Achieving Six Sigma rating in a system simulation model

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Abstract: This paper describes an approach for achieving Six Sigma rating in Critical-to-Quality (CTQ) criteria measured through a system Discrete Event Simulation (DES) model. Lean manufacturing techniques are utilised at the Improve (I) phase of DMAIC to reduce manufacturing lead time. DES provides a flexible platform for applying DMAIC analyses as well as lean manufacturing techniques. An example of a simple manufacturing process is used to clarify the application of the proposed approach. Results showed that while achieving Six Sigma rating may not be always practically attainable at system level, significant relative improvement can still be achieved.

Keywords: Six Sigma; Define, Measure, Analyse, Improve and Control (DMAIC) process; Discrete Event Simulation (DES); lean manufacturing.

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1 Introduction

Companies today often face the new millennium challenges of fierce competition and decreasing business safety margins. As a result, high quality and low cost products with short lead time are increasingly becoming core competencies in today's marketplace. Hence, the latest developments in Industrial Engineering collectively aim at helping companies improve the quality of products and services, increase operations effectiveness, reduce costs, and increase market share. Initiatives such as Total Quality Management (TQM), Business Process Re-engineering (BPR), Lean and Agile Manufacturing, Six Sigma, and Kaizen are examples of such developments.

As a quality initiative, Six Sigma has received wide acclaim among world-class companies such as General Electric (GE), Motorola, and Allied Signal (Harry and Schroeder, 2000; General Electric Company, 2002; Motorola Company, 2002). As a well-structured problem solving and continuous improvement methodology, the Six Sigma DMAIC process is widely-used in problem-solving and improvement of products/processes falling below specifications. Sigma Rating (SR) provides a statistical quantitative metric to measure a process performance in terms of a set of CTQ criteria. A process is considered Six Sigma capable when its long term performance achieves 3.4 Defects per Million Opportunities (DPMO). Further details of Six Sigma methods can be found in Breyfogle (1999).

Applying Six Sigma at the system-level (e.g., a production system) often entails some enhancements to the conventional DMAIC process. Production systems are often characterised by dynamic, complex, and stochastic behaviour. Hence, CTQ improvement is often made to time-based performance metrics such as throughput and lead time. Examples and definitions of such metrics can be found in Al-Aomar (2003). With the use of computer capabilities in logical programming, random generation, fast computations, and animation, simulation modelling can be a perfect engineering tool for representing the dynamic behaviour of production systems and providing estimates of time-based performance measures under complex and stochastic conditions. Thus, simulation models are playing an increasing role in Six Sigma application to production and business systems. As discussed in Ferrin et al. (2002), the major simulation contribution to Six Sigma is mainly attributed to its capability of capturing the complex and stochastic characteristics of a real-world process as it evolves over time. DES, in particular, is an effective system simulation technique that has undergone a tremendous development in the last decade. This development can be pictured through the growing capabilities of DES packages and the application of simulation solutions to a variety of real-world problems. Examples of DES applications can be found in Law and Kelton (1991), Banks et al. (2001) and Smith (2003).

Six Sigma application at the system-level also intersects with the concept of lean manufacturing. This has lead to the Lean Six Sigma (LSS) initiative (George, 2002; George et al., 2004). LSS aims at combining Six Sigma quality (high performance with less variation) with lean effectiveness (process speed and reduced waste). Lean is mainly aimed at the elimination of waste 'muda' in every process activity by incorporating less effort, less inventory, less time and less space. Main lean techniques include the use of pull/Kanban production system with single-unit flow, short changeover (SMED), organised workplace (5S), and balanced and standardised workstations. This ultimately leads to establishing a Just-in-Time (JIT) environment with short lead time, reduced production cost and quick response to customer demands. Further details on lean techniques are discussed in Womack and Jones (1996) and Feld (2000).

This paper, therefore, focuses on presenting a structured approach for utilising DES and lean manufacturing in the Six Sigma methodology to seek improvement in system-level performance metrics. DES provides a flexible and efficient platform for applying the Six Sigma DMAIC process and lean manufacturing techniques. The remainder of this paper is organised as follows. Section 2 gives some conceptual background on defining Six Sigma and lean manufacturing. The section also examines the process of determining the Six Sigma rating using a five-step procedure. In addition, we elaborate on the pillars of the DMAIC process. In Section 3, we present the concept of simulation-based SR and explain the DMAIC-DES interaction and the DMAIC-lean interaction. In Section 4, we present an application example where we apply the proposed approach to a hypothetical widget manufacturing process. Section 5 is the concluding segment of this paper.

2 Sigma Rating (SR) and Define, Measure, Analyse, Improve and Control (DMAIC) process

The Six Sigma literature is replete with definitions and applications of Six Sigma. As discussed in Breyfogle (1999), Six Sigma is a rigorous and disciplined methodology that measures quality simply and strives for near perfection, commonly defined as 3.4 DPMO. The wide-range of Six Sigma applications clearly indicate that Six Sigma is a holistic approach, for it goes beyond the 'factory floor' to other sectors of the economy. Hence, Snee and Hoerl (2005) view Six Sigma as a strategic approach that works across all processes, all products and all industries. On a long term basis, the fundamental objective of Six Sigma is the implementation of a measurement-based strategy that focuses on product/process improvement and variation reduction. In addition to being a quality philosophy, Six Sigma is based on two distinct functions: a quality metric (SR) and an improvement methodology (DMAIC process).

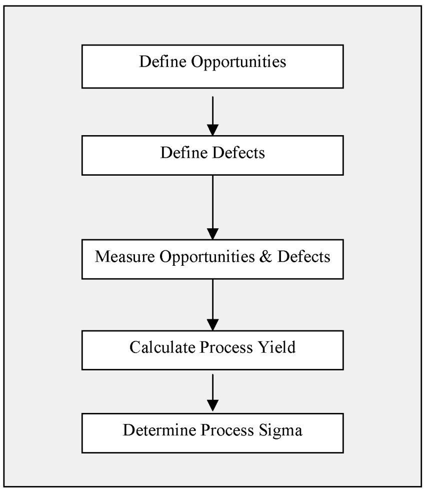
2.1 Determining process Sigma Rating (SR)

In Six Sigma, process SR is determined for the identified process CTQs. Process CTQs represent characteristics that are essential to satisfy customers. The needs and wants of a company's customers (internal or external) are often the starting point in determining CTQ issues. Various techniques are used for hearing the Voice Of Customer (VOC) such as feedbacks, surveys, focus groups and so on. CTQ criteria are then measured in terms of count of opportunities and ND in order to calculate process Sigma.

Two assumptions often impact process Sigma: process stability and normality. The Six Sigma method assumes that the process is stable in the short-run and an expected standard Sigma shift of 1.5 is likely to occur in the process mean due to long-term process variation. This shift was initially observed in industrial processes at Six Sigma pioneering companies, particularly Motorola, where Long-Term Dynamic Mean Variation was found to typically fall between 1.4 Sigma and 1.6 Sigma (Motorola Company, 2002). Without the shift, however, the 3.4 DPMO corresponds to only 4.5 Sigma. It is, therefore, conventional to add a 1.5 Sigma shift to short term performance when the true long term performance is unknown, and vice versa. If a process is in a state of true statistical control there will be no difference between short term and long term process capabilities.

Since many real-world processes may not be normally distributed, we can still apply Six Sigma to non-normal processes. The normality assumption is needed to convert the Sigma level to DPMO, based on the relative area beyond the specification limits. For continuous data, the defect rate is computed by fitting a non-normal distribution and computing the relative area beyond the specification limits. This relative area is then used for a normal distribution to compute the SR without assuming normality of the original data. For discrete (i.e., defective/not defective) data, one generally collects enough data to ensure that the binomial distribution approximates well to a normal distribution. Non-normal data can be treated in different ways such as sub-group averaging, segmenting and transforming data, and using non-parametric statistics (Montgomery and Runger, 2003). With such assumptions, process Sigma is determined in a 5-step procedure as shown in Figure 1.

Figure 1 Determining process Sigma Rating



Define process opportunities

Defining process defect opportunities in the produced units is key factor in Sigma calculation. Each defined opportunity must be independent of other opportunities, measurable and observable, and directly relates to the customer CTQ. Complexity in the product or service, however, often results in more than one opportunity per unit. Examples include assembling a product from two or more components, machining a part on several machines, or entering several fields of data onto a computer screen.

Define process defects

A defect is defined as any part of a product or service that does not meet internal or external customer specifications and requirements. A unit may have defects but not be necessarily defective. Examples include a pager that did not function properly, a one-minute power outage for customers, or a late delivery.

Measure total process opportunities

Total process opportunities are determined by multiplying the number of units by the number of opportunities per unit. A unit is a measurable output of the process such as products of a plant, customers of a bank, and hours of electrical service. Process defects are measured in the output by checking product specifications, reviewing system history (if available), surveying customers, or through the set up of a formal data collection plan.

Calculate process yield

The process yield is calculated by first determining the defect percentage (total defects/total opportunities) and then subtracting the defect (%) from 100. DPMO is obtained by multiplying defect (%) by 10,000. For discrete data CTQs, the yield percentage represents the area under the standard normal curve up to the standard z-score value for the upper specification limit.

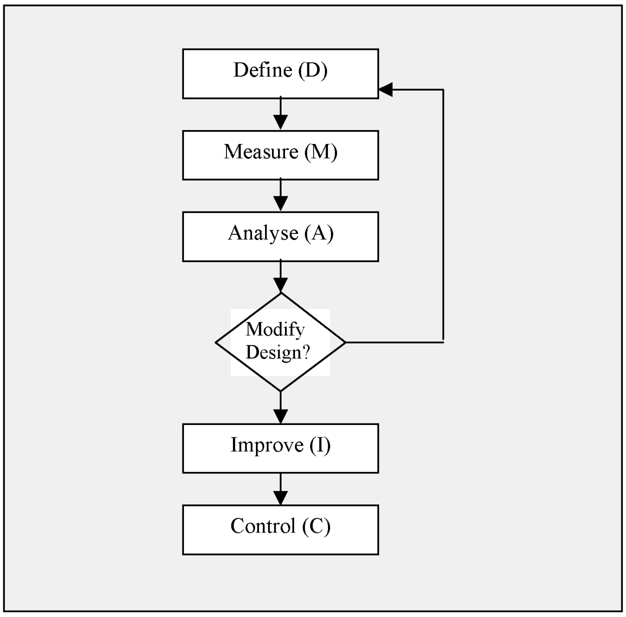
Determine process sigma

SR of a process is basically the standard z-score assuming process data is normal. Process Sigma is thus determined by looking up the z-score from normal tables using the process yield calculated in Step 4. Under the assumption that the data was long term, a Sigma shift of 1.5 is then added to the standard z-score obtained from normal tables.

2.2 Define, Measure, Analyse, Improve and Control (DMAIC) process

The DMAIC process is an integral part of Six Sigma and a roadmap for problem solving and system improvement. In DMAIC, the Define (D) step provides concise definitions of process customers and their requirements and expectations. It also defines the scope of the process to be improved, and the CTQ's (and hence definition of a defect). Based on such definitions, a plan is developed to collect process data and Measure (M) process performance, opportunities, and defects. In the Analyse (A) step, the data collected are thoroughly analysed, gaps between current performance and goal performance are identified, and opportunities to improve are prioritised. Based on the analysis, it is decided if a design modification is necessary or not. In the Improve (I) step, DMAIC strives to improve the process by adjusting process parameters, configuring structure, and enhancing logic to reduce/eliminate defect causes and reach performance targets. Finally, in the Control (C) step, DMAIC aims at controlling the improvements obtained to maintain the new the performance level and prevent reverting back to low performance. This is achieved by proper documentation and the implementation of an ongoing monitoring and improvement plan along with training and incentives. The five interconnected steps of DMAIC are shown in Figure 2.

Figure 2 The DMAIC process

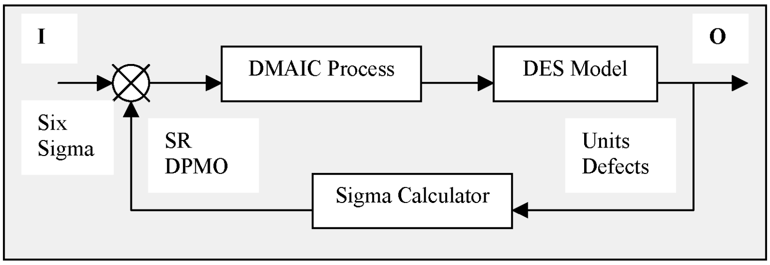


3 Simulation-based Sigma Rating (SR)

The proposed approach is focused on assessing and improving a system-level SR based on two interactions; DMAIC-DES and DMAIC-lean. Hence, a DES model of the underlying system is first developed in order to be used for system measurement and improvement. Applying Six Sigma in a simulation environment provides a major advantage to analysts and engineers through a data-driven approach that seeks performance improvement at the system-level. DMAIC utilises the data generated from the DES model since it represents a prediction of the actual behaviour of the real-world process. Key criteria for the simulation choice include applying DMAIC to a system of considerable complexity to seek improvement in terms of a stochastic and dynamic (time-based) performance measure. Such characteristics are common in real-world production or business system where performance is often measured in terms productivity, lead time, and delivery speed.

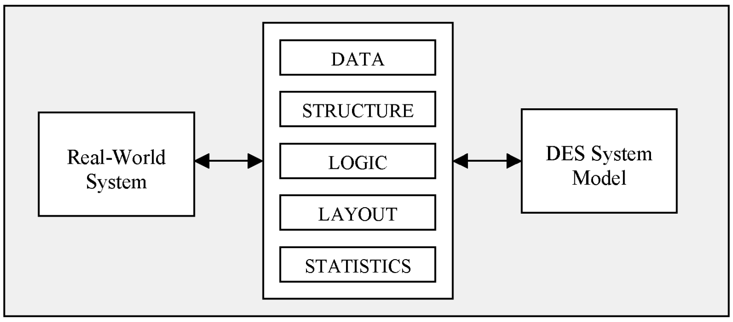
Figure 3 presents the proposed functionality of the DMAIC-DES-Sigma system. The DMAIC process represents the control system over the DES model. System feedback comes from a Sigma calculator that converts the DES model outcome (in terms of number of units produced and the ND) into a system-level SR and corresponding DPMO. SR and DPMO are compared to the Six Sigma target. DMAIC analyses and improvement methods are applied to adjust the structure, data, layout, and logic of the DES model in order to improve system performance towards Six Sigma rating, or to the closest practically attainable Sigma level.

Figure 3 DMAIC-DES-Sigma system



The primary role of DES in the Six Sigma approach is to evaluate system performance measures and to provide a flexible platform for DMAIC experimental design and analyses. A system modelling approach is used in order to develop a DES model of the underlying system. The elements of the DES system modelling process are illustrated in Figure 4. System DES is built by mimicking the data, structure, logic and layout of the actual system. In a production system, for example, the model imitates the parts flow between a set of logically configured workstations. The model is constructed using modules for part, machine, labour and material handling. Model logic is programmed to enforce actual flow and routing rules and actual production data are used in simulation modules. The model is also set to collect essential statistics on performance criteria that measure process CTQs. The simulation model is then verified against the intended design and logic and validated to reflect the behaviour of the real-world process. Details of model building, validation, and verification can be found in Law and McComas (2001).

Figure 4 System modelling with DES



3.1 DMAIC-DES interaction

The DMAIC-DES interaction is core functionality in the proposed approach. The DMAIC process enhances the DES model iteratively to improve system performance in terms of SR. The five phases of the DMAIC process benefit from the flexibility of the DES model. In the Define (D) step, DES provides a more realistic process map by capturing the complex, stochastic, and dynamic characteristics of the real-world process. Further, and since DMAIC is an iterative process, adjustments made to system structures and logic are easily and quickly implemented with the DES model. In the Measure (M) step, the DES is used to verify historical data and provide steady-state system performance measures with various statistics and results. In the Analyse (A) step, the model is used extensively for experimental design and various types of DMAIC analyses. DMAIC analyses cost and time can be significantly reduced using the DES model. In the Improve (I) step, DES is used to validate improvement plans and actions aiming at fixing problems and improving process performance. This includes applying lean manufacturing techniques. Finally, in the Control (C) step, different control schemes and feedback measures are evaluated and tested using the model, especially with the distinctive DES capability to predict future events and scenarios. The interaction of DES with the five DMAIC steps is summarised in Table 1.

Table 1 DMAIC-DES interaction

DMAIC step	*DMAIC-DES interaction*
Define (D)	Representing process data, structure, logic, and layout
Measure (M)	Measuring process dynamic and stochastic performance
Analyse (A)	Running experimental design and DMAIC analyses
Improve (I)	Validating improvement actions and lean techniques
Control (C)	Testing monitoring plans and collecting feedback measures

3.2 DMAIC-lean interaction

The benefits of integrating lean manufacturing techniques into Six Sigma are emphasised at the Improve (I) step of the DMAIC process. The DMAIC-lean interaction aims at eliminating and reducing waste (in material, time, and resources), streamlining operations, and increasing overall system effectiveness. To this end, system-level measures of CTQs such as productivity, defects, and lead-time are treated as lean measures. Lean techniques are then applied to increase the system SR by improving these measures. Examples of lean techniques that directly impact productivity, lead-time, and process defects include:

- analysing flow with Value Stream Mapping (VSM) to determine opportunities of cutting waste and reducing lead-time
- eliminating unnecessary buffers from within the system and reducing the levels of Work-In-Process (WIP)
- applying effective work methods to eliminate unnecessary movements and transfers from the system, reduce Cycle Time (CT), and increase productivity
- improving machines uptime/reliability with effective maintenance plans to reduce downtime and process interruptions
- applying at-source quality controls to fix quality problems and reduce process defects.

Table 2 summarises the aspects of DMAIC-lean interaction. The prospected gains from such interaction include combining process accuracy and quality with process effectiveness and speed.

Table 2 DMAIC-lean interaction

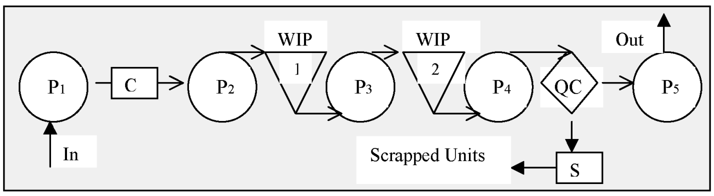
	DMAIC	*Lean*
Goal	Improve process capability	Reduce lead time and process waste
Focus	Process outcomes	Process flow and structure
Philosophy	Variability within specifications is cost	Time in system and over capacity is cost
Tools	Statistical analyses	Lean techniques
Application	Product-oriented	Process-oriented
Key measure	SR/DPMO	Lead time/unit cost
Key driver	CTQs	Added-value
Gains	Process accuracy and quality	Process effectiveness and delivery speed

4 Application example

We now apply the simulation-based SR and improvement approach to an example of a simple hypothetical manufacturing process. The focus will be on clarifying the role of simulation and lean manufacturing in the proposed approach rather than on the conventional aspects of DMAIC methodology. DMAIC statistical tools (e.g., experimental design and ANOVA) can be also used to reduce process variability. Approach application primarily includes building the case DES model, determining process SR, and using simulation and lean manufacturing to improve process Sigma.

The case example consists of five sequential operations in a widget manufacturing process. First, the part is manually cleaned at operation P_1 and transferred to the machining department on a system conveyor (C). At the machining department, the part goes through metal cutting operations; turning (P_2), milling (P_3), and drilling (P_4). As shown in Figure 5, two WIP buffers: WIP_1 and WIP_2 are used to hold units flow with the three machining operations. Since each unit is subject to machining defects at the lathe, mill, and drill, a Quality Control (QC) station is used to test each unit's geometric specifications. Finally, good units are wrapped at a packaging (P_5) and shipped to customers while bad units are sent to Scrap station (S).

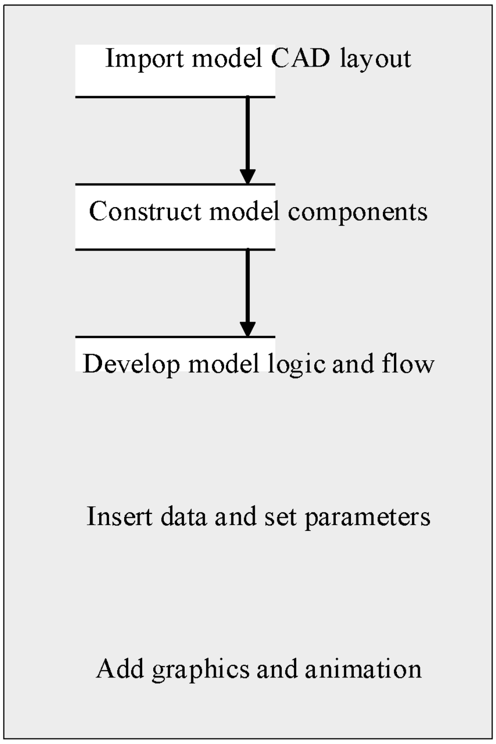
Figure 5 Process flow of widget manufacturing



4.1 DES model building

Based on the structure, layout, data, and logic of the widget manufacturing process, a DES model is built using WITNESS simulation package. A conceptual model of the process is first developed, data are then collected at each model element, and a computer model is constructed to reflect the structure and logic described by Figure 5. A procedure for the example DES model building with WITNESS is shown in Figure 6.

Figure 6 DES model building procedure



The layout in Figure 5 is first imported into the WITNESS simulation environment. WITNESS design elements used to construct model components include: PART (widget), MACHINE (P_1 through P_5), BUFFER (WIP_1 and WIP_2), and CONVEYOR (C). Model logic is programmed using WITNESS routing rules and PART attributes definition. The flow of simulation entities is set to match that depicted in Figure 5. The model-inputted data for the five operations are summarised in Table 3. Collected data include Cycle Time (CT), Time Between Failure (TBF), Time To Repair (TTR), and Scrap Rate (SR). Corresponding distributions and parameters used include Uniform (U) with [Min, Max], Triangular (T) with [Min, Mode, Max], Erlang (E) with [Mean, K = number of exponential distributions to sum], and Binomial (B) with [S = % Success].

Table 3 Data for processes operating parameters

	P_1	P_2	P_3	P_4	P_5
Name	*Cleaning*	*Turning*	*Milling*	*Drilling*	*Packaging*
CT	U [0.5, 1.0]	T [0.5, 1.0, 1.5]	T [0.75, 1.0, 1.25]	T [0.6, 1.0, 1.4]	U [0.75, 1.25]
TBF	–	E [120, k = 3]	E [100, k = 3]	E [160, k = 3]	–
TTR	–	T [2.0, 2.5, 3.0]	T [0.5, 1.0, 1.5]	T [3.0, 3.5, 4.0]	–
SR	–	B [S = 0.5%]	B [S = 0.1%]	B [S = 0.2%]	–

The rationale for using these particular distributions is typically based on fitting standard distributions to historical data collected at each station from subject matter observations, work sampling, and motion and time studies. For example, the percentage of S can be determined by reviewing the available machine history and determining the frequency of producing defect products. Binomial distribution is then used based on the probability profile of defect occurrence. The case is similar for CT, TBF and TTR where used distributions are typically selected by constructing a frequency histogram and testing the statistical goodness-of-fit. In this hypothetical example, however, distributions are assumed based on experience with similar situations. Further details on selection statistical distributions for simulation parameters can be found in Banks et al. (2001).

The automated QC station requires one minute of testing time for each unit. Conveyor parameters are set to 8-unit capacity and with constant conveyance speed of 0.5 minutes index time per unit. A capacity of 5 and 6 units are used for WIP_1 and WIP_2 buffers, respectively. Graphics and animation of the process flow are developed using WITNESS graphical library.

4.1.1 Model verification and validation

The model logic is verified by observing model behaviour and comparing flow/logic to the intended logical design used in building the model. This often results in debugging logical (programming) errors as well as errors in inputting data and setting model parameters. The corrected potential code and data discrepancies are verified by carefully observing the changes in model behaviour. The model is validated when model execution of the logic when running the model is matched with the way the modeller has initially designed it. Key validation techniques include checking if the model reads the input data in Table 3 correctly, tracking parts flow within the operation in Figure 5, enforcing machine failures and observing behaviour, and checking if the model provides the right output in terms of production rate.

4.1.2 Model results and analyses

Model run controls are tested through pilot runs and ultimately set to a warm-up period of one shift (8 hours), a run time of 30 shifts or 240 hours (non-terminating simulation), with 5 independent replications of different streams of random numbers. The model is set to collect key productivity, quality, and efficiency measures at a system-level. This includes produced Jobs Per Hour (JPH), Jobs-Per-Shift (JPS) of 8 hours, number of good units shipped, ND, and MLT. The model is also set to mark units whose MLT exceeds 30 minutes. Both ND and MLT will be used as metrics for estimating SR for the process CTQs. Sample of collected model statistics in 20 shifts of run time is shown in Table 4.

Simulation results are also used to validate process stability and normality. MLT associated with produced units is observed as a process response to check process behaviour. Figure 7 shows a plot of simulation results in terms of MLT for the first 1000 units. It is observed that the response goes through a relatively short warm-up period before exhibiting a steady-state profile. At the start of simulation, where buffers are empty, parts move faster through the process resulting in shorter MLT. As the system get filled with units, queues result in longer and steady MLT. MLT still exhibits some variability due to stochastic process elements caused by varying CTs and machine breakdowns. After trimming the warm-up period, the observed steady-state response is used to verify process stability, which is essential to the accuracy of Sigma calculation.

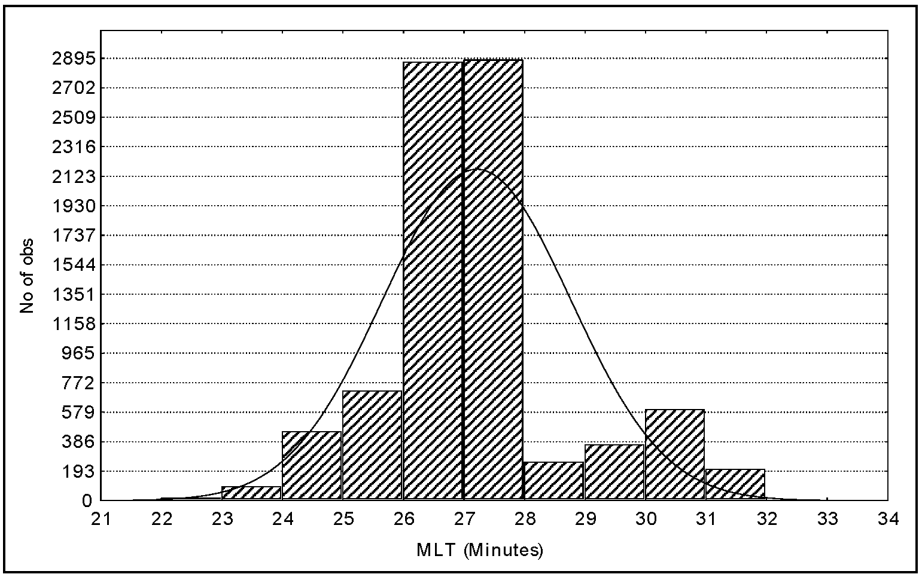
Table 4 A single-run simulation results for 20 shifts

Shift	*Total JPS*	*Avg. JPH*	*Shipped units*	*Defects (ND)*	*Avg. MLT (minutes)*	*Units with MLT > 30 minutes*
1	434	54.25	431	3	26.59	28
2	429	53.63	424	5	26.81	33
3	433	54.13	424	9	27.15	34
4	427	53.38	424	3	27.31	22
5	433	54.13	431	2	26.98	23
6	426	53.25	426	0	27.29	27
7	422	52.75	419	3	27.42	66
8	431	53.88	425	6	26.98	55
9	428	53.50	426	2	27.03	33
10	424	53.00	421	3	27.42	47
11	432	54.00	429	3	26.96	24
12	428	53.50	427	1	27.40	42
13	429	53.63	426	3	27.48	54
14	423	52.88	422	1	27.52	62
15	431	53.88	430	1	26.89	33
16	429	53.63	426	3	27.25	31
17	424	53.00	421	3	27.59	48
18	428	53.50	423	5	27.33	39
19	425	53.13	422	3	27.70	58
20	430	53.75	429	1	27.10	45

Figure 7 Steady-state simulation response in terms of MLT

Figure 8 shows the distribution of MLT for all produced units within simulation run time (i.e., 240 hours). The distribution is constructed based on a total production of 12,841 units. Distribution statistics indicate that the mean MLT is 27.2 minutes while the median is 27.0 minutes. Overall, the distribution satisfies the normality assumption essential to calculate DPMO and SR for MLT. The large number of produced units (12,841) also satisfies the normality assumption for determining DPMO and SR for the ND measure.

Figure 8 Distribution of simulation results in terms of MLT



4.2 Determining process Sigma Rating (SR)

To determine the simulation-based SR, two response statistics (CTQs) are recorded in the model: ND and MLT (in minutes). Process Sigma for the two CTQs is determined as follows.

Define process opportunities

Each unit produced has one opportunity for having a long MLT and three opportunities for having a machining defect because of the SR on operations P_2, P_3 and P_4.

Define process defect

The strictly applied Activity-Based Costing (ABC) on the process considers the excess time spent in the process as an extra cost leading to less profit per unit. Hence, each unit produced is subject to two defects: having a MLT > 30 minutes and being rejected by the QC station for not meeting the required geometric specifications.

Measure process opportunities and defects

To measure process opportunities and defects, the DES model is run for 30 shifts of five replications. At the end of each run, the following statistics are collected: total units produced, average throughput (in JPS), number of good units shipped to customers, total ND, average MLT, and number of units produced with MLT > 30 minutes. The results of the simulation are summarised in Table 5.

Table 5 Simulation results summary

Simulation statistic	*Simulation replication*					*Average*
	1	*2*	*3*	*4*	*5*	
Total units produced	12,838	12,841	12,863	12,836	12,828	12,840.80
Throughput (JPS)	427.93	428.03	428.77	427.87	427.53	428.03
Total units shipped	12,742	12,744	12,769	12,752	12,739	12,749.20
Defects (ND)	96	97	94	84	89	92.00
Avg. MLT (minute)	27.24	27.19	27.17	27.23	27.27	27.22
Units with MLT > 30	1,259	1,296	1,169	1,298	1,363	1,277.00

Determine process Sigma

Using the measured opportunities and defects, process Sigma was calculated for the two CTQs. Table 6 shows the Sigma calculations for both ND and MLT.

Table 6 Sigma calculation for ND and MLT

Sigma calculator inputs	*Input values*		*Sigma calculator outputs*	*Output values*	
	CTQ criteria			*CTQ criteria*	
	ND	*MLT*		*ND*	*MLT*
Units	12,841	12,749	Defect/unit (DPU)	0.01	0.10
Opportunities/unit	3	1	DPMO	2,388	100,165
Defects	92	1,277	Defect (%)	0.24%	10.02%
Sigma Shift	1.5	1.5	Yield (%)	99.76%	89.98%
			Process Sigma	*4.32*	*2.78*

4.3 Improving process Sigma

The five DMAIC steps were applied to reduce ND and MLT. The focus of the analyses in this example is on highlighting the role of simulation as a flexible platform for applying DMAIC analyses and lean manufacturing techniques. The D-phase identified ND and MLT as CTQs. At the M-phase, simulation was used to measure system performance in terms of ND and MLT as shown in Table 4. The A-phase is typically focused on applying statistical analyses to diagnose the factors impacting ND and MLT. I-phase is focused on applying lean techniques. In the C-phase, the simulation can also be used to test monitoring schemes and continuous improvement plans.

In a real-world application, simulation-based process changes will be implemented on the actual process. In this example, however, we will just show how DMAIC application in a simulation environment can lead to identifying and testing correction measures. For example, in the real-world, machining parameters and conditions will be investigated and improved to reduce the SR at the three machines in order to reduce ND. The example herein will not get into investigating the root causes of SR. Instead, the example shows how the model used to test the impact of reduced SR. For the MLT, simulation will be of a greater value since the model can be used to implement and test the impact of lean manufacturing techniques in reducing sources of delays and waste within the manufacturing process.

4.3.1 Reducing ND with better machining

As shown in Table 6, the process Sigma based on ND is relatively high (4.32). Some improvement actions can be taken to further reduce SR at each operation and improve the process. It should be noted that the simulation model does not pinpoint the root causes and actual process changes that contribute to reducing SR. In a real-world situation, SR reduction may entail actual machine changes such as using better cutting tools, adjusting machining parameters, using better lubricants, and so on. Experimental design at each machining operation can play a key role in determining critical process parameters that impact the machine SR and in setting such parameters to their levels at which SR is minimised. The hypothetical nature of this example did not allow for conducting physical experiments. The DMAIC analyses recommends making the process change and the simulation is used for assessing the impact of feasible changes on the process performance in terms of ND. The first practically feasible improvement action was to reduce the relatively high SR of the lathe machine from 0.5% to 0.1%. After doing so, process Sigma has improved from 4.32 to 4.56.

The second improvement action was to reduce the SR at the Drill from 0.2% to 0.1%. Process Sigma has improved from 4.56 to 4.67. Practically, that was the limit of improvement that could be achieved in ND while still feasible and realistic. ND was reduced from 92 to 29 and DPMO was reduced from 2,388 to 753. This results in a relatively significant process improvement, although the performance did not reach the Six Sigma level. Table 7 summarises actions of improving process Sigma based on ND.

Table 7 Improving process sigma based on ND

DMAIC improvement action	*ND*	*Process sigma*
Current state SR = [0.5%, 0.1%, 0.2%]	92	4.32
Reducing Lathe's SR from 0.5% to 0.1%	42	4.56
Reducing Drill's SR from 0.2% to 0.1%	29	*4.67*

4.3.2 Reducing MLT with lean techniques

Current state process Sigma based on MLT is relatively low (2.78); significant improvement can be achieved through the reduction of MLT. The simulation will have a better role in improving system performance in terms of MLT, where the model is used to recommend actual process changes. Techniques used to reduce MLT in DMAIC are, therefore, different from those used to reduce ND. While ND is dependent on machine cutting conditions, MLT is highly dependent on multiple operational and flow conditions (i.e., CT, transfer time, MTBF, and WIP levels). Hence, lean techniques are applied to reduce flow time, CT, downtime, and WIP level.

The model is set to record the MLT for each unit shipped from packaging and to mark the unit as defective only if its MLT exceeds 30 minutes. Simulation results after improving ND showed that the number of shipped good units has increased from

12,749 to 12,811 and units with MLT > 30 minute have increased from 1,277 to 1,280. Investigating the model reveals that reducing ND from 92 to 29 has improved the flow of good units from QC to packaging leading to higher number of units with recorded MLT. This shows a key advantage of utilising the DES in DMAIC analyses, where unexpected system interdependencies and dynamic interactions are captured.

Actions taken for reducing MLT focus the combined effort of Six Sigma and lean manufacturing techniques on reducing transfer time, CT, MTBF and WIP level. The first action taken was to speed up the system conveyor so that unit indexing-time is reduced from 0.50 to 0.25 minute. This resulted in reducing the number of units with MLT > 30 from 1,280 to 1,269 with a process Sigma of 2.79. The second action was to improve the maintenance of the lathe, mill, and drill so that machines' uptime (in terms of MTBF) is increased respectively from (120, 100 and 160) minutes to 240 minutes each. As a result, defects were reduced to 692 with a process Sigma of 2.94. The third action was to reduce the CT at the cleaning and the packaging stations by automating both operations with a fixed CT of 0.50 minute. As a result, defects were reduced to 437 with a process Sigma of 3.34. Finally, the WIP buffers capacities were reduced gradually to achieve improvement in MLT without impacting system throughput. It was found that reducing the capacity of the two WIP buffers by one unit results in reducing the number of units with MLT > 30 to 6 without impacting throughput. This leads a process Sigma of 4.82.

Although the performance did not reach the Six Sigma level, significant improvement (from 2.78 Sigma to 4.82 Sigma) was found to be satisfactory from a practical point of view. Units with MLT > 30 were reduced from 1,280 to 6 and DPMO was reduced from 99,914 to 452. This proves the drastic impact of lean techniques, where the process gets leaner with significant improvement in overall system performance. Table 8 summarises actions of improving process Sigma based on MLT.

Table 8 Improving process Sigma based on MLT

Lean-based improvement action	*Shipped units*	*MLT > 30 minutes*	*Process Sigma*
Current state after improving ND	12,811	1,280	2.78
Reducing conveyor's unit index time to 0.25 minutes	12,810	1,269	2.79
Improving machines MTBF to 240 minutes	12,905	962	2.94
Automating cleaning and packaging [0.5 minutes]	13,273	437	3.34
Reducing capacity of WIP buffers by one unit	13,273	6	*4.82*

5 Conclusion

This paper presented an approach that provides a system-level application of the Six Sigma methodology, where quality becomes an attribute for both products and systems. The approach combines the benefits of simulation flexibility and lean principles into the swell-structured DMAIC process. A DES model representing the actual process of the underlying system is developed and set to estimate CTQ performance measures. The model is used to estimate the process SR at system CTQs. The model also serves as a flexible platform for DMAIC application to increase process rating toward the Six Sigma level. At the 'Improve' step of DMAIC, lean manufacturing techniques are applied to achieve improvement in system performance by reducing waste, lead-time, and defects. The approach provides better results when focusing DMAIC on achieving an incremental improvement in SR toward a practically attainable level; not necessarily the Six Sigma level. The benefits of the approach were illustrated through an example of a simple manufacturing process where significant improvement in SR is achieved based on two system-level CTQs; ND and MLT. The approach application can be extended to production systems that are larger in scale and complexity.

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