

# IS THERE MEASURABLE LEARNING IN PROCESS IMPROVEMENT PROJECTS?

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## ABSTRACT

In this work, we study the organizational learning that occurs when trained facilitators gain experience from carrying out sequential process improvement projects. We used panel data from a large oil and natural gas company to track the performance of trained lean Six Sigma facilitators on projects over a course of five years. Individual facilitators carry out many different projects of varying sizes. Facilitators were grouped into cohorts, where cohort members of the  $n^{\text{th}}$  group are facilitators each leading their  $n^{\text{th}}$  project. We investigate the distribution of project durations for each cohort group and find that the means of the distributions trend downward by cohort number, indicative of learning. The learning rate appears to be about 90%.

**Keywords:** Learning rate, process improvement, Lean Six Sigma, DMAIC

## INTRODUCTION

Companies have long recognized the importance of continuous process improvement and have committed significant amounts of resources to train their employees in continuous improvement (CI) methodology. The strategic benefits from resulting improved operations are well documented. Thus, it becomes important to understand the role of learning that accrues from experience in repeatedly carrying out lean Six Sigma projects. Is there measurable learning occurring over time? Do employees become more adept at carrying out CI projects with experience? The extant literature on lean Six Sigma has not addressed this question using observational data. In our work, we attempt to make a beginning through empirical investigation of data from a large oil and natural gas exploration company.

These data track the performance of about seventy trained lean Six Sigma facilitators over a course of five years. Individual facilitators carry out many different projects of varying sizes and complexity. This enables us to characterize the distributional properties of cohort performance. If we model the aggregate organizational performance through this distribution then changes to the distribution resulting from experience capture learning. Our preliminary work shows a likely learning effect. We are continuing efforts to obtain additional data and carry out further statistical testing. In this work we report on our initial findings.

## LITERATURE REVIEW

Other authors have attempted to empirically investigate learning in Six Sigma process improvement projects, but they typically use survey instruments or other subjective assessments as the data source. For example, Arumugam, et.al focused on the impact of Six Sigma technical resources and team psychological safety. Three hypotheses were developed and tested using data from 52 Six Sigma

projects. Data were collected using a Web-based survey, where personalized emails were sent to all members and leaders of 110 completed projects, including links to the questionnaire [1].

Easton and Rosenzweig examined the likelihood of Six Sigma project success as a function of four experience variables: individuals, the organization, the team leader, and team familiarity. The study was conducted using data drawn from a large company with approximately 20,000 employees and \$6 billion in revenue. Logistic regression analysis was used to assess a binary indicator variable ‘project success’, as determined by the project team leader, in consultation with their supervisor, the master black belt, and the Director of Six Sigma. The authors concluded that team leader experience had the strongest relationship with project success [2].

Three Finnish multinational companies implementing Six Sigma programs were examined by Savolainen and Haikonen. The goal of this research was to study the dynamics of learning processes and understand how progressive learning is achieved, in the context of Six Sigma deployment. Their work was based on case studies, and concluded Six Sigma implementation within the three companies was primarily single-loop learning. The research methodology was strictly qualitative, and the authors developed a two-by-two classification table that mapped the maturity and efficiency of the organizations development activities [4].

In summary, our preliminary literature review indicates that few *quantitative* studies exist that assess organizational or team learning within lean Six Sigma environments. Furthermore, most studies that do exist are either entirely survey based, use opinion-based metrics, or rely on qualitative assessment only.

In the next section, we describe the data set and the data collection method. In the following section, we describe our model and data analysis. Finally, we conclude with a discussion of further planned work.

## THE DATASET

### Background

The traditional Six Sigma system consists of project teams improving processes using a structured method for problem solving known as the DMAIC framework; Define-Measure-Analyze-Improve-Control [3]. This DMAIC model was subsequently adopted by companies integrating lean methods with Six Sigma, and therefore lean Six Sigma programs are predominantly driven by this same problem-solving approach. The company in this study, a large oil and gas extraction company, also chose to adopt the DMAIC framework.

At the time of this writing, the firm had a corporate-wide lean Six Sigma program in place for over ten years (known within the company as Lean Sigma or LS). It ran numerous operating divisions around the world, and the level of commitment and progress towards LS varied within its divisions. Originally, the company rolled-out the LS program for key scientists, engineers, and other production personnel, beginning with two-weeks of intensive classroom training. The classroom content was created in collaboration with an independent consulting firm, which then hired third party Lean Sigma master black belts to conduct the actual training.

The company created a hierarchy of training levels typical of companies adopting lean Six Sigma, and used project teams as the primary method for analyzing and improving a process. A hierarchical belt structure was established that consisted of trained green belts as project team facilitators, with mentoring

support provided by more extensively trained black belts and master black belts.

Initially, green belt training and certification consisted of two, 5-day sessions, separated by several weeks (occasionally these sessions were held back-to-back). At the conclusion of the training, attendees were considered green belt trained, but were not officially certified by the company until they facilitated at least two LS project teams through the first four phases of the DMAIC process. Specifically, green belt candidates were required to organize and lead at least two projects to the control phase within 18 months of training course completion. Furthermore, the projects needed to meet a pre-determined minimum level of accrued financial benefit (AFB). The AFB was used as a reasonable estimation of the value created by a Lean Sigma project. These financial benefits could be measured in various ways, including revenue increases, savings in operating expenses, as well as soft non-AFB savings consisting of intangible benefits.

Green belt candidates were expected to bring several project ideas to the first training class. Project ideas were then compared, analyzed, and winnowed down during the training so that by the time of training completion the green belt could immediately form the process improvement team and follow the DMAIC framework forward. Occasionally, green belts completing training would begin two projects simultaneously, hoping to complete the two-project requirement, and thus earn certification, more quickly.

After completion of training, mentoring support was available to the green belts, in order to keep projects progressing and provide a source of expert advice in terms of actually applying LS principles learned in the classroom. Over time, the company shortened its green belt training program to six days, creating two, 3-day classroom sessions, spaced a few weeks apart.

In addition, a computerized project tracking system was created by the company, and all green belt candidates were required to enter relevant project information, beginning with the Define phase and its requisite problem statement and input-process- output (IPO) diagram. Since the Control phase had a fixed length of 12 months, for purposes of this study, the authors only considered the elapsed time between project initiation and the beginning of the control phase (i.e., the time to progress through DMAI phases only). Once the project moved into the Control phase, the facilitator monitored and entered financial benefits into the project tracking system on a regular basis, over the course of 12 months. The time values representing the start and finish of each project duration are referred to as Project start and project end. The difference between these two dates is the Duration, and was used as one of our primary metrics.

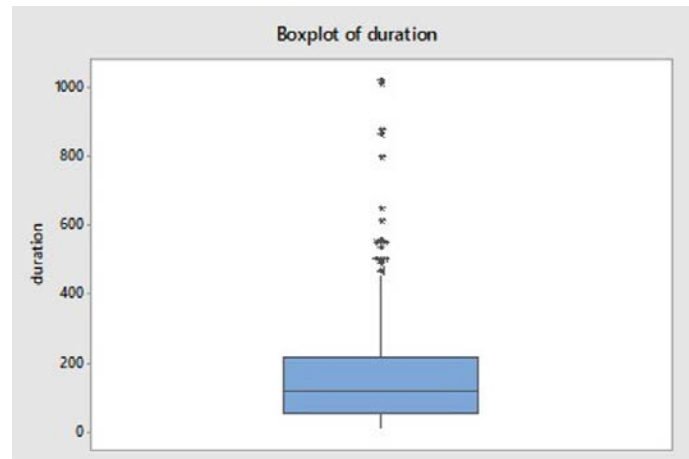
## **Description of Data**

The dataset that we received contained only the information described next. Essentially, for each project, we were given the start and end dates that allowed us to compute the duration. We deleted projects that had a duration of less than 10 days, and those with duration greater than 472 days. The reason for the former is that the dataset also listed mini-projects that were not DMAIC-type projects, and these were generally thought to last less than 10 days. Seventeen projects had a duration greater than 472 days; these we deemed as outliers based on the boxplot (see Figure 1).

Projects generally last about a year and longer durations are suspect from tardy or erroneous logging in the project tracking system. This yielded data on 326 projects. These 326 projects were performed by 72 facilitators. These facilitators have all been trained on the DMAIC method of process improvement through one or two week training programs (flagged by a suitable indicator variable in the data). As noted,

a facilitator might undertake projects of different sizes. Multiple facilitators might work on a given project but the start and end dates of their involvement are separately logged. Furthermore, for each facilitator we have information on when they completed DMAIC training. Additional information included details such as the facility identifier for each project; Table 1 shows a sample of the data.

**Figure 1. Boxplot Method used to Discard Outliers**



**Table 1: Excerpt from Dataset**

Facilitator ID	Training Type	Training Time-stamp	Project ID	Operating Unit Code	Project Start	Project End
1001	2	456	10634	2015	678	909
1001	2	456	11229	2015	776	994
1001	2	456	8078	2015	406	504
1001	2	456	10110	2015	613	642
1001	2	456	14113	2015	1009	1028

## MODEL AND DATA ANALYSIS

### Hypothesis

In our model, we consider cohorts of facilitators; the  $n^{\text{th}}$  cohort consists of facilitators each doing their  $n^{\text{th}}$  project. We model the  $n^{\text{th}}$  cohort as having project durations given by the distribution  $f_n(x)$ . This captures the range of projects undertaken as well as the skill of the facilitators. If  $\mu_n$  is the mean of  $f_n(x)$  we hypothesize that  $\mu_{n+1} < \mu_n$ , indicating that the cohort is learning from experience and that on average the duration on their succeeding projects are shorter. The null and alternative hypothesis can be written as follows:

$$H_0: \mu_1 = \mu_2 = \mu_3 = \dots = \mu_n$$

$$H_1: \text{Not all } \mu_i \text{ are equal (where } i = 1, 2, \dots, n)$$

We then quantify this organizational learning by tracking several such cohort performance and computing a Wright Learning Rate.

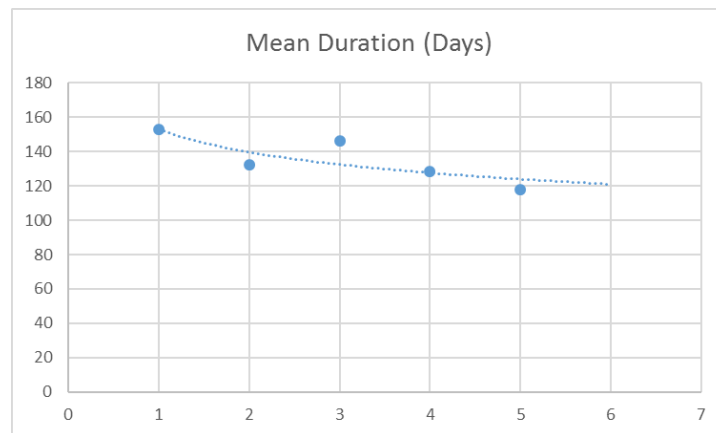
## Empirical Estimation of $f_n(x)$

Table 2 shows the frequency of samples in each cohort group of projects. We also note that in the aggregate, the mean durations are decreasing and that the standard deviations are approximately equal. Probability plots of log duration values in general suggested that durations in each cohort group follow the lognormal distribution, although p-values in cohort groups 3 and 5 fell below 0.05, suggesting more data are needed to confirm this assumption. Empirically,  $f_n(x), n = 1, \dots, 5$  is lognormal with mean and standard deviations as shown in Table 2. In Figure 2, we plot the cohort means, which shows a distinct downward trend.

**Table 2: Statistics on Cohort Groups**

Cohort Group	Sample Size	Mean duration (days)	Duration Std. Deviation (days)	Mean Log Duration	Log Duration Std. Deviation
1	72	152.7	108.6	4.760	0.79
2	69	132.5	103.3	4.540	0.91
3	62	146.4	113.7	4.620	0.94
4	54	128.6	94.2	5.540	0.89
5	34	117.8	91.5	4.412	0.93

**Figure 2. Plot of Cohort Mean Duration**



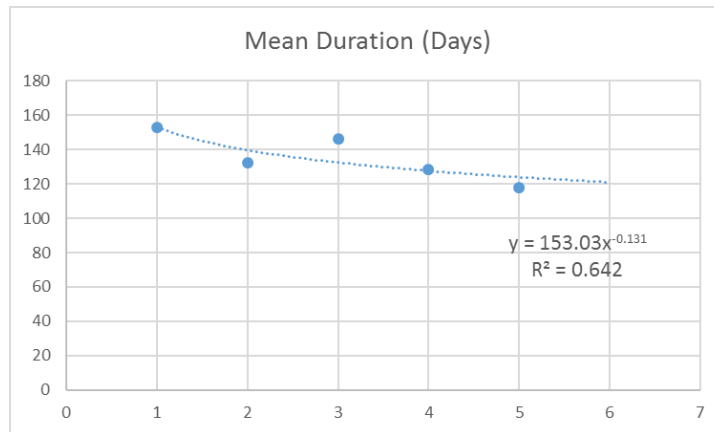
## Estimation of Wright Learning Curve Rate

Motivated by the downward trend in cohort means, we fitted a power curve to the observed means. Figure 3 shows the fitted curve, the equation, and the  $R^2$  value. The  $R^2$  is 0.64 indicating a reasonable fit. From the fitted equation:

$$\text{Duration} = 153.03n^{-0.131} \text{ (where } n = \text{cohort number)}$$

From this relationship, we can estimate the learning rate to be approximately 0.90 [from  $e^{-0.131 \cdot \ln(2)}$ ].

**Figure 3. Fitted Learning Curve**



### **CONCLUSION**

Our preliminary analysis appears to indicate a measurable learning curve rate of around 90%. It denotes the improvement in cohort mean durations with experience, and may be viewed as a measure of organizational learning. Clearly, it is unlike the individual learning that occurs when an operator performs identical tasks repeatedly. Here we find that cohorts perform projects with varying durations and complexity. However, the mean duration decreases with experience and must be attributed to the learning of the whole cohort. Our work with the data analysis, including hypothesis testing, continues.

### **REFERENCES**

- [1] Arumugam, V., Antony, J. & Kumar, M. Linking learning and knowledge creation to project success in Six Sigma projects: An empirical investigation. *International Journal of Production Economics*, 2013, 141 (1), 388 - 402.
- [2] Easton, G.S. & Rosenzweig, E.D. The role of experience in six sigma project success: An empirical analysis of improvement projects. *Journal of Operations Management*, 2012, 30 (7-8), 481- 493.
- [3] Pyzdek, T. & Keller, P.A. *The Six Sigma handbook*, 3rd edition, McGraw-Hill, 2009.
- [4] Savolainen, T. & Haikonen, A. Dynamics of organizational learning and continuous improvement in six sigma implementation. *The TQM Magazine*, 2007, 19 (1), 6 - 17.