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QUALITY PAPER

Utilizing Kaizen process and DFSS methodology for new product development

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Abstract

Purpose – The purpose of this paper is to propose a new framework for early design stage utilizing the benefits of Kaizen events, and Design for Six Sigma (DFSS) methodology. To gain a better understanding of the proposed method, a case study of a diesel engine development was presented where the proposed methodology was followed.

Design/methodology/approach – This paper proposes a hybrid Kaizen DFSS methodology consisting of four Kaizen milestone events with pre-work preceding these events. The events are in line with the four phases of DFSS methodology (define, characterize, optimize, and verify).

Findings – In order for the proposed method to succeed, few key enablers should be available such as management buy-in and support, effective resources utilization, and proper planning. However, this methodology should be utilized for key projects where criticality is high and deadlines are nearby.

Practical implications – As proved by two projects, one of them is presented in this paper; the use of the proposed methodology is effective and can bring significant positive changes to an organization.

Originality/value – Although Kaizen is an old and well-known process, it is to the best of the author's knowledge that Kaizen has not been utilized in the early design stages of new product development projects. In this paper, a hybrid methodology combining traditional DFSS systematic approach conducted using Kaizen improvement events is proposed and supported by a real-life case study.

Keywords Kaizen, Design for Six Sigma, Design of experiments, Oil consumption, SHAININ

Paper type Research paper

1. Introduction

Across industry, Design for Six Sigma (DFSS) methodology has been widely used as a scientific approach to translate the voice of the customer into engineering metrics in the context of product development (PD). These engineering metrics are then met by providing optimized designs using statistical tools. Optimization typically includes meeting certain targets as well as reducing variations around these targets (referred to as robustness). DFSS provided structuring guidelines as well as suggestions regarding tools and techniques implementation for PD (Ericsson *et al.*, 2015). There have been different proposals and different practices for DFSS; in this paper, a four phase approach is used as shown in Figure 1: define-characterize-optimize-verify (DCOV). A brief summary of each phase is given below:

- Define phase: in this phase, customer needs are defined and translated into engineering or service requirements (y's) that can be measured and assessed.
- Characterize phase: this phase includes measurement system analysis (MSA) and utilizes p-diagrams to list all potential control and noise variables (x's) that impact the engineering requirements (y's) in the define phase. In addition, experiments are carried out either physically or analytically using computer experiments to explicitly model the relationship between the requirement y's and x's.

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- Optimize phase: the availability of models allow for the generation of plots depicting the effect of the random variables, *x*'s, on the mean as well as the variability of the response. New designs are then proposed that reduce variability and meet, or exceed functional requirements.
- Verify phase: design selection is finally verified using hardware testing to correlate the computer model, if used, and verify the results obtained in the previous stages.

The mentioned DFSS methodology has gained significant adoption in industrial practices in recent years (Hoffman *et al.*, 2003; Aboelmaged, 2010; Gijo and Tummala, 2005; Mehrjerdi, 2013, Kumar *et al.*, 2008; Pusporini *et al.*, 2013).

Kaizen is another well-known process that has been traditionally used for lean operational applications in various industries such as Toyota, Ford Motor Company, GE, and Lockheed Martin among others (Nelson *et al.*, 2005). Kaizen originated in Japan and moved to the western industries in the early 1980s. It means continuous change for the better by involving all employees (Imai, 1986). Kaizen events (KE) have been utilized traditionally to optimize processes and relied on focused workshops o that may extend from one day to one week. In these events, key resources are leveraged and led by lean expert known as sensei to improve processes.

KE require a large investment of time, energy, and money, making it crucial to maximize the benefit of conducting such event (Natale *et al.*, 2013). Despite the increased adoption and reported benefits of KE programs, there is a lack of research documenting their design, implementation, and outcomes (Glover *et al.*, 2013). Although the Kaizen process has gained a lot of popularity across industry and to some extent business operations, it is to the best of author's knowledge that Kaizen has not been utilized in the early design stages of new PD projects. The authors surveyed several journals and came to the same conclusion that Nilsson-Witell *et al.* (2005) reached which is "actually there are few studies in quality management journal that focus on continuous improvement in the context of product development." In this project, a hybrid methodology combining traditional DFSS systematic approach conducted using Kaizen improvement events is proposed and supported by a real-life case study.

The plan of this paper is as follows: the proposed methodology will be presented in Section 2, followed by a case study in Section 3. Finally, concluding remarks will be presented in Section 4.

2. Proposed methodology

In this paper, an accelerated DCOV known as "Kaizen DFSS" is proposed and summarized in Figure 2. The methodology consists of four main KE proceeded by some activities prior to these events and described below:

(1) Disciplined business case assessment event: at this stage a fast and rigorous project scoping is done by top management along with the key resources needed to execute the project. Project scope, objectives, and resources should be well-documented in a charter format.

(2) Define and characterize event: in this event, the key team members will meet and call any additional resources needed to: define the failure modes on hand; identify the functional response(s) of the systems studied; select potential key design and

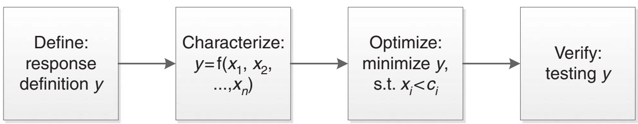


Figure 1. DFSS methodology phases

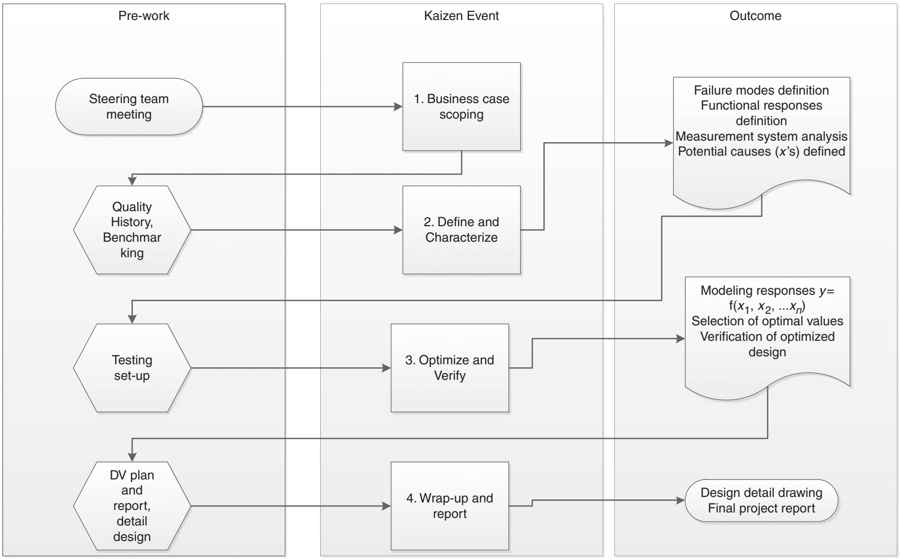


Figure 2.
Kaizen DFSS proposed methodology

process factors impacting the responses; and assess the measurement system used to measure the functional response. The pre-work needed ahead of the event should be spent on grasping the historical knowledge gained from previous projects. Benchmarking studies and analyzing the current system performance, if any, should also be done before the event. Some of the tools that can be used during the event: MSA such as gage repeatability and reproducibility (R&R), DFMEA, *p*-diagram, and cause and effect diagram.

(3) Optimize and verify event: a designed experiment (DOE) should be conducted to describe and optimize the response(s) studied as a function of the factors selected. A significant pre-work should be done ahead of this event to determine whether the DOE will be done physically (hardware experiment) or using simulation (computer experiment). Section 2.1 provides an introduction to computer experiments. In any case, the setup of the DOE or the selection of the software should be prepared ahead of the event. Once the optimization is done, i.e. the selection of the optimal values of the factors studied, the DOE should be augmented with verification experiments to verify the conclusions from the optimization stage. At this stage, hardware experiments should be used to cover any missing factors from the DOE, especially if a computer experiment is selected, and to verify any impact on other responses that the DOE did not include. Tools that can be used in this event are designed experiments and optimization tools. It is worth noting that the experimentation done at this stage is not comprehensive and cannot be replaced by a full and sound design verification (DV) plan. Hence, a full DV plan and execution should be carried out once this event is done. Similarly, detailing the design and tolerance analysis should be conducted separately at the conclusion of this event.

(4) Wrap up and reporting event: in this event, a thorough review of the detailed design and DV results should be done and any major discoveries at this stage should be discussed with team first and management as well. It is a good practice to keep monitoring the progress afterword's to insure proper implementation and control of findings of the project during the succeeding stages such as manufacturing and assembly.

2.1 Computer experiments

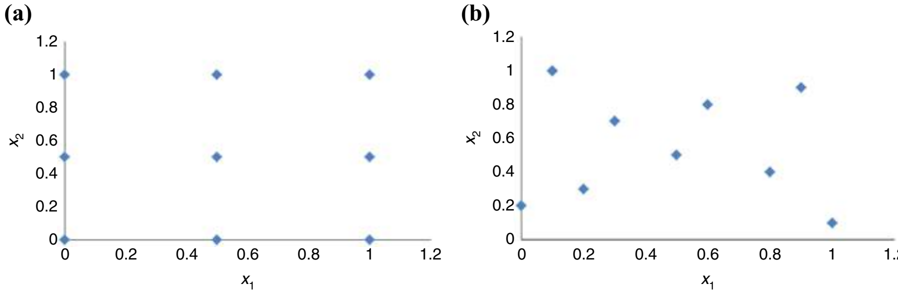
Computer experiments are very effective and economical relative to hardware experiments. There are few differences between hardware and computer experiments that make the criteria for designing each one different. The output of computer experiments is fixed and factors can be changed easily with relatively low to no cost. On the other hand, measurement errors affect hardware experiments output and factor alterations are challenging if not impossible. Moreover, majority of hardware experiments utilizes factorial designs which have a high emphasis on selecting the corner points of design space which result in a good spread of design points in design space (space-filling). However, factorial DOE's have poor projections onto lower-dimensional spaces which is undesirable when only few factors are active. A good computer DOE should have a balance between space-filling and projection properties. Figure 3 shows an example of a two-factor three levels DOE with good space filling (a) with poor projection properties, and (b) a good projection DOE with good space filling. The former DOE is a full factorial DOE used traditionally for hardware experiments while the latter is a computer experiment developed using distance-based filling and projection techniques. If design points are projected to any factor space (X_1 or X_2), this projection will generate three different levels in the full factorial DOE and nine different levels in the distance-based one.

Levy and Steinburg (2010) provided a good introduction to computer experiments and strategies to select design points in computer experiments.

Due to cost and time constraints, most complex simulations with a relatively large number of factors can only afford a limited number of runs and are restricted to scarce sampling plans. The accuracy of the model is affected by the degree of the underlying non-linearity, the sample size, sampling strategy, and the type of model (Awad *et al.*, 2005). For the purpose of our experiment, a collection of $n = 30$ runs in the design space will be used to study the oil consumption behavior under different conditions. The technique used to design and select these points utilizes a distance-based optimality criterion called "maximin" design, where the minimum distance between any set of n points is maximized (Johnson *et al.*, 1990). Johnson *et al.* (1990) made the analogy between this design and a franchise-store placement problem. The objective is to have the customer, furthest from the nearest store location, brought as close as possible to the store. Keep in mind that distance here means either rectangular or Euclidean distance defined as:

$$\mathrm{d}(x_s,\ x_t) = \left[\sum_{l=1}^{k}\left(x_s^{(l)} - x_t^{(l)}\right)^r\right]^{1/r} \tag{1}$$

where r stands for the type of rectangular distance ($r = 1$) or Euclidian distance ($r = 2$). This technique of selecting the optimal design points is very useful especially when it is not



Notes: (a) Good space-filling; (b) good projection

Figure 3.
DOE examples

possible or desirable to select a model in advance which is the case in our situation. Morris and Mitchell (1995) realized that there might be many designs that satisfy (3) and enhanced the maximin criterion by developing a scalar-valued design criterion function which can be used to break the tie between competing designs.

To develop the computer experiment, first a DOE is developed with all possible combinations of the design variables is developed. This can be done by generation of large random numbers of each design variable using quasi Monte Carlo simulation with consideration of design variable distributions. Next, all infeasible design points in the DOE which do not meet design variables constraints are eliminated. Next, the distance of each pair of design points (experiments) is calculated per Equation (3) and ranked from maximum distance to minimum distance. Finally, an iterative optimization scheme is used to select a subset of experiments with the largest distance as starting point then add additional deign points in a stepwise manner such that each new point is as far as possible from initial points selected while the projection of design variables settings or levels is maximized (Joseph *et al.*, 2015).

It is worth noting that the DFSS Kaizen methodology proposed above should not be used for day-to-day projects since key resources will be dedicated to work on these projects and take priority over any other project or activity. The normal process of PD cycle should be followed as much as possible, and follow the Kaizen DFSS method for the vital few key projects that the success of the company depends upon.

The above proposed methodology was used in two projects: optimize diesel engine oil consumption in a short period of time, and construction equipment break design. The first project will be presented in the next section as an evidence of the validity of the methodology. The second project, i.e. brake design, will not be presented due to confidentiality agreement with the manufacturer.

3. Case study: oil consumption reduction

The case study will be presented based on the proposed methodology KE outlined in Figure 2.

3.1 Business case scoping KE

As per the emissions regulations body in North America, an automobile manufacturer should meet an aggregate emission target calculated based on the new product portfolio offered by that manufacturer. Alongside to gas engines, automobile manufacturers offer more energy-efficient alternatives such as diesel, electric, and hybrid vehicles to meet the stringent emission targets and meet customers' needs. Part of this product portfolio, a new V8 diesel engine was developed. Unfortunately, and due to multiple reasons, the current design did not meet the targets and the deadline was very close (two months). A cross-functional team consisting of: process owner, Kaizen coach (sensei), Six Sigma black belt, engineering manager, two senior design engineers, supplier representative, and manufacturing engineer was assembled and tasked with the objective of: "optimize the current design of a V8 engine to meet oil consumption target which is less than the current design by 50% within two months."

Diesel engines are complex systems and oil consumption reduction is crucial for the following reasons:

(1) Oil consumption impacts oil economy and determines the maximum total mileage a driver can go without an oil change. Lower oil consumption means reduced oil top-offs and lower cost of ownership.

(2) Emission violation: when oil is consumed and burned with diesel, it will generate ash particles that contribute to the plugging of the diesel particulate filter (DPF) which is

crucial to filter and isolate combustion by-products impacting environment. A plugged filter will result in increased exhaust back pressure which affects tail pipe emission, thus flagging a warning light. As a matter of fact, the size of the DPF is determined based on oil consumption. Takashi *et al.* (1997) conducted a study to reduce unburned oil fractions in diesel particulate matter by improving oil consumption utilizing a radioisotope ^{14}C method.

(3) Drivability: excessive oil consumption may lead to vehicle lack of power.

(4) Warranty and potential recall campaigns.

In general, oil can be consumed or burned in a diesel engine through different means such as:

(1) Piston rings: lubricant oil can adhere to the cylinder walls and fill crevices/pockets and when the piston reciprocates, oil may transfer into the combustion chamber, burn, and exit the engine through the exhaust system. Similarly, combustion generates a high pressure and combusted gases can be pushed through piston rings into the crankcase causing a phenomenon known as Blow By (BB).

(2) Valve system: oil can leak internally to the combustion chamber through the exhaust and intake valve stems.

(3) Turbo loss: air consumed by engines is forced into the engine using single or double stage turbochargers which are driven by exhaust flow. Oil is used for bearing lubrication in the turbocharger system and may leak into air or exhaust through bearing seals and bushings. Oil consumption through turbo loss is generally known to be small (<10 percent of total oil consumption), but could influence oil consumption variability from engine to engine. In some new engines, this factor can be eliminated by isolating engine oil from the turbocharger and using an external oil feed to turbocharger.

(4) Vent system: oil vapors' in the upper engine head can be recirculated into the crankcase system to improve lubrication efficiency. The vent system is known to be a significant noise factor contributing to oil consumption.

3.2 Define and characterize KE

In this event, the team met for two days to accomplish a prepared plan set by the sensei and engineering manager ahead of time with expected main objectives of: selecting potential key engineering responses, potential key factors affecting responses, and MSA of oil consumption.

3.2.1 Response and factor selection. After extensive discussions among team members, it was determined to use the following five responses to analyze oil consumption in the power cylinder:

(1) BB which is strongly and negatively correlated to oil consumption (Pearson correlation of 0.98) and simulates the phenomenon of having gases in the combustion chamber go through the piston ring gaps down to the crankcase sump and mix with oil resulting in lowering oil ability to lubricate. Oil consumption usually takes the opposite path, from crankcase oil sump through ring gaps to the combustion chamber-see features 4 and 5 in Figure 4.

(2) Reverse gas flow (RGF) at top ring which represents the gas flow rate from the combustion chamber circulating around the ring. This circulation should be minimized to avoid any carbon build up which may negatively change the dynamics of the top ring.

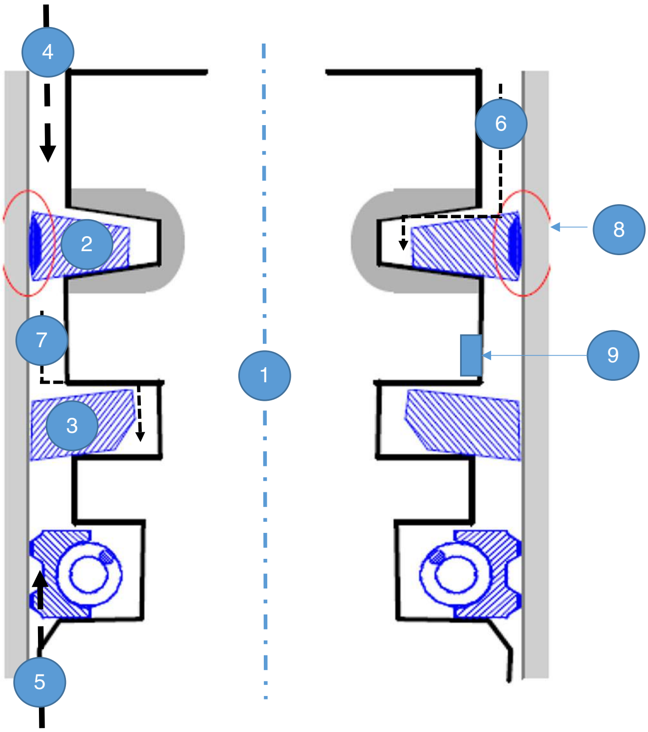


Figure 4.
Power cylinder DOE responses

Notes: 1, piston; 2, top ring; 3, second ring; 4, blow by; 5, oil consumption; 6, top ring reverse gas flow; 7, second ring reverse gas flow; 8, top ring gap; 9, SLV increase feature

(3) Second ring collapse (SRC) is an undesirable condition (go, no go response) which may occur when the pressure above and below the ring is unequal due to gas circulation. When SRC occurs, excessive BB will occur increasing the potential for cylinder scoring.

(4) Top ring lift (TRL) which is measured in terms of the maximum crank angle when lifting occurs. An early lifting of the top ring may provide a flow path for oil around the ring and into the combustion chamber. This increases oil consumption, hence the larger the crank angle when TRL happens the better.

(5) Second ring gas flow (SRGF) is measured in terms of percentage of gas flowing from the lower ring area circulating around the second ring and tends to cause ring flutter which should be minimized.

Except for BB, all other responses are studied to verify ring stability which may result in ring fluttering and engine instability.

In general oil consumption is a very challenging task due to the difficulty of the measurement process during development and the numerous factors that may contribute to it. Figure 5 summarizes potential control and noise factors impacting oil consumption categorized by four subsystems: power cylinder, turbochargers, valve guide/stem seals, and breather system.

3.2.2 Benchmarking. Based on an extensive study of competitive, similarly sized engines, a few design factors proved to be crucial in oil consumption reduction related to cylinder bore geometry. In particular, crevice volume (C_V) is used to characterize pockets of

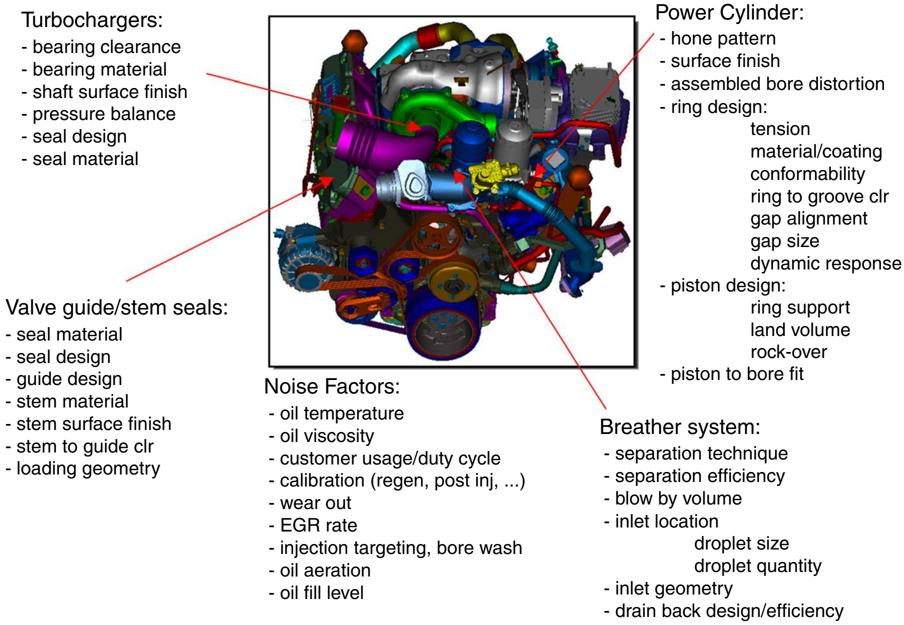


Figure 5.
Factors affecting diesel engine oil consumption

volume in the cylinder that oil can be trapped in during reciprocation and burned during consumption. It is defined as:

$$C_v = \frac{(100\% - \mathrm{MR}_2)R_{\mathrm{vk}}}{200} \tag{2}$$

where MR_2 is the material component relative to valleys, i.e. lower limit of roughness profile, R_{vk} the reduced valley depth, the lowest part of the surface that retains the lubricant (oil).

Typical range of C_V is 0.05-0.20 $\mu\mathrm{m}^3/\mu\mathrm{m}^2$ measured as an average of readings taken at several depths of the bore and using a pyramid stylus tip with a maximum radius of 5.0 μm.

As a result of the discussion of quality history, *p*-diagram and benchmarking, six factors were investigated with factor levels determined using actual measurements on benchmarked engines or obtained through literature review. Factors studied were:

(1) Top ring gap (TRG): the circumferential gap in the top ring when the ring is constrained in the cylinder.

(2) Second ring gap (SRG): the circumferential gap in the second ring when the ring is constrained in the cylinder.

(3) Second land volume (SLV): the area of the rectangular land cutout above the second ring. The SLV can be increased by adding a J-groove feature at the top of the second ring groove as shown by feature 9 in Figure 4.

(4) Top ring crevice volume: the axial clearance between the top ring and groove (back and side clearance).

(5) Top ring groove interface angle.

(6) Second ring groove interface angle.

In addition to the six above mentioned factors, it was decided upfront that a crevice volume of 0.1 $\mu m^3/\mu m^2$ on average will be used to minimize oil consumption. A lower value of crevice volume may affect ring performance and generate different failure modes.

3.2.3 MSA. In general two methods are used for oil consumption measurement:

(1) Drain and weigh method: a simple method where an engine is warmed up to an oil temperature > 85°C then turned off, and the oil is drained through oil pan plug after five minutes. The container of drained oil is weighed and oil is added back to the engine sump. Then engine will go through a test cycle and the drain and weigh steps are repeated after each test cycle. The oil weight loss is attributed to engine oil consumption. This measurement method has poor R&R and is impacted by many sources of noise such as temperature control, engine angle, ambient conditions, and test cycle.

(2) Radiometric measurement: a very sensitive and expensive method where a radiometric material is added to the oil and tracked after combustion by collecting exhaust samples and estimating the quantity of radiometric material in exhaust gas as an indicator of oil consumed in engine.

The use of conventional Gage R&R would be very challenging to validate the radiometric measurement method due to several reasons such as cost, change of engines over time during the measurement, and variability in engine calibration. Instead, a SHAININ™ technique known as Isoplot was utilized to assess the radiometric measurement (Logothetis, 1990; Shainin, 1993). As per this technique, two measurement carts were used to measure samples taken from a running engine simultaneously and independently at different load/speed points. Ideally, since the same test engine is used, the measurements should be identical and when plotted a 45° slope line should be obtained. Any differences in the two oil consumption measurements can be attributed to the measurement system itself. The measurement data from both carts are shown in Figure 6 along with a 45° center line or Iso line and two additional lines: the first limit line drawn includes the farthest point from the Iso line from one side and a second limit line which is the same distance from the Iso line as the first limit line, but on the opposite side. The measurement error (ΔM) defines the region of uncertainty which represents the perpendicular distance between the two limit lines. As per SHAININ™ recommendation, a good measurement should result in less than 1/6 of the product variation (ΔP), $\Delta P/\Delta M > 6.0$. The calculation of the product variation to the

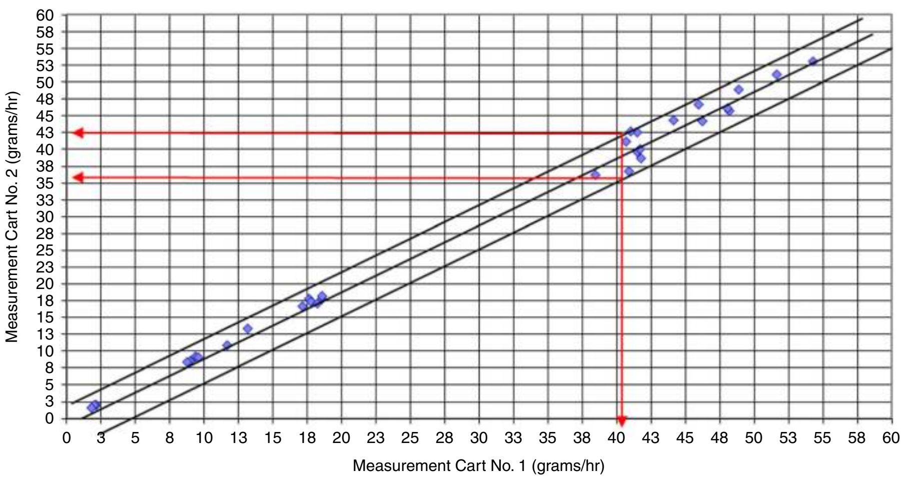


Figure 6.
Radiometric measurement system Isoplot

radiometric measurement system ration is shown below and indicates that the current measurement system is acceptable:

$$\Delta P = 42.5 - 35.5 = 7.0$$

$$\Delta M = 54.3 - 1.8 = 52.5$$

$$\frac{\Delta M}{\Delta P} = \frac{52.5}{7.0} = 7.5 \tag{3}$$

where ΔM was estimated using the difference between the maximum measurement obtained by CART1 and the minimum measurement obtained by CART2. A paired t-test was also carried out and showed a 95 percent CI for mean difference of (0.212, 1.951) and a p-value of 0.018 which is sufficient to reject the hypothesis of a difference mean of 0. A deeper review of the data shows a slight bias in CART2 of 1 gm/hr and once the measurements of CART2 are adjusted by subtracting all readings from CART1, the paired t-test resulted in a p-value of 0.84 supporting a decision of failing to reject the hypothesis that the difference between the two carts mean of 0.

In order to establish a higher limit of measurement variance, the running cycle was repeated on the same engine while both carts were taking samples. A total of 16 samples were taken indicating a standard deviation as high as 2.21 gm/hr at maximum speed. Keep in mind that this variance includes the engine change over time due to wear. Hence, the estimated measurement variance is considered as a worst case scenario. In order to reduce this variance, a decision was made to increase sampling frequency and taking the average of these samples every time oil consumption of an engine is assessed.

3.3 Optimize and verify KE

The optimize and verify KE took an extensive effort of the team and lasted for almost five days. In this event, a simulation DOE was conducted, results were analyzed, optimal factor settings were determined, and finally verification tests were conducted and analyzed.

As shown by Figure 5, there are a relatively high number of noise and control factors that potentially impact oil consumption and need to be investigated. Hence, experimentation was divided into two stages. In stage 1, computer simulation is utilized to investigate the impact of different power cylinder design factors while in stage 2, hardware experiments are used to verify the computer simulation results and include other factors such as crevice volume and breather type.

3.3.1 Power cylinder simulation DOE. Table I summarizes the analytical DOE carried out for high load, high speed (HH) while Figure 4 depicts some of the factors and responses studied in this DOE. The same simulation DOE was carried out for other load/speed conditions.

MIT Ring Dynamics Simulation Software was used to generate a 2D model of the power cylinder (piston, piston rings, and cylinder). One of the critical steps carried out was to correlate the simulation model with engine testing. The measured responses were within 90 percent of the simulation outputs for the same engine configuration. The disagreement between modeling and actual testing is due to the inability of the 2D modeling to model bore distortion, however thermal expansion in the bore was an input to the model.

Each run took one to two hours to be executed and processed, thus the total number of runs was limited to 30 in addition to the base run. Again, it should be emphasized that conducting such testing on an actual engine in the field would have introduced additional noise factors such as, but not limited to, variation in operators and ambient conditions. This would result in added uncertainty in the test response and additional expense.

Several regression models were tried to model input factors relative to responses. Non-linear polynomials proved to be the most powerful in explaining these relationships, see

Objec.	TRG (mm)	SRG (mm)	SLV (mm^2)	TRCV (mm^2)	TRGA (deg.)	SRGA (min.)	BB (CFM) Min.	RGF (CA) Min.	TRL (kg/s) Max.	SRC (kg/s) Min.	SRGF (% Flow) Max.
1	0.42	0.72	−1	125	1	0	351.8	3.2E-03	284	5.8E-05	1.7
2	0.32	0.72	−1	160	1	12	265.7	1.0E-02	257	0	0.7
3	0.42	0.72	1	160	1	0	288.0	4.9E-02	221	6.1E-05	0.8
4	0.42	1.5	1	125	−1	12	362.8	3.0E-03	288	0	0.5
5	0.32	1.5	1	125	−1	12	292.7	2.3E-03	291	0	0.4
6	0.32	1.5	−1	125	−1	0	281.9	2.4E-03	292	1.4E-03	0.9
7	0.32	0.72	−1	160	−1	12	266.0	1.0E-02	258	0	0.7
8	0.42	1.5	1	160	1	0	361.5	2.7E-03	292	0	0.8
9	0.42	1.5	−1	125	1	0	356.6	2.5E-03	292	8.0E-06	1.2
10	0.42	1.5	1	160	−1	0	363.7	2.7E-03	292	0	0.8
11	0.42	1.5	−1	160	−1	12	355.3	3.0E-03	292	0	0.4
12	0.42	0.72	1	125	1	0	289.6	4.6E-02	219	5.7E-05	0.8
13	0.32	0.72	−1	125	1	0	279.7	2.6E-03	291	2.8E-05	1.6
14	0.32	0.72	−1	160	−1	0	283.1	3.2E-03	292	2.4E-05	1.7
15	0.32	1.5	1	160	−1	12	288.9	2.9E-03	292	0	0.4
16	0.32	0.72	−1	160	1	0	281.7	3.3E-03	292	2.4E-05	1.7
17	0.42	1.5	−1	160	1	0	357.4	3.3E-03	292	8.0E-06	1.2
18	0.42	0.72	1	160	1	12	269.9	6.2E-02	210	0	0.6
19	0.32	0.72	−1	125	1	12	263.4	8.3E-03	256	0	0.7
20	0.32	0.72	1	125	−1	12	239.8	3.7E-02	230	0	0.7
21	0.42	1.5	−1	125	1	12	355.1	2.4E-03	292	0	0.4
22	0.32	1.5	1	160	−1	0	288.5	2.8E-03	292	0	0.6
23	0.42	1.5	1	160	−1	12	358.0	3.4E-03	289	0	0.5
24	0.32	0.72	1	160	1	12	242.8	3.4E-02	239	0	0.7
25	0.32	1.5	−1	125	−1	12	282.0	2.4E-03	292	0	0.7
26	0.42	0.72	−1	160	−1	0	352.5	4.6E-03	281	5.8E-05	1.7
27	0.42	0.72	1	125	1	12	270.3	6.2E-02	210	0	0.6
28	0.32	0.72	1	125	−1	0	249.7	2.8E-02	240	0	0.8
29	0.42	1.5	1	125	−1	0	362.8	2.3E-03	291	0	0.8
30	0.32	1.5	−1	125	1	12	281.1	1.9E-03	292	0	0.8

Table I.
Engine power cylinder analytical DOE

below equations as examples:

$$\mathrm{BB} = 223.4 + 14.5\mathrm{SRG} - 6.55\mathrm{SLV} - 10.9\mathrm{SRG}^2 - 1.48\mathrm{SLV}^2 + 14.5\mathrm{SRG} \times \mathrm{SLV}$$

$$\mathrm{TRL} = 288 + 16.5\mathrm{SRG} - 13\mathrm{SLV} - 12.2\mathrm{SRG}^2 - 1.67\mathrm{SLV}^2 + 15.5\mathrm{SRG} \times \mathrm{SLV}$$

$$\mathrm{RGF} = 10^{-4}\left(7.98 - 79.3\mathrm{SRG} + 70.2\mathrm{SLV} + 63.7\mathrm{SRG}^2 + 45.8\mathrm{SLV}^2 - 95.1\mathrm{SRG} \times \mathrm{SLV}\right) \quad (4)$$

The ability of these models to accurately predict responses can be evaluated using the traditional metrics such as coefficient of correlations R^2 which ranged from 83 to 94 percent. Since testing can be done at different engine load and speed condition, a correlation study was conducted which revealed that testing conditions at high load high speed (HH) are strongly correlated to other testing conditions (MM, LH, HL). Table II shows Pearson correlation factors along with p-values leading to reject the hypothesis that the two conditions have a zero correlation coefficient.

Figure 7 shows examples of some of the significant interaction plots for some of the responses under the high load high speed condition (HH). For example, the top left corner plot shows the BB as a function of SLV and SRG. The relationship is highly non-linear with high deflection of the surface response when SLV is high and SRG is low. Similarly, TRL and RGF response surfaces exhibit high non-linear behavior in the same region, i.e. high SLV and low SRG. On the other hand, SRGF shows a linear behavior with no signs of interaction between the two design variables.

3.3.2 Power cylinder simulation optimization. Simulation studies revealed that the main contributors to BB are TRG, SRG and SLV while the remaining factors contribute to a lesser extent. A desirability function was used to model the multi-response problem in order to

Table II. Blow by correlation at different load and speed conditions

	HH	MM	HL	LH
MM	0.887			
	0.000			
HL	0.922	0.924		
	0.000	0.000		
LH	0.909	0.967	0.946	
	0.000	0.000	0.000	
LL	0.749	0.891	0.885	0.892
	0.000	0.000	0.000	0.000

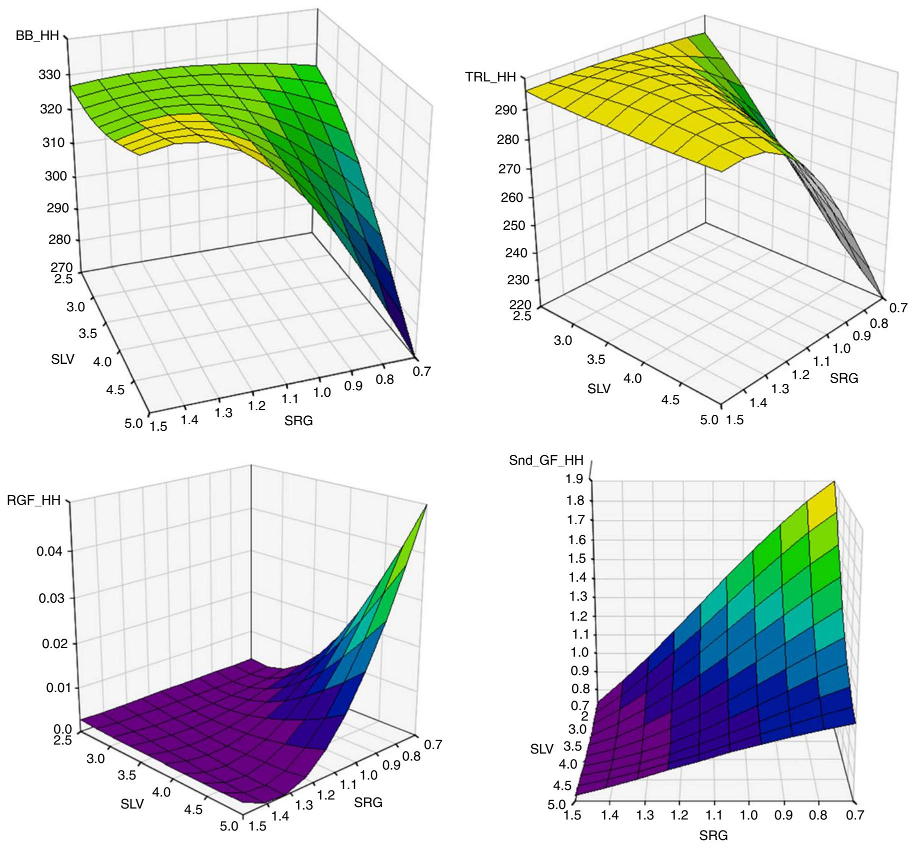


Figure 7. DOE responses as a function of input factors

give flexibility to the prioritization of the importance of the responses; the formulation is summarized below:

$$\text{Minimize}\left[0.4\times\frac{\text{BB}}{\text{SF}_1}+0.15\times\frac{\text{RGF}}{\text{SF}_2}-0.2\times\frac{\text{TRL}}{\text{SF}_3}+0.1\times\frac{\text{SRC}}{\text{SF}_4}-0.15\times\frac{\text{SRGF}}{\text{SF}_5}\right]$$

where $\text{SF}_1 - \text{SF}_5$ are scale factors with:

$$\text{SF}_1 = 323.2,\ \text{SF}_2 = 0.035,\ \text{SF}_3 = -270.9,\ \text{SF}_4 = 2.8E{-}05,\ \text{SF}_5 = 1$$

$$\text{s.t. } 0.32 < \text{TRG} < 0.42$$

$$0.72 < \text{SRG} < 1.5$$

$$2.6 < \text{SLV} < 4.85 \tag{5}$$

Table III summarizes the current settings of the variables, the optimized settings and corresponding values of responses. Since the design problem on hand deals with multiple responses, a trade-off between all responses should be considered. Figure 8 show different solutions to the power cylinder problem and the impact of these solutions on both BB which needs to be minimized and TRL which needs to be maximized. Each point on the graph corresponds to a different design. The design represented by a square at the top left corner represents the optimized solution while the design represented by a round circle at the top middle of the plot represents the current settings. It is evident that some solutions, i.e. designs, may satisfy one response objective but not the other.

3.3.3 Sensitivity analysis. One of the important aspects of computer experiments is sensitivity analysis (ranking the importance of the input variables to the output responses). In the context of probabilistic design (Wu and Wang, 1998; Du and Chen, 2002; Kalagnanam and Diwekar, 1997; Du and Sudjianto, 2004), one is interested in studying the effect of input uncertainty (which is characterized by a statistical distribution associated with

Table III. Engine power current and optimized settings

	TRG	SRG (mm)	SLV (mm^2)	BB (CFM)	RGF (CA)	TRL (kg/s)	SRG (kg/s)	SRGF
Objective				Min.	Min.	Max.	Min.	Max.
Current settings	0.42	1.5	−1 (2.6)	321.9	0.002463	292	0	1.075
Optimal settings	0.37	1.11	1 (3.125)	280.9	0.040645	285	0.000067	0.786

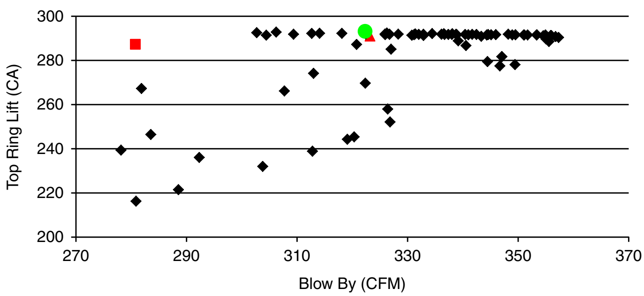


Figure 8. Pareto plot of different solutions to the power cylinder problem

input variables) on the variation of the output response so that design improvements can be made effectively to mitigate risk caused by the input variation. The need for sensitivity analysis becomes more important when dealing with a large number of variables and when design improvements to control these variables are costly. Sensitivity analysis includes the following steps:

(1) assign probability density function to each input variable; when there is a lack of information on these functions, assumptions can be made such as trigonometric distributions or uniform distributions;

(2) generate samples or an input matrix using a certain sampling scheme and probability density functions of input variables;

(3) evaluate the model output to generate the output distribution of response variable using meta-models; and

(4) calculate the influences or relative contributions of each input variable on the output variable.

Figure 9 reveals that the biggest contributors to BB are TRG (62 percent) followed by SRG (20 percent). Similar results were also obtained when other responses were studied. The sensitivity analysis indicates that the variability of TRG and SRG variables should be controlled using tight tolerance.

3.3.4 Hardware verification testing. From the simulation modeling in the previous section it was concluded that the optimized power cylinder design (minimized BB and avoiding oil transport mechanisms that could increase oil consumption) can be done by reducing TRG from 0.42 to 0.37 mm, reducing SRG from 1.5 to 1.11 mm, and increasing second land area (2D slice) from 2.6 to 3.725 mm^2. When this optimized power cylinder was run physically using a hardware engine, however, there was an unexpected significant increase in both transient and steady state oil consumption.

The optimized power cylinder resulted in a 29 percent increase in oil consumption at high speed high load. In examining the analytical DOE results, the only oil transport mechanism that was increased in the optimized design was through SRC. An expert team indicated, based on past experience, that slight SRC does not significantly increase oil consumption. Based on the test results, however, it was confirmed that it is significant in this new diesel engine. As a result, the optimized settings were modified to increase the SRG in order to prevent the SRC.

Table IV summarizes the hardware validation test results which include the Crevice volume C_v volume and breather values. The modified optimized engine resulted in a 50 percent reduction in oil consumption without the breather and a 55 percent reduction with breather addition.

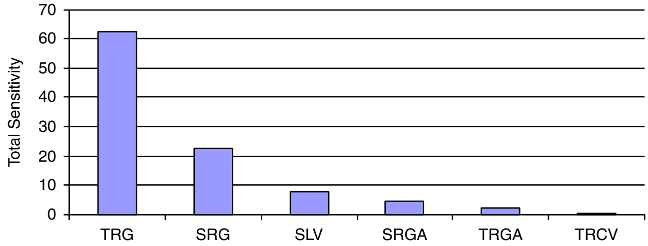


Figure 9.
Blow by sensitivity analysis

4. Conclusions

DFSS is a systematic method where a design can be optimized and variations reduced. Kaizen on the other hand, is cadence process where resources are utilized efficiently to achieve targets in an expedited way. The combination of both DFSS and KE is an effective and efficient way of optimizing new products in a short period of time. In this paper, a DFSS Kaizen methodology is proposed and demonstrated using a diesel engine oil reduction case study. The adaption of the proposed methodology resulted into 55 percent oil consumption reduction, a tremendous success considering project short duration. The power of simulation was used to find out the most significant noise factors that impact oil consumption in a new diesel engine. In addition to simulation, hardware testing verification is extremely important for several reasons, among those reasons are confirmation of computer models and assumptions, and the opportunity to identify and capture more sources of noise that were not captured by modeling.

Few key elements required for the success of DFSS Kaizen projects are listed below:

- Project charter development: a well-documented with a clear problem statement and clear and feasible scope of the project is necessary to set the pace and planning of the project.
- Awareness training: management and team should be familiarized to the DFSS Kaizen method upfront and share the ownership of the project before the project starts.
- Positive internal team dynamics: the team should cover all key expertise needed and should be willing to work as a team to achieve objectives. Organizations are encouraged to use team building structured mechanisms such as ice breakers and team ground rules. Conflicts are expected and should be resolved by team leader and process owner if needed.
- Coach leadership: in the oil consumption project, the Kaizen champion (sensei) performed dual functionality; coaching and leadership of the team. The leadership is the key to sail along and focus on objectives and plan execution.
- Management buy-in: the most important pitfall in any project is lack of management support, or management priorities changes. Such pitfall could be detrimental to the success of the project and should be avoided. Management buy-in and support further develop employee motivation to participate and take ownership of the project (Farris *et al.*, 2009).
- Pre-work execution: in order for the events to succeed, a proper planning and work should be conducted prior to KE. The pre-work activities may change based on the outcome of the event preceding the pre-work. Resources should be flexible to adapt to these changes.

Table IV. Hardware validation testing

Power cylinder settings (TRG, SRG, SLV)	Breather	Cv	Oil consumption (relative to current settings)
Current (0.42, 1.5, 2.6)	No breather	1.1	–
Optimized based on simulation DOE (0.37, 1.11, 3.125)	No breather	0.05	+29%
Optimized with modification (0.37, 1.5, 3.125)	No breather	0.05	−50%
Optimized with modification (0.37, 1.5, 3.125)	With breather	0.05	−55%

Glossary

DFSS	Design for Six-Sigma
BB	Blow by
KE	Kaizen event
DCOV	Define, characterize, optimize, and verify
FMEA	Failure mode and effect analysis
MSA	Measurement system analysis
DV	Design verification
PM	Diesel particulate matter
RGF	Reverse gas flow
SRC	Second ring collapse
TRL	Top ring lift
SRGF	Second ring gas flow
TRG	Top ring gap
SRG	Second ring gap
SLV	Second land volume
TRCV	Top ring crevice volume

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Further reading

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