A Combined Analytical and Simulation Based Approach to WIP Improvement

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Abstract

Discrete-event simulation is an effective tool to evaluate manufacturing systems and support the development of improvement plans. However, the use of simulation alone to optimize all forms of inventory in addition to throughput can result in a highly complicated, cumbersome model. In order to effectively analyze the contributing factors easier, a combined methodology that concurrently applies mathematical equations and discrete-event simulation is developed. The approach permits inventory within the system to be an additional parameter of improvement since its evaluation can be conducted with a greater level of accuracy. A cost per piece breakdown formed the basis of the objective function, where improvements were analyzed through discrete-event simulation in the attempt to achieve a minimized unit cost.

Keywords:

Manufacturing system optimization, Discrete-event simulation, WIP reduction, Unit cost reduction

1. Introduction

The need to minimize the cost to manufacture products is very important, especially at a time of global challenges to the U.S. manufacturing sector. However, to reduce the unit cost effectively, the ability to analyze and test action plans that provide improved performance in a thorough and systematic approach is required. Also, since many manufacturing systems are moving toward an agile and flexible method of production, such an approach must be able to focus on multi-part manufacturing processes.

The objective of this applied research is to investigate the development of a structured methodology to minimize the unit cost for a multi-part manufacturing system. To most effectively reduce the unit cost, both throughput and inventory are the primary focus of improvement.

In this paper, the concepts will be applied to the optimization of a multi-part engine block machining system, described in detail in section 4.1: Building the Simulation Model.

2. Literature Review

It is known that many manufacturing systems are far too complex for analytical calculation. The stochastic and dynamic nature of these systems requires numerical based methods in order to provide effective evaluations that yield more accurate solutions. Over the past thirty years, a significant amount of research has been published in nearly every aspect of its use. Therefore, only those studies that demonstrate an approach outlining the improvement of inventory and throughput were investigated.

The use of simulation for inventory analysis is a powerful tool, but it is one that must be thoroughly understood, since it has specific advantages and disadvantages. The major disadvantages are its complexity of model building and the large amount of data required to obtain a valid model. As Fu [1] points out, a major determinant for a simulation model is its computational cost, e.g. the number of simulation replications needed to estimate the resulting impact for each variable in the system. Fu further states that differences in the simulation methods which separate academic research from practical applications where the need for complete confidence in optimality versus rough and ready solution that do not guarantee a global optimum solution. To increase the likelihood of finding an optimum solution, experimental design can be employed in conjunction with simulation. This facilitates the development of uniquely designed tests to observe the effects of multiple factors, such as cycle time and machine variability to increase modeling efficiency.

Practical examples using simulation based methods, Montevechi [2] used simulation on an automotive process to improve the performance of simulation and avoid trial and error solutions. Trocine and Malone [3] discussed and showed how factorial designs can help reach an optimum solution via simulation. Kyle [4] addressed the use of discrete-event simulation to determine scheduling and batch size runs for the furniture industry. Faget [5] applied experimental design to simulation to determine the areas of constraint on an automotive production system.

Hurley and Whybark [6] explored the trade-offs between inventory and throughput capacity in a manufacturing system, with focus on an engine block machining system that supplies an engine assembly line. They used simulation models to evaluate the effect of push and pull methods of production on the effects on buffering, capacity utilization, throughput time and output rate. The push system was modeled by "pushing" a pre-determined production schedule into the block manufacturing system, whereas the "pulling" system was model by using both JIT and DBR approaches. It was concluded that each method provided conflicting benefits. The "push" method showed promising capacity increases, and the "pull" method created a reduction in inventory.

Buffers are a term used to signify a general compilation of WIP, and do not generally add value to the product. However, as Battini [7] explained, buffers play an important multi-functional role. He indicated that buffers serve are part material transport mechanisms and to decouple operations from downtimes. Carrying and loading parts to the machines within the manufacturing system. His paper also suggested that they act as "compensation cushions", used primarily to alleviate difference in cycle times, shifts and maintenance activities. Finally, he stated that quality control area and product re-sequencing zones are additional functions of buffers. He also noted that although buffers are required in the optimal operation of a manufacturing system, care must be taken not to incur inventory costs by having too much buffer capacity.

Spedding [8] used this idea of buffers to optimize a keyboard assembly cell. In his research, he analyzed three buffer locations in an assembly process in addition to having a variable number of pallets. He used a simulation analysis coupled with DOE to determine that increasing a single buffer size, along with adding more pallets to the system can yield significant gains in throughput.

As indicated earlier, a buffer is a generic term. Many manufacturing systems have too much buffer, or they are often established in the wrong location, providing little or no benefit. Therefore, buffers must be further analyze in detail to find which components of WIP are important and how much. However, very few studies were found in literature survey that specifically describe and/or mention the various reasons of inventory accumulation within RMI, FGI and WIP, and only two studies have been found that outline a rough sub-categorization of inventory. Hopp and Spearman [9] summarized the reasons for parts accumulation within the three primary classifications of inventory: RMI, FGI and WIP. Their conclusions are shown in Table I.

Bai and Gershwin [10] focused on WIP in their study, and concluded that the reasons for accumulation are operational independence, breakdown impact absorption, setup changes and spatial decomposition.

Table 1: Components of Inventory [9]

RMI	FGI	WIP
Batching	Customer Responsiveness	Queuing
Variability	Batched Production	Processing
Obsolesence	Forecasting Errors	Waiting for Batch
	Production Variability	Moving
	Seasonality	Waiting for Match

3. Problem Formulation

3.1 Developing an Objective Function

The objective function resulting from the stated intent for this research is to minimize the unit cost, which is a function of inventory and throughput. The unit cost objective function is a variation of the Cost of Ownership (CoO) formula. The semiconductor industry developed the CoO model ($/piece), shown by Nanez [11] in equation 1, to evaluate different manufacturing systems based on the total lifetime cost.

$$CoO = \frac{(FC + RC + YC)}{L * CY * U} \tag{1}$$

Where FC is the fixed costs, RC is the recurring costs, YC is the yield costs, L is the remaining life of the system in years, CY is the composite yield and U is the utilization.

The CoO concept is utilized for developing the unit cost where evaluating different process improvement alternatives can be compared. The modified CoO is shown in equation 2, and will be used as the objective function in this research:

$$C = \frac{(FC + RC + IC + YC)}{(L * TH)} \tag{2}$$

Where TH is the total number of good parts produced per year.

3.2 Identification and Collection of Relevant Data

There are a number of general variables that need to be collected and investigated in detail in order to build a credible model. Variables such as cycle time, downtime, scrap rate, buffer sizes and changeover time are commonly used in most simulation studies and were determined from the literature review.

In addition to the model building variables, other specific system variables are important in the determination of the deterministic inventory capacity. These items are:

- Rate and location of the bottleneck
- Difference in production hours within the system
- Index time and number of spaces on the conveyors
- Customer demand and frequency
- Supplier delivery and frequency
- Number of stations within the system
- Transit time to move parts within the system
- Number of parts per container or pallet

The method of collection for each of the variables can utilize a number of available resources found within a manufacturing plant. Some of these sources of information are line-side computerized data collection systems, MES systems and maintenance management databases. Another important method can include interviews with personnel knowledgeable in specific areas on the system such as, supply chain management, production supervisors, maintenance staff, engineers and operators.

In this case study, three months of data were collected and reviewed for each data set. Since all of the operations in this system are automated CNC machines, the cycle time variability is assumed to be minimal, thus a constant value is used in the model, as stated by Taraman [12]. The important factor of downtime, namely MCBF and MTTR, are fit with the best representative distribution using Best-Fit data analysis software, along with the distribution parameters.

The average daily throughput of the real system was taken from the industry engineering records database during the same three months as the machine data collection. It was found that the average throughput of the engine block machining system over the three month period was 61.1 JPH.

The casting supplier is responsible to provide the machining system with 3,550 raw block castings per week. This is 50 pieces more than the end customer requirement to cover the losses due to scrap and other miscellaneous rejects. A three month review the shipping logs help to determine the supplier in providing raw castings. Upon review of the logs, it has been determined that the supplier has delivered all 3,550 parts every week for the three month period in a timely manner. As a result, no distribution was used, and the delivery of raw castings was held at a constant 3,550 pieces, being delivered once per week in the simulation model.

3.3 Understanding the Assumptions

Assumptions are an important aspect of any simulation analysis. This research has a number of general assumptions that pertain to almost any system, and a set of specific ones that outline the uniqueness of the system under study were made.

The primary assumptions for this research are the exclusion of the variables and influences exogenous (outside) of the system of interest. It is assumed that these factors lie outside the bounds of direct influence of the objective, and can be safely ignored. Items specifically exogenous in this case are fork truck routes within the plant, employee attendance and behavior, stock of perishable tooling and general maintenance items and supply of line-side items for assembly.

It was also assumed that endogenous (inside) parameters are constant, such that tool life and quality is uniform, and part to part variation is negligible. Furthermore, the research did not take into account other general factors such as ambient temperature and lighting conditions within the plant, efficiency of manual offload hoists, condition of the machining coolant and system air/hydraulic pressure fluctuations.

In addition to the general assumptions, the model has the following system specific assumptions:

- Dunnage is always available to offload parts.
- Operators are considered 100% efficient and always available.
- All offline buffers of the real system are managed by either robots or operators. However, because of the difficulty in programming human behavior into the model, the analysis assumed that the loading and unloading of parts of the offline buffer is done in an instantaneous and a 100% efficient manner. This assumption is often called "perfect" buffering.
- Since all the operations in this systems are CNC based machines, the cycle times are considered constant since the variation is very small for automated machines, as indicated by Taraman [12].
- All automation (robots, conveyors, fork trucks and RGVs) are considered to have negligible downtime.
- Online part repairs are completed within takt time, and do not affect the operation of the system.

4. Current-State Analysis

4.1 Building the Simulation Model

The process under study has a total of 30 CNC machines, utilizing a process flow that contains both parallel and serial operations. This system produces two distinct part types, labelled as "A" and "B" in this research.

The first part type, "A", is the primary product style required by the customer. This type will be produced by the manufacturing system more than any other, and is often called the "high runner" or highest running type. This part type is processed at 17 CNC operations, each connected in series by powered conveyors that move at a rate of four seconds per block position. All of these operations are located directly on the main line.

The second part type, "B", is the second product style required by the customer. This part type will be produced the least in the manufacturing system, and is often called the "low runner" or least running type. This type is processed through all but one of the CNC operations on the main line (the same operations that process part type "A"), in addition to one more processing step that is completed on another leg of the process flow, and in an "annex" processing location, located in another area of the plant. Movement for part type "B" is done via the same powered conveyor that the "A" type uses, in addition to a batched move to the "annex" location. This batched move is done using a fork truck with full pallets of 18 blocks at a time. On average, it takes three minutes to move a single batch of blocks to and from the annex area.

Nine off-line buffers, having a total maximum capacity of over 500 blocks, are present throughout the line to hold additional parts. The intention of these buffers is to protect the system against maintenance downtime and changeovers. At these locations, parts are downloaded and uploaded by robots, and are considered 100% efficient. Both in-line and off-line buffer types can hold either type of part, and functions on a First In First Out (FIFO) basis.

Since this system is responsible for the production of two part types, a number of machines must undergo a program sequence changeover before production of the new part type can begin. Specifically, five machines must undergo fixture and program changes before production of a new part type. These machines are: OP20, OP60, OP90, OP110 and OP150.

The current batch size of part type "A" to "B" is a 2:1 ratio, having a batched sequence of 2,325 blocks for part type "A", followed by a batched sequence of 1,175 blocks for part type "B". The raw blocks castings are delivered weekly to the receiving dock in batch sizes of 2,350 part type "A" and 1,200 part type "B", where they are stored until needed by the machining line. When required, batches of 18 raw blocks are sent to the loading point at OP05, and are loaded onto the line by an operator.

The finished products are collected into batches of 18 at the end of the line, where they are taken to a holding area for the customer (external engine assembly). The facility operates this system 11.5 hours per day, five days per week, and produces approximately 175,950 blocks per year.

Prior to the actual simulation modelling of this system, it was conceptualized to determine which parts of the real system are important for representation within the model, and discard all other items not important to this analysis. It was determined that all processes before OP10 and after OP170, operator inefficiencies and behaviors, and the routing patterns of fork trucks will not be included, as they are not of importance to the overall focus of this research. Once the system was conceptualized, it was translated into a generalized discrete-event simulation model and ran to "verify" that the actual programming logic represents the real system, before the data was entered into the model. It was verified that only "B" part types were sent to the additional operations, and that they correctly returned to the main line after processing. It was also checked to ensure that all parts entering the system were accounted for, and were not skipping steps in the model through a possible routing error.

4.2 Model Validation

The collected data, previously fitted into distributions during the data collection stage, was input into the model. Ten simulation runs at 5,000 minutes of warm-up and 100,000 minutes of runtime were conducted with different pseudo-random number seeds (PRN) to generate a sampling of the results output from the model. The data was collected from each run and a confidence level of the simulation model was calculated with respect to the real system.

Once the model's results have been tabulated, a detailed analysis was conducted to validate the model. For a valid the representation, the model must accurately reproduce results that are found in the real system. One of the measures used to test the validity is the application of the two sided Student's t-Test to compare the average throughput of the real system to the average of ten collected simulation results [13]. It tests the null hypothesis, H_o, that both averages are equal. The results from the ten simulation runs are outlined in Table 2.

$H_o: \bar{x}(n) = \mu_o$
$H_1: \bar{x}(n) \neq \mu_o$

The calculated value of "t" of the Student's t-Test distribution can be determined using equation 3.

$$t_o = \frac{(\bar{x} - \mu)}{S/\sqrt{n}} \tag{3}$$

If $|t_o| < t_{(\alpha/2.n-1)}$, the H_o cannot be rejected and the model is valid.

Table 2: Throughput results from ten simulation runs

Trial	Simulated System Throughput (JPH)
1	61.06
2	61.26
3	60.93
4	61.39
5	60.96
6	61.88
7	61.24
8	61.16
9	61.08
10	61.11

The real system throughput average (μ) was 61.1 JPH, and the simulation model yielded an average throughput ($\bar{x}$) of 61.2 JPH and a standard deviation (S) of 0.29 JPH. The calculated t_o value is 1.09.

Ten sample trials were conducted (n = 10), resulting in nine degrees of freedom (df = 9). The two-tailed t-table for ($\alpha = 0.05$) $t_{0.975,9}$ is 2.26.

Since $|t_o| < t_{0.975.9}$, we cannot reject H_o at 95% confidence interval. Therefore, the model is valid and the improvement analysis can now be conducted with assurance on result quality.

Since this research focused on the reduction of unit cost, the unit cost of the current system must first be determined. An interview with the finance department indicated the information, shown below:

Cost of Inventory (IC) = $18,340,100

Cost of Yield Loss (YC) = $1,080,000

Variable Cost (RC) = $57,141,041

Fixed Cost (FC) = $100,500,647

Remaining Life of the system (L) = 5 years

Baseline yearly throughput (TL) = 175,950

Using the objective function for unit cost determination, it has been found that the cost of each block for the current state system is $201.26. The team agreed that this unit cost is appropriate.

4.3 Calculate the Non-Randomly Influenced Values

From the information collected from the current system, the deterministic components of inventory (system fill, batch move, shift differential and planned downtime) can be determined.

In this case study for system fill, it is known that each CNC operation can hold one part each. Since there are 30 CNC operations and the machines themselves must have a part for processing, the system fill will be at least 30 parts. Additionally, to prevent any machine from a starved state after its cycle, one part must be ready and in queue to enter the machine. Therefore, there must be at least 30 more parts in this system to be immediately available for each machine. Furthermore, some of the conveyors within this system are longer, and some machines are a little faster the others, requiring some conveyors to queue more than one piece. The system fill formula shown in Shortt [14], was used to determine which conveyors require more pieces than others. Table 3 shows the breakdown of system fill for each operation. This system fill is also the critical inventory amount, in that it's the smallest amount of the inventory to maintain steady-state production.

Table 3: System fill results

Operation	# Sta.	Low Net (JPH)	Index Time (hr)	Conv. Cap. (pcs)	Demand (JPH)	Transit (hr)	System Fill (pcs)
OP10	1	75	0.001	20	0	0	3
OP20	1	75	0.001	20	0	0	3
OP30	1	75	0.001	20	0	0	3
OP40	5	75	0.001	20	0	0	7
OP50	1	75	0.001	17	0	0	2
OP60	1	75	0.001	25	0	0	3
OP70	1	75	0.001	30	0	0	4
OP78A	1	75	0.001	4	0	0	1
OP78B	1	75	0.001	3	0	0	1
OP78C	1	75	0.001	3	0	0	1
OP80	1	75	0.001	40	0	0	4
OP90	1	75	0.001	15	0	0	2
OP100	1	75	0.001	13	0	0	2
OP110	1	75	0.001	15	0	0	2
OP120	1	75	0.001	22	0	0	3
OP130	1	75	0.001	24	0	0	3
OP132A	1	75	0.001	5	0	0	1
OP132B	1	75	0.001	5	0	0	1
OP132C	1	75	0.001	5	0	0	1
OP134A	1	75	0.001	5	0	0	1
OP134B	1	75	0.001	5	0	0	1
OP134C	1	75	0.001	5	0	0	1
OP136A	1	75	0.001	10	0	0	2
OP136B	1	75	0.001	10	0	0	2
OP136C	1	75	0.001	10	0	0	2
OP140	1	75	0.001	14	0	0	2
OP142	1	75	0.001	14	0	0	2
OP150	1	75	0.001	10	0	0	2
OP160	8	75	0.001	13	0	0	9
OP170	1	75	0.001	1	0	0	1
						Total	**75**

Next, batched move occurs when a number of blocks are collected before they are moved to the next operation. This system has two batched moves that occur to move the "B" part type to and from the "annex" operations. As indicated in the system description, a fork truck moves batches of 18 blocks to and from the "annex" operations and taking 3.5 and 5.5 minutes, respectively.

Knowing the pieces per load size, pieces per unload size and the move time via fork truck, the equation shown in Shortt [14] can be used to determine the number of parts required at a minimum to keep the "annex" operations in a busy state. Table 4 shows the inventory requirements for this movement.

Table 4: Batched move results

From	To	Load Size (pcs)	Unload Size (pcs)	Demand Rate (JPH)	Transit Time (hr)	Batch Move (pcs)
OP130	OP132	18	18	60.2	0.058	22
OP142	OP150	18	18	60.2	0.092	24
					Total	**45**

Inventory due to having different shift schedules is also present in this system. The finish machining operations (OP90 to OP170) run on average four hours longer than the rough machining operations (OP10 to OP80). The hours of shift differential, the bottleneck's throughput rate and the frequency in which this shift difference occurs, were used in equation described by Shortt [14] to calculate an average inventory build-up due to shift difference. The result indicated that this operational procedure caused a net accumulation of 150 parts held between OP80 and OP90.

The inventory held in the system to protect the production rate from planned downtime, shown later in Table 6, can be determined from reviewing the scheduled preventive maintenance tasks outlined in the maintenance management database.

This plant uses MAXIMO as the preventive maintenance task scheduler. Critical information such as the number of cycles between maintenance tasks, and the average duration to complete these tasks is recorded in the database. With this information known, the equation outlined in Shortt [14] can be used to determine the amount of inventory required to buffer the system from the downtime associated with completing planned maintenance.

In this system, the planned downtime associated with tool changes is considered negligible since most of the tools reside in a tool "magazine" within the CNC, and can be replaced while the machine is in operation.

4.4 Statistically Analyze the Randomly Influenced Values

The categorization of stochastic inventory is difficult to determine in the real system due to the combined accumulation of highly variable causes. Therefore, the simulation model must be used to dissect the accumulation of inventory resulting from quality control, unplanned downtime and customer/supplier variation.

Parts held for quality control were differentiated from other causes by the application of an attribute indicator placed on these parts. The indicator was statistically monitored by the simulation model, and the results showing the quality control related inventory are outlined later in Table 6.

Unplanned downtime is very often the largest contributor of inventory in many manufacturing systems. It is extremely difficult to actively manage this accumulation due to its highly variable nature, changing consistently over time. Large concentrations on one area one day, may not necessarily describe the behavior of the entire system over time. Therefore, simulation will used to provide insight in regard to unplanned downtime by running the model over a large period of time.

The unplanned downtime in this system can accumulate parts at nine locations only. These areas have an offline buffer used primarily for throughput protection. A highly reliable robot manages the unloading and loading of these parts, and is considered to have a negligible cycle time. Table 5 shows the average accumulation based upon the results of the simulation runs.

Table 5: Average unplanned accumulation results

Name	Avg. Size (pcs)
Buffer_OP10	12
Buffer_OP20	48
Buffer_OP50	41
Buffer_OP80	113
Buffer_OP100	36
Buffer_OP110	12
Buffer_OP120	17
Buffer_OP140	2
Buffer_OP142	10
Total Unplanned Inventory	**291**

The inventory profile due to interaction between the weekly supplier delivery and the manufacturing system pull is shown in Figure 1. The "saw tooth" pattern shows that the parts were delivered from the supplier at the beginning of the week, and the manufacturing system slowly depletes the raw stock to nearly zero.

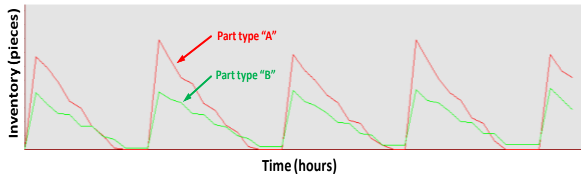

Figure 1: Supplier delivery profile chart

The single-run histogram, shown in Figure 4, indicates that the "saw tooth" profile has an average weekly inventory of 1,380 parts. And the high runner, part type "A", having the larger fluctuation with respect to part type "B". This makes sense since the average of a full 3,550 delivery of raw stock on Monday morning to a zero stock condition on Friday afternoon is approximately 1,775 parts.

In order to model the customer pull variation correctly, a random number generator was used in the customer entity to allow for a randomized pull of either "A" and "B" parts. The customer demands 3,500 total blocks per week in a 2:1 proportion of "A" type blocks to "B" type blocks. This equates to 2,325 type "A" and 1,175 type "B" blocks per week. From reviewing historical shipping records, it has been determined that the customer pulls weekly, at a normally distributed rate having an average of 61.1 blocks per hour and a standard deviation of 4.3.

Figure 2 shows the customer pull profile for a given simulation run. Note that part type "A" shows a larger range of inventory due to the fact that it is the produced in a greater quantity the "B" part type. The total inventory due to customer/supplier variation is documented in Table 6.

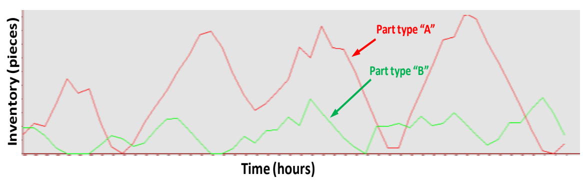

Figure 2: Customer pull profile chart

A summary total inventory broken down into each component for the current state system is shown in Table 6.

Table 6: Total system inventory

System Fill	75
Batch Move	45
Shift Pattern	150
Planned Downtime	379
Total Deterministic Inventory	**649**
Customer/Supplier Average	1530
Unplanned Downtime	291
Quality Control	80
Total Stochastic Inventory	**1901**
Total System Inventory	**2550**

5. Application of Structured Improvement Process to Engine Block System

5.1 Action Plan Development

Once a model is created and validated, outputs of the baseline model are analyzed to identify the system's bottleneck operations and areas of inventory accumulation. A list of quantitative improvement action plans in terms of the model's input variables such as MTTR, MCBF, cycle time, scrap rate, changeover time, buffer capacity and batch size are generated. These process improvement plans will be individually tested in the simulation model using the estimated improvement parameters to determine their effect on the system's throughput, inventory, and unit cost. All improvement iterations are to be recorded onto a table for comparison. For each improvement plan, A_i = 1,2,3…N, the unit cost will be compared to the base model's unit cost, C_o, using a two sided confidence interval for $C_o - C_i$, given by equation 4 [13]:

$$(\overline{Y_o} - \overline{Y_i}) \pm t_{\alpha/2,\nu},* S_e(\overline{Y_o} - \overline{Y_i}) \qquad (4)$$

Where $\overline{Y_o}$ is the sample mean of the baseline system, $\overline{Y_i}$ is the sample mean for i^{th} action, ν is the degree of freedom, $t_{\alpha/2,\nu}$ is the 100(1-α)% of the standard distribution and S_e is the standard error for C_o-C_i

If the confidence interval for C_o-C_i is completely to the left of zero, then there is strong evidence for the hypothesis that:

$C_o - C_i < 0$ Or, $C_i > C_o$

i.e. the action plan will not reduce the unit cost.

If the confidence interval for C_o-C_i is completely to the right of zero, then there is strong evidence for the hypothesis that:

$C_o - C_i > 0$ Or, $C_i < C_o$

i.e. the action plan will significantly reduce the unit cost.

If the confidence interval C_o-C_i contains zero, then there is no strong evidence that the action will reduce the unit cost.

The action plans which will significantly reduce the unit cost must also satisfy the following three constraints to be selected:

1. Throughput of the improvement must meet or exceed required throughput: $T \geq T_r$
2. Inventory of the improvement must meet or exceed "critical" inventory: $WIP \geq WIPC$
3. Fixed cost of the improvement must be less than the budget constraint: $CF < B$

Let the improvement plans that significantly reduce the unit cost and meet all the constraints be "K" out of "N". These "K" plans will be documented on the comparison table and sorted in ascending order according to unit cost, such that $C_1 < C_2 < C_3 \ldots C_K$.

In this case study, action plans were simulated for a total of ten replications each, so that a confidence level for each can be calculated. To determine which action plans are acceptable, C_o-C_i must be a positive value in accordance to equation 4. Additionally, in order to be an acceptable action plan, it must also not decrease the system's net throughput to be less than the customer demand rate and not reduce the inventory below the critical level and must be within the budget allowance. In this research project, the improvement budget was set at $50,000

5.2 Action Plan Combination

Individual plans that have been identified and proven to satisfy all the constraints, each plan (A_1, A_2, $A_3 \ldots A_K$) on the action list will be tested in combination, such that A_1+A_2, $A_1+A_2+A_3$, $A_1+A_2+A_3 \ldots + A_K$. This process will continue until all possible combinations have been tested in order to achieve the greatest improvement result, as long as the total improvement cost does not exceed the allowed budget.

Once the best combination of action plans that minimizes the unit cost and yet satisfying the given constraints has been found, the team is tasked with the implementation of these items to the manufacturing system. Monitoring of the progressive and final result by the team is required to determine the effectiveness of the simulation study.

Six acceptable action plans were selected based upon the significant level of unit cost improvement with $500 left in the budget for an additional low cost improvement. The idea list was reviewed, and a single $370 plan was discovered that allowed for a small, but valuable decrease in unit cost.

After the action plans have been developed and selected to achieve the most savings, the team was tasked to implement these plans on the current state system.

6. Calculate the Improved Unit Cost

After the implementation of the process improvements, the output of the system was observed for three months, and the output was documented in order to develop the final unit cost of the improved system. It was found that the system achieves a new net throughput of 64.8 JPH. This improvement, which focused on the constraining locations, also slightly reduced the inventory found in the system, primarily relating to the improvement of downtime. As a result, the yield losses have somewhat improved since finding quality defects affecting a large stock of parts are faintly reduced.

Variable costs have also decreased to some extent due to this research. The throughput of the original system only allowed for a single mid-week changeover on second shift. Now that the throughput is significantly greater, changeovers can now occur during the first shift, saving the additional costs of a second shift mid-week changeover.

The improved results were sent to the finance department, to determine the estimated financial impact of the improvements.

Cost of Inventory (IC) = $18,000,000*

Cost of Yield Loss (YC) = $1,075,000*

Variable Cost (RC) = $55,000,000*

Fixed Cost (FC) = $100,500,647

Remaining Life of the system (L) = 5 years

Baseline yearly throughput (TL) = 183,149

*Projected yearly estimates

Using the unit cost formula, shown in equation 3, the improved cost per piece due to improvements in throughput and inventory is $190.64.

7. Conclusions

A structured simulation methodology to optimize unit cost on a multi-part manufacturing system (engine block) was developed. The developed methodology contains two distinct phases in which the minimization of unit cost can be achieved. The first phase is the collection of pertinent data and the creation of a valid simulation model of the existing system. The second phase was the development, testing and selection of the best combination of process improvement plans which most minimize the unit cost without violating the system's constraints, and still being within the budget allotment.

The current state system yielded a net system throughput of 61.1 JPH and had an average of 2,550 blocks in the inventory. As a result, the unit cost for each block using equation 3 was $201.26/block

The use of this structured methodology provided a throughput of 64.8 blocks per hour improving the net throughput of the original system by 3.8 NJPH, a 6.1% improvement.

The CoO calculation indicated a unit cost of the improved system was reduced to $190.64/block, or a savings of $10.62 per block. This produces a total yearly savings of $1,945,042/year.

Much of the inventory held in this system is a direct result of supplier and customer variation. Future work will focus on the improvement of these areas of inventory, since most of it is needlessly kept, increasing the inventory holding costs, and ultimately keeping the unit costs high.

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Biography

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