

USING SIMULATION TO EXPLORE POTENTIAL IMPROVEMENTS
IN AN EXISTING AUTOMATED ASSEMBLY SYSTEM

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ABSTRACT

A newly-installed, nonsynchronous, palletized assembly system was analyzed extensively, using simulation and automatically-collected machine fault data, to examine the viability of proposed improvements and to identify additional areas of opportunity for improvement.

The completely serial line, with very limited buffering, performed at a fraction of its specified throughput when first installed. Simulation, using the SIMAN simulation language (Systems Modeling Corp., Sewickley, Pennsylvania), was first employed to determine the effects of certain proposed changes. Thorough model validation and accurate analysis were facilitated through the use of computer-collected machine fault data. By fitting probability distributions to the data, the data could be easily manipulated for experimentation.

When the simulation showed that the proposed changes would fail to produce the required output, the simulation study continued, with the objectives of isolating the areas of greatest opportunity and steering redesign efforts in the direction of greatest return.

And finally during the course of the study, the simulation model came to be relied on as an operational tool, used to understand the implications of, and requirements for, short-term changes in operating patterns and production requirements.

This paper will explore the methodology employed, including data preparation, and the conclusions reached.

1. INTRODUCTION

Simulation, as a manufacturing tool, can be employed at various stages, from birth to death, in the life cycle of a manufacturing system. Of course the ideal would be to use it at every applicable stage, from conceptual design to capacity determination to ongoing operations. Generally, the earlier in the life cycle that simulation is first employed, the greater the potential influence and potential benefit. However, simulation is a tool often employed once things have already gone wrong; this paper describes an example of such a case, and how simulation methodologies were adopted in attempts to remedy the problems.

After characterizing the manufacturing system under consideration here, we will relate the methodologies used for the collection and analysis of data. We will also review the use of the data in the SIMAN simulation model, including some pitfalls to avoid. Finally we will deal with the experimentation phases of the study and review the results.

2. THE MANUFACTURING SYSTEM

The system under consideration (Figure 1) is a palletized, nonsynchronous, serial transfer line with six automatic assembly stations, a manual unload station, and an automatic pallet reset station. One of the assembly stations (station 4) is fed directly from an in-line fabrication process; the remaining assembly stations are bowl-fed. There are two automatic inspection points which can direct the pallet to each of two repair loops. Finally, a crossover is provided for an empty pallet to bypass the downstream stations if the part cannot be repaired and must be removed from the pallet at the first repair loop. Buffering between each of the assembly stations is very limited.

The system is designed to assemble two part types randomly, with unique pallets for each part type; four of the six assembly stations are capable of performing the tasks required for either of the part types (though three of the four require more time to complete one part type than the other). However, the last step in the process requires separate stations for each part type.

One contributor to the system's problems, other than mechanical failure, was the failure on the part of the system designers to view the manufacturing line as a system rather than as a group of independent machines. Unfortunately, experience has shown that this is not an uncommon oversight. Initially this failure to take a systemic view of equipment surfaces in the assessment of the system's capacity, which often is calculated as a function of slowest machine cycle time (mean) and some efficiency factor to cover breaks and downtime. Unfortunately, this philosophy does nothing to account for the problems of blocking and starving in a limited-buffering system, nor for the variability imposed by different part types and downtime.

Furthermore, this lack of a "system view" can cause problems long after the design stage: Improvements may be made to some of the stations individually resulting in little or no net system improvement, due to continuing problems either up- or downstream. Even worse, improvements known not to have a direct impact on system throughput, but which may be required in conjunction with some other change to show system improvement, may be avoided because, taken out of the context of the system, they cannot be cost-justified.

However, without some sort of model, capturing the intricacies and variability in this system would be difficult at best, if not impossible. Furthermore, the vendor delivered a system with machine downtimes far in excess of anything that may have been anticipated, further exacerbating the situation. And hence, simulation entered the fray.

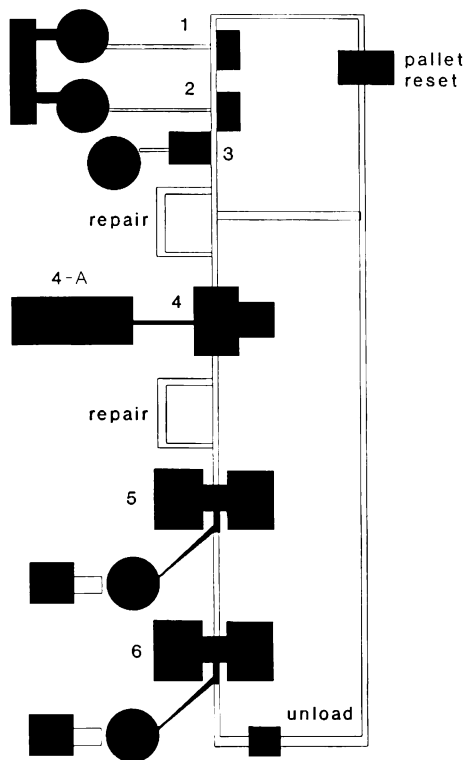


Figure 1. System Layout -- Original Design

3. TREATMENT OF INPUT DATA

3.1 Data Collection

One potential advantage of a simulation study performed at this late stage is the availability of "real data", rather than "best guesses" which must often be used prior to system implementation. Additionally, the real system provides the means to accomplish the often-impossible model validation step - system output can readily be compared with simulated output to validate the simulation model.

Coincidentally, this assembly system had been a pilot implementation for an automatic, data-collection system. The data-collection system, VISTA by Allen Bradley, is custom-programmed for each application to record or monitor information as required. In this application, VISTA records machine fault information as diagnosed by the PLC (programmable logic controller), with time of fault occurrence, duration, and fault type recorded for each machine on the manufacturing line. It was also programmed to record blocking and starving statistics for each station, total cycle counts, average cycle times, part defect frequency, total downtime, etc.

3.2. Data Representation

There are at least two options for use of "real" (observed) data in a simulation model: 1) use probability distributions to represent the data, or 2) use the data directly instead of sampling from a representative distribution. For this application, the latter methodology was discarded, due to model and data management concerns, as well as experimentation issues.

The choice of options noted above is a complicated issue, which will not be explored fully here. There are several factors which may influence the simulation practitioner's choice of method, including, but not limited to, number of observations available, experimentation required, feasibility of use of sample versus use of a distribution. Law [1982] does not recommend the use of observed data for simulation experimentation. Observed data is recommended for use, however, in model validation, particularly as a method akin to variance-reduction techniques, to compare simulation-generated output with observed output for the period over which the data was collected.

Strictly speaking, collected data points are merely a sample of some underlying distribution. Subsequent experimentation using only the observed data would be limited to the number of observations actually collected, and would be subject to the (unknown) factors which contributed to the particular non-random sequence of the collected data points. Additionally, some types of experimentation are very difficult, if not impossible, to perform with observed data sets rather than a probability distribution. For example, if we want to test the sensitivity of an input element to variability, it is a simple task to change the variance parameter of a distribution, but an impractical task to change the variance of sample.

No conclusions are drawn here as to which method, use of observed data or probability distributions, is most suitable for simulation analysis in general. Instead, we will assert only that, in this case, data management (of literally hundreds of fault files) and experimentation concerns (such as the example given above) drove the decision toward use of probability distributions.

3.3. Data Preparation

Two measures are required to define machine downtime: duration and frequency. Often, sometimes erroneously, downtime frequency in simulation models is structured based on time alone. In other words, machine failures are scheduled to occur based on time, rather than machine use. In the case where a machine runs continuously, whether or not parts are being processed, e.g., an oven, this is an accurate representation. Similarly, in the case where a machine is stand-alone, restricted neither by input nor output buffers, it may be safe to assume that the machine is running (and processing parts) during all available time.

However, in many cases, machines do not run because they are either blocked or starved by other machines in series. This causes idle time on a machine which should not contribute to downtime frequency. The most direct way to avoid the difficult problem of accounting for idle time (in a simulation model) is to base failure frequency on machine cycles rather than time. To do so requires that each time a part is processed through a machine, the cycle count be incremented and then compared to the randomly drawn "cycles between failures" variable for that machine. When that cycle number is reached, the machine fails, the counter is reset to zero, and a new number of cycles before the next failure is drawn. This coding practice also avoids the potential (modeling) problem of a machine failing when it is not even running.

The VISTA system provides a vast quantity of information about the assembly line, not often available for most manufacturing systems, particularly at this level of detail. However, the data is neither stored nor presented in a format suitable for use in a

simulation model. As an example, downtime information (total time down and number of occurrences) is cumulated per day, for as many as 150 fault types for a particular machine. However, this information provides only mean time to repair and mean cycles to failure. Law [1989] has demonstrated the risk of using only mean values to represent variable data.

The process of preparing the data for use in the simulation model required several steps. We used the Unifit software (Simulation Modeling and Analysis, Co., Tucson, Arizona) to fit probability distributions to the data. Unifit requires ASCII data files, and so the first several steps in the process are required to convert the data to the appropriate ASCII format. The VISTA system creates four log files to store fault information about the six machines in the system. These files include fault type, date, and time of fault occurrence, and fault duration. VISTA provides a mechanism to convert log files of downtime data to DIF-formatted files. A Microsoft C program was written to sort the information, by fault type, in the DIF-formatted files and write out flat ASCII files for use with Unifit.

Using Unifit, faults occurring at the same machine were tested for homogeneity, and where appropriate merged into a common data set. Next, distributions were fit to the data sets, again using Unifit, which employs several heuristic and formal goodness-of-fit tests. Finally, the resulting information was input to the SIMAN experiment files. Analysis of failure data, almost invariably, revealed failure duration distributions greatly skewed to the left, with a high degree of kurtosis. The most commonly occurring distributions were weibull and gamma.

At first the VISTA system was not programmed to collect information on cycles between failures and so an exponential inter-failure rate was used, based on total number of failures/total cycles. Later, as the data became available, appropriate distributions were fit to inter-failure data and substituted for the exponential. However, this step doubled the tasks of data management and fitting distributions, and made experimentation much more tedious. For example, to run an experiment to determine the effects of reducing the downtime at a station by fifty percent, it is a simple matter to double the (exponential) mean inter-failure time. Adjusting the scale and shape parameters for other distributions such as gamma, weibull, and beta is not nearly as straightforward. After some very cursory analysis (simple means test comparing system throughput with fitted distributions and exponential distributions for inter-failure rate) the approach of using exponential distributions for inter-failure rate was reinstated because of the ease-of-use issues.

4. MODEL VALIDATION

The availability of (so much) observed data provided the opportunity for very thorough model validation. Simulation-collected observations for average cycle time, as well as blocking and starving instances at each station, were compared with the VISTA-collected data using a confidence-interval approach, as well as a simple inspection approach. These comparisons proved to be crucial for establishing significant model credibility with the system design team, and, particularly, with upper management.

A potential pitfall uncovered via the validation step was the assumption, on the part of the simulation practitioner, that the automatically-collected (VISTA)

data is indeed valid data. This assumption proved to be problematic in this application in several instances, requiring that input data be adjusted and simulation runs repeated. Since the VISTA system was a pilot on this manufacturing line, it was continually in the throes of debugging, personnel training, and growing pains as the VISTA was expanded to include the collection of more and more information. These problems tended to be exacerbated by misunderstandings, early in the life of the data-collection system, about how information is collected.

The fault (downtime) data which is collected in this way is entirely dependent on how faults are defined within the PLC logic. Some of these faults may not, in fact, contribute to overall station downtime. Conversely, there may be some factor(s) which contributes to station downtime which is not recorded as a fault. For example, at several of the stations we realized that it was possible for a pallet to be sitting in a station waiting for parts, and no downtime would be recorded. If no specific fault had occurred to cause the problem, but the feeder system, for instance, just couldn't keep up with the demand for parts, no fault was ever registered and the lost production time was never recorded. After this realization, the definition of downtime had to be revised at several of the stations to ensure that all relevant information was captured. The time required of the simulation practitioner to learn exactly how information is or is not being captured by automatic, data-collection systems is time well-spent.

5. PROPOSED CHANGES

When the simulation study began, the system design team already had a number of changes for the system in mind. In fact, they were really just looking for verification of these plans, fully anticipating that these changes would result in adequate system throughput. We will briefly describe the proposed changes and their implementation in the simulation, and general results.

Two of the proposed changes involved the placement of stations in a parallel arrangement; straightforward modeling (layout/flow) changes represented these changes. Another proposed change involved the substitution of simplified systems for four of the parts feeding systems. To represent this in the simulation model required that an estimate be made for the resultant change in machine failures. To develop this estimate, analyses were performed of "before" machine faults and anticipated "after" faults. Failure frequencies were adjusted to reflect the gross improvements, with the ratios of fault types adjusted as required. Failure duration by fault type was assumed to remain consistent with historical data. The final proposed change provided a manual backup for station number 4 in the event of "long" (greater than ten minutes) machine failures. This change was represented by a simple modeling (logic) change. Figure 3 below shows a revised layout which incorporates all proposed changes.

The placement of stations 1 and 2 in parallel proved to be of little advantage. The concept here was to combine the steps performed at each station, doubling the cycle time. This would keep the line running, albeit at half the normal throughput, in the event of a catastrophic failure at either station 1 or 2. However, the bulk of failures at both of these stations were very short in duration; so, on average, this solution did not enhance throughput.

On the other hand, the placement of stations 5 and 6 in parallel proved to be very worthwhile. These two stations are duplicates of each other, except that each is dedicated to a certain part type. In a serial arrangement, the parts had to pass through both stations unnecessarily, and, due to the random nature of the pallet mix, often cause blocking or starving of the other station. So, what would seem to be extra capacity actually caused a reduction in throughput. Additionally, a machine failure at one of the stations blocked production for the entire line, not just for that part type. With the parallel rearrangement, as well as the addition of a spur to offload the appropriate type pallets in the event of a machine failure, both of these problems could be eliminated.

The implementation of simplified feeding systems was proposed on stations 1, 2, 5, and 6. Based on the estimated station improvements, the simulation analysis demonstrated that the feed systems would allow for significant overall system improvement. Similarly, the use of a manual backup at station 4 showed promise for system improvement, particularly because it could be used during raw material replenishment of the fabrication portion of this station. This restocking occurs approximately every six hours, requiring an average of twenty minutes. Remaining downtime at this station adheres to a skewed-left distribution of failure time, rendering the backup system useless in the majority of instances.

Even with the inclusion of all proposed changes, the projected system throughput fell far short of the required throughput. The proposed changes discussed here concentrated predominantly on the front and rear ends of the assembly system. Failure to address problems in the middle merely shifted the bottleneck(s) to the center of the process, blocking the front end and starving the rear.

6. FURTHER EXPERIMENTATION

Faced with a still-inadequate system throughput, the simulation was put to task to find the solution(s), "chase the bottlenecks," if you will, until the required level of throughput was achieved. The first step in this process was to establish the "upper-bound" capacity of the system. Next we followed a systematic procedure of decreasing (arbitrarily) the downtime at the worst-offending station, until another station became the worst offender, etc. Finally, there were brain-storming sessions to generate added ideas to test with the simulation.

The vendor asserted that the system had been designed to produce about 14,000 parts per day, even though, at the time, it was capable of producing only about 4000, and was required to produce about 8500. The message was that the system had lots of untapped capacity. To establish a relative measure of current performance, the maximum throughput of the system was established by simulating production with no downtime. Variability inherent to random pallet type order, and machine cycle time were retained in the model. The simulation projected maximum throughput to be approximately 10,000 parts daily, well below the vendor's stated capacity, far enough below, in fact, to cause reconsideration as to what throughput is realistic to expect.

Having established a more realistic "upper-bound" on expected system throughput, the simulation was used to isolate and then systematically eliminate the worst-performing station in the system. To determine the "worst-offender," a (somewhat arbitrary) ratio was used

in order to consider more than one factor simultaneously. It is important to keep in mind that this ratio is just an heuristic to help guide the analysis efforts. This measure, dubbed "Demand," is simply Utilization divided by Uptime, where Uptime is the sum of all Idle and Busy time. In this application it was important to consider both utilization and downtime and so the ratio was developed as a measure which combined both factors. (Although one might expect the utilization factors at all stations to be nearly identical, they are not since the machine cycle times are quite different at some stations. This is particularly important because it has the effect of causing greater or less buffering, which can be especially significant for downtimes of short duration, known to be prevalent in this system.)

Stations subject to the highest Demand were the focus of (arbitrary) reductions in downtime, sequentially, until a suitable level of throughput was simulated. Because there is not just one correct solution to the distribution of station Demand, this method of "chasing the bottleneck" can serve only as a guide, an approximate measure of the performance required at each station individually in order to achieve the performance required by the whole system

Finally, to generate new ideas, particularly in support of the arbitrary reductions in downtime noted above, brainstorming sessions took place and the ideas subsequently evaluated for input to the simulation model. In the final analysis, there were so many ideas that the experimentation got very cumbersome. This would have been a good application for a Taguchi-approach experimental design simply to reduce the necessary computer runtime and subsequent analysis.

7. OPERATIONS TOOL

Throughout the course of this study, the simulation methodology gained tremendous and repeated exposure at all levels of the organization, from the plant-floor operators and engineers to the executive vice-president. The simulation was discussed often enough that there came to be a general acceptance of the model's ability to predict the behavior of the system under various conditions. Instead of evaluating only long-term machine changes, we began to receive, and respond to, requests for information about what would happen as a result of transient deviations from the norm.

As an example, production requirements changed rather drastically about one year into production, virtually eliminating, temporarily, the need for one of the part types. Up to that point, the system had been studied under the assumption that the part mix would remain approximately equal. Once the change was made to only one part type, system throughput fell. Initially, the cause of the lower throughput was attributed to an insufficient number of pallets: with only one part (and pallet) type, it was theorized that we didn't have enough pallets to keep the system full. The simulation was immediately called upon to test the theory.

Unfortunately, prohibitively long computer runtimes (for statistically sound analysis), stand in the way of using this simulation model to study very temporal conditions. In order to accommodate the level of analysis required throughout the study, the system was modeled in great detail, contributing to the long runtime. Furthermore, the high degree of variability in the system, particularly for machine downtime, contributes further to this problem by dictating long

simulation run lengths. For use as a true day-to-day operations tool the model would have to be restructured to facilitate faster analysis.

8. CONCLUSIONS

While the use of simulation to evaluate systems once they already exist is perhaps not the optimal point at which to begin such analysis, it may be the only way to really understand the implications of problems and proposed solutions. If the willingness to make significant changes to an existing system is demonstrated, as it was in this case, then the simulation study has much the same potential for benefit as a study undertaken during the planning stages, albeit at greater cost, with the added benefits of accurate data availability, and model validation capability. Due at least in part to the simulation study, plans are now in place which will return the system described here to its planned production levels.

REFERENCES

Law, A. M. and Kelton, W. D. (1982). Simulation Modeling and Analysis. McGraw-Hill Book Company, New York.

Law, A. M. and McComas. M. G. (1989). Pitfalls to Avoid in the Simulation of Manufacturing Systems. Industrial Engineering 31:5, 28-31, 69.

FOR FURTHER READING

Law, A. M. and Vincent, S. G. (1983). Unifit: An Interactive Computer Package for Fitting Probability Distributions to Observed Data. Select Software Services. Tucson, Arizona.

Pegden, C. D. (1986). Introduction to SIMAN. Systems Modeling Corp. State College, Pennsylvania.

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