A joint application of Design for Six Sigma and Taguchi-Response Surface Method in Supply Chain Process Design

Cesarotti V.*, Gubinelli S.*, Introna V.*

** Department of Enterprise Engineering, "Tor Vergata" University of Rome, Via del Politecnico, 1, 00133, Rome – Italy (cesarotti@uniroma2.it, silvia.gubinelli @uniroma2.it, vito.introna@uniroma2.it,)"*

Abstract: In the current competitive context, the effective design of the supply chain process is even more important for businesses. Practitioners need to design robust and efficient processes that are at the same time focalized on business needs. In the present work we propose to combine two different methods: metamodel based design optimization (MBDO) and Design for Six Sigma (DFSS). The approach proposed, take advantage from DFSS structure to reduce the metamodel input variables. Most of MBDO techniques are complex and requires huge quantity of simulation. Therefore among the MBDO techniques, we have chosen to implement Taguchi and Response surface method (T-RSM). DFSS is a structured method, therefore easy to merge with other techniques and easily integrable with MBDO. In this paper we use T-RSM to obtain a robust metamodel performing a small number of simulations, therefore resulted less complex to apply than other MBDO techniques. The DFSS's Method used in this paper was: DIDOV. The first two phases of DIDOV have been focalized on business goal and needs. In those phases degrees of freedom of the metamodel input variables were reduced. Merging DIDOV and T-RSM we got a reduced and focalized on business experiment plan. In this paper we show that the joint implementation of DFSS and T-RSM allows to obtain a design process focalized on business goal and leaner than other application of MBDO techniques in process design. A Case study of applying DFSS and MBDO is provided to show the implementation of this approach in a Supply chain process design. The presented approach results implementable in various context like product development and service process design.

Keywords: Process Design, Metamodel Based Design Optimization, Design for Six Sigma, Supply Chain

1. Introduction

Due to increasing market competition, the process optimization focalized on business goal has become crucial in corporate strategies. In recent decades, therefore, industry focused attention on quality engineering method: probabilistic design analysis and optimization method. The research for quality has led to the creation of numerous standards also in the non-manufacturing sector (Cesarotti & Di Silvio, 2006). In the production industry, the Six Sigma and Metamodel Based Design Optimization (MBDO) techniques have been very successful in the parameter design and process design optimization.
The search for process efficiency has led operation managers to choose between optimal design and computational complexity. Despite the technological advancement, functional relationships often remain unknown due a large number of factors. Sometimes advanced analytics methods results impractical for all, so operation managers use them in vary critical cases. Often only academics use these tools for investigations (Koch, 2002.) MBDO is born to answer the problem of optimize complex real problems (Simpson, Peplinski, & Koch, 2001). MBDO allows optimizing the real process through a model that approximates it (metamodel). Parallel to the MBDO practiced in the field of research, in the industrial field the Design for Six Sigma (DFSS). It provides a more systematic way to manage the deliverable, resources and trade-offs. The DFSS method focalises on achieving business goal and customer needs at Six Sigma Level. "At the heart of DFSS methods is Design of Experiments (DOE) and other statistical analysis methods used to capture performance variation."(Koch, 2002). "With DFSS arising from manufacturing quality control initiatives, DOE with a minimum number of physical experiments is often critical. Like Taguchi methods, optimization is again generally not performed since physical experiments are conducted; optimization is usually not even mentioned in the few available DFSS references" (Koch, Yang, & Gu, 2004).
This paper proposes a process design methodology applicable to the real processes. That meets the needs of the practitioners from the following points of view: Robustness; simplicity of application; parameter optimization; focus on business goals and customer needs. The method presented in this research joins DFSS e MBDO in order to maximize the benefits pertaining to the individual methodologies and obtain a tool that practitioners can implement easily. DFSS is a structured approach and can accommodate various MBDO techniques. According with the scope to obtain a method easy to implement by practitioners, we chose the T-RSM, a joint implementation of Taguchi Method (TM) and

Response Surface Method (RSM). The T-RSM allows you to overcome the limits of RSM and to consider in the modeling both controllable and non-controllable factors (Simpson, Peplinski, & Koch, 2001).

2. Background information and existent knowledge

Most of the literatures defined DFSS as a proactive approach focused on design by doing things right the first time. DFSS is "a data-driven methodology based on analytical tools which provide users with the ability to prevent and predict defects in the design of a product or service" (De Feo & Bar-El, 2002). DFSS was born after the success obtained by the implementation of the Six Sigma. DFSS foundations are: Customer-oriented design; Systematic and creative design; Robust performance and prevention philosophy (Antony & Coronado, 2002). The main goal of DFSS is the prediction of design drivers in early stage of design (Treichler et al., 2002). The Benefits of DFSS application are: provide structure to development process; anticipate problems and avoid them; reduce life cycle cost; improve product quality; reliability and durability; cultural change; minimise design changes; improve communication between functions (Usman, et al., 2006).

Compared to Six Sigma, DFSS approach still lacks a single methodology (Hoerl, 2004). "In the case of DFSS there are several methodologies which are equally applicable to product and service innovation." (Asad, Chakraborty, & Chuan, 2006). There is no better approach at all. In literature the most used approach are DMADV, IDOV, and DIDOV. (Patil et al., 2013). Al Omar proposed DFSS-IDOV approach on providing a deployment simulation-based approach that integrates the Lean techniques and the Six Sigma methodology. (Al-Aomar, 2006). In the presented case study, we used the DIDOV (Define, Identify, Design, Optimize, Validate) approach.

In the literature are described cases of successful implementation of DFSS in many areas. The authors "give insights into issues of perceived best practice" (Patil & Paul, 2013). Many successful applications of the DFSS are not only for product design, but also in the Healthcare and Financial Service Sector. The DFSS proves useful also for the flexible design of a complex system such as supply chain (Hari & Beng, 2010).

The heart of the Design (for DFSS) and Improve (for Six Sigma) phases is DOE (Design of Experiment). TM is one of the most used techniques for doing the DOE in the DFSS. (Koch, Yang, & Gu, 2004). Taguchi was one of the first to propose the Robust Design (RD) (Phadke, 1989). "To achieve desirable product quality by design, Taguchi suggests a three-stage process: system design, parameter design, and tolerance design."(Wysk, Niebel, Cohen, & Simpson, 2000). In the last decades, TM has proved to be very effective for improving product quality. Numerous authors had stated the advantage of Multi-objective Taguchi Method (MTM) for multi-objective design (Rowlands & Antony, 2003) (Dubey & Yadava, 2008).

In this research, we proposed TM both for the reduction of the number of experiment (using Orthogonal Arrays – OA) and for the parameter design (using Signal to Noise – SN)(Pignatiello, 1988). We proposed the SN to define the qualitative variables; suddenly we used RSM for precision parameter design.

RSM is one of the most popular MBDO method. It comprises a group of statistical techniques useful for developing, improving and optimizing process (Myers, Montgomery, & Anderson-Cook, 2016). "Popularity of this approach is due, at least in part, to the maturity of RSM, its simplicity and readily accessible software tools." (Simpson, Peplinski, & Koch, 2001). The RSM approach has three basic steps:

1. The screening of the factors that most influence the "responses",
2. The first order experimentation used to quickly and economically approach the optimality area
3. The second order experimentation, which fit in the region of the first order solution to evaluate curvature effects and to attempt to improve the solution (Simpson, Peplinski, & Koch, 2001).

RSM are easy to use and has various optimization techniques on it. RSM let to identify the relationship between the controllable input parameter and the response surface (Raissi & Eslami Farsani, 2009).

It has been widely applied for modelling and analysing engineering problems. RSM results appropriate for application with less ten factors, so some research presents T-RSM (Simpson, Peplinski, & Koch, 2001). In these cases, the RSM provides the best approximation to the functional relationship between the independent variables and the response surface. (Muhammad et al., 2012). Literature concerning robust design and process parameter design treated the joint implementation of TM and RSM (Myers, Montgomery, & Anderson-Cook, 2016). T-RSM was used in the study of composites, (Appadurai, Nagarathinam, Santhanakumar, & Adalarasan, 2014) healthcare (Dash, Mohammed, & Humairab, 2016). The most common uses of the T-RSM are in manufacturing area, as in the studies of surface roughness (Palanikumar & Karthikeyan, 2006) (Palanikumar , 2008) (Çiçek, Kıvak, & Ekici, 2015) (Sarıkaya & Güllü, 2014), Resistance Spot Welding (RSW) (Muhammad et al., 2012) and electrical discharge machining (WEDM) operation (Datta & Mahapatra, 2010). In literature, authors applied T-RSM in several ways. In most cases, the authors chose to use Taguchi's OA to define the reduced experiment plan, while used the RSMs to fin the optimal parameter setting. In all case, the excellent predictive skills of the technique emerged. (Myers & Montgomery, 1995)

3. Method

This paper proposes a methodology that aims to provide a robust supply chain process design, focused on business needs and easy to implement. This method wants to solve the trade-off between complexity of optimization techniques and the simplicity of application required by practitioners.

At the base of this method, there are the assumptions that the analyses carried out in the early stages of DFSS let to identify the main factors and levels that affect the process performance. These analyses allows reducing the complexity of the initial model and obtain a "reduced

model", which consider only the influencer factors. Suddenly, we optimized the reduced model using T-RSM.
The DFSS's analysis toolkit and T-RSM applied to the "reduced model" (i.e. metamodel) make the design optimization easy to implement.
The method, in its application, is flexible. According with the literature, you can choose witch DFSS's approach (Patil, Andhale, & Paul, 2013) and which RSM optimization techniques to implement (Myers et al., 2004). In the case study, we applied the DIDOV approach for its fractal nature "At every level and in every phase it is possible to delve deeper and do a lower level whole or partial DIDOV cycle." (Sleeper, 2005). We integrated T-RSM transversely into the Design and Optimize phases. Each phase of the DIDOV has many tools avaible. To solve the case, we had used only some of these.
The Define and Identify phases are essential to identify KPI and factors that affect the performance of the process. In Define Phase, define process and business requirements and constraints. In the Identify Phase, the information collected were explained in CTQ (characteristics critical to quality), main factor, levels and constrains. Signal Factors (parameter set by the designer to express the intended value for the response of the service system) and Process response variables were identified. A high-level process map was made. Also in this phase, you can carry out feasibility and risk analysis. As outcome of this phase, you have the knowledge to build a reduced model of starter process.
In Design phase, define the main process design alternatives considering only factors that really can affect the performance required. By implementing T-RSM in Design and Optimization phases, define the new process design and identify optimal parameters settings.

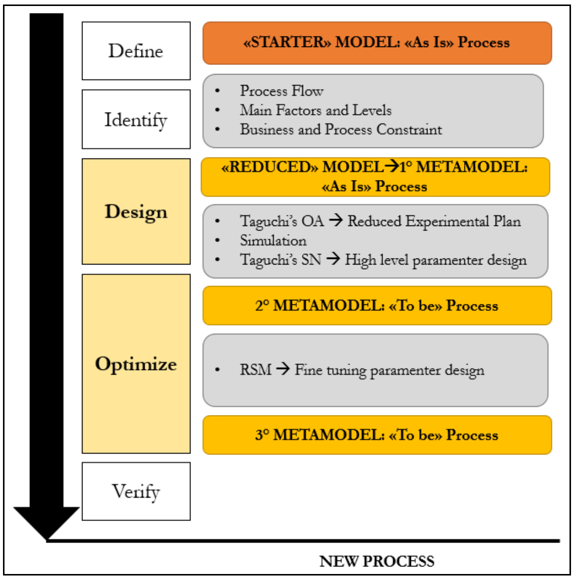

Figure 1: T-RSM Implementation in DIDOV Structure

In Verify Phase, validate the new process on bases of KPI previously identified. Use first simulation and if the results are good, implement the new process.

4. Case Study

The proposed case study showed the application of the methodology to a project of reducing transportation cost of material packed by a postal sorting centre.

DEFINE

In Define phase, we defined the project management (PM) aspect first (project charter, gantt, OBS, WBS).
Business Case: The Sorting Centre (SC) receive every day different product packed in Handling unit (HU) by different supplier. The SC collect the incoming HU, sort it and send it to a Collection Centre by a distribution network. A commercial agreement established the creation of a new distribution network managed by an external company. Operations managers needs to redesign the following phases: acceptance, sorting and reallocation of material in Handling Unit (HU).
Problem Statement: The agreement changed the payment method from payment for a truck, to payment for a single HU.
Project goal: Redesign the sorting process in order to reduce process cost, i.e. the number of HU shipped.

In this phases we made SIPOC diagram to do a high level mapping of the process and to identify the boundaries of the anlysis. We did interview to collect VOP, VOC and VOB. These showed that:

- It was possible to introduce in the process new function made by existent personal.
- Main constraints: Product lead-time (SLA). Budget availed for investments in operation effort and machines (500 000 euro). Break event point equal to 5 years. Different kind of product can't be compacted with each other.
- Main KPI: Number of HU shipped, saturation rate of HU, percentage of empty HU sent, compact rate (HU in/HU out)

IDENTIFY

In this phase, we identified the factors and levels that had the main influence on the process. The aim is to reduce the number of variables that will constitute the metamodel to optimize in the following phases.

Pareto analysis was performed on a rational subgroup of 240 000 HU, sampled over a three-month reference period. We extracted the data from a management software. Pareto analysis showed that:

- There are a total of 7 container types. The 74, 8% of the containers was PALT type, and 11, 6% was CL00 type. In the subsequent analyses, we considered only these two type out of seven.
- About the eleven types of product, Pareto Analysis did not produce significant results.

Subsequently a sample of 95.000 HU was analyses. The sampling concerned 3 month of shipping. We have carried out two main analyses:

- Saturation analysis.
- Shipping analysis

We analysed Saturation of HU with Ishikawa Diagram and ANOVA. The analysis showed a strong dependence between saturation and format/type of product (p value=0,002).
Pareto Analysis on the format of the UH showed that 75% of HU are PALT, 11% are CL00, remaining percentage of product were in the format to the product CL00. In the subsequent analyses, we considered only these two categories (PALT and CL00) of product. We analysed the saturation of the two product categories. The average saturation of type CL00 was 80%, while PALT 28%.

Based on saturation criteria (format and type), the products have classified into two categories: "P" type (letter format) and "M" type (magazine format). The T test of the average saturation showed the higher saturation reached by type "M" products (34%) compared to "P" type products (20%). Pareto analysis showed also that containers (both PALT and CL00) are mainly used for three types of products: PJ3, PMAS, MJ3. The use of containers were homogeneous. The saturation distributions were homoschedastic. We grouped together products with similar format, volume occupied and homoschedastic saturation distributions. In accordance with the results of the analyses, we have clustered the eleven types of product in two class: "M" and "P".

Shipping analysis concerned the incoming HU (rate and type of product) and the categories of supplier. From the Pareto Analysis carried out on the senders, we cannot reach any conclusions. Based on the format (PALT and CL00) and the frequency with which they send the materials, we divided suppliers into two categories: Great Customers (GC), which send only PALT, and Other Officers (OO), which send only CL00.

Table 1: Number of levels of design factor, before and after Identify Phase

Design factors	N.Container Type	N. Product Type	N. Supplier Type
Before	7	11	13
After	2: PALT, CL00	2: M, P	2: GC, OO

DESIGN

Based on the results of the analyses we have reduced the starting model. In the design phase, we hypothesized different design solutions.
For design purposes, it is necessary to consider that the CL00 have a capacity of 400kg, while the PALT have a capacity of 800kg. Currently the process involves sorting exclusively by product based on the format. The products were stored on two types of PALT that were to make the HU: 700kg and 800kg of capacities. The VOP has brought out the possibility of stacking two CL00s between them.
To reduce the number of possible solutions, we used the solution selection matrix. The goal of design was to reduce the transport cost. The cost of transport was proportional to the number of HU sent. The possible design solutions concern the introduction of an acceptance phase that monitors the saturation of the incoming HUs, with respect to a reference threshold (to be defined), and the introduction of one or more of the following functions:

- De-palletizing of PALT and CL00 (DeP): breakdown of the HU if unsaturated of 50%
- Saturation Compaction (SC): De-palletize every HU and compact the final HU to achieve a minimum saturation of 80%
- Stacking of CL00 (St): Stack the CL00 in pairs, regardless of saturation, to form a final HU.

Functions can be combined with each other or exist independently. To define which functions to insert into the design, we have applied the TM. We have optimized the number of simulations with OAs. We considered as noise factor the saturation of incoming HU. The identify phase showed that saturation follows a triangular distribution.

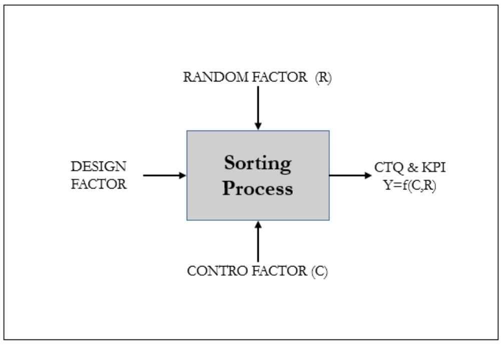

Figure 2: Process P-Diagram

We performed the simulation with the software ARENA ROKWELL.

Table 2: Factor considered for TM

CONTROL FACTORS	
DEP	Yes/No
SC	Yes/No
St	Yes/No
RANDOM FACTORS	
SP[m,p]	T(15%, 34%,90%), T(10%,20%,70%)
SC[m,p]	T(60%, 80%,89%), T(40%,75%,85%)

The simulation provides as output the mean value of the requested variables and the half-width of the confidence interval with which the variable was estimated. Arena imposes a confidence interval of 95% by default. The number of runs of each simulation must guarantee a level of acceptable significance (95%). Therefore, we calculated the number of replicas for each simulation as:
n = n0 (h0/h) ^2, where n0 is the minimum number of replicates (ten), h0 is half of the confidence interval

corresponding to the number of replications n0 (Halfwidth/Average) and h is 0,025. By the simulation, we want to monitor the lead-time of the service and the number of outgoing HU. Thus, we have chosen the value of "n", as the greater of the one calculated according to these two variables, calculated by simulating the "as is" status.

N (outgoing HU) =10[(19, 8/788, 5)/0,025] ^2=11
N (Lead Time) =10[(6, 39/166, 05)/0,025] ^2=24

For each simulation, we made 24 replicas. Each replica represents 3 months of work of the sorting center. The analyzes were carried out during the Identify phase concern 3 months of work of the sorting center, so we have chosen to simulate three months of work.
Through the simulation, we have identified for each alternative the following variables: outgoing HU, Lead Time (min), and usage of resources (min). At each alternative, we have assigned a cost as follows:

Cost= [outgoing HU*18(euro)] + fixed costs of the alternative + [Cost of resources (euro/min)*usage of resources (min)]

We monitored the "lead time" solely to verify that the considered alternative is within the limits imposed by the SLA. The alternatives considered are within the limits set for more than 20%.
We implemented the DOE with OAs, **L8 (two^3)** for Control Factor and L4 (two^2) for Random Factor.
To identify the best alternative, we have applied the analysis "SN" considering as variables the presence or absence of the additional phases (DeP, SC, St). We evaluated the alternatives against their cost, so the criterion chosen for the SN analysis was Smaller-the-better. We did the SN analysis with the MINITAB software. The analysis shows that the additional phases to consider in the final alternative are DeP and SC. Based on the saturation of the incoming containers, the final HUs are recomposed. CL00 and PALT are both decomposed.

OPTIMIZE

Defined the structure of the design, to choose the optimal process parameters we have applied the RSM
With the RSM, we want to identify the optimal threshold saturation levels (identified in the field thanks to the weight) based on which to decide whether to de-palletize and recompile, or whether to stack directly the incoming HUs divided by Great Customers (GC) and other offices (OO). We considered resources and technologies as inbound constraints, so we did not considered their costs.
Based on the saturation analyzes carried out in the Identify phase, we have defined the range of possible threshold saturation levels. The VOB has highlighted the possibility of defining the periodic mix of incoming products by both GC customers (Mix_GC) and OOs (Mix_OO) through commercial agreements. Therefore, we considered also these factors (Mix_GC and Mix_OO) in the RSM analysis. In RSM Analysis, we considered as Response Variable: %outgoing_HU/%incoming_HU.

Table 3: Factors and levels considered in RSM analysis

Factor	Level
SPAL_ GC	0,3-0,6
SPAL_OO	0,4-0,6
Mix_GC	0-1
Mix_OO	0-1

We did the RSM analysis with the MINITAB software. We obtained the response variable through the simulation with the ARENA Rockwell software.
The first model was built with Box-Behnken design, followed by a full factorial analysis. The P value analysis showed that Mix_GC and Mix_OO do not influence the response surface (p value<5%). Since the incoming mix was not significant, we considered the mix of the arrival of the products as random. We replicate the analysis without considering these variables. The multiple response prediction showed the optimal saturation threshold values:
SPAL_ GC: 0, 3
SPAL_OO: 0, 6

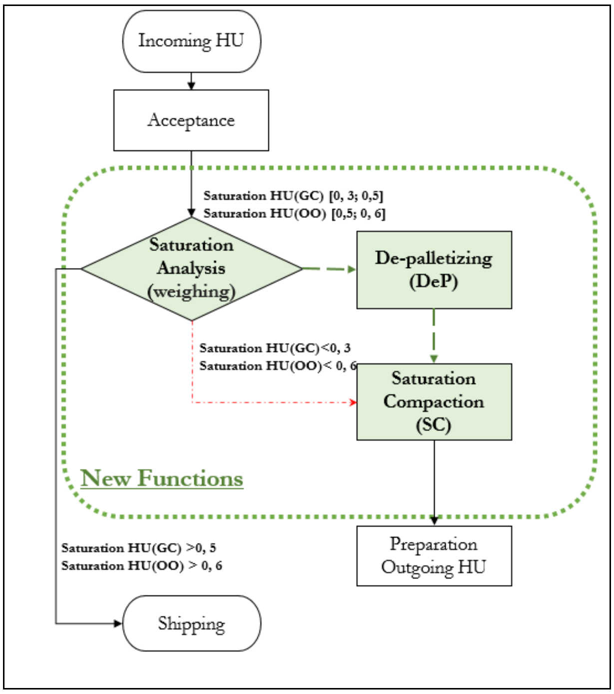

Figure 3: Swimlane of the New Process

VERIFY

In the Verify Phase, we simulated the new process with the new parameter design.
Using the simulation, we compared the performances, expressed as HU output / HU input, of the metamodel of the "as is" state with the metamodel of the new process. The analyses have shown that the new process guarantees a 25% reduction of outgoing Hus, on average. We estimated an economic saving between 5% and 10%, at the end of the second year.
The implementation of the new process showed that the saving obtained compared to the costs prior to the implementation of the new process is about 9%.

5. Discussion and future research

The results emerged from the implementation of the new process have confirmed the goodness of the design. The approximation due to the metamodel was effective in terms of saving obtained and computational complexity (function of the number of factors and variables considered) found in applying the T-RSM techniques in this context (Table 4).

Compared to the separate application of MBDOs, the preliminary application of the DFSS phases allowed reducing the number of factors, levels and consequently degrees of freedom that considered in the direct application of the MBDO (T-RSM).

As with the T-RSM (Jen S. Shang, 2004), the joint use of the same leads to significant advantages: Reduce the complexity of the experimental plan; Robust process design; Process design focalized on business needs; Effective parameter design.

This study is located in the literature related to the process design, to the application in service design of T-RSM and to the simulation-based DFSS. Moreover, being a loose approach, it can be easily applied to different service processes design and adapted to different declinations.

The research presented in these papers is limited in terms of explicit calculation of the savings in the computational complexity. Evolution of this research will provide insights on this.

Future research developments include the investigation of the joint use of DFSS and T-RSM, (like other MBDO techniques) for the definition of an explicit function that acts as a Decision Support System within a process of continuous improvement. As possible future developments, we considered the application of the methodology to the Lean Service system

Table 4: Project Summar

Design Variables	Starter model	Metamodel after Define&Identify Phases	Metamodel after Design	Metamodel after Optimize
N. Supplier Type	13	2	TM	RSM
N.Product Type	11	2		
N.Container Type	7	2		
Saturation_ Container		Saturation_ Palt [MP]: (T(15%, 34%,90%), T(10%,20%,70%) Saturation_CL00[MP]: T(60%, 80%,89%), T(40%,75%,85%)		
Product Mix	(0-100%); (0-100%)			
Implementable solutions		8 (3 phases combination: DeP, SC, St)	Dep, SC	
Saturation Analysis Levels		SPAL_ GC (0,3-0,6) SPAL_OO (0,4-06)		SPAL_GC: 0,3 SPAL_OO: 0,6

References

Al-Aomar, R. (2006). A simulation-based DFSS for Lean service System. *International Journal Product Development*, 349-368.

Antony, J., & Coronado, R. (2002). Design for Six Sigma. *IEEE Manufacturing Engineer,* 24-26.

Appadurai, M., Nagarathinam, N., Santhanakumar, M., & Adalarasan, R. (2014). Application of Taguchi-Response Surface Methodology (T-RSM) to Study the Sliding Wear Behavior of Mg/SiCp Composites. *MIT International Journal of Mechanical Engineering,* 4 (2), 71-74.

Asad, U., Chakraborty, A., & Chuan, T. K. (2006). Comparative Study of DFSS in Product and Service Innovation . *Proceedings Asian Network for Quality Congress 2006 Singapore,* ANQ, Singapore.

Cesarotti, V., & Di Silvio, B. (2006). Quality management standards for facility services in the Italian health care sector. *International Journal Health Care Quality Assurance*, 451-462

Çiçek, A., Kıvak, T., & Ekici, E. (2015). Optimization of drilling parameters using Taguchi technique and response surface methodology (RSM) in drilling of AISI 304 steel with cryogenically treated HSS drills. *Journal of Intelligent Manufacturing,* 26 (2), 295-305.

Dash, R. N., Mohammed, H., & Humairab, T. (2016). An integrated Taguchi and response surface methodological approach for the optimization of an HPLC method to determine glimepiride in a supersaturatable self-nanoemulsifying formulation. *Saudi Pharmaceutical Journal,* 24 (1), 92–103.

Datta, S., & Mahapatra, S. (2010). Modeling, simulation and parametric optimization of wire EDM process using response surface methodology coupled with grey-Taguchi technique. *International Journal of Engineering, Science and Technology,* 2 (5), 162-183.

De Feo, J., & Bar-El, Z. (2002). Creating strategic change more efficiently with a new Design for Six Sigma process. *Journal of Change Management,* 3 (1), 60–80.

Dubey, A., & Yadava, V. (2008). Multi-objective optimisation of laser beam cutting process. *Optics & Laser Technology*, p. 562–570.

Hoerl, R. (2004). One perspective on the future of Six Sigma. *International Journal of Six Sigma and Competitive Advantage ,* 1 (1), 112–119.

Jen S. Shang, S. L. (2004). Operational Design of a Supply Chain system using the Taguchi method, response surface methodology, simulation, and optimization. *International Journal of Production Research*, 42 (18), 3823-3849.

Koch, P. (2002). Probabilistic Design: Optimizing for six sigma quality. *43rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, Structures, Structural Dynamics, and Materials and Co-located Conferences.* American Institute of Aeronautics and Astronautics, Denver, Colorado

Koch, P. N., Simpson, T. W., Allen, J. K., & Mistree, F. (1999). Statistical Approximations for Multidisciplinary Design Optimization: The Problem of Size. *Journal of Aircraft,* 36 (1), 275-286.

Koch, P. N., Wujek, B., & Simpson, O. G. (2002). Facilitating Probabilistic Multidisciplinary design optimization using kriging approximation models. *9th AIAA/ISSMO symposium on multidisciplinary Analysis and Optimization.* Atlanta, Georgia.

Koch, P. N., Yang, R., & Gu, L. (2004). Design for six sigma through robust optimization. *Journal Structural and Multidisciplinary Optimization,* 26 (3-4), 235-248.

Muhammad, N., Manurung, Y.H.P., Hafidzi, M. et al. (2012). Optimization and modeling of spot welding parameters with simultaneous multiple response consideration using multi-objective Taguchi method and RSM. *Journal of Mechanical Science and Technology,* 26 (8), 2365–2370.

Myers, R. H., Montgomery, D. C., Vining, G. G., Borror, C. M., & Kowalski, S. M. (2004). Response Surface Methodology: A Retrospective and Literature Survey, *Journal of Quality Technology*, 36 (1), 53-77.

Myers, R., Montgomery, C., & Anderson-Cook, C. (2016). *Response Surface Methodology: Process and Product Optimization Using Designed Experiments.* John Wiley & Sons.

Palanikumar, K. (2008). Application of Taguchi and response surface methodologies for surface roughness in machining glass fiber reinforced plastics by PCD tooling. *The International Journal of Advanced Manufacturing Technology*, 36 (1), 19–27.

Palanikumar, K., & Karthikeyan, R. (2006). Optimal machining conditions for turning of particulate metal matrix composities using Taguchi and Response Surface Methodologies. *Machining Science and Technology,* 10 (4), 417-433.

Patil, V. S., Andhale, S. R., & Paul, I. D. (2013). A Review of DFSS: Methodology, Implementation and Future Research. *International Journal of Innovations in Engineering and Technology; 2 (1)*, 369-375.

Phadke, M. S. (1989). *Quality Engineering Using Robust Design.* Prentice Hall PTR, USA

Pignatiello, J. J. (1988). An Overview of the Strategy and Tactics of Taguchi. *IIE Transactions*, 20 (3), 247-254.

Raissi, S., & Eslami Farsani, R. (2009). Statistical Process Optimization Through Multi-Response Surface Methodology. *International Journal of Mathematical, Computational, Physical, Electrical and Computer Engineering,* 3 (3), 197-201.

Rowlands, H., & Antony, J. (2003). Application of design of experiments to a spot welding process. *Assembly Automation,* 23 (3), 273-279.

Sarıkaya, M., & Güllü, A. (2014). Taguchi design and response surface methodology based analysis of machining parameters in CNC turning under MQL. *Journal of Cleaner Production*, 65, 604-616.

Simpson, T. W., Peplinski, J., & Koch, P. a. (2001). Metamodel for Computer-based Engineering Design: Survey and reccommendations. *Engineering with Computers*, 17, 129-150.

Sleeper, A. D. (2005). *Design for Six Sigma Statistics: 59 Tools for Diagnosing and Solving Problems in DFFS Initiatives.* McGraw-Hill, New York

Treichler, D., Carmichael, R., Kusmanoff, A., Lewis, J., & Berthiez, G. (2002, January). Design for six sigma: 15 lesson learned. *Quality Progress*, 33-42.

Usman, Asad, Chakraborty, Ayon, Chuan, & Chuan, K. (2006). Comparative study of DFSS in product and service innovation. *Proceedings Asian Network for Quality Congress 2006 Singapore.* ANQ, Singapore.

Wysk, R. A., Niebel, B. W., Cohen, P. H., & Simpson, T. W. (2000). *Manufacturing Processes: Integrated Product and Process Design.* McGraw Hill, New York: