In Search of the Production Steady State: Mission Impossible?

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ABSTRACT

Learning Curves are a vital tool for cost estimators when predicting the number of direct labor hours required for a production run. One challenge of utilizing learning curves is predicting when no additional improvement can be expected, otherwise known as the steady state of the production run. This paper will address the formal definition of a learning curve, the different types of learning that impact production systems and why the steady state plays such a critical role in cost estimates. The steady state concept, as well as its importance and impact will be explored. Interpretation of data and causes of the steady state, both genuine and artificial, will also be addressed. A sample estimate will be developed that utilizes historical data to identify an anticipated steady state and predict direct labor requirements for a new system. Lastly, the unique nature of Department of Defense (DoD) acquisition and its impact on production environments will help us determine whether the steady state truly exists or not.

TABLE OF CONTENTS

INTRODUCTION

One of the most common cost estimating and analysis techniques is learning curve theory. It is critical to estimating direct labor requirements and can have substantial impacts on costs that are derivatives of direct labor requirements, including facility/space requirements and support labor staffing.

As long as learning curve theory has been used in cost estimating, a key question asked is:

"Even though the mathematical model indicates that learning will continue indefinitely, is that really the case?"

The state of the process when learning ceases, or is mathematically negligible from unit-to-unit, is called the steady state. Understanding how to analyze historical production data to determine when a system enters the steady state and utilizing that determination for estimating future system requirements is critical. Not accounting for a steady state could result in underestimating direct labor requirements. Alternatively, predicting a steady state will occur too early could result in an overestimation of direct labor requirements. Before addressing these scenarios and answering the question as to whether the steady state even exists, a brief recap of learning curve theory is warranted.

LEARNING CURVE THEORY RECAP

The universally agreed upon definition of learning curve theory is that it is a measure of progress or improvement observed in a *constant* system as the number of repetitions to complete a task or units produced increase over time. A critical component of this definition, and ultimately our search for the existence of a steady state is the phrase "constant system". In a production environment, a learning curve analysis in its truest form would mean that we are tracking the rate of reduction with regards to resources required (e.g. labor hours) over a period of time for the production of multiple units with the following variables remaining the same throughout:

- Production rate or throughput
- The employees performing the work
- The facility, tools and equipment used
- The scope of work being performed (including the materials and sub-assemblies used)
- Quality requirements
- Safety Requirements
- Labor Laws

Albeit with slightly different techniques, Wright and Crawford both sought to capture this improvement mathematically by theorizing that as the quantity of items produced or tasks completed double there will be constant rate of reduction in terms of resources required. Their techniques reflect the mathematical representations presented below.

Crawford's Unit Improvement Curve Theory

$Y = aX^b$, where:

Y = Cost of the X^{th} unit
a = Theoretical cost (T1) of the first unit in the production run
X = Sequential unit number of unit being calculated
b = log2(LCS), a constant reflecting the rate of cost decrease from unit to unit
LCS = Learning Curve Slope

Wright's Cumulative Average Curve Theory

$Y = aX^b$, where:

Y = Cumulative average cost of X units
a = Theoretical cost (T1) of the first unit in the production run
X = Sequential unit number of unit being calculated
b = log2(LCS), a constant reflecting the rate of cost decrease from unit to unit
LCS = Learning Curve Slope

Both theories address "learning" in terms of the reduction of resources required. However, Konz[1] points out that in production environments, there are actually two distinctly different types of learning that take place. This concept can have a substantial impact on how we utilize learning curve theory in the search of the steady state, so we address each learning type below.

INDIVIDUAL LEARNING VS ORGANIZATIONAL LEARNING

Konz defines individual learning as the improvement demonstrated by an individual worker or entire workforce while utilizing a "constant product design and constant tools and equipment". In contrast, Konz defines organizational learning as the learning attributed to modifying the product design, tools and equipment. Individual learning clearly echoes our definition of learning in the previous section. However, and as discussed later in this paper, organizational learning must be considered in determining the existence and timing of the steady state in a specific production environment.

Individual Learning

Individual learning can be represented by two distinctly different scenarios:

Suppose a manufacturer wins a U.S. Army contract that will require the company to build 1,000 units of a particular ground vehicle system. The manufacturer typically builds commercial items, so it is starting up a separate assembly line specifically for this weapon system that will have ten dedicated workstations. The manufacturer does not want to disrupt its commercial business, so it hires brand new staff and purchases all new tooling, machines and fixtures in order to deliver the Army vehicles. The Army has indicated that the delivery schedule is somewhat flexible, so the manufacturer decides that it will hire 100 workers who will start on the first day of the project and work in one, 8 hour shift per day to accomplish the work. As time passes and the workers become more experienced, improvement will be achieved in the number of hours required to assemble and deliver each unit. As the delivery schedule will not be firm, improvement will also be achieved in the number of vehicles completed in a single day (i.e. the production rate will be variable as a function of individual learning).

Konz provides another example that only involves a single person to help further demonstrate individual learning. Suppose a novice golfer decides to learn by playing one hundred rounds this year using only a driver, 5-iron and putter. The golfer will play the exact same course at noon each day and use the exact same type of golf balls for each round. For the first round, the golfer takes 135 strokes to complete the round. The second round, he takes 127 strokes. Over the course of the year he sees his stroke total starting to level out around 100, plus or minus a few strokes each round.

In both cases, the environment and resources available to those performing the work remain constant.

Organizational Learning

Konz introduces the idea of organizational learning by defining it as improvement that results from “changing product design, changing tools and equipment, and changing work methods”. We again use the two scenarios from above to demonstrate organizational learning.

Returning again to the new contract for 1,000 Army vehicles, suppose that instead of hiring all 100 workers on the first day, the workforce increases ten employees at a time over the first several weeks. Also, assume that after completing the first 100 units, the tooling and equipment purchased to complete this effort is not optimal. Then new equipment to increase efficiency is purchased. In addition, after 500 units are completed and delivered, the Army notifies the manufacturer of some design changes that will be incorporated into the assembly in order to improve survivability.

Konz introduces organizational learning in the golfer example by proposing that during the year, the golfer decides to add additional clubs to his bag (e.g. a 7 iron and sand wedge). The golfer may also decide to switch the brand of balls he is using and also move his tee time to 8:00 AM because he found it to be too hot playing at noon and he would become fatigued.

In both scenarios, substantial changes were made to the “systems” while they were active which more than likely altered the performance of the system and, subsequently, the measurable output or results. This is a very important concept as you will recall that one of the major tenets of learning curve theory is that the system, and the parameters that define the system, remain constant.

THE STEADY STATE DEFINED

Now that we have revisited learning curve theory and explored the two different types of learning, we will focus on what the steady state should look like and how we can test whether the system has truly reached that state. Gagniuc[2] provides a general definition of a steady state by stating that if the variables which define the behavior of the system are unchanging over time, the system has reached a steady state. In continuous time, this means that for those properties *p* of the system, the partial derivative with respect to time (t) is zero and remains so:

$$\frac{\delta p}{\delta t} = 0,$$

for all present and future t.

In discrete time, it means that the first difference of each property is zero and remains so:

$$p_t - p_{t-1} = 0,$$

for all present and future t.

The term steady state is used in several fields and can mean many different things to many different individuals, organizations and environments. We will attempt to define what a steady state means in a DoD production environment. First, we consider a couple of causes for individual learning slowing down and eventually stopping in a DoD production environment.

Production Steady State Causes

While there are several variables and influences within production systems that could cause individual learning to level off, we consider three of the most common:

1. Time/Repetition

This is the most easily understood cause of the production steady state because we all experience this phenomenon in various aspects of our lives. For example, consider commuting to work. Given constant system parameters, we all eventually reach a best case commute time. Assuming we travel to work by car, our system parameters would be as follows:

- Home and workplace location
- Car functionality
- Speed limits
- Lack of construction
- Stop signs/Traffic lights
- Traffic patterns
- Time of day

Assuming these parameters are held constant, the learning we experience would come in the form of identifying the fastest route to take and the improvement is measured in the time it takes us to commute to work form day-to-day. Over time, the best route will be identified and the improvement will eventually cease.

2. Achievement of Quality Thresholds

Another steady state forcing function within production systems is the influence of quality control on the behavior of the system. Up to this point, our discussion has focused solely on the measurement and reduction of direct labor hours from unit-to-unit relative to a defined delivery schedule. However, the majority of projects are also concerned with the quality of the end-items being produced. Quality thresholds and standards can be a major forcing function. When they are not met, cost can increase and schedule can be delayed. Because of this, quality receives quite a bit of attention (and deservedly so).

When production quality standards are not being met, the end-item is often "re-worked". This additional work can either occur at the station where the work content being corrected initially occurred, or, there can be a station at the end of the assembly line where all rework is performed. Either way, additional hours are incurred and recorded for each unit that required rework. As learning and quality increase, the amount of rework decreases and hours required per unit tend to level off. If management sees that the quality standards are being met, less emphasis may be placed on the need to improve efficiency.

3. Physical Space Limitations

The third forcing function for reaching the steady state in a production environment is the limitation of physical space to complete the work. A production manager may decide that if each employee is responsible for completing less work content for each unit, they are likely to increase their rate of individual learning and cost savings will be realized earlier in the production run. In addition, if there are more employees completing less work content per unit, throughput can be increased.

However, there is certainly an upper bound to this strategy. For instance, management might consider analyzing a station on an assembly line that requires 20 hours of work content per unit that is currently being performed by 5 workers over an 8 hour work day and has a throughput of 2 units per day. The manager might then say, if my 5 workers are each performing 4.0 hours of work content apiece per unit and I doubled my staff to 10, then I could have them each do 2.0 hours of work content per unit and double my throughput for the 8.0 hour shift. This thought process could continue by adding staff and even having multiple shifts. However, the station might eventually get to a point where there is physically not enough room for workers to effectively maneuver and complete their processes without getting in each other's way, effectively slowing the process back down.

The Production Steady State Defined

Hopp and Spearman[3] address the concept of steady state in manufacturing, production or assembly environments using intriguing terminology. First and foremost, they define the steady state as just that – a concept. Secondly, they use the following, two part statement to define steady state that will be impactful to us as cost estimators:

"For a system to be in steady state, the parameters of the system must never change and the system must have been operating long enough that the initial conditions no longer matter."

A strict translation of this definition for the purpose of applying them to a production environment is production steady state is the point during a production run when the difference between the labor hours required from unit-to-unit is zero and remains unchanged until the end of the production run. It also means that at a certain point the starting parameters of the system no longer matter. Given the mathematical construct of Wright's Cumulative Average theory and its reliance on all data points on the curve until it ends (1 through *n*), a steady state could never truly commence as the cumulative average would always rely on the behavior of the system when it began. Because of this, we will utilize the Crawford's unit curve theory throughout the remainder of this paper.

Now, anyone who has spent a substantial amount of time in production facilities with a low-to-moderate production rate (a typical situation for DoD weapon systems) knows that finding a point where labor hour requirements remain exactly constant until the end of production is next to impossible. This impossibility exists not so much from individual learning ceasing and then starting again, but from the seemingly endless number of variables that can impact low-to-moderate rate environments. Below we identify just a fraction of the issues that can occur at any point of a production run:

- Facility/Equipment/Tooling Issues
- Staffing Irregularities (sick, vacation, etc.)
- Supplier Quality Defects

Instead, we will modify the definition of production steady state to account for the unique nature of the defense production environment:

"In weapon system production environments, the steady state commences at unit *n* when the probability of unit *n+1*'s hours being higher than those required for unit *n* are equal to the probability of unit *n+1*'s hours being lower than those required for unit *n*". For this to be true, both of these probabilities would be 50%.

We define these as follows:

$P_{n+1,h} = P_{n+1,l} = 0.5$, for:

$P_{n+1,h}$ = Probability of Unit n+1 requiring the *same amount or more* direct labor hours than unit n

$P_{n+1,l}$ = Probability of Unit n+1 requiring *same amount or less* direct labor hours than unit n

This definition is critical to us as estimators when attempting to identify and confirm the steady state. Below we look at a plot of direct labor hour requirements for a commercial ground vehicle program (Figure 1) to get a better idea of what a steady state typically looks like:

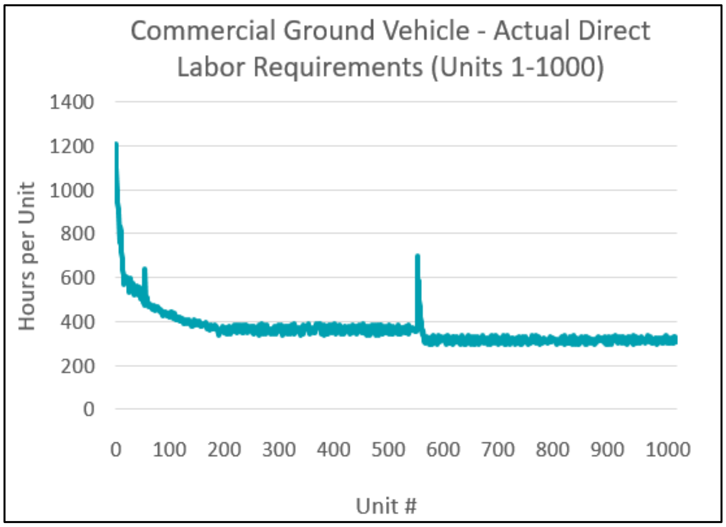

Figure 1

Note how the curve begins to level off at unit 200, albeit with a reasonable amount of variation still occurring from unit-to-unit until we get out past unit 500. Figure 2 is presented to help us explain what is occurring between unit 200 and the point around unit 550 (it is actually unit 539) where the curve spikes back up.

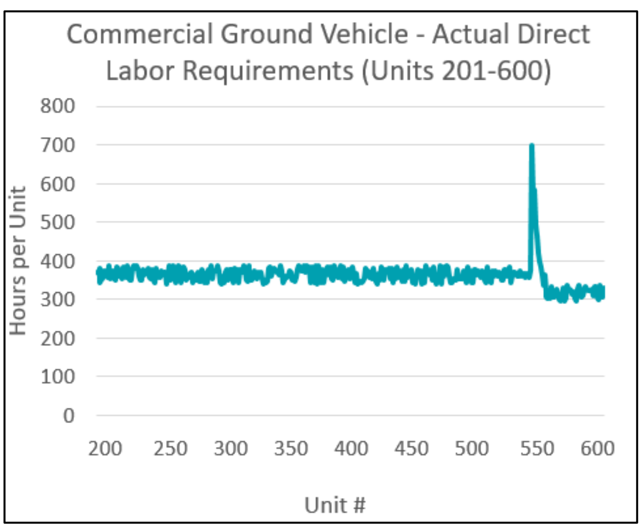

Figure 2

The plot seems to indicate that we are in steady state for these 338 data points. However, it is important to perform statistical analysis and testing to help confirm that observation.

Statistical Analysis and Stationarity Testing

Descriptive statistics for the data (Table 1) tell us that the mean of the 338 data points is 364.16 hours per unit. However, we still see some variance within the data (albeit not much since the coefficient of variation is only 0.039), so we remain uncertain about this being the steady state.

Descriptive Statistics for Units 201-538	
Mean	364.16
Standard Error	0.77
Median	365.82
Mode	364.57
Standard Deviation	14.22
Sample Variance	202.28
Kurtosis	-1.19
Skewness	-0.07
Minimum	338.08
Maximum	388.51
Sum	123085.43
Count	338.00
Confidence Level (95.0%)	1.52

Table 1

Figure 3 gives us a much better graphical representation of how the data is behaving for these 338 units, in revealing that the system appears to be behaving as a stationary process. A stationary process, or system, consists of time-series data that does not have any upward or downward trend or seasonal effects, if applicable. Consequently, the statistical properties of the system, such as mean and variance, also do not change over time.

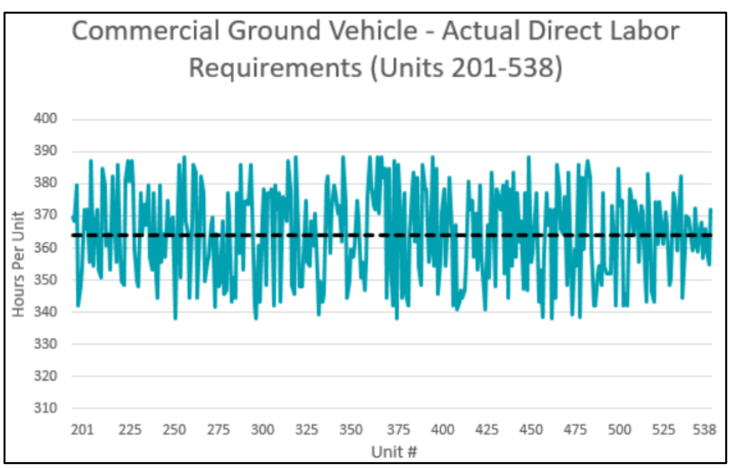

Figure 3

Before getting to a formal statistical test, we can also perform a quick sanity check of the data to see if it meets the definition of a stationary process as defined above. We can quickly check to see if metrics such as the mean and variance stay relatively constant by dividing the dataset into bins. In Table 2 we break the data up into ten (almost) equal sized bins and calculate the mean and variance for each sub-set of data:

	Bin 1	Bin 2	Bin 3	Bin 4	Bin 5	Bin 6	Bin 7	Bin 8	Bin 9	Bin 10
Qty	34	34	34	34	34	34	34	34	34	32
Mean	367.02	364.50	361.69	363.42	368.00	365.32	363.43	363.10	361.69	363.35
Variance	187.22	182.90	211.49	228.38	203.02	258.02	197.80	252.73	212.64	96.73

Table 2

While the mean stays relatively constant, we do still notice a fair amount of change in the variance across the bins. So we turn to statistical testing to further support our observation that the system is stationary. One statistical test that can help us determine whether or not the system is stationary, and subsequently whether our production system is in steady state, is the Dickey-Fuller test. The Dickey-Fuller test considers a stochastic process (y_n):

$y_n = \phi y_{n-1} + \varepsilon_n$,

where $|\phi| \leq 1$ and ε_n is white noise. If $|\phi| = 1$, we have what is called a unit root. In particular, if $\phi = 1$, we have a random walk (without drift), which is not stationary. In fact, if $|\phi| = 1$, the process is not stationary, while if $|\phi| < 1$, the process is stationary. We will not consider the case where $|\phi| > 1$ further since in this case the process is called explosive and increases over time. The null hypothesis for the Dickey-Fuller test is that a unit root is present in a time series sample. The more negative the Dickey-Fuller statistic is, the stronger the rejection of the hypothesis that there is a unit root and the system is stationary:

Null Hypothesis (H_0): If accepted, it suggests the time series has a unit root, meaning it is non-stationary and has some time dependent structure.

Alternative Hypothesis (H_1): The null hypothesis is rejected; it suggests the time series does not have a unit root, meaning it is stationary.

The first step in applying the Dickey-Fuller test is calculating the difference for consecutive data points ($\Delta y = y_n - y_{n-1}$).

We can use the usual linear regression approach to calculate our Dickey Fuller statistic, except that when the null hypothesis holds, the t coefficient doesn't follow a normal distribution and so we can't use the usual t test, and subsequently, the t tables. Instead, this coefficient follows a tau distribution. Therefore, we are testing to determine whether the tau statistic τ (which is equivalent to the usual t statistic) is less than τ_{crit} based on a table of critical tau statistics values shown in the Dickey-Fuller Table (Table 3).

If the calculated tau value is less than the critical value in the table of critical values, then we have a significant result. Otherwise we accept the null hypothesis that there is a unit root and the time series is not stationary.

Dickey Fuller Table

N \ α	0.01	0.025	0.05	0.10
25	-3.724	-3.318	-2.986	-2.633
50	-3.568	-3.213	-2.921	-2.599
100	-3.498	-3.164	-2.891	-2.582
250	-3.457	-3.136	-2.873	-2.573
500	-3.443	-3.127	-2.867	-2.570
>500	-3.434	-3.120	-2.863	-2.568

Table 3

We perform regression analysis on the following data set in Excel (Table 4) to determine the t statistic for our test:

$\Delta y = y_n - y_{n-1}$, for n = 202-538

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.703669
R Square	0.49515
Adjusted R Square	0.493643
Standard Error	14.26107
Observations	337

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	66822.47991	66822.48	328.5629	1.17536E-51
Residual	335	68131.63537	203.378		
Total	336	134954.1153			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	360.6892	19.91345053	18.11284	1.33E-51
X Variable 1	-0.99052	0.054645335	**-18.1263**	1.18E-51

Table 4

From Table 4, we see that the t statistic for the coefficient is -18.1263. Comparing this with the tau critical values in Table 3, we can reject the null hypothesis and safely conclude with a high degree of confidence that the system is stationary and in steady state, beginning with unit 201. Before moving on, we end with a couple of notes:

1. One parameter of the analogous system that was not explored was the production schedule and the rate that was needed to fulfill delivery requirements. For simplicity purposes, we assume that the analogous system had a comparable delivery schedule and rate. However, if the rate for the analogous system was substantially different than the future system, it may impact the suitability of utilizing the conclusion that the steady state starts at the 201st unit for future, similar systems.
2. The high level of variance occurring within the system could be driven by something occurring on the assembly line that is driving the peaks and valleys. For instance, there could be one or multiple bottlenecks in the system that are causing disruptions and/or reassignment of resources to keep the line moving. Below we address how finding the steady state can help us in addressing issues such as this.

Why Should We Care About the Production Steady State?

In order to stress the importance of predicting when the steady state will occur on an estimate, we return to our example involving 1,000 Army vehicles. Based on analysis of production data for five commercial vehicles, we determine that the typical learning rate is approximately 85% and assume this slope for the new vehicle. The data for some of these vehicles indicates the steady state starts around 50 for some and 1000 for others. We decide to analyze how impactful the prediction of our steady state could be in increments between the units of 50 and 1,000. For the purposes of exhibiting the significance, we assume a theoretical first unit value (T1) of 1,000 hours.

We begin by plotting this curve for all 1,000 units with no steady state being reached (Figure 4):

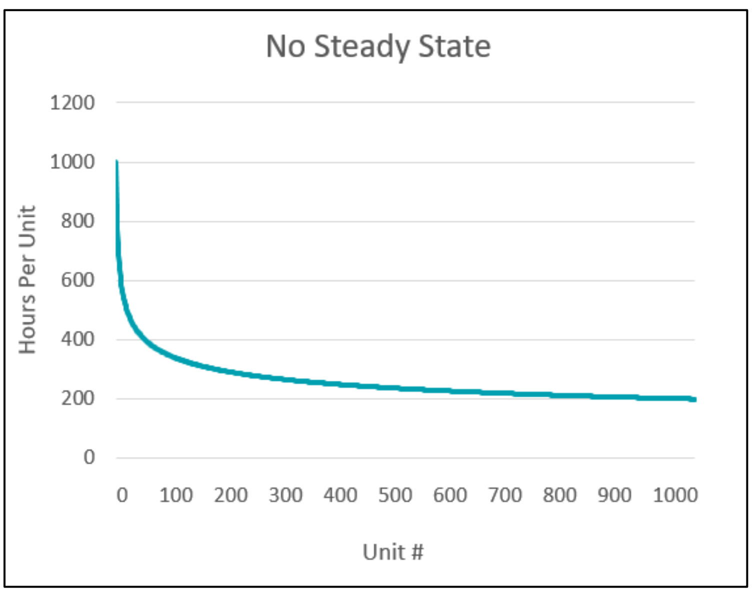

Figure 4

The resulting total hours required for all 1,000 units would be 215,978. We then decide to look at the other extreme – what if our system were to reach a steady state at the 50th unit as is true for at least one of our commercial items? We compare this curve with our curve from Figure 4 below in Figure 5:

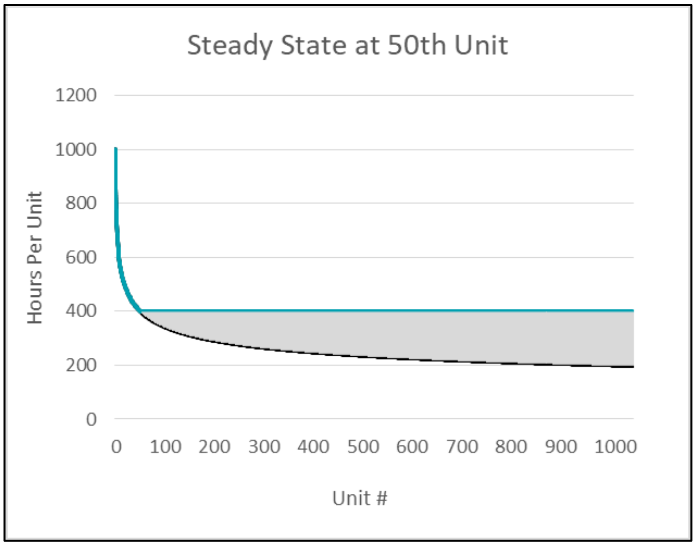

Figure 5

If we assume steady state begins at the 50th unit, our total hours required would increase to 405,155. The gray shaded area in Figure 5 depicts this 57.1% increase. Table 5 provides the sensitivity of total hours to changes in the steady state starting unit:

Steady State Starting Unit	1,000	750	500	250	100	50
Total Hours Required	257,918	259,754	267,905	294,340	349,466	405,155
Difference in Hours Required	N/A	1,836	9,987	36,422	91,548	147,237
% Increase in Hours	N/A	0.7%	3.9%	14.1%	35.5%	57.1%

Table 3

Clearly, when the steady state is estimated to begin can have a big impact on the direct labor estimate as a whole. If the learning curve slope is estimated to be lower (i.e. our curve is steeper), this statement is even truer.

In addition to impacting the amount of direct hours that are estimated, identifying when the learning curve will happen and at what the direct labor hours will be at that point can provide substantial benefits with regards to how we predict the system will behave. As Hopp and Spearman point out, analyzing a system in steady state, or one that we will assume to be in steady state, can help us in analyzing other key metrics of the system including cycle time, work in process (WIP), bottleneck rates and also help in optimizing the design and layout of the system.

In addition, McCarthy[4] introduced the concept of utilizing the steady state to enhance the analysis and increase the quality of estimates in integrated production environments (i.e. environments where two or more products with at least some common work content are being produced concurrently with the same resources). The concepts presented in that research utilized the identification of the point where the steady state commences to recognize commonality across all end items or any subsets of end items being produced in the integrated environment. The commonality identification and subsequent extraction of common work content enabled inter-product learning curves to be developed and more accurately depict how learning would occur in the environment. By analyzing work content from a static perspective, which is what the steady state provides, the direct labor requirements that were deemed to be duplicative for two or more end items could be extracted and analyzed for anticipated rates of learning separate from end-item unique work content.

A SAMPLE ESTIMATE WITH THE STEADY STATE

Now that we have established the importance of identifying the steady state, we return to the 1,000 Army vehicles described in the sections above on individual and organizational learning. When defining individual learning, we held the number of employees constant and let their rate of learning dictate the delivery schedule. As this is almost never the case, we introduce the following monthly delivery schedule requested by the Army (Table 6):

Month	Units		Month	Units
1	3		13	50
2	5		14	50
3	10		15	50
4	25		16	50
5	35		17	50
6	45		18	50
7	50		19	50
8	50		20	50
9	50		21	50
10	50		22	50
11	50		23	45
12	50		24	32

Table 6

The delivery schedule indicates production ramps up to 50 units per month and stays there from months 7-22. As mentioned above, we will assume that the commercial item used to identify a steady state point of the 201st unit had a comparable schedule and rate. Before estimating direct labor hour requirements we must identify some more characteristics about our system, including:

- Learning Curve Slope
- Budgeted Work Standards

Learning Curve Slope

The learning curve slope for a production environment can easily be estimated by looking at actual data for an analogous system produced the same environment with more or less the same parameters (e.g. workforce, material, and tooling). We again return to the commercial system and, as shown in Figure 6, use the first 200 units of our system (i.e., where it was clear learning was taking place) to identify a representative rate of learning:

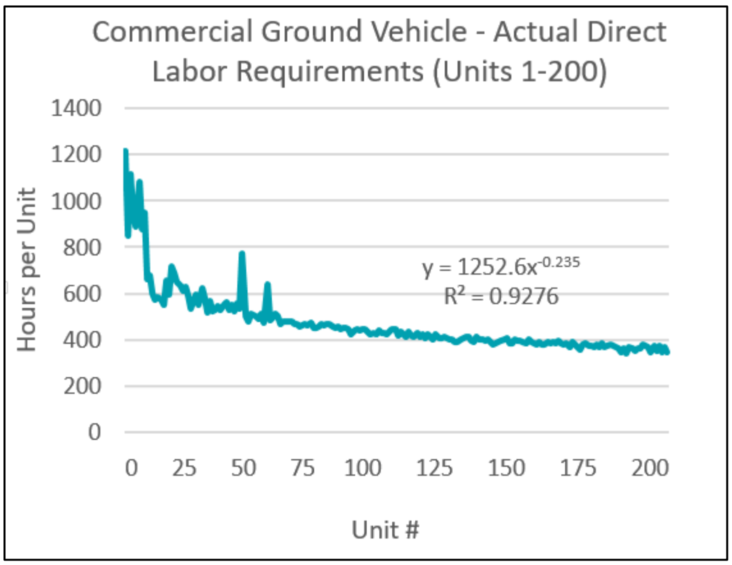

Figure 6

Fitting a power model trend line to the data results in an R^2 value of 0.9276 and model equation of $125.6x^{-0.235}$. For the purposes of predicting the rate at which we can expect future systems with comparable parameters to learn, we now know that our learning curve slope is $2^{-0.235}$, or, 85.0%.

Budgeted Work Standards

Developing budgeted work standards can be a very beneficial tool in managing a facility and help cost estimators predict future costs. The true definition of what a standard hour means varies by industry. Some industries set the standard to be "the lower bound" amount of time that an operation should take to complete. Others define the standard as the time an operation *should* take to complete, but operator's performing at greater than 100% efficiency can perform it in less time. Either definition is acceptable, but must be consistently applied. Labor and time standards can be developed using a variety of methods:

- Time and motion studies can be used to develop work standards by measuring how long it takes an operator to complete a specified task or series of tasks. The person performing the time study can then “rate” the operator in terms of the level of efficiency achieved. Multiplying these values and then normalizing for established personal fatigue and delay allowances provides us with the standard.

- Industry established, pre-determined time measurements, such as Methods Time Measurement (MTM) or Maynard Operation Sequence Technique (MOST), break down work content into very specific, measurable motions that have specific times associated with them that are then adjusted for other parameters (e.g. weight lifted, degrees the body will turn during a movement).

Regardless of how budgeted work standards are developed, they can often be re-used from system-to-system based on commonality. However, it is critical that the standards be updated as production proceeds for the new system. For our commercial item in the section above, if our BWS for that system was 330.0 hours per unit and the mean hour requirement in steady state was 364.16, we can infer that our steady state efficiency was 90.6%. For our new system, we have established a BWS of 258.75 total hours per unit for assembly, paint, test and delivery of the new system. Assuming the same steady state efficiency for the DoD environment means we will require 285.6 hours per unit.

Developing the Estimate

Based on the information we have gained from our commercial item data, we can now estimate our direct labor requirements for a system that we expect to reach steady state at the 201st unit and have a direct labor requirement of 285.6 hours per unit from units 201-1,000. For units 1-200, we assume learning will take place at a rate of 85.0%, culminating in the 201st unit requiring 285.6 hours. We compute for our theoretical first unit hours as follows:

$285.6 = T1 * 201^{(\ln(0.85)/\ln(2))}$,

T1 = 990.3 hours

The resulting learning curve for predicting total direct labor hour requirements (302,543 total hours for 1,000 units) is shown in Figure 7.

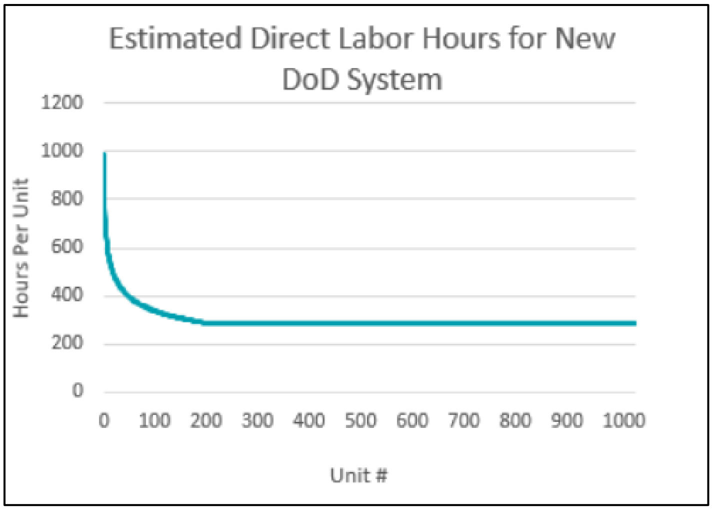

Figure 7

BEWARE OF FALSE ALARMS: THE IMPACT OF ORGANIZATIONAL LEARNING ON THE STEADY STATE

Recall from Figures 1 and 2 the large spike that occurred in labor requirements at unit 539 before returning to what appears to be another steady state unit after unit 550. The lead manufacturing engineer for that system indicated that a new machine was integrated into the assembly line that enabled increased throughput at one of the highly staffed stations. The same engineer explained that it took the staff a few days to learn how to operate the machine (hence the spike in hours), but thereafter less staff were needed at the station due to the new machine's capability. This explains why the system was able to return to a steady state so quickly and why less hours were required. This is a perfect example of production data alerting us to explore the root cause of the data's behavior. A lot of times, this alert is not so evident.

As cost analysts and estimators, we are trained to collect, normalize and analyze data in helping us make sound decisions or develop reliable estimates. However, analysis of direct labor data can pose a unique challenge. Manufacturing and assembly facilities are complex, dynamic environments with many variables at play that can impact our data and potentially mislead or misinform us. These variables can lead us to believe that a production system or environment is behaving one way and that is truly not the case at all. Figure 8 depicts a system that appears to be in steady state. However, the individual learning that is still taking place is being offset by a series of changes impacting the system parameters, leaving the system in a unique state of equilibrium.

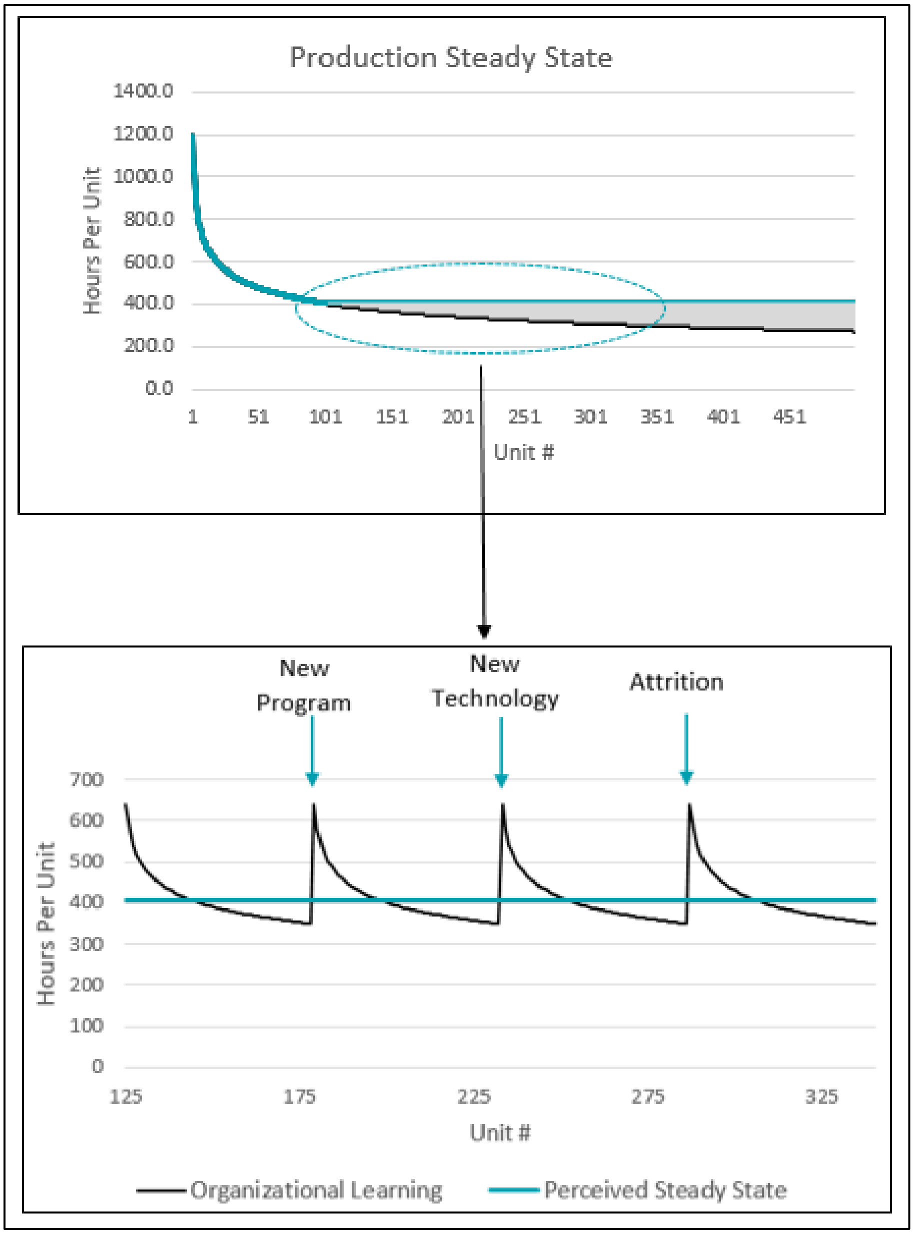

Figure 8

Below we discuss several scenarios that can alter the parameters of our system and leave our system experiencing what amounts to a false alarm (i.e. believing that we are in steady state when we are not). The majority of the scenarios relate to what was defined as organizational learning earlier. Whether these scenarios occur by themselves or in conjunction with each other, they can have a substantial impact on what is occurring in a system and, more importantly, impact the data that is recorded for the system.

1. Modifications to Scope

Rarely, if ever, does the configuration of a particular weapon system remain the same during a production run, much less its lifecycle. As the needs of the user for the end item evolve, so too will the configuration of the end item and subsequently the scope and effort required to produce it. Depending on the modification, work content and the direct labor requirements can either increase or decrease. More often than not, the work content will increase due to something that has been learned about the performance, safety, reliability or maintainability of the system.

2. Variable Production Rates

The rate at which end items are built generally varies over a production run. Once a production contract is awarded, a manufacturer will typically start out with a Low Rate Initial Production (LRIP) phase to help the staff ease into the production process in order to track lessons learned and not overload the system with too much staff too early. As more staff become increasingly familiar with the work content they are responsible for, and as the production process becomes more defined, the amount of expected throughput will increase. In order to do this and meet delivery schedule requirements, the manufacturer will be required to add staff. So long as new staff is being added, there will be individual learning taking place.

3. Business Base Additions/Subtractions

As McCarthy[4] addressed, when dealing with integrated production environments, parameter modifications to other systems could subsequently impact our system or end-item of interest. For example, it is not uncommon for a DoD system to be produced on the same line as other DoD systems or even commercial items that have common work content or operations. Variations in the delivery schedules, and subsequently rates, for other systems could then impact the performance of our system of interest by influencing the number of times an operator accomplishes a certain task where there is commonality. Additionally, if new systems/end-items are introduced to the assembly line or even the facility, the impact could be felt by management reassigning members of our staff to the new program, either for experience or capability purposes, leaving our system parameters modified.

4. New Technology

As production runs evolve, we often learn quite a bit about our system. We learn which workers are most efficient, we learn how to re-order operations in order to enable higher efficiency/maximize throughput and we also learn about alternative tools, equipment and technology that can improve our system's performance. These upgrades could be the result of either new technology being developed during our run or perhaps the result of cost benefit analysis being performed during our run (i.e. an upgrade to a piece of machinery may initially require training and additional individual learning, but it will eventually double throughput through efficiency gains experienced by the employees or the capability of the machinery itself). Regardless of what inspires management to invest in new technology, the performance and subsequent output of operations impacted by that technology could experience significant variance in data reported.

5. Attrition

Organizations rarely, if ever, experience a production run with the exact same staff from start to finish. Team members get promoted, retire, rotate and leave the organization constantly throughout a production run. Depending on the size of the organization and resource requirements needed for a particular end-item, the impact of staff churn may be negligible, but it may also be quite significant. Simply put, for every person that leaves an organization, so does their individual learning. It is possible that an equivalent amount of learning that has been lost via attrition must be gained by a replacement.

Another phenomenon that occurs in production organizations is bumping, a process used by companies to retain high-valued or longer tenured staff members when downsizing. Typically, the employee being retained “bumps” another employee from their position. Ironically, despite the seniority of the retained employee and their experience within the organization at large, their new assignment may require substantial individual learning. In some cases, the employee doing the bumping may be getting moved to a new role with which they have no familiarity. Small scale bumping likely does not have a large impact. However, mass bumping prompted by a variety of factors (e.g. other programs ending, contracts not being won) would likely have a substantial impact on the performance of a particular production run.

POTENTIAL REMEDIES

As the last section demonstrated, organizational learning can (and will!) occur in DoD production environments. This begs the question - Is it reasonable to assume that individual learning will continue, unimpeded by various organizational learning impacts, long enough to reach a steady state? The short answer to this is yes, but not always. Delivery schedule and production rate is usually the best place to look for this answer. If a new system had a rate of 1.0 unit per day, the chance of organizational learning impacting the system prior to the steady state being reached is much higher than for a rate of 20.0 units per day. To fully explore the reasonableness of a steady state being reached in a future system, analysis of how often and when various cases of organizational learning occurred in analogous systems should be performed.

In order to accomplish this analysis, communication with key team members with direct experience in the analogous systems is critical. For instance, we could talk to the following organizations regarding the type of organizational learning listed:

1. Human Resources: Attrition statistics, including labor category/level of expertise and dates that people left, as well as any bumping due to down-sizing.
2. Industrial Engineering/Production Management: Production rate data, including staffing levels and efficiency reports relative to the BWS at particular times.
3. Manufacturing Engineering: New technology and modifications to scope. As manufacturing engineers typically develop and update work instructions, they represent the most reliable resources in terms of identifying when scope and/or technology took place.
4. Program Management: Business base changes. Plant management will be aware of all programs occurring at a particular facility and to what extent resources were shared between systems.

CONCLUSIONS & RECOMMENDATIONS

Throughout this paper, we have explored several facets of the learning and improvement that occur in production environments. We have also identified the significance of the impact that comes from estimating when a system will enter into steady state as well as the criticality of predicting the steady state will occur too early or not at all. Unfortunately, the volatility that occurs within and around the system parameters for DoD production environments makes the likelihood of a system remaining in such a state for an extended period highly unlikely. Moreover, even though we know that parameters are going to change, it will still be next to impossible to predict when those parameters will change and what the subsequent impact on the system will be.

Despite these challenges, all estimators are strongly advised to study the behavior of analogous systems and attempt to identify when a steady state will occur for a particular production environment. Simply assuming that organizational learning will continuously impact individual learning and negate the presence of a steady state can lead to direct labor hours being drastically underestimated.

Our analysis of the commercial system in Figure 1 led us to a three step approach for identifying whether a system is in steady state:

1. Analyze a visual display of the data
2. Divide the data into bins and check for low variance in system parameters across bins
3. Statistical Testing (i.e. Dickey-Fuller Test)

In analyzing the analogous systems, we must stress the importance of not solely relying on production data to determine how future systems will perform. Only by performing root-cause analysis on key system parameters in conjunction with the data analysis will we be able to distinguish system improvement caused by individual learning from improvement driven by organizational learning. As discussed, a system operating under a constant set of parameters will eventually reach a steady state as a result of individual learning due to either time/repetition, quality thresholds, facility constraints or any combination of these forcing functions. In order to identify when steady states have commenced in analogous systems, it is critical to account for modifications to system parameters whenever feasible.

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BIOGRAPHY

Pat McCarthy, a Project Manager with Technomics, has over 18 years of experience in Federal and private industry performing cost analysis and Industrial Engineering studies. He has previously worked as a Cost/Price Analyst and Team Lead with Booz Allen Hamilton and the Army Contracting Command and as a Senior Industrial Engineer and Team Leader with General Dynamics Land Systems. Pat is CCEA certified and holds B.S. and M.S. degrees in Industrial Engineering from Purdue University.