REDUCTION OF PROCESS VARIATION USING STATISTICAL ENGINEERING

[a]JAN KOSINA

VŠB – Technical University of Ostrava, Faculty of Metallurgy and Materials Engineering, 17. listopadu 15, 708 33 Ostrava-Poruba, Czech republic
email: [a]jan.kosina@continental-corporation.com

Abstract: Statistical engineering is known as a discipline integrated within existing problem solving methodologies such as Six Sigma or Shainin for several decades. Recent effort to formalize the statistical engineering as a discipline and to establish statistical engineering as quality improvement methodology is significant. This paper summarizes the relation between statistical engineering and existing improvement methodologies – Lean Six Sigma and Shainin Red X[®] - as well as the contribution of statistical engineering to monitoring and improvement of the process variation. The wide deployment of the problem solving methodologies led to the lack of statistical thinking. The deployment of the statistical thinking by the integration of the statistical engineering system into the Lean Six Sigma or Shainin hierarchy could be a solution which would lead to better utilization of the statistical tools and more effective problem solving.

Keywords: Statistical Engineering, Shainin, Shainin Red X[®], QPDAC, Lean Six Sigma, quality improvement, problem solving.

1 Statistical Engineering

The effort to formalize statistical engineering as a discipline started in first decade of new millennium (Hoerl, 2010) and brings several interesting discussions about the definition, scope and purpose of the new discipline. Surely the statistical engineering was the part of the quality improvement methodologies before the formalization started. Searching in the literature we would find the statistical engineering as the discipline mentioned in the statistical and quality literature from 1940s. Quality improvement methodologies widely applied to solve the industrial problems – Lean Six Sigma and Shainin Red X[®] - are based on the statistical approach. Wide introduction of quality improvement methods brought on the development of user-friendly statistical software and the responsibility for the statistical analysis moved from statisticians to problem solvers. A problem solver is typically an engineer, an expert in a technical discipline who went through an intensive statistical training program. It means the statistical work is nowadays performed by non-statisticians particularly in case of routine tasks. This is called "democratization of statistics" (Hoerl, 2010 (2)). In the past statistical engineering was seen as a consultant job done by statisticians to advise, guide and assist other disciplines to plan experiments and tests, to plan the data collection and to evaluate data. This is not the case recently because of democratization of statistics.

Why is there a need to define or re-define the statistical engineering? Democratization of statistics could lead to the situation the deep analysis of data is not performed properly in terms of content and context of the data. On the other hand the interpretation of the data would not be beneficial without deeper analysis of the process which produced the data. It is obvious a successful problem solver understands statistics as well as an engineering discipline. It seems to be a contradiction. There could be two ways to overcome this situation: an integration of engineering knowledge and problem solving tools into the profession of statistician or to integrate statistical thinking with statistical methods and tools into the problem solving methodology.

Integration of engineering knowledge and problem solving tools into the profession of statistician would lead to the definition of statistical engineering as an improvement methodology. Typical problem to be solved by such methodology have following attributes: high degree of complexity with no known solution of the problem, high impact to organization, more than one statistical technique is needed to find a solution (typically statistical and non-statistical), a solid theoretical foundation is required to perform problem solving steps. The concept of statistical engineering for problem solving consists of four blocks (Snee, 2011):

1. Defining the problem, objective or concern.
2. Identifying the stakeholders involved in and affected by the problem.
3. Creating a strategy and high level approach that will be used to provide structure to the problem.
4. Establishing initiatives (tactics) for implementing the strategy that is unique to the problem.

The difficulty is the scope of the statistical engineering problem matches the scope of the typical problem to be solved by Lean Six Sigma or Shainin Red X[®]. One definition of statistical engineering says simply "Statistical engineering is a special marriage of engineering and statistics applied to solving technical problem" (Shainin, 1993). This definition fits to most common application of the statistical engineering within improvement activities represented by Six Sigma and Shainin Red X[®]. We can dispute these are the methodologies which are bringing the democratization of the statistics. The missing link is statistical thinking.

The aim of this article is to show the contribution of the statistical engineering to quality improvement and the deployment of the statistical thinking within existing improvement concepts. The quality improvement in most cases is equal to reduction of process variation therefore the link of statistical engineering to following methodologies will be discussed: statistical process control, improvement of high-volume manufacturing processes and problem solving methodologies – Shainin as well as Six Sigma.

2 Methodologies for reduction of process variation

2.1 Statistical process control

Statistical process control is preventive tool of quality management as the early detection of the significant process deviations from the upfront defined level allows realize appropriated process adjustments. The goal is to keep the process on required and stable level as well as continuously improve the process (Tosenovsky, 2000). Statistical process control itself is not the tool to reduce the variation. The goal of statistical process control is to monitor process variation using statistical tools. SPC distinguishes variability caused by random causes (the process is considered to be statistically stable) from variability caused by abnormal assignable causes (the process is considered not to be statistically stable) (Tosenovsky, 2000). Although SPC is quite well-known technique (SPC is part of the 7 basic quality tools), the SPC application is in many cases intended to fail. The key point of the SPC utilization is analysis of variation. If the analysis is not performed continuously (as part of the standard process evaluation process) SPC application will turn to creation of graphs which are just archived without a benefit. The responsibility for correct application of SPC starting from selection of the relevant chart, calculation of the control limits as well as warning limits to proper interpretation of the results is typically part of the quality engineering job.

The role of statistical engineering is recently seen in the other area of SPC application: the implementation of the real-time SPC systems. One of the definitions says: "statistical engineering is defined as the study of how to best use statistical concepts, methods and tools, and integrate them with IT and other relevant sciences to generate improved results" (Hoerl, 2010). The application of the SPC especially in high-volume manufacturing requires the implementation of the real-time SPC system which collects data online from the production processes and creates the SPC charts automatically. The output of such system is usually connected to visualization and production systems as Jidoka and Andon. On the other side the real-line SPC system can be used as the base for identification of problems – both chronic and urgent – as well as for decision making process on different management levels. Statistical

engineering has to play new role as the SPC implementation is more focused on the preparation phase: selection of the proper software, definition of the data interfaces and connection to production systems (Jidoka, Andon, EPC - engineering process control, MES – manufacturing execution system). The analytical phase is performed as SPC driven manufacturing analysis rather than pure statistical analysis of the data. This approach to SPC analysis requires the knowledge of both - the statistics and the related manufacturing processes.

2.2 Improvement of high-volume manufacturing processes – Statistical Engineering

The algorithm for reducing process variation called Statistical Engineering (Steiner, 2005) is a framework for the application of statistical engineering within a problem solving methodology. The algorithm (Pic. 1) was designed to solve long-term repetitive problems on high- and medium-volume manufacturing and assembly processes. To use the algorithm properly requires the combination of the statistical knowledge as well as empirical knowledge about the concerned process. It means to learn about process by observation and experimentation.

Picture 1 Statistical engineering algorithm (modified from Steiner, 2005)
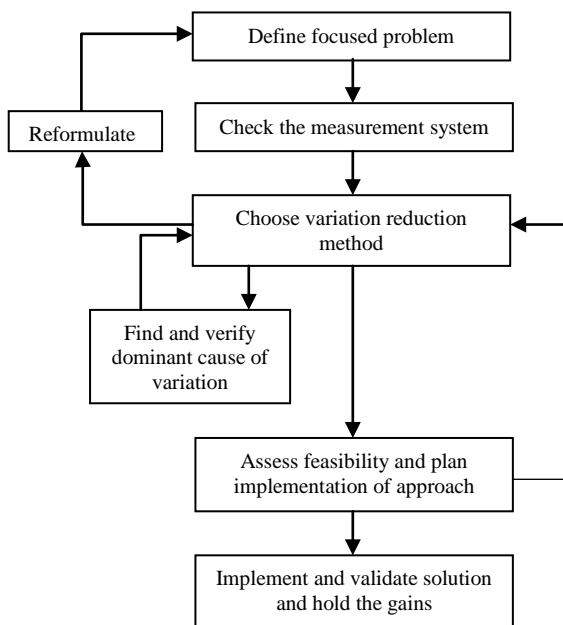
The framework of Statistical Engineering- QPDAC - is used to plan and execute the related investigations:

- Question – develop a clear statement what we are trying to learn
- Plan – determine how we will carry out investigations
- Data – collect the data according to plan
- Analysis – analyze the data to answer given question
- Conclusion – draw conclusion about what has been learned

The algorithm classifies seven methods for variation reduction:

1. Fixing the obvious based on knowledge of a dominant cause. This method requires team who has sufficient knowledge about process to determine an obvious solution. The availability of obvious corrective action depends on the knowledge of the process strongly. Team has to be confident the obvious solution is feasible, the possible side effects and costs has to be taken in account.
2. Desensitizing the process variation in a dominant cause. Desensitization will not eliminate a dominant cause. The goal is detect a process input which will reduce the sensitivity of the relationship between dominant cause and related process output. In this case the decision is to live

with the dominant root cause but the effect of the dominant root cause is reduced.
3. Feedforward control based on a dominant root cause. A feedforward controller is used reduce the effect of the detected dominant root cause. The basic principle is the measurement of the cause, prediction of the output and comparison of the predicted output value to the target. If the predicted value deviates from the target out of a specified range the process adjustment will follow.
4. Feedback control is based on the prediction of the process output based on the trend of previously measured output values. The feedback control is particularly effective in case of time-to-time output variation. The adjustment of process centre follows in case of an unacceptable deviation of predicted process output value to the target.
5. Making the process robust to cause variation. To make a process robust means to reduce the effect of the unknown dominant cause by the change of the fixed inputs. The DOE (Design of Experiments) methods are used to detect relevant inputs and evaluate related effects to unknown dominant cause as well as level of the process variation. Recently not only optimized inputs but also the noise factors are taken in account to design robust processes as the noise factors may have big influence to the process outputs (Tosenovsky, 2013). The noise factors cannot be adjusted.
6. 100% inspection. This is the simplest and most controversial approach. We are simply talking about comparison of the output value of each production unit to the inspection limits. The units out of the limits has to be reworked, repaired or scrapped. It is important to not use specification limits for 100% inspection as the specification limits are usually customer related. The inspection limits for 100% inspection has to be tighter.
7. Moving the process centre closer to target. This method is applicable on processes which were detected as off-target mean value of process. The goal is to define a way to move the mean of a respective process characteristic closer to the target value. Generally the target could be to move the mean to any direction within a specification limits depending on the target value. There are surely processes where the target value requirements are specified as higher or lower is better. The application of this method demands the identification of an adjuster: the process input that influence the output.

The aim of the root cause investigation is to find a dominant root cause. This is the approach similar to Shainin Red X® methodology. The first three methods mentioned above cannot be applied without dominant root cause being identified. The last four methods represent the effective solutions in case the root cause is not known or there is several contributors causing the variation. These methods are based on elimination of symptom rather than root cause. We can state the methods based on the elimination of the dominant root cause are more efficient but the methods listed as last four are widely used in the real industrial world. At the end the goal is to define the cost-effective solutions to reduce the process variation by increased knowledge of process. Selection of the variation reduction method leads to effective and efficient solution.

2.3 Shainin Red X® methodology

The Shainin Red X® methodology was developed by Dorian Shainin in from 1950s to 1990s. The basic concept can be summarized by 6 statements:

- Variation exists in all processes
- Understanding and reducing variation are keys to success
- In the real world nothing happens without a reason
- There is always a dominant root cause (called RedX® in Shainin terminology)
- Finding and controlling the Red X® is the only way to reduce variation
- Executing a progressive search by "talking to the parts" is the best way to find the Red X®

Most of problem solving methodologies use divergent approach: X to Y, from input to output. It means the first step is to study symptoms and then in the next step the relation of inputs to outputs is assessed using an empirical knowledge of the process or product. Typical output is the list of potential causes gained out of Ishikawa, brainstorming and an engineering analysis. It usually leads to the situation symptoms are understood but failure mechanism not. Root cause hypothesis assumes the combination of several possible contributors but the identification of the real dominant root cause is missing.

Shainin Red X® methodology uses convergent approach Y to X, from outputs to inputs. What does it mean? It is absolutely necessary to understand the output of the process – the Green Y®. No problem can be solved without knowledge of the output, distribution of the output values, detail knowledge of the product and related manufacturing process, symptoms of the failure as well as difference between good and bad parts. This is ensured by approach which is described as "talking to parts", the progressive search methodology based on elimination of suspects, comparison between good and bad parts, finding extremes and contrasts.

The key idea of Shainin Red X® methodology is Red X® paradigm. This paradigm is coming out of the application of the Pareto principle to the causes of the variation (Pic. 2). By application Pareto principle you would get contribution of the Xs (process inputs) to the ΔY (increment of the output) as shown on Pic. 2. The Red X® is dominant root cause. It does not mean it is the only root cause. The Red X® is the strongest root cause. Following the logic of Shainin Red X® concept there could be maximum three causes identified – two additional called Pink X® and Pale Pink X® - which are usually in the interaction with Red X®.

Picture 2 Red X® paradigm
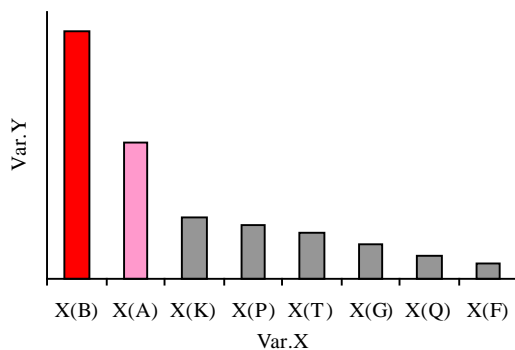
Source: www.shainin.com

The identification and control of Red X® is the key result which will bring process improvement. Once the Red X® is identified the determination of a mathematical model in the form of Y=f(X) is not necessary. In fact, it would be unproductive to look for the relation. We would spend too much time to determine relationships which are already controlled.

Shainin problem solving roadmap is called FACTUAL™ (Focus, Approach, Converge, Test, Understand, Apply, Leverage) is shown in table 1. (Hysong, Shainin and Six Sigma). Shainin Red X® methodology is particularly strong in the diagnostic journey, it means in phases Focus, Approach, Converge and Test. The usage of the right tools is driven by strategy, strategy which is defined as the outcome of the Green Y® analysis at the beginning of the problem solving project and which is continuously updated after each step.

What is actually the role of a statistical engineer within Shainin Red X® concept? The answer is simple: problem solving. Problem solving which can be expressed in three steps: study symptoms, identify the root cause and propose a solution. Shainin techniques are statistically simple, graphical analysis is

preferred and keeps the statistics in the background. This allows an engineer to keep focus on technical background of the problem and critical relationships.

Table 1 Shainin roadmap: FACTUAL™

| Focus	- Leverage probable events - Project Definition - Estimate the impact
Approach	- Green Y® Identification and Description - Development of Investigation Strategy - Measurement System Verification
Converge	- Converging on the Red X® - Compare best and worst case - Red X® Candidate Identification
Test	- Risk Assessment - Red X® Confirmed by Trial
Understand	- Green Y® to Red X® Relationship Understood - Optimization of interactions - Customer needs translated to limits - Appropriate Tolerance Limits Established
Apply	- Corrective Action Implemented and Verified - Procedures updated - Green Y® monitoring - Project Benefits and Cost Savings
Leverage	- Read Across Red X® Control - Savings Calculated - Lessons Learned

2.4 Lean Six Sigma

Lean Six Sigma is a managerial concept combining Lean and Six Sigma approach which was first published by Michael George in 2002 (George, 2002). Lean Six Sigma combines the Six Sigma DMAIC (Define, Measure, Analyse, Improve, Control) concept and Lean tools in the methodology which aims to improve quality and efficiency of the process. Defects are considered as waste in the Lean concept. Target of Lean Six Sigma is a sustainable improvement of quality, elimination of waste, decrease of costs, improved metrics and introduction of the change in company culture.

Shainin Red X® concept insists on application and regular update of problem solving strategy while Six Sigma is rather wide collection of the tools which can be used within DMAIC framework. The usage of the related statistical tools within Shainin is determined by strategy, Six Sigma allows problem solver to using variety of the statistical and non-statistical tools. This could be on one hand an advantage of Six Sigma but it can become a big disadvantage in case of inadequate usage. This conflict is one of the reasons Six Sigma methodology is being criticized due to extensive demand of statistical knowledge.

While Shainin Red X® methodology is more focused on technical problem solving Lean Six Sigma can be applied across multiple business models. Six Sigma is very often used to solve large, complex, unstructured problems with high impact to an organization. Such problems could require effective application of statistical tools, at some point an integration of several statistical tools in case of high complexity would be necessary. This is in line with the recent definition of the statistical engineering. To solve the large, complex problems require team approach, creation of multidisciplinary teams. The question stays same: what should be the role of statistical engineer? The ongoing discussion about statistical engineering contains the point related to leadership of a statistical engineer. Taking in account the experience from industrial problem solving projects a leadership is in hands of an engineer experienced in technical area rather than a statistical expert. The missing link - insufficient statistical thinking - can be deployed within Six

Sigma structure. Snee defines the statistics and statistical engineering as a system (Snee, 2010). The combination of the statistical engineering system with well-known hierarchy of the Six Sigma belts is shown on Pic. 3. The statistical thinking can be deployed in direction from Master Black Belt to Black Belt and to Green Belt. The role of statistical engineer is overlapping with Black Belt role then. So the deployment of the statistical thinking and statistical engineering is actually related to the proper organization of the Six Sigma structure within an organization. This would allow an organization to select suitable candidates to the key positions (Master Black Belt/Black Belt) taking in account their education and knowledge base and plan an appropriate long-term training program to build sufficient knowledge in both statistical and technical area. The same approach could is established within Shainin following top-down hierarchy: Master, Journeyman, Apprentice (see Pic. 3).

Picture 3 Statistical engineering system built-in the Lean Six Sigma and Shainin hierarchy
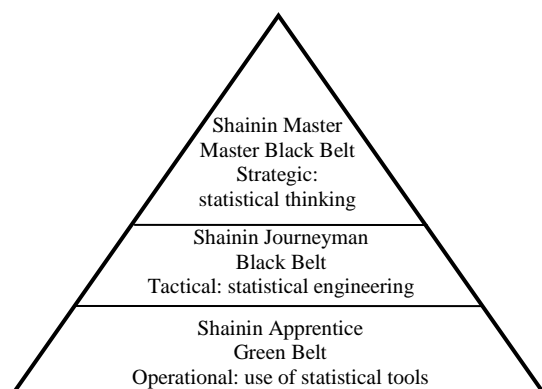
3 Conclusion

Statistical engineering is currently being established as new discipline. One of the results of this effort should establish statistical engineering as a quality improvement methodology. The creation of the separate statistical engineering improvement methodology can be quite long journey. The quicker and more reasonable way to improve application of statistical tools is alignment of statistical engineering with existing concepts– Lean Six Sigma and Shainin Red X®. The contribution of statistical engineering to monitoring and improvement of the process variation is significant and brings the results: the algorithm for process variation reduction proposed by Steiner and MacKay (Steiner, 2005) or the long successful history of the Shainin Red X® application in the field of industry could be taken as evidence of that. For sure there are other fields which would require the attention of the statistical engineer in the future as Statistical Process Control or an improvement of statistical toolkit within Lean Six Sigma. It is clear the position of the statistical engineering changed in last decades. The statistical analysis is performed by non-statisticians largely which is related to wide deployment of the improvement methodologies. This could lead to lack of statistical thinking as side effect. This can be solved by the integration of the statistical engineering system into the Lean Six Sigma or Shainin hierarchy which would bring the new role of statistical engineering in the area of the problem solving and the support of problem solving activities.

Note: Red X®, Green Y®, FACTUAL™ are legally protected marks of Shainin LLC.

Literature:

1. George, M.: *Lean Six Sigma: Combining Six Sigma with Lean Speed*, New York: McGraw-Hill, 2002, 300 s., ISBN: 978-0-07-138521-3
2. Hoerl, R. W., Snee, R. D.: *Closing the Gap: Statistical Engineering Can Bridge Statistical Thinking with Methods and Tools*, Quality Progress, Vol. 43, No. 5, May 2010, p. 52-53, ISSN: 0033-524X
3. Hoerl, R. W., Snee, R. D.: *Statistical Thinking and Methods in Quality Improvement: A Look to the Future*, Quality Engineering, Vol. 22, No. 3, June 2010, p. 119-129, ISSN: 1532-4222
4. Hysong, C., Shainin, R.: *Shainin and Six Sigma*, available at https://shainin.com/library/FACTUALvDMAIC
5. Shainin, R.: *Strategies for Technical Problem Solving*, Quality Engineering, Vol. 5, No. 3, 1993, s. 443-448, ISSN: 1532-4222
6. Snee, R. D., Hoerl, R. W.: *Engineering an Advantage*, Six Sigma Forum Magazine, Vol. 10, No. 2, February 2011, p. 6-7, ISSN: 1539-4069
7. Snee, R. D., Hoerl, R. W. *Further Explanation. Clarifying points about statistical engineering*, Quality Progress, Vol. 43, No. 12, December 2010, p. 68-72, ISSN: 0033-524X
8. Steiner S.H., MacKay R.J.: *Statistical Engineering: An Algorithm for Reducing Variation in Manufacturing Processes,* Milwaukee: ASQ Quality Press, 2005, 716 p., ISBN: 0-87389-646-7
9. Tosenovsky J., Noskievicova D.: *Statistické metody pro zlepšování jakosti,* Ostrava: Montanex, 2000, 362 p., ISBN: 80-7225-040-X
10. Tosenovsky J., Tosenovsky F., Kudelka O.: *Analysis of Robust Technology Design Methods* in Conference proceedings 22nd International on Metallurgy and Materials Metal 2013, *2013,* p. 1662-1667, ISBN:978-80-87294-41-3

Primary Paper Section: J

Secondary Paper Section: JS