, the variables are checked to see if the value is greater than or equal to one. When a coin module, ticket unit, and cabinet are available, the final assembly is allowed to begin and one coin module, ticket unit and cabinet are subtracted from their respective counter variable. The policy stating that the final production stage does not begin until the work orders driving the subassemblies are built to completion was simulated by waiting until the three-counter variables equal the batch size. In both cases, run time was adjusted so that each batch size could be completed.

Validation of the models was performed by removing all the variability found in the processing times and calculations were performed to confirm that the model matched with the mathematical predictions using constant processing rates.

Results

Exhibit 4 shows the time at which the first and last final assembly was built.

Exhibit 4. Average Build Times

	First Unit Built		**Last Unit Built**	
WO Size	**Pull (Hrs.)**	**WO Complete (Hrs.)**	**Pull (Hrs.)**	**WO Complete (Hrs.)**
1	6.99	6.97	6.99	6.97
5	7.01	32.55	33.05	34.23
10	7.01	64.89	65.41	68.86
15	7.01	97.21	97.46	103.31
20	7.01	128.84	129.81	137.19

Exhibits 5 and 6 show the 95% confidence intervals on the mean build time for the first and last unit built. Exhibit 5 shows the confidence intervals for the pull policy and exhibit 6 shows the confidence intervals (CIs) for the wait policy.

Exhibit 5. Mean Build Time 95% CIs Pull Policy.

Pull Policy W.O. Size	**First Built Time (hrs.)**	**Last Built Time (hrs.)**
1	(6.70, 7.28)	
5	(6.72, 7.30)	(32.44, 33.67)
10	(6.72, 7.29)	(64.30, 66.52)
15	(6.72, 7.30)	(96.24, 98.69)
20	(6.72, 7.30)	(128.16, 131.46)

Exhibit 6. Mean Build Time 95% CIs Wait Policy

Wait Policy W.O. Size	**First Built Time (hrs.)**	**Last Built Time (hrs.)**
1	(6.70, 7.24)	
5	(31.79, 33.31)	(33.56, 34.90)
10	(63.81, 65.96)	(67.79, 69.94)
15	96.29, 98.13)	(102.39, 104.23)
20	(127.51, 130.18)	(135.81, 138.57)

With the pull policy, the first fare box is built much sooner than with the policy that waits for work order completions. Exhibit 7 shows the time a built subassembly waits before being used in production.

Exhibit 7. Average Wait Times.

	Built CMs		**Built TPUs**		**Built Ucs**	
WO Size	**Pull**	**WO Complete**	**Pull**	**WO Complete**	**Pull**	**WO Complete**
1	1.86	1.86	2.52	2.52	0.44	0.44
5	2.86	17.47	3.00	20.26	0.45	14.07
10	2.84	37.45	3.03	42.74	0.44	31.25
15	2.77	57.47	2.96	65.28	0.44	48.59
20	2.81	76.89	2.94	86.96	0.44	65.55

As expected, assemblies wait less with the pull policy than with the waiting policy. Obviously, the wait times get longer as the batch size increases.

Waiting for the work order to be completed before a sub-assembly can be used is risky. Manufacturing problems would be discovered much later using this policy.

Next, the simulation model was used to examine manufacturing times and the effect of adding an additional resource to a process. Both manufacturing policies were considered. Five setups were examined, adding one person to a station while keeping one at the other three and having two people at all, four stations. Exhibits 8 and 9 show the mean times to build the first unit and last unit for the two policies as the resource assignment change.

Exhibit 8. Policy Results when Sorting is Done by Pull System.

Policy = PULL – Sorted By W.O. Size						
CM	**TPU**	**UC**	**Final**	**Size**	**First Built**	**Last Built**
1	1	1	1	1	6.99	6.99
2	1	1	1	1	6.99	6.99
1	2	1	1	1	6.99	6.99
1	1	2	1	1	6.99	6.99
1	1	1	2	1	6.99	6.99
2	2	2	2	1	6.99	6.99
1	1	1	1	5	7.01	33.05
2	1	1	1	5	6.9	32.8
1	2	1	1	5	6.89	32.53
1	1	2	1	5	6.7	*24.49*
1	1	1	2	5	7.01	33.05
2	**2**	**2**	**2**	**5**	**6.68**	**19.77**
1	1	1	1	10	7.01	65.41
2	1	1	1	10	6.9	64.28
1	2	1	1	10	6.89	65
1	1	2	1	10	6.7	*48.03*
1	1	1	2	10	7.01	65.41
2	**2**	**2**	**2**	**10**	**6.68**	**33.71**
1	1	1	1	15	7.01	97.46
2	1	1	1	15	6.9	96.29
1	2	1	1	15	6.89	97.42
1	1	2	1	15	6.7	*72.48*
1	1	1	2	15	7.01	97.47
2	**2**	**2**	**2**	**15**	**6.68**	**51.26**
1	1	1	1	20	7.01	129.81
2	1	1	1	20	6.9	128.7
1	2	1	1	20	6.89	129.67
1	1	2	1	20	6.7	*96.16*
1	1	1	2	20	7.01	129.81
2	**2**	**2**	**2**	**20**	**6.68**	**65.5**

The results from this study rule out some setups. It was shown that adding one additional resource to the coin module, the ticket processing unit, or the final assembly station had no affect on manufacturing times. Doubling the resources at the upper cabinet assembly station did show some decrease in the manufacturing times to complete the last unit. The shortest manufacturing time to complete the last final assembly occurred when the resources were doubled at every station and the work order size was greater than one.

There was no difference in the manufacturing times no matter the number of people at the stations when the work order size was one. These results apply to either manufacturing policy. Exhibit 8 shows the times to build the first and last final assembly while the number of resources and work order size are changed for the four manufacturing stations for the pull policy.

Exhibit 9 shows the times to build the first and last final assembly while the number of resources and work order size are changed for the four manufacturing stations for the pull policy

Exhibit 9. Policy Results when Operator Waits for Work Order.

Policy = Wait For W.O. – Sorted By W.O. Size						
CM	**TPU**	**UC**	**Final**	**Size**	**First Built**	**Last Built**
1	1	1	1	1	6.97	6.97
2	1	1	1	1	6.99	6.99
1	2	1	1	1	6.99	6.99
1	1	2	1	1	6.99	6.99
1	1	1	2	1	6.99	6.99
2	2	2	2	1	6.99	6.99
1	1	1	1	5	32.55	34.23
2	1	1	1	5	32.67	34.51
1	2	1	1	5	32.5	34.34
1	1	2	1	5	24.27	*26.1*
1	1	1	2	5	32.51	33.39
2	2	2	2	5	19.17	20.05
1	1	1	1	10	64.89	68.86
2	1	1	1	10	64.8	68.78
1	2	1	1	10	64.75	69.73
1	1	2	1	10	48.37	*52.34*
1	1	1	2	10	64.82	66.75
2	2	2	2	10	33.36	35.33
1	1	1	1	15	97.21	103.31
2	1	1	1	15	96.79	102.99
1	2	1	1	15	97	103.1
1	1	2	1	15	72.7	*78.8*
1	1	1	2	15	97.15	100.16
2	2	2	2	15	51.3	54.29
1	1	1	1	20	128.84	137.19
2	1	1	1	20	128.75	137.13
1	2	1	1	20	128.05	136.41
1	1	2	1	20	96.83	*105.22*
1	1	1	2	20	128.78	132.91
2	2	2	2	20	66.08	70.2

Conclusions

Many tools are available to assist in production planning. When engineering time and resources are limited, simulation is shown to be the tool of choice for rapid evaluation of the production environment. Simulation can answer production questions quickly and eliminate some setups without trying them on the manufacturing floor. The model in this paper eliminated possible resource configurations by demonstrating how simulation may be used to address placement of extra resources. Simulation can be used to examine different manufacturing policies. This paper compared two policies – one, which allowed a subassembly to be used when ready, and one requiring the work order to be completed before the subassembly can be used in subsequent manufacturing stages.

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